Institut für Lebensmittel- und Ressourcenökonomik (ILR)

Characterizing and assessing drought risks for agricultural systems

Integrating socioecological approaches at global and national levels

Dissertation

zur Erlangung des Grades

Doktorin der Agrarwissenschaften (Dr. agr.)

der Landwirtschaftlichen Fakultät

der Rheinischen Friedrich-Wilhelms-Universität Bonn

von

Maria Isabel Meza Rodriguez

aus

Jalisco, Mexiko

Bonn 2024

Referent: *Prof. Dr. Jakob Rhyner*
Korreferentin: Prof. *Dr. Zita Sebesvari*

Tag der mündlichen Prüfung: 22.04.2024

Angefertigt mit Genehmigung der Landwirtschaftlichen Fakultät der Universität Bonn

Acknowledgements

I would like to acknowledge many people that have supported me during this journey. Those who without their support, guidance and inspiration this thesis would not have been written.

To my supervisors, Prof Dr Jakob Rhyner and Dr Zita Sebesvari, many thanks for your understanding, support and guidance on the thesis. Thanks for trusting me and providing a patient guidance on my research. I would like to express a special gratitude to Dr Michael Hagenlocher, thanks for making me part of this amazing project, thanks for believing in my capacity and for teaching me many things. I will always be grateful for the opportunity to work together and learn from someone like you! Thanks for always being there and supporting me until the last part of this research, your invaluable mentorship has been an important driving force behind the completion of this research.

I would like to thank the German Federal Ministry of Education and Research (BMBF) for providing financial support on the research as part of the project GlobeDrought (grant no. 02WGR1457A-F) through its Global Resource Water (GRoW) funding initiative. I also extend my gratitude to my GlobeDrought colleagues. I always felt supported by the other institution colleagues and also learned a lot from you. Thanks also to the external people that I met and were important part of this journey, especially Dr. Gustavo Naumann and Dr Jürgen V. Vogt, from the JRC, the University of Free State and the National Disaster Management Centre (NDMC) in South Africa.

My warm gratitude goes to my UNU-EHS colleagues many thanks for your support, friendship, trust, and hugs. You really made my time at UNU very special; thanks for being more than amazing colleagues! I am grateful beyond words to all the great friends I got there and all the things I learned with you. Thanks also to my WWF colleagues, especially Maria Walsh, for always being supportive and remembering the important deadlines. A special thanks go also to Eric Walsh for proofreading and providing inputs to this thesis.

I would like to close with a special thank to my family, to Carlos, for listening to me and always providing your loving advice. Thank the countless individuals that I have in my life during this journey. I am very lucky to be surrounded by such amazing people!

Table of Contents

List of Figures

List of Tables

Abstract

Droughts are complex, multifaceted hazards that affect many regions of the world. They cascade through socioecological systems at different scales and cause severe environmental and social impacts. Agriculture bears much of the impact and, in many countries, it is the most heavily affected sector. As agricultural systems are social-ecological systems characterised by close human-environmental interaction, drought risk assessments for agricultural systems should be based on a socioecological system's perspective. Despite this, comprehensive drought risk assessments that consider the complex interaction of drought hazards, exposure, and vulnerability factors with a social-ecological approach are still the exception. Addressing this gap, this thesis presents for the first time an integrated assessment of drought risk for both irrigated and rainfed agricultural systems at the global and national scales. At the global scale, composite hazard indicators were calculated for irrigated and rainfed systems separately using different drought indices based on historical climate conditions. Exposure was analysed for irrigated and non-irrigated crops. Vulnerability was assessed through a socioecological-system (SES) perspective, using socioecological susceptibility and lack of coping-capacity indicators weighed by drought experts from around the world.

The findings of the global assessment show that drought risk of rainfed and irrigated agricultural systems displays a heterogeneous pattern at the global level, with higher risk for southeastern Europe as well as northern and southern Africa (e.g., South Africa and Zimbabwe). In fact, environmental and socioeconomic factors in South Africa's and Zimbabwe's agricultural systems have been affected by drought in the past, creating cascading pressures on the nation's agro-economic and water supply systems. To understand the key drivers of drought risk and to inform proactive drought risk management, a sub-national level drought risk assessment is also presented for both countries. This assessment pioneered national-level assessments for irrigated and rainfed systems that take into account the complex interaction between different risk components, using modelling and remote sensing approaches and involving national experts in selecting vulnerability indicators and providing information on human and natural drivers.

Recognising that global drought risk assessments have been conducted to highlight the regions or countries most at risk, and that their outcomes are deemed useful to inform adaptation finance decisions, this thesis also compares the outcomes of global and regional drought risk assessments for different clusters of countries of particular relevance to international climate and disaster risk policy. The findings highlight the importance of analysing

risk at multiple spatial scales to ensure no country is "left behind" in global risk and adaptation finance decisions.

Finally, the thesis discusses a systemic perspective as a way forward to assess and manage drought risks effectively. A novel drought risk framework that highlights the systemic nature of drought risks is presented. This thesis highlights the need for solutions to tackle the growing drought risks that not only consider the underlying drivers of drought risks for different sectors, systems or regions but also require an understanding of sector/system interdependencies, feedback, dynamics, compounding and concurring hazards, as well as possible tipping points and globally and/or regionally networked risks.

Zusammenfassung

Dürren bergen komplexe, vielschichtige Gefahren (‚hazards'), die viele Regionen der Welt betreffen. Sie wirken sich auf verschiedenen Ebenen von sozioökologische Systemen aus und verursachen schwerwiegende ökologische und soziale Folgen. Einen Großteil dieser Folgen trägt die Landwirtschaft. Diese ist in vielen Ländern auch der am stärksten betroffene Sektor. Bei landwirtschaftlichen Systemen handelt es sich um sozial-ökologische Systeme, die durch eine enge Interaktion zwischenMensch und Umwelt gekennzeichnet sind. Daher sollten auch Dürrerisikobewertungen für landwirtschaftliche Systeme eine sozio-ökologische Systemperspektive berücksichtigen. Trotzdem sind umfassende Dürrerisikobewertungen, die die komplexen Wechselwirkungen zwischen Gefahr (‚hazards') , Exposition (‚exposure') und Vulnerabilität (‚vulnerability')mit einem sozial-ökologischen Ansatz berücksichtigen, immer noch die Ausnahme. Um diese Lücke zu schließen, wird in dieser Arbeit zum ersten Mal eine integrierte Bewertung des Dürrerisikos sowohl für bewässerte als auch für regengespeiste landwirtschaftliche Systeme auf globaler und nationaler Ebene vorgestellt. Auf globaler Ebene wurden zusammengesetzte Gefahrenindikatoren für bewässerte und regengespeiste Systeme getrennt berechnet, wobei verschiedene Dürreindexe auf der Grundlage historischer Klimabedingungen verwendet wurden. Die Exposition wurde für bewässerte und unbewässerte Kulturpflanzen analysiert. Die Vulnerabilität wurde aus der Perspektive des sozio-ökologischen Systems (SES) bewertet, wobei Indikatoren für sozio-ökologische Vulnerabilität und fehlende Bewältigungskapazitäten verwendet wurden, die von Dürreexperten aus aller Welt gewichtet wurden.

Die Ergebnisse der globalen Bewertung zeigen, dass das Dürrerisiko von regengespeisten und bewässerten landwirtschaftlichen Systemen auf globaler Ebene ein heterogenes Muster aufweist, mit einem höheren Risiko für Südosteuropa sowie für das nördliche und südliche Afrika (z. B. Südafrika und Simbabwe). In der Tat waren die Umwelt- und sozioökonomischen Faktoren in den landwirtschaftlichen Systemen Südafrikas und Simbabwes in der Vergangenheit von Dürre betroffen, was zu einer kaskadierendenBelastung der agrarökonomischen und wasserwirtschaftlichen Systeme der Länder führte. Um die wichtigsten Faktoren für das Dürrerisiko zu verstehen und Informationen für ein proaktives Dürrerisikomanagement zu erhalten, wird für Südafrika und Simbabwe auch eine Bewertung des Dürrerisikos auf subnationaler Ebene vorgelegt. Mit dieser Bewertung wurde auf nationaler Ebene für bewässerte und regengespeiste Systeme Pionierarbeit geleistet, denn sie berücksichtigt die komplexen Wechselwirkungen zwischen verschiedenen Risikokomponenten, nutzt Modellierungs- und Fernerkundungsansätze und bezieht nationale

Experten in die Auswahl von Vulnerabiliätsindikatoren und die Bereitstellung von Informationen über menschliche und natürliche Faktoren mit ein.

In Anerkennung der Tatsache, dass globale Dürrerisikobewertungen durchgeführt wurden, um die am stärksten gefährdeten Regionen oder Länder hervorzuheben, und deren Ergebnisse als nützlich erachtet werden, um Entscheidungen zur Anpassungsfinanzierung zu treffen, werden in dieser Arbeit auch die Ergebnisse globaler und regionaler Dürrerisikobewertungen für verschiedene Ländergruppen verglichen, die für die internationale Klima- und Katastrophenrisikopolitik von besonderer Bedeutung sind. Die Ergebnisse verdeutlichen, wie wichtig es ist, das Risiko auf mehreren räumlichen Ebenen zu analysieren, um sicherzustellen, dass kein Land bei globalen Risiko- und Anpassungsfinanzierungsentscheidungen "zurückgelassen" wird.

Abschließend wird in dieser Arbeit eine systemische Perspektive erörtert, die eine wirksame Bewertung und Bewältigung von Dürrerisiken ermöglichen soll. Es wird ein neues Rahmenwerk für Dürrerisiken vorgestellt, der den systemischen Charakter von Dürrerisiken hervorhebt. Diese These unterstreicht die Notwendigkeit von Lösungen zur Bewältigung der zunehmenden Dürrerisiken, die nicht nur die zugrunde liegenden Faktoren für Dürrerisiken in verschiedenen Sektoren, Systemen oder Regionen berücksichtigen, sondern auch ein Verständnis der gegenseitigen Abhängigkeiten von Sektoren/Systemen, Rückkopplungen, Dynamiken, sich verstärkenden und konkurrierenden Gefahren sowie möglicher Kipppunkte und global und/oder regional vernetzten Risiken erfordern.

1. Introduction

1.1. Research background and problem statement

Drought is a recurrent global phenomenon considered one of the most complex hazards with manifold cascading impacts on many sectors - including agriculture, water supply energy production, water-borne transportation, among others - communities, ecosystems, and economies. It is generally defined as an exceptional and sustained lack of water caused by a deviation from normal conditions over a given region, which is long enough to cause a serious hydrological imbalance (IPCC, 2012; Van Loon et al., 2016; Schwalm et al., 2017). Due to the strong influence of human activities on the water balance, droughts are the result of a complex interplay between natural and anthropogenic processes.

Drought propagates through the hydrological cycle and will likely have more impacts on ecosystem services and human activities as the propagation in the hydrological cycle advances (UNDRR, 2021). While droughts can develop gradually over several months, they can also act as a sudden trigger for famine or ecosystem loss when an ecological or social tipping point is crossed (Hagenlocher et al., 2023). Drought can affect different systems at the same time, but sometimes also asynchronously, including propagation from one sector to another creating cascading effects (Brunner & Tallaksen, 2019, UNDRR, 2021, Hagenlocher et al., 2023). In fact, drought is the most significant of all natural hazards when measured in terms of the number of people affected (WMO, 2021; Guha-Sapir, D. et al., 2023, UNDRR 2021). Moreover, according to the IPCC, (2023) drought occurrence as a result of climate change is projected to increase across the continents and several regions (i.e. Southern Europe and the Mediterranean, central Europe, central America and Mexico, north-east Brazil, and southern Africa) and become more common in many susceptible parts of the world, particularly in areas with rapid population growth, vulnerable populations, and food security issues (CRED & UNDRR, 2020, Cook et al., 2020; Spinoni et al., 2020).

To obtain an overview of the potential impacts of droughts and to represent the different aspects of it, droughts are often characterised in terms of their frequency, magnitude or severity, duration, intensity and extent (Zargar et al., 2011, UNDRR, 2021). However, severe droughts in recent years have clearly shown that impacts associated with droughts are not only linked to the onset, duration, severity and frequency of drought events. Instead, the risk of drought impacts depends on the degree of exposure, the intrinsic and dynamic vulnerability conditions of a given socioecological system (SES), as well as adaptation decisions and their interconnectedness (Wens et al., 2019; Hagenlocher et al., 2023).

While many sectors are affected by drought, agriculture's high dependency on water makes it particularly susceptible and it is often the first of the most heavily affected sectors (Dilley et al., 2005; UNDRR, 2019), threatening the livelihoods of many, and hampering the achievement of the Sustainable Development Goals. In fact, 82 per cent of all drought-related losses and damages globally between 2008 and 2018 are concentrated in the agricultural sector (FAO, 2021). Furthermore, drought is considered a major driver of crop yield volatility, with direct impacts in reduced crop yields, leading to substantial financial losses (Bucheli et al., 2021). With nearly 866 million people (i.e. 27% of the global workforce) employed in agriculture (FAO, 2022), droughts are putting the livelihoods of many at risk.

Diverse authors have been assessing and proposing new methodologies to capture drought risk in agricultural systems better. However, most of the assessments are focused just on the hazard (Blauhut, 2020; Hagenlocher et al., 2019) and the most used conceptual frameworks aiming to explain the propagation from drought hazards to drought impacts (Van Loon et al., 2016; Wilhite & Glantz, 1985) also remain primarily hazard-focused and do not consider systematically the exposure and vulnerability of the assets of potentially affected sectors and their associated socioecological systems (SES). This is particularly relevant, especially when assessing drought risk in the context of agricultural systems, which are, by definition, themselves SES. An SES perspective can help to better understand the role of ecosystems and their regulating services as an opportunity for drought risk reduction (Kloos and Renaud, 2016).

Given the characteristics, complexities, and cascading impacts of drought risks, no country is immune to drought (UN-Water 2021) and the need to identify pathways towards more drought-resilient societies remains a global priority of many different political agendas (e.g. Sendai Framework for Disaster Risk Reduction (UN, 2015), the Integrated Drought Management Programme (https://www.droughtmanagement.info), the UNCCD 2018/19 Drought Initiative (https://www.unccd.int/actions/drought-initiative) and the GAR Special Report on Drought 2021 (UNDRR, 2021)).

Developing adequate risk management strategies to reduce drought's social and ecological impacts is essential to understanding droughts' physical and socioecological drivers. This includes how droughts propagate through the water cycle, as well as the related societal and environmental vulnerabilities of different actors, sectors, and systems (UNDRR, 2021). As the decisions made by national stakeholders might differ from those made by international stakeholders and policymakers, assessing drought risk at different scales ensures that the information is actionable at the relevant level and enables the development of appropriate mitigation and adaptation strategies (Tijdeman et al., 2022). While global assessments are important to highlight drought risk hotspots and guide initial assistance decisions, in-depth, country-level assessments are also necessary. Relying solely on global assessments can limit and potentially bias the ability of decision-makers, regional organisations, and funding mechanisms to focus their assistance efforts in an equitable and effective manner (King-Okumu et al., 2020; Dudley et al., 2022). Understanding and then reducing the impacts of drought will contribute to achieving SDGs such as poverty reduction, zero hunger, good health and well-being, clean water and sanitation, and sustainable cities and communities (UNDRR, 2021).

While major progress has been made in mapping, predicting, and monitoring drought events at different spatial scales (local to global), comprehensive drought risk assessments that consider the complex interaction of drought hazards, exposure, and vulnerability factors with an SES approach are still the exception. According to the IPCC (2014), for effective development of targeted drought risk reduction, resilience and adaptation strategies, it is necessary to conduct impact or sector-specific assessments. These assessments should identify the who (e.g., farmers) and what (e.g., crops) are at risk, specify what they are at risk of (e.g., abnormally low soil moisture, rainfall deficit, below-average streamflow), and determine where and why. So far, a global and national drought risk assessment for agricultural systems which addresses these aspects and integrates hazard, exposure and vulnerability to risk for irrigated and rainfed agriculture separately at the national and sub-national scale was lacking (Meza et al., 2020, 2021 see Chapter 4).

The global scale can capture the spatial and temporal variability of drought patterns and recognise the transboundary nature of drought risks, enabling the examination of shared vulnerability drivers and the identification of potential cooperation opportunities for drought management and resilience building. By providing information on the underlying drivers and patterns of drought risk, a global-scale approach supports the identification of priority regions and provides entry points for targeted drought risk reduction and adaptation options to move towards resilient agricultural systems. Also, global assessments can encourage the exchange of knowledge and best practices amongst nations facing similar challenges, facilitating the formulation of effective adaptation strategies.

Countries with weak economies often suffer the most from the impacts of drought, given the restricted amount of resources available to deal with it proactively (Belle et al., 2017). Hence, the highest drought mortality risk arises in Sub-Saharan Africa. In contrast, regions like western and southern Europe, Central America, the Middle East, Australia, and north-eastern China have the highest economic losses (Carrão et al., 2016; Hohenthal & Minoia, 2017). Global assessments focused on drought risk of impacts on agriculture have shown that southern Africa is at particularly high risk (Carrão et al., 2016; Meza et al., 2020). Zimbabwe and South Africa are among the countries in southern Africa that are heavily affected by droughts (Jiri et al., 2017; Brazier, 2015; WFP, 2014; Makaudze & Miranda, 2010; Ndlovu, 2014; Baudoin et al., 2017; Gibberd et al., 1996; Jordaan et al., 2017a). The agricultural sector, in particular, is severely challenged by this hazard (World Bank, 2019), exposing farmers to insufficient rainfall patterns (Leichenko, 2002).

Distinguishing the risk components for irrigated and rainfed agriculture is crucial as highlighted in Meza et al. (2021), since i) rainfall deficit is the main factor impacting drought hazard for rainfed systems, whereas availability of irrigation water is more relevant for irrigated systems, ii) spatial patterns and growing periods of irrigated and rainfed crops are diverse, resulting in different exposure for different systems, iii) factors and weights affecting the vulnerability of the systems differ for irrigated and rainfed systems as the vulnerability levels may constantly change due to variability in farming systems and associated technologies. Therefore, vulnerability can differ significantly even in the same region (Downing and Bakker, 2000).

Over the past years, composite-indicator approaches have been promoted as useful tools to assess, compare, and monitor the complexity of drought risk from local to global scales (e.g., Blauhut et al., 2016; Hagenlocher et al., 2019; de Sherbinin et al., 2019; Meza et al., 2019). However, the contribution of the individual indicators in explaining drought vulnerability and ultimately the risk of sectoral drought impacts is often only weakly understood. As a result, the majority of assessments, notably at the global scale (e.g. Carrão et al., 2016), rely on equal weights for all indicators (Hagenlocher et al., 2019). As different sectors are affected in distinct ways, different indicators, weightings, and variables need to be used to characterise and assess their vulnerability according to the geographical and socioecological context (Peduzzi et al., 2009; World Bank, 2019).It is necessary to recognise the dynamics and variability in the climate, vulnerable communities, exposed elements, and the environment to understand and mitigate drought impacts and start moving towards drought-resilient agricultural systems.

1.2. Research objective and questions

To address the gaps identified in the sections above, the present thesis aims at assessing drought risk from a novel perspective - which, as opposed to the classical hazard and humancentred approach - considers, along with climate drivers, socioeconomic preconditions through a coupled perspective on socioecological systems. Also, this thesis makes a contribution to the way in which we characterise and understand drought risks (chapter 6.2) with a novel drought risk framework that highlights the systemic nature of drought risks.

Further knowledge gaps are identified in Chapter 2.4 (see Table 2.5). This thesis addresses specifically the next gaps:

Table 1.1 Summary of knowledge gaps of conceptual, methodological, and practical nature identified in chapter 2.4, and where the gaps are addressed in this thesis.

Identified gaps	Addressing the gaps
Conceptual perspective on drought risk for people	
1. Existing frameworks that explain pathways from drought hazard to impacts are hazard-centric and do not sufficiently take into account exposure and vulnerability as drivers of drought risk and impacts	1. The assessments adopted a conceptual framework(s) for characterising drought risk that defines the risk of negative impacts as a function of hazard, exposure, and vulnerability (see Chapters 3, 4). Further, chapter 6.2 proposes a novel framework.
2. Human-environmental interaction is increasingly attributed to the occurrence of droughts, but not yet well conceptualised in drought vulnerability and risk assessments	2. The thesis focuses on understanding the role of ecosystems and their services as a driver of drought risk and opportunity for increasing resilience. (see chapters 3 and 4).
Methodological perspective on assessing drought risk for people	
1. Assessments often use the same set of vulnerability indicators for different sectors, context, and scales, neglecting inherent differences	1. Research with experts and on literature was conducted to identify the most relevant vulnerability specifically for the agricultural sector at global and country levels (see chapters 3 and 4).
2. There is little evidence of relevance of individual drought vulnerability indicators as determinants of drought risk and potential impacts	2. Research on the relevance of individual drought vulnerability indicators was conducted (i.e. expert indicator weights) (see chapters 3 and 4).
Practical perspective on drought risk for people	
1. Less than half of the assessments provide entry points for potential solutions (e.g. drought risk reduction or adaptation measures)	1. Chapters 4, 5 and 6 provide guidance on how risk assessments can support the identification, planning, monitoring, and evaluation of risk reduction and adaptation strategies.

The thesis also aims at performing a drought risk assessment that considers drought exposure and vulnerability socioecological factors, complemented by spatially- and temporally-consistent hazard information. Finally, the thesis also explores which drought vulnerability indicators are the most representative for the society and the environment, and at what scale they are relevant.

The broad objective, therefore, is to develop a drought risk assessment across multiple scales at the global level and national levels, with specific analyses in Zimbabwe and South Africa by operationalising a drought risk framework that brings together a socioecological perspective as well as data from multiple sources and disciplines for rainfed and irrigated agricultural systems, taking into account relevant indicators of drought hazard, exposure and vulnerability at the global and national scale.

Specific questions are formulated in order to guide the research:

1. Which key gaps exist in understanding, characterising, and assessing drought risk?
2. What are the most relevant drought vulnerability indicators for the agricultural sector according to expert judgement?
3. What is the current drought risk at global level for agricultural systems? And which regions are most severely affected by droughts?
4. What is the current drought risk at the national level for agricultural systems in Zimbabwe and South Africa? And which regions are most severely affected by droughts?
5. How do drought risk patterns of irrigated and rainfed systems manifest when assessing them separately within agricultural systems?
6. How does considering social and ecological factors help us to understand and manage drought risk in agricultural systems?
7. What are the most relevant drought risk indicators and drivers that lead to greater impacts on the agricultural sector?
8. How does country selection bias at the global level influence the outcomes of drought risk assessments?

The link between the research questions and the different thesis chapters is shown in Figure 1.1.

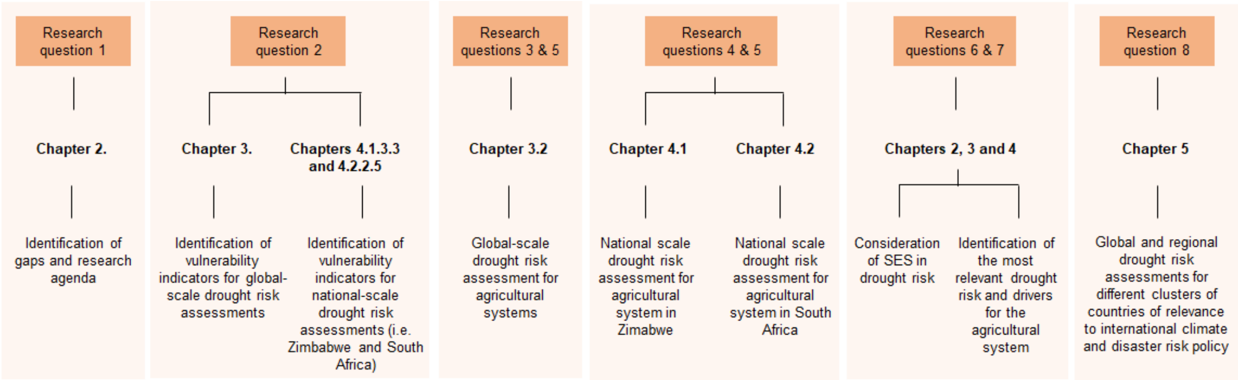


Figure 1.1. Breakdown of the research questions addressed in the different chapters of the thesis.

1.3. Study area

1.3.1. Zimbabwe

Zimbabwe faces climate-related hazards regularly, of which droughts represent the major share; other hazards, such as floods and cyclones, have less severe isolated impacts (World Bank 2019b). In fact, drought development and monitoring have received increased attention in Zimbabwe due to the devastating impacts of droughts in many parts of the country (Frischen et al., 2020). The impacts of drought expose farmers to new and unfamiliar conditions (Leichenko & O'brien 2002); in particular, smallholders growing crops under rainfed conditions are highly susceptible to drought and will be disproportionately affected due to their high dependency on climate-sensitive resources (Muzari et al., 2016; Mudzonga 2012; Makaudze & Miranda 2010).

Zimbabwe is characterised by a semi-arid climate with limited and unreliable rainfall patterns (Ndlovu et al., 2014). The cool, dry season usually lasts from April to August, whereas the hot rainy season persists from late October to March (Mutowo & Chikodzi, 2014). For detailed information regarding Zimbabwe's climatic regions, location, drought challenges, and policy relevance see Chapter 4.1.

1.3.2. South Africa

Severe drought affects Africa more than any other continent, with more than 300 events recorded in the last 100 years, accounting for 44% of the global total; more recently, sub-Saharan Africa has experienced the negative impacts of climate-related hazards becoming more frequent and intense (Taylor et al., 2017; Guha-Sapir, D. et al., 2021). In fact, in many regions of Africa, the combined impacts of climate change, accelerated population growth, and several socioeconomic factors will intensify drought hazards, exposure, and vulnerability in the long term (Ahmadalipour et al., 2019).

Drought in South Africa has led to increased unemployment and substantial water restrictions in many regions (Baudoin et al., 2017). In fact, in 2020, the South African treasury invested over USD 13 million in the Drought Relief Intervention Project (Government of South Africa, 2020). With rainfed agriculture accounting for most of the country's harvested area (Hardy et al., 2011), the agricultural sector is highly susceptible to drought. Further, agriculture is an important source of livelihood for 14% of the households in South Africa (approximately 8.5 million people), with 35% focused on crop farming (DAFF, 2018).

South Africa exhibits diverse agro-climatic regions, ranging from arid and semi-arid areas to temperate highlands. Agricultural systems range from rainfed agriculture to large-scale irrigation systems. By examining the drought risk in the different rainfed and irrigated agricultural systems, a holistic understanding of the drivers and spatial patterns of agricultural systems to drought can be explored in order to identify the implications for drought risk management. For detailed information regarding South Africa's climatic regions, location, drought challenges, and policy relevance see Chapter 4.2.2.1 (case study region).

1.4. Outline of the thesis

The thesis is organised into seven chapters, which are informed by different articles published in peer-reviewed journals as shown in Table 1.2.

Table 1.2 Structure of the thesis based on the different publications

Chapters 1 and 7	United Nations Office for Disaster Risk Reduction (2021). GAR Special Report on Drought 2021. Geneva (**Lead author**) https://www.undrr.org/media/49386/download Minor contribution
Chapter 2	Hagenlocher, M., **Meza, I.**, Anderson, C. C., Min, A., Renaud, F. G., Walz, Y., Siebert, S., & Sebesvari, Z. (2019). Drought vulnerability and risk assessments: state of the art, persistent gaps, and research agenda. https://doi.org/10.1088/1748-9326/ab225d Major contribution
Chapter 3 Subchapter 3.1	**Meza I.**, Hagenlocher M., Naumann G., Vogt J. V., Frischen J. (2019) Drought vulnerability indicators for global-scale drought risk assessments. https://doi.org/10.2760/73844 Major contribution
Chapter 3 Subchapter 3.2	**Meza I.**, Siebert, S., Döll, P., Kusche, J., Herbert, C., Rezaei, E. E., Nouri, H., Gerdener, H., Popat, E., Frischen, J., Naumann, G., Vogt, J., Walz, Y., Sebesvari, Z., & Hagenlocher, M. (2020). Global-scale drought risk assessment for agricultural systems. https://doi.org/10.5194/nhess-20-695-2020 Major contribution
Chapter 4 Subchapter 4.1	Frischen, J., **Meza, I.**, Rupp, D., Wietler, K., & Hagenlocher, M. Drought risk of agricultural systems in Zimbabwe (2020). A spatial analysis of hazard, exposure and vulnerability. Sustainability. https://doi.org/10.3390/su12030752 Major contribution
Chapter 4 Subchapter 4.2	**Meza, I.**, Rezaei, E. E., Siebert, S., Ghazaryan, G., Nouri, H., Dubovyk, O., Gerdener, H., Herbert, C., Kusche, J., Popat, E., Rhyner, J., Jordaan, A., Walz, Y., & Hagenlocher, M. (2021). Drought risk for agricultural systems in South Africa: Drivers, spatial patterns, and implications for drought risk management. https://doi.org/10.1016/j.scitotenv.2021.149505 Major contribution
Chapter 5	Dudley, A. L., **Meza, I.**, Naumann, G., & Hagenlocher, M. (2022). Do global risk assessments leave countries behind? How the selection of countries influences outcomes of drought risk assessments. https://doi.org/10.1016/j.crm.2022.100454 Major contribution
Chapter 6 Subchapter 6.1	Hagenlocher, M., Naumann, G., **Meza, I.**, Blauhut, V., Cotti, D., Döll, P., Ehlert, K., Gaupp, F., Van Loon, A. F., Marengo, J. A., Rossi, L., Sabino Siemons, A. S., Siebert, S., Tsehayu, A. T., Toreti, A., Tsegai, D., Vera, C., Vogt, J., & Wens, M. (2023). Tackling growing Drought Risks – The Need for a Systemic Perspective. https://doi.org/10.1029/2023EF003857 Major contribution

Chapter 1 presents the introduction, the research background and problem statement for drought risk assessment at global and national levels (i.e. Zimbabwe and South Africa). This chapter also presents the research objective and guiding questions. It also includes a short introduction of the Zimbabwean and South African study areas, which are further developed in Chapter 4. Chapter 1 concludes with this outline of the thesis, describing the structure of the thesis.

Chapter 2 provides a comprehensive literature review of the state of the art, persistent gaps, and research agenda in drought vulnerability and risk assessments. The systematic review of 105 research articles helps to identify persistent knowledge gaps in the field as well as to propose a research agenda to advance our understanding of drought risk and support pathways towards more drought-resilient societies. Some of these gaps, as well as the research agenda identified in this chapter are addressed in this thesis; they are highlighted in Chapter 1.2 "Research objectives and questions". Chapter 2 was published as a topical review in Environmental Research Letters with the title "Drought vulnerability and risk assessments: state of the art, persistent gaps, and research agenda".

Chapter 3 presents the assessment of drought risk for agricultural systems at global scale. The chapter is divided into two subchapters: i) chapter 3.1 presents the results of an expert survey conducted to weigh drought vulnerability indicators according to their relevance for agricultural systems and domestic water supply, in order to identify the most relevant drought vulnerability indicators for global-scale drought risk assessments. This chapter was published as a technical report with the Joint Research Centre (JRC), the European Commission's science and knowledge service. The report is entitled "Drought vulnerability indicators for global-scale drought risk assessments", and informs the global assessment in Chapter 3.2. ii) chapter 3.2 presents a global-scale drought risk assessment for agricultural systems and discusses the main findings showing that drought risk of rain-fed and irrigated agricultural systems display different heterogeneous patterns at the global level. Findings from this chapter inform the selection of the countries for the national-level assessment in Chapter 4, as the higher drought risk areas for agricultural systems are located in southeastern Europe as well as northern and southern Africa. This chapter was published as a peer-reviewed paper in the Natural Hazards Earth System Sciences (NHESS) journal.

Chapter 4 explores the drivers, spatial patterns, and implications for drought risk management for agricultural systems in Zimbabwe and South Africa. This chapter is divided into two subchapters for each country, respectively. Chapter 4.1 focuses on drought risk to agricultural systems in Zimbabwe. The chapter was published in Sustainability as a peer-reviewed paper under the title, "Drought Risk to Agricultural Systems in Zimbabwe: A Spatial Analysis of Hazard, Exposure, and Vulnerability". Chapter 4.2 focuses on drought risk to agricultural systems in South Africa; it analyses the drivers and spatial patterns of drought risk for rainfed and irrigated agricultural systems in order to identify entry points for action. The chapter was published in the journal, Science of the Total Environment, as a peer-reviewed paper entitled, "Drought Risk for Agricultural Systems in South Africa: Drivers, Spatial Patterns, and Implications for Drought Risk Management".

Chapter 5 examines the impact of selecting different clusters of countries on the outcomes of global drought risk assessments. It also discusses the limitations of global assessments and highlights the importance of analysing risk at multiple spatial scales to ensure that no country is "left behind" in global risk and adaptation finance decisions. The paper also emphasises the need for tailored risk reduction and adaptation strategies that address the most relevant elements contributing to risk in each subset of countries. The chapter was published as a peer-reviewed paper in the Climate Risk Management journal with the title, "Do global risk assessments leave countries behind? How the selection of countries influences outcomes of drought risk assessments."

Chapter 6 discusses the thesis's main findings and proposes in Chapter 6.1 a new approach to assess and manage drought risks, emphasising the interconnected nature of drought risks, impacts, and responses. The chapter was published as a commentary with the title, "Tackling Growing Drought Risks—The Need for a Systemic Perspective," in the journal Earth's Future.

Lastly, Chapter 7 provides a conclusion drawn from the previous chapters

2. Drought vulnerability and risk assessments: state of the art, persistent gaps, and research agenda

Hagenlocher, M., **Meza, I.**, Anderson, C. C., Min, A., Renaud, F. G., Walz, Y., Siebert, S., & Sebesvari, Z.

Published as topical review in Environmental Research Letters (2019):
https://doi.org/10.1088/1748-9326/ab225d

Abstract

Reducing the social, environmental, and economic impacts of droughts and identifying pathways towards drought resilient societies remains a global priority. A common understanding of the drivers of drought risk and ways in which drought impacts materialize is crucial for improved assessments and for the identification and (spatial)planning of targeted drought risk reduction and adaptation options. Over the past two decades, we have witnessed an increase in drought risk assessments across spatial and temporal scales, drawing on a multitude of conceptual foundations and methodological approaches. Recognizing the diversity of approaches in science and practice as well as the associated opportunities and challenges, we present the outcomes of a systematic literature review of the state of the art of people-centered drought vulnerability and risk conceptualization and assessments, and identify persisting gaps. Our analysis shows that, of the reviewed assessments, (i)more than 60% do not explicitly specify the type of drought hazard that is addressed, (ii)42% do not provide a clear definition of drought risk, (iii) 62% apply static, index-based approaches, (iv) 57% of the indicator- based assessments do not specify their weighting methods, (v)only 11% conduct any form of validation, (vi) only ten percent develop future scenarios of drought risk, and (vii)only about 40% of the assessments establish a direct link to drought risk reduction or adaptation strategies, i.e. consider solutions. We discuss the challenges associated with these findings for both assessment and identification of drought risk reduction measures, and identify research needs to inform future research and policy agendas in order to advance the understanding of drought risk and support pathways towards more drought resilient societies.

2.1. Introduction

Droughts are recurring slow-onset hazards that can potentially have major direct and indirect impacts on human and natural systems, including terrestrial and freshwater ecosystems, agricultural systems, public health, water supply, water quality, food security, energy, or economies (e.g. through tourism, transport on waterways, forestry) (Schwalm et al., 2017).

While drought generally refers to a lack of water compared to normal conditions (Van Loon et al., 2016), droughts are commonly grouped into four major types, including (i) meteorological or climatological, (ii) hydrological, (iii) agricultural or soil moisture, and (iv) socio-economic drought (Wilhite and Glantz 1985). They are characterized in terms of their frequency, severity, duration, and extent (Zargar et al., 2011). According to existing conceptual models (Wilhite and Glantz 1985, Van Loon et al., 2016), these drought types generally occur in a particular sequence: climate variability leads to a precipitation deficit that instigates a meteorological drought, which when combined with high potential evapotranspiration leads to an agricultural or soil moisture drought. Hydrological droughts occur as a delayed hazard associated with the effects of temperature anomalies, precipitation shortfalls, and/or anthropogenic demand pressures on surface or sub- surface water supply, such as streams, reservoirs, lakes or groundwater. Socioeconomic drought is associated with the impact of an inadequate supply of some economic goods resulting from meteorological, agricultural, and hydrological droughts (Wilhite 2000, Zargar et al., 2011, Van Loon et al., 2016, Wang et al., 2016). However, despite the progress that has been made in classifying and characterizing different drought types, no commonly accepted definition of what comprises a drought hazard exists (Mukherjee et al., 2018).

Over the past decades, drought events across the world have caused damage to human wellbeing, the environment, and the economy. While there is ambiguity regarding drought trends in the past century (Andreadis and Lettenmaier 2006, Sheffield et al., 2012, IPCC 2013, Trenberth et al., 2013, McCabe and Wolock 2015) due to a lack of direct observations and the dependency of trends on drought index choice, it is expected that drought hazards will increase in both frequency and severity in many regions across the globe in the coming decades as a result of climate change (Sheffield and Wood 2008, Dai 2011, IPCC 2012, Trenberth et al., 2013, UNCCD 2016). Despite the high uncertainty regarding future trends, risk assessments are needed in order to understand and ultimately reduce the risk of negative impacts associated with droughts.

Today it is widely acknowledged that risk, i.e. the potential for adverse impacts or consequences, is not driven only by natural hazards (droughts, floods, etc), but results from the interaction of hazards, exposure, and vulnerability (IPCC 2012, 2014). According to the Intergovernmental Panel on Climate Change (IPCC), exposure in this context refers to the 'presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places that could be adversely affected' by such hazards (IPCC 2014, p 5). Vulnerability is the predisposition to be adversely affected, resulting from the sensitivity or susceptibility of a system and its elements to harm combined with a lack of short-term coping capacity and long-term adaptive capacity (IPCC 2014). Due to its complex, multi-dimensional nature (Turner et al., 2003, IPCC 2014), drought risk can therefore not be adequately represented solely by a single factor or variable, such as a rainfall deficiency or poverty (Chambers 1989). Rather, it is often driven by a variety of context and impact-specific factors, including environmental, social, economic, cultural, physical and/or governance-related aspects (Birkmann et al., 2013, Hagenlocher and Castro 2015).

Cross-sectoral and impact-specific assessments of who and what (e.g. people, agricultural land) is at risk to what (e.g. meteorological or soil moisture drought), as well as where and why, will be key for the identification of targeted drought risk reduction, resilience- building, and drought adaptation strategies (IPCC 2014, González Tánago et al., 2016, UNCCD 2016). The need to understand, assess, and monitor drought risk is underscored by relevant international agreements and initiatives such as the Sendai Framework for Disaster Risk Reduction 2015–2030[1] (UNISDR 2015) or the 2018/19 UNCCD Drought Initiative[2]. A range of approaches exist for assessing vulnerability and risk in the context of climate change and natural hazards such as droughts. These include quantitative, qualitative, and increasingly mixed-methods approaches that combine both (Schneiderbauer et al., 2017). Promoting and integrating a plurality of approaches can produce complementary information to better explain the complexity of processes that mediate vulnerability and risk. The choice of the approach depends not only on the scale of analysis (local to global), but also on the scope of the assessment, such as understanding root causes, identifying spatial and temporal patterns and hotspots of risk, etc. Qualitative vulnerability and risk analysis often makes use of a wide array of data collection techniques such as interviews, focus group discussions (FDGs), or storylines to reveal context-specific root causes of risk. In contrast, quantitative assessments tend to apply criteria and indicators to assess vulnerability and risk, often in a spatially explicit manner.

In addition to assessing current patterns of risk such as risk hotspots, the analysis of past trends and dynamics and the development of future scenarios in vulnerability and risk have sparked increasing interest and attention in recent years for a number of reasons. The analysis of past trends or risk dynamics through repeated risk assessments can support the monitoring and evaluation of risk reduction and adaptation options (Hagenlocher et al., 2018b). Future

---

[1] The Sendai Framework for Disaster Risk Reduction (2015–2030) is a 15 year non-binding agreement adopted by UN member states that serves as a road map for disaster risk reduction until 2030.

[2] The UNCCD Drought Initiative (2018/2019) promotes the development of national drought risk management plans.

risk scenarios can provide useful inputs for precautionary, preventive, and adaptive planning (Garschagen and Kraas 2010, Birkmann et al., 2015). A recent review of climate risk assessments concluded that while the number of studies that include temporal dynamics is growing, the majority of future-oriented assessments do not consider scenarios of exposure and vulnerability (Jurgilevich et al., 2017) instead focusing on the hazard element of the risk concept.

Many of the steps in quantitative drought risk assessments, such as data imputation, outlier treatment, normalization, weighting of indicators or proxies, and aggregation, introduce uncertainty into the modeling/analysis result. Statistical validation—in the form of both sensitivity/uncertainty analysis and the regression of risk assessment outcomes against observed impacts or losses (e.g. crop losses, number of people affected)—has proven to provide relevant information on the reliability, validity, and methodological robustness of risk assessments and their outcomes (Schmidtlein et al., 2008, Fekete 2009, Tate 2012, 2013, Hagenlocher and Castro 2015, Welle and Birkmann 2015, Feizizadeh and Kienberger 2017). However, its application in the field of risk assessment remains largely underdeveloped.

Over the past decades, a number of review articles have been published focusing on (i) drought classifications and definitions (Mishra and Singh 2010), (ii) the assessment and monitoring of drought hazards in general (Rossi et al., 1992, Mishra and Singh 2011, Zargar et al., 2011, Li and Zhou 2014, Hao and Singh 2015, Yihdego et al., 2019), (iii) the role of remote sensing for mapping drought hazards (Belal et al., 2014, Agha- Kouchak et al., 2015), and (iv) vulnerability to drought (González Tánago et al., 2016, Zarafshani et al., 2016). However, a review of existing concepts, methods, approaches, and studies on drought vulnerability and people-centered integrated risk assessments is still lacking. This paper seeks to close this gap by analyzing the state of the art and identifying key gaps regarding the assessment of drought risk with a focus on people. Furthermore, the paper aims to evaluate to what extent existing drought risk assessments suggest potential solutions for drought risk reduction or adaptation. A synthesis of the findings informs a recommended agenda for future research.

2.2. Methods

A systematic literature review was conducted to synthesize and better understand (i) how people-centered drought risk is currently conceptualized and assessed in the scientific literature, (ii) how existing assessments are linked to the identification of drought risk reduction or adaptation strategies and measures, and (iii) what gaps and research needs exist. The following questions guided the analysis:

1. How are existing assessments distributed across geographic regions (e.g. continents, countries) and spatial scales (local to global)?

2. How is drought risk conceptualized?

3. Does each assessment specify the drought type analyzed, and if so, which type of drought hazard was considered?

4. Which drivers of vulnerability and drought risk are used in existing risk assessments?

5. Which assessment approaches (e.g., qualitative, quantitative, or mixed methods; index-based assessments versus. dynamic simulations) were used? Was sensitivity and/or uncertainty analysis or any form of validation of results applied?

6. Are temporal dynamics considered (e.g., past trends, future scenarios of drought risk) or is the focus largely on evaluating current patterns and hotspots of drought risk?

7. To what extent are assessments of drought vulnerability and risk linked to the identification and planning of drought risk reduction and/or adaptation options? When they are, which measures are proposed?

8. Which key gaps exist in understanding, characterizing, and assessing drought risk?

Peer-reviewed research articles were identified from the Web of Science and Scopus databases covering the period from January 1970 to December 2018 based on a set of pre-defined search terms focusing on people-centered drought risk assessments (table 2.1). The search was conducted between December 2017 and January 2018 and re-run during the revision process in February 2019. A systematic approach that only includes peer-reviewed articles was selected to ensure transparency, reproducibility, and quality of the analysis following an adapted workflow for systematic literature reviews as proposed by Rudel (2008), Hofmann et al., (2011) and Plummer et al., (2012).

In a second step, the titles, keywords, and abstracts of the identified articles were screened independently by three researchers and allocated to a ‘YES’, ‘NO’, or ‘PERHAPS’ list based on each author’s judgment of relevance to the search criteria. The respective decision was cross-checked by the two other researchers and assessed for its relevance for the review. Whenever an article was allocated to the PERHAPS list by one of the three authors, the full article was read by all three researchers in order to decide whether or not to include it in the review (YES list) or not (NO list), and the outcomes discussed and cross-checked. In a third step, a coding scheme focused on the aforementioned guiding questions was developed for in-depth content analysis of the final set of articles and implemented in MAXQDA software (VERBI Software 2017). Finally, the information was analyzed using descriptive and statistical methods in Excel software. The following sections are structured according to the eight questions outlined above.

In order to respond to question number four on vulnerability factors a classification scheme was developed to inform the content analysis of the articles, drawing on a scheme proposed by González Tánago et al., (2016). In a first review of factors of vulnerability in the context of droughts they grouped vulnerability factors into biophysical and socioeconomic dimensions and 11 sub-dimensions. Based on their work and the more recent grouping of drought vulnerability indicators into social, economic, and infrastructural dimensions by Carrão et al., (2016), the finale scheme

Table 2.1 Search terms and inclusion and exclusion criteria used to identify studies to be considered for this review.

Database	Search terms	
Web of Science (Topic)		drought risk OR drought vulnerab*
	AND	driver* OR factor* OR caus*
	AND	assess* OR index OR indic* OR analy* OR evaluat* OR map* OR quantif* OR monitor* OR measur* OR model* OR spatial
	AND	socioecon* OR socio-econ* OR social OR econom* OR social ecological OR socioecological OR socio-ecolog* OR SES OR environm* OR ecolog* OR politic* OR governan* OR demograph* OR institution*
	NOT	forest OR tree
Scopus (Title)		(drought AND risk) OR (drought AND vulnerability)
Inclusion criteria	· Peer-reviewed articles from January 1970 to December 2018 (no articles are listed in Scopus or Web of Science dating back to before 1976) · English literature · Articles conducting an assessment of vulnerability and drought risk for people (acknowledging that drought risk for people can be directly linked to the vulnerability of social-ecological systems)	
Exclusion criteria	· Review articles, opinion pieces, non-peer reviewed literature · Drought hazard assessments that do not consider exposure or vulnerability · Assessments focusing only on exposure, vulnerability, or risk of natural resources or ecosystems (e.g. water resources, plant/tree species, crop types, aquatic ecosystems)	

2.3. Results

2.3.1. Bibliometric analysis

Based on the systematic search protocol, a total of 1141 articles were identified, including 568 articles from Web of Science and 573 from Scopus. Following the multi-step process described above, the number of articles considered for the final review was reduced to 105 (table 2.2; Appendix A1, the appendix is also available online at stacks.iop.org/ERL/14/083002/mmedia).

Table 2.2 Number of articles initially identified and finally considered in the review

		1st review			Final review	
	Initial Search	YES	NO	PERHAPS	YES	NO
Scopus	573	73	450	46	91	478
Web of Science	568	10	530	27	14	553
Combined	1,141	83	980	73	**105**	1,031
Double counting	5					

Overall, more than 95% of the assessments were published after 2005—the year the Hyogo Framework for Action (HFA)[3] (UNISDR 2005) was adopted by 168 governments—and almost 60% of all assessments were published in the past four years, i.e. between 2015–2018 (appendix A1). This is not surprising given the strong call for risk assessments in the HFA 2005–2015 and in the Sendai Framework for Disaster Risk Reduction 2015–2030 (UNISDR 2015), which was adopted in 2015.

Figure 2.1 shows the geographic distributions, by climate zone and by spatial scale, of all the assessments reviewed. The most assessments (46%) were conducted in Asia, followed by Africa (29%) (figure 2.1), and in mainly dry (34%) or tropical (19%) climates or across climates. As such, the studies are highly concentrated in a few countries, namely China (18), India (11), the United States (9), Ethiopia (6), and Brazil (5). In terms of spatial scales, assessments at

[3] The Hyogo Framework for Action (HFA 2005–2015) 'Building the Resilience of Nations and Communities to Disasters' was endorsed by the UN General Assembly in the Resolution A/RES/60/195

following the 2005 World Disaster Reduction Conference in Hyogo, Japan. It is a 10 year plan to explain, describe and detail the work that is required from all different sectors and actors to reduce disaster losses until 2015. In 2015, the Hyogo Framework for Action was replaced by the Sendai Framework for Disaster Risk Reduction (2015–2030).

the sub-national level are dominant, with only very few studies that draw conclusions at the global or local/community level.

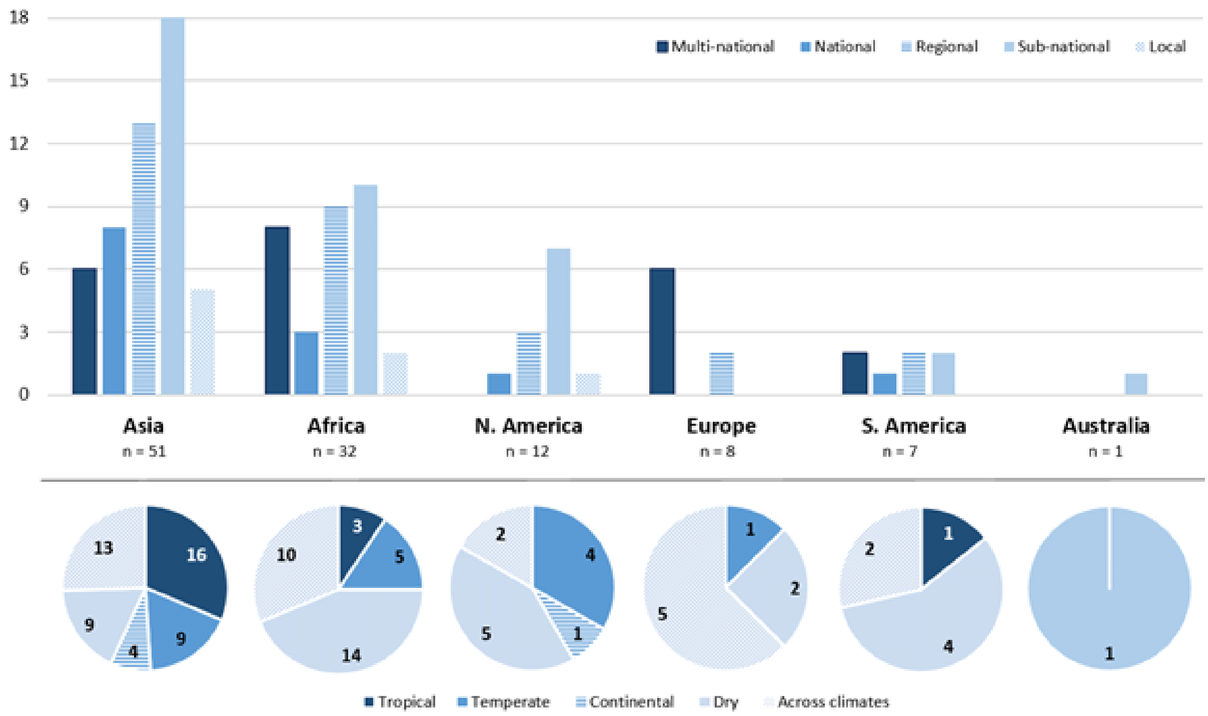


Figure 2.1. Number of drought risk assessment articles considered in this review by spatial scale and climate zone. One global assessment (Carrão et al., 2016) is excluded from this figure.

2.3.2. Conceptualization of drought risk

The review demonstrates that a variety of different risk definitions have been used as a conceptual underpinning for characterizing and assessing drought risk and highlights two contrasting developments (figure 2.2). First, there is an increasing number of studies that follow the conceptual understanding of risk as promoted by the IPCC. Second, there is an increasing number of drought risk assessments that do not specify how drought risk is conceptualized in their assessment (i.e. they do not provide any definition of risk).

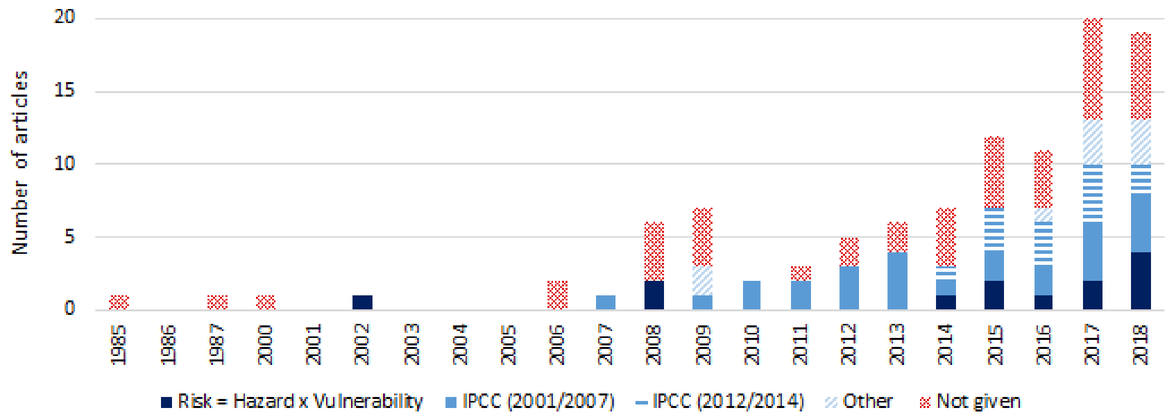


Figure 2.2 Risk definitions considered in the reviewed articles (including trend over the years).

The majority of articles that provided a definition of drought risk used the IPCC concepts of 2001 (IPCC 2001) and 2007 (IPCC 2007). However, since the publication of the IPCC SREX Report (IPCC 2012) and the subsequent Fifth Assessment Report (IPCC 2014), there has been a shift in the conceptualization of risk towards a stronger focus on assessing the risk of specific consequences or impacts that may harm a system, wherein risk is a function of (drought) hazard, exposure, and vulnerability (IPCC 2014). This has been reflected to some degree in studies assessing drought risk (Kim et al., 2015, van Duinen et al., 2015, Zhang et al., 2015, Blauhut et al., 2016, Carrão et al., 2016, Asare-Kyei et al., 2017, Bacon et al., 2017, Sena et al., 2017), although the share of assessments applying this newest concept since its release has remained fairly stable. For information on definitions classified as 'other' in figure 2.2 is provided in appendix A3.

The ambiguity in definitions is also reflected when analyzing how vulnerability—as a key component of risk in the IPCC AR5—is conceptualized and operationalized in existing drought risk assessments. Of the articles reviewed, 34% consider sensitivity and/or susceptibility, 25% consider adaptive capacities and only 14% consider coping capacity as sub-components of vulnerability. Eleven percent of all papers include drought hazard characteristics and 14% include exposure[4] as part of vulnerability.

The review reveals that although different types of drought hazards are acknowledged in the scientific literature, more than 60% of the assessments published on drought risk do not explicitly specify the type of drought hazard that is addressed (figure 2.3). This is particularly

[4] Here, exposure is understood based on the IPCC (2014) definition as 'exposed elements'. Thus, even if authors used the term 'exposure', it was not considered to have been conceptually applied if only hazard characteristics were used as proxies.

relevant for drought given that the different drought types have very different implications in terms of potential impacts and policies to mitigate these impacts (Wilhite 2000).

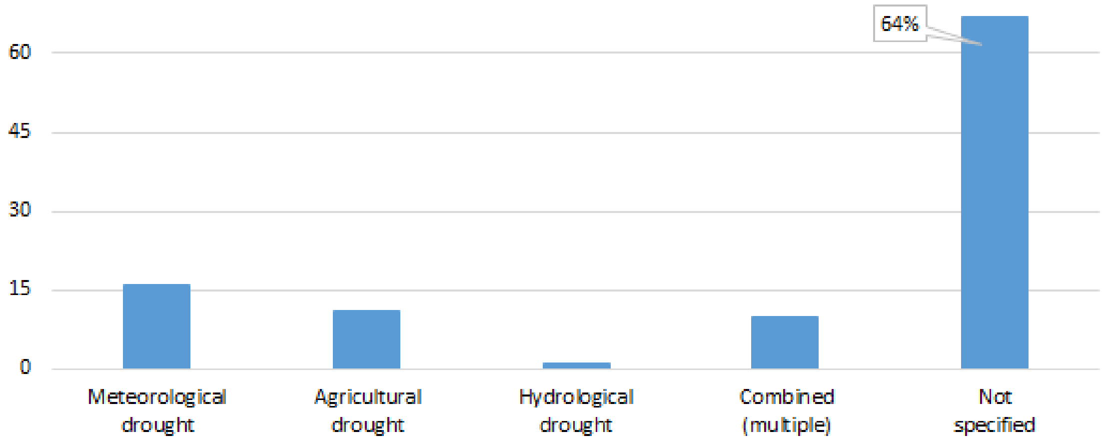


Figure 2.3. Type of drought hazard(s) explicitly considered in the 105 reviewed articles. Combined (multiple) means that multiple types of drought hazards (and associated indices) were considered in the analysis.

Although it is increasingly acknowledged that droughts cannot be seen as purely natural hazards (Van Loon et al., 2016) and there is a need to consider the complex interactions between natural and human systems when analyzing vulnerability and risk (Turner et al., 2003), the review clearly shows that the majority of existing drought vulnerability and risk assessments still focus largely on the social dimension and do not apply an integrative social-ecological systems (SES) perspective. Out of the 105 articles that were reviewed, only 18 (17%) applied an SES perspective. This confirms a persistent gap in vulnerability and risk assessments that was recently highlighted by Sebesvari et al., (2016) in their review of vulnerability assessments in coastal river deltas.

2.3.3. Assessment of drought risk

2.3.3.1. Assessment approaches

The review of existing drought risk assessments revealed that the majority of studies applied quantitative (56%) or mixed-methods (32%) approaches, while purely qualitative approaches are rather rare (11%) and have mostly been applied at the subnational level with results extrapolated to explain phenomena at broader spatial scales (Nelson and Finan 2009, Saha et al., 2012, Ayantunde et al., 2015, Birhanu et al., 2017).

In terms of assessment methodology, more than half of the assessments used an index-based approach (62%) to tackle the complexity of drought risk, followed by dynamic simulation methods (12%) and lastly the more qualitative method of using narratives or story lines (8%).

For example, Carrão et al., (2016) use a static, index-based approach to map the global patterns of drought risk by integrating hazard, exposure, and vulnerability indicators into a composite risk index. Meanwhile, Martin et al., (2016) apply a process-based, spatially-explicit social-ecological model for analyzing system dynamics contributing to drought risk for pastoral households in Morocco. In contrast, Ayantunde et al., (2015) use qualitative methods (FDGs, community workshops, seasonal calendars, etc) to analyze the patterns and causes of drought risk in three agropastoral communities in Western Africa.

2.3.3.2. Factors and indicators to characterize drought vulnerability and risk

The review of literature conducted here has revealed that factors related to poverty and income (49%), technology (47%), education levels (34%), or the availability and quality of infrastructure (34%) were deemed important drivers of vulnerability and risk by almost one third of all reviewed assessments (table 2.3).

Table 2.3. Vulnerability dimensions and sub-dimensions used in the 105 studies considered in this review.

Vulnerability dimensions and sub-dimensions (factors)	Number of papers (*n*=105)
Social	
● Education (e.g. illiteracy; indigenous and local knowledge)	34 (32%)
● Gender (e.g. gender inequality)	14 (13%)
● Social capital (e.g. social networks)	11 (10%)
● Health status (e.g. alcohol & substance use; restricted mobility/disability; malnutrition; mental health; disease prevalence)	13 (12%)
● Health services (e.g. health insurance)	7 (6%)
● Remoteness (e.g. rural/remote populations)	9 (9%)
● Awareness & information (e.g. drought awareness; early warning, access to information; underestimation of drought risk)	9 (9%)
● Water demand	8 (8%)
Economic	
● Poverty & income (e.g. income diversification; poverty; unemployment; problematic debt; dependency ratio)	49 (47%)
● Inequality	3 (3%)
● Savings, credits & loans (access to)	8 (8%)
● Markets (e.g. access to markets; market fragility)	12 (11%)
● Insurance (e.g. agricultural/animal/crop/drought insurance)	5 (5%)
Physical	
● Availability & quality of infrastructure (e.g. transportation; water & sanitation; energy; water tanks; reservoirs; wells; water quality)	34 (32%)
Crime & conflict	
● Stability (e.g. crime; war & conflict)	6 (6%)
Governance	

• Plans & strategies (e.g. drought planning and investment in disaster prevention and preparedness; water management planning)	8 (8%)
• Corruption & law enforcement (e.g. lack of trust in institutions)	3 (3%)
• Participation (e.g. public participation in governance; political representation)	6 (6%)
• Assistance (e.g. availability of food aid; development/aid projects (ODA))	6 (6%)
Environmental	
• Soil condition & quality (e.g. degradation/desertification)	15 (14%)
• Protection & conservation (e.g. protected areas; livestock health condition; soil & water conservation practices)	14 (13%)
Farming practices	
• Technology (e.g. access to technology; irrigation; use of agricultural inputs (fertilizer); fodder)	49 (47%)
• Pesticide use	2 (2%)
• Crop type (e.g. resistance; diversification)	7 (7%)

Following the classification scheme of table 2.3, 65 different indicators (18 belonging to the social dimension, 13 to the economic dimension, seven to the physical dimension, two to the crime and conflict dimension, eight to the governance dimension, nine to the environmental dimension, eight to the farming practices dimension) were identified during the review which can serve as a basis for future vulnerability and risk assessments (see appendix A2 for the complete list of indicators).

In order to identify and incorporate the potentially varying relevance and contribution of factors and indicators to vulnerability and risk in the context of natural hazards, a wide variety of weighting schemes have been developed (OECD 2008). These schemes can be categorized as being based on statistical models (e.g. regression analysis, principal component analysis) or on experts and/or community participatory consultation (e.g. ranking, budget allocation, Delphi methods). In most of the assessments reviewed here (57%) the authors did not explicitly specify their weighting methods, which is also in line with findings from a recent review of disaster risk, vulnerability, and resilience indices (Beccari 2016). Thirty-two percent of the reviewed assessments used statistical methods and ten percent used participatory, expert-based approaches.

2.3.3.3. Past trends, current patterns, and future scenarios

Fifty-four percent of the reviewed drought risk assessments are static, that is, they represent a snapshot in time. For the remaining 46%, most studies focus on assessing past trends (32%) and only 11 articles (10%) explore future scenarios of drought risk. Four percent of the articles do not specify the time frame of their analysis. Similar to other future-oriented risk assessments (e.g. in the context of sea level rise, flooding, etc)—where the focus is often on the modeling-based analysis of different hazards (Garschagen and Kraas 2010)—the review has revealed that out of the 11 articles that claim to develop future 'risk scenarios', only two studies analyzed future scenarios combining multiple risk components (hazard, exposure or vulnerability) (Melkonyan 2014, Vargas and Porter 2017). The remaining nine future-oriented assessments also focused only on future drought hazards without including future exposure or vulnerability scenarios.

2.3.3.4. Validation of risk assessments

Our analysis shows that less than 20% of the drought risk assessments reviewed here have conducted any form of validation of their results and only 12% have conducted a statistical sensitivity or uncertainty analysis. To date, only four studies (less than four percent) have conducted both a validation of the outcomes of the risk assessment against observed impacts and sensitivity analysis (Huang et al., 2014, Asare-Kyei et al., 2017, Wu et al., 2017).

2.3.4. Drought risk reduction and adaptation

Effective drought risk assessments are those that center around the ultimate objective of being used or useful for disaster risk reduction (DRR)[5] and/or adaptation[6] strategies. While strategies should be based on context-specific empirical findings—taking into account both drivers and patterns of risk—the assessments should also consider what actions individuals and institutional bodies are already taking and their effectiveness.

Less than half (40%) of the assessment papers reviewed make a direct link to drought risk reduction or adaptation strategies. Those that do comprise a wide array of structural (i.e. engineering-based or technological) and non-structural (e.g. capacity building, ecosystem-based approaches) solutions (table 2.4).

Table 2.4 Drought risk reduction and adaptation options proposed by the authors of the reviewed studies.

DRR or adaptation solution	Examples
Structural measures	● Implementation and use of irrigation infrastructure ● Water supply systems (e.g. dams, pipelines, cisterns) ● Maintenance of water supply systems (desalinization and wastewater treatment plants, reducing leakage rates) ● Early warning systems ● Farming technology (use of, investment in) (e.g. machinery)

[5] Disaster risk reduction aims at preventing new and reducing existing disaster risk and managing residual risk (based on UNISDR terminology; https://unisdr.org/we/inform/terminology).

[6] Here, adaptation refers to the process of adjustment to changing drought frequency, intensity, duration, or extent (based on IPCC 2014).

Non-structural measures (individual, household, or farm level)	● Water conservation ● Diversification of livelihood strategies ● Education and training (e.g. in water conservation, farming practices, drought awareness, drought risk management) ● Fertilizer/manure (use of, increase in) ● Pesticide/herbicide/pest control (use of, increase in) ● Migration (temporal, permanent)
Non-structural measures (government level)	● Providing better access to credits and financial instruments ● Implementation of social assistance and social protection programs ● Access to finance instruments (credit, savings, markets) ● Implementation of crop/climate risk insurance schemes ● Investment in research and development ● Water management practices/policies ● Drought, water and climate change adaptation plans/policies ● Mainstreaming indigenous and local knowledge into policy planning ● Drought/emergency response and preparedness (equipment, facilities, funds) ● Risk-informed (land use) planning
Non-structural measures (ecosystem-based)	● Soil conservation practices ● Changing farming practices (e.g. crop diversification, drought resistant crops, adjusting planting dates, climate-smart agriculture, horticulture, intercropping, rotations) ● Reclamation of degraded land ● Water harvesting ● Expanding the number and coverage of protected natural areas

2.4. Discussion: persisting gaps, and research agenda

Existing review articles on the topic so far have primarily concentrated on (i) drought concepts and definitions (Mishra and Singh 2010), (ii) indicators, methods and tools for the assessment and monitoring of drought hazards (e.g. Mishra and Singh 2011, Zargar et al., 2011, Li and Zhou 2014, Hao and Singh 2015, Yihdego et al., 2019), or more recently (iii) vulnerability to drought (González Tánago et al., 2016, Zarafshani et al., 2016). This paper complements these reviews by conducting a systematic review of people-centric drought risk assessments published between January 1970 and December 2018. Despite the boost in drought risk research over the past decades, the review has revealed and reconfirmed a number of persistent knowledge gaps of conceptual, methodological, and practical nature and relevance. In synthesizing these gaps, a number of needs have been identified that should be addressed in future research.

Table 2.5 summarizes persisting gaps and the related needs from a conceptual, methodological and practical perspective.

Table 2.5 Summary of knowledge gaps of conceptual, methodological, and practical nature and identified needs related to people-centered drought vulnerability and risk assessments that could inform future research and policy agendas.

	Gaps	Needs
Conceptual perspective on drought risk for people	1. Existing frameworks that explain pathways from drought hazard to impacts are hazard-centric and do not sufficiently take into account exposure and vulnerability as drivers of drought risk and impacts 2. Human-environmental interaction is increasingly attributed to the occurrence of droughts, but not yet well conceptualized in drought vulnerability and risk assessments	1. Adoption of conceptual framework(s) for characterizing drought risk that define risk of negative impacts as a function of hazard, exposure, and vulnerability 2. More attention should be devoted to understanding the role of ecosystems and their services as a driver of drought risk and opportunity for increasing resilience
Methodological perspective on assessing drought risk for people	1. Vulnerability and risk assessments are mostly static and do not employ dynamic approaches (e.g. simulation) to tackle the complexity of drought vulnerability and risk 2. Assessments often use the same set of vulnerability indicators for different sectors, context, and scales, neglecting inherent differences 3. There is little evidence of relevance of individual drought vulnerability indicators as determinants of drought risk and potential impacts 4. Few drought vulnerability and risk assessments conduct any form of validation	1. Further research to assess the dynamics of risk (spatial dynamics, temporal dynamics, inter-indicator relations) 2. Further research on sector, context, and scale-specific indicators and the development of an indicator library that could be used for different contexts 3. Further research on the relevance of individual drought vulnerability indicators (e.g. indicator weights) 4. Further research on validation of assessments (including technical and user validation) and analysis of the sensitivity of the contribution of individual indicators to an overall assessment

Practical perspective on drought risk for people	1. Assessments that focus on current conditions or past trends dominate; there is a lack of future scenarios of drought hazards, exposure, vulnerability, and risk (relevant for preventive planning) 2. Less than half of the assessments provide entry points for potential solutions (e.g. drought risk reduction or adaptation measures) 3. Ecosystem-based solutions for risk reduction and adaptation are underrepresented	1. Linking of future research on exposure, vulnerability and risk to scenarios of relevant planning processes and a consideration of global change 2. Provision of guidance on how risk assessments can support the identification, planning, monitoring and evaluation of risk reduction and adaptation strategies 3. Further research on the role of ecosystem-based solutions

2.4.1. Conceptual gaps and needs

Our analysis shows that more than 60% of the reviewed studies do not explicitly specify the type of drought hazard that is addressed and reconfirms that a broad variety of definitions of drought vulnerability and risk are used. This creates not only terminological and taxonomic confusion when operationalized in assessments, but also complicates the comparability of assessments and their outcomes—a gap that has also been emphasized in previous studies (Ebi and Bowen 2016, Bacon et al., 2017, Wu et al., 2017). While context is crucial and other operational definitions of risk may be more appropriate depending on region and purpose (Wilhite 2000), providing a definition is important for producing scientifically rigorous and comparable work. There is increasing recognition that the causes of drought impacts on people and factors that dictate severity are complex, interact with each other, and are often features of coupled SESs (Van Loon et al., 2016). The majority (83%) of existing people-centric drought risk assessments still focus largely on the social dimension and do not necessarily apply an integrative approach when characterizing drought hazards, vulnerability, or risk. As demonstrated in table 2.3, only 13%–14% of the reviewed articles considered factors such as soil conditions or quality or the protection of ecosystems in their assessments. Particularly when assessing drought risk in the context of agricultural systems (including people whose livelihood depends on agriculture), which are by definition SES, an SES perspective could help to understand and evaluate the role of degraded ecosystems as a driver of drought risk. Furthermore, an SES perspective can help to better understand the role of ecosystems and their regulating services as an opportunity for drought risk reduction—a gap that has also been highlighted by Asare-Kyei et al., (2017). These gaps demonstrate the need for enhanced conceptual models that underscore the complex, differential interplay between drought hazards, exposure, vulnerability, and impacts while acknowledging the relevance of human-environmental interaction in each of these components. The latest definitions put forward by the IPCC in its Fifth Assessment Report (IPCC 2014), widely acknowledged by both the DRR and climate change adaptation communities, can help to overcome the existing terminological confusion.

2.4.2. Methodological gaps and needs

When dealing with droughts, embracing complexity is necessary for understanding the multi-dimensional nature of drought risk. Over recent years, index-based approaches have been promoted as useful tools to measure, compare, and monitor the complexity of risk associated with natural hazards and climate change (Sherbinin et al., 2017) and have been gaining in popularity. Our analysis confirms this trend, with more than half of the reviewed assessments using index-based approaches (62%). However, their usefulness for policy support has also been subject to criticism (Hinkel 2011), given that indices are static in nature and do not capture the complexities and dynamics (e.g. nonlinearities and feedback loops) of vulnerability and risk (Hagenlocher et al., 2018a). It is thus crucial to develop and apply methods, such as Bayesian or system dynamics modeling, that are able to both capture complexity and deliver simple messages for policy-making and allocation of resources. The analysis has also shown that the relevance of individual hazard, exposure, and vulnerability indicators for explaining different drought impacts is poorly understood and tackled in assessments: 57% of the indicator-based risk assessments that were reviewed did not explicitly specify any weighting method. Future research should tackle this gap by exploring different ways for evaluating indicator weights (e.g. expert-based versus statistical approaches) and compare the findings by means of sensitivity analysis to evaluate the effect of weighting schemes.

Preventive planning for risk reduction and of adaptation measures requires a forward-looking perspective, and ideally should be based on different scenarios of future drought risk for a given region and impact—a need that has been increasingly emphasized over the past years (Garschagen and Kraas 2010, Birkmann et al., 2015). In addition, the monitoring of risk trends and changes in risk components and indicators over time can contribute to the monitoring and evaluation of risk reduction and adaptation measures. This has also been recently highlighted as a pressing need (Hagenlocher et al., 2018b). Interestingly, 54% of the existing drought risk assessments are static in nature, i.e. they represent a snapshot in time, while the evaluation and development of future scenarios of drought risk (ten percent of all studies) is a rather recent phenomenon (the first paper in our review to develop future scenarios was published in 2009) and heavily underdeveloped aspect. In order to support the planning of adaptation strategies, scenarios of future risk pathways—in all components of hazard, exposure, and vulnerability—are urgently required.

The validation of risk assessments presents another persisting gap given the need of decision makers and practitioners for up-to-date and reliable data and information. Despite major progress in sensitivity and uncertainty analysis in the context of risk research (Fekete 2009, Tate 2012, 2013, Feizizadeh and Kienberger 2017), our analysis has shown that less than ten percent of all risk assessments reviewed here have conducted any form of validation of their results using impact data and only 12% have conducted a statistical sensitivity or uncertainty analysis. These findings are in line with gaps identified by Asare-Kyei et al., (2017).

2.4.3. Practical gaps and needs

Risk assessments should ideally not be an end in themselves, but be linked to the identification, planning and prioritization of options for preventing and managing drought risk or adapting to changing conditions. The IPCC AR5 (IPCC 2014) identified the lack of assessments focusing on the actual implementation of adaptation measures and their potential positive or negative effects, a finding further confirmed in this review. While just under half of the studies reviewed here (40%) make a direct link to drought risk reduction or adaptation strategies, only very few of these articles consider or recommend ecosystem-based approaches, leaving the potential of nature-based solutions (NbS) for drought risk reduction and mitigation (Kloos and Renaud 2016, UN 2018) far from being realized. Hence, more research is needed to evaluate the role of ecosystems and their services not only as drivers of drought risk, but also as an option for drought risk reduction and adaptation.

2.5. Conclusions

Reducing drought risk and associated direct and indirect impacts through targeted risk reduction and adaptation has become a global priority, as reflected by recent global initiatives and frameworks (e.g. the 2018/19 UNCCD Drought Initiative, Sendai Framework for Disaster Risk Reduction 2015–2030, Sustainable Development Goals, and the upcoming 2020 GAR Special Report on Drought) as well as by the steadily increasing number of drought risk assessments over the past decades. Efforts to reduce drought risk and adapt to changing environmental conditions by prioritizing and allocating funding and resources should be based on a sound understanding, characterization, and assessment of the drivers, patterns, and past trends as well as projected future patterns of drought risk. However, despite major advances over the past decades in terms of developing better methods and tools for characterizing individual components of risk, the review has revealed and reconfirmed a number of persistent knowledge gaps—of conceptual, methodological, and practical nature—which need to be urgently confronted in order to advance the understanding of drought risk for people, improve its assessment, and support pathways towards more drought resilient societies

3. Assessing drought risk for agricultural systems at global scale

3.1. Drought vulnerability indicators for global-scale drought risk assessments

Meza I., Hagenlocher M., Naumann G., Vogt J. V., Frischen J.

Published as JRC Technical Report (2019) in EU publications: https://doi.org/10.2760/73844

Summary

Droughts are complex, multifaceted hazards that affect multiple regions of the world and cause severe environmental and social impacts. The vulnerability to droughts, however, is complex to assess and strongly depends on the sectoral focus as well as on the geographical context of the assessment. This report presents the results of an expert survey that was conducted to weigh drought vulnerability indicators according to their relevance for agricultural systems and domestic water supply. Indicators originate from multiple dimensions (social, economic, infrastructure, crime and conflict, environmental and farming practices) and are grouped into four subcategories: social susceptibility, environmental susceptibility, lack of coping capacity and lack of adaptive capacity. The findings underline that the relevance of indicators strongly varies depending on the sector which is susceptible to the negative impacts of drought. Hence, the most relevant indicators for agricultural systems differentiate significantly from the most important ones for domestic water supply. The results are used in the GlobeDrought project to include expert judgement in the vulnerability assessments. This information will be compiled together with drought hazard and exposure information into a global drought risk assessment.

3.1.1. Background

Drought risk and its related impacts depend not only on the drought hazard, but also on the exposure and vulnerability of the different socioeconomic sectors (e.g. agriculture, domestic water supply, energy production, waterborne transport, tourism) or ecosystems (e.g. wetlands, forests) (IPCC, 2014, UNDRR, 2019, Vogt et al., 2018). Cross-sectoral and impact-specific assessments of who and what (e.g. people, agricultural land) is at risk to what (e.g. meteorological or soil moisture drought), as well as where and why, can provide relevant baselines for the identification of targeted risk reduction and adaptation strategies (UNCCD, 2016).

Vulnerability is a key component of any drought risk assessment, indicating which sectors, populations or ecosystems are particularly susceptible to suffer negative impacts, but also the level of their capacity to cope with and adapt to droughts (IPCC, 2014). According to the Fifth Assessment Report (AR5, Working Group II) of the Intergovernmental Panel on Climate

Change (IPCC, 2014) vulnerability, defined as the propensity or predisposition to be adversely affected, has three components: susceptibility, coping capacity and adaptive capacity. Thereby, susceptibility is defined as the likelihood of damage in an extreme natural event (describes the structural conditions of ecosystems and society characteristics), coping capacity as the capacity of a system to properly face adverse consequences in the short term, and adaptive capacity as a longer-term process which includes adjustments in the system as part of a learning, experimentation, and change process. When assessing vulnerability in the context of droughts, it is important to go beyond the social, economic, or political dimensions of societal vulnerability, and to also take into consideration factors determining the vulnerability of natural ecosystems. Vulnerability assessments support mid- and long-term preparedness actions and water resources planning for targeted sectors and sensitive populations.

Over the past years, indicator-based approaches have been promoted as useful tools to assess, compare, and monitor the complexity of drought risk from local to global scales (e.g., Carrão et al., 2016; Blauhut et al., 2016). However, the contribution of the individual indicators to explain drought vulnerability and ultimately the risk of sectoral drought impacts is often only weakly understood. As a result, the majority of assessments, notably at the global scale (e.g. Carrão et al., 2016), are based on equal weights for all indicators. In order to address the limitation of using equal weights, a global expert survey on vulnerability indicators for global-scale, sectoral drought risk assessments was conducted from November to December 2018 as a joint effort between JRC's Global Drought Observatory (GDO) and United Nations University (UNU-EHS). The objective was to identify and weigh relevant drought vulnerability indicators with regard to potential impacts of drought hazards on agricultural systems and domestic water supply.

This report summarizes the results of the "Drought Global Expert Survey", and provides a general overview of the most relevant vulnerability indicators according to expert judgement. In addition, in-depth information on the indicator relevance is provided broken down by the expert's years of experience, gender, world region, and sector. The results will inform sectoral global drought vulnerability and risk assessments for agricultural systems and domestic water supply within the GlobeDrought project and the Global Drought Observatory (GDO).

3.1.2. Methodology

The survey was conducted using the e-encuesta online software[7]. The list of drought vulnerability indicators was derived from both a systematic literature review (Hagenlocher et

[7] https://www.e-encuesta.com/

al., 2019) and through expert consultations. In total, **64 indicators for agricultural systems** and **domestic water supply** were identified and included in the online survey.

In order to be able to synthesize expert knowledge on relevant indicators for assessing and mapping drought vulnerability at the global scale, experts from around the world were selected based on their publication track record and expertise in the field of drought risk, following the relevant literature selection proposed by Hagenlocher et al., (2019). In total, 124 experts were identified and contacted. A pre-test was run during the JRC European Drought Observatory (EDO) User Meeting 2018 which took place in October 2018 in Ispra, Italy (Spinoni et al., 2018). The pre-test has resulted in minor modifications regarding the specific wording of some of the questions.

In the online survey, experts were asked to weigh each indicator based on its relevance for drought vulnerability and the risk of negative impacts of drought on agricultural systems (incl. people, crops, livestock, etc.) and domestic water supply (survey questions are presented in the Appendix F7). A rating scale from zero to four (0 = not relevant; 4 = highly relevant) defined the level of global relevance of the different statements. An “I don’t know” option was provided for each indicator, however the answers were not considered for the assessment, since this option does not indicate the relevance of an indicator. In the online survey, experts were given the option to also suggest and weigh additional indicators.

The final selection of relevant indicators at the global level for agricultural systems and domestic water supply based on the survey results followed a two-step approach:

(1) Indicators were kept when more than 50% of the experts considered them a medium-high or highly relevant indicator

(2) Z-scores with a 95% confidence interval were applied to ensure that there was high level of agreement across experts.

The results were normalized to receive a value between 0 and 1 for each indicator. The amount of responses in each category was multiplied with the following values: not relevant*0, low relevance*0.25, low-medium relevance*0.5, medium-high relevance*0.75 and highly relevant*1. Finally, the sum was divided by the total number of answers given per indicator to receive the average. Indicators with a value close to 1 are highly relevant, whereas indicators with a value close to 0 indicate lower relevance (Figure 3.1).

3.1.3. Results

Out of the 124 experts that were initially contacted, 78 (63%) participated in the survey (incl. 45 complete and 33 partial responses). The results clearly show that the majority of experts works in academia (52%) or for governmental organizations (34%), and has more than 5 years of relevant work experience (>65%). Their geographic focus of work across continents is fairly balanced. A detailed overview about the participant's backgrounds, their experience, research fields and geographic focus of work is provided in Appendix F1. In total, the experts ranked 64 indicators according to their relevance. Table 3.1 shows the total number of indicators categorized by different vulnerability dimensions (e.g. social, economic, infrastructure), and provides an overview of how many indicators were considered as relevant by the experts.

Table 3.1 Total number of indicators proposed according to the different vulnerability dimensions and the final list of relevant indicators after the selection process.

Vulnerability dimension	Indicators weighed (N)	Final list of relevant indicators for agricultural systems (N)	Final list of relevant indicators for domestic water supply (N)
Social	18	7	9
Economic	13	11	8
Infrastructure	7	6	6
Crime & conflict	2	1	1
Governance	10	8	8
Environmental	7	5	2
Farming practices	7	7	1
TOTAL	64	45	35

Following the break-down of vulnerability into its components, as proposed by the IPCC (2014), Table 3.2 shows the number of indicators for each vulnerability component (i.e. social susceptibility, environmental ecological susceptibility, lack of coping capacity, and lack of adaptive adaptive capacity), and provides an overview of how many indicators were considered as relevant by the experts.

Table 3.2 Total number of indicators proposed according to the different vulnerability components (social susceptibility, environmental susceptibility, lack of coping capacity, lack of adaptive capacity) and the final list of relevant indicators after the selection process.

Vulnerability component	Indicators weighed (N)	Final list of relevant indicators for agricultural systems (N)	Final list of relevant indicators for domestic water supply (N)
Social susceptibility	30	21	20
Environmental susceptibility	10	8	3

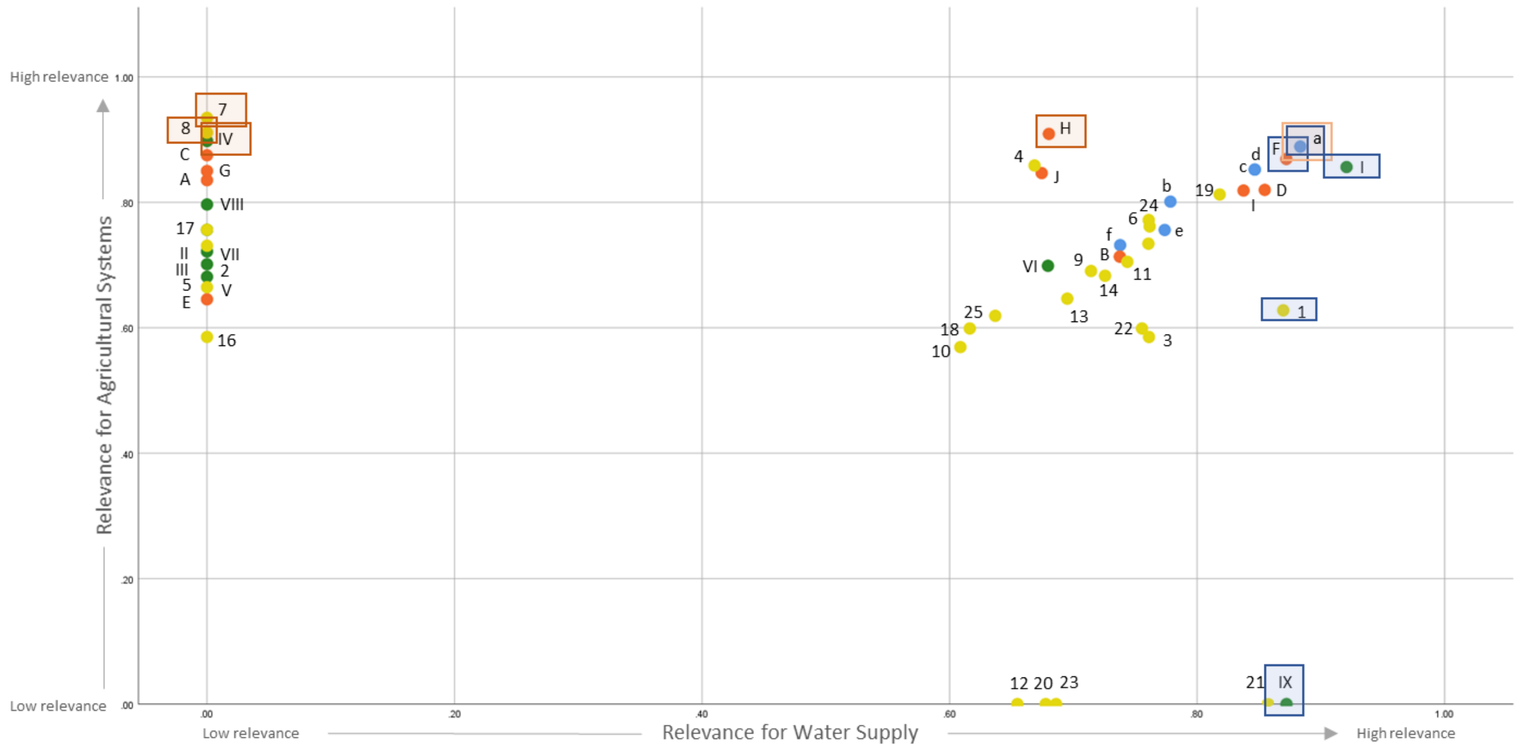
Coping capacity	17	10	6
Adaptive capacity	7	6	6
TOTAL	64	45	35

Table 3.3 shows the most and least relevant indicators for agricultural systems and water supply. The indicator 'Existence of adaptation plans and policies' is highly relevant for both sectors (Agricultural Systems: rank 4 out of 45, Water supply: rank 2 out of 35). However, the degree of relevance among other indicators varied considerably. 'Access to clean water' is the fourth most important indicator for water supply, but only on rank 39 for agricultural systems. These results clearly indicate that the vulnerability indicator selection for drought risk assessments must always be adapted to the specific context in which drought risk is assessed. A detailed overview about all indicators for agricultural systems and water supply is provided in the following graphs and in Appendix F4 and Appendix F5 respectively.

Table 3.3 Top five most relevant and least relevant indicators for agricultural systems and water supply.

	Agricultural Systems	**Water Supply**
Most relevant	1. Dependency on agriculture for livelihood	1. Baseline water stress
	2. Cultivation of drought-resistant crops	2. Existence of adaptation policies & plans
	3. Irrigated land	3. Water quality
	4. Existence of adaptation policies & plans	4. Government effectiveness
	5. Degree of land degradation and desertification	5. Access to clean water
Least relevant	41. Electricity production from hydroelectric sources	31. Expenditure on health
	42. Unemployment rate	32. Unemployment rate
	43. Population without access to (improved) sanitation	33. Population ages 15-64
	44. Population ages 15-64	34. Area protected and designated for the conservation of biodiversity
	45. Life expectancy at birth	35. Refugee population

Figure 3.1. Relevance of indicators for agricultural systems and water supply.



Social Susceptibility

1. **Access to clean water**
2. Access to fodder
3. Access to sanitation
4. Agricultural GDP
5. Agricultural machinery
6. Conflict and insecurity
7. **Dependency on agriculture**
8. **Drought-resistant crops**
9. GDP
10. Gender inequality
11. GINI index
12. Health expenditure
13. Hydroelectricity
14. Ill-health
15. Illiteracy
16. Life expectancy
17. Market fragility
18. Population ages 15-64
19. Poverty
20. Refugee population
21. Risk Perception
22. Rural population
23. Tourism
24. Undernourishment
25. Unemployment

Environmental Susceptibility

I. **Baseline water stress**
II. Fertilizer use
III. Insecticides and pesticides
IV. **Land degradation and desertification**
V. Livestock health
VI. Protected areas and biodiversity
VII. Soil depth
VIII. Soil organic matter
IX. **Water quality**

Lack of Coping Capacity

A. Access to credit
B. Corruption
C. Crop varieties
D. Dam capacity
E. Distance to markets
F. **Government effectiveness**
G. Insurance
H. **Irrigated land**
I. Retained renewable water
J. Savings

Lack of Adaptive Capacity

a. **Adaptation policies and plans**
b. Adaptation projects
c. Disaster prevention and preparedness
d. Disaster risk policies
e. Public participation in local policy
f. Research and development expenditure

Most relevant indicators for Agricultural Systems

Most relevant Indicators for Water supply

Figure 3.2. Most relevant indicators for agricultural systems by region.

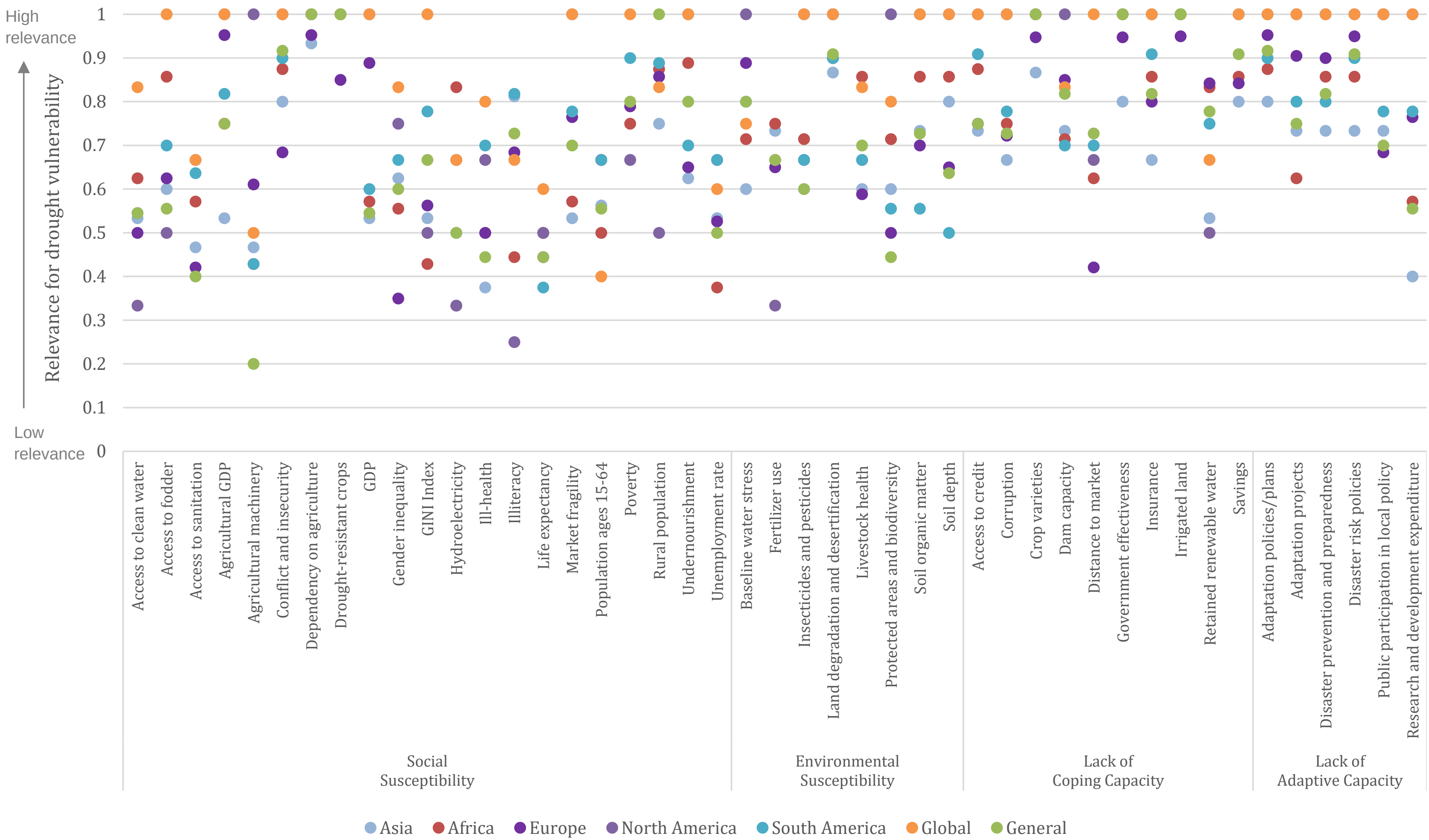
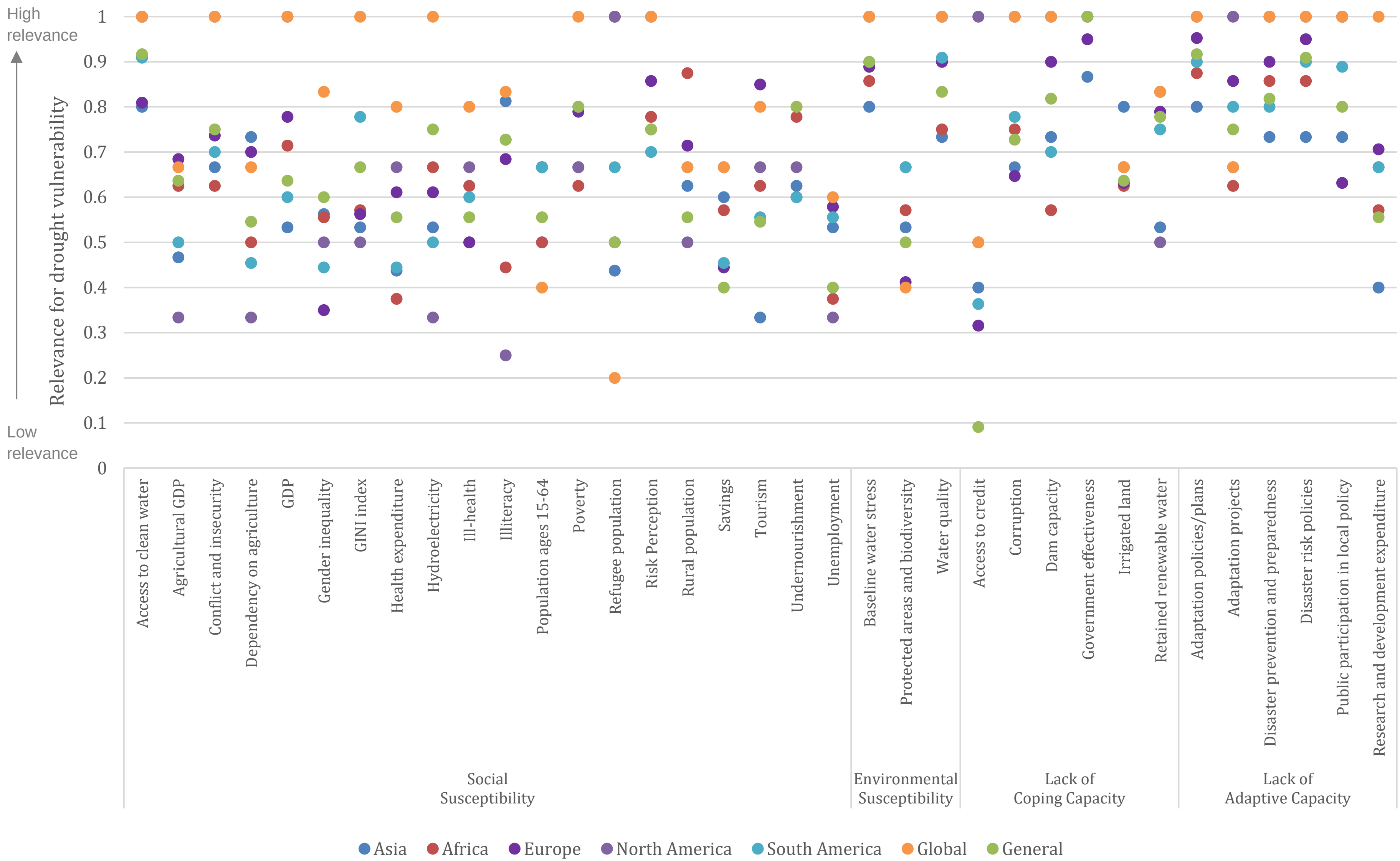


Figure 3.3. Most relevant indicators for water supply by region.



3.2. Global-scale drought risk assessment for agricultural systems

Meza I., Siebert, S., Döll, P., Kusche, J., Herbert, C., Rezaei, E. E., Nouri, H., Gerdener, H., Popat, E., Frischen, J., Naumann, G., Vogt, J., Walz, Y., Sebesvari, Z., & Hagenlocher, M.
Published as research article in Natural Hazards And Earth System Sciences (2020): https://doi.org/10.5194/nhess-20-695-2020

Summary

Droughts continue to affect ecosystems, communities and entire economies. Agriculture bears much of the impact, and in many countries it is the most heavily affected sector. Over the past decades, efforts have been made to assess drought risk at different spatial scales. Here, we present for the first time an integrated assessment of drought risk for both irrigated and rainfed agricultural systems at the global scale. Composite hazard indicators were calculated for irrigated and rainfed systems separately using different drought indices based on historical climate conditions (1980–2016). Exposure was analyzed for irrigated and non-irrigated crops. Vulnerability was assessed through a socioecological-system (SES) perspective, using socioecological susceptibility and lack of coping-capacity indicators that were weighted by drought experts from around the world. The analysis shows that drought risk of rainfed and irrigated agricultural systems displays a heterogeneous pattern at the global level, with higher risk for southeastern Europe as well as northern and southern Africa. By providing information on the drivers and spatial patterns of drought risk in all dimensions of hazard, exposure and vulnerability, the presented analysis can support the identification of tailored measures to reduce drought risk and increase the resilience of agricultural systems.

3.2.1. Introduction

Droughts exceed all other natural hazards in terms of the number of people affected and have contributed to some of the world's most severe famines (FAO, 2018; CRED and (UNISDR, 2018). Drought is conceived as an exceptional and sustained lack of water caused by a deviation from normal conditions over a certain region (Tallaksen and Van Lanen, 2004; Van Loon et al., 2016). It can have manifold impacts on social, ecological and economic systems, for instance agricultural losses, public water shortages, reduced hydropower supply, and reduced labor or productivity. While many sectors are affected by drought, agriculture's high dependency on water means it is often the first of the most heavily affected sectors (Dilley et al., 2005; UNDRR, 2019). With nearly 1.4 billion people (18 % of the global population) employed in agriculture, droughts threaten the livelihoods of many and hamper the achievement of the Sustainable Development Goals (SDGs) – notably SDG 1 (no poverty), SDG 2 (zero hunger), SDG 3 (good health and well-being) and SDG 15 (life on land). While there is ambiguity regarding global drought trends over the past century (Sheffield et al., 2012;

Trenberth et al., 2013; McCabe and Wolock, 2015), drought hazards will likely increase in many regions in the coming decades (Sheffield and Wood, 2008; Dai, 2011; Trenberth et al., 2013; Spinoni et al., 2017, 2019b; UNDRR, 2019). Identifying pathways towards more drought resilient societies therefore remains a global priority.

Recent severe droughts in southeastern Brazil (2014–2017), California (2011–2017), the Caribbean (2013–2016), northern China (2010–2011), Europe (2011, 2015, 2018), India (2016, 2019), the Horn of Africa (2011–2012), South Africa (2015–2016, 2018) and Vietnam (2016) have clearly shown that the risk of negative impacts associated with droughts is not only linked to the severity, frequency and duration of drought events but also to the degree of exposure, susceptibility and lack of coping capacity of a given socioecological system (SES). Despite this, proactive management of drought risk is still not a reality in many regions across the world. Droughts and their impacts are still mostly addressed through reactive crisis management approaches, for example, by providing relief measures (Rojas, 2018). To improve the monitoring, assessment, understanding and ultimately proactive management of drought risk effectively, we need to acknowledge that the root causes, patterns and dynamics of exposure and vulnerability need to be considered alongside climate variability in an integrated manner (Spinoni et al.,2019a; Hagenlocher et al., 2019).

Over the past decades, major efforts have been made to improve natural hazard risk assessments and their methodologies across scales, ranging from global risk assessments to local-level assessments. At the global scale several studies have been published in recent years, focusing on the assessment of flood risk (Hirabayashi et al., 2013; Ward et al., 2013, 2014), seismic risk (Silva et al., 2018), cyclone risk (Peduzzi et al., 2012) or multi-hazard risk (e.g., Dilley et al., 2005; Peduzzi et al., 2009; Welle and Birkmann, 2015; Garschagen et al., 2016; INFORM, 2019; Koks et al., 2019; UNDRR, 2019). While major progress has been made regarding the mapping, prediction and monitoring of drought events at the global scale (e.g., Yuan and Wood, 2013; Geng et al., 2013; Spinoni et al., 2013, 2019b; Damberg and AghaKouchak, 2014; Hao et al., 2014; Carrão et al., 2017), very few studies have assessed either exposure to drought hazards (Güneralp et al., 2015) or drought risk at the global level (Carrão et al., 2016; Dilley et al., 2005; Li et al., 2009). The study by Carrão et al. (2016) presents the first attempt to map drought risk at the global scale while considering drought hazard (based on precipitation deficits), exposure (population, livestock, crops, water stress) and societal vulnerability (based on social, economic and infrastructural indicators). While generic drought risk assessments are useful for establishing an overview of the key patterns and hotspots of drought risk, it is increasingly acknowledged that drought risk assessment should be tailored to the needs of specific users so that management plans can be developed to reduce impacts (Vogt et al., 2018; UNDRR, 2019). Impact or sector-specific assessments of who (e.g., farmers) and what (e.g., crops) are at risk as well as what they are at risk of (e.g., abnormally low soil moisture, deficit in rainfall, below average streamflow), where they are at risk and why are needed to inform targeted drought risk reduction, resilience and adaptation strategies (IPCC, 2014). Such analyses are currently lacking. Furthermore, in their exposure analysis, Carrão et al. (2016) do not distinguish between rainfed and irrigated agriculture, although different hazard indicators are relevant when assessing drought risk for these systems. In addition, the vulnerability analysis presented by Carrão et al. (2016) is based on a reduced set of social, economic and infrastructure-related indicators and does not account for the role of ecosystem-related indicators as a driver of drought risk – a gap that was recently highlighted in a systematic review of existing drought risk assessments across the globe (Hagenlocher et al., 2019). A socioecological-system perspective, especially when assessing drought risk in the context of agricultural systems, where livelihoods depend on ecosystems and their services, can help to better understand the role of ecosystems and their services not only as a driver of drought risk but also as an opportunity for drought risk reduction (Kloos and Renaud, 2016).

This paper addresses some of the above gaps by presenting, for the first time, an integrated drought risk assessment that brings together data from different sources and disciplines for rainfed and irrigated agricultural systems considering relevant drought hazard indicators, exposure and vulnerability at the global scale. The spatial variability in drought risk on global and regional scales might help to identify leverage points for reducing impacts and properly anticipate, adapt and move towards resilient agricultural systems.

3.2.2. Methods

Today, it is widely acknowledged that risk associated with natural hazards, climate variability and change is a function of hazard, exposure and vulnerability (IPCC, 2014; UNDRR, 2019). Following that logic, Figure 3.4 shows the overall workflow of the assessment, while the subsequent sections describe in detail how drought risk for agricultural systems, including both irrigated and rainfed systems, was assessed at the global scale.

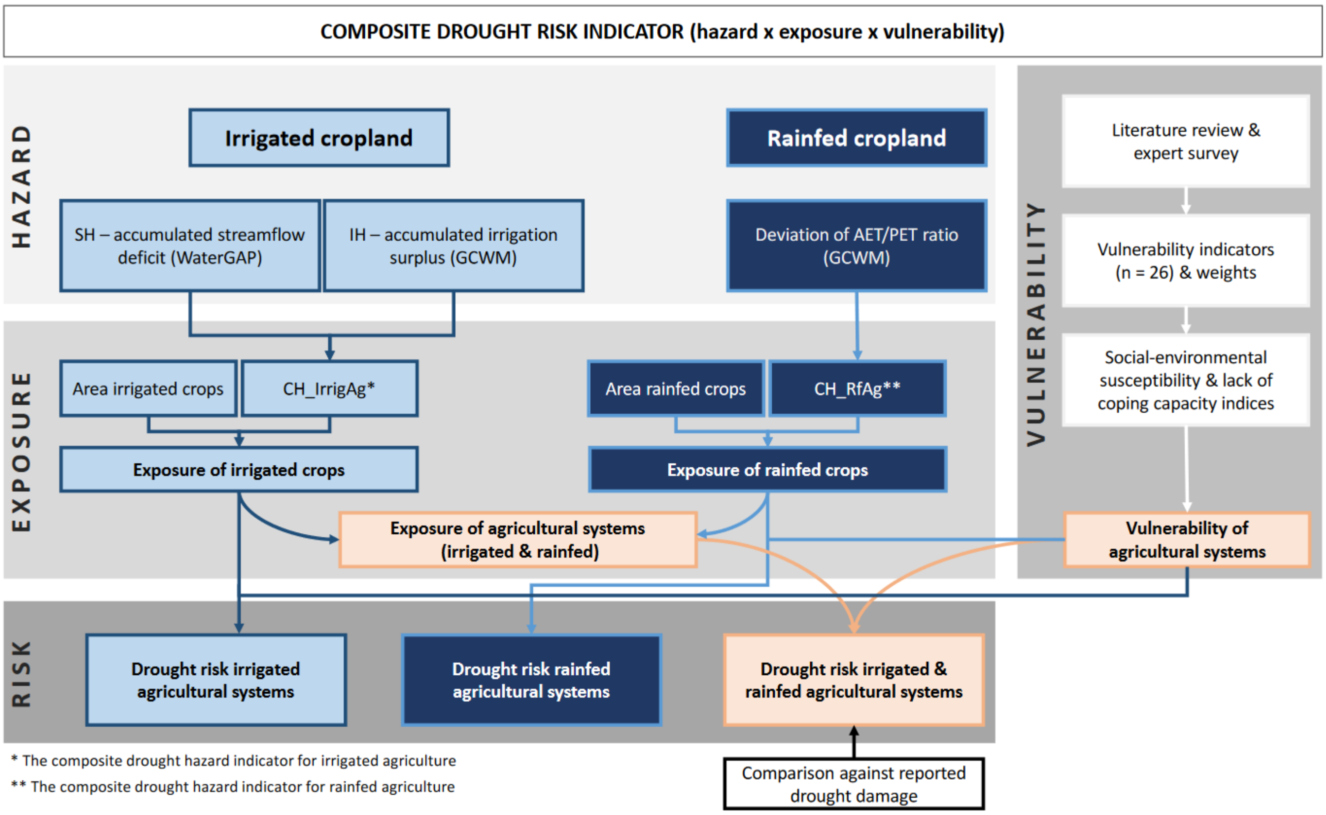


Figure 3.4. Workflow for the overall global drought risk assessment for agricultural systems (including irrigated and rain-fed systems).

The composite drought hazard indicators were calculated for irrigated and rainfed systems separately using drought indices based on historical climate conditions (1980–2016), which resulted in integrated hazard maps for both rainfed and irrigated agricultural systems, respectively. The different irrigated and non-irrigated crops by country were considered to be the exposed element. Due to the lack of high-resolution gridded data on an agricultural-dependent population at the global scale, this exposure indicator was not considered. The vulnerability component was assessed through a SES lens, where socioecological susceptibility and a lack of coping capacity indicators were weighted by drought experts around the world.

3.2.2.1. Drought hazard and exposure indicators

The drought hazard indicators considered here represent the average drought hazard during the period 1980 to 2016 in each spatial unit for which it is computed. Drought hazard is defined as a deviation of the situation in a specific year or month from long-term mean conditions in the 30-year reference period from 1986 to 2015. To quantify drought hazard for such a long period, we used the global water resources and water use model WaterGAP (Müller Schmied et al., 2014) and the global crop water model (GCWM; Siebert and Döll, 2010). The models simulate terrestrial hydrology (WaterGAP) and crop water use (GCWM) for daily time steps on a spatial resolution of 30 arcmin (WaterGAP) or 5 arcmin (GCWM). The most recent version, WaterGAP 2.2d, was forced by the WFDEI-GPCC climate data set (Weedon et al., 2014), which was developed by applying the forcing data methodology developed in the EU project WATCH on ERA-Interim reanalysis data (Table 3.4). The GCWM used the CRU-TS 3.25 climate data set (Harris et al., 2014) as input. CRU-TS 3.25 was developed by the Climate Research Unit of the University of East Anglia by interpolation of weather station observations and is provided as a time series of monthly values. Pseudo-daily climate was generated by the GCWM as described in Siebert and Döll (2010). Following the definitions of the Intergovernmental Panel on Climate Change put forward in their Fifth Assessment Report (IPCC, 2014), exposure is defined as the elements located in areas that could be adversely affected by drought hazard. The distinct exposure of irrigated and rainfed agricultural systems to drought was considered by weighting grid-cell-specific hazards with the harvested area of irrigated and rainfed crops according to the monthly irrigated and rainfed crop areas' (MIRCA2000) data set (Portmann et al., 2010) when aggregating grid-cell-specific hazards to exposure at a national scale. MIRCA2000 was also used to inform the models used in the hazard calculations about growing areas and growing periods of irrigated and rainfed crops. The data set refers to the period centered around the year 2000; time series information is not available at the global scale. To maximize the representativeness of the land use, the reference period and evaluation period used in this study were centered around the year 2000.

Table 3.4. Hazard and exposure indicators used in the analysis and their processed data

Risk component	Composite indicator	Indicator	Processed data
Drought hazard	CH_IrrigAg	Accumulated streamflow deficit	WaterGAP (1980-2016) with climate forcing WFDEI-GPCC. Streamflow monthly time series.
		Accumulated irrigation surplus	GCWM (1980-2016) with climate forcing CRU TS3.25. Monthly time series of net irrigation requirements
	CH_RfAg	AET/PET deviation ratio	GCWM (1980-2016) with climate forcing CRU TS3.25. Annual time series of the deviation of the ratio AET / PET from the long-term (1986-2015) median of the ratio AET / PET
Exposed elements	Rainfed & irrigated	Aggregation of pixel level data to national scale	MIRCA 2000 dataset was used to compute harvested area weighted averages of the indicators

3.2.2.1.1. Irrigated agricultural systems

The composite drought hazard indicator is defined as the product of mean severity and frequency of drought events. For irrigated agriculture (CH_IrrigAg) it combines an indicator for streamflow drought hazard (SH), i.e., for abnormally low streamflow in rivers, with an indicator of an abnormally high irrigation water requirement (IH; Figure 3.4). It thus considers the deviations of both demand and supply of water from normal conditions. SH and IH are computed with a spatial resolution of 0.5◦ by 0.5◦ (55 km by 55 km at the Equator). Greenland and Antarctica are excluded. As IH is not meaningful in grid cells without irrigation, CH_IrrigAg is only computed for grid cells in which irrigated crops are grown according to MIRCA2000 (Portmann et al., 2010).

IH was calculated by using the GCWM based on a monthly time series of net irrigation requirements from 1980 to 2016. The net irrigation requirement is the volume of water needed to ensure that the AET of irrigated crops is similar to their PET (Figure 3.4). The calculations were performed for 487 121 grid cells with a resolution of 5 arcmin, containing irrigated crop areas, and then aggregated to 26 478 grid cells with a 30 arcmin resolution to be consistent with the resolution used by WaterGAP. SH was calculated by using WaterGAP based on a monthly time series of streamflow from 1980 to 2016 in 66 896 grid cells with a 0.5◦ × 0.5◦ resolution worldwide.

For both IH and SH, drought hazard per grid cell was quantified as the product of the (scaled or transformed) mean severity of all drought events during the evaluation period 1980–2016 and the frequency of drought events during this period. Drought events for IH and SH were determined independently. In the case of IH computation, a drought event starts as soon as the monthly irrigation requirement exceeds the irrigation requirement threshold and ends when the surplus reaches zero. In the case of SH computation, a drought starts if the monthly streamflow drops below the streamflow threshold and ends as soon as the deficit reaches zero. For each grid cell and each of the 12 calendar months, a drought threshold was defined as the median of the variable values in the respective calendar month during the reference period 1986–2015. To avoid spurious short droughts and drought interruptions, it was defined that a drought event starts (1) with at least 2 consecutive months with an IH surplus or a SH deficit and (2) 1 month without an IH surplus or if a SH deficit does not break the event (Spinoni et al., 2019). The accumulated surplus (IH) divided by the deficit (SH) during each drought event is the severity of the drought event. Mean severity is computed as the arithmetic average of the severity of all drought events during the evaluation period. As in the case of SH, the deficit and thus the severity of streamflow drought are strongly correlated with the mean annual streamflow; mean severity is therefore scaled by dividing the accumulated streamflow deficit by mean annual streamflow. In this way scaled mean streamflow drought severity is expressed as the fraction of the mean annual flow volume that is on average missing during drought events. In the case of IH, mean severity is transformed logarithmically before computation of IH, as in most grid cells the volume of irrigation water needed additionally in drought periods is relatively small (volume in 569 out of the 26 478 irrigated grid cells is lower than 100 m3; in 1450 grids it is lower than 1000 m3). However, there are also some grids with extremely high values (95 grids where the additional irrigation water requirement per drought event is larger than 100 000 000 m3). The logarithmic transformation accounted for the specific value distribution.

CH_IrrigAg was then calculated for each grid cell by combining SH and IH. To ensure that both indicators are weighted equally, their native values were first scaled to a range between 0 and 1 by dividing SH and IH in each grid cell by the maximum SH or IH detected globally. The frequency distribution of the SH values calculated that way was shifted to the left, with a mean of 0.244, while the frequency distribution of IH was shifted to the right, with a mean of 0.664. Therefore, CH_IrrigAg was calculated foreach grid cell as

$$\text{CH\_IrrigAg} = 0.5\,(SH/SH + IH/IH)\,, \qquad (1)$$

with SH being the grid-cell-specific streamflow hazard, IH being the grid-cell-specific irrigation requirement hazard, and SH and IH being the mean of SH or IH calculated across all grid cells.

The exposure of irrigated agricultural systems to drought at the national scale was derived as the harvested-area weighted mean of the CH_IrrigAg across all grid cells belonging to the respective aggregation units.

3.2.2.1.2. Rainfed agricultural systems

The composite drought hazard indicator for rainfed agriculture (CH_RfAg) was quantified based on the ratio of actual crop evapotranspiration (AET in $m^3\ d^{-1}$) to potential crop evapotranspiration (PET in $m^3\ d^{-1}$), calculated for the evaluation period 1980–2016 and compared to the reference period 1986–2015 (Figure 3.4). PET quantifies the water requirement of the crop without water limitation, while AET refers to the evapotranspiration under actual soil moisture conditions.

The GCWM was applied for 24 specific rainfed crops and the two groups “others, annual” and “others, perennial” to calculate crop-specific AET and PET on a daily time step. Together, the

24 crops and two crop groups cover all crop species distinguished by FAO in their database FAOSTAT. The sum of daily crop-specific AET and PET was calculated for all crops and for each year in the period 1980–2016 for 927 857 grid cells containing rainfed cropland and aggregated to 37 265 grid cells with the resolution 0.5◦ × 0.5◦. The mean ratio between AET and PET (AET/PET) for the reference period 1986–2015 was then calculated for each grid cell. AET/PET reflects long-term water limitations for the geographic unit, with low values representing high aridity and high values for low aridity. CH_RfAg was then determined by calculating the ratio AET / PET for each year from 1980–2016 and by deriving the percentile of a relative difference of 10 % to the long-term mean ratio AET/PET from the time series. Consequently, CH_RfAg reflects the probability of occurrence of a drought year in which the ratio between total AET and total PET across all rainfed crops is 10 % lower than the long-term mean ratio AET/PET. We also tested other percentage thresholds (20 %, 30 %, 50 %), but for many parts of the world we never computed reductions of the ratio AET / PET by more than 10 % of the long- term mean ratio (Table in Appendix B5). Therefore, it was decided to use the 10 % threshold consistently.

3.2.2.1.3. Integration of drought exposure of irrigated and rainfed cropping systems

The combined drought exposure of rainfed and irrigated cropping systems was evaluated at the country level by averaging the harvested-area weighted drought exposure of irrigated and rainfed cropping systems. As described before, distinct methods were used to calculate hazard and exposure of irrigated and rainfed systems so that a direct comparison of the exposure values is not meaningful. In addition, the frequency distributions differed considerably, with a harvested-area weighted global mean of the drought exposure of 0.455 for irrigated systems and 0.189 for rainfed systems. To ensure a more similar weight of rainfed and irrigated drought exposure, country-specific exposures were divided by the global mean, and then the integrated exposure was calculated as harvested-area weighted mean:

$$Exp_{tot} = ((AH_{rf} \cdot Exp_{rf}/0.189) + (AH_{irr} \cdot Exp_{irr}/0.455)) /AH_{tot}, \quad (2)$$

with Exp_{tot}, Exp_{rf} and Exp_{irr} being the exposure of the whole, rainfed and irrigated cropping systems to drought and AH_{tot}, AH_{rf} and AH_{irr} being the harvested area of all crops, rainfed crops and irrigated crops.

3.2.2.2. Vulnerability and risk assessment

According to the Intergovernmental Panel on Climate Change (IPCC, 2014), vulnerability is the predisposition to be adversely affected as a result of the sensitivity or susceptibility of a system and its elements to harm, coupled with a lack of coping and adaptive capacity. The assessment of drought vulnerability is complex because it depends on both biophysical and socioeconomic drivers (Naumann et al., 2014). Due to this complexity, the most common method to assess vulnerability in the context of natural hazards and climate change is using composite indicators or index-based approaches (Beccari, 2016; de Sherbinin et al., 2019). Although their usefulness for policy support has also been subject to criticism (Hinkel, 2011; Beccari, 2016), it is widely acknowledged that composite indicators can identify generic leverage points for reducing impacts at the regional to global scale (De Sherbinin et al., 2017, 2019; UNDRR, 2019).

Following the workflow to calculate composite indicators proposed by the Organisation for Economic Cooperation and Development (OECD, 2008) and Hagenlocher et al. (2018), the methodological key steps on which the vulnerability assessment is based are (1) the definition of the conceptual framework, (2) identification of valid indicators, (3) data acquisition and preprocessing, (4) analysis and imputation of missing data, (5) detection and treatment of outliers, (6) assessment of multicollinearities, (7) normalization, (8) weighted aggregation, and (9) visualization.

An initial set of vulnerability indicators for agricultural systems was identified based on a recent review of existing drought risk assessments (Hagenlocher et al., 2019). In total 64 vulnerability indicators, including social, economic and physical indicators; farming practices; and environmental, governance, and crime and conflict factors, were selected and classified by socioecological susceptibility (SOC_SUS, ENV_SUS), a lack of coping capacity (COP) and a lack of adaptive capacity (AC) following the risk framework of the IPCC (IPCC, 2014). Indicator weights, which express the relevance of the identified indicators to characterizing and assessing the vulnerability of agricultural systems to droughts, were identified through a global survey of relevant experts (n = 78), the majority of whom have worked in academia and for governmental organizations with more than 5 years of work experience (Meza et al., 2019). In total, 46 of the 64 indicators were considered relevant by the experts, comprising susceptibility, coping- and adaptive-capacity indicators. However, since adaptive capacity is only relevant when assessing future risk scenarios and less relevant to current risk, indicators related to adaptive capacity and indicators that could be measured with the same data source due to the similarity in what they represent were removed. For instance agriculture (% of GDP) and dependency on agriculture for livelihood (%) were averaged into one income indicator, and the variables GDP per capita (PPP – purchasing-power parity) and population below the national poverty line (%) both refer to poverty and therefore were also averaged to a combined indicator. This resulted in a set of 26 indicators as part of the vulnerability assessment (Table 3.5).

Table 3.5 Vulnerability indicators used in the analysis and their related expert-weights*.

Indicator	Data source	Weight*
Social susceptibility (SOC_SUS)		
Share of GDP from agr., forestry and fishing in US$ (%)	FAO (2016a)	0.96
Rural population (% of total population)	World Bank (2011-2017)	0.85
Prevalence of undernourishment (% of population)	World Bank (2015e)	0.82
Literacy rate, adult total (% of people ages 15 and above)	World Bank (2015d)	0.80
Prevalence of conflict/insecurity (Crime and Theft, Index (0-30))	World Bank (2017a)	0.76
Proportion of population living below the national poverty line (%)	SDG indicators (2015-2017)	0.75
Access to improved water sources (% of total population with access)	World Bank/FAO (2015a)	0.66
DALYs (Disability-Adjusted Life Years)(DALYs per 100,000, Rate)	GBD (2016)	0.65
GINI index	World Bank (2017b)	0.64
Insecticides and pesticides used (ton/ha)	FAO (2016b)	0.63
Gender Inequality Index	UNDP (2018)	0.62
Electricity production from hydroelectric sources (% of total)	World Bank (2015b)	0.62
Unemployment, total (% of total labor force) (national estimate)	World Bank (2017)	0.60
Dependency ratio (Population ages 15-64 (% of total population))	World Bank (2011-2016)	0.60
Population using at least basic sanitation services (%)	WHO (2015)	0.60
Healthy life expectancy (HALE) at birth (years)	WHO (2014)	0.56
Ecological susceptibility (ECO_SUS)		
Average land degradation in GLASOD erosion degree	FAO (1991)	0.92
Fertilizer consumption (kilograms per hectare of arable land)	World Bank (2015)	0.74
Average soil erosion	FAO (1991)	0.72
Terrestrial and marine protected areas (% of total territorial area)	World Bank (2016-2017)	0.63
Lack of coping capacity (COP)		
Saved any money in the past year (% age 15+)	Global FINDEX (2014-2017)	0.87
Government Effectiveness: Percentile Rank	World Bank (2017)	0.85
Total dam storage capacity per capita. Unit: m3/inhab	FAO Aquastat (2017)	0.82
Total renewable water resources per capita (m3/inhab/year)	FAO (2014)	0.76
Corruption Perception Index (CPI)	Transparency International (2017)	0.68
Travel time to cities ≤30 min (population) (%)	JRC (2015)	0.65

** derived from a global expert survey (Meza et al., 2019)*

Following data acquisition, the data were preprocessed by transforming absolute to relative values and standardized when necessary (e.g., travel time to cities ≤ 30 min – population, divided by the total population). Descriptive statistics were used to evaluate the degree of missing data. The imputation of missing values was done with data from previous years and using secondary sources following Naumann et al. (2014) in cases where the r value lay between −1.0 and −0.9 or 1.0 and 0.9 using a Spearman correlation matrix and scatter diagram for visual interpretation. Following suggestions by Roth et al. (1999), Peng et al. (2006) and Enders (2003), listwise and pairwise deletion thresholds were selected when > 30 % of data were missing on a country level and when > 20 % of data were missing on the indicator level. After the deletion, 168 countries and 26 indicators were considered for the final analysis. To detect potential outliers, scatter plots and box plots for each indicator were created. Potential outliers were further examined using triangulation with other sources and past years. On this basis, outliers were identified in only one indicator (i.e., fertilizer consumption – kg ha−1 of arable land) and treated using winsorization following Field (2013). Multicollinearities were identified using a Spearman correlation matrix for the different vulnerability components (social susceptibility, environmental susceptibility and a lack of coping capacity). Following the rule proposed by Hinkle et al. (2003), any values higher than $r > 0.9$ or smaller than $r < -0.9$ were considered very highly correlated. The correlation was considered only if it was significant at the 0.05 level (two-tailed). Two indicators for the lack of a coping-capacity component and two from social susceptibility (e.g., healthy life expectancy at birth – years – and disability-adjusted life) showed high and significant correlations. However, no indicators were excluded on this basis due to the difference in concepts they represented and their relevance at the global level. In order to render the indicators comparable, the final selected indicators were normalized to a range from 0 to 1 using min–max normalization (Naumann et al., 2014; Carrão et al., 2016):

$$Z_i = X_i - X_{min}/X_{max} - X_{min}, \quad (3)$$

where Z_i is the normalized score for each indicator score X_i . For variables with negative cardinality to the overall vulnerability the normalization was defined as:

$$Z_i = 1 - (X_i - X_{min}/X_{max} - X_{min}) . \quad (4)$$

Finally, the normalized indicator scores were aggregated into vulnerability components (SOC_SUS, ENV_SUS, COP) using weighted arithmetic aggregation based on (using the example of SOC_SUS)

$$SOC\_SUS = \sum W_i Z_i , \quad (5)$$

where W_i is the weights for each normalized data set, and Z_i is the weights as obtained from the global expert survey. Therefore, weights were normalized to add up to 1. The final indicators and their respective weights are listed in Table 3.5. The vulnerability components of socioecological susceptibility (SE_SUS) were combined using an average, which was then combined with COP to obtain a final vulnerability index (VI) score:

$$VI = V(SE\_SUS) + V(COP)/2. \quad (6)$$

The final drought risk index (DRI; Figure 3.4) was calculated by multiplying the indices for drought hazard and exposure by vulnerability. At the pixel level, the presence of hazard and vulnerability point to a certain drought risk, independent of how much crop area is contained in the specific pixel. At the aggregated level, the different crop areas in the specific pixels must be considered; therefore exposure was calculated as harvested-area weighted mean of the pixel-level hazard and then multiplied by vulnerability to calculate drought risk at the country level.

The total drought risk score for irrigated and rainfed systems combined (DRI_{tot}) is derived by multiplying the exposure of the whole cropping system Exptot (Eq. 2) by the VI.

3.2.2.3. Comparison against drought impact data

The outcomes of the risk assessment for irrigated and rainfed systems combined (DRI_{tot}) were compared against impact data from the international Emergency Events Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters (CRED) using visual correlation (Figure 3.9). EM-DAT systematically collects reports of drought events and drought impacts from various sources, including UN agencies, NGOs, insurance companies, research institutes and press agencies. Here, the number of drought events within the period 1980–2016 was used as an input for the comparison. Therefore, a drought event is registered in EM-DAT when at least one of the following criteria applies: 10 or more people are dead, 100 or more people are affected, or a declaration of a state of emergency or a call for international assistance is made.

3.2.3. Results

This section presents the results of the global drought risk assessment for agricultural systems (irrigated and rainfed) at the pixel level (Figures 3.5 and 3.6) and for the total risk of both systems combined at national resolution (Figure 3.7). The dark- red patterns show high levels of the different risk components, while dark blue reflects low scores of the different risk components.

3.2.3.1. Drought risk for irrigated agricultural systems

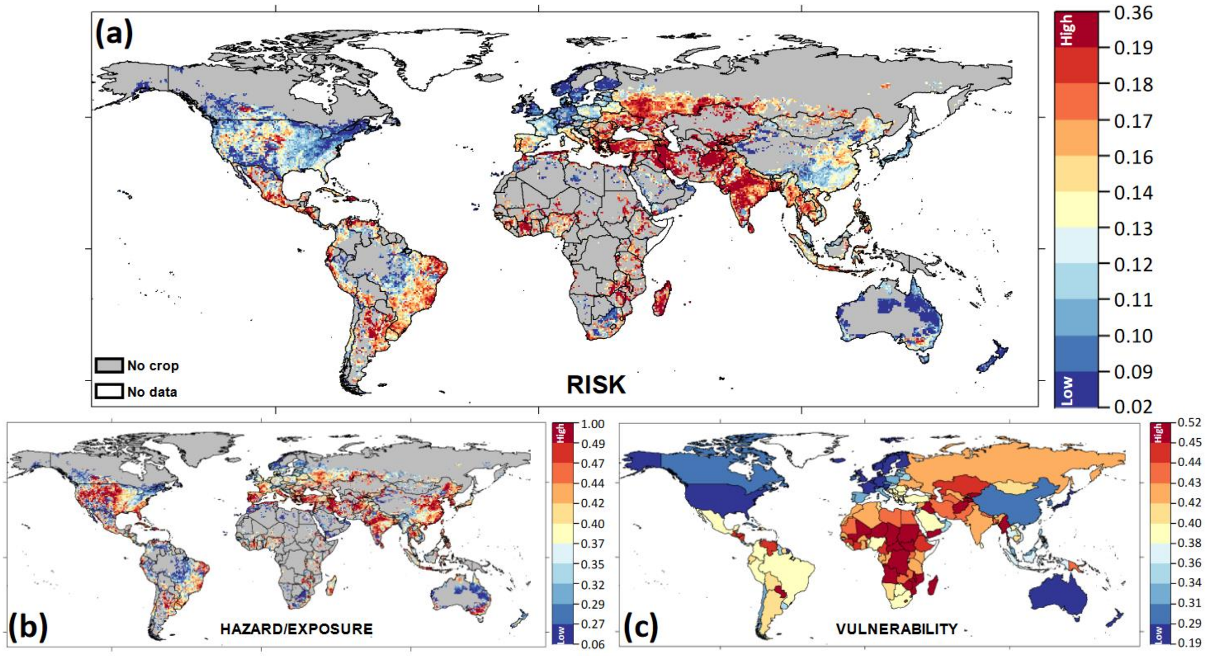


Figure 3.5. Drought risk (a), hazard/exposure (b) and vulnerability (c) for irrigated agricultural systems. The legends were defined by assigning the median of the value distribution to the yellow color in the center, the 90th percentile to the deepest red color, the 10th percentile to the deepest blue color, and by determining the class ranges of the other colors by linear interpolation. Risk was directly calculated by multiplying hazard with vulnerability (pixel-level analysis).

The drought risk for irrigated agricultural systems varies significantly among continents and countries. Especially large countries such as the USA, Brazil, China and Australia show a high variation at the country level due to varying climatic conditions. Drought hazard and exposure was highest in regions with a high density of irrigated land and high irrigation water requirements such as the western part of the USA, central Asia, northern India, northern China and southern Australia. Vulnerability was high particularly in sub-Saharan Africa but also in some countries in central Asia and the Middle East and low in general for industrialized and high-income countries. The combination of hazard and vulnerability to risk resulted in the highest values for large parts of western, central and southern Asia; eastern Africa; and the eastern part of Brazil. Low-risk areas include western Europe, the USA, Australia and most parts of China (Figure 3.5).

3.2.3.2. Drought risk for rainfed agricultural systems

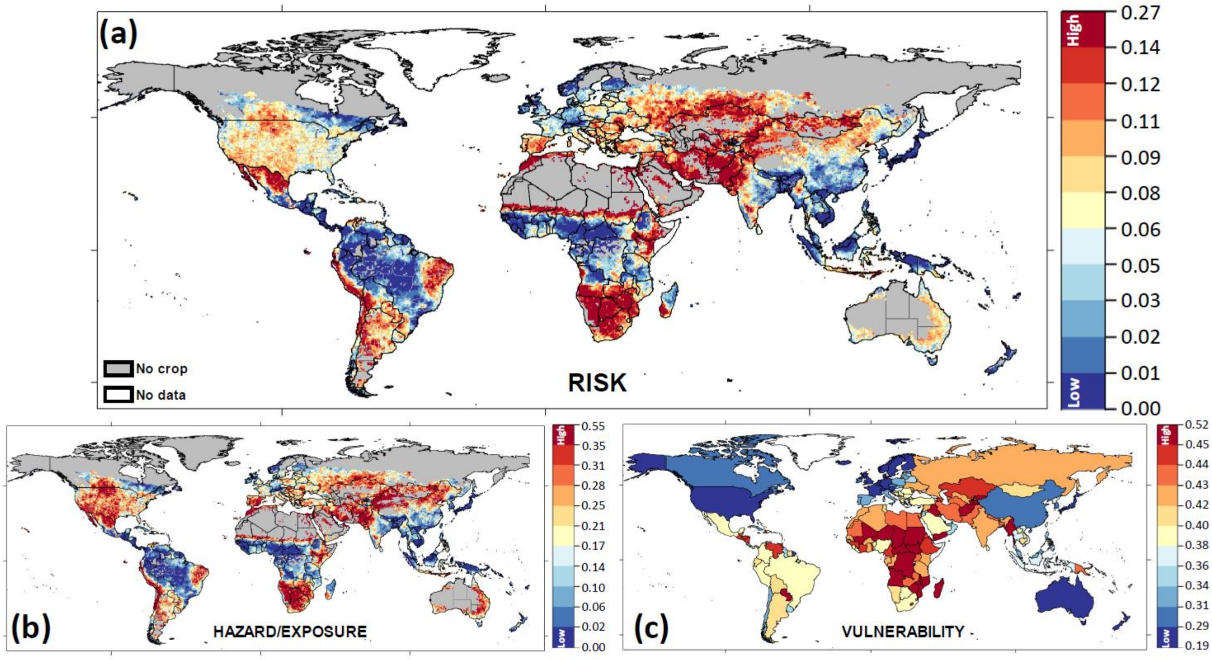


Figure 3.6. Drought risk (a), hazard/exposure (b) and vulnerability (c) for rain-fed agricultural systems. The legends were defined by assigning the median of the value distribution to the yellow color in the center, the 90th percentile to the deepest red color, the 10th percentile to the deepest blue color and by determining the class ranges of the other colors by linear interpolation. Risk was calculated by multiplying hazard/exposure with vulnerability (pixel level analysis).

High levels of risk (dark yellow to red color scheme) for rainfed agricultural systems are observed in southern Africa, in southeastern Europe, in northern Mexico, in northeastern Brazil, at the western coast of South America, in southern Russia and in western Asia. The vulnerability to drought highlights the relevance to increasing the coping capacity of the countries in order to reduce their overall drought risk. For instance, Australia, despite being highly exposed to drought hazard, has low socio-ecological susceptibility and high enough coping capacities to considerably reduce the overall drought risk.

3.2.3.3. Drought risk for agricultural systems (irrigated and rainfed combined)

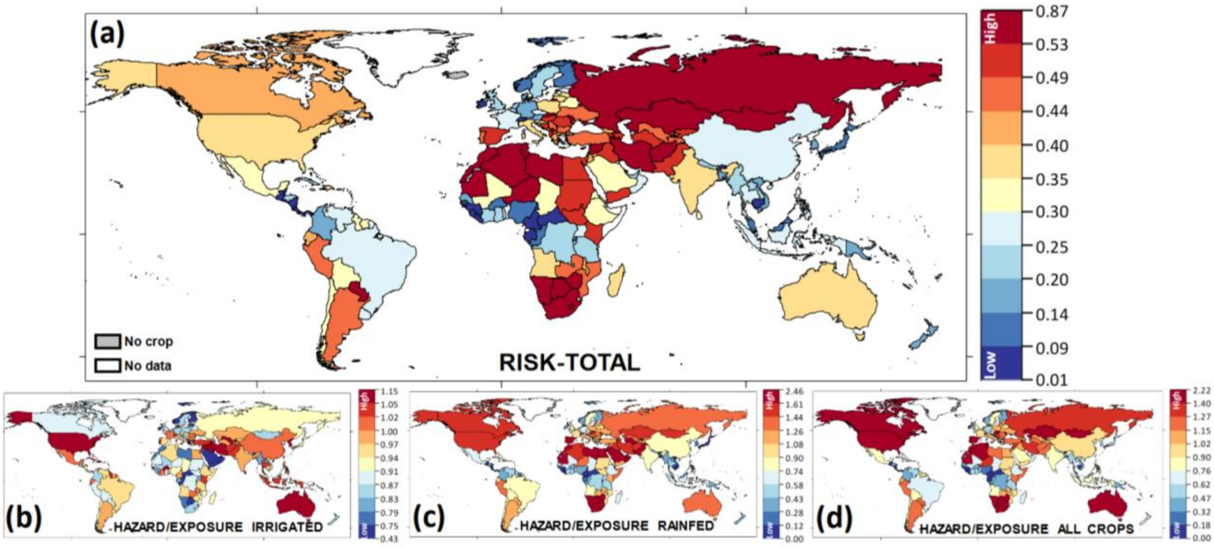


Figure 3.7. Drought risk (a), hazard/exposure of irrigated (b), rain-fed (c), and the whole crop production sector (d). The legends were defined by assigning the median of the value distribution to the yellow color in the center, the 90th percentile to the deepest red color, the 10th percentile to the deepest blue color, and by determining the class ranges of the other colors by linear interpolation. Risk was calculated by multiplying hazard/exposure with vulnerability shown in Figures 3.5c and 3.6c.

The hazard and exposure maps shown in Figures 3.7 are slightly different to the ones shown in Figures 3.5 and 3.6 due to the aggregation at the country level. The analysis shows that regions with low hazard and exposure of rainfed and irrigated crops to drought tend to be tropical and subarctic regions following the Köppen–Geiger climate classification (1980–2016; Beck et al., 2018). There are significant regional differences when comparing irrigated and rainfed drought hazard and exposure. For instance, the northern parts of Latin America and central Africa have low hazard and exposure levels, given the humid climate conditions resulting in a low total risk, even though those regions are characterized by high vulnerability levels. Southern Africa, however, has a high amount of drought-exposed rainfed crops but lower vulnerability compared to other African countries. Despite this, risk scores in that region are very high. Very high drought hazard and exposure and vulnerability levels can be found in the Middle East and northern Africa.

Although the drought hazard was computed differently for the different agricultural systems, the countries with high risk of drought to both farming systems are Botswana, Namibia and Zimbabwe (Figures 3.5 and 3.6). These countries share the same relevant indicators that define their high vulnerability: a high soil and land degradation rate, a low literacy rate and low total renewable water (Figure B3 in appendix). Table 3.6 shows the top and bottom 10 countries with the highest and lowest total drought risk (DRI_{tot}) as well as their hazard and exposure and vulnerability scores.

Table 3.6 Rank of countries with the highest and lowest risk of drought for combined agricultural systems (rain-fed and irrigated)

Country	Drought risk (countries rank)	Risk score total	Hazard/Exposure			Vulnerability score
			Haz/Exp irrigated	Haz/Exp rain-fed	Haz/Exp total	
Zimbabwe	1	0.871	0.967	1.885	1.804	0.483
Namibia	2	0.846	0.769	2.122	2.061	0.411
Botswana	3	0.811	0.466	2.095	2.076	0.391
Morocco	4	0.786	0.774	2.172	1.873	0.419
Kosovo	5	0.728	0.936	1.871	1.854	0.393
East Timor	6	0.701	0.971	1.882	1.854	0.378
Mauritania	7	0.692	0.886	1.670	1.580	0.438
Lesotho	8	0.692	0.840	1.562	1.556	0.445
Kazakhstan	9	0.670	0.974	1.573	1.499	0.447
Algeria	10	0.636	0.969	1.595	1.492	0.426
Guatemala	158	0.039	0.857	0.026	0.087	0.446
Gambia	159	0.037	0.760	0.093	0.094	0.394
Belize	160	0.035	0.943	0.079	0.093	0.375
Sierra Leone	161	0.023	0.934	0.005	0.057	0.402
Brunei	162	0.020	0.741	0.000	0.077	0.254
Guinea	163	0.019	0.822	0.033	0.042	0.452
Switzerland	164	0.017	0.695	0.046	0.068	0.247
Guinea-Bissau	165	0.017	0.723	0.026	0.042	0.401
Fiji Islands	166	0.011	0.833	0.017	0.033	0.329
Central African Republic	167	0.008	0.646	0.016	0.016	0.505

Seven out of the 10 countries with the highest overall drought risk are located on the African continent. However, Kosovo, East Timor and Kazakhstan also possess high risk levels (Table 3.6). Zimbabwe ranks as the country with the highest drought risk, mainly due to its high exposure combined with its high vulnerability (Figure B1 in the appendix).

In general, the countries that present higher drought risk have a high amount of exposed crops. Vulnerability varies among them, with Zimbabwe being the country with the highest vulnerability. The lack of coping capacity and socioecological susceptibility were determinant factors for countries like Botswana and Zimbabwe (Figure B1 in appendix). There were cases where countries such as Namibia presented high socioecological susceptibility in contrast with high coping capacity, reducing its overall vulnerability. The drought risk in countries such as Lesotho and Mauritania that have, in contrast, limited coping capacities is notably higher

(Figure B1 in appendix). The analysis also reveals that, although risk is currently close to zero in several countries (e.g., Fiji, Central African Republic, Guinea-Bissau, etc.), this could rapidly change once these countries are affected by droughts given their very high vulnerability.

The comparison of the drought risks of rainfed and irrigated cropping systems (Figure 3.8) shows that several countries such as Zimbabwe, Iraq and Algeria are exposed to high risk for both cropping systems. These countries are frequently hit by drought and similarly have a high vulnerability to drought (Figures 3.5 and 3.6). In contrast, countries such as Switzerland, Finland and New Zealand are characterized by low drought hazard and exposure of irrigated and rainfed systems and low vulnerability to drought (Figures 3.5 and 3.6). In countries such as Botswana, Oman and the United Arab Emirates, drought risk is high for rainfed cropping systems but low for irrigated cropping systems (Figure 3.8). These countries are defined by arid climate conditions, exposing rainfed crops to high risk, while the drought risk for irrigated cropping systems is low because of relatively low interannual variability in climatic conditions resulting in low variability in the irrigation water requirement and streamflow. Their risk is also determined by their different vulnerability dynamics (e.g., hydroelectric sources, retaining renewable water). In contrast, drought risk for irrigated cropping systems is high and drought risk of rainfed cropping systems is small in countries such as Burkina Faso, Madagascar and Côte d’Ivoire (Figure 3.8). In these three countries, there is a big variability in climatic conditions, with irrigated crops being cultivated in the more arid parts of the country and rainfed crops being cultivated in more humid parts. In addition, aquatic crops with high water demand, such as rice and sugarcane, are the most commonly cultivated irrigated crops in these countries (Frenken, 2005).

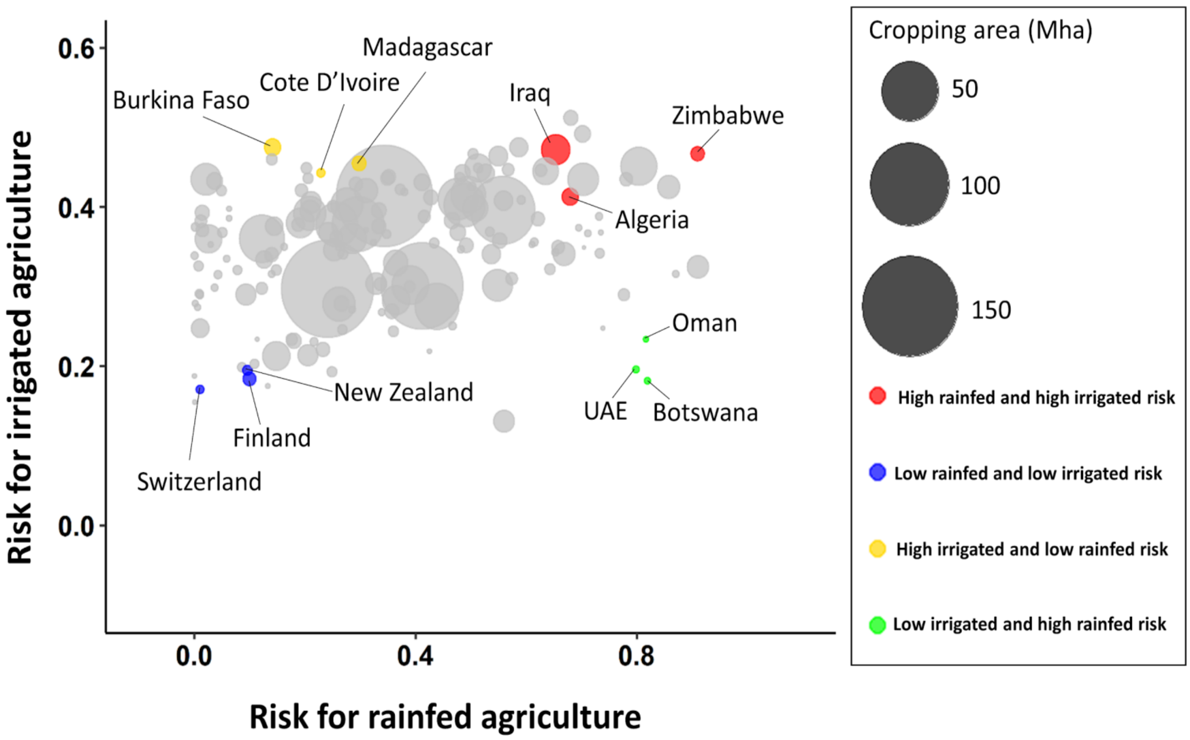


Figure 3.8. Country profiles contrasting the drought risk of irrigated and rain-fed agricultural systems. The size of the bubbles indicates the crop growing area (sum of rain-fed and irrigated areas per country in Million ha).

3.2.3.4. Comparison

The comparison of drought risk (DRI_{tot}) with drought events registered in EM-DAT shows good agreement in many countries. For countries which have low drought risk, such as the countries in tropical Africa, northern and western Europe, or the northern part of South America, there are either no droughts or just one drought registered in EM-DAT (Figure 3.9a and b). There is also good agreement for countries in southern Africa and some countries in the African transition zone with very high drought risk and many registered drought events and for countries with intermediate drought risk, such as Canada, Australia or Italy. However, some disagreement between calculated risk and the number of reported drought events is acknowledged. For instance, Brazil does not show high agreement between EM-DAT and the country risk level, even though the eastern part of the country presents a high risk for irrigated and rainfed systems (Figures 3.5 and 3.6), and the total drought risk level is affected by the other regions with lower risk in the country. The same occurs in other large countries such as the USA, Russia, China and India, where the calculated drought risk is low or intermediate, although a large number of drought events have been registered in EM-DAT. The reason for this disagreement is that the risk shown in Figure 3.9a is representative of the whole country, while drought events which only have local or regional impacts are also registered in EM-DAT (see Sect. 3.2.2.3). For all these big countries, we detected considerable spatial heterogeneity with regard to drought risk, where regions with high drought risk such as the central part of the USA, northeastern Brazil, northern China and northwestern India are complemented by other regions of low drought risk (Figure 3.9a). Therefore, the high number of registered drought events in EM-DAT is corroborated by the presence of high regional drought risk (Figures 3.5 and 3.6).

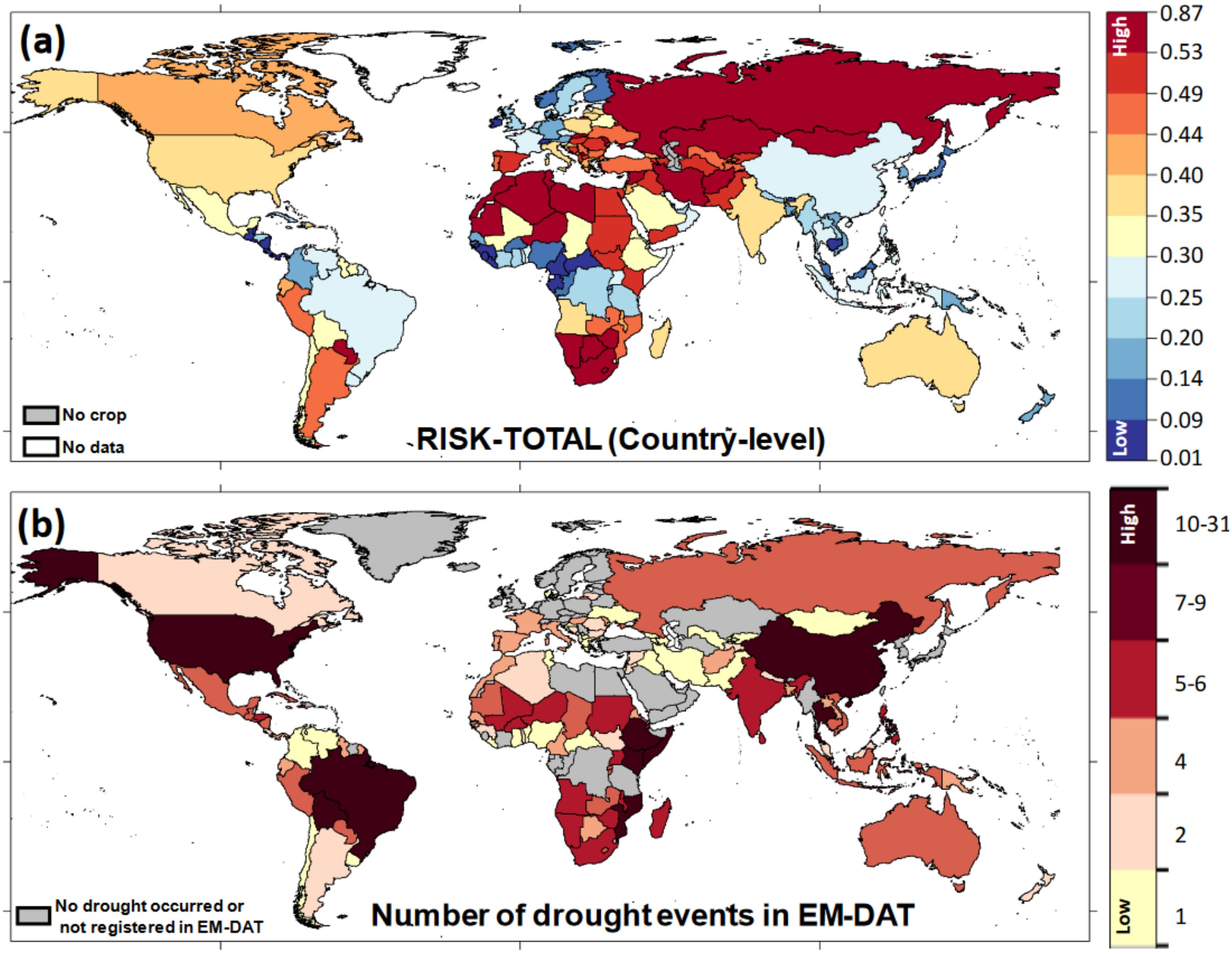


Figure 3.9. Comparison of total risk against drought impact data

3.2.4. Discussion

The present study performs, for the first time, a separate global drought risk analysis for irrigated and rainfed cropping systems, including regions that indicate a high vulnerability to droughts and are particularly exposed. In previous assessments, the share of irrigated cropland was either ignored or considered to be a vulnerability indicator (Carrão et al., 2016). The drought hazard analysis is based on three indicators: SH, IH and CH_RfAg, which quantify drought as a deviation from normal conditions consistent with common definitions. In agreement with the results for drought hazard obtained by Carrão et al. (2016), the largest drought hazard is obtained for arid and semi-arid regions such as northern and southern Africa, northern Mexico, along the coastline of Peru and Chile, the Arabian Peninsula, and Mongolia for rainfed systems; Italy, Turkey and western Mexico for irrigated systems; and the western USA, northeastern Brazil, western Argentina, central Asia, the Middle East, western India, northern China and southern Australia for both irrigated and rainfed systems. In contrast, previous studies based on standardized indices such as the standardized precipitation index (SPI) have detected the highest drought hazard mainly in humid regions such as central Europe, southeastern Asia, southern Brazil and tropical Africa (Geng et al., 2016). The reason for this difference could be that deviations from normal conditions should not be treated similarly for arid and humid regions, as not every precipitation or streamflow deficit in humid regions will automatically become a hazard for cropping systems. In fact, in humid regions, crops often perform better in relatively dry years (Holzkamper et al., 2015). We account for these effects by normalizing streamflow deficits with long-term mean annual river discharge (SH) or by calculating the probability of reductions in the AET / PET ratio of rainfed crops in relative terms (CH_RfAg).

In the present study, the rainfed hazard is computed as the probability of a 10 % decline in the AET / PET ratio compared to long-term mean conditions, whereas the irrigated drought hazard represents the combination of severity and frequency values derived from the streamflow or irrigation water requirement (see section 3.2.2). While the methodology reflects the common understanding of the factors most influential for drought hazard in the two cropping systems well, a direct numerical comparison of the calculated hazard for rainfed and irrigated systems is not meaningful. The hazards and exposure calculated in this study should be used to rank or compare countries within the rainfed or irrigated domain but not in between. The reasoning for the calculation of the total exposure and risk in this study was less to support comparisons across countries but more to account for the different extent of irrigated and rainfed systems within the specific countries. There are countries in which crop production is completely rainfed and countries in which all crops are irrigated so that only the risk for the rainfed or irrigated systems is relevant. Aside from these extremes, crop production in most countries is either predominantly irrigated or predominantly rainfed. We account for this by calculating total crop exposure to drought (Figure 3.7d) as the harvested-area weighted mean of the exposures of irrigated crops (Figure 3.7b) and of the rainfed crops (Figure 3.7c). Our attempt to calculate hazard, exposure and risk for the whole crop production sector by assigning a similar weight to the hazard exposures for rainfed and irrigated systems must be viewed critically, and results should be analyzed with care. A potential way to derive specific weights for rainfed and irrigated exposure could be validating not only calculated hazard and exposure but also vulnerability and risk, with information about drought impacts separately, for both irrigated and rainfed systems. A lack of data for drought impacts distinguishing rainfed and irrigated systems was the main reason why this approach was not implemented for the current study.

The calculation of the drought hazard of irrigated cropping systems in this study is based on the two components SH and irrigation IH reflecting the water supply and water demand, respectively, of irrigated systems. Therefore we do not consider specifically in our approach the availability and use of groundwater resources for irrigation. It is well known that dynamics in streamflow are usually larger than dynamics in groundwater storage so that groundwater is used by many farmers to substitute temporary deficits in surface water supply for irrigation systems. In general, access to groundwater should therefore be considered to reduce drought hazard and vulnerability of irrigated cropping systems. Consideration of groundwater resources would, however, require dynamic quantification of groundwater storage and groundwater levels, which is challenging for global-scale analyses and not possible with the models applied in this study. In addition, more conceptual work is needed to decide which degree of temporal variability in groundwater levels constitutes a hazard and how to treat long-term depletion of groundwater resources (negative trends) in drought risk studies.

The multi-dimensional nature of vulnerability of agricultural systems is represented by a set of 26 expert-weighted indicators. One of the major limitations of this data-driven approach is the spatial detail information for computing the model; however, at a global level it is not feasible to get a harmonized data set of all the proxy variables, but some caution must be advised when zooming in at the subnational level (Naumann et al., 2018). When interpreting the results, it is necessary to consider that some highly correlated indicators were maintained in the analysis, as they present different drivers of vulnerability and hence different entry points for vulnerability reduction. The selected indicators comprise social, economic, environmental, physical and governance-related factors contributing to socioecological susceptibility and the lack of coping capacity. In doing so, the present study goes beyond existing global drought risk assessments (Carrão et al., 2016), which are based on equal weights and do not consider relevant environmental vulnerability indicators to be a driver of drought risk. The latter, however, is relevant when assessing drought risk for agricultural systems, where factors such as land degradation and soil erosion are shown to exacerbate drought risk (Hagenlocher et al., 2019). In future assessments an alternative to the expert-based weighting of vulnerability indicators chosen here could be the use of statistical approaches (e.g., principal component analysis – PCA) to identify relevant indicators. However, given the high number of experts who participated in the weighting exercise (n = 78) the expert-based approach seems more suitable for identifying relevant indicators when compared to an approach that builds on statistical significance only. Further, Hagenlocher et al. (2013) evaluated the outcomes of PCA- based and expert-based indicator choice on a composite vulnerability index and did not find major differences.

The findings of the drought risk assessment presented here correspond to a certain degree to the findings of Carrão et al. (2016). Although the focus of the current paper is more explicitly on agriculture, both studies present methodological similarities. In Carrão et al. (2016) the percentage of crop land per grid cell is one factor in the exposure analysis, and the percentage of irrigated agricultural land is one of the vulnerability factors. Although Carrão et al. (2016) include other factors such as population density, livestock density and baseline water stress in the analysis, the results give a high weight to the risk for agriculture. In both studies the regions less affected by droughts correspond to the regions with little or no exposure of agriculture and population (e.g., deserts and tropical forests). This is mainly the case in Amazonia and central Africa. Also, similarities between areas of high levels of risk are evident, including southern and eastern Europe, the Eurasian steppe, northern Africa and the Middle East, northeastern Brazil, and southeastern South America.

Similarities are also found for the risk of irrigated agricultural systems. Examples are irrigated croplands in India, the US and Australia. Differences in the overall patterns are due to the separation of irrigated and non-irrigated agriculture in the current study and the aggregated exposure information in Carrão et al. (2016). In an updated version of the risk map from Carrão et al. (2016), using a higher-resolution population database and grid-level exposure information, as shown in Vogt et al. (2018, Figure 7), similarities are even more evident.

However, the present study includes a spatially explicit model of AET for the main crop types of two different agricultural systems (irrigated and rainfed agriculture) and includes a specialized vulnerability index for this sector according to expert judgment. These differences revealed the importance of focusing more clearly on distinct impacts (e.g., on irrigated vs. rainfed systems) when conducting drought risk assessments, even within the same sector. For instance, irrigated agricultural systems in Latin America are highly exposed to droughts, whereas the probability of droughts occurring in rainfed agricultural systems in that region is comparably low.

Despite these advancements, the presented analysis does have limitations. First, due to the lack of up-to-date land use data on irrigated vs. rainfed agriculture at the global scale, the exposure analysis is based on MIRCA data from the year 2000 (Portmann et al., 2010). Given that cropping systems are subject to change, this adds uncertainty to the results. Second, data used for the vulnerability analysis stem from different sources, which makes it difficult to evaluate the inherent uncertainties in the data. Third, the data are not consistently available for all countries for the same years (Table 3.5). Fourth, the vulnerability analysis is based on nation–state–resolution data, which do not allow for mapping spatial variability in vulnerability at the subnational level. Fifth, applying expert opinions to weight drought vulnerability indicators according to their relevance brings subjectivity to the assessment, which necessitates a strong network of relevant experts. Sixth, preventive or adaptive planning requires going beyond evaluating drivers of risk and mapping current patterns of risk. Future scenarios of drought risk, considering both changing environmental and climate conditions as well as possible future socioeconomic development pathways, are needed in order to anticipate future challenges.

Future research should address these challenges by also investigating subnational patterns in vulnerability and developing future drought risk scenarios in all dimensions of drought hazards, exposure and vulnerability. In addition, attempts to investigate changes and trends in drought risk and risk components are highly needed to better understand trajectories of drought risk in different countries and for the whole world. Further, inherent uncertainties, as well as the sensitivity of the risk assessment outcomes towards changes in the input parameters (e.g., indicator choice and weighting), should be investigated and validated statistically. This gap has also been highlighted in a recent review of climate vulnerability assessments (de Sherbinin et al., 2019) in general as well as in a recent review of drought risk assessments (Hagenlocher et al., 2019) in particular.

The comparison conducted in this study has shown that there are limited data available on agricultural losses and impacts caused by droughts at the global level. Furthermore, impacts are not always direct, as droughts can have cascading indirect impacts (Freire-Gonzáles et al., 2017; Van Lanen et al., 2017) which are difficult to assess. In addition, for countries where we find high drought risk (e.g., Mongolia, Iran, Kazakhstan and the countries in southeastern Europe), no or very few drought events are registered in EM-DAT. The reason for this mismatch could be that drought events in these countries were not registered in EM-DAT. For example, in Romania, EM-DAT reports two drought events, while according to other reports, 12 years between 1980 and 2012 were classified as drought years, with 48 % of the agricultural land affected (Lupu et al., 2010; Mateescu et al., 2013). On top of this, in Iran, EM-DAT reports one drought event while other sources recounted several droughts during 1980–2005, with the most extreme drought lasting for 4 years, from 1999 to 2002 (Javanmard et al., 2017; Zoljoodi & Didevarasl, 2013). These examples suggest that it cannot be concluded from missing drought records in EM-DAT that specific countries were not affected by drought. Once improved and reliable impact data are available at the global scale, future research should also focus on the statistical validation of drought risk assessments with drought events and impact data. Ongoing efforts of countries to report their losses and impacts due to natural hazards (e.g., as part of the Sendai monitoring) are considered to be a first important step towards that direction.

Lastly, while this study presents the first attempt to assess drought risk for agricultural systems, more work is needed to analyze drought risk for other sectors, such as public water supply, tourism, energy production and waterborne transport, among others.

3.2.5. Conclusions

This paper presents, for the first time, a global-scale drought risk assessment for both irrigated and rainfed agricultural systems from a socioecological perspective by integrating drought indicators for hazard, exposure and vulnerability. It goes beyond previous studies by including a separated and spatially explicit analysis of the drought hazard and exposure of irrigated and rainfed agricultural systems as well as an empirically based weighting of vulnerability indicators. The latter is based on the judgment of drought experts around the globe. The presented methodology can serve as a blueprint for the analysis of other affected sectors, such as water or energy. Findings from this study underscore the relevance of analyzing drought risk from a holistic perspective (i.e., including the sector-specific hazard, exposure and vulnerability) and are based on a spatially explicit approach. By providing information on high-risk areas and underlying drivers, this approach helps to identify priority regions as well as entry points for targeted drought risk reduction and adaptation options. While this first attempt provides valuable information at the global level, improvements could be achieved with the availability of more spatially explicit vulnerability information (i.e., at subnational levels) and the availability of standardized drought impact information that can serve as a quantitative validation of risk levels.

***Data availability*.** Data can be accessed under the following link: https://grow-globedrought.net/data/global-scale-drought-risk-assessment-for-agricultural-systems/ (last access: 27 February 2020) (Meza et al., 2020a)

4. Assessing drought risk for agricultural systems at national scale

4.1. Drought Risk to Agricultural Systems in Zimbabwe: A Spatial Analysis of Hazard, Exposure, and Vulnerability

Frischen, J., **Meza, I.**, Rupp, D., Wietler, K., & Hagenlocher, M.

Published as research article on Sustainability (2020). https://doi.org/10.3390/su12030752

Summary

The devastating impacts of drought are fast becoming a global concern. Zimbabwe is among the countries more severely affected, where drought impacts have led to water shortages, declining yields, and periods of food insecurity, accompanied by economic downturns. In particular, the country's agricultural sector, mostly comprised of smallholder rainfed systems, is at great risk of drought. In this study, a multimethod approach is applied, including a remote sensing-based analysis of vegetation health data from 1989–2019 to assess the drought hazard, as well as a spatial analysis combined with expert consultations to determine drought vulnerability and exposure of agricultural systems. The results show that droughts frequently occur with changing patterns across Zimbabwe. Every district has been affected by drought during the past thirty years, with varying levels of severity and frequency. Severe drought episodes have been observed in 1991–1992, 1994–1995, 2002–2003, 2015–2016, and 2018–2019. Drought vulnerability and exposure vary substantially in the country, with the south-western provinces of Matabeleland North and South showing particularly high levels. Assessments of high-risk areas, combined with an analysis of the drivers of risk, set the path towards tailor-made adaptation strategies that consider drought frequency and severity, exposure, and vulnerability.

4.1.1. Introduction

Climate change and its diverse environmental and societal impacts have become a major global concern (Carrão et al., 2016; IPCC 2012; IPCC 2014). Droughts are complex, multifaceted, slow-onset hazards that can last for several months or years, affecting wide geographic areas and a large number of people (Jordaan et al., 2019; Meza et al., 2019; Vogel et al., 2010), with severe consequences for human wellbeing, the environment, and the economy (Hagenlocher et al., 2019). Moreover, it is likely that droughts will increase in the future due to climate change (Ahmadalipour et al., 2019; Mishra et al., 2010). Global warming has resulted in a higher frequency and severity of droughts in the Mediterranean, many parts of South America, much of Africa, and north-eastern Asia (IPCC, 2019). Drought as a hazard is a product of climate related-factors such as rainfall, moisture deficiency, and temperature, but is also influenced by anthropogenic alterations of hydrological processes and the physical environment (Van Loon et al., 2016). Commonly, droughts are classified into four major types, i.e., (i) meteorological, (ii) hydrological, (iii) agricultural, and (iv) socio-economic (Wilhite & Glantz, 1985). Since drought development cannot solely be attributed to climate drivers, the consideration of socio-economic preconditions through a coupled perspective on human-environment systems is crucial (Tortajada et al., 2017; Sebesvari et al., 2016; Hohenthal & Minoia, 2017). However, these fields are often considered in isolation from each other, ignoring the complex feedback between natural and human drivers (Van Loon et al., 2016).

Given the devastating impacts of droughts, there has been increasing global cooperation and priority setting with regards to proactive drought risk management (UNDRR, 2015), which has been identified for many parts of the world as either inefficient or altogether absent (Hohenthal & Minoia, 2017; Sivakumar et al., 2014; Pozzi et al., 2013). Dealing with drought is very complex, as the dimensions of this hazard are not fully understood, and it remains a challenge to precisely assess drought onset, duration, and spatial extent (Hagenlocher et al., 2019; Van Loon et al., 2016). In wealthy countries that have adequate adaptive and coping capacities, droughts cause high financial and economic losses that can often be addressed through existing contingency funds or insurance schemes, whereas in countries lacking these capacities, droughts often lead to food shortages and famine (Rojas et al., 2011; Msangi, 2004; Vogt et al., 2018). Food-deficit countries with a high dependence on rainfed agriculture as the primary economic sector are more susceptible to drought, with the rural population particularly being vulnerable (Carrão et al., 2016). Countries with weak economies often suffer the most from the impacts of drought, given the restricted amount of resources available to proactively deal with it (Belle et al., 2017). Hence, the highest drought mortality risk arises in Sub-Saharan Africa, whereas the highest economic losses occur in western and southern Europe, Central America, the Middle East, Australia, and north-eastern China (Carrão et al., 2016; Hohenthal & Minoia, 2017).

Zimbabwe is among the countries in southern Africa that are heavily affected by droughts (Jiri et al., 2017; Brazier, 2015; WFP, 2014; Makaudze & Miranda, 2010; Ndlovu, 2014). In particular, the agricultural sector is severely challenged by this hazard (World Bank, 2019), exposing farmers to insufficient rainfall patterns (Leichenko, 2002). Agriculture accounts for approximately 12% of the country’s Gross Domestic Product (GDP) (World Bank, 2018). About 70% of the population directly depends on agricultural outputs (UN Zimbabwe, 2010), and more than 60% conducts rainfed subsistence and semisubsistence agriculture (Makaudze & Miranda, 2010). In particular, smallholder farmers growing crops under rainfed conditions are highly susceptible to drought due to their dependency on climate-sensitive resources (Makaudze & Miranda, 2010; Muzari et al., 2016; Mudzonga, 2012). Climate-induced water stress intensifies preexisting problems including declining agricultural and economic productivity coupled with poverty and insecurity (Brown et al., 2012). Maize is the most commonly grown staple food in Zimbabwe, cultivated by smallholder farmers for subsistence farming, but is highly sensitive to dry conditions and erratic rainfall (Jiri et al., 2017; Michler et al., 2019; Chigwada, 2005; Kogan, 1995). Rural households face enormous challenges due to drought impacts that, in combination with crop diseases and pest attacks, lead to yield losses and highly uncertain incomes, representing the biggest poverty trap in Zimbabwe (Lunduka et al., 2019; Creitaru, 2017; Kinsey et al., 1998). By threatening agricultural livelihoods, droughts are also hampering the achievement of the sustainable development goals in Zimbabwe, notably SDG1 (no poverty), SDG2 (zero hunger), and SDG3 (good health and well-being). Research and investigations into the drivers and patterns of drought risk are increasing global in scope (Carrão et al., 2016; Hagenlocher et al., 2019; Sivakumar et al., 2014), due to its multifaceted impacts on water availability, agricultural outputs, health, economy, and the natural environment (Hohenthal & Minoia, 2017; Sivakumar et al., 2014; Pozzi et al., 2013). Studies focusing on drought vulnerability, however, have been less numerous than those dealing with the physical perspective of drought development (González Tánago et al., 2016; Naumann et al., 2014), even though the coupling of both dimensions has been identified as crucial (Hagenlocher et al., 2019; van Loon et al., 2016; Carrão et al., 2018). Drought development and monitoring have also received increased attention in Zimbabwe, since droughts have devastating impacts in many parts of the country. Commonly, the drought hazard in the country is quantified with precipitation records (Mazvimavi, 2010; Chamaillé-Jammes et al, 2007); however, weather stations are not homogeneously distributed in Zimbabwe, nor do they provide spatially- and temporally-consistent records that make multidecadal analyses possible (Mutowo & Chikodzi, 2014). The potential of remote-sensing techniques for drought monitoring has not been fully explored in Zimbabwe, but has enormous potential to provide spatially- and temporally-consistent drought (Mutowo & Chikodzi, 2014) and early-warning information (Makaudze & Miranda, 2010). In addition to drought monitoring, several studies have emerged concerning Zimbabwe's vulnerability to drought in the context of climate change (Muzari et al., 2016; Mudzonga, 2012; Murungwen et al., 2011; Mutekwa, 2019). Many of these have focused on the negative impacts on agricultural production (Makaudze & Miranda, 2010; Muzari et al., 2016; Mudzonga, 2012; Brown et al., 2012; Chigwada, 2005, UNEP, 2009), as Zimbabwe has suffered from periods of severe food insecurity and famine, given its dependency on rainfed agriculture. Furthermore, several studies have dealt with adaptation and coping strategies in the context of drought (Belle et al., 2017; Jiri et al., 2017; Ndlovu, 2014; Michler et al., 2019; Kinsey et al., 1998; Ndlovu et al., 2011; Chagutah, 2010). Existing studies on drought vulnerability have been primarily conducted on the local and district levels (Chigwada, 2005; Ndlovu et al., 2011; Ncube et al., 2018), often investigating the various factors that are relevant in the context of drought vulnerability, including economic, social, health, environmental, and political dimensions. There is lack of comprehensive drought risk assessments on the national level (Creitaru, 2017; Government of Zimbabwe, 2015a) that consider spatially- and temporally-consistent hazard information complemented by drought exposure and vulnerability factors. Since proactive drought management requires a better understanding of both natural and human drivers, comprehensive risk assessments are a prerequisite for identifying drought adaptation and vulnerability reduction strategies (Hagenlocher et al., 2019; Sivakumar et al., 2014; Sherbinin et al., 2017). This paper aims to address this gap by providing a multidimensional drought risk assessment specifically for Zimbabwe. Drought hazard, exposure, and vulnerability information is compiled into a drought risk index. The focus lies on agricultural systems, hereby defined as systems including crops and people engaged in agricultural activities, due to the country's dependence on agriculture (UN Zimbabwe, 2010). High-risk areas are identified, and the interplay of all risk components is analyzed. Such information has been stated as a clear need in Zimbabwe (World Bank, 2019; Creitaru, 2017; Government of Zimbabwe, 2015; UNCCD, 2020) and is a preliminary step towards addressing drought in a strategic and coordinated manner.

4.1.2. Materials and Methods

4.1.2.1. Case Study

Zimbabwe is a landlocked country in southern Africa, occupying an area of 390,800 km2, with a population of 13.60 million people (ZimStat, 2017). It is a low income and food-deficit country (WFP, 2017), and was ranked 156 out of 188 countries on the Human Development Index (UNDP, 2018) and 109 out of 117 countries on the Global Hunger Index (Deutsche Welthungerhilfe, 2019). The Republic of Zimbabwe is divided into ten administrative provinces, which are further subdivided into 59 districts and 1200 wards. The capital and largest city is Harare, in the north-central part of the country, followed by Bulawayo, an equally important economic city situated in the south-west. A large proportion of the country is covered by croplands, mainly consisting of rainfed agriculture (Muzari et al., 2016; Landmann et al., 2019). Based on NDVI observations from 2013–2018 (Landmann et al., 2019), show that rainfed agricultural systems represent the largest share in the country, whereas irrigated systems have a smaller extent (Figure 4.1).

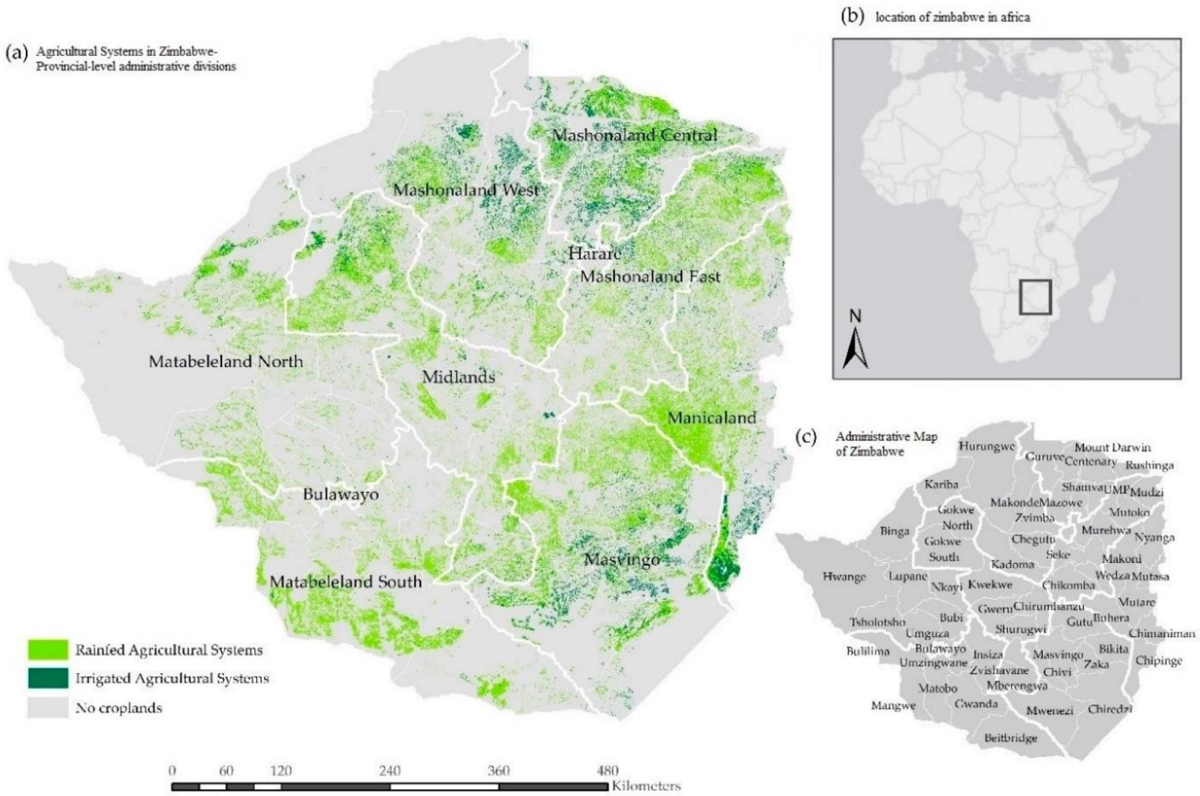


Figure 4.1. Agricultural Systems in Zimbabwe. Differentiation between rainfed and irrigated agriculture based on data from Landmann et al. (2019). Overview map: Esri, HERE, Garmin (c) OpenStreet contributers, and the GIS user community.

4.1.2.2. Conceptual Risk Framework

The presented drought risk analysis builds on the conceptual risk framework proposed by Working Group 2 of the Intergovernmental Panel on Climate Change (IPCC) in its 5th Assessment Report, where risk is a function of (drought) hazard, exposure, and vulnerability IPCC, 2014). Exposure is defined as the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected by drought hazard. Exposure and hazard are interconnected elements. Drought vulnerability is understood as the predisposition to be adversely affected by drought, and is assessed through a social-ecological system lens by considering the subcomponents social susceptibility, ecosystem susceptibility, and a lack of coping capacity (Sebesvari et al., 2016; Hagenlocher et al., 2018). Adaptive capacity (or the lack thereof) is often conceptualized as a subcomponent of vulnerability (e.g., IPCC, 2014); however, due to the forward-looking nature of the concept, adaptation is framed in this analysis as part of potential solutions that will shape future risk pathways, instead of considering it as a factor that determines present-day drought risk, which is the focus of this analysis.

4.1.2.3. Workflow

Figure 4.2 shows the overall workflow of the analysis. Hazard, exposure, vulnerability, and ultimately, risk are assessed using a multimethod approach. The drought hazard analysis builds on remote sensing data incorporating seasonal vegetation health composites over the last thirty years (1989–2019). Exposure is derived from the integrated analysis of the hazard data with a dataset differentiating between rainfed and irrigated crops provided by Landmann et al. (2019). To assess vulnerability, a composite indicator-based approach is applied (Naumann et al., 2014; JRC, 2019; Ahmadalipour et al., 2018; Hagenlocher et al., 2016), comprising a widespread approach to assessing vulnerability and risk associated with climate-related hazards (Sherbinin et al., 2019). The drought vulnerability indicator selection is based on a systematic literature review focusing on drought vulnerability in Africa and Zimbabwe. Data was acquired from multiple sources, including spatial and statistical data, followed by statistical operations including missing data and outlier treatment, as well as multicollinearity analysis. An expert survey was conducted to weight drought vulnerability indicators according to their relevance. As a final step, drought hazard, exposure, and vulnerability are compiled into a drought risk index.

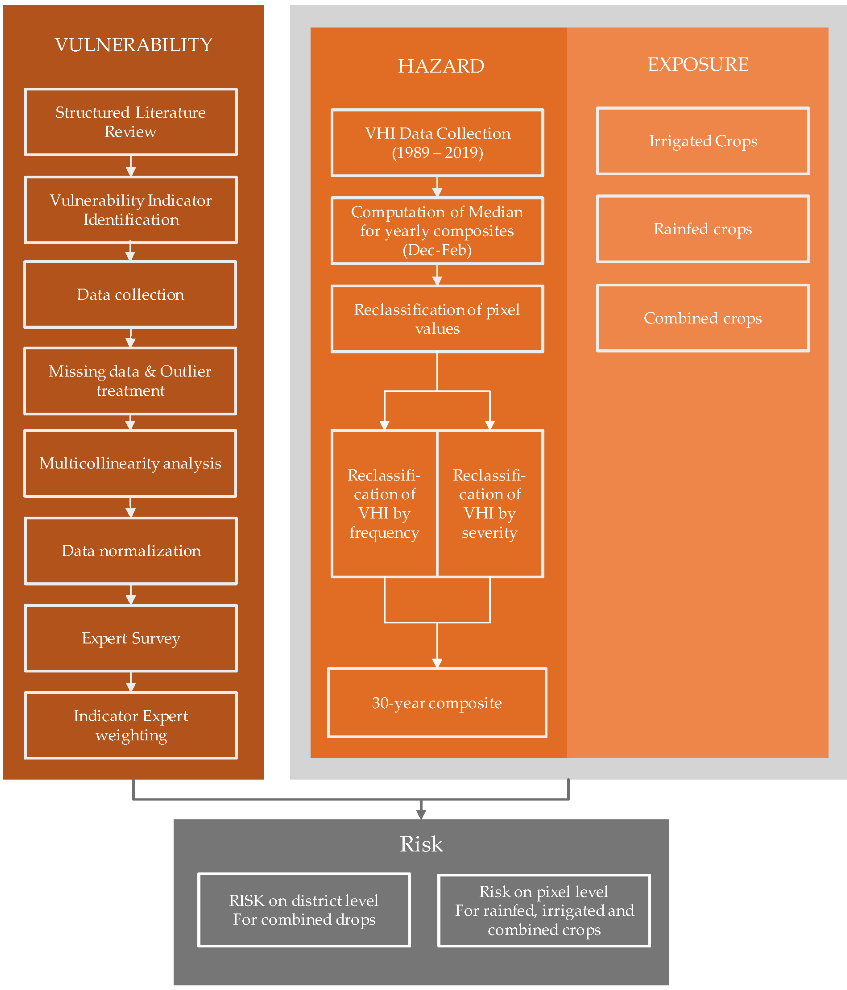


Figure 4.2. Workflow for the drought risk assessment.

4.1.2.3.1. Drought Hazard Analysis

The Normalized Difference Vegetation Index (NDVI= (NIR-RED)/(NIR+RED)) is a ratio between the red band (RED) and near-infrared (NIR) band, and is the most commonly applied index to measure the status of vegetation (Dutta et al., 2015). However, vegetation stress caused by drought conditions is closely related to weather conditions. Thus, other vegetation indices considering weather impacts are more appropriate for drought risk analyses (Kogan, 1995; Bhuiyan et al., 2017).

The Vegetation Condition Index (VCI = (NDVI-NDVImin)/(NDVImax+NDVImin) is derived from the NDVI by scaling values between minimum and maximum values over a defined time period to detect plant stress (AghaKouchak et al., 2015; Kogan, 1997; Walz et al., 2018). This pixel-based normalization of the NDVI contains percentage values (0 to 100%), and is frequently applied to capture the severity of agricultural droughts (Graw et al., 2017). The VCI separates weather-related NDVI fluctuations from observed long-term changes in vegetation condition (Kogan, 1995); hence, it is particularly useful for making relative assessments and detecting drought dynamics during a season (Graw et al., 2017;, Belal et al., 2014). Since drought is defined as a phenomenon with below normal water availability over an extended period of time (Tallaksen & van Lanen, 2004), relative assessments are essential to estimate normal and abnormal levels of water availability.

To identify temperature-related vegetation stress, the Temperature Condition Index ($TCI = (Tmax-T)/(Tmax-Tmin)\times100$) is suitable, with Tmax referring to the maximum temperature envelope and Tmin indicating the minimum temperature envelope (Kogan, 1995). This algorithm is based on thermal infrared observations (AghaKouchak et al., 2015; Graw et al., 2017). In contrast to the NDVI and VCI, high TCI values indicate undesirable conditions, whereas low temperature values imply mostly favorable conditions (Kogan, 1995).

The Vegetation Health Index (VHI) is derived from both the VCI and TCI ($VHI = \alpha VCI+(1-\alpha) TCI$), where α refers to the relative contribution of the VCI and TCI (AghaKouchak et al., 2015). It has been widely applied for drought monitoring (Ghaleb et al., 2015), and is frequently used in case studies in the context of drought monitoring on a global level (AghaKouchak et al., 2015, as well as in Africa (Rojas et al., 2011; Unganai & Kogan, 1998), Asia (Bhuiyan et al., 2017), and Europe (Bento et al. 2018).

The VHI, as a combined index of TCI and VCI, can be used as a proxy for drought development, taking both temperature conditions and vegetation stress into account (Bhuiyan et al., 2017). High VHI values correspond to healthy undisturbed vegetation, whereas low VHI values indicate thermal stress in vegetation due to high temperature and dryness (AghaKouchak et al., 2015). Thresholds have been developed to detect drought conditions according to the vegetation health status (Kogan 1995, 2002). VHI values between 0 and 40 indicate drought conditions with different severity levels (Table 4.1), and provide the hazard information in this assessment.

Table 4.1 VHI thresholds for drought development. Sources: Dutta et al., 2015; Bento et al. 2018; Kogan, 2002.

Drought severity	**VHI values**	**Reclassification value**
Extreme Drought	<10	4
Severe Drought	≥10 and <20	3
Moderate Drought	≥20 and <30	2
Mild Drought	≥30 and <40	1
No Drought	≥40	0

VHI data was derived from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) from 1989–2012 and the Visible Infrared Imaging Radiometer Suite (VIIRS) from 2013–2019. Data is available as 4 km Blended-VHP (Vegetation Health Product) in GEO-TIFF format in weekly composites (NOAA, 2019). Seasonal VHI composites adjusted to the cropping season of maize in Zimbabwe (December – February) from 1989–2019 provide inputs to identify regions that are affected by drought, either with a high frequency or high severity. Two different datasets were produced: one incorporating drought severity levels according to the drought severity thresholds (Table 4.1), and a second consisting of an aggregated drought scene indicating the number of drought events over the last thirty years on a pixel-level, following the methodology of Rojas et al. (2011) and Kogan (1995, 2001). A binary map was created for each season, with 0 indicating no drought (VHI values higher than 35) and 1 indicating drought conditions (VHI values below 35).

4.1.2.3.2. Drought Exposure Analysis

Exposure of agricultural systems to drought was computed with a land use/land cover (LULC) dataset differentiating between rainfed and irrigated agriculture in Zimbabwe, derived from NDVI observations from 2013–2018 provided by Landmann et al. (2019). Rainfed systems are more common in Zimbabwe, whereas irrigated systems show more isolated patterns in northern and southern Zimbabwe (Figure 4.1). For the risk analysis on a pixel level, the breakdown of rainfed, irrigated, and combined agriculture was considered. Pixels were reclassified for each agricultural system (rainfed, irrigated, and combined). Drought exposure was calculated using Geographic Information Systems (GIS) by combining the drought hazard data (reclassified among the severity levels presented in Table 4.1) with the LULC dataset. The amount of exposed croplands for each severity class was subtracted from the total amount of croplands per district.

4.1.4.3.3. Drought Vulnerability Analysis

A systematic literature review based on predefined search terms was conducted using the search engines Web of Science and Scopus in order to synthesize the main underlying drivers of drought vulnerability in Africa and Zimbabwe, and to identify suitable drought vulnerability indicators. The following guiding questions were used to identify suitable papers: Which vulnerability dimensions are considered as relevant? What are the main drivers of drought vulnerability? How is drought vulnerability assessed? What type of data is useful to represent the indicators? The search query and relevant keywords are presented in Table 2.

Table 4.2 Search terms to identify relevant papers for the vulnerability indicator selection.

Database	Search Equation	Papers retrieved	Papers selected
Web of Science	("drought*") OR ("drought risk") OR ("drought hazard") OR ("drought vulnerability") OR ("drought adaptation") OR ("drought resilience") AND ("Zimbabwe*") OR ("Southern Africa") OR ("SADC") OR ("Africa*") OR ("South Africa")	40	12
Scopus	TI = drought* OR drought risk OR drought hazard OR drought vulnerability OR drought adaptation OR drought resilience AND TS = Zimbabwe* OR Southern Africa OR SADC OR Africa* OR South Africa	50	13

with TI = title and TS = topic

In the next step, the titles and abstracts of the retrieved articles were screened to identify relevant papers that refer to the identified guiding questions. Seven additional papers were retrieved through a nonsystematic search for the vulnerability indicator selection. The selected papers were analyzed with the MAXQDA software (VERBI, 2014). A coding scheme was developed to identify all relevant drought vulnerability indicators. Indicators were grouped among the vulnerability subcategories, including social susceptibility, ecosystem susceptibility, lack of coping capacities, and lack of adaptive capacities.

A drought expert survey in Zimbabwe was conducted to rank indicators according to their relevance, and to apply a weighting to the final set of indicators. A Likert scale from 0 to 4 was used, whereby 0 indicates not relevant, 1 represents low relevance, 2 equals medium–low relevance, 3 indicates medium–high relevance, and 4 represents high relevance (Meza et al., 2019). Furthermore, an “I don’t know option” was provided; however, inputs were not considered for the final indicator weights. For reasons of clarity, all indicators were grouped according to their thematic dimension: agriculture, economy, infrastructure, social, health, and land use. Twelve experts participated in the survey, the majority of whom work in academia (41.7%) and NGOs (41.7%). Most of the experts had either more than ten years of working experience in Zimbabwe (33.3%) or three to five years (33.3%), and worked specifically in the context of drought (83.3%). More information on the background of the experts who participated in the survey is provided in the appendix C.5.

In total, 65 different drought vulnerability indicators were identified. Indicators referring to adaptive capacities were excluded, since adaptive capacity does not affect present-day drought risk, but is only considered relevant when it comes to future drought risk pathways. Based on data availability, 32 indicators were selected to perform the vulnerability assessment (Table 4.3).

Table 4.3 Final selection of drought vulnerability indicators, data sources and expert weights.

Dimension	Code	Indicator	Data Source	Direc-tion	Expert weight*
		Social Susceptibility			
Economic	S_FOO	Food poverty prevalence (%)	UNICEF 2015	+	1.00
Social	S_FEM	Gender equality (female-headed households, %)	ZimStat 2012**	+	0.90
Infrastructure	S_TOI	Access to improved sanitation facilities (prevalence of open defecation, %)	ZimVAC 2017	+	0.90
Economic	S_POV	Poverty prevalence (%)	UNICEF 2015	+	0.86
Social	S_RUR	Rural population (% of total population)	ZimStat 2012**	+	0.86
Social	S_CON	Prevalence of conflict and insecurity (# of events between 2001-2018)	ACLED 2017	+	0.84
Economic	S_INC	Average household income (mean income of rural population, US$)	GAR 2015	-	0.84
Social	S_AGE S_CHI	Social dependency (dependency ratio, % of population <15 and >64 years old, child-headed households, %)	ZimStat 2012**	+	0.84 0.81
Economic	S_EMP	Unemployment rate (%)	ZimStat 2012**	+	0.83
Agriculture	S_AGRI	Labour force in agriculture (% of total population)	ZimStat 2012**	+	0.81
Economic	S_MAR	Access to markets (estimated travel time to the nearest city of 50,000 inhabitants)	Nelson 2015	+	0.81
Infrastructure	S_DRI	Population with access to safe drinking water (%)	ZimStat 2012**	-	0.79
Health	S_HIV	Prevalence of HIV (%)	MOHCC 2018	+	0.79

Infrastructure	S_INF	Access to transportation infrastructure (distance to main roads, km)	HOT 2019	-	0.79
Health	S_HEA	Access to health facilities (health facilities within 20 km distance)	OCHA ROSA 2018	-	0.72
Economic	S_GINI	GINI index (income inequality)	UNICEF 2015	+	0.65
Social	S_LIT S_SEC	Education (% of population attending secondary school Literacy rate, %), access to educational facilities,)	ZimStat 2012**	-	0.63 0.56
Infrastructure	S_ELE	Access to electricity (% of households in dwelling units without electricity)	ZimStat 2012**	+	0.51
Health	S_MAT	Maternal mortality rate (deaths per 100 000 live birth)	ZimStat 2012	+	0.67
Health	S_MOR	Infant mortality (deaths per 1000 live birth)	ZimStat 2012**	+	0.63
Social	S_MAS	Marital status (% of population married)	ZimStat 2012**	-	0.47
		Ecosystem Susceptibility			
Land Use	E_TREE	Forest resources (% of area covered by forests)	World Resource Institute 2019	-	0.95
Land Use	E_SOIL	Soil quality (soil organic carbon content (g/kg))	OpenGeoHub 2018	-	0.93
Land Use	E_DEF	Forest degradation (deforestation rate, %)	Hansen et al. 2019	+	0.86
Land Use	E_NAT	Protected areas, national parks and conservation areas (% of total district area)	UNEP-WCMC 2019	-	0.86
		Lack of Coping Capacities			
Agriculture	C_LIV	Livestock ownership (# of cattle herds)	Livestock Geo Wiki 2019	-	1.00
Economic	C_REM	Access to credit (remittances received per household, $)	ZimStat 2018	-	1.00
Land Use	C_WAT	Access to improved water resources (%)	ZimVAC 2017	-	0.91

Land Use	C_REN	Renewable internal freshwater resources (distance to nearest water bodies)	HOT 2019	-	0.88
Infrastructure	C_DAM	Dam capacity (million m3)	Suganan 1997	-	0.79

* 1 indicates the highest relevance according to expert judgement, whereas 0 means no relevance.

The data for the vulnerability indicators were collected from multiples sources (e.g., statistical reports and spatial data portals). All utilized datasets are open access, to ensure that the results can be validated and reproduced. Potential outliers in the data were examined using box plots based on the interquartile range, skewness, and kurtosis. A skewness value higher than 1 and a kurtosis value greater than 3.5 flag potential outliers (Saisana, 2010). The variables S_SEC and S_LIT were averaged under one education indicator, and the variables S_AGE and S_CHI both included under social dependency.

A multicollinearity analysis was performed to avoid overrepresentation of selected indicators (JRC, 2019). If a dataset has variables showing a correlation coefficient lower than -0.9 and higher than 0.9, both indicators should be excluded (Bühl, 2010). However, no indicators indicated a very strong positive or negative correlation (r = 0.9); hence, all indicators were included in the final assessment. The results of the multicollinearity analysis are presented in the appendix C.

Since the data results from multiple sources are provided in different formats, all inputs were normalized using a min-max-normalization approach (Naumann et al., 2014), one of the most common approaches for index construction in the field of vulnerability, risk, and resilience research (Beccari, 2016). For variables with a positive correlation, the following linear transformation was applied: Xi‘ = (Xi-Xmin)/(Xmax-Xmin), with Xi representing the generic value of a district, Xmin referring to the minimum value, and Xmax to the maximum value in a dataset. For variables with a negative contribution to vulnerability, the following formula was applied: Xi‘ = 1-(Xi-Xmin)/(Xmax-Xmin) (Naumann et al., 2014). After doing this, all indicators have an identical range between 0 and 1, with 0 indicating the lowest vulnerability and 1 marking the highest Carrão et al., 2016). In the next step, the normalized indicators were aggregated into a vulnerability index (VI) based on weighted arithmetic aggregation, where Xi‘ refers to the normalized indicators and Wi to the respective indicator weight given by the experts.

$$VI = \sum_{i=1}^{n}(\mathrm{Wi} * \mathrm{Xi}') \quad (1)$$

4.1.2.4. Drought Risk Index

The results of the hazard exposure analysis and the vulnerability index were then further combined in a drought risk index (DRI) through multiplicative aggregation, whereby both risk components (i.e. exposure to droughts and vulnerability) were weighted equally:

$$DRI = HazardExposure * VI \tag{2}$$

Two risk datasets were created following this approach. One risk map considers drought frequency by aggregating the amount of drought years (VHI < 35) that have occurred during the past thirsty years (1989–2019). The second approach focuses on drought severity by considering the thresholds for mild, moderate, severe, and extreme events (Table 4.1).

4.1.3. Results

4.1.3.1. Drought Hazard

The findings reveal that droughts frequently occur in many regions of Zimbabwe. During the last thirty years, intense drought seasons occurred in 1991–1992, 1994–1995, 2002–2003, 2015–2016, and 2018–2019 (Figure 4.3). Every district of Zimbabwe has been affected by drought development, in particular, the south-western provinces Matabeleland North and Matabeleland South. There are also seasons showing isolated patterns of droughts that vary spatially (e.g., 2003–2004, 2006–2007, 2011–2012, and 2017-2018). Mashonaland East and Manicaland are generally less affected by drought.

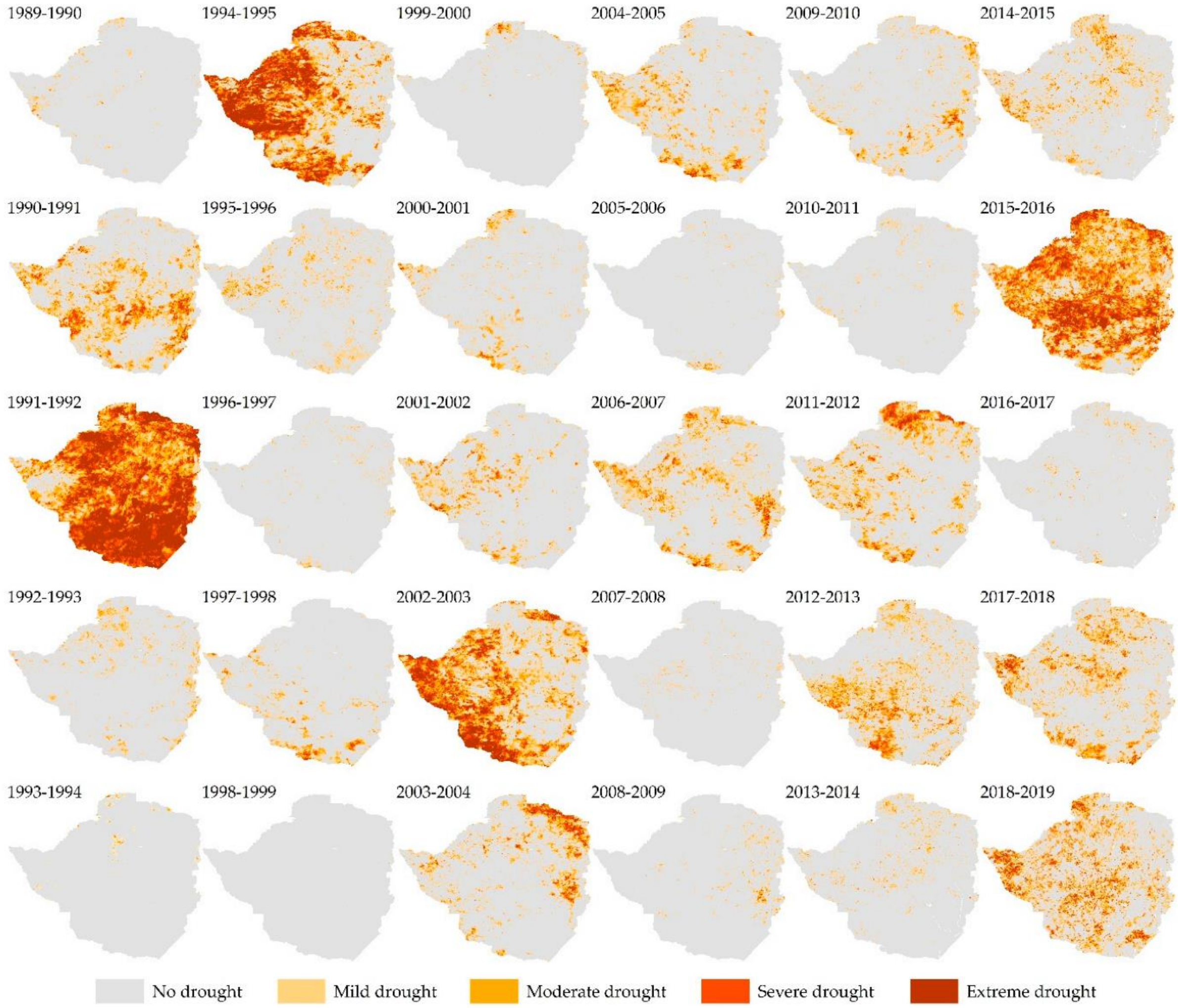


Figure 4.3. Seasonal vegetation health index (VHI) composites (1989–2019) based on NOAA AVHRR and VIIRS data (edited and aggregated) (NOAA, 2019).

VHI values below 35 were aggregated to identify spatial patterns of drought frequency over the period of thirty years, and then averaged on a district level (Figure 4.4). The five districts with the highest average number of drought events were Beitbridge (7.05 droughts in 30 years), Hwange (6.91), Bulilima (6.90), Buhera (6.84), and Tsholotsho (6.70). The five districts with the lowest average of drought events were Mutasa (1.99), Zaka (2.36), Morondera (2.69), Wedza (2.74), and Nyanga (2.89) (Figure 4.4). When looking at the average number of drought events on a provincial level, Matabeleland South and Matabeleland North indicated the highest average of drought events, followed by the Midlands Province, Mashonaland West, Mashonaland Central, and Manicaland. Masvingo and Mashonaland East have the lowest average of drought events.

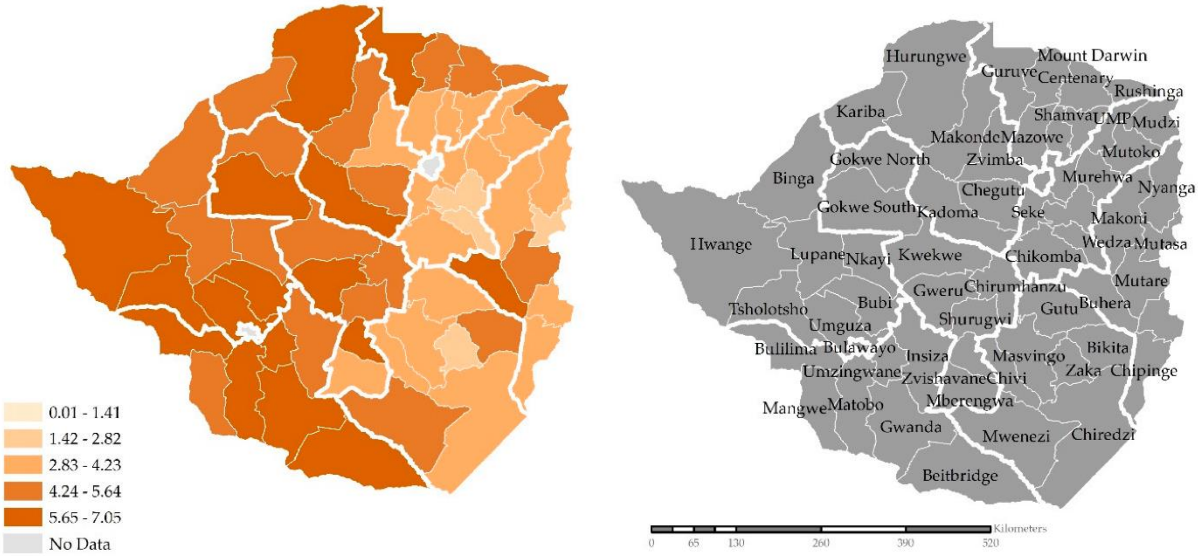


Figure 4.4. Average of drought years during 1989–2019 (VHI values below 35) per district based on NOAA AVHRR and VIIRS data (edited and aggregated) (NOAA, 2019).

4.1.3.2. Drought Exposure

While almost all cropland is exposed to mild and moderate droughts (Figure 4.5a, 4.5b), the exposure to severe and extreme droughts (Figure 4.5c, 4.5d) is significantly lower, in particular in the central-eastern provinces of Zimbabwe (Mashonaland East, and Manicaland). Those regions lie in agro-ecological zones I and II, which are more fertile, and generally more suitable for farming activities (FAO, 2006). It is also visible that the western parts of Zimbabwe have a low share of croplands, but are exposed to mild, moderate, severe, and extreme droughts (agro-ecological zones VI and V).

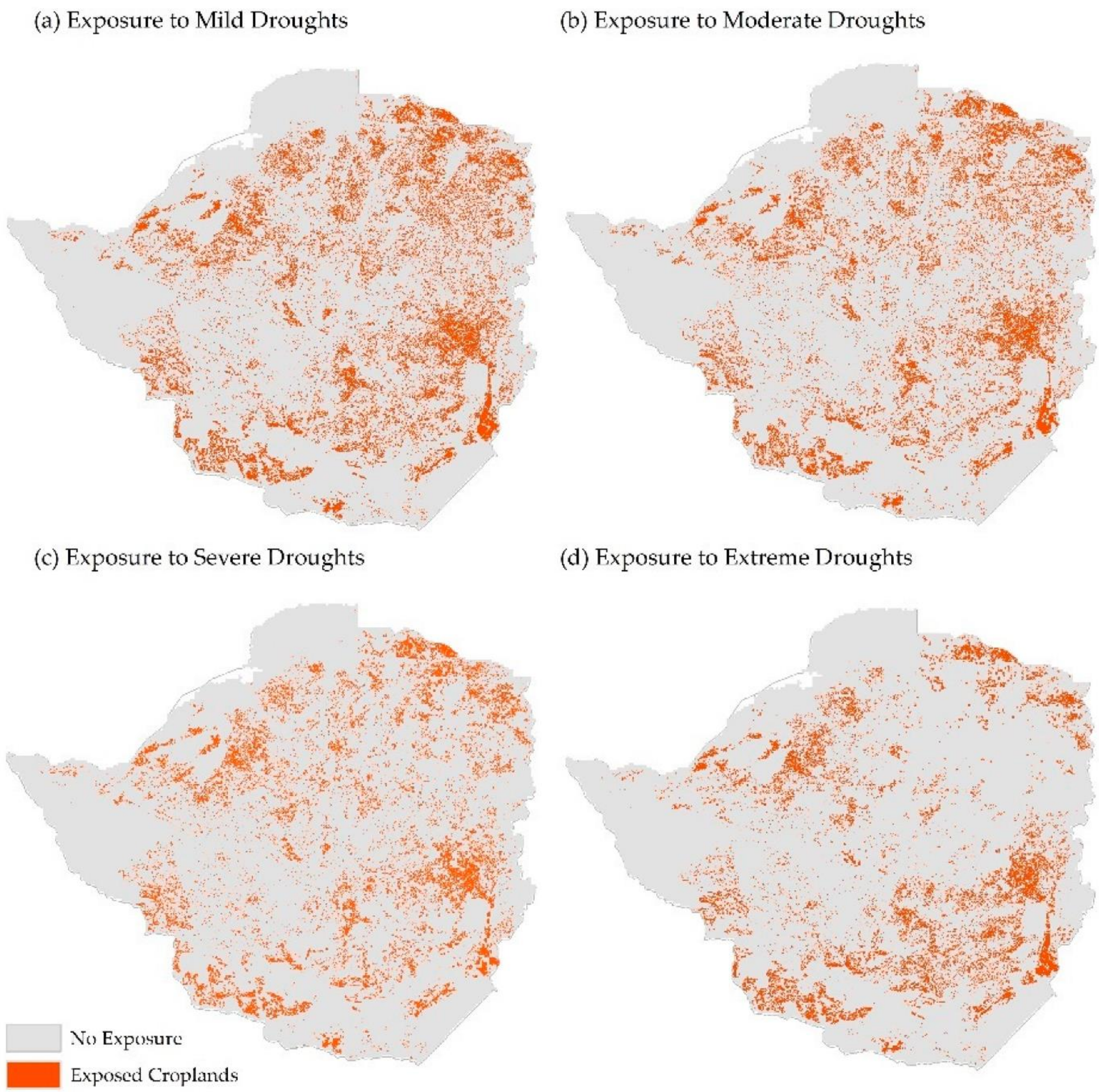


Figure 4.5. Drought exposure by drought severity classes. Data sources: hazard data based on NOAA AVHRR and VIIRS data (edited and aggregated) (NOAA, 2019) and agricultural systems in Zimbabwe based on data from Landmann et al. (2019).

4.1.3.3. Drought Vulnerability

The findings of the expert survey reveal the importance of a multidimensional assessment, as indicators from several dimensions were ranked with a high relevance (Table 4.3). The five most and least relevant indicators for the available dataset are presented in Table 4.4. An overview of all indicator scores derived from the expert weighting is presented in Table 4.3. A chart visualizing the results of the expert survey for each indicator is presented in the appendix C.4.

Table 4.4 Most and least relevant indicators based on expert judgement.

Five Most Important Indicators	Expert weight
Livestock ownership (# of cattle herds)	1.00
Access to credit (remittances received per household, $)	1.00
Food poverty prevalence (%)	1.00
Forest resources (% of area covered by forests)	0.95
Soil quality (soil organic carbon content)	0.93
Five Least Important Indicators	**Expert weight**
Infant mortality (deaths per 1000 live birth)	0.63
Literacy rate (%)	0.56
Access to improved sanitation facilities (% of total population)	0.53
Access to electricity (% of Households in dwelling units without electricity)	0.51
Marital status (% of population married)	0.47

Drought vulnerability varies substantially across the country. Low levels are particularly observed in Manicaland, which also performs comparably well in all social indicators. Contrastingly, provinces with high vulnerability scores are Matabeleland South, Matabeleland North, and Masvingo (Figure 4.6). These provinces are characterized by remoteness, with a bad state of public infrastructure including transportation, electricity, and sanitation and health facilities. The provinces additionally indicate a high state of land degradation and limited natural vegetation cover, given the low annual rainfalls. A breakdown according to the subcategories of social susceptibility, ecosystem susceptibility, and lack of coping capacities is presented in the appendix C.6.

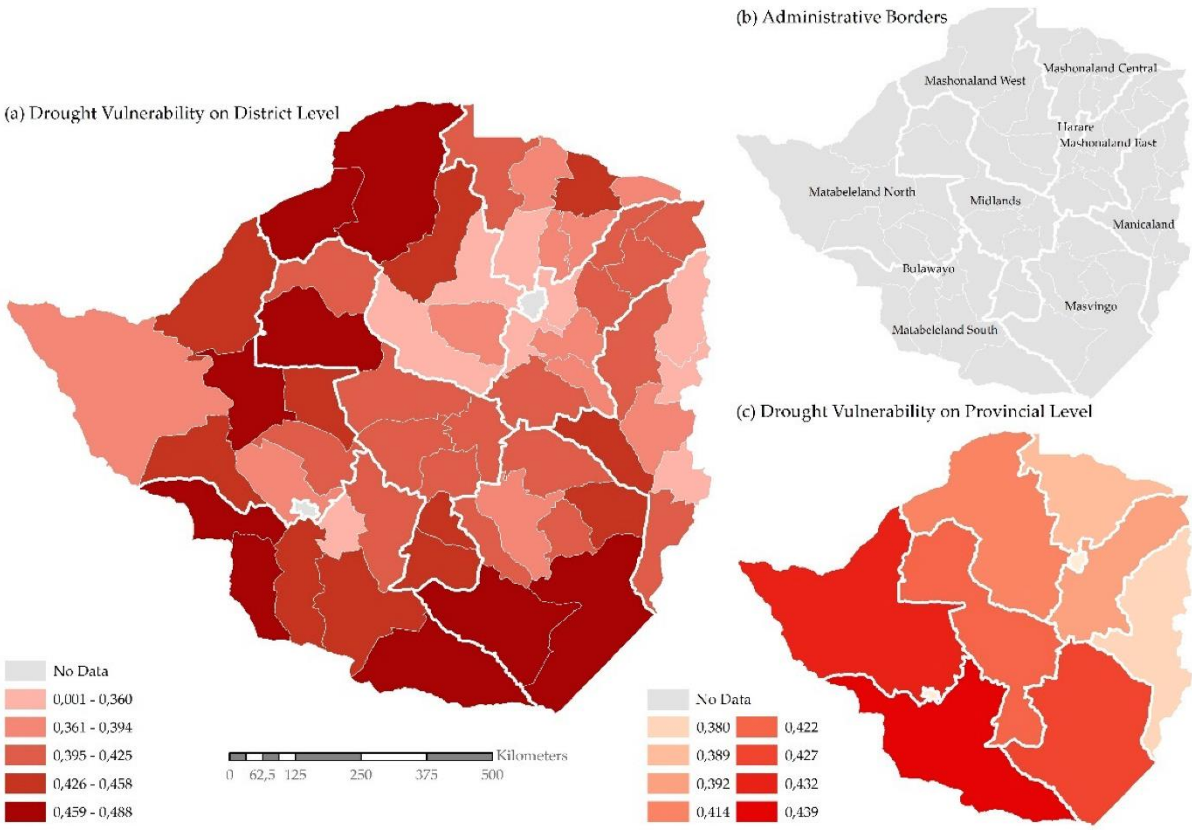


Figure 4.6. Drought vulnerability in Zimbabwe. Classification scheme: natural breaks between 0.001 and 0.4888, to better represent the spatial variance of vulnerability. For an overview of datasets and sources, see Table 4.3.

4.1.3.4. Drought Risk

Figure 4.7 visualizes drought risk on a pixel level with a size of 1 km2. This map incorporates drought frequency during the past thirty years (1989–2019). The highest drought risk to irrigated agricultural systems is observed in Chipinge, whereas a high drought risk to rainfed agriculture occurs in multiple districts, including Buhera (Manicaland), Mount Darwin (Mashonaland Central), Gokwe South (Midlands), Beitbridge, Gwanda, Matobe, and Mangwe (Matabeleland South). Agricultural systems in Mashonaland East indicate the lowest risk scores; however, the exposure is relatively high. These maps provide an overview of the spatial distribution of agricultural systems at risk to drought, whereas the next map complements these findings by taking the severity of drought events into account.

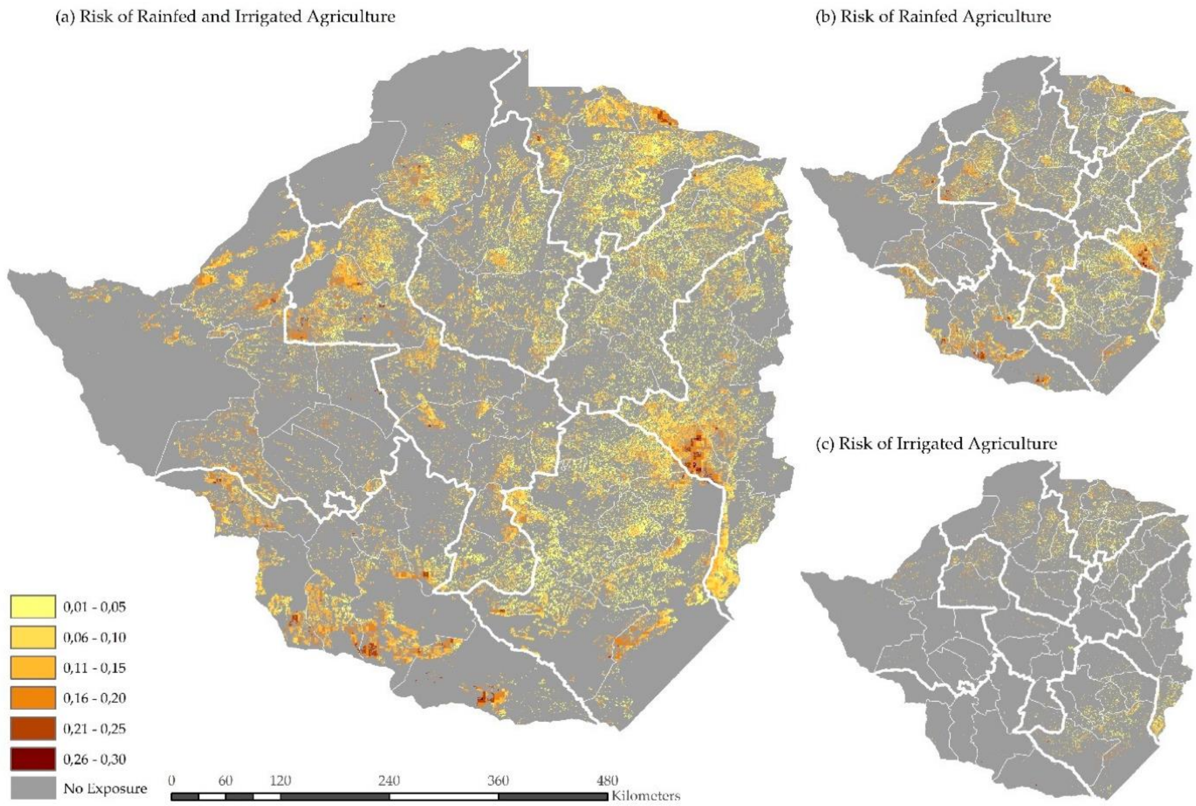


Figure 4.7. Drought risk to rainfed and irrigated agriculture considering drought frequency. Classification scheme: equal intervals between 0.01 and 0.3. Data sources: hazard/exposure based on NOAA AVHRR and VIIRS data (edited and aggregated) (NOAA, 2019) and agricultural systems in Zimbabwe based on data from Landmann et al. (2019). Vulnerability data derived from sources presented in Table 4.3.

Figure 4.8 shows the drought risk on a district level according to the drought severity classes: mild, moderate, severe, and extreme. The spatial variation of the severe and extreme severity classes is much higher compared to mild and moderate droughts. Mashonaland East and Manicaland are generally less at risk to severe and extreme drought. Beitbridge and Bulilima indicate the highest risk of severe droughts. Mangwe, Matobo, Gwanda, Mwenezi, and Chiredzi show the highest risk to extreme drought. This analysis complements the hazard frequency assessment (Figure 4.4). Beitbridge, for instance, is frequently affected by drought, and subsequently has very high risk scores for mild, moderate, and severe droughts. Hwange also indicates a high frequency of drought events; however, the risk of extreme drought is just moderate. Chipinge has a moderate to high risk to all severity classes, but is less frequently affected by drought.

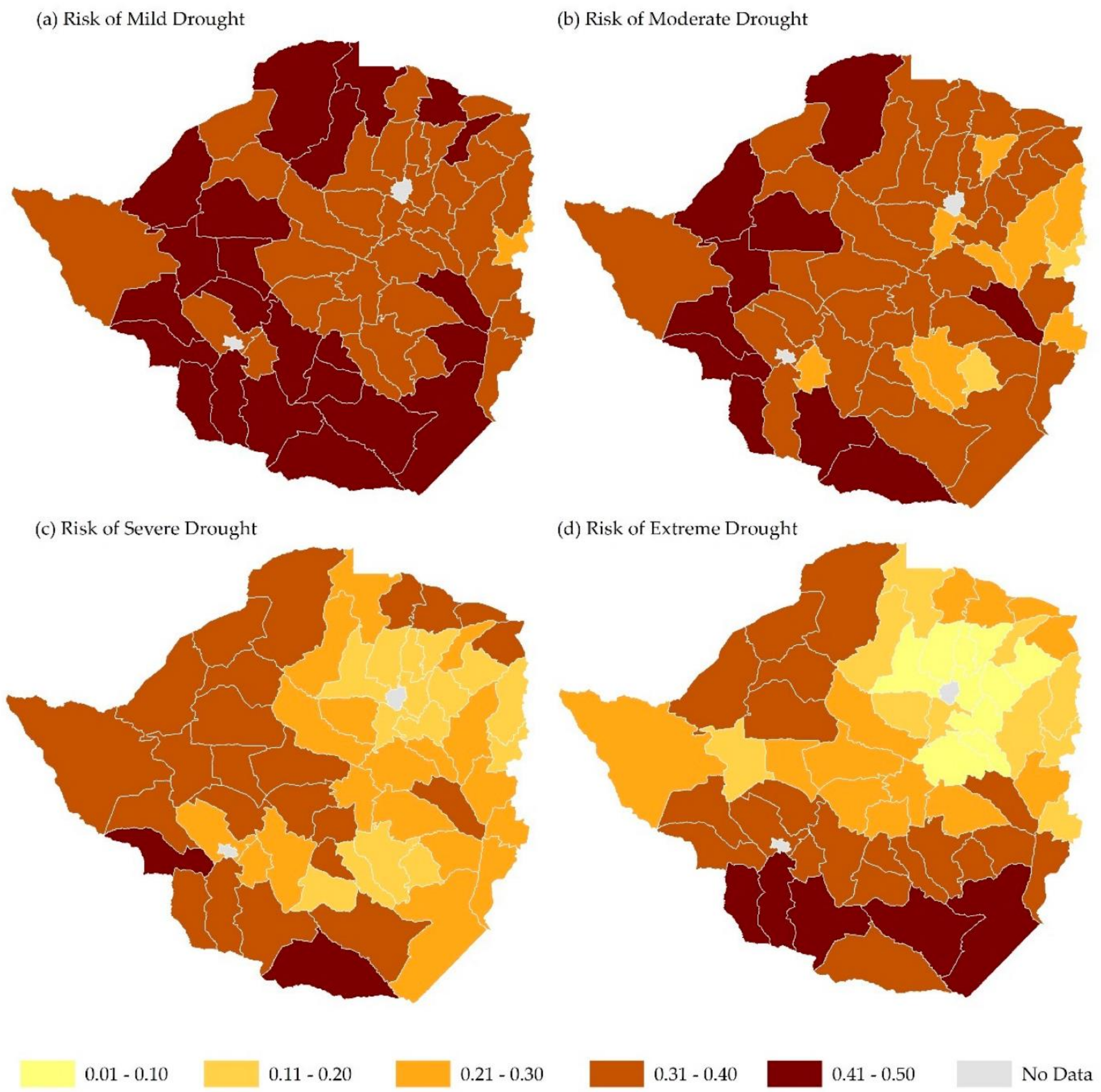


Figure 4.8. Drought risk on district level by severity classes. Classification Scheme: Equal intervals between 0.01 and 0.5. Data sources: hazard/exposure based on NOAA AVHRR and VIIRS data (edited and aggregated) (NOAA, 2019) combined with data of agricultural systems in Zimbabwe provided by Landmann et al. (2019). Vulnerability data derived from sources presented in Table 4.3.

Since the focus of this analysis is on agricultural systems, the drought risk index was plotted against the population working in the agricultural sector and the size of exposed agricultural lands (represented by the bubble size) (Figure 4.9). This graphic is particularly important to complement the results of the spatial risk analysis (Figure 4.7 and 4.8). Mangwe and Hurungwe, for instance, are at high risk to mild, moderate, severe, and extreme droughts, but have a comparably low share of people working in the agricultural sector. Mutare also has a high percentage of people dependent on agriculture, but is less affected by drought compared to the neighboring district Chipinge, that equally indicates a large share of population working in this sector.

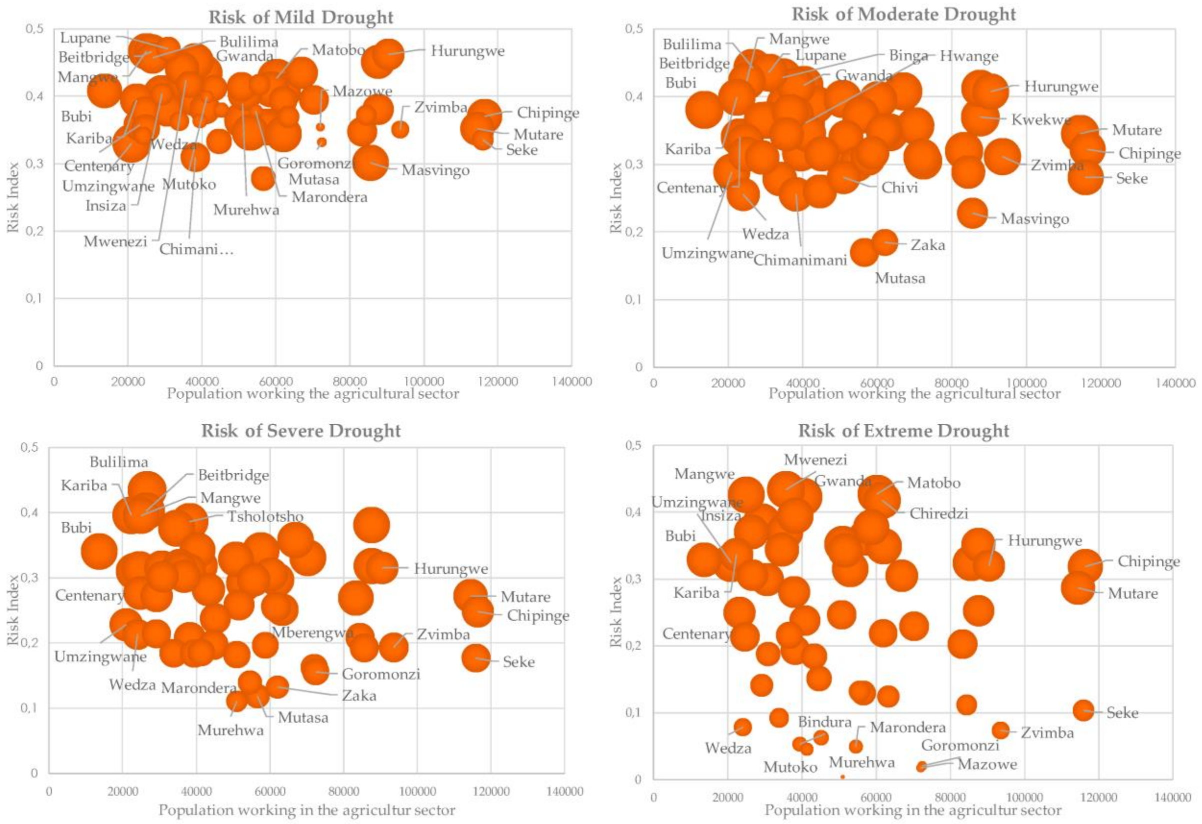


Figure 4.9. Drought risk by severity classes contrasted with exposure and agricultural labor force. Bubble size represents the size of exposed cropland per district.

4.1.4. Discussion

Like many Sub-Saharan countries, Zimbabwe faces frequent and severe droughts with adverse impacts on people, ecosystems and rural livelihoods in the agricultural sector. Against this background, the Government of Zimbabwe, in collaboration with the United Nations Convention to Combat Desertification (UNCCD, 2019), has recently developed the 'National Drought Plan for Zimbabwe' with the intention of providing a guideline for proactive drought risk management. Among other things, the National Drought Plan identifies drought vulnerability and risk assessment, including GIS mapping, as a key priority for the country (UNCCD, 2019).

This paper responds to these articulated policy needs, and presents the first attempt to assess drought risk for irrigated and rainfed systems in a spatially-explicit manner. By integrating drought hazard information, as well as data on the associated exposure and vulnerability of agricultural systems to drought hazards, our analysis goes beyond existing studies in the country which have either focused on drought monitoring and early warning (Makaudze & Miranda, 2010; Mutowo & Chikodzi, 2014), or on the assessment of the country's general vulnerability to climate change (Muzari et al., 2016; Mudzonga, 2012; Murungwen et al., 2011; Mutekwa, 2019).

The use of remote sensing techniques, in particular the VHI, is very useful as a proxy for drought development. The findings provide a spatially- and temporally-consistent time series of drought events of the past thirty years (Figure 4.3). Moreover, a combined approach of drought frequency and severity based on remote sensing data was lacking for Zimbabwe, in spite of its high relevance to identifying drought prone regions. The utilized raw data is open source and can be adapted to different time periods and geographical areas. A clear advantage of remote sensing-derived data is the independence from monitoring stations (e.g., weather stations in the field).

However, given the complexity of conceptualizing drought hazard, representing this slow-onset hazard with only one indicator is a narrow approach. In general, a drought hazard analysis would be more meaningful if it included multiple parameters (i.e. precipitation, groundwater flow, evapotranspiration and soil moisture). Common indices by which to quantify droughts include, for instance, the Palmer Drought Severity Index (PDSI) (Palmer, 1965), the standardized precipitation index (SPI) (McKee et al., 1993), the Surface Water Supply Index (SWSI) (Schafer & Dezman, 1982), and the Crop Specific Drought Index (CSDI) (Meyer et al., 1993). Those indices have specific advantages and shortcomings; however, all of them require spatially- and temporally-consistent climatological and hydrological data inputs, which are restricted in Zimbabwe (Makaudze & Miranda, 2010). Additionally, many input parameters, e.g., precipitation data, are mainly recorded in a tabular manner, rather than cartographically, which complicates the determination of spatial patterns (Mutowo & Chikodzi, 2014). Further, as VHI is not only used as a proxy for monitoring drought development, but also as an indicator of land degradation, the results of the VHI analysis must be interpreted with care, in particular in the context of Zimbabwe, where land degradation has been identified as a pressing issue .

From a conceptual perspective, it is also debatable whether the VHI is suitable to quantify drought hazard, since decreased vegetation health is already an observed impact of drought. Nevertheless, comparing vegetation health values over many seasons makes it possible to identify drought years (Kogan, 1995; AghaKouchak et al., 2015; Belal et al., 2014), but the index is probably less suitable when looking at one single season. The analysis also shows that it is crucial to look at longer time spans when analyzing drought, since this hazard displays fundamentally different spatial patterns during the last thirty years in Zimbabwe (Figure 4.3).

Composite-indicator approaches are very valuable for aggregating multiple underlying vulnerability factors (Sherbinin et al., 2017, 2019; Meza et al., 2019; Beccari, 2016), though using large datasets has certain limitations. Vulnerability indicators must address multiple dimensions that are highly relevant in the context of drought (Hagenlocher et al., 2019; Naumann et al., 2014; Ahmadalipour et al., 2018); however, aggregating individual indicators in a coherent manner reflecting reality is challenging (JRC, 2019). Moreover, given the limited data availability in Zimbabwe, it was not possible to assess drought vulnerability in a temporally-dynamic way. This is a clear limitation in the case of Zimbabwe (UNCCD, 2019), since the country's political system and the agricultural sector have gone through major changes during the last thirty years (World Bank, 2019; Shonhe, 2018), accompanied by changing vulnerability levels, in particular among the rural population (Chagutah, 2010).

Despite the presented limitations, vulnerability assessments are crucial to understanding why people are disproportionately affected by drought, and to identifying entry points for vulnerability reduction. As such, the importance of vulnerability assessments is on the national agenda, and vulnerability is frequently assessed by the Zimbabwe Vulnerability Assessment Committee (ZimVAC) (ZimVAC, 2017; ZimVAC, 2019). However, the institutionalization of this information and its incorporation into efficient vulnerability reduction approaches is a slow process that needs to be strengthened in the future (Vogel, 2010). It was found that high vulnerability levels undermine the implementation of drought adaptation strategies, which makes the impacts of drought even more devastating (Mudzonga, 2012; Mutekwa, 2019). Hence, comprehensive drought assessments should give entry-points for vulnerability reduction to set the path towards efficient drought adaptation.

In districts that indicate particularly high vulnerability scores, for instance Mangwe and Bulilima, negative coping strategies are applied to deal with drought, most commonly selling livestock (Ndlovu, 2011), which further exaggerates vulnerability. Humanitarian assistance often comes too late to prevent depletive coping, which also includes reducing meals and pulling children out of school in Zimbabwe (World Bank, 2019). Diversifying livelihood strategies and supporting farming households before the hazard materializes is key to prohibiting the uptake of negative coping strategies (World Bank, 2019; Rockström, 2003).

The prevalence of shock–recovery–shock cycles in Zimbabwe due to the high frequency and severity of droughts must be addressed with long-term risk mitigation and risk transfer strategies instead of providing costly food aid when a state of disaster is declared (World Bank, 2019). Continuous drought monitoring has the potential to support this, as drought predictability will improve preparedness and strengthen the development of early warning mechanisms (Nhamo et al., 2019). Furthermore, national assessments give an overview of priority regions, but must be complemented by local-level, in-depth analyses of drought hazard, exposure, and vulnerability. The output of those assessments should be compiled into drought management plans with local ownership (UNCCD, 2019).

Strategies focusing on risk mitigation, including sustainable agricultural techniques and drought-resistant crops, are particularly useful for regions that are frequently hit by drought, but with low to moderate severity (e.g., Kadoma). For districts that are less often affected by drought, but with high severity (e.g., Chipinge), risk transfer schemes carry enormous potential. Drought risk insurance, for example, is very useful in this context (Makaudze & Miranda, 2010; World Bank, 2019). Other districts are frequently and severely affected by drought (e.g., Beitbridge, Buhera and Bulilima). Hence, forecast-based financing is another option to decrease the costs and dependency on humanitarian aid by predicting drought seasons and providing assistance before the hazard materializes (Laganda, 2018; Coughlan de Perez et al., 2015). This can also give entry points for drought adaptation, e.g., selecting drought-tolerant varieties for that season or adjusting the planting period.

However, the adoption of agricultural innovations, such as drought-resistant varieties or conservation agriculture, is often undermined by the financial constraints of low-resourced farmers (Makate et al., 2018), but carries enormous potential to make the overall agricultural production more resilient to drought (Michler et al., 2019). During drought years in Zimbabwe, farmers are sometimes forced to replant several times, which is a large financial burden and could be avoided by agricultural adaptation strategies (Oxfam, 2016). This also requires temporally- and spatially-consistent drought monitoring. Since the lack of adaptation and preparedness strategies has also been acknowledged by the government (Government of Zimbabwe, 2012, 2015), future investments and capacity building might set the path towards more proactive risk reduction supporting case-specific and tailor-made adaptation strategies.

In light of climate change and expected increases in the magnitude and frequency of natural hazards, the dependency on agricultural outputs makes Zimbabwe extremely vulnerable. While hazard analyses outline which districts are frequently and severely affected by drought, vulnerability analyses help identifying entry points for vulnerability reduction measures. Thus, these analyses could support policy and decision makers in prioritizing key intervention areas and formulating strategies that will be essential to dealing with future drought episodes in a proactive manner. A deeper understanding of risks and their underlying factors, as presented in this analysis, will be key in encouraging a paradigm shift from reactive towards proactive drought risk management (Sivakumar et al., 2014; World Bank, 2019). Systematic drought risk assessments, if taken up by policy and decision makers, have the potential to enforce the mainstreaming of proactive drought risk management approaches in planning and programming on different levels across spatial, temporal, and sectoral boundaries (UNDP, 2011).

4.1.5. Conclusions

A combined assessment of hazard, exposure, and vulnerability for Zimbabwe was lacking, and is presented here for the first time as an integrated approach. The findings highlight the added value of mixed-methods approaches, in particular, combining remote-sensing techniques for hazard and exposure assessments with statistical and spatial data to quantify vulnerability. To date, most drought risk assessments have focused either on the hazard or vulnerability context, ignoring the interplay between the components of risk, which are essential to developing a comprehensive risk reduction strategy. The outcome of such an assessment is the development of powerful visualization tools that can inform policy makers about regions that are particularly at risk and are suitable for awareness raising to communicate the results in a simple and efficient manner. Moreover, the results provide entry points for drought adaptation, and may support a more strategic implementation of risk reduction measures.

Supplementary Material: The following are available online at www.mdpi.com/2071-1050/12/3/752/s1: Results of the multicollinearity analysis; results of the expert survey and further details on the experts' background; drought vulnerability subcategories.

4.2. Drought risk for agricultural systems in South Africa: Drivers, spatial patterns, and implications for drought risk management

Meza, I., Rezaei, E. E., Siebert, S., Ghazaryan, G., Nouri, H., Dubovyk, O., Gerdener, H., Herbert, C., Kusche, J., Popat, E., Rhyner, J., Jordaan, A., Walz, Y., & Hagenlocher, M..

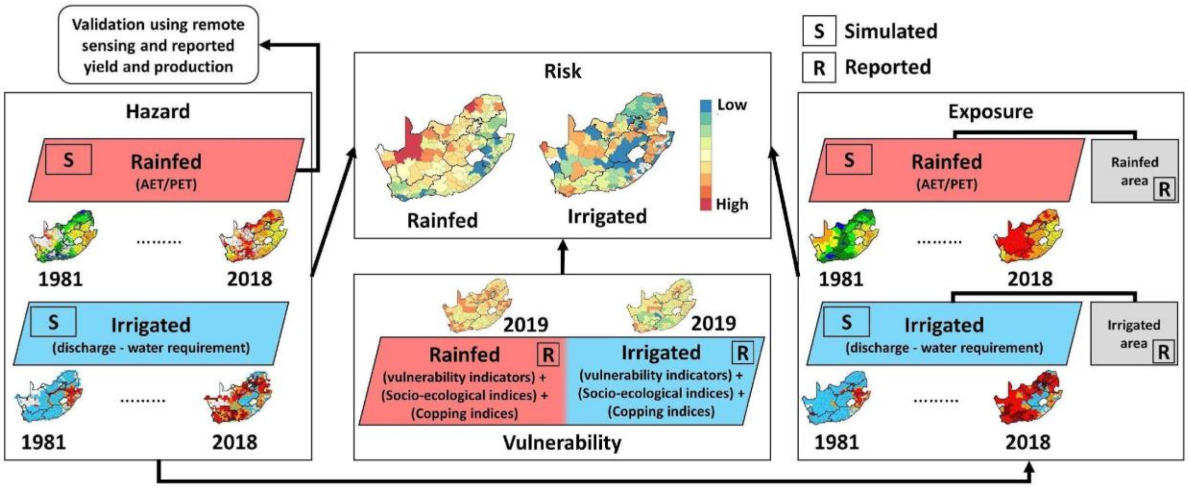
Published as research article in Science of the Total Environment (2021): https://doi.org/10.1016/j.scitotenv.2021.149505

Abstract

The regular drought episodes in South Africa highlight the need to reduce drought risk by both policy and local community actions. Environmental and socioeconomic factors in South Africa's agricultural system have been affected by drought in the past, creating cascading pressures on the nation's agro-economic and water supply systems. Therefore, understanding the key drivers of all risk components through a comprehensive risk assessment must be undertaken in order to inform proactive drought risk management. This paper presents, for the first time, a national drought risk assessment for irrigated and rainfed systems, that takes into account the complex interaction between different risk components. We use modeling and remote sensing approaches and involve national experts in selecting vulnerability indicators and providing information on human and natural drivers.

Our results show that all municipalities have been affected by drought in the last 30 years. The years 1981–1982, 1992, 2016 and 2018 were marked as the driest years during the study period (1981–2018) compared to the reference period (1986–2015). In general, the irrigated systems are remarkably less often affected by drought than rainfed systems; however, most farmers on irrigated land are smallholders for whom drought impacts can be significant. The drought risk of rainfed agricultural systems is exceptionally high in the north, central and west of the country, while for irrigated systems, there are more separate high-risk hotspots across the country. The vulnerability assessment identified potential entry points for disaster risk reduction at the local municipality level, such as increasing environmental awareness, reducing land degradation and increasing total dam and irrigation capacity.

Graphical Abstract



4.2.1. Introduction

Drought is a recurrent feature of all climates and among the most complex, damaging, and least understood of all so-called "natural hazards" (Dai, 2013; Heim Jr., 2002). It is generally defined as a period of abnormally low precipitation (compared with the long-term average climate of a given region), which is long enough to severely impact the hydrological resources (IPCC, 2014). This complex phenomenon often leads to major impacts on the environment, society and economy (Naumann et al., 2014), often with cascading effects. Moreover, with the added pressures of climate change, the frequency, severity, and duration of droughts will likely increase in many regions across the globe (Asadieh and Krakauer, 2017; Trenberth et al., 2014). The long-lasting impacts of droughts are felt in many sectors, including public water supply, energy production, tourism and agriculture, the last often being the most heavily affected sector (Dilley et al., 2005; UNDRR, 2019). This is more noticeable in countries with a large agricultural share of GDP or a large percentage of the labour force employed in agriculture, with the rural population particularly affected (Carrão et al., 2016). This demonstrates that the negative impacts associated with droughts are not only linked to the frequency, severity, and duration of drought events but also the degree of exposure, susceptibility and coping capacity of a given socio-ecological system (SES) (Meza et al., 2020). Furthermore, the combined impacts of climate change, accelerated population growth, and several declining socioeconomic factors will intensify drought hazards, exposure, and vulnerability in the long-term (Ahmadalipour et al., 2019). This highlights the need to understand and manage drought from a complex system perspective. It is necessary to consider climate and environmental drivers along with socioeconomic factors that determine how susceptible a community, region, system or sector is to drought and their capacity to cope.

Global assessments focused on drought risk of impacts on agriculture have shown that southern Africa is at particularly high risk (Carrão et al., 2016, Meza et al., 2020). South Africa is recognised as a drought-prone country (Baudoin et al., 2017; Gibberd et al., 1996, Jordaan et al., 2017a) that has experienced several "severe" drought events (as occurred in early 1980s and 1990s, the period 2014–16 (Baudoin et al., 2017), and the recent ongoing drought since 2018 (Mahlalela et al., 2020). During these years, environmental and socioeconomic factors in the agricultural system of South Africa were impacted by the drought, creating cascading pressures on the nation's agro-economic and water supply systems.

Agriculture is a core component of the economy and has major implications for job creation, food security, rural development and foreign exchange (National Treasury, 2003). The agricultural sector directly contributes 3% to the national GDP (DAFF, 2018, Schreiner et al., 2018), and indirectly (through manufacturing, textiles, food processing) at least 14% (WWF, 2018). Approximately 8.5 million people (i.e. 14% of the population) are either directly or indirectly dependent on agriculture for employment and income (DAFF, 2018; Schreiner et al., 2018).

The agricultural sector in South Africa is composed of commercial farmers as well as subsistence farmers. These sectors experience drought risks differently. Historical root causes such as development support and economic reforms have favoured and benefited commercial farmers who are largely exporters (FAO, 1997), exacerbating the difference in coping capacity and socio-environmental susceptibilities between the two groups. Therefore, subsistence farmers have fundamentally different risk profiles and responses compared to the commercial farming sector (Thamaga-Chitja and Morojele 2014). While commercial farming underpins South Africa's food security, subsistence farming provides income and food security on a household scale for much of the population. With the projected increase in the frequency, severity, and duration of droughts (WMO, 2020), subsistence farmers growing rainfed crops are particularly susceptible to drought as they highly depend on climate-sensitive resources (Schreiner et al., 2018).

South Africa has extensive disaster risk reduction (DRR) legislation (e.g. the National Disaster Management Act, 2002), which has evolved over the decades (Vogel and Zyl 2016). Thus, various policy documents, assessments and strategies for DRR have been compiled (e.g. the 2004 National Climate Change Response Strategy, the 2010 National Climate Change Response Green Paper, and the 2011 National Climate Change Response (Baudoin et al., 2017). Efforts to implement risk reduction approaches are also supported through global frameworks such as the Sendai Framework for DRR (UNDRR, 2015), and various reporting commitments to international organisations (e.g. UNFCCC, UNCCD). The South African National Disaster Management Framework (NDMF) clearly states the need for disaster risk assessments (drought in this case) as one of the key performance areas for any DRR strategy (Jordaan et al., 2017). However, the South African government has historically responded to drought with drought relief schemes that focus mainly on addressing the farmer's immediate needs rather than preemptively building resilience to possible future droughts (Ngaka, 2012; Jordaan, 2011).

There is significant literature in South Africa regarding the assessment of drought impacts on agriculture, e.g. at national level (Masupha and Moeletsi, 2020; Muyambo et al., 2017; du Pisani et al., 1998), quaternary catchment level (Magombeyi and Taigbenu, 2008) and regional level (Kamali et al., 2018). However, when assessing the risk of drought impacts specifically for agricultural systems, there is one assessment at national level (Schwarz et al. 2020), and there are only few studies at local level (Jordaan et al., 2013; Walz et al., 2018). Most of the drought risk assessments in South Africa still miss the connection between holistic consideration of socio-ecological vulnerability, exposure, and hazard from the local to the national scale. A comprehensive drought risk assessment is crucial to inform drought policies that foster proactive drought management (Sivakumar et al., 2014). So far a national drought risk assessment that integrates hazard, exposure and vulnerability to risk for irrigated and rainfed agriculture separately at the sub-national scale is lacking.

Distinguishing the risk components for irrigated and rainfed agriculture is important because: i) rainfall deficit is the main factor impacting drought hazard for rainfed systems while for irrigated systems, availability of irrigation water is more relevant, ii) spatial patterns of irrigated and rainfed systems and growing periods of irrigated and rainfed crops are diverse resulting in different exposure of irrigated and rainfed systems, iii) factors and weights affecting the vulnerability of the systems differ for irrigated and rainfed systems as the vulnerability levels may constantly change due to changes in farming systems and associated technologies, so that even in the same region vulnerability can vary greatly (Downing and Bakker, 2000).

Efforts to assess drought risk for agricultural systems at sub-national level for specifics regions in the world have increased over the past years (Chen et al., 2017; Deng et al., 2018; Han et al., 2016; Kamruzzaman et al., 2018; Ortega-Gaucin et al., 2021; Pei et al., 2018; Zeng et al., 2019; Zhang et al., 2011); however, none of these assessments considered the inherent differences between irrigated and rainfed cropping systems. Frischen et al. (2020) analysed drought risk for irrigated and rainfed systems at the sub-national scale in Zimbabwe, however, the only differentiation in the methodology for each cropping system was considered at the exposure component while the hazard and vulnerability indicators were the same for both systems.

This paper aims at addressing the above gaps by conducting a sector-specific assessment of the drivers and spatial patterns of drought risk for rainfed and irrigated agricultural systems in South Africa in order to identify entry points for action. This is the first integrated drought risk assessment for South Africa at the sub-national level, which considers spatio-temporal consistent hazard-specific indicators, complemented by drought exposure and socio-ecological vulnerability factors – weighted by local experts - at the local municipality scale, specifically for irrigated and rainfed agricultural systems.

The paper presents a risk assessment based on a mixed-method approach, starting from the hazard assessment (section 2.3), which is based on composite drought hazard indicators calculated for irrigated and rainfed crop systems separately using drought indices based on historical climate conditions (1986–2015). The exposed elements are described in section 2.4 and were derived from a dataset differentiating irrigated and non-irrigated crops by local municipality. The vulnerability component was assessed through a composite-indicator based approach, where drought experts in South Africa weighted each indicator (section 2.5). Then, the drought hazard, exposure and vulnerability information was compiled into a final drought risk assessment (section 2.6), which resulted in integrated risk maps for both rainfed and irrigated agricultural systems, respectively (section 3). Lastly, the paper discusses the results (section 4) and identifies potential ways forward, including future research needs.

4.2.2. Data and Methods

4.2.2.1. Case study region

South Africa is located in the southern part of Africa, spreading over 122 million ha with approximately 12% croplands (FAO, 2020a). The country is composed of nine provinces and has a wide range of climates from arid to subtropical, temperate, and mediterranean (Figure 4.10) (Waldner et al. 2017). About 91% of South African territory is arid or semi-arid, with only 10% of the land generating half of the annual run-off (Le Maitre, 2018). The country has uneven rainfall distribution with a mean annual rainfall of 550 mm and annual mean temperature of 18°C (FAO, 2020a). The potential annual mean evaporation for the whole country is about three times greater than its annual rainfall, 1800 mm per year (WWF, 2018). According to the general household survey performed in 2018 almost 15% of the households were active in agricultural activities, of which more than 75% are involved in order to ensure an additional source of food (DALRRD, 2020).

The agricultural economy comprises technically developed commercial farming on the one hand and more subsistence-based production in the remote rural areas on the other hand (Waldner et al., 2017). The dominant activities include: i) intensive crop production and mixed farming in areas characterised by winter and summer rainfall, ii) cattle ranching in the bushveld and iii) sheep farming in the arid regions (Waldner et al., 2017). Considering climate and soil properties, only 12% of the country is suitable for crop production; of which 22% is considered as high potential land in terms of production capacity (Waldner et al., 2017; WWF, 2018).

In general, rainfed agriculture prevails in South Africa, accounting for the majority of the harvested area (Figure 4.10) (Hardy et al., 2011). This means that only 1.35 million ha (8.5%) of the potentially arable land is irrigated (DAFF, 2019). Nevertheless, irrigated agriculture contributes 30% to agricultural production (FAO, 2020b). Irrigation application in South Africa can be permanent, supplementary, or occasional. Most of the commercial irrigation schemes are located in large river basins (e.g. Orange, Lower Vaal, Fish) and in the Western Cape region (FAO, 2016).

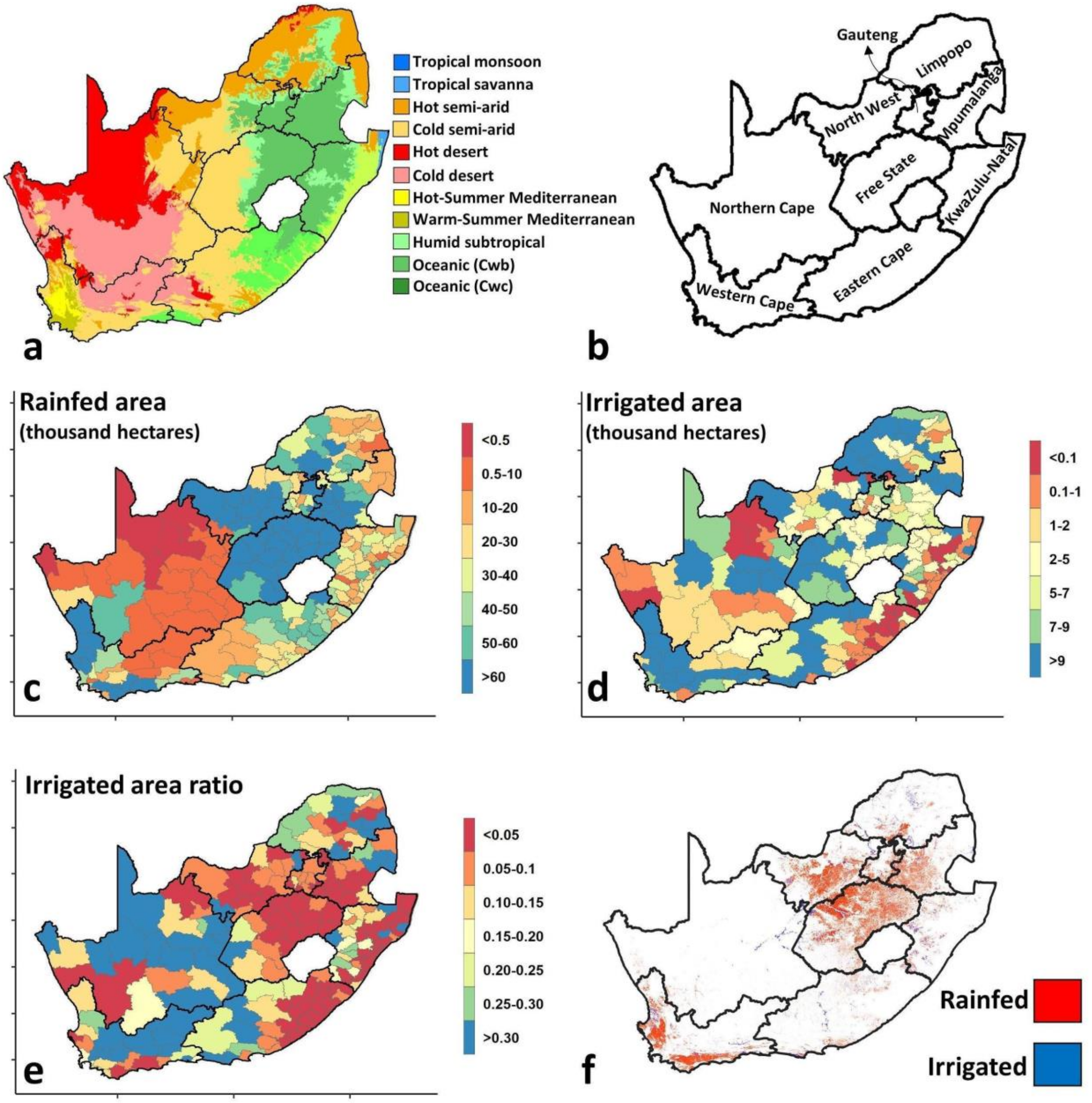


Figure 4.10. a) Köppen-Geiger climate classification map for South Africa (1980-2006) (Beck et al., 2018). b) South African provinces. c) and d) Rainfed and irrigated areas per municipality, respectively. e) Ratio between irrigated and total agricultural area per municipality. f) Irrigated and rainfed agriculture in South Africa at pixel level. Maps are based on data from the national land use/land cover dataset 2018 (Thompson, 2019). Black lines indicate provincial boundaries.

South Africa has been frequently affected by droughts in the last four decades. Major drought periods include 1982-1984, 1991-1992, 1994-1995, 2004-2005, 2008-2009, 2015-2016, and the most recent in 2018-2020 (Mahlalela et al., 2020; FAO, 2019; Walz et al., 2020, Unganai et al., 1998). During those years, drought not only impacted the environment, but also the social and the economic systems. The 1992 drought affected around 250,000 people, with an estimated 50,000 job losses in the agriculture sector, and 20,000 additional jobs losses in related sectors (AFRA, 1993). In 2007-2008, the South African government spent over R285 million (19 million US dollars) on drought relief measures for the agricultural sector, primarily on the purchase and supply of subsidised fodder depending on farms' sizes (Ngaka, 2012). Recent droughts such as the one in 2015-2016 revealed the cascading impacts of the drought. The BFAP (2016) reported that the area of maize planted for the 2016-17 season was 25% lower than the area planted in the 2015-16 season, which was reflected in the year-on-year declines in seasonally adjusted sectoral GDP. In addition to the direct impact on agriculture, general economic indicators pointed to an aggravated situation (e.g., input providers were hard hit due to the lack of purchasing power in the agricultural sector; given the suppliers´ import propensity and the local currency depreciation (BFAP, 2016)). Inflationary pressures resulting, inter alia, from drastic increases in food prices drove up interest rates, which had a negative effect on farming enterprises' debt servicing costs and further restricted access to credit in the sector (BFAP, 2016).

Drought policy and strategies have included efforts from as early as the 1920s, concentrating on land use change, land reforms, soil management and agricultural practices (e.g., kraaling of stock) (Bruwer et al. 1993, Hassan, 2013). The most recent strategy towards drought is compiled in the National Development Plan which sets a vision of eliminating poverty and reducing inequality by 2030 (DALRRD, 2020). However, a rethinking of drought governance is still required, which should look back in time and critically reflect on past drought experiences, perceptions and needs of drought risk reduction and how local context influences drought response (Baudoin et al. 2017; Vogel & Oliver 2019). The government is still challenged to change the unbalanced land-ownership patterns while sustaining economic growth, food security and implementing effective drought management plans; as by 2018 according to the DALRRD (2020) over 60% of South Africans did not have their land/property rights recorded or registered.

4.2.2.2. Risk framing and workflow

Following the IPCC (2014) definition, risk results from the interaction between hazard, with exposure of human and natural systems and the systems' vulnerabilities. In this paper, exposure is defined as the presence of agricultural systems that could be negatively affected by hazards. Vulnerability is the predisposition or propensity to be adversely affected by drought. It encompasses a variety of concepts and elements, including social-ecological sensitivity or susceptibility to harm and lack of capacity to cope (IPCC 2014). Also, following the IPCC (2014) definition, susceptibility is understood as the likelihood of suffering harm in the event of a drought hazard process, and coping capacities refer to the use of available skills, opportunities, and resources to address, manage, and overcome adverse conditions in order to achieve basic functioning in short to medium terms. The workflow for the three risk components and risk aggregation is visualized in Figure 4.11; the indicators and data sources for hazard, exposure and vulnerability are presented in table 4.5 and 4.6.

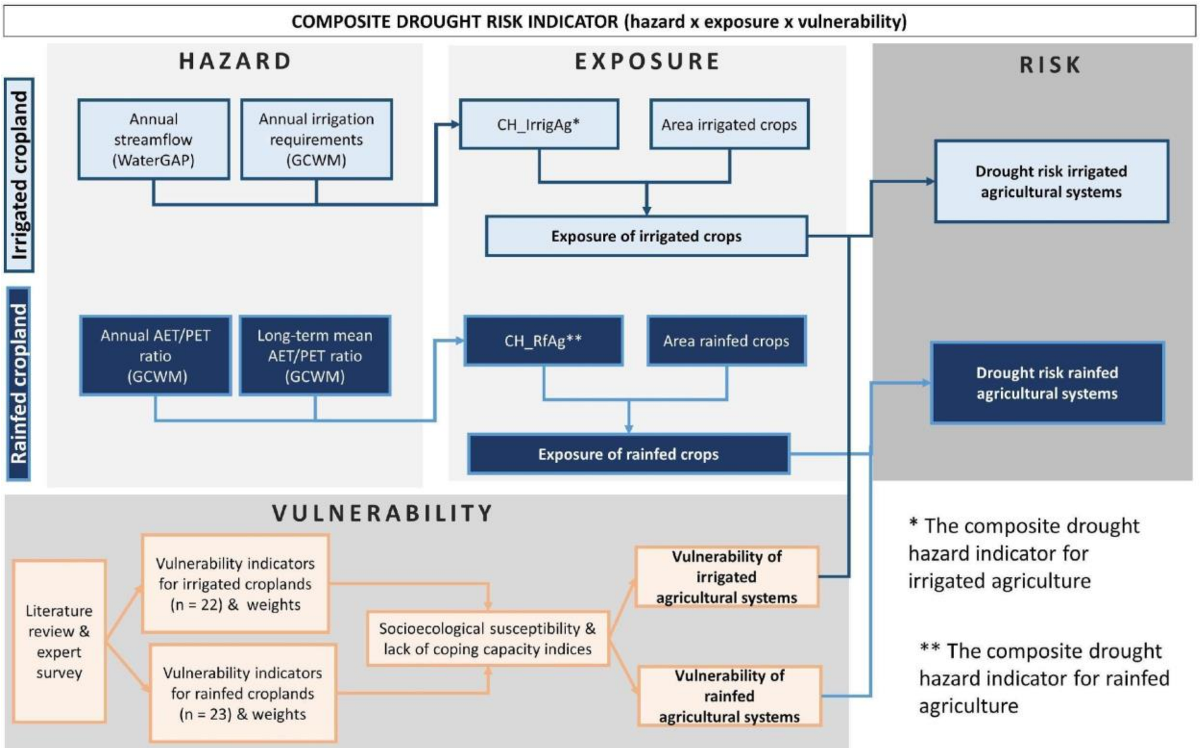


Figure 4.11. Workflow for the drought risk assessment for irrigated and rainfed agricultural systems in South Africa. The workflow is explained in detail in sections 2.3-2.6.

4.2.2.3. Hazard assessment

4.2.3.2.1. Rainfed hazard composite index

The rainfed hazard indicator was computed using the ratio between actual evapotranspiration (AET) and potential (PET) evapotranspiration of crops in the crop growing season for the period 1981-2018. AET refers to the amount of water consumed by a crop and evaporated from the soil under actual soil moisture calculated by performing a soil water balance in daily time steps, while PET assumes no limitation in crop water availability. The ratio is highly associated with crop yield and is widely used as a drought indicator for cropland (Peng et al., 2019). The Global Crop Water Model (GCWM) (Siebert and Döll, 2010) was employed to simulate AET and PET for specific crops grown in South Africa based on prescribed crop calendars and cropping patterns derived from the the MIRCA2000 dataset (Portmann et al., 2010). The ERA5 global reanalysis (Hersbach et al., 2020) and ISRIC-WISE30sec v1.0 (Batjes, 2016) were used as the climate and soil input. The spatial resolution of GCWM's is five arcmin (8.3 km). Drought hazard in specific years was defined as deviation from the long-term mean condition in the reference period 1986-2015 (Meza et al., 2020). The annual hazard indicator for rainfed agricultural systems CH_RfAg_y was calculated as:

$$CH\_RfAg_y = 1 - \frac{AETy/PETy}{\underline{AET}/\underline{PET}} \qquad (1)$$

where *AETy* and *PETy* are annual sums of actual and potential evapotranspiration of all cultivated crops in year *y* (m^3 yr^{-1}). $\underline{AET}$ and $\underline{PET}$ are the long-term annual mean of actual and potential evapotranspiration (m^3 yr^{-1}) in the reference period 1986-2015. Consequently, positive values of CH_RfAg_y represent conditions dryer than usual, while negative values indicate wet years. The long term hazard during the study period at grid level was computed as the frequency (percentile rank) of years in which the AET/PET ratio was at least 10% lower than the mean AET/PET ratio in the reference period 1986-2015 (Meza et al., 2020). A long-term hazard of 0.5 means therefore that in every second year the AET/PET ratio is lower than 90% of the long-term mean AET/PET ratio.

4.2.3.2.2. Irrigated hazard composite index

The irrigated hazard index $CH\_IrrigAg_y$ (-) is defined based on the annual difference between the water resource available for irrigation and irrigation water requirement. The water resource available for irrigation was simulated using the WaterGAP model (Müller-Schmied et al., 2020) as annual sum of discharge *Q* at a spatial resolution of 30 arcmin for the period 1981-2018. The irrigation water requirement *IWR* was simulated using GCWM as the volume of water needed to increase the AET of irrigated crops to their PET (Siebert and Döll, 2010). Drought hazard for irrigated crops $CH\_IrrigAg_y$ was computed for each year as:

$$CH\_IrrigAg_y = \frac{(Q-IWR)_{med} - (Q_y - IWR_y)}{Q_{med}} \qquad (2)$$

where $(Q - IWR)_{med}$ is the median of the difference between discharge and irrigation water requirement (m^3 yr^{-1}) in the reference period 1986-2015, *Qy* and *IWRy* are discharge and irrigation water requirements in year *y* (m^3 yr^{-1}), and Q_{med} is the median of the annual discharge in the reference period 1986-2015 (m^3 yr^{-1}). Positive values of $CH\_IrrigAg_y$ indicate drought, while negative values indicate that the difference between water resources and water demand for irrigation is larger than usual (wetness). Both models (GCWM and WaterGAP) used the same soil and climate input data and the same simulation period (1981-2018). The outputs of GCWM (for crops grown in South Africa) were aggregated to 30 arcmin to match the spatial resolution used by WaterGAP. The long-term hazard for irrigated conditions at grid level was computed as the frequency of the years with an irrigated hazard index $CH\_IrrigAg_y$ of bigger than 0.5 meaning that the deficit in the annual difference between discharge and irrigation requirement exceeded half of the long-term median of annual discharge. A long term hazard for irrigated conditions of 0.2 means then that such a deficit occurs every 5 years.

4.2.2.4. Exposure assessment

Based on the drought risk assessment workflow (Figure 4.11), agricultural land (irrigated and rainfed) was used to analyse drought exposure. The estimation of exposed agricultural land was based on the South African National Land Cover dataset 2018 (Thompson, 2019), from which irrigated and rainfed land were extracted as separate classes. The SANLC 2018 map has 20 meters spatial resolution and was generated using multi-seasonal Sentinel 2 satellite time series data acquired during the period 01 January 2018 to 31 December 2018, 20 meters spatial resolution and 90.14% accuracy (Thompson, 2019). Rainfed systems are mostly located in the North Eastern provinces, as well as in Northern and Western Cape (DAFF, 2018). The hazard indicators - CH_RfAg_y and $CH\_IrrigAg_y$ - were aggregated from pixel to municipality level as average of the pixel values, using the rainfed or irrigated area within each pixel derived from the SANLC 2018 dataset for weighting. From this point, the combined components of hazard and exposure are referred to as 'hazard/exposure'.

The simulated hazard/exposure for rainfed conditions was validated using the remotely sensed AET/PET ratio in the period 2001-2018. AET and PET values were extracted from the Moderate Resolution Imaging Spectroradiometer (MODIS) product (MOD16A2.006) which provides data at 500m spatial resolution (Running et al., 2017). The dataset is derived from meteorological reanalysis data coupled with remotely sensed products of land cover and vegetation properties (Huang et al., 2017). The dataset was preprocessed based on the quality control layer, and pixels with low quality were excluded. The original data set provided the AET and PET in 8 days intervals, which were summed up to yearly values. The CH_RfAg_y was recalculated for model results and remote sensing observations considering the reference period 2001-2018 to account for the limited availability of remote sensing observations. Both datasets were aggregated to the municipality level considering the extent of the rainfed growing area in each pixel. The Pearson correlation coefficient was calculated between model and remote sensing driven CH_RfAg_y at the municipality level.

Table 4.5 Hazard and exposure indicators used for the irrigated and rainfed assessment and the origin of the input data.

Risk component	Agricultural system	Indicator	Data source	Processed data
Drought hazard	Irrigated	Water availability	WaterGAP (Müller-Schmied et al., 2020)	Annual time series of the difference between discharge *Q* and irrigation requirement *IR* compared to the long-term (1986-2015) mean of that difference (Equation 2) Calculated for period 1981-2018
		Water requirement	GCWM (Siebert and Döll, 2010)	
	Rainfed	Crop drought stress	GCWM (Siebert and Döll, 2010)	Annual time series of the deviation of the ratio AET / PET from the long-term (1986-2015) mean of that ratio (Equation 1) calculated for period 1981-2018
Exposed elements	Rainfed or irrigated	Area rainfed or irrigated in the local municipality	Thompson, 2019	National land use/land cover dataset 2018 (DEA, 2019) differentiating between rainfed and irrigated agriculture

4.2.2.5. Vulnerability assessment

Drought impacts are often associated with drought hazard severity, but the degree of the impact is mediated by the vulnerability of the exposed agricultural system, i.e. its susceptibility and the (lack of) capacity to cope with drought events (IPCC, 2014; World Bank, 2019). While an array of methods for assessing vulnerability to natural hazards exists, indicator-based approaches are amongst the most common to represent the multi-dimensional nature of vulnerability (Hagenlocher et al., 2019; de Sherbinin et al., 2019). For this assessment, composite indicators were developed according to the impacted sector: i) irrigated agriculture and ii) rainfed agriculture, considering a wide array of environmental, social, and economic indicators.

Relevant indicators were identified through a combination of literature review and expert consultation. The review was conducted based on pre-defined search terms (Table D1 in appendix) in Web of Science and Scopus. The selected articles (n = 17) were coded with MAXQDA software (VERBI Software, 2019) to extract suitable indicators. Later, these indicators were compared and complemented with the ones identified by Hagenlocher et al. (2019) in their review of existing drought risk assessments, and within South Africa at a local municipality level by Walz et al. (2018) and a quaternary catchment level by Jordaan et al. (2017a, 2017b). In total, 44 suitable indicators for rainfed and irrigated systems in South Africa were identified (Figure D2 in appendix).

To assess which of those 44 indicators are the most relevant for representing vulnerability of these two systems towards drought, an online expert survey was conducted as a joint effort with the National Disaster Management Centre (NDMC) of South Africa. A total of 33 experts representing all provinces of South Africa participated in this survey. They selected 36 relevant indicators for irrigated systems and 40 for rainfed (Figure D2 in appendix). These experts were from multiple sectors including academia (n=4), private sector (n=5), NGO (n=1), government (n=20), international organizations (n=1) and others (n=2). The final selection of relevant indicators for each agricultural system based on the survey results followed a two-step approach as proposed by the European Commision, JRC (2019): i) Indicators were kept if more than half of the experts considered them a medium-high or highly relevant and ii) Z-scores with a 95% confidence interval were used to ensure that there was high level of agreement among the experts. The data was then standardized to give each indicator a value between 0 and 1 in each category (i.e. not relevant, low relevance, low-medium relevance, medium high relevance and highly relevant). The average was then calculated by dividing the total number of replies given for each indicator by the total number of answers given for each indication. Indications with a value near 1 are extremely relevant, while indicators with a value near 0 are less relevant (Figure D2 in appendix).

Open-source data for the selected indicators was retrieved (table 4.6, e.g. statistics from South Africa (STATS SA) (2011, 2016); National Treasury (2019), World Bank (2019, 2020)) in order to ensure that the final results can be validated and reproduced in a different context - as recommended by Naumann et al. (2014). Following the methodological suggestions by Hagenlocher et al. (2018), Meza et al. (2020), Nauman et al. (2014), and OECD (2008), statistical operations were performed to prepare an indicator dataset to perform the vulnerability assessment (Appendix D1 and Figure D1 in appendix): i.e., i) imputation of missing data, ii) normality test, iii) outlier detection and treatment, iv) multicollinearity assessment, v) normalization and vi) expert weighted aggregation.

The selected vulnerability indicators were normalized to make them comparable. A linear min-max normalization was applied to create a range between 0 (lowest vulnerability) to 1 (highest vulnerability) (Beccari, 2016; Carrão et al., 2016).

Table 4.6 Final list of indicators used to perform the vulnerability assessment with expert weighting for irrigated and rainfed systems. The weights with a value close to 1 are highly relevant, whereas indicators with a value close to 0 indicate lower relevance. Only indicators with selected values were used for the respective vulnerability assessment (Irrigated, Rainfed)

Indicator	Data Source	Expert Weight Irrigated	Expert Weight Rainfed
Social Susceptibility			
Unemployment rate (%)	StatsSA Labour force (Census 2011)	1	0.91
Population with assistive devices and medication-Chronic medication	StatsSA census 2011 (Boundaries 2016) - Disability	0.95	0.76
Population with Inadequate sanitation/sewerage/toilet services	StatsSA (Community survey 2016)	0.91	0.75
Population with environmental awareness by district	StatsSA (Labour Force Survey)	0.89	0.88
Dependency ratio (population at the age of 0-14 and >65)	StatSA (Agricultural Household survey 2016)	0.88	0.79
Accessibility to high-density urban centers by travel time	Weiss et al. 2018	0.85	0.79
HH with alternative on farm income	StatsSA (Agricultural Household survey 2016)	0.84	1
People skipping a meal for five or more days in the past 30 days	StatsSA (Community survey 2016)	0.83	0.88
Population that have experienced violence and crime	StatsSA (Community survey 2016)	0.81	0.78
Debtors by municipality (%)	National Treasury (Balance Sheet) Municipal Finance Data Tables	0.73	0.95
Hydropower installed capacity [MW]	World Bank (Global - Dams Database) and the Global Reservoir and Dam Database (GRanD)	0.71	No selected
Gender inequality (gender parity)	SatsSA 2016 Gender Series Empowerment	0.69	0.7
Population per municipality that rate the overall quality of the water services poor	StatsSA (Community survey 2016)	0.63	0.68
Population that has experience of crime - Theft of livestock; poultry and other animals	StatsSA (Community survey 2016)	0.63	0.61
Population with ill-health (mental) (%)	StatsSA (Community Survey 2007) - Disability	No selected	0.73
Environmental Susceptibility			
Farm land ratio	StatsSA (Agricultural household survey 2016)	0.89	0.85
Land Degradation Index (LADA)	Department Of Agriculture, Forestry And Fisheries (DAFF)	0.87	0.86
Clay content (0-2 micro meter) in (g/100g) (w%) at depth 0-5 cm	Hengl et al. 2015	0.8	0.81
Maximum fertilizer application rate kg/h	Mueller et al. 2012 and West et al. 2014 for mineral fertilizer data and manure and atmospheric deposition.	0.79	0.74
Coping Capacity			
Total dam storage capacity in million cubic meters	Lehner et al. 2011 for GRanD	0.87	0.7
Borrowed money from total municipality liability	National Treasury (Balance Sheet) Municipal Finance Data Tables	0.8	0.84
People that receive social grants	StatsSA (Welfare - Community Survey 2007)	0.75	0.85
Road density m/km2	Meijer et al., 2018	0.72	0.75
Area equipped for irrigation expressed as percentage of total area	FAO, 2020	No selected	1

The final step to build the composite vulnerability index (CVI) for each agricultural system (irrigated and rainfed) was the weighted arithmetic aggregation for each vulnerability component (SOC-ENV_SUS and lack of COP) based on the normalised indicators (Z_i) and the weights obtained from the expert survey (W_i).

$$\text{CVI}_{\text{Irrigated}}=\sum_{i=1}^{n}(Zi * Wi) \qquad \text{CVI}_{\text{rainfed}}=\sum_{i=1}^{n}(Zi * Wi) \tag{3}$$

4.2.2.5.1. Reliability analysis

In order to increase the transparency on the data quality used to perform the vulnerability assessment, a metric to calculate the reliability of the data for each local municipality was developed. Following suggestions of the European Commission, JRC (2017) in their Index for Risk Management (INFORM) and Hagenlocher et al. (2018), the reliability metric included two dimensions i) average year of the data sources (recency) and ii) percentage of missing data across all indicators. Each dimension score was then normalized to a scale from 0 to 1, aggregated and averaged in order to have the final reliability scores. Where the tendency to 1 indicates that the vulnerability score for that particular local municipality is based on more reliable data, while the tendency to 0 indicates less reliable data (Appendix D Figure D3).

The reliability metric was computed separately for each of the two agricultural systems considered in this article (irrigated and rainfed).

4.2.2.6. Risk assessment

Drought risk, in any particular area, is composed of hazard, exposure, and vulnerability (IPCC, 2014). For this paper, hazard/exposure and vulnerability were combined through a matrix approach (Figure D8 in appendix). Two different drought risk assessments were performed - one for irrigated agricultural systems and one for rainfed systems - at the municipality level. Following methodological suggestions of the International Standard on Risk Norm ISO/IEC 31010 (IEC, 2019), Frigerio et al. (2016) and Tung et al. (2019) the CVI and hazard/exposure for each agricultural system was classified into seven classes using equal intervals from the maximum, and then those classes were combined to obtain the final risk for each agricultural system (Figure D8 in appendix).

4.2.3. Results

4.2.3.1. Drought hazard and exposure of agricultural systems

Our results demonstrate a large variability in drought hazard and exposure among provinces and local municipalities. The most extreme drought hazard/exposure for rainfed conditions is observed in the North Cape, North West and Limpopo provinces during the study period (Figure 4.12). On the other hand, the lowest hazard and exposure in the period 1981-2018 is computed for Kwazulu Natal province (Figure 4.12). Western and central parts of Eastern Cape and Mpumalanga provinces also have a low level of rainfed drought hazard/exposure (Figure 4.12). The time series analysis of drought hazard and exposure showed that 1992 and 2016 were the driest years during the study period under rainfed conditions (Figure 4.13 and Figure D4 in appendix). The year 2000 and 2006 are classified as wettest years across South Africa (Figure 4.13 and Figure D4 in appendix). The frequency of dry years for rainfed systems remarkably increased after year 2010.

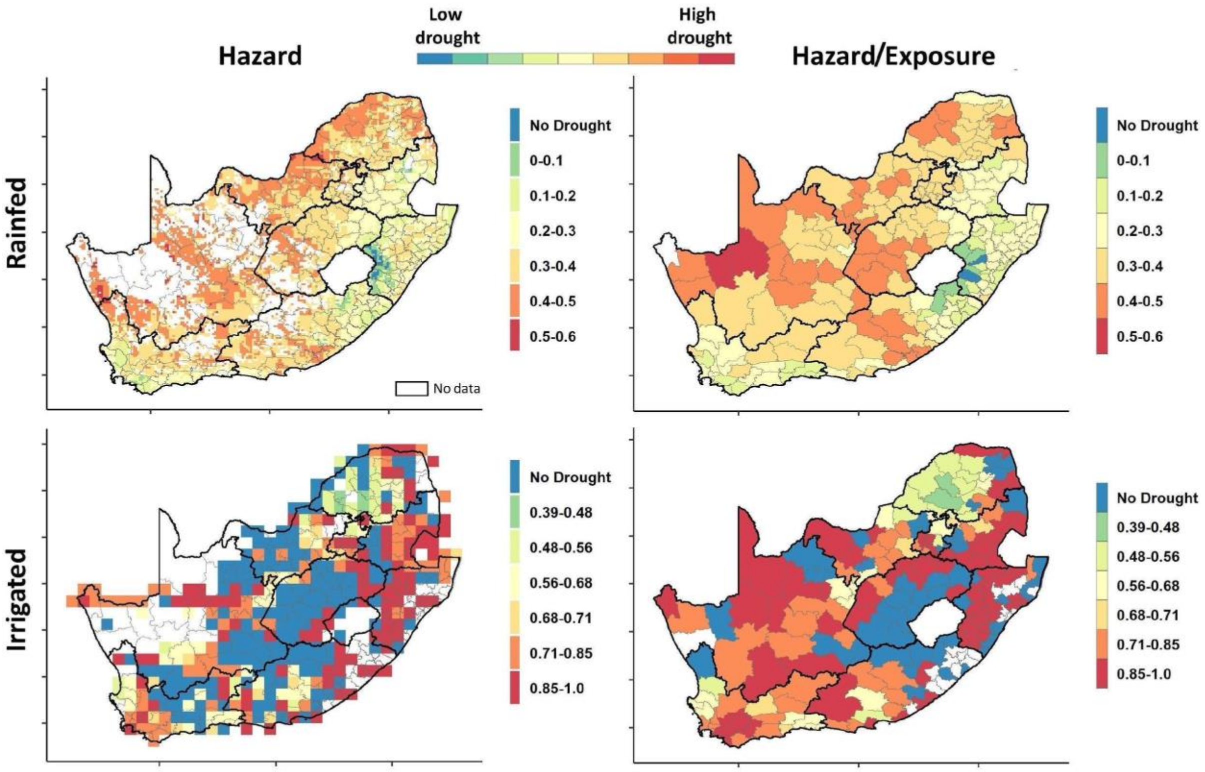


Figure 4.12. Long-term drought hazard and combined hazard/exposure for rainfed (top row) and irrigated (bottom row) cropping systems across South Africa at grid and local municipality levels in the period 1981-2018.

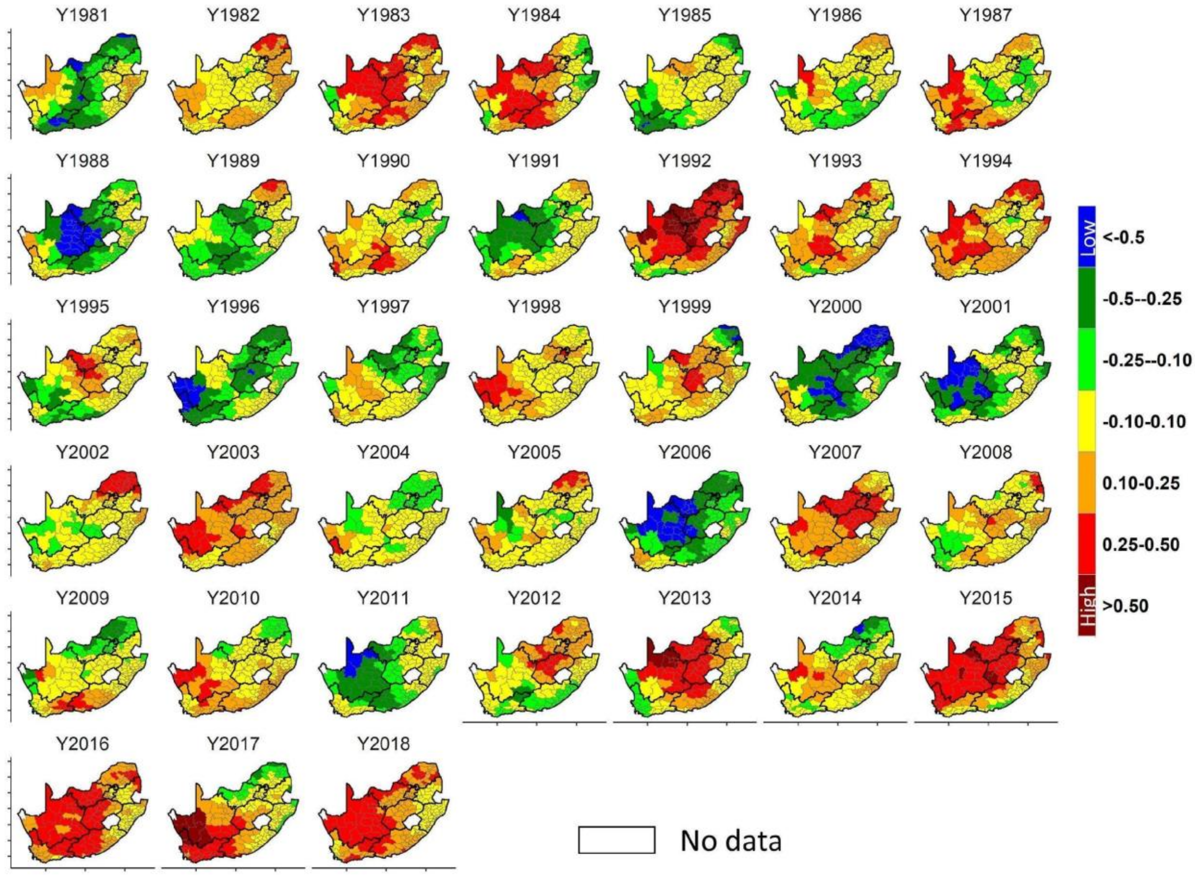


Figure 4.13. Annual drought hazard/exposure for rainfed cropping systems across local municipalities of South Africa in the period 1981-2018.

In general, the irrigated systems are less often affected by drought than rainfed systems, with larger areas exposed to drought in Limpopo and Eastern Cape provinces of South Africa (Figure 4.12). These areas have semi-arid to arid climates and are characterised with less annual precipitation than the rainfed growing areas of the country. For irrigated croplands, larger areas were affected by drought hazard/exposure since 2012, even in areas that have low share of irrigated croplands, such as north western municipalities in the Northern Cape (Fiures 4.12 and 4.14). Despite smaller areas of hazard/exposed irrigated land compared to rainfed areas, the impacts can be significant due to the number of affected people. Roughly about 230,000 irrigation farmers were affected, mostly smallholders often with very small plots for self-consumption (FAO, 2016). The highest hazard/exposure was found in years 2015-2016 and the lowest in year 2001 (Figure 4.14 and figure D5 in appendix).

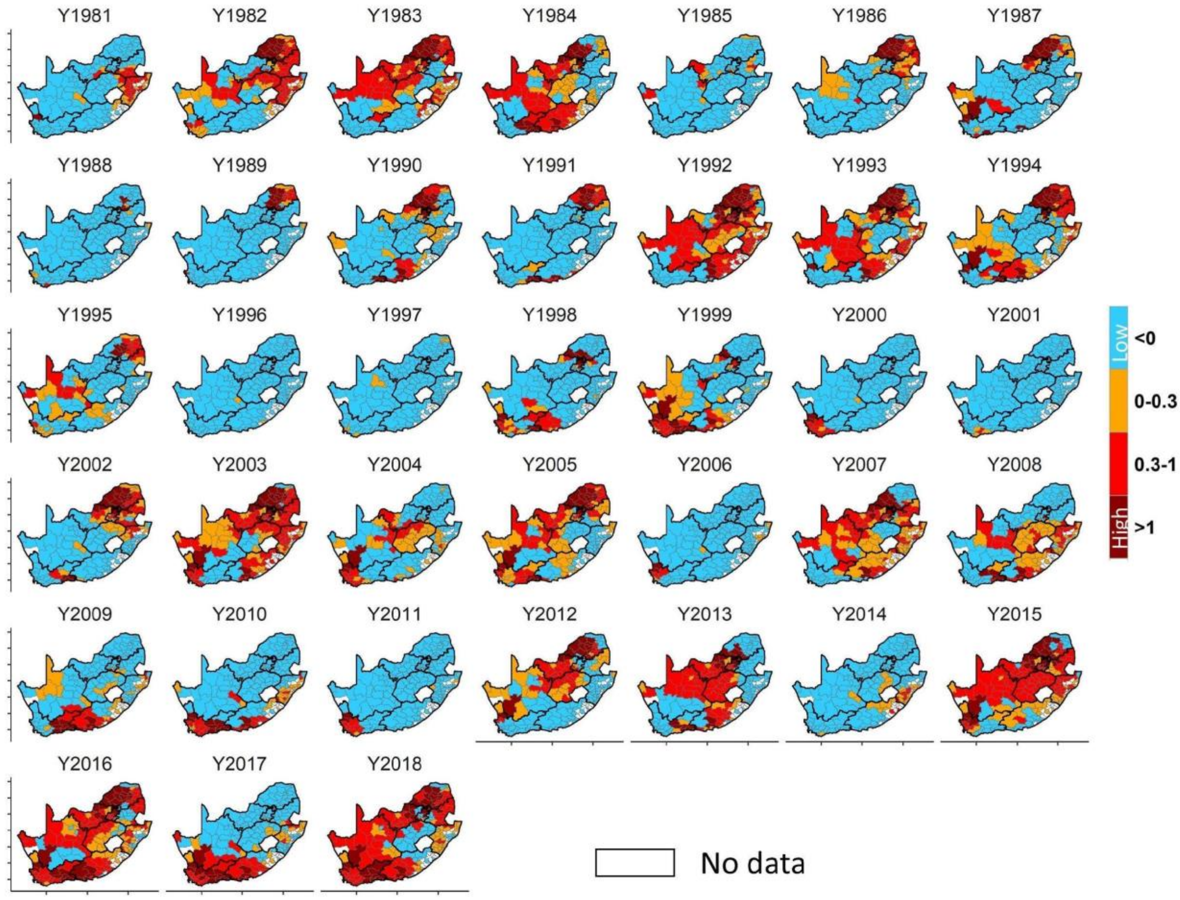


Figure 4.14. Drought hazard/exposure for the irrigated cropping system across local municipalities of South Africa for the period 1981-2018.

The accuracy of simulated hazard/exposure for rainfed agricultural systems was tested by comparing modelling outputs with remotely sensed exposure data in the period 2001-2018 (Figure 4.15). There was a strong correlation (0.5 to 0.9) between remotely sensed and simulated drought exposure for rainfed conditions for most of the municipalities across South Africa. The lowest correlation (0 to 0.2) was obtained in a limited number of municipalities mainly in KwaZulu-Natal and Eastern Cape provinces, which are largely covered by natural grasslands. The annual drought signal obtained by remote sensing may therefore deviate considerably from the conditions in the cropping period considered in the model.

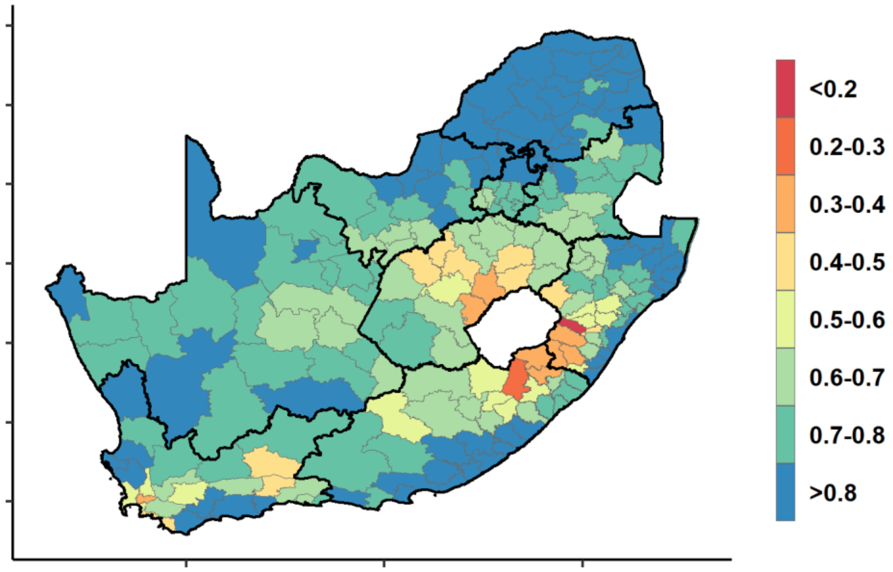


Figure 4.15. Correlation coefficient between drought exposure of rainfed systems obtained by modeling and remote sensing.

Moreover, we assessed the relationships between annual drought exposure simulated for rainfed systems and yield/production reported at the country scale (FAO, 2021). The correlation coefficient among simulated drought exposure and reported yield and production anomalies were -0.32 and -0.41, respectively (Figure D6 in appendix) which means that drought resulted in lower yields and production. The model reproduced the drought for the years (1992-2015-2016) which showed the largest yield/production reduction. As a second analysis, we performed the assessment for maize production anomaly in South Africa in the period 1986 to 2018 and its relationship with the annual rainfed hazard/drought simulated for rainfed systems across five most important maize production provinces in South Africa (Figure D7 in appendix). The results showed a remarkable overlap between negative production anomalies and simulated drought hazard for all provinces, e.g. in years 1992-93, 2007, 2013 and 2016. In contrast, positive production anomalies were recorded in all provinces in years with low drought hazard such as 1991, 2006 or 2014 (Figure D7 in appendix). It is important to note that the FAO and regional yield/production data did not distinguish between rainfed and irrigated systems. Therefore, we expected even higher correlations when separate data would become available.

4.2.3.2. Vulnerability and risk of rainfed and irrigated systems

The vulnerability assessment shows heterogeneity across the country (Figure 4.16) for both systems. Our assessment highlights that crops under rainfed systems are more vulnerable to drought than irrigated systems. Several indicators contribute to the difference, but the most relevant are the lack of area equipped for irrigation, which affects the coping capacity of the system, followed by a low fertilizer application rate.

According to the experts (table 4.6 and Figure D2 in appendix), the most relevant vulnerability indicator for irrigated systems is unemployment rate (%). This is also recognized as a relevant indicator by the scientific community in the South African context as the country suffers from deep structural unemployment having a direct impact on poverty levels (Chibba and Luiz, 2011). Agriculture proved to be the best way to reduce rural poverty according to the rural development literature, besides, in most developing countries, agriculture and agriculture-related activities provide most of the rural employment (Machethe, 2004). Irrigation schemes have had great impact in South Africa, not only in food production but also alleviating poverty. One notable example is the one caused by the Great Depression by resettling of returning soldiers that reduced the unemployment rate in the country (FAO, 2016). Irrigated agriculture employs between 10% and 15% of the total agricultural workforce (DWA 2002).

The most relevant indicator for rainfed systems according to the experts (table 4.6) is the percentage of households with an alternative to farm income. Low harvests threaten the households that only depend on their farm income (~97%); this could result from a drought period that requires compromising their entire livelihoods. Having an alternative income may increase their coping capacities as they do not depend solely on the agricultural income derived from crop sales.

The experts assigned to the two indicators “population with assistive devices and medication (disability)” and “total dam storage capacity” high weights for irrigated systems but much lower weights for rainfed systems. In contrast, the indicators “households with alternative farm income” and “debtors” received high weights for rainfed systems and much lower importance for irrigated systems.

The vulnerability maps display high values particularly on irrigated systems for the Western Cape municipalities and for rainfed agricultural systems in KwaZulu-Natal. Our findings underline that determining factors of vulnerability vary depending on the sector which is susceptible to the negative impacts of drought. For instance, the main indicators which shape the vulnerability for irrigated systems and are potential entry points for the drought risk reduction is the lack of environmental awareness, poor water quality, and low total dam storage capacity. In the South African context this is due to the limited access to extension services (e.g. geographically remote farmers tend to have little network coverage), and very limited financial resources to invest in technologies or utilities. Resulting in a lack of accessible, relevant, and practical information to share, as well as few or no opportunities to expand the irrigation farmers' capacities (FAO, 2020b).

For rainfed agricultural systems, the key indicators shaping the socio-environmental susceptibility and the coping capacities of the local municipalities are the small fertilizer application rate, the lack of area equipped for irrigation, and land degradation. This last indicator is relevant for both systems; land degradation is linked to different factors in the context of agricultural systems in South Africa, one of them is the lack of environmental awareness that led to unsustainable farming practices (Rother et al., 2008; Schulze, 2016).

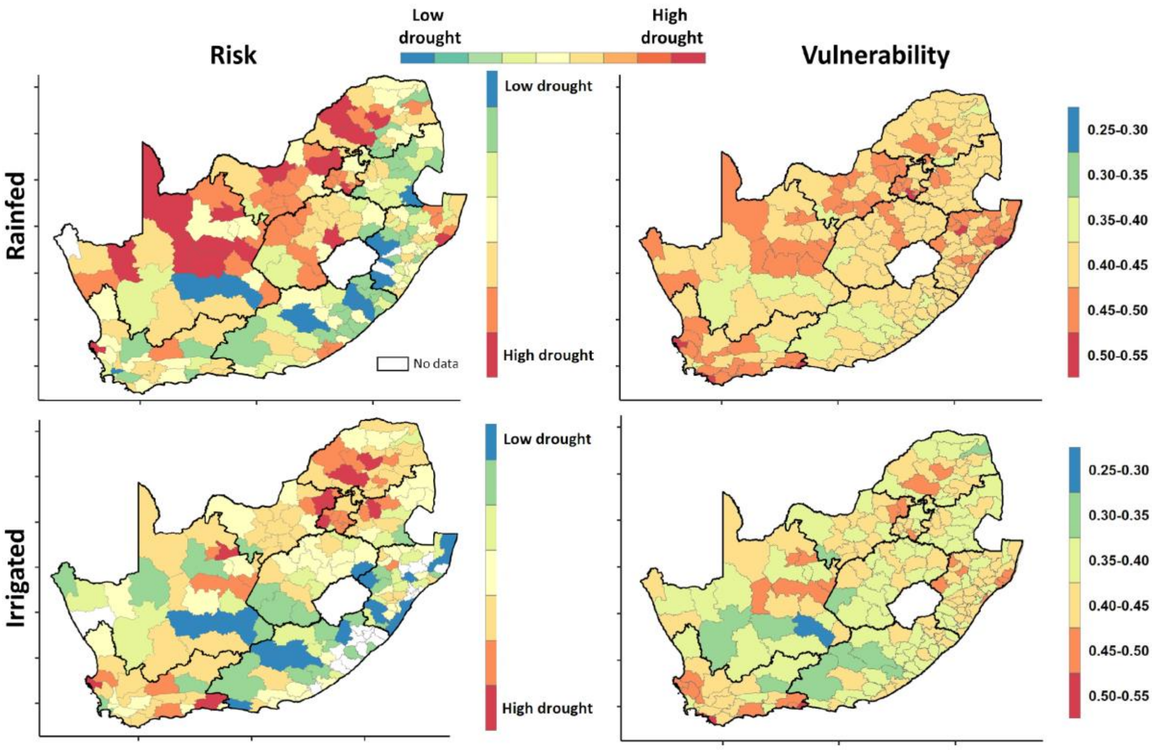


Figure 4.16. Drought vulnerability and risk in South Africa at local municipality level for rainfed (top row) and irrigated agriculture (bottom row). Tendency to dark blue shows lower levels of vulnerability and risk, the tendency to red shows higher vulnerability or risk values.

The drought risk assessment highlights its context-specificity and how different communities of a country experience different levels of risk. Drought risk varies substantially for rainfed and irrigated systems (Figure 4.16). There is a high-risk pattern towards the North provinces for rainfed agricultural systems. Meanwhile, high-risk hotspots for irrigated agricultural systems can be found in some local municipalities of Limpopo (e.g. Modimolle, Polokwane local municipalities), North West (e.g. Merafong, Rustenburg) and Gauteng (e.g. Merafong city, Rand West city) provinces.

When analysing the risk for rainfed systems, among the local municipalities in the Northern Cape, Emthanjeni has the lowest risk score than other provinces despite its high hazard and exposure levels; it is explained by a lower social susceptibility (e.g. overall quality of water services, less population have experienced crime and theft of livestock), and higher coping capacities (e.g. access to credits). In contrast, the local municipality of Khai-Ma in the same province has lower vulnerability than other local municipalities, but its high hazard and exposure scores result in a high risk.

In order to identify priority areas for disaster risk management, the risk assessment of each agricultural system was plotted against the crop dependent population in each local municipality (Figure 4.17). The comparison shows that the local municipalities with higher irrigated and rainfed systems are not among the highest in terms of crop dependent population. The city of Johannesburg presents a higher crop dependency, but also has high risk for both systems. Its drought hazard and exposure are high, and the vulnerability analysis reveals that their lack of environmental awareness, fertilization rate and land degradation are key factors contributing to their overall very high risk; highlighting the relevance to take actions in this municipality. Johannesburg, the largest city in South Africa, is facing enormous challenges which reflect on the drought vulnerability level. Challenges like urbanisation's impact on the soil and water quality and availability, and facing non-sustainable growth paths (SACN, 2016) have significant impacts on the magnitude of Johannesburg's vulnerability toward drought.

In contrast, the city of Tshwane has a high number of crop dependent population, but it presents a medium rainfed risk and very low irrigated risk. Its medium risk is explained by its medium-low vulnerability as a result of better performance in nutrition level, good water quality and road density, among others.

The Northern-Cape province has the lowest population dependent on crops. However, it is one of the provinces with more local municipalities on high rainfed risk, as this province has arid climate which exposes rainfed crops to high drought hazard. In contrast, the Limpopo province has a higher amount of population dependent on crops, but more local municipalities are at high risk for irrigated systems.

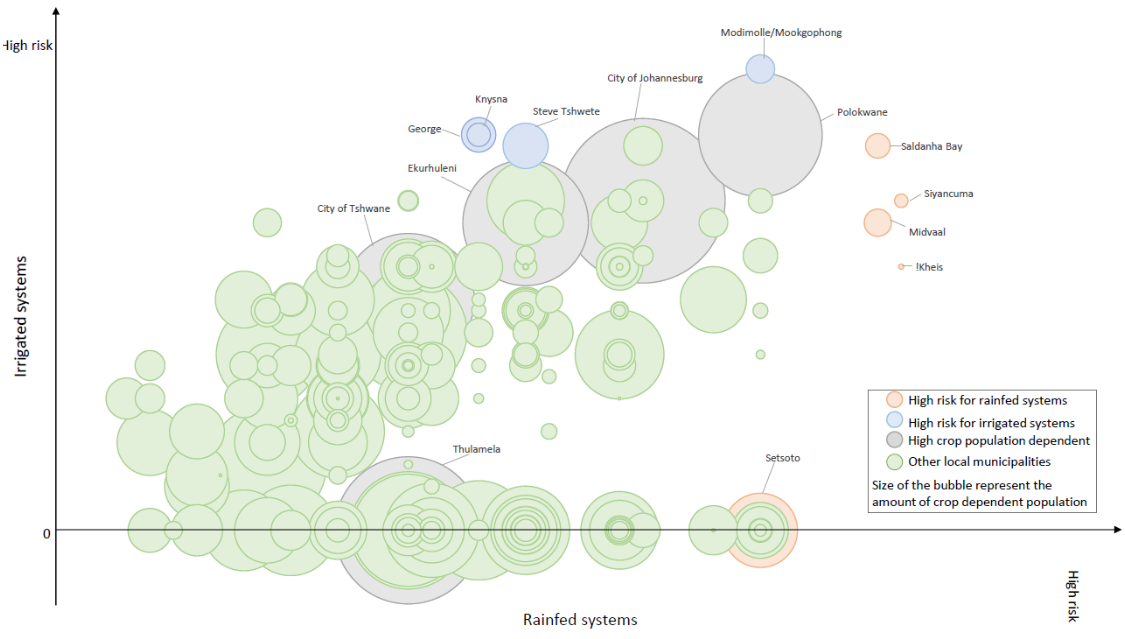


Figure 4.17. Local municipalities contrasted with drought risk for rainfed (x axis) and irrigated (y axis) systems. The size of the bubbles represent the amount of crop dependent population by local municipality (Data from Statsa, 2016).

4.2.4. Discussion

The dependency of agriculture on water resources (approx. 60% of the total water demand (Schreiner et al., 2018) is making water availability one of the key factors for the agricultural system, furthermore, the predominance of rain-fed agriculture in South Africa makes the country extremely susceptible to drought. Despite this, drought risk management remains ambiguous and mainly reactive (Hornby et al., 2016, Baudoin et al., 2017; Vogel and Olivier, 2019). Drought is a recurrent phenomenon in South Africa's climate and is one of the most relevant hazards (Gibberd et al., 1996, Jordaan et al., 2017a). In fact, all local municipalities were affected by drought during the last 30 years (Figure 4.13 and 4.14). The dependency of South Africa's economy on agricultural products emphasises the importance of drought risk assessments and the identification of potential entry points for reducing its vulnerability. An integrated hazard, exposure and vulnerability assessment of the agricultural sector (irrigated, rainfed) specifically was lacking so far for South Africa at national level, and it is presented here for the first time. Furthermore, the methodology can be transferable in other regions, the hazard and exposure assessment can be reproduced in any country, however the vulnerability assessment is context specific and some indicators that might be relevant for South Africa will not be for another country, therefore, we suggest to identify key indicators following the methodology applied on this paper.

4.2.4.1. Limitations

Our innovative methodology to simulate hazard indicators captured the spatiotemporal pattern of the drought for a long-term period (back to 1980s); the time that remote sensing was not available (generally available from early 2000s). Our results show that exposure to drought in croplands varies for rainfed and irrigated systems, spatially and temporally. A time series of exposure for irrigated and rainfed agriculture shows different patterns; this proves the necessity for separate analysis for these two cropping systems. The hazard indicators for rainfed and irrigated systems were computed in different ways; for rainfed systems, we assume a strong impact of meteorological drought on the system while for irrigated systems, we assume a strong impact of hydrological drought on the system. Therefore, hazard indicators and, subsequently, risk indicators for irrigated and rainfed systems should not be directly compared.

To better manage and mitigate drought risk, it is necessary to improve the response to drought impacts, the preventive actions and actively address the root causes of vulnerability as well as build capacities as in the local communities and the government. The vulnerability assessment helps to identify potential entry points to reduce the level of drought risk for both irrigated and rainfed systems; which include better water quality, reduction of land degradation, and increasing the dam storage capacity. Specifically for rainfed systems with high risk could become irrigated if they are located in regions where irrigated risk is low as areas equipped for irrigation can help in supporting the livelihood of rural communities and food production. However, it is relevant to consider the water availability, the access to the water source, the soil and topography conditions, among others before installing any irrigation system.

The contribution of relevant experts on selecting and weighting vulnerability indicators is an added value of this assessment. However, the expert survey consultation could be enhanced by expert interviews, where more details and the rationality behind the ranking of the different indicators could be further explained. Another point of improvement is the number of experts who responded to the survey. With more time and resources, more experts could participate.

As this study is the first to separately assess the drought risk for rainfed and irrigated agricultural systems, there is no comparison of our findings with other national assessments.

However, the drought risk analysis results and its components agree with other studies conducted at the local level for agricultural systems. For instance, Eastern Cape's vulnerability pattern follows an east-west descending gradient reported by Walz et al. (2018). Jordaan et al. (2013) showed that the coping capacities such as the land ratio and management, access to credit and markets are key in determining the level of risk in the Northern Cape. Similar to the results of this study, Schreiner et al. (2018) suggests that expanding the storage capacity of existing dams and water conservation practices would reduce drought risk, especially for irrigated agricultural systems. Furthermore, the low drought risk values identified for the Northern Cape for irrigated systems also agree with previous drought risk assessments performed by Jordaan (2011) and Jordan et al. (2013).

It is necessary to analyse and interpret the drought risk through systems perspective (Vogel and Oliver 2019), as extreme droughts and its impacts are not a result of a linear equation, rather they reflect the dynamic and complex realities of the socio-ecological system. To address the complex realities in this assessment, we considered the nature of farming in South Africa in terms of climate and social factors (e.g. dependency ratio, unemployment rate). An enhancement for future assessments could be the integration of temporal dynamic exposure and vulnerability with the hazard data. As Schreiner et al. (2018) stated, the South African government knows that drought is a recurrent hazard, and particularly with climate change, it is critical to implement the necessary structures to support the diverse makeup of the agricultural sector. Further, it is necessary to plan actions according to specific needs of the system, irrigated or rainfed. We also need to understand better how severe, prolonged and repetitive drought events might shift policies, local and rural economies, and actions (Schreiner et al., 2018).

Despite the wealth of climate change and drought policies and responses in South Africa, recent droughts are a stark reminder of the realities of climate variability and the difficulty of effectively responding. Notwithstanding the examples and legislation mentioned, recent responses to drought reveal a lack of awareness and a need for a broadly informed assessment of drought in a rapidly changing socio-environmental context (Vogel and Olivier, 2019). So far, while the changes on policy over time have had the goal to improve drought risk management, the focus is still largely on relief and emergency support instead of implementing proactive policies (Vogel and Zyl, 2016; Bruwer, 1989; Vogel et al. 2010; South African Weather Service, 2017 in Baudoin et al., 2017). Interdisciplinary drought risk assessments like the one presented here can be used in decision-making processes. These assessments help to identify potential pathways and actions towards proactive drought risk reduction policies such as the increasing access to finance, increasing extension services and programs in order to improve the environmental awareness, reducing land degradation and increasing farmers' capacities towards a sustainable agroecosystems.

Limitations in data availability impact the accuracy of our research like many others. For instance, the hazard and exposure analysis is based on the land cover data from one timestep (static input data), which can impact the results (i.e., as cropping patterns are dynamic and often can change over time).

Furthermore, future analysis can be improved by accounting for risk differences of individual crop types, and exposed farmers.

4.2.4.2. Recommendations and next steps

There are various ways to measure drought hazard, and composite indices could make additional use of surface and ground water deficit, provided that time series for these variables can be reliably derived from hydrological modelling. In recent years the observation of surface water volume changes from remote sensing, and of groundwater variability from the GRACE and GRACE-FO satellite missions combined with data assimilation, has made tremendous progress and we expect that adding such indices would lend more robustness to our risk assessment framework.

Future assessments may benefit from new approaches to assess vulnerability beyond administrative boundaries (e.g., pixel-level vulnerability data), since much of the information and effort in analyzing hazard and exposure at the smallest possible resolution is lost when aggregated at administrative boundary levels reducing the capacity to accurately reflect reality. In addition to examining the environmental, social and political processes shaping drought risk, an enhancement for this assessment could be developing a reliable and standardised database of losses and damages regarding agricultural systems in South Africa. Such database can help better examine the medium- and long-term impacts of drought and allow the comparison of impacts of similar hazard events in different parts of the country (e.g. drought of 2015-2016) (JRC, 2014). It could also help identify indirect and cascading effects even after the drought hazard event is finished. Moreover, loss data collections can be useful to identify trends and patterns in data over time (JRC, 2014), and to achieve consistent and coordinated implementation of risk reduction strategies.

4.2.5. Conclusions

Drought impacts on South Africa's agricultural sector are recurrent; these drought events provide opportunities to learn and to improve drought risk reduction efforts. We present, for the first time, an integrated drought risk assessment that considers hazard, exposure and vulnerability to evaluate the impact of drought on irrigated and rainfed systems (separately) at national level. In addition, we pioneer an expert survey to weigh relevant indicators at national level. Our spatially explicit results assist to identify priority regions to take actions. Our findings highlight the relevance of assessing and discussing drought risk in relation to specific impacts and diagnosing entry points to reduce drought risk in a context-specific manner (i.e. irrigated and rainfed systems). This ensures that relevant proactive policies and planning can be effective even within the same sector (i.e. agricultural sector) before the worst impacts occur. While this assessment provides valuable information at local municipality level, the assessment can be enhanced with a temporal dynamic exposure and more spatially explicit vulnerability information.

5. Do global risk assessments leave countries behind? How the selection of countries influences outcomes of drought risk assessments

Dudley, A. L., **Meza, I.**, Naumann, G., & Hagenlocher, M.

Published as research article in Climate Risk Management (2022): https://doi.org/10.1016/j.crm.2022.100454

Abstract

Global drought risk assessments have been conducted with the objective of highlighting the regions or countries most at risk, and their outcomes are deemed useful to inform decisions on the implementation of risk reduction, transfer, financing, and adaptation strategies. However, by virtue of the scale of the assessment, some countries and regions experiencing negative impacts of droughts may not appear in “high” risk categories in global comparisons. This limits and potentially biases the ability of decision-makers, regional organisations, or funding mechanisms to recognise which countries under their purview should be targeted for assistance. This paper addresses this gap by comparing the outcomes of global and regional drought risk assessments for different clusters of countries of particular relevance to international climate and disaster risk policy. Results show that 50 countries changed the risk category to “high” or “very high” in their clusters compared to a lower risk category at the global level, due to the renormalisation of raw indicator values with different ranges for each cluster. The findings highlight the importance of analysing risk at multiple spatial scales to ensure no country is “left behind” in global risk and adaptation finance decisions.

5.1. Introduction

It is now widely acknowledged that drought risk is a function of drought hazard, exposure of one or multiple elements to drought, and multi-dimensional vulnerability of these elements incorporating both human and natural factors (Hagenlocher et al., 2019, Hagenlocher et al., 2018, UNDRR, 2019, UNDRR, 2021. GAR Special Report on Drought, , 2021). As drought occurrence is projected to increase around the world (Cook et al., 2020, Spinoni et al., 2020), global drought risk assessments incorporating hazard, exposure, and vulnerability are deemed useful to guide investments in disaster risk reduction and international climate finance to build resilience (UN, 2015, UNDRR, 2015, UNDRR, 2017, UNDRR, 2019). Notably, such assessments might be of relevance for organisations and funding bodies that have the mandate to focus on the “most at-risk” and “most vulnerable” such as the Adaptation Fund (AF), the Green Climate Fund (GCF), the Global Environment Facility (GEF) Trust Fund and its Special Climate Change Fund (SCCF), the InsuResilience Solutions Fund (ISF), and the recently established Global EbA fund. For example, the AF states they have allocated over

US $850 million to projects in developing countries that are particularly vulnerable to climate change for adaptation and resilience-building projects (The Adaptation Fund, 2022). The GCF is mandated to allocate at least a quarter of its resources to adaptation in the most climate-vulnerable countries and, in the March 2021 board meeting, committed a total US $1.2 billion to 15 different climate projects (The Green Climate Fund, 2021). The ISF also limits its co-financing allocation to a selection of countries that are vulnerable to extreme weather events, offering up to €2.5 million per project in their 8th call for proposals (InsuResilience Solutions Fund, 2022). The SCCF is open to all vulnerable developing countries and supports a wide spectrum of adaptation activities. Over the past 20 years, the SCCF has invested $355 million in 87 projects around the world (GEF, 2021). While recent studies found that other factors than vulnerability contribute to the allocation of adaptation aid, they also found that vulnerability assessments remain an important tool for both donor and recipient countries (Doshi and Garschagen, 2020, Garschagen and Doshi, 2022). Further, the stated motivations for funding and the mandate of organisations to focus on countries most vulnerable or at risk to climate change or extreme weather events, suggest that a comparison of risk across countries should impact resource allocation.

At present, drought risk assessments that can be used for comparison of risk, exposure and vulnerability across multiple countries at the country scale are limited to a handful of global assessments (Carrão et al., 2016, Meza et al., 2020), global tools/platforms (Global Drought Observatory (GDO), Water Risk Filter (WWF)); and regional assessments for Europe and Africa (see Blauhut, 2020, Hagenlocher et al., 2019 for a review of existing assessments). This means that when determining which country or countries are the most at-risk or vulnerable, organisations are mostly limited to global assessments. However, by virtue of the scale of these assessments some countries and regions that experience the negative impacts of drought might not appear in “high” risk categories in global comparisons. For example, looking to the global risk assessment results from Meza et al. (2020), Brazil had a lower drought risk than most other countries, yet Brazil has recently suffered through a drought that had devastating consequences for agriculture in the country (Marengo et al., 2017) and has one of the highest numbers of drought events registered in the international Emergency Events Database (EM-DAT) in the world (Meza et al., 2020). Spatial scale has been identified as an important factor informing investment in drought risk reduction (King-Okumu et al., 2020) and the restriction to global risk assessments when comparing countries’ drought risk and vulnerability can limit and potentially bias the ability of decision-makers, regional organisations, or funding mechanisms to recognise which countries under their remit should be targeted for assistance. This may result in countries that are potentially “left behind” as the international community scales up financial investments towards more drought resilient futures.

This paper intends to show the effect of changing the selection of countries included in a drought risk assessment on its outcomes and highlight the countries that are “left behind” by a global drought risk assessment. Here, we use an updated version of the global drought risk analysis by Meza et al. (2020) as the foundation, and reanalyse the data used in this assessment by subsets of countries (hereafter called “clusters”) of particular relevance for international climate and disaster risk policy. We then discuss how the results could influence decision making.

The primary question driving the analysis is: How might decision making for drought risk reduction, resilience building, or funding be influenced depending on the selection of countries assessed? To inform the discussion, two sub-questions will be addressed: 1) How does drought hazard/exposure, vulnerability, and risk change when reanalysing data from a global risk assessment by clusters of countries?, and 2) Which countries are “left behind” in the global assessment?

5.2. Methods

To answer these questions, three steps of analysis were performed. First, the global drought risk assessment by Meza et al. (2020) was updated to create a baseline global assessment for comparison with the cluster assessments (see chapter 3.2). Second, 14 clusters of countries of particular relevance for international climate and disaster risk finance and policy were identified, and data from the global assessment were reanalysed to create new hazard/exposure, vulnerability, and risk indexes for each of the clusters (Figure 5.1). Lastly, the outcomes of the global and cluster assessments were compared, and then the risk indexes were split into quintiles to identify in which clusters drought risk severity categorisation changed the most compared to the global assessment. Countries that moved into a “high” or “very high” drought risk category in the cluster assessment from a lower risk category in the global assessment were identified as the countries “left behind” by the global assessment.

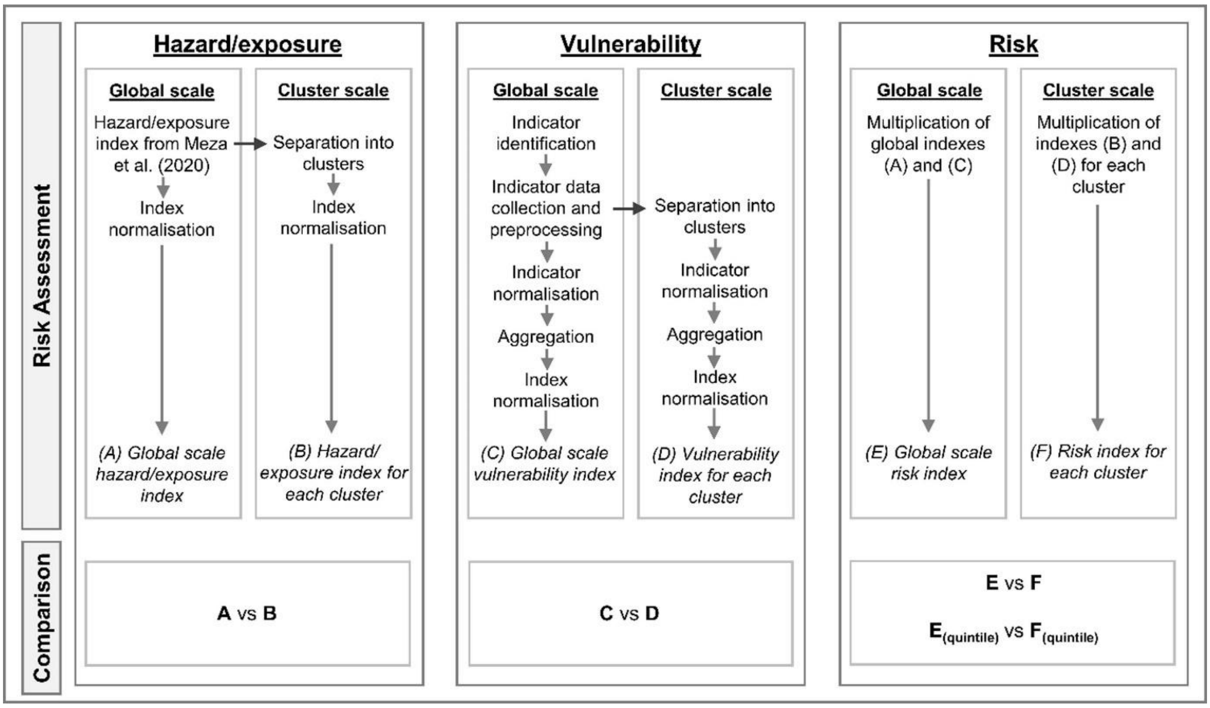


Figure 5.1. Diagram of the workflow for the global and cluster-scale risk assessments. A, C, and E are the outcomes of the global assessment and B, D, and F are the outcomes of the 14 cluster-scale assessments. A was compared with B, C with D and E with F. E and F were also split into quintiles and countries' risk categorisation was compared.

As this paper builds on well-established index-based approaches to assess risk and the aim of the paper is the comparison of the global and cluster risk assessments, the detailed methods for index creation, including justification for decisions made, are provided in appendix E.1. A short overview is provided here, followed by description of the cluster identification and comparative analysis methods.

5.2.1. Global drought risk assessment

A drought risk assessment at the global scale was conducted to create a baseline for comparison with the cluster assessments. This was achieved by updating the global drought risk analysis for agricultural systems by Meza et al. (2020), where risk is a function of hazard, exposure, and vulnerability. The most common methods for composite indicators according to a review conducted by Beccari (2016) were followed in the assessment.

Firstly, the drought hazard/exposure index for irrigated and rainfed agriculture in all countries was drawn directly from Meza et al. (2020) and normalised using linear max normalisation for comparability with the vulnerability index (OECD, 2008). Then, the vulnerability index was created by identifying 14 indicators for analysis.[8]

These were selected based on Meza et al., 2020, Meza et al., 2019), further review of the literature, and data availability. Indicators were pre-processed to address missing data, outliers, and multicollinearity (appendix E 1d). 30 countries and one indicator were removed from the analysis to reduce the level of missing data; 165 countries and 13 indicators remained in the analysis (Table 5.1 shows the indicators used in the analysis and their data sources. appendix E shows the countries that were included in the analysis).

Table 5.1 Indicators and their respective data sources used in the vulnerability assessment.

Indicator	Data source	Contribution to vulnerability*
Literacy rate, adult total (% of people ages 15 and above)	[dataset] World Bank (2015a)	-
Prevalence of undernourishment (population)	[dataset] World Bank (2015b)	+
Unemployment (% of total labour force) (national estimate)	[dataset] World Bank (2017a)	+
GINI index (wealth inequality)	[dataset] World Bank (2017b)	+
Share of GDP from agriculture, forestry, and fishing in US$ (%)	[dataset] FAO (2016)	+
Population with access to an improved water source (%)	[dataset] World Bank (2015c)	-
Government Effectiveness: Percentile Rank	[dataset] World Bank (2017c)	-
Saved any money in the past year (age 15+)	[dataset] World Bank (2017d)	-
Proportion of population living below the national poverty line (%)	[dataset] SDG Indicators (2017)	+
GDP per capita	[dataset] FAO (2018)	-

[8] An index is an aggregation of several indicators that are combined to provide a single composite measure of a complex concept that cannot be represented by a single indicator, such as vulnerability (OECD, 2008).

Average soil erosion for exposed area (t ha-1 yr-1)	[dataset] JRC ESDAC (2019)	+
**Access to information (# mobile phone subscriptions per 100 people, max threshold 100)	[dataset] World Bank (2017e)	-
**Cultivation of drought-resistant crops (% of total crop yield)	Calculated***	-

* Refers to whether a high value for an indicator increase (+) or decrease (−) vulnerability.
** Indicators additional to Meza et al. (2020).
*** See appendix E3 for the method.

Three indicator values were treated using Winzorisation (Field, 2013), and no issues of multi-collinearity were detected using a Spearman correlation matrix with the threshold for high correlation set at r = ±0.9 (Hinkle et al., 2003) with two-tailed significance at the 0.05 level. Then the vulnerability indicators were normalised using linear min–max as this is the most common approach to composite indicator creation according to Beccari (2016), and aggregated using additive arithmetic aggregation. Finally, the vulnerability index was normalised using linear max to render it comparable to the exposure index.

The drought risk index (DRIc) was created by multiplying the hazard/exposure index (HEc) by the vulnerability index (VIc) for each country (Equation (1)):

$$DRI_c = HE_c \times VI_c \tag{1}$$

5.2.2. Cluster drought risk assessments

To undertake the drought risk assessments at the cluster scale, relevant clusters were identified. Then the raw hazard/exposure and vulnerability values used in the global risk assessment were grouped into clusters, renormalised, and aggregated to create the cluster-scale risk indexes.

5.2.2.1. Cluster identification

Countries analysed in the global assessment were grouped into clusters based on existing political and economic divisions and countries with a strong link to agriculture. In total, 14 clusters were identified (Table 5.2).

Table 5.2 Clusters used in the assessment, number of countries analysed, and their defining data sources. See excel in appendix E.1.3.2 for a list of countries in each cluster.

Cluster	Data Source

Continents Geographic regions*#: Africa (49 countries) Asia (43 countries) Europe (38 countries) Latin America and the Caribbean* (27 countries)	[dataset] UN DESA Population Division (2019)
Income Groups High income (45 countries) Upper middle income (45 countries) Lower middle income (48 countries) Low income (27 countries)	World Bank (2019)
Annex Classification Annex I (39 countries) Non Annex I (126 countries)	UNFCCC (2021)
Least Developed Countries Least Developed Countries (43 countries)	[dataset] UN DESA Population Division (2019)
V20 The Vulnerable 20 (V20) Group of Ministers of Finance of the Climate Vulnerable Forum (39 countries)	V20 (2021a)
Breadbasket *Countries with a breadbasket region* Breadbasket (17 countries)	Gaupp et al. (2019)
Reliance on agriculture based on employment *Countries with the highest per cent employment in agriculture were determined using Jenks Natural Breaks Optimisation (3 classes for this data).* Reliance on agriculture (35 countries)	[dataset] UNDP (2019)

* North America was not analysed within the geographic regions due to the small number of countries (n = 2). Neither was it included in the analysis with Latin America and the Caribbean to create an "Americas" cluster given the vastly different socio-economic circumstances between the USA and Canada compared to other countries in Latin America and the Caribbean and the presence of organisations that focus specifically on this cluster.
# Oceania was excluded due to the small number of countries with sufficient data (n = 6) and the presence of highly developed and less developed countries within the cluster (i.e. Australia and Vanuatu), which would have produced poor comparative results.

All clusters except for "Reliance on Agriculture" were constructed directly from these existing political and economic groups. Continent-based clusters were analysed given the existence of regional disaster risk funds and programmes such as the EU Solidarity Fund and the USAID Office of U.S. Foreign Disaster Assistance Latin America and the Caribbean Program. World Bank Income Group-based clusters were analysed as they are widely recognised and represent groups of similar economies (World Bank, 2019). Annex I and Non Annex I clusters of countries were chosen for analysis, as the United Nations Framework Convention on Climate Change (UNFCCC) uses the classification for the allocation of roles and responsibilities regarding climate mitigation and adaptation (Lucas, 2021, UNFCCC, 2021). The LDCs were also classified by the United Nations as countries with limited capacity to respond and adapt to climate change (UNFCCC, 2021) and were thus included in this analysis. The V20 countries were included as a cluster as these are globally recognised as being at high risk to climate change (V20, 2021b) and are part of specific programs targeting adaptation and resilience to climate change and disasters such as the InsuResilience Global Partnership (InsuResilience Global Partnership, 2021). Finally, two clusters with a strong link to agriculture were formed given the significant impact of drought on the agricultural sector and the potential global implications of drought events on these countries (Lunt et al., 2016). The first cluster was formed from countries with a high reliance on agriculture in the labour force (using data from [dataset] UNDP, 2019). Countries were divided into three classes based on their per cent employment in agriculture using Jenks Natural Breaks Optimisation, and the class with the highest percentages formed the cluster. Jenks Natural Breaks Optimisation was used as it reduces the variance within classes and maximises the variance between classes (Jenks and Caspall, 1971). Additional analysis on the significance of this cluster was outside the scope of the paper, however, would be necessary in future assessments that specifically aim to assess risk for countries with high reliance on agriculture in the labour force. The second cluster was formed from countries that were considered breadbaskets based on analysis of wheat, maise, soybean, and rice crop yield data by Gaupp et al. (2019). Breadbasket countries produce enough food to feed their population and to export elsewhere. These regions are major contributors to the world's food supply.

5.2.2.2. Cluster risk assessment

To conduct the cluster risk assessments, the global analysis' raw hazard/exposure values were grouped by cluster and normalised using linear max. Countries' vulnerability indicators were grouped by cluster as well and normalised with linear min–max at the cluster scale before aggregation into the preliminary vulnerability index. This was then normalised again using linear max to create the final vulnerability index comparable with the respective hazard/exposure indexes. With these modifications, a new risk index for each cluster was created by multiplying the cluster hazard/exposure indexes with the corresponding cluster vulnerability index. For example, Africa's hazard/exposure index was multiplied by the vulnerability index for Africa, resulting in the risk assessment for Africa. This created 14 new drought risk indexes, one for each cluster.

5.2.3. Comparison between global and cluster assessments

To understand the effect of grouping countries on the outcomes of risk assessments, the global hazard/exposure, vulnerability, and risk index scores were plotted against each of the cluster hazard/exposure, vulnerability, and risk scores using scatterplots. This highlighted how these elements of a risk assessment change when assessing risk at different scales.

For both the global risk index and the cluster-scale risk indexes, countries were then split into quintiles based on their risk index scores. The five quintiles represent “very low”, “low”, “medium”, “high”, and “very high” risk categories. To determine which clusters were most affected by renormalisation due to the change in the countries analysed (from the full global list to the restricted cluster-list of countries), the percentage of countries that changed category relative to the global assessment was calculated.

Finally, the countries that switched from a lower risk category in the global assessment to the “high” or “very high” risk category in the cluster assessment were identified to find countries that could be “left-behind” by the global risk assessment.

5.3. Results

5.3.1. Global assessment results

Here we present the results of the global assessment, i.e., when comparing 165 countries. The global index scores were regrouped into the clusters and displayed as box and whisker plots to uncover the patterns of hazard/exposure, vulnerability, and risk that emerge with a global-scale assessment (Figure 5.2).

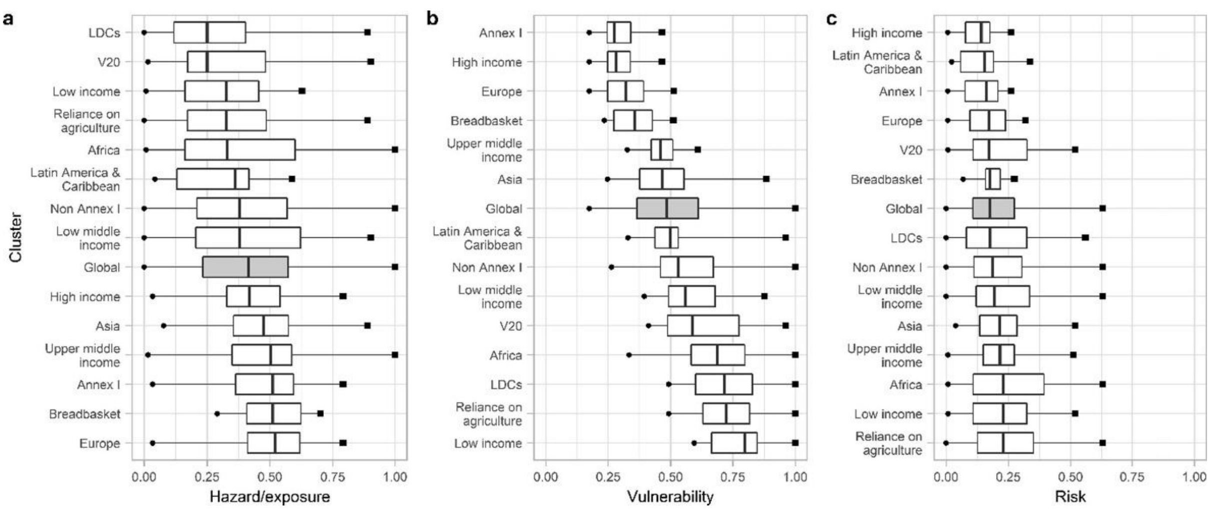


Figure 5.2. Global (a) hazard/exposure (b) vulnerability and (c) risk index scores grouped by clusters and ordered from lowest to highest by the median value. The vertical axis describes the cluster, and the horizontal axis refers to the index score. In the box plot, the vertical line

represents the median value for that cluster based on the global assessment results. The box represents the interquartile range (IQR), or the 25th percentile (Q1) to the 75th percentile (Q3). The circle is the absolute minimum value, and the square is the absolute maximum value.

Based on the median value in the global assessment, the LDCs, V20, and low income countries had the lowest hazard/exposure, however, had relatively higher vulnerability than other clusters. Conversely, Europe, breadbasket countries, and Annex I (or more developed countries) had the highest hazard/exposure but were among the clusters with the lowest vulnerability. In terms of risk, the low income, Africa, and reliance on agriculture clusters all shared the highest risk, while high income, Latin America and the Caribbean, and Annex I clusters had the lowest risk based on the global risk index.

For hazard/exposure, most of the clusters that had a median below the global median still hosted countries with the highest absolute values. For example, Timor-Leste had the fourth-highest hazard/exposure and is in the LDCs cluster, which had the lowest median hazard/exposure overall. Conversely, for vulnerability and risk, most clusters with medians above the global median hosted the countries with highest absolute values globally. Table 5.3 outlines the five countries with the highest hazard/exposure, vulnerability, and risk based on the global assessment and the clusters to which they belong.

Table 5.3 The five countries with the highest hazard/exposure, vulnerability, and risk to drought based on the global assessments. The italic text outlines the clusters in which they belong.

Hazard/exposure	Vulnerability	Risk
Namibia Upper middle income, Africa, Non Annex I	**Central African Republic** Low income, Africa, LDCs, Non Annex I, Reliance on agriculture	**Zimbabwe** Low middle income, Africa, Non Annex I, Reliance on agriculture
Botswana Upper middle income, Africa, Non Annex I	**Haiti** Low income, Latin America & Caribbean, LDCs, Non Annex I, V20, Reliance on agriculture	**Lesotho** Low middle income, Africa, LDCs, Non Annex I, Reliance on agriculture
Morocco Low middle income, Africa, Non Annex I, V20	**South Sudan** Low income, Africa, LDCs, Non Annex I, V20, Reliance on agriculture	**Djibouti** Low middle income, Africa, LDCs, Non Annex I, Reliance on agriculture

Timor-Leste Low middle income, Asia, LDCs, Non Annex I, Reliance on agriculture	**Chad** Low income, Africa, LDCs, Non Annex I, Reliance on agriculture	**Afghanistan** Low income, Asia, LDCs, Non Annex I, V20
Zimbabwe Low middle income, Africa, Non Annex I, Reliance on agriculture	**Afghanistan** Low income, Asia, LDCs, Non Annex I, V20	**Namibia** Upper middle income, Africa, Non Annex I

5.3.2. Cluster assessment results

For each cluster, the rankings changed, and different countries were highlighted as the most exposed, vulnerable, and at risk to drought with the reanalysis. The countries with the highest hazard/exposure, vulnerability, and risk scores for each cluster are outlined in Table 5.4.

Table 5.4 The top five countries for hazard/exposure, vulnerability, and risk based on the cluster assessments. Numbers in brackets refer to the country's rank from the overall global assessment. The countries in bold do not appear in the top 5 of the respective cluster based on the global assessment.

	Hazard/exposure	Vulnerability	Risk
Africa	Namibia (1) Botswana (2) Morocco (3) Zimbabwe (5) Cabo Verde (6)	Central African Republic (1) South Sudan (3) Chad (4) Comoros (6) Burundi (7)	Zimbabwe (1) Lesotho (2) Djibouti (3) Mauritania (6) **Niger (9)**
Asia	Timor-Leste (4) Kazakhstan (12) Palestine (15) Mongolia (18) Syria (26)	Afghanistan (5) Yemen (8) Democratic Republic Korea (32) Syria (36) **Pakistan (40)**	Afghanistan (4) Timor-Leste (7) Palestine (8) Yemen (16) Syria (13)
Europe	Slovakia (7) Spain (10) Moldova (16) Montenegro (17) Hungary (19)	Albania (80) Macedonia (100) **Moldova (119)** Bosnia and Herzegovina (67) Serbia (98)	Moldova (37) Albania (31) **Macedonia (48)** Bosnia and Herzegovina (29) Montenegro (33)

Latin America & Caribbean	Paraguay (36) Argentina (40) Peru (45) Ecuador (62) Chile (71)	Haiti (2) Honduras (42) Paraguay (53) Guatemala (50) **Nicaragua (66)**	Paraguay (22) Ecuador (43) Peru (39) Argentina (42) Guyana (68)
High income	Slovakia (7) Spain (10) Hungary (19) Canada (20) USA (22)	Panama (95) **Oman (139)** Romania (105) Chile (113) Greece (91)	Romania (47) Hungary (52) Greece (55) Spain (50) Slovakia (61)
Upper middle income	Namibia (1) Botswana (2) Kazakhstan (12) South Africa (13) Montenegro (17)	Iraq (43) Guatemala (50) Paraguay (53) **Ecuador (60)** **Albania (80)**	Namibia (5) Botswana (10) South Africa (12) Iraq (27) Paraguay (22)
Lower middle income	Morocco (3) Timor-Leste (4) Zimbabwe (5) Cabo Verde (6) Djibouti (8)	Comoros (6) Papua New Guinea (19) Lesotho (20) Eswatini (13) Zambia (21)	Zimbabwe (1) Lesotho (2) Mauritania (6) Djibouti (3) Timor-Leste (7)
Low income	Syria (26) Niger (31) Afghanistan (38) Sudan (61) Tajikistan (67)	Central African Republic (1) South Sudan (3) Haiti (2) Chad (4) Afghanistan (5)	Afghanistan (4) Niger (9) Mozambique (15) Yemen (16) Syria (13)
Annex I	Slovakia (7) Spain (10) Hungary (19) Canada (20) USA (22)	Bulgaria (114) Greece (91) Turkey (108) Romania (105) Ukraine (118)	**Bulgaria (59)** Turkey (54) Romania (47) **Russia (56)** Greece (55)
Non Annex I	Namibia (1) Botswana (2) Morocco (3) Timor-Leste (4) Zimbabwe (5)	Central African Republic (1) Haiti (2) South Sudan (3) Chad (4) Afghanistan (5)	Zimbabwe (1) Lesotho (2) Djibouti (3) Afghanistan (4) **Timor-Leste (7)**

LDCs	Timor-Leste (4) Djibouti (8) Mauritania (9) Lesotho (11) Niger (31)	Central African Republic (1) Haiti (2) South Sudan (3) Chad (4) Afghanistan (5)	Lesotho (2) Afghanistan (4) **Niger (9)** Mauritania (6) Djibouti (3)
V20	Morocco (3) Timor-Leste (4) Palestine (15) Mongolia (18) Tunisia (21)	Haiti (2) South Sudan (3) Comoros (6) Afghanistan (5) **Madagascar (10)**	Afghanistan (4) Niger (9) Timor-Leste (7) Palestine (8) **Sudan (17)**
Reliance on agriculture	Timor-Leste (4) Zimbabwe (5) Djibouti (8) Mauritania (9) Lesotho (11)	Central African Republic (1) Haiti (2) South Sudan (3) Chad (4) **Burundi (7)**	Zimbabwe (1) Lesotho (2) **Niger (9)** Mauritania (6) Djibouti (3)
Breadbasket	Hungary (19) USA (22) Portugal (23) Australia (25) Russia (28)	India (68) Brazil (69) Indonesia (104) Argentina (86) **China (117)**	**India (63)** Argentina (42) Romania (47) **Ukraine (66)** Hungary (52)

5.3.3. Comparison between global and cluster risk assessments

5.3.3.1. Hazard/exposure, vulnerability, and risk

Figure 5.3 shows how the patterns of hazard/exposure, vulnerability, and risk change between the global and cluster assessments. The solid line represents a 1:1 ratio between the global analysis and cluster analysis values. Points that lie above the line represent a higher score in the cluster analysis compared to the global analysis, and points that lie below the line represent a lower cluster score compared to the global analysis. Points that lie on the solid line show the same score in the cluster and global analysis.

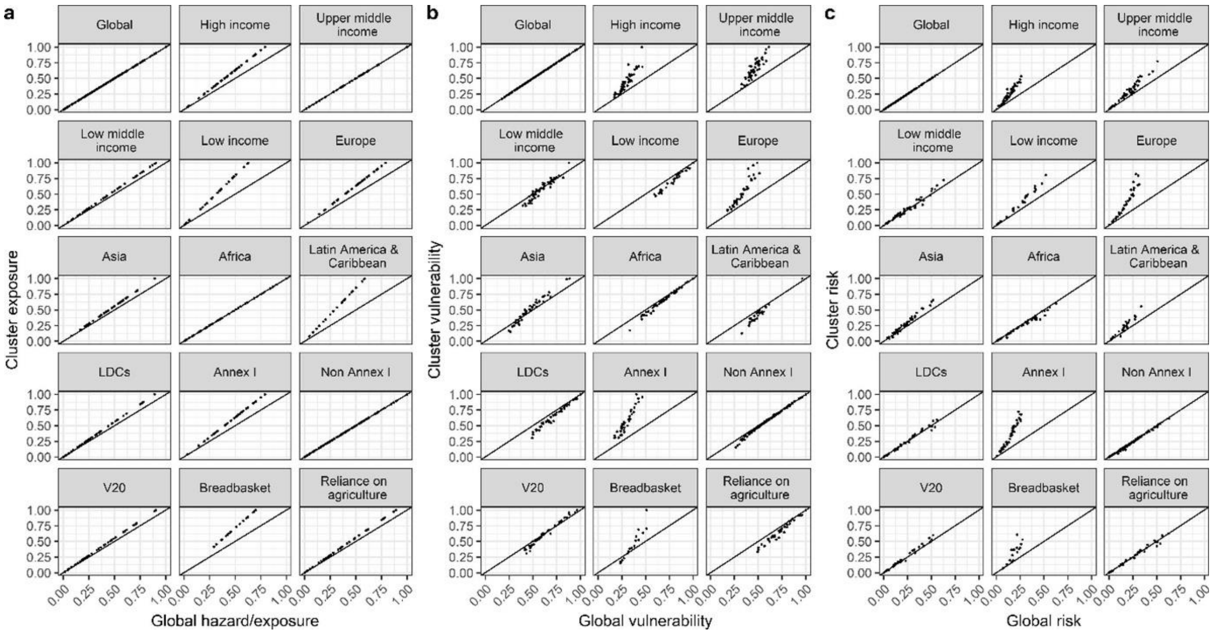


Figure 5.3. (a) Global hazard/exposure scores plotted against cluster hazard/exposure scores; (b) Global vulnerability scores plotted against cluster vulnerability scores; (c) Global risk scores plotted against cluster risk scores. The solid line represents a 1:1 ratio where the global and cluster assessment scores are the same.

Figure 5.3a shows that when comparing global and cluster-scale hazard/exposure values, every cluster had the same or higher hazard/exposure in the cluster assessment compared to the global assessment. For vulnerability, Figure 5.3b shows that vulnerability scores for the high income, upper middle income, Europe, and Annex I clusters are higher in the cluster assessment compared to the global assessment. Scores for the clusters, reliance on agriculture, Latin America and the Caribbean, low income, Africa, LDCs, and Non Annex I are the same or lower. Finally, for risk (Figure 5.3c), most clusters have similar or higher risk scores in the cluster assessments compared to the global assessment, with only few clusters with some scores slightly lower. Importantly, a change in score does not reflect a change in absolute hazard/exposure, vulnerability, or risk for the countries, but the change relative to other countries included in the assessments.

5.3.3.2. Categorisation of risk

Drought risk categorisation changes the most in the high income, Latin America and Caribbean, and breadbasket clusters when comparing the cluster-scale analysis to the global analysis (Figure 5.4). For the high income and Annex I clusters, all countries that changed risk categorisation switched to a more severe risk category in the cluster-scale analysis compared to the global analysis. For example, from “medium” to “high”. For Africa, low income, Non Annex I, and reliance on agriculture clusters, all countries that changed risk categorisation switched to a less severe risk category in the cluster-scale analysis compared to the global assessment. For example, “medium” to “low”. Appendix 1e contains an additional table that shows how many countries were in each risk category in the cluster analysis and the global analysis.

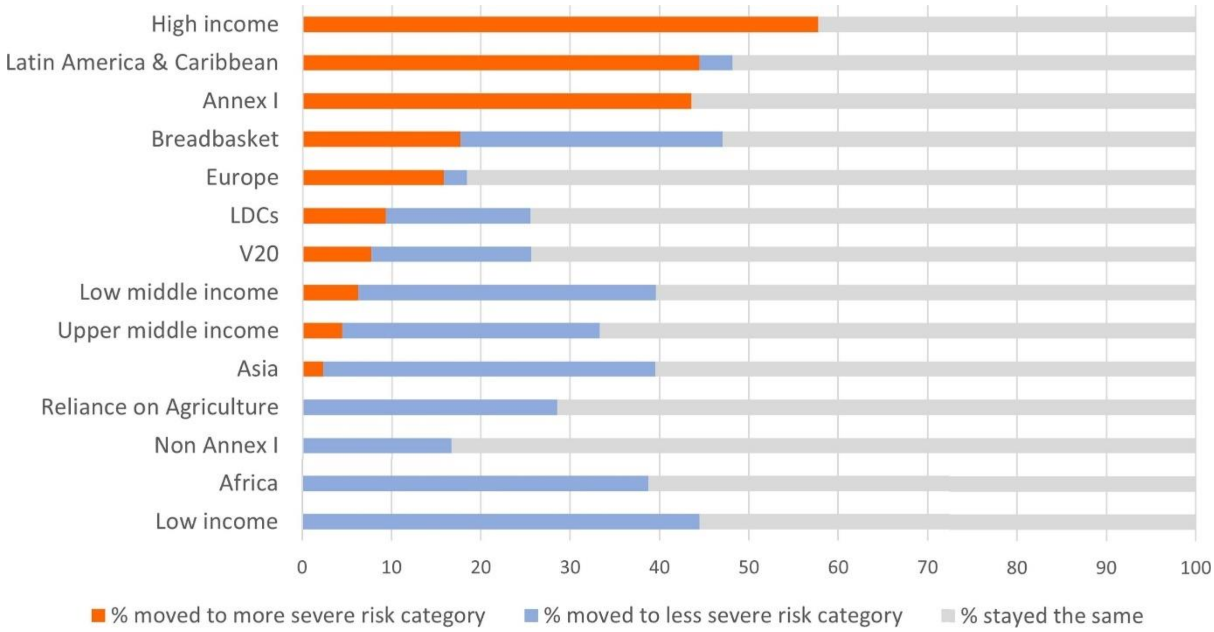


Figure 5.4. Per cent change to a more severe and less severe drought risk classification in the cluster-scale risk assessments, compared to the global risk assessment.

5.3.3.3. Countries “left behind”

In total, there were 50 cases where a country switched to the “high” or “very high” drought risk category in the cluster-scale risk assessment from a lower risk category in the global risk assessment (Figure 5.5).

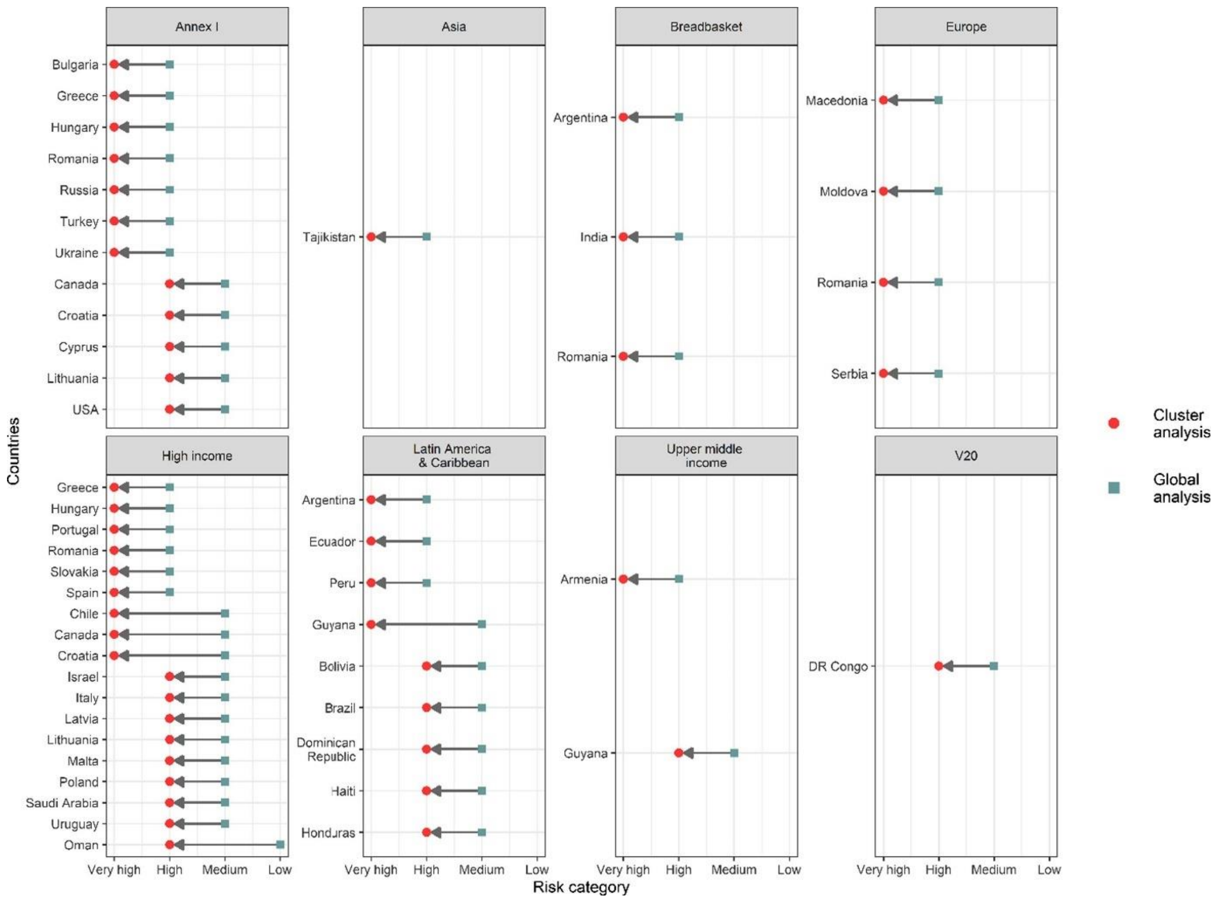


Figure 5.5. Countries that moved from a lower risk category in the global assessment (petrol square) to a "high" or "very high" category in the cluster assessment (red circle).

The clusters that had the highest percentage of countries moving to the "high" or "very high" risk quintile from a lower quintile in the global assessment were the high income (40 %), Latin America and Caribbean (33 %) and Annex I (31 %) clusters.

There were 29 cases where a country switched to the "very high" risk category in the cluster assessment from a lower risk category in the global assessment. For example, Hungary and Greece moved from the "high" risk category in the global assessment to the "very high" risk category in the high income and Annex I cluster assessments and Croatia, Chile, and Canada switched from "medium" risk in the global assessment to "very high" risk in the high income assessment. In the Asia cluster, Tajikistan switched to "very high" risk, from "high" risk in the global assessment, as did Romania, India, and Argentina in the Breadbasket cluster assessment.

Twenty-one countries also moved from a lower risk category in the global analysis to the "high" risk category with reanalysis at the cluster scale. For instance, Oman moved from "low" risk in the global assessment to "high" risk in the high income cluster assessment. The Democratic

Republic of Congo also switched to “high” risk in the V20 cluster assessment from “medium” risk in the global assessment.

Several countries also switched to a less severe risk category in 12 of the 14 clusters as well. A full breakdown of risk quintile categorisations for both the global and cluster assessments can be found in the link provided in the appendix E.1.3.2.

5.4. Discussion

5.4.1. Synthesis of findings

This paper shows the effect of changing the selection of countries included in a drought risk assessment on its outcomes. Country-level data used in a global indicator-based drought risk assessment was reanalysed by clusters of countries of policy relevance based on established socio-economic and geographic factors, such as income level or continent. Changes from the global assessment in hazard/exposure, vulnerability, and risk are presented and countries that moved from a lower-risk category into a “high” or “very high” risk category are highlighted as those “left behind” by the global drought risk assessment.

Our results highlight that the selection of countries included in a comparative risk assessment influences the outcome given that index-based assessments are commonly relative comparisons by design. By grouping and renormalising the global data by subsets of countries, relative hazard/exposure, vulnerability, and risk changed, and some countries moved to a higher risk severity categorisation based on the cluster analysis.

Behind the change in the distribution of hazard/exposure, vulnerability and risk index scores between the global drought risk assessment and the cluster risk assessments is the method to create the indexes, specifically the process of normalisation. For the vulnerability index, the indicators were renormalised within the clusters before being aggregated. For clusters such as Europe, which had overall lower vulnerability in the global assessment (Figure 5.2), the removal of more acute absolute (non-normalised) vulnerability indicator values from countries outside Europe, meant that the acute indicator values from European countries received normalised indicator scores closer to one. Thus, after aggregation of the renormalised indicator scores followed by index normalisation, most countries in the European cluster vulnerability index had higher vulnerability scores than in the global assessment. For the hazard/exposure indexes, all clusters that showed no change from the global assessment shared the country with the highest absolute hazard/exposure, Namibia. For the results of the cluster assessments without Namibia, the next highest hazard/exposure value for each cluster received an index score of 1 and all other values were transformed through linear normalisation, thus resulting in cluster hazard/exposure indexes with overall higher scores than in the global assessment. For risk, higher scores were observed generally across most cluster risk indexes compared to the global index as the magnitude of increase of the hazard/exposure index scores was mostly greater than any decrease in the vulnerability index scores, which was reflected in the outcome of multiplicative aggregation of these indices.

To explain the change in drought risk categorisation, Figure 5.2, Figure 5.4 are revealing. It was not a result of change in absolute risk between the global and cluster assessments, but rather the grouping of countries and the aggregation of the respective hazard/exposure and vulnerability indexes reflecting change in relative risk between countries in the cluster. Figure 5.2, Figure 5.4 show that the clusters that had the lowest risk medians based on the global assessment (and therefore would have had more countries in the least severe drought risk categories), had the highest percentage of countries switch to a more severe drought risk category in the cluster assessment (high income, Latin America and Caribbean, Annex I). The grouping of countries resulted in countries that were previously overshadowed by others with higher drought risk at the global scale, being highlighted as having “high” or “very high” drought risk within the cluster assessment.

These results have direct implications for climate change and disaster-related policy and finance decision makers, as according to the United Nations Convention to Combat Desertification (UNCCD), “understanding who and what are at risk provides critical information to deploy meaningful mitigation and adaptation strategies” (Barker et al., 2020p.xxiii). While global drought risk assessments achieve the goal to identify the most at-risk or most vulnerable from all countries globally, if funding or resources are aimed at a particular subset of countries, a cluster-based risk assessment for these countries could change the outcome. Countries considered not at “high” or “very high” risk based on the global scale assessment may be at “high” or “very high” risk within a subset of countries. This could impact the assistance received and focus on drought risk adaptation and have ramifications beyond country borders if the drought risk is not addressed.

For example, in the high income cluster, 18 countries moved from a lower risk category in the global assessment to the “high” or “very high” risk category in the cluster assessment. Croatia, Canada, and Chile switched from “medium” risk to “very high” risk, representing a significant shift in relative drought risk. This shift could influence the perception of action needed to address drought in these countries. All three have experienced or are currently experiencing significant drought impacts. In Croatia, drought is the most frequent hazard, causing the most economic loss in the agricultural sector of all hydro-meteorological hazards (Perčec Tadić et al., 2014), Chile has been experiencing a so-called mega drought since 2010 and modelling has shown it to be the most severe dry period for 700 years in the country (Muñoz et al., 2020), and nearly all regions in Canada experience drought (Bonsal et al., 2011) with major agricultural impacts experienced in the prairies (Quiring and Papakryiakou, 2003). Oman also switched from “low” risk in the global assessment to “high” risk in the high income cluster assessment, representing a significant shift in relative, and potentially perceived, drought risk. In Oman, droughts are acknowledged to be one of the worst hazards, having severe agricultural impacts (El Kenawy et al., 2020). Many of the other countries that switched from “medium” to “high” risk or “high” to “very high” risk categories, have experienced severe drought impacts in recent years as well, such as the Mediterranean countries (Naumann et al., 2021).

Changes in drought risk categorisation in the breadbasket cluster are also important for decision makers to consider, as simultaneous droughts in these countries could have cascading impacts and global implications. Climatic interdependence is important for the global food system, where low precipitation and low crop yields in one area can be offset by higher precipitation and higher crop yield in another. For example, Gaupp et al. (2019) found that drought risk for soybean in India can generally be mitigated with imports from Argentina as the drought risks are negatively correlated. Both these countries switched to the “very high” drought risk category in the breadbasket cluster risk assessment. However unlikely due to the negatively correlated drought risk, simultaneous drought in these countries could have impacts beyond their own borders, contributing to rising food prices and food insecurity. Further, simultaneous breadbasket failures have been linked to cascading impacts on income, employment, and consumption decisions as well as increased displacement and migration (Naqvi et al., 2020). Understanding which breadbasket countries are at “very high” risk to drought is a first step towards reducing drought risk and the associated cascading impacts, yet in a global assessment several of these countries were overshadowed. For decision makers, these results may influence the decisions made and allocation of resources to achieve resilience both within these breadbasket countries and globally as well.

Extending this analysis beyond the implications for decision makers based on the change in drought risk categorisation, to the patterns of hazard/exposure and vulnerability that were revealed in the global assessment, it is evident that different risk reduction or adaptation strategies may be appropriate depending on the subset of countries focused on as well. For example, European countries had high hazard/exposure and low vulnerability to drought, whereas Africa had high vulnerability and lower hazard/exposure to drought, compared to the global medians. For drought adaptation and risk reduction strategies aimed at multiple countries, ensuring that the most relevant element contributing to risk is addressed is an important consideration for decision makers.

While the paper had an explicit focus on drought, the findings of this research likely also apply for other global risk assessments, such as the World Risk Index (Welle and Birkmann, 2015), the INFORM Global Risk Index (UN OCHA, 2020), the ND-GAIN Country Index (Chen et al., 2015), the Global Climate Risk Index (Eckstein et al., 2021) or the Global InsuRisk Index (Sett et al., 2021) which are based on similar risk assessment approaches.

5.4.2. Limitations and recommendations for future research

While comprehensive and suitable to show how selection of countries can influence the outcomes of risk assessments, this study had several limitations. Imputation of missing data introduced uncertainty and the exclusion of countries to reach acceptable levels of missing data at the global scale limited analysis. For example, Small Island Developing States (SIDS) are considered at risk to drought (OECD and World Bank, 2016) but were not analysed due to exclusion of nearly 50 % of the countries. Further, the acceptable thresholds of missing data were applied at a global scale and the same indicators were used across all cluster analyses for consistency. However, this resulted in high levels of missing data for some of the cluster analyses. For example, 49 % of countries in the Annex I cluster did not have data for the literacy rate indicator. This means that the results for some clusters have a higher level of uncertainty than others (see E6 for a comprehensive overview of missing data).

In addition, several elements of the assessment were aggregated or generalised to the national level. While there is a difference in drought risk between irrigated and rainfed systems (Meza et al., 2020), this assessment used the aggregation of the exposed systems as the hazard/exposure indicator. Also, the breadbasket cluster was created from countries where a region in the country was considered a breadbasket (Gaupp et al., 2019). These regions may have different hazard/exposure and vulnerability to drought compared to the whole country average thereby influencing risk. Considering regional drought hazard, exposure, and vulnerability characteristics would be necessary if conducting a regional risk assessment in the future.

Further, equal weighting of all indicators was used to construct the vulnerability index despite wide acknowledgement that indicators do not equally contribute to vulnerability (Crossman, 2019, Meza et al., 2019). Weighting of each indicator should be informed by the relative importance of the indicator to the area or group of countries under assessment (Barker et al., 2021). However, research on the importance of indicators for each of the clusters in this paper does not exist and thus equal weighting was used as it is the most common approach to index construction (Beccari, 2016), and was considered appropriate for accuracy and comparability. Future work that aims to specifically conduct a risk assessment should consider weighting the vulnerability indicators as this may change the outcomes.

Moreover, a sensitivity analysis was not conducted as this was outside the scope of the paper which was to show how changing the scale of an assessment using the same method changes the outcome and may result in countries being “left-behind”. Therefore, different methods for data normalisation, imputation, aggregation, and the impact of weighting were not tested. A sensitivity analysis would also be recommended for a risk assessment that specifically aims to analyse risk for a particular grouping of countries in the future.

Finally, there are several recommendations and areas for future research that arise from this analysis. When targeting a specific subset of countries for risk reduction or adaptation finance and decision making, for example through the Least Developed Countries Fund (LDCF) established under the UNFCCC to address the unique needs of those Least Developed Countries that are especially vulnerable to the adverse impacts of climate change, a specific assessment for those countries is necessary. This can be extended to any spatial unit. Further, global tools and platforms that provide an assessment of global drought risk like the GDO could be improved by also sub-setting target regions or countries. As the findings of our research likely hold true for other existing global risk assessments that build on similar assessment approaches, such as the World Risk Index, the INFORM Global Risk Index, the ND-GAIN Index, the Global Climate Risk Index or the Global InsuRisk Index, future research should examine whether similar effects can be observed for these global risk assessment products as well.

5.5. Conclusion

Many organisations in the disaster risk reduction and climate change adaptation field have the mandate to focus on the “most at-risk” or “most vulnerable” countries and hence need risk information as a basis for decision making. At the global scale, this analysis has presented the general pattern of drought hazard/exposure, vulnerability, and risk by clusters of countries. By comparing the results of the global drought risk assessment and the cluster risk assessments, this analysis illustrated that hazard/exposure, vulnerability, and risk indexes are impacted by the selection of countries included in the analysis. Further, comparing the categorisation of drought risk between the global and cluster assessments has revealed that some countries that do experience the negative impacts of drought and are highlighted as having “high” or “very high” risk at the cluster scale, are overshadowed in a global assessment. This may impact decision making as these countries could be overlooked when determining drought risk reduction and adaptation resourcing. With 50 cases of countries switching drought risk category to “high” or “very high” in a cluster risk assessment from a lower category in the global risk assessment across 8 of the 14 clusters, the results emphasise the importance of utilising context-specific drought risk assessments to inform decision making to ensure that a country that experiences the negative impacts of drought is not “left behind”.

6. Discussion

6.1. Synthesis

The drivers of drought risk for agricultural systems vary substantially across and within countries. Drought risk needs to be analysed from a holistic and integrated perspective that brings together data from different sources and disciplines and is based on a spatially explicit approach, which can inform spatially targeted risk reduction and adaptation options.

As identified by the IPCC AR5 (IPCC, 2014), the literature review in Chapter 2 (Hagenlocher et al., 2019) confirmed the lack of assessments focusing on the actual implementation of adaptation measures and their potential positive or negative effects, with just under half of the studies reviewed (40%) making a direct link to drought risk reduction or adaptation strategies. Additionally, only very few of these articles consider or recommend ecosystem-based approaches, leaving the potential of nature-based solutions (NbS) for drought risk reduction and mitigation (Kloos and Renaud 2016, UN 2018) far from being realised. It is necessary, therefore, to move away from hazard-centric conceptualisations towards holistic approaches that also take into account the complex interaction of natural (ecological) and human (social) factors contributing to exposure and vulnerability. We need to draw our attention not only to enhanced monitoring and prediction of drought hazards, but must also consider the people and ecosystems which are affected, and their respective conditions. Chapter 2 showed through an extensive literature review that the relevance of individual hazard, exposure, and vulnerability indicators for explaining different drought impacts is poorly understood and tackled in assessments (Hagenlocher et al., 2019). Furthermore, 57% of the indicator-based risk assessments reviewed did not explicitly specify any weighting method, and less than ten percent of all risk assessments reviewed conducted some form of validation of their results.

Over the past years, indicator-based approaches have been promoted as useful tools to assess, compare, and monitor the complexity of drought risk from local to global scales (e.g., Carrão et al., 2016; Blauhut et al., 2016). However, the individual indicators' contribution to explaining drought vulnerability and, ultimately, the risk of sectoral drought impacts is often only weakly understood. As a result, the majority of assessments, notably at the global scale (e.g. Carrão et al., 2016), are based on equal weights for all indicators. In order to address the limitation of using equal weights, a global expert survey on vulnerability indicators for global-scale, sectoral drought risk assessments was conducted and presented in Chapter 3.1 as a joint effort between JRC's Global Drought Observatory (GDO) and United Nations University (UNU-EHS). The objective was to identify and weigh relevant drought vulnerability indicators with regard to potential impacts of drought hazards on agricultural systems and domestic water supply.

Chapter 3.1 summarises the results of the "Drought Global Expert Survey" and provides a general overview of the most relevant vulnerability indicators according to expert judgement. The drought vulnerability indicators list was derived from a systematic literature review (Hagenlocher et al., 2019, Chapter 2) and expert consultations. In total, 64 indicators for agricultural systems and domestic water supply were identified and included in the online survey. The results informed the vulnerability indicator weightings in Chapter 3.2. The global expert survey highlighted that the relevance of indicators varies strongly according to the sector, as different drivers are relevant for different impacts. Furthermore, the national expert survey performed in Chapters 4.1 and 4.2 showed that the relevance of indicators, even within the same sector (e.g. agricultural systems), might vary for different contexts and scales. The three expert surveys emphasised the relevance of vulnerability assessments and the identification of key drivers with a socioecological approach, as vulnerability shapes the risk of current and future droughts for the different sectors.

Chapter 3.2 has shown, for the first time, a separate global drought risk analysis for irrigated and rainfed cropping systems from a socioecological perspective by integrating drought indicators of hazard, exposure, and vulnerability. In previous assessments, the share of irrigated cropland was either ignored or considered to be a vulnerability indicator (Carrão et al., 2016). Chapter 3.2 went beyond previous studies by including a separate and spatially explicit analysis of the drought hazard and exposure of irrigated and rainfed agricultural systems and includes a specialised vulnerability index for this sector according to expert judgment. These differences revealed the importance of focusing more clearly on distinct impacts (e.g., on irrigated vs. rainfed systems) when conducting drought risk assessments, even within the same sector. For instance, irrigated agricultural systems in Latin America are highly exposed to droughts, whereas the probability of droughts occurring in rainfed agricultural systems in that region is comparably low. While the study in Chapter 3.2 presents the first attempt to assess drought risk for agricultural systems, more work is needed to analyse drought risk for other sectors, such as public water supply, tourism, energy production, and water-borne transportation, among others.

The national level assessments on Zimabwe's (Chapter 4.1) and South Africa's (Chapter 4.2) agricultural sectors pioneer an integrated drought risk assessment that considers hazard, exposure, and vulnerability to evaluate the impact of drought on rainfed and irrigated systems (separately) at a national level. The chapters also respond to articulated national policy needs, show how vulnerability assessments are crucial to understanding why certain peoples are disproportionately affected by drought, and identify entry points for vulnerability reduction. While hazard analyses outline which districts/provinces are frequently and severely affected by drought, vulnerability analyses help in identifying entry points for vulnerability reduction measures. It was found that high vulnerability levels undermine the implementation of drought adaptation strategies, making drought impacts even more devastating (Fischer et al., 2020). Thus, these analyses could support policy and decision-makers in prioritising key intervention areas and formulating strategies that will be essential in proactively dealing with future drought episodes. A deeper understanding of risks and their underlying factors, as presented in this thesis, will be key in encouraging a paradigm shift from reactive towards proactive drought risk management (Sivakumar et al., 2014; World Bank, 2019). Additionally, spatially explicit results are highly suitable for raising awareness to communicate the results of such assessments in a simple and efficient manner (Meza et al., 2020).

Finally, Chapter 5 discusses how changing the selection of countries included in a global drought risk assessment affects its outcomes. While global drought risk assessments achieve the goal of identifying the most at-risk or most vulnerable countries globally, if funding or resources are aimed at a particular subset of countries, a cluster-based risk assessment for these countries could change the outcome (Dudley et al., 2022). Countries not considered at "high" or "very high" risk based on the global scale assessment may still be at "high" or "very high" risk within a specific subset of countries. This could impact both the assistance received as well as the approach to drought risk adaptation and have ramifications beyond country borders if the appropriate drought risk is not addressed (Dudley et al., 2022). Country-level data used in the global indicator-based drought risk assessment presented in Chapter 3.2 was reanalysed by clusters of countries on policy relevance based on established socioeconomic and geographic factors, such as income level or continent. Results highlighted that the selection of countries included in a comparative risk assessment influences the outcome, given that index-based assessments are commonly relative comparisons by design. By grouping and renormalising the global data by subsets of countries, the relative hazard/exposure, vulnerability, and risk all changed, and some countries moved to a higher risk severity categorisation based on the cluster analysis. This limits and potentially biases the ability of decision-makers, regional organisations, or funding mechanisms to recognise which countries under their purview should be targeted for assistance.

It is widely acknowledged that a paradigm shift from 'reactive' and 'crisis-based' approaches towards 'proactive' and 'risk-based' drought management approaches is indispensable (Tsegai & Brüntrup, 2019). The findings of this thesis highlight the relevance of assessing and discussing drought risk in relation to specific impacts with a socioecological approach and diagnosing entry points to reduce drought risk in a context-specific manner (i.e. irrigated and rainfed systems). This ensures that relevant, proactive policies and planning can be effective even within the same sector (i.e. agricultural sector) before the worst impacts occur. While this thesis provides valuable information at the national and municipal levels, the assessments can be enhanced with a temporal dynamic exposure, more spatially explicit vulnerability information, and a systems approach, which all consider the multiple direct, indirect, and cascading impacts of drought risk on the different social and ecological systems.

Finally, being based on open-source data, the approach presented in this thesis allows for reproduction in various regions and at different spatial scales. The hazard and exposure assessment can be reproduced in any country. However, the vulnerability assessment is context-specific, and some indicators that might be relevant at the global level or, for some specific countries (e.g. South Africa or Zimbabwe), might not be relevant for other countries. Therefore, further research in other countries or regions will be needed to identify key indicators following the methodology applied in this thesis.

Overall, this thesis contributed to bridging the gap between disciplines and providing a comprehensive understanding of the socioecological drivers of drought risk. The findings underscore the need for integrated approaches that consider the interconnectedness between human systems and the environment. By providing information on the underlying drivers and patterns of drought risk, the approach developed in this thesis supports the identification of priority regions and provides entry points for targeted drought risk reduction and adaptation options to move towards resilient agricultural systems.

6.2. Way Forward

Tackling Growing Drought Risks—The Need for a Systemic Perspective

Hagenlocher, M., Naumann, G., **Meza, I**., Blauhut, V., Cotti, D., Döll, P., Ehlert, K., Gaupp, F., Van Loon, A. F., Marengo, J. A., Rossi, L., Sabino Siemons, A. S., Siebert, S., Tsehayu, A. T., Toreti, A., Tsegai, D., Vera, C., Vogt, J., & Wens, M.

Published as a commentary in Earths Future (2023): https://doi.org/10.1029/2023EF003857

Abstract

In the last few years, the world has experienced numerous extreme droughts with adverse direct, cascading, and systemic impacts. Despite more frequent and severe events, drought risk assessment is still incipient compared to that of other meteorological and climate hazards. This is mainly due to the complexity of drought, the high level of uncertainties in its analysis, and the lack of community agreement on a common framework to tackle the problem. Here, we outline that to effectively assess and manage drought risks, a systemic perspective is needed. We propose a novel drought risk framework that highlights the systemic nature of drought risks, and show its operationalization using the example of the 2022 drought in Europe. This research emphasizes that solutions to tackle growing drought risks should not only consider the underlying drivers of drought risks for different sectors, systems or regions, but also be based on an understanding of sector/system interdependencies, feedbacks, dynamics, compounding and concurring hazards, as well as possible tipping points and globally and/or regionally networked risks.

Key Points:

- Drought risks are on the rise and their effects are increasingly felt across communities, economic sectors, ecosystems, borders and entire societies
- To effectively assess and manage drought risks, a systemic perspective is needed
- We propose a novel systemic framework to better inform drought risk research and policy

Plain Language Summary

In recent years, the world has faced severe and frequent droughts, resulting in significant direct and indirect impacts. However, our understanding and assessment of drought risks are still limited which has important implications for risk management. Here, we propose a new approach—a systemic perspective on drought risks—to effectively assess and manage drought risks. Our framework highlights the interconnected nature of drought risks, impacts and responses. We demonstrate the framework's application by analyzing the 2022 drought in Europe. This research emphasizes the need for a comprehensive understanding of drought risks and offers a practical tool for policymakers and researchers to guide future drought risk research and policy.

6.2.1. Introduction

Droughts are temporary, recurring, usually slow-onset water deficits that can lead to devastating impacts on many sectors and systems and, eventually, affect ecosystems, entire societies and economies (Chiang et al., 2021; IPCC, 2022; Pokhrel et al., 2021; UNDRR, 2021). These water deficits are caused by the interaction of meteorological imbalances propagating through the hydrological cycle and human activities (Bartholomeus et al., 2023; Van Loon et al., 2022). Drought impacts, resulting from an inbalance between water availability and water needs, are severe, spatially and temporally complex, interlinked, and often slowly evolving, rendering their assessment a challenge. Between 2001 and 2021, droughts affected on average about 67 million people globally every year, with variations across the years, and caused global economic losses of USD 146 billion (CRED, 2022). While agriculture is the most affected sector, the lack of water due to droughts also affects ecosystems, public water supply, power generation, tourism, water-borne transport and buildings often with non-linear cascading and systemic impacts across economic sectors and systems (UNDRR, 2021). For example, low streamflow directly affects power generation from fossil fuels, nuclear energy and hydropower as well as river-borne transportation, which in turn increases the risk of systemic failure for societies as a whole due to possible cascading effects on entire industries—as it could be observed in Europe in 2018–2019 and 2022. While droughts can develop gradually over several months, they can also act as a sudden and dramatic trigger for famine or ecosystem loss when an ecological or social tipping point is crossed—as experienced in the Horn of Africa in 2022–2023, which is enduring its longest drought in 40 years (WMO, 2022). Droughts also increase the risk of wildfires, as observed in the Amazon and Pantanal in 2020–2021 (Marengo et al., 2021) and during the concurrent drought and heat wave affecting Europe in the summer of 2022. In addition, over the past few decades, the occurrence of droughts, compounded by unsustainable water management practices, have generated severe water crises that affected water, energy and food security, as in Central Chile (Garreaud et al., 2019), California (Mann & Gleick, 2015), South Africa (Meza et al., 2021) and Sao Paulo and the Parana-La Plata basin (Naumann et al., 2023). These characteristics pose a serious challenge to our ability to grasp the complexities of drought risks and to manage them in a comprehensive way. This is particularly concerning as extreme drought-heat compound events are expected to further increase in anthropogenically forced warmer climates (IPCC, 2021, 2022; Kreibich et al., 2022; Naumann et al., 2018) while vulnerabilities of communities, sectors and systems to drought are high in many parts of the world (UNDRR, 2021).

Identifying pathways toward more drought-resilient societies is high-up on global political agendas (UN, 2022). Cross-sectoral assessments of who and what is at risk to what (e.g., lower than normal soil moisture or streamflow as well as temporal water shortages and its cascading effects), where, when, and why, will be key for proactive risk management and adaptation. This has also been underscored by relevant international agendas and initiatives, such as the Sendai Framework for Disaster Risk Reduction (UN, 2015), the Integrated Drought

Management Programme (https://www.droughtmanagement.info) by the World Meteorological Organization and the Global Water Partnership which originated in the 2013 High-level Meeting on National Drought Policy (WMO, 2013), the 2018/2019 Drought Initiative (https://www.unccd.int/actions/drought-initiative) of the United Nations Convention to Combat Desertification (UNCCD) and the GAR Special Report on Drought 2021 (UNDRR, 2021). Furthermore, UNCCD Parties made a land mark decision to establish an Intergovernmental Working Group (IWG) on Drought at the 14th session of the UNCCD Conference of Parties (COP 14) and a new IWG at COP 15 with the aim to tackle the issue of drought in a deeper, sustainable and more systemic manner (https://www.unccd.int/convention/governance/intergovernmental-working-group-drought-2).

Besides, African Nations urged the United Nations to improve research and data on drought and drought risks during the UNCCD Conference of the Parties (COP14) that took place in New Delhi, India (Padma, 2019). Spearheaded by the governments of Spain and Senegal, an International Drought Resilience Alliance was launched in November 2022 at COP27 Leaders' Summit in Egypt (https://idralliance.global/). Moreover, in 2023 the first UN water conference in decades took place, a global event aimed to speed up actions to achieve the internationally agreed goals on water resilience, security and cooperation.

6.2.2. Progress and Persisting Gaps

Over the past decades, major progress has been made in understanding the physical processes underlying drought onset and evolution (Schumacher et al., 2022), the human role in enhancing and mitigating droughts (AghaKouchak et al., 2021; Di Baldassarre et al., 2018; IPCC, 2021, 2022; Rangecroft et al., 2019; Savelli et al., 2022; Van Loon et al., 2016, 2022; Wendt et al., 2020), mutual feedbacks between human and water systems in general (Höllermann & Evers, 2020; Huggins et al., 2022; Sivapalan et al., 2012, 2014), as well as approaches to proactive drought management (Pischke & Stefanski, 2016). Drought hazard monitoring and event-based early warning systems have also been implemented in many countries, regions (e.g., East Africa Drought Watch) and at the global level (e.g., the EC-JRC Copernicus Global Drought Observatory). However, a multi-sectoral global drought hazard early warning system is not yet operational. While a plethora of hazard indicators for monitoring droughts exists, a clear understanding and communication of the conceptual basis of the selected drought hazard indicators and their relation to specific drought risks are less developed (Bachmair et al., 2016). A systematic approach for selecting drought hazard indicators that are specific to the risk system under consideration has recently been presented by Herbert and Döll (2023), who also propose to take into account the habituation of the system at risk to less water than normal when deciding which drought hazard indicators are suitable for a drought risk assessment. Impact-based forecasts that include risk information are largely missing (Sutanto et al., 2019). Meanwhile, the conceptual understanding of risks associated with meteorological and climatic hazards has evolved from hazard-focused and environmental-deterministic concepts to a holistic one that considers environmental, socio-economic, physical and governance-related drivers of hazard, exposure, and vulnerability as well as the dynamic nature of risks and responses (IPCC, 2022). Further advances have been made regarding the conceptualization of (a) risks linked to connected extreme events (Raymond et al., 2020; Zscheischler et al., 2018), (b) the nexus approach to drought risks (Reichhuber et al., 2019), (c) multi-risk (Curt, 2021) and complex climate risk (Simpson et al., 2021) and (d) cascading and systemic risks and impacts linked to multiple hazards, threats and shocks (Chatzopoulos et al., 2021; Hochrainer-Stigler et al., 2023; Sillmann et al., 2022; UNDRR & UNU-EHS, 2022), including compound and cascading drought impacts (Cotti et al., 2023; de Brito, 2021; Niggli et al., 2022). These concepts are now widely used to assess the risks associated with floods, storms, tsunamis, or earthquakes. However, according to recent reviews of drought risk and impact assessments (Blauhut, 2020; Hagenlocher et al., 2019) the most used conceptual frameworks aiming to explain the propagation from drought hazards to drought impacts (Van Loon et al., 2016; Wilhite & Glantz, 1985) have not been updated with these recent developments and remain largely hazard-focused, deterministic and do not consider cascading or systemic effects. Efforts to quantify drought risks on multiple systems through a probabilistic risk assessment approach at continental scale have been recently carried out (Rossi et al., 2023), but focus remained confined to direct losses on individual systems. Severe droughts in recent years have however clearly shown that impacts are not only linked to the onset, duration, severity and frequency of drought events. Instead, the risk of drought impacts depends on the degree of direct and indirect exposure, the intrinsic and dynamic vulnerability conditions of different communities, sectors and systems, as well as (transient) adaptation decisions and their interconnectedness (Wens et al., 2019). A static and incomplete view of the system bears the potential for insufficient and conflicting solutions.

6.2.3. A Novel Systemic Framework

Recognizing the recent conceptual advances in the field of drought evolution, drought and society, socio-hydrology and complex risk (incl. compounding, cascading, systemic and multi-risk), we aim to bring together these separate contributions into a comprehensive framework to advance drought risk research. We propose a novel conceptual framework that captures the complex, dynamic and non-linear interactions of drought (and possible concurring) hazards, direct and indirect exposures and vulnerabilities of interconnected sectors and systems across scales from a systemic perspective (Figure 6.1). This framework aims to provide guidance for drought risks assessments and the identification of integrated solutions to reduce and manage risks holistically which in turn can help to inform drought policies now and in the future.

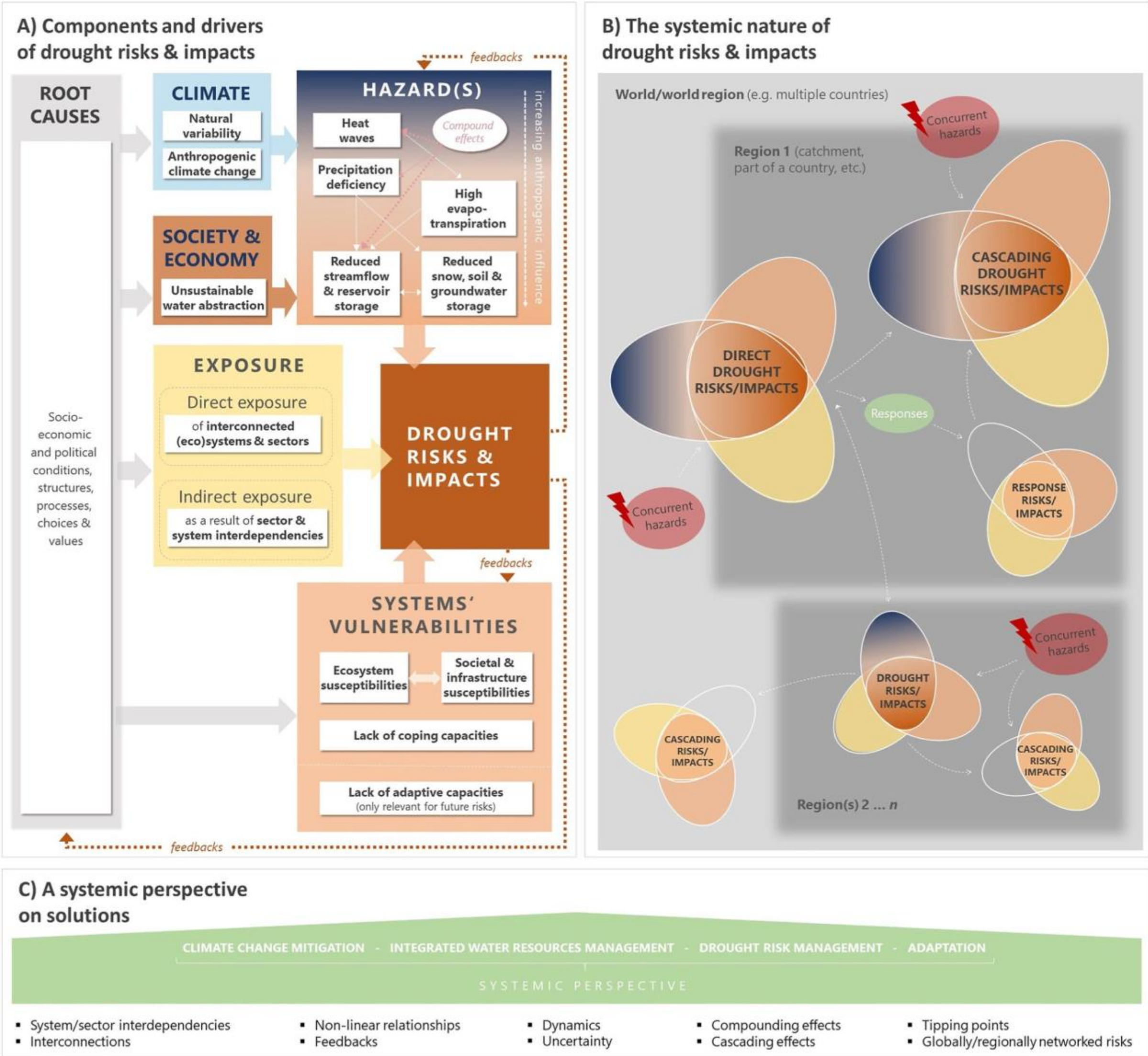


Figure 6.1. Characterizing the systemic nature of drought risks and impacts: (a) drought risks and impacts for communities, sectors and systems result from the complex, dynamic, non-linear interaction of drought hazards, direct and indirect exposure and systems' vulnerabilities. Drought hazards are influenced by climate change as well as societal pressures on water resources, such as unsustainable water abstraction leading to water scarcity. Underlying these components of risks are root causes that stem from socio-economic and political structures, processes, choices and values. (b) Direct drought risks and impacts can lead to further cascading effects on communities, sectors and systems in the same region or distant areas (indicated as region(s) 2 to *n*) which are not necessarily directly affected by the drought hazard (indicated by a blank hazard propeller) as a result of indirect exposures through the interdependence of sectors and systems and their vulnerabilities. Often these risks and impacts are compounded and further exacerbated by concurrent hazards. Furthermore, risk

management and adaptation responses to drought impacts can lead to possible response risks. (c) The systemic nature of drought risks calls for systemic solutions, that is, actions that consider system/sector interdependencies, interconnections, non-linear relationships, feedbacks, dynamics, compounding and cascading effects, possible tipping points, globally/regionally networked risks, and account for uncertainty.

Persistent anomalies in large-scale atmospheric circulation patterns leading to reduced rainfall and/or increased temperatures can cascade through the hydrological cycle leading to severe droughts, with less water than normal in snow packs, soils, groundwater and surface water bodies—aggravated or alleviated by human activities (Figure 6.1, panel a), such as water abstractions (Di Baldassarre et al., 2018; Van Loon et al., 2022) and water use regulations. The severity of the resulting impacts, however, depends on the vulnerability of who or what is exposed to specific water shortages (Gonzáles Tánago et al., 2016; Hagenlocher et al., 2019; IPCC, 2022; UNDRR, 2021). Analyzing the root causes and dynamics of direct and indirect exposure and vulnerability of communities, interconnected economic sectors and human and natural systems (e.g., ecosystems) is therefore vital to understand why communities, sectors or systems facing the same drought event may experience fundamentally different impacts (Figure 6.1, panel a). For example, the 2018 drought event that led to widespread water shortages and almost to “Day Zero” in Cape Town has shown that human actions exacerbated the drought hazard (here: streamflow, reservoir and groundwater storage) through overconsumption, but also that socio-economic disparities influenced access to information as well as the choices households had to prepare for and cope with the drought (Savelli et al., 2021, 2023; Ziervogel, 2019). In a review of governmental financial assistance in Tropical Asian countries, Goodwin et al. (2022) found that even when institutional schemes are available, high levels of social vulnerability prevent many potential beneficiaries from accessing them, therefore leaving vulnerable communities/sectors (e.g., farmers) with little to no options to cope with drought impacts. The impacts of droughts, however, are not only exacerbated or ameliorated by social, economic, or institutional factors that influence societal susceptibilities and the ability of communities economic sectors and systems to cope and adapt, but are also directly linked to physical and biological factors determining the susceptibility of ecosystems and the services they provide (Figure 6.1, panel a).

As a result of the interdependence of economic sectors and systems in our highly connected world, direct drought risks and impacts can lead to cascading effects (Figure 6.1, panel b) on (a) other sectors and systems in the same region, (b) other regions that are not even directly affected by the drought hazard or (c) global repercussions (Challinor et al., 2018; Chatzopoulos et al., 2020; UNDRR, 2021). At the same time, research has shown that responses to climate-related hazards such as droughts can also lead to response risks (IPCC, 2022). For example, Di Baldassarre et al. (2018) have highlighted how the establishment of reservoirs in response to droughts can lead to an overreliance on these reservoirs and in turn increase the vulnerability of communities, sectors and systems to droughts. This is reflected by the propeller labeled “response risks/impacts” in the framework shown in Figure 6.1 (panel b). Furthermore, often the effects of droughts are compounded by concurring hazards and shocks (Kreibich et al., 2022; Lin et al., 2023; Mishra et al., 2021; Mukherjee & Mishra, 2020; Singh et al., 2022; Toreti et al., 2019; Yaddanapudi & Mishra, 2022) and their risk management strategies (e.g., Ward et al., 2020), such as heat waves, wildfires, floods, global pandemics or armed conflict as the global COVID-19 pandemic and the Russian aggression on Ukraine have revealed (Figure 6.1, panel b). Given the systemic nature of risks, a systemic perspective is also needed to manage and adapt to growing drought risks (Figure 6.1, panel c). These solutions should not only consider the drivers of drought risks presented in Figure 6.1 (panel a), but also be based on an understanding of key characteristics of the systemic nature of drought risks, such as sector/system interdependencies, feedbacks, dynamics, compounding and concurring hazards, as well as possible tipping points and globally and/or regionally networked risks.

To illustrate how the framework can be applied, we draw on lessons from the concurrent drought and heat wave event that affected Europe in the summer of 2022 to illustrate the systemic nature of drought risks and impacts across economic sectors and systems (Figure 6.2).

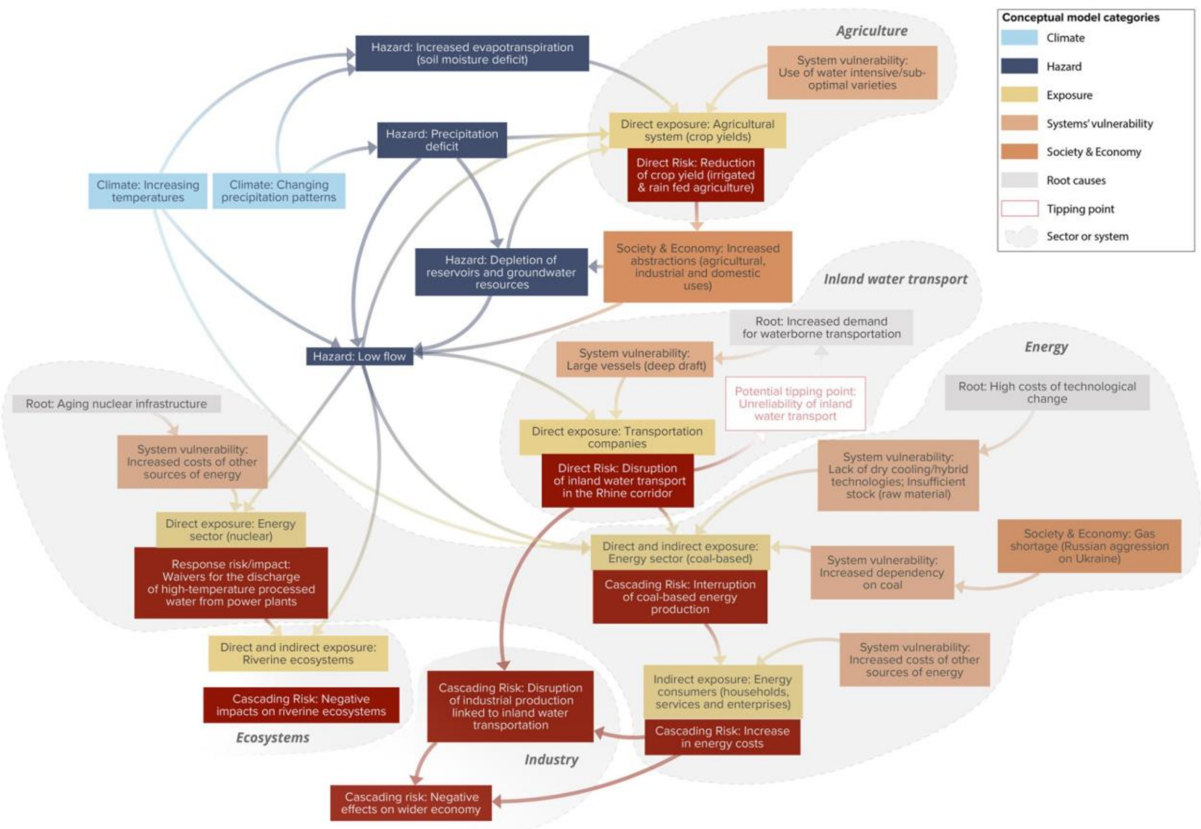


Figure 6.2. Application of the conceptual risk framework to illustrate the systemic nature of drought risks and impacts using the drought that affected Europe in summer 2022 as an illustrative example (cf. text below for a description). The figure applies the categories of the conceptual risk framework (Figure 6.1) to the example (see legend in top right corner), using connectors to showcase the relationships between interconnected risks and drivers. To facilitate the interpretation, elements were clustered in sectors or systems of interest (gray shading).

Europe is widely understood to be at risk of suffering major and costly cross-sectoral impacts from droughts, especially in the context of expected climate change (Naumann et al., 2021). In the summer of 2022, a concurrent drought (which already started in winter with precipitation deficits) compounded with a sequence of heat waves affected Europe (Copernicus Climate Change Service, 2023; Toreti et al., 2022b). These manifested in a precipitation deficit as well as increased evapotranspiration, contributing to significant low flows in surface water, a reduction of soil moisture and of the water volume stored in reservoirs (Baruth et al., 2022a, 2022b; Toreti et al., 2022a). Consequently, reduced water availability resulted in water demands for both rain fed and irrigated agriculture not being met, which negatively affected crop yields in large parts of Europe (Baruth et al., 2022a, 2022b, 2023; BMEL, 2022). Water intensive crop varieties, such as rice, were particularly affected, resulting also in a decrease in farmers' sowing area and high percentages of unproductive fields (Baruth et al., 2022a;

Ente Nazionale Risi, 2022). Compounding with decreased water availability, the decrease in yield was exacerbated by the acceleration in the phenological cycle induced by increased temperatures/heat stress, which reduced the length of the grain filling phase (Baruth et al., 2022a, 2022b, 2023). As a response to the unavailability of sufficient surface water, multiple European countries restricted abstractions for irrigation purposes (ibid.) in order to reduce the competition for water resources between sectors (Toreti et al., 2022a) which was also a partial cause for yield losses.

The 2022 low flow event also had severe effects on major European rivers, such as the Rhine corridor (Toreti et al., 2022a), where it significantly affected the inland water transport (IWT) sector. The Rhine is one of the river systems that compose the European network of almost 40,000 km of navigable inland waterways. This network has undergone exponential growth in terms of traffic and tonnage of goods transported in the last four decades (Notteboom, 2007), establishing itself as a reliable and high-capacity mode of transportation for a variety of goods, including raw materials. This means that disruptions of IWT can be of significant importance for the region and beyond. Driven by the growth of IWT volumes (Vinke et al., 2022)—a reflection of the increase in global maritime container transport (Bishop et al., 2011; Corbett et al., 2010; Notteboom, 2007)—riverine transportation companies increasingly make use of large vessels with deep drafts. Because of the reduced navigable depth during the low flow in the Rhine, such vessels had to restrict their load factors, in order to decrease their drafts and still be able to navigate safely (Federal Institute of Hydrology, 2022). In addition to transportation surcharges (Federal Institute of Hydrology, 2022), this load reduction affected, for instance, coal and oil transport in the Netherlands (Toreti et al., 2022c). Moreover, to compensate for the reduced loads, a higher number of vessels had to be employed (Wrede, 2022), a response that can lead to an increase in traffic intensity and berth occupancy in ports (Vinke et al., 2022). Added to the reduced vessel speeds resulting from the low water depth at local levels, this contributed to further delays and interruptions of deliveries of goods in the Rhine corridor (Connolly, 2022; Wrede, 2022).

The high level of interconnectedness between different sectors and systems meant that the disruption of IWT in the Rhine posed for example, a cascading risk for the coal-based energy sector, notably in Germany, which is dependent on riverine transport of the raw material. Especially since the gas shortages caused by the Russian aggression on Ukraine, the European energy sector has an increased dependency on coal (European Commission, 2022a; Wrede, 2022), which augments its vulnerability to shortages of the material. For example, in the third quarter of 2022 more than 36% of the total energy produced in Germany stemmed from coal, with an increase of over 13% compared to the same quarter in 2021

(DESTATIS, 2022). It is not inconceivable that an increased recurrence of prolonged low-flow conditions due to climate change may push the sector to a tipping point, where other industries might look into alternative supply chains to avoid regular disruptions.

At the same time, thermoelectric energy production is directly dependent on water at a suitable temperature for power plant cooling (De Stefano et al., 2015). This means that warmer river water as a result of the heatwave has a decreased plant cooling capacity, making it unsuitable for this purpose (De Stefano et al., 2015). Moreover, the excessive discharge of the warmed-up water used for cooling processes back into the river is a major disturbance to riverine ecosystems due to its disruption of the environmental flow, and as such is usually regulated through a restriction of abstractions and discharge in case of too high temperatures (Carlino et al., 2021; De Stefano et al., 2015). In France, however, these restrictions were waived in 2022 for operational nuclear plants to avoid further disruption to production, given the unavailability of multiple other plants due to maintenance (Boulle, 2022). As such, this constitutes an example of response risk, whereby an intervention to safeguard a system (energy) resulted in aggravated negative consequences for another (riverine ecosystems). Outside this specific case, pre-existing drivers of vulnerability contributed to impacts in the energy sector. The lack of implementation by energy producers of dry and hybrid cooling technologies due to the high costs of technological change exacerbates this problem, which is aggravated during low-flows (De Stefano et al., 2015). As a result of these processes and cascading impacts, energy prices in Europe soared during summer 2022, affecting consumers all throughout the continent (European Commission, 2022b).

As highlighted in our framework, understanding growing drought risks for people, communities, economic sectors and systems hence calls for a systems perspective that considers the non-linear feedbacks and dynamics between human, environmental, technological and governance-related drivers of multiple interconnected drought risks. Accordingly, in our highly interconnected world, where the effects of droughts on one sector or system can lead to cascading effects on other sectors and systems even in distant areas, that is, regionally or globally networked risks (Challinor et al., 2018; Chatzopoulos et al., 2020), more efforts are needed to better understand and map how sectors and systems are interconnected in order to strengthen resilience towards cascading effects and reduce the risk of systemic failures. While the framework has been designed with a specific view on droughts (Figure 6.1a), elements of it, such as the notion of the systemic nature of risks, impacts and responses (Figure 6.1b) and the systemic perspective on possible solutions (Figure 6.1c), can also inform research and policies linked to other hazards and shocks where systemic perspectives are also less common to date.

6.2.4. Implications for Drought Risk Management

In times when interconnectedness characterizes growing drought risks, we need to move beyond crisis and hazard-oriented, sectoral perspectives, and instead develop just/fair, prospective, risk-informed, multi-scale, multi-sectoral and adaptive drought risk management policies, plans and strategies that consider the whole spectrum of compounding and cascading effects. The proposed novel conceptual framework offers an entry point to understand this complexity, and aims to inspire addressing growing drought risks from a systemic lens. This implies that for managing the systemic nature of drought risks, we need to expand and broaden the actor space toward a transdisciplinary, whole-of-society approach. To achieve this, multi-level governance frameworks and associated working groups that share responsibilities for drought risk/water management and increase collaboration across sectors, spatial scales, borders and actors (incl. citizens, authorities, private sector, civil society organizations, decision makers), are needed (Blauhut et al., 2022; UNDRR, 2021), calling for institutional reform where these are not in place.

Addressing the systemic nature of drought risks requires actions in multiple domains. First and foremost, more actions are needed to prevent drought hazards from becoming more frequent and severe. This includes accelerated and deeper efforts for greenhouse gas emissions reductions to tackle anthropogenic climate change. To limit the impacts of droughts, it is also important to incentivize sustainable water management, including water saving, equitable water sharing and ecosystem restoration practices. In addition, an enhanced evidence base is needed on direct as well as cascading and systemic impacts of droughts, responses and adaptation to drought, and their feedback on vulnerability dynamics of systems and sectors. Drought hazard monitoring, forecasting and impact-based warning capacities should be strengthened and scaled up, but also approaches and methods for systemic risk assessment should be developed that can provide actionable knowledge for comprehensive drought risk management and adaptation.

New analytical tools have become available that could support these efforts. In particular, the emergence of systems thinking, network and system approaches, such as causal loop diagrams or impact webs (Sparkes et al., 2023), but also agent-based modeling (e.g., Wens et al., 2019) are promising developments for systemic risk analysis. Scenarios, serious games and adaptation pathways (Schlumberger et al., 2022; Werners et al., 2021) can be useful tools to bring stakeholders together to engage with the complexity of drought risks, and co-create pathways toward systemic risk management—both in the short and the long-term.

All this means that we, as society as a whole, need to be open to transformative and more radical changes to our risk management approach overall. For example, existing water/drought risk management and adaptation plans and strategies should be reviewed, and where necessary revised, to evaluate if and how these are cognizant of possible compounding, cascading and systemic effects of droughts and potentially concurring hazards, and also of possible response risks and maladaptations. In some cases this might require transformation of the water management system, rather than modest revision and optimization (Bartholomeus et al., 2023). As risks cannot be eliminated from systems, managing the systemic nature of drought risks also implies that we have to engage with questions of which risk levels are acceptable and fair for whom, and if, and how, the possible impacts of exceeding safe and just water boundaries can be transferred for example, through drought/climate risk insurance or financial instruments, such as dedicated drought funds. Further, as the COVID-19 pandemic has shown, scaling up social protection might also help buffering against the direct and cascading effects of hazards and prevent people from falling (back) into poverty (UNDRR & UNU-EHS, 2022). If we want to achieve the goals of the Sendai Framework and the SDGs, supra-national systemic efforts are needed to address the transboundary effects and globally networked risks linked to droughts. Without these changes, despite our best efforts, adverse impacts of droughts will further increase, and stories of successful drought risk management will remain scarce (Kreibich et al., 2022), thus undermining sustainable development.

7. Conclusions

Drought impacts on the agricultural sector are recurrent. Such drought events provide opportunities to learn and to improve drought risk reduction efforts. Reducing drought risk and all associated direct and indirect impacts through targeted risk reduction and adaptation has become a global priority, as reflected by different global initiatives and frameworks (e.g. the 2018/19 UNCCD Drought Initiative, Sendai Framework for Disaster Risk Reduction 2015–2030, Sustainable Development Goals, and 2021 GAR Special Report on Drought). Alongside these global efforts, a growing number of drought risk assessments have been conducted over the past decades, underlining the importance of understanding and addressing the multifaceted aspects of drought risk. Efforts to reduce drought risk and adapt to changing environmental conditions by prioritising and allocating funding and resources should be based on sound understanding, characterisation, and assessment of the drivers, patterns, and past trends as well as projected future patterns of drought risk. However, despite substantial progress in refining methodologies for characterising individual components of drought risk, the second chapter of this thesis has identified persistent knowledge gaps of conceptual, methodological, and practical nature. These gaps need immediate attention to enhance our understanding of drought risk and to promote pathways toward more drought-resilient societies. It is clear that the path to effective drought risk reduction and adaptation hinges upon a robust comprehension of the drivers, patterns, and historical trends, as well as the projected future patterns of drought risk.

This thesis presents, for the first time, a global and national-scale drought risk assessment for both irrigated and rainfed agricultural systems from a socioecological perspective by integrating drought indicators for hazard, exposure, and vulnerability. Going beyond previous studies, it includes a separated and spatially explicit analysis of the drought hazard and exposure of irrigated and rainfed agricultural systems as well as an empirically based weighting of vulnerability indicators based on the judgment of drought experts around the globe or in the respective countries. Past assessments often focused on a single aspect of drought risk (i.e. hazard/exposure or vulnerability), neglecting the interconnectedness of its components. Findings from this thesis underscore the relevance of analysing drought risk from a holistic perspective (i.e., including the sector-specific hazard, exposure and vulnerability) that is based on a spatially explicit approach. The findings also highlight the relevance of assessing and discussing drought risk in relation to specific impacts and diagnosing entry points to reduce drought risk in a context-specific manner (i.e. irrigated and rainfed systems). This ensures that relevant proactive policies and planning can be effective even within the same sector (i.e. agricultural sector) before the worst impacts occur. By providing information on high-risk areas and underlying drivers, this approach helps identify priority regions and entry points for targeted drought risk reduction and adaptation options.

While this first attempt provides valuable information at the global and national levels, improvements could be achieved with a temporal dynamic exposure, the availability of more spatially explicit vulnerability information (i.e., at subnational levels), and the availability of standardised drought impact information that can serve as a quantitative validation of risk levels. Further, the thesis has also shown that the effect of changing the selection of countries included in a drought risk assessment can have a significant impact on its results. This is particularly important when determining drought risk reduction and adaptation resourcing, as some countries that are at high risk of drought may be overshadowed in a global assessment. The results emphasise the importance of utilising context-specific drought risk assessments to inform decision-making in order to ensure that a country that experiences the negative impacts of drought is not "left behind".

In times when interconnectedness characterises growing drought risks, a shift is needed from crisis and hazard-oriented, sectoral perspectives, towards the development of equitable, prospective, risk-informed, multi-scale, multi-sectoral, and adaptive drought risk management policies, plans, and strategies that consider the whole spectrum of compounding and cascading effects. The proposed novel conceptual framework in this thesis offers a way forward to understand this complexity, and aims to inspire addressing growing drought risks through a systemic lens. To achieve the goals of the Sendai Framework and the SDGs, supra-national systemic efforts are needed to address the transboundary effects and globally networked risks linked to droughts. With a better understanding of the complex nature of drought across different sectors and scales, it is possible to identify entry points to enhance the resilience of people and ecosystems against drought.

8. References

ACLED. Armed Conflict Location & Event Data Project (ACLED) Codebook. (2017). Available online: https://www.acleddata.com (accessed on 21 January 2020).

AFRA (Association for Rural Advancement). (1993). Drought relief and rural communities. Special Rep. No. 9. Pietermaritzburg, South Africa

AghaKouchak, A., Mirchi, A., Madani, K., Di Baldassarre, G., Nazemi, A., Alborzi, A., et al. (2021). Anthropogenic drought: Definition, challenges, and opportunities. Res of Geophysics, 59(2), e2019RG000683. https://doi.org/10.1029/2019RG000683

AghaKouchak, A.; Farahmand, A.; Melton, F.S.; Teixeira, J.; Anderson, M.C.; Wardlow, M.C.; Hain, C.R. (2015). Remote sensing of drought: Progress, challenges and opportunities. Rev. Geophys 2015, 53, 452–480.

Ahmadalipour, A., Moradkhani, H., Castelletti, A., Magliocca, N. (2019). Future drought risk in Africa: Integrating vulnerability, climate change, and population growth. Science of the Total Environment, 662, 672–686. https://doi.org/10.1016/j.scitotenv.2019.01.278

Ahmadalipour, A.; Moradkhani, H. (2018). Multi-dimensional assessment of drought vulnerability in Africa: 1960–2100. Sci. Total. Environ., 644, 520–535.

Andreadis, K. M. and Lettenmaier, D. P. (2006). Trends in 20th century drought over the continental United States. Geophysical Research Letters, 33(10). doi: 10.1029/2006GL025711.

Asadieh, B., Krakauer, N.Y. (2017). Global change in streamflow extremes under climate change over the 21st century. Hydrol. Earth Syst. Sci. 21, 5863–5874. https://doi.org/10.5194/hess-21-5863-2017

Asare-Kyei, D., Renaud, F. G., Kloos, J., Walz, Y., & Rhyner, J. (2017). Development and validation of risk profiles of West African rural communities facing multiple natural hazards. PLOS ONE, 12(3), e0171921. https://doi.org/10.1371/journal.pone.0171921

Ayantunde, A. A., Turner, M. D. and Kalilou, A. (2015). Participatory analysis of vulnerability to drought in three agro-pastoral communities in the West African Sahel., Pastoralism. Pastoralism, 5(1). doi: 10.1186/s13570-015-0033-x.

Bachmair, S., Stahl, K., Collins, K., Hannaford, J., Acreman, M., Svoboda, M., et al. (2016). Drought indicators revisited: The need for a wider consideration of environment and society. WIREs Water, 3(4), 516–536. https://doi.org/10.1002/wat2.1154

Bacon, C. M. et al. (2017). Vulnerability to Cumulative Hazards: Coping with the Coffee Leaf Rust Outbreak, Drought, and Food Insecurity in Nicaragua., World Development. The Authors, 93, pp. 136–152. doi: 10.1016/j.worlddev.2016.12.025.

Barker, L.J., Rickards, N.J., Sarkar, S., Hannaford, J., King-Okumu, C., Rees, G., (2021). Good Practice Guidance for National Reporting on UNCCD Strategic Objective 3: To mitigate, adapt to, and manage the effects of drought in order to enhance resilience of vulnerable populations and ecosystems. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany.

Bartholomeus, R., Van der Wiel, K., Van Loon, A., Van Huijgevoort, M., Van Vliet, M., Mens, M., et al. (2023). Managing water across the flood–drought spectrum: Experiences from and challenges for the Netherlands. Cambridge Prisms: Water, 1, E2–E22. https://doi.org/10.1017/wat.2023.4

Baruth, B., Bassu, S., Ben Aoun, W., Biavetti, I., Bratu, M., Cerrani, I., et al. (2023). JRC MARS bulletin—Crop monitoring in Europe—May 2023 (Vol. 31) In M. Van Den Berg, S. Niemeyer, & B. Baruth (Eds.), Publications Office of the European Union. https://doi.org/10.2760/950817

Baruth, B., Bassu, S., Ben Aoun, W., Biavetti, I., Bratu, M., Cerrani, I., et al. (2022a). JRC MARS bulletin—Crop monitoring in Europe—July 2022 (Vol. 30). In M. Van Den Berg, & S. Niemeyer (Eds.), Publications Office of the European Union. https://doi.org/10.2760/577529

Baruth, B., Bassu, S., Ben Aoun, W., Biavetti, I., Bratu, M., Cerrani, I., et al. (2022b). JRC MARS bulletin—Crop monitoring in Europe—August 2022 (Vol. 30). In M. Van Den

Berg, & B. Baruth (Eds.), Publications Office of the European Union. https://doi.org/10.2760/31930
Batjes, N.H. (2016). Harmonized soil property values for broad-scale modelling (WISE30sec) with estimates of global soil carbon stocks. Geoderma 269, 61–68. https://doi.org/10.1016/j.geoderma.2016.01.034
Baudoin, M.-A., Vogel, C., Nortje, K., Naik, M. (2017). Living with drought in South Africa: lessons learnt from the recent El Niño drought period. International Journal of Disaster Risk Reduction 23, 128–137. https://doi.org/10.1016/j.ijdrr.2017.05.005
Beccari,B. (2016). A Comparative Analysis of Disaster Risk, Vulnerability and Resilience Composite Indicators PLoS Curr., 8, 10.1371/currents.dis.453df025e34b682e9737f95070f9b970
Beck, H.E., Zimmermann, N.E., McVicar, T.R., Vergopolan, N., Berg, A., Wood, E.F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. Scientific Data 5, 180214. https://doi.org/10.1038/sdata.2018.214
Belal, A.-A.; El-Ramady, H.R.; Mohamed, E.S.; Saleh, A.M. Drought risk assessment using remote sensing and GIS techniques. Arab. J. Geosci. 2014, 7, 35–53 doi: 10.1007/s12517-012-0707-2.
Belle, J.; Sithabile, M.; Ogundeji, A.A. Assessing communal farmers' preparedness to drought in the Umguza District, Zimbabwe. Int. J. Disaster Risk Reduct. 2017, 22, 194–203.
Bento, V.A.; Gouveia, C.M.; DaCamara, C.C.; Trigo, I.F. A climatological assessment of drought impact on vegetation health index. Agric. For. Meteorol. 2018, 259, 286–295.
Berg, A., & Sheffield, J. (2018). Climate Change and Drought: The Soil Moisture Perspective. Current Climate Change Reports, 4(2), 180–191. https://doi.org/10.1007/s40641-018-0095-0
Berkes, F., Colding, J., & Folke, C. (2000). REDISCOVERY OF TRADITIONAL ECOLOGICAL KNOWLEDGE AS ADAPTIVE MANAGEMENT. Ecological Applications, 10(5), 1251–1262. https://doi.org/10.1890/1051-0761(2000)010[1251:ROTEKA]2.0.CO;2
BFAP (Bureau for Food and Agricultural Policy) (2016). Policy brief on 2015/2016 drought. Available at http://www.nstf.org.za/wp-content/uploads/2016/06/Agri-SA-Drought-Report_CS4.pdf (accessed 23.11.2020)
Bhuiyan, C.; Saha, A.K.; Bandyopadhyay, N.; Kogan, F.N. Analyzing the impact of thermal stress on vegetation health and agricultural drought—A case study from Gujarat, India. GIScience Remote Sens. 2017, 54, 678–699.
Birhanu, Z. et al. (2017). Understanding resilience dimensions and adaptive strategies to the impact of recurrent droughts in Borana Zone, Oromia Region, Ethiopia: A grounded theory approach., International Journal of Environmental Research and Public Health, 14(2), pp. 1–18. doi: 10.3390/ijerph14020118.
Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., Kienberger, S., Keiler, M., Alexander, D., Zeil, P., & Welle, T. (2013). Framing vulnerability, risk and societal responses: The MOVE framework. Natural Hazards, 67(2), 193–211. https://doi.org/10.1007/s11069-013-0558-5
Birkmann, J., Cutter, S. L., Rothman, D. S., Welle, T., Garschagen, M., Van Ruijven, B., O'Neill, B., Preston, B. L., Kienberger, S., Cardona, O. D., Siagian, T., Hidayati, D., Setiadi, N., Binder, C. R., Hughes, B., & Pulwarty, R. (2015). Scenarios for vulnerability: Opportunities and constraints in the context of climate change and disaster risk. Climatic Change, 133(1), 53–68. https://doi.org/10.1007/s10584-013-0913-2
Bishop, T., Reinke, J., & Adams, T. (2011). Globalization: Trends and perspectives. Journal of International Business Research, 10, 117.
Blauhut V., Stahl K., Stagge J.H., Tallaksen L.M., De Stefano L., and Vogt J.V. (2016). Estimating drought risk across Europe from reported drought impacts, drought indices, and vulnerability factors. Hydrol. Earth Syst. Sci., 20, 2779–2800
Blauhut, V. (2020). The triple complexity of drought risk analysis and its visualisation via mapping: A review across scales and sectors. Earth-Science Reviews, 210, 103345. https://doi.org/10.1016/j.earscirev.2020.103345

Blauhut, V., Stoelzle, M., Ahopelto, L., Brunner, M. I., Teutschbein, C., Wendt, D. E., et al. (2022). Lessons from the 2018–2019 European droughts: A collective need for unifying drought risk management. Natural Hazards and Earth System Sciences, 22(6), 2201–2217. https://doi.org/10.5194/nhess-22-2201-2022

BMEL. (2022). Ernteberich 2022. Retrieved from https://www.bmel.de/SharedDocs/Downlo/DE/Broschueren/ernte-2022.pdf

Bonsal, B. R., Wheaton, E. E., Chipanshi, A. C., Lin, C., Sauchyn, D. J., & Wen, L. (2011). Drought Research in Canada: A Review. Atmosphere-Ocean, 49(4), 303–319. https://doi.org/10.1080/07055900.2011.555103

Boulle, D. (2022). Chaleur et sécheresse: une dérogation de rejets pour cinq centrales nucléaires jusqu'au 11 septembre prochain. France Bleu. Retrieved from https://www.francebleu.fr/infos/environnement/chaleur-et-secheresse-une-derogation-de-rejets-pour-cinq-centrales-nucleaires-jusqu-au-11-septembre-1659805848

Brazier, A. Climate Change in Zimbabwe. Facts for Planners and Decision Makers. 2015. Available online: https://www.kas.de/web/simbabwe/publikationen/einzeltitel/-/content/climate-change-in-zimbabwe (accessed on 21 January 2020).

Brown, D.; Rance Chatiz, R.; Dhliwayo, M.; Dodman, D.; Masiiwa, M.; Muchadenyika, D.; Prisca Mugabe, P.; Zvigadza, S. Climate Change Impacts, Vulnerability and Adaptation in Zimbabwe, IIED Climate Change Working Paper, No. 3; International

Bruwer J.J. (1993). Drought Policy in the Republic of South Africa. In: Wilhite D.A. (eds) Drought Assessment, Management, and Planning: Theory and Case Studies. Natural Resource Management and Policy, vol 2. Springer, Boston, MA. https://doi-10.1007/978-1-4615-3224-8_11

Bucheli, J., Dalhaus, T., & Finger, R. (2021). The optimal drought index for designing weather index insurance. European Review of Agricultural Economics, 48(3), 573–597. https://doi.org/10.1093/erae/jbaa014

Bühl, A. PASW 18. Einführung in Die Moderne Datenanalyse; [Ehemals SPSS. 12th ed. 2010. Munich, Germany: Pearson Studium (Pearson Studium—Scientific Tools)]. Available online: http://sub-hh.ciando.com/book/?bok_id=35429 (accessed on 21 January

Carlino, A., de Vita, A., Giuliani, M., Zamberletti, P., Capros, P., Recanati, F., et al. (2021). Hydroclimatic change challenges the EU planned transition to a carbon neutral electricity system. Environmental Research Letters, 16(10), 104011. https://doi.org/10.1088/1748-9326/ac243f

Carrão H., Naumann G., and Barbosa P. (2016). Mapping global patterns of drought risk: An empirical framework based on sub-national estimates of hazard, exposure and vulnerability. Global Environmental Change 39. https://doi.org/10.1016/j.gloenvcha.2016.04.012

Carrão, H., Naumann, G., and Barbosa, P. (2017). Global projections of drought hazard in a warming climate: a prime for disaster risk management, Clim. Dynam., 50, 2137–2155, https://doi.org/10.1007/s00382-017-3740-8.

Chagutah, T. Climate Change Vulnerability and Adaptation Preparedness in South Africa. (2010). Available online: https://za.boell.org/2014/02/03/climate-change-vulnerability-and-adaptation-preparedness-southern-africa (accessed on 21 January

Challinor, A. J., Adger, N., Benton, T. G., Conway, D., Joshi, M., & Frame, D. (2018). Transmission of climate risks across sectors and borders. Philosophical Transactions of the Royal Society A, 376(2121), 20170301. https://doi.org/10.1098/rsta.2017.0301

Chamaillé-Jammes, S.; Fritz, H.; Murindagomo, F. (2007). Detecting climate changes of concern in highly variable environments: Quantile regressions reveal that droughts worsen in Hwange National Park, Zimbabwe. J. Arid Environ, 71, 321–326.

Chambers, R. (1989). Vulnerability, coping and policy. IDS Bull., 37(2), p. 33. doi: 10.1111/j.1759-5436.1989.mp20002001.x.

Chatzopoulos, T., Pérez Domínguez, I., Toreti, A., Adenäuer, M., & Zampieri, M. (2021). Potential impacts of concurrent and recurrent climate extremes on the global food

system by 2030. Environmental Research Letters, 16(12), 124021. https://doi.org/10.1088/1748-9326/ac343b
Chatzopoulos, T., Pérez Domínguez, I., Zampieri, M., & Toreti, A. (2020). Climate extremes and agricultural commodity markets: A global economic analysis of regionally simulated events. Weather and Climate Extremes, 27, 100193. https://doi.org/10.1016/j.wace.2019.100193
Chen, C., Noble, I., Hellmann, J., Coffee, J., Murillo, M., Chawla, N., (2015). University of Notre Dame Global Adaptation Index Country Index Technical Report. [WWW Document]. URL https://gain.nd.edu/assets/254377/nd_gain_technical_document_2015.pdf (accessed 20.07.22).
Chen, J., Deng, M., Xia, L., & Wang, H. (2017). Risk Assessment of Drought, Based on IDM-VFS in the Nanpan River Basin, Yunnan Province, China. Sustainability, 9(7), 1124. https://doi.org/10.3390/su9071124
Chiang, F., Mazdiyasni, O., & AghaKouchak, A. (2021). Evidence of anthropogenic impacts on global drought frequency, duration, and intensity. Nature Communications, 12(1), 2754. https://doi.org/10.1038/s41467-021-22314-w
Chibba, M., Luiz, J.M. (2011). Poverty, Inequality and Unemployment in South Africa: Context, Issues and the Way Forward: POVERTY, INEQUALITY AND UNEMPLOYMENT IN SOUTH AFRICA. Economic Papers: A journal of applied economics and policy 30, 307–315. https://doi.org/10.1111/j.1759-3441.2011.00129.x
Chigwada, J. Case Study 6: Zimbabwe Climate Proofing Infrastructure and Diversifying Livelihoods in Zimbabwe. IDS Bull. 2005, 36, 103–116.
Connolly, K. (2022). Low water levels mean Rhine is days from being shut for cargo. The Guardian. Retrieved from https://www.theguardian.com/world/2022/aug/05/rhine-low-water-levels-shut-cargo
Cook, B. I., Mankin, J. S., Marvel, K., Williams, A. P., Smerdon, J. E., & Anchukaitis, K. J. (2020). Twenty-First Century Drought Projections in the CMIP6 Forcing Scenarios. *Earth's Future*, *8*(6). https://doi.org/10.1029/2019EF001461
Copernicus Climate Change Service. (2023). European state of climate. Retrieved from https://climate.copernicus.eu/esotc/2022
Corbett, J. J., Winebrake, J., Endresen, Ø., Eide, M., Dalsøren, S., Isaksen, I. S., & Sørgård, E. (2010). International maritime shipping: The impact of globalization on activity levels. In Globalization, transport and the environment (pp. 55–79). OECD. https://doi.org/10.1787/9789264072916-5-en
Cotti, D., Sabino Siemons, A.-S., Naumann, G., Wens, M., de Moel, H., Blauhut, V., et al. (2023). Conceptual models of drought risks for Europe: A step towards a systemic perspective on drought. In EGU General Assembly. https://doi.org/10.5194/egusphere-egu23-7991
Coughlan de Perez, E.; van den Hurk, B.; van Aalst, M.K.; Jongman, B.; Klose, T.; Suarez, P. Forecast-based financing: An approach for catalyzing humanitarian action based on extreme weather and climate forecasts. Nat. Hazards Earth Syst. Sci.
CRED & UNDRR. (2020). The Human Cost of Disasters: an overview of the last 20 years: 2000–2019. *CRED, UNDRR, Geneva*. Retrieved June 11, 2023, from https://reliefweb.int/sites/reliefweb.int/files/resources/Human%20Cost%20of%20Disasters%202000-2019%20Report%20-20UN%20Office%20for%20Disaster%20Risk%20Reduction.pdf
CRED and UNISDR. (2018). Economic losses, poverty & disasters: 1998–2017, available at: https://www.unisdr.org/files/61119_credeconomiclosses.pdf (last access: 13 May 2019).
CRED. (2022). Disasters in numbers 2021. Retrieved from https://www.cred.be/disasters-numbers-2021
Creitaru, I. Capacity Assessment of the Disaster Risk Management System in Zimbabwe. 2017. Available online: https://www.cadri.net/sites/default/files/Zimbabwe-Report-May-2017.pdf (accessed on 21 January 2020).

Crossman, D., (2019). Drought resilience, adaptation and management policy framework: supporting technical guidelines. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany.
Curt, C. (2021). Multirisk: What trends in recent works?—A bibliometric analysis. Science of the Total Environment, 763, 143951. https://doi.org/10.1016/j.scitotenv.2020.142951
DAFF. (2018). Abstract of agricultural statistics. South African Department of Agriculture, Forestry and Fisheries. Available at http://www.daff.gov.za/Daffweb3/Portals/0/Statistics%20and%20Economic%20Analysis/Statistical%20Information/Abstract%202018.pdf. (Accessed 10.07.2020).
DAFF. (2019). Abstract of agricultural statistics. South African Department of Agriculture, Forestry and Fisheries. Available at hhttps://www.dalrrd.gov.za/Portals/0/Statistics%20and%20Economic%20Analysis/Statistical%20Information/Abstract%202019.pdf (Accessed 05.01.2021).
Dai, A. (2011) Drought under global warming: a review, Wiley Interdisciplin. Rev.: Clim. Change, 2, 45–65, https://doi.org/10.1002/wcc.81.
Dai, A. (2013). Increasing drought under global warming in observations and models. Nature Climate Change, 3(1), 52.
DALRRD (Department of Agriculture, Land Reform and Rural Development). (2020). Agriculture, land reform and rural development | South African Government. Available at https://www.gov.za/about-sa/agriculture (Accessed 20.05.2021)
Damberg, L. and AghaKouchak, A. (2014). Global trends and patterns of drought from space, Theor. Appl. Climatol., 117, 441–448, https://doi.org/10.1002/wcc.81.
de Brito, M. M. (2021). Compound and cading drought impacts do not happen by chance: A proposal to quantify their relationships. Science of the Total Environment, 778, 146236. https://doi.org/10.1016/j.scitotenv.2021.146236
De Sherbinin, A., Apotsos, A., and Chevrier, J. (2017). Mapping the future: policy applications of climate vulnerability mapping in West Africa, Geogr. J., 183, 414–425, https://doi.org/10.1111/geoj.12226.
de Sherbinin, A., Bukvic, A., Rohat, G., Gall, M., McCusker, B., Preston, B., Apotsos, A., Fish, C., Kienberger, S., Muhonda, P., Wilhelmi, O., Macharia, D., Shubert, W., Sliuzas, R., Tomaszewski, B., Zhang, S. (2019). Climate vulnerability mapping: A systematic review and future prospects. WIREs Clim Change. https://doi.org/10.1002/wcc.600
De Stefano, L., Tánago, I. G., & Ballesteros, M. (2015). Methodological approach considering different factors influencing vulnerability–Pan-European scale. Technical Report No. 26.
Deng, M., Chen, J., Huang, J., & Niu, W. (2018). Agricultural Drought Risk Evaluation Based on an Optimized Comprehensive Index System. Sustainability, 10(10), 3465. https://doi.org/10.3390/su10103465
Department of Agriculture, Forestry and Fisheries (DAFF). (2016). LADA Degradation Index. https://doi.org/10.15493/DEA.CARBON.10000018
DESTATIS. (2022). Stromerzeugung im 3. Quartal 2022: 13,3% mehr Kohlestrom als im Vorjahreszeitraum. Retrieved from https://www.destatis.de/DE/Presse/Pressemitteilungen/2022/12/PD22_518_433.html
Deutsche Welthungerhilfe e.V. Global Hunger Index. (2019). Available online: https://www.globalhungerindex.org (accessed on21 January 2020).
Di Baldassarre, G., Wanders, N., AghaKouchak, A., Kuil, L., Rangecroft, S., Veldkamp, T. I. E., et al. (2018). Water shortages worsened by reservoir effects. Nature Sustainability, 1(11), 617–622. https://doi.org/10.1038/s41893-018-0159-0
Dilley, M., Chen, R.S., Deichmann, U., Lerner-Lam, A. L., Arnold, M., Agwe J., Buys, P., Kjekstad, O., Lyon, B., Yetman, G. (2005). Natural Disaster Hotspots: A Global Risk Analysis (Disaster risk management series ; no. 5). The World Bank Group.
Doshi, D. and Garschagen, M., (2020). Understanding adaptation finance allocation: Which factors enable or constrain vulnerable countries to access funding? Sustainability, 12 (2020), p. 4308, 10.3390/su12104308

Downing, T.E. & Bakker, K. (2000). Drought Discourse and Vulnerability. Chapter 45. In: Wilhite, D.A., Ed., Drought: A Global Assessment, Natural Hazards and Disasters Series, Routledge Publishers, Abingdon.
du Pisani, L.G., Fouché, H.J., Venter, J.C. (1998). Assessing rangeland drought in South Africa. Agricultural Systems 57, 367–380. https://doi.org/10.1016/S0308-521X(98)00024-9
Dutta, D., Kundu, A., Patel, N. R., Saha, S. K., & Siddiqui, A. R. (2015). Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). The Egyptian Journal of Remote Sensing and Space Science, 18(1), 53–63. https://doi.org/10.1016/j.ejrs.2015.03.006DWA. (2002). Governing Board Induction Manual. Department of Water Affairs.
DWA. (2002). Governing Board Induction Manual. Department of Water Affairs.
Ebi, K. L. and Bowen, K. (2016). Extreme events as sources of health vulnerability: Drought as an example., Weather and Climate Extremes. Elsevier, 11, pp. 95–102. doi: 10.1016/j.wace.2015.10.001.
Eckstein, D., Künzel, V., Schäfer, L., (2021). Global climate risk index 2021. Who suffers most from extreme weather events? Wether-Related Loss Events in 2019 and 2000 to 2019. Germanwatch Bonn, Germany.
El Kenawy, A. M., Al Buloshi, A., Al-Awadhi, T., Al Nasiri, N., Navarro-Serrano, F., Alhatrushi, S., Robaa, S. M., Domínguez-Castro, F., McCabe, M. F., Schuwerack, P.-M., López-Moreno, J. I., & Vicente-Serrano, S. M. (2020). Evidence for intensification of meteorological droughts in Oman over the past four decades. Atmospheric Research, 246, 105126. https://doi.org/10.1016/j.atmosres.2020.105126
Enders, C. K. (2003). Using the Expectation Maximization Algorithm to Estimate Coefficient Alpha for Scales With Item-Level Missing Data, Psychol Meth., 8, 322–337, https://doi.org/10.1037/1082989X.8.3.322.
Ente Nazionale Risi. (2022). Il Risicoltore LXV n.10.
European Commission. (2022a). Directorate-general for communication. In REPowerEU actions. Publications Office of the European Union. Retrieved from https://data.europa.eu/doi/10.2775/09107
European Commission. (2022b). Directorate-general for energy. Quarterly report on European electricity markets, Market Observatory for Energy DG Energy, 15(3). Retrieved from https://energy.ec.europa.eu/system/files/2023-01/Quarterly%20Report%20on%20European%20Electricity%20markets%20Q3%202022.pdf
European Commission. Joint Research Centre. (2017). Index for risk management - INFORM: concept and methodology, version 2017. Publications Office, LU. Available at https://drmkc.jrc.ec.europa.eu/inform-index. Accessed 18.02.2020
European Commission. Joint Research Centre. (2019). Drought vulnerability indicators for global-scale drought risk assessments: global expert survey results report. Publications Office, LU. Available at https://publications.jrc.ec.europa.eu/repository/handle/JRC117546. Accessed 15.03.2020
FAO AQUASTAT. (2014). Main Database: Total renewable water resources per capita, available at: http://www.fao.org/nr/water/aquastat/ data/query/index.html?lang=en (last access: 16 April 2019).
FAO. (1997). The political economy of food, agriculture and irrigation development in East and Southern Africa [WWW Document], n.d. URL http://www.fao.org/3/w7314e/w7314e09.htm (accessed 1.26.21).
FAO. (2006). Fertilizer Use by Crop in Zimbabwe; FAO: Rome, Italy, 2006.
FAO. (2016). [dataset] Statistical Database: Agriculture, forestry, and fishing, value added (% of GDP) [WWW Document]. URL http://www.fao.org/faostat/en/#data/MK (accessed 5.8.21).

FAO. (2016). AQUASTAT Country Profile –South Africa. Food and Agriculture Organization of the United Nations (FAO). Rome, Italy
FAO. (2018). [dataset] FAOSTAT Statistical Database: GDP per capita ($US) [WWW Document]. URL http://www.fao.org/faostat/en/#data/MK (accessed 5.8.21).
FAO. (2019). GIEWS Update. Southern AfricaDry weather conditions reduce agricultural production prospects in 2019. Available at https://reliefweb.int/sites/reliefweb.int/files/resources/ca3071en_0.pdf (accessed 07.10.2020)
FAO. (2020). FAOSTAT crops dataset. Available at http://www.fao.org/faostat/en/#data/QC (Accessed 05.02.2021)
FAO. (2020a). Country profile, South Africa http://www.fao.org/3/x9751e/x9751e07.htm (accessed 1.8.2020).
FAO. (2020b). Digital Agriculture Profile South Africa, http://www.fao.org/3/cb2506en/CB2506EN.pdf (accessed 1.2.2021).
FAO. (2021). FAOSTAT crops dataset. Available at http://www.fao.org/faostat/en/#data/QC (Accessed 05.02.2021)
FAO. (2021). The impact of disasters and crises on agriculture and food security: 2021. https://doi.org/10.4060/cb3673en
FAO. (2022). World Food and Agriculture – Statistical Yearbook 2022. Rome. https://doi.org/10.4060/cc2211en
FAO: (2018). The impact of disasters and crises on agriculture and food security, available at: http://www.fao.org/3/I8656EN/i8656en.pdf (last access: 1 July 2019).
FAO: FAOSTAT Statistical Database. (1991a). Average land degradation in GLASOD erosion degree, available at: http://www.fao.org/ faostat/en/#data/ES (last access: 25 March 2019).
FAO: FAOSTAT Statistical Database. (1991b). Average soil erosion, available at: http://www.fao.org/faostat/en/#data/ES (last access: 25 March 2019).
FAO: FAOSTAT Statistical Database. (2016a). Agriculture, forestry, and fishing, value added (% of GDP), available at: http://www.fao. org/faostat/en/#data/MK (last access: 15 May 2019).
FAO: FAOSTAT Statistical Database. (2016b). Pesticides and insecticides (total), available at: http://www.fao.org/faostat/en/#data/RP (last access: 12 April 2019).
FAO: Main Database. (2017). Total dam storage capacity per capita, available at: http://www.fao.org/nr/water/aquastat/data/query/index. html?lang=en (last access: 16 April 2019).
Federal Institute of Hydrology (BfG). (2022). Niedrigwasser-Berichtsperiode 15.-21.07.2022. Hitze und Niederschlagsarmut verstärken das Niedrigwasser. Retrieved from https://www.bafg.de/DE/07_Nachrichten/220623_nw_download5.pdf?__blob=publicationFile
Feizizadeh, B. and Kienberger, S. (2017). Spatially explicit sensitivity and uncertainty analysis for multicriteria-based vulnerability assessment., Journal of Environmental Planning and Management. Routledge, 60(11), pp. 2013–2035. doi: 10.1080/09640568.2016.1269643.
Fekete, A. (2009). Validation of a social vulnerability index in context to river-floods in Germany. Natural Hazards and Earth System Science, 9(2), pp. 393–403. doi: 10.5194/nhess-9-393-2009.
Felton, A. (2018). Drought matters: A social-ecological perspective – natural resource ecology laboratory at Colorado state university. Colostate.edu. Retrieved June 11, 2023, from https://www.nrel.colostate.edu/drought-matters-a-social-ecological-perspective/
Field, A. (2013). Discovering statistics using IBM SPSS statistics, 4th Edn., Sage, London.
Flintan, F. E. (2020). Restoration of degraded land for food security and poverty reduction in East Africa and the Sahel. Summary of 2nd Webinar in the Land Tenure and Governance Webinar series, 13 October 2020.

Freire-González, J., Decker, C., and Hall, J. W. (2017). The Economic Impacts of Droughts: A Framework for Analysis, Ecol. Econ., 132, 196–204, https://doi.org/10.1016/j.ecolecon.2016.11.005.
Frenken, K. (2005). Irrigation in Africa in figures, AQUASTAT Survey – 2005, FAO Water Reports 29, FAO, Rome, Italy, available at: http://www.fao.org/3/A0232E/a0232e.pdf (last access: 14 June 2019).
Frischen, J., Meza, I., Rupp, D., Wietler, K., & Hagenlocher, M. (2020). Drought Risk to Agricultural Systems in Zimbabwe: A Spatial Analysis of Hazard, Exposure, and Vulnerability. Sustainability, 12(3), 752. https://doi.org/10.3390/su12030752
GAR. (2015). Global Assessment Report on Disaster Risk Reduction. UNDRR. Available online: https://www.preventionweb.net/english/hyogo/gar/2015/en/home/index.html (accessed on 21 January 2020).
Garreaud, R. D., Boiser, J. P., Rondanelli, R., Montecinos, A., Sepúlveda, H., & Veloso-Aguila, D. (2019). The Central Chile mega drought (2010-2018): A climate dynamics perspective. International Journal of Climatology, 40(1), 421–439. https://doi.org/10.1002/joc.6219
Garschagen, M. and Doshi, D.(2022). Does funds-based adaptation finance reach the most vulnerable countries? Glob. Environ. Chang., 73 (2022), pp. 1-10, 10.1016/j.gloenvcha.2021.102450
Garschagen, M. and Kraas, F. (2010). Assessing Future Resilience to Natural Hazards – The Challenge of Capturing Dynamic Changes under Conditions of Transformation and Climate Change., in Custer, R., Sutter, C. & Ammann, W. (ed.) Proceedings. International Disaster and Risk Conference, IDRC 2010. Davos, pp. 209–213.
Garschagen, M., Hagenlocher, M., Comes, M., Dubbert, M., Sabelfeld, R., Lee, Y. J., Grunewald, L., Lanzendörfer, M., Mucke, P., Neuschäfer, O., Pott, S., Post, J., Schramm, S., Schumann-Bölsche, D., Vandemeulebroecke, B., Welle, T., and Birkmann, J. (2016). World Risk Report 2016, Bündnis Entwicklung Hilft and UNU-EHS, ISBN 9783946785026.
Gaupp, F.,. Hall, J., Mitchell, D., Dadson, S. (2019). Increasing risks of multiple breadbasket failure under 1.5 and 2 °C global warming Agric. Syst., 175 (2019), pp. 34-45, 10.1016/j.agsy.2019.05.010
GBD: Compare, Institute for Health Metrics and Evaluation (IHME). (2016). DALYs (Disability-Adjusted Life Years) – All causes – Sex: Both – Age: Age-standardized (Rate) (DALYs per 100 000), available at: http://vizhub.healthdata.org/ gbd-compare (last access: 28 April 2019).
GEF. (2021). Special Climate Change Fund - SCCF [WWW Document]. URL https://www.thegef.org/topics/special-climate-change-fund-sccf (accessed 6.10.21).
Geng, G., Wu, J., Wang, Q., Lei, T., He, B., Li, X., Mo, X., Luo, H., Zhou, H., and Liu, D. (2016). Agricultural drought hazard analysis during 1980–2008: A global perspective, Int. J. Climatol., 36, 389–399, https://doi.org/10.1002/joc.4356.
Ghaleb, F.; Mario, M.; Sandra, A. Regional Landsat-Based Drought Monitoring from 1982 to 2014. Climate 2015, 3, 563–577.
Gibberd, V., Rook, J., Sear, C. B., Williams, J. B. (1996). Drought risk management in southern Africa. The potential of long lead climate forecasts for improved drought management.
Global Dams Database (2020). GraND Data Catalog [WWW Document], n.d. URL https://datacatalog.worldbank.org/dataset/global-dams-database (accessed 3.12.20).
Global FINDEX, World Bank: Saved any money in the past year (% age 15+), available at: https://globalfindex.worldbank.org/ (last access: 28 April 2019), 2014–2017.
González Tánago, I., Urquijo, J., Blauhut, V., Villarroya, F., & De Stefano, L. (2016). Learning from experience: A systematic review of assessments of vulnerability to drought. Natural Hazards, 80(2), 951–973. https://doi.org/10.1007/s11069-015-2006-1
Goodwin, D., Holman, I., Pardthaisong, L., Visessri, S., Ekkawatpanit, C., & Rey Vicario, D. (2022). What is the evidence linking financial assistance for drought-affected agriculture and resilience in tropical Asia? A systematic re. Regional Environmental Change, 22(1), 1–13. https://doi.org/10.1007/s10113-021-01867-y

Government of South Africa. (2020). Drought relief project bearing fruit in Free State. Reliefweb. https://reliefweb.int/report/south-africa/drought-relief-project-bearing-fruit-free-state
Government of Zimbabwe (2012). Zimbabwe National Contingency Plan. December 2012–November 2013. Available online: https://www.ifrc.org/docs/IDRL/Zimbabwe%20National%20Contigency%20Plan%202012-2013.pdf (accessed on 21 January 2020).
Government of Zimbabwe (2015). Department of Civil Protection. Available online: https://www.drmzim.org/about/ (accessed on 21 January 2020).
Government of Zimbabwe (2015a). Zimbabwe's National Climate Change Response Strategy. Available online: https://www.preventionweb.net/english/professional/policies/v.php?id=59667 (accessed on 21 January 2020).
Graw, V.; Ghazaryan, G.; Dall, K.; Delgado Gómez, A.; Abdel-Hamid, A.; Jordaan, A.; Piroska, R.; Post, J.; Szarzynski, J.; Walz, Y.; et al. Drought Dynamics and Vegetation Productivity in Different Land Management Systems of Eastern Cape,
Guha-Sapir, D. & Below, R. & Hoyois, Ph. (2023). EM-DAT: The CRED/OFDA International Disaster Database. www.emdat.be. Université Catholique de Louvain – Brussels – Belgium.
Güneralp, B., Güneralp, I., and Liu, Y. (2015). Changing global patterns of urban exposure to flood and drought hazards, Global Environ. Change, 31, 217–225, https://doi.org/10.1016/j.gloenvcha.2015.01.002.
Hagenlocher M., Meza I., Anderson C., Min A., Renaud F.G., Walz Y., Siebert S., Sebesvari Z. (2019). Drought vulnerability and risk assessments: state of the art, persistent gaps, and research agenda. In: Environmental Research Letters.
Hagenlocher, M. and Castro, M. C. (2015). Mapping malaria risk and vulnerability in the United Republic of Tanzania: A spatial explicit model, Population Health Metrics, 13(1), pp. 1–14. doi: 10.1186/s12963-015-0036-2.
Hagenlocher, M., Delmelle, E., Casas, I., and Kienberger, S. (2013). Assessing socioeconomic vulnerability to dengue fever in Cali, Colombia: Statistical vs expert-based modeling, Int. J. Health Geogr., 12, 36, https://doi.org/10.1186/1476-072X-12-36.
Hagenlocher, M., Meza, I., Anderson, C. C., Min, A., Renaud, F. G., Walz, Y., Siebert, S., & Sebesvari, Z. (2019). Drought vulnerability and risk assessments: State of the art, persistent gaps, and research agenda. Environmental Research Letters, 14(8), 083002. https://doi.org/10.1088/1748-9326/ab225d
Hagenlocher, M., Meza, I., Anderson, C. C., Min, A., Renaud, F. G., Walz, Y., et al. (2019). Drought vulnerability and risk assessments: State of the art, persistent gaps, and research agenda. Environmental Research Letters, 14(8), 083002. https://doi.org/10.1088/1748-9326/ab225d
Hagenlocher, M., Naumann, G., Meza, I., Blauhut, V., Cotti, D., Döll, P., Ehlert, K., Gaupp, F., Van Loon, A. F., Marengo, J. A., Rossi, L., Sabino Siemons, A. S., Siebert, S., Tsehayu, A. T., Toreti, A., Tsegai, D., Vera, C., Vogt, J., & Wens, M. (2023). Tackling Growing Drought Risks—The Need for a Systemic Perspective. Earth's Future, 11(9), e2023EF003857. https://doi.org/10.1029/2023EF003857
Hagenlocher, M., Renaud, F. G., Haas, S., and Sebesvari, Z. (2018). Vulnerability and risk of deltaic social-ecological systems exposed to multiple hazards, Sci. Total Environ., 631–632, 71–80 https://doi.org/10.1016/j.scitotenv.2018.03.013.
Hagenlocher, M., Schneiderbauer, S., et al. (2018). Climate Risk Assessment for Ecosystem-based Adaptation A guidebook for planners and practitioners. 53, p. 63. Available at: www.giz.de;
Hagenlocher, M.; Comes, M.; Dubbert, M.; Sabelfeld, R.; Lee, Y.J.; Grunewald, L.; Lanzendörfer, M.; Mucke, P.; Neuschäfer, O.; Pott, S.; et al. (2016). World Risk Report 2016; Bündnis Entwicklung Hilft and UNU-EHS: Berlin, Germany.

Hagenlocher, M.; Renaud, F.G.; Haas, S.; Sebesvari, Z. (2018). Vulnerability and risk of deltaic social-ecological systems exposed to multiple hazards. Sci. Total. Environ, 631, 71–80.
Han, L., Zhang, Q., Ma, P., Jia, J., & Wang, J. (2016). The spatial distribution characteristics of a comprehensive drought risk index in southwestern China and underlying causes. Theoretical and Applied Climatology, 124(3–4), 517–528. https://doi.org/10.1007/s00704-015-1432-z
Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S.V.; Goetz, S.J.; Loveland, T.R.; et al. High-resolution global maps of 21st-century forest cover change. Science (New York, NY.) 201
Hao, Z. and Singh, V. P. (2015). Drought characterization from a multivariate perspective: A review. Journal of Hydrology, 527, pp. 668–678. doi: 10.1016/j.jhydrol.2015.05.031.
Hao, Z., AghaKouchak, A., Nakhjiri, N., and Farahmand, A. (2014). Global integrated drought monitoring and prediction system, Scient. Data, 1, 1–10, https://doi.org/10.1038/sdata.2014.1.
Hardy, M., Dziba, L., Kilian, W., Tolmay, J. (2011). Rainfed Farming Systems in South Africa, in: Tow, P., Cooper, I., Partridge, I., Birch, C. (Eds.), Rainfed Farming Systems. Springer Netherlands, Dordrecht, pp. 395–432. https://doi.org/10.1007/978-1-4020-9132-2_16
Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset, Int. J. Climatol., 34, 623–642, https://doi.org/10.1002/joc.3711.
Hassan R. (2013). Drought Management Strategies in South Africa and the Potential for Economic Policy Instruments. In: Schwabe K., Albiac J., Connor J., Hassan R., Meza González L. (eds) Drought in Arid and Semi-Arid Regions. Springer, Dordrecht. https://doi.org/10.1007/978-94-007-6636-5_21
Heim Jr. (2002). A Review of Twentieth Century Drought Indices Used in the United States. Bulletin of the American Meteorological Society, 83(8), 1149-1165.
Hengl, T., Heuvelink, G.B.M., Kempen, B., Leenaars, J.G.B., Walsh, M.G., Shepherd, K.D., Sila, A., MacMillan, R.A., Mendes de Jesus, J., Tamene, L., Tondoh, J.E. (2015). Mapping Soil Properties of Africa at 250 m Resolution: Random Forests Significantly Improve Current Predictions. PLoS ONE 10, e0125814. https://doi.org/10.1371/journal.pone.0125814
Herbert, C., & Döll, P. (2023). Analyzing the informative value of alternative hazard indicators for monitoring drought hazard for human water supply and river ecosystems at the global scale. Natural Hazards and Earth System Sciences, 23(6), 2111–2131. https://doi.org/10.5194/nhess-2022-174
Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., Thépaut, J. (2020). The ERA5 global reanalysis. Q.J.R. Meteorol. Soc. 146, 1999–2049. https://doi.org/10.1002/qj.3803
Hinkel, J. (2011). Indicators of vulnerability and adaptive capacity: Towards a clarification of the science-policy interface, Global Environ. Change, 21, 198–208, https://doi.org/10.1016/j.gloenvcha.2010.08.002.
Hinkle, D. E., Wiersma, W., and Jurs, S. G. (2003). Applied statistics for the behavioral sciences, 5th Edn., Houghton Mifflin College Division.
Hirabayashi, Y., Roobavannan, M., Sujan, K., Lisako, K., Dai, Y., Satoshi, W., Hyungjun, K., and Shinjiro, K. (2013). Global flood risk under climate change, Nat. Clim. Change, 3, 816–821, https://doi.org/10.1038/nclimate1911.
Hochrainer-Stigler, S., Trogrlić, R. S., Reiter, K., Ward, P. J., de Ruiter, M. C., Duncan, M. J., et al. (2023). Towards a framework for systemic multi-hazard and multi-risk

assessment and management. Iscience, 26(5), 106736. https://doi.org/10.1016/j.isci.2023.106736
Hofmann, M. E., Hinkel, J. and Wrobel, M. (2011). Classifying knowledge on climate change impacts, adaptation, and vulnerability in Europe for informing adaptation research and decision-making: A conceptual meta-analysis. Global Environmental Change, 21(3), pp. 1106–1116. doi: 10.1016/j.gloenvcha.2011.03.011.
Hohenthal, J.; Minoia, P. Social aspects of water scarcity and drought. In Handbook of Drought and Water Scarcity: Principle of Drought and Water Scarcity; Eslamian, S., Eslamian, F.A., Eds.; CRC Tailor & Francis LTD Press: Abingdon, UK, 2
Holden, P. B., Rebelo, A. J., Wolski, P., Odoulami, R. C., Lawal, K. A., Kimutai, J., Nkemelang, T., & New, M. G. (2022). Nature-based solutions in mountain catchments reduce impact of anthropogenic climate change on drought streamflow. *Communications Earth & Environment*, *3*(1), 51. https://doi.org/10.1038/s43247-022-00379-9
Höllermann, B., & Evers, M. (2020). Identifying the sensitivity of complex human-water systems using a qualitative systems approach. Frontiers in Water, 2, 25. https://doi.org/10.3389/frwa.2020.00025
Holzkamper, A., Fossati, D., Hiltbrunner, J., and Fuhrer, J. (2015). Spatial and temporal trends in agro-climatic limitations to production potentials for grain maize and winter wheat in Switzerland, Reg. Environ. Change, 15, 109–122, https://doi.org/10.1007/s10113-014-0627-7.
Hornby D., Vanderhaeghen Y., Versveld D., Ngubane M. (2016). A harvest of dysfunction – rethinking the approach to drought, its causes and impacts in South Africa. Oxfam Report, Johannesburg. https://www.oxfam.org.za/wp-content/uploads/2017/03/Final-Final-OZA-Oxfam-Drought-Report.pdf (accessed 15.06.20)
Huang, L., He, B., Han, L., Liu, J., Wang, H., Chen, Z. (2017). A global examination of the response of ecosystem water-use efficiency to drought based on MODIS data. Science of The Total Environment 601–602, 1097–1107. https://doi.org/10.1016/j.scitotenv.2017.05.084
Huang, L., Yang, P. and Ren, S. (2014). IFIP AICT 419 - The Vulnerability Assessment Method for Beijing Agricultural Drought., pp. 269–280.
Huggins, X., Gleeson, T., Kummu, M., Zipper, S. C., Wada, Y., Troy, T. J., & Famiglietti, J. S. (2022). Hotspots for social and ecological impacts from freshwater stress and storage loss. Nature Communications, 13(1), 439. https://doi.org/10.1038/s41467-022-28029-w
Humanitarian OpenStreetMap Team T1. 2019. Available online: https://www.hotosm.org/tools-and-data (accessed on 21 January 2020).
IEC (International Electrotechnical Commission) Technical Committee 56, International Organization for Septuagint and Cognate Studies, Congress. (2019). Risk management: risk assessment techniques = Management du risque -Techniques d'appreciation du risque.
INFORM: INFORM report. (2019). Shared evidence for managing crises and disasters, available at: http://www.inform-index.org, last access: 1 July 2019.
InsuResilience Global Partnership, (2021). About – InsuResilience [WWW Document]. URL https://www.insuresilience.org/about/ (accessed 3.21.21).
Insuresilience Solutions Fund, (2022). Call for Proposals – Insuresilience Solutions Fund [WWW Document]. URL https://www.insuresilience-solutions-fund.org/call-for-proposals (accessed 7.18.22).
IPCC. (2001) Climate change 2001 : Impacts, Adaptation, and Vulnerability, Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. doi: 10.1002/joc.775.
IPCC. (2007) Climate Change 2007: impacts, adaptation and vulnerability: contribution of Working Group II to the fourth assessment report of the Intergovernmental Panel, Genebra, Suíça. doi: 10.1256/004316502320517344.
IPCC. (2012) Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the

Intergovernmental Panel on Climate Change. Edited by Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor and P. M. M. (eds.). Cambridge, UK and New York, USA: Cambridge University Press.

IPCC. (2013) Climate Change 2013: The Physical Science Basis. Contribution of Working Group 1 to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Edited by D. et al. (eds. Stocker. Cambridge, New York: Cambridge University Press.

IPCC. (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. (V. R. Barros, C. B. Field, D. J. Dokken, M. D. Mastrandrea, K. J. Mach, T. E. Bilir, … L. L. White, Eds.). New York - Cambridge: Cambridge University Press

IPCC. (2014a). Climate Change Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Core Writing Team, Pachauri, R. K., and Meyer, L. A., IPCC, Geneva, Switzerland, 151 pp., 2014.

IPCC. (2019). IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse gas fluxes in Terrestrial Ecosystems. Summary for Policymakers Approved Draft. Available online

IPCC. (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, 3056 pp.

IPCC Climate Change 2014: Impacts, Adaptation, and Vulnerability. In Part A: Global and Sectoral Aspects.Contribution of Working Group II to the Fifth Assessment Report of the intergovernmental Panel on Climate Change; Field, C.B., Barros,

IPCC. (2021). Summary for policymakers. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, et al. (Eds.), Climate change 2021: The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change (pp. 3–32). Cambridge University Press.

Javanmard, S., Emamhadi, M., BodaghJamali, J., and Didehvarasl, A. (2017). Spatial-Temporal Analysis of Drought in Iran Using SPI During a Long-Term Period, Earth Sci., 6, 15–29, https://doi.org/10.11648/j.earth.20170602.12.

Jenks, G.F and Caspall, F. G. (1971). Error on choropleth maps: definition, measurement, reduction Ann. Assoc. Am. Geogr., 61, pp. 217-244, 10.1111/j.1467-8306.1971.tb00779.

Jiri, O.; Mtali-Chafadza, L.; Mafongoya, P.L. Influence of smallholder farmers' perceptions on adaptation strategies to climate change and policy implications in Zimbabwe. Chang. Adapt. Socio Ecol. Syst. 2017, 3, 47–55.

Jombo, S.; Adam, E.; Odindi, J. Quantification of landscape transformation due to the Fast Track Land Reform Programme (FTLRP) in Zimbabwe using remotely sensed data. Land Use Policy 2017, 68, 287–294.

Jordaan A.J. (2011). Drought Risk Reduction in the Northern Cape. (PhD) Thesis, University of the Free State, Bloemfontein.

Jordaan, A., Sakulski, D., Jordaan, A., (2013). Interdisciplinary drought risk assessment for agriculture: the case of communal farmers in the Northern Cape Province, South Africa. South African Journal of Agricultural Extension. 41. 01-16.

Jordaan, A.; Bahta, Y.T.; Phatudi-Mphahlele, B. (2019). Ecological vulnerability indicators to drought: Case of communal farmers in Eastern Cape, South Africa. Jamba (Potchefstroom, South Africa), 11, 1–11.

Jordaan, A.J., Sakulski, D.M., Muyambo, F. (2017a). South Africa, Water Research Commission, South Africa, Department of Agriculture, F., and Fisheries. Vulnerability, adaptation to and coping with drought: the case of commercial and subsistence rain fed farming in the Eastern Cape. Volume I : report to the Water Research Commission and Department of Agriculture, Forestry and Fisheries Volume I : report to the Water Research Commission and Department of Agriculture, Forestry and Fisheries. Available at http://www.wrc.org.za/Knowledge%20Hub%20Documents/Research%20Reports/TT%20716-17.pdf. Accessed 5 September, 2020.

JRC (Joint Research Centre. European Commission). Institute for the Protection and the Security of the Citizen. (2014). Current status and best practices for disaster loss data recording in EU Member States. Publications Office, LU.

JRC ESDAC, (2019). [dataset] Global Soil Erosion Modelling platform [WWW Document]. URL https://esdac.jrc.ec.europa.eu/content/global-soil-erosion (accessed 5.8.21).

JRC. (2015). Global accessibility map: Travel time to major cities: A global map of Accessibility, available at: https://forobs.jrc.ec.europa.eu/ products/gam/ (last access: 10 April 2019).

JRC. COIN (Competence Centre on Composite Indicators and Scoreboards). (2019). Available online: https://composite-indicators.jrc.ec.europa.eu/?q=10-step-guide/step-4-multivariate-analysis (accessed on 21 January 2020).

Jurgilevich, A. et al. (2017). A systematic review of dynamics in climate risk and vulnerability assessments. Environmental Research Letters, 12(1), p. 13002. Available at: http://stacks.iop.org/1748-9326/12/i=1/a=013002.

Kamali, B., Abbaspour, K.C., Wehrli, B., Yang, H. (2018). Drought vulnerability assessment of maize in Sub-Saharan Africa: Insights from physical and social perspectives. Global and Planetary Change 162, 266–274. https://doi.org/10.1016/j.gloplacha.2018.01.011

Kamruzzaman, Md., Kabir, Md. E., Rahman, A. T. M. S., Jahan, C. S., Mazumder, Q. H., & Rahman, M. S. (2018). Modeling of agricultural drought risk pattern using Markov chain and GIS in the western part of Bangladesh. Environment, Development and Sustainability, 20(2), 569–588. https://doi.org/10.1007/s10668-016-9898-0

Kim, H., Park, J., Yoo, J., & Kim, T. (2015). Assessment of drought hazard, vulnerability, and risk: A case study for administrative districts in South Korea. Journal of Hydro-environment Research, 9(1), 28–35. https://doi.org/10.1016/j.jher.2013.07.003

King-Okumu, C., Tsegai, D., Pandey, R. P., & Rees, G. (2020). Less to Lose? Drought Impact and Vulnerability Assessment in Disadvantaged Regions. Water, 12(4), 1136. https://doi.org/10.3390/w12041136

King-Okumu, C., Tsegai, D. W., Sanogo, D., Kiprop, J., Cheboiwo, J., Sarr, M. S., Cunha, M., & Salman, M. (2021). How can we stop the slow-burning systemic fuse of loss and damage due to land degradation and drought in Africa? Current Opinion in Environmental Sustainability, 50, 289–302. https://doi.org/10.1016/j.cosust.2021.04.008

Kinsey, B.; Burger, K.; Gunning, J.W. Coping with drought in Zimbabwe: Survey evidence on responses of rural households to risk. World Dev. 1998, 26, 89–110.

Kloos J. and Renaud F. G. (2016). Overview of ecosystem-based approaches to drought risk reduction targeting small-scale farmers in Sub-Saharan Africa Ecosystem-Based Disaster Risk Reduction and Adaptation in Practice ed F G Renaud et al (Cham: Springer International Publishing) pp 199–226. https://doi.org/10.1007/978-3-319-43633-3_9.

Kogan, F.N. (1995). Application of vegetation index and brightness temperature for drought detection. Adv. Space Res. 15, 91–100.

Kogan, F.N. (1997). Global Drought Watch from Space. Bull. Amer. Meteor. Soc. 78, 621–636.

Kogan, F.N. (2001). Operational Space Technology for Global Vegetation Assessment. Bull. Amer. Meteor. Soc, 82, 1949–1964.

Kogan, F.N. (2002). World droughts in the new millennium from AVHRR-based vegetation health indices. Eos. Trans. AGU, 83, 557.

Koks, E. E., Rozenberg, J., Zorn, C., Tariverdi, M., Vousdoukas, M., Fraser, S. A., Hall, J. W., and Hallegatte, S. (2019). A global multihazard risk analysis of road and railway infrastructure assets, Nat. Commun., 10, 1–11, https://doi.org/10.1038/s41467-019-10442-3.

Kreibich, H., Van Loon, A. F., Schröter, K., Ward, P. J., Mazzoleni, M., Sairam, N., Abeshu, G. W., Agafonova, S., AghaKouchak, A., Aksoy, H., Alvarez-Garreton, C., Aznar, B., Balkhi, L., Barendrecht, M. H., Biancamaria, S., Bos-Burgering, L., Bradley, C., Budiyono, Y., Buytaert, W., … Di Baldassarre, G. (2022). The challenge of unprecedented floods and droughts in risk management. *Nature*, *608*(7921), 80–86. https://doi.org/10.1038/s41586-022-04917-5

Laganda, G. Forecast-Based Financing. Moving From Crisis Response to Risk Management. 2018. Available online: https://docs.wfp.org/api/documents/WFP-0000069094/download/ (accessed on 21 January 2020).

Landmann, T.; Eidmann, D.; Cornish, N.; Franke, J.; Siebert, S. Optimizing harmonics from Landsat time series data: The case of mapping rainfed and irrigated agriculture in Zimbabwe. Remote Sens. Lett. 2019, 10, 1038–1046.

Le Maitre, DC., Seyler, H., Holland, M., Smith-Adao, L., Nel, JL., Maherry, A., Witthüser, K. (2018). Identification, Delineation and Importance of the Strategic Water Source Areas of South Africa, Lesotho and Swaziland for Surface Water and Groundwater, Report No. TT 743/1/18, Pretoria: Water Research Commission

Lehner, B., Liermann, C.R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P., Endejan, M., Frenken, K., Magome, J., Nilsson, C., Robertson, J.C., Rödel, R., Sindorf, N., Wisser, D. (2011). High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. Frontiers in Ecology and the Environment 9, 494–502. https://doi.org/10.1890/100125

Leichenko, R.M.; O'Brien, K.L. The dynamics of rural vulnerability to global change: The case of southern Africa. Mitig. Adapt. Strateg. Glob. Chang. 2002, 7, 1–18.

Li, B. and Zhou, G. (2014). Advance in the study on drought index., Shengtai Xuebao/ Acta Ecologica Sinica, 34(5), pp. 1043–1052. doi: 10.5846/stxb201210201457.

Li, Y., Ye, W., Wang, M., and Yan, X. (2009). Climate change and drought: A risk assessment of crop-yield impacts, Clim. Res., 39, 31–46, https://doi.org/10.3354/cr00797.

Lin, F., Li, X., Jia, N., Feng, F., Huang, H., Huang, J., et al. (2023). The impact of Russia-Ukraine conflict on global food security. Global Food Security, 36, 100661. https://doi.org/10.1016/j.gfs.2022.100661

Lucas, A. (2021). Risking the earth Part 1: Reassessing dangerous anthropogenic interference and climate risk in IPCC processes Clim. Risk Manag., 31, Article 100257, 10.1016/j.crm.2020.100257

Lunduka, R.W.; Mateva, K.I.; Magorokosho, C.; Manjeru, P. Impact of adoption of drought-tolerant maize varieties on total maize production in south Eastern Zimbabwe. Clim. Dev. 2019, 11, 35–46.

Lunt, T., Jones, A. W., Mulhern, W. S., Lezaks, D. P. M., & Jahn, M. M. (2016). Vulnerabilities to agricultural production shocks: An extreme, plausible scenario for assessment of risk for the insurance sector. Climate Risk Management, 13, 1–9. https://doi.org/10.1016/j.crm.2016.05.001

Lupu, A. B., Ionescu, F. C., and Borza, I. (2010). The phenomenon of drought and it's effects within Romania, Res. J. Agricult. Sci., 42, 102–109.

Machethe, C.L. (2004). Agriculture and poverty in South Africa: Can agriculture reduce poverty, in: Overcoming Underdevelopment Conference Held in Pretoria. Citeseer, p. 29.

Magombeyi, M.S., Taigbenu, A.E. (2008). Crop yield risk analysis and mitigation of smallholder farmers at quaternary catchment level: Case study of B72A in Olifants river basin, South Africa. Physics and Chemistry of the Earth, Parts A/B/C 33, 744–756. https://doi.org/10.1016/j.pce.2008.06.050

Mahlalela, P.T., Blamey, R.C., Hart, N.C.G., Reason, C.J.C. (2020). Drought in the Eastern Cape region of South Africa and trends in rainfall characteristics. Clim Dyn 55, 2743–2759. https://doi.org/10.1007/s00382-020-05413-0
Makate, C.; Makate, M.; Mango, N.; Siziba, S. Increasing resilience of smallholder farmers to climate change through multiple adoption of proven climate-smart agriculture innovations. Lessons from Southern Africa. J. Environ. Manag. 2018, 231,
Makaudze, E.M.; Miranda, M.J. Catastrophic drought insurance based on the remotely sensed normalised difference vegetation index for smallholder farmers in Zimbabwe. Agrekon 2010, 49, 418–432.
Mann, M. E., & Gleick, P. H. (2015). Climate change and California drought in the 21st century. Proceedings of the National Academy of Sciences of the United States of America, 112(13), 3858–3859. https://doi.org/10.1073/pnas.1503667112
Marengo, J. A., Cunha, A. P., Cuartas, L. A., Deusdará Leal, K. R., Broedel, E., Seluchi, M. E., et al. (2021). Extreme drought in the Brazilian Pantanal in 2019-2020: Characterization, causes, and impacts. Frontiers in Water, 3, 639204. https://doi.org/10.3389/frwa.2021.639204
Marengo, J.A., Torres, R.R., Alves, L. M. (2017). Drought in Northeast Brazil—past, present, and future Theor. Appl. Climatol., 129 pp. 1189-1200, 10.1007/s00704-016-1840-8
Martin, R. et al. (2016). Livelihood security in face of drought - Assessing the vulnerability of pastoral households., Environmental Modelling and Software, 75, pp. 414–423. doi: 10.1016/j.envsoft.2014.10.012.
Masupha, T.E., Moeletsi, M.E. (2020). The use of Water Requirement Satisfaction Index for assessing agricultural drought on rain-fed maize, in the Luvuvhu River catchment, South Africa. Agricultural Water Management 237, 106142. https://doi.org/10.1016/j.agwat.2020.106142
Mateescu, E., Smarandache, M., Jeler, N., and Apostol, V. (2013). Drought conditions and management strategies in Romania. Initiative on "Capacity Development to support National Drought Management Policy" (WMO, UNCCD, FAO and UNW-DPC) – Country Report, available at: http://www.droughtmanagement.info/literature/UNW-DPC_ NDMP_Country_Report_Romania_2013.pdf (last access: 17 June 2019).
Mazvimavi, D. Investigating changes over time of annual rainfall in Zimbabwe. Hydrol. Earth Syst. Sci. 2010, 14, 2671–2679.
McCabe, G. J. and Wolock, D. M. (2015). Variability and trends in global drought, Earth Space Sci., 2, 223–228, https://doi.org/10.1002/2015EA000100.
McKee, T.; Doesken, N.; Kleist, J. The Relationship of Drought Frequency and Duration to Time Scales. In Proceedings of the Eighth Conference on Applied Climatology, Boston, MA, USA, 1993.
Meijer, J.R., Huijbegts, M.A.J., Schotten, C.G.J. and Schipper, A.M. (2018). Global patterns of current and future road infrastructure. Environmental Research Letters, 13-064006. Data is available at www.globio.info
Melkonyan, A. (2014). Environmental and socio-economic vulnerability of agricultural sector in Armenia., Science of the Total Environment. Elsevier B.V., 488–489(1), pp. 333–342. doi: 10.1016/j.scitotenv.2014.03.126.
Meyer, S.J.; Hubbard, K.G.; Wilhite, D.A. A Crop-Specific Drought Index for Corn: II. Application in Drought Monitoring and Assessment. Agron. J. 1993, 85, 396.
Meza, I., Eyshi Rezaei, E., Siebert, S., Ghazaryan, H., Nouri, H., Dubovyk, O., et al. (2021). Drought risk for agricultural systems in South Africa: Drivers, spatial patterns, and implications for drought risk management. Science of the Total Environment, 799, 149505. https://doi.org/10.1016/j.scitotenv.2021.149505
Meza, I., Hagenlocher, M., Naumann, G., Vogt, J., and Frischen, J. (2019). Drought vulnerability indicators for global-scale drought risk assessments, EUR 29824 EN, Publications Office of the European Union, Luxembourg, JRC117546, ISBN 978-92-76-09210-0, https://doi.org/10.2760/73844.
Meza, I., Siebert, S., Döll, P., Kusche, J., Herbert, C., Eyshi Rezaei, E., Nouri, H., Gerdener, H., Popat, E., Frischen, J., Naumann, G., Vogt, J.V., Walz, Y., Sebesvari, Z.,

Hagenlocher, M. (2020). Global-scale drought risk assessment for agricultural systems. Natural Hazards and Earth System Sciences 20, 695–712. https://doi.org/10.5194/nhess-20-695-2020
Michler, J.D.; Baylis, K.; Arends-Kuenning, M.; Mazvimavi, K. Conservation agriculture and climate resilience. J. Environ. Econ. Manag. 2019, 93, 148–169.
Mishra, A. K. and Singh, V. P. (2010). A review of drought concepts. Journal of Hydrology, 391(1–2), pp. 202–216. doi: 10.1016/j.jhydrol.2010.07.012.
Mishra, A. K. and Singh, V. P. (2011). Drought modeling - A review., Journal of Hydrology, 403(1–2), pp. 157–175. doi: 10.1016/j.jhydrol.2011.03.049.
Mishra, A., Bruno, E., & Zilberman, D. (2021). Compound natural and human disasters: Managing drought and COVID-19 to sustain global agriculture and food sectors. Science of the Total Environment, 754, 142210. https://doi.org/10.1016/j.scitotenv.2020.142210
MOHCC. Zimbabwe National and Sub-National HIV Estimates Report. 2018. Available online: http://nac.org.zw/wp-content/uploads/2019/01/Zimbabwe-HIV-Estimates-Report-2018.pdf (accessed on 21 January 2020).
Msangi, J.P. (2004). Drought Hazard and Desertification Management in the Drylands of Southern Africa. Environ. Monit. Assess. 99, 75–87.
Mudzonga, E. (2012). Farmers' Adaptation to Climate Change in Chivi District of Zimbabwe; Trade and Development Studies Centre: Zimbabwe.
Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J.A. (2012). Closing yield gaps through nutrient and water management. Nature 490, 254–257. https://doi.org/10.1038/nature11420
Mukherjee, S., & Mishra, A. K. (2020). Increase in compound drought and heatwaves in a warming world. Geophysical Research Letters, 48(1), e2020GL090617. https://doi.org/10.1029/2020GL090617
Mukherjee, S., Mishra, A. and Trenberth, K. E. (2018). Climate Change and Drought: a Perspective on Drought Indices., Current Climate Change Reports, 4(2), pp. 145–163. doi: 10.1007/s40641-018-0098-x.
Müller Schmied, H., Cáceres, D., Eisner, S., Flörke, M., Herbert, C., Niemann, C., Peiris, T. A., Popat, E., Portmann, F. T., Reinecke, R., Schumacher, M., Shadkam, S., Telteu, C.-E., Trautmann, T., Döll, P. (2020). The global water resources and use model WaterGAP v2.2d: Model description and evaluation, Geosci. Model Dev. Discuss., https://doi.org/10.5194/gmd-2020-225
Müller Schmied, H., Eisner, S., Franz, D., Wattenbach, M., Portmann, F. T., Flörke, M., and Döll, P. (2014). Sensitivity of simulated global-scale freshwater fluxes and storages to input data, hydrological model structure, human water use and calibration, Hydrol. Earth Syst. Sci., 18, 3511–3538, https://doi.org/10.5194/hess-18-3511-2014.
Muñoz, A. A., Klock-Barría, K., Alvarez-Garreton, C., Aguilera-Betti, I., González-Reyes, Á., Lastra, J. A., Chávez, R. O., Barría, P., Christie, D., Rojas-Badilla, M., & LeQuesne, C. (2020). Water Crisis in Petorca Basin, Chile: The Combined Effects of a Mega-Drought and Water Management. Water, 12(3), 648. https://doi.org/10.3390/w12030648
Murungweni, C.; van Wijk, M.T.; Andersson, J.A.; Smaling, E.M.A.; Giller, K.E. Application of Fuzzy Cognitive Mapping in Livelihood Vulnerability Analysis. Ecol. Soc. 2011, 16, 1–17.
Mutekwa, V.T. Climate Change Impacts and Adaptation in the Agricultural Sector: The case of smallholder famrers in Zimbabwe. J. Sustain. Dev. Afr. 2009, 11, 237–256.
Mutowo, G.; Chikodzi, D. Remote sensing based drought monitoring in Zimbabwe. Disaster Prev. Manag. 2014, 23, 649–659.
Muyambo, F., Bahta, Y. T. And A. J. Jordaan. (2017). The role of indigenous knowledge in drought risk reduction: A case of communal farmers in South Africa. In: Jamba 9, no. 1, p. 420.

Muyambo, F., Jordaan, A.J., Bahta, Y.T. (2017). Assessing social vulnerability to drought in South Africa: Policy implication for drought risk reduction. Jàmbá 9. https://doi.org/10.4102/jamba.v9i1.326

Muzari, W.; Nyamushamba, G.; Gabriel, S. Climate Change Adaptation in Zimbabwe's Agricultural Sector. Int. J. Sci. Res. (IJSR) 2016, 5, 1762–1768.

Naqvi, A., Gaupp, F., Hochrainer-Stigler, S., (2020). The risk and consequences of multiple breadbasket failures: an integrated copula and multilayer agent-based modeling approach OR Spectr., 42 (2020), pp. 727-754, 10.1007/s00291-020-00574-0

National Oceanic and Atmospheric Administration (NOAA) AVHRR, (2019). STAR—Global Vegetation Health Products. Available online: https://www.star.nesdis.noaa.gov/smcd/emb/vci/VH/vh_ftp.php (accessed on 21 January 2020).

National Treasury. (2003). Intergovernmental Fiscal Review, Republic of South Africa.

National Treasury. (2019). Balance Sheet Municipal Finance Data Tables Municipal Money Data [WWW Document], URL https://municipaldata.treasury.gov.za/table/aged_creditor/?year=2019&amountType=AUDA (accessed 3.13.21).

Naumann, G., Alfierei, L., Wyser, K., Mentaschi, L., Betts, R. A., Carrao, H., et al. (2018). Global changes in drought conditions under different levels of warming. Geophysical Research Letters, 45(7), 3285–3296. https://doi.org/10.1002/2017GL076521

Naumann, G., Barbosa, P., Garrote, L., Iglesias, A., Vogt, J. (2014). Exploring drought vulnerability in Africa: an indicator based analysis to be used in early warning systems. Hydrology and Earth System Sciences, 18(5), 1591–1604. https://doi.org/10.5194/hess-18-1591-2014

Naumann, G., Cammalleri, C., Mentaschi, L., & Feyen, L. (2021). Increased economic drought impacts in Europe with anthropogenic warming. Nature Climate Change, 11(6), 485–491. https://doi.org/10.1038/s41558-021-01044-3

Naumann, G., Carrao, H., and Barbosa, P. (2018). Indicators of social vulnerability to drought, in: chap. 6 in Wiley Book on Drought: Science and Policy, Part II: Vulnerability, risk and policy, Wiley-Blackwell, Chichester, WS.

Naumann, G., Podestá, G., Marengo, J., Luterbacher, J., Bavera, D., Acosta Navarro, J., et al. (2023). Extreme and long-term drought in the La Plata Basin: Event evolution and impact assessment until September 2022: A joint report from EC-JRC. CEMADEN, SISSA and WMO, Publications Office of the European Union. Retrieved from https://data.europa.eu/doi/10.2760/62557

Ncube, A.; Mangwaya, P.T.; Ogundeji, A.A. Assessing vulnerability and coping capacities of rural women to drought: A case study of Zvishavane district, Zimbabwe. Int. J. Disaster Risk Reduct. 2018, 28, 69–79.

Ndlovu, P.V.; Mazvimavi, K.; An, H.; Murendo, C. Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe. Agric. Syst. 2014, 124, 21–31.

Ndlovu, S. Coping with Drought. Research Findings From Bulilima and Mangwe Districts, Matabeleland South, Zimbabwe. 2011. Available online: https://www.preventionweb.net/publications/view/17979 (accessed on 21 January 2020).

Nelson, A. (2015). Estimated travel time to the nearest city of 50,000 or more people in year 2000. Global Environment Monitoring Unit—Joint Research Centre of the European Commission. Available online: https://forobs.jrc.ec.europa.eu/produc

Nelson, D. R. and Finan, T. J. (2009). Praying for drought: Persistent vulnerability and the politics of patronage in Ceará, Northeast Brazil. American Anthropologist, 111(3), pp. 302–316. doi: 10.1111/j.1548-1433.2009.01134.x.

Ngaka, M. (2012). Drought preparedness, impact and response: A case of the Eastern Cape and Free State provinces of South Africa. *Jàmbá: Journal of Disaster Risk Studies*, *4*(1), 1-10.

Nhamo, L.; Mabhaudhi, T.; Modi, A.T. Preparedness or repeated short-term relief aid? Building drought resilience through early warning in southern Africa. WSA 2019, 45, 75.

Niggli, L., Huggel, C., Muccione, V., Neukom, R., & Salzmann, N. (2022). Towards improved understanding of cading and interconnected risks from concurrent weather extremes: Analysis of historical heat and drought extreme events. PLOS Climate, 1(8), e0000057. https://doi.org/10.1371/journal.pclm.0000057

Notteboom, T. (2007). Inland waterway transport of containerized cargo: From infancy to a fully-fledged transport mode. Journal for Maritime Research, 4(2), 63–80.

OCHA ROSA. Zimbabwe—Health Institutions. Zimbabwe Ministry of Health. 2018. Available online: https://data.humdata.org/dataset/zimbabwe-health (accessed on 21 January 2020).

OECD, (2008). Handbook on Constructing Composite Indicators: Methodology and User Guide. https://doi.org/10.1787/9789264043466-en.

OECD, World Bank, (2016). Summary report: Climate and disaster resilience financing in Small Island Developing States.

OpenGeoHub. LandGIS—Open Land Data Services. (2018). Available online: https://openlandmap.org.

Ortega-Gaucin, D., Ceballos-Tavares, J. A., Ordoñez Sánchez, A., & Castellano-Bahena, H. V. (2021). Agricultural Drought Risk Assessment: A Spatial Analysis of Hazard, Exposure, and Vulnerability in Zacatecas, Mexico. Water, 13(10), 1431. https://doi.org/10.3390/w13101431

Otto, F. E. L., Harrington, L. J., Frame, D. J., Boyd, E., Lauta, K. C., Wehner, M., Clarke, B., Raju, E., Boda, C., Hauser, M., James, R., & Jones, R. G. (2020). Toward an inventory of the impacts of Human-Induced climate change. Bulletin of the American Meteorological Society, 101(11), E1972–E1979. https://doi.org/10.1175/bams-d-20-0027.1

Oxfam. Our Seeds: Lessons learned from the drought. Voices of farmers in Zimbabwe. 2016 (Jount Agency Briefing Note). Available online: https://policy-practice.oxfam.org.uk/publications/our-seeds-lessons-from-the-drought-voices-of-farmers-in-z

Padma, T. V. (2019). African nations push UN to improve drought research. Nature, 573(7774), 319. https://doi.org/10.1038/d41586-019-02760-9

Palmer, W.C. Meteorological Drought. Res. Pap. 1965, 45, 1–58.

Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Herold, C., Kossin, J., Mouton, F., and Nordbeck, O. (2012). Global trends in tropical cyclone risk, Nat. Clim. Change, 2, 289–294, https://doi.org/10.1038/nclimate1410.

Peduzzi, P., Dao, H., Herold, C., and Mouton, F. (2009). Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index, Nat. Hazards Earth Syst. Sci., 9, 1149–1159, https://doi.org/10.5194/nhess-9-1149-2009.

Pei, W., Fu, Q., Liu, D., Li, T., Cheng, K., & Cui, S. (2018). Spatiotemporal analysis of the agricultural drought risk in Heilongjiang Province, China. Theoretical and Applied Climatology, 133(1–2), 151–164. https://doi.org/10.1007/s00704-017-2182-x

Peng, C.-Y. J., Harwell, M., Liou, S.-M., and Ehman, L. H. (2006). Advances in missing data methods and implications for educational research, in: Real data analysis, edited by: Sawilowsky, S., Information Age, Greenwich, CT, 31–37.

Peng, L., Zeng, Z., Wei, Z., Chen, A., Wood, E.F., Sheffield, J. (2019). Determinants of the ratio of actual to potential evapotranspiration. Glob Change Biol 25, 1326–1343. https://doi.org/10.1111/gcb.14577

Perčec Tadić, M., Gajić-Čapka, M., Zaninović, K., Cindrić, K., 2014. Drought vulnerability in Croatia. Agric. Conspec. Sci. 79, 31–38. https://hrcak.srce.hr/120753.

Pischke, F., & Stefanski, R. (2016). Drought management policies—From global collaboration to national action. Water Policy, 18(S2), 228–244. https://doi.org/10.2166/wp.2016.022

Plummer, R., de Loë, R. and Armitage, D. (2012). A Systematic Review of WateWater Vulnerability Assessment Tools., Water Resources Management, 26(15), pp. 4327–4346. doi: 10.1007/s11269-012-0147-5.

Pokhrel, Y., Felfelani, F., Satoh, Y., Boulange, J., Burek, P., Gädeke, A., et al. (2021). Global terrestrial water storage and drought severity under climate change. Nature Climate Change, 11(3), 226–233. https://doi.org/10.1038/s41558-020-00972-w

Portmann, F. T., Siebert, S., and Döll, P. (2010). MIRCA2000-Global monthly irrigated and rain-fed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling, Global Biogeochem. Cy., 24, Gb1011, https://doi.org/10.1029/2008gb003435.

Pozzi, W.; Sheffield, J.; Stefanski, R.; Cripe, D.; Pulwarty, R.; Vogt, J.V.; Heim, R.R.; Brewer, M.J.; Svoboda, M.; Westerhoff, R.; et al. Toward Global Drought Early Warning Capability: Expanding International Cooperation for the Develop

Quiring, S.M. and Papakryiakou, T.N., (2003). An evaluation of agricultural drought indices for the Canadian prairies Agric. For. Meteorol., 118 (2003), pp. 49-62, 10.1016/S0168-1923(03)00072-8

Rajsekhar, D., Singh, V. P. and Mishra, A. K. (2015). Integrated drought causality, hazard, and vulnerability assessment for future socioeconomic scenarios: An information theory perspective., Journal of Geophysical Research, 120(13), pp. 6346–6378. doi: 10.1002/2014JD022670.

Rangecroft, S., Van Loon, A. F., Maureira, H., Verbist, K., & Hannah, D. M. (2019). An observation-based method to quantify the human influence on hydrological drought: Upstream–downstream comparison. Hydrological Sciences Journal, 64(3), 267–287. https://doi.org/10.1080/02626667.2019.1581365

Raymond, C., Horton, R. M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., et al. (2020). Understanding and managing connected extreme events. Nature Climate Change, 10(7), 611–621. https://doi.org/10.1038/s41558-020-0790-4

Reichhuber, A., Gerber, N., Mirzabaev, A., Svoboda, M., López Santos, A., Graw, V., et al. (2019). The land-drought nexus: Enhancing the role of land-based interventions in drought mitigation and risk management. A Report of the Science-Policy Interface. United Nations Convention to Combat Desertification (UNCCD).

Rockström, J. Resilience building and water demand management for drought mitigation. Phys. Chem. Earth 2003, 28, 869–877.

Rojas, O. (2018). Agricultural extreme drought assessment at global level using the FAO-Agricultural Stress Index System (ASIS), Weather Clim. Extr., 100184, https://doi.org/10.1016/j.wace.2018.09.001.

Rojas, O.; Vrieling, A.; Rembold, F. Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. Remote Sens. Environ. 2011, 115, 343–352.

Rossi, G. et al. (1992). On regional drought estimation and analysis., Water Resources Management, 6(4), pp. 249–277. doi: 10.1007/BF00872280.

Rossi, L., Bláhová, M., Blauhut, V., De Moel, H., Cotti, D., Hagenlocher, M., et al. (2023). The EDORA project: Towards a multi-sectoral drought risk assessment in Europe. In EGU General Assembly 2023. https://doi.org/10.5194/egusphere-egu23-5948

Roth, P. L., Switzer III, F. S., and Switzer, D. M. (1999). Missing data in multiple item scales: A Monte Carlo analysis of missing data techniques, Organiz. Res. Meth., 2, 211–232, https://doi.org/10.1177/109442819923001.

Rother, H., Hall, R. & London, L. (2008). Pesticide use among emerging farmers in South Africa: contributing factors and stakeholder perspectives. Development Southern Africa, 25(4): 399-424.

Rudel, T. K. (2008). Meta-analyses of case studies: A method for studying regional and global environmental change., Global Environmental Change, 18(1), pp. 18–25. doi: 10.1016/j.gloenvcha.2007.06.001.

Running, S., Mu, Q., & Zhao, M. (2017). *MOD16A2 MODIS/Terra Net Evapotranspiration 8-Day L4 Global 500m SIN Grid V006* [Data set]. NASA EOSDIS Land Processes DAAC. https://doi.org/10.5067/MODIS/MOD16A2.006

SACN. (2016). State of South African Cities Report 2016. Johannesburg: SACN,Available at http://www.socr.co.za/wp-content/uploads/2016/06/SoCR16-Main-Report-online.pdf (Accessed 01.02.2021)
Saha, D. K., Kar, A. and Roy, M. M. (2012). Indicators of drought vulnerability for assessing coping mechanism in arid Western Rajasthan., Annals of Arid Zone, 51, pp. 1–9.
Saisana, M. The Luxembourg Competitiveness Index: Analysis & Recommendations. Perspect. Polit. Économique 2010, 15.
Savelli, E., Mazzoleni, M., Di Baldassarre, G., Cloke, H., & Rusca, M. (2023). Urban water crises driven by elites' unsustainable consumption. Nature Sustainability. https://doi.org/10.1038/s41893-023-01100-0
Savelli, E., Rusca, M., Cloke, H., & Di Baldassarre, G. (2021). Don't blame the rain: Social power and the 2015–2017 drought in Cape Town. Journal of Hydrology, 594, 125953. https://doi.org/10.1016/j.jhydrol.2020.125953
Savelli, E., Rusca, M., Cloke, H., & Di Baldassarre, G. (2022). Drought and society: Scientific progress, blind spots, and future prospects. WIREs Climate Change, 13(3), e761. https://doi.org/10.1002/wcc.761
Schafer, B.A.; Dezman, L.E. (1982). Development of a Surface Water Supply Index (SWSI) to Assess the Severity of Drought Conditions in Snowpack Runoff Areas. Proc. West. Snow Conf., 164–175.
Schlumberger, J., Haasnoot, M., Aerts, J., & de Ruiter, M. (2022). Proposing DAPP-MR as a disaster risk management pathways framework for complex, dynamic multi-risk. Iscience, 25(10), 105219. https://doi.org/10.1016/j.isci.2022.105219
Schmidtlein, M. C. et al. (2008). A sensitivity analysis of the social vulnerability index., Risk Analysis, 28(4), pp. 1099–1114. doi: 10.1111/j.1539-6924.2008.01072.x.
Schneiderbauer, S. et al. (2017). The most recent view of vulnerability., Science for Disaster Risk Management 2017: knowing better and loosing less, (June), pp. 68–82. doi: 10.2788/688605.
Schreiner, B. G., Mungatana, E. D., Baleta, H. (2018). Impacts of Drought Induced Water Shortages in South Africa: Sector Policy Briefs.
Schulze, R.E. (2016). On Observations, Climate Challenges, the South African Agriculture Sector and Considerations for an Adaptation Handbook. In: Schulze, R.E. (Ed.) Handbook for Farmers, Officials and Other Stakeholders on Adaptation to Climate Change in the Agriculture Sector within South Africa. Section A: Agriculture and Climate Change in South Africa: Setting the Scene, Chapter A1.
Schumacher, D. L., Keune, J., Dirmeyer, P., & Miralles, D. G. (2022). Drought self-propagation in drylands due to land–atmosphere feedbacks. Nature Geoscience, 15(4), 262–268. https://doi.org/10.1038/s41561-022-00912-7
Schwalm, C. R., Anderegg, W. R. L., Michalak, A. M., Fisher, J. B., Biondi, F., Koch, G., Litvak, M., Ogle, K., Shaw, J. D., Wolf, A., Huntzinger, D. N., Schaefer, K., Cook, R., Wei, Y., Fang, Y., Hayes, D., Huang, M., Jain, A., & Tian, H. (2017). Global patterns of drought recovery. Nature, 548(7666), 202–205. https://doi.org/10.1038/nature23021
Schwarz, M., Landmann, T., Cornish, N., Wetzel, K.-F., Siebert, S., & Franke, J. (2020). A Spatially Transferable Drought Hazard and Drought Risk Modeling Approach Based on Remote Sensing Data. Remote Sensing, 12(2), 237. https://doi.org/10.3390/rs12020237
SDG Indicators, (2017). [dataset] Global SDG Indicators Database: Proportion of population below international poverty line (%) [WWW Document]. URL https://unstats.un.org/sdgs/indicators/database/ (accessed 5.8.21).
SDG indicators: Global SDG Indicators Database (database): Proportion of population below international poverty line (%), available at: https://unstats.un.org/sdgs/indicators/database/ (last access: 9 April 2019), 2015–2017.
Sebesvari, Z., Renaud, F. G., Haas, S., Tessler, Z., Hagenlocher, M., Kloos, J., Szabo, S., Tejedor, A., & Kuenzer, C. (2016). A review of vulnerability indicators for deltaic social–

ecological systems. Sustainability Science, 11(4), 575–590. https://doi.org/10.1007/s11625-016-0366-4
Sena, A. et al. (2017). Indicators to measure risk of disaster associated with drought: Implications for the health sector., PLoS ONE, 12(7). doi: 10.1371/journal.pone.0181394.
Sett, D., Hagenlocher, M., Cotti, D., Reith, J., Harb, M., Kreft, S., Kaiser, Zwick, A., Garschagen, M. , 2021. Disaster risk, social protection and readiness for insurance solutions. UNU-EHS, MCII, LMU, BMZ, GIZ. Bonn, Munich, Germany.
Sheffield, J. and Wood, E. F. (2008). Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations., Climate Dynamics, 31(1), pp. 79–105. doi: 10.1007/s00382-007-0340-z.
Sheffield, J. and Wood, E. F. (2012). Projected changes in drought occurrence under future global warming 16 from multi-model, multiscenario, IPCC AR4 simulations, Clim. Dynam., 31, 79–105, https://doi.org/10.1007/s00382-007-0340-z, 2008. Sheffield, J., Wood, E. F., and Roderick, M. L.: Little change in global drought over the past 60 years, Nature, 491, 435–440, https://doi.org/10.1038/nature11575.
Sheffield, J., Wood, E. F. and Roderick, M. L. (2012). Little change in global drought over the past 60 years. Nature. Nature Publishing Group, a division of Macmillan Publishers Limited. All Rights Reserved., 491, p. 435. Available at: http://dx.doi.org/10.1038/nature11575.
Sherbinin, A. De, Apotsos, A. and Chevrier, J. (2017). Mapping the future: policy applications of climate vulnerability mapping in West Africa. The Geographical Journal, 183(4), pp. 414–425. doi: 10.1111/geoj.12226.
De Sherbinin, A., Bukvic, A., Rohat, G., Gall, M., McCusker, B., Preston, B., Apotsos, A., Fish, C., Kienberger, S., Muhonda, P., Wilhelmi, O., Macharia, D., Shubert, W., Sliuzas, R., Tomaszewski, B., & Zhang, S. (2019). Climate vulnerability mapping: A systematic review and future prospects. WIREs Climate Change, 10(5), e600. https://doi.org/10.1002/wcc.600
Shonhe, T. The Political Economy of Agricultural Commercialisation in Zimbabwe. APRA Working Paper 12. 2018. Available online: https://www.future-agricultures.org/publications/working-papers-document/the-political-economy-of-agricultural-comme
Siebert, S., Döll, P. (2010). Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation. Journal of Hydrology 384, 198–217. https://doi.org/10.1016/j.jhydrol.2009.07.031
Sillmann, J., Christensen, I., Hochrainer-Stigler, S., Huang-Lachmann, J.-T., Juhola, S., Kornhuber, K., et al. (2022). Briefing note on systemic risk. Re and opportunities for research, policy and practice from the perspective of climate, environmental and disaster risk science and management. Retrieved from https://www.undrr.org/publication/briefing-note-systemic-risk
Silva, V., Amo-Oduro, D., Calderon, A., Dabbeek, J., Despotaki, V., Martins, L., Rao, A., Simionato, M., Viganò, D., Yepes, C., Acevedo, A., Horspool, N., Crowley, H., Jaiswal, K., Journeay, M., and Pittore, M. (2018). Global Earthquake Model (GEM) Seismic Risk Map (version 2018.1), https://doi.org/10.13117/GEM-GLOBAL-SEISMIC-RISK-MAP-2018.
Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., et al. (2021). A framework for complex climate change risk assessment. One Earth, 4(4), 489–501. https://doi.org/10.1016/j.oneear.2021.03.005
Singh, J., Ashfaq, M., Skinner, C. B., Anderson, W. B., Mishra, V., & Singh, D. (2022). Enhanced risk of concurrent regional droughts with increased ENSO variability and warming. Nature Climate Change, 12(2), 163–170. https://doi.org/10.1038/s41558-021-01276-3
Sivakumar, M.V.K., Stefanski, R., Bazza, M., Zelaya, S., Wilhite, D., Magalhaes, A.R. (2014). High Level Meeting on National Drought Policy: Summary and Major Outcomes.

Weather and Climate Extremes 3, 126–132. https://doi.org/10.1016/j.wace.2014.03.007
Sivapalan, M., Konar, M., Srinivasan, V., Chhatre, A., Wutich, A., Scott, C. A., et al. (2014). Socio-hydrology: Use-inspired water sustainability science for the Anthropocene. Earth's Future, 2(4), 225–230. https://doi.org/10.1002/2013EF000164
Sivapalan, M., Savenije, H. H. G., & Blöschl, G. (2012). Socio-hydrology: A new science of people and water. Hydrological Processes, 26(8), 1270–1276. https://doi.org/10.1002/hyp.8426
Söderström, B., Hedlund, K., Jackson, L.E., Kätterer, T., Lugato, E., Thomsen, I.K., Bracht Jørgensen, H. (2014). What are the effects of agricultural management on soil organic carbon (SOC) stocks? Environmental Evidence 3, 2. https://doi.org/10.1186/2047-2382-3-2
Sparkes, E., Cotti, D., Shekhar, H., Werners, S. E., Valdiviezo-Ajila, A., Banerjee, S., et al. (2023). Impact webs: A novel approach for characterising and assessing multi-risk in complex systems. In EGU General Assembly. https://doi.org/10.5194/egusphere-egu23-3461
Spinoni, J. Barbosa, P., De Jager, A., McCormick, N., Naumann, G., Vogt, J. V., Magni, D., Masante, D., and Mazzeschi, M. (2019a). A new global database of meteorological drought events from 1951 to 2016, J. Hydrol.: Reg. Stud., 22, 2793–2804, https://doi.org/10.1016/j.ejrh.2019.100593.
Spinoni, J., Arias Muñoz, C., Masante, D., McCormick, N., Vogt, J.V, Barbosa, P. (2018). European Drought Observatory User Meeting 2018, European Commission, Ispra (VA), Italy, JRC114677.
Spinoni, J., Barbosa, P., Bucchignani, E., Cassano, J., Cavazos, T., Christensen, J. H., Christensen, O. B., Coppola, E., Evans, J., Geyer, B., Giorgi, F., Hadjinicolaou, P., Jacob, D., Katzfey, J., Koenigk, T., Laprise, R., Lennard, C. J., Kurnaz, M. L., Li, D., … Dosio, A. (2020). Future Global Meteorological Drought Hot Spots: A Study Based on CORDEX Data. *Journal of Climate*, *33*(9), 3635–3661. https://doi.org/10.1175/JCLI-D-19-0084.1
Spinoni, J., Naumann, G., and Vogt, J. V. (2017). Pan-European seasonal trends and recent changes of drought frequency and severity, Global Planet. Change, 148, 113–130, https://doi.org/10.1016/j.gloplacha.2016.11.013.
Spinoni, J., Naumann, G., Carrão, H., Barbosa, P., and Vogt, J. (2013). World drought frequency, duration, and severity for 1951–2010, Int. J. Climatol., 34, 2792–2804, https://doi.org/10.1002/joc.3875.
StatSA. (2011). Statistics South Africa Data. URL http://superweb.statssa.gov.za/webapi/jsf/dataCatalogueExplorer.xhtml (accessed 05.08.2019)
StatSA. (2016). Statistics South Africa Data. URL http://superweb.statssa.gov.za/webapi/jsf/dataCatalogueExplorer.xhtml (accessed 06.08.2019)
Sugunan, V.V. Fisheries Management of Small Water Bodies in Seven Countries in Africa, Asia and Latin America; FAO: Rome, Italy, 1997.
Sutanto, S. J., van der Weert, M., Wanders, N., Blauhut, V., & Van Lannen, H. A. J. (2019). Moving from drought hazard to impact forets. Nature Communications, 10(1), 4945. https://doi.org/10.1038/s41467-019-12840-z
Tallaksen, L. M. and Van Lanen, H. A. (Eds.). (2004). Hydrological drought: processes and estimation methods for streamflow and groundwater, Elsevier, Amsterdam.
Tate, E. (2012). Social vulnerability indices: A comparative assessment using uncertainty and sensitivity analysis. Natural Hazards, 63(2), pp. 325–347. doi: 10.1007/s11069-012-0152-2.
Tate, E. (2013). Uncertainty Analysis for a Social Vulnerability Index. Annals of the Association of American Geographers, 103(3), pp. 526–543. doi: 10.1080/00045608.2012.700616.

Taylor, C. & Belušić, D. & Guichard, F. et al. (2017) Frequency of extreme Sahelian storms tripled since 1982 in satellite observations. Nature 544, 475–478. https://doi.org/10.1038/nature220699
Thamaga-Chitja, J.M., Morojele, P. (2014). The Context of Smallholder Farming in South Africa: Towards a Livelihood Asset Building Framework. Journal of Human Ecology 45, 147–155. https://doi.org/10.1080/09709274.2014.11906688
The Green Climate Fund, 2021. About GCF | Green Climate Fund [WWW Document]. URL https://www.greenclimate.fund/about (accessed 3.21.21).
Thompson. (2019). South African National Land-Cover (SANLC) 2018. Department of Environmental Affairs of the Republic of South Africa, 2019. URL https://www.environment.gov.za/projectsprogrammes/egis_landcover_datasets (accessed 07.08.2020)
Toreti, A., Bavera, D., Acosta Navarro, J., Cammalleri, C., de Jager, A., Di Ciollo, C., et al. (2022c). Drought in Europe August 2022. Publications Office of the European Union. https://doi.org/10.2760/264241
Toreti, A., Bavera, D., Avanzi, F., Cammalleri, C., De Felice, M., de Jager, A., et al. (2022a). Drought in Europe April 2022. Publications Office of the European Union. https://doi.org/10.2760/40384
Toreti, A., Cronie, O., & Zampieri, M. (2019). Concurrent climate extremes in the key wheat producing regions of the world. Scientific Reports, 9(1), 5493. https://doi.org/10.1038/s41598-019-41932-5
Toreti, A., Masante, D., Acosta Navarro, J., Bavera, D., Cammalleri, C., De Felice, M., et al. (2022b). Drought in Europe July 2022. Publications Office of the European Union. https://doi.org/10.2760/014884
Tortajada, C.; Kastner, M.J.; Buurman, J.; Biswas, A.K. (2017). The California drought: Coping responses and resilience building. Environ. Sci. Policy, 78, 97–113.
Transparency International. (2017). Corruption perceptions index 2017, available at: https://www.transparency.org/news/feature/corruption_perceptions_index_2017#table (last access: 3 May 2019).
Trenberth, K. E., Dai, A., Van der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R. and Sheffield, J. (2014). Global warming and changes in drought. Nature Climate Change, Vol. 4, pp. 17–22. doi.org/10.1038/nclimate2067.
Tsegai, D., & Brüntrup, M. (2019). Drought challenges and policy options: Lessons drawn, and the way forward. In *Current Directions in Water Scarcity Research* (Vol. 2, pp. 325–336). Elsevier. https://doi.org/10.1016/B978-0-12-814820-4.00022-5
Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., & Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. Proceedings of the National Academy of Sciences of the United States of America, 100(14), 8074–8079. https://doi.org/10.1073/pnas.1231335100
UN. (2015). Sendai Framework for Disaster Risk Reduction. Geneva, Switzerland
UN. (2018) The United Nations World Water Development Report 2018: Nature-Based Solutions for Water. Available at: http://unesdoc.unesco.org/images/0026/002614/261424e.pdf.
UN DESA Population Division, 2019. Locations [WWW Document]. World Popul. Prospect. 2019, Online Ed. Rev. 1. URL https://population.un.org/wpp/Download/Metadata/Documentation/.
UN OCHA, (2020). INFORM REPORT 2020 [WWW Document]. URL https://drmkc.jrc.ec.europa.eu/inform-index/Portals/0/InfoRM/Publications/01%20Inform%202020%20ONLINE.pdf (accessed 20.7.22).
UN Zimbabwe (2010). Country Analysis Report for Zimbabwe. Available online: http://www.zw.one.un.org/sites/default/files/Country%20Analysis%20Report%20for%20Zimbabwe%202010.pdf (accessed on 21 January 2020).
UN. (2015). Paris Agreement. Paris.

UN. (2022). United Nations 2023 Water Conference. Global Online Stakeholder Consultation for the Proposed Themes of the Interactive Dialogues. Summary Report. Retrieved from https://www.un.org/sites/un2.un.org/files/final_water_consultation_report_19_oct.pdf

UNCCD (2016) The ripple effect: A Fresh Approach to Reducing Drought Impacts and Building Resilience. Available at: https://www.unccd.int/sites/default/files/documents/27072016_The ripple effect_ENG.pdf.

UNCCD, (2016). Land Degradation Neutrality Target Setting – A technical Guide. UNCCD, Bonn, Germany.

UNCCD, (2019). National Drought Plan Zimbabwe. Available online: https://knowledge.unccd.int/sites/default/files/inline-files/1%20FINAL_NDP_Zimbabwe.pdf (accessed on 21 January 2020).

UNCCD, (2022). Drought in Numbers 2022, restoration for readiness and resilience. https://www.unccd.int/sites/default/files/2022-06/Drought%20in%20Numbers%20%28English%29.pdf

UNDDR. Sendai Framework for Disaster Risk Reduction 2015-2030; United Nations Office for Disaster Risk Reduction (UNDRR): Sendai, Japan, 2015.

UNDP. (2011). Mainstreaming Drought Risk Management. Available online: https://www.undp.org/content/dam/undp/library/Environment%20and%20Energy/sustainable%20land%20management/Mainstreaming%20DRM-English.pdf (accessed on 21 January 2020).

UNDP. (2018) Zimbabwe Country Profile. Available online: http://hdr.undp.org/en/countries/profiles/ZWE# (accessed on 21 January 2020).

UNDP. (2018). Human Development Reports: Gender Inequality Index, available at: http://hdr.undp.org/en/composite/GII (last access: 15 April 2019).

UNDP. 2019. [dataset] Human Development Reports: Employment in agriculture (% of total employment) [WWW Document]. Hum. Dev. Reports. URL http://hdr.undp.org/en/indicators/150606 (accessed 11.11.19).

UNDRR & UNU-EHS. (2022). Understanding and managing cading and systemic risks: Lessons from COVID-19. Retrieved from https://www.undrr.org/publication/understanding-and-managing-cading-and-systemic-risks-lessons-covid-19

UNDRR. (2021). GAR Special Report on Drought 2021. Geneva.

UNDRR. (2017). Words into Action guidelines: National disaster risk assessment.

UNDRR. (2019). Special section on Drought, Chapter 6, in: Global Assessment Report on Disaster Risk Reduction (GAR 2019). United Nations Office for Disaster Risk Reduction (UNDRR), Geneva, Switzerland.

UNDRR. (2015). Sendai Framework for Disaster Risk Reduction 2015-2030. Geneva, Switzerland. Available at http://www.unisdr.org/files/43291_sendaiframeworkfordrren.pdf (Accessed 18.10.2020)

UNDRR. (2019). Special section on Drought, Chapter 6 in Global Assessment Report on Disaster Risk Reduction (GAR 2019). Geneva, Switzerland: United Nations Office for Disaster Risk Reduction (UNDRR).

UNDRR. (2021). Global Assessment Report on Disaster Risk Reduction. Special Report on Drought 2021. United Nations Office for Disaster Risk Reduction (UNDRR).

UNEP.; SARDC. (2009.).Droughts and floods in Southern Africa. In Environmental Change and Human Vulnerability; UNEP: Nairobi, Kenya; SARDC: Harare, Zimbabwe.

UNEP-WCMC and IUCN. World Database on Protected Areas. UNEP-WCMC. 2019. Available online: https://www.protectedplanet.net/c/world-database-on-protected-areas (accessed on 21 January 2020). 96. Livestock Geo-Wiki T1. 2019.

UNFCCC, 2021. Parties & Observers | UNFCCC [WWW Document]. URL https://unfccc.int/parties-observers (accessed 3.21.21).

Unganai, L.S., Kogan, F.N. (1998). Drought Monitoring and Corn Yield Estimation in Southern Africa from AVHRR Data. Remote Sensing of Environment 63, 219–232. https://doi.org/10.1016/S0034-4257(97)00132-6.

UNICEF.; World Bank; ZimStat. Zimbabwe Poverty Atlas. Small Area Poverty Estimation. 2015. Available online: www.zimstat.co.zw › img › Finance › Zimbabwe_Food_Poverty_Atlas_2016 (accessed on21 January 2020).

UNISDR (2005). Hyogo framework for action 2005–2015: Building the resilience of nations and communities to disasters., World Conference on Disaster Reduction, January. doi: 10.1017/CBO9781107415324.004.

UNISDR (2015) Sendai Framework for Disaster Risk Reduction 2015-2030. Geneva, Switzerland. Available at: http://www.unisdr.org/files/43291_sendaiframeworkfordrren.pdf.

V20. (2021a). Members - V20: The Vulnerable Twenty Group [WWW Document]. URL https://www.v-20.org/members (accessed 3.7.21).

V20. (2021b). About - V20: The Vulnerable Twenty Group [WWW Document]. URL https://www.v-20.org/about (accessed 3.21.21).

van Duinen, R. et al. (2015). Empirical Analysis of Farmers. Drought Risk Perception: Objective Factors, Personal Circumstances, and Social Influence. Risk Analysis, 35(4), pp. 741–755. doi: 10.1111/risa.12299.

Van Lanen, H. A. J., Vogt, J. V., Andreu, J., Carrão, H., De Ste-ano, L., Dutra, E., Feyen, L., Forzieri, G., Hayes, M., Iglesias, A., Lavaysse, C., Naumann, G., Pulwarty, R., Spinoni, J., Stahl, K., Stefanski, R., Stilianakis, N., Svoboda, M., and Tallaksen, L. M. (2017). Climatological risk: droughts, in: Science for disaster risk management. Knowing better and losing less, chap. 3.9, EUR 28034 EN, edited by: Poljanšek, K., Marín Ferrer, M., De Groeve, T., and Clark, I., Publications Office of the European Union, Luxembourg, https://doi.org/10.2788/6886052017.

Van Loon, A. F., Gleeson, T., Clark, J., Van Dijk, A. I. J. M., Stahl, K., Hannaford, J., Di Baldassarre, G., Teuling, A. J., Tallaksen, L. M., Uijlenhoet, R., Hannah, D. M., Sheffield, J., Svoboda, M., Verbeiren, B., Wagener, T., Rangecroft, S., Wanders, N., & Van Lanen, H. A. J. (2016). Drought in the Anthropocene. *Nature Geoscience*, *9*(2), 89–91. https://doi.org/10.1038/ngeo2646

Van Loon, A. F., Rangecroft, S., Coxon, G., Werner, M., Wanders, N., Di Baldassarre, G., et al. (2022). Streamflow droughts aggravated by human activities despite management. Environmental Research Letters, 17(4), 044059. https://doi.org/10.1088/1748-9326/ac5def

Vargas, R. and Porter, C. (2017). Vulnerability to Drought and Food Price Shocks : Evidence from Ethiopia. World Development, 96(December), pp. 65–77. doi: 10.1016/j.worlddev.2017.02.025.

VERBI Software (2014). Consult. Sozialforschung. Hg. v. GmbH Berlin. Available online: http://www.maxqda.de (accessed on 21 January 2020).

VERBI Software. (2019). *MAXQDA 2020*, computer program, VERBI Software, Berlin.

Vinke, F., van Koningsveld, M., van Dorsser, C., Baart, F., van Gelder, P., & Vellinga, T. (2022). cading effects of sustained low water on inland shipping. Climate Risk Management, 35, 100400. https://doi.org/10.1016/J.CRM.2022.100400

Vogel C., Van Zyl K. (2016). Drought - in search of sustainable solutions to a persistent 'wicked' problem in South Africa. In Salzmann N, C Huggel, SU Nussbaumer, G Ziervogel (eds) Climate change adaptation strategies: an upstream-downstream perspective. Springer, Cham, 197–211. https://doi.org/10.1007/978-3-319-40773-9_11

Vogel, C., Olivier, D. (2019). Re-imagining the potential of effective drought responses in South Africa. Reg Environ Change 19, 1561–1570. https://doi.org/10.1007/s10113-018-1389-4

Vogel, C.; Koch, I.; van Zyl, K. (2010). A Persistent Truth—Reflections on Drought Risk Management in Southern Africa. Weather Clim. Soc., 2, 9–22.

Vogt J.V., Naumann G., Masante D., Spinoni J., Cammalleri C., Erian W., Pischke F., Pulwarty R., Barbosa P. (2018). Drought Risk Assessment. A conceptual Framework. EUR 29464 EN, Publications Office of the European Union, Luxembourg, 2018. doi:10.2760/057223.

Waldner, F., Hansen, M.C., Potapov, P.V., Löw, F., Newby, T., Ferreira, S., Defourny, P. (2017). National-scale cropland mapping based on spectral-temporal features and outdated land cover information. PLoS ONE 12, e0181911. https://doi.org/10.1371/journal.pone.0181911

Walz, Y., Dall, K., Graw, V., León, J., Haas, S., Kussul, N., Jordaan, A. (2018). Understanding and reducing agricultural drought risk: Examples from South Africa and Ukraine. United Nations University—Institute for Environment and Human Security (UNU-EHS)

Walz, Y., Min, A., Dall, K., Duguru, M., Villagran de Leon, J.-C., Graw, V., Dubovyk, O., Sebesvari, Z., Jordaan, A., Post, J. (2020). Monitoring progress of the Sendai Framework using a geospatial model: The example of people affected by agricultural droughts in Eastern Cape, South Africa. Progress in Disaster Science 5, 100062. https://doi.org/10.1016/j.pdisas.2019.100062

Wang, W. et al. (2016). Propagation of drought: From meteorological drought to agricultural and hydrological drought., Advances in Meteorology, 2016. doi: 10.1155/2016/6547209.

Ward, P. J., de Ruiter, M. C., Mård, J., Schröter, K., Van Loon, A., Veldkamp, T., et al. (2020). The need to integrate flood and drought disaster risk reduction strategies. Water Security, 11, 100070. https://doi.org/10.1016/j.wasec.2020.100070

Ward, P. J., Jongman, B., Kummu, M., Dettinger, M. D., Sperna Weiland, F. C., and Winsemius, H. C. (2014). Strong influence of El Niño Southern Oscillation on flood risk around the world, P. Natl. Acad. Sci. USA, 111, 15659–15664, https://doi.org/10.1073/pnas.1409822111

Ward, P. J., Jongman, B., Sperna Weiland, F., Bouwman, A., van Beek, R., Bierkens, M. F. P., Ligtvoet, W., and Winsemius, H. C. (2013). Assessing flood risk at the global scale: model setup, results, and sensitivity, Environ. Res. Lett., 8, 4, https://doi.org/10.1088/1748-9326/8/4/044019.

Weedon, G. P., Balsamo, G., Bellouin, N., Gomes, S., Best, M. J., and Viterbo, P. (2014). The WFDEI meteorological forcing data set: WATCH forcing data methodology applied to ERA-Interim reanalysis data, Water Resour. Res., 50, 7505–7514, https://doi.org/10.1002/2014WR015638.

Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T.C.D., Howes, R.E., Tusting, L.S., Kang, S.Y., Cameron, E., Bisanzio, D., Battle, K.E., Bhatt, S., Gething, P.W. (2018). A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature 553, 333–336. https://doi.org/10.1038/nature25181

Welle, T., & Birkmann, J. (2015). The World Risk Index – An Approach to Assess Risk and Vulnerability on a Global Scale. Journal of Extreme Events, 02(01), 1550003. https://doi.org/10.1142/s234573761550037.

Wendt, D. E., Van Loon, A. F., Bloomfield, J. P., & Hannah, D. M. (2020). Asymmetric impact of groundwater use on groundwater droughts. Hydrology and Earth System Sciences, 24(10), 4853–4868. https://doi.org/10.5194/hess-24-4853-2020

Wens, M., Johnson, J. M., Zagaria, C., & Veldkamp, T. I. E. (2019). Integrating human behavior dynamics into drought risk assessment—A sociohydrologic, agent-based approach. *WIREs Water*, *6*(4). https://doi.org/10.1002/wat2.1345

Werners, S. E., Wise, R. M., Butler, J. R. A., Totin, E., & Vincent, K. (2021). Adaptation pathways: A re of approaches and a learning framework. Environmental Science & Policy, 116, 266–275. https://doi.org/10.1016/j.envsci.2020.11.003

West, P.C., Gerber, J.S., Engstrom, P.M., Mueller, N.D., Brauman, K.A., Carlson, K.M., Cassidy, E.S., Johnston, M., MacDonald, G.K., Ray, D.K., Siebert, S. (2014). Leverage

points for improving global food security and the environment. Science 345, 325–328. https://doi.org/10.1126/science.1246067
WFP. (2014). Integrated Context Analysis (ICA) Zimbabwe. Available online: https://www.wfp.org/publications/zimbabwe-integrated-context-analysis-ica-october-2014 (accessed on 21 January 2020).
WFP. (2017). Zimbabwe Country Strategic Plan (2017–2021). Available online: https://reliefweb.int/report/zimbabwe/zimbabwe-country-strategic-plan-2017-2021 (accessed on 21 January 2020).
WHO. (2014). Global Health Observatory data repository: Healthy life expectancy (HALE), available at: http://apps.who.int/gho/data/ view.main.HALEXv (last access: 15 April 2019).
WHO. (2015). Global Health Observatory data repository: Basic and safely managed sanitation services, available at: http://apps.who.int/gho/data/view.main.WSHSANITATIONv?lang=en, (last access: 15 April 2019).
Wilhite, D. A. (2000). Drought as a natural hazard: Concepts and definitions. Drought: A Global Assessment, pp. 3–18. doi: 10.1177/0956247807076912.
Wilhite, D. A., & Glantz, M. H. (1985). Understanding: The Drought Phenomenon: The Role of Definitions. *Water International*, *10*(3), 111–120. https://doi.org/10.1080/02508068508686328
WMO (World Meteorological Organization (2021). WMO Atlas of Mortality and economic losses from weather, climate and water extremes (1970-2019). (2021). Wmo.int. Retrieved June 11, 2023, from https://library.wmo.int/doc_num.php?explnum_id=10989
WMO World Meteorological Organization. (2020). World Meteorological Organization Commission for Climatology. State of the Climate in Africa 2019. World Meteorological Organisation, Geneva. Report WMO-No.1253
WMO. (2013). High-level meeting on national drought policy final declaration. WMO. Retrieved from https://community.wmo.int/en/meetings/high-level-meeting-national-drought-policy-hmndp
WMO. (2021b). WMO Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes 1970–2019. https://library.wmo.int/doc_num.php?explnum_id=10902
WMO. (2022). Meteorological and humanitarian agencies sound alert on East Africa. Retrieved from https://public.wmo.int/en/media/news/meteorological-and-humanitarian-agencies-sound-alert-east-africa
World Bank (2018). Agriculture, Forestry, and Fishing, Value Added (% of GDP)—Zimbabwe. Available online: https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=ZW&name_desc=true (accessed on 21 January 2020).
World Bank (2019). Zimbabwe: Agriculture Sector. Disaster Risk Assessment. Available online: https://www.gfdrr.org › default › files › publication (accessed on 21 January 2020).
World Bank. (2015a). [dataset] World Development Indicators: Literacy rate, adult total (% of people ages 15 and above) [WWW Document]. URL https://databank.worldbank.org/reports.aspx?source=2&series=SE.ADT.LITR.ZS&country= (accessed 5.8.21).
World Bank. (2015b). [dataset] World Development Indicators: Prevalence of undernourishment (% of population) [WWW Document]. URL https://databank.worldbank.org/reports.aspx?source=2&series=SN.ITK.DEFC.ZS&country= (accessed 5.8.21).
World Bank. (2015c). [dataset] World Development Indicators: Improved water source (% of population with access), [WWW Document]. URL https://databank.worldbank.org/source/world-development-indicators (accessed 5.8.21).

World Bank. (2017a). [dataset] World Development Indicators: Unemployment, total (% of total labour force) modeled ILO estimate) [WWW Document]. URL https://databank.worldbank.org/reports.aspx?source=2&series=SL.UEM.TOTL.ZS&country= (accessed 5.8.21).
World Bank. (2017b). [dataset] World Development Indicators: GINI index (World Bank estimate) [WWW Document]. URL https://databank.worldbank.org/reports.aspx?source=2&series=SI.POV.GINI&country= (accessed 5.8.21).
World Bank. (2017c). [dataset] World Governance Indicators: Government Effectiveness: Percentile Rank [WWW Document]. URL https://databank.worldbank.org/reports.aspx?source=1181&series=GE.PER.RNK (accessed 5.8.21).
World Bank. (2017d). [dataset] Global FINDEX: Saved any money in the past year (% age 15+) [WWW Document]. URL https://globalfindex.worldbank.org/ (accessed 5.8.21).
World Bank. (2017e). [dataset] World Development Indicators: Mobile Cellular Subscriptions (per 100 people) [WWW Document]. URL http://data.worldbank.org/data-catalog/world-development-indicators (accessed 5.8.21).
World Bank. (2019). WDI - Classifying countries by income [WWW Document]. URL https://datatopics.worldbank.org/world-development-indicators/stories/the-classification-of-countries-by-income.html (accessed 3.21.21).
World Bank. (2015b). World Development Indicators: GINI index (World Bank estimate), available at: https://databank.worldbank.org/reports.aspx?source=2&series=SI.POV.GINI&country= (last access: 9 April 2019), 2017b.
World Bank. (2017a). TCdata360: Crime and Theft, available at: https:// tcdata360.worldbank.org/indicators/mpf.cri.the?country=BRA&indicator=3284&viz=line_chart&years=2008,2017#table-link (last access: 7 April 2019).
World Bank. (2019). Assessing Drought Hazard and Risk: Principles and Implementation Guidance. Washington, DC: World Bank.
World Bank: (2015c). World Development Indicators: Fertilizer consumption (kilograms per hectare of arable land), available at: https://databank.worldbank.org/reports.aspx?source=2&series= AG.CON.FERT.ZS&country= (last access: 20 April 2019).
World Bank: World Development Indicators. (2015a). Improved water source (% of population with access), available at: https: //databank.worldbank.org/source/world-development-indicators (last access: 27 March 2019).
World Bank: World Development Indicators. (2015d). Literacy rate, adult total (% of people ages 15 and above), available at: https://databank.worldbank.org/reports.aspx?source=2& series=SE.ADT.LITR.ZS&country= (last access: 8 April 2019).
World Bank: World Development Indicators. (2015e). Prevalence of undernourishment (% of population), available at: https://databank.worldbank.org/reports.aspx?source=2&series=SN.ITK.DEFC.ZS&country= (last access: 10 April 2019).
World Bank: World Development Indicators: Age dependency ratio (% of working-age population), available at: https://databank.worldbank.org/reports.aspx?source=2&series=SP.POP.DPND&country= (last access: 11 April 2019), 2011– 2016.
World Bank: World Development Indicators: Electricity production from hydroelectric sources (% of total), available at: https://databank.worldbank.org/reports.aspx?source=2&series=EG.ELC.HYRO.ZS&country= (last access: 25 April 2019).
World Bank: World Development Indicators: Rural population, available at: https://databank.worldbank.org/reports.aspx?source=2&series=SP.RUR.TOTL&country= (last access: 10 April 2019), 2011–2017.

World Bank: World Development Indicators: Terrestrial and marine protected areas (% of total territorial area), available at: https://databank.worldbank.org/reports.aspx?source=2&series=ER.PTD.TOTL.ZS&country= (last access: 14 April 2019), 2016–2017.
World Meteorological Organization (WMO). WMO Atlas of Mortality and economic losses from weather, climate and water extremes (1970-2019). (2021). Wmo.int. Retrieved June 11, 2023, from https://library.wmo.int/doc_num.php?explnum_id=10989
World Resources Institute. Global Forest Watch. 2019. Available online: https://www.globalforestwatch.org (accessed on 21 January 2020).
Wrede, I. (2022). Trockenheit: Niedrigwasser am Rhein schadet Wirtschaft. DW. Retrieved from https://p.dw.com/p/4EMYI
Wu, H. et al. (2017). Assessment of Agricultural Drought Vulnerability in the Guanzhong Plain, China. Water Resources Management. Water Resources Management, 31(5), pp. 1557–1574. doi: 10.1007/s11269-017-1594-9.
Wu, J. J. et al. (2017). Global vulnerability to agricultural drought and its spatial characteristics. Science China Earth Sciences, 60(5), pp. 910–920. doi: 10.1007/s11430-016-9018-2.
WWAP (United Nations World Water Assessment Programme)/UN-Water. (2018). The United Nations World Water Development Report 2018: Nature-Based Solutions for Water. Paris, UNESCO
WWF (World Wide Fund for Nature). (2018). Agriculture: Facts and Trends, South Africa [online]. World Wide Fund. Available from (http://awsassets.wwf.org.za/downloads/facts_brochure_mockup_04_b.pdf (Accessed 7.06.2020).
Yaddanapudi, R., & Mishra, A. K. (2022). Compound impact of drought and COVID-19 on agricultural yield in the USA. Science of the Total Environment, 807(1), 150801. https://doi.org/10.1016/j.scitotenv.2021.150801
Yihdego, Y., Vaheddoost, B. and Al-Weshah, R. A. (2019). Drought indices and indicators revisited., Arabian Journal of Geosciences, 12(3). doi: 10.1007/s12517-019-4237-z.
Yuan, X. and Wood, E. F. (2013). Multimodel seasonal forecasting of global drought onset, Geophys. Res. Lett., 40, 4900–4905, https://doi.org/10.1002/grl.50949.
Zarafshani, K. et al. (2016). Vulnerability Assessment Models to Drought: Toward a Conceptual Framework., Sustainability, 8(6), p. 588. doi: 10.3390/su8060588.
Zargar, A. et al. (2011). A review of drought indices., Environmental Reviews. NRC Research Press, 19(NA), pp. 333–349. doi: 10.1139/a11-013.
Zeng, Z., Wu, W., Li, Z., Zhou, Y., Guo, Y., & Huang, H. (2019). Agricultural Drought Risk Assessment in Southwest China. Water, 11(5), 1064. https://doi.org/10.3390/w11051064
Zhang, D., Wang, G., & Zhou, H. (2011). Assessment on agricultural drought risk based on variable fuzzy sets model. Chinese Geographical Science, 21(2), 167–175. https://doi.org/10.1007/s11769-011-0456-2
Zhang, Q. et al. (2015). Assessment of drought vulnerability of the Tarim River basin, Xinjiang, China', Theoretical and Applied Climatology, 121(1–2), pp. 337–347. doi: 10.1007/s00704-014-1234-8.
Ziervogel, G. (2019). Unpacking the Cape Town drought: Lessons learned. Retrieved from https://www.africancentreforcities.net/wp-content/uplo/2019/02/Ziervogel-2019-Lessons-from-Cape-Town-Drought_A.pdf
ZimStat. Facts and Figures 2017. (2017). Available online: http://www.zimstat.co.zw/sites/default/files/img/publications/Facts%20and%20Figures/Fact_Figures_2017.pdf (accessed on 21 January 2020).
ZimStat. (2018). Poverty, Income, Consumption and Expenditure Survey 2017 Report. Zimbabwe National Statistics Agency. Available online: www.zimstat.co.zw/sites/default/…/PICES_2017%20Final_Report_2019.pdf (accessed on 21 January 2020).
ZimStat (2012). Zimbabwe Population Census 2012. Zimbabwe National Statistics Agency. Available online: www.zimstat.co.zw (accessed on 21 January 2020).

ZimVAC. (2017). Rural Livelihoods Assessment Report. Hg. v. FAO. Available online: https://www1.wfp.org/publications/zimbabwe-vulnerability-assessment-rural-livelihoods-assessment-july-2017 (accessed on 21 January 2020).
ZimVAC. (2019). Lean Season Monitoring Report. Available online: http://fnc.org.zw/wp-content/uploads/2019/02/zimvac-2019-lean-season-assessment_final.pdf (accessed on 21 January 2020).
Zoljoodi, M. and Didevarasl, A. (2013). Evaluation of Spatial Temporal Variability of Drought Events in Iran Using Palmer Drought Severity Index and Its Principal Factors (through 1951–2005), Atmos. Clim. Sci., 3, 193–207, https://doi.org/10.4236/acs.2013.32021.
Zscheischler, J., Westra, S., van den Hurk, B. J. J. M., Seneviratne, S., Ward, P., Pitman, A., et al. (2018). Future climate risk from compound events. Nature Climate Change, 8(6), 469–477. https://doi.org/10.1038/s41558-018-0156-3

9. Appendices

Appendix A

A1 Reviewed articles

Appendix A1 provides an overview of the 105 articles that were reviewed. Figure A1 shows the trend in the number of people-centered drought risk assessments over the years.

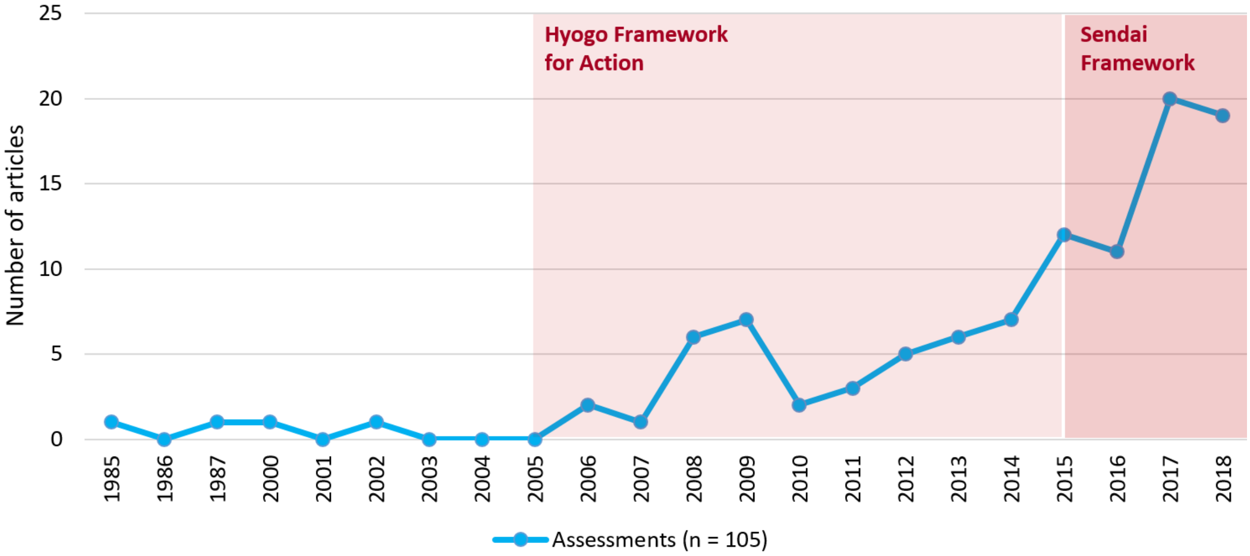


Figure A1. Trend in the number of people-centered drought risk assessments per year (showing the strong increase in drought risk assessments since 2005).

Reviewed articles:

1. Ahmadalipour, A., & Moradkhani, H. (2018). Multi-dimensional assessment of drought vulnerability in Africa: 1960–2100. Science of the Total Environment, 644, 520–535. https://doi.org/10.1016/j.scitotenv.2018.07.023
2. Alcamo, J., Acosta-Michlik, L., Carius, A., Eierdanz, F., Klein, R., Krömker, D., & Tänzler, D. (2008). A new approach to quantifying and comparing vulnerability to drought. Regional Environmental Change, 8(4), 137–149. https://doi.org/10.1007/s10113-008-0065-5
3. Antwi-Agyei, P., Fraser, E. D. G., Dougill, A. J., Stringer, L. C., & Simelton, E. (2012). Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. Applied Geography, 32(2), 324–334. https://doi.org/10.1016/j.apgeog.2011.06.010
4. Asare Kyei, D., Renaud, F. G., Kloos, J., Walz, Y., & Rhyner, J. (2017). Development and validation of risk profiles of West African rural communities facing multiple natural hazards. PLoS ONE, 12(3). https://doi.org/10.1371/journal.pone.0171921
5. Austin, E. K., Handley, T., Kiem, A. S., Rich, J. L., Lewin, T. J., Askland, H. H., Kelly, B. J. (2018). Drought-related stress among farmers: Findings from the Australian rural mental health study. Medical Journal of Australia, 209(4), 159–165. https://doi.org/10.5694/mja17.01200
6. Ayantunde, A. A., Turner, M. D., & Kalilou, A. (2015). Participatory analysis of vulnerability to drought in three agro-pastoral communities in the West African Sahel. Pastoralism, 5(1). https://doi.org/10.1186/s13570-015-0033-x
7. Bacon, C. M., Sundstrom, W. A., Stewart, I. T., & Beezer, D. (2017). Vulnerability to Cumulative Hazards: Coping with the Coffee Leaf Rust Outbreak, Drought, and Food Insecurity in Nicaragua. World Development, 93, 136–152.

https://doi.org/10.1016/j.worlddev.2016.12.025
8. Barbier, B., Yacouba, H., Somé, B., Karambiri, H., & Zoromé, M. (2009). Human Vulnerability to Climate Variability in the Sahel: Farmers' Adaptation Strategies in Northern Burkina Faso. Environmental Management, 43(5), 790–803. https://doi.org/10.1007/s00267-008-9237-9
9. Berman, J. D., Ebisu, K., Peng, R. D., Dominici, F., & Bell, M. L. (2017). Drought and the risk of hospital admissions and mortality in older adults in western USA from 2000 to 2013: a retrospective study. The Lancet Planetary Health, 1(1), e17–e25. https://doi.org/10.1016/S2542-5196(17)30002-5
10. Bhavani, P., Roy, P. S., Chakravarthi, V., & Kanawade, V. P. (2017). Satellite Remote Sensing for Monitoring Agriculture Growth and Agricultural Drought Vulnerability Using Long-Term (1982–2015) Climate Variability and Socio-economic Data set. Proceedings of the National Academy of Sciences India Section A - Physical Sciences, 87(4), 733–750. https://doi.org/10.1007/s40010-017-0445-7
11. Biazin, B., & Sterk, G. (2013). Drought vulnerability drives land-use and land cover changes in the Rift Valley dry lands of Ethiopia. Agriculture, Ecosystems and Environment, 164, 100–113. https://doi.org/10.1016/j.agee.2012.09.012
12. Birhanu, Z., Ambelu, A., Berhanu, N., Tesfaye, A., & Woldemichael, K. (2017). Understanding resilience dimensions and adaptive strategies to the impact of recurrent droughts in Borana Zone, Oromia Region, Ethiopia: A grounded theory approach. International Journal of Environmental Research and Public Health, 14(2). https://doi.org/10.3390/ijerph14020118
13. Blauhut, V., Gudmundsson, L., & Stahl, K. (2015). Towards pan-European drought risk maps: Quantifying the link between drought indices and reported drought impacts. Environmental Research Letters, 10(1). https://doi.org/10.1088/1748-9326/10/1/014008
14. Blauhut, V., Stahl, K., Stagge, J. H., Tallaksen, L. M., Stefano, L. De, & Vogt, J. (2016). Estimating drought risk across Europe from reported drought impacts, drought indices, and vulnerability factors. Hydrology and Earth System Sciences, 20(7), 2779–2800. https://doi.org/10.5194/hess-20-2779-2016
15. Boultif, M., & Benmessaoud, H. (2017). Using climate-soil-socioeconomic parameters for a drought vulnerability assessment in a semi-arid region: Application at the region of El Hodna, (M'sila, Algeria). Geographica Pannonica, 21(3), 142–150. https://doi.org/10.5937/GeoPan1703142B
16. Carrão, H., Naumann, G., & Barbosa, P. (2016). Mapping global patterns of drought risk: An empirical framework based on sub-national estimates of hazard, exposure and vulnerability. Global Environmental Change, 39, 108–124. https://doi.org/10.1016/j.gloenvcha.2016.04.012
17. Chen, J., Deng, M., Xia, L., & Wang, H. (2017). Risk assessment of drought, based on IDM-VFS in the Nanpan River Basin, Yunnan province, China. Sustainability (Switzerland), 9(7). https://doi.org/10.3390/su9071124
18. Chuah, C. J., Ho, B. H., & Chow, W. T. L. (2018). Trans-boundary variations of urban drought vulnerability and its impact on water resource management in Singapore and Johor, Malaysia. Environmental Research Letters, 13(7). https://doi.org/10.1088/1748-9326/aacad8
19. Dabanli, I. (2018). Drought hazard, vulnerability, and risk assessment in Turkey. Arabian Journal of Geosciences, 11(18). https://doi.org/10.1007/s12517-018-3867-x
20. De Silva, M. M. G. T., & Kawasaki, A. (2018). Socioeconomic Vulnerability to Disaster Risk: A Case Study of Flood and Drought Impact in a Rural Sri Lankan Community. Ecological Economics, 152, 131–140. https://doi.org/10.1016/j.ecolecon.2018.05.010
21. De Waal, A., Taffesse, A. S., & Carruth, L. (2006). Child survival during the 2002-2003 drought in Ethiopia. Global Public Health, 1(2), 125–132. https://doi.org/10.1080/17441690600661168
22. Debela, N., Mohammed, C., Bridle, K., Corkrey, R., & McNeil, D. (2015). Perception of climate change and its impact by smallholders in pastoral/agropastoral systems of Borana, South Ethiopia. SpringerPlus, 4(236). https://doi.org/10.1186/s40064-015-1012-9

23. Deng, M., Chen, J., Huang, J., & Niu, W. (2018). Agricultural drought risk evaluation based on an optimized comprehensive index system. Sustainability (Switzerland), 10(10). https://doi.org/10.3390/su10103465
24. Dow, K. (2010). News coverage of drought impacts and vulnerability in the US Carolinas, 1998-2007. Natural Hazards, 54(2), 497–518. https://doi.org/10.1007/s11069-009-9482-0
25. Dumitraşcu, M., Mocanu, I., Mitrică, B., Dragotă, C., Grigorescu, I., & Dumitrică, C. (2018). The assessment of socio-economic vulnerability to drought in Southern Romania (Oltenia Plain). International Journal of Disaster Risk Reduction, 27, 142–154. https://doi.org/10.1016/j.ijdrr.2017.09.049
26. Eklund, L., & Thompson, D. (2017). Differences in resource management affects drought vulnerability across the borders between Iraq, Syria, and Turkey. Ecology and Society, 22(4). https://doi.org/10.5751/ES-09179-220409
27. Eriksen, S., & Silva, J. A. (2009). The vulnerability context of a savanna area in Mozambique: household drought coping strategies and responses to economic change. Environmental Science and Policy, 12(1), 33–52. https://doi.org/10.1016/j.envsci.2008.10.007
28. Etemadi, M., & Karami, E. (2016). Organic fig growers' adaptation and vulnerability to drought. Journal of Arid Environments, 124, 142–149. https://doi.org/10.1016/j.jaridenv.2015.08.003
29. Ezra, M., & Kiros, G. E. (2000). Household vulnerability to food crisis and mortality in the drought-prone areas of northern Ethiopia. Journal of Biosocial Science, 32(3), 395–409. https://doi.org/10.1017/S0021932000003953
30. Fan, G., Zhang, Y., He, Y., & Wang, K. (2017). Risk Assessment of Drought in the Yangtze River Delta Based on Natural Disaster Risk Theory. Discrete Dynamics in Nature and Society, 2017, 1–7. https://doi.org/10.1155/2017/5682180
31. Fontaine, M. M., & Steinemann, A. C. (2009). Assessing Vulnerability to Natural Hazards: Impact-Based Method and Application to Drought in Washington State. Natural Hazards Review, 10(1), 11–18. https://doi.org/10.1061/(asce)1527-6988(2009)10:1(11)
32. Ghimire, Y. N., Shivakoti, G. P., & Perret, S. R. (2010). Household-level vulnerability to drought in hill agriculture of Nepal: Implications for adaptation planning. International Journal of Sustainable Development and World Ecology, 17(3), 225–230. https://doi.org/10.1080/13504501003737500
33. Gil-Guirado, S., Espín-Sánchez, J. A., & Del Rosario Prieto, M. (2016). Can we learn from the past? Four hundred years of changes in adaptation to floods and droughts. Measuring the vulnerability in two Hispanic cities. Climatic Change, 139(2), 183–200. https://doi.org/10.1007/s10584-016-1768-0
34. Greene, C. (2018). Broadening understandings of drought – The climate vulnerability of farmworkers and rural communities in California (USA). Environmental Science and Policy, 89, 283–291. https://doi.org/10.1016/j.envsci.2018.08.002
35. Habiba, U., Shaw, R., & Takeuchi, Y. (2011). Drought risk reduction through a socio-economic, institutional and physical approach in the northwestern region of Bangladesh. Environmental Hazards, 10(2), 121–138. https://doi.org/10.1080/17477891.2011.582311
36. Han, L., Zhang, Q., Ma, P., Jia, J., & Wang, J. (2015). The spatial distribution characteristics of a comprehensive drought risk index in southwestern China and underlying causes. Theoretical and applied climatology, 124(3-4), 517-528. https://doi.org/10.1007/s00704-015-1432-z
37. Hannaford, M. J. (2018). Long-term drivers of vulnerability and resilience to drought in the Zambezi-Save area of southern Africa, 1505–1830. Global and Planetary Change, 166, 94–106. https://doi.org/10.1016/j.gloplacha.2018.05.001
38. Hill, R. V., & Porter, C. (2017). Vulnerability to Drought and Food Price Shocks: Evidence from Ethiopia. World Development, 96, 65–77. https://doi.org/10.1016/j.worlddev.2017.02.025
39. Hill, T. D., & Polsky, C. (2007). Suburbanization and drought: A mixed methods vulnerability assessment in rainy Massachusetts. Environmental Hazards, 7(4), 291–301. https://doi.org/10.1016/j.envhaz.2007.08.003

40. Jülich, S. (2015). Development of a Composite Index with Quantitative Indicators for Drought Disaster Risk Analysis at the Micro Level. Human and Ecological Risk Assessment, 21(1), 37–66. https://doi.org/10.1080/10807039.2013.871989
41. Kamruzzaman, M., Kabir, M. E., Rahman, A. T. M. S., Jahan, C. S., Mazumder, Q. H., & Rahman, M. S. (2018). Modeling of agricultural drought risk pattern using Markov chain and GIS in the western part of Bangladesh. Environment, Development and Sustainability, 20(2), 569–588. https://doi.org/10.1007/s10668-016-9898-0
42. Kanchebe Derbile, E. (2013). Reducing vulnerability of rain-fed agriculture to drought through indigenous knowledge systems in north-eastern Ghana. International Journal of Climate Change Strategies and Management, 5(1), 71–94. https://doi.org/10.1108/17568691311299372
43. Keil, A., Teufel, N., Gunawan, D., & Leemhuis, C. (2009). Vulnerability of smallholder farmers to ENSO-related drought in Indonesia. Climate Research, 38(2), 155–169. https://doi.org/10.3354/cr00778
44. Keshavarz, M., Maleksaeidi, H., & Karami, E. (2017). Livelihood vulnerability to drought: A case of rural Iran. International Journal of Disaster Risk Reduction, 21, 223–230. https://doi.org/10.1016/j.ijdrr.2016.12.012
45. Kim, H., Park, J., Yoo, J., & Kim, T. W. (2015). Assessment of drought hazard, vulnerability, and risk: A case study foradministrative districts in South Korea. Journal of Hydro-Environment Research, 9(1), 28–35. https://doi.org/10.1016/j.jher.2013.07.003
46. Kim, S. M., Kang, M. S., & Jang, M. W. (2018). Assessment of agricultural drought vulnerability to climate change at a municipal level in South Korea. Paddy and Water Environment, 16(4), 699–714. https://doi.org/10.1007/s10333-018-0661-z
47. Krömker, D., Eierdanz, F., & Stolberg, A. (2008). Who is susceptible and why? An agent-based approach to assessing vulnerability to drought. Regional Environmental Change, 8(4), 173–185. https://doi.org/10.1007/s10113-008-0049-5
48. Kurosaki, T. (2015). Vulnerability of household consumption to floods and droughts in developing countries: Evidence from Pakistan. Environment and Development Economics, 20(2), 209–235. https://doi.org/10.1017/S1355770X14000357
49. Lindoso, D. P., Rocha, J. D., Debortoli, N., Parente, I. I., Eiró, F., Bursztyn, M., & Rodrigues-Filho, S. (2014). Integrated assessment of smallholder farming's vulnerability to drought in the Brazilian Semi-arid: a case study in Ceará. Climatic Change, 127(1), 93–105. https://doi.org/10.1007/s10584-014-1116-1
50. Liu, X., Wang, Y., Braimoh, A. K., Peng, J., & Yin, H. (2013). Assessing vulnerability to drought based on exposure, sensitivity and adaptive capacity: A case study in middle Inner Mongolia of China. Chinese Geographical Science, 23(1), 13–25. https://doi.org/10.1007/s11769-012-0583-4
51. Lwasa, S. (2018). Drought and Flood Risk, Impacts and Adaptation Options for Resilience in Rural Communities of Uganda. International Journal of Applied Geospatial Research, 9(1), 36–50. https://doi.org/10.4018/ijagr.2018010103
52. Martin, R., Linstädter, A., Frank, K., & Müller, B. (2016). Livelihood security in face of drought - Assessing the vulnerability of pastoral households. Environmental Modelling and Software, 75, 414–423. https://doi.org/10.1016/j.envsoft.2014.10.012
53. McNeeley, S. M. (2014). A "toad's eye" view of drought: Regional socio-natural vulnerability and responses in 2002 in Northwest Colorado. Regional Environmental Change, 14(4), 1451–1461. https://doi.org/10.1007/s10113-014-0585-0
54. McNeeley, S. M., Beeton, T. A., & Ojima, D. S. (2016). Drought Risk and Adaptation in the Interior United States: Understanding the Importance of Local Context for Resource Management in Times of Drought*. Weather, Climate, and Society, 8(2), 147–161. https://doi.org/10.1175/wcas-d-15-0042.1
55. Mdungela, N. M., Bahta, Y. T., & Jordaan, A. J. (2017). Indicators for economic vulnerability to drought in South Africa. Development in Practice, 27(8), 1050–1063. https://doi.org/10.1080/09614524.2017.1361384
56. Melkonyan, A. (2014). Environmental and socio-economic vulnerability of agricultural sector in Armenia. Science of the Total Environment, 488–489(1), 333–342.

https://doi.org/10.1016/j.scitotenv.2014.03.126
57. Mogotsi, K., Nyangito, M. M., & Nyariki, D. M. (2012). Vulnerability of rural agro-pastoral households to drought in semi-arid Botswana. Livestock Research for Rural Development, 24(10).
58. Mohmmed, A., Zhang, K., Kabenge, M., Keesstra, S., Cerdà, A., Reuben, M., … Ali, A. A. S. (2018). Analysis of drought and vulnerability in the North Darfur region of Sudan. Land Degradation and Development, 29(12), 4424–4438. https://doi.org/10.1002/ldr.3180
59. Mthembu, N. N., & Zwane, E. M. (2017). The adaptive capacity of smallholder mixed-farming systems to the impact of climate change: The case of KwaZulu-Natal in South Africa. Jàmbá: Journal of Disaster Risk Studies, 9(1). https://doi.org/10.4102/jamba.v9i1.469
60. Muyambo, F., Bahta, Y. T., & Jordaan, A. J. (2017). The role of indigenous knowledge in drought risk reduction: A case of communal farmers in South Africa. Jàmbá: Journal of Disaster Risk Studies, 9(1). https://doi.org/10.4102/jamba.v9i1.420
61. Muyambo, F., Jordaan, A. J., & Bahta, Y. T. (2017). Assessing social vulnerability to drought in South Africa: Policy implication for drought risk reduction. Jàmbá: Journal of Disaster Risk Studies, 9(1). https://doi.org/10.4102/jamba.v9i1.326
62. Nasrollahi, M., Khosravi, H., Moghaddamnia, A., Malekian, A., & Shahid, S. (2018). Assessment of drought risk index using drought hazard and vulnerability indices. Arabian Journal of Geosciences, 11(20), 606. https://doi.org/10.1007/s12517-018-3971-y
63. Naumann, G., Barbosa, P., Garrote, L., Iglesias, A., & Vogt, J. (2014). Exploring drought vulnerability in Africa: An indicator based analysis to be used in early warning systems. Hydrology and Earth System Sciences, 18(5), 1591–1604. https://doi.org/10.5194/hess-18-1591-2014
64. Ncube, A., Mangwaya, P. T., & Ogundeji, A. A. (2018). Assessing vulnerability and coping capacities of rural women to drought: A case study of Zvishavane district, Zimbabwe. International Journal of Disaster Risk Reduction, 28, 69–79. https://doi.org/10.1016/j.ijdrr.2018.02.023
65. Nelson, D. R., & Finan, T. J. (2009). Praying for drought: Persistent vulnerability and the politics of patronage in Ceará, Northeast Brazil. American Anthropologist, 111(3), 302–316. https://doi.org/10.1111/j.1548-1433.2009.01134.x
66. Neri, C., & Magaña, V. (2015). Estimation of Vulnerability and Risk to Meteorological Drought in Mexico. Weather, Climate, and Society, 8(2), 95–110. https://doi.org/10.1175/wcas-d-15-0005.1
67. Nguyen, H., Prabhakar, S. V. R. K., & Shaw, R. (2009). Adaptive drought risk reduction in cambodia: Reality, perceptions and strategies. Environmental Hazards, 8(4), 245–262. https://doi.org/10.3763/ehaz.2009.0005
68. Ortega-Gaucin, D., Bartolón, J. de la C., & Bahena, H. V. C. (2018). Drought vulnerability indices in Mexico. Water (Switzerland), 10(11). https://doi.org/10.3390/w10111671
69. Palchaudhuri, M., & Biswas, S. (2016). Application of AHP with GIS in drought risk assessment for Puruliya district, India. Natural Hazards, 84(3), 1905–1920. https://doi.org/10.1007/s11069-016-2526-3
70. Panda, A. (2017). Vulnerability to climate variability and drought among small and marginal farmers: a case study in Odisha, India. Climate and Development, 9(7), 605–617. https://doi.org/10.1080/17565529.2016.1184606
71. Pei, W., Fu, Q., Liu, D., Li, T. xiao, & Cheng, K. (2016). Assessing agricultural drought vulnerability in the Sanjiang Plain based on an improved projection pursuit model. Natural Hazards, 82(1), 683–701. https://doi.org/10.1007/s11069-016-2213-4
72. Pei, W., Fu, Q., Liu, D., Li, T. xiao, Cheng, K., & Cui, S. (2018). Spatiotemporal analysis of the agricultural drought risk in Heilongjiang Province, China. Theoretical and Applied Climatology, 133(1–2), 151–164. https://doi.org/10.1007/s00704-017-2182-x
73. Reardon, T., & Matlon, P. (1985). Seasonal Food Insecurity and Vulnerability in Drought-Affected Regions of Burkina Faso. World Health, 118–136.
74. Saha, D. K., Kar, A., & Roy, M. M. (2012). Indicators of drought vulnerability for assessing coping mechanism in arid Western Rajasthan. Annals of Arid Zone, 51(November), 1–9.

75. Saleh Safi, A., James Smith, W., & Liu, Z. (2012). Rural Nevada and Climate Change: Vulnerability, Beliefs, and Risk Perception. Risk Analysis, 32(6), 1041–1059. https://doi.org/10.1111/j.1539-6924.2012.01836.x
76. Sam, A. S., Kumar, R., Kächele, H., & Müller, K. (2017). Quantifying household vulnerability triggered by drought: evidence from rural India. Climate and Development, 9(7), 618–633. https://doi.org/10.1080/17565529.2016.1193461
77. Schroeder, R. A. (1987). Gender Vulnerability to Drought: A Case Study of the Hausa Social Environment. Natural Hazard Research, 8(1), 75–76. Retrieved from http://www.scopus.com/redirect/linking.url?targetURL=http://www.csa.com/ids70/ipauthenticate.php?vid=1&auth_Type=ip&san=91a74192%28SA%29&locationID=19&categoryID=2&eid=2-s2.0-34247746613&issn=&linkType=ThirdPartyLinking&year=&dbs=CSASA&platform=CSA+Illumi
78. Sena, A., Barcellos, C., Freitas, C., & Corvalan, C. (2014). Managing the health impacts of drought in Brazil. International Journal of Environmental Research and Public Health, 11(10), 10737–10751. https://doi.org/10.3390/ijerph111010737
79. Sena, A., Ebi, K. L., Freitas, C., Corvalan, C., & Barcellos, C. (2017). Indicators to measure risk of disaster associated with drought: Implications for the health sector. PLoS ONE, 12(7). https://doi.org/10.1371/journal.pone.0181394
80. Shahid, S., & Behrawan, H. (2008). Drought risk assessment in the western part of Bangladesh. Natural Hazards, 46(3), 391–413. https://doi.org/10.1007/s11069-007-9191-5
81. Simelton, E., Fraser, E. D. G., Termansen, M., Forster, P. M., & Dougill, A. J. (2009). Typologies of crop-drought vulnerability: an empirical analysis of the socio-economic factors that influence the sensitivity and resilience to drought of three major food crops in China (1961-2001). Environmental Science and Policy, 12(4), 438–452. https://doi.org/10.1016/j.envsci.2008.11.005
82. Smucker, T. A., & Wisner, B. (2008). Changing household responses to drought in Tharaka, Kenya: Vulnerability, persistence and challenge. Disasters, 32(2), 190–215. https://doi.org/10.1111/j.1467-7717.2007.01035.x
83. Sun, Z., Zhang, J., Zhang, Q., Hu, Y., Yan, D., & Wang, C. (2014). Integrated risk zoning of drought and waterlogging disasters based on fuzzy comprehensive evaluation in Anhui Province, China. Natural hazards, 71(3), 1639-1657. https://doi.org/10.1007/s11069-013-0971-9
84. Tänzler, D., Feil, M., Krömker, D., & Eierdanz, F. (2008). The challenge of validating vulnerability estimates: The option of media content analysis for identifying drought-related crises. Regional Environmental Change, 8(4), 187–195. https://doi.org/10.1007/s10113-008-0064-6
85. Toni, F., & Holanda, E. (2008). The effects of land tenure on vulnerability to droughts in Northeastern Brazil. Global Environmental Change, 18(4), 575–582. https://doi.org/10.1016/j.gloenvcha.2008.08.004
86. Van Duinen, R., Filatova, T., Geurts, P., & van der Veen, A. (2015). Empirical Analysis of Farmers' Drought Risk Perception: Objective Factors, Personal Circumstances, and Social Influence. Risk Analysis, 35(4), 741–755. https://doi.org/10.1111/risa.12299
87. Vatsa, K. S. (2006). Employment guarantee scheme in Maharashtra: Its impact on drought, poverty and vulnerability. Indian Journal of Labour Economics, 49(3), 429–453.
88. Villholth, K. G., Tøttrup, C., Stendel, M., & Maherry, A. (2013). Integrated mapping of groundwater drought risk in the Southern African Development Community (SADC) regionCartographie intégrée du risque d'assèchement de nappe dans la région de la Southern African Developpement Community (SADC)Mapeo integrado del riesgo. Hydrogeology Journal, 21(4), 863–885. https://doi.org/10.1007/s10040-013-0968-1
89. Von Uexkull, N. (2014). Sustained drought, vulnerability and civil conflict in Sub-Saharan Africa. Political Geography, 43, 16–26. https://doi.org/10.1016/j.polgeo.2014.10.003
90. Von Uexkull, N., Croicu, M., Fjelde, H., & Buhaug, H. (2016). Civil conflict sensitivity to growing-season drought. Proceedings of the National Academy of Sciences, 113(44),

12391–12396. https://doi.org/10.1073/pnas.1607542113
91. Wilhelmi, O. V., & Wilhite, D. A. (2002). Assessing vulnerability to agricultural drought: A Nebraska case study. Natural Hazards, 25(1), 37–58. https://doi.org/10.1023/A:1013388814894
92. Winsemius, H. C., Jongman, B., Bangalore, M., Hallegatte, S., Ward, P. J., & Veldkamp, T. I. E. (2018). Disaster risk, climate change, and poverty: assessing the global exposure of poor people to floods and droughts. Environment and Development Economics, 1–21. https://doi.org/10.1017/s1355770x17000444
93. Wittrock, V., Kulshreshtha, S. N., & Wheaton, E. (2011). Canadian prairie rural communities: Their vulnerabilities and adaptive capacities to drought. Mitigation and Adaptation Strategies for Global Change, 16(3), 267–290. https://doi.org/10.1007/s11027-010-9262-x
94. Wu, D., Yan, D. H., Yang, G. Y., Wang, X. G., Xiao, W. H., & Zhang, H. T. (2013). Assessment on agricultural drought vulnerability in the Yellow River basin based on a fuzzy clustering iterative model. Natural Hazards, 67(2), 919–936. https://doi.org/10.1007/s11069-013-0617-y
95. Wu, H., Qian, H., Chen, J., & Huo, C. (2017). Assessment of Agricultural Drought Vulnerability in the Guanzhong Plain, China. Water Resources Management, 31(5), 1557–1574. https://doi.org/10.1007/s11269-017-1594-9
96. Wu, J., Lin, X., Wang, M., Peng, J., & Tu, Y. (2017). Assessing agricultural drought vulnerability by a VSD Model: A case study in Yunnan Province, China. Sustainability (Switzerland), 9(6). https://doi.org/10.3390/su9060918
97. Xenarios, S., Nemes, A., Sarker, G. W., & Sekhar, N. U. (2016). Assessing vulnerability to climate change: Are communities in flood-prone areas in Bangladesh more vulnerable than those in drought-prone areas? Water Resources and Rural Development, 7, 1–19. https://doi.org/10.1016/j.wrr.2015.11.001
98. Yaduvanshi, A., Srivastava, P. K., & Pandey, A. C. (2015). Integrating TRMM and MODIS satellite with socio-economic vulnerability for monitoring drought risk over a tropical region of India. Physics and Chemistry of the Earth, 83–84, 14–27. https://doi.org/10.1016/j.pce.2015.01.006
99. Yanbin, L., Tiantian, D., & Feng, Y. (2016). Risk Analysis on Agricultural Drought Disaster in Henan Province. International Journal of Earth Sciences and Engineering, 9(4), 1695–1699.
100. Yuan, X. C., Tang, B. J., Wei, Y. M., Liang, X. J., Yu, H., & Jin, J. L. (2015). China's regional drought risk under climate change: a two-stage process assessment approach. Natural Hazards, 76(1), 667-684. https://doi.org/10.1007/s11069-014-1514-8
101. Yuan, X. C., Wang, Q., Wang, K., Wang, B., Jin, J. L., & Wei, Y. M. (2013). China's regional vulnerability to drought and its mitigation strategies under climate change: data envelopment analysis and analytic hierarchy process integrated approach. Mitigation and Adaptation Strategies for Global Change, 20(3), 341–359. https://doi.org/10.1007/s11027-013-9494-7
102. Zarafshani, K., Sharafi, L., Azadi, H., Hosseininia, G., De Maeyer, P., & Witlox, F. (2012). Drought vulnerability assessment: The case of wheat farmers in Western Iran. Global and Planetary Change, 98–99, 122–130. https://doi.org/10.1016/j.gloplacha.2012.08.012
103. Zhang, D., Wang, G., & Zhou, H. (2011). Assessment on agricultural drought risk based on variable fuzzy sets model. Chinese Geographical Science, 21(2), 167–175. https://doi.org/10.1007/s11769-011-0456-2
104. Zhang, Q., Sun, P., Li, J., Xiao, M., & Singh, V. P. (2015). Assessment of drought vulnerability of the Tarim River basin, Xinjiang, China. Theoretical and Applied Climatology, 121(1–2), 337–347. https://doi.org/10.1007/s00704-014-1234-8
105. Zhu, Y., Li, L., Zhao, Y., Liang, Z., Li, H., Wang, L., & Wang, Q. (2018). Regional comprehensive drought disaster risk dynamic evaluation based on projection pursuit clustering. Water Policy, 20(2), 410-428. https://doi.org/10.2166/wp.2018.010

A2 Exposure and vulnerability indicators

Appendix A2 provides an overview of factors and indicators (exposure, vulnerability) that were identified from the review. These are complemented with potential proxy indicators (where additional sources based on expert knowledge where consulted).

Table A2.1: Exposure factors and indicators (incl. potential proxy indicators)

Factors (from review)	Indicator (from review)	Proxy indicators	Source (review)
People	Farmers & laborers in drought-prone areas (#, %)	Population density in drought-prone areas	Asare-Kyei et al. 2017; Carrao et al. 2016; De Waal et al. 2006; Fontaine & Steinmann 2009; Gil-Guirado et al. 2016; Gonzales et al. 2016; Hill & Porter 2017; Keil et al. 2009; Lindoso et al. 2014; Liu et al. 2013; Panda 2017; Pei et al. 2016; Saleh et al. 2012; Sam 2017; Sena et al. 2017; Tingting et al. 2014; Wittrock et al. 2011; Wu et al. 2017a; Xenarios et al. 2016; Yaduvanshi et al. 2015; Yuan et al. 2013; Zhang et al. 2015; Reardon 1989; Mohmmed et al. 2018; Mogotsi 2012; Naumann 2014; Pei 2018; Shahid-Behrawan 2008; Villholth 2013; Wu 2013; Dumitrascu et al. 2018; Bhavani 2017
Livestock	Livestock in drought-prone areas (#, %)	Livestock density	Ayantunde et al. 2015; Guimire et al. 2010; Carrao et al. 2016; Villholth 2013; Dabanli 2018
Agricultural land	Agricultural land in drought-prone areas (km^2, %)	n/a	Asare-Kyei et al. 2017; Carrao et al. 2016; De Waal et al. 2006; Fontaine & Steinmann 2009; Gil-Guirado et al. 2016; Gonzales et al. 2016; Hill & Porter 2017; Keil et al. 2009; Lindoso et al. 2014; Liu et al. 2013; Panda 2017; Pei et al. 2016; Saleh et al. 2012; Sam 2017; Sena et al. 2017; Tingting et al. 2014; Wittrock et al. 2011; Wu et al. 2017a; Xenarios et al. 2016; Yaduvanshi et al. 2015; Yuan et al. 2013; Zhang et al. 2015; Dabanli 2018

Table A2.2 Vulnerability factors and indicators (incl. potential proxy indicators)

Sub-dimension	Factors (from review)	Indicator (from review)	Proxy indicators	Source (review)
Social dimension				
Education	Education / illiteracy	Illiteracy rate (%)	Education (years); literacy rate (%); lack of investment in education; expenditure on education (%); adults without primary education (%); households having below primary education (%); Science higher education level; Children dropping out of school	Alcamo et al. 2008; Ayantunde et al. 2015; Etemadi & Karami 2016; Carrao et al. 2016; Debela et al. 2015; Hill & Porter 2017; Muyambo et al. 2017; Keshavarz et al. 2017; Kurosaki 2015; Lindoso et al. 2014; Mohammed et al. 2018; Nelson & Finan 2009; Panda 2017; Sam 2017; Wittrock et al. 2011; Blauhut et al. 2016; Duinen et al. 2015; Ezra and Kiros 2000; Yaduvanshi et al, 2015; Antwi-Agyei et al. 2012; Zarafshani et al. 2012; Zhang et al. 2015; Asare-Kyei et al. 2017; Naumann 2014; Austin et al. 2018; Sun 2014; Villholth 2013; Wu 2013; Mohmmed et al. 2018; Nguyen 2009; Ortega-Gaucin 2018; DeSilva and Kawasaki 2018; Bhavani 2017
	Indigenous and local knowledge	People using local knowledge (%)	n/a	Muyambo et al. 2017; Asare-Kyei et al. 2017; Etemadi & Karami 2017
Gender	Gender	Female headed households (%)	Sex ratio; Females in labor force (%); female headed households (%); female literacy (%); Gender inequality index (categorical)	Alcamo et al. 2008; Guimire et al. 2010; Hill & Porter 2017; Asare-Kyei et al. 2017; Sam 2017; Kurosaki 2015; Zhang et al. 2015, De Waal et al. 2006; Etemadi & Karami 2016; Mogotsi 2012; Austin et al. 2018; Mthembu and Zwane 2017; Shahid-Behrawan 2008; Greene 2018
		Discrimination	Presence of stigma against women in public space; Discrimination in inheritance laws; Women excluded from development plans	Schroeder 1987
Social capital	Social capital	Social capital index (categorical)	Lack of social integration; Participation in organizations (%); Households whose heads are engaged in associations or unions (%); Refugees (% total population); Number of migrants; Sense of place scale; Sense of community index	Alcamo et al. 2008; McNeeley 2014; Etemadi & Karami 2016; Muyambo et al. 2017; Duinen et al. 2015; Guimire et al. 2010; Lindoso et al. 2014; Wittrock et al. 2011; Naumann 2014; Austin et al. 2018; Toni 2008
Health status	Restricted mobility / disability	Population with restricted mobility (%)	Receiving disability grant from government	Mthembu and Zwane 2017
	Malnutrition	Meals skipped per month (#);	Households with insufficient food for consumption in a year (%); Stunting children under age 5 (%); Mortality rate under 5; Food supply and consumption (grams per capita per day); Population undernourished (%); Access to nutritious food; Caloric intake per capita	Sam 2017; Asare-Kyei et al. 2017; Saha et al. 2012; Sena et al. 2014; Ahmadalipur 2018; Uexkull et al. 2016; Toni 2008; Nguyen 2009
	Mental health	Farmers/laborers with mental health issues (%)	Government expenditures on mental health (% of total government expenditures on health); People with depression, distress, anxiety, frustration, fear, and hopelessness (%)	Sena et al. 2014; Birhanu et al. 2017; Muyambo et al. 2017; Nguyen 2009

	Disease prevalence	Disease prevalence in population (fever, respiratory problems, water-borne, pneumonia, etc.) (%)	Population with ill-health (%); Incidence of Tuberculosis; Mortality rate under 5; Self-rated health	Saha et al. 2012; Ahmadalipur 2018; Austin et al. 2018; Nguyen 2009
	Life expectancy	Life expectancy	Life expectancy at birth	Ahmadalipur 2018; Naumann 2014
Health services	Health services	Physicians per 1,000 (#)	Hospital beds per 1,000 (#); Distance to closest hospital (km); Medical doctors per thousand inhabitants	Liu et al. 2013; Sena et al. 2014; Ortega-Gaucin 2018; Dumitrascu et al. 2018
		Average distance to public health center (km)	Population with access to health services (%); General government expenditure on health (%); Out-of-pocket expenditure on health (%); Population with access to urban health care (use)	Sam 2017; Saha et al. 2012;
	Health insurance	Households without a health insurance (%)	Total public and primary private health insurance (% of total population covered); Expenditures for health (USD/year)	Sam 2017; Alcamo et al. 2008; Ortega-Gaucin 2018
Remoteness	Rural / remote population	Rural population (% of total population)	Urbanization rate (%); Distance to town (minutes); Rural population 0-14 and 65+ (%); Travel time to closest city (mins); Land covered by ways of communications and railways (% of total land area); Ratio of urban to rural area	Mohmmed et al. 2018; Simelton et al. 2009; Hill & Porter 2017; Gil-Guirado et al. 2016; Carrao et al. 2016; Yuan et al. 2013; Dumitrascu et al. 2018; Mogotsi 2012; Naumann 2014
Awareness & information	Drought awareness	People who attended drought meeting (%)	Households that have not attended any disaster preparedness training (%), Catastrophic events in last ten years (#); Population who has experienced hazard(s) in the past 10 years (%)	McNeeley 2014; Etemadi & Karami 2017; Blauhut et al. 2016
	Access to information	People that received drought information (%)	Households with access to one of the following (%): Radio, TV, mobile phones, internet access (max. value of the four used); ICT Development Index; Access to information during drought periods (qualitative); Existence of early warning systems (yes/no); Level of progress in EWS according to UNISDR; Households who previously received EW messages (%); Availability of a functioning drought early warning system (yes/no)	Liu et al. 2013; Eriksen & Silva 2009; Etemadi & Karami 2016; Wittrock et al. 2011; Mogotsi 2012; Mthembu and Zwane 2017
	Underestimation of drought risk	Drought risk perception (qualitative)	Perception of future drought impact; Farm revenue (higher = more aware = more likely to cope/adapt);	Duinen et al. 2015; Etemadi & Karami 2016; Liu et al. 2013

			Participating in extension classes related to coping with drought (%)	
Water demand, quality	Water demand	Demand coverage of water use (%)	Freshwater scarcity; Freshwater withdrawal rate as % of total renewable water resources; Baseline Water Stress (ratio of withdrawals to supply); Annual freshwater withdrawals, total (billion cubic meters); water consumption (/L)	Wilhelmi & Wilhite 2002; Rajsekhar et al. 2015; Yuan et al. 2013; Carrao et al. 2016; Zarafshani et al. 2012, Blauhut et al. 2016; Hill & Polsky 2007; Sun 2014
Economic dimension				
Poverty & income	Income diversification	Population with alternate food and income sources (%)	Contribution of agriculture to GPD (%); Agriculture, value added (% of GDP); GDP from agr. forestry and fishing, Employment diversification (%); Main source of income; Dependency on agriculture for livelihood (%); Households depending on own farm for food (%); Agricultural value added/GDP %; Inability to engage in secondary occupations; Economy proportion from easy-drought farmland; Livestock ownership	Kurosaki 2015; Pei et al. 2016; Carrao et al. 2016; Simelton et al. 2009; Alcamo et al. 2008; Sam 2017; Panda 2017; Mohmmed et al. 2018; Lindoso et al. 2014; Liu et al. 2013; Keshavarz et al. 2017; Sam 2017; Etemadi & Karami 2016; Zarafshani et al. 2012; Nelson & Finan 2009; Guimire et al. 2010; Panda 2017; Mogotsi 2012; Naumann 2014; Mthembu and Zwane 2017; Uexkull et al. 2016; Pei 2018; Schroeder 1987; Toni 2008; Sun 2014; Wu 2013; Yuan 2015; Mohmmed et al. 2018; Nguyen 2009; Dumitrascu et al. 2018; Fan 2017; Greene 2018; Bhavani 2017; Chen et al. 2017
	Poverty	Population below national poverty line (%)	Poverty headcount ratio at national poverty lines (% of population); Population below 1.9 US$ per day (%);Population living below USD 1.25 PPP per day (%); asset-based poverty index; GDP per capita, PPP (current international $); Average regional GDP; Average annual household income (US$); Rural per capita income; Poverty gap total, ratio; Receiving pension from private employer; receiving child support grant; receiving remittances; cattle/livestock ownership; Landless household percentage; Dependence on food aid	Carrao et al. 2016; Sena et al. 2014; Saleh et al. 2012; Panda 2017; Gil-Guirado et al. 2016; Keil et al. 2009; Antwi-Agyei et al. 2012; Asare-Kyei et al. 2017; Nelson & Finan 2009; Birhanu et al. 2017; Etemadi & Karami 2016; Blauhut et al. 2016; Naumann 2014; Mthembu and Zwane 2017; Uexkull et al. 2016; Pei 2018; Reardon 1989; Shahid-Behrawan 2008; Toni 2008; Wu 2013; Mohmmed et al. 2018; Zhang 2011; Ortega-Gaucin 2018; DeSilva and Kawasaki 2018; Greene 2018; Deng et al. 2018; Ahmadalipur 2018; Mohmmed et al. 2018; ; Fan 2017; Mogotsi 2012; Naumann 2014; Reardon 1989; Fan 2017
	Unemployment	Population without employment (%)	Unemployed people per household (%); Unemployment, total (% of total labor force); Employee in permanent, temporary, or casual job; Lack of job opportunities	Keshavarz et al. 2017; Mdungela et al. 2017; Austin et al. 2018; Mthembu and Zwane 2017; Schroeder 1987; Nguyen 2009; Dumitrascu et al. 2018; DeSilva and Kawasaki 2018; Greene 2018; Ahmadalipur 2018
	Problematic debt	Farmers/laborers struggling to pay debt (%)	Household debt Total (% of net disposable income)	Mdungela et al. 2017; Alcamo et al. 2008; Saha et al. 2012
	Dependency ratio	Dependency ratio (%)	Children < 5 years (%); Population in retirement (%); Population 0-14 and 65+ years (%), Household dependency ratio (%); Dependents per household	Asare-Kyei et al. 2017; Panda 2017; Zhang et al. 2015; Alcamo et al. 2008; Muyambo et al. 2017; Guimire et al. 2010; Krömker et al. 2008; Sam 2017; Kurosaki 2015; Gil-Guirado et al., 2016; Muyambo et al., 2017; Keshavarz et al., 2017; Carrao et al. 2016; Mthembu and Zwane

			(#); Receiving old-age grant from government; Dependence on child labor	2017; Schroeder 1987; Ncube 2018; Austin et al. 2018; Mthembu and Zwane 2017; Reardon 1989; Dumitrascu et al. 2018; DeSilva and Kawasaki 2018; Greene 2018
Inequality	Inequality	Economic inequality (qualitative)	GINI index	Sam 2017; Carrao et al. 2016; DeSilva and Kawasaki 2018
Savings, credits & loans	Savings	Farmers having an account in the nearest rural banks (%)	Saving rate total (% of GDP); Saved any money in the past year, income, poorest 40% (% ages 15+); Saved for emergencies, income, poorest 40% (% ages 15+); Farmers/laborers without savings (%); Amount of cash assets saved by household (USD); Small dowries; Forced sale of livestock	Liu et al. 2013; Birhanu et al. 2017; Keshavarz et al. 2017; Mdungela et al. 2017; Schroeder 1987; Mogotsi 2012; Nguyen 2009; Bhavani 2017
	Credit/loans	People with access to credits (%)	Population (age 15+) who has not borrowed any money in the last year (%); Account ownership at a financial institution or with a mobile-money-service provider (% of population ages 15+); Credit to Agriculture; Farmers/labourers without access to bank loans / (micro-) credits (%); Per Capita Savings Deposit; Lack of investment capital	Sam 2017; Birhanu et al. 2017; Etemadi & Karami 2016; Kurosaki 2015; Panda 2017; Mohmmed et al. 2018; Zarafshani et al. 2012; Barbier et al. 2009; Liu et al. 2013; Schroeder 1987; Ortega-Gaucin 2018; Jülich 2019
Markets	Access to markets	Distance to closest market (km)	Travel time to closest city (km); Density of markets per 100,000; density of settlement points; Market concentration of up to top 5 (%); Nearest urban market (km)	Hill & Porter 2017; Kurosaki 2015; Mohmmed et al. 2018; Asare-Kyei et al. 2017; Mdungela et al. 2017; Ayantunde et al. 2015; Guimire et al. 2010; Bhavani 2017
	Market fragility	Price sensitivity (%)	Producer Price Index; Producer protection (Total, Ratio); Food price fluctuations; Commodity retail price index	Mdungela et al. 2017; Sena et al. 2014; Zarafshani et al. 2012; Ncube 2018
		Consumer price index	Production value (R$)	Smucker & Wisner 2008;
Insurance (excl. health insurance)	Agricultural / Animal / crop / drought insurance	Farmers with crop/drought insurance (%)	Agricultural insurance coverage (%), Total gross premiums (non-life insurance); Insurance indicators (US dollar, millions); Micro insurance penetration (%); Membership in the Sovereign Catastrophe Risk Pools CCRIF, ARC, PCRAFI	Mohmmed et al. 2018; Panda 2017; Zarafshani et al. 2012; Mdungela et al. 2017
		Farmers with animal insurance (%)	Vaccination doses used (%) (could be chosen the species)	Birhanu et al. 2017
Physical dimension				

Infrastructure	Transportation	Rail & road density (km/km2) per 10,000	Rail lines (total route-km); Damage in transport communications (%); ; Access to transportation network; Road density (km of road per 100 sq. km of land area); Distance from the main road (km)	Simelton et al. 2009; Carrao et al. 2016; Saha et al. 2012; Gil-Guirado et al. 2016; Keshavarz et al. 2017
	Quality of infrastructure	Poor infrastructure (qualitative)	Investment in physical infrastructure (energy, roads, etc.) (USD); Existence of infrastructure; Households with dirt floor	Nelson & Finan 2009; Saha et al. 2012; Etemadi & Karami 2016; Naumann 2014; Ortega-Gaucin 2018
	Energy	Electricity and fuel access	Access to clean fuels for cooking; Household has electricity (%); Energy use	Ahmadalipur 2018; Naumann 2014
	Water & Sanitation	Water treatment volume/ urban water supply volume	Households without access to waste/water treatment (%); Households without access to sewage drainage system (%); Population without access to (improved) sanitation (%); The built-up area density of sewer (km/resources km2)	Hill & Porter 2017; Lindoso et al. 2014; Neri & Magana 2016; Neri & Magana 2016; Ahmadalipur 2018; Ncube 2018; Ortega-Gaucin 2018
		Population with access to clean water (%)	Water stress index; Improved water source (% of population with access); Total population supplied by water supply industry; Renewable internal freshwater resources per capita (cubic meters); Population that can obtain at least 20 liters per person per day from an “improved” source that is within one kilometer of the user’s dwelling (%); Distance to drinking water source; Rate of groundwater resources; Households without running water; Total length of drinking water supply network	Gil_Guirado et al. 2016; Rajsekhar et al. 2015; Jain et al. 2015; Asare-Kyei et al. 2017; Blauhut et al. 2016; Hill & Polsky 2007; Duinen et al. 2015; Sam 2017; Wittrock et al. 2011; Zarafshani et al. 2012; Fontaine & Steinmann 2009; Sena et al. 2014; Birhanu et al. 2017; Asare-Kyei et al. 2017; Deng et al. 2018; Dumitrascu et al. 2018; Villholth 2013; Wu 2013; Ortega-Gaucin 2018; Dumitrascu et al. 2018; Blauhut 2015
	Water tanks / reservoirs/ wells (public & private)	Total dam capacity km3	Volume of water storage in a safe reservoir/container (m3); Average dam yields and projected supply percentages according to river basin; Reservoir storage capacity	Blauhut et al. 2016; Pei 2018; Deng et al. 2018
	Water quality	Groundwater quality (qualitative score)	Area under fresh and marginal groundwater quality (%); Arsenic in groundwater (probability of occurrence); Groundwater quality; Wastewater treatment; Water quality of freshwater bodies; People using safely managed drinking water services (%); Water Quality Index; Population without access to improved water	Neri & Magana 2016; Hill & Polsky 2007; Sena et al. 2014; Duinen et al. 2015; Palchaudhuri-Biswas 2016; Nguyen 2009; Blauhut 2015; Naumann 2014; Zhang 2011

		Crime & conflict dimension		
Stability	Crime	Stock theft (%)	Crime and Theft, Index (0-30)	Muyambo et al. 2017
	War & conflict	Water conflicts (%)	Fatalities caused by terrorists per 10,000 (# per year); Homicide rate per 100,000 inhabitants; temporal dependence in conflict risk; at least one other ethnic group in the same country engaged in armed conflict against the state during the previous year; increased conflicts over water use; social disputes	Smucker & Wisner 2008; Ezra and Kiros 2000; Alcamo et al. 2008; Uexkull et al. 2016; Nguyen 2009
		Governance dimension		
Plans & strategies	Drought planning and investment in disaster prevention and preparedness	Disaster Prevention & Preparedness (US$/Year/capita)	Drought governance & management frameworks (qualitative); Availability of drought plans in the community and preparedness strategies for drought (qualitative); Lack of involvement in drought mitigation planning	Muyambo et al. 2017; Asare-Kyei et al. 2017; Carrao et al. 2016; Wittrock et al. 2011; Ncube 2018
	Water management planning	River basin management plans (yes/no);	Programs to bring water to new populations (#); Existence of flexible adaptive water use policies (yes/no); Existence of an emergency management committee (yes/no)	Carrao et al. 2016; Blauhut et al. 2016; Gil-Guirado et al. 2016; McNeeley 2014; Asare-Kyei et al. 2017
Corruption & law enforcement	Corruption	Level of corruption (Rank)	Failed States Index; WGI Corruption Percentile Rank; Corruption Perception Index (CPI); Political patronage and clientelism	Blauhut et al. 2016; Alcamo et al. 2008; Toni 2008
	Law enforcement	Law enforcement (qualitative)	Strength of legal rights index	Blauhut et al. 2016
Participation	Public participation in governance	Opportunities for participation (%)	Do ministries or regulatory agencies in your jurisdiction solicit comments on proposed (not yet adopted) regulations from the general public? (yes/no)	Alcamo et al. 2008; Blauhut et al. 2016; Naumann 2014
	Political representation	Functioning of government	QoG Index (EQI); Government Effectiveness: Percentile Rank; Ethnopolitical exclusion (Ethnic Power Relations database);	Etemadi & Karami 2016; Uexkull et al. 2016; Schroeder 1987
Assistance	Availability of food aid	Food aid (USD), per population	Lacking availability of food reserves (yes/no); Food for work programs (yes/no); Government support for seed supply (yes/no); Beneficiaries of social programs (%); Lack of technical assistance for farmers (%); Drought relief expenditure rate (%); Disaster relief capacity	De Waal et al. 2006; Barbier et al. 2009; Nguyen 2009; Ortega-Gaucin 2018; Deng et al. 2018

	Development projects (ODA)	Development projects of the government and NGOs (%)	Existence of integrated development plans: conservation, protection; land use planning (yes/no); Level in drought mitigation and response Research and development expenditure (% of GDP)	Muyambo et al. 2017
Environmental dimension				
Soil condition	Soil quality	Soil organic matter	Average carbon content in the topsoil as a % in weight (%); Area covered by "problem soils" (%); Thickness of the soil organic layer; Nutrient retention capacity; Nutrient availability; Soil organic carbon levels; Soil fertility (physical and chemical properties); Soil texture; Soil water holding capacity; Size of arable land	Asare-Kyei et al. 2017; Jain et al. 2015; Ayantunde et al. 2015; Boultif & Benmessaoud 2017; Palchaudhuri-Biswas 2016; Shahid-Behrawan 2008; Bhavani 2017; Mogotsi 2012
		Soil depth (mm)	Soil absorption rate; Return Flow Ratio; Average soil erosion; Annual losses of soil in t/ha from water erosion; soil drainage (%)	Jain et al. 2015; McNeeley 2014; Wilhelmi & Wilhite 2002
	Degradation / desertification	Degraded areas (%)	Vegetation Condition Index; Environmental Performance Index; Vegetation Health Index; Average land degradation in GLASOD erosion degree; Eroded surface; Loss of forests; Exhaustion of crop fields; Loss of biodiversity; Depletion of grasslands; Overexploitation of natural resources	Asare-Kyei et al. 2017; Ezra and Kiros 2000; Toni 2008; Nguyen 2009; Ortega-Gaucin 2018; Bhavani 2017
Protection & conservation	Protected areas	Protected biodiversity areas (%)	Area protected and designated for the conservation of biodiversity (%); Protected natural areas; Natural vegetation areas	Blauhut et al. 2016; Ortega-Gaucin 2018; Toni 2008
	Pest	Increased number of pests (per year)	Countries that had signed the pest free contract with FAO; Increased pests in livestock	Wittrock et al. 2011; Nguyen 2009
	Disease (plant / animal)	Plant diseases (%)	Livestock losses; Animal disease prevalence; Higher animal mortality rates; Lack of access to improved animal breeds; Lack of veterinary doctor	Toni 2008; Nguyen 2009
	Livestock health condition	Animal health care (%)	Veterinarians and veterinary para-professionals (# Personnel)	Birhanu et al. 2017
	Soil conservation practices	Indigenous soil conservation measures (qualitative)	Mitigation strategies that may be used to conserve soil resources under drought (#); Reforested surface (ha)	Keshavarz et al. 2017; Kanchebe Derbile 2013; Ortega-Gaucin 2018
	Water conservation practices	Households doing water-conservation practices (%)	Recycling irrigation water (#, %); Any water-saving strategy (#, %); Indigenous water conservation measures (qualitative); Mitigation strategies that may be used to conserve water resources under drought (#); Water consumption per unit GDP (m^3);	Panda 2017; Kanchebe Derbile 2013; McNeeley 2014; Keshavarz et al. 2017; Sun 2014; Nasrollahi 2018; Pei 2018; Yuan 2015

			Share of municipal, industrial and agricultural water consumption; Investments in water conservancy	
'Farming practices' dimension				
Technology	Access to farming technology	Agricultural machinery power per unit area (X12) (kWh ha-1)	Tractors per agricultural land (#); Agricultural machinery in use (#); Type of draught power; Investment in machinery/equipment (USD); Agricultural power consumption	Pei et al. 2016; Wu et al. 2017b; Ezra and Kiros 2000; Guimire et al. 2010; Alcamo et al. 2008; Liu et al. 2013; Mogotsi 2012; Toni 2008; Bhavani 2017; Bhavani 2017; Reardon 1989; Ahmadalipur 2018
		Number of people with access to technology (#)	Mobile cellular subscriptions; Secure internet services	Ahmadalipur 2018
	Irrigation	Irrigated land (%)	Cultivated area equipped for irrigation (%); Irrigation potential per 1000 hectares; Individual water use for irrigation index; Households without access to irrigation (%), crop area irrigated (%); Total of days irrigation available per year (#); Land non-irrigated (%); Rainfed smallholder farms (#, %)	Barbier et al. 2009; Keil et al. 2009; Vatsa 2006; Nelson & Finan 2009; Carrao et al. 2016; Mohmmed et al. 2018; Zhang et al. 2015; Yuan et al. 2013; Zarafshani et al. 2012; Gil-Guirado et al. 2016; Wu et al. 2017a; Pei et al. 2016; Guimire et al. 2010; Simelton et al. 2009; Alcamo et al. 2008; Wilhelmi & Wilhite 2002; Jain et al. 2015; Kim et al. 2015; Panda 2017; Zhang et al. 2015; Rajsekhar et al. 2015; Lindoso et al. 2014; Nasrollahi 2018; Naumann 2014; Shahid-Behrawan 2008; Chen et al. 2017; Sun 2014; Wu 2013; Yuan 2015; Kamruzzaman 2018; Kim 2018; Deng et al. 2018; Villholth 2013; Wu 2013; Zhang 2011; Nguyen 2009; Bhavani 2017; Dabanli 2018
	Use of agricultural inputs (fertilizer)	Fertilizer (ton)	Multi-nutrient fertilizers (Thousand metric tons); Fertilizers by nutrient (agricultural use); Fertilizer scalar unit area (ton ha-1); Fertilizer supply – percent of population within 10 km of supply sources	Simelton et al. 2009; Pei et al. 2016; Eriksen & Silva 2009; Mohmmed et al. 2018; Zarafshani et al. 2012; Barbier et al. 2009; Naumann 2014
	Fodder	Access to fodder (kg purchased per year)	Units of straw or fodder balers (including pickup balers); Fodder area (ha); Lack of fodder; Insufficient storage facilities for fodder	Saha et al. 2012; Birhanu et al. 2017; Toni 2008; Nguyen 2009; Zhang 2011
	Insecticide and pesticide use	Households that use insecticide and pesticide (%)	Insecticide and pesticide (he population within km to supply sources %); Total pesticide use; Tonnes of active ingredients of insecticides and pesticides used; High cost of pesticide; Percentage of households that use insecticide; Lack of access to integrated pest management practices	Mohmmed et al. 2018; Nguyen 2009
	Crop type (resistance)	Use of drought-resistant varieties (%)	Different crops yield by country; Drought resistant crops (%); Lack of access to drought, pest, and disease-tolerant crops	Panda 2017; Mohmmed et al. 2018; Mdungela et al. 2017; Zarafshani et al. 2012; Mogotsi 2012; Nguyen 2009
	Crop diversification	Crop diversity index (%);	Different crops yield by country; crop diversity - The inverse of (the number of crops grown by a	Panda 2017; Mohmmed et al. 2018; Asare-Kyei et al. 2017

			household +1); Farmers who use different crop varieties (%)	

A3 Risk concepts classified as “other”

Appendix A3 provides an overview of risk concepts that were classified as ‘other’ in Figure 2.2 of the manuscript (see also Figure A3.1 below). Authors are listed in alphabetical order.

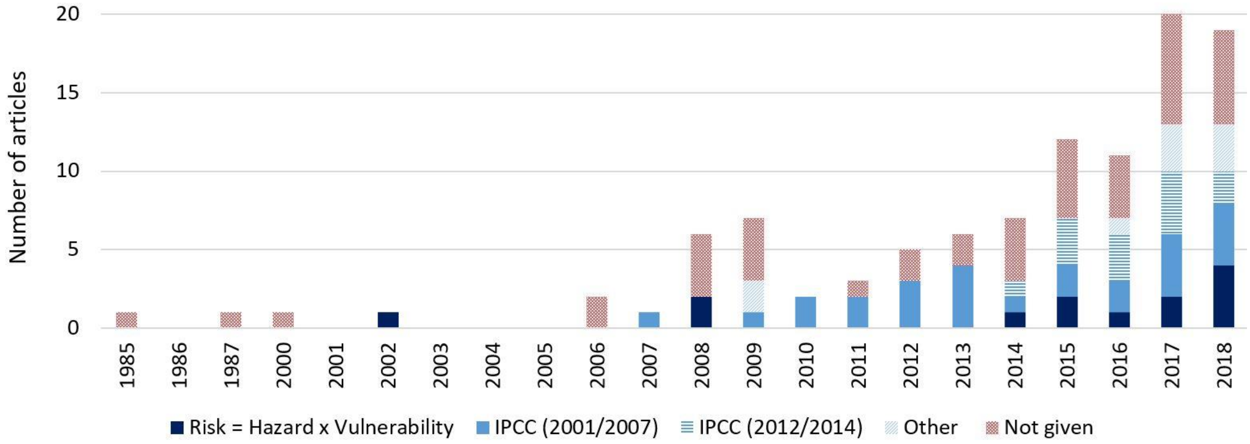


Figure A3.1: Risk definitions considered in the reviewed drought risk assessment articles (including trend over the years).

Table A3.1: Risk definitions classified as “other” in the reviewed drought risk assessment articles.

Authors	Risk definition used by the authors	Interpretation or equation
Chen et al. 2017	*“The comprehensive agricultural drought risk is defined as a composite function of dangerousness, sensitivity, and vulnerability based on the natural disaster system theory”* (page 2).	The occurrence of drought is due to dangerousness of hazard-formative factors, sensitivity of hazard-inducing environment, and vulnerability of hazard-affected bodies. The authors combine elements from different risk definitions taken from the IPCC’s 4th Assessment Report (IPCC 2007) and the UNISDR terminology on disaster risk (UNISDR 2017).
Chuah et al. 2018	*“The potential for consequences where something of value is at stake and where future outcomes are uncertain, recognizing the diversity of values.”* (page 1)	The authors draw on the first part of the risk definition of the IPCC 5th Assessment Report (IPCC 2014), but then does not include exposure, hazard and vulnerability. Instead risk is seen as an outcome and does not have a clear definition.
Deng et al. 2018	*“Agricultural drought risk is the comprehensive results of pressure, state, and response (PSR)”* (page 17)	The authors build on a modified version of the DPSIR framework (Driving forces, Pressures, States, Impacts and Responses) to characterize and assess drought risk. The purpose of the PSR is to analyze the interactions between environmental pressures, the state of the environment and environmental responses (OECD, 2004)
Gil_Guirado et al. 2016	*“The evolution of four key factors in risk processes: perception of the agents responsible for the impact, natural hazard perception, vulnerability and strategy of adaptation and resilience”* (page 187)	The authors mix different concepts (vulnerability, adaptation, resilience) to assess drought risk. *Perceptual Index for Changes in Climate Risk = Dangerous perception + global vulnerability + resilience and adaptation strategy.*
Keil et al. 2009	*“Risk as stochastic simulation of crop production”* (page 158)	Risk is the result of combining a linear programing model (which identifies suitable crop management strategies for different climate scenarios and compares them with

		observed farmers' practices) with stochastic simulation of random yield fluctuations. Hence, risk is defined as an outcome.
Mdungela et al. 2017	*"We first identified each municipality's economic vulnerability indicators for drought using the BBC (Bogardi, Birkman, Cardona) framework"* (page 1054)	According to the BBC model, which builds on Wisner et al. (2004) risk is a function of hazard and vulnerability. Vulnerability is a function of exposed and vulnerable elements including their coping capacity.
Simelton et al. 2009	*"Food security framework that links local-level exposure to a risk with the capacity of members of a community to adapt to that risk, and the potential of the problem to have severe consequences at a range of scales"* (page 440)	The authors integrate exposure, adaptive capacity and impact to assess risk: *Risk = Exposure x adaptive capacity x Impact*
Wu et al. 2017	*"The higher the degree of exposure, the more probable it is that agricultural risk may happen; thus, the higher the vulnerability value is"* (page 4)	Risk is largely driven by exposure (hazard-centric).
Zhang, 2011	*"Agricultural drought risk in terms of drought dangerousness, vulnerability, exposure and drought-resistibility"* (page 169)	The risk is assessed through variable fuzzy sets model using the drought dangerousness, vulnerability, exposure and drought-resistibility as variables.

Appendix B

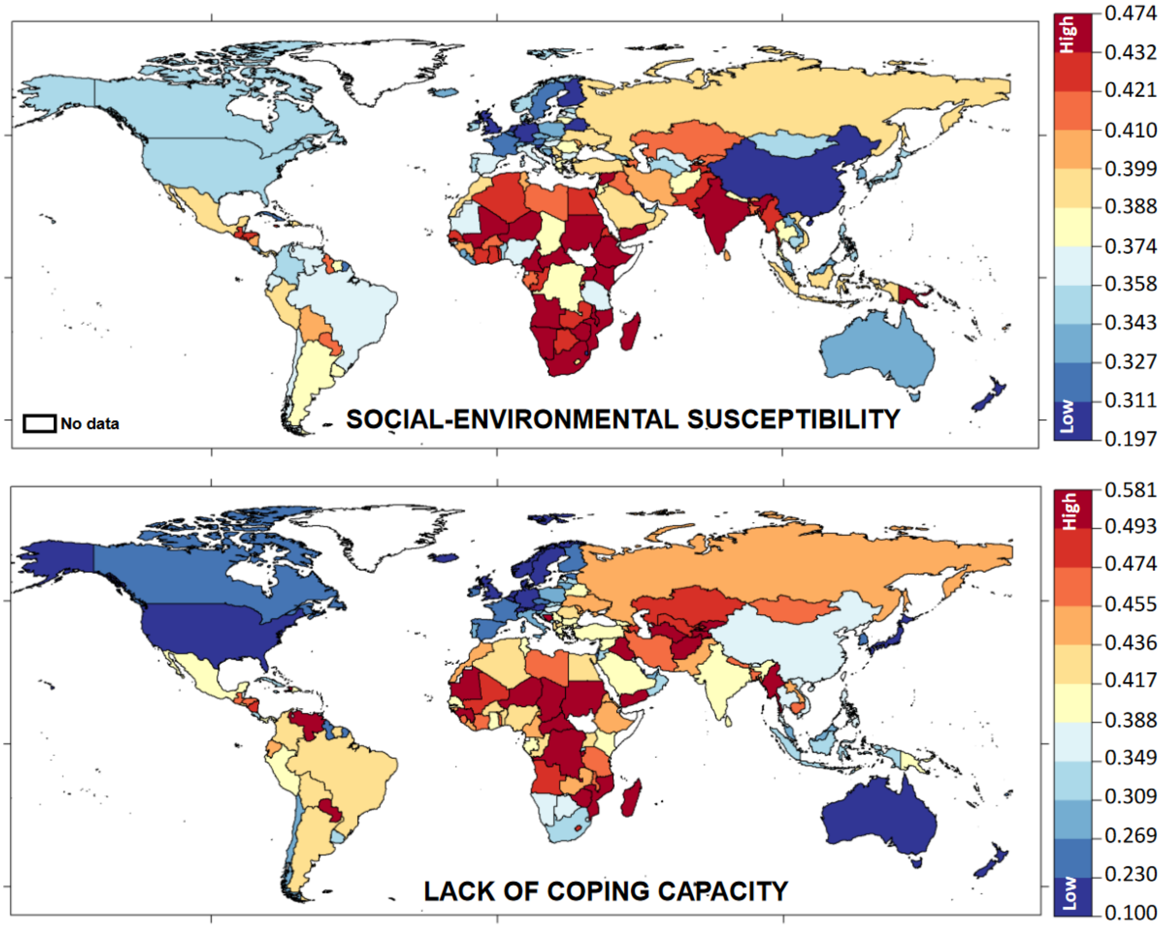


Figure B1. Social-environmental susceptibility and lack of coping capacity by country

Table B2. Final indicators for the vulnerability assessment and their respective code

Indicator	CODE
Social susceptibility (SOC_SUS)	
Prevalence of conflict/insecurity	C_STA1
Dependency ratio (Population ages 15-64 (% of total population))	E_DEP
Unemployment, total (% of total labor force) (national estimate)	E_EMP
Share of GDP from agr., forestry and fishing in US$ (%)	E_INC
GINI index	E_INQ
Proportion of population living below the national poverty line (%)	E_POV
Insecticides and pesticides used (ton/ha)	F_INPE
Electricity production from hydroelectric sources (% of total)	P_ELE
Population using at least basic sanitation services (%)	P_W&S2
Access to improved water sources (% of total population with access)	P_W&S1
DALYs (Disability-Adjusted Life Years)(DALYs per 100,000, Rate)	S_DISP
Literacy rate, adult total (% of people ages 15 and above)	S_EDU
Gender Inequality Index	S_GNDR
Healthy life expectancy (HALE) at birth (years)	S_LEB
Prevalence of undernourishment (% of population)	S_NUT
Rural population (% of total population)	S_RUR
Ecological susceptibility (ECO_SUS)	

Average land degradation in GLASOD erosion degree	E_DEGR
Terrestrial and marine protected areas (% of total territorial area)	E_PROA
Average soil erosion	E_SOIL2
Fertilizer consumption (kilograms per hectare of arable land)	F_FERT
Lack of coping capacity (COP)	
Saved any money in the past year (% age 15+)	E_SAV
Corruption Perception Index (CPI)	G_CORP
Government Effectiveness: Percentile Rank	G_REP
Total renewable water resources per capita (m3/inhab/year)	P_RW
Travel time to cities ≤30 min (population) (%)	P_TRNS
Total dam storage capacity per capita. Unit: m3/inhab	P_WAT

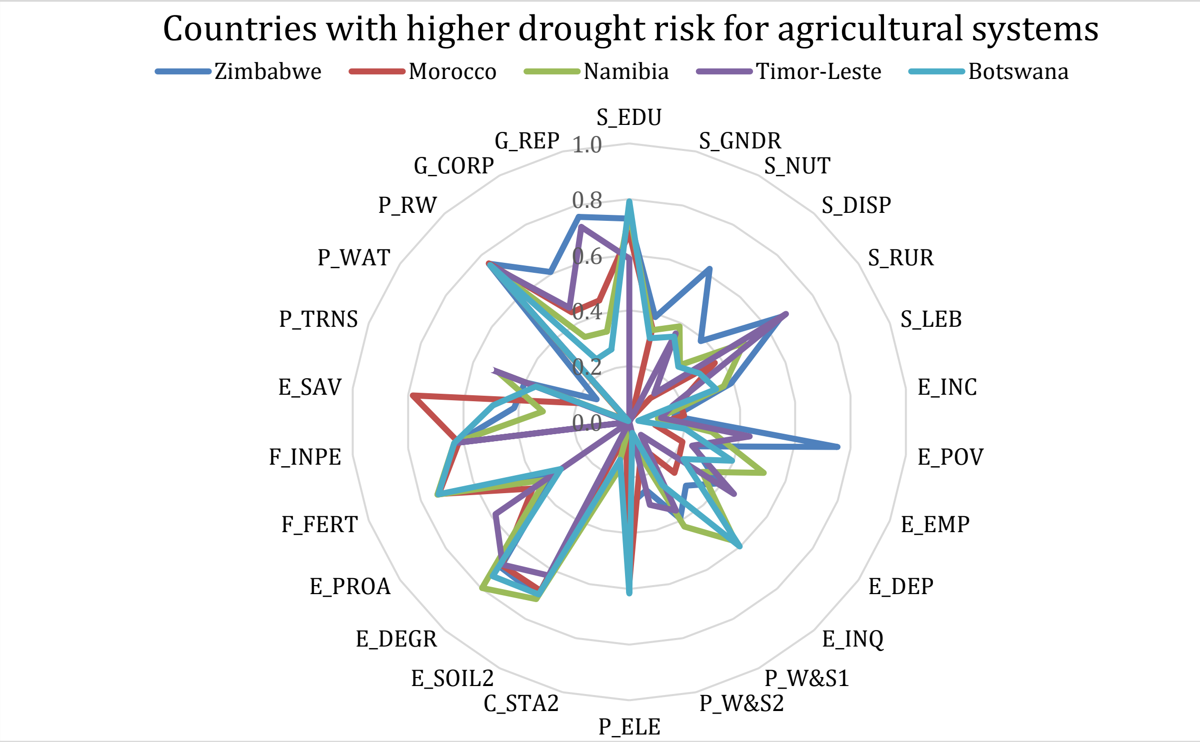


Figure B3. Weighted normalized vulnerability indicators scores for the five countries with highest drought risk for combined agricultural systems (irrigated and rain-fed)

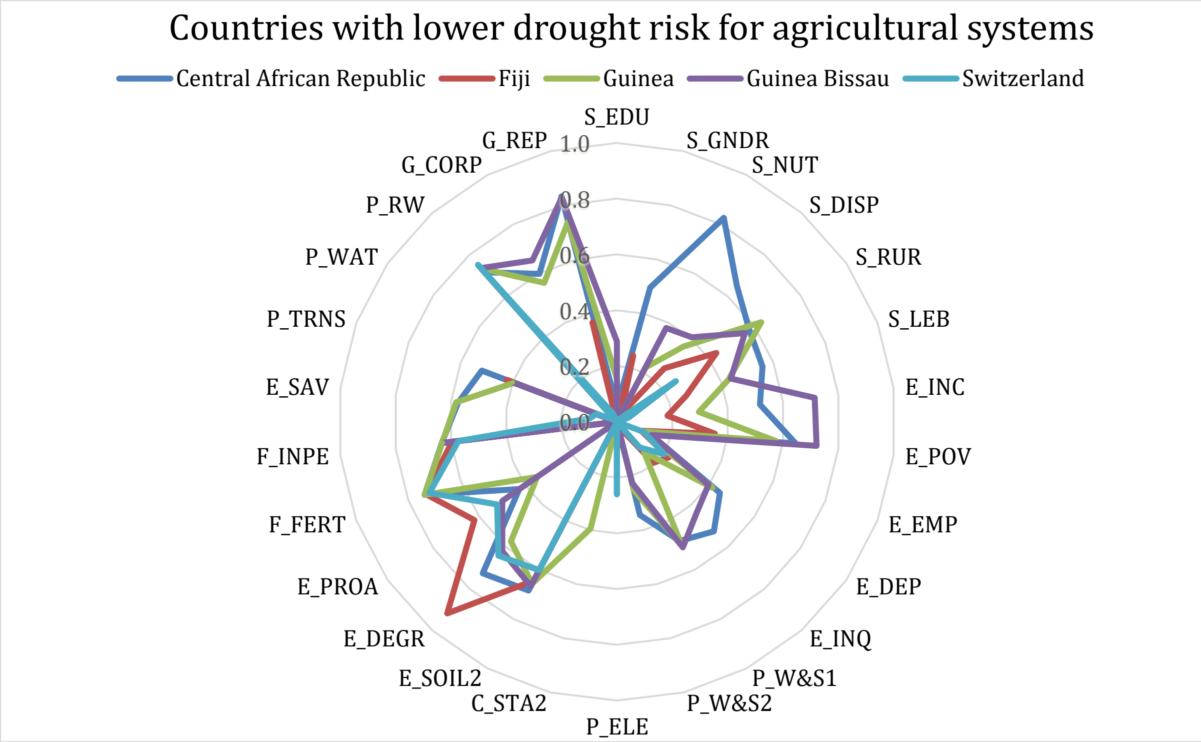


Figure B4. Weighted normalized vulnerability indicators scores for the five countries with lowest drought risk for combined agricultural systems (irrigated and rain-fed).

Table B5. Number of grid cells and harvested area of rainfed crops for the thresholds 10%, 20% and 50% for the deviation of the annual ratio AET/PET from the long-term median of the ratio AET/PET in different percentile classes. A percentile of 0.01 means that such an event can be expected every 100 years, a percentile of 0.5 means that such an event can be expected every 2 years.

	10		20		50	
Percentile	**Grid cells**	**Harv. Area (%)**	**Grid cells**	**Harv. Area (%)**	**Grid cells**	**Harv. Area (%)**
0	3997	7.15	11877	28.44	32265	91.80
< 0.01	4611	8.47	13137	32.12	33280	94.14
<0.02	5450	10.85	14823	37.23	34172	96.26
<0.05	7730	17.17	19082	50.89	35639	98.94
<0.10	11115	26.62	24384	69.66	36495	99.76
<0.20	19119	51.09	31656	91.09	37095	99.96
<0.30	28461	81.17	35785	98.87	37241	100.00
<0.50	37195	99.96	37264	100.00	37265	100.00

Appendix C

C.1 Multicollinearity Analysis for **Social Susceptibility.**

		S_AGRI	S_CHI	S_CON	S_AGE	S_DRI	S_SEC	S_ELE	S_EMP	S_FEM	S_FOO	S_GIN	S_HEA	S_HIV	S_INC	S_INF	S_LIT	S_MAR	S_MAS	S_MAT	S_MOR	S_POV	S_RUR	S_TOI
S_AGRI	Correlation Coefficient	1.000	0.169	-0.021	.273*	- 0.255	-0.124	.440**	-.374**	-0.070	-.311*	- .414**	-0.028	- .480**	0.190	-0.068	-.306*	.398**	.455**	-0.048	.416**	0.083	.470**	0.057
	Sig. (2-tailed)		0.216	0.877	0.044	0.058	0.364	0.001	0.007	0.607	0.021	0.002	0.836	0.000	0.160	0.621	0.022	0.002	0.000	0.727	0.001	0.542	0.000	0.675
	N		55	56	55	56	56	56	50	56	55	56	56	56	56	56	56	56	56	56	56	56	56	56
S_CHI	Correlation Coefficient		1.000	-0.169	.629**	- 0.125	0.074	.315*	-.418**	.610**	-0.242	-0.140	-0.155	0.074	- 0.023	0.025	-0.096	0.205	-.367**	0.201	-0.126	0.018	0.151	0.111
	Sig. (2-tailed)			0.208	0.000	0.353	0.585	0.018	0.002	0.000	0.073	0.298	0.249	0.590	0.864	0.853	0.477	0.127	0.005	0.133	0.349	0.895	0.262	0.410
	N			57	55	57	57	56	51	57	56	57	57	56	57	57	57	57	57	57	57	57	57	57
S_CON	Correlation Coefficient			1.000	-0.091	0.114	0.047	-0.223	0.176	-0.209	0.065	0.042	-0.057	- 0.087	0.251	-0.154	0.057	-0.079	0.162	0.004	0.045	0.083	0.229	-0.147
	Sig. (2-tailed)				0.503	0.394	0.725	0.096	0.213	0.116	0.628	0.757	0.669	0.519	0.057	0.247	0.673	0.557	0.223	0.978	0.737	0.534	0.084	0.272
	N				56	58	58	57	52	58	57	58	58	57	58	58	58	58	58	58	58	58	58	58
S_AGE	Correlation Coefficient				1.000	- .618**	-.397**	.506**	-.532**	.551**	0.005	- .486**	0.228	0.118	- 0.182	.362**	-.523**	.431**	-.293*	.277*	-.315*	.374**	0.198	.352**
	Sig. (2-tailed)					0.000	0.002	0.000	0.000	0.000	0.971	0.000	0.091	0.391	0.180	0.006	0.000	0.001	0.028	0.038	0.018	0.004	0.144	0.008
	N					56	56	55	50	56	55	56	56	55	56	56	56	56	56	56	56	56	56	56
S_DRI	Correlation Coefficient					1.000	.473**	- .645**	0.258	-0.213	-0.206	.382**	-.401**	- 0.040	0.219	-.471**	.642**	-.588**	0.020	-0.128	0.206	-.445**	-0.026	-.373**
	Sig. (2-tailed)						0.000	0.000	0.065	0.108	0.125	0.003	0.002	0.770	0.099	0.000	0.000	0.000	0.881	0.339	0.121	0.000	0.846	0.004
	N						58	57	52	58	57	58	58	57	58	58	58	58	58	58	58	58	58	58
S_SEC	Correlation Coefficient						1.000	-.280*	.279*	0.167	-.318*	.303*	-.475**	0.043	0.246	-.314*	.709**	-.573**	-0.202	-0.091	0.223	-.430**	-0.094	-0.148
	Sig. (2-tailed)							0.035	0.045	0.209	0.016	0.021	0.000	0.753	0.062	0.016	0.000	0.000	0.128	0.498	0.092	0.001	0.482	0.268
	N							57	52	58	57	58	58	57	58	58	58	58	58	58	58	58	58	58
S_ELE	Correlation Coefficient							1.000	-0.087	.299*	-0.048	-.330*	0.237	0.028	- 0.120	.300*	-.560**	.462**	-0.026	0.196	-0.040	0.199	-0.088	0.251
	Sig. (2-tailed)								0.544	0.024	0.725	0.012	0.076	0.833	0.373	0.023	0.000	0.000	0.851	0.145	0.769	0.137	0.516	0.060
	N								51	57	56	57	57	57	57	57	57	57	57	57	57	57	57	57
S_EMP	Correlation Coefficient								1.000	-.317*	0.042	.487**	0.105	0.205	- 0.046	0.032	0.228	-0.253	0.116	-0.169	0.082	-0.214	-.303*	0.088
	Sig. (2-tailed)									0.022	0.772	0.000	0.461	0.148	0.744	0.822	0.104	0.070	0.413	0.232	0.563	0.127	0.029	0.534
	N									52	51	52	52	51	52	52	52	52	52	52	52	52	52	52
S_FEM	Correlation Coefficient									1.000	-0.110	-0.117	-0.043	0.243	- 0.076	0.104	-0.020	-0.047	-.579**	.319*	-.299*	-0.042	0.025	0.083
	Sig. (2-tailed)										0.415	0.380	0.747	0.068	0.573	0.438	0.880	0.729	0.000	0.015	0.023	0.753	0.851	0.534
	N										57	58	58	57	58	58	58	58	58	58	58	58	58	58
S_FOO	Correlation Coefficient										1.000	-0.110	0.156	.268*	- 0.123	0.182	-0.176	0.034	-0.140	0.050	-0.232	.354**	-.263*	0.093
	Sig. (2-tailed)											0.417	0.245	0.046	0.363	0.175	0.190	0.801	0.299	0.709	0.082	0.007	0.048	0.490
	N											57	57	56	57	57	57	57	57	57	57	57	57	57
S_GIN	Correlation Coefficient											1.000	0.008	0.233	-.290*	-0.029	.363**	-.377**	-0.135	-0.018	-0.036	-.563**	-0.244	-0.138
	Sig. (2-tailed)												0.951	0.082	0.027	0.826	0.005	0.004	0.312	0.893	0.789	0.000	0.065	0.300
	N												58	57	58	58	58	58	58	58	58	58	58	58
S_HEA	Correlation Coefficient												1.000	.308*	- .730**	.685**	-.523**	0.242	-0.132	0.131	-.457**	.320*	-0.246	.479**
	Sig. (2-tailed)													0.020	0.000	0.000	0.000	0.068	0.323	0.327	0.000	0.014	0.063	0.000
	N													57	58	58	58	58	58	58	58	58	58	58

		S_AGRI	S_CHI	S_CON	S_AGE	S_DRI	S_SEC	S_ELE	S_EMP	S_FEM	S_FOO	S_GIN	S_HEA	S_HIV	S_INC	S_INF	S_LIT	S_MAR	S_MAS	S_MAT	S_MOR	S_POV	S_RUR	S_TOI
S_HIV	Correlation Coefficient													1.000	-.357**	0.239	0.109	-.379**	-.736**	.457**	-.490**	0.003	-.575**	0.215
	Sig. (2-tailed)														0.006	0.073	0.418	0.004	0.000	0.000	0.000	0.983	0.000	0.109
	N														57	57	57	57	57	57	57	57	57	57
S_INC	Correlation Coefficient														1.000	-.631**	.261*	-0.128	.373**	-0.110	.512**	-0.153	.479**	-.490**
	Sig. (2-tailed)															0.000	0.048	0.337	0.004	0.413	0.000	0.253	0.000	0.000
	N															58	58	58	58	58	58	58	58	58
S_INF	Correlation Coefficient															1.000	-.447**	.342**	-.286*	0.044	-.397**	.288*	-.423**	.457**
	Sig. (2-tailed)																0.000	0.009	0.030	0.745	0.002	0.028	0.001	0.000
	N																58	58	58	58	58	58	58	58
S_LIT	Correlation Coefficient																1.000	-.756**	-0.139	-0.088	.304*	-.470**	-0.127	-.405**
	Sig. (2-tailed)																	0.000	0.299	0.510	0.020	0.000	0.343	0.002
	N																	58	58	58	58	58	58	58
S_MAR	Correlation Coefficient																	1.000	.328*	0.028	-0.045	.418**	0.198	0.138
	Sig. (2-tailed)																		0.012	0.832	0.736	0.001	0.137	0.303
	N																		58	58	58	58	58	58
S_MAS	Correlation Coefficient																		1.000	-.384**	.596**	-0.035	.429**	-0.223
	Sig. (2-tailed)																			0.003	0.000	0.793	0.001	0.092
	N																			58	58	58	58	58
S_MAT	Correlation Coefficient																			1.000	-0.137	-0.031	-0.160	-0.036
	Sig. (2-tailed)																				0.306	0.817	0.231	0.789
	N																				58	58	58	58
S_MOR	Correlation Coefficient																				1.000	-.271*	0.251	-.431**
	Sig. (2-tailed)																					0.040	0.057	0.001
	N																					58	58	58
S_POV	Correlation Coefficient																					1.000	0.016	.383**
	Sig. (2-tailed)																						0.904	0.003
	N																						58	58
S_RUR	Correlation Coefficient																						1.000	-0.110
	Sig. (2-tailed)																							0.413
	N																							58
S_TOI	Correlation Coefficient																							1.000
	Sig. (2-tailed)																							

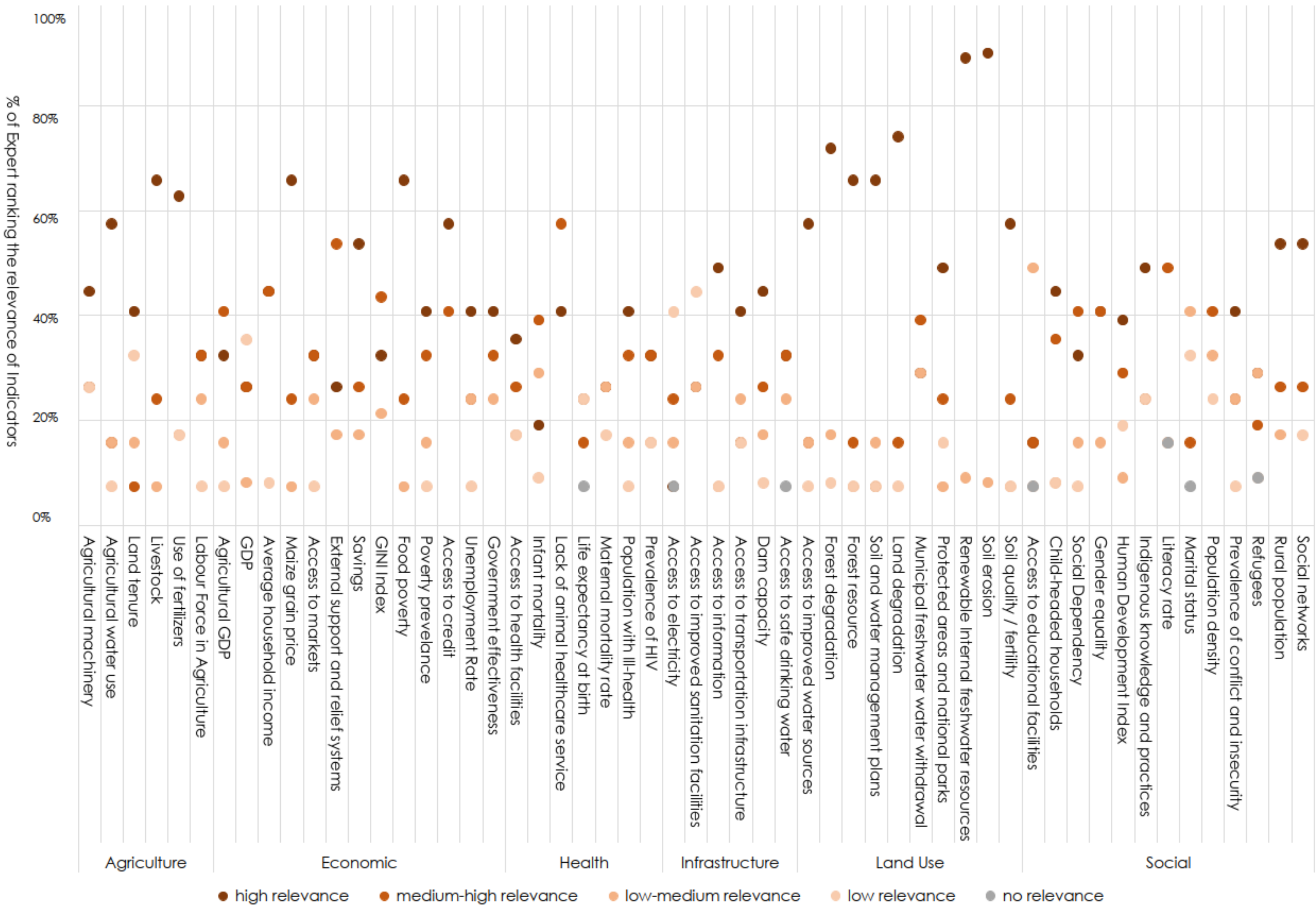
C.2 Multicollinearity Analysis for **Environmental Susceptibility.**

		E_DEF	E_NAT	E_SOIL	E_TREE
E_DEF	Correlation Coefficient	1.000	-0.091	.531**	.510**
	Sig. (2-tailed)		0.499	0.000	0.000
	N		58	58	58
E_NAT	Correlation Coefficient		1.000	-0.020	-0.030
	Sig. (2-tailed)			0.882	0.820
	N			58	58
E_SOIL	Correlation Coefficient			1.000	.709**
	Sig. (2-tailed)				0.000
	N				58
E_TREE	Correlation Coefficient				1.000
	Sig. (2-tailed)				
	N				

C.3 Multicollinearity Analysis for **Lack of Coping Capacity.**

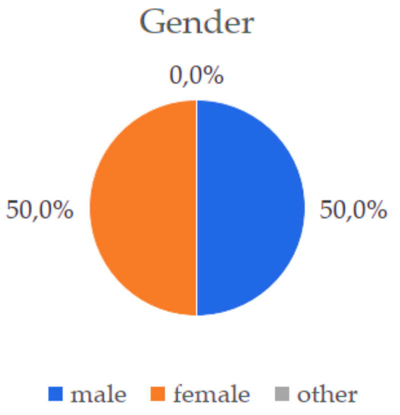
		C_DAM	C_LIV	C_REM	C_REN	C_WAT
C_DAM	Correlation Coefficient	1.000	0.077	.341*	-0.065	-0.102
	Sig. (2-tailed)		0.568	0.015	0.632	0.449
	N		57	50	57	57
C_LIV	Correlation Coefficient		1.000	0.138	-0.039	0.081
	Sig. (2-tailed)			0.336	0.771	0.545
	N			51	58	58
C_REM	Correlation Coefficient			1.000	-.307*	-0.046
	Sig. (2-tailed)				0.029	0.747
	N				51	51
C_REN	Correlation Coefficient				1.000	0.223
	Sig. (2-tailed)					0.093
	N					58
C_WAT	Correlation Coefficient					1.000
	Sig. (2-tailed)					
	N					

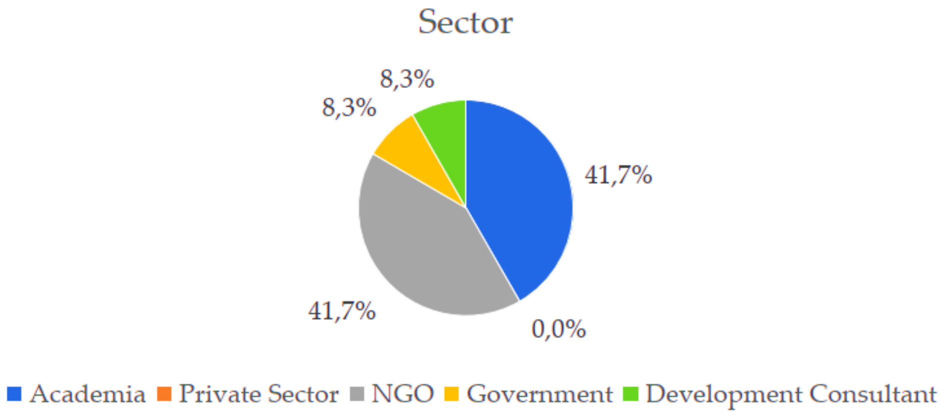
C.4 Relevance of drought vulnerability indicators based on expert opinions.

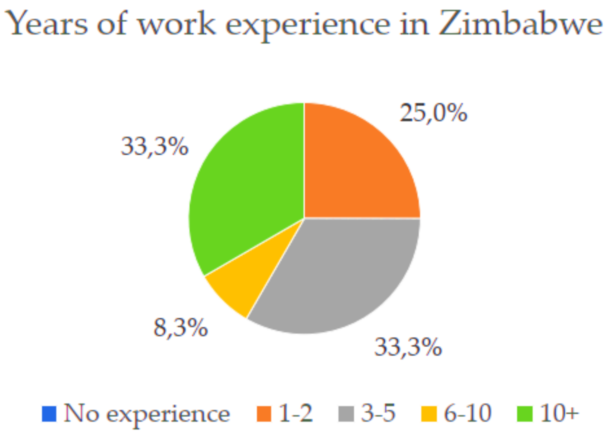


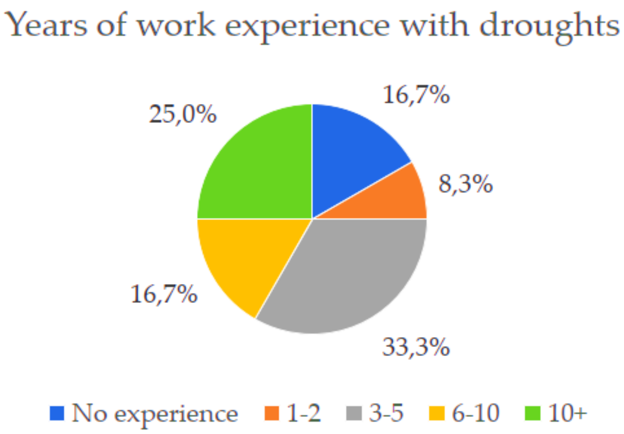
C.5 Institutions and backgrounds of experts that participated in the survey on drought vulnerability indicators.

- Welthungerhilfe Zimbabwe
- Department of Civil Protection, Zimbabwe
- Department of Agricultural and Resource Economics, University of Arizona, Tucson, USA
- School of Agricultural Sciences and Technology, Chinhoyi University of Technology Zimbabwe
- University of the Free State, South Africa
- University of Zimbabwe, Harare, Zimbabwe

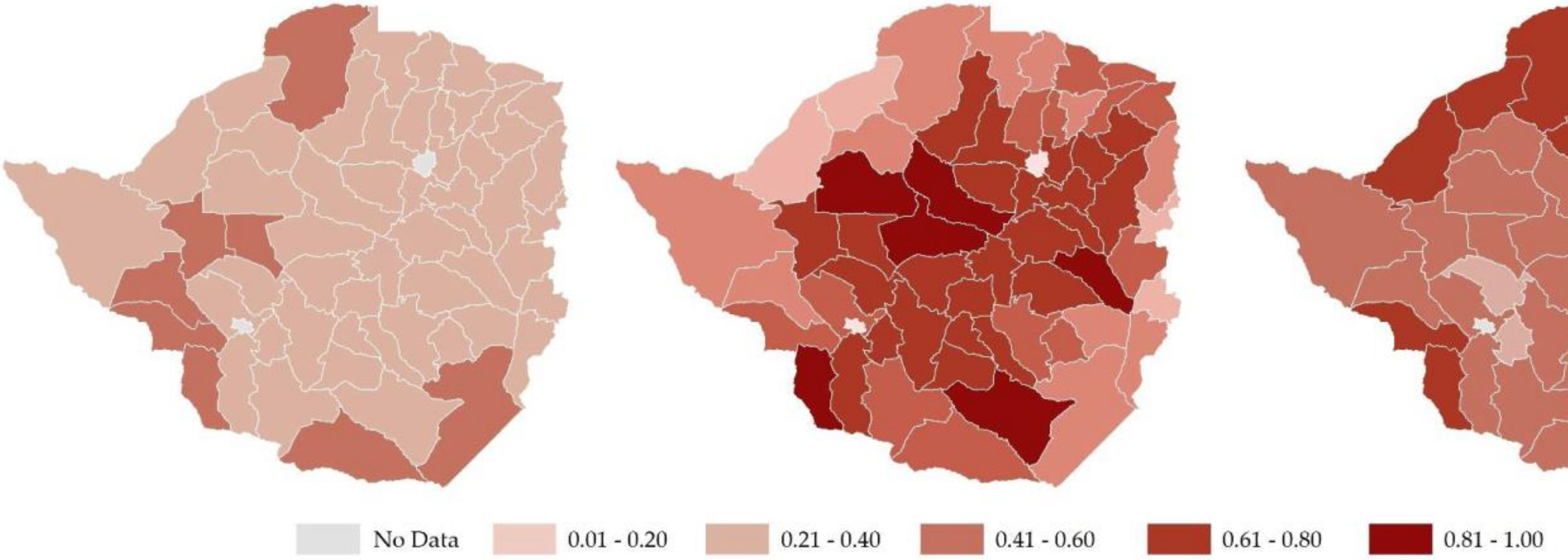








C.6 Drought Vulnerability by subcategory



Appendix D

D.1. Statistical steps and results of the vulnerability assessment.

Following the methodological suggestions by Hagenlocher et al. (2018), Meza et al. (2020), Nauman et al. (2014), and OECD (2008), statistical operations were performed to prepare an indicator dataset to perform the vulnerability assessment: i.e., i) imputation of missing data, ii) normality test, iii) outlier detection and treatment, iv) multicollinearity assessment, v) normalization and vi) expert weighted aggregation.

To detect potential outliers box plots and visualization using scatter plots were created for each indicator. Potential outliers were further examined using triangulation with other sources and past years. On this basis, no outliers were treated.

To assess the relationship between the indicators, a multicollinearity test was performed using the Spearman's rank correlation coefficient since only three indicators were normally distributed; the multicollinearity was done for all indicators and the different vulnerability components (S4 a,b). The correlations were considered significant from the 0.01 level (two-tailed). No variables were found very highly correlated ($-0.9 \leq rs \leq 0.9$); however, some variables showed high and significant correlations ($-0.7 \leq rs \leq 0.7$). For social susceptibility the poverty level, unemployment rate and dependency ratio are highly correlated (0.858), and for environmental susceptibility, the soil organic carbon content and clay content were highly correlated (0.719). Dependency ratio was retained due to what it represents and its different implications for social susceptibility since lower dependency ratio means higher working efficiency and greater contribution to economic growth. Poverty level was excluded, but unemployment was retained as one of the root causes of poverty in South Africa lies in the labour market (i.e the growing inability of the labour market to generate opportunities) (Chibba and Luiz, 2011). Furthermore, unemployment was mentioned and measured by more articles from the literature review and all experts that answered the survey agreed that it is a highly relevant indicator for South Africa for rainfed and the 95% for irrigated systems. Regarding environmental susceptibility, the clay content indicator was kept for the analysis and the organic carbon content removed as this indicator on arable fields highly depends on crop management (e.g. fertilization, treatment of crop residues, cropping intensity, crop rotation) (Söderström et al., 2014). Furthermore, most of the experts on the online survey considered this indicator highly relevant for rainfed (88.89%) and irrigated (78.95%) South African agricultural systems.

	Test of Normality (Irrigated)			Test of Normality (Rainfed)		
	Shapiro-Wilk			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
S_GNDR	0.94	213	0.00	0.94	213	0.00
S_NUT	0.97	213	0.00	0.97	213	0.00
P_ELE	0.27	213	0.00	No selected		
S_DISP	No selected			0.85	211	0.00
S_CHC	0.99	213	0.22	0.99	213	0.22
E_INC	0.70	213	0.00	0.70	213	0.00
E_POV	0.97	213	0.00	0.97	213	0.00
E_EMP	0.99	213	0.25	0.99	213	0.25
E_DEBT	0.93	213	0.00	0.93	213	0.00
E_DEP	0.76	213	0.00	0.76	213	0.00
E_ACM	0.85	213	0.00	0.85	213	0.00
P_W&S1	0.84	213	0.00	0.84	213	0.00
P_W&S2	0.95	213	0.00	0.95	213	0.00
C_STA1	0.70	213	0.00	0.70	213	0.00
C_STA2	0.81	213	0.00	0.81	213	0.00
G_CCA	0.78	201	0.00	0.78	201	0.00
F_FERT	0.80	194	0.00	0.80	194	0.00
E_SOIL1	0.97	213	0.00	0.97	213	0.00
E_SOIL2	0.98	213	0.00	0.98	213	0.00
E_DEGR	0.98	213	0.01	0.98	213	0.01
P_SW	0.79	213	0.00	0.79	213	0.00
E_CRED	0.71	213	0.00	0.71	213	0.00
S_GRNT	0.98	212	0.00	0.98	212	0.00
P_TRNS	0.69	213	0.00	0.69	213	0.00
P_WAT	0.57	213	0.00	0.57	213	0.00
P_IRRI	No selected			0.42	213	0.00

a)

b)

Multicollinearity irrigated systems

			S_GNDR	S_NUT	P_ELE	S_CHC	E_INC	E_POV	E_EMP	E_DEBT	E_DEP	E_ACM	P_W&S1
Spearman's rho	S_GNDR	Correlation Coefficient	1.000	0.080	-0.019	-,347**	0.007	,236**	0.125	0.115	,151*	0.003	-0.032
		Sig. (2-tailed)		0.247	0.785	0.000	0.916	0.001	0.070	0.095	0.027	0.960	0.637
	S_NUT	Correlation Coefficient		1.000	0.021	-,324**	-0.050	,557**	,490**	0.081	,455**	0.002	-0.096
		Sig. (2-tailed)			0.757	0.000	0.468	0.000	0.000	0.241	0.000	0.977	0.163
	P_ELE	Correlation Coefficient			1.000	-0.058	-0.028	0.095	0.072	0.048	,156*	0.126	0.009
		Sig. (2-tailed)				0.397	0.686	0.167	0.292	0.488	0.023	0.067	0.891
	S_CHC	Correlation Coefficient				1.000	-0.051	-,624**	-,581**	0.012	-,458**	0.087	,261**
		Sig. (2-tailed)					0.459	0.000	0.000	0.862	0.000	0.204	0.000
	E_INC	Correlation Coefficient					1.000	-,195**	-,149*	-,160*	-,291**	-,257**	0.020
		Sig. (2-tailed)						0.004	0.030	0.020	0.000	0.000	0.774
	E_POV	Correlation Coefficient						1.000	,858**	-0.044	,874**	0.129	-,193**
		Sig. (2-tailed)							0.000	0.521	0.000	0.060	0.005
	E_EMP	Correlation Coefficient							1.000	-0.018	,715**	-0.029	-0.098
		Sig. (2-tailed)								0.797	0.000	0.675	0.156
	E_DEBT	Correlation Coefficient								1.000	-0.100	-0.008	,254**
		Sig. (2-tailed)									0.144	0.912	0.000
	E_DEP	Correlation Coefficient									1.000	,314**	-,214**
		Sig. (2-tailed)										0.000	0.002
	E_ACM	Correlation Coefficient										1.000	-0.083
		Sig. (2-tailed)											0.227
	P_W&S1	Correlation Coefficient											1.000

		P_W&S2	C_STA1	C_STA2	G_CCA	F_FERT	E_SOIL1	E_SOIL2	E_DEGR	P_SW	E_CRED	S_GRNT	P_TRNS	P_WAT
S_GNDR	Correlation Coefficient	,194**	0.105	-,191**	-0.093	0.076	-0.005	0.113	-0.076	0.075	-,200**	0.105	0.065	,212**
	Sig. (2-tailed)	0.005	0.127	0.005	0.188	0.292	0.939	0.101	0.271	0.278	0.003	0.126	0.345	0.002
S_NUT	Correlation Coefficient	,400**	,522**	-0.107	-,146*	-,260**	0.116	,255**	,148*	0.121	-,163*	,403**	-,243**	-,173*
	Sig. (2-tailed)	0.000	0.000	0.120	0.038	0.000	0.092	0.000	0.030	0.077	0.017	0.000	0.000	0.012
P_ELE	Correlation Coefficient	0.046	0.126	0.027	0.003	0.121	0.053	,137*	0.100	0.052	0.011	0.113	-0.004	-0.018
	Sig. (2-tailed)	0.506	0.067	0.700	0.969	0.093	0.440	0.045	0.145	0.454	0.870	0.100	0.955	0.790
S_CHC	Correlation Coefficient	-,607**	-,308**	0.115	,298**	,338**	-,281**	-,442**	-,281**	,221**	,235**	-,338**	,410**	0.096
	Sig. (2-tailed)	0.000	0.000	0.095	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.162
E_INC	Correlation Coefficient	-0.011	-0.121	,227**	0.024	,160*	0.116	-0.035	-0.065	-,314**	,214**	-,317**	-0.067	0.078
	Sig. (2-tailed)	0.877	0.078	0.001	0.736	0.026	0.091	0.612	0.348	0.000	0.002	0.000	0.332	0.257
E_POV	Correlation Coefficient	,653**	,458**	-,288**	-,210**	-,441**	,225**	,405**	,283**	0.129	-,485**	,775**	-,390**	-,184**
	Sig. (2-tailed)	0.000	0.000	0.000	0.003	0.000	0.001	0.000	0.000	0.059	0.000	0.000	0.000	0.007
E_EMP	Correlation Coefficient	,629**	,390**	-,161*	-,199**	-,365**	,269**	,455**	,255**	-0.096	-,408**	,651**	-,418**	-,158*
	Sig. (2-tailed)	0.000	0.000	0.019	0.005	0.000	0.000	0.000	0.000	0.163	0.000	0.000	0.000	0.021
E_DEBT	Correlation Coefficient	-0.013	0.011	-0.087	-0.132	,172*	-,264**	-0.003	-0.046	,164*	0.017	-0.029	,246**	0.092
	Sig. (2-tailed)	0.849	0.871	0.204	0.062	0.016	0.000	0.960	0.502	0.017	0.809	0.670	0.000	0.180
E_DEP	Correlation Coefficient	,554**	,375**	-,376**	-,146*	-,432**	,230**	,324**	,284**	,298**	-,494**	,821**	-,332**	-,233**
	Sig. (2-tailed)	0.000	0.000	0.000	0.039	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001
E_ACM	Correlation Coefficient	0.070	-0.118	-,486**	0.048	-,259**	-,358**	-,347**	0.007	,530**	-,246**	,331**	,256**	-0.111
	Sig. (2-tailed)	0.309	0.086	0.000	0.500	0.000	0.000	0.000	0.916	0.000	0.000	0.000	0.000	0.105
P_W&S1	Correlation Coefficient	-,178**	-0.111	0.129	0.080	,179*	-,243**	-0.035	-,209**	-0.049	0.090	-0.111	,310**	-0.003
	Sig. (2-tailed)	0.009	0.108	0.060	0.260	0.012	0.000	0.613	0.002	0.479	0.193	0.107	0.000	0.968
P_W&S2	Correlation Coefficient	1.000	,322**	-,324**	-,286**	-,326**	,225**	,396**	,239**	-0.014	-,424**	,513**	-,376**	-0.066
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.840	0.000	0.000	0.000	0.338
C_STA1	Correlation Coefficient		1.000	-0.015	-0.110	-0.083	,240**	,411**	,207**	0.081	-,184**	,373**	-,217**	-0.104
	Sig. (2-tailed)			0.823	0.120	0.252	0.000	0.000	0.002	0.240	0.007	0.000	0.001	0.132
C_STA2	Correlation Coefficient			1.000	0.076	0.111	,174*	0.001	-0.080	-,483**	,325**	-,369**	-0.038	0.114
	Sig. (2-tailed)				0.283	0.125	0.011	0.988	0.243	0.000	0.000	0.000	0.576	0.096
G_CCA	Correlation Coefficient				1.000	0.070	-,157*	-,234**	0.061	0.009	0.079	-,143*	0.103	-0.130
	Sig. (2-tailed)					0.347	0.026	0.001	0.387	0.894	0.264	0.044	0.145	0.066
F_FERT	Correlation Coefficient					1.000	-,250**	-,141*	-,248**	-0.062	,335**	-,404**	,311**	,159*
	Sig. (2-tailed)						0.000	0.050	0.000	0.390	0.000	0.000	0.000	0.027
E_SOIL1	Correlation Coefficient						1.000	,719**	,155*	-,224**	-0.012	0.112	-,641**	-0.049
	Sig. (2-tailed)							0.000	0.024	0.001	0.864	0.105	0.000	0.480
E_SOIL2	Correlation Coefficient							1.000	,152*	-0.128	-,154*	,263**	-,475**	-0.010
	Sig. (2-tailed)								0.027	0.062	0.025	0.000	0.000	0.883
E_DEGR	Correlation Coefficient								1.000	-0.001	-0.040	,177**	-,342**	-,217**
	Sig. (2-tailed)									0.994	0.566	0.010	0.000	0.001
P_SW	Correlation Coefficient									1.000	-,172*	,340**	,277**	-0.088
	Sig. (2-tailed)										0.012	0.000	0.000	0.199
E_CRED	Correlation Coefficient										1.000	-,495**	0.123	0.047
	Sig. (2-tailed)											0.000	0.074	0.491
S_GRNT	Correlation Coefficient											1.000	-,163*	-0.084
	Sig. (2-tailed)												0.017	0.225
P_TRNS	Correlation Coefficient												1.000	,217**
	Sig. (2-tailed)													0.001
P_WAT	Correlation Coefficient													1.000
	Sig. (2-tailed)													

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Deleted indicator due to high correlation

Highly correlated

Multicollinearity rainfed systems

			S_GNDR	S_NUT	S_DISP	S_CHC	E_INC	E_POV	E_EMP	E_DEBT	E_DEP	E_ACM
Spearman's rho	S_GNDR	Correlation Coefficient	1.000	0.080	-0.014	-,347**	0.007	,236**	0.125	0.115	,151*	0.003
		Sig. (2-tailed)		0.247	0.845	0.000	0.916	0.001	0.070	0.095	0.027	0.960
	S_NUT	Correlation Coefficient		1.000	,183**	-,324**	-0.050	,557**	,490**	0.081	,455**	0.002
		Sig. (2-tailed)			0.008	0.000	0.468	0.000	0.000	0.241	0.000	0.977
	S_DISP	Correlation Coefficient			1.000	0.039	-,260**	,322**	,267**	0.018	,359**	,141*
		Sig. (2-tailed)				0.574	0.000	0.000	0.000	0.792	0.000	0.041
	S_CHC	Correlation Coefficient				1.000	-0.051	-,624**	-,581**	0.012	-,458**	0.087
		Sig. (2-tailed)					0.459	0.000	0.000	0.862	0.000	0.204
	E_INC	Correlation Coefficient					1.000	-,195**	-,149*	-,160*	-,291**	-,257**
		Sig. (2-tailed)						0.004	0.030	0.020	0.000	0.000
	E_POV	Correlation Coefficient						1.000	,858**	-0.044	,874**	0.129
		Sig. (2-tailed)							0.000	0.521	0.000	0.060
	E_EMP	Correlation Coefficient							1.000	-0.018	,715**	-0.029
		Sig. (2-tailed)								0.797	0.000	0.675
	E_DEBT	Correlation Coefficient								1.000	-0.100	-0.008
		Sig. (2-tailed)									0.144	0.912
	E_DEP	Correlation Coefficient									1.000	,314**
		Sig. (2-tailed)										0.000
	E_ACM	Correlation Coefficient										1.000

			P_W&S1	P_W&S2	C_STA1	C_STA2	G_CCA	F_FERT	E_SOIL1	E_SOIL2	E_DEGR	P_SW	E_CRED	S_GRNT	P_TRNS	P_WAT	P_IRRI
Spearman's rho	S_GNDR	Correlation Coefficient	-0.032	,194**	0.105	-,191**	-0.094	0.076	-0.005	0.113	-0.076	0.075	-,200**	0.105	0.065	,212**	0.071
		Sig. (2-tailed)	0.637	0.005	0.127	0.005	0.186	0.292	0.939	0.101	0.271	0.278	0.003	0.126	0.345	0.002	0.305
	S_NUT	Correlation Coefficient	-0.096	,400**	,522**	-0.107	-,146*	-,260**	0.116	,255**	,148*	0.121	-,163*	,403**	-,243**	-,173*	-,215**
		Sig. (2-tailed)	0.163	0.000	0.000	0.120	0.038	0.000	0.092	0.000	0.030	0.077	0.017	0.000	0.000	0.012	0.002
	S_DISP	Correlation Coefficient	0.089	,163*	,212**	-0.071	-0.035	-,172*	0.016	0.087	0.065	,215**	-,180**	,481**	-0.012	0.043	-0.044
		Sig. (2-tailed)	0.199	0.018	0.002	0.307	0.622	0.017	0.815	0.209	0.345	0.002	0.009	0.000	0.860	0.539	0.518
	S_CHC	Correlation Coefficient	,261**	-,607**	-,308**	0.115	,298**	,338**	-,281**	-,442**	-,281**	,221**	,235**	-,338**	,410**	0.096	0.133
		Sig. (2-tailed)	0.000	0.000	0.000	0.095	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.162	0.052
	E_INC	Correlation Coefficient	0.020	-0.011	-0.121	,227**	0.024	,160*	0.116	-0.035	-0.065	-,314**	,214**	-,317**	-0.067	0.078	,206**
		Sig. (2-tailed)	0.774	0.877	0.078	0.001	0.735	0.026	0.091	0.612	0.348	0.000	0.002	0.000	0.332	0.257	0.003
	E_POV	Correlation Coefficient	-,193**	,653**	,458**	-,288**	-,210**	-,441**	,225**	,405**	,283**	0.129	-,485**	,775**	-,390**	-,184**	-,297**
		Sig. (2-tailed)	0.005	0.000	0.000	0.000	0.003	0.000	0.001	0.000	0.000	0.059	0.000	0.000	0.000	0.007	0.000
	E_EMP	Correlation Coefficient	-0.098	,629**	,390**	-,161*	-,199**	-,365**	,269**	,455**	,255**	-0.096	-,408**	,651**	-,418**	-,158*	-,302**
		Sig. (2-tailed)	0.156	0.000	0.000	0.019	0.005	0.000	0.000	0.000	0.000	0.163	0.000	0.000	0.000	0.021	0.000
	E_DEBT	Correlation Coefficient	,254**	-0.013	0.011	-0.087	-0.132	,172*	-,264**	-0.003	-0.046	,164*	0.017	-0.029	,246**	0.092	0.008
		Sig. (2-tailed)	0.000	0.849	0.871	0.204	0.062	0.016	0.000	0.960	0.502	0.017	0.809	0.670	0.000	0.180	0.905
	E_DEP	Correlation Coefficient	-,214**	,554**	,375**	-,376**	-,146*	-,432**	,230**	,324**	,284**	,298**	-,494**	,821**	-,332**	-,233**	-,281**
		Sig. (2-tailed)	0.002	0.000	0.000	0.000	0.038	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
	E_ACM	Correlation Coefficient	-0.083	0.070	-0.118	-,486**	0.048	-,259**	-,358**	-,347**	0.007	,530**	-,246**	,331**	,256**	-0.111	-0.079
		Sig. (2-tailed)	0.227	0.309	0.086	0.000	0.501	0.000	0.000	0.000	0.916	0.000	0.000	0.000	0.000	0.105	0.249
	P_W&S1	Correlation Coefficient	1.000	-,178**	-0.111	0.129	0.080	,179*	-,243**	-0.035	-,209**	-0.049	0.090	-0.111	,310**	-0.003	-0.001
		Sig. (2-tailed)		0.009	0.108	0.060	0.261	0.012	0.000	0.613	0.002	0.479	0.193	0.107	0.000	0.968	0.993
	P_W&S2	Correlation Coefficient		1.000	,322**	-,324**	-,286**	-,326**	,225**	,396**	,239**	-0.014	-,424**	,513**	-,376**	-0.066	-,175*
		Sig. (2-tailed)			0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.840	0.000	0.000	0.000	0.338	0.011
	C_STA1	Correlation Coefficient			1.000	-0.015	-0.110	-0.083	,240**	,411**	,207**	0.081	-,184**	,373**	-,217**	-0.104	-,208**
		Sig. (2-tailed)				0.823	0.120	0.252	0.000	0.000	0.002	0.240	0.007	0.000	0.001	0.132	0.002
	C_STA2	Correlation Coefficient				1.000	0.076	0.111	,174*	0.001	-0.080	-,483**	,325**	-,369**	-0.038	0.114	0.124
		Sig. (2-tailed)					0.283	0.125	0.011	0.988	0.243	0.000	0.000	0.000	0.576	0.096	0.072
	G_CCA	Correlation Coefficient					1.000	0.070	-,157*	-,234**	0.061	0.010	0.080	-,143*	0.103	-0.130	,140*
		Sig. (2-tailed)						0.347	0.026	0.001	0.387	0.893	0.261	0.044	0.145	0.066	0.041
	F_FERT	Correlation Coefficient						1.000	-,250**	-,141*	-,248**	-0.062	,335**	-,404**	,311**	,159*	,318**
		Sig. (2-tailed)							0.000	0.050	0.000	0.390	0.000	0.000	0.000	0.027	0.000
	E_SOIL1	Correlation Coefficient							1.000	,719**	,155*	-,224**	-0.012	0.112	-,641**	-0.049	-0.046
		Sig. (2-tailed)								0.000	0.024	0.001	0.864	0.105	0.000	0.480	0.500
	E_SOIL2	Correlation Coefficient								1.000	,152*	-0.128	-,154*	,263**	-,475**	-0.010	-,192**
		Sig. (2-tailed)									0.027	0.062	0.025	0.000	0.000	0.883	0.005
	E_DEGR	Correlation Coefficient									1.000	-0.001	-0.040	,177**	-,342**	-,217**	-,237**
		Sig. (2-tailed)										0.994	0.566	0.010	0.000	0.001	0.000
	P_SW	Correlation Coefficient										1.000	-,172*	,340**	,277**	-0.088	-,199**
		Sig. (2-tailed)											0.012	0.000	0.000	0.199	0.004
	E_CRED	Correlation Coefficient											1.000	-,495**	0.123	0.047	,193**
		Sig. (2-tailed)												0.000	0.074	0.491	0.005
	S_GRNT	Correlation Coefficient												1.000	-,163*	-0.084	-,236**
		Sig. (2-tailed)													0.017	0.225	0.001
	P_TRNS	Correlation Coefficient													1.000	,217**	0.064
		Sig. (2-tailed)														0.001	0.352
	P_WAT	Correlation Coefficient														1.000	,340**
		Sig. (2-tailed)															0.000
	P_IRRI	Correlation Coefficient															1.000
		Sig. (2-tailed)															

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Deleted indicator due to high correlation

Highly correlated

c)

Figure D1. a) Test of normality using Shapiro-Wilk (S-W) test for irrigated and rainfed systems, b) Spearman's Rho multicollinearity assessment for irrigated systems indicators and, c) Spearman's Rho multicollinearity assessment for rainfed systems indicators. Red cells are the deleted indicators due to high correlation. The blue light cells highlight the highly correlated indicators. Tables in excel formatting in separated supplementary material II.

Table D1. Pre-defined search terms in the search engines Web of Sciences and Scopus, selection and exclusion criteria

Database	Search query	Papers retrieved	Papers selected
Scopus (On title, abstract and keywords)	Drought AND risk OR Drought AND vulnerability AND Southern Africa OR SADC OR South Africa AND assess* OR index OR indic* OR analy* OR evaluat* OR map* OR quantif* OR monitor* OR measur* OR model* OR spatial	77	12
Web of sciences (On title and topic)	drought AND risk OR drought AND vulnerability) On topic AND Southern Africa OR SADC OR South Africa	12	5

Inclusion criteria	Exclusion criteria
• Peer-reviewed articles from 1976 (no articles are listed in Scopus or Web of Science dating back to before 1976) • Written in English or Spanish	• Review articles, opinion pieces, non-peer-reviewed literature. • Drought hazard assessments that do not consider exposure or vulnerability

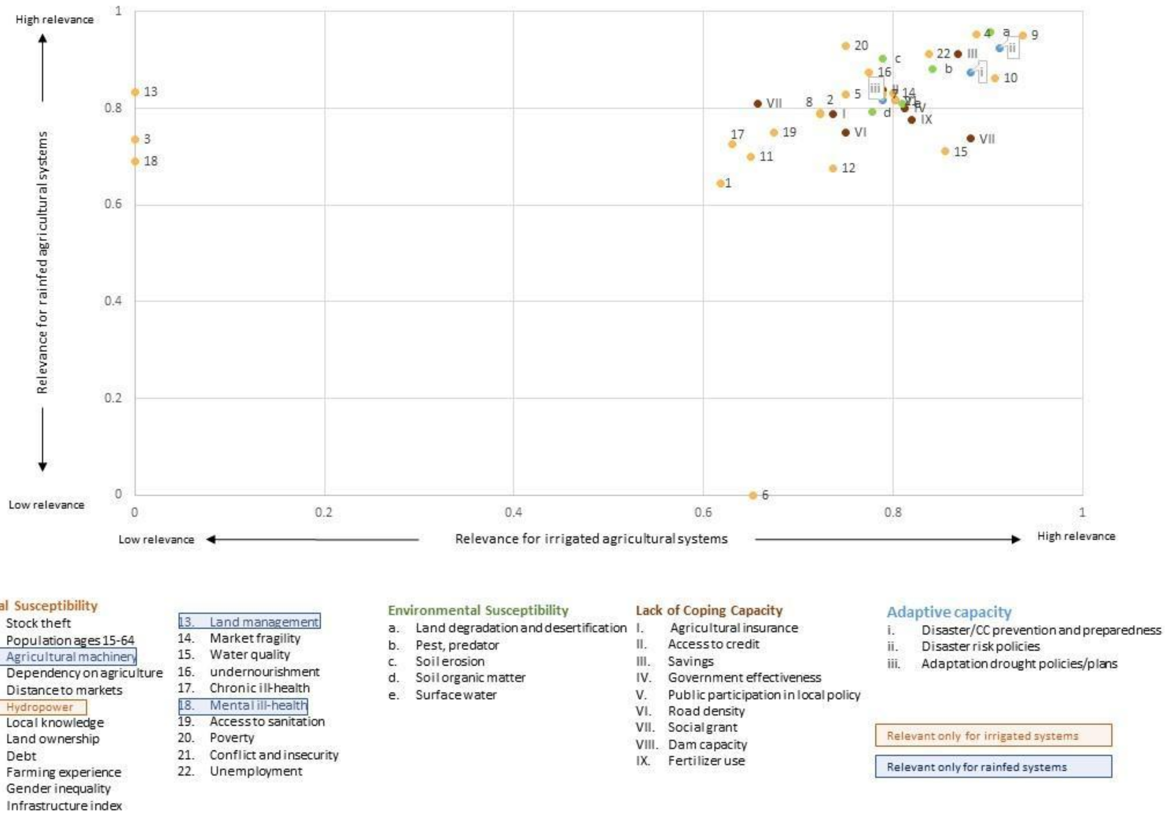


Figure D2. Relevance of indicators for rainfed and irrigated agricultural systems.

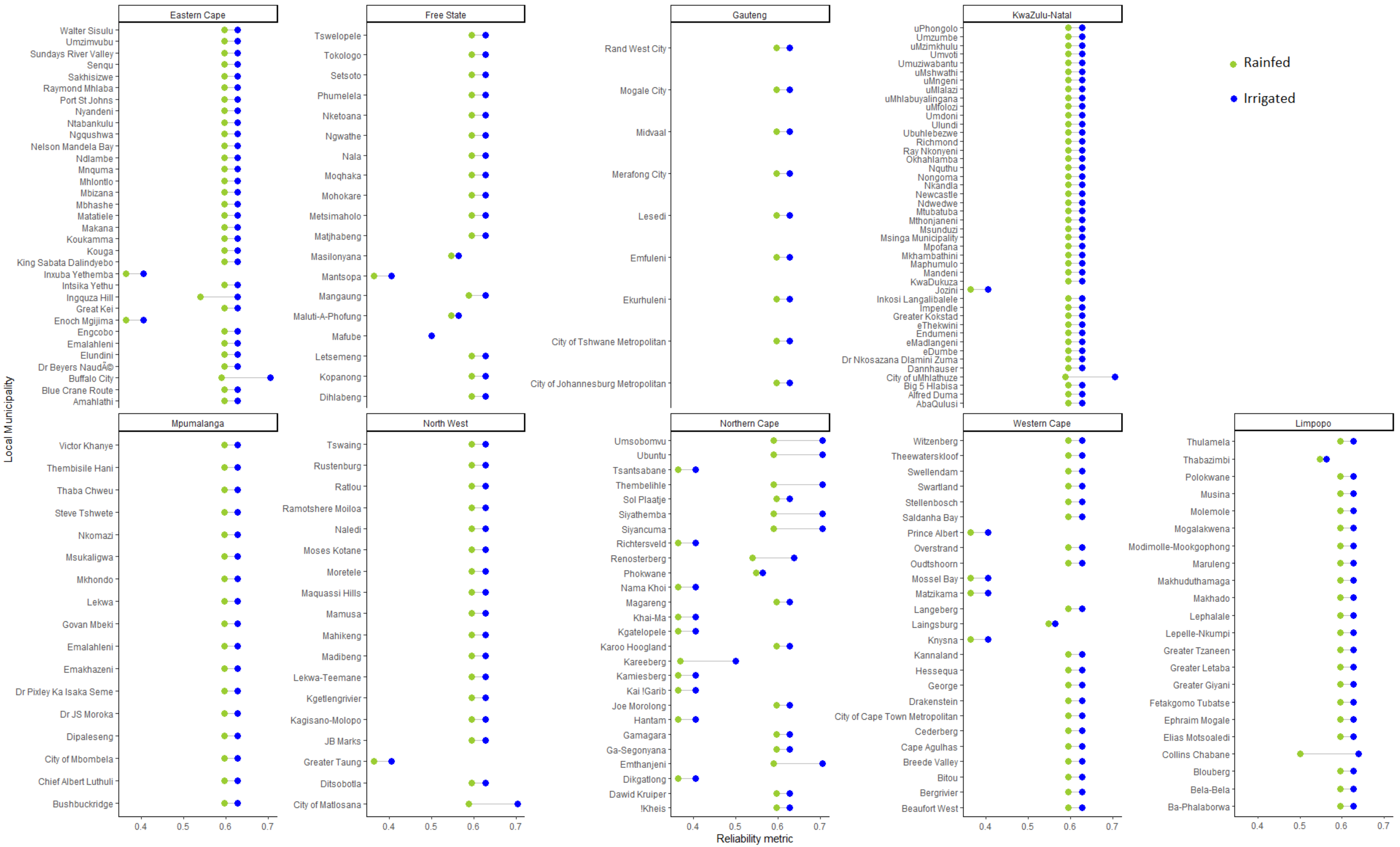


Figure D3. Reliability metric on vulnerability indicators per local municipality

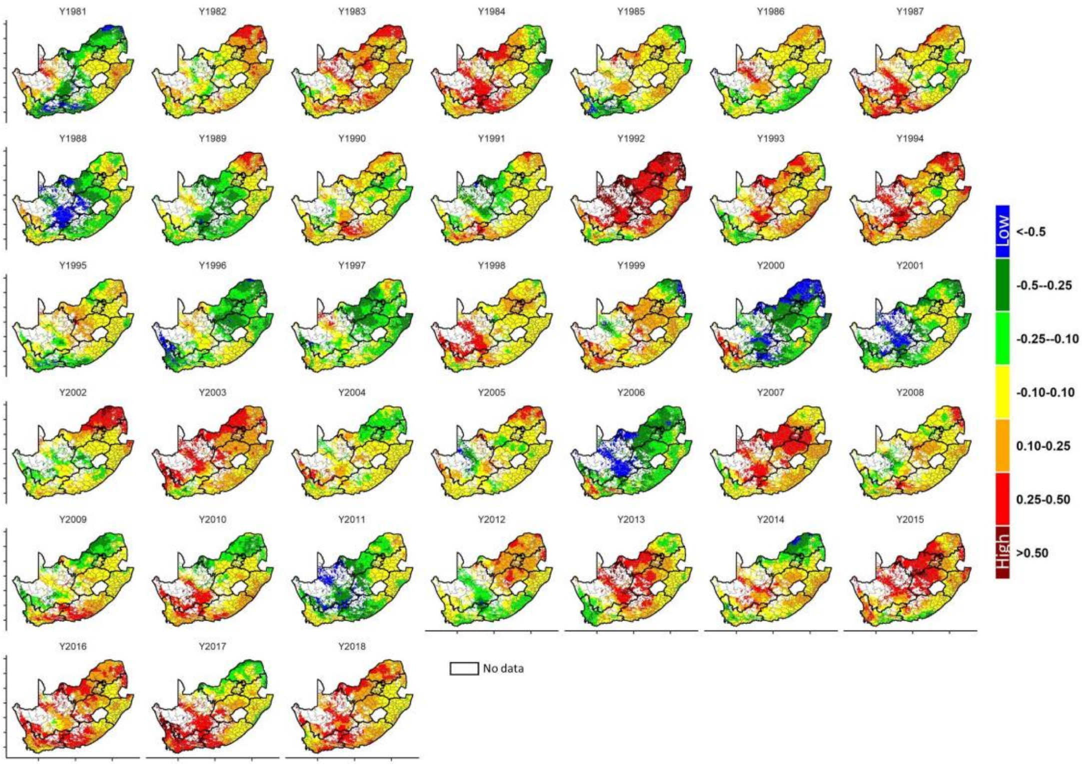


Figure D4. Time series of drought hazard for the rainfed cropping system across South Africa at grid and local municipality levels in the period 1981-2018. Black lines indicate provincial boundaries (see Figure 4.1 in main text).

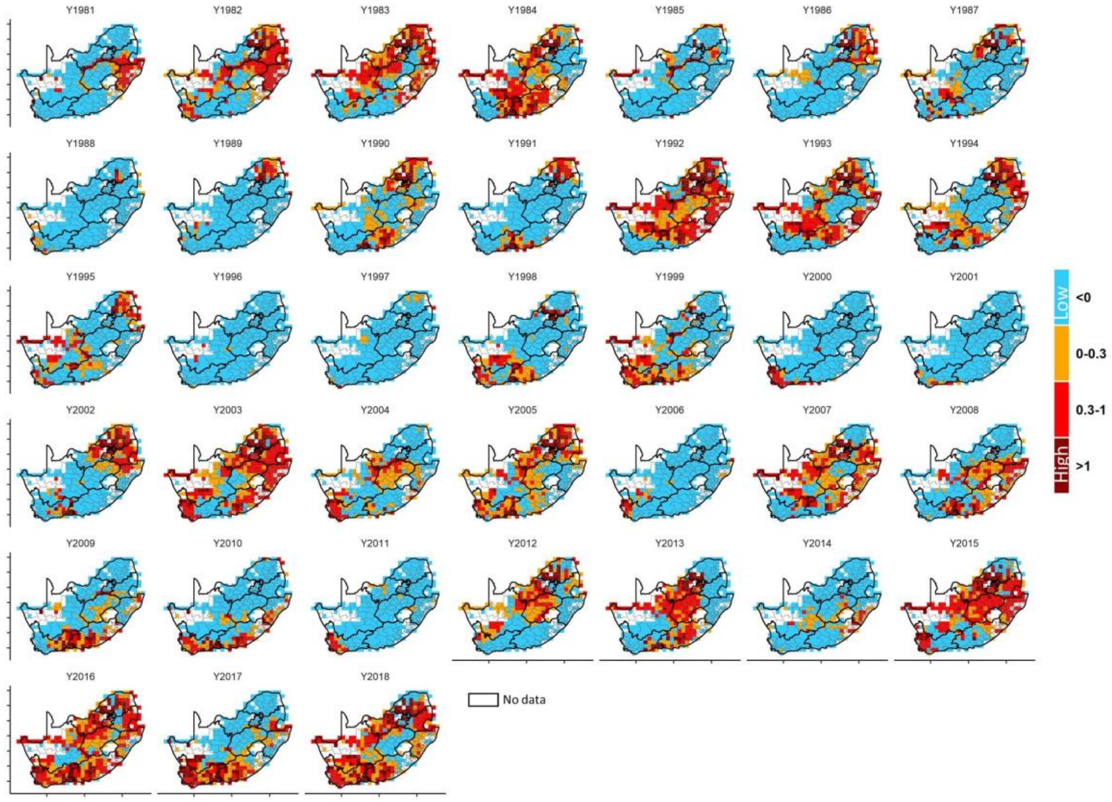


Figure D5. Time series of drought hazard for irrigated cropping systems across South Africa at grid level in the period 1981-2018. Black lines indicate provincial boundaries (see Figure 4.1 in main text)

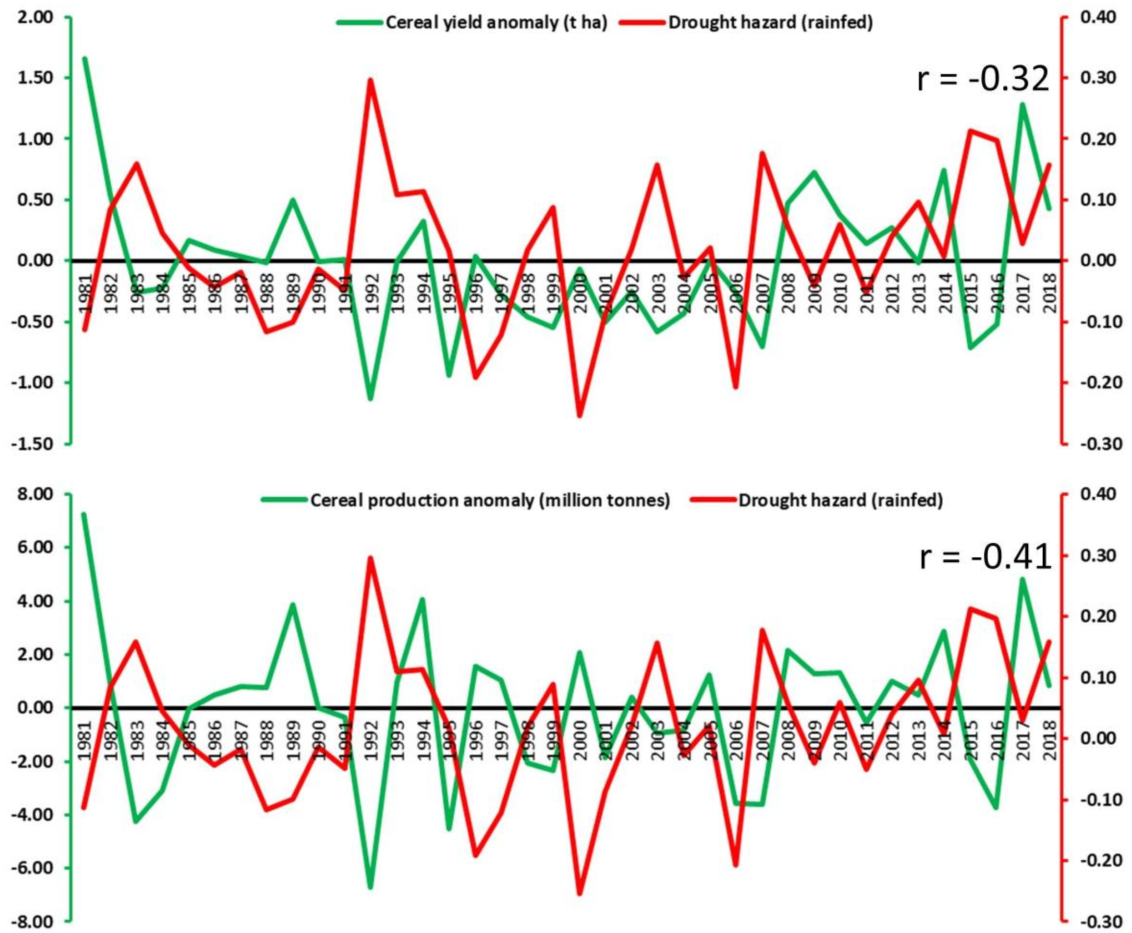


Figure D6. The time series of rainfed hazard (positive values indicate drought) and cereal yield and production anomaly in South Africa in the period 1981 to 2018. The r values show the Pearson correlation coefficient.

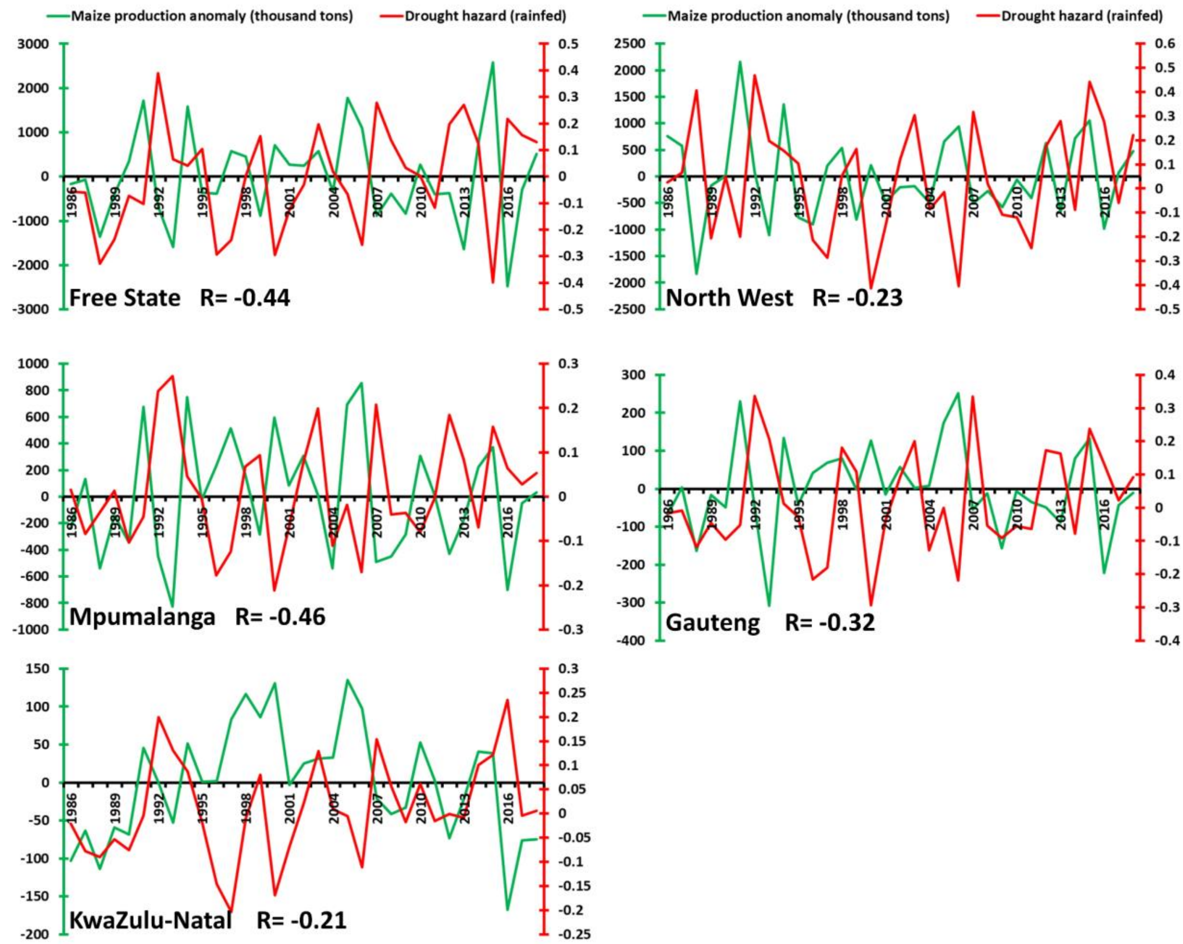


Figure D7. The time series of rainfed hazard (positive values indicate drought) and maize production anomaly in South Africa in the period 1981 to 2018. The r values show the Pearson correlation coefficient.

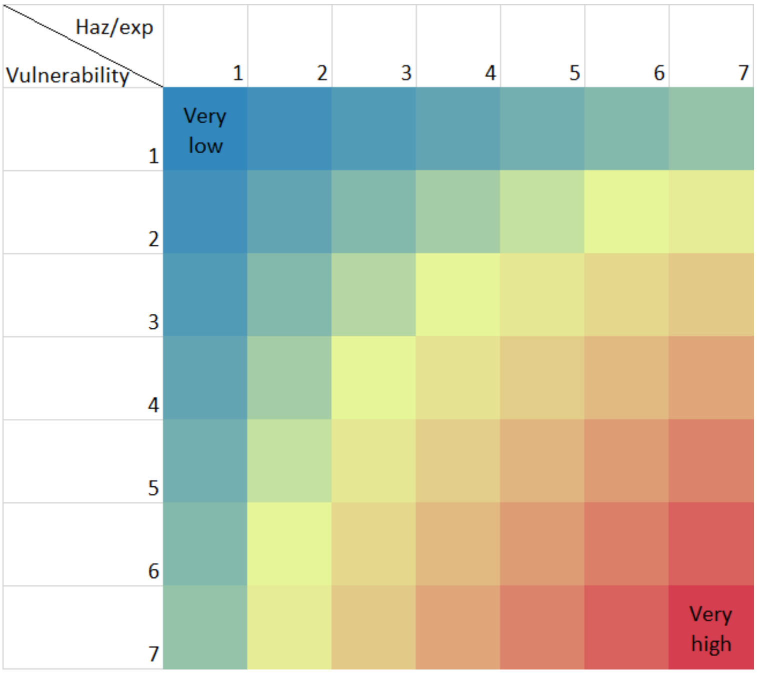


Figure D8. Risk matrix

References:

Chibba, M., Luiz, J.M., 2011. Poverty, Inequality and Unemployment in South Africa: Context, Issues and the Way Forward: POVERTY, INEQUALITY AND UNEMPLOYMENT IN SOUTH AFRICA. Economic Papers: A journal of applied economics and policy 30, 307–315. https://doi.org/10.1111/j.1759-3441.2011.00129.x

Hagenlocher, M., Renaud, F. G., Haas, S., Sebesvari, Z. 2018. Vulnerability and risk of deltaic social-ecological systems exposed to multiple hazards, Sci. Total Environ., 631–632, 71–80https://doi.org/10.1016/j.scitotenv.2018.03.013

Meza, I., Siebert, S., Döll, P., Kusche, J., Herbert, C., Eyshi Rezaei, E., Nouri, H., Gerdener, H., Popat, E., Frischen, J., Naumann, G., Vogt, J.V., Walz, Y., Sebesvari, Z., Hagenlocher, M., 2020. Global-scale drought risk assessment for agricultural systems. Natural Hazards and Earth System Sciences 20, 695–712. https://doi.org/10.5194/nhess-20-695-2020

Naumann, G., Barbosa, P., Garrote, L., Iglesias, A., Vogt, J., 2014. Exploring drought vulnerability in Africa: an indicator based analysis to be used in early warning systems. Hydrology and Earth System Sciences, 18(5), 1591–1604. https://doi.org/10.5194/hess-18-1591-2014

OECD, 2008. Handbook on Constructing Composite Indicators: Methodology and User Guide. https://doi.org/10.1787/9789264043466-en.

Söderström, B., Hedlund, K., Jackson, L.E., Kätterer, T., Lugato, E., Thomsen, I.K., Bracht Jørgensen, H., 2014. What are the effects of agricultural management on soil organic carbon (SOC) stocks? Environmental Evidence 3, 2. https://doi.org/10.1186/2047-2382-3-2

Appendix E

E.1. Detailed methods for index creation

E.1.1 Global drought risk assessment

A drought risk assessment at the global scale was conducted to create a baseline for comparison with the cluster assessments. This was achieved by updating the global drought risk analysis by Meza et al. (2020) and following the most common methods for composite indicators according to a review conducted by Beccari (2016). Meza et al. (2020) analysed drought hazard and exposure for irrigated and rainfed agriculture to create hazard/exposure scores for each country, assessed the socioecological vulnerability, and then combined the hazard/exposure and vulnerability indexes to calculate risk. The steps modified for this global risk assessment included the selection and weighting of vulnerability indicators and normalisation of the final hazard/exposure and vulnerability indexes[9] using the linear max method. The vulnerability indicators were modified to better reflect the authors' understanding of factors contributing to drought vulnerability, based on further literature research. Equal weighting of vulnerability indicators was applied to ensure comparability of the global assessment with the cluster assessments. Equal weighting is also the most common approach for composite indicator assessments (Beccari, 2016). The addition of linear max normalisation of the global hazard/exposure and global vulnerability indexes was necessary to ensure comparability between the global indexes and the cluster-scale indexes. While min-max methods are the most common normalisation method (Beccari, 2016), this approach resulted in countries with drought exposure or vulnerability being assigned an index value of zero, resulting in a false representation of zero risk in the final risk index. Therefore linear max was used.

E.1.2 Global hazard/exposure assessment

Drought hazard/exposure values for each country were obtained from Meza et al. (2020). The hazard/exposure index (HE_c) was created by normalising the values using linear max normalisation (Equation 1):

$HE_c = X_c / X_{max}$ [Eq.1]

where X_c is the raw hazard/exposure value for country (c) and X_{max} is the maximum hazard/exposure value across all countries in the analysis. This transformed the range to have a maximum of 1 and was necessary to remove the measurement units and create comparability with the vulnerability index (OECD, 2008).

[9] An index is an aggregation of several indicators that are combined to provide a single composite measure of a complex concept that cannot be represented by a single indicator, such as vulnerability (OECD, 2008).

E.1.3 Global vulnerability assessment

The standard steps to create a vulnerability index include indicator identification, data collection and pre-processing, indicator normalisation and aggregation (Hagenlocher et al., 2018; OECD, 2008). A last step of index normalisation was added to this analysis to linearly transform the range of the vulnerability index so that one country had a maximum of 1 (representing the most vulnerable country relative to others included in the assessment) to align with the hazard/exposure index.

E.1.3.1 Indicator identification

The initial list of indicators considered were based on the vulnerability analysis of Meza et al. (2020) and refined to a final list of 14 indicators after further review of the literature.

E.1.3.2 Indicator data collection and pre-processing

After the selection of indicators was finalised, data at the country level was acquired, pre-processed to address missing data and outliers, and analysed for collinearity. This analysis used the same data sets as in Meza et al. (2020). For these datasets, the same imputed values were used as well. Of the two additional indicators, missing data was only imputed for access to information from the same data source from past years as there was no additional data for the cultivation of drought resistant crops. To address the residual high levels of missing data, the threshold for deletion of indicators was set at 20% missing data and for countries 30% missing data following Meza et al. (2020). One indicator (credit to agriculture) and 30 countries were removed from the analysis (see appendix E.1.1c); 13 indicators and 165 countries remained. Table 5.1 in the main paper contains the list of indicators and their data sources. The excel here https://ars.els-cdn.com/content/image/1-s2.0-S2212096322000614-mmc2.xlsx shows the countries that were included in the analysis.

Outliers were then detected using box and scatter plots, and extreme values were analysed in relation to other data sources and values from past years. One value each for unemployment, cultivation of drought-resistant crops, and average soil erosion were treated using Winzorisation (Field, 2013). No issue of multicollinearity was detected using a Spearman correlation matrix with the threshold for high correlation set at $r = \pm 0.9$ (Hinkle et al., 2003) with two-tailed significance at the 0.05 level. See supplementary material E3 for details on data pre-processing.

E.1.3.3 Indicator normalisation

Following data pre-processing, each indicator was normalised to remove units and render them comparable to each other using the linear min-max method (Carrão et al., 2016; Naumann et al., 2014). While this method is sensitive to outliers, it is also the most common in composite indicator approaches (Beccari, 2016). For indicators where high values represented high vulnerability, Equation 2 was applied. For indicators where low values represented high vulnerability, Equation 3 was applied to invert the normalisation:

$Z_c = (Y_c – Y_{min}) / (Y_{max} – Y_{min})$ [Eq.2]

$Z_c = (Y_c – Y_{max}) / (Y_{min} – Y_{max})$ [Eq.3]

Y_c refers to the indicator value for a country (c) before transformation, Y_{min} refers to the minimum value for the indicator across countries analysed, Y_{max} to the maximum value for the indicator across countries analysed, and Z_c is the indicator value after transformation.

E.1.3.4 Aggregation

The normalised indicators were then aggregated to create a preliminary vulnerability index ($VI_{prelim(c)}$). Using additive arithmetic aggregation, all indicators for each country (Z_c) were summed and then divided by the number of indicators with data (N_c) to create a vulnerability index score for each country (Equation 4):

$VI_{prelim(c)} = \sum Z_c / N_c$ [Eq.4]

This aggregation approach resulted in indicators with no data being implicitly assigned the mean value of the other normalised indicators for each country. This meant that country's vulnerability scores were not higher or lower based on the number of indicators with data, but did introduce uncertainty in the results, which is discussed in more detail in the limitations in the chapter 5 of the main text.

E.1.3.5 Index normalisation

To create the final vulnerability index (VI_c) the preliminary vulnerability index was normalised using the linear max method (Equation 5):

$VI_c = I_{prelim(c)} / VI_{prelim(max)}$ [Eq.5]

This transformed the vulnerability index so that the highest index score was 1, to align with the maximum score in the hazard/exposure index.

E.1.4 Global risk assessment

The drought risk index (DRI_c) was created by multiplying the hazard/exposure index (HE_c) by the vulnerability index (VI_c) for each country (Equation 6):

$DRI_c = HE_c \times VI_c$ *[Eq.6]*

E.2 Cluster drought risk assessments

To undertake the drought risk assessments at the cluster scale, relevant clusters were first identified. Then, the global analysis' raw hazard/exposure values were grouped into clusters and normalised. Countries' vulnerability indicators were grouped by cluster as well and normalised at the cluster scale before aggregation into the preliminary vulnerability index. They were then normalised again to create the final vulnerability index. With these modifications, a new risk index for each cluster was created by multiplying the cluster hazard/exposure indexes with the corresponding cluster vulnerability index.

E.2.1 Cluster identification

See chapter 5.2.2.1 in the main text

E.2.2 Cluster assessments

E.2.2.1 Cluster hazard/exposure assessments

The countries were grouped into the 14 clusters outlined in Table 2 of section 2.2.1 of the main paper. Then their hazard/exposure values were normalised using the linear max method, to create a hazard/exposure index for each cluster.

E.2.2.2 Cluster vulnerability assessments

Countries remained grouped by the 14 clusters outlined in Table 2 of section 2.2.1 of the main paper. Using the same indicators and data as used in the global vulnerability assessment for comparability, the method in sections b1.3.3-b1.3.5 of supplementary material 1 was followed. The indicators were normalised within each cluster using the linear min-max method, aggregated using additive arithmetic aggregation (resulting in indicators with no data being assigned the mean of the other normalised indicators for the country), and the preliminary vulnerability indexes were renormalised using the linear max method to render them comparable to the hazard/exposure indexes. This created new vulnerability indexes for each cluster.

E.2.2.3 Cluster risk assessments

For each cluster, the respective hazard/exposure indexes were multiplied by the respective vulnerability indexes to create the final risk indexes. For example, Africa's hazard/exposure index was multiplied by the vulnerability index for Africa, resulting in the risk assessment for Africa. This created 14 new drought risk indexes, one for each cluster.

E.3. Method to calculate the cultivation of drought resistant crops (% of total crop yield) (Equation 7)

(Total yield of drought resistance crops x 100) / Total yield of all crops [Eq.7]

where drought resistant crops were cabbages and other brassicas, cotton link, cottonseed, dry cowpeas, groundnuts with shell, safflower seed, seed cotton, sorghum, soybeans, sunflower seed based on findings from Steduto et al. (2012) and the yield of crops obtained from ([dataset] FAO, 2018).

E.4. Data preprocessing

Data deleted

Indicator

Credit to Agriculture, Forestry and fishing (US$, share of total credit)

Countries

Andorra	Antigua and Barbuda	Libya	Tuvalu

Brunei Darussalam	Bahamas	Micronesia (Federated States of)	Iceland*
Holy See	Bahrain	Palau	Maldives*
Liechtenstein	Barbados	Qatar	Samoa*
Marshall Islands	Equatorial Guinea	Saint Kitts and Nevis	Singapore*
Monaco	Eritrea	Saint Lucia	Tonga*
Nauru	Grenada	Seychelles	
San Marino	Kiribati	Somalia	

*no exposure data available

Outlier treatment

Indicator	Country	Outlier value	New value
Unemployment (% of total labor force) (national estimate)	Djibouti	59.5	27.3 (South Africa)
Cultivation of drought-resistant crops (% of total crop yield)	Botswana	0.30	0.16 (Namibia)
Average soil erosion for exposed area (t ha-1 yr-1)	Comoros	200.0	58.8 (Haiti)

Multicollinearity

Correlations

			Prevalence of undernourishment (population %)	Share of GDP from agr., forestry and fishing in US$	Proportion of population living below the national povertyline (%)	Unemployment, total (% of total labor force) (national estimate)	Literacy rate, adult total (% of people ages 15 and above)	GINI index	Saved any money in the past year (age 15+)	Improved water source (% of population with access)	Government Effectiveness : Percentile Rank	Cultivation of drought resistant crops	GDP per capita	Average soil erosion for exposed area	Access to information - mobile phone subscription per 100 people
Spearman's rho	Prevalence of undernourishment (population	Correlation Coefficient	1.000	.716**	.732**	-0.110	-.626**	.500**	-.270**	-.795**	-.748**	-0.041	-.821**	.473**	-.605**
		Sig. (2-tailed)		0.000	0.000	0.170	0.000	0.000	0.001	0.000	0.000	0.614	0.000	0.000	0.000
		N		157	143	157	134	144	140	157	157	152	154	154	156
	Share of GDP from agr., forestry and fishing in	Correlation Coefficient		1.000	.646**	-.197*	-.649**	.296**	-.427**	-.710**	-.757**	-0.105	-.890**	.400**	-.557**
		Sig. (2-tailed)			0.000	0.011	0.000	0.000	0.000	0.000	0.000	0.185	0.000	0.000	0.000
		N			151	165	142	151	145	165	165	160	162	162	164
	Proportion of population living below the national	Correlation Coefficient			1.000	-0.002	-.637**	.484**	-.359**	-.729**	-.769**	-0.069	-.774**	.378**	-.571**
		Sig. (2-tailed)				0.982	0.000	0.000	0.000	0.000	0.000	0.409	0.000	0.000	0.000
		N				151	130	147	137	151	151	146	148	148	150
	Unemployment, total (% of total labor force)	Correlation Coefficient				1.000	0.151	-0.050	-.199*	0.138	0.025	0.023	0.100	-.194*	.209**
		Sig. (2-tailed)					0.073	0.545	0.017	0.077	0.755	0.775	0.205	0.014	0.007
		N					142	151	145	165	165	160	162	162	164
	Literacy rate, adult total (% of people ages 15 and	Correlation Coefficient					1.000	-.260**	0.016	.646**	.637**	.395**	.716**	-.232**	.579**
		Sig. (2-tailed)						0.003	0.858	0.000	0.000	0.000	0.000	0.006	0.000
		N						129	125	142	142	138	140	139	141
	GINI index	Correlation Coefficient						1.000	-0.126	-.420**	-.352**	-.198*	-.347**	.307**	-.336**
		Sig. (2-tailed)							0.138	0.000	0.000	0.017	0.000	0.000	0.000
		N							139	151	151	146	148	149	150
	Saved any money in the past year (age 15+)	Correlation Coefficient							1.000	.328**	.524**	-0.082	.462**	-.230**	.188*
		Sig. (2-tailed)								0.000	0.000	0.333	0.000	0.006	0.024
		N								145	145	143	142	143	145
	Improved water source (% of population	Correlation Coefficient								1.000	.793**	0.091	.815**	-.365**	.605**
		Sig. (2-tailed)									0.000	0.253	0.000	0.000	0.000
		N									165	160	162	162	164
	Government Effectiveness : Percentile Rank	Correlation Coefficient									1.000	0.074	.852**	-.345**	.661**
		Sig. (2-tailed)										0.354	0.000	0.000	0.000
		N										160	162	162	164
	Cultivation of drought resistant crops	Correlation Coefficient										1.000	0.043	-0.010	0.126
		Sig. (2-tailed)											0.592	0.896	0.113
		N											157	157	159
	GDP per capita	Correlation Coefficient											1.000	-.437**	.657**
		Sig. (2-tailed)												0.000	0.000
		N												159	161
	Average soil erosion for exposed area	Correlation Coefficient												1.000	-.277**
		Sig. (2-tailed)													0.000
		N													161
	Access to information - mobile phone	Correlation Coefficient													1.000
		Sig. (2-tailed)													
		N													

**. Correlation is significant at the 0.01 level (2-tailed).

E.5. Number of countries in each risk category by cluster and in the global analysis.

This table compares the number of countries belonging to each risk category between each cluster and the global analysis and can be understood in the following way: For the high-income cluster, there were 9 countries in each of the risk categories from very high to very low. However in the global analysis, no high income countries were in the very high risk category, only 6 were in the high risk category, and so on.

	Very High	High	Medium	Low	Very Low
High income	9	9	9	9	9
Global	0	6	14	14	11
Upper middle income	9	9	9	9	9
Global	9	14	9	5	8
Low middle income	9	9	10	10	10
Global	15	8	5	12	8
Low income	5	5	5	6	6
Global	9	5	5	2	6
Europe	7	7	8	8	8
Global	3	12	6	8	9
Asia	8	8	9	9	9
Global	9	12	8	10	4
Africa	9	10	10	10	10
Global	20	6	5	9	9
Latin America & Caribbean	5	5	5	6	6
Global	1	3	11	4	8
LDCs	8	8	9	9	9
Global	13	5	5	6	11
Annex I	7	8	8	8	8
Global	0	10	10	9	10
Non-Annex I	25	25	25	25	26
Global	33	23	23	24	23
V20	7	8	8	8	8
Global	12	3	6	11	7
Breadbasket	3	3	3	4	4
Global	0	7	6	2	2
Reliance on agriculture	7	7	7	7	7
Global	12	6	4	6	7

E.6. Limitations

% missing indicator data by cluster

	Literacy rate, adult total (% of people ages 15 and above)	Prevalence of undernourishment (population %)	Share of GDP from agr., forestry and fishing in US$	Proportion of population living below the national poverty line	Unemployment, total (% of total labor force) (national estimate)	GINI index	Saved any money in the past year (age 15+) (%)	Improved water source (% of population with access)	Government Effectiveness: Percentile Rank	Cultivation of drought resistant crops (% yield)	GDP per capita	Average soil erosion for exposed area	Access to information - mobile phone subscription per 100 people	Total missing
Global	13.94	4.85	0.00	8.48	0.00	8.48	12.12	0.00	0.00	3.03	1.82	1.82	0.61	4.24
High income	44.44	0.00	0.00	15.56	0.00	8.89	2.22	0.00	0.00	0.00	2.22	2.22	0.00	5.81
Upper middle income	4.44	0.00	0.00	13.33	0.00	13.33	13.33	0.00	0.00	2.22	2.22	0.00	0.00	3.76
Low middle income	2.08	8.33	0.00	0.00	0.00	2.08	18.75	0.00	0.00	8.33	2.08	4.17	2.08	3.69
Low income	0.00	14.81	0.00	3.70	0.00	11.11	14.81	0.00	0.00	0.00	0.00	0.00	0.00	3.42
Europe	36.84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.63	2.63	2.63	0.00	3.44
Asia	4.65	6.98	0.00	16.28	0.00	16.28	9.30	0.00	0.00	0.00	0.00	0.00	0.00	4.11
Africa	2.04	8.16	0.00	0.00	0.00	2.04	14.29	0.00	0.00	6.12	2.04	4.08	2.04	3.14
Latin America and Caribean	3.70	0.00	0.00	22.22	0.00	22.22	18.52	0.00	0.00	0.00	3.70	0.00	0.00	5.41
LDCs	2.33	11.63	0.00	0.00	0.00	2.33	18.60	0.00	0.00	6.98	2.33	0.00	0.00	3.40
SIDS	10.00	10.00	0.00	30.00	0.00	35.00	70.00	0.00	0.00	10.00	5.00	5.00	0.00	13.46
V20	2.56	15.38	0.00	0.00	0.00	2.56	15.38	0.00	0.00	2.56	5.13	0.00	0.00	3.35
Annex I	48.72	0.00	0.00	2.56	0.00	0.00	0.00	0.00	0.00	0.00	2.56	2.56	0.00	4.34
Non-Annex I	3.17	6.35	0.00	10.32	0.00	11.11	15.87	0.00	0.00	3.97	1.59	1.59	0.79	4.21
Breadbasket	35.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.71
Reliance on agriculture (employment)	2.86	17.14	0.00	2.86	0.00	2.86	22.86	0.00	0.00	5.71	0.00	0.00	0.00	4.18

Countries included in the assessment by cluster

	Countries before deletion based on global missing data thresholds	Countries after deletion	% of countries analysed by cluster
Global	195	165	84.62
High income	61	45	73.77
Upper middle income	54	45	83.33
Low middle income	50	48	96.00
Low income	29	27	93.10
Europe	44	38	86.36
Asia	48	43	89.58
Africa	54	49	90.74
Latin America and Carribean	33	27	81.82
LDCs	47	43	91.49
SIDS	38	20	52.63
V20	42	39	92.86
Annex I	42	39	92.86
Non-Annex I	152	126	82.89
Breadbasket	17	17	100.00
Reliance on agriculture (employment)	37	35	94.59

References

[dataset] FAO, 2018. FAOSTAT: Crops: Yield [WWW Document]. URL http://www.fao.org/faostat/en/?#data/QC (accessed 5.8.21).

Beccari, B., 2016. A Comparative Analysis of Disaster Risk, Vulnerability and Resilience Composite Indicators. PLoS Curr. 8, https://doi.org/10.1371/currents.dis.453df025e34b682e9737f95070f9b970

Carrão, H., Naumann, G., Barbosa, P., 2016. Mapping global patterns of drought risk: An empirical framework based on sub-national estimates of hazard, exposure and vulnerability. Glob. Environ. Chang. 39, 108–124. https://doi.org/10.1016/j.gloenvcha.2016.04.012

Field, A., 2013. Discovering statistics using IBM SPSS statistics, 4th ed. Sage, London.

Hagenlocher, M., Meza, I., Anderson, C.C., Min, A., Renaud, F.G., Walz, Y., Siebert, S., Sebesvari, Z., 2019. Drought vulnerability and risk assessments: state of the art, persistent gaps, and research agenda. Environ. Res. Lett. 14, 083002. https://doi.org/10.1088/1748-9326/ab225d

Hagenlocher, M., Renaud, F.G., Haas, S., Sebesvari, Z., 2018. Vulnerability and risk of deltaic social-ecological systems exposed to multiple hazards. Sci. Total Environ. 631–632, 71–80. https://doi.org/10.1016/j.scitotenv.2018.03.013

Hinkle, D.E., Wiersma, W., Jurs, S.G., 2003. Applied statistics for the behavioral sciences, 5th ed. Houghton Mifflin College Division.

Meza, I., Siebert, S., Döll, P., Kusche, J., Herbert, C., Eyshi Rezaei, E., Nouri, H., Gerdener, H., Popat, E., Frischen, J., Naumann, G., Vogt, J. V., Walz, Y., Sebesvari, Z., Hagenlocher, M., 2020. Global-scale drought risk assessment for agricultural systems. Nat. Hazards Earth Syst. Sci. 20, 695–712. https://doi.org/10.5194/nhess-20-695-2020

Müller Schmied, H., Eisner, S., Franz, D., Wattenbach, M., Portmann, F.T., Flörke, M. and Döll, P., 2014. Sensitivity of simulated global-scale freshwater fluxes and storages to input data, hydrological model structure, human water use and calibration. Hydrol. Earth Syst. Sci. 18, 3511-3538. https://doi.org/10.5194/hess-18-3511-2014

Naumann, G., Barbosa, P., Garrote, L., Iglesias, A., Vogt, J., 2014. Exploring drought vulnerability in Africa: an indicator based analysis to be used in early warning systems. Hydrol. Earth Syst. Sci. 18, 1591–1604. https://doi.org/10.5194/hess-18-1591-2014

OECD, 2008. Handbook on constructing composite indicators: Methodology and user guide, Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD. https://doi.org/10.1787/9789264043466-en

Portmann, F.T., Siebert, S. and Döll, P., 2010. MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Global Biogeochem. Cy. 24. https://doi.org/10.1029/2008gb003435

Siebert, S. and Döll, P., 2010. Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation. J. Hydrol. 384, 198-217. https://doi.org/10.1016/j.jhydrol.2009.07.031

Steduto, P., Hsiao, T.C., Fereres, E., Raes, D., 2012. Crop yield response to water. Rome.

Appendix F

F1. Background of experts

Background of experts who participated in the online survey

Gender Identity	***Quantity (N)***	***Respondents (%)***
Female	32	47.1
Male	36	52.9
Other	0	0
Sector	**Quantity (N)**	**Respondents (%)**
Academia	38	52.1
Government	25	34.2
International Organization	5	6.8
Private	2	2.7
NGO	2	2.7
Other	1	1.4
Years of experience working on drought	**Quantity (N)**	**Respondents (%)**
No previous experience working on vulnerability and risk	1	1.4
1-2	5	6.9
3-5	19	26.4
6-10	18	25.0
10+	29	40.3
Geographic focus of work	**Quantity (N)**	**Respondents (%)**
Australia	0	0.0
Asia	23	20.9
Africa	12	10.9
Europe	31	28.2
North America	8	7.3
South America	11	10.0
Global	7	6.4
General/ theoretical (e.g. methods oriented)	18	16.4
Research field	**Quantity (N)**	**Respondents (%)**
Agricultural sciences	7	17.5
Anthropology and development	1	2.5
Climate Change	3	7.5
Climate science/services	3	7.5
Drought hazard assessment and disaster risk analysis	2	5
Environmental policy	1	2.5
Geography	4	10.0
Health	2	5.0
Hydrology	7	17.5
Interdisciplinary	2	5.0
Sociology	1	2.5
Soil and Water Conservation	1	2.5
Economics	3	7.5
Water resources management	3	7.5

F2: Relevant Indicators for Agricultural Systems

Relevant indicators for agricultural systems vulnerability assessments at global level. Experts ranked the indicators according to the categories not relevant, low relevance, low-medium relevance, medium-high relevance and highly relevant. The results were normalized to receive a value between 0 and 1 for each indicator. The amount of responses in each category was multiplied with the following values: not relevant*0, low relevance*0.25, low-medium relevance*0.5, medium-high relevance*0.75 and highly relevant*1. Finally, the sum was divided by the total number of answers given per indicator to receive the average. Indicators with a value close to 1 are highly relevant, whereas indicators with a value close to 0 indicate lower relevance. However, in this overview, only indicators are included that more than 50% of the experts considered as medium-high or highly relevant. An indicator or proxy indicator can be positively or negatively correlated with the vulnerability assessment; this correlation is represented on the column "direction". Additionally, the standard deviation shows the variation of agreement and disagreement among the experts. High values indicate a higher range of opinions, whereas low values represent a high level of agreement.

Indicator	**Direction**	**Relevance** Weighted relevance	**Standard deviation**
Social Susceptibility			
Access to fodder (kg purchased per year)	-	0.731	10.00
Agriculture (% of GDP)	+	0.859	16.18
Agricultural machinery in use (#)	-	0.665	9.13
Dependency on agriculture for livelihood (%)	+	0.935	18.62
Electricity production from hydroelectric sources (% of total)	+	0.646	8.87
GDP per capita, PPP	-	0.690	10.33
Gender inequality (categorical)	+	0.569	9.22
GINI index (income inequality)	+	0.705	9.71
Illiteracy rate (%)	+	0.734	11.98
Life expectancy at birth (years)	-	0.585	7.98
Market fragility	+	0.756	10.77
Population ages 15-64 (% of total population)	-	0.599	8.92
Population below the national poverty line (%)	+	0.813	13.41
Population undernourished (%)	+	0.772	13.15
Population with ill-health (%)	+	0.683	10.03
Population without access to clean water (%)	+	0.628	9.50
Population without access to (improved) sanitation (%)	+	0.585	8.65
Prevalence of conflict/insecurity	+	0.762	12.05
Rural population (% of total population)	+	0.799	13.78
Unemployment rate (%)	+	0.619	8.70
Environmental Susceptibility			
Baseline water stress (ratio of withdrawals to renewable supply)	+	0.856	14.13
Area protected and designated for the conservation of biodiversity (%)	-	0.699	9.37
Degree of land degradation and desertification	+	0.898	16.01
Use of fertilizer (ton)	-	0.722	10.97
Insecticides and pesticides used (ton/ha)	-	0.681	9.64
Livestock health	-	0.701	9.87
Soil organic matter (g*kg)	-	0.797	12.68
Soil depth (mm)	-	0.756	10.86
Lack of Coping Capacity			
Distance to closest market (km)	+	0.645	9.27
Corruption (e.g. Corruption Perception Index)	+	0.713	10.34
Farmers use different crop varieties (%)	-	0.875	14.15
Farmers with crop, livestock or drought insurance (%)	-	0.850	15.67
Farmers/laborers without access to bank loans/(micro-) credits (%)	+	0.835	14.09
Farmers/laborers without savings (%)	+	0.847	14.35
Government effectiveness	-	0.869	14.46
Irrigated land (% total arable)	-	0.909	16.20
Total dam capacity (m3)	-	0.820	13.18
% of retained renewable water	-	0.819	12.10
Existence of adaptation policies/plans (yes/no)	+	0.889	16.92
Public participation in local policy	+	0.756	11.12
Cultivation of drought-resistant crops (%)	-	0.911	17.69
Lack of Adaptive Capacity			

National investment in disaster prevention & preparedness (US$/Year/capita)	-	0.852	15.04
Disaster risk taken into account in public investment and planning decisions (yes/no)	-	0.852	14.68
Number of (drought-related) adaptation projects in the past 10 years	-	0.801	13.00
Research and development expenditure (% of GDP)	-	0.732	10.53

F3: Relevant Indicators for Water Supply

Relevant indicators for water supply vulnerability assessments at global level.

Experts ranked the indicators according to the categories not relevant, low relevance, low-medium relevance, medium-high relevance and highly relevant. The amount of responses in each category was multiplied with the following values: not relevant*0, low relevance*0.25, low-medium relevance*0.5, medium-high relevance*0.75 and highly relevant*1. Finally, the sum was divided by the total number of answers given per indicator to receive the average. Indicators with a value close to 1 are highly relevant, whereas indicators with a value close to 0 indicate lower relevance. However, in this overview, only indicators are included that more than 50% of the experts considered as medium-high or highly relevant. An indicator or proxy indicator can be positively or negatively correlated with the vulnerability assessment; this correlation is represented on the column “direction”. Additionally, the standard deviation shows the variation of agreement and disagreement among the experts. High values indicate a higher range of opinions, whereas low values represent a high level of agreement.

Indicator	**Direction**	**Relevance** Weighted relevance	**Standard deviation**
Social Susceptibility			
Population without access to clean water (%)	+	0.870	11.67
Agriculture (% of GDP)	+	0.669	4.60
Dependency on agriculture for livelihood (%)	+	0.717	6.26
Electricity production from hydroelectric sources (% of total)	+	0.695	4.79
GDP per capita, PPP	-	0.714	5.61
Gender inequality (categorical)	+	0.609	4.72
GINI index (income inequality)	+	0.744	5.64
Expenditure on health (out-of-pocket) (%)	+	0.655	4.10
Illiteracy rate (%)	+	0.761	7.18
Population ages 15-64 (% of total population)	-	0.616	4.53
Population below the national poverty line (%)	+	0.818	8.48
Population undernourished (%)	+	0.761	7.44
Population with ill-health (%)	+	0.726	5.70
Population without access to (improved) sanitation (%)	+	0.761	6.88
Prevalence of conflict/insecurity	+	0.762	6.96
Refugee population (% of total population)	+	0.678	4.94
Risk perception (% of population who has experienced droughts in the past 10 years)	+	0.856	12.10
Rural population (% of total population)	+	0.755	6.89
Tourism (% of GDP)	+	0.686	5.89
Unemployment rate (%)	+	0.637	3.88
Environmental Susceptibility			

Area protected and designated for the conservation of biodiversity (%)	-	0.679	5.23
Baseline water stress (ratio of withdrawals to renewable supply)	+	0.921	12.80
Water quality (categorical)	-	0.872	11.32
Lack of Coping Capacity			
Corruption (e.g. Corruption Perception Index)	+	0.738	5.83
Farmers/laborers without savings (%)	+	0.674	4.30
Government effectiveness	-	0.872	10.81
Irrigated land (% total arable)	-	0.680	5.79
Total dam capacity (m3)	-	0.855	9.78
% of retained renewable water	-	0.838	8.89
Existence of adaptation policies/plans (yes/no)	-	0.883	12.28
Public participation in local policy	-	0.774	6.42
Lack of Adaptive Capacity			
Disaster risk taken into account in public investment and planning decisions (yes/no)	-	0.847	9.74
National investment in disaster prevention & preparedness (US$/Year/capita)	-	0.847	10.22
Number of (drought-related) adaptation projects in the past 10 years	-	0.778	8.09
Research and development expenditure (% of GDP)	-	0.738	5.51

F4: Detailed sector analysis for agricultural systems

F4.1 Social dimension

Most experts identified the following indicators as globally relevant: Illiteracy rate (%), gender inequality (categorical), population undernourished (%), population with ill-health (%), life expectancy at birth (years), rural population (% of total population) and population ages 15-64 (% of total population).

The top relevance indicators for female experts (population undernourished (%) and rural population (% of total population)) are also the top for male experts. The most significant discrepancy between genders is the life expectancy at birth indicator where only 28% of women consider it relevant in contrast to 53% of males.

The gender inequality indicator is highly relevant for male experts, people with more than six years of experience, respondents from the academia and NGO sector, and experts with focus on Asia, North America, South America, global and general/theoretical.

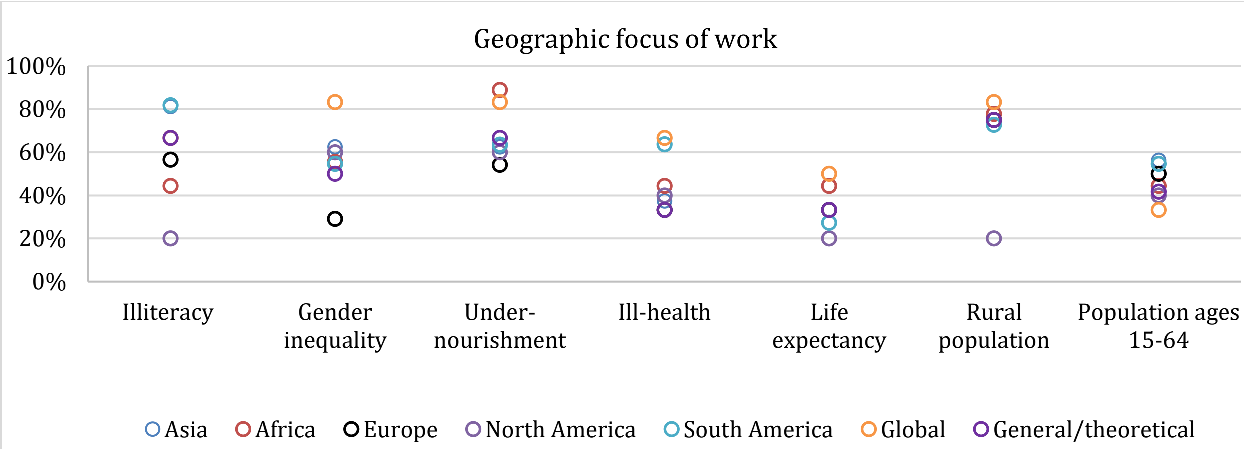


Figure 3 Proportion of experts who consider the indicators globally relevant depending on their geographic work focus.

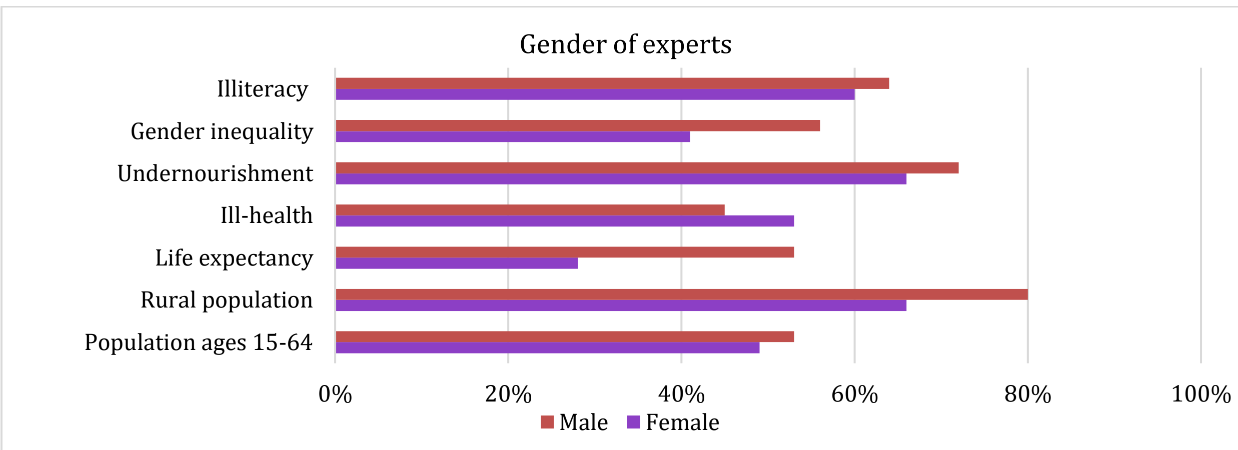


Figure 4 Proportion of experts who consider the indicators globally relevant depending on their gender.

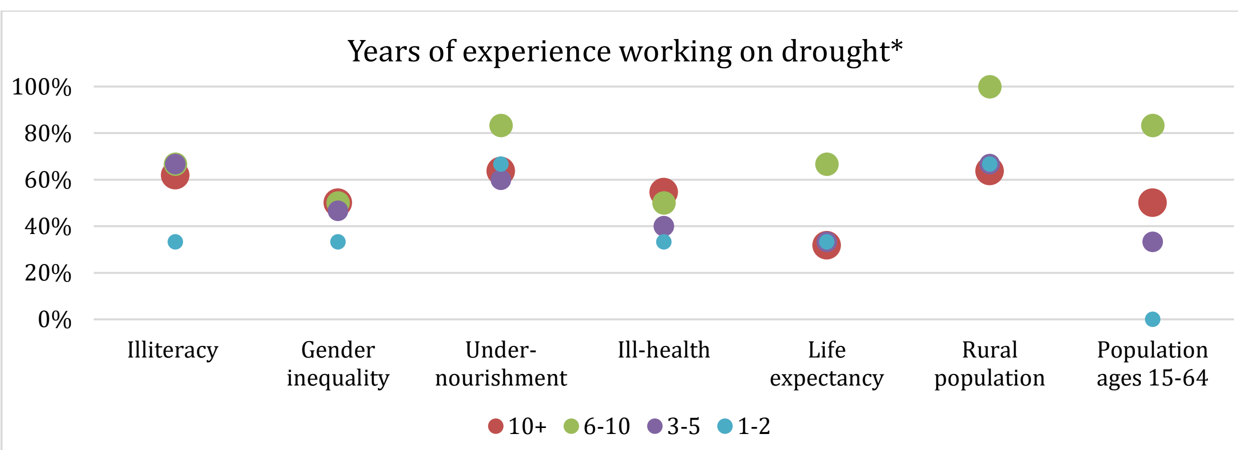


Figure 5 Proportion of experts who consider the indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

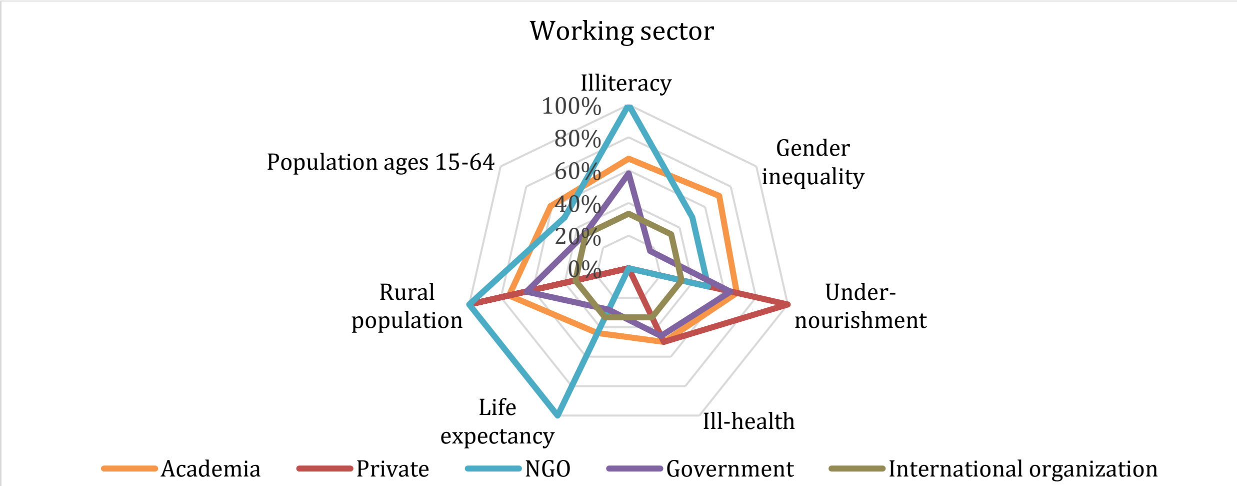


Figure 6 Proportion of experts who consider the indicators globally relevant depending on their working sector.

F4.2 Economic dimension

In the economic dimension, there was more consensus according to the indicators that are considered applicable at the global level. Eleven indicators were identified as globally relevant: dependency on agriculture for livelihood (%), agriculture (% of GDP), population below the national poverty line (%), unemployment rate (%), GDP per capita, GINI index (income inequality), farmers/laborers without savings (%), farmers/laborers without access to bank loans / (micro-) credits (%), distance to closest market (km), market fragility and farmers with crop, livestock or drought insurance (%).

Experts working in drought for more than six years identified as the top three relevant indicators dependency on agriculture for livelihood (%), farmers/laborers without savings (%) and farmers with crop, livestock or drought insurance (%). Experts from all the geographic areas agreed on the relevance to consider agriculture (% of GDP), population below the national poverty line (%), GDP per capita, and market fragility in global drought vulnerability assessment on agricultural systems.

More than half of the experts working in academia highlight the relevance of the unemployment rate. Market fragility and distance to closest market were identified as for all the different sectors as relevant; only the private sector classified these indicators as low to low medium relevance.
Income inequality is a higher vulnerability relevance for experts that work in Asia, South America, global and general/theoretical focus.

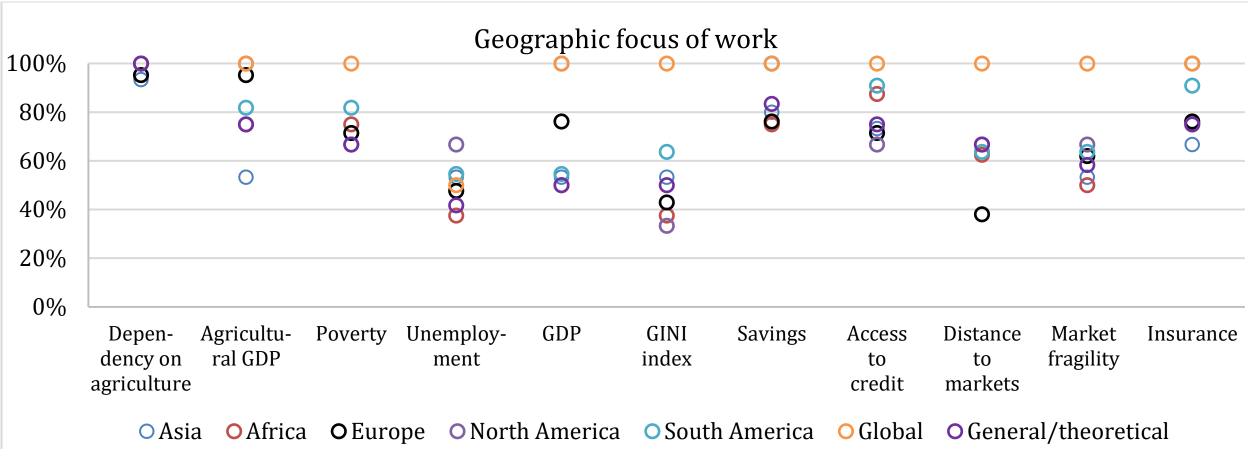


Figure 7 Proportion of experts who consider the indicators globally relevant depending on their geographic work focus.

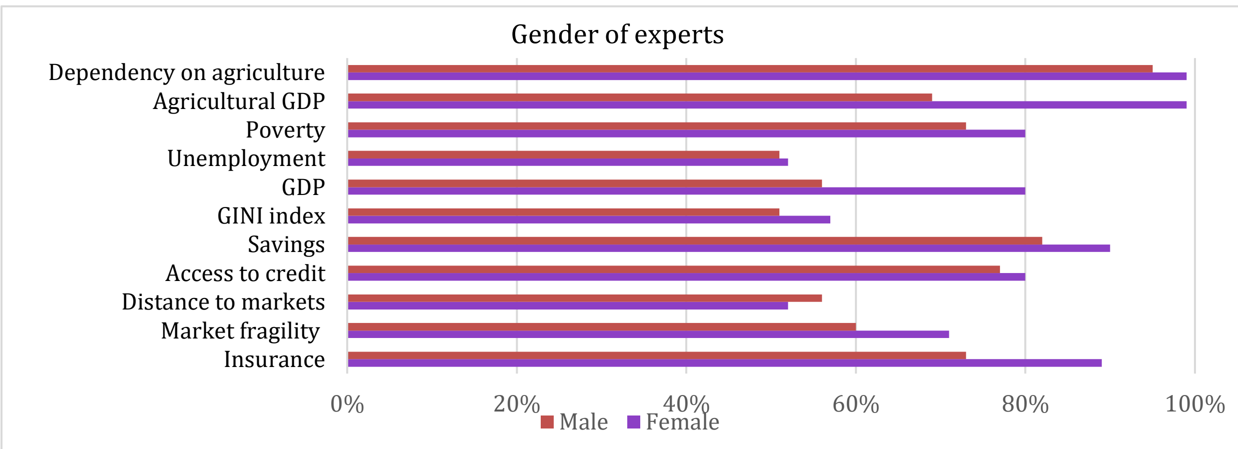


Figure 8 Proportion of experts who consider the indicators globally relevant depending on their gender.

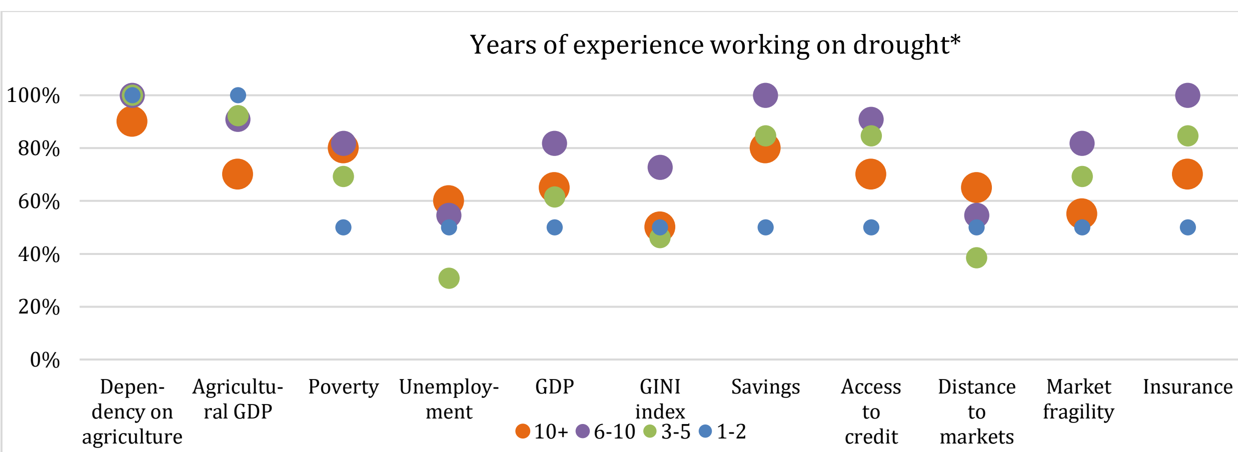


Figure 9 Proportion of experts who consider the indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

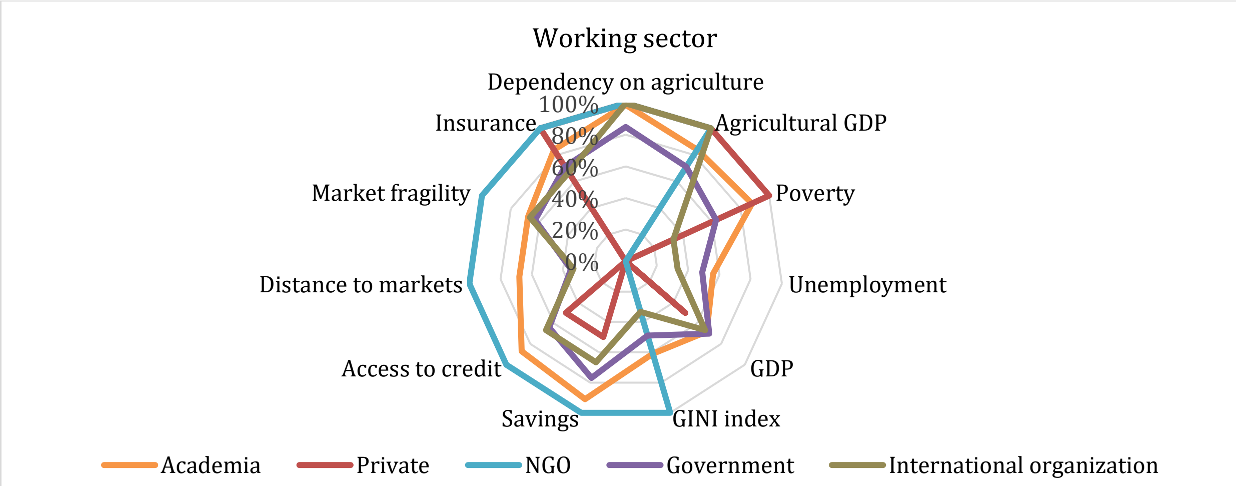


Figure 10 Proportion of experts who consider the indicators globally relevant depending on their working sector.

F4.3 Infrastructural dimension

All the experts agreed that the most relevant indicators for the infrastructure dimension are "water quality (categorical)", total dam capacity (m3) and % of retained renewable water.

The indicator population without access either to clean water or to improved sanitation was considered more relevant by female experts compared to male experts. Further, these indicators were selected as relevant for experts with more than ten years of experience. Around 40% of the experts whose work is focused on Europe consider them relevant on a global level.

Electricity production from hydroelectric sources (% of total), is relevant for experts from private, NGO's and governmental sector. However, for experts focusing on America and Asia, there are other more relevant indicators such as water quality or total dam capacity.

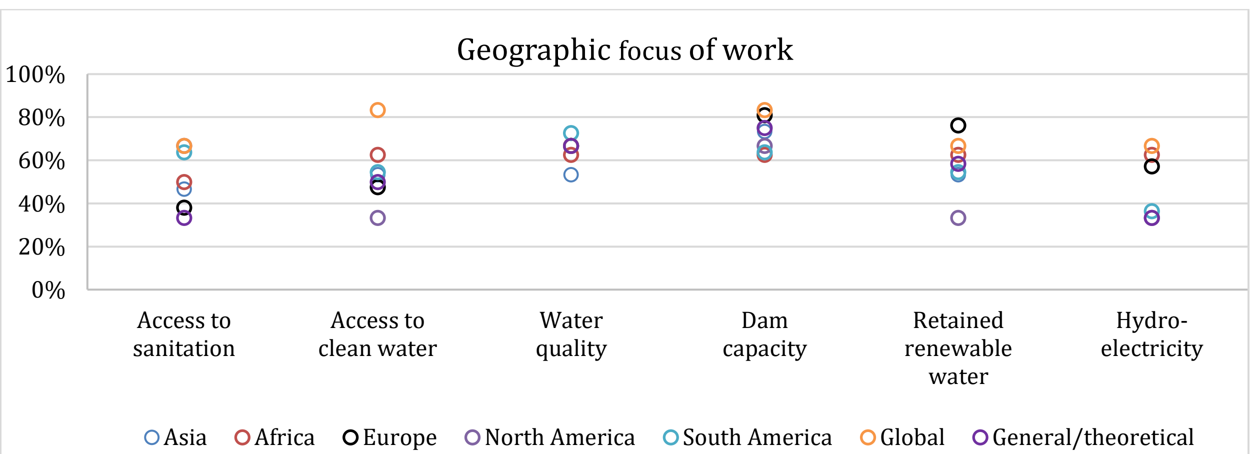


Figure 11 Proportion of experts who consider the infrastructural indicators globally relevant depending on their geographic work focus.

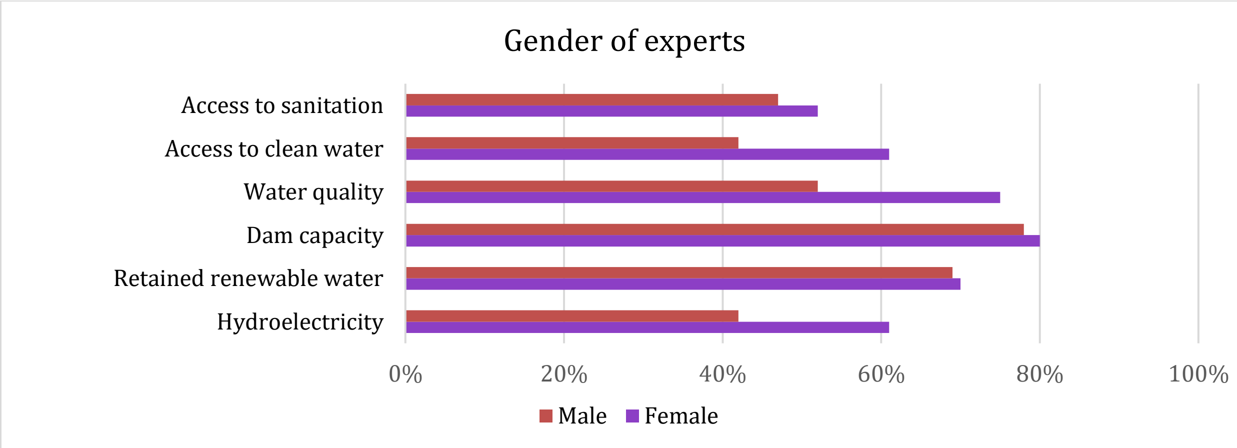


Figure 12 Proportion of experts who consider infrastructural indicators globally relevant depending on their gender.

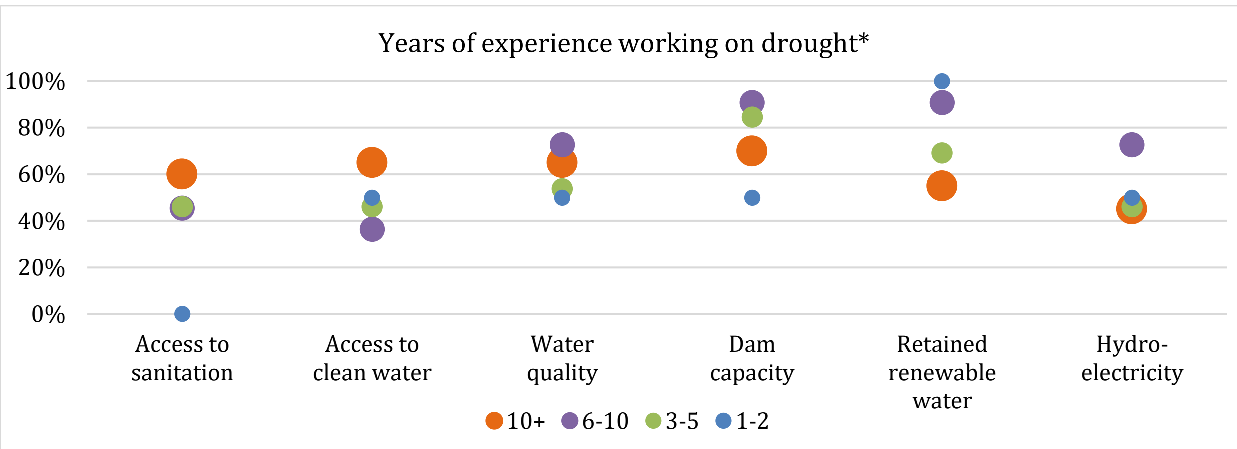


Figure 13 Proportion of experts who consider the infrastructural indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

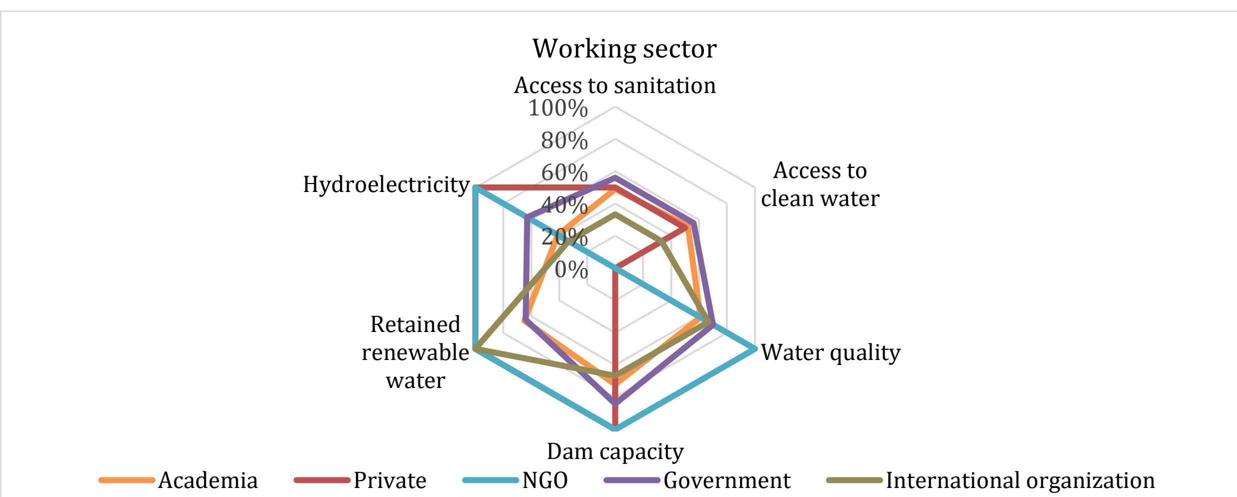


Figure 14 Proportion of experts who consider the infrastructural indicators globally relevant depending on their working sector.

F4.4 Crime and Conflict

The prevalence of conflict/insecurity was the only indicator where more than 50% of the total experts considered it relevant at the global level. The only group in which less agreement was found was among people working in the government sector. For this sector, 14% considered the indicator not relevant, low relevant or low-medium relevant for 28% of the experts, the prevalence of conflict/insecurity is medium-high relevant and is highly relevant to 21% of respondents.

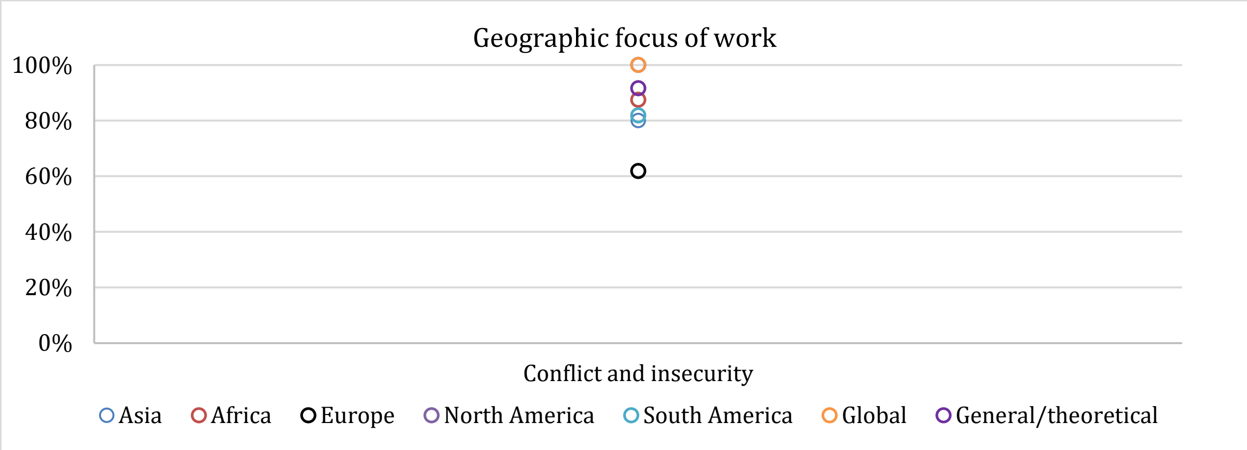


Figure 15 Proportion of experts who consider the prevalence of conflict/insecurity as a globally relevant indicator, depending on their geographic work focus.

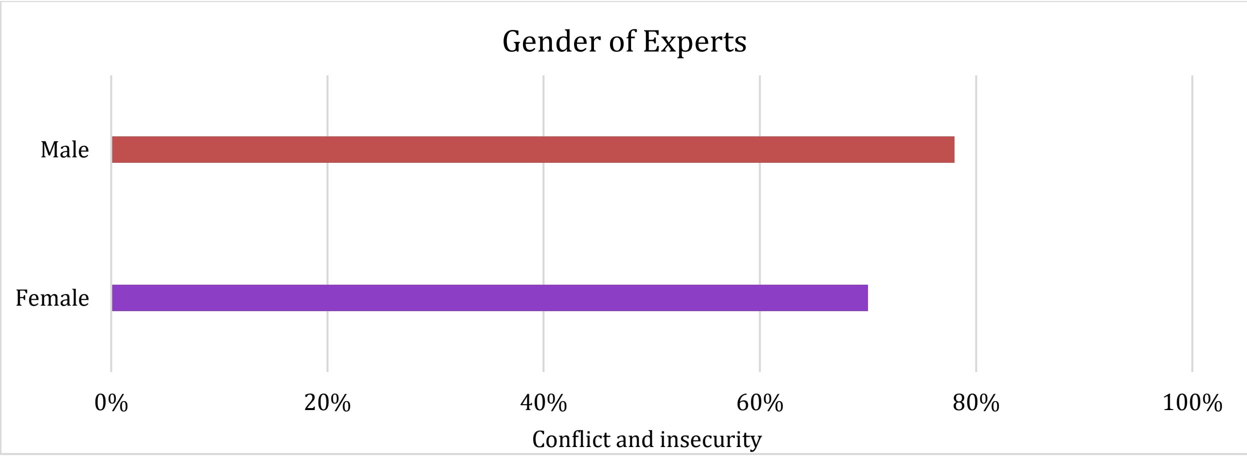


Figure 51 Proportion of experts who consider the prevalence of conflict/insecurity globally relevant depending on their gender.

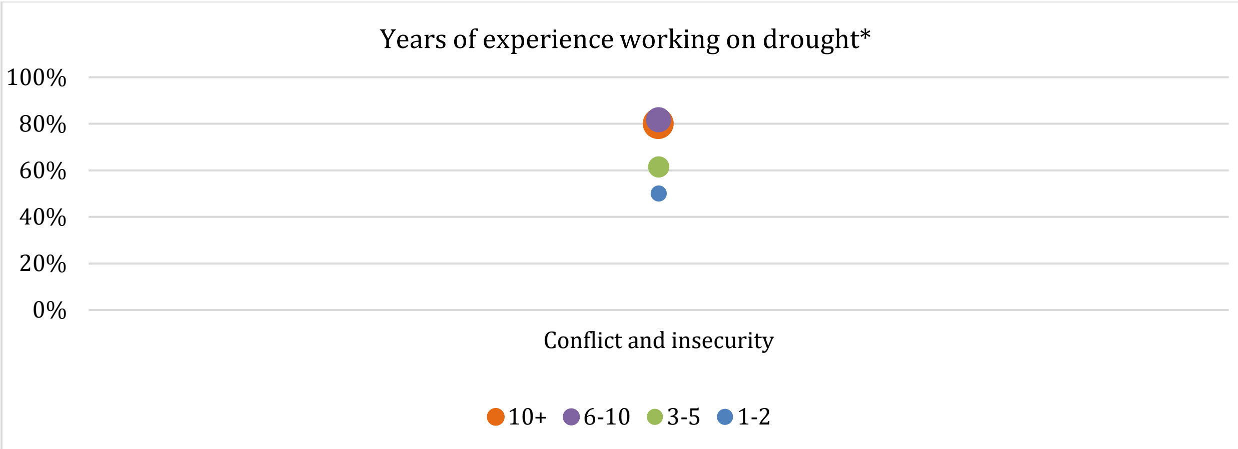


Figure 17 Proportion of experts who consider the prevalence of conflict/insecurity globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

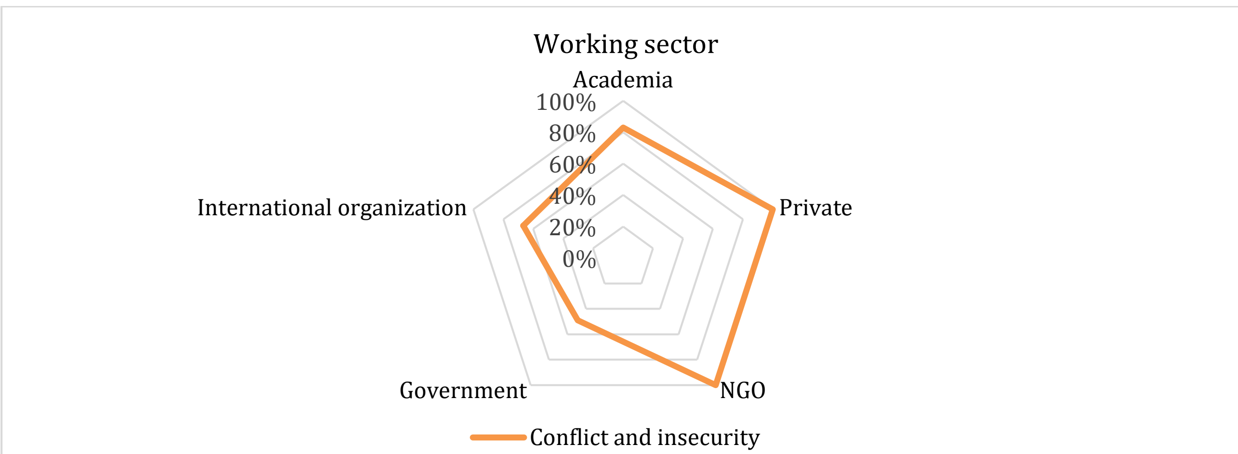


Figure 18 Proportion of experts who consider the prevalence of conflict/insecurity globally relevant depending on their working sector.

F4.5 Governance

In the governance dimension, eight indicators were chosen as the most relevant at the global level (disaster risk taken into account in public investment and planning decisions (yes/no), national investment in disaster prevention & preparedness (US$/Year/capita), existence of adaptation policies/plans (yes/no), government effectiveness, number of (drought-related) adaptation projects in the past 10 years, corruption, public participation in local policy and research and development expenditure (% of GDP)). The expert's gender and the number of years working with drought did not show any difference among the selected indicators. All indicators were classified as relevant in the different groups and categories.

The number of (drought-related) adaptation projects in the past ten years and corruption indicators are relevant to all experts except those in the private sector for whom these indicators are of low relevance. Less than half (40%) of the respondents that work on Asia or general/theoretical topics considered "research and development expenditure (% of GDP)" as a relevant indicator.

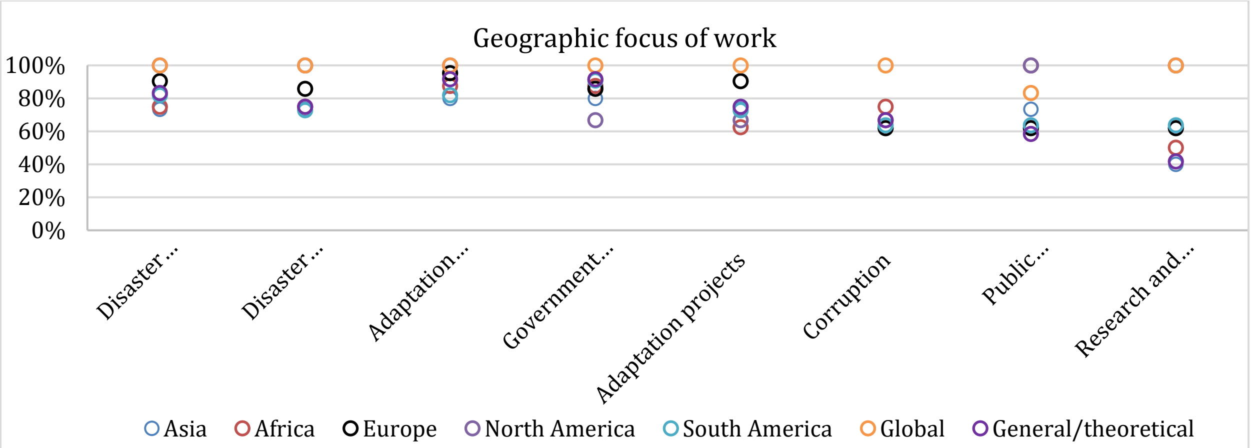


Figure 19 Proportion of experts who consider these governmental indicators globally relevant depending on their geographic work focus.

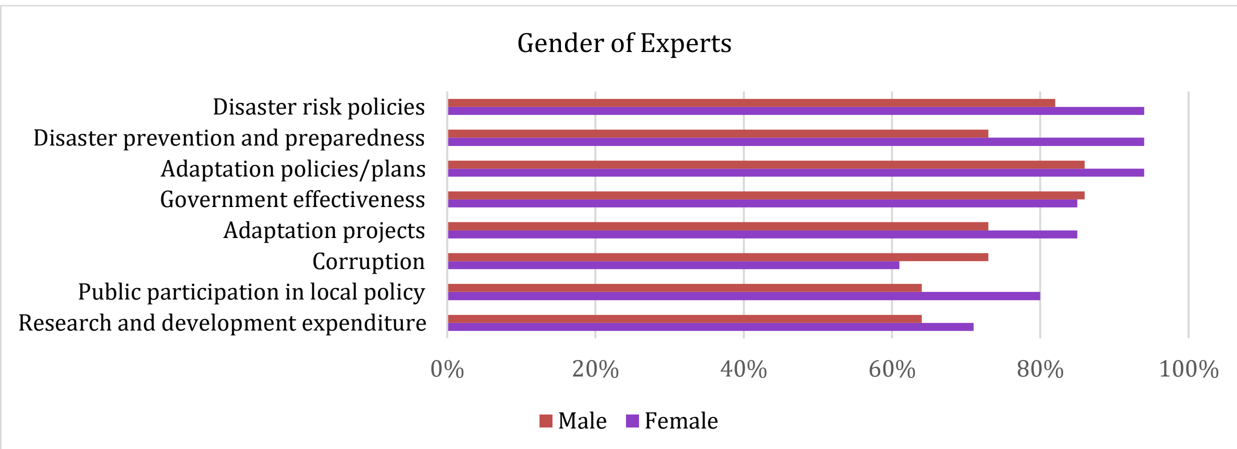


Figure 20 Proportion of experts who consider the governmental indicators globally relevant depending on their gender.

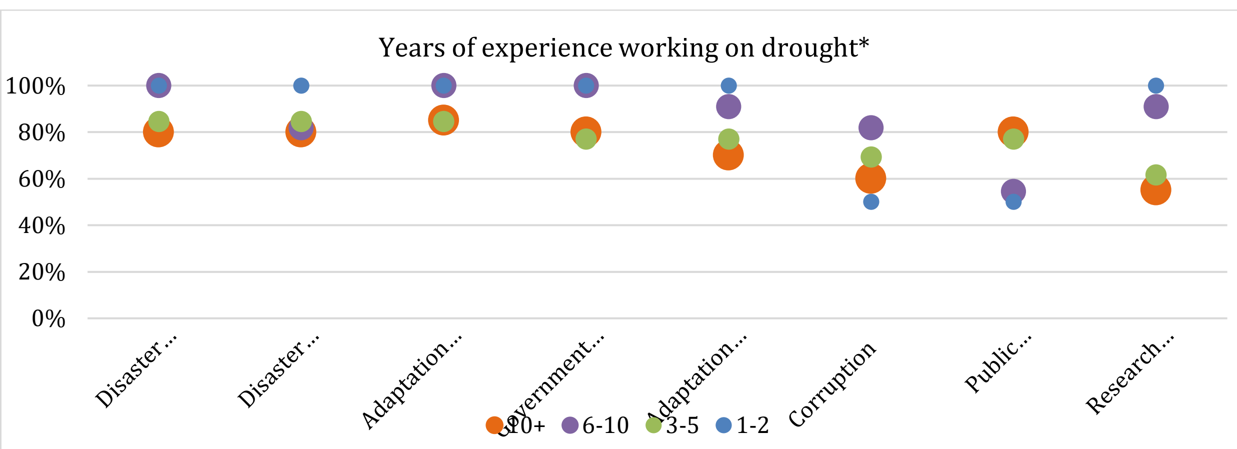


Figure 21 Proportion of experts who consider the governmental indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

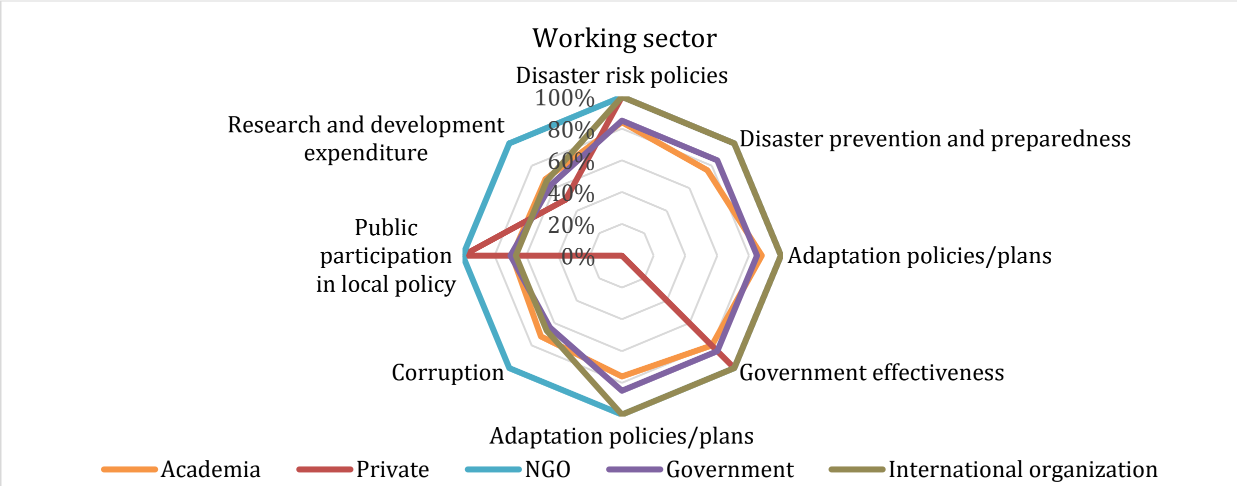


Figure 22 Proportion of experts who consider these governmental indicators globally relevant depending on their working sector.

F4.6 Environmental

Soil depth (mm), degree of land degradation and desertification, area protected and designated for the conservation of biodiversity (%), livestock health and baseline water stress (ratio of withdrawals to renewable supply) are currently perceived as a relevant indicators to measure vulnerability to drought at global level. The degree of land degradation/ desertification and the baseline water stress are the most relevant according to all the different categories and groups.

There was also plurality of eight out of ten global experts (83%) that rates the livestock health as relevant, close by 75% Africa focus experts, while almost half (48%) of experts focused on Europe considered it relevant. The percentage of area protected is considered relevant by people who have been working on drought topic for more than three years.

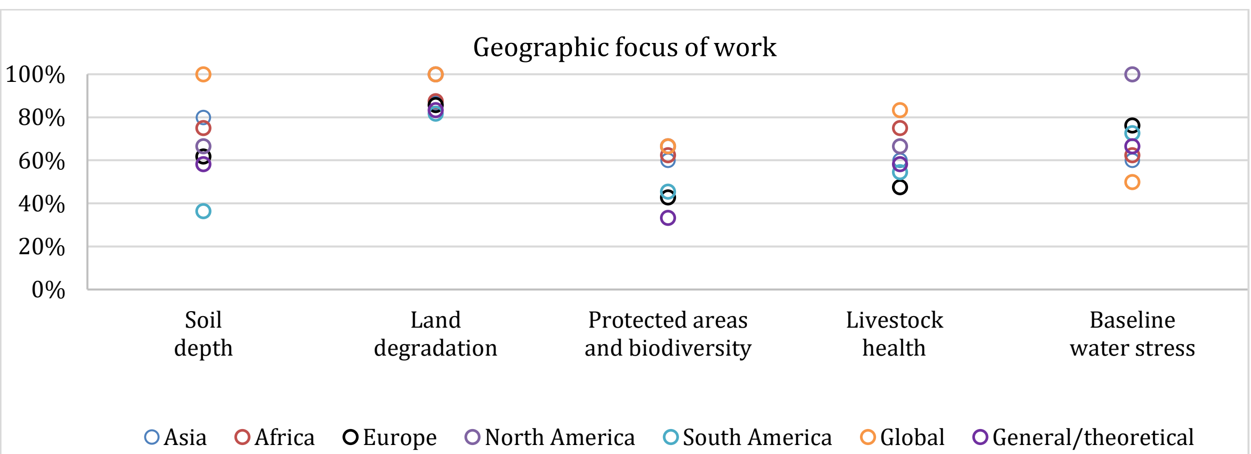


Figure 23 Proportion of experts who consider the environmental indicators globally relevant depending on their geographic work focus.

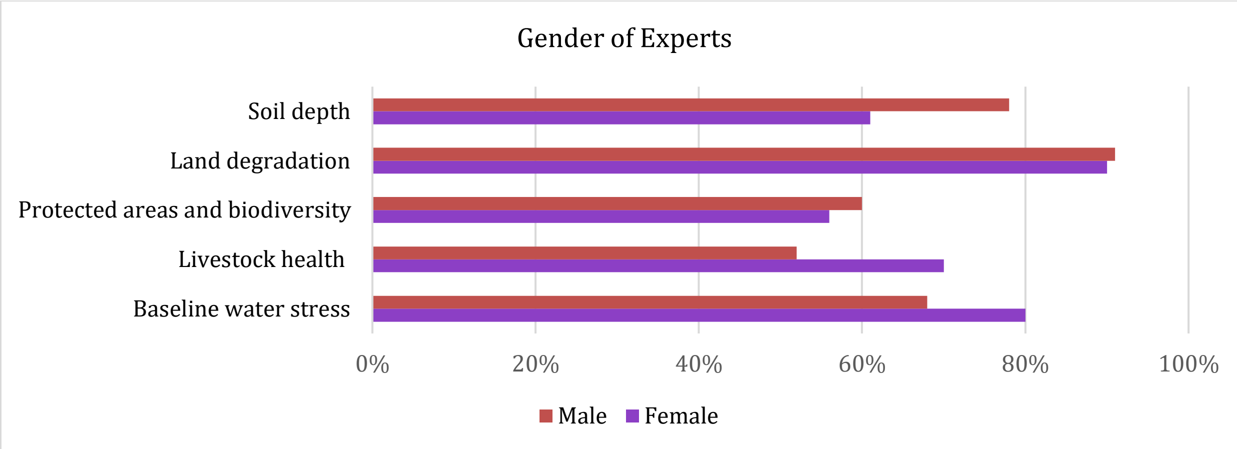


Figure 24 Proportion of experts who consider the environmental indicators globally relevant depending on their gender.

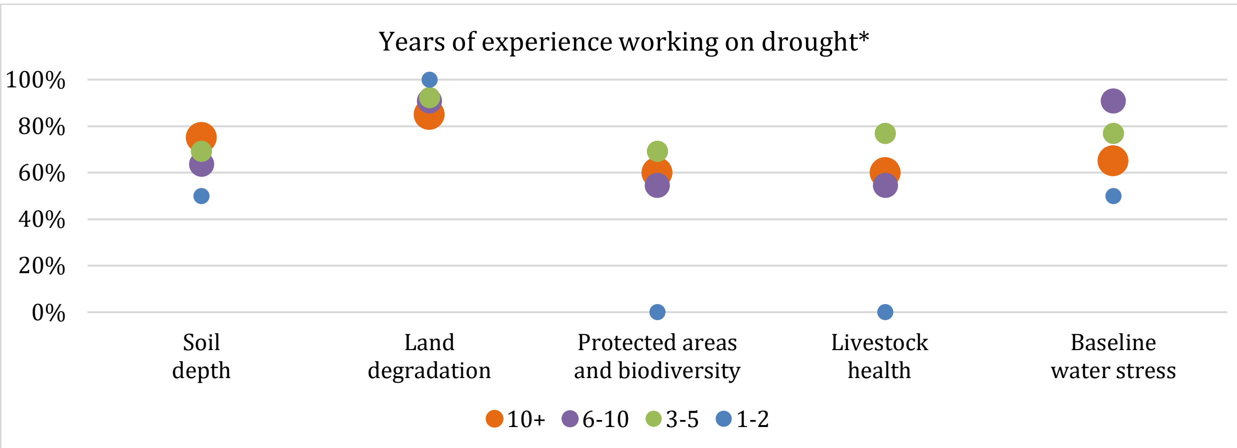


Figure 25 Proportion of experts who consider the environmental indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

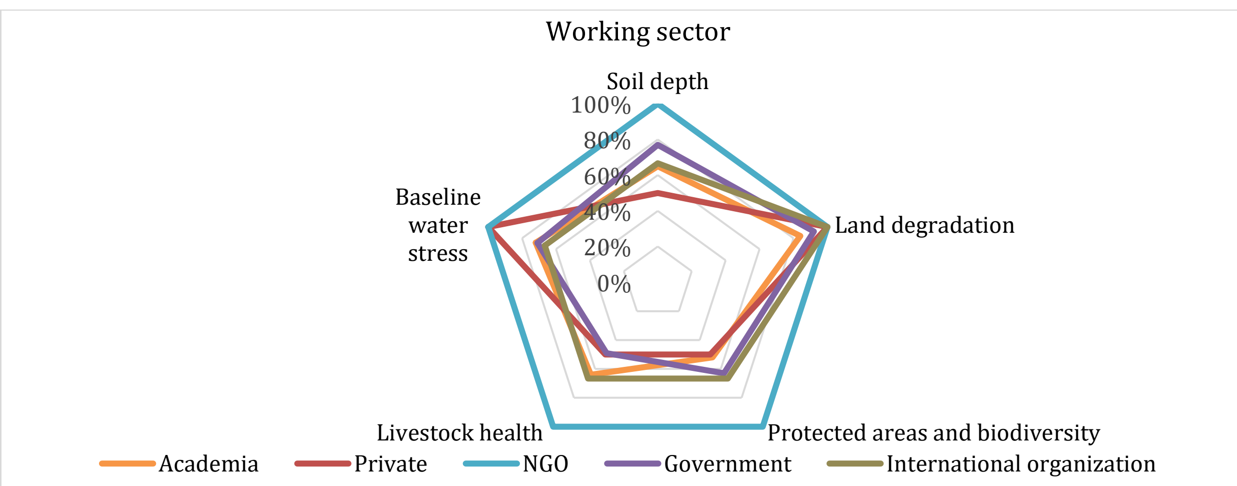


Figure 26 Proportion of experts who consider the environmental indicators globally relevant depending on their working sector.

F4.7 Farming practices

Farming practices was the only dimension of vulnerability where all indicators were considered relevant for agricultural systems at the global level. Looking at the different working sectors, it was found that most of the experts working in academia and in the government sector express greater relevance than private, NGO's and international sectors about the agricultural machinery in use (#) indicator. This indicator was also weighed as the least relevant in the dimension of agricultural practices.

Those more likely to score insecticides and pesticides used (ton/ha) as medium-high or highly global relevant include: female experts, six to ten years of working experiences, global geographic focus of work, and, experts from non-governmental organizations.

The use of different crop varieties (%) and the cultivation of drought-resistant crops (%) are considered ecosystem-based approaches to drought risk reduction (Kloos and Renaud 2016). These indicators were equally relevant for female and male experts. However, the cultivation of drought-resistant crops (%) was considered by 95% of the experts with more than ten years of experience as a global relevant indicator. In contrast, 85% of experts considered farmers use different crop varieties (%) as globally relevant. This pattern is repeated throughout the various working sectors and geographic focus areas, where the cultivation of drought-resistant crops (%) was catalogued as relevant by more experts than the cultivation of drought-resistant crops.

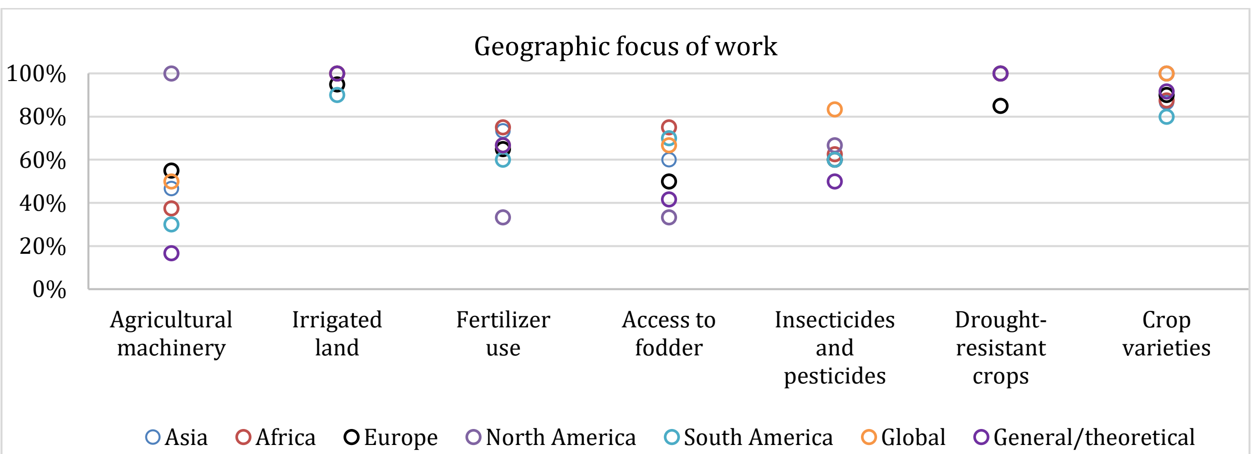


Figure 27 Proportion of experts who consider farming practices indicators as globally relevant depending on their geographic work focus.

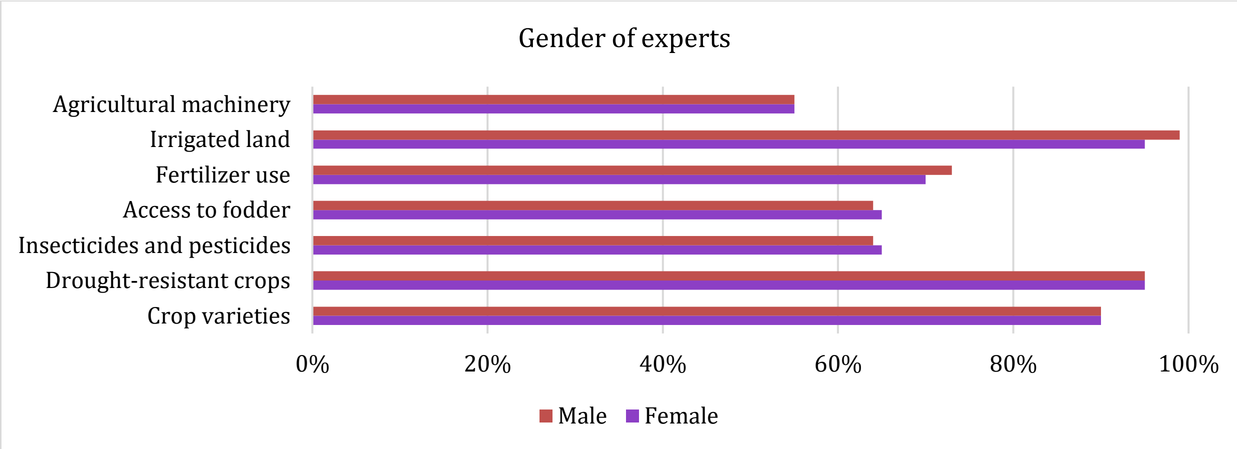


Figure 28 Proportion of experts who consider farming practices indicators globally relevant depending on their gender.

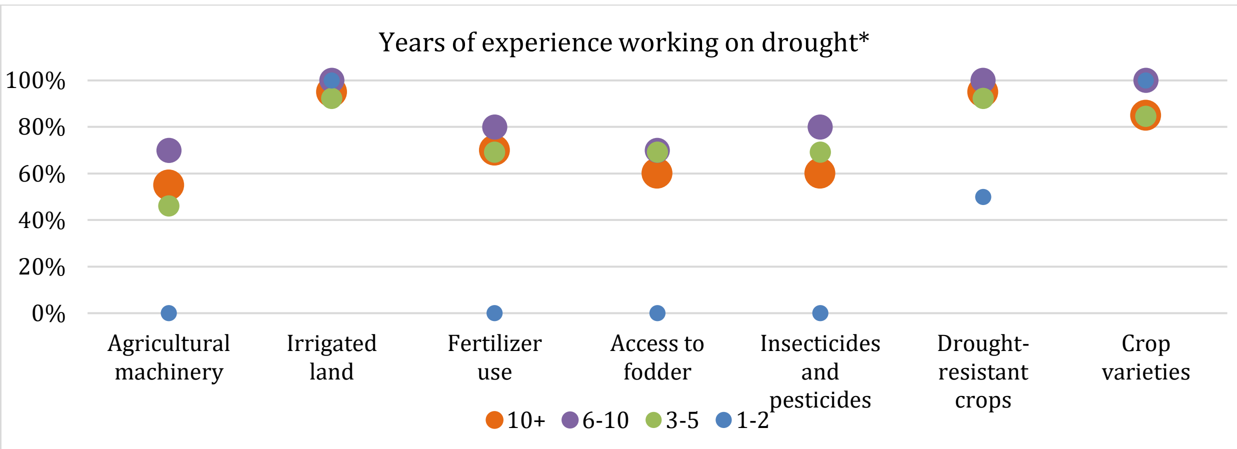


Figure 29 Proportion of experts who consider farming practices indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

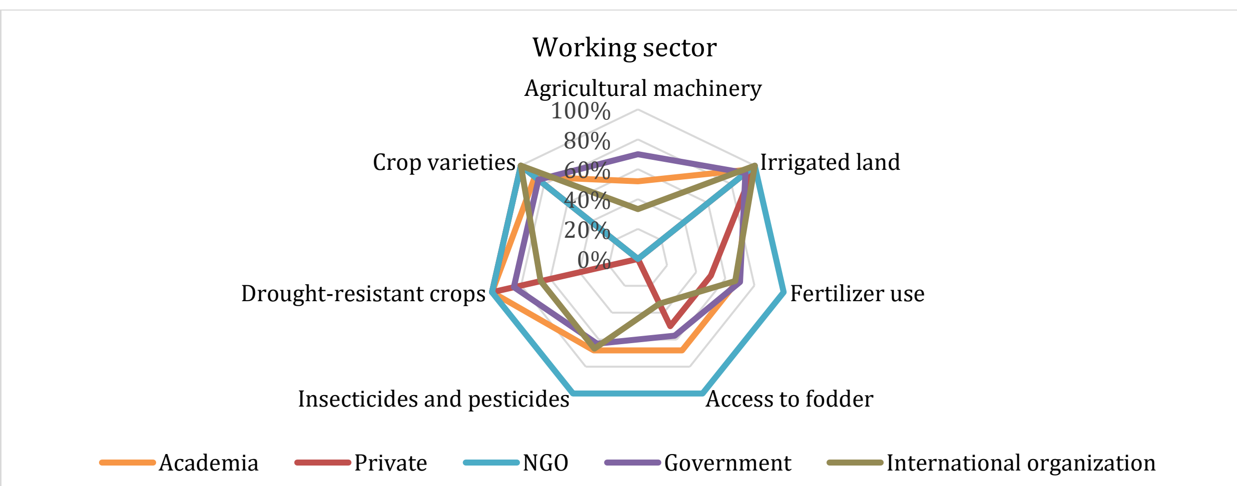


Figure 30 Proportion of experts who consider farming practices indicators globally relevant depending on their working sector.

References:

Kloos J., Renaud F.G. (2016). Overview of Ecosystem-Based Approaches to Drought Risk Reduction Targeting Small-Scale Farmers in Sub-Saharan Africa. In: Renaud F., Sudmeier-Rieux K., Estrella M., Nehren U. (eds) Ecosystem-Based Disaster Risk Reduction and Adaptation in Practice. Advances in Natural and Technological Hazards Research, vol 42. Springer, Cham.

F5: Detailed sector analysis for Water Supply

F5.1 Social dimension

In the online survey, the experts agreed on the global relevance of seven indicators for the vulnerability's social dimension. More than three-quarters of experts strongly agree that risk perception is an essential indicator of global drought vulnerability assessments. Those who are more certain than others that risk perception plays a crucial role in drought vulnerability assessment to water supply are: female experts that have six to ten years of experience working on drought, with a main geographic focus in Africa or on global assessments and experts that work on NGOs or private sectors.

The top relevance indicator by gender in the social dimension is risk perception (% of population who has experienced droughts in the past 10 years) and illiteracy rate (%). Gender inequality was scored as relevant for 57% of male experts, while just 36% of female experts weighed this indicator as globally relevant.

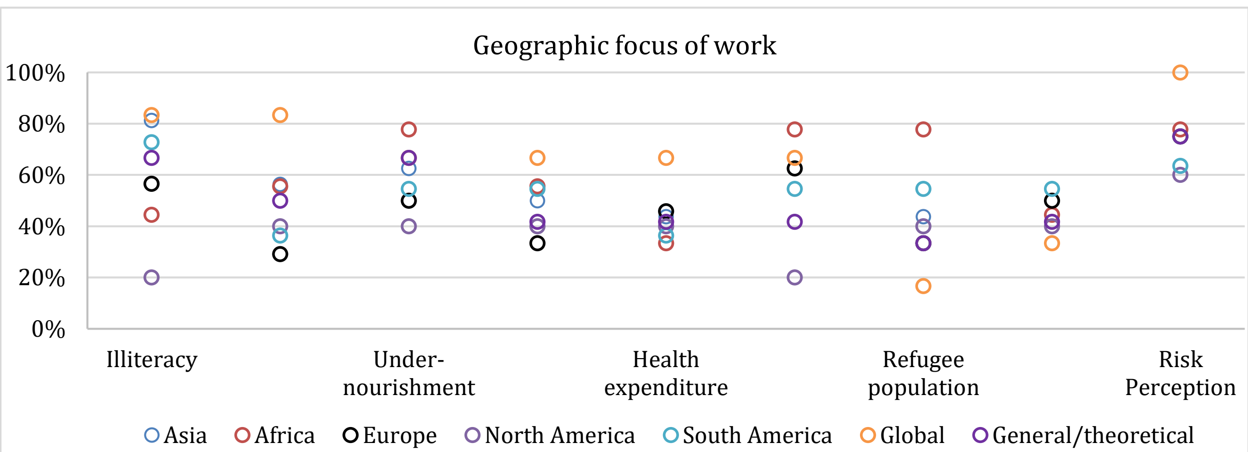


Figure 31 Proportion of experts who consider the indicators globally relevant depending on their geographic work focus.

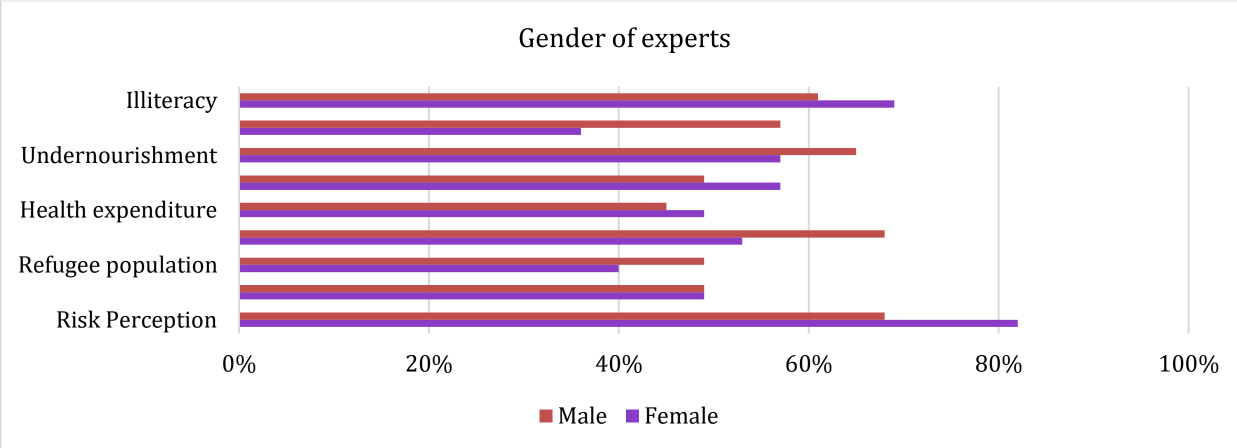


Figure 32 Proportion of experts who consider the indicators globally relevant depending on their gender.

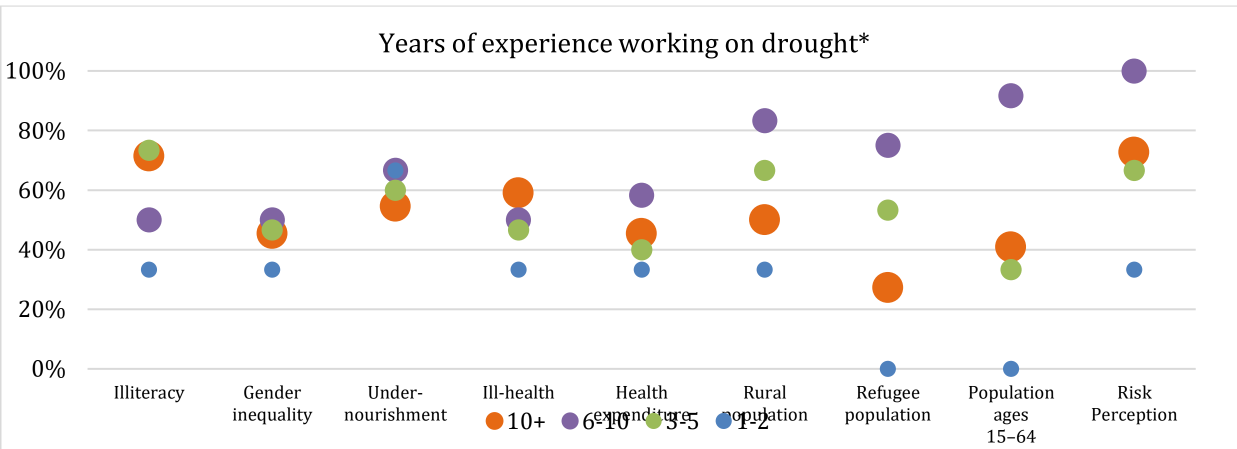


Figure 33 Proportion of experts who consider the indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

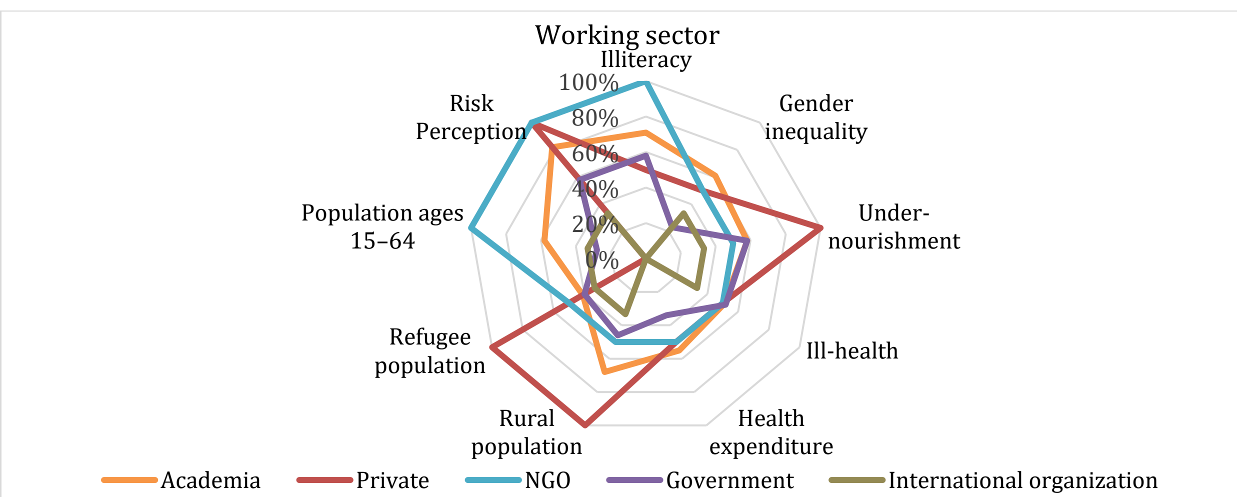


Figure 34 Proportion of experts who consider the indicators globally relevant depending on their working sector.

F5.2 Economic dimension

The majority of experts agreed on eight indicators with relevance at the global level for the economic dimension of vulnerability. For 80% of female experts, the GDP per capita is relevant, in contrast to 51% percent of male experts.

The unemployment rate (%) was one of the indicators with more discrepancy between the different categories. It was cataloged as relevant by less than half of the male experts, respondents with no experience working on drought or with 3 to 5 years of experience, for the private and NGO, and international sectors and experts that focus on Africa, North America, South America and in general/theoretical areas.

Almost seven in ten (65%) agree on the relevance to consider tourism (% GDP) as an indicator. Those most likely to agree with this include: female experts, one to ten years of experience, NGO, international organization and private sectors and Europe focus experts.

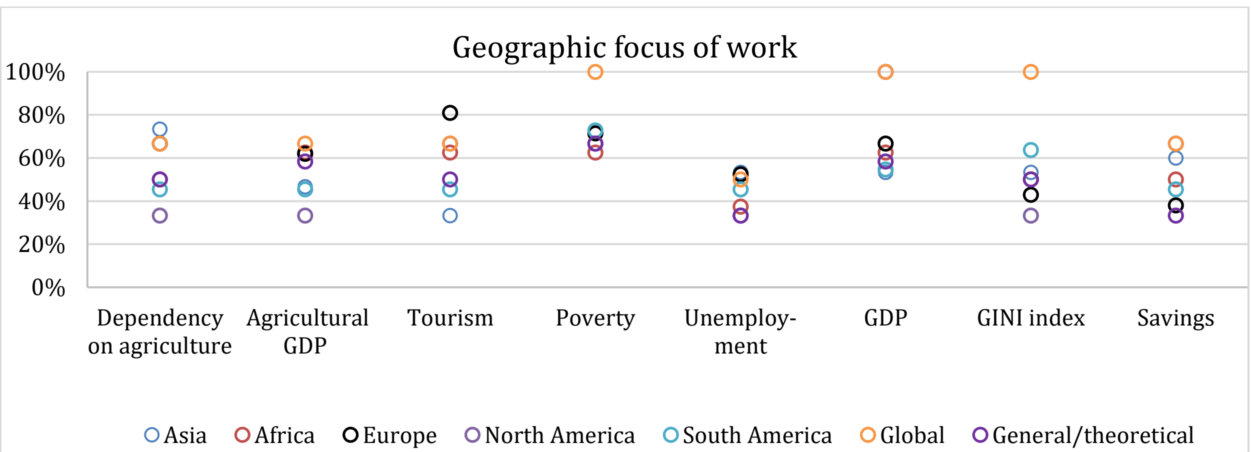


Figure 35 Proportion of experts who consider the indicators globally relevant depending on their geographic work focus.

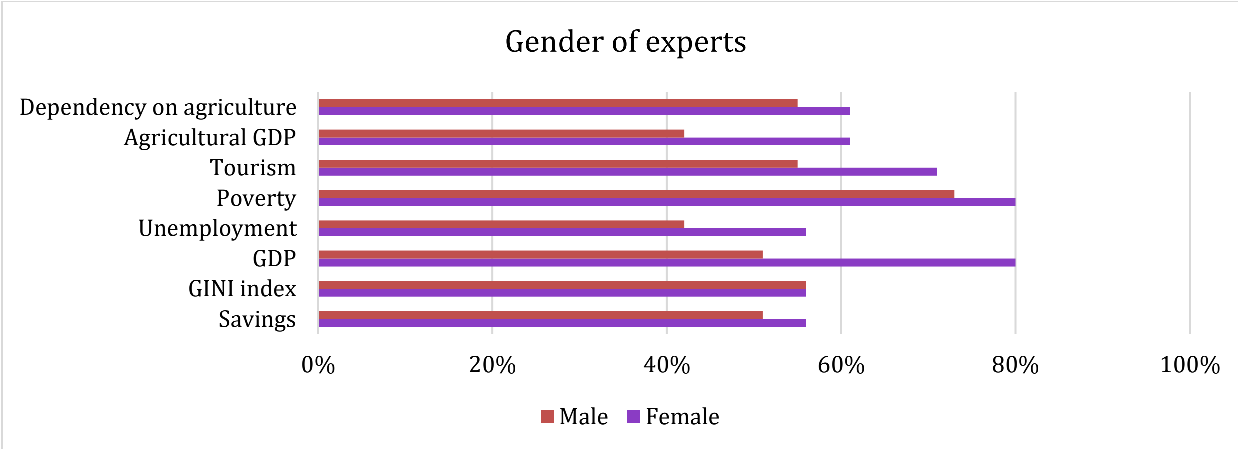


Figure 36 Proportion of experts who consider the indicators globally relevant depending on their gender.

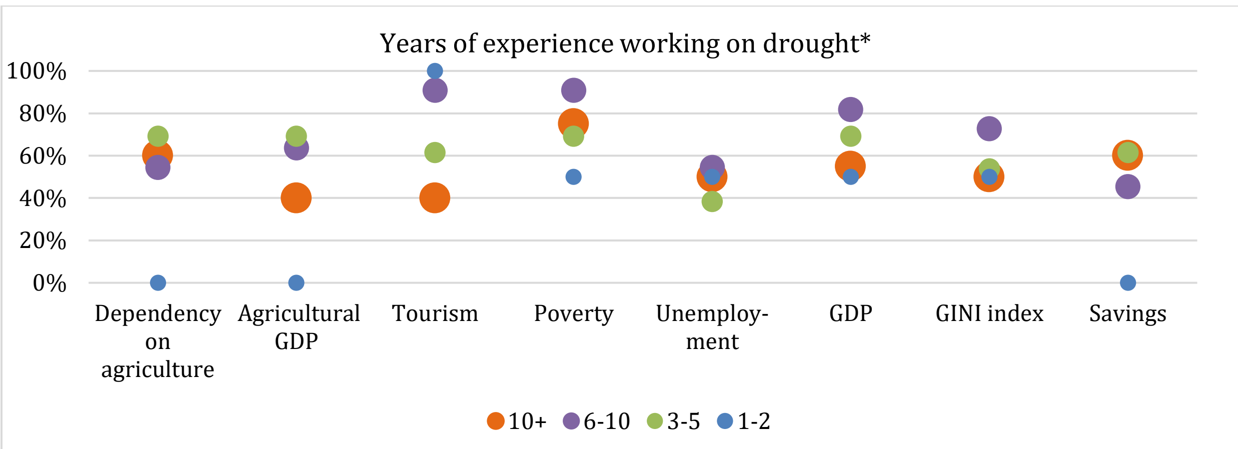


Figure 37 Proportion of experts who consider the indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

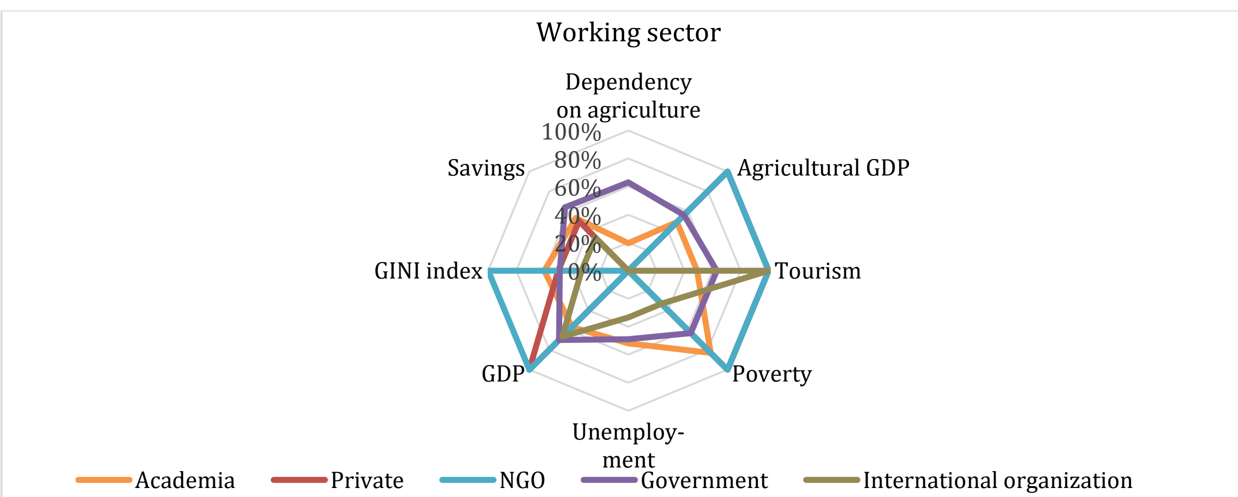


Figure 38 Proportion of experts who consider the indicators globally relevant depending on their working sector.

F5.3 Infrastructural dimension

More than 50% of the experts agreed on the relevance of population without access to (improved) sanitation (%), population without access to clean water (%), water quality (categorical), total dam capacity (m3), % of retained renewable water and electricity production from hydroelectric sources (% of total) as global drought vulnerability indicators to impacts in domestic water supply.

Sixty-one percent agree that electricity production from hydroelectric sources (% of total) is globally relevant. Male experts, people that focus on America (North and South) and international organization are the less likely to consider this indicator highly or medium-high relevant.

There is little disagreement among experts working in different sectors about the relevant indicators; however, the highest variation is found among the geographical focus.

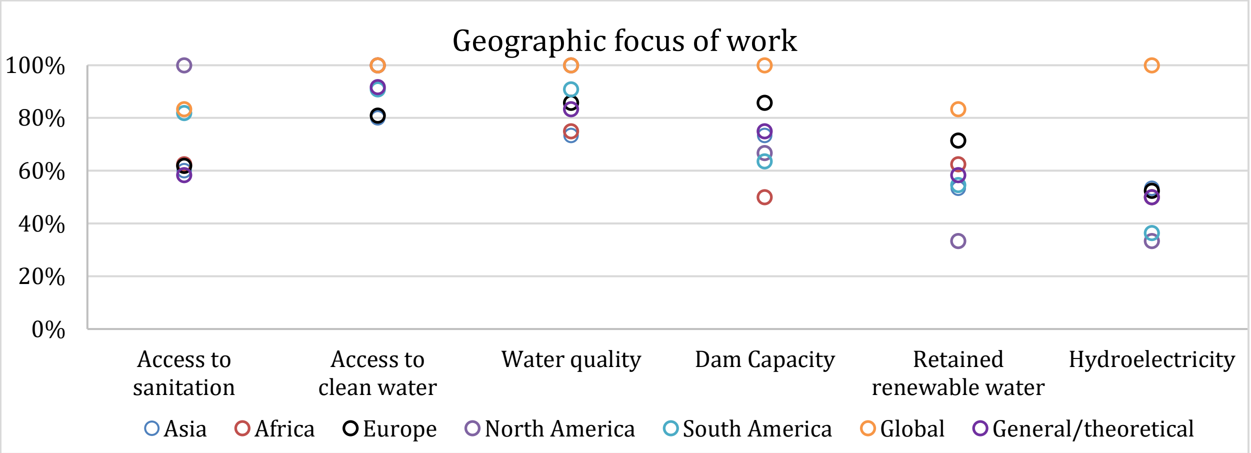


Figure 39 Proportion of experts who consider the infrastructural indicators globally relevant depending on their geographic work focus.

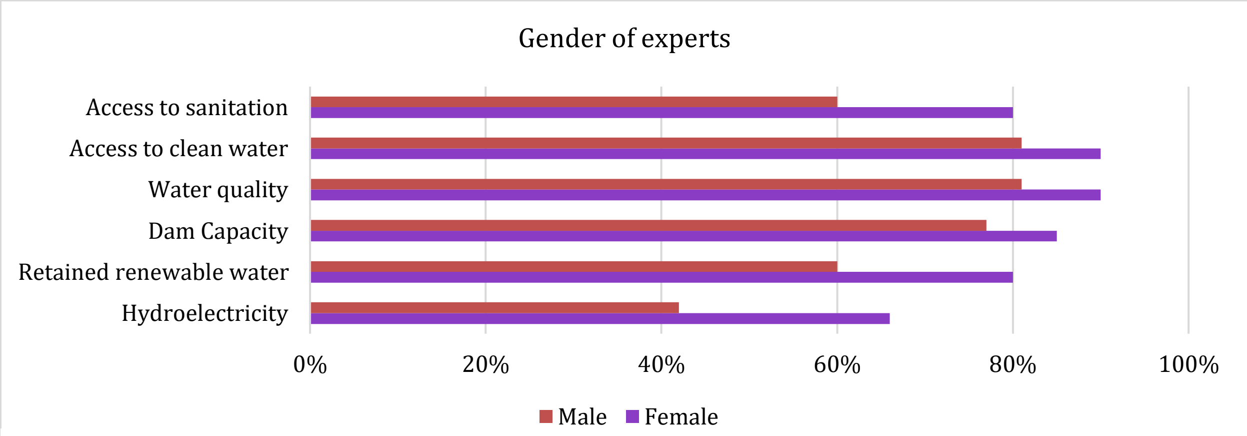


Figure 75 Proportion of experts who consider infrastructural indicators globally relevant depending on their gender.

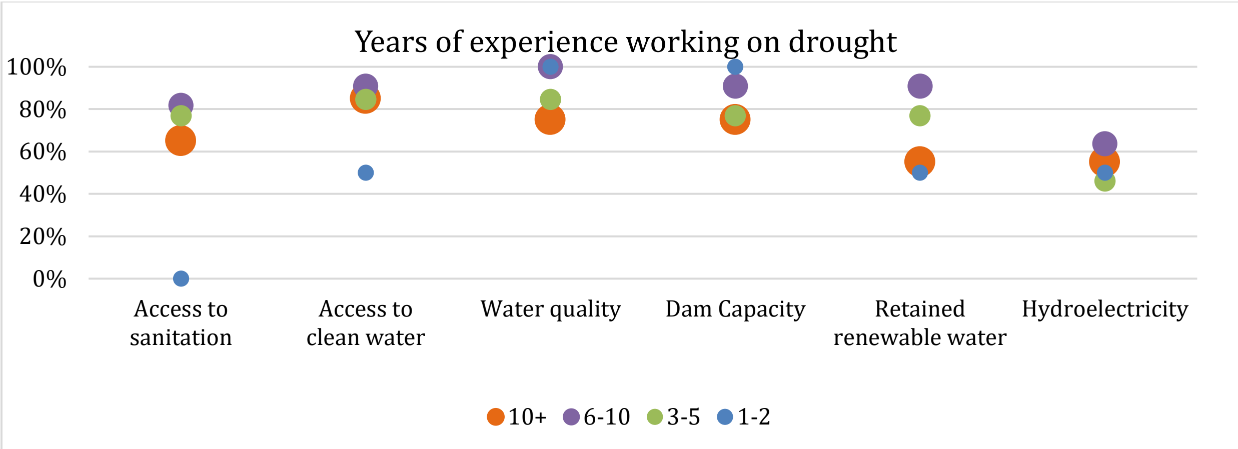


Figure 41 Proportion of experts who consider the infrastructural indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

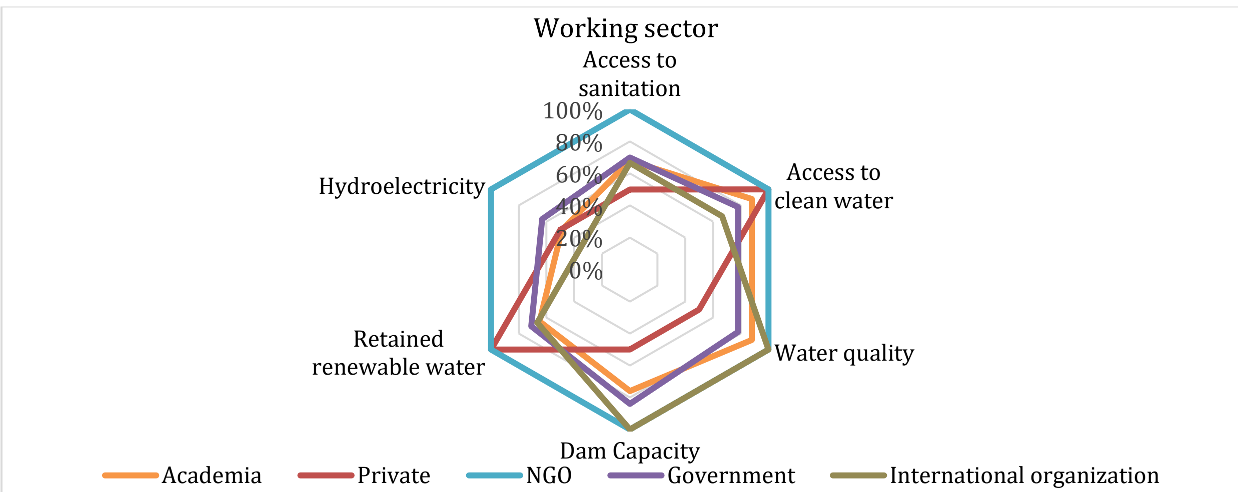


Figure 42 Proportion of experts who consider the infrastructural indicators globally relevant depending on their working sector.

F5.4 Crime and Conflict

The prevalence of conflict/insecurity was the only indicator that the experts selected as relevant at the global level. All the different categories agreed on this indicator, only six experts working on drought for more than three years weighed it as not relevant or low relevance. Some female experts, private sector, NGO or experts from international organizations identified this indicator as not relevant at all.

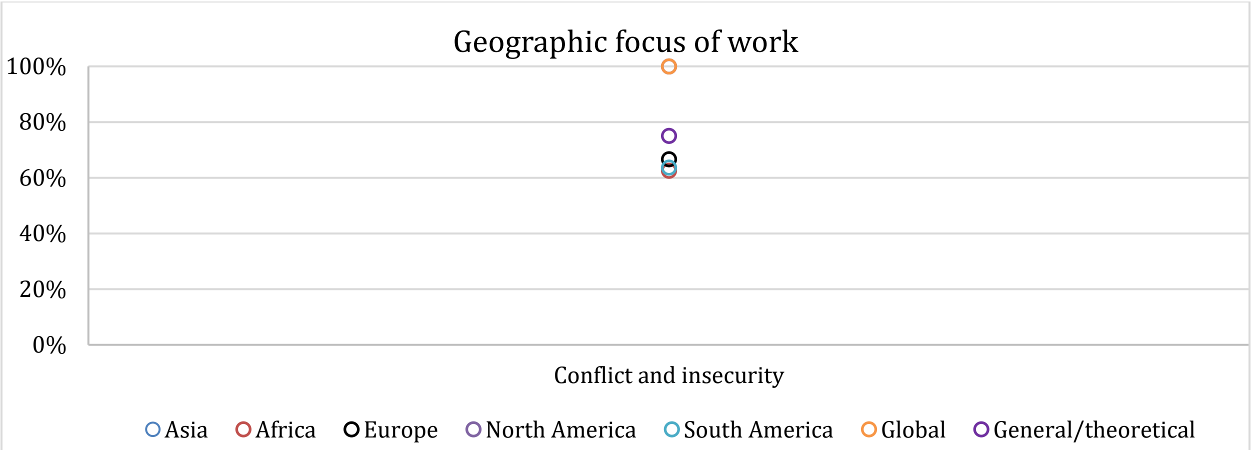


Figure 43 Proportion of experts who consider the prevalence of conflict/insecurity as a globally relevant indicator, depending on their geographic work focus.

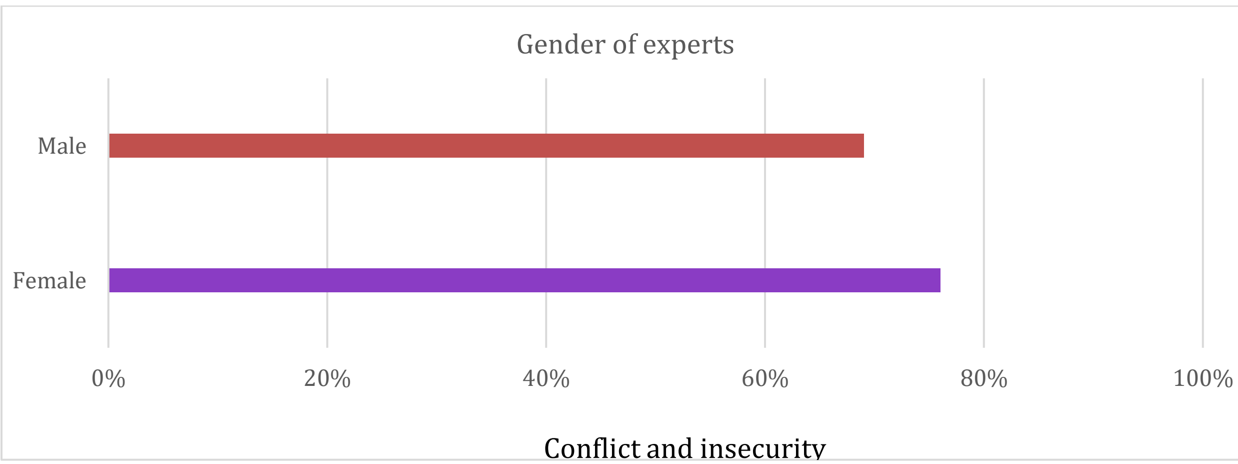


Figure 79 Proportion of experts who consider the prevalence of conflict/insecurity globally relevant depending on their gender.

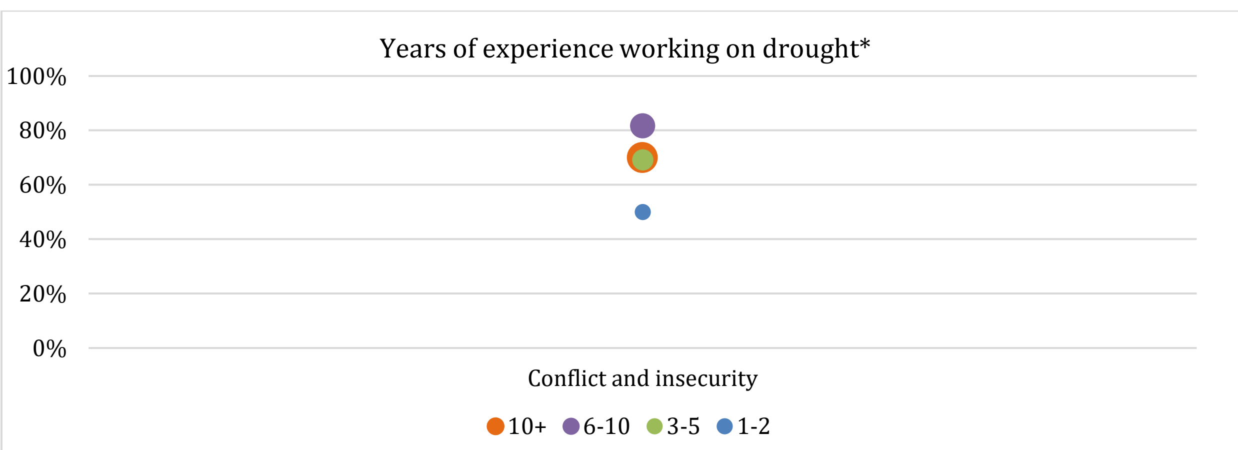


Figure 45 Proportion of experts who consider the prevalence of conflict/insecurity globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

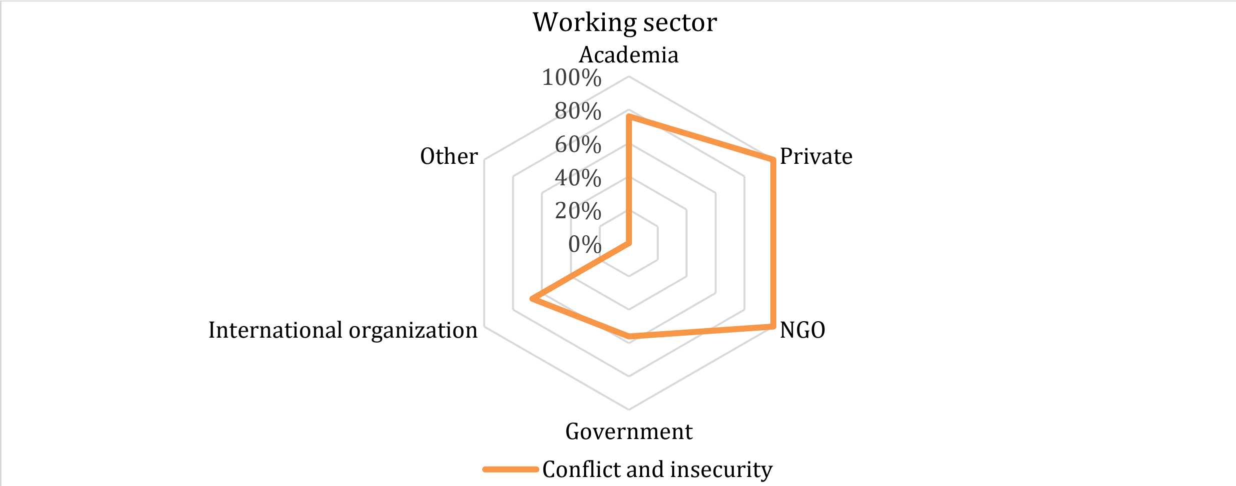


Figure 46 Proportion of experts who consider the prevalence of conflict/insecurity globally relevant depending on their working sector.

F5.5 Governance

The top three indicators identified for the governance dimension among the different categories were: existence of adaptation policies/strategies (yes/no), government effectiveness and disaster risk taken into account in public investment.

Similar to the agricultural systems, the number of (drought-related) adaptation projects in the past ten years and corruption indicators are relevant to all experts except for some in the private sector for whom these indicators are of low relevance. Less than half (40%) of the respondents that work in Asia on general/theoretical considered "research and development expenditure (% of GDP) as a relevant indicator.

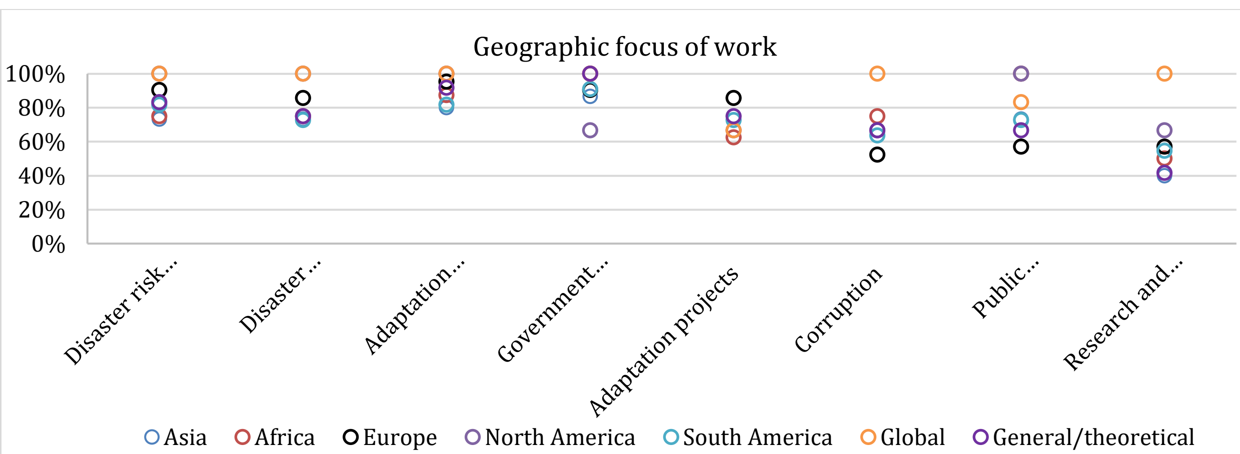


Figure 47 Proportion of experts who consider these governmental indicators globally relevant depending on their geographic work focus.

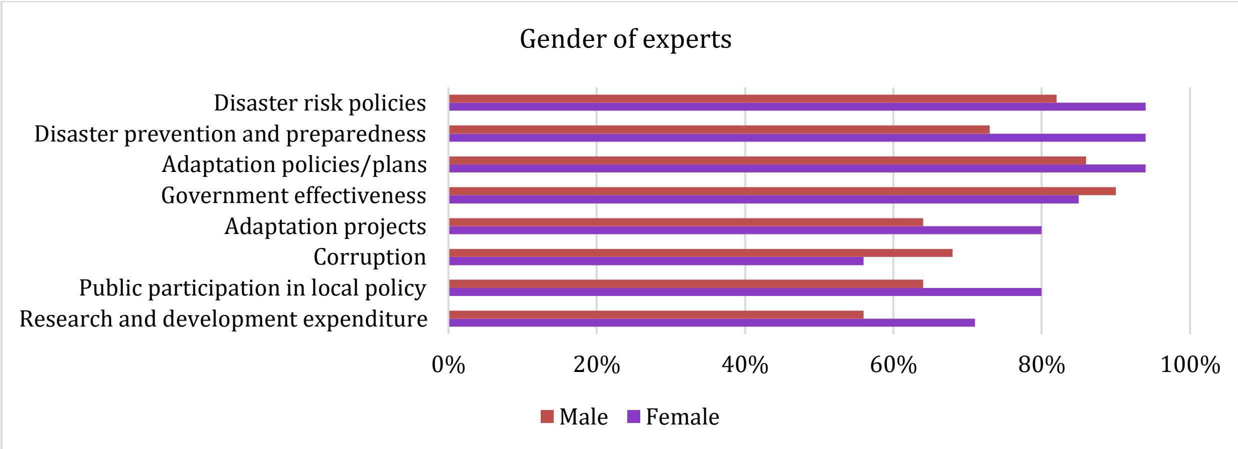


Figure 48 Proportion of experts who consider the governmental indicators globally relevant depending on their gender.

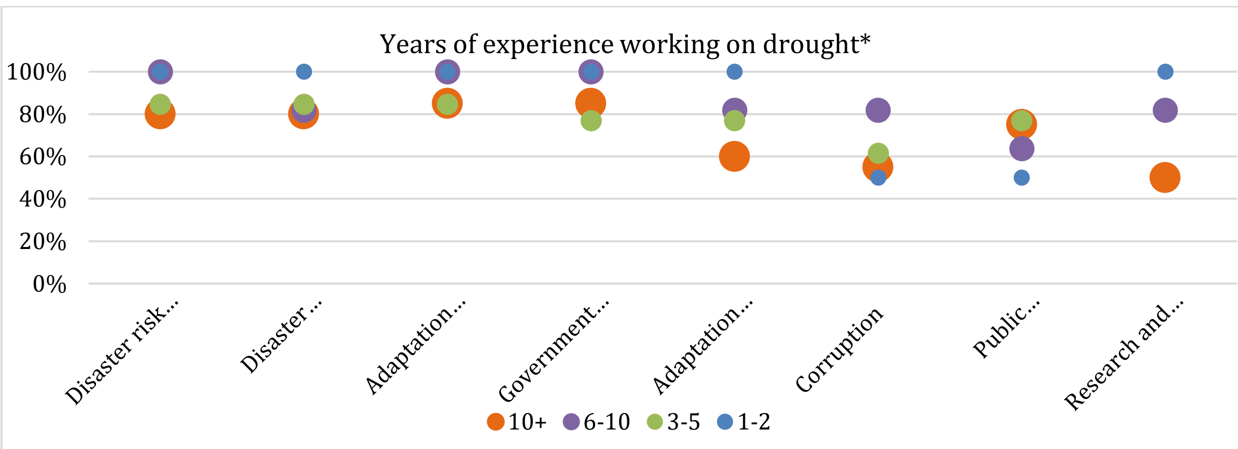


Figure 49 Proportion of experts who consider the governmental indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

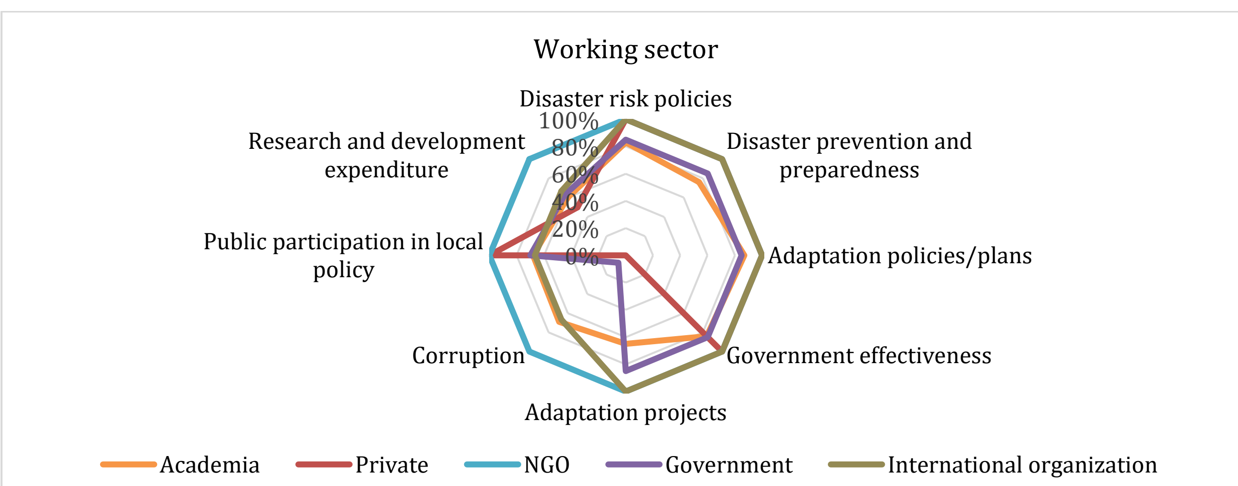


Figure 50 Proportion of experts who consider these governmental indicators globally relevant depending on their working sector.

F5.6 Environmental

Two out of seven indicators were selected as globally relevant: The area protected and designated for the conservation of biodiversity (%) and the baseline water stress (ratio of withdrawals to renewable supply). This last indicator was selected as relevant for more than 50% of the experts in all the different categories.

The percentage of area protected and designated for the conservation of biodiversity was less relevant for people with less than two years of experience working on drought, experts from the private sector, and those who focus on global, general and Europe assessments.

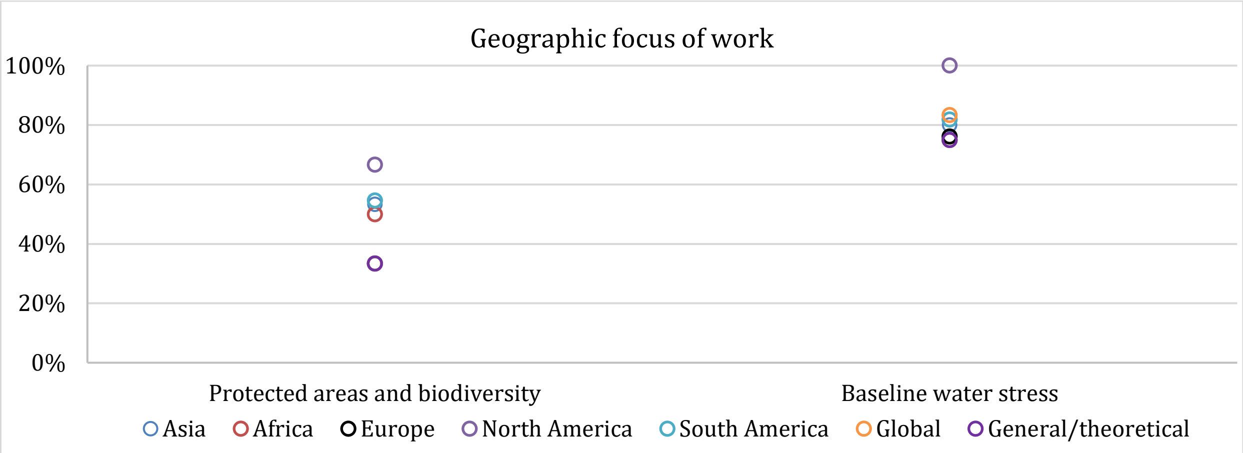


Figure 51 Proportion of experts who consider the environmental indicators globally relevant depending on their geographic work focus.

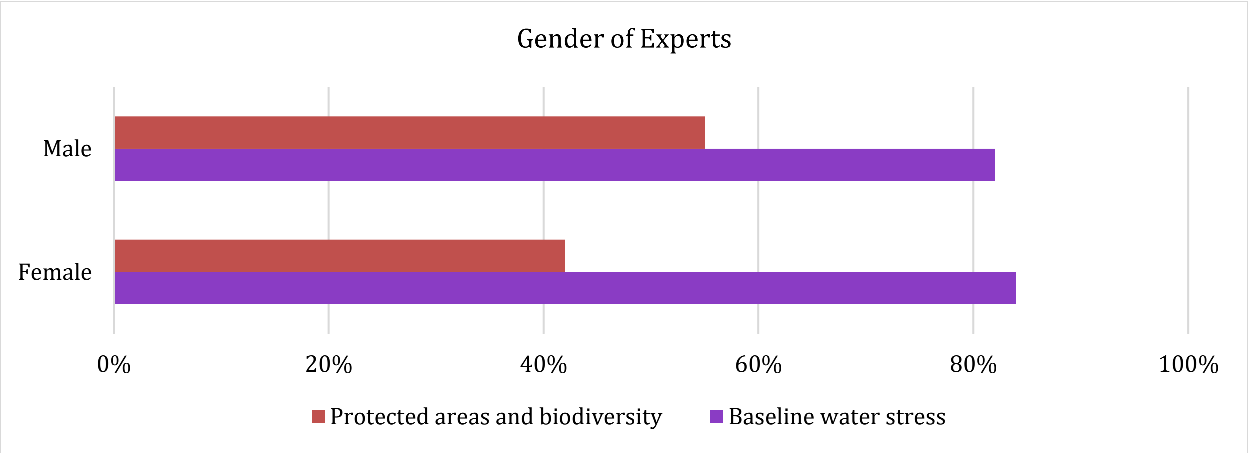


Figure 52 Proportion of experts who consider the environmental indicators globally relevant depending on their gender.

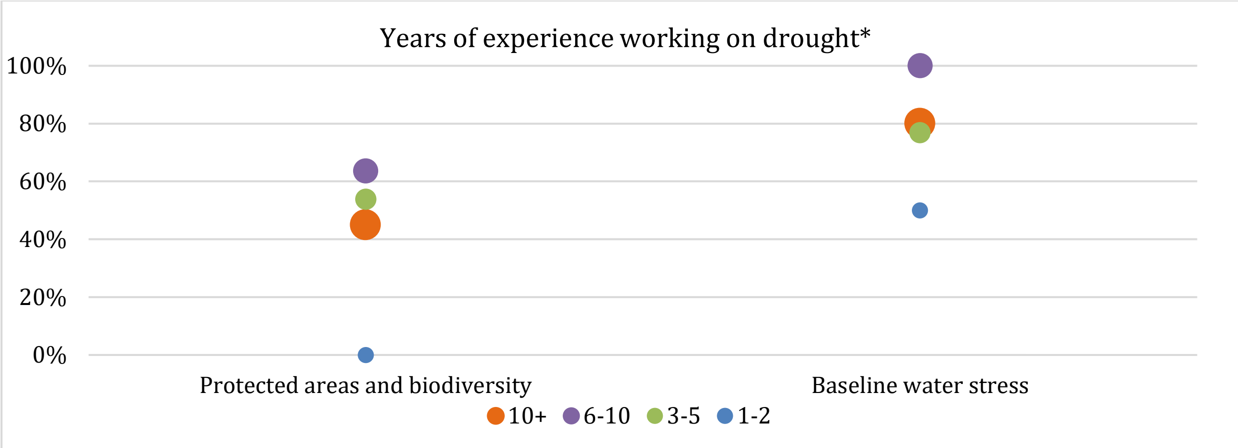


Figure 53 Proportion of experts who consider the environmental indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience.

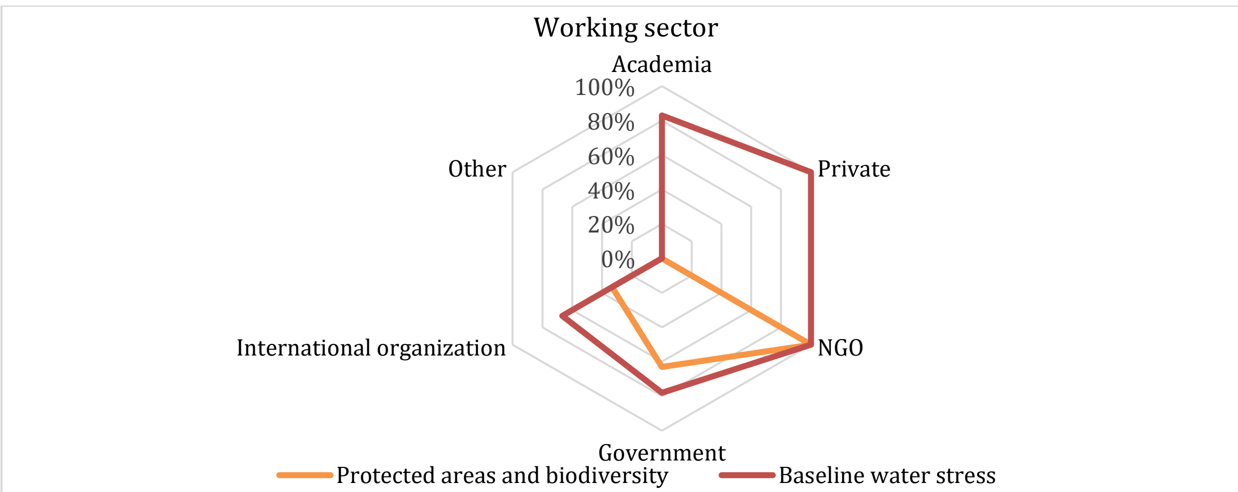


Figure 54 Proportion of experts who consider the environmental indicators globally relevant depending on their working sector.

F5.7 Farming practices

Farming practices got one relevant indicator at the global level "Irrigated land (% total arable)". This indicator was in particular considered by male experts, experts with more than three years of experience working in drought, Asia focus experts and NGOs. A quarter of respondents with more than ten years of experience working in drought considered this indicator not relevant at all. Same for 12% of academics, all private sector respondents, and 7% of experts from the governmental sector.

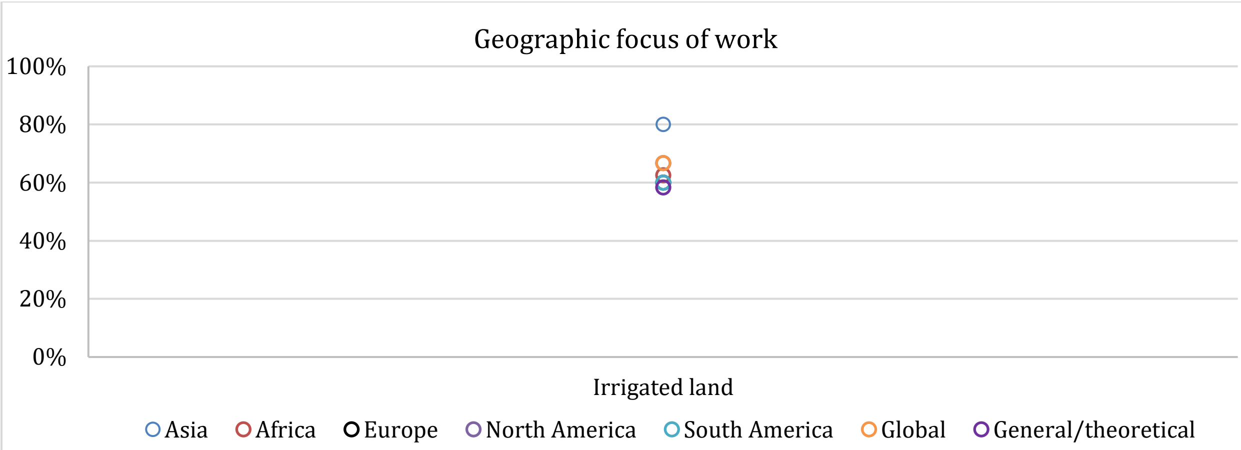


Figure 55 Proportion of experts who consider farming practices indicators as globally relevant depending on their geographic work focus.

Figure 56 Proportion of experts who consider irrigated land globally relevant depending on their gender.

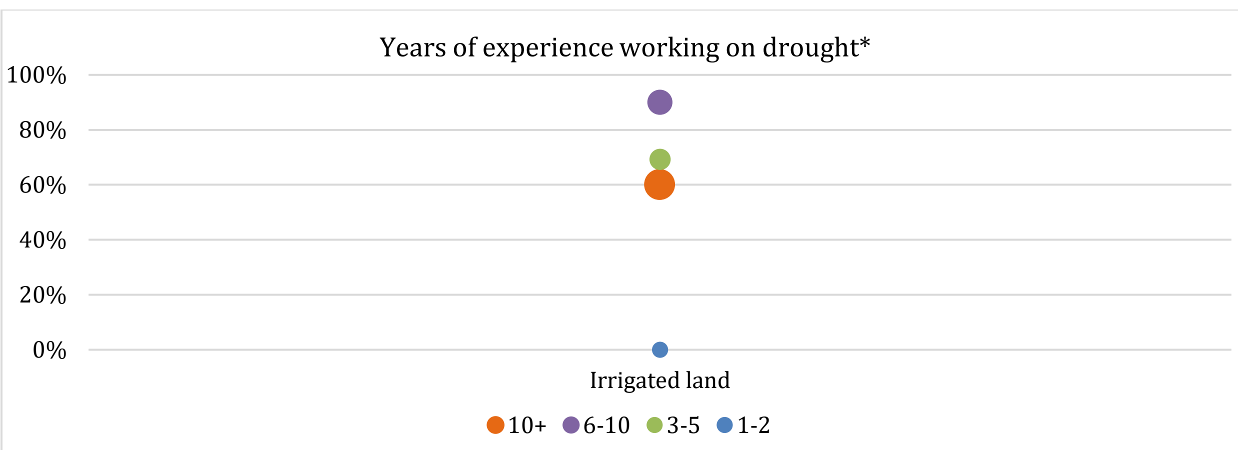


Figure 57 Proportion of experts who consider farming practices indicators globally relevant depending on their years of experience working with drought. *Dot size represent the years of experience

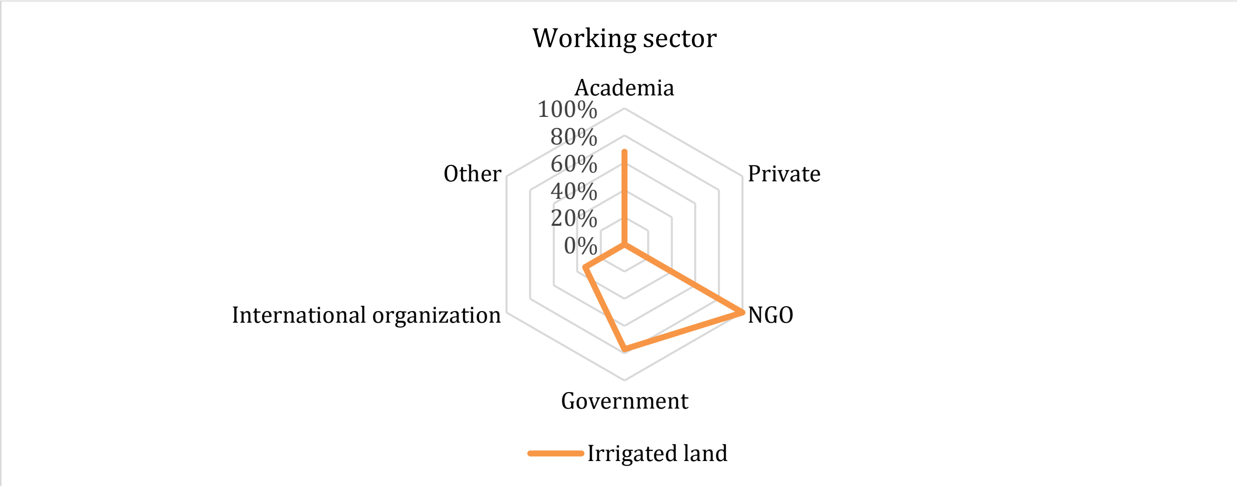


Figure 58 Proportion of experts who consider farming practices indicators globally relevant depending on their working sector.

F6. Contingency Table

Gender identity (Optional)			Working sector						Years of experience working on drought					Geographic focus of work						
Research field (optional)	***Fem***	***Male***	***Academia***	***Gov.***	***Int. Org***	***NGO***	***Other***	***Private***	***1-2***	***3-5***	***6-10***	***10+***	***No prev experience***	***Asia***	***Africa***	***Europe***	***North America***	***South America***	***Global***	***General/ theoretical***
Agricultural sciences	0	7	4	2	0	0	0	1	0	2	1	4	0	4	2	0	0	1	0	0
Anthropology and development	0	1	1	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	1
Climate Change	0	3	2	1	0	0	0	0	0	1	2	0	0	2	0	0	0	1	0	2
Climate science/services	2	1	0	3	0	0	0	0	0	1	1	1	0	1	0	3	0	1	0	1
Drought hazard and disaster risk assessment	0	2	0	1	0	1	0	0	0	0	1	1	0	2	0	0	0	0	0	2
Economics (Water, environmental)	0	3	2	0	0	0	1	0	0	1	1	1	0	3	1	1	0	0	1	3
Environmental sciences	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0
Geography	1	3	3	1	0	0	0	0	0	0	2	2	0	1	0	2	1	0	1	0
Health	2	0	2	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	1	0
Hydrology	5	2	2	2	2	1	0	0	0	4	2	1	0	1	1	4	1	1	0	2
Interdisciplinary	1	1	2	0	0	0	0	0	0	0	0	2	0	1	1	1	0	1	0	1
Sociology	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	1
Soil and Water Conservation	0	1	1	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0
Water resources management	2	1	1	0	1	0	0	1	1	0	1	1	0	0	0	3	0	1	0	1
Geographic focus of work	***Fem***	***Male***	***Academia***	***Gov.***	***Int. Org***	***NGO***	***Other***	***Private***	***1-2***	***3-5***	***6-10***	***10+***	***No prev exp***							
Asia	6	17	15	4	1	2	1	0	0	5	5	13	0							

Africa	4	8	6	2	2	0	0	2	1	3	3	5	0
Europe	19	10	12	15	3	0	0	1	4	8	8	11	0
North America	4	3	4	4	0	0	0	0	0	2	2	3	1
South America	6	5	8	3	0	0	0	0	0	3	4	4	0
Global	3	3	7	0	0	0	0	0	2	2	1	2	0
General/ theoretical (e.g. methods-oriented)	7	11	9	5	1	1	1	1	2	5	5	6	0

Years of experience working in drought	***Fem***	***Male***	***Academia***	***Gov.***	***Int. Org***	***NGO***	***Other***	***Private***
1-2	1	4	2	2	1	0	0	0
3-5	13	5	8	8	1	1	0	1
6-10	5	12	8	5	3	1	1	0
10+	13	14	20	8	0	0	0	1
No previous experience working on vulnerability/risk	0	1	0	1	0	0	0	0

Sector	***Fem***	***Male***
Academia	16	20
Government	12	11
International Organization	2	2
NGO	1	1
Other	0	1
Private	1	1

F7: Complete list of questions and indicators weighed on the online survey

Respondent background information
Name (optional)
Email (optional)
Gender identity
Sector
Years of experience working on drought
Years of experience working on vulnerability and risk

Drought vulnerability indicators
SOCIAL

1. Population with at least completed post-secondary education (%)
2. Illiteracy rate (%)
3. Gender inequality (categorical)
4. Social capital (categorical)
5. Alcohol consumption litres per capita (people aged 15 years and older)
6. Disabled persons (%)
7. Population undernourished (%)
8. Population with ill-health (%)
9. Life expectancy at birth (years)
10. Number of physicians per 1,000 inhabitants
11. Out-of-pocket expenditure on health (%)
12. Households without health insurance (%)
13. Rural population (% of total population)
14. Refugee population (% of total population)
15. Age dependency ratio (% of working-age population)
16. Risk perception (% of population who has experienced droughts in the past 10 years)
17. Availability of a drought early warning system (yes/no)
18. Households/farmers with access to information (radio/TV/internet) (%)
19. Please add any additional indicators you feel are missing

ECONOMIC

1. Dependency on agriculture for livelihood (%)
2. High dependence on tourism for income and employment (% of GDP)
3. Agriculture (% of GDP)
4. Population below the national poverty line (%)
5. Unemployment rate (%)
6. GDP per capita, PPP
7. GINI index (income inequality)
8. Farmers/laborers without savings (%)
9. Farmers/laborers without access to bank loans / (micro-) credits (%)
10. Distance to closest market (km)
11. Market fragility
12. Farmers with crop, livestock or drought insurance (%)
13. Energy consumption per capita
14. Please add any additional indicators you feel are missing

INFRASTRUCTURE

1. Road density (km of road per 100 sq. km of land area)
2. Population without access to (improved) sanitation (%)
3. Population without access to clean water (%)
4. Poor water quality
5. Total dam capacity
6. % of retained renewable water
7. Electricity production from hydroelectric sources (% of total)
8. Please add any additional indicators you feel are missing

CRIME & CONFLICT

1. (Livestock) theft (%)
2. Prevalence of conflict/insecurity
3. Please add any additional indicators you feel are missing

GOVERNANCE

1. Disaster risk taken into account in public investment and planning decisions (yes/no)
2. National investment in disaster prevention & preparedness (US$/Year/capita)
3. Existence of national adaptation policies/plans (yes/no)
4. Government effectiveness
5. Number of (drought-related) adaptation projects in the past 10 years
6. Corruption (e.g. Corruption Perception Index)
7. Strength of legal rights
8. Public participation in local policy
9. Food aid (US$ per capita)
10. Research and development expenditure (% of GDP)
11. Please add any additional indicators you feel are missing

ENVIRONMENTAL

1. Soil organic matter (g*kg)
2. Soil depth (mm)
3. Degree of land degradation and desertification
4. Area protected and designated for the conservation of biodiversity (%)
5. Veterinarians and veterinary para-professionals (per capita)
6. Livestock health
7. Water stress
8. Please add any additional indicators you feel are missing

FARMING PRACTICES

1. Agricultural machinery in use (#)
2. Irrigated land (% total arable)
3. Use of fertilizer (ton)
4. Access to fodder (kg purchased per year)
5. Tonnes of active ingredients of insecticides and pesticides used
6. Cultivation of drought-resistant crops (%)
7. Farmers use different crop varieties (%)
8. Please add any additional indicators you feel are missing