Households at Risk

Integrated Assessment of Drought Hazard and Social Vulnerability in the Cuvelai-Basin of Angola and Namibia

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Summary

Droughts are phenomena that occur worldwide, in humid and arid environments as well as in the Global North and the Global South. They are considered as slow onset hazards that affect more people than any other natural process with an estimated economic damage of USD 135 Billion and 12 Million casualties globally between 1900 and 2013 (Masih et al., 2014, p. 3636). Sub-Saharan Africa (SSA) is a major drought hot-spot due to vulnerable livelihoods (e.g. dominance of rain-fed agriculture), limited capacities (e.g. financial, institutional), weak infrastructure (e.g. water, mobility) and political instability (e.g. conflicts, corruption). When droughts occur, as recently triggered by El Niño (2015/2016), vulnerability conditions of the affected societies determine, if drought risk manifests as a disaster. As a critical, recent example, the drought in Somalia resulted in a serious humanitarian disaster primarily as the precarious vulnerability situation was further deteriorated by political and violent conflicts (Maxwell et al., 2016). Overall, SSA faces severe challenges to manage drought risk, primarily due to two reasons: First, despite progress, the living conditions remain difficult with prevailing poverty, limited health services and ongoing political unrest in many regions (UNECA et al., 2015). This is alarming, especially against the projected population growth of about 1.3 Billion people in Africa until 2050 (UN-DESA, 2015, p. 3). Second, achieving good living conditions for all, as envisioned by the Sustainable Development Goals (SDG), is a challenge, as climate projections indicate a likely increase of drought frequency and severity in SSA. Higher rainfall variability paired with a strong increase in average temperatures (Niang et al., 2014) will render today's exceptional droughts as the new normal in the near future.

These urgent problems require sustainable solutions to improve short- and long-term adaptation. Transdisciplinary science that conflates the strengths of academic disciplines and stakeholders from politics and society is needed to develop risk reduction strategies. Under the umbrella of the Southern African Science Service Centre for Climate Change and Adaptive Land Management (SASSCAL), this thesis makes a contribution to integrated drought risk management schemes by assessing the drought hazard conditions and the societal vulnerability settings in a case study region: the Cuvelai-Basin. This transnational region across Namibia and Angola regularly experiences droughts as recently during 2012 – 2015 with hundreds of thousands of people being water and food insecure (DDRM, 2013; UN-OCHA, 2012). Environmentally, it covers a gradient from humid in the north to semi-arid conditions in the south with associated vegetation patterns. The population practices subsistence agriculture and livestock herding with tendencies of urbanization and lifestyle changes. The societal pre-conditions in both countries are heterogeneous with Angola having experienced decades of civil war until 2002 while Namibia saw continuous institutional and infrastructural development particularly after independence in 1990.

To capture the multi-layered impacts of droughts on people's livelihoods, the thesis follows an interdisciplinary approach in the sense of integrating methodologies from physical and human geography. Key questions to be answered are (i) how droughts impact on local livelihoods, (ii) how the environmental drought hazard manifests, (iii) which societal groups are most vulnerable and (iv) what are risk mitigation strategies. Based on the theory of societal relations to nature, a guideline for a social-ecological drought risk assessment is proposed and exemplarily carried out in this thesis. First, a qualitative research phase was conducted to gain system knowledge, followed by quantitative analyses of environmental parameters on the drought hazard and socio-economic variables for drought vulnerability. Finally, this data was conflated in the Household Drought Risk Index (HDRI) to gain orientation knowledge and quantify risk levels among the households in the basin. This provided transformation knowledge to develop and identify risk mitigation strategies.

The initial qualitative survey (n = 26) explored the drought impact on local livelihoods. It revealed structural insights into people's utilization of water resources and the negative impacts of drought on physical and mental health, family/community life and livelihood maintenance. Coping mechanisms were identified on multiple levels from the household level (e.g. selling of agricultural products) via the community (e.g. neighbourly support) to the governmental level (e.g. drought relief). As critical entry point for droughts, the water and food consumption patterns were identified that shape a household either more or less sensitive. The internal capital endowment (human, social, financial, physical and natural) and the infrastructural and institutional endowment of an area determine a household's ability to cope with drought. These qualitative insights culminated in the construction of the HDRI indicator that was populated with data in the subsequent research phases.

To capture the drought hazard, three common drought indicators were combined in the Blended Drought Index (BDI). This integrated drought indicator incorporates meteorological and agricultural drought characteristics that impair the population's ability to ensure food and water security. The BDI uses a copula function to combine common standardized drought indicators that describe precipitation, evapotranspiration, soil moisture and vegetation conditions. Remote sensing products were processed to analyse drought frequency, severity and duration. In this regard, the uncertainty among a range of rainfall products was evaluated to identify the product that corresponds best to local rain gauge measurements. The integrated drought hazard map indicates the north of the Etosha pan and the area along the Kunene River to be most threatened by droughts. Temporally, the BDI correlates well with millet/sorghum yield ($r = 0.51$) and local water consumption ($r = -0.45$) and outperforms conventional indicators.

The vulnerability perspective was captured using primary socio-economic data from a household survey (n = 461). The consumption patterns reveal a statistically significant switch from critical sources (e.g. wells, subsistence products) during the rainy season to more reliable sources (e.g. tap water, markets) during the dry period. Households with a high dependence on critical sources are particularly sensitive to drought. The capital endowment of households is heterogeneous, especially on a rural-urban gradient and between Namibia and Angola. Human and financial capital turned out to be important control variables in addition to the infrastructural and institutional endowment of an area. Overall, the HDRI results show that the Angolan population shows higher levels of risk, particularly caused by less developed infrastructural systems, weaker institutional capabilities and less coping capacities. Urban inhabitants follow less drought-sensitive livelihood strategies, but are still connected to drought conditions in rural areas due to family relations with obligations and benefits. Furthermore, the spatial HDRI estimates point to areas in Angola and Namibia that are both drought-threatened and vulnerable.

The thesis results indicate the following recommendations for policy and science: First, the continuous monitoring of drought patterns in the basin should consider drought indicators that go beyond precipitation metrics and incorporate people's vulnerability to develop integrated Drought Information Systems. Second, reducing the sensitivities of the population requires enhanced local water buffers via better water use efficiencies. This is true for both blue and green water flows. Water-saving irrigation schemes in combination with decentral rain- and floodwater harvesting are promising opportunities. Furthermore, centralized backup infrastructures of water supply and market systems need to be expanded. Third, local community solidarity is an important institutional backbone for the population to cope with drought and adapt to future changes. In particular rural development efforts should go beyond technological interventions and support community-building, collective-action and capacity development in water management and agricultural production to decouple livelihoods from local rainfall.

Zusammenfassung

Dürren sind Phänomene, die weltweit sowohl in humiden als auch ariden Räumen sowie im Globalen Norden und im Globalen Süden auftreten. Sie gelten als langsam einsetzende Gefahren, die mehr Menschen betreffen als jeder andere natürliche Prozess mit einem geschätzten wirtschaftlichen Schaden von 135 Mrd. US-Dollar und 12 Mio. Toten weltweit zwischen 1900 und 2013 (Masih et al., 2014, p. 3636). Sub-Sahara Afrika gilt als Krisenherd aufgrund vulnerabler Lebensgrundlagen (z.B. Dominanz des Regenfeldbaus), begrenzter Kapazitäten (z.B. finanzielle, institutionelle), schwacher Infrastruktur (z.B. Trinkwasser, Mobilität) und politischer Instabilität (z.B. Konflikte, Korruption). Treten Dürren auf, wie kürzlich verstärkt durch El Niño (2015/2016), bestimmt die Vulnerabilität der Gesellschaft, ob sich das Dürrerisiko als Katastrophe manifestiert. Ein kritisches Beispiel ist die Dürre in Somalia, die v.a. zu einer humanitären Katastrophe wurde, da die prekären Vulnerabilitätsbedingungen durch gewaltsame, politische Konflikte weiter verschlechtert wurden (Maxwell et al., 2016). Insgesamt steht Afrika aus zwei Gründen vor großen Herausforderungen bei der Bewältigung des Dürrerisikos: Erstens, sind die Lebensbedingungen u.a. aufgrund anhaltender Armut, begrenzter Gesundheitsversorgung und politischer Unruhen weiterhin schwierig (UNECA et al., 2015). Dies ist alarmierend, v.a. vor dem Hintergrund eines prognostizierten Bevölkerungswachstums von 1,3 Mrd. bis 2050 (UN-DESA, 2015, p. 3). Zweitens, ist die Schaffung guter Lebensbedingungen nach den Zielen für nachhaltige Entwicklung (SDG) eine Herausforderung, da mit dem Klimawandel eine Zunahme von Dürrehäufigkeit und -stärke zu erwarten ist. Höhere Niederschlagsvariabilität gepaart mit einem starken Anstieg der Durchschnittstemperatur (Niang et al., 2014) werden die heutigen extremen Dürren in Zukunft zur neuen Normalität machen.

Diese Probleme erfordern nachhaltige Lösungen, um kurz- und langfristige Anpassungen zu ermöglichen. Transdisziplinäre Forschung ist gefordert, welche die Stärken wissenschaftlicher Disziplinen und Akteure aus Politik und Gesellschaft bündelt, um geeignete Strategien zur Risikominderung zu erarbeiten. Unter dem Dach des Southern African Science Service Centre for Climate Change and Adaptive Land Management (SASSCAL) leistet diese Dissertation einen Beitrag zu integrierten Managementansätzen von Dürrerisiken, indem sie die naturräumliche Gefährdung kombiniert mit der gesellschaftlichen Vulnerabilität anhand einer Fallstudie untersucht: dem Cuvelai-Becken. Diese transnationale Region in Namibia und Angola ist regelmäßig Dürren ausgesetzt, wie zuletzt in den Jahren 2012 – 2015 mit Wasser- und Ernährungsunsicherheit für Hunderttausende von Menschen (DDRM, 2013; UN-OCHA, 2012). Naturräumlich erstreckt sich die Region von einem humiden Norden in einen semi-ariden Süden mit entsprechenden Vegetationsverhältnissen. Die Bevölkerung betreibt Subsistenzlandwirtschaft und Viehzucht, wobei Urbanisierungstendenzen und Lebensstiländerungen an

Dynamik gewinnen. Die gesellschaftlichen Voraussetzungen sind heterogen: Während Angola bis 2002 Jahrzehnte des Bürgerkriegs erlebte, erfuhr Namibia v.a. nach der Unabhängigkeit 1990 eine kontinuierliche institutionelle und infrastrukturelle Entwicklung.

Um die vielschichtigen Auswirkungen von Dürren auf die Lebensgrundlagen zu erfassen, verfolgt diese Dissertation einen interdisziplinären Ansatz im Sinne der Integration von Methoden aus der Physischen- und Humangeographie. Kernfragen darin sind (i) wie sich Dürren auf die Lebensgrundlagen auswirken, (ii) wie sich die naturräumliche Dürregefährdung manifestiert, (iii) welche gesellschaftlichen Gruppen vulnerabel sind und (iv) welche Strategien zur Risikominderung geeignet sind. Dabei entwickelt die Dissertation auf Basis der Theorie gesellschaftlicher Naturverhältnisse einen Leitfaden für eine sozial-ökologische Risikoabschätzung und wendet diesen in der vorliegenden Fallstudie an. Zunächst wurde eine qualitative Forschungsphase durchgeführt, um Systemwissen zu gewinnen, gefolgt von einer quantitativen Analyse von Umweltparametern zur Abschätzung der Dürregefahr sowie sozioökonomischer Variablen für die Abschätzung der Vulnerabilität. Schließlich wurden diese Daten im Household Drought Risk Index (HDRI) zusammengeführt, um Orientierungswissen zu generieren und das Dürrerisiko der Haushalte zu bestimmen. Daraus abgeleitetes Transformationswissen ermöglichte dann die Identifizierung geeigneter Risikominderungsstrategien.

Die qualitative Erhebung (n = 26) explorierte die Wirkung von Dürren auf die lokalen Lebensbedingungen. Sie eröffnete Einblicke in die Nutzung von Wasserressourcen und die negativen Auswirkungen von Dürren auf die körperliche/geistige Gesundheit, das Familien-/Gemeinschaftslebens sowie den Lebensunterhalts. Bewältigungsmechanismen konnten auf mehreren Ebenen identifiziert werden, vom Haushalt (z.B. Verkauf landwirtschaftlicher Produkte) über die Gemeinde (z.B. Nachbarschaftshilfe) bis hin zur staatlichen Ebene (z.B. Dürrehilfe). Als kritische Wirkpunkte für Dürren wurden Nutzungsmuster von Wasser- und Nahrungsmitteln identifiziert, die einen Haushalt mehr oder weniger anfällig machen. Die interne Kapitalausstattung (Humanes, Soziales, Finanzielles, Physisches und Natürliches) und die infrastrukturelle und institutionelle Ausstattung eines Gebiets bestimmen weiterhin die Fähigkeit eines Haushalts, mit der Dürregefahr umzugehen. Diese Erkenntnisse ermöglichten die Konstruktion des HDRI Indikators, der in den Folgephasen mit entsprechenden Daten bestückt wurde.

Zur Erfassung der Dürregefahr wurden drei Dürreindikatoren im Blended Drought Index (BDI) zusammengefasst. Dieser integrierte Dürreindikator berücksichtigt meteorologische und landwirtschaftliche Merkmale, die die Ernährungs- und Wassersicherheit der Bevölkerung beeinträchtigen. Der BDI verwendet eine Copula-Funktion, um gängige Dürreindikatoren zu kombinieren, die auf Niederschlag, Evapotranspiration, Bodenfeuchte und Vegetation zurückgreifen. Fernerkundungsprodukte wurden verarbeitet, um

Häufigkeit, Stärke und Dauer der Dürren zu analysieren. Dabei wurden verschiedene Niederschlagsprodukte einer Unsicherheitsanalyse unterzogen, um jenes Produkt zu identifizieren, das am besten mit lokal gemessenen Stationsdaten korrespondiert. Die resultierende, integrierte Dürregefahrenkarte zeigt den Norden der Etosha-Pfanne und das Gebiet entlang des Kunene-Flusses als am stärksten von Dürren bedroht an. Zeitlich korreliert der BDI gut mit den Daten des Hirseertrages (r = 0,51) und dem lokalen Wasserverbrauch (r = -0,45) und übertrifft dabei konventionelle Indikatoren.

Die Vulnerabilität wurde anhand von sozioökonomischen Daten aus einer Haushaltsbefragung (n = 461) erfasst. Die Nutzungsmuster zeigen einen statistisch signifikanten Schwenk von kritischen Wasser- und Nahrungsquellen (z.B. Brunnen, Subsistenzprodukte) hin zu verlässlichen Quellen (z.B. Leitungswasser, Märkte) während der Trockenzeit. Haushalte mit einer starken Abhängigkeit von kritischen Quellen sind besonders sensitiv gegenüber Dürren. Die Kapitalausstattung der Haushalte variiert v.a. zwischen Land und Stadt sowie zwischen Namibia und Angola. Dabei treten Human- und Finanzkapital gemeinsam mit der infrastrukturellen und institutionellen Raumausstattung als wichtige Kontrollvariablen hervor. Die HDRI Ergebnisse zeigen, dass die angolanische Bevölkerung ein höheres Risiko aufweist, was v.a. durch weniger entwickelte Infrastruktursysteme, schwächere institutionelle- und geringere Bewältigungskapazitäten verursacht wird. Insgesamt gehen Stadtbewohner weniger dürresensitiven Nutzungsmustern nach, sind aber aufgrund familiärer Beziehungen weiterhin mit den ländlichen Gebieten verbunden. Die integrierte, räumliche Risikoabschätzung zeigt Gebiete in Angola und Namibia die sowohl dürregefährdet als auch vulnerabel sind.

Die Ergebnisse erlauben zentrale Empfehlungen für Politik und Wissenschaft: Erstens sollte die Dürrebeobachtung im Cuvelai-Becken ein breiteres Spektrum von Indikatoren berücksichtigen und zusätzlich die Verwundbarkeit der Bevölkerung einbeziehen. Dies ermöglicht die Entwicklung von integrierten Dürreinformationssystemen. Zweitens, zur Verringerung der Sensitivität der Bevölkerung müssen lokale Wasserspeicher durch eine verbesserte Wassernutzungseffizienz erhöht werden. Dies gilt sowohl für blaues als auch grünes Wasser. Wassersparende Bewässerungssysteme in Kombination mit dezentralen Regen- und Flutwasserspeichern sind vielversprechende Möglichkeiten. Darüber hinaus müssen zentrale Infrastrukturen der Wasserversorgung und der Marktsysteme ausgebaut werden. Drittens, ist der Zusammenhalt der lokalen Gemeinschaften ein wichtiges institutionelles Rückgrat zur Bewältigung von Dürren und zur Anpassung an künftige Veränderungen. Anstrengungen zur Entwicklung des ländlichen Raums sind erforderlich, die über technische Interventionen hinausgehen und Gemeinschaften durch kollektive Maßnahmen und Ausbildung sowohl in der Wasserwirtschaft als auch der Landwirtschaft unterstützen und so die Lebensgrundlagen von den Niederschlägen entkoppeln.

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Abbreviations

AIS	Agricultural Innovation Systems
AMDR	Acceptable Macronutrient Distribution Ranges
APSIM	Agricultural Production Systems Simulator
ARC	African Rainfall Climatology
AVHRR	Advanced Very High Resolution Radiometer
BDI	Blended Drought Index
BSRN	Basal Societal Relations to Nature
CBRLM	Community-based Rangeland Management
CDF	Cumulative Distribution Function
CFS	Climate Forecast System
CHANS	Coupled Human and Natural Systems
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CHPClim	Climate Hazards Group's Precipitation Climatology
CM	Cascade Model
CMORPH	Climate Prediction Center Morphing Technique
CRU	Climate Research Unit
CUVECOM	Cuvelai Watercourse Commission
DIR	Dietary Reference Intake
DIS	Drought Information System
DVI	Drought Vulnerability Index
EER	Estimated Energy Requirements
ES	Ecosystem Services
EWS	Early Warning System
FAO	Food and Agriculture Organization of the United Nations
FEGS	Final Ecosystem Goods and Services
FEWS-NET	Famine Early Warning System Network
GIMMS	Global Inventory Modeling and Mapping Studies
GLDAS	Global Land Data Assimilation System
GOF	Goodness-Of-Fit
GPCC	Global Precipitation Climatology Centre
GPCP	Global Precipitation Climatology Project
HDRI	Household Drought Risk Index
IPCC	Intergovernmental Panel on Climate Change
IRP	Infrared Precipitation
ISO	International Organization for Standardization
ISOE	Institute for Social-Ecological Research
JNRD	Journal of Natural Resources and Development
LSU	Large Stock Unit
MAE	Mean Absolute Error
MASL	Meters Above Sea Level
MAWF	Namibian Ministry for Agriculture, Water and Forestry
MDPI	Multidisciplinary Digital Publishing Institute
MRM	Multi-Resources Mix
MSWEP	Multi-Source Weighted-Ensemble Precipitation
MW	Microwave
NDVI	Normalized Difference Vegetation Index
NGO	Non-Governmental Organization
NOAA	National Oceanic and Atmospheric Administration
PCA	Principal Component Analysis
PDF	Probability Density Function
PERSIANN-CDR	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks – Climate Data Record
PET	Potential Evapotranspiration

PPS	Probability Proportional to Size
QM	Quantile Mapping
RCP	Representative Concentration Pathway
RFE	Rainfall Estimate
RFWH	Rain- and Floodwater Harvesting
RG	Rain Gauge
RP	Rainfall Product
RQ	Research Question
RSE	Relative Standard Error
SADC	Southern African Development Corporation
SAE	Small Area Estimation
SASSCAL	Southern African Science Service Centre for Climate Change and Adaptive Land Management
SES	Social-Ecological System
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SRN	Societal Relations to Nature
SSA	Sub-Saharan Africa
SSI	Standardized Soil Moisture Index
SVI	Standardized Vegetation Index
TAMSAT	Tropical Application of Meteorology Using Satellite Data and Ground-Based Observations
TCI	Temperature Condition Index
TRMM	Tropical Rainfall Measuring Mission
UCSB	University of California
UEA	University of East Anglia
UoR	University of Reading
USD	US-Dollar
USDA	United States Department of Agriculture
VCI	Vegetation Condition Index
WASCAL	West African Science Service Center on Climate Change and Adapted Land Use
WEF	Water-Energy-Food Nexus
WPI	Water Poverty Index
WVI	Water Vulnerability Index

1

Research challenge

Drought risk from an interdisciplinary perspective

1.1 Motivation

Droughts are phenomena that occur worldwide, in humid and arid environments as well as in the Global North and the Global South (Mishra and Singh, 2010; Spinoni et al., 2014). They are considered as slowly creeping hazards that affect more people than any other natural process (UNISDR, 2009). Drought events are basically spatially and temporally confined situations of deviations from normal water availability. This deviation can be measured in different terms such as from a climatological or hydrological perspective, as well as from an agricultural or socio-economic point of view (Mishra and Singh, 2010). In the discourse around the notion of Anthropocene, droughts are rarely a purely natural phenomenon but often a result of human-nature interactions (Van Loon et al., 2016).

During the last century, numerous droughts of varying severities and durations were recorded worldwide (Spinoni et al., 2014). Central Europe for instance, experienced a major drought in 2003 with an intense heat-wave (Rebetez et al., 2006) and California struggled with a multi-annual drought period from 2011 – 2016 (Tortajada et al., 2017). In addition, Australia recorded a millennium drought in 2006 (Kirby et al., 2014) with low water levels in the Murray-Darling Basin and around 8.8 Million people in Brazil's state of Sao Paulo experienced water shortage in 2015 due to low water levels in the Cantareira water supply system (Dobrovolski and Rattis, 2015). Africa is one of the drought hotspots worldwide. East Africa for instance, is still struggling with water scarcity triggered by El Niño (2015/2016) which is even further aggravated by conflicts among different (international) parties (Maxwell et al., 2016). Southern Africa saw high levels of rainfall variability during the summer months between 2014 and 2016 with associated drought conditions in several countries (Archer et al., 2017). Today, South Africa and in particular Cape Town are still dealing with the consequences of this water scarce period, as reservoir levels are low and the population is required to restrict its water consumption (Baudoin et al., 2017; Loon, 2018).

It becomes clear that droughts are a typical feature of many regions worldwide but with differing impacts, depending on the regions' specific, water-related sensitivities and coping capacities. Conventional drought hazard assessment tools such as the African Drought Monitor, the Famine Early Warning System Network (FEWSnet) and the Global Information and Early Warning System on Food and Agriculture, among others often confine their perspective to monitoring key environmental parameters with precipitation leading the way (Vicente-Serrano et al., 2012). While there is no doubt on the importance of monitoring these parameters for instance to populate Early Warning Systems (EWS) of drought, it is still required to incorporate the location-specific vulnerabilities of the society to fully capture drought risk. While progress is visible in moving away from assessments that solely focus on hazards to more localized, contextual analyses of risk and vulnerability, still more elaborated ways are required (Colette, 2016). This aspect is still in its infancy, making it highly relevant to construct holistic Drought Information Systems (DIS) to come from crisis-driven to pro-active approaches in drought risk management (Pulwarty and Sivakumar, 2014).

Despite the fact that societies in the Global North are also vulnerable to drought as in the case of California, in particular societies of the Global South are threatened as their sensitivities are often higher (e.g. dependence on agriculture) and coping capacities are lower (e.g. limited financial means for response and recovery). In combination with challenges of enhancing the population's living conditions (e.g. water supply, sanitation, education, poverty reduction, health) (UNECA et al., 2015), this predisposition can hamper future development opportunities. This is particularly relevant for subsistence-based livelihoods, as climate-sensitive agriculture is expected to play a dominant role in the medium to long-term development, for instance on the African continent (Collier and Dercon, 2014; Diao et al., 2010). Among other developing regions, sub-Saharan Africa (SSA) is a critical example. In the younger past, the far-reaching consequences of droughts have been particularly noticeable here. Severe continental droughts occurred in the early 1970s, the mid 1980s and the early 1990s (Masih et al., 2014; Spinoni et al., 2014) with failed harvests, dead livestock and water shortages, leading to social conflicts, economic damages, health issues, migration and even casualties. In total, between 1900 and 2013, almost 850,000 people died and more than 350 Million people were affected by numerous drought events (Masih et al., 2014, p. 3636; von Uexkull, 2014).

Though the above-mentioned numbers are alarming, variability in water resources is still a common feature of many parts in SSA, especially the semi-arid environments of the Sahel and southern Africa (Hoerling et al., 2006). In these areas, water has always been a major factor for human settlement patterns and overall development. The availability of water for instance, guided human settlement expansion in southern Africa around 100,000 years ago, when Bantu societies migrated from central Africa southwards practicing animal husbandry and later settled to establish farming communities (Ehret, 2001; Niemann, 2000). The societies were able to cope with water scarce periods, e.g. via temporal migration. The recent decades show however that social-ecological patterns have changed. The growing population on the African continent, paired with changing lifestyles and associated resources utilization and environmental degradation (Holechek et al., 2016) change the framing conditions. Today, in SSA about 70% of the population relies on rain-fed subsistence agriculture (IAASTD, 2009, p. 22) and is hence directly connected and dependent on hydro-climatic conditions. Thus, people strongly depend on predictable rainfall patterns to sustain their livelihoods and ensure water and food secure conditions. If these patterns change and reliability is reduced, for instance due to later rainfall onset, dry spells during the growing cycle or heavy rains that destroy the harvests, smallholder farmers are severely at risk. This is being aggravated by population projections indicating that Africa will grow by about 1.3 Billion people until 2050 to a size of about 2.48 Billion (UN-DESA, 2015, p. 3). This is the strongest population growth of all continents that is likely to result in a large number of people in a highly uncertain environment, exposed to droughts and numerous other threats with only low coping capacities.

One region that can serve as an example with respect to the above-mentioned challenges is the transnational Cuvelai-Basin in northern Namibia and southern Angola (Figure 1). It covers an environmental gradient from rather humid to arid conditions and associated vegetation characteristics of dense woodland to wide grasslands (see section 1.3). The population mainly practices subsistence agriculture and livestock herding with tendencies of urbanization and lifestyle changes gaining momentum (Mendelsohn and Weber, 2011). Droughts are a recurring threat to this region with the most recent multi-year drought from 2012 to 2015 that made several hundreds of thousands of people water and food insecure (DDRM, 2013; UN-OCHA, 2012). Some studies in the 1990s (e.g. Imbamba, 1993; Sweet, 1998) and the recent past (e.g. Acidri, 2010; FAO, 2016) attempted to investigate the livelihood situation of the Cuvelai population. These studies build a valuable starting point for the investigation of the causes and effects of droughts and their impacts. These insights contributed to legislative frameworks in both countries to handle short-term crisis situations and adapt to changing climatic conditions in the long-term (MINAMB, 2011; Republic of Namibia, 2012, 1997). Nevertheless, challenges remain to improve the efficiency of respective measures, wherefore more and up to date information is required to enhance the decision-basis for both governmental agencies and non-governmental organizations (NGO). Recently, this need was particularly highlighted by the African member states of the United Nations Convention to Combat Desertification (UNCCD) who compiled the Windhoek Declaration that states to "[*reduce*] *underlying factors of drought risk*" and carry out "[*d*]*rought vulnerability and impact assessments*" to enhance the resilience of African states to drought events (UNCCD, 2016, p. 1).

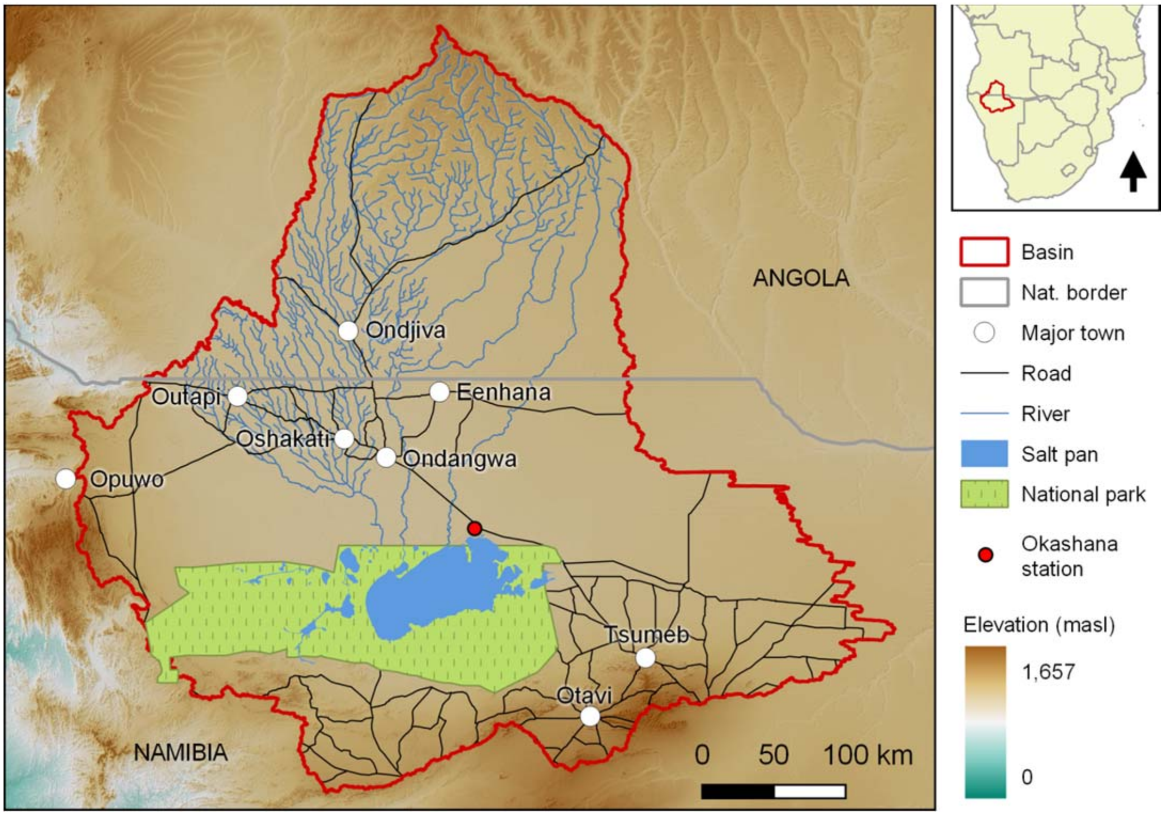

Figure 1: Key geographical features of the Cuvelai-Basin in northern Namibia and southern Angola. Map elements were derived from (Mendelsohn et al., 2013; OSM, 2015a, 2015b), while basin boundaries are based on SRTM90 data from Jarvis et al., 2008.

Unfortunately, the exceptional droughts that were recorded in the past probably become the new normal in the near future as climate change is likely to trigger more extreme hydro-meteorological events (Hoffman and Vogel, 2008). Overall, the climatic conditions in southern Africa are expected to become worse during the course of the 21st century. Human-induced climate change will alter precipitation conditions in the southwest of the continent with increased severity of dry extremes and lowered mean precipitation during the southern hemispherical winter months (Shongwe et al., 2009). The most recent fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC) hence notes that "*[t]he southwestern regions are projected to be at a high risk to severe droughts during the 21st century and beyond*" (Niang et al., 2014, p. 1211). Though the climate models still have difficulties in projecting future precipitation patterns and amounts, the signal for a strong reduction of precipitation in the late 21st century for southern Africa is solid, at least in the radiative forcing scenario RCP8.5 (Representative Concentration Pathway). Even more likely is the projected change in mean annual temperature for the southern African region. While global mean temperatures are likely to increase by about 4.8°C under the RCP8.5 scenario until 2081 – 2100 (compared to 1986 – 2005) on average (IPCC, 2013, p. 20), southern Africa is likely to experience a mean temperature increase of up to 6 degrees Celsius (Niang et al., 2014, p. 1207). This is an immense increase in temperature, keeping in mind that the natural variability and hence certain extreme events such as heat-waves will still come on top (Figure 2).

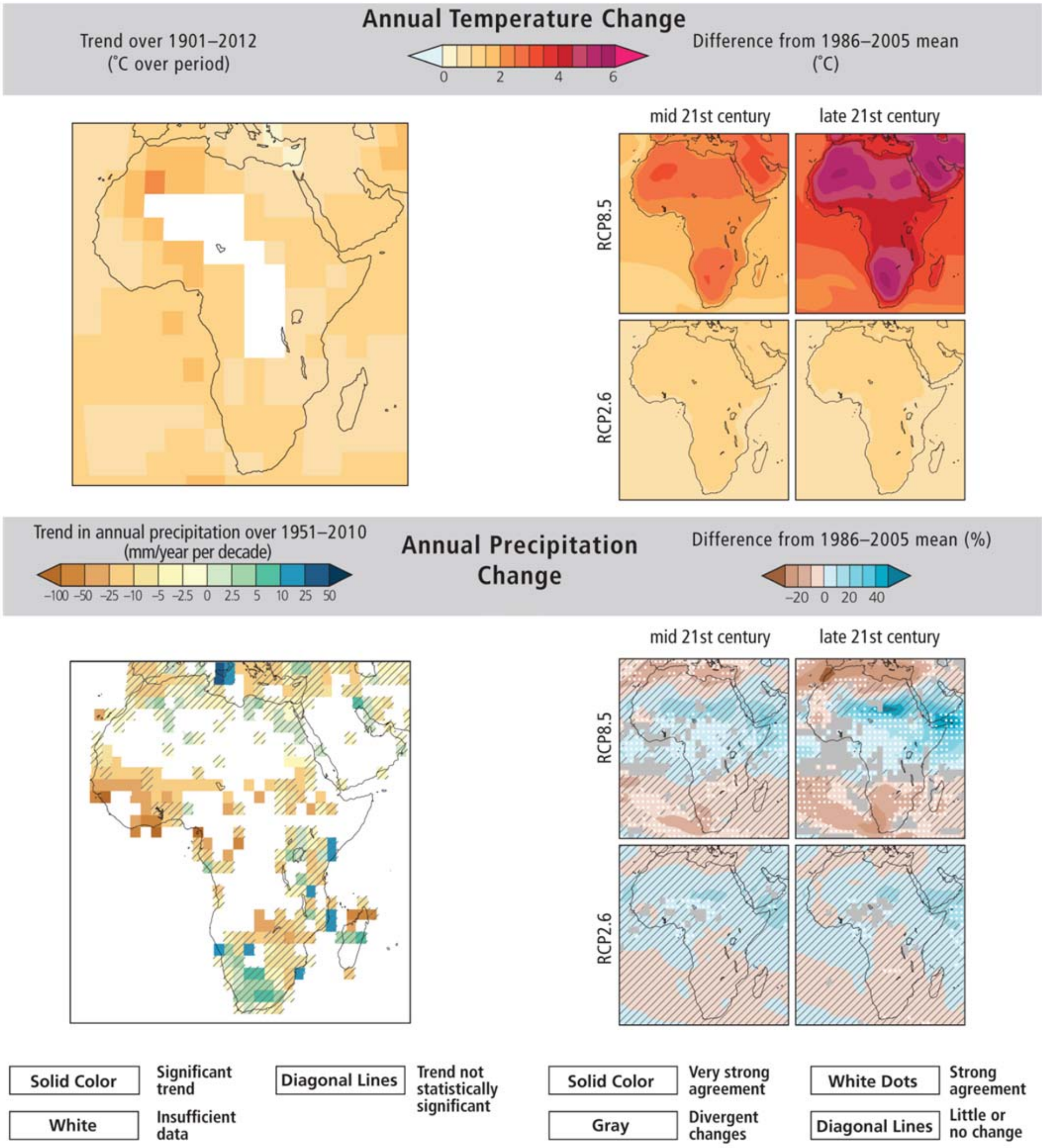

Figure 2: Comparison of historical changes and future projections for temperature and precipitation. Historical change (left column) and model projections for both variables under two different scenarios of radiative forcing (Representative Concentration Pathway, RCP) (Niang et al., 2014, p. 1207).

The previous paragraphs briefly outlined the key challenges southern Africa and the Cuvelai in particular are facing. Against this background, this thesis will take an integrated perspective on drought risk to contribute to the scientific and practical challenges around drought risk management by enhancing the knowledge basis and developing quantitative tools to measure drought risk. This will contribute to the improvement of risk management schemes in place and the construction of drought EWS and larger scale DIS on the local and regional level. The thesis will investigate the case study area of the Cuvelai-Basin to develop and carry out the drought risk assessment. Hereafter, the results can serve as a blueprint for other regions to conduct similar drought risk assessments.

The following sub-sections will introduce the thesis's framing in more detail. Therefore, (i) the project context is briefly depicted with (ii) a sub-sequent presentation of the study area in northern Namibia and southern Angola. Building upon this information, (iii) the overall research questions are presented and the thesis design is illustrated. Finally, (iv) the overall thesis structure is explained, as it is composed of individual research phases that constitute rather self-confined research elements.

1.2 Project context

This thesis can be considered as interdisciplinary, as the research integrates approaches and methodologies from the physical and human geography domain to characterize drought risk. In addition, it is part of a larger scale transdisciplinary process, as the thesis is embedded into a sub-project, a so called research task, of the Southern African Science Service Centre for Climate Change and Adaptive Land Management (SASSCAL). Task016, entitled "*water related vulnerabilities and risks based on water demand analyses*" is one out of 88 sub-projects that were jointly funded by the German Federal Ministry for Education and Research (BMBF) and the five SASSCAL partner countries South Africa, Namibia, Angola, Botswana and Zambia (SASSCAL, 2009). The service centre was set up in 2013 to enhance interregional knowledge transfer and foster applied research. The target is to provide applicable knowledge to the transnational challenges the region is facing in the fields of water, forestry, biodiversity, agriculture and climate. SASSCAL is an initiative of the BMBF funded regional science service centres of which the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL) and SASSCAL being the ones currently implemented. The research challenges were identified by the partner countries during the preparatory phase on the ministerial level. Thus, the overall design, implementation and research process can be described as transdisciplinary, in particular since the results of the 88 individual research projects are explicitly combined to provide new, integrated knowledge and thus enhance the decision basis for local institutions. The current thesis contributes to this knowledge basis and provides its results to the relevant political, scientific and public stakeholders via the SASSCAL service module, basically the open access data centre (OADC) that serves as a science-policy interface (SASSCAL OADC, 2018).

1.3 Study area: social-ecological characteristics

This sub-section will introduce the geographical space (German: "Geographischer Raum") of the Cuvelai-Basin in northern Namibia and southern Angola. While doing so, it will not follow a classic geographical approach of outlining characteristics of the physical environment and human domain in isolation but rather take an integrated perspective on the area's chorology. For this purpose, the following paragraphs will present the evolution of the social-ecological setting with links to key geographical features and a special emphasis on historical aspects that serve as an important background to understand the current human-nature interactions.

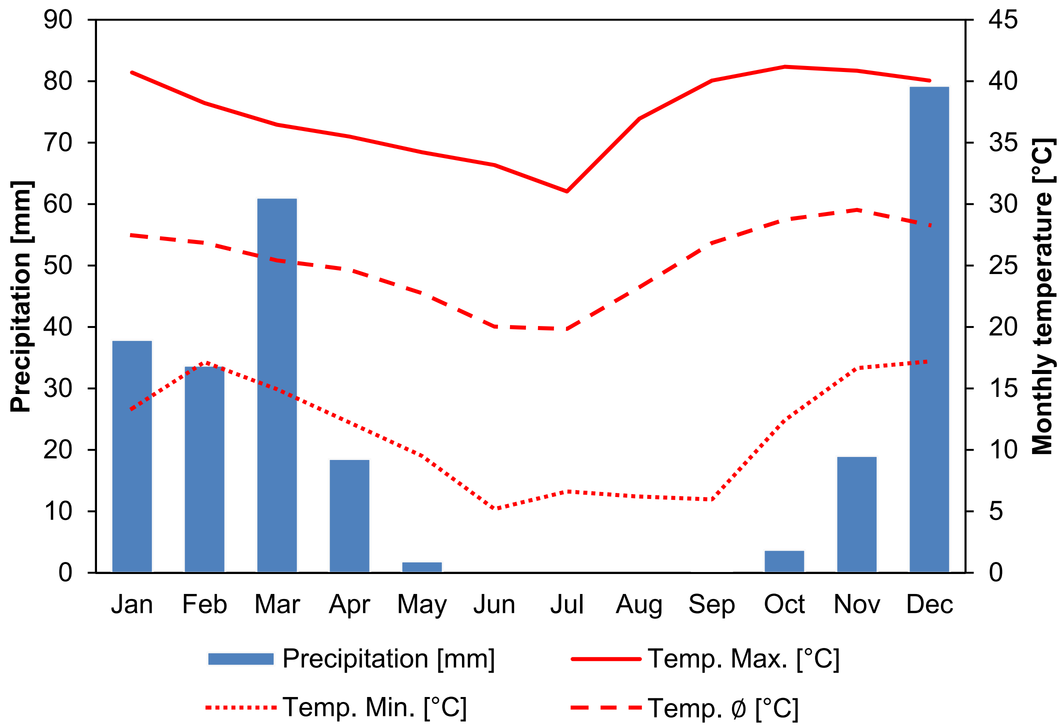

Figure 3: Climate diagram for Okashana station in northern Namibia for the period 2012 to 2017.
Data was obtained from SASSCAL WeatherNet (SASSCAL WeatherNet, 2018). Though climate diagrams normally fall back on at least 30 years of data, no station data is available that has a suitable temperature time series in addition to precipitation records than the short-term data provided by SASSCAL WeatherNet.

The Cuvelai-Basin is an endorheic watershed that drains the southern Angolan highlands into the Etosha pan of central-northern Namibia (Miller, 1997). It covers an area of approximately 172,000 km^2, 31% of which belong to Angola and 69% to Namibia at an average elevation of above 1,000 MASL (Figure 1). The hydrological system is complex in the sense that water availability depends not only on rainfall amount, temporal distribution and temperature but also on regular flooding which fills a multitude of ephemeral streams, swales, and channels, locally called Iishana (sing. Oshana). This river system only carries water on a seasonal basis and hence serves for the replenishment of soil moisture and groundwater reservoirs during the rainy season between October and April (Mendelsohn et al., 2013; Mendelsohn and Weber, 2011). Most of the rivers are seasonal, especially between the towns of Ondjiva and Oshakati, where most of the population is located. The central area, north of the dry Etosha pan, has a mean annual rainfall depth of about 255mm at Okashana station (Figure 3), at least when considering the past few years where reliable rainfall measurements are available from the SASSCAL WeatherNet (SASSCAL WeatherNet, 2018). Mean annual rainfall varies strongly across the basin with an increasing gradient from the southwest to the northeast (more information on local climate is provided in section 4).

In particular these relatively favourable hydrological characteristics of the basin compared to the arid conditions further south served as an attractor for the earliest hunter-gatherer societies that immigrated from the Okavango delta region in the east about 100,000 years ago (Ehret, 2001; Marsh and Seely, 1992; Niemann, 2000). Later, about 2,000 years before present, first communities of Bantu speaking ethnic groups initiated an agrarian revolution in the Cuvelai, making use of the limited soil fertility. Most likely, seasonal migration was established in these times to escape severe droughts in the south while temporary staying in the northern areas where rainfall is more abundant (Niemann, 2000). The Owambo people largely settled in the basin during the 16th and 17th century and intensified the agricultural utilization of the area. It is assumed that the slightly elevated dunes between the Iishana river streams served as a favourable spot for settlements and the nearby water resources enabled the early farming communities to practice agriculture on the river banks while livestock was held in the dried up river beds during the dry season (Mendelsohn et al., 2000).

For the most part, the basin's sediments are of Aeolian (sands) and alluvial (clays) origin. In particular, the eastern and western parts of the basin show large deposits of Kalahari sands. There, Arenosols developed as a typical soil type of arid and semi-arid environments that shows low nutrient content and limited water holding capacities characterizing these areas as unfavourable for crop cultivation (Figure 4). The same holds true for the dense clay sediments that were deposited by the Iishana river system. These soils, basically the Solonchacks north of the Etosha pan, are often water logged and show high levels of salinity. Only further north, the Solonetz soils and Calcisols, though still showing high levels of salinity, offer better opportunities for crop cultivation as they have a suitable composition of sand and clay proportions (European Commission, 2013; Mendelsohn and Weber, 2011). This area, today stretching across the border from Angola to Namibia, was and still is the primary settlement area.

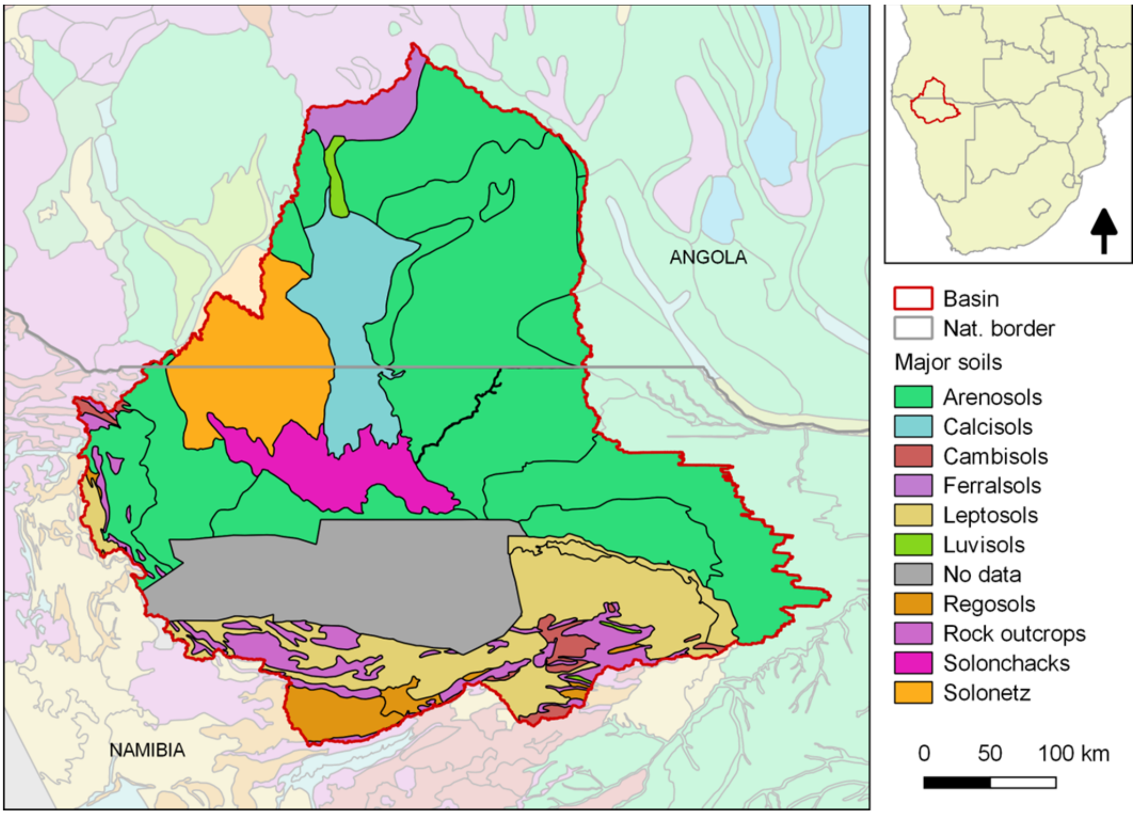

Figure 4: Major soils in the Cuvelai-Basin, according to the FAO soil classification.
Map shows the soil classes from the SOTER database for southern Africa (SOTERSAF) (Batjes, 2014).

In addition to the emerging agricultural activities, the more dense woodland in the east and the north complemented people's diets with wild fruits and opportunities to hunt animals. As the population grew, the dense woodland in the central settlement area was logged to provide energy and building material as well as new land for agricultural cultivation and livestock herding (Marsh and Seely, 1992). Today, the vegetation patterns show a gradient from the southwest to the east and the north with increasing proportions of woody vegetation (Figure 5). In total, about 61% of the entire basin is dominated by grassland savannahs. These areas are particularly relevant for livestock herding, especially since they were equipped with artificial water sources that increased the water-based carrying capacity of the rangeland. However, the increased stocking rates led to overgrazing and degradation which became an important problem today (Imbamba, 1993; Klintenberg and Verlinden, 2008). Efforts are already underway to make local livestock management more environmentally friendly, e.g. via adapted rotational grazing techniques (GOPA, 2014) that imitate the natural behaviour of savannah herbivores.

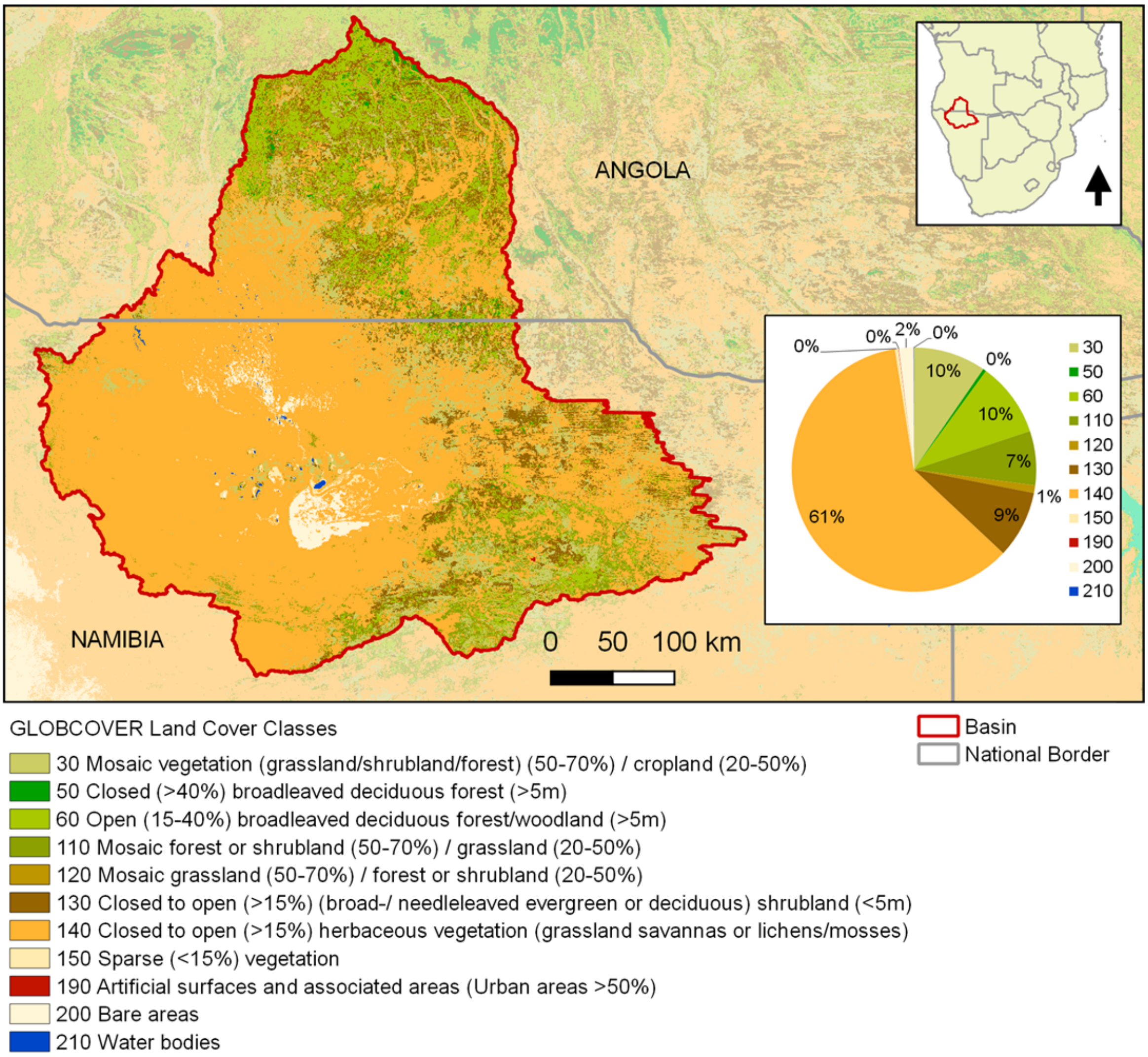

Figure 5: Land cover in the Cuvelai-Basin for the year 2009 at a spatial resolution of 300m.
Data obtained from the GlobCover Project of the European Space Agency (ESA) and the University of Louvain (ESA & UCLouvain, 2010).

While the people inhabiting this area were primarily confronted with typical environmental challenges of semi-arid areas such as droughts and regular flooding of the Cuvelai river system, the 19th century marks an important change as European colonial powers arrived. While it is not the objective of this thesis to review the colonial history on the African continent and in this region particularly, a brief overview should be given as it turns out to be important to understand today's living conditions on the Namibian and the Angolan side of the border. The interested reader is nevertheless referred to scientific work ups of this period (Birmingham, 2016; Kössler, 2015). With the colonial powers that encroached on the native population in southern Africa in the early 19th century, the population's freedom of movement and autonomy of decision was restricted. In particular, the border between the colonial territories of Portugal in the north and of Germany in the south cut across the Owambo region. The fenced border was introduced after the Berlin Conference in

1884/1885 and separated the rather homogeneous ethnic group into two distinct parts. This arbitrary demarcation cut established trade routes and cultural relations, leading to refugee migration, in particular from the northern to the southern part of the basin (Udelsmann Rodrigues, 2017). The colonial time impaired the society's development as multiple conflicts with the respective colonial powers arose with genocides among the Nama and Herero people in the German colonial territory (Kössler, 2015; Niemann, 2000). Though the living conditions improved after the German colonial period ended in 1919 with Namibia falling under South African and hence British rule, further political oppressions emerged such as the introduction of the Apartheid regime (Udelsmann Rodrigues, 2017).

From here, Angola and Namibia developed in different directions. From an infrastructural perspective, the north of Namibia saw improvements in the 1950s and 1960s where investments into water supply schemes began (Mendelsohn et al., 2000). These investments and the continuous expansion resulted in an advanced pipeline network that today supplies the entire Namibian side of the basin with abstracted water from the Kunene River in the west. After the war for independence and Namibia's national sovereignty (1990), the development of the northern regions continued, partly due to the fact that the Owambo people formed the largest ethnic group in Namibia and hence controlled the national political arena. The Angolan population however, experienced ongoing repercussions after their independence from Portugal in 1975. With a number of national and international political and paramilitary organizations, Angola entered a post-independence civil war that lasted until 2002 (Birmingham, 2016; Unruh, 2012). During this period, the civil population was displaced, agricultural activities were abandoned and infrastructures were destroyed (Udelsmann Rodrigues, 2017). Even today, land mines make certain areas uninhabitable, specifically the north-eastern areas. In contrast to their neighbours in Namibia, the Owambo people in Angola are a minority and still challenged by the consequences of the civil war, as the south of Angola, particularly the Cunene Province, still lacks essential infrastructures such as roads and a tap water network.

Comparing Namibia and Angola today reveals that the Namibian side is better endowed with modern infrastructure such as a road network, electricity and a tap water system. The Angolan part is generally less developed, only providing comparable systems in major urban agglomerations (Mendelsohn and Weber, 2011). These developments render the Cuvelai-Basin heterogeneous with a further developed south and a less developed north.

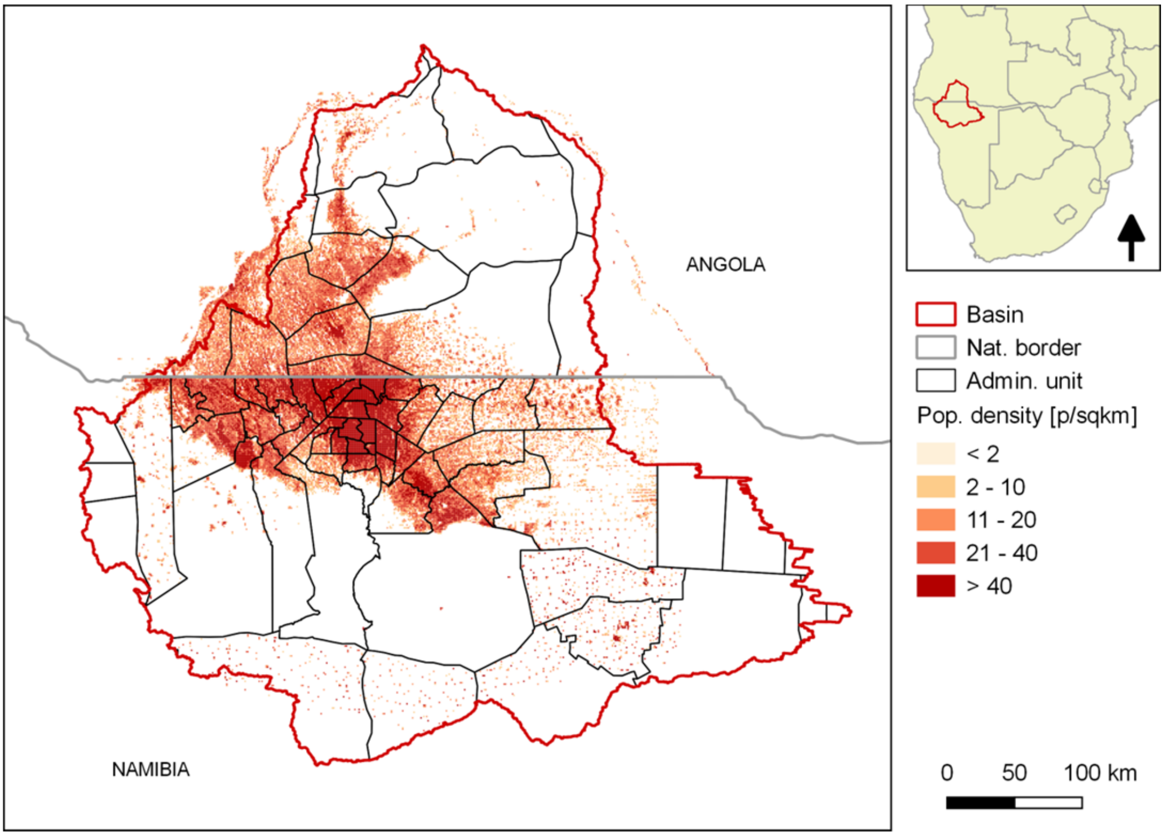

Figure 6: Population density in the Cuvelai-Basin.
Data obtained from spatial information on household numbers and -sizes (Mendelsohn and Weber, 2011).

Today, the total population of the basin is approximately 1.8 Million (INE, 2016, p. 89; NSA, 2013, p. 7, Figure 6)[1] that mainly lives in rural areas with a high level of subsistence agriculture. Rain-fed farming of local varieties of pearl millet, inter-cropped with sorghum, maize and a range of vegetables is the main agricultural activity and an essential component of local livelihoods. Taking rainfall onset variability into account, farmers use multiple planting dates from November/December through to January in order to minimise the risk of crop failure. Nevertheless, average yield is low with values between 100 – 400 kg/ha (Andreas, 2015; MAWF, 2011) which often only meets the domestic food demand on the household level (see section 4.4.4).

Livestock herding constitutes the second important pillar of livelihood activities and plays an important role in the socio-economic and cultural settings (Mendelsohn et al., 2013). Apart from the tap water system that is available in central-northern Namibia, traditional water sources such as shallow and deep wells, open water, and rainwater constitute important water sources for domestic consumption (see section 3). Overall, this kind of

[1] Population estimated by considering the census data of the Namibian regions Oshikoto, Omusati, Oshana and Ohangwena as well as the census data for the Cunene Province in Angola. The latter estimate is likely to overestimate the Angolan Cuvelai population, as the Province is larger than the basin boundaries.

lifestyle is closely connected to local hydro-climatic conditions. Thus, droughts immediately impact on the living conditions and challenge local water and food security. Local hydro-climatic settings in this semi-arid environment are thus one key to sustaining water and food security[2] among a large share of the population. Nevertheless, new lifestyles emerge with accelerated urbanization processes, new economic activities and trading opportunities, in particular across the Angolan-Namibian border (Mendelsohn and Weber, 2011; Rodrigues, 2010). However, inter- and intra-annual rainfall variability is pronounced that resulted in numerous drought events throughout the past decades with severe droughts in the late 1980s and mid-1990s and recently in 2012, 2015, and 2016 (EM-DAT, 2016), while ongoing drought conditions prevail due to the effects of El Niño.

1.4 Research objectives and study design

In the light of the aforementioned socio-economic conditions, the projected changes in local climate patterns and environmental conditions as well as previous studies on vulnerability and the livelihood conditions, this thesis aims to contribute to the transdisciplinary challenge of enhancing people's abilities to deal with droughts. This overarching epistemological interest can be condensed into the following research questions (RQ) that serve to structure and guide the thesis's research process:

RQ1: How does drought impact on the livelihoods of the population in the Cuvelai-Basin and how can this impact be measured?

RQ2: What are key environmental determinants of the drought hazard in the Cuvelai-Basin and how do these manifest spatially and temporally?

RQ3: How are the key determinants of sensitivity and coping capacity distributed among the population and which societal groups are most vulnerable to drought?

RQ4: Which interventions can serve to reduce drought risk among the population from a social-ecological perspective?

The RQs frame the entire research process and indicate the necessity of taking an interdisciplinary approach in the sense that a methodological mix is required to obtain relevant information on both the environmental and socio-economic determinants of

[2] Definition of food security: *"Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life."* (FAO, 1996). Definition of water security: *"The capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems in a climate of peace and political stability."* (UN-Water, 2013, p. iv).

drought risk. RQ1 sheds light on the local problem context and seeks to develop a tool for drought risk assessment. Therefore, this first research phase makes use of a qualitative, socio-empirical approach. It serves to explore the drought impact on people's livelihoods under local social-ecological conditions and to derive a first-hand understanding rather than solely inferring hypothetical assumptions from other case studies. RQ2 will build upon the qualitative insights and specifically focus on the environmental domain of drought risk. Herein, answers are provided regarding which key environmental parameters need to be considered and quantified to depict the drought hazard in its spatial and temporal manifestation. Remote sensing techniques are regarded as adequate tools for this task against the background of critical ground data availability. RQ3 likewise seeks to identify key determinants of drought risk but focuses on the socio-economic domain. It will guide the process of finding answers about how sensitivity and coping capacity are characterized and how these dimensions can be measured in order to identify those societal groups that are most vulnerable. While the first research phase followed a qualitative approach, this phase carries out quantitative socio-empirical surveys to assess primary data. RQ4 provides recommendations on how drought risk can be reduced, e.g. for specific groups of vulnerable people. While the individual research phases that are presented in the following sections provide new knowledge that contribute to the RQs, section 8 will specifically take them up and condense the thesis's findings, accordingly.

1.5 Thesis structure

The previous sections introduced the overall framing of the thesis and indicated its diversity, in particular with regard to the selection and combination of methodological techniques from the social and natural sciences. There is not one single method being applied in this thesis but rather a range of methods and research steps that build upon one another in a consecutive way. In order to enhance the readability of the thesis and enable the reader to reconstruct the research process and causal dependencies, the document is structured into distinct segments that are best thought of as individual research articles. Each of these segments is structured as a classical scientific paper with the sub-sections introduction, material and methods, results, discussion and conclusion while the entire thesis is framed by a general introduction, the conceptual and theoretical approach as well as an overall discussion and conclusion.

As a first step, the overall introduction (section 1) introduced the topic of drought risk and presented the motivation and the context of the thesis under the umbrella of the SASSCAL project. It described the overall transdisciplinary framing of SASSCAL and derived the specific research questions to be answered in this thesis. Furthermore, it informed the reader about the geographical setting of the target region by describing key social-ecological characteristics with particular importance for drought risk.

Building upon this introduction, section 2 provides the theoretical and conceptual basis for the empirical work conducted at later stages. Herein, special emphasis is given to theoretical perspectives of societal relations to nature (SRN) and social-ecological systems (SES). These framing concepts take up recent approaches on ecosystem services (ES) and human well-being and are regarded as essential for a thorough drought risk assessment. The latter conceptually builds upon two academic chains of thought from risk-hazard and vulnerability traditions. The section will close with a guideline for a social-ecological drought risk assessment that seeks to be applicable in the field of the Water-Energy-Food (WEF) nexus.

Having presented the theoretical fundamentals of the envisaged drought risk assessment, section 3 constitutes the first empirical study segment. The centrepiece of it is the qualitative exploration of the research topic to receive first-hand information on drought impact on the population's livelihoods in the Cuvelai-Basin and for the author to acclimate in the new cultural and physical environment. The section presents insights into green and blue water utilization by urban and rural households, derives an understanding of the drought hazard and the population's vulnerability and develops a quantitative tool, a composite indicator, to measure drought risk. This so called Household Drought Risk Index (HDRI) will be populated with appropriate data in the following sections. The section was presented in an early version at the International Conference on Drought: Research and Science-Policy Interfacing in Valencia, Spain (2015) and subsequently peer-reviewed and published as a chapter in the conference book (Luetkemeier and Liehr, 2015).

The exploratory research phase outlines the structure of the composite indicator HDRI, incorporating environmental and socio-economic parameters. The following section 4 paves the way for the estimation of the physical drought hazard component by analysing precipitation data from multiple satellite rainfall products on which most drought indicators build upon. Six commonly used products were compared to one another and evaluated against local station measurements. The research presents the domain of uncertainty between the products and to the observed time series of rainfall. In addition, it exemplarily shows the trickle-down effect of uncertain input data on crop model results of pearl millet yield. As a result of this research segment, the best-performing product was identified (CHIRPS 2.0) and thus used for further drought analysis steps in combination with other environmental parameters. Overall, this section is an excursus on the use of environmental information in data-scarce environments. The section was peer-reviewed and published as a modified version in the Journal MDPI Water (Luetkemeier et al., 2018).

As the previous section identified the most suitable dataset on precipitation for the Cuvelai-Basin, section 5 deals with characterizing the environmental drought hazard in quantitative terms as part of the HDRI. Besides precipitation, further environmental parameters were chosen being evapotranspiration, soil moisture and vegetation conditions. These variables were statistically analysed and combined to create a new, copula-based drought indicator that is capable of capturing the effect of drought events in the blue- and green water flows in the Cuvelai-Basin. This so called Blended Drought Index (BDI) provides the opportunity to trace the drought hazard over time and analyse it spatially in terms of frequency of occurrence, severity and duration. This section was peer-reviewed and published as a modified version in the Journal MDPI Climate (Luetkemeier et al., 2017).

While the BDI accounts for the environmental perspective on drought, section 6 takes a socio-economic perspective and elaborates on one aspect of vulnerability, the population's sensitivity. Herein, the centrepieces are the results of a structured household survey, carried out in Namibia and Angola with a total sample size of 461 households to collect necessary socio-economic data to populate the sensitivity dimension of the HDRI. The section presents the methodological techniques for acquiring the empirical data, analysing them with a specific focus on the seasonal water and food consumption patterns and finally measuring a household's drought sensitivity. This section was peer-reviewed and published as a modified version in the SASSCAL research book (Luetkemeier and Liehr, 2018).

In order to carry on the quantification of the HDRI's vulnerability component, section 7 sheds light on the coping capacity dimension. In this regard, it builds upon further results of the structured household survey in Namibia and Angola with a special focus on the parameters that determine a household's capital endowment (human, social, financial, physical and natural capital). In addition to this, the section serves the purpose of conflating all previous thesis results from both the environmental perspective (section 5) and the sensitivity dimension (section 6) to populate the HDRI composite indicator. In this regard the section presents data processing and analysing techniques with a special focus on how to construct the composite indicator with adequate weighting and aggregating schemes to account for uncertainty. Furthermore, a regression approach is presented to retrieve preliminary spatial results on drought risk in the basin. Finally, the section presents the overall study results and specifically explores drought risk among different groups and the spatial patterns that emerge when considering drought risk from an integrative perspective. This section was presented at the Water Security and Climate Change Conference in Cologne, Germany (2017) and a modified version of it is currently under review at the Journal of Natural Resources and Development (Luetkemeier and Liehr, under review).

The previous sections produced new knowledge on household drought risk in the Cuvelai-Basin. Section 8 will provide an overall discussion of the thesis with special emphasis on (i) providing answers to the RQs, (ii) reflecting the social-ecological framing, (iii) exploring the benefit of combining qualitative and quantitative research methods and (iv) outlining how this research can support the development of integrated DIS that consider the linkages within the WEF nexus.

Finally, the thesis closes with the concluding section 9 that derives recommendations for both further scientific investigations into drought risk and for short- and long-term drought responses and adaptation strategies in the target region and beyond. The latter aspect is currently under final preparation for publication as an ISOE policy brief, targeted towards institutional stakeholders in Angola and Namibia (Luetkemeier and Liehr, forthcoming).

2

Theoretical approach

Guideline for social-ecological risk assessments

2.1 Conceptual integration

This section seeks to develop a guideline for the analysis of drought impact with regard to its multi-layered effect on society and departs from the challenges outlined in the previous section (Kallis, 2008; Mishra and Singh, 2010). Interdisciplinary expertize is required in this regard, as droughts can be triggered by environmental phenomena such as El Niño or societal actors like in upstream-downstream conflicts along rivers. Therein, multiple cause-effect relations are inherent that link humans and nature. A thorough risk assessment of drought thus requires an operational guideline that accounts for these complex cause-effect relations. This cannot be bound to solely sociological or natural science perspectives but rather requires an integrated consideration.

For this purpose, the following sub-sections discuss (i) the societal relations to nature as a basic theory of human-nature interactions, and (ii) the social-ecological system model for system knowledge generation. Furthermore, key concepts will be examined, namely (iii) ecosystem services and human well-being as well as (iv) the role of vulnerability and hazard within the risk concept. This will build the basis to (v) develop a comprehensive guideline for social-ecological risk assessments. This is a first attempt to develop a transferable and adaptable tool to assess risks in a social-ecological problem context.

2.1.1 Societal relations to nature and social-ecological systems

Conventional risk assessments often assume rather simple linear relationships of hazardous events and affected objects with economic parameters as the key measuring units (SRU, 1999). Social-ecological research shows however that cause-effect relations between potentially threatening processes and affected objects are complex and multi-layered, cascading as well as mutually responsive (Völker et al., 2017). Risk assessments in the social-ecological domain hence require a more in-depth examination of human-nature interactions. As a first step, this vague formulation of human-nature interactions requires a theoretical foundation from which suitable risk assessment techniques can be developed. The following paragraphs will hence provide a brief background on societal relations to nature as the central, theoretical starting point.

Conceptualizations around the interactions between nature and society are common among several scientific disciplines that consider the role of societal actors in ecosystem management (Glaser, 2006). One of the most elaborated ways to understand human-nature interactions is the theory of societal relations to nature that carves out the cognitive core of various competing concepts (Becker et al., 2006). "*Societal relations to nature refer to the dynamical patterns of relations between humans, society and nature. They emerge from the culturally specific and historically variable forms and practices in which individuals, groups, and cultures design and regulate their relations to nature*" (Becker et al., 2011, p. 76). The theory evolved as a response to the ecological crisis that became a focal point of interest in the public discourse in the 1970s and '80s. While it gained momentum among scholars in a number of variations, the Frankfurt School of Social Ecology narrows it down to the question of how "*human activities link society to nature and which natural processes place limits on these activities or threaten societal reproduction and development*" (Becker et al., 2011, p. 8). social ecology in this sense is closely linked with the Vienna School of Social Ecology in particular with respect to the concept of ecosystem colonisation (Haberl et al., 2016). This rather European perspective shows differences to the way, the American School of Social Ecology defines this field of research. While the European perspective rather operates on aggregated levels such as groups and societies, the American School with its origins in human ecology, focuses on the individual person and its environments like the natural, the social and the digital one as a new emerging environment (Lejano and Stokols, 2013; Stokols, 2018). Overall, the different trains of thought share the perspective of multiple and complex links between society and nature. In the SRN theory of the Frankfurt School, these links are the central reference of research. Herein, it acknowledges both physical-material and cultural-symbolic relations between the two spheres, giving credit to the role of socially and cognitively constructed links. Special attention is given to the regulation of those relations that are vital to satisfy the societies' basic needs (Hummel et al., 2017). These basal societal relations to nature (BSRN) are essential since their failure results in severe crisis situations that undermine long-term sustainability and hence the existence/reproduction of societies. The specific configuration and regulation of BSRN is historically and culturally shaped and provides the context in which a society's basic needs are satisfied (Becker et al., 2011; Hummel and Becker, 2006).

Though it is not clearly defined as such by the Frankfurt School of Social Ecology, the author considers SRN to essentially centre on the question of how societies interact with nature to organize the satisfaction of basic needs. It hence becomes an anthropocentric theory in which nature particularly takes on the role of providing both physical-material and cultural-symbolic satisfaction for society. This latter aspect is an important assumption that will be discussed in the context of the ecosystem services and human well-being concepts in section 2.1.2 in more detail.

Acknowledging the core assumption of the SRN theory that the dynamic patterns of relations between the two spheres are essential to understand human-nature interactions, the question arises how these relations can practically be assessed or applied. For this purpose, SRN have to be operationalized as a system in which elements of natural and societal kind are related to one another. A number of integrated system approaches exist with the Coupled Human and Natural Systems (CHANS) narrative being popular in human ecology, ecological anthropology and environmental geography (Liu et al., 2007). The CHANS concept remains however, rather broad and fuzzy, while the term social-ecological system seems more applicable and became popular among scholars with a number of varying priorities. On a larger scale, SES are regarded as an adequate analysis framework to explore challenges of the Anthropocene (Glaser et al., 2012). The Stockholm-based Resilience Alliance emphasizes the adaptive management of ecosystems from a resilience perspective (Folke, 2006), while others apply SES as a framework to analyse institutional and governance systems with reference to the tragedy of the commons (Ostrom, 2009). In this sense, Anderies et al. (2004) examined the robustness of SES by means of analysing the institutions that govern resources use (Anderies et al., 2004). In addition, Cumming et al. (2006) highlight the issue of scale within SES. They find that mismatches of scales between (institutional) management and ecosystem processes often result in reduced resilience and impaired human well-being (Cumming et al., 2006). Liehr et al. (2017) discuss the suitability of the SES model to be applied in transdisciplinary research. They explore this issue empirically against the background of water challenges in northern Namibia (Liehr et al., 2017).

The Frankfurt School of Social Ecology developed an SES model explicitly as the operationalization of the SRN theory. While it serves as a boundary object in transdisciplinary research and hence facilitates the collaboration among different stakeholders on a specific problem setting (Liehr et al., 2017), it can also be applied as an analytical tool when specifically conceived as a provisioning system (Hummel et al., 2011). These systems centre on the question of how basic needs are met via interactions with nature. The construction of a social-ecological system or provisioning system[3] requires four deliberate steps, the initial one being the distinction between natural and societal elements that are of relevance for a specific case. According to systems theory (Liehr et al., 2006), a relation essentially requires a minimum of two elements that can be linked. The identified elements are subsequently related again, deliberately by the operation of association to build a network of interrelated entities. By structuring the set of entities and their relations and limiting the entire elements and their relations functionally, spatially and temporally, a social-ecological system emerges as an abstracted model of reality. It is important to note that the SES is composed of specific elements from the natural and societal sphere with their respective relations. In other words, the constructed systems take different shapes when changing the provisioning focus from one BSRN to another, for instance from nutrition to shelter or mobility. They emerge as particular tools to understand societal relations to nature and are thus shaped differently from case to case (Becker et al., 2011).

Figure 7: Generic setup of a social-ecological system (Mehring et al., 2017).

This rather theoretical perspective on the operations distinction, association, structuring and limitation to construct a SES is made more explicit in the following paragraphs. Research at ISOE over the past decade on analysing SRN provided the basis for a generic set up of social-ecological systems that is graphically depicted in Figure 7. Herein, the green ellipsis represents the social-ecological system that has a specific provisioning focus. It entails actors and ecosystem functions as basic elements from the societal and the natural sphere. The SRN theory postulates that the relations between these elements

[3] Though the differences between both terms are not yet clarified at ISOE, the author treats them as synonyms.

are the central reference of research for a thorough system understanding. These relations are condensed to two major types of relations that are both unidirectional[4], from society towards nature and from nature back to society. On the one hand, management and unintended side effects capture the idea of both diffuse and targeted human actions that alter ecosystem properties. On the other hand, nature provides ecosystem services to society that are relevant to meet the societies' basic needs. These elements and their unidirectional relations can be conceived as a cyclic model that emerges from social-ecological structures and processes of knowledge, practices, institutions and technologies. These are hybrid system characteristics that regulate the mutual interactions between the elements (Hummel et al., 2011). The knowledge category encompasses different kinds of knowledge from scientific and practical to everyday life knowledge. Practices in essence, include activities of actors carried out to alter specific ecosystem functions or utilize ecosystem services while technology refers to all man-made structures and tools that serve these purposes. Institutions are those formal and informal rules that are established in a society and regulate everyday life. These factors are hybrid in the sense that they cannot be understood without either the natural or the societal sphere. They are strongly interrelated and provide a holistic set of categories to gain a system understanding. It facilitates knowledge organization and is hence suitable to design empirical research projects that seek to analyse human-nature interactions with a specific provisioning focus (Hummel et al., 2011).

In essence, the SES model is the operationalization of the SRN theory and hence centres on the same question of how nature contributes to society's needs satisfaction. With this system perspective it becomes clear that two essential relations need to be considered in empirical research, human influence on nature (management) and society's utilization of natural resources (ecosystem services). To understand the regulation of these links, the social-ecological structures and processes, captured in the four categories, give guidance for the assessment process.

2.1.2 Ecosystem services and human well-being

The previous section shed light on the two types of relations between society and nature: (Un-)intended management and utilization of ecosystem services. The ES concept is an important system element within the latter relation of the SES model that links the social-ecological perspective to a large scientific debate on how nature contributes to human well-being. As the ES and human well-being concepts are well known among scholars

[4] Practically, feedback processes are in-built but the overall direction of influence is rather unidirectional.

and practitioners as well as policy makers, the current section will examine the concepts in more detail and describe their role in the SES model.

Box 1: Terminology of the FEGS approach.

As a first step, the FEGS approach distinguishes between a benefit and the final ES. The latter is regarded as the end-point of nature, preferably thought of as a product that humans can utilize and process, while the first is perceived as the satisfaction humans obtain when utilizing final ES. Several final ES hence generate a benefit to society as these "*typically require other forms of capital to [be] realize[d]*" (Fisher et al., 2009, p. 646). Benefits are hybrids that directly alter human well-being, but the MEA and its derivatives do not acknowledge this difference and rather equate services to benefits. Consequently, they create confusion and inconsistency by mixing up purely biophysical contributions of nature with hybrids of social and natural origin. In addition to this first distinction, the FEGS approach regards processes that are defined as regulating or supporting services by the MEA as intermediate services. These are not ends in themselves but rather means of nature to generate final ES. The MEA and its derivatives frequently mix up intermediate and final services and thus create the problem of double-counting (Johnston and Russell, 2011; Wallace, 2007).

These arguments do not mean that the so called cultural ES like recreation, aesthetics and spirituality are not important. Actually, the contrary is the case as these are rather benefits people obtain from consuming final ES in one way or the other than actual services. Likewise, the distinction between intermediate and final is not an expression of importance but rather an opportunity to clearly figure out, how human well-being is connected to nature, namely via a clear sequence of processes. As Nahlik et al. comprehensively delineate, the advantages of adopting the FEGS definition are (i) avoidance of ambiguity by focusing on ecosystem characteristics directly relevant to beneficiaries, (ii) prevention of double-counting since only end-products of nature are valued, (iii) encouragement of collaboration among scientific disciplines due to consistent and clearly defined language and (iv) tangibility for non-scientists such as policy-makers and local stakeholders (Nahlik et al., 2012).

The notation/term ecosystem services emerged at the turn to the 21th century (Costanza et al., 1997; Daily, 1997) and gained momentum with the Millennium Ecosystem Assessment (MEA) in 2005 (MEA, 2005). The concept became popular quickly and was frequently applied in numerous contexts, mainly relying on the MEA classification of provisioning, regulating, supporting and cultural services (MEA, 2005). An important insight gained from these first applications and their scientific, political and societal debate is the necessity to critically question the definitional foundation of the initial ES concept (Fisher et al., 2009). The large number of definitions (Hermann et al., 2011; Nahlik et al., 2012; Potschin and Haines-Young, 2009) is an indication of the concept's diversity that creates confusion and avoids comparability of study results (Lamarque et al., 2011). Although, the report of the MEA was a milestone in mainstreaming ES (MEA, 2005), their definition and classification system is rather a heuristic approach than a practical guide to identify relevant ES and their contribution to human well-being (Fisher et al., 2009; Nahlik et al., 2012). Therefore, a number of authors stressed the point that the concept has to be broken down into three basic terms: benefits, intermediate and Final Ecosystem Goods and Services (FEGS) (Boyd and Banzhaf, 2007; Fisher et al., 2009; Fisher and Kerry Turner, 2008).

The FEGS approach clearly identifies the end-points of nature and carves out, where human actions or inputs are required to create benefits for human well-being. Hence, the FEGS approach is currently the most consistent and applicable way to define and apply the ES concept. For more information on this concise definition, Box 1 provides some explanations. Within the SES model, the ES concept, conceptualized according to the FEGS approach, reflects central ideas from the SRN theory. It is basically hybrid that clearly delineates natural and societal components that conflate at a specific point to provide added value for human well-being. The overall target of ensuring a constant provision of ES to keep or enhance well-being is thus the motivation of human actors to manage nature in a certain way.

In the terminology of the SRN theory and the SES model, the notion of societies' (basal) needs is common to describe the incentive to manage nature for human survival and thereby meet the society's needs. The Frankfurt School of Social Ecology herein refers to basal SRN like shelter, nutrition, mobility and reproduction as the focal points around which to construct a SES provisioning system (Hummel et al., 2017). While first approaches exist to spell out these specific basic needs structures, in particular building upon the hierarchy of needs (Maslow and Green, 1943), a more common concept to capture this idea was brought forward by the MEA, known as human well-being. Herein, five essential categories are delineated, being freedom of choice and action, security, health, materially enough for a good life and good social relations (MEA, 2005). These categories were developed explicitly as the opposite of ill-being as outlined in the world development report of 2000/2001 (The World Bank, 2001). While the human well-being categories are thought to be applicable to every human being, their specific configuration differs from one person to the other, even from one cultural background to another. Within the SES model, the society is composed of actors (e.g. individuals, households, companies, communes) that are interrelated and influence each other. These actors are managers and users of nature at the same time. What is important here is that every actor is seeking to meet its specific well-being configuration, keeping in mind that some aspects of well-being can only be met exclusively within the social sphere (e.g. good social relations) while others involve the direct or indirect utilization of nature (e.g. materially enough for a good life). The process of meeting human well-being requires a certain management of nature, in particular of specific ecosystems. Herein, not simply intended management effects are generated but rather unintended effects might occur since multiple actors act simultaneously in partly unregulated ways resulting in uncertainty. Within the ecosystem itself, specific ecosystem functions, as bundles that stem from ecosystem structures and processes, are managed for a certain reason. The maintenance or enhancement of human well-being is thus, at least from a theoretical perspective on the societal level, the core incentive of human actors to manage nature and derive a certain set of final ES that can be utilized to meet well-being. If human well-being is unmet, a crisis situation can emerge that undermines the system's long-term sustainability.

2.1.3 Risk, hazard and vulnerability

The previous sections presented the SES model as a means to describe the functioning and regulation of human-nature interactions to ensure societies' well-being. The model provides knowledge on the system's normal mode of operation. This essential system knowledge is a pre-requisite to take a problem perspective to assess e.g. how drought events potentially impact on society. For this problem perspective, the concept of risk is discussed in the following with special emphasis on its constituting components hazard and vulnerability.

"*Disaster risk derives from a combination of physical hazards and the vulnerabilities of exposed elements and will signify the potential for severe interruption of the normal functioning of the affected society once it materializes as disaster*" (Lavell et al., 2012, p. 32). Since the term risk is part of everyday life and language, it has a range of different connotations and meanings, all of them relevant in their respective contexts (SRU, 1999). The International Organization for Standardization (ISO) attempted to give a general definition of risk as an "*effect of uncertainty on objectives*" with a clarification that "*[r]isk is often expressed in terms of a combination of the consequences of an event […] and the associated likelihood […] of occurrence*" (ISO, 2009). Although the key terms are properly defined in a range of ISO documents, scientific disciplines, however, tend to use different operationalizations of these with quantitative terminologies in e.g. economics, the insurance industry and natural sciences and rather qualitative/descriptive representations in medicine, psychology and sociology (SRU, 1999). Nevertheless, despite definitional varieties, risks can be categorized as either classical or non-classical. While the former assign the causes of risk to the natural or human sphere (e.g. volcanic eruptions or wars), the latter acknowledges interrelated causes such as climate change or desertification (Schramm and Lux, 2014).

The Intergovernmental Panel on Climate Change (IPCC) condenses current research on climate change as a non-classical risk in its recent report. Herein, it defines risk as "*the potential for consequences where something of human value is at stake and where the outcome is uncertain. Risk is often represented as probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends occur. Risk results from the interaction of vulnerability, exposure, and hazard*" (IPCC, 2014, p. 1772). This definition has a common ground with the one from ISO, presented above. It basically comes down to an event that has negative consequences for a clearly defined object, while the impact is associated with uncertainty. Wisner et al. (2003) put this into an applicable pseudo equation of Risk = Hazard * Vulnerability (Wisner et al., 2003, p. 49) that is commonly used in the global environmental change community (Birkmann, 2006; Taubenböck et al., 2018). It is the central component of their pressure and release model (PAR) which assumes that people are metaphorically located in the middle of a nutcracker of increasing pressures from the vulnerability side, conceptualized as a multi-layered construct of root causes, dynamic pressures and unsafe conditions as well as the hazard side (Wisner et al., 2003). Their conceptual findings and in particular their central reference, the above mentioned pseudo equation were frequently adopted and adapted in research and practice. It can hence be regarded as the current state of the art in risk research and is thus taken up in this thesis to develop a guideline for social-ecological risk assessments.

Besides vulnerability, the hazard is the critical component within this risk conceptualization. If a hazard occurs and vulnerability is challenged, then risk materializes and a disaster is present (Cardona et al., 2012; Lavell et al., 2012). Hazards can take very different shapes from purely natural processes such as volcanic eruptions via hybrid hazards such as flood events to hazards that rather stem from the societal sphere such as the introduction of artificial, anthropogenic substances into the water system. Hazardous processes in general are often characterized by means of statistical figures such as frequency of occurrence, magnitude, duration as well as spatial and temporal extent (Lavell et al., 2012). As a result it is closely linked to the definition of exposure – another key term in the risk conceptualization of the IPCC. Exposure rather takes the perspective of affected objects like people or buildings. Therein, it basically comes down to the question, if an affected object is located in the vicinity of a hazardous event both spatially and temporally (Cardona et al., 2012; Lavell et al., 2012). A clear distinction between both terms is difficult to make, as spatial and temporal extent are an inherent attribute of a hazardous process and the exposure of an affected object is actually incorporated in the vulnerability of this object towards a specific hazard type.

In this sense, the term vulnerability, as the second critical component within the risk conceptualization, shows a long and variable history. "*Vulnerabilis was the term used by the Romans to describe the state of a soldier lying wounded on the battlefield, i.e., already injured therefore at risk from further attack*" (Kelly and Adger, 2000, p. 328). This quotation about the etymology of the word vulnerability already spans two important dimensions that are part of the scientific debate about the concept of vulnerability. On the one hand, it describes the internal state of a possibly susceptible object (the wounded soldier) and on the other hand it describes the object's exposition to an external threat (further attacks on the battlefield). By analogy, two theoretical approaches to the concept of vulnerability can be identified. First, vulnerability as a social construct is determined by the subject's sensitivity towards a perturbation and its capacity to adapt or cope (Adger, 2006). This is referred to as social vulnerability which depends on historical, cultural, social and economic processes and originates within sociology and political economy (Cutter, 1996). Second, biophysical vulnerability focusses on the object's exposure to a hazardous event, characterized by the magnitude, duration, impact, frequency, areal extent and rapidity of onset of the stressor. This tenet has evolved primarily within risk and hazard research (Adger, 2006; Cutter, 1996). A third approach, which at least was dominant within the climate change debate, tries to integrate both aspects and is based on the three pillars exposition, sensitivity and adaptive/coping capacity (Adger, 2006; Cutter et al., 2003; Füssel, 2007; Liverman, 1990; Wisner et al., 2003). Soares et al. (2012) even state that the integrated perspective can be perceived as the current paradigm in vulnerability research (Soares et al., 2012). However, since "*it would be an exhausting, and probably rather meaningless, task to review all the different ways in which people have used the word vulnerability*" (Liverman, 1990, p. 29) as Liverman puts it already 28 years ago, the reader is directed to authors like Birkmann who nevertheless attended this matter and give a well-founded overview on the concept's origin (Adger, 2006; Birkmann, 2006; McLaughlin and Dietz, 2008; Soares et al., 2012).

One of the most recent and widely acknowledged definitions of vulnerability was brought forward by the IPCC in its fifth assessment report. Herein, the authors distinguish between contextual and outcome vulnerability and define vulnerability in general as "*the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts including sensitivity or susceptibility to harm and lack of capacity to cope and adapt*" (IPCC, 2014, p. 1775). While contextual or starting-point vulnerability is seen as "*a present inability to cope with external pressures or changes, such as changing climate conditions*" (IPCC, 2014, p. 1762), outcome or end-point vulnerability is defined "*as the end point of a sequence of analyses beginning with projections of future emission trends, moving on to the development of climate scenarios, and concluding with biophysical impact studies and the identification of adaptive options*" (IPCC, 2014, p. 1769). Consequently, the concept of contextual vulnerability is closely related to those of social vulnerability and vulnerability within the PAR model, as described above. Outcome vulnerability, on the other hand, emphasizes the biophysical character and may arguably be regarded as the combination of social and biophysical vulnerability.

In summary, it can be stated that the use of the vulnerability concept is highly context-specific and diverse in its approaches of conceptualization and measurement. While these diverse concepts may be seen as confusing and barely comparable, they may also be seen as a sign of wide applicability and a strong and vital academic field (Adger, 2006).

2.2 Social-ecological risk assessment

The previous sections provided an overview on the underlying theory and core concepts that are relevant to develop a guideline for social-ecological risk assessments as applied in this thesis. Recently, scholars intensified the debate around the question, how to characterize risks from a social-ecological perspective. In this regard, Schramm & Lux (2014) state that in social ecology, systemic risks are located at the interface between society and nature and that research addresses societal dealings with risks and their material basis (Schramm and Lux, 2014). In this sense, Völker et al. (2017) observe that current practices in risk identification, assessment and management fall short in addressing critical links between societal and natural processes. They identify key characteristics of risk when viewed from a social-ecological perspective: In contrast to conventional risk assessments, a transdisciplinary approach ensures that key linkages within the provisioning system are identified, the varying modes of societal risk production are acknowledged (e.g. perception) and different knowledge domains are considered (Völker et al., 2017).

What can be carved out from the previous sections on SRN, SES and risk is the following: Since social-ecological research basically focuses on provisioning systems, human actors are always in the centre of attention as managers and consumers/users. Hence, if risks are to be assessed, human actors are the protected good. In other words, it is the specific configuration of the provisioning system at a given point in time that sustains the actors' well-being in the long-term that is threatened by a particular hazard. These hazardous processes that might be of societal or natural origin, affect social-ecological structures and processes in one way or the other which results in a reduced provision of ES and thus impaired well-being. As a result, social-ecological risk assessments always focus on human actors (e.g. households, communities, companies, countries) and their specific provisioning system that is threatened by a particular hazardous process. However, the ongoing debate around social-ecological risks shows that up to now, no consistent guidance on how to perform respective assessments exists. Hence, this section seeks to present a first attempt of an overall guideline on how to assess risks from a social-ecological perspective. The exploratory research phase, presented in section 3 will take up this guideline to identify key parameters of household drought risk in the Cuvelai-Basin.

In a nutshell, Figure 8 provides an overview on the proposed three-step process that starts with (i) focusing on a specific hazard and the affected actors, (ii) constructing the provisioning system around these components to gain a system understanding and (iii) derive relevant control variables for a targeted risk assessment.

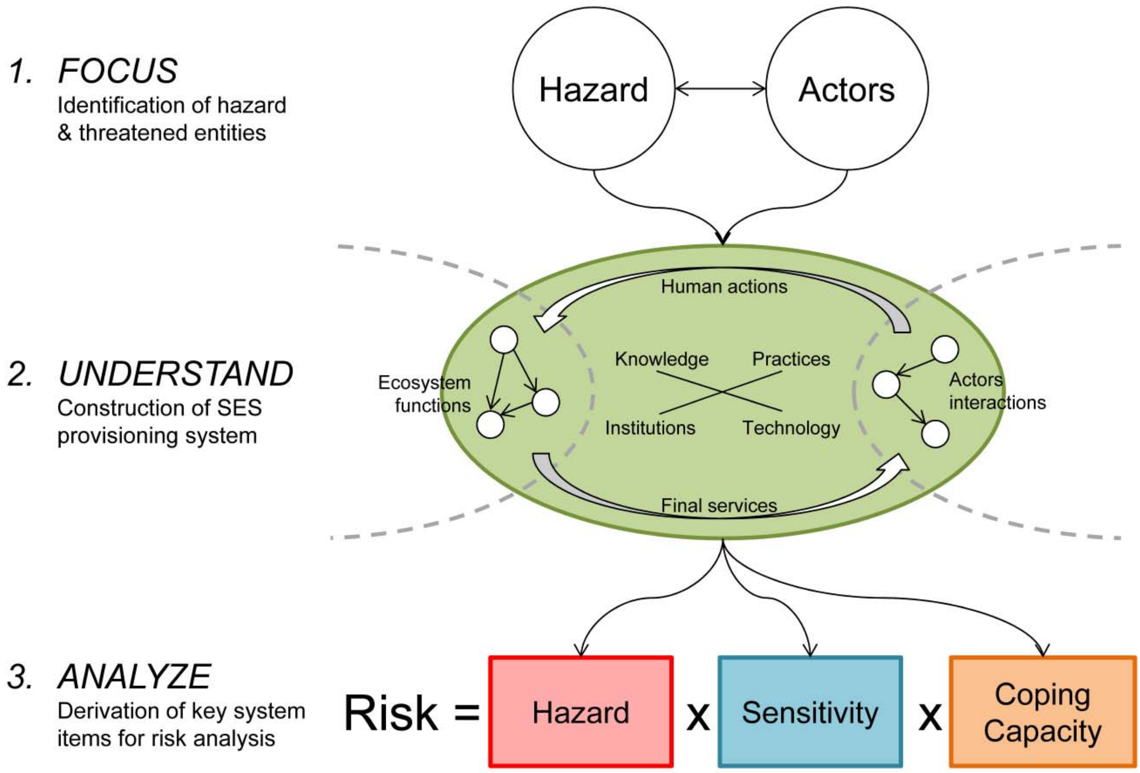

Figure 8: Three step process for a social-ecological risk assessment.
Figure expanded and adapted from Mehring et al., 2017.

The first step seeks to clearly delineate the hazard that should be analysed and the actors that are potentially threatened. This is required, as the vulnerability of actors at least partly depends on specific hazard characteristics. Some authors highlight the necessity of considering multiple hazards that act simultaneously or consecutively and hence create positive feedback effects that might challenge the vulnerability of threatened actors more than a single-hazard situation (Kloos et al., 2015). Though this is valid critique, this thesis pursues a single-hazard focus, arguing that a single-hazard analysis is a necessary pre-requisite for subsequent multi-hazard assessments. In general, the hazard under consideration can take different shapes. In the case of drought for instance, the hazard might have a natural (e.g. rainfall variability) or societal origin (e.g. dam construction, upstream-downstream conflict). Likewise, the actors under consideration might vary, depending on the specific research or practical challenge at hand and might differ from individuals, households, communities up to countries.

In the second step, the hazard and the actors are interrelated to understand their mutual influences. For this purpose, the explanations brought forward in section 2.1 on how to deliberately construct a SES model, conceptually following the steps distinction, association, structuring and limitation is proposed. This technique provides a qualitative system understanding and enables to explain, how a particular hazardous process, either natural or societal, impacts on certain components of a functioning SES. The alteration this hazardous process triggers permeates through the components' links and finally results in reduced human well-being. The social-ecological structures and processes are the key to understand the influence of a hazard within the system. After the provisioning system was qualitatively set up and an understanding was gained about the key processes, the third step finally attempts to populate the risk equation. The aim is, to filter out those system characteristics/processes/items that were found to be essential for the functioning of the system. These are assigned to the conventional risk dimensions of hazard, sensitivity and coping capacity.

The proposed guideline for social-ecological risk assessments contributes to an overall disaster risk management, defined as "*the processes for designing, implementing, and evaluating strategies, policies, and measures to improve the understanding of disaster risk, foster disaster risk reduction and transfer, and promote continuous improvement in disaster preparedness, response and recovery practices*" (Lavell et al., 2012, p. 34). It primarily supports the pre-disaster processes within the disaster management cycle by enhancing the information basis and finding suitable measures for prevention (Taubenböck et al., 2008).

3
Drought risk

A qualitative exploration[5]

3.1 Abstract

Drought is a recurring threat to the inhabitants of the Cuvelai-Basin in northern Namibia and southern Angola as recently during the drought period from 2012 to 2015. Since climate change projections for southern Africa indicate that hydro-meteorological extreme events will become more frequent in the future, an understanding of how drought events impact on the local population is a pre-requisite to develop adaptation strategies.

This study[6] presents the results of a qualitative household survey to understand the impact of drought on local livelihoods and identify key parameters that characterize the hazard and determine a household's vulnerability. Within the survey, 26 semi-structured interviews were conducted to shed light on (i) local water use patterns, (ii) the impact of drought in rural and urban environments and (iii) coping strategies in drought situations.

The results show primary impacts on households' ability to meet water and food requirements due to strong dependence on subsistence agriculture and traditional water supply systems. These lead to second-order effects on physical and mental health, social life and livelihood maintenance. Furthermore, several coping mechanisms could be identified on the individual, community and national level. Based on the results, the Household Drought Risk Index was developed to quantify drought risk in the Cuvelai-Basin in an integrated way.

[5] This section was published as a modified version in the conference book of the "International Conference on Drought: Research and Science-Policy Interfacing" (Luetkemeier and Liehr, 2015).

[6] The term "study" is used in the thesis's main sections to refer to the respective research phase and not to the entire thesis.

3.2 Introduction

Seasonal variation in water availability is a common hydro-meteorological feature of southern Africa (Hoerling et al., 2006). However, when it comes to extraordinary reductions of seasonal and inter-annual water availability, even those societies adapted to semi-arid conditions are being threatened. For instance, Namibia as one of the driest countries in sub-Saharan Africa (The World Bank, 2014) declared more than 460,000 citizens (approx. 22% of total population) as food insecure as a result of the far below-average rainy season 2012/2013 (DDRM, 2013; NSA, 2013). Similar patterns were observed in southern Angola in early 2013 showing significantly below-average harvests due to reduced water availability. For that reason, the Angolan provinces Namibe and Cunene were rated as stressed on the Integrated Food Security Phase Classification (FEWS-NET, 2013). Overall, the hydro-meteorological conditions in southern Africa are expected to become worse during the course of the 21st century. Human induced climate change will alter precipitation conditions in the southwest of the continent with increased severity of dry extremes and lowered mean precipitation during the southern hemispherical winter months (Shongwe et al., 2009). The most recent fifth assessment report of the Intergovernmental Panel on Climate Change hence notes that "*[t]he south-western regions are projected to be at a high risk to severe droughts during the 21st century and beyond*" (Niang et al., 2014, p. 1211).

The transnational Cuvelai-Basin stretches from southern Angola to central-northern Namibia and thus covers both of the above mentioned drought-prone areas. Semi-arid climate conditions with high spatio-temporal rainfall variability, a lack of perennial rivers and high salinity of groundwater resources challenge the inhabitants on both sides of the border. Local livelihoods depend on subsistence agriculture in terms of crop farming and livestock herding. Water availability determines local ecosystem conditions and is thus important to sustain the peoples' livelihoods. However, recent societal developments such as population growth, urbanization and lifestyle changes as well as extensive, largely uncontrolled livestock grazing increase the pressure on land- and water resources (Mendelsohn and Weber, 2011).

Both countries admit the risk of drought for the population and present policy strategies and programmes for drought relief and adaptation. Though it is not the aim of this study to provide a comprehensive policy analysis, the most important documents are mentioned in the following. In the Namibian case, the government updated the national drought policy and strategy in 1997 (Republic of Namibia, 1997). Therein, several shortcomings of prior legislation were addressed like an inadequate drought definition, wrong incentives for farmers and poorly targeted relief measures for the population. In essence, the 1997 update hence restricts relief measures to scientifically defined drought periods that address both food and water assistance. Short (e.g. food and cash for work, school feeding) and long-term programmes (e.g. health, crop farming, livestock) are envisaged to encourage and enable the population to take pro-active action against drought via adapted practices (Republic of Namibia, 1997). Afterwards, the Namibian government passed a bill to establish a range of institutions to carry out disaster risk management more efficiently. Therein, the National Disaster Risk Management Committee and in particular the Namibia Vulnerability Assessment Committee are relevant institutions in the case of drought response (Republic of Namibia, 2012). The Angolan government has likewise policy instruments in place for drought response and adaptation (MINAMB, 2011). The national plan for preparation, contingencies, response and recovery from calamities and natural disasters guides the governmental response in the case of flood and drought events. This short-term relief programme coordinates national and provincial response plans (República de Angola, 2014). On a longer-term perspective, the national strategy for food and nutritional security outlines the pathway to enhance overall living conditions of the population with a particular focus on food security and poverty reduction (República de Angola, 2009). While the overall setup of the drought response measures is well established on paper, actual practice seems to lack behind the objectives. In particular newspaper articles and statements of stakeholders indicate that certain components of legal drought relief measures lack an adequate enforcement (Schlechter, 2016).

Against this background, the exploratory research phase investigates the impact of drought on the population's livelihood in the Cuvelai-Basin to develop and carry out a quantitative assessment of drought risk in subsequent research phases. In this regard, section 3.3 presents the qualitative research approach chosen for this purpose and briefly explains why the complex water use patterns may serve as a suitable entrance point. Section 3.4 briefly presents the structural household characteristics of the study sample, describes the household water management and explores the drought impact and potential responses. Finally, section 3.5 conceptualizes the water and food provisioning system and identifies key elements that determine drought risk in the dimensions hazard, sensitivity and coping capacity. The general structure of the Household Drought Risk Index is derived from this. The conclusions in section 3.6 give an outlook to the subsequent research phases of the thesis.

3.3 Material and methods

For the purpose of understanding the impact of drought and developing a locally adapted, quantitative tool to measure drought risk on the household level, this study builds upon qualitative, socio-empirical insights. In this regard, the following sub-sections will elaborate on (i) the exploratory analytical approach, (ii) the applied qualitative research techniques, (iii) the sampling procedure and the resulting study sites as well as (iv) the data analysis and a suitable composite indicator design for the HDRI.

3.3.1 Analytical approach

In the study setting of the Cuvelai-Basin with an epistemological interest to understand drought risk, the current research phase serves the purpose of exploration. Exploratory research is a typical and recommended component of a social-empirical investigation (Diekmann, 2007; Friedrichs, 1990), especially when it comes to empirical research in cultural settings that are different from the researcher's background (Rafipoor, 1988). With respect to the conceptual empirical research process (German: "forschungslogischer Ablauf") proposed by Friedrichs (1990), the exploration belongs to the "*context of discovery*" and extends/improves the prior knowledge of the researcher (Friedrichs, 1990, p. 51f.). This increases the reliability of the research concept and thus enhances the efficiency of subsequent analytical and interpretative steps. Stebbins (2001) comprehensively illustrates that exploration, as a specific qualitative research technique, can take different shapes depending on the research objective. While the primary intention of an exploratory research is an inductive theory development in the sense of grounded theory, certain bounding concepts are often required to guide the exploration (Stebbins, 2001). As a consequence, the exploration of a research topic can be regarded as a combination of deductive, conceptually guided and inductive, theory development research. Following this assumption, the current exploratory research phase builds upon the theoretical and conceptual foundations presented in section 2.1. It seeks to use the guideline for a social-ecological risk assessment (deductive element) in order to develop an understanding of how hazards impact on the population's livelihoods, why people are sensitive to these events and how they cope with these situations (inductive element).

In practical terms this means that the perspective of SRN, conceptualized as social-ecological (provisioning) systems, may facilitate the analysis of human-nature interactions. This systemic approach requires the identification of societal actors, ecosystem functions and relevant social-ecological structures and processes (practices, knowledge, institutions and technology) to depict the current configuration of the SES provisioning system to ensure the population's well-being. It is assumed that the provisioning system is basically determined by the local water management on the household and community level. Since drought events are spatially and temporally confined periods of water scarcity (see section 5.2 for a more detailed definition), the way people act upon local water and ecosystem resources (management) as well as how benefits they obtain from their natural environment are utilized (ecosystem services) is key to understand the causal relationships within the SES. Hence, this exploratory research phase particularly focuses on the assessment of water use patterns to work out the pathways, drought events may impact on the people via impaired ecosystem services. In this context, households as a multi-generational familial entity are regarded as the key actors to be considered. They constitute important socio-economic subjects in the cultural setting of the Cuvelai-Basin in both Namibia and Angola (Mendelsohn and Weber, 2011).

3.3.2 Qualitative research techniques

The exploration builds upon two primary techniques, namely expert consultations/key informant interviews and semi-structured individual interviews. These qualitative methods are often applied for studies in the Global South (Keshavarz and Karami, 2014; Lei et al., 2016; Mutsvangwa-Sammie et al., 2017), sometimes combined with group interview techniques such as focus groups (Belle et al., 2017; Tran et al., 2010) or are part of longer-term ethnographic assessments (Schnegg and Bollig, 2016).

Prior to the household interviews, experts/key informants were consulted from several institutions in northern Namibia, including the three Basin Support Offices (BSO) Olushandja, Niipele, and Iishana, the Ongwediva Rural Development Center, the Red Cross Society Eenhana and the Community based Rangeland and Livestock Management Project (CBRLM). While the BSOs are official water management agencies under the umbrella of the Namibian Ministry for Agriculture, Water and Forestry (MAWF) (Liehr et al., 2016), the other institutions are stakeholders in rural development activities, drought relief programs and agricultural extension services. The primary objectives of the consultations were to gain an overall understanding of drought impact, particularly from an institutional perspective and to find suitable study sites and hence receive better access to the communities and individual households. Furthermore, the institutions supported the research permit applications to the regional administrations and helped to expand the network of potential interview partners.

The individual household interviews had a more targeted focus on local living conditions in rural and urban settings. Based on the theoretical considerations on drought risk within the SES (section 2.2), the objective was to gain an in-depth understanding of the drought impact on the household level. Against the background of social-ecological structures and processes, the interview guideline consisted of three components (Annex 1). First, socio-structural parameters were assessed in order to gain a quick overview on the household conditions (e.g. member structure, agricultural and economic activities). This facilitated a more targeted formulation of subsequent questions. Second, water consumption patterns were assessed for both the rainy and the dry season, following the assumption that complex water use patterns exist (Elliott et al., 2017; Fiedler, 2013; Nauges and Whittington, 2008). Third, the risk dimensions of hazard, sensitivity and coping capacity were assessed. Herein, open questions were formulated to encourage the respondents to report about their perceptions and perspectives on drought issues. The specific questions and potential answer categories evolved over time from interview to interview. If new aspects appeared, they were integrated into the questionnaire and, if applicable, verified in subsequent interviews. Overall, the three-stage questionnaire served to gain a system understanding in terms of relevant social-ecological structures and processes and to understand the drought specific challenges people are confronted with.

Formally, before an interview started, each respondent was guaranteed that any information obtained from the interview will be anonymized and only used for research purposes. Each interview was conducted with the head of a household or if he or she was not available, his or her life partner was interviewed instead. Though the official administrative language in Namibia is English, most people rather speak varieties of Oshiwambo, the native language in the Cuvelai-Basin. Therefore, the individual interviews were conducted with the assistance of an English and Oshiwambo speaking interpreter. This person was trained in a half-day session on the semi-structured questionnaire to ensure that interviewer and interpreter share the same understanding of the guiding questions. In accordance with the respondents, the geographical coordinates of the interview location were noted, the conversations were audio-recorded and subsequently transcribed. For confirmation and quality-control of the interpreter's in-time translations, another native-speaker cross-checked the audio files and the produced transcripts. Misinterpretations and omissions of the interpreter could hence be identified and corrected.

3.3.3 Sampling procedure and study sites

The qualitative research phase was intended to depict the living conditions in the entire Cuvelai-Basin on both sides of the border. Due to project limitations (in particular time and funding) and delays in the application process for a working visa in Angola, interviews could only be conducted in Namibia. This is a drawback as the socio-economic setting in Angola differs from the Namibian case, in part due to the historic development pathways (section 1.3). This disadvantage was partly compensated as expert consultations in Namibia also dealt with the Angolan conditions, as well. In addition, the selection of study sites on the Namibian side of the border was intended to depict a social-ecological gradient that was assumed to be representative for the Angolan population, as well. In this regard, three broad locations were identified prior to the research stay, covering urban and rural areas as well as differences in mean annual rainfall and vegetation conditions. On the ground, the intended study sites were mirrored against local constraints of e.g. the timing of the research permit's issuance and physical accessibility. Furthermore, after each interview, preferably contrasting cases were identified in cooperation with the supporting institutions, the BSO officers and the constituency councillors. Hence, the chosen communities were a compromise between the social-ecological gradient considerations, local constraints and theoretical sampling techniques (Kruse, 2010; Kuckartz et al., 2008).

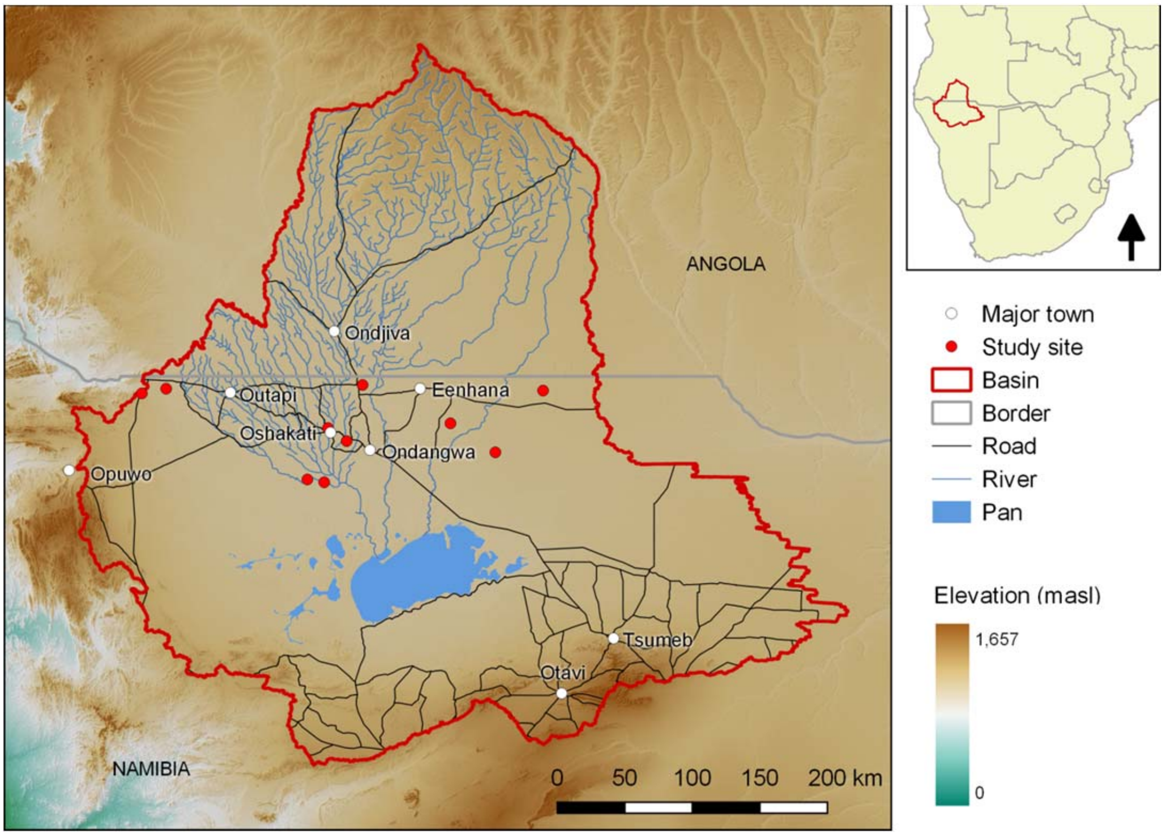

Figure 9: Study sites of the exploratory research phase in northern Namibia.

Finally, a total of 10 locations in all of the 4 central-northern regions have been chosen. All in all, 26 interviews were conducted at the locations depicted in Figure 9. Within the communities, either the headman or the headwomen was interviewed, or specific households that were in contact with the cooperating organizations.

3.3.4 Data analysis and composite indicator design

The primary data for further analysis were the produced and quality controlled transcripts of the 26 household interviews in combination with the field notes the interviewer took during the conversation on e.g. dialog atmosphere, abnormalities and homestead characteristics. As the primary target of the exploratory research phase is the development of a quantitative tool to measure drought risk on the household level rather than an in-depth qualitative analysis, case-specific interpretative inventories (Kruse, 2010) were regarded as a feasible solution. Hence, every interview was analysed on a case-specific basis, meaning that an interpretative inventory was created for each interview with respect to the dimensions of risk and water use patterns as the leading questions. This way, condensed information could be obtained on the key aspects of drought risk and which parameters are essential on the household level.

This condensed information on water use patterns, drought hazard, household sensitivity and coping capacities was used to build a composite indicator. These are a common tool in the scientific literature to quantify vulnerability (Babel et al., 2011; Malcomb et al., 2014; Pandey et al., 2010; Shahid and Behrawan, 2008; Shiau and Hsiao, 2012; Sullivan, 2002, 2011). One of the most relevant indicators with respect to the impact of water scarcity is the Water Poverty Index (WPI), developed by Caroline Sullivan at the Centre for Ecology and Hydrology (Sullivan, 2002). Sullivan and colleagues derive five key components from participatory workshops that cover the impact of water scarcity on the poor (Sullivan et al., 2003). Each of these key components (resources, access, capacity, use and environment) entails a set of sub-components to describe the site-specific conditions of the physical and social environment relevant to the water scarcity situation. The WPI can contribute to set spatially referenced priorities of water management and planning and serves as a tool to monitor progress (Sullivan et al., 2003). Criticism is often being levelled to composite indicators due to their low level of empirical evidence (Malcomb et al., 2014; Plummer et al., 2012). In contrast to most studies however, the composite indicator developed in this study builds upon qualitative empirical evidence from the research area itself and is thus more legitimate than purely literature based indices.

From the considerations above Gain et al. (2012) is followed in noting that the decision on an appropriate model of vulnerability has to be taken after the problem was defined precisely and the spatial and temporal scales were set (Gain et al., 2012). Thus, it would be misleading to decide upon an understanding of vulnerability and an associated way of calculating or describing it, without having a more thorough understanding of people's relation to water. Knowledge on the local social-ecological conditions and people's personal perception on the hazard of drought is a prerequisite for the analysis of vulnerability and is thus the task of the exploratory research phase.

3.4 Results

The results of the exploratory research phase are presented in the following sub-sections. First, overall household parameters are shown to give an impression of the representativeness of the sample. Second, the local water management strategies are depicted in order to describe the general functioning of the SES provisioning system. Third, the way droughts impact on the ecosystem and subsequently on the society is delineated. All interview transcripts are available in the Digital Annex 2.

3.4.1 Household parameters

This sub-section will provide a brief description of key structural household parameters. All parameters of the 26 respondents can be obtained from the Digital Annex 1. The households interviewed are mainly headed by men, though almost half of the respondents were female as the heads were unavailable. The number of household members differs, with an average of nine persons, three children under the age of fourteen and three persons who do not stay at the house for the whole year. In terms of education, about one third of the household heads does not have a formal education, while about two thirds of the households accommodate a family member who has an education level of grade ten or higher. For more than half of all households, pension money is the main source of income and almost three out of four of the respondents use firewood as their main source of energy for cooking. Taking a look at the homestead itself, about half of them use different kinds of bricks for at least one room (hut), while a homestead comprises around eight rooms on average. More than half of the households do not have access to a toilet at all and most of them practice grain farming with almost half of the respondents also performing orcharding and/or horticulture. On average, a household owns livestock in the amount of 35 animals (cattle, donkeys, goats, sheep, pig and chicken).

From an environmental point of view, the interview locations cover a wide range of landscapes, as it was intended. The rainfall gradient spans from 360mm to 605mm of average annual rainfall. Furthermore, rural environments in the dense woodlands of the east are covered as well as areas without significant vegetation cover in the south of the Oshana region. With respect to the availability of surface water, most respondents in the central research area are located in close vicinity to the Iishana river system. In the east and the west, people do not have access to surface water and rely on groundwater of sufficient quality to a larger extend.

3.4.2 Local water management

Local water management in developing countries is far more complex compared to Western European patterns (Elliott et al., 2017; Nauges and Whittington, 2008). Following the concept of blue and green water (Falkenmark and Rockström, 2006; Freire-González et al., 2017), this has two main reasons: First, people utilize blue water not just from one single source, but rather from a number of different water sources in a complex way depending on e.g. water quantity and quality aspects. Second, blue water is not the only water source that is being used, especially by rural smallholders. The green water flow is at least as important as the blue water flow, since subsistence farmers highly depend on their own agricultural production for household nutrition. This link between green water flow in the local environment and nutrition is largely decoupled in non-subsistence systems. To capture the complexity of household water management, the following paragraphs will present the results of the interviews by distinguishing between both water flows and their respective importance for livelihood security.

The conventional consideration of water demand only covers the consumption of blue water. In this regard, the interviews reveal that water using activities on the household level can be subdivided into three categories:

- *Domestic:* Households use blue water for the activities of drinking, cooking, personal hygiene, cleaning, dish washing, laundry and dust prevention,
- *agricultural:* Although traditional grain farming is rain-fed, some households practice small-scale horticulture and orcharding that require irrigation. Furthermore, livestock is an important agricultural water consumer on the household level and
- *economic:* To a lesser extent, households are involved in self-employment and thus utilize water for cooking, baking, brewing products for sale as well as brick-making (the latter is either for domestic or economic purposes).

The total amount of water used for each of the activities is difficult to estimate. Although, the question of how much water is being used for the activities was posed during the majority of the interviews, the answers are diffuse and vary greatly. Therefore, no reliable numbers of water volumes can be assigned to the activities. Nevertheless, benchmark values taken from the literature give a good indication of blue water consumption. In this regard, the Namibian Water Cooperation (NamWater) takes the value of 25lpd (litres per person per day) in urban and 15lpd in rural areas as benchmarks for infrastructure planning purposes (DWA, 1992). The World Health Organization (WHO) regards 20lpd as the quantity to "*realise minimum essential levels of health and hygiene*" (Reed and Reed, 2013, p. 9.2).

Considering the origin of the water, the respondents confirm that people use a wide variety of water sources in combination. Traditional water sources such as shallow wells (omufima) that access water of discontinuous perched aquifer (max. 10m depth) and deeper wells (ondungu) that make use of groundwater at depth of at least 30m (Niemann, 2000; Wanke et al., 2014) are frequently being used, partly in combination with improved sources and/or tap water. The latter is available in northern Namibia as a result of improvements of the water infrastructure that started in the 1950s and 1960s. Since this time, a water transfer scheme that extracts water from the Kunene River and distributes it in northern Namibia was expanded in a stepwise fashion and today supplies a large share of the population on the Namibian side of the border (du Plessis et al., 2005; Niemann, 2000). Nevertheless, only a small number of respondents solely relies on the tap water system, primarily urban inhabitants in Oshakati. Most respondents indicate to use both, unimproved water sources and tap water in a combined way. This practice can be dedicated to two different patterns of utilization that are partly interwoven. On the one hand, respondents confirm that water is being used quality specific, meaning that i.e. high quality tap water is only used for high quality activities such as drinking, cooking and personal hygiene. This practice is often carried out without any changes throughout the year. On the other hand, some respondents indicate that tap water is only used when unimproved water sources run short.

"As long as the water quality of the well is good, we use it for all the activities we need water for." (OS7)

In other words, as long as traditional unimproved water sources offer sufficient quantity and quality water, people prefer to use them for some or even all of their activities. As soon as quantity or quality deteriorates people switch to the public tap water system. One of the main reasons for both kinds of utilization patterns is the price of water. People seek to save money in order to have better opportunities of purchasing water and food in emergency situations and cover essential expenditures like school fees and medical treatments. With regard to the pricing of water, a critical attitude persists among the (rural) population (du Plessis et al., 2005). This is partly rooted in the contradictory traditional perception of water being a free good and the expansion of the tap water system and the introduction of water point committees. Though tap water is regarded as a positive asset, the societal changes that occurred within the communities as a result of water pricing and the rather top-down construction of water point committees as institutions that create a hitherto non-existent societal entity remains a challenge (Polak, 2014; Werner, 2007). Beside the price however, other reasons have been mentioned not to solely rely on tap water. First of all, physical fitness seems to be a determinant, since older and/or ill people are not able to walk longer distances and carry heavy water-filled buckets. Second, opening-hours of water points force people to make a trade-off between investing time to collect water from the public tap or work in the farmland. Furthermore, people keep on utilizing unimproved water sources because the tap water system sometimes fails for a few days or even a longer period of time. In these cases, people are forced to switch to other sources of water. These results show that despite modern water infrastructure, like a public water tap, people tend to handle tap water as an additional source that complements traditional sources.

Besides blue water that is being used by households for a range of activities, the green water flow, meaning water that is available as soil moisture for plant growth, is highly relevant for people's nourishment. Rural smallholders cultivate pearl millet (locally known as Mahangu) as staple food mainly for own household consumption. According to the respondents, the amount of harvestable grain depends on a range of factors: (i) amount of rain, (ii) timing of cultivation, (iii) health/strength of farmer to till the field, (iv) money to pay someone for ploughing and (v) the availability of fertilizers such as dung (manure). If all the requirements come true, the grain harvest can sustain the household nourishment for more than one or even several years. If this is not the case, food has to be purchased at local markets or acquired from neighbours and relatives.

"If there was a good rain – it still depends on the man's work and the fertility of your farmland – yes, if we are strong enough, then we can get more or less one and a half grain baskets. Even though we have people in the house, it can last to the next harvest." (OS8)

Not only the rural population depends on locally produced food. Although an urban inhabitant's livelihood is different from a farmer's one, people living in towns have close relations to relatives in rural areas. These relatives provide a certain share of food to the urban people. All in all, even the urban population is affected by drought in terms of food, since they need to spend a higher amount of money for the purchase of groceries.

In essence, water utilization is characterized by a complex seasonal utilization of blue water and an important use of green water for plant growth and thus human and animal nourishment.

3.4.3 Drought impact and response

The previous sub-section outlined the way people utilize blue and green water in their every-day life. Water scarcity hence impacts on the households via water and food shortages. Thus, their livelihood, defined as "*the capabilities, assets […] and activities* *required for a means of living*" (DFID, 1999, p. 1), is threatened. The challenged satisfaction of people's basic needs brings about problems that can be best described as second order effects. Due to the lack of drinking water and food, the inhabitants of the research area clearly state health problems such as malnutrition and general weakness. Combined with a higher workload e.g. by longer walking distances, physical fitness is challenged. The entire situation creates continuous mental stress since especially older persons have serious concerns and ruminate. All these factors contribute to social tensions both, within a family/household and within the larger community among neighbours.

"We also get affected in our mind-sets. The moment our cattle dies or the Mahangu does not grow, we ruminate about how to survive until next year, if the rain does not come."
(OG7)

In the end, the lack of water and food impairs some households in the practice of their profession for income generation. Thus, the situation creates a budgetary bottleneck, since income is being reduced while expenditures for food, water, medical treatments, etc. increase.

Now, what do people think are the main factors that make a household more or less affected by water scarcity/drought? The analysis reveals that people perceive those households as being less affected that show the following attributes:

- *Harvest:* Those households that are able to grow a large amount of food under normal conditions are able to bridge shortage situations.
- *Income:* Opportunities to generate income via paid work at the government or big companies lift households into a more favourable position.
- *Manpower:* The number of persons that are able to work is highly relevant to manage agricultural and livestock activities as well as to generate cash income.
- *Physical fitness:* Those people who do not suffer from diseases and are not too old are better off than others.

Beside the factors mentioned above, some respondents indicate their perception that some people simply refrain from subsistence work. This behaviour cannot be equated with laziness due to their willingness to work for payment in kind or cash. In addition to that, alcohol was mentioned several times as being both, an important component of expenditure and the reason for people's affectedness.

Above, the sensitivity of households by drought was carved out. In the following lines, the focus is on the question how people deal with scarcity situations. The coping mechanisms can be attributed to different scales from the individual via the community to the regional or national level. On the individual household level, people are busy with income generating activities. This can assume very different shapes starting from casual work, selling of livestock, horticultural and/or handicraft products to the support from relatives. These strategies are being applied in the short-term as an immediate emergency response. On the longer term, households apply adaptation measures such as improved farming practices (i.e. intercropping, application of machinery, livestock specialization, application of fertilizers) or water management activities (i.e. diversification of sources, quality-specific utilization, minimization of wasted water). On the community level, neighbourly support and help among family members are common. This often takes the shape of food and water donations among the extended family network. However, the respondents indicate that this practice can only be followed a small number of times. If requests are addressed to a neighbour more often, the donor asks for payment, either in kind or cash. Taking a look at the communal or regional level, a mechanism was in place that can be referred to as the king's relief programme. In former times, every villager had the duty to deliver a certain amount of grain harvest to the king's house, where the food was stored. Additionally, every household had to provide a worker to the king's house, who worked in his large farming area. These two sources of food have been stored and served as a backup in emergency situations. In the case of drought, this food was distributed either to the ones who reported themselves as being suffering, or to the whole village community. Today this system does not exist anymore, but it was replaced by other mechanisms. Nowadays, the government purchases grain surpluses from local farmers and stores it as a backup, similar to the king in former times. This amount of food is being distributed to the population as part of the governmental drought relief programme. Additionally, people who cannot survive with their own production are able to report themselves to the village headman, who forwards their request to the constituency councillor. This councillor has a specific quota of the governmental drought relief that he/she is able to distribute to emergency cases upon request.

3.5 Discussion

Based on the empirical findings, the following sub-sections will condense the results to (i) briefly depict the general functioning of the SES provisioning system and subsequently (ii) define the risk dimensions of hazard, sensitivity and coping capacity as part of the Household Drought Risk Index.

3.5.1 Water and food provisioning system

With reference to the proposed guideline for a social-ecological risk assessment presented in section 2.1 the above mentioned results serve the purpose of deriving an understanding of the SES provisioning system. For reasons of clarity and comprehensibility, the system relevant to drought risk can be defined as a water and food provisioning system. Figure 10 adopts the generic SES system from Figure 7 to the conditions in the Cuvelai-Basin. It spells out who the primary actors are (right hand-side), which ecosystem functions are managed (left hand-side) and which social-ecological structures and processes regulate the system functioning. The following paragraphs will present how the system works under normal operation and which characteristics change when it switches to stress mode in times of water scarcity/drought.

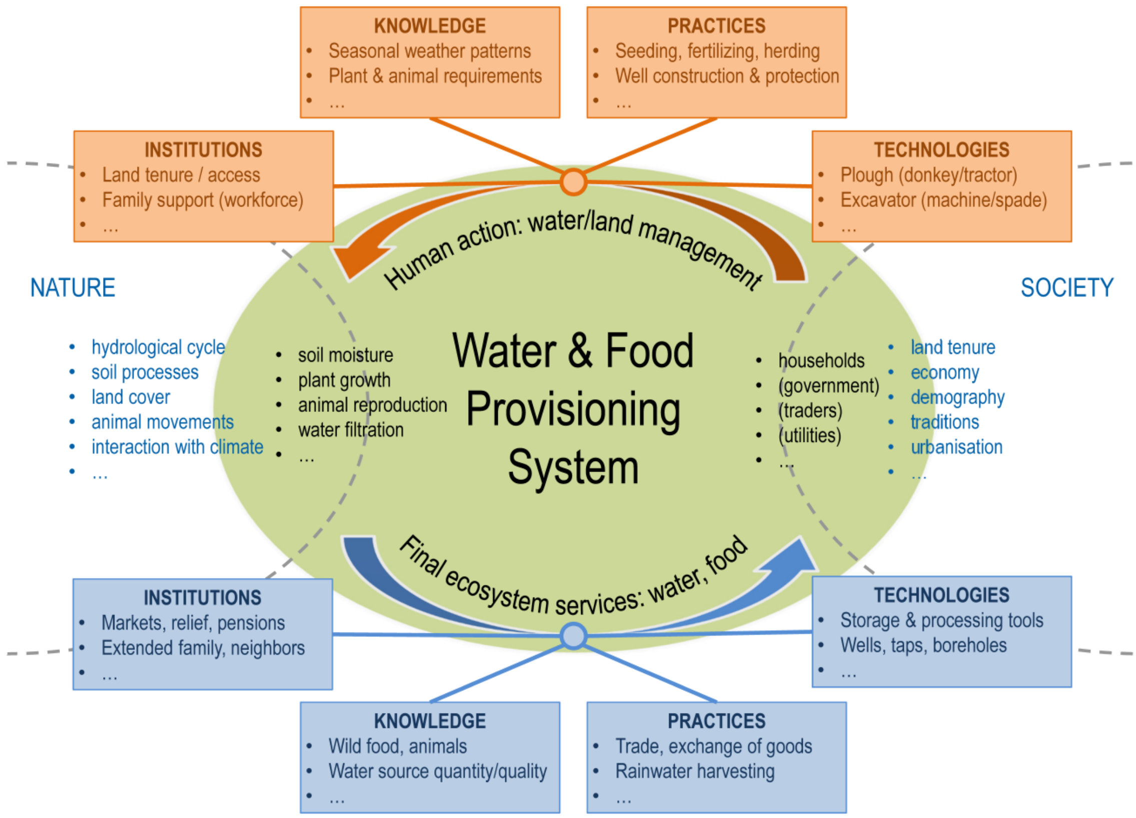

Figure 10: The social-ecological system conceptualized as water and food provisioning system.
Depicted are exemplary relevant system components, in particular items that characterize the social-ecological structures and processes of the two relations of human action and final ES utilization (adapted from Liehr et al., 2017; Mehring et al., 2017).

In a nutshell, the primary actors are the households that are both managers and users of their natural environment. Further actors come into play like governmental agencies and supra-regional traders (supermarkets) as well as utilities (water supply), in particular when the system switches from normal operation (mainly self-supply) to stress mode (mainly external-supply). From a system's perspective, the households are considered as the primary group of actors who are embedded into their country-specific societal settings of politics, economy and traditions. This group performs water and land management activities that alter specific ecosystem functions. These functions (or intermediate ecosystem services), such as soil moisture, plant growth, animal reproduction and water filtration are hence influenced, mainly with the intention to enhance the availability of final ecosystem services. These latter services are basically blue water for domestic consumption and raw food items. The latter have to be processed like in the case of millet grains that serve as the basis for several staple food meals. Both blue water and the food items generate a benefit for the actors and thus enhance or maintain people's well-being. Essentially, ecosystem services support well-being in the field of basic material for good life while this has side effects on adjoining well-being dimensions such as health and good social relations.

This briefly depicted cyclic functioning of the water and food provisioning system is regulated by the hybrid social-ecological structures and processes. The land and water management as well as the utilization of final ecosystem services in normal operating mode is performed by the actors building upon local and native knowledge of seasonal environmental patterns. For instance, experience in interpreting weather phenomena for planting date decisions or vegetation conditions for finding temporal locations of shallow water wells. Therein, hybrid practices are embedded such as seeding, planting, fertilizing, irrigating, harvesting (green water management) as well as water harvesting, well protection and watering of animals (blue water management). Accompanying technologies are required that range from simple ploughing (e.g. hoe or oxen powered) or water harvesting techniques (e.g. corrugated iron for rainwater collection) to advanced, partly motorized tools (e.g. tractor, water pump, improved well, borehole). The institutions in place are of various forms. While formal institutions such as land tenure or at least access to land is clearly defined and regulated by traditional authorities, informal rules are essential that primarily concern the social network households maintain. These (kinship and neighbourly support) serve as important backup structures when the system enters into stress mode, temporarily. In these cases the above-mentioned secondary actors come into play to provide coping opportunities for the population. The normal mode of operation is furthermore characterized by a market-based exchange/trade of food items. As the actors are only rarely able to sustain their household nutritional demand with subsistence activities, the local market system gains importance under stress conditions and is essential for complementing own resources.

In essence, the water and food provisioning system in normal operating mode is mainly characterized by self-supply in blue and green water related ecosystem services. Under stress situations such as a water scarcity period, the focus shifts from self-supply to external supply using both local informal institutional coping opportunities as well as larger scale backup infrastructures and institutions.

3.5.2 Household drought risk

From outlining the functioning of the SES provisioning system above, key characteristics can be derived that are relevant to keep the system functioning under stress conditions. These characteristics are conflated according to the three risk dimensions hazard, sensitivity and coping capacities. They form the basis for the composite indicator proposed here, the Household Drought Risk Index as indicated in Figure 11. The HDRI is not supposed to quantify risk in absolute terms, but should rather be a relational measure to compare households to one another and provide the basis for long-term monitoring of key environmental and socio-economic variables over time. For reasons of clarity, the aggregation levels indicated in Figure 11 are referred to as dimensions (hazard, sensitivity and coping capacity) and indicators (from drought frequency on the left hand-side to physical capital on the right hand-side). Each of the indicators is supposed to be populated with appropriate variables that would formally be depicted below the indicator level. The selection of suitable variables is however, always a compromise between suitability and availability of data. For instance, in a data scarce environment such as southern Africa, a pragmatic selection of variables is inevitable. The concrete selection of variables is beyond the scope of the exploratory research phase but will be explained step-wise in the subsequent sections 5 to 7.

From the elaboration above it turns out that the hazard of drought in the Cuvelai-Basin is primarily regarded as a natural phenomenon of spatial and temporal rainfall variability. The origin of this hazard is hence beyond the system's boundaries, as societal activities were not found to contribute to drought hazard significantly in the current study setting. The reduction of available rainfall impacts on local ecosystem functions and results in reduced quantity and quality of blue and green water. Important parameters in this regard are the frequency of drought occurrence as well as its temporal duration and severity. They form the underlying indicators to be assessed in order to depict the drought hazard in spatial terms as frequently conducted in similar, hazard-focused assessments (e.g. Halwatura et al., 2015; Spinoni et al., 2014). The impaired ecosystem functions and the lowered provision of ecosystem services to society directly impact on the households. The entry point for this, the sensitivity of the households is primarily located within their water and food consumption patterns. Due to the subsistence-based livelihoods of the population, reduced blue and green water affect the households to provide sufficient quantities and qualities of drinking water (for domestic purposes in general) and food items that are either grown on the own field, collected individually from the environment or purchase from local markets. The sensitivity dimension assumes that larger households in the sense of more household members are more sensitive as they have to acquire more quantities of food. Furthermore, the degree of dependence on unreliable water and food sources is a critical control variable. Households that primarily depend on traditional source types that quickly respond to drought conditions are more sensitive.

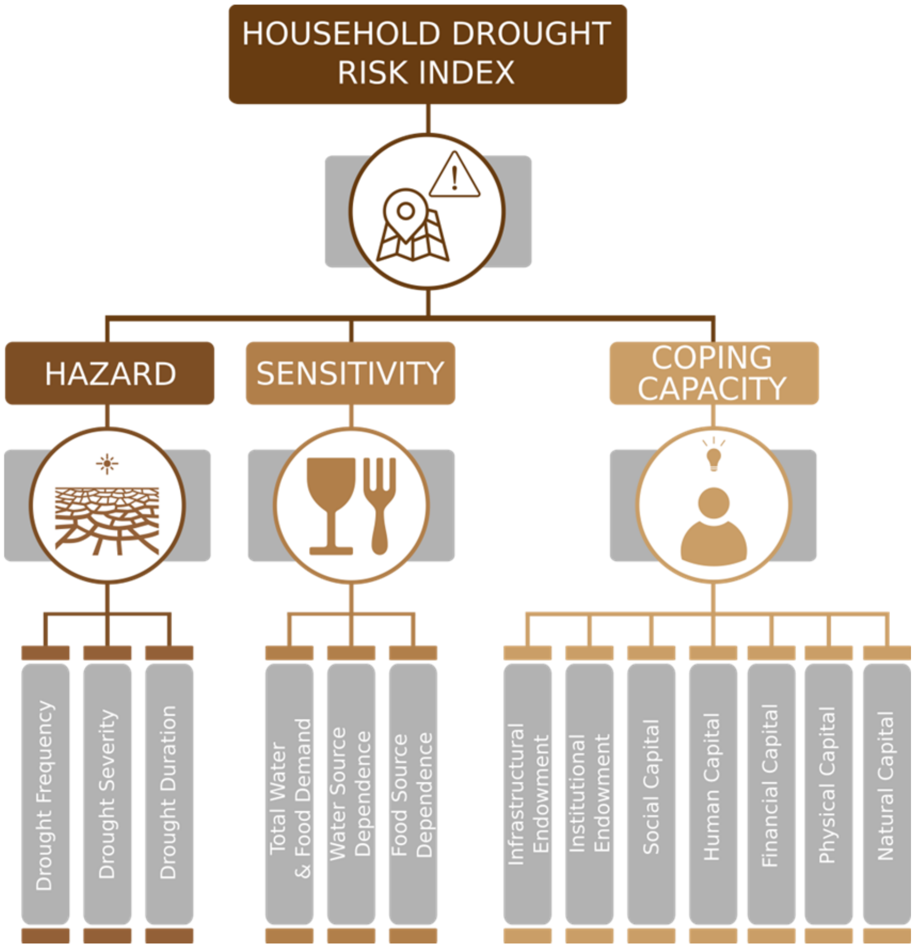

Figure 11: Conceptualization of the Household Drought Risk Index.

The households apply a wide range of strategies that stem from the individual via the community level up to the national sphere. Despite the diversity of activities, a common ground can be identified which can be generally described as a partial shift from a self-supply dominated system to an external supply system. In other words, people fall back on larger scale coping infrastructures of water and food supply. These infrastructures are not readily available for everyone since access is being regulated (e.g. via monetary mechanisms). Furthermore, in kind support provided by neighbours and/or relatives as an extended family network (Bahta et al., 2016; Chaudhury et al., 2017) is a common practice, but it seems as if this strategy cannot be pursued for a longer period of time. This is mainly due to restrictions of the donors' capacities, because they find themselves in a similar situation of shortage. On the larger societal levels, further coping mechanisms are in place like the governmental distribution of food aid and water purification tablets (e.g. DDRM, 2013). To capture these aspects, the rather internal coping capacities on the household level build upon a diverse set of aspects. In order to guarantee a holistic description of a household's capacity to cope with drought, the Sustainable Livelihoods Approach, developed by the Department for International Development is followed (DFID, 1999) that builds upon Amrita Sen's insights into empowerment and deprivation (Sen, 1981). Herein, the five types of capital (human, social, financial, natural and physical) are considered as guidance for selecting appropriate variables as conducted in similar studies (e.g. Khayyati and Aazami, 2016; van Rijn et al., 2012). The rather external coping capacities primarily concern the opportunities people have available in a certain region. If no adequate infrastructure or effective institutions are in place, even well-established capitals on the household level might not be sufficient for coping. Hence, characteristics of the region a household is located in, need to be taken into account, especially the infrastructural (e.g. mobility, water, markets, electricity networks) and institutional endowment (e.g. administrative bodies, health and education facilities) are regarded as suitable categories that have to be populated with appropriate variables. This external framing of coping capacity is often the way larger scale vulnerability assessments select their indicators from secondary statistics (Carrão et al., 2016)

3.6 Conclusion

This study explores the impact of drought on the inhabitants of the Cuvelai-Basin on a qualitative basis. Building upon the guideline for social-ecological risk assessments, a comprehensive understanding of the water and food provisioning system could be gained. The analysis of the system, in particular its operation under stress conditions, revealed specific characteristics that determine drought risk among households. While the hazard of drought is primarily driven by natural rainfall variability that results in varying exposures in the basin, local water and food consumption patterns shape the households sensitivities. Their coping capacities, conceptually framed as different kinds of capitals and the spatial endowment with infrastructure and institutions, are essential to maintain their well-being during water scarce periods. These overall findings of how drought impacts on the society are in line with other studies, though most of them concentrate on the food systems that are impaired by drought events (von Uexkull, 2014).

While the developed composite indicator is outlined in its basic structure above, the following research phases will take up this structure and develop suitable variables to populate the individual indicators against the background of data availability in the study area. In this regard, the following two sections 4 and 5 focus on the drought hazard and seek to obtain, process and condense suitable environmental data. The sections 6 and 7 rather focus on the socio-economic variables. Therein, the development, conduction and analysis of a structured household survey are presented to obtain relevant variables for the sensitivity and coping capacity dimensions. Finally, section 8 will reflect upon the overall research process and put the findings into the scientific contexts.

4

Rainfall product uncertainty

Modelling household nutrition from yield data[7]

4.1 Abstract

Good quality data on environmental parameters such as precipitation are a prerequisite for applications like short-term weather forecasts, medium-term humanitarian assistance and long-term climate modelling. In sub-Saharan Africa however, the terrestrial climate station networks are frequently insufficient as in the Cuvelai-Basin in Namibia and Angola. This study analyses six rainfall products (ARC2.0, CHIRPS2.0, CRU-TS3.23, GPCCv7, PERSIANN-CDR, TAMSAT) to assess the uncertainty among their precipitation estimates. This is particularly being done with respect to their performance in a crop model (APSIM) to obtain nutritional scores of a household's requirements for dietary energy and further macronutrients. All products were calibrated to an observed time series using Quantile Mapping. The crop model output was compared against official yield data. The results show that the products (i) well reproduce the basin's spatial patterns and (ii) temporally agree to station records (r = 0.84). However, differences exist in absolute annual rainfall, rainfall intensities, dry spell duration, rainy day counts and the rainy season onset. Though, calibration aligns key characteristics, the remaining differences lead to varying crop model results. While the model well reproduces official yield data using the observed rainfall time series (r = 0.52), the products' results are heterogeneous (e.g. CHIRPS: r = 0.18). Overall, 97% of a household's dietary energy demand is met. The study emphasizes the importance of considering the differences among multiple rainfall products when ground measurements are scarce.

[7] This section was published as a modified version in the MDPI Journal Water (Luetkemeier et al., 2018)

4.2 Introduction

Precipitation, as the immediate source of water, is the most critical input variable of the water balance. For that reason, it is used in a wide array of models estimating hydrological variables ranging from runoff and discharge through drought intensity down to impacts of climate change. An especially sensitive area of modelling is the estimation of agricultural yields and associated nutritional conditions, as decisions relating to food aid depend on these (Brown and Brickley, 2012). Due to the importance of precipitation in modelling, any inaccuracies in the input data will have a strong impact on estimated results and thus can directly compromise management decisions (McMillan et al., 2011). Errors in the spatial extrapolation of rainfall are often introduced because long-term time series from terrestrial rain gauge stations, especially in poorly equipped regions such as sub-Saharan Africa, are rarely available (WMO, 2015). Rainfall estimates derived from satellite-borne sensors or terrestrial radar stations therefore provide a promising alternative in supplying near real-time precipitation data for large areas and long time series at fine spatial and temporal resolutions (Liu, 2015; Yuter, 2015). Nevertheless, the rainfall products (RPs) available are constructed with different sensor types and processing algorithms, resulting in uncertainties that have to be accounted for, since they impact on subsequent application stages (AghaKouchak et al., 2012). In recent years, a number of studies have evaluated a range of rainfall products, in particular their application in hydrological (Hughes, 2006; Moazami et al., 2014; Pessacg et al., 2015; Skinner et al., 2015) and agricultural models (Ramarohetra et al., 2013; Roca et al., 2010; Thornton et al., 1997; Yuan et al., 2016). The studies confirm significant discrepancies in model output if uncalibrated rainfall products are used (Ramarohetra et al., 2013).

This becomes particularly relevant, if the yield estimations of agricultural models are used to support decision-making in critical tasks such as emergency responses to humanitarian crises. Agricultural models can be used to estimate and monitor the nutritional situation and food security conditions in a certain area as partly build upon by the Famine Early Warning System Network (Brown and Brickley, 2012). Information on local food security conditions and the populations' ability to meet their nutritional demand is particularly vital for aid organisations, governments and local agencies to identify people in need and act effectively, both in the short-term emergency situations and in the context of long-term adaptation strategies.

The conditions in subsistence food systems can be described well via a range of nutritional status indicators (Herforth and Ballard, 2016) due to the direct link between agricultural yields and household nutrition. In sub-Saharan Africa, rain-fed grain farming and livestock herding, known as mixed crop-livestock systems, remain the dominant livelihood strategy (Collier and Dercon, 2014; Diao et al., 2010; Shiferaw et al., 2014;

Thornton and Herrero, 2015). This is true for the majority of the population that still lives in rural settings (FAOSTAT, 2016). Though, urbanisation processes and changing lifestyles are apparent, they largely depend on local hydro-climatic conditions to sustain their livelihood (Cooper et al., 2008). Despite evidence of progress towards the achievement of the Millennium Development Goals (UN, 2015), the population is still challenged by high levels of poverty, non-inclusive economic growth and low access to drinking water and sanitation infrastructures (UNECA et al., 2015). Recurring threats such as droughts and famines impact on the vulnerable population and result in a precarious situation of poverty persistence, civil conflicts, and food and water insecurity (Gautam, 2006; Shiferaw et al., 2014; von Uexkull, 2014).

Against the background of the exploratory research phase (section 3) and the envisaged drought hazard characterization (section 5), this section sheds light on the uncertainty in remote sensing data products. It exemplarily conducts this extended uncertainty analysis with respect to precipitation data in preparation of the drought indicator analysis and the development of the Blended Drought Index. The current section analyses six commonly used RPs with special emphasis on their spatial and temporal quality in comparison with sparsely available climate station records. For the purpose of estimating the degree of uncertainty that propagates through a modelling stage, the six daily RPs are calibrated to observed rainfall data and subsequently used as input data for an exemplary crop growth model, the Agricultural Production Systems Simulator (APSIM) (Holzworth et al., 2014). The model output of millet yield is transformed to nutritional scores of an average household's requirements for dietary energy, proteins, lipids and carbohydrates. Official millet yield data from central-northern Namibia is used to validate the model results.

4.3 Material and methods

This study builds upon multiple public datasets and a range of processing methods that are presented in the following sub-sections. First, the processing of the RPs is outlined against the backdrop of insufficient local rainfall station data. This is accompanied by a description of the disaggregation and calibration procedures used to adjust the products' estimates. Second, the APSIM crop model is presented that facilitates the exemplary estimation of local staple food production. Finally, nutritional scores are introduced to characterise the nutritional situation of the local population.

4.3.1 Terrestrial rainfall observations

Good quality data on precipitation in terms of spatial and temporal coverage is a prerequisite for a range of applications, in particular hydrological and agricultural modelling (Di Piazza et al., 2011; Hoffmann et al., 2016; Skinner et al., 2015). Rain gauges are the primary and most reliable source of information on precipitation at a certain location, often measured via tipping-bucket techniques as one element of multi-purpose climate stations.

Climate station networks in Europe, North America, South Asia and Australia provide particularly good spatial coverages and long time series spanning more than one hundred years (WMO, 2015, p. 57). Sub-Saharan Africa, however, does not have an extensive terrestrial climate station network, and some regions have no station at all. However, this problem is not necessarily caused by a lack of infrastructural development. The Angolan civil war from 1975-2002 (Unruh, 2012), for instance, coincides temporally with a massive drop in the availability of climate station records compared to the late 1960s when the country already enjoyed good station coverage (Kaspar et al., 2015, p. 173). The current distribution of climate stations within the Cuvelai-Basin is heterogeneous. Rainfall data from gauge measurements provided by the Namibian Meteorological Service (NMS, 2013) are available for the Namibian part of the Cuvelai. These time series have data gaps, but the information from a few stations near major settlements and the Etosha National Park in the central north extends back to 1901. The Angolan part does not provide any official stations, which is why the SASSCAL WeatherNet initiative recently set up a number of climate stations in order to improve the monitoring infrastructure (Kaspar et al., 2015).

Since rain gauges provide point information, they only give a good indication of rainfall at a specific location. Reliable estimates for spatial rainfall patterns, however, require the interpolation of point information. Interpolation of rainfall is commonly performed using different methods, depending on the availability of station data, type of input and auxiliary information. On the one hand, univariate methods such as Inverse Distance Weighting (IDW), Thiessen Polygons or Ordinary Kriging are simple to apply and only require precipitation as input variable. On the other hand, multivariate models such as Geographically Weighted Regression or Artificial Neural Networks are more complex and require additional information, since they incorporate further explanatory variables such as elevation (Di Piazza et al., 2011). While the more complex, multivariate interpolation schemes have been found to provide good results, IDW is a common interpolation method for monthly and annual precipitation data (Di Piazza et al., 2011; Wagner et al., 2012) and provides sufficient results for the purpose of this study. The IDW technique builds upon the spatial correlation of rainfall occurrence, meaning that the validity of point data is reduced with increasing distance from its source location. The measured rainfall depth z

at location x_i is thus weighted (λ_i) with the distance d_{i0} between the station's location and the ungauged point of interest x_0 (Di Piazza et al., 2011). The interpolated rainfall for a specific location $\bar{z}(x_o)$ in between stations can thus be calculated by summing the weighted rainfall values of the surrounding stations as

$$\bar{z}(x_0) = \sum_{i=1}^{n} \lambda_i \cdot z(x_i) \quad (1)$$

where n is the number of observed data points. The weights are derived from the relative distances as

$$\lambda_i = \frac{d_{i0}^{-2}}{\sum_{i=1}^{n} d_{i0}^{-2}} \quad (2).$$

Processing was conducted using the gdal_grid interpolation tool in QuantumGIS 2.14 (QGIS Project, 2016) and the raster package in R (Hijmans et al., 2017).

4.3.2 Rainfall products

The use of RPs in data scarce regions is a popular approach in science and practice for various purposes. Today, many RPs are available, differing in terms of platforms, sensors, processing algorithms, spatial and temporal resolutions, and auxiliary information. To contribute to the ongoing evaluation of performance of all these products in different regions, this study makes use of six publicly available RPs, namely ARC 2.0, CHIRPS 2.0, CRU-TS 3.23, GPCC v7, PERSIANN-CDR and TAMSAT (Table 1).

Table 1: Metadata of rainfall products used in this study.

Product	Instrument	Spatial Cov.	Spatial Res.	Temporal Cov.	Temporal Res.	Provider	Reference
CHIRPS 2.0	IR,MW,RG	50°N-50°S	0.05°	1981-2015	d	UCSB,CHG	(Funk et al., 2015)
GPCCv7	RG	global	0.5°	1901-2013	m	DWD	(Schneider et al., 2015)
ARC 2.0	IR,RG	Africa	0.1°	1983-2015	d	NOAA	(Novella and Thiaw, 2012)
CRU-TS 3.23	RG	global	0.5°	1901-2013	m	UEA,CRU	(Harris et al., 2014)
TAMSAT	IR,RG	Africa	0.0375°	1983-2015	d	UoR	(Tarnavsky et al., 2014)
PERSIANN-CDR	MW,IR,RG	60°N-60°S	0.25°	1983-2015	d	NASA	(Ashouri et al., 2014)

(CHG = Climate Hazards Group, Cov. = Coverage, CRU = Climate Research Unit, d = daily, DWD = Deutscher Wetterdienst, IR = infrared, m = monthly, MW = microwave imager, NASA = National Aeronautics and Space Administration NOAA = National Oceanic and Atmospheric Administration, Res. = Resolution, RG = rain gauges, UCSB = University of California, Santa Barbara, UEA = University of East Anglia, UoR = University of Reading)

The RPs under consideration make use of varying methods to estimate rainfall. In the following, major characteristics and differences among the products are briefly presented. Overall, the products make use of infrared sensors (IR) and passive/active microwave imagers (MW). As satellite rainfall estimates are still highly uncertain compared to ground data, most products calibrate their data using existing rain gauge (RG) station data.

The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks – Climate Data Record (PERSIANN-CDR) product primarily builds upon IR data obtained from satellite sensors to estimate cloud temperatures since cold and high cloud tops indicate rainfall. The artificial neural network processing algorithm utilizes this correlation to estimate surface rainfall on a daily basis and a spatial resolution of 0.25°. Monthly RG data is incorporated from Global Precipitation Climatology Project (GPCP) to further adjust the rainfall estimates (Ashouri et al., 2014). The TAMSAT data product (Tropical Applications of Meteorology using SATellite data and ground-based observations) measures the duration of cloud temperature below a certain threshold over a 10-day period (Tarnavsky et al., 2014). The correlation function differs across Africa, as the continent is split into multiple homogeneous climate zones which vary with every calendar month. The final product provides daily rainfall estimates on a 0.0375° resolution (Maidment et al., 2014). The African Rainfall Climatology (ARC) version 2.0, measures cold cloud cover in a 24-hour period and assumes a constant empirical rain rate of 3 mm * h^{-1} to provide daily estimates on a 0.1° grid resolution. It is closely linked to the Rainfall Estimator (RFE) product, which is used by FEWS NET for early warning purposes (Novella and Thiaw, 2012). CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), uses the IR data to calculate cold cloud duration as well, but divides it by the mean long-term cold cloud duration precipitation estimates of TRMM 3b42 (Tropical Rainfall Measuring Mission). This results in a percent precipitation estimate that displays the deviation from normal. The percentages are then multiplied by long-term monthly average precipitation values and calibrated with in situ observations to offer a higher degree of accuracy and provide daily rainfall data at a fine spatial resolution of 0.05° (Funk et al., 2015, 2014).

Besides the products that build upon remotely sensed information, this study includes two products that build upon a global network of several thousands of climate stations and provide time series that span more than 100 years. The Global Precipitation Climatology Centre Full Data Product (GPCC v7) incorporates around 75,000 climate stations and provides a gridded data product at 0.5° resolution and monthly time steps for the period from 1901-2013 (Schneider et al., 2015). The climate product from the Climate Research Unit (CRU-TS 3.23) provides 0.5° gridded estimates on monthly rainfall, temperature (mean, min, max) as well as vapour pressure, cloud cover, rain day counts and potential evapotranspiration (Harris et al., 2014).

For all of the RPs considered, data processing, including data format transformation, quality control and resampling at 0.05° grid resolution, was performed using the R raster package (Hijmans et al., 2017).

4.3.3 Time series calibration

Direct measurements of precipitation, as commonly obtained from rain gauges, are the most reliable information on local rainfall amounts. Observations from weather radar systems and satellite-borne sensors however, show deviations in estimated rainfall compared to in situ measurements from ground stations that have to be accounted for. These indirect measurements have to be calibrated with other sensors data (e.g. rain gauges) to obtain rainfall estimates (Ringard et al., 2017). Several techniques for bias correction are available, from simple linear adjustment methods where the adjustment of estimated rainfall is performed by considering the ratio between direct and indirect measurements to long-term static (e.g. arithmetic mean ratio, geometric mean ratio) and short-term dynamic adjustment factors (Wood et al., 2000).

Due to limited ground data availability to adjust the RPs spatially, the calibration procedure was conducted by falling back on a single time series from Okatana station in northern Namibia. As the study intends to explore the uncertainty that is introduced by the RPs in a modelling stage, this pragmatic approach is required to feed the crop model with both ground data (from Okatana station) and calibrated rainfall estimates. Hence, the following sections will provide details on the calibration procedure performed. Before calibration, the two monthly product time series from CRU and GPCC were disaggregated to daily values, using a multiplicative Cascade Model (CM). Subsequently, all daily product time series were calibrated to the observed daily rainfall time series from Okatana station using the Quantile Mapping (QM) technique.

4.3.3.1 Cascade Model

As this study uses the RPs' estimates for crop model, daily data were obtained for four out of the six products. Only CRU and GPCC are solely available on a monthly basis and hence require disaggregation to obtain daily rainfall estimates. Therefore, a multiplicative, micro-canonical Cascade Model (Olsson, 1998) was used for the rainfall disaggregation. The model has been used before for rainfall disaggregation over a wide range of scales, e.g. from monthly to daily values (Thober et al., 2014) as well as from daily to hourly values (Müller and Haberlandt, 2015) and to 5 min values (Müller and Haberlandt, 2018) to generate input for rainfall-runoff-modelling (Ding et al., 2016; Müller and Haberlandt, 2018).

The rainfall amount of one time step is divided into b finer time steps of equal length (with b = branching number, see Figure 12 for a schematic illustration). With b = 2 throughout the whole disaggregation process, a daily resolution can only be achieved under the assumption that every month consists of 32 days. Hence, additional days in the time series (19 for each year) have to be removed afterwards on a monthly basis by deleting the first dry day(s) to obtain accurate month lengths. The rainfall amount is conserved exactly during the disaggregation process, so an aggregation of the disaggregated time series would result in the original time series. However, to cover the random behaviour of the disaggregation, 80 realizations for each dataset have been created (after 80 realizations the dry spell duration shows only slight changes for the median value as well as maximum and minimum).

The model parameters are estimated from the observed time series at Okatana station. For a more detailed description of the Cascade Model, the interested reader is referred to Müller and Haberlandt, 2015.

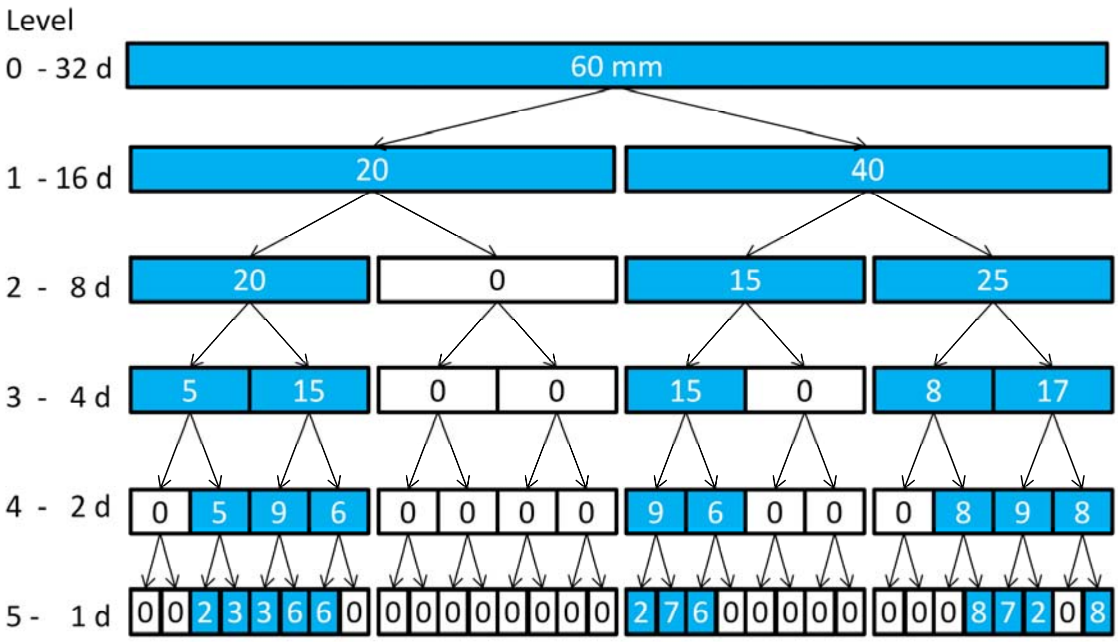

Figure 12: Scheme of the Cascade Model for rainfall disaggregation.
Exemplarily, a single realization is depicted (example: 60mm monthly precipitation) including the levels of disaggregation and corresponding temporal resolution.

To evaluate the performance of the disaggregation, the observed time series at Okatana station was aggregated to monthly values (32 days) and afterwards disaggregated to daily values. This enables the comparisons between observed and disaggregated time series at the same location. Rainfall characteristics show good results in terms of rainfall generation for the number of wet time steps (relative error of -8%), average intensity (9%) and number of dry intervals (1%).

4.3.3.2 Quantile Mapping

The Quantile Mapping technique adjusts the statistical characteristics of the products' rainfall estimates (e.g. arithmetic mean, standard deviation) to the observed time series. It corrects the distributions of the RP's daily precipitation estimates (P_{rp}) with the distribution of the observed daily precipitation at Okatana station (P_{os}) (Gudmundsson et al., 2012). The QM technique is mainly applied and evaluated for calibration purposes in global and regional climate models as well as hydrological contexts (Cannon, 2017; Ehret et al., 2012; Muerth et al., 2013; Ngai et al., 2017; Ringard et al., 2017). The transfer function h is used to map the original RP values to the ones of the observed time series, following the equation

$$P_{os} = h(P_{rp}) \quad (3).$$

As the distribution of P_{rp} is known, the transformation is carried out as

$$P_{os} = F_{os}^{-1}(F_{rp}(P_{rp})) \quad (4),$$

with F_{rp} being the cumulative distribution function (CDF) of P_{rp} and F_{os}^{-1} being the inverse CDF of P_{os}. Instead of relying on parametric distributions, empirical CDFs for the RPs' time series and Okatana station were used (Gudmundsson et al., 2012; Ringard et al., 2017). In this regard, the respective CDFs and the corresponding QM-parameters were estimated on a monthly basis (Figure 13). This means, the available time series at Okatana station from 2001 to 2009 was split into the twelve months from January to December and specific QM-parameters were derived for each of the twelve months. The mapping of daily RP values was then performed using the non-parametric transfer functions of the month-specific QM-parameters. This ensures a better fit to monthly rainfall characteristics which is particularly relevant in semi-arid environments that show pronounced dry periods.

Overall, the QM procedure was carried out by applying a Monte-Carlo cross-validation using 100 model runs for each rainfall product. Each time, the available time series of 9 years (2001-2009) was randomly split into 7 years for calibration and 2 years for validation. Based on the mean absolute error (MAE, eq. 5) between the observed and the RP time series in the validation dataset, the best QM transfer function was identified and applied to the entire product time series. Each of the 80 realizations for CRU and GPCC were also cross-validated using the Monte-Carlo technique. The entire procedure was carried out using the qmap package in R (Gudmundsson, 2016).

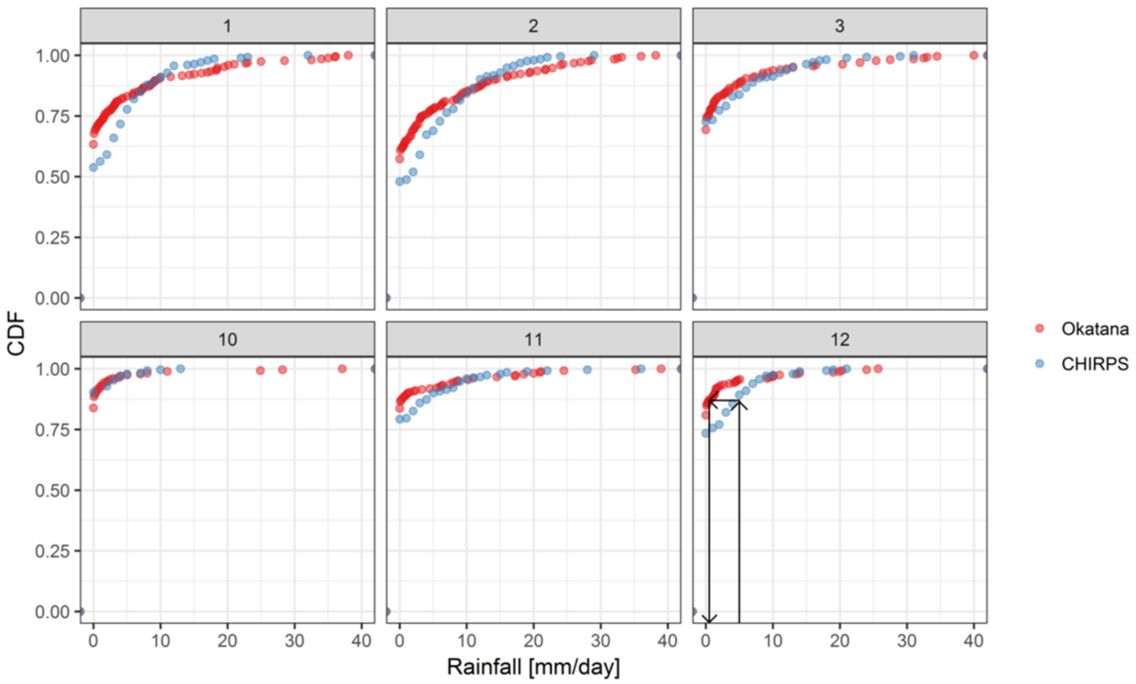

Figure 13: Cumulative distribution functions of rainfall from Okatana station and CHIRPS.
The CDFs are presented for the months from January to March (1 – 3) and October to December (10 – 12). The arrows in the lower right plot indicate that estimated rainfall values are mapped onto the observed rainfall values.

4.3.3.3 Rainfall statistics

For the purpose of evaluating the performance of the calibration procedure, the subsequent rainfall statistics were calculated before and after calibration. Besides the MAE as a standard measure of model performance using the equation (Chai and Draxler, 2014)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \quad (5),$$

where e is the absolute error term, other key statistical parameters were evaluated that are relevant for crop modelling in semi-arid environments. In this regard, only the rainy season from October to April was analysed. First, the mean dry spell duration (days between two rainfall events with at least 1mm of rainfall) was calculated. Second, the number of rainy days (minimum of 1mm rainfall) was assessed as annual averages. Third, the daily maximum precipitation was calculated as well as fourth, the mean daily rainfall intensity. Last, the average onset of the rainy season was assessed, using the threshold of at least 2 days of rain with a minimum of 5mm.

4.3.4 Crop growth model

The six calibrated, daily RPs and the observed time series at Okatana station were used as input for a crop growth model to assess and analyse the uncertainty between the time series when modelling staple food yields and corresponding nutritional scores in the study area. The Agricultural Production Systems Simulator (Holzworth et al., 2014) model was chosen as an appropriate tool to model millet yield in the Cuvelai-Basin, since it was successfully applied to smallholder systems in semi-arid environments of sub-Saharan Africa (Chimonyo et al., 2016; Mupangwa et al., 2011; Roxburgh and Rodriguez, 2016; Whitbread et al., 2010). APSIM is an easy-to-use crop model which offers pre-defined crop configurations that can be adjusted according to data availability. In addition to daily precipitation, the model requires input data of maximum and minimum daily temperature and surface solar radiation. Information on temperature [°C] were derived from the Climate Research Unit dataset (CRU TS3.23) (Harris et al., 2014) and linearly interpolated from monthly to daily values. Information on daily surface solar radiation [MJ/m2] was derived from monthly cloudiness data from the CRU TS3.23 dataset, as well. The transformation from cloudiness information [% cloud cover] to surface solar radiation was performed using the Supit-van Kappel approach (Supit and van Kappel, 1998), implemented in the R package sirad (Bojanowski, 2015) and calibrated with location-specific empirical constants from short-term time series at recently installed climate stations from the SASSCAL WeatherNet (SASSCAL WeatherNet, 2018).

As empirical field level data on soil characteristics were not available to the current study, the model's soil component, in particular the soil water characteristics were configured using the ISRIC World Soil Information Database (Batjes, 2015) and information on local field management techniques (Matanyaire, 1994). The planting date was set to be variable in the window from 1st of December to 31st of January, based on the threshold of at least 5mm rainfall within 2 consecutive days. Table 2 depicts the key soil characteristics that were obtained from the ISRIC database at the location of Okatana station. Empirical pedotransfer functions (Jabloun and Ali, 2006) that are used in the Water Evaluation and Planning Software were applied to calculate soil water characteristics. The air dry conditions were assumed to be 50%, 80% and 100% of LL15 for the first, second and deeper soil levels, respectively (Zeng et al., 2016). Overall, model configuration was kept constant in all model runs except the precipitation input that was taken from the six RPs and the Okatana time series. As CRU and GPCC were disaggregated from monthly time series, the 80 realizations of each product were processed in APSIM, while the output in yield was averaged.

Table 2: Soil water characteristics in APSIM model.
Data was obtained from the World Soil Information Database (Batjes, 2015) at Okatana station.

Depth [cm]	BD	AirDry	LL15	DUL	SAT	CLL	OC	KL	XF
0-20	1.480	0.012	0.024	0.271	0.579	0.130	0.684	0.06	1
20-40	1.490	0.172	0.215	0.353	0.503	0.170	0.501	0.06	1
40-60	1.520	0.251	0.251	0.394	0.469	0.180	0.382	0.06	1
60-80	1.540	0.244	0.244	0.388	0.448	0.200	0.292	0.06	1
80-100	1.550	0.226	0.226	0.368	0.433	0.200	0.233	0.06	1
100-150	1.550	0.176	0.176	0.314	0.413	0.200	0.169	0.06	1
150-200	1.560	0.148	0.148	0.291	0.408	0.200	0.139	0.06	1

(BD = Bulk density (g/cc), AirDry = Water content in air dry soil (mm/mm), LL15 = Drained lower limit (mm/mm), DUL = Drained upper limit (mm/mm), SAT = Saturated water content (mm/mm), CLL = Crop lower limit (mm/mm), OC = Organic carbon (%), KL = Water extraction coefficient, XF = Root exploration factor)

The yield estimated by the APSIM model was compared to official millet yield data from central-northern Namibia for validation. The data is provided by the agricultural statistics bulletin of the Namibian Ministry for Agriculture, Water and Forestry (MAWF) for the period 2000-2009 (MAWF, 2011, p. 21). Other sources of yield data are available, such as FAOSTAT and the Namibian Agronomic Board. However, the metadata provided on these platforms is insufficient to determine the origin of the yield data, if it is a national average, measured in northern Namibia or obtained from other parts of the country. The MAWF dataset was then preferred for the validation.

4.3.5 Nutritional scores

Characterising the nutritional situation of individuals or groups, particularly in the context of developing countries, is a major issue of scientific debate. Numerous indicators exist to assess food security conditions or the nutritional status. These include but are not limited to the FAO Indicator of Undernourishment (FAOIU), the Poverty and Hunger Index (PHI), the Diet Diversity Scores (DDS) (Pangaribowo et al., 2013) and the Integrated Food Security Phase Classification (IPC) adopted by the Famine Early Warning System Network (FEWS NET) (IPC Global Partners, 2012). The selection of appropriate indicators is important when it comes to the empirical investigation of the effect of agriculture on human nutrition (Maire and Delpeuch, 2005). Recent reviews give an overview on indicator sets used by researchers to empirically assess nutritional status. These indicators cover the areas of anthropometry, biochemistry, diet and food consumption and food security (Herforth and Ballard, 2016; Turner et al., 2013; Webb and Kennedy, 2014).

For the purpose of characterising the nutritional status of households in this study, simple nutritional scores were calculated for dietary energy and the macro-nutrients proteins, lipids and carbohydrates. In this regard, a household's demand for food was measured against the potential quantities of millet that can be produced in a subsistence farming system of the Cuvelai-Basin. First, the results of the APSIM model runs (kg/ha) were extrapolated to the average farming area per household in the basin of about 2.4 ha (Mendelsohn et al., 2000, p. 54). The total yield was subsequently transformed into nutritional indicators as referenced in the United States Department of Agriculture (USDA) National Nutrient Database for Standard Reference (USDA NDL, 2016). Respective values for millet are given in Table 3.

Table 3: Daily dietary demand for energy, proteins, lipids and carbohydrates.
Benchmarks are subdivided into different age and gender groups. The household average (HH-AV) is given according to the mean household composition (gender and age) in central-northern Namibia according to the recent census (NSA, 2013). The nutritional content of millet refers to one kilogram of raw material (USDA reference number 20031).

Classes	Dietary energy [kcal]		Proteins [g]		Lipids [g]		Carbohydrates [g]	
	Male	Female	Male	Female	Male	Female	Male	Female
< 14	1 907.25	1 726.07	190.73	172.61	381.45	345.21	858.26	776.73
15-64	2 866.80	2 193.20	286.68	219.32	573.36	438.64	1 290.06	986.94
> 65	2 457.00	1 793.00	245.70	179.30	491.40	358.60	1 105.65	806.85
HH-AV.	11 513.47		1 151.35		2 302.69		5 181.06	
Millet	3 780.00		11.02		4.22		72.85	

Second, a household's demand for dietary energy and particularly for the macronutrients proteins, lipids and carbohydrates were estimated to generate a wider picture of human nutrition. Assessments of nutritional status commonly apply nutritional benchmarks to assess the adequacy of food items available to individuals or groups (FAO, 2008). However, since these benchmarks neglect the importance of physical activity levels as part of the total energy expenditure (DeLany, 2013, p. 86) and only seldom account for other nutritional indicators such as macro-nutrients, this study adopts the concept of Dietary Reference Intakes (DRI) (Institute of Medicine, 2005). Herein, the Estimated Energy Requirements (EER) (Gerrior et al., 2006) and Acceptable Macro-nutrient Distribution Ranges (AMDR) are considered for specific age and gender groups within a certain population. EER benchmarks represent the amount of dietary energy "*that is predicted to maintain energy balance in a healthy adult of a defined age, gender, weight, height, and level of physical activity consistent with good health*" (Institute of Medicine, 2005, p. 3). To incorporate the important role of macro-nutrients in the provision of dietary energy, group-specific AMDR benchmark values were calculated. "*An AMDR is defined as a range of intakes for a particular energy source that is associated with reduced risk of chronic diseases while providing adequate intakes of essential nutrients*" (Institute of Medicine, 2005, p. 14). The nutritional benchmarks are represented in Table 3 (row 4) based on the assumption of an average household size of 5.5 people and a specific age and gender composition, derived from the last census of Namibia in 2011 (NSA, 2013).

4.4 Results

This sub-section is divided into four major parts. First, the precarious endowment of the Cuvelai-Basin with reliable rain gauge stations is presented. The second sub-section shows the estimated rainfall of the six products and their specific spatial and temporal characteristics. Therein, calibrated and uncalibrated time-series are evaluated against each other. The third sub-section focuses on the results of the APSIM model. The estimated yields are compared to official millet yield data. Fourth, the derived nutritional scores are presented with special emphasis on the fulfilment of a household's dietary energy demand and its range of uncertainty.

4.4.1 Local rain gauge measurements

Local rainfall data from gauge stations are available for part of the Cuvelai-Basin (NMS, 2013). Although the sparsely available rain gauge measurements provide long-term rainfall time series, they do not capture well the spatial rainfall variability in the study area. For clarification of this problem, Figure 14 shows the result of the Inverse Distance Weighting interpolation, including stations that – in the period 1980–2009 – encompass at least 20 years with complete monthly data records (without any data gaps).

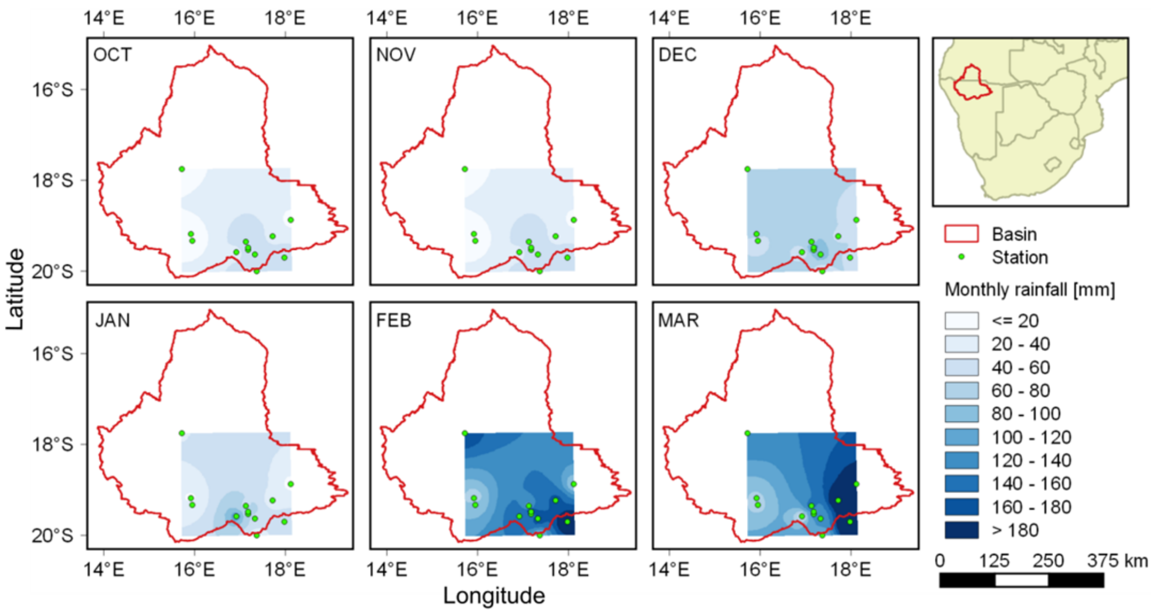

Figure 14: Average rainfall in the Cuvelai-Basin for the months of the rainy season.
Spatial rainfall is interpolated using the IDW technique with stations that encompass at least 20 years with complete monthly data records in the period 1980–2009 (without any data gaps).

The maps indicate the average rainfall for the months of the rainy season from October to March. Only a fraction of the entire basin can be described with respect to its long-term mean precipitation conditions, as meteorological stations in the north and the west do not provide sufficient data. Even the rectangle in the southeast of the basin is biased, as most stations are located in the south, while only one station provides information on areas further north. Hence, limited opportunities exist to provide a comprehensive picture on average rainfall conditions for the basin that stems solely from rain gauge measurements. For this reason, other options to retrieve rainfall data are outlined in the following sub-sections.

With respect to suitable ground data for RP calibration, daily rainfall data are required. While the stations used for spatial interpolation provide monthly rainfall data for longer periods, they only offer daily data from 1999 to 2010. Table 4 gives an overview of the 12 stations selected, indicating the covered time period, the share of missing values and the longest period available without any data gaps. No station provides a complete daily time series as the share of missing values ranges from 1.5% to 31.9%. Against this background, Okatana station is regarded as the most appropriate time series for RP calibration as it provides the longest daily time series of 3,437 days from 1 January 2001 to 31 December 2009 without any missing values.

Table 4: Availability of daily time series data from ground stations in northern Namibia.
The table indicates the covered time period (also represented as number of days) and the share of missing values within this time. Furthermore, the last column indicates the length of the longest period available without missing days (NMS, 2013).

Ground Station	Covered Period	Covered Period [days (years)]	Missing Values [%]	Longest Period [days (years)]
Arbeidsgenot	1 January 2000–31 May 2010	3804 (10.4)	7.2	2919 (8.0)
Choantsas	1 January 1999–31 December 2009	4018 (11.0)	6.9	1794 (4.9)
Goabforte	1 January 1999–30 September 2009	3926 (10.8)	10.9	1427 (3.9)
Huttenhof	1 January 2001–30 June 2010	3468 (9.5)	1.8	1731 (4.7)
Okatana	1 January 1999–31 December 2009	4018 (11.0)	9.1	3437 (9.0)
Okaukuejo	1 January 1999–31 May 2010	4169 (11.4)	8.8	3284 (9.0)
Ombika	1 January 1999–31 December 2009	4018 (11.0)	31.9	2251 (6.2)
Otavi	1 January 1999–30 September 2007	3195 (8.8)	11.4	2098 (5.8)
Otjirukaku	1 September 1999–31 May 2010	3926 (10.8)	10.1	2311 (6.3)
Soavis	1 January 1999–30 April 2010	4138 (11.3)	1.5	2191 (6.0)
Tsumeb	1 January 1999–31 December 2009	4018 (11.0)	13.7	2128 (5.8)
Una	1 January 2005–31 January 2010	1857 (5.1)	1.7	1792 (4.9)

4.4.2 Estimated rainfall

The low quality of available rain gauge measurements necessitates the use of RPs to estimate rainfall conditions for the basin as a whole. Figure 15 presents the uncalibrated annual rainfall as estimated by each of the products. Although the maps show the varying spatial resolution of the products, a consistent spatial pattern is apparent with increasing rainfall from the southwest to the northeast.

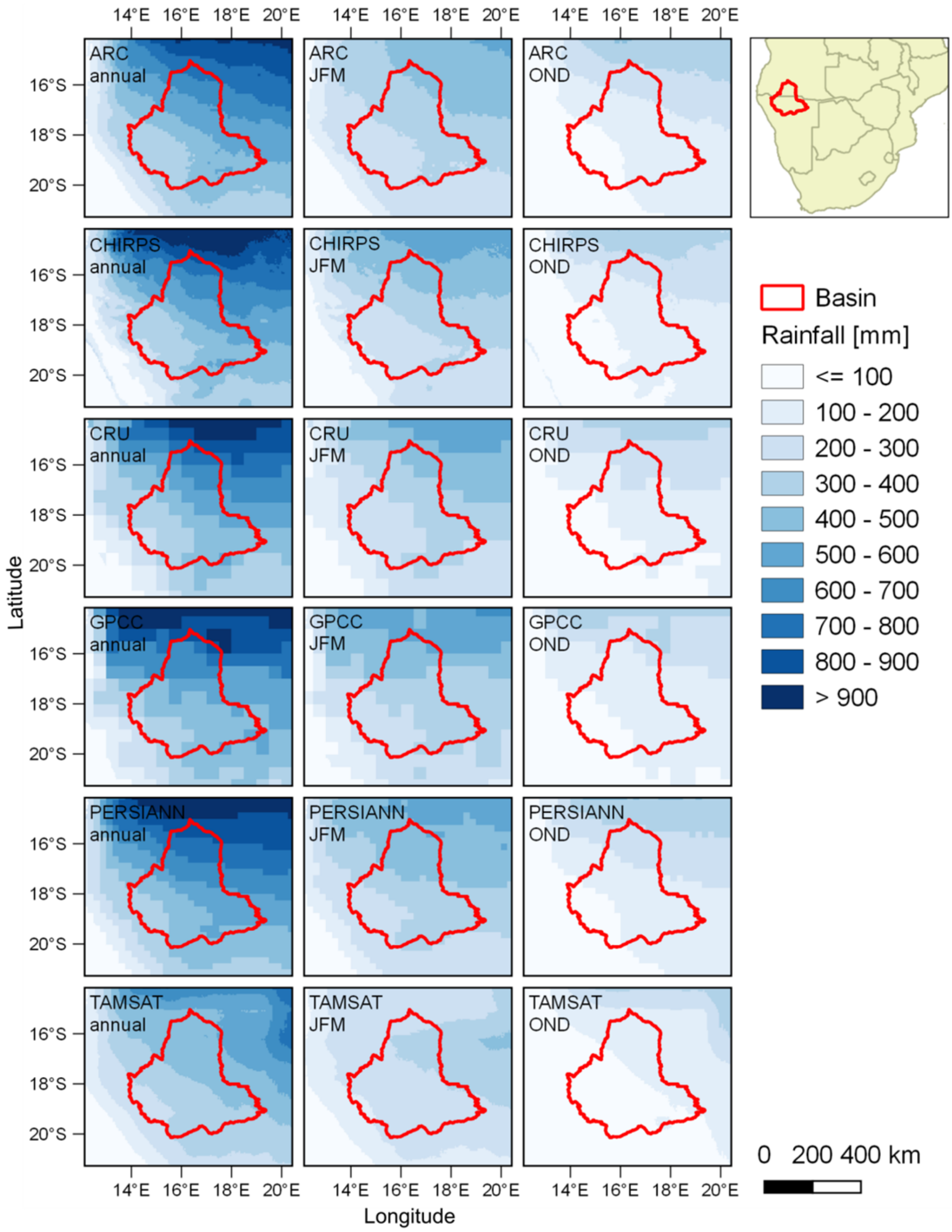

Figure 15: Spatial distribution of mean rainfall for the period 1983–2013.
The left column presents the mean annual rainfall, while the remaining two columns present the situation in the first (JFM) and fourth (OND) quarter of the year. The missing quarters do not show significant amounts of rainfall and were, thus, excluded from this figure.

This spatial pattern, captured by the raster images in Figure 15 with an increasing mean annual rainfall to the northeast, correlates strongly among the products when comparing the raster cell values from one product to another. In this regard, each RP has a Pearson correlation coefficient with every other product of at least r = 0.9. Likewise, considering the basin's mean annual rainfall as the average raster cell values per year, all RPs show a similar signal over time, with a Pearson coefficient of at least r = 0.73 among the products. Despite these similarities, differences still exist. The absolute amount of mean annual rainfall differs among the products. Particularly the lowest (TAMSAT, 390mm) and the highest values (PERSIANN, 544mm) differ with a range of about 154mm. Together with CHIRPS, CRU, and GPCC the PERSIANN product estimates higher amounts of rainfall, especially beyond the basin's boundary in the far north where more than 900mm are estimated. In comparison to low values of around 200–300mm per year in the south, this gradient is a key factor of the basin, characterizing the north as rather humid, while the south is semi-arid. Overall, rainfall occurs during the rainy season between October and May, while the winter months are rather dry. The quarterly plots in Figure 15 show that the fourth quarter (OND) receives less rainfall than the first quarter of a year (JFM). This is particularly relevant for local farmers to decide upon planting which normally starts around December and January, offering the crop favourable water conditions during the growing period in the first months of a year. This quarterly pattern is well reproduced again by all RPs, with TAMSAT being the one with the lowest absolute estimates.

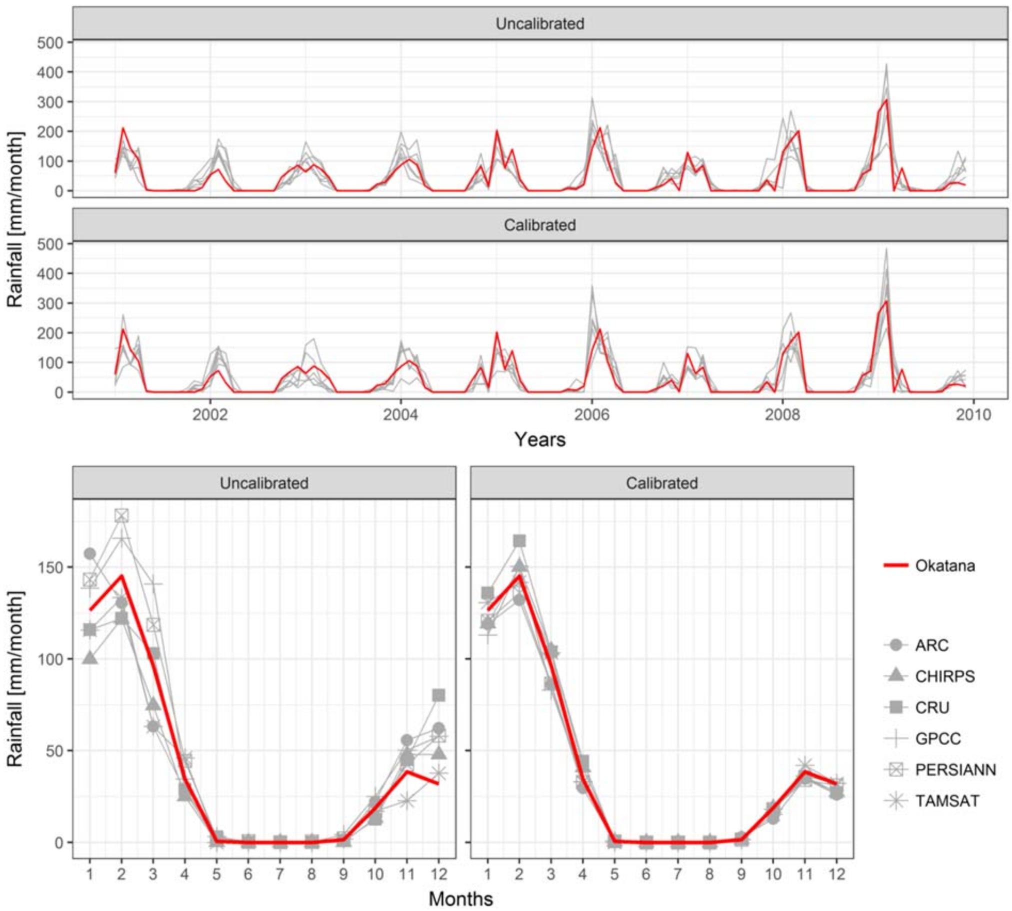

Figure 16: Uncalibrated and calibrated time series of RPs and Okatana station (2001 to 2009).
The upper plots show monthly rainfall while the lower plots present the monthly average rainfall.

The RPs presented above were calibrated to the observed rainfall time series from Okatana station in central-northern Namibia. Prior to this, the CRU and GPCC products were disaggregated from the monthly to the daily scale. Afterwards, they were treated in the same way as the other RPs. The QM calibration technique aligns key rainfall characteristics to the observed time series. Figure 16 presents the results of the calibration procedure. The upper plots show the uncalibrated and calibrated monthly rainfall at Okatana station, estimated by the RPs at the specific pixel location. Overall, the seasonality of the basin's climate becomes obvious with peak rainy seasons recorded in the years 2006, 2008, and 2009. The RPs reproduce well the Okatana time series signal with an average Pearson correlation coefficient of r = 0.84. The lower plots present the monthly precipitation, averaged over the available nine years. In particular, the months January, February, and March, as well as November and December, show deviations among the products before calibration. After the QM procedure, all deviations in the monthly average values were reduced and aligned to the Okatana time series (lower right plot). The MAE between the observed and the estimated monthly averages is reduced from 6.20 to 2.94mm. Nevertheless, a perfect fit cannot be obtained, as the selection of the best transfer functions is based on the QM model's performance in the validation dataset (ca. 29% of available data). Hence, not all data of the available nine years (remaining 71%) serve to parameterize the transfer functions which results in persisting residuals that are specifically obvious in the month of February.

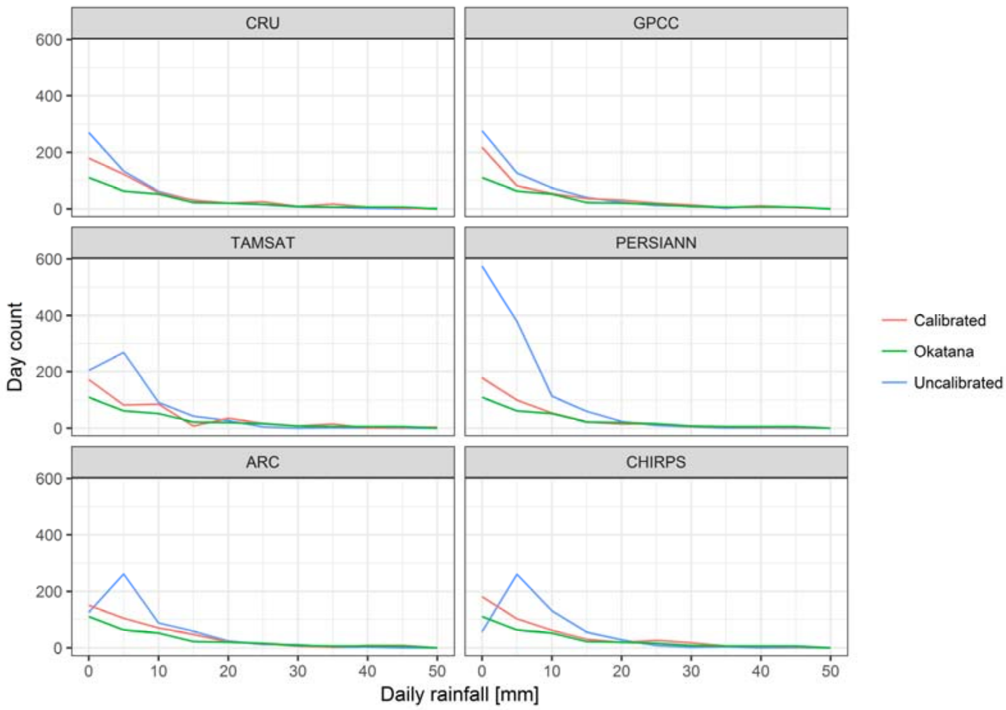

Figure 17: Frequency distribution of daily rainfall values for the month of February (2001 to 2009).
For each RP, the (un-)calibrated frequency distributions are presented and compared to the observed one from Okatana station. The x-axis is limited to 50 mm/day as only few events show higher rainfall amounts.

Since the month of February still shows the largest deviations after calibration, Figure 17 presents the frequency distributions of the month's daily rainfall. All products improve, as the frequency distributions are better aligned to the observed one. As observable in Figure 17, in particular the PERSIANN product overestimates the frequency of small rainfall events (<10 mm/day) before calibration. The rainfall statistics confirm a better fit to Okatana station data.

Table 5: Rainfall statistics of uncalibrated and calibrated rainfall products.
Statistics are compared to the observed values from Okatana station.

Rainfall Time Series		Mean Annual Dry Spell Duration (d)	Mean Annual Number of Rainy Days (d)	Average Daily Rainfall (mm)	Average Daily Rainfall Intensity (mm)	Rainy Season Onset (day of year)	Average Annual Daily Maximum (mm)	Mean Absolute Error (MAE)
	Okatana station	8.34	39.00	1.35	9.02	297	59.64	0.00
Uncal-ibrated	CHIRPS	6.73	56.56	1.18	7.31	315	26.00	1.58
	TAMSAT	6.15	59.67	1.20	6.30	293	21.44	1.49
	ARC	7.24	56.67	1.43	8.53	305	47.52	1.62
	PERSIANN	5.16	85.00	1.67	4.78	324	29.63	1.82
	GPCC	5.33	47.71	1.40	7.12	312	58.00	2.65
	CRU	5.36	50.13	1.70	7.47	305	82.20	2.41
Calibrated	CHIRPS	* 8.35	* 41.56	* 1.36	* 9.67	* 304	* 57.64	1.74
	TAMSAT	* 9.31	* 38.56	* 1.37	* 8.76	* 298	* 54.98	1.61
	ARC	9.94	* 35.67	1.22	* 9.10	* 293	* 52.39	* 1.52
	PERSIANN	* 9.14	* 37.78	* 1.26	* 8.37	* 304	* 55.16	* 1.70
	GPCC	* 6.37	* 40.74	1.43	* 9.25	* 303	65.69	* 2.42
	CRU	* 6.71	* 39.96	* 1.43	* 9.38	* 303	* 69.94	2.43

*Values improved, compared to uncalibrated rainfall statistics.

Table 5 presents key rainfall characteristics, comparing the uncalibrated and calibrated RP time series to the observed one from Okatana station between the years 2001 and 2009. Overall, the QM calibration procedure improves most of the statistics, compared to the raw data. This is particularly true for the number of rainy days and the rainfall intensities that improve for all RPs. Only the fit of the ARC product in terms of the dry spell duration and average daily rainfall slightly decreases. The latter is also true for the GPCC product. With regard to the MAE, the CHIRPS and TAMSAT, as well as CRU products, slightly decrease in performance, while all other products are enhanced.

4.4.3 Estimated yield

Having presented the rainfall results in the previous sections, the following ones now focus on the estimated millet yield from the APSIM model runs. Therein, the six RPs were used as model input and compared to official millet yield data. It has to be noted that the 80 disaggregated and calibrated time series from CRU and GPCC were all processed in the APSIM model. The results were averaged (median) over all model runs to obtain a final, product-specific result.

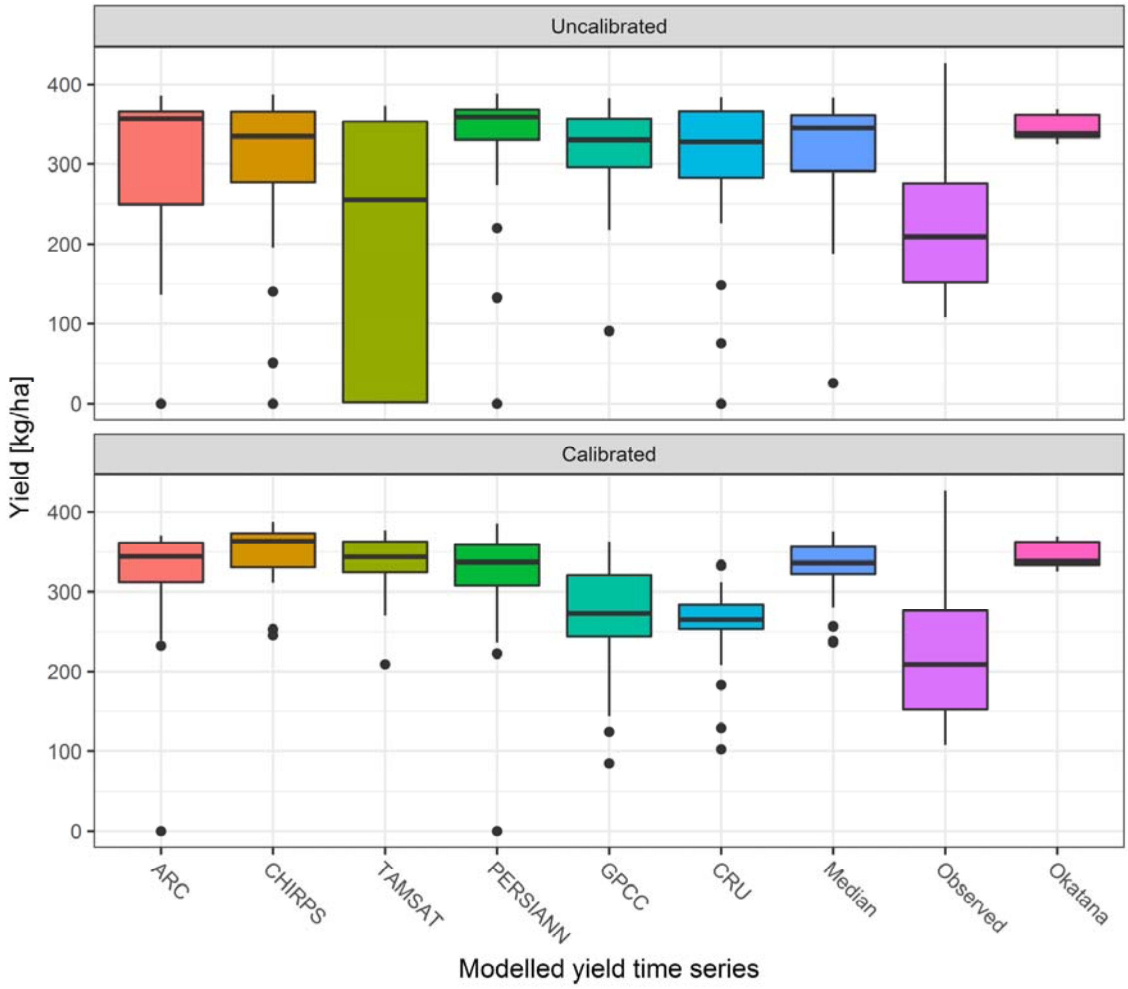

Figure 18: Boxplot diagrams comparing the temporal distribution ranges of the yield model results. Therein, model runs are depicted that use uncalibrated and calibrated rainfall data. In addition, the median yield results (median of all products) are presented along the observed yield data and the model results for Okatana station.

Figure 18 compares the APSIM model results that use the uncalibrated (upper plot) and the calibrated rainfall estimates (lower plot). Despite the deviations in absolute yield, the crop model performs well in estimating the extraordinary low yields from subsistence agriculture in northern Namibia (Andreas, 2015). Nevertheless, the median values of the calibrated products range between 264.74 kg/ha (CRU) and 363.08 kg/ha (CHIRPS) compared to 208.88 kg/ha as officially recorded. In comparison to the modelled yield that used the uncalibrated products, the results of the calibrated ones show smaller distribution ranges and fewer failed harvest events. Overall, these results fit better to the model results that make use of the observed rainfall time series from Okatana station.

While most products score above 300 kg/ha, the CRU and GPCC products score below this threshold. This is primarily triggered by the fact that some of the 80 APSIM model runs failed and produced no harvestable yield, resulting in a decreased overall product performance.

In terms of temporal consistency, the reader is referred to Figure 19 that depicts the yield results in terms of nutritional coverage ratios. Against the background of the study's design in which no crop model calibration could be performed with on-site data, the APSIM model configuration can be regarded as suitable, since the modelled yield that uses rainfall data from Okatana station shows a moderate correlation with the official data (r = 0.52). With regard to the calibrated products, the modelled yields only achieve Pearson correlation coefficients of up to 0.18 (CHIRPS). The official yield time series largely scores below the RPs and shows a higher inter-annual fluctuation (Figure 19). This fluctuation can be explained by drought and flood events that had an impact on agricultural production. While the years 1995, 2003, and 2013 are known as drought years (EM-DAT, 2016), the years 2008 and 2009 were recorded as flood years and, hence, potentially caused reduced yields (Andreas, 2015). In these flood years, however, the precipitation conditions would have made higher yields possible as indicated by the RPs' results. In particular, the adverse impact from flood events is not captured in the crop model and may explain part of the deviations between modelled and officially-observed yields.

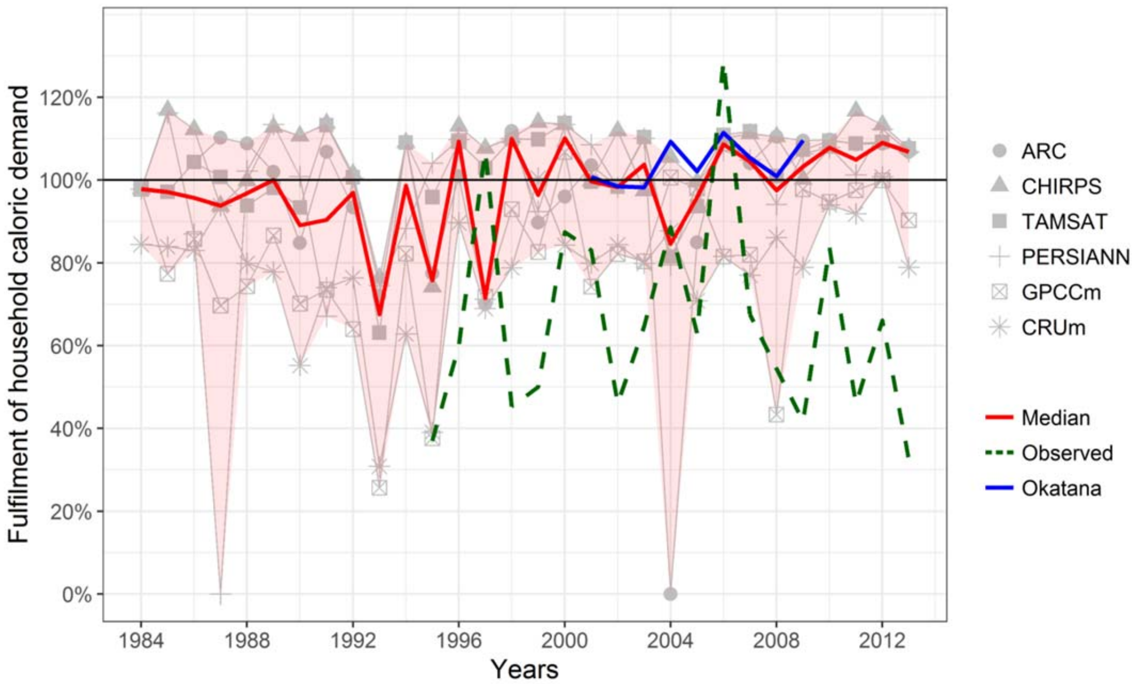

Figure 19: Degree of fulfilment of an average household's dietary energy demand.
Along the individual product results, the signal from Okatana station, as well as the officially-observed yield is presented.

4.4.4 Nutritional scores

The estimated yields from the APSIM model runs were transformed into nutritional supply indicators for dietary energy, proteins, lipids, and carbohydrates. These indicators were measured against the nutritional demand of a typical Cuvelai household to obtain nutritional scores. Figure 19 shows the degree of fulfilment of a household's dietary energy demand over time from 1984 to 2013. The red line represents the median degree of fulfilment by considering all model runs, while the light red area indicates the domain of uncertainty, generated by the model results of the individual RPs. The specific nutritional scores estimated by the products are depicted in light grey. For the purpose of comparison, the green line indicates the degree of fulfilment based on the observed data of millet yield from central-northern Namibia (1995–2013).

It becomes obvious that the degree of fulfilment fluctuates around the total fulfilment of the dietary energy demand with an average of 97%. However, differences are apparent for a range of years. In this regard, Figure 19 shows large differences in 1987 and 2004. In these years, the PERSIANN and ARC products fail in generating yield as limited soil moisture prevents the crop from germinating. Both products show longer dry spell durations and fewer rainy days compared to the observed data (Table 4) which might be an explanation for model failure in specific years. The year 1992 stands out in which all products point to low yield and, hence, a critical energy demand fulfilment of only 68% (median). This year is well known to be a severe drought year, particularly affecting the agricultural production of the northern regions (EM-DAT, 2016; Sweet, 1998). The remaining years show heterogeneous RP signals, while the median stays rather constant around 90–100% of fulfilment. The same temporal signal is valid for the other macro-nutrient indicators. Based on the nutrient content of the millet plant, however, the mean degree of fulfilment of a household's protein, lipid, and carbohydrate demand differs from the dietary energy demand (114%, 49%, and 167%, respectively).

4.5 Discussion

The interpolation of available rainfall data from gauge stations in the Cuvelai-Basin uncovered a deficit in the spatial endowment with meteorological stations. The Angolan part of the basin is poorly equipped, while the Namibian side manifests better coverage. Anyhow, the last years showed an improvement of the data situation. Despite this progress, no reliable estimate on current and past rainfall can be obtained from the station network for the basin as a whole. The use of RPs is, therefore, necessary to perform a range of applications in the field of hydrological and agricultural modelling.

The disaggregation technique applied in this study to obtain daily rainfall estimates from monthly aggregates proved to be a promising opportunity for application in agricultural modelling. Though it was predominantly used on smaller time scales before (disaggregation of daily data) (Müller and Haberlandt, 2018, 2015) and requires a higher computational effort (in this study, 80 realizations were generated for CRU and GPCC products, each), the disaggregated daily rainfall estimates were largely able to reproduce the characteristics of the observed time series. This is particularly true when considering the final rainfall time series after the calibration procedure. The Quantile Mapping calibration technique offers a feasible solution to obtain rainfall estimates that are aligned to key statistics of observed time series (Ngai et al., 2017; Yira et al., 2017). Especially, parameters such as dry spell duration, rainy day count, and onset of the rainy season, are important determinants for crop model applications that can be improved using the QM methodology.

Nonetheless, the RPs still show differences, notably in terms of absolute rainfall on both the daily, monthly and annual level. These differences stem from multiple influencing factors such as sensor types, processing algorithms and spatial resolutions. As in the case of the ARC product, the fixed rainfall rate of 3mm * h^{-1} might only be the correct correlation between cloud cover duration and precipitation at some locations. While it proves very accurate for the Sahel zone (Sanogo et al., 2015) and satisfactory for some locations in central Africa (Diem et al., 2014) it underestimates precipitation in comparison to station data in eastern Africa (Dinku et al., 2007) and in rain shadows (Diem et al., 2014). Likewise, the other products build on certain assumptions that might not perfectly fit the conditions of a particular study site. Hence, the calibration of RPs with locally observed rainfall data is a prerequisite. Furthermore, research into the suitability of other RPs, such as CMORPH (Joyce et al., 2004) and MSWEP (Beck et al., 2017) that are also used for studies in Africa, constitute valuable prospects for further analyses.

The different rainfall signals have an impact on subsequent modelling stages, as shown in the exemplary APSIM crop model. Though the modelled yield does not entirely reproduce the observed data, the results are reasonable first estimates for the nutritional situation in the Cuvelai-Basin. However, the quality and reliability of the official time series on millet yield must also be regarded as questionable as auxiliary information on how the data was assessed (e.g., location, timing, and sampling) is not available. Overall, this study fell back on auxiliary information from a literature survey and a large-scale soil property dataset to configure the crop model. Model performance can be enhanced by calibrating the model with locally-collected data on soil water and plant growth characteristics, and with management practices in terms of plant density, planting depth, and date of planting. In conjunction with the consideration of third variables such as the effect of flooding, model performance can potentially be enhanced.

All in all, the results provide insights into the nutritional situation of a typical household in the Cuvelai-Basin from a remote sensing perspective. Recent food consumption assessments show that subsistence grain farming is not necessarily capable of constantly fulfilling a household's nutritional demand (Acidri, 2010). This is confirmed by the official and the modelled yield results, both of which manifest a fluctuating fulfilment of demand. Although the dietary energy demand of a typical Cuvelai household is almost met on average, the provision of lipids is not sufficient. Here, other food sources such as animal products, vegetables and purchased groceries complement the diet obtained from subsistence farming.

4.6 Conclusion

This study explores the uncertainty among six rainfall products in the Cuvelai-Basin. It compares the rainfall estimates to locally-observed time series and performs Quantile Mapping to calibrate key rainfall characteristics. As a result, the RPs correlate well with the observed rainfall (r = 0.84) and better reproduce dry spell durations, rainy day counts, and rainfall intensities. Nevertheless, the persisting differences among the products percolate through the exemplary crop model into the final results of millet yield and associated nutritional scores. The crop model reproduces the extraordinary low yields from the study area and, in particular, the temporal fluctuation of the observed yield when ground data on rainfall from Okatana station are processed (r = 0.52). The individual products' performances, however, are rather heterogeneous with CHIRPS performing best to capture the temporal yield signal (r = 0.18). Translated into the fulfilment of a household's dietary energy demand, 97% can be met on average. Nevertheless, high annual fluctuations are apparent due to input data uncertainty. Overall, this study makes contributions to the field of rainfall data analysis, agricultural modelling, and food security monitoring. From the knowledge gained in this study, the following conclusions can be drawn:

First, it shows that rainfall products entail uncertainties due to differences in sensor techniques, processing algorithms, and spatial and temporal coverage and resolution. These have to be taken into account when RPs are used for further processing. Since in situ measurements of rainfall are scarce in large areas of SSA, modellers need to fall back on rainfall products to perform their calculations. In these cases, the selection of an appropriate rainfall product must be made explicit, since multiple options exist, all leading to different results. Thus, in the absence of observed data with which to identify the most accurate RP, precedence should be given to a multi-model approach to account for inter-product uncertainty.

Second, crop models that are driven by high-resolution rainfall data and auxiliary information provide promising opportunities for the identification of food insecurity hot spots. The results presented in this study can be made spatially explicit by incorporating census information on household characteristics, such as household size and composition, farming area, and agricultural activities. Applying seasonal rainfall forecasts to the model may help to improve early warning capabilities, against the background of the minor role crop models play in the current configuration of famine early warning systems (Brown and Brickley, 2012). Reducing data input uncertainty improves the accuracy of current models and consequently advances the precision of predictions for the future.

Third, the coverage of rain gauge stations in sub-Saharan Africa is insufficient for a range of modelling and monitoring purposes. Hence, prompt extension of the current station network is required to improve short and long-term capacities for tackling food security challenges.

The following section will take up these results on the suitability of rainfall products to develop and create an integrated tool for drought hazard assessments. It will utilize the CHIRPS product and conflate it with further environmental parameters of evapotranspiration, soil moisture and vegetation conditions to holistically characterize drought in the Cuvelai-Basin.

5

Blended Drought Index

Integrated drought hazard assessment[8]

5.1 Abstract

Drought is one of the major threats to societies in sub-Saharan Africa, as the majority of the population highly depends on rain-fed subsistence agriculture and traditional water supply systems. Hot-spot areas of potential drought impact need to be identified to carry out targeted risk reduction measures and adapt a growing population to a changing environment.

This paper presents the Blended Drought Index, an integrated tool for estimating the impact of drought as a climate-induced hazard in the semi-arid Cuvelai-Basin of Angola and Namibia. It incorporates meteorological and agricultural drought characteristics that impair the population's ability to ensure food and water security. The BDI uses a copula function to combine common standardized drought indicators that describe precipitation, evapotranspiration, soil moisture and vegetation conditions. Remote sensing products are processed to analyse drought frequency, severity and duration.

As the primary result, an integrated drought hazard map is built to spatially depict drought hot-spots. Temporally, the BDI correlates well with millet/sorghum yield (r = 0.51) and local water consumption (r = –0.45) and outperforms conventional indicators. In the light of a drought's multifaceted impact on society, the BDI is a simple and transferable tool to identify areas highly threatened by drought in an integrated manner.

[8] This section was published as a modified version in the MDPI journal Climate (Luetkemeier et al., 2017).

5.2 Introduction

Droughts affect more people in Africa than any other natural hazards (UNISDR, 2009, p. 3). In particular, mixed crop-livestock systems in sub-Saharan Africa are highly sensitive to drought events due to their dependence on local hydro-climatic conditions (Collier and Dercon, 2014; Cooper et al., 2008; Diao et al., 2010; Shiferaw et al., 2014; Thornton and Herrero, 2015). This is true for the majority of the population since rural subsistence economies remain the prevalent livelihood strategy (IAASTD, 2009). Droughts especially impact on the livelihoods of the population that is highly exposed and sensitive to water scarcity and has limited capacities to cope with these conditions (section 3). Against the background of the challenging social-ecological situation in SSA (UN, 2015; UNECA et al., 2015) and projections about increased drought frequency and intensity (Handmer et al., 2012; Niang et al., 2014; Seneviratne et al., 2012), the population is likely to remain in a precarious situation of poverty persistence, civil conflicts, and food and water insecurity (Gautam, 2006; Shiferaw et al., 2014; von Uexkull, 2014). The identification of drought-prone areas interlinked with a thorough characterization of the populations' sensitivities and coping capacities is thus essential to improve short-term emergency responses and develop long-term adaptation strategies on the political level for the most vulnerable groups (section 3).

The identification of drought-prone areas is however, challenging due to the complex nature of drought events with their slow onset and unclear definition (Mishra and Singh, 2010; Wilhite et al., 2007). Four types of drought can be identified (Wilhite and Glantz, 1985): (i) Meteorological drought is defined as a less-than-normal amount of precipitation for a certain region and time period (Kallis, 2008; Mishra and Singh, 2010; Wilhite and Glantz, 1985). If the water deficit leads to a drop in soil moisture, thus affecting plant health, the drought situation is defined as (ii) an agricultural drought. Other than through a water deficit, this type of drought can also be caused by higher-than-usual evapotranspiration as soil moisture depletes at a faster rate. The limited surface and subsurface water resources potentially lead to (iii) a hydrological drought as discharge, groundwater and reservoir levels decrease (Nalbantis and Tsakiris, 2008; Tallaksen and Lanen, 2004; Zelenhasi and Salvai, 1987). (iv) A socio-economic drought, on the contrary, is not solely related to the climatic conditions, but refers to a water deficit caused by allocation difficulties (Mishra and Singh, 2010; Wilhite and Glantz, 1985).

These different types of drought play an important role in the Cuvelai-Basin at the border between northern Namibia and southern Angola. Recurring droughts and floods heavily affect the population in the basin, where a majority practices rain-fed subsistence agriculture (Mendelsohn et al., 2013). Characterizing the hazard of drought in the basin and comparable regions is essential, yet difficult in areas with a low climate station density and irregular precipitation records. This study therefore uses remotely-sensed climate products, which offer high resolution data reaching back long enough to compute different drought indicators. It seeks to incorporate the quantifiable traits of the aforementioned types of drought by using a copula equation (Hao and AghaKouchak, 2013) to generate the Blended Drought Index, which can be used to determine the combined exposure of the population in the Cuvelai-Basin to meteorological and agricultural droughts. As the input variables are entirely taken from remote sensing products, the index is especially suitable for data-scarce regions that are less well-equipped with monitoring infrastructure. This study makes hence a contribution to both the preparatory phase of disaster management as well as for the design of adequate responses to drought events (Vicente-Serrano et al., 2012).

5.3 Material and methods

This section provides an overview on the procedures to calculate and analyse the BDI. First, the study design and the indicator selection are presented. This is followed by a detailed description of the individual drought indicators (Table 6) and their processing. Third, the process of combining the individual indicators via a suitable copula function is described. An outline of the drought dimensions to be analysed, such as frequency of occurrence, severity, and duration, follows. Finally, observed data on millet/sorghum yield and tap water consumption from northern Namibia are presented that are used to validate the temporal BDI signal.

Table 6: Datasets used to calculate the drought indices.

Parameter	Dataset	Spatial coverage	Spatial resolution	Temporal coverage	Temporal resolution	Provider	Reference
Precipitation	CHIRPS 2.0	50°N-50°S	0.05°	1981-2015	monthly	UCSB,CHG	(Funk et al., 2015)
Evapotransp.	CRU TS3.23	global	0.5°	1901-2013	monthly	UEA,CRU	(Harris et al., 2014)
Soil Moisture	GLDAS	global	0.25°	1980-2010	monthly	NASA	(Rodell, 2015)
Vegetation	NDVI3g	global	0.08°	1981-2013	15 days	GIMMS	(Pinzon and Tucker, 2014)

(UCSB = University of California, Santa Barbara, CHG = Climate Hazards Group, UEA = University of East Anglia, CRU = Climate Research Unit, NASA = National Aeronautics and Space Administration)

5.3.1 Study design and indicator selection

As outlined in section 3, the inhabitants of the Cuvelai-Basin are challenged by drought with respect to their ability to secure adequate levels of water and food supply during water-scarce periods as a result of their dependence on local hydro-climatic conditions. This holds true for both the rural and urban population due to i.e. familial relationships between the sub-systems. Conceptually speaking, this means that households are at risk of drought since their ability to meet their (indirect) demand for blue and green water (Freire-González et al., 2017; Rockström, 1999) is impaired by spatio-temporal water scarcity. The term risk is often used in an unspecified manner, but in this study it encompasses two dimensions, the environmental hazard itself to which societal entities (i.e., households) are exposed and their vulnerability, which specifically includes the sensitivity of these entities to drought and their inherent ability to cope with adverse conditions in the short-term (Lavell et al., 2012). While the vulnerability dimension rather takes a sociological perspective with a focus on the affected population, this study sheds light on the climate-induced drought hazard and seeks to develop an integrated drought hazard map for the entire basin. Further investigations will follow on the specific vulnerabilities of the population (sections 6 and 7) to depict drought risk in a comprehensive way.

Standardized drought indicators are a common choice in science and practice to quantify drought events. Up to now, more than one hundred drought indicators have been developed (Lloyd-Hughes, 2013), offering a huge repository of options on the one hand but on the other hand making it almost impossible to select the right indicator for a specific situation. Most drought indicators compare the current status of hydro-climatic parameters like precipitation, evapotranspiration, temperature, and soil moisture to their respective long-term normal configurations. Mishra and Singh (2010) as well as Pedro-Monzonís et al. (2015) comprehensively reviewed the use of drought indicators in recent years and identified the most frequently used ones. According to their analysis, the Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), the Crop Moisture Index (CMI), the Surface Water Supply Index (SWSI) and the Vegetation Condition Index (VCI) belong to the most popular drought indicators (Mishra and Singh, 2010; Pedro-Monzonís et al., 2015).

Some of these tools are integrated into drought monitoring and early warning systems such as the Famine Early Warning System Network and the African Drought Monitor. The latter includes for instance different temporal SPI configurations, the Normalized Difference Vegetation Index (NDVI), and stream flow percentiles among other parameters (Brown and Brickley, 2012; Princeton Univeristy, 2016; Pulwarty and Sivakumar, 2014). The overall problem of most drought indicators is however, their limited scope, often focusing on one single parameter and thus neglecting other important determinants of meteorological, hydrological, agricultural, or socio-economic droughts. While the individual indicators often show comparable signals (Naumann et al., 2014b), relying on a singular index is not suitable to describe drought conditions accurately in the study area, as soil moisture and evaporation in addition to precipitation heavily influence the blue and green water flows that support the population. Some drought indicators already address this issue like in the case of the PDSI. It combines precipitation data, soil moisture evaporation, and runoff into a single index. However, being calibrated for the United States, it does not perform well in other climatic regions and is thus not comparable, spatially (Kallis, 2008). More recently, advanced methods of coupling individual drought indicators via copula functions have led to the development of new multivariate integrated drought indicators (Mishra and Singh, 2011). For instance, the Multivariate Standardized Drought Index (MSDI) incorporates precipitation and soil moisture data and has proved to adequately represent drought conditions in California and North Carolina (Hao and AghaKouchak, 2013) as well as east Africa (AghaKouchak, 2015). Chang et al. (2016) combined four separate drought indicators to construct the Multivariate Integrated Drought Index (MIDI) and analysed its suitability to depict drought onset, duration, severity and termination in central China (Chang et al., 2016). Likewise, studies on drought conditions in central Iran examined the strengths of the copula approach by constructing the Hybrid Drought Index (HDI) that makes use of SPI, PDSI and SWSI (Karamouz et al., 2009). These approaches are promising and hence taken up in this study to combine indicators that cover different aspects of drought that are of relevance in the Cuvelai-Basin.

5.3.1.1 Standardized Precipitation Index

The SPI is a commonly used indicator to monitor drought occurrence for different time scales (McKee et al., 1993). It is recommended by the World Meteorological Organization (WMO) as the mandatory tool for all national meteorological and hydrological services to characterize meteorological droughts (WMO, 2012). The SPI is simple to calculate, since it only requires a long-term precipitation record of 20–30 years as input variable and offers the opportunity to analyse both dry and wet periods at a specific location. In essence, the long-term precipitation record at one location is compared to the current rainfall, which produces a standardized deviation from normal as the index value which is either positive (wet conditions) or negative (dry conditions). The respective size of the standard deviation reflects the intensity of a drought as represented in Table 7, while the threshold value of –1 is commonly considered for distinguishing near normal conditions from real drought situations (McKee et al., 1993; WMO, 2012).

The SPI can be calculated for varying timescales reflecting different types of drought or affected depletable water storages. While McKee et al. (1993) initially proposed the consideration of 3, 6, 12, 24, and 48 months moving average periods (McKee et al., 1993, p. 18), shorter periods of 1 and 2 months can provide important information for drought early warning systems (EWS) (WMO, 2012, p. 6).

Table 7: Drought intensities according to the size of standard deviation (McKee et al., 1993, p. 18).

SPI values	Drought severity
0 to -0.99	Mild drought
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
< -2.00	Extreme drought

The Standardized Index (SI) is calculated by creating a moving sum time series of monthly precipitation and fitting this times series to a Probability Density Function (PDF). The PDF is transformed to a standardized normal distribution with a mean of zero and standard deviation of 1. The resulting standard z-score is the SPI value (McKee et al., 1993). Finding the right PDF is however, a challenge, in particular for other hydrological parameters. In the case of precipitation data, Guttman (1999) compared a three-parameter Pearson type III and a two-parameter Gamma distribution and did not find sizable differences, though he recommended the Pearson III distribution since it allows more flexibility (Guttman, 1999). However, the gamma distribution is more widely used to calculate the SPI (Edwards et al., 1997; McKee et al., 1993; Stagge et al., 2015; Wu et al., 2007, 2005) as it fits the bounded and positively skewed precipitation values best (Wilks, 2011). Because precipitation values are fit to a probability distribution and then normalized, the SPI is location-independent and comparable across different climate zones. While short-term durations like 3- or 6-month SPI are more related to agricultural drought, a low 12- or 24-month SPI can indicate major water resources deficits and thus define hydrological droughts (Edwards et al., 1997; Vicente-Serrano, 2006; Vicente-Serrano et al., 2010).

In the case of precipitation, the Climate Hazards Group Infrared Precipitation with Station Data (CHIRPS 2.0) product has been used (Funk et al., 2015, 2014). CHIRPS data is continuously produced by blending three components to an unbiased gridded estimate: (i) the percent of normal Infrared Precipitation (IRP) estimates are derived from cloud cover temperature and local regression previously determined from TRMM 3B42 precipitation data, (ii) the long-term precipitation normals (CHPClim) (Funk et al., 2015) and (iii) the precipitation station data. In case of missing IRP values, atmospheric model rainfall fields from NOAA Climate Forecast System (CFSv2) are used. The data cover the period from 1981 to present and are available at 0.05 degree resolution (Funk et al., 2014). Nevertheless, quality of CHIRPS data is controversial. While Hessels (2015) attests CHIRPS (v. 1.8) and TRMM the highest accuracy in comparison with station data in the lower Nile basin (Hessels, 2015), Toté et al. (2015) criticize CHIRPS for overestimating the frequency of low rainfall events in Mozambique (Tote et al., 2015). Ceccherini et al. (2015) on the other hand find CHIRPS and GPCC to have the highest precision in calculating mean annual precipitation (Ceccherini et al., 2015). For the current study area, it is found to reproduce observed rainfall time series best and better correlates with yield data than other rainfall products (section 4). Calculation of the standardized indicators for SPI and the subsequently presented indicators was conducted using the R package SPEI (Beguería and Vicente-Serrano, 2017).

5.3.1.2 Standardized Precipitation Evapotranspiration Index (SPEI)

In seasonal wetlands, a large amount of floodwater is lost by evaporation, thus diminishing the amount left for soil and groundwater (McCarthy, 2006). The Standardized Precipitation Evapotranspiration Index (SPEI), developed by Vicente-Serrano et al. (2010), therefore covers drought due to water loss by evaporation and phenomena like flash droughts, where hot, windy conditions with high potential evaporation rates deplete soil moisture rapidly (Vicente-Serrano et al., 2010).

Potential evapotranspiration (PET) data were taken from the Climatic Research Unit's monthly global climate dataset (CRU TS3.23) that covers the period from 1901 to 2014 at a 0.5 degree grid resolution. Data stem from global quality-checked station data. Here, PET is calculated using the FAO variant of the Penman–Monteith method, the grass reference evapotranspiration equation (Ekström et al., 2007), using air temperature minimum, maximum, and mean, vapour pressure, cloud cover, and wind speed. For calculating the water balance, precipitation data from the CHIRPS product were used, as presented in the previous section. Since the SPEI basically builds upon a simple water balance that can reach values of below zero, a three-parameter distribution was needed. Vicente-Serrano et al. (2010), who developed the index, tested four different distributions (Pearson III, Log-normal, General Extreme Value and Log-logistics) and found the Log-logistic distribution to best fit the data even at extreme values (Vicente-Serrano et al., 2010). Stagge et al. (2015) on the other hand recommended the General Extreme Value distribution (Stagge et al., 2015). However, since the method developed by Vicente-Serrano et al. (2010) is more commonly used (Hassanein et al., 2013; McEvoy et al., 2012; Yu et al., 2014), the Log-logistic distribution was used in this study. Likewise to the SPI calculation, the procedure was performed using the R package SPEI (Beguería and Vicente-Serrano, 2017).

Every raster dataset was transformed into WGS84 projection and the resolution is adjusted to fit the precipitation data. This was done for the purpose of calculating and comparing the indicators later for every raster cell. Bilinear interpolation of raster with lower resolution was avoided by using the nearest-neighbour method in order to avoid simulating with a seemingly higher certainty than the original data provides.

5.3.1.3 Standardized Soil Moisture Index (SSI)

While abnormal precipitation relates to meteorological drought, agricultural drought is connected most to a decrease in soil moisture, which affects crops and yield (Kallis, 2008). An indicator measuring depletion of soil moisture is therefore an important part of a combined index, which especially focuses on drought effects in agriculture.

Remote sensing offers the opportunity to estimate soil moisture via optical, thermal infrared and active/passive microwave techniques (Wang and Qu, 2009). Further approaches incorporate these raw data from satellite-based sensors and use ground measurements to combine this input data in a land surface model (Ek, 2003). This latter type of data is utilized in this study, namely monthly soil moisture data from the Global Land Data Assimilation System (GLDAS) by NASA for the years 1980 to 2010 (Chen et al., 1996; Ek, 2003; Rodell, 2015). Therein, soil moisture was generated from the Noah Model 3.3 that incorporates land cover, land water mask, soil texture and elevation information, among others. Data are available at a 0.25° grid resolution for the depth 0–10 cm, 10–40 cm, 40–100 cm and 100–200 cm, and is summed to represent total moisture content for the depth of 0 to 200 cm, measured in m^3/m^3. Temporal distributions for soil moisture are less-often discussed in the literature. Sheffield et al. (2004) decided to use the beta distribution for soil moisture data in the United States, since it can fit positively and negatively skewed shapes (Sheffield et al., 2004). It is however, the only reference recommending a certain distribution for soil moisture data. Therefore, to determine which distribution is most suitable for the study area, normal, beta, and gamma distributions were fit to every data point with the fitdist-function of the R-package fitdistrplus (Delignette-Muller et al., 2017) using moment matching estimation. Comparison of the log-likelihood shows that the gamma distribution proved to be the best fit in the study area.

5.3.1.4 Standardized Vegetation Index (SVI)

For the purpose of incorporating the effect of drought on vegetation, this study utilizes data on the NDVI obtained from NASA's Global Inventory Monitoring and Modeling Systems (GIMMS) Advanced Very High Resolution Radiometer (AVHRR) product. This dataset, also referred to as NDVI3g, contains global NDVI observations from 1981 to 2013 at a 8-km grid resolution (Pinzon and Tucker, 2014). The Vegetation Condition Index (VCI) was calculated using the Min-Max normalization technique (Kogan, 1995) and thus compares current NDVI values to their long-term characteristics and gives evidence on decreased vegetation conditions (Kogan, 1995).

The VCI has successfully been applied in multiple regions and climate zones around the globe, both to calculate meteorological as well as agricultural drought (Dutta et al., 2015; Kogan, 1995; Quiring and Ganesh, 2010; Unganai and Kogan, 1998). However, since vegetation stress is not necessarily related to water-scarce periods but can also be attributed to flooding conditions, especially in the Cuvelai-Basin, the VCI was complemented with temperature information. As Kogan (1995) illustrates, low VCI values during low temperature periods are an indicator of flooding stress rather than drought stress. The Temperature Condition Index (TCI) is calculated similar to the VCI, while the resulting Vegetation Index (VI) is thus generated by complementing the initial VCI with the TCI in an additive way with relative weights of 70/30 (Kogan, 1995). Since the VI ranges between 0 (dry) and 1 (wet), it was transformed to a standardized index, the Standardized Vegetation Index (SVI), to be comparable to the other indicators, using the R-package SCI (Gudmundsson and Stagge, 2016).

5.3.1.5 Copula

Copulas became popular throughout the last years for multivariate characterizations of drought events (Chang et al., 2016; Hao and AghaKouchak, 2013; Kao and Govindaraju, 2010; Saghafian and Mehdikhani, 2014). They are functions that link two or more variables and construct a single dependent one that incorporates key characteristics of the originals. In essence, the relationship between p uniform random variables $U(0,1)$ can be captured using their joint distribution function

$$C(u_1, \dots, u_p) = \Pr(U_1 \leq u_1, \dots, U_p \leq u_p) \quad (6)$$

with C being the copula. For a p-dimensional distribution function F with respective margins, the copula for all x can be derived as

$$F(x_1, \dots, x_p) = C(F_1(x_1), \dots, F_p(x_p)) \quad (7).$$

For a comprehensive overview on the copula approach, its origin, technical aspects, and application, the interested reader is referred to respective key publications (Favre et al., 2004; Nelson, 2006; Sklar, 1959; Yan, 2007). A number of studies employed copulas to combine drought characteristics (duration, severity, peak intensity, and interval times) of a single indicator like the SPI (Saghafian and Mehdikhani, 2014). Other studies seek to incorporate different drought indicators that build upon a range of parameters such as precipitation, soil moisture, and vegetation (Chang et al., 2016; Hao and AghaKouchak, 2013; Kao and Govindaraju, 2010). Several copula families exist with the Archimedean and Gaussian copulas being the most popular ones. In this study, four copula candidates were chosen, namely the Frank, Clayton, Gumbel, and the Normal (Gaussian) copula which are evaluated for their suitability to match the drought indicators with a goodness-of-fit (GOF) test. The GOF test was conducted using the Cramér-von Mises statistics (S_n) test (Hao and AghaKouchak, 2013). Here, p-values higher or equal to 0.05 indicate that the respective copula cannot be rejected. The GOF test in this study clearly revealed that the Gaussian copula fits the data best:

$$C_P(u_1, \dots, u_d) = \sigma_P(\sigma^{-1}(u_1), \dots, \sigma^{-1}(u_d)), \quad (8),$$

where σ denotes the standard normal distribution function and σ_P the multivariate standard normal distribution function with correlation matrix P. The Gaussian copula was hence used to combine the individual indicators and to create integrated time series for each available pixel in the study area. The calculation procedure was carried out using the R-package VineCopula (Schepsmeier et al., 2018).

5.3.2 Drought dimensions

The individual drought indicators and the derived copula were calculated as 6-months running averages to capture the drought conditions on a seasonal basis. Since water and food security conditions in the Cuvelai-Basin primarily depend on the hydro-climatic situation of the rainy season from November to April (Mendelsohn et al., 2013), this study considers the indicator values of April as being relevant for further analysis and spatial representation. These values capture the drought conditions during the growing period of millet/sorghum from December/January to March/April (Mendelsohn et al., 2000) and give an indication of the green and blue water flows at the start of the dry season. Another reason for not including all-year-round values is the indicators' high uncertainty during the dry season and under arid conditions in general (Spinoni et al., 2014). Zero precipitation during June, July, and August are not uncommon and can bias the results (Wu et al., 2007).

The change of the April values over time serves the statistical analysis of three key drought dimensions: (i) frequency of occurrence, (ii) severity, and (iii) duration. Drought frequency measures the number of years that have April values of below the threshold of –1. Drought severity is measured as the integral area between the indicator curve and the threshold of –1. It should not be confused with drought intensity that rather refers to the most extreme value in a certain period (Spinoni et al., 2014). Drought duration, which is often calculated as the time from drought start (first month of below 0) to its end (last month of below 0) (Halwatura et al., 2015), is measured in a different way here. Since only annual drought values are considered, duration in this study is regarded as the number of consecutive years that show April values of below –1. It is thus a measure of inter-annual drought duration, which is particularly relevant to subsistence systems in the Cuvelai-Basin, as longer lasting droughts challenge the coping capacities of the local population.

The pixel-based copula time series were evaluated with regard to frequency, severity, and duration. The average of these three dimensions was defined as the Blended Drought Index to depict hot-spot areas spatially. For temporal comparison with validation data, the frequency dimension was used.

5.3.3 Validation

Validating the results of drought indicators is a challenging task. Since the impact of drought on subsistence societies is multi-layered (section 3), it is difficult to find single indicators that cover the entire effect. Although the Cuvelai-Basin is a data-scarce environment, central-northern Namibia offers a few options for validation. Data on agricultural yields are available from the Namibian Ministry for Agriculture, Water, and Forestry, in particular on millet and sorghum which constitute the staple food in the target area (MAWF, 2011, 2009, 2005). The ministry provides data for the period 1995 to 2010 with an explicit link to the conditions of central-northern Namibia. Other statistics exist like from FAOSTAT; however the data that these platforms provide are not unequivocally attributable to the Cuvelai-Basin, while the MAWF reports explicitly state the data origin. Therefore, this 16-year period of yield data is used to validate the results of the copula frequency analysis. Moreover, data on tap water consumption in rural villages of central-northern Namibia for the period 2000–2010 provided by the Namibian Water Cooperation (NamWATER) are used as a second option for validation (NamWater, 2014). The central idea behind this variable is that the population in the villages utilizes tap water as a major backup resource, meaning that if traditional water sources such as wells, open waters, and rainwater decline in quantity or quality, people switch to the tap network. Thus, if the rainy season is dry, water consumption from the network should increase.

5.4 Results

The study results are presented in the following four sub-sections. First, the temporal signal of the individual drought indicators and the resulting copula are shown. Second, the effect of threshold variation is presented using the SPEI indicator as an example. Third, the individual drought indicators are depicted spatially with special emphasis on frequency of occurrence, severity, and duration. Finally, the spatial configuration of the BDI is presented with its specific characteristics, followed by the temporal validation of the results using yield and water consumption data.

5.4.1 Temporal drought signal

Every drought indicator is initially calculated as a standardized index of the 6-months running average. Figure 20 presents the temporal signal of the individual drought indicators, averaged over the entire basin.

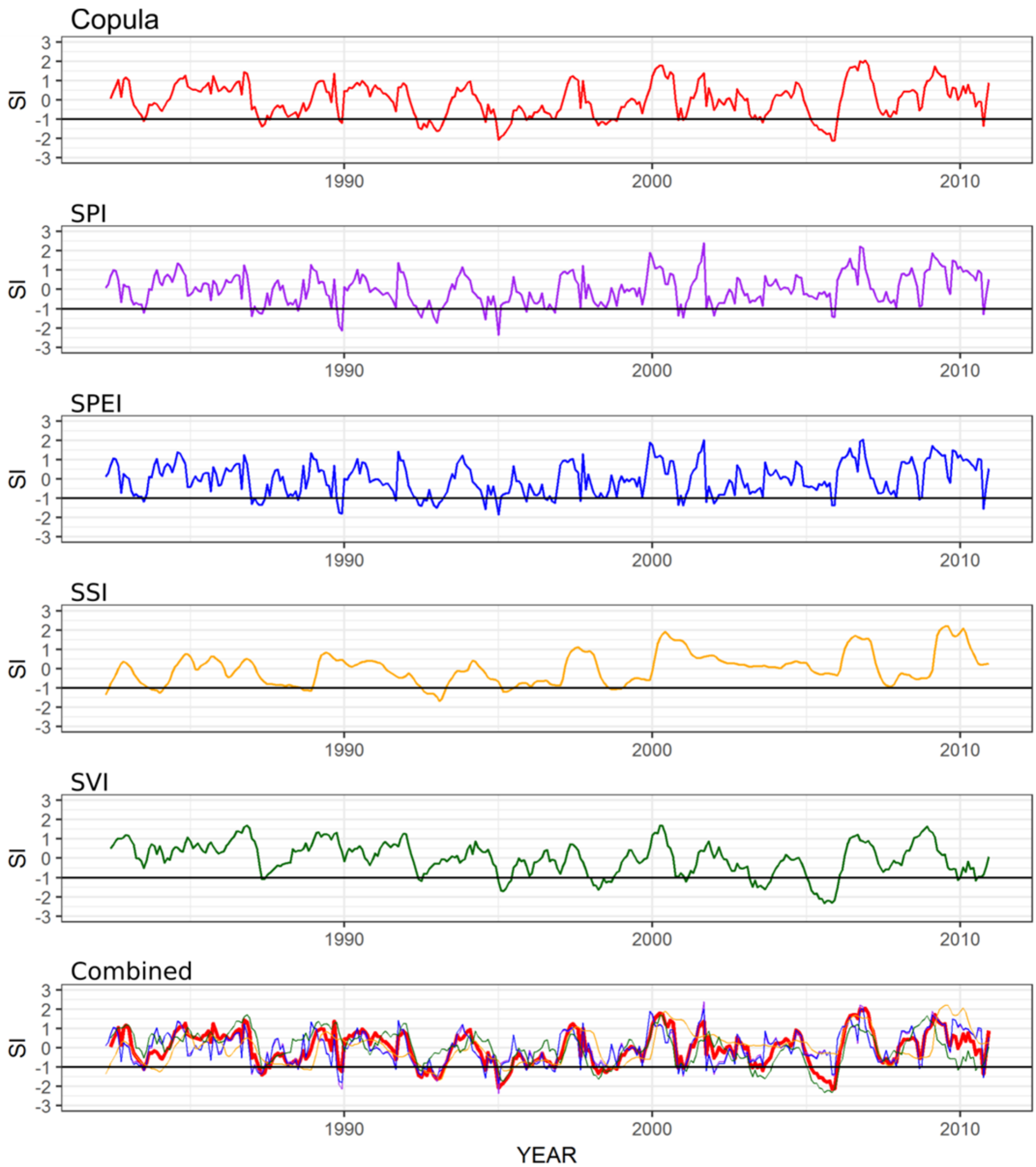

Figure 20: Drought indicators as standardized 6-months running averages of the entire basin.
The solid horizontal line indicates the threshold value of –1. SI = Standardized Index, SPI = Standardized Precipitation Index, SPEI = Standardized Precipitation Evapotranspiration Index, SSI = Standardized Soil Moisture Index, SVI = Standardized Vegetation Index.

In addition, the copula time series is plotted that incorporates the SPEI, SSI, and SVI. Since SPI and SPEI correlate strongly, the SPI was not incorporated into the copula. SPI and SPEI show almost an identical temporal signal, as confirmed by Vicente-Serrano et al. (2010) for regions with low inter-annual temperature variability. Solely, the extreme values of the SPI are surpassing the ones of the SPEI. Both indicators predict significant drought conditions between 1990 and 1995 and major wet periods between 2006 and 2010. The soil moisture-based SSI differs from the precipitation-based indicators. The data show less variation and only identify drought conditions in the 1980s and 1990s while after the year 2000, no droughts were recorded when considering the basin's mean. The vegetation conditions covered by the SVI show less variability compared to the precipitation-based indicators but still more than the SSI. It identifies drought conditions in the 1990s and mid-2000s with the most intense drought event in 2006. The resulting copula function incorporates characteristics of the individual indicators as can be seen in the lowest plot of Figure 20. The years 1995 and 2006 stand out as below –2 drought events. The recent years between 2006 and 2010 are rather wet, instead.

5.4.2 Threshold variation

Identifying a drought event necessitates the selection of an appropriate threshold value. Commonly, –1 is chosen to distinguish dry conditions from a real drought event. However, the spatial pattern strongly varies with the selection of this threshold. The spatial analyses presented hereafter are based on the evaluation of the time series of April values, as these are regarded to give the best estimation of drought conditions of the rainy season. Figure 21 exemplarily presents the results of the SPEI and shows the frequency of drought occurrence if different threshold values are considered. Herein, a mild drought is evident if the SPEI values range between 0 and –0.99, while extreme drought events are recorded if the SPEI shows values below –2.

The areas at risk of high drought frequencies vary strongly, with the southwest being the most affected region in terms of mild droughts, while the northwest in particular shows most extreme drought events. According to the Namibian National Drought Policy & Strategy, disaster droughts are declared in Namibia if the seasonal aggregates of a respective environmental parameter fall below the lowest 7% of the long-term average (Republic of Namibia, 1997). In the case of the SPEI, the threshold would then be set to –0.91 which is depicted on the right hand-side of Figure 21, highlighting the southeast as being the region of highest risk levels in terms of drought occurrence. For the purpose of consistency, this study applies the widely accepted –1 threshold value for further processing.

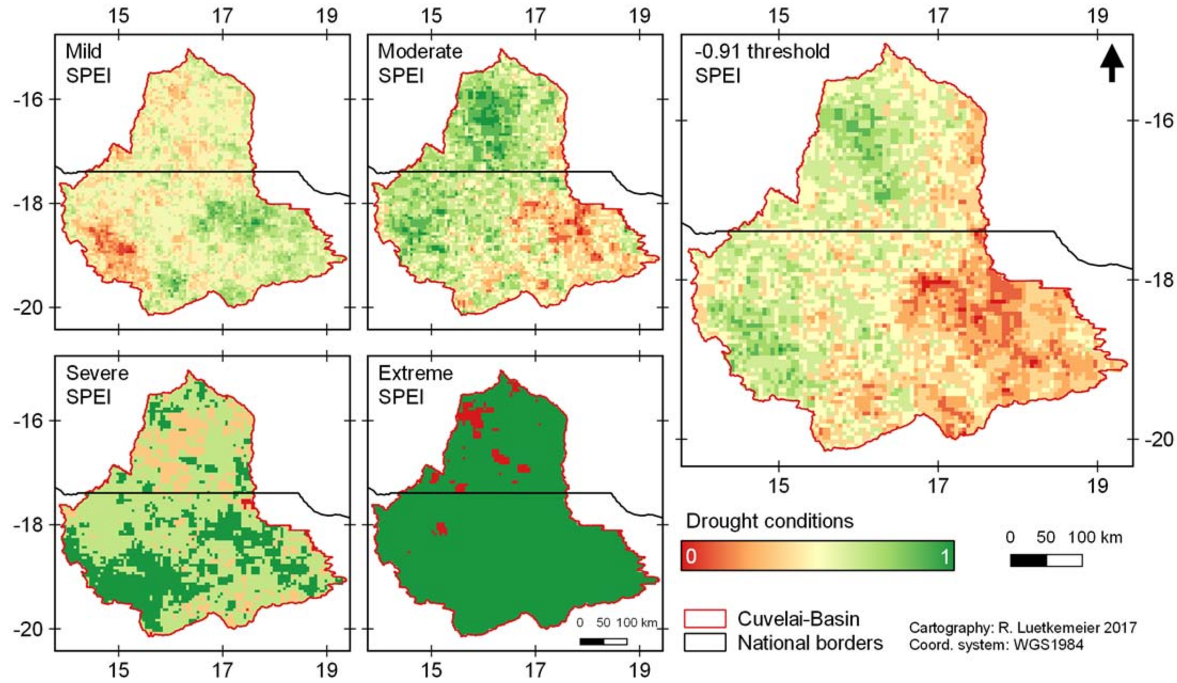

Figure 21: Drought index threshold variation for Cuvelai-Basin.
Maps show the frequency of drought occurrence on a normalized scale from 0 (often) to 1 (rare) depending on the drought threshold chosen. Exemplarily, the SPEI indicator was chosen for illustration. Mild (0 to –0.99), Moderate (–1 to –1.49), Severe (–1.5 to –1.99) and Extreme (<–2) droughts are distinguished from the official Namibian drought threshold based on the lowest 7% quantile.

5.4.3 Spatial drought hot-spots

The frequency of occurrence is not the only important parameter to determine a drought. In this study, two more dimensions are regarded as being important for an overall drought hazard assessment. Figure 22 presents the results of each drought indicator, broken down into frequency of occurrence, severity, and duration.

It becomes obvious that the three dimensions depict different spatial characteristics of each indicator. While the frequency of occurrence is often estimated to be highest in the southeast (SPI & SPEI) and southwest (SVI), drought severity shows different results with a stronger focus on the southwest and south. Drought duration likewise highlights different areas. Here, the central and north-western areas are threatened (SPI, SPEI, and SSI) and the northern part as well (SVI). Obviously, SPI and SPEI show similar patterns in all of the three dimensions, which is caused by the partly common database (CHIRPS 2.0). Due to their similarity, the SPI was excluded when applying the copula function to generate the BDI.

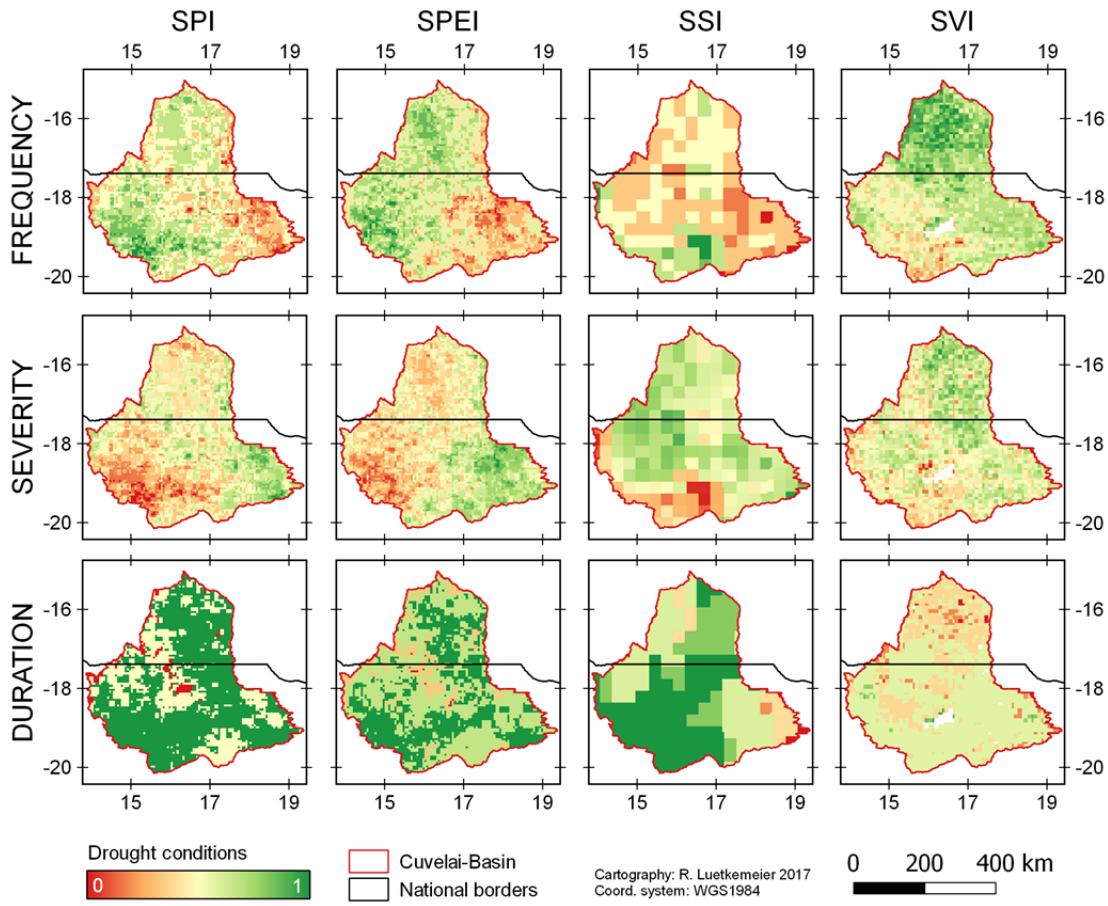

Figure 22: Drought indicator dimensions of frequency of occurrence, severity and duration.
The results are represented spatially on a normalized scale from 0 (unfavourable) to 1 (favourable). White pixels within the basin are the result of no-data-pixels from the initial NDVI vegetation dataset.

5.4.4 Blended Drought Index

To generate an integrated drought hazard map for the Cuvelai-Basin, the BDI was derived from the copula that builds upon the SPEI, SSI, and VCI time series. In accordance with the other drought indicators, the April-values are selected for drought impact analysis and spatial representation.

Since all of the three dimensions are relevant for an integrated drought hazard map and analysis, the final BDI is generated as the average of frequency, severity, and duration, equally weighted and normalized. The resulting map depicted in Figure 23 clearly shows important drought hot-spot areas in the centre, north of the Etosha Pan, and along the north-western watershed boundary near the Kunene River.

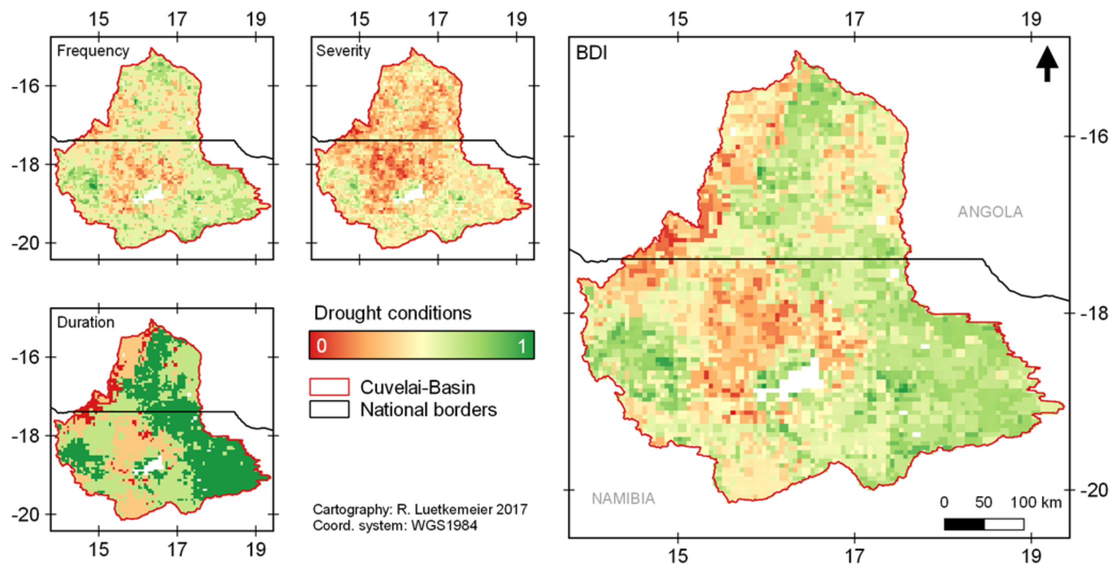

Figure 23: Spatial representation of the copula in the Cuvelai-Basin.
Beside frequency of occurrence, severity and duration, the BDI itself is presented as the average of the individual dimensions on a pixel-basis.

In order to evaluate the temporal drought signal of the copula, the frequency dimensions were averaged over the entire basin and compared to millet/sorghum yield and water consumption data from central-northern Namibia.

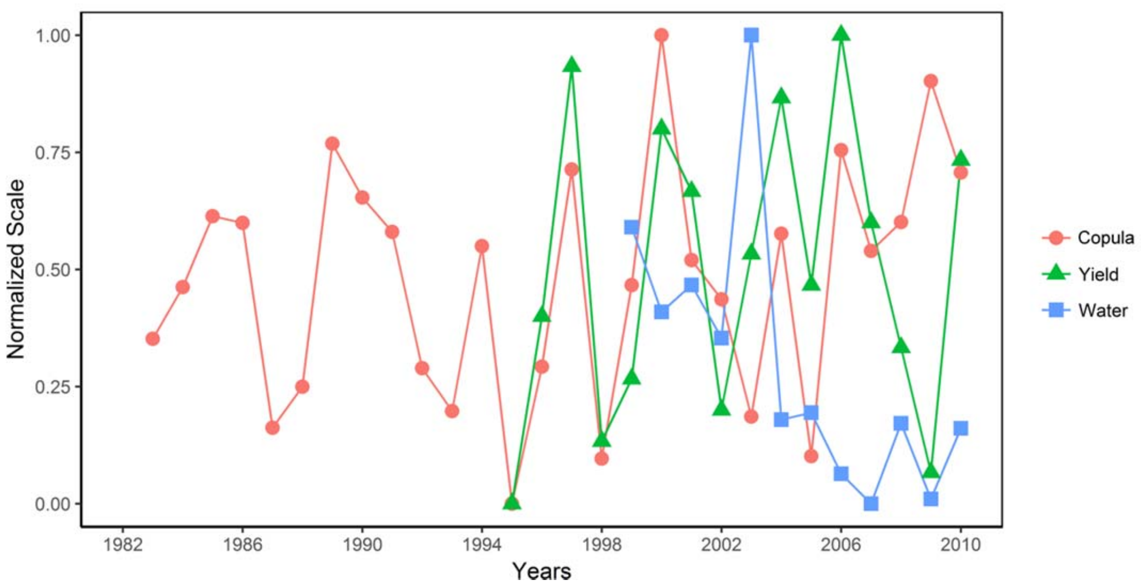

Figure 24: Temporal copula frequency signal in comparison with the validation datasets.
Validation data includes millet/sorghum yield and water consumption from central-northern Namibia. The time series were normalized from 0 (copula: unfavourable, yield: low, water consumption: low) to 1 (copula: favourable, yield: high, water consumption: high).

Figure 24 hence shows the normalized copula frequency values, with 1 indicating favourable and 0 unfavourable conditions in comparison with yield and water consumption. It becomes obvious that the yield data visually correlate well with the copula, except after the year 2006. The water consumption data should ideally work in an opposite direction according to the assumption that water consumption increases if drought conditions exist. From a visual interpretation, this is again true for most of the years except the period after 2006. This visual impression is confirmed by the correlation analysis. Table 8 presents the Pearson and Spearman correlation coefficients of the drought indicators, including the copula, as well as yield and water consumption. The overall positive correlation of the copula with yield and the overall negative correlation with water consumption are confirmed and outperform the other indicators, in particular when considering the yield data.

Table 8: Pearson and Spearman correlation matrix.
Correlations are depicted between the drought indicators, millet/sorghum yield, and rural water consumption in central-northern Namibia.

	Copula		SPI		SPEI		SSI		SVI	
	P	S	P	S	P	S	P	S	P	S
Copula										
SPI	*** 0.86	*** 0.87								
SPEI	*** 0.86	*** 0.87	*** 1.00	*** 1.00						
SSI	*** 0.77	*** 0.70	*** 0.63	** 0.54	*** 0.62	** 0.55				
SVI	*** 0.81	*** 0.78	** 0.50	** 0.56	** 0.51	** 0.56	* 0.35	* 0.36		
Yield	* 0.51	* 0.56	* 0.43	* 0.50	* 0.46	* 0.50	* 0.46	* 0.48	0.35	0.16
Water	–0.45	* –0.52	–0.45	–0.42	–0.45	–0.42	–0.31	–0.38	–0.30	–0.17

* $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$, P = Pearson-r, S = Spearman-r.

5.5 Discussion

The main target of this study is the development of a drought hazard map that depicts the multi-layered drought impact in the Cuvelai-Basin, as carved out in the exploratory research phase presented in section 3. For this purpose, multiple drought indicators that are commonly used individually as tools for drought analysis (SPI, SPEI, SSI, and VCI) (Mishra and Singh, 2011) were analysed and processed. However, their spatial manifestations, in particular the frequency of drought occurrences shows strongly diverging signals. Although each indicator is valid for a specific focus, it is difficult to decide which one to use for a drought hazard map in the current study area.

Against this background, the use of a copula function was chosen as a suitable technique to account for the multi-layered characteristics of droughts. Copula approaches to combine individual drought indicators became prominent in recent years and more importantly proved to reveal good results (e.g. AghaKouchak, 2015; Mishra and Singh, 2011). Hence, using a copula function in this study to link three individual drought indicators is regarded as an appropriate procedure for incorporating multiple drought effects into one single time series for further analysis. The copula-based BDI incorporates the characteristics of the underlying indicators and serves to analyse multiple dimensions, namely frequency of occurrence, severity, and duration which are common ways to describe the drought phenomenon (e.g. Spinoni et al., 2014). The resulting drought hazard map identifies hot-spot areas in the basin, in particular the area north of the Etosha pan and the north-western boundary of the basin, near the Kunene River. These areas are threatened by drought events since these landscapes are highly degraded due to population density and intensive, continuous (rather uncontrolled) grazing activities (Mendelsohn and Weber, 2011). These human impacts are reflected in the SSI and SVI indicators, highlighting the shortcomings of drought indicators that solely rely on precipitation as they miss respective signals. In this context not only can the frequency of occurrence and severity of droughts pose a problem but also consecutive (annual) droughts that result in recurring crop failures. With respect to this latter aspect, most indicators correlate well with the validation data of millet/sorghum yield and water consumption. The copula likewise reveals good results and outperforms the individual indicators. While the period from 1995 – 2006 shows a good correlation, the subsequent years are less well correlated. This might be attributed to extraordinary wet conditions, in particular flooding events that might have led to yield reductions as already assumed to impair the crop model results in section 4.4.3. Low water consumption from the tap network confirms this, assuming that the population was able to meet its water demand via traditional sources. These rather good correlations underpin the procedure applied in this study of considering the 6-months running mean April values as the rainy season's aggregate. Due to the SPI's and SPEI's sensitivity to low precipitation values in the dry season (Spinoni et al., 2014; Wu et al., 2007), this procedure was chosen and hence constitutes a rather new approach. Comparing these values reveals direct insights into the status of the rainy season and makes it comparable over the years.

With respect to the challenge of threshold setting, the indicator analyses show that, for instance in the case of the SPEI, drought estimates change if the threshold varies. The literature commonly sets the threshold to –1 (McKee et al., 1993), while other thresholds can also be used to delineate drought events. It is thus important to point out that using a certain threshold will have a pronounced impact on the study results. The importance of threshold values should not be understated since they are necessary for clearly identifying emergency situations with all necessary relief measures associated to this. Nevertheless, the appropriate threshold value must be selected for every location, individually.

Considering the selection and construction of drought indicators in this study, the following can be noted. First, the suitability of further indicators can be evaluated in future research for the study area. Promising indicators to capture the drought impact in terms of surface water availability for instance, may be the Surface Water Supply Index (SWSI) (Mizuochi et al., 2014; Shafer and Dezman, 1982). Second, while the precipitation data obtained from the CHIRPS product was found to be the most suitable product for the Cuvelai-Basin (section 4), the other environmental parameters would require an equally detailed analysis of their suitability. Similar differences are likely to be observable among other data products that provide information on evapotranspiration (e.g. Khan et al., 2018), soil moisture (e.g. Kumar et al., 2018; Wang and Qu, 2009) and vegetation (Tarnavsky et al., 2008), among others. Hence, future research on drought may consider a more in-depth analysis of quality aspects when using remote sensing products.

5.6 Conclusion

Drought is a recurring threat to sub-Saharan Africa and the Cuvelai-Basin in Namibia and Angola, in particular. The current research phase seeks to shed light on the drought hazard itself with a focus on its temporal and spatial characteristics that are of relevance for the functioning of the social-ecological provisioning system. Based on insights from the previous exploratory research phase, this study makes a contribution to characterizing the drought hazard in more detail. For this purpose, four commonly used drought indicators, the SPI, SPEI, SSI, and SVI (VCI) were used to construct a copula-based Blended Drought Index that captures the effects of meteorological and agricultural droughts. The BDI can be presented as an integrated drought hazard map to depict hot-spot areas that are particularly threatened by drought events. Herein, drought frequency, severity, and duration are merged into one single indicator.

The drought hazard map is one important part of a comprehensive drought risk assessment and the disaster management cycle (Vicente-Serrano et al., 2012). Hence, the results will enhance the decision basis for disaster preparation in both countries among the relevant stakeholders such as the Protecção Civil in Angola and the National Disaster Risk Management Committee in Namibia. This hazard perspective however, requires an extended view on the vulnerability of the population in order to gain a full understanding of drought risk. As most people practice subsistence agriculture and utilize traditional water sources which makes them highly sensitive to blue and green water scarcity, the following research phases presented in sections 6 and 7 will shed light on both the sensitivities of rural and urban households as well as their capacities to cope with drought. This study is hence one contribution to the Household Drought Risk Index.

6

Drought sensitivity

Seasonal water and food consumption patterns[9]

6.1 Abstract

The population in sub-Saharan Africa is regularly affected by droughts, such as those recently triggered by El Niño. Rural smallholders in semi-arid environments directly depend on local blue and green water flows and are hence at risk of drought, like in the transnational Cuvelai-Basin in southern Angola and northern Namibia.

This study builds upon local knowledge of seasonal water and food consumption patterns to estimate household drought sensitivity. An empirical survey was conducted with 461 households (i) to determine the reliability of water and food source types under dry conditions, (ii) to estimate consumption dependencies and (ii) to contribute to drought risk assessments.

The consumption patterns reveal differences in the reliability of source types. In particular, traditional types are used extensively during the rainy season, but become unavailable during the dry season. Households with a strong dependence on these types are particularly sensitive to drought. This is true for rural areas, notably in Angola where reliable water and food infrastructures are less available.

While the results feed into a holistic household drought risk assessment, the methodology can be implemented into conventional surveys to continuously monitor drought sensitivity conditions on the household level.

[9] This section was published as a modified version in the SASSCAL research book (Luetkemeier and Liehr, 2018).

6.2 Introduction

Droughts are a critical threat throughout sub-Saharan Africa (UNISDR, 2012). People who inhabit particular semi-arid environments adapted to the conditions centuries ago (Ehret, 2001). They developed adequate strategies to utilize the limited blue and green water resources (Falkenmark and Rockström, 2006; Freire-González et al., 2017) in an efficient way to meet their needs for domestic water and food consumption (Collier and Dercon, 2014; Diao et al., 2010). However, enhanced population growth, economic development and urbanization in conjunction with a changing climate and limited coping capacities (Thornton and Herrero, 2015) alter the way societies interact with their environment and create challenges not experienced in the past. Consequently, severe and prolonged droughts, such as those recently aggravated by El Niño (2015/2016) in large parts of sub-Saharan Africa (Baudoin et al., 2017; Smith and Ubilava, 2017), are occurring more frequently and have a stronger impact.

Droughts play a major role in the transnational Cuvelai-Basin in southern Angola and northern Namibia (section 5). The majority of the population is strongly connected to the hydro-climatic conditions to sustain their livelihoods, since subsistence agriculture and traditional water supply systems remain dominant (section 3). As commonly found in developing countries, food and water consumption follow complex patterns (Fiedler, 2013; Nauges and Whittington, 2008). Households utilize a broad range of source types (e.g. shallow wells and tap water, self-collected wild food and supermarkets), depending on determinants such as seasonal availability and quality aspects, infrastructural endowment and price as well as distance as found in the study area. Though this consumption strategy reduces the risk of individual source failures, the traditional food and water source types respond quickly to drought-induced blue and green water scarcity. As a result, households that strongly depend on unreliable sources are highly sensitive to drought events and suffer second-order effects if they are not able to switch to more reliable sources (section 3).

Methodologically, the assessment of household water demand in developing countries remains a challenge because of complex patterns and multiple influencing factors. Household surveys are a commonly used method to assess the water quantities withdrawn and the purposes water is used for (Dagnew, 2012; Gleick, 1996; Inocencio et al., 1999; Nauges and Whittington, 2008). Similarly, food consumption, especially nutritional content, is typically assessed via interviews. In these surveys, methods such as 24-h recall and observed-weighed food records are preferred but require larger assessment efforts (Fiedler, 2013). The Household Economy Approach (HEA) instead takes a pragmatic perspective and assesses the range and relative importance of food sources by converting available dietary energy into monetary terms (Seaman et al., 2014).

Conventional household surveys deliver less detailed information on water and food consumption since they neglect the underlying complexity by focusing on the main sources utilized (INE, 2016; NSA, 2013). Recently, Elliott et al. (2017) made a strong case for considering multiple water sources when assessing consumption patterns. They found that detailed assessments in this regard provide valuable information to determine the adaptive capacities of communities in the Pacific Island countries, particularly with respect to climate change adaptation (Elliott et al., 2017). This study takes up these methodological developments and expands the focus to include food consumption patterns as well.

The more in-depth consideration of water utilization in the Cuvelai-Basin is particularly relevant because of the increasing share of unsafe water sources in recent years. In the case of northern Namibia, the utilization of safe water sources (WHO and UNICEF, 2017) declined from 2001 to 2011, which is true for the northern regions of Ohangwena (78% to 56%), Oshikoto (88% to 70%), Oshana (93% to 84%) and Omusati (83% to 52%) (NSA, 2013). Research is needed to uncover the underlying complexity of consumption patterns. Conventional survey techniques that assess the main water and food source types are not suitable for this purpose and hide valuable seasonal and structural information.

Building on the qualitative insights into drought risk from the exploratory research phase (section 3), methodological opportunities and shortcomings and development challenges in Namibia and Angola, this study seeks to determine a household's sensitivity to drought by assessing seasonal water and food consumption patterns. This supports the integrated Household Drought Risk Index as a holistic drought risk assessment tool (section 7) and presents a transferable methodology to be included in conventional census survey techniques for continuous drought sensitivity monitoring. Specifically, this study develops and applies an empirical assessment tool to make contributions to:

1. Determine unreliable water and food source types under dry conditions,
2. identify households that strongly depend on unreliable water and food source types,
3. use those data to estimate drought sensitivities on the household level and thereby contribute to the household drought risk assessment and
4. present methodological advancements to improve conventional survey techniques.

The following sub-sections first introduce the conceptual approach of risk research. Subsequently, the key methodological techniques of the empirical survey are presented along the analytical steps to draw conclusions on source reliability and consumption dependence. The results provide insights into drought sensitivity estimates for the Angolan and the Namibian populations as well as people living in rural and urban settings. The discussion and the conclusion will reflect on the results with special emphasis on the method's potential to improve conventional survey techniques.

6.3 Material and methods

The following sections provide a brief description of the study's methodological setup. First, the conceptual approach is presented, in which drought sensitivity is incorporated into the concept of risk and vulnerability. Second, the design of the structured household survey is presented, followed by a description of the analytical procedure to analyse and process the data.

6.3.1 Conceptual approach

Droughts are regarded as a critical hazard in the study area. For the purpose of assessing the impact of the drought hazard on the livelihood of the local population, a holistic conceptual approach was adapted, in which risk is a function of hazard and vulnerability (section 2). While drought is regarded as the environmental hazard that can be characterized by frequency of occurrence, severity and duration (section 5), vulnerability is a function of the dimensions sensitivity and coping capacity that characterizes the ability of a household to handle a drought situation. Within this conceptual framing, this study specifically focuses on the sensitivity aspect to make a contribution to the integrated Household Drought Risk Index (section 7).

6.3.2 Structured household survey

The data requirements to populate the HDRI indicators (Figure 11), in particular the sensitivity and coping capacity dimensions cannot be met with existing primary information. Therefore, data for the respective indicators was collected via a structured household survey. The following sub-sections present the process of preparing and conducting the field work in both countries.

6.3.2.1 Questionnaire design and pre-test

The structured questionnaire (Annexes 2 & 3) was the primary tool to assess the required socio-economic information and was set up, based on (i) the indicators' data requirements, (ii) a desired overlap with census information to perform subsequent regression analysis (relevant for HDRI results, section 7) and (iii) time limitations for each interview. Overall, the questionnaire is composed of different assessment tools. Among standard questions on structural parameters (e.g. household size, age, gender) and descriptive aspects (e.g. housing quality, sanitation conditions, energy utilization), several questions assessed perspectives on e.g. drought impact and the relations to neighbors. As an important component, seasonal ranking schemes were included on water and food consumption patterns, among others, to characterize the sensitivity dimension. If possible, the questions were phrased in accordance with the recent census surveys in both countries to ensure comparability of results. Furthermore, several questionnaire items were cross-validated, using multiple, differently phrased questions for the same purpose. The initial questionnaire was pre-tested among 6 households in Oshikango constituency, close to the Angolan border. After the interviews were conducted, the respondents gave brief information on the understandability of the questions that served to update the entire questionnaire. The final version was translated from English (Annex 2) into Portuguese for application in Angola (Annex 3).

6.3.2.2 Sampling and field work

The total statistical population of about 350,000 comprises every single household located within the boundaries of the hydrological watershed of the Cuvelai-Basin at the time of the surveys (INE, 2016, p. 159; NSA, 2013, p. 16-20). Due to this high number, a sample of households was selected to carry out a structured household survey. Against the background of a maximum Relative Standard Error (RSE) of 0.1, as often envisaged in comparable demographic surveys (MEASURE DHS/ICF, 2012), a desired sample size of about 500 households was targeted. A multi-staged sampling methodology was identified as the most suitable tool. At the first stage, 10 administrative units all over the basin were selected (communes and constituencies) as indicated in Figure 25. Due to the fact that some administrative units only have a small population share, the Probability Proportional to Size (PPS) sampling method was applied. Herein, administrative units that show a higher number of households receive a higher probability of being included in the sample. Compared to a simple cluster sample design, the probability of each household to become part of the sample is more equal in the PPS scheme (Lavrakas, 2008). The PPS sampling methodology fulfills the requirements of a random sample design. At the second stage, villages were selected via expert consultations. Experts of the respective administrative units were supposed to pick two communities in their unit that are accessible within a few hours of 4x4 trips so that the community can be surveyed in a day including a return journey. At the third stage, households were selected by the interviewers via random walk methodology. After the survey team introduced themselves and the research purpose to the community headman or headwoman, the interviewers started their walk by picking every household in a certain direction. The interviewers were supposed to ask the household's head or his or her life partner. If a household was unavailable or refrained from answering, the interviewers proceeded to the next one. The aim was to survey all the households of the respective community.

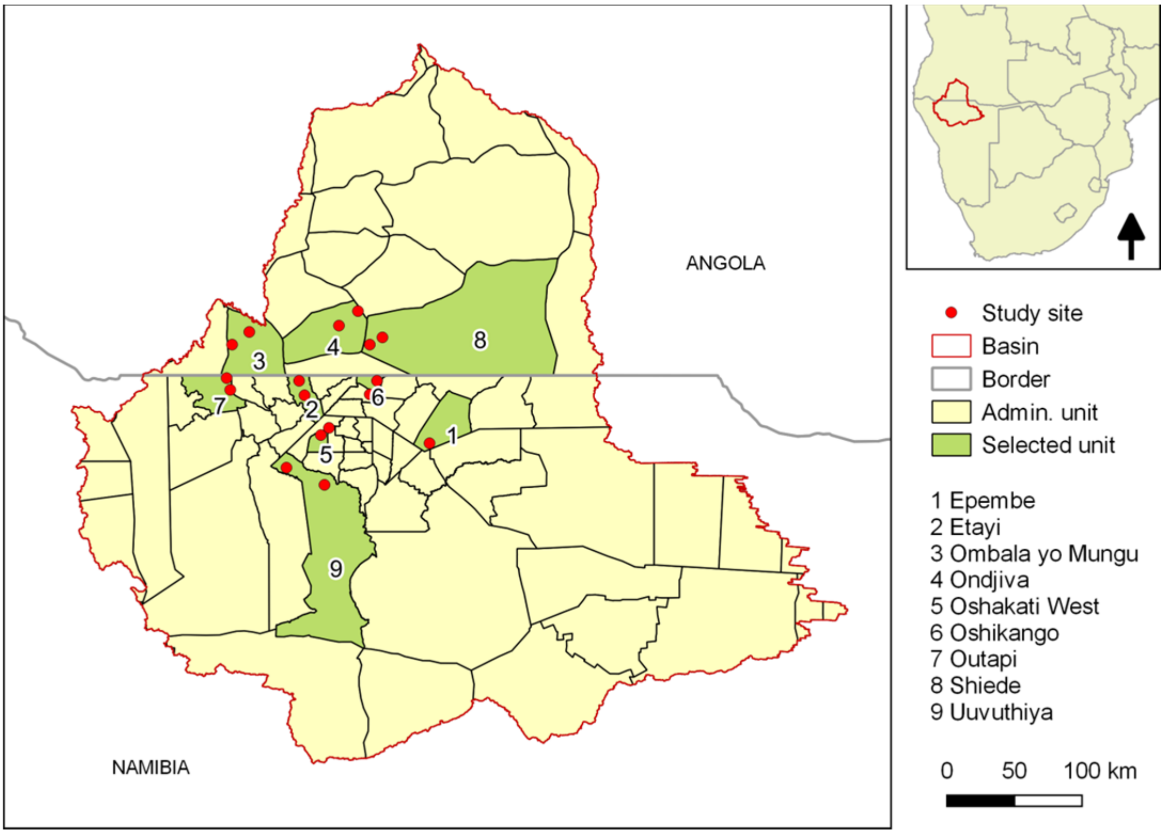

Figure 25: Cuvelai-Basin, indicating the locations of the structured household survey.
The study sites are indicated along with the 10 selected administrative units in Angola and Namibia.

6.3.2.3 Interviewer training and quality control

The household survey was conducted with the help of seven interviewers. Their employment was necessary due to (i) the envisaged sample size of about 500 households, (ii) limited travel costs and associated time constraints as well as (iii) language barriers, in particular for the rural population that rather speaks varieties of Oshiwambo in Namibia and/or Portuguese in Angola. Due to these reasons, interviewers were employed that could prove experience in the conduction of empirical surveys. In this regard, three Namibian university students, two female and one male, were chosen while in Angola, four official employees from the Protecção Civil in Ondjiva were employed. Both, the Namibian and the Angolan team were trained in a half-day session on the intention of the survey, the scientific background and the specific questions. For clarification, in-depth queries of the interviewers were dealt with and additional photo material was discussed to provide a precise understanding of key terms such as the range of water and food source types.

The entire household survey in both countries required a four-staged research permission procedure. On the first stage, research visa were acquired for both countries, while on the second level, official permit applications were addressed towards the regional (Namibia) and provincial (Angola) governments. As soon as these permits were granted, the respective lower levels of constituencies (Namibia) and communes (Angola) were approached in a similar way, according to the sample design. Before approaching the households individually, the headman/headwoman of every single community was approached by the entire interviewer team and the supervisor (author) to introduce the purpose of the survey and guarantee data privacy regulations.

6.3.3 Demand for water and food

The overall demand for water and food on the household level is regarded as essential for depicting the sensitivity to drought. Though the capacity to cope with drought situations is likely to be higher in a household with more members (e.g. more workforce), the challenge of acquiring adequate quantities of high-quality water and food is more acute than in a smaller household. Hence, larger households are regarded as being more sensitive to drought than smaller households. This assumption was incorporated by estimating the demand for water and food from the number, age and gender of the household members. While in the case of water consumption a nonlinear degressive relationship was assumed as domestic water consumption does not increase linearly with additional members (Arouna and Dabbert, 2009), food consumption per household member was adapted to the age- and gender-specific dietary energy requirements (Institute of Medicine, 2005).

6.3.4 Consumption quantities

Besides the water and food quantities that a household requires, it is important to characterize the predisposition of the household’s consumption patterns to drought. This predisposition is composed of two parameters, (i) relative water and food quantity withdrawn per source type and (ii) source type reliability. To assess data on both parameters, the pre-tested structured questionnaire served to assess the number and type of water and food sources a household utilizes as well as the relative quantities that are withdrawn from these source types (Figure 26).

11. Where does your household normally get food from in the rainy season? (Tick boxes)
12. If two or more food sources are used, please rank (R:) them according to the amount of food received.

	CATEGORY	SOURCES	CODE	RAINY SEASON		DRY SEASON
FOOD	Own production	Field / grain basket	[01]	☐ R:	13. Different in dry season? If yes, please fill in here →	☐ R:
		Garden / fruit trees	[02]	☐ R:		☐ R:
		Livestock (meat, milk, eggs)	[03]	☐ R:		☐ R:
		Self-collected wild food	[04]	☐ R:		☐ R:
		Self-caught fish	[05]	☐ R:		☐ R:
		Self-hunted bush meat	[06]	☐ R:		☐ R:
	Markets	Local market	[07]	☐ R:		☐ R:
		Supermarket	[08]	☐ R:		☐ R:
	Social network	Relatives	[09]	☐ R:		☐ R:
		Neighbors	[10]	☐ R:		☐ R:
	Donations	Church	[11]	☐ R:		☐ R:
		Government	[12]	☐ R:		☐ R:
	Other: ...		[13]	☐ R:		☐ R:
	Comments: ...					

1. Which water sources do you use for domestic purposes in the rainy season? (Tick boxes)
2. If two or more sources are used, please rank (R:) them according to the amount of water withdrawn.

	CATEGORY	SOURCES	CODE	RAINY SEASON		DRY SEASON
WATER (DOMESTIC)	Modern sources	Private tap	[01]	☐ R:	3. Different in dry season? If yes, please fill in here →	☐ R:
		Public tap	[02]	☐ R:		☐ R:
		Bottled water	[03]	☐ R:		☐ R:
		Borehole	[04]	☐ R:		☐ R:
		Water vendor	[05]	☐ R:		☐ R:
		Canal	[06]	☐ R:		☐ R:
		Improved deep well	[07]	☐ R:		☐ R:
	Traditional sources	Unimproved deep well	[08]	☐ R:		☐ R:
		Shallow well	[09]	☐ R:		☐ R:
		Earth dam	[10]	☐ R:		☐ R:
		Oshana/ Lake / Pan	[11]	☐ R:		☐ R:
		Rainwater	[12]	☐ R:		☐ R:
	Other: ...		[13]	☐ R:		☐ R:
	Comments: ...					

Figure 26: Seasonal ranking schemes as part of the household drought risk survey.
Upper plot assesses the food source types, while the lower plot assesses the water source types for domestic purposes.

As a first step, the household head or his/her partner was supposed to select the water and food source types they utilize in an average rainy and an average dry season. If the respondents mentioned more than one source type, they were asked subsequently to rank the selected source types according to the amount of water or food withdrawn. In this regard, higher quantities are withdrawn from a source type ranked 2nd than from a source type ranked 4th, for instance. This assessment and the evaluation of source types was conducted for the rainy and the dry seasons in order to uncover changes that serve as an indication of a source type's reliability under dry conditions. Both the water and food source types included a range of traditional and modern types that were assessed in a qualitative research phase (section 3) and the pre-test. The rankings constitute a household's expression of how much water and food are withdrawn from a specific source type during the dry and the rainy seasons to meet household demand. Thus, the responses are aggregated statements that incorporate a complex decision-making and evaluation process. Therein, influencing factors such as price, distance and quality aspects are already incorporated by the respondents, but this complexity is hidden in the ranking scheme.

While the assessment of absolute values for water and food quantities via questionnaires is time-consuming and prone to misinterpretations, the assigned rankings had to be transformed into relative estimates of water and food quantities. Herein, it was assumed that the source types mentioned meet 100% of the entire household demand and that the rankings provide insight into the relative quantities obtained. The formal transformation from ranks to relative quantities follows the equation

$$q_t = \frac{(R+1-r_t)^p}{\sum(R+1-r_t)^p} \tag{9}$$

where, q is the relative quantity of water or food assigned to source type t, R is the total number of ranks, r is the specific rank assigned to source type t and p is a weighting factor. The higher the value of p, the stronger the importance of higher ranks. In the current case, a p-value of 2 is assumed as a reasonable first approximation. This procedure transforms the ranks into relative quantities of water and food by assuming a non-linear relationship between the ranks.

6.3.5 Source type reliability

Now that each household provided information on how much water or food it withdraws from a particular source type, the patterns can be compared between the two seasons. If a difference between the seasons is apparent, conclusions can be drawn on the reliability of specific source types under dry conditions. As an example, a household might utilize three water source types in the rainy season: (1) shallow well, (2) improved deep well and (3) public tap. In the dry season however, the pattern might switch to (1) public tap and (2) improved deep well. The shallow well was abandoned because of either quantity or quality constraints while the public tap became the primary source type. From this seasonal consumption change it is possible to draw conclusions on reliability, assuming that during a drought period, dry-season conditions prevail and are even more intense. Hence, analysing the sample with regard to the average change in source type utilization offers the possibility of calculating a reliability benchmark for every single source type. This benchmark follows the equation

$$rl_t = nu_t * 2 + iu_t * 1 + pe_t * 0 + du_t * -1 + ab_t * -2 \quad (10),$$

where rl is the source type t's reliability under dry conditions and the remaining variables are the number of cases a source type was newly used (nu), was increasingly used (iu), persisted in utilization (pe), was decreasingly used (du) or was even abandoned (ab). The variables were weighted from 2 (high reliability) to -2 (low reliability) and then averaged over the entire sample and normalized according to eq. 12 (see next sub-section).

6.3.6 Drought sensitivity

Sensitivity to drought is defined in this study as a household's dependence on unreliable water and food sources. Formally, the following equation was used

$$s_i = \frac{p_{i,w}}{d_{i,w}} + \frac{p_{i,f}}{d_{i,f}} \quad (11),$$

where s is the household i's sensitivity to drought, d_w and d_f are the demands for water and food, while p_w and p_f are measures of consumption-based predisposition. This predisposition is the product of the relative water and food quantities consumed (q_t, eq. 9) and the source-specific reliability levels (rl_t, eq. 10). The resulting sensitivity s was normalized on a scale from 0 (high sensitivity, unfavourable) to 1 (low sensitivity, favourable) using a min-max normalization technique according to the equation

$$s\_norm_i = \frac{s_i - s_{min}}{s_{max} - s_{min}} \quad (12),$$

with s_norm_i being the normalized drought sensitivity of household i, s_i as the current household's sensitivity level, s_{min} and s_{max} for the minimum and maximum values within the entire sample.

6.4 Results

The results section will first present the seasonal consumption patterns and subsequently show the reliability levels of the individual water and food source types. Third, the drought sensitivity estimates are given, grouped according to certain socio-economic characteristics.

6.4.1 Seasonal consumption patterns

The households provided information on the number and types of food and water sources they utilize during an average rainy and dry season and indicated the relative quantities they withdraw. Figure 27 provides an overview of the shares of households that utilize specific water source types on a seasonal basis.

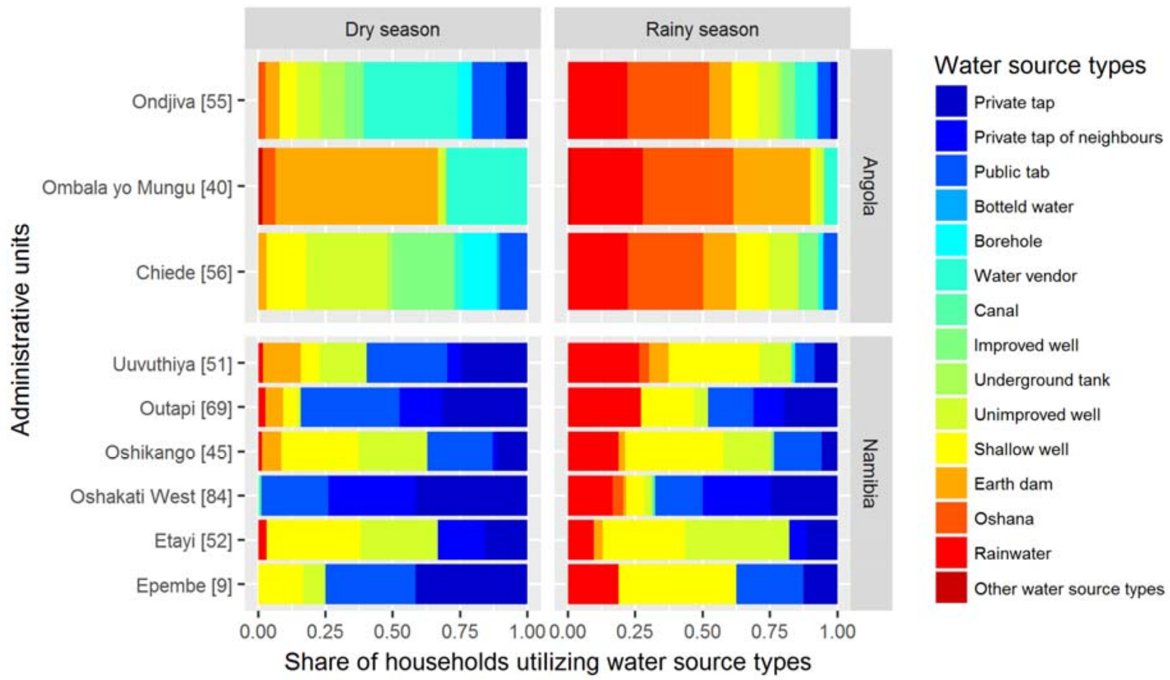

Figure 27: Relative utilization of water source types in the dry and the rainy season.
Values in brackets behind names of administrative units indicate the sample size.

Modern water source types such as tap water and purchased water from vendors are used more intensively during the dry season, whereas the rainy season shows a higher utilization of traditional, free source types such as earth dams, shallow wells and rainwater that make use of local blue water resources. This seasonal change between the water sources types is statistically significant ($p < 0.05$). The urban agglomerations in Namibia (Oshakati and Outapi) show higher proportions of tap water utilization in both seasons compared to rural Namibian areas. Furthermore, the data show that the Angolan population does not use tap water, except in major urban agglomeration such as Ondjiva. This confirms the limited access people have to tap water, as the infrastructural endowment of the area is weaker than in Namibia. Instead, water vendors are a more common institution in Angola that often takes over the role of the public water supply but at higher costs.

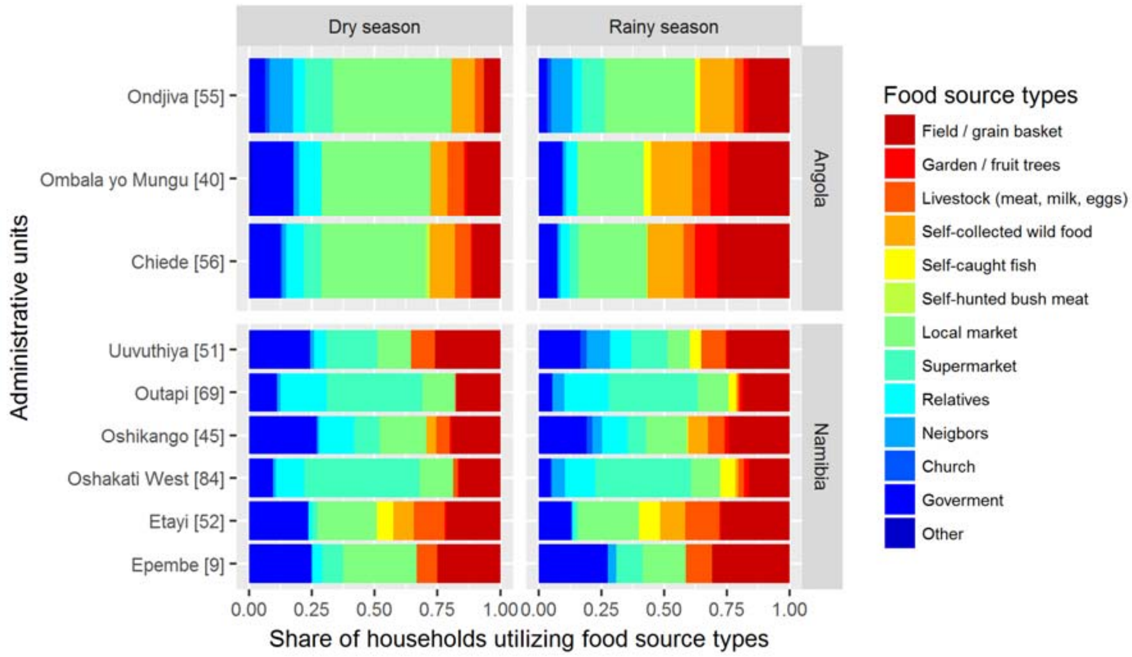

Figure 28: Relative utilization of food source types in the dry and the rainy season.
Values in brackets behind names of administrative units indicate the sample size.

With regard to the utilization of specific food source types, Figure 28 shows that the change between rainy and dry season is less pronounced compared to the water consumption. Nevertheless, changes are evident particularly in Angola, with subsistence food products from own grain farming and livestock being important during the rainy season, while under dry conditions, local markets and governmental relief gain importance. The latter source type also plays an important role for Namibian households, for instance providing food to around 25% of the sampled households in Uuvuthiya, Oshikango, Etayi and Epembe constituencies. Thus, for many people, relief food items are essential to complement their diets even during the rainy season before the first harvests are brought in. Overall, nearly half of the households food demand in rural areas is covered via neighbours, relatives, supermarkets and local markets. In urban areas, this share increases but still, subsistence food products play a supplementary role that stem from the extended family network into the villages.

6.4.2 Source type reliability

Shifting the focus from the administrative units to the water and food source types and their reliabilities under dry conditions, Figure 29 illustrates the seasonal changes in utilization.

The coloured categories indicate whether a specific source type gained or lost importance from the rainy to the dry season. In other words, the categories reveal whether a specific source type (i) was newly used in the dry season, (ii) was increasingly used, (iii) persisted in utilization, (iv) was decreasingly used, or even (v) was abandoned. If the last case appeared, the specific source type was not available anymore because of either quality or quantity constraints.

With respect to the water source types, the tap water sources show increased utilization while the traditional source types such as Iishana (surface water) and rainwater are abandoned in the dry season. With regard to food, the subsistence food sources such as households' own agricultural activities decline in utilization during the dry season while types such as local markets and supermarkets as well as governmental relief gain importance. This visual impression is confirmed by quantifying the reliability of the source types. Table 9 presents the results on a normalized scale from 0 (less reliable) to 1 (more reliable).

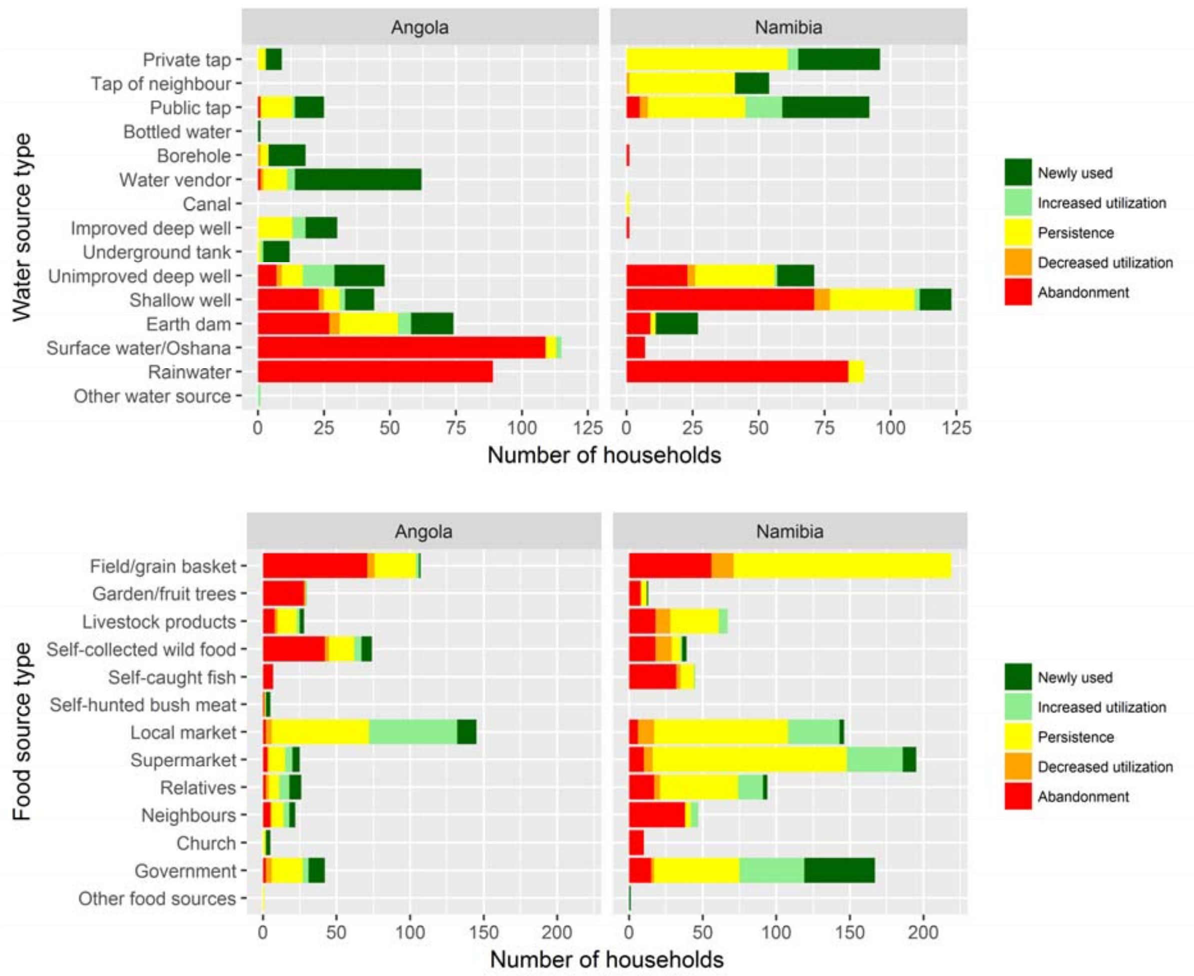

Figure 29: Seasonal change of water and food source type utilization.
The coloured categories indicate changes in utilization from the rainy to the dry season.

Though the results of some source types such as *Canal* and *Self-hunted bush meat* have to be interpreted with caution since they are based on only a few cases, the overall ranking seems reasonable. As such, the most reliable water source types appear to be water vendors, the tap water sources as well as boreholes and deep wells that make use of groundwater that is less prone to drought conditions. Similarly, the most reliable food source types are governmental relief, market infrastructures and relatives who provide food in the case of emergencies.

Table 9: Reliability levels of water and food source types (0: less reliable, 1: more reliable).

Water source types	Reliability	Food source types	Reliability
Water vendor	1.00	Government	1.00
Public tap	0.98	Local market	0.92
Private tap	0.97	Supermarket	0.78
Tap of neighbour	0.84	Relatives	0.69
Borehole	0.84	Self-hunted bush meat	0.69
Improved deep well	0.84	Other food sources	0.69
Underground tank	0.83	Church	0.65
Unimproved deep well	0.81	Livestock products	0.56
Bottled water	0.79	Garden/fruit trees	0.51
Canal	0.78	Neighbours	0.51
Earth dam	0.77	Self-caught fish	0.48
Other water sources	0.76	Self-collected wild food	0.41
Shallow well	0.45	Field/grain basket	0.00
Surface water/Oshana	0.26		
Rainwater	0.00		

6.4.3 Drought sensitivity

From the findings above, drought sensitivity estimates can be calculated for every household by combining the specific source reliability benchmarks with the estimated quantities of a household's demand. Figure 30 illustrates the distribution of drought sensitivity scores in the sample, grouped according to rural and urban as well as Namibian and Angolan households.

It becomes obvious that rural households are more sensitive to drought events than urban citizens as the histograms are rather skewed to low sensitivity values. Though Namibian rural households show a similar range of sensitivity values as their Angolan neighbours, they score better when considering their median, giving a hint to better infrastructural endowment of the Namibian area. By focusing on the urban households, the differences become more apparent. While the Namibian urban households show the best sensitivity scores (values close to 1), their Angolan counterparts give a more heterogeneous picture. This is particularly driven by urban agglomerations in Angola that are less well equipped as only Ondjiva, as the main town in the Cunene Province, shows good infrastructural settings.

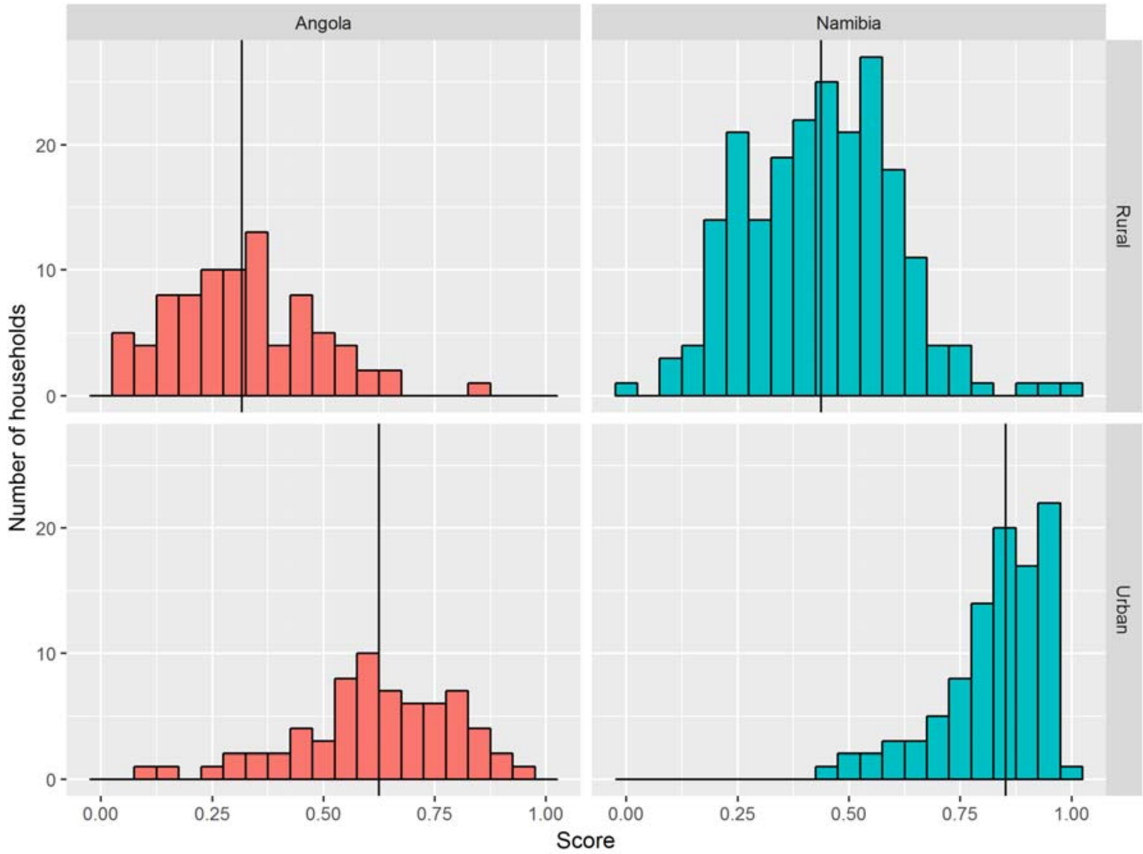

Figure 30: Histograms of drought sensitivity estimates.
Data is grouped according to settlement pattern and citizenship, while the black vertical line indicates the median sensitivity score for the respective groups.

6.5 Discussion

The study results reveal empirical evidence for complex water and food consumption patterns in the Cuvelai-Basin. The population utilizes a wide range of source types and responds to dry conditions by switching the sources structurally (multiple sources simultaneously) and temporally (different sources in the dry and the rainy seasons). This mechanism is an expression of a self-regulated social-ecological system to alleviate the potential impact of drought (section 3.5.1). The risk of failure is mitigated by utilizing a broad range of source types that have varying levels of reliability under dry conditions. While this aspect is assumed for developing countries, empirical surveys that confirm this complexity are lacking (e.g. Elliott et al., 2017). This study provides a reasonable household sample size to analyse seasonal consumption patterns in order to gain insights into the way households act during the course of a year under rainy and dry conditions. This complexity in consumption patterns is often overlooked, in particular in larger scale assessments such as census surveys where only the main water and food sources are assessed (INE, 2016; NSA, 2013). These surveys hide the underlying complexity and thus prevent more in-depth analyses. The overall methodology is quick and simple to carry out. Hence, if this ranking scheme procedure will be incorporated into conventional household surveys such as regular census assessment (NSA, 2011), continuous monitoring of key parameters for drought sensitivity would be made possible. Two major tasks for future research in this field require priority: First, the temporal resolution of the empirical assessment may be increased to quarterly or even monthly time steps with adequate questionnaire tools, i.e. by combining the ranking scheme with seasonal calendar techniques that are well-known in food security assessments. Second, the drought sensitivity scores need to be validated, i.e. via household surveys during pronounced drought periods using conventional food security and nutrition surveys (Dagnew, 2012; Fiedler, 2013).

The estimates on water and food source type reliability that stem from the seasonal changes seem reasonable against the background of conventional classification systems (WHO and UNICEF, 2017). In terms of water quality constraints, this perspective is supported by laboratory tests on organic and inorganic contaminations of traditional wells (Wanke et al., 2014). Traditional types that make use of local green and blue water flows are less reliable, since many households reduce the level of utilization or even abandon them during the dry season. Modern infrastructural types such as tap water and water vendors as well as local markets and supermarkets are often used when traditional types fail under dry conditions. The estimates presented on the sources' reliabilities solely stem from a socio-empirical survey that builds upon local and native knowledge on environmental conditions. This technique can help to support and complement the assessment of water resources from a hydro-geological perspective (Wanke et al., 2018).

The sensitivity scores show that rural Angolan households are most sensitive to drought. This is a reasonable result, as the rural population does only have limited access to modern water and food infrastructures (Mendelsohn and Weber, 2011). Nevertheless, it is interesting to see that urban inhabitants are also closely connected to drought conditions, in particular with regard to consumed food items that are obtained from family members living in the villages. This link between urban and rural food systems is currently largely ignored in research and practice (Crush and Caesar, 2017) and would have been hidden if only the main food source was explored in the current study.

6.6 Conclusion

The study results show that reliable water and food infrastructures serve as an important backup resource, if traditional, free sources fail. While the Namibian households show improved access to respective backup resources, their Angolan neighbours are less well equipped and hence require more investments into infrastructural development. Specifically, the extension of the tap water network in Angola is an important step to reduce the rural population's sensitivity to drought. Community-based approaches to provide tap water to rural villages can be a feasible solution and may serve as a blueprint (Schnegg and Bollig, 2016). Nevertheless, experiences gained in Namibia require a critical reflection of the suitability of top-down approaches when implementing new, rather unknown institutional setups in local communities (Hossain and Helao, 2008; Polak, 2014; Werner, 2007). Besides these centralized, infrastructural solutions, decentralized options exist. In this regard, local blue water buffers need to be strengthened, e.g. via the support of rain and flood water harvesting techniques (RFWH) that capture water during the rainy season and store it for later use. Promising experiences were already gained, especially when combining these technologies with small-scale irrigation and gardening activities that also enhance the green water buffers (Kluge et al., 2008; Woltersdorf et al., 2014). This supports local nutrition and generates income opportunities. In this regard, improved market access to sell and purchase food items is required (Barrett, 2008; Ferris et al., 2014). Market systems need to be supported and established in remote areas and people need to be enabled to get access for purchasing food if necessary, e.g. via grant or subsidy systems. In Namibia, pension money is an important source of monetary means particularly for elderly people, enabling them to acquire food and water. Since many households rely on subsistence grain framing, the improvement of pre and post-harvest management via upgraded production techniques and enhanced grain storage facilities improve people's ability to sustain the dry season and drought events, particularly (e.g. Collier and Dercon, 2014).

Overall, the results on drought sensitivity will be taken up by the sub-sequent section to combine them with quantitative insights on the drought hazard (section 5) and people's coping capacities. As a result, the Household Drought Risk Index will be populated to enhance the decision-basis of local institutional stakeholders and improve short-term emergency responses and design targeted adaptation measures for drought policies and strategies (Republic of Namibia, 1997).

7

Household drought risk

A social-ecological assessment[10]

7.1 Abstract

Droughts threaten many regions worldwide, in particular semi-arid environments of sub-Saharan Africa such as the Cuvelai-Basin, where the population depends on critical water-related ecosystem services. Since droughts are multi-layered phenomena, risk assessment tools are required that capture the societal relations to nature and identify those who are most threatened. This study presents the integrated Household Drought Risk Index that builds upon empirical data from the study area to provide insights into hazard and vulnerability conditions of households in different socio-economic and environmental settings. The HDRI integrates environmental measures of drought hazard (frequency, severity, duration) and the vulnerability of households (sensitivity, coping capacity) obtained from a structured survey (n = 461). The results reveal that the Angolan population shows higher levels of risk, particularly caused by less developed infrastructural systems, weaker institutional capabilities and less coping capacities. Overall, urban inhabitants follow less drought-sensitive livelihood strategies, but are still connected to drought conditions in rural areas due to family relations with obligations and benefits. The study results provide knowledge for decision-makers to respond to drought in the short- and long-term. The latter may build upon the extension of centralized and decentralized water and food supply/production systems as well as the support of households via targeted educational and community-building measures. Specific HDRI components may be included in census surveys to receive continuous drought risk data.

[10] This section is under review as a modified version in the Journal of Natural Resources and Development (Luetkemeier and Liehr, under review).

7.2 Introduction

Drought events threaten many regions worldwide in both developed and developing countries (Spinoni et al., 2014). Particularly, sub-Saharan Africa is at risk since 70% of the population lives in rural settings (IAASTD, 2009, p. 22) and is hence strongly dependent on water-related ecosystem services to ensure water and food security. Water scarce periods, as recently triggered by El Niño (Archer et al., 2017; Baudoin et al., 2017), impair the ecosystems' ability to provide fundamental services to the society which results in impaired human well-being (Hoffman and Todd, 2013) and a precarious situation of poverty persistence and humanitarian disasters (Gautam, 2006). As droughts are multi-layered and slowly creeping phenomena (Kallis, 2008; Mishra and Singh, 2010) that impact on both the environment and the society in a multitude of ways, risk assessment tools are required that capture the complex relations between the social and ecological domains (Van Loon et al., 2016; Vicente-Serrano et al., 2012, section 2.2).

The Cuvelai-Basin in northern Namibia and southern Angola was chosen as a case study to conduct the social-ecological drought risk assessment (section 2.2), since extensive insights into qualitative and quantitative aspects of drought impacts were gained in the previous research phases. As a semi-arid environment with a population that mainly practices subsistence agriculture of rain-fed grain farming and livestock herding (Mendelsohn et al., 2013), the basin can be regarded as representative for many regions in sub-Saharan Africa. It is periodically dealing with droughts that challenge the population and regularly result in food and water insecure conditions (FAO, 2016). Governmental and non-governmental short- and long term relief measures are frequently required for large proportions of the population (FEWS-NET, 2013; UN-OCHA, 2013; UN-ORC, 2013). It is essential in this regard, to understand the causes and consequences of drought events, how these impact on society directly and indirectly via the environment. Decision-making requires adequate instruments to identify those people who are most at risk (DDRM, 2013) by following an integrative approach, since solely environmental assessments neglect the role of societal capacities on the one hand and approaches that exclusively focus on societal actors neglect the fundamental role of environmental conditions, on the other hand. Recently, the African member states of the United Nations Convention to Combat Desertification (UNCCD) compiled the Windhoek Declaration and highlighted to "[*reduce] underlying factors of drought risk*" and carry out "[*d]rought vulnerability and impact assessments*" to enhance the resilience of African states to drought events (UNCCD, 2016, p. 1).

The scholarly discourse in the field of risk and vulnerability research shows a pronounced shift towards integrated approaches during the past decades (Adger, 2006; Birkmann, 2006; Cutter, 1996; Liverman, 1990; Wisner et al., 2003). On the one hand, risk-hazard approaches focus on the environmental parameters of an event, assuming that all valued objects in the vicinity of this event are particularly threatened. On the other hand, earlier vulnerability studies took a constructivist position, assuming that all disasters primarily occur as a result of negative pre-dispositions of the affected society (Cutter, 1996; Liverman, 1990). This original differentiation between natural and social science perspectives on disaster risks and hazard as well as vulnerability in particular was weakened in favour of combined perspectives in which both schools of thought are regarded as indispensable components. Though, the Intergovernmental Panel on Climate Change defined disaster risk as a product of hazard, exposure and vulnerability, rather recently (Cardona et al., 2012), the basic idea of combining parameters of societal vulnerability and environmental hazards can already be traced back to earlier studies. Therein, the vulnerability concept encompassed the physical hazard component and was frequently defined as a function of hazard, sensitivity and coping or adaptive capacity (Adger, 2006; Birkmann, 2006; Young et al., 2006; Wisner et al., 2003). This study basically follows the aforementioned IPCC definition of risk by assuming that household drought risk can be understood as a function of hazard and vulnerability (section 2.1.3).

In the target area of this study, the Cuvelai-Basin, drought as a spatio-temporal water scarcity situation was already assessed from an environmental perspective. The Blended Drought Index was developed to depict the hazard perspective of drought risk and incorporates precipitation, evapotranspiration, soil moisture and vegetation conditions to represent a drought's impact on water and food resources in the basin (section 5). To guarantee an integrated drought risk assessment however, information on the population's vulnerability had to be collected and combined with the BDI-results. This study builds upon previous research from the study area, in particular a qualitative exploratory study on drought risk and vulnerability (section 3) and measures of household drought sensitivity (section 6). These provide valuable insights into specific components of drought risk and are thus taken up and combined with quantitative measures of coping capacity to populate the composite indicator, the Household Drought Risk Index. The study hence seeks to contribute to the challenges identified in the Windhoek Declaration and to enable the population, administrative bodies and non-governmental organizations to design and carry out efficient short-term emergency responses and long-term adaptation strategies.

The section is organized as follows: The first sub-section briefly describes the material and methods used for data assessment and analysis as well as the HDRI construction. The second one introduces descriptive statistics on the assessed data, followed by the hazard and vulnerability results, acknowledging for uncertainty effects due to weighting schemes in the aggregation process. The sub-section is finalized by a regression analysis to transfer the HDRI sample results to the spatial scale of the Cuvelai-Basin. Third, the sub-section critically reflects upon the results and the methodology of constructing and populating the composite indicator. Finally, the transferability of the approach is discussed against the background of the Water-Energy-Food Nexus debate.

7.3 Material and methods

This section serves three major purposes. First, the construction of the HDRI and the selection of variables and indicators are outlined against the background of data availability and research project constraints. Second, the primary assessment tool of the socio-economic data, the structured household questionnaire, is presented in detail. Third, the statistical analysis and data processing techniques are described.

7.3.1 Composite indicator

This study adapts a risk definition that incorporates measures of hazard and vulnerability. This conceptualization was already operationalized by a number of studies that specifically addressed the challenge of assessing drought risk and drought vulnerability by constructing quantitative tools that mainly build on a certain set of indicators. In this regard, Plummer et al. (2012) conducted a systematic review on water vulnerability assessment tools as preparation of a project that attempted to investigate water vulnerability of three indigenous communities in Canada (Plummer et al., 2012). They found 55 studies that consider vulnerability from an integrative perspective and derive 50 different ways to define water vulnerability in terms of instruments, indices and collections of indicators. Thus, heterogeneity of available approaches is still high and confusing.

Shiau & Hsiao (2012) apply an index-based approach to quantify drought risk based on the assessment of hazard, exposure and vulnerability (Shiau and Hsiao, 2012). They utilize one indicator for each of the three dimensions and apply them to the municipal scale in Taiwan. Each indicator is rescaled to a value between 0 and 1 and subsequently combined to generate the Drought Risk Index. Shahid & Behrawan (2008) develop another drought risk index that determines risk as the product of hazard and vulnerability (Shahid and Behrawan, 2008). They describe the drought hazard in terms of spatial extent, severity and frequency by calculating the Standardized Precipitation Index. Drought vulnerability (DVI) is captured as an index composed of seven socio-economic and physical/infrastructural indicators. The combined DRI gives insights into the spatial distribution of drought risk on the district level in western Bangladesh. Pandey et al. (2010) create a spatially explicit drought vulnerability index by combining seven indicators (including water utilization) to quantify the vulnerability to drought in Madhya Pradesh, India (Pandey et al., 2010). They construct a map and verify their estimations by conducting a two months survey. Unfortunately, they give no information on how residents have been asked for their "real vulnerability" to drought which was the benchmark to verify their model results. Babel et al. (2011) develop a more balanced representation of vulnerability by creating a vulnerability index composed of a Water Stress Index and an Adaptive Capacity Index (Babel et al., 2011). The sub-indices consist of eight parameters that create the overall vulnerability index after weighting. They apply their model to the Bagmati River Basin in the Kathmandu valley, Nepal. By comparing different time steps (1991 & 2001) the authors uncover that although the water stress level increased, the level of vulnerability did not change significantly due to the simultaneous enhancement of adaptive capacity. Sullivan (2002) developed the Water Poverty Index, where five key components describe the water scarcity situation and contribute to set priorities of water management and planning as well as monitoring (Sullivan, 2002). Later, Sullivan (2011) combines the Water System Vulnerability (supply side) and Water User Vulnerability (demand side) and creates an integrated Water Vulnerability Index (WVI) (Sullivan, 2011). She applies the index to the South African part of the Orange River Basin and compares the municipalities in their total water vulnerability. Brown et al. (2016) define drought vulnerability as a function of exposure, sensitivity and adaptive capacity within a socioecological framework. They use indicators from the socio-economic and environmental domain to assess drought vulnerability in a rangeland system of New Mexico, USA (Brown et al., 2016). On a larger scale that considers the entire African continent, Naumann et al. (2014) explore drought vulnerability on the country level and combine 17 variables from natural resources, economics, human resources, infrastructure and technology to create a composite indicator (Naumann et al., 2014a). They use readily available data from national and international databases and apply different weighting schemes to explore the uncertainty in the drought vulnerability scores. Similarly, Carrão et al. (2016) collect and combine a range of indicators from the economic, social and infrastructural domains to assess drought risk on the national and sub-national scale (Carrão et al., 2016). Among other things, they find that drought vulnerability is strong on the African continent but the resulting drought risk is smaller compared to Central Asia, when taking into account the hazard component. Overall, Fang et al. (2016) provide a comprehensive review of household vulnerability studies (Fang et al., 2016).

The approaches described above can all be attributed to an integrative perspective on vulnerability and risk, as each study includes some kind of biophysical and social variables. One key problem however, remains, in particular for those studies that are conducted on larger scales. The indicator sets often lack adequate foundation as local legitimacy is not assessed. Plummer et al. (2012) uncover that 40% of all the instruments included in their review do not build upon empirical data (e.g. household surveys) but are rather purely conceptual in nature. This challenges the reliability of a large number of approaches and again highlights the importance of exploring the research topic in the respective area of interest, as conducted in the current study (section 3).

7.3.2 HDRI construction

The HDRI dimensions of hazard, sensitivity and coping capacity are operationalized with a set of indicators that were found to be relevant to determine household drought risk in the Cuvelai-Basin (section 3).

Table 10: Construction of the Household Drought Risk Index.
The table depicts variables, indicators and dimensions as well as the sources, data are obtained from.

Dimension	Indicator	Variable	Source
Hazard	IND1: Frequency IND2: Severity IND3: Duration	BDI: SPEI*, SSI**, SVI***	Section 5
Sensitivity	IND4: Water and food demand	Household size Age, gender composition	Household survey
	IND5: Water source dependence	Source type reliability Source utilization	Household survey
	IND 6 Food source dependence	Source type reliability Source utilization	Household survey
Coping Capacity	IND 7: Infrastructural endowment	Distance to road network Distance to tap water	OpenStreetMap (OSM, 2015a, 2015b) (Mendelsohn and Weber, 2011)
	IND8: Institutional endowment	Distance to centres Population density	(Mendelsohn and Weber, 2011) Census data (INE, 2016; NSA, 2013)
	IND9: Social capital	Neighbourhood Relatives	Household survey
	IND10: Human capital	Education Workforce	Household survey
	IND11: Financial capital	Income Expenditure	Household survey
	IND12: Physical capital	Assets Housing quality	Household survey
	IND13: Natural capital	Livestock Property	Household survey Digital Globe 2015 (Google, 2015)

*SPEI: Standardized Precipitation Evapotranspiration Index, **SSI: Standardized Soil Moisture Index, ***SVI: Standardized Vegetation Index

These insights stem from a qualitative exploratory research phase that assessed the causal linkages within the social-ecological provisioning system, the key determinants of vulnerability and the second-order effects drought events result in. The indicators are populated with variables that make use of remote sensing products, secondary spatial socio-economic data and primary empirical data from a household survey. Table 10 gives an overview on the HDRI structure, its constituting dimensions, indicators and variables as well as the sources, data are obtained from. Against the overall background of limited data availability in the study area, the following sub-sections provide a detailed description of each indicator's configuration and reasoning.

7.3.2.1 Drought hazard

The hazard dimension is populated with data from the Blended Drought Index that builds upon multiple remote sensing products to capture a drought's impact on blue and green water flows (section 5). Based on the qualitative survey, the BDI was explicitly constructed for the Cuvelai-Basin and combines the common drought metrics Standardized Precipitation Evapotranspiration Index, Standardized Soil Moisture Index and Standardized Vegetation Index (Mishra and Singh, 2010). It generates a single standardized index, using a copula function to preserve the characteristics of the individual metrics' signals and uses the established threshold of -1 for drought event identification. The HDRI makes use of three key characteristics of the BDI (frequency of occurrence, severity, duration) that are relevant to the population in the Cuvelai-Basin in the light of subsistence economy and reliance on traditional water supply systems.

Overall, the BDI measures the conditions of precipitation, evapotranspiration, soil moisture and vegetation at the end of the rainy season and applies the -1 threshold to determine, if a drought is prevalent. This identification of drought events specifically represents the environmental conditions of the rainy season that are essential for the living conditions in the basin. In order to determine *IND1 frequency of drought occurrence*, the BDI counts the number of years, in which the index value falls below the -1 threshold during the available time period of 29 years (1982 – 2010). *IND2 drought severity* is likewise measured as the cumulative sum of BDI index values below -1 and *IND3 drought duration* is the number of consecutive years in which the index value falls below -1. These three characteristics are important to determine the overall impact of drought and are hence combined in the HDRI hazard dimension.

7.3.2.2 Sensitivity

The qualitative insights into drought impact in the study area reveal that blue and green water scarce periods predominantly affect food and water availability on the household level that lead to second-order effects of social conflict, mental and physical illness and crime, among others (section 3). Therefore, the indicators chosen to populate the sensitivity dimension focus on these two compartments and consider the total demand for food and water on the one hand and the respective source types, water and food are withdrawn from, on the other hand. The empirical assessment of water and food consumption patterns was conducted using a seasonal ranking scheme in questions 1, 2, 11 and 12 of the structured questionnaire (Annexes 2 & 3). The sensitivity results presented in section 6 are taken up in this study for further processing.

IND4: Water and food demand

During a drought situation, households are challenged to provide adequate quantities and qualities of food and water to meet the household members' dietary demands. Hence, the more members a household has, the more food and water is required and therefore, the more sensitive it is to droughts. Although, larger households may have more capacities to cope with drought situations (e.g. higher human capital via more workforce and better education), they are more affected by water scarce periods in the first place, as they are obliged to acquire more quantities of food and water than smaller households. Therefore, *IND4 water and food demand* considers a household's size, age and gender composition in order to estimate the amount of food and water required. The indicator utilizes common metrics for respective food and water requirements (FAO/WHO/UNU, 2001; Institute of Medicine, 2005).

IND5: Water source dependence

Since the amounts of water and food alone are not sufficient for being highly sensitive to drought, two more indicators are considered. Both deal with the types of sources the households utilize to meet their water and food demands. This builds upon the assumption that source types of water and food differ in terms of their reliability in drought periods. Assuming that two households have an equal member structure, they will have the same value for the *IND4 water and food demand* indicator. However, the types of sources they withdraw their water from, might differ, tremendously. While the first household might utilize traditional water sources such as shallow wells and open waters, the second household might rely on tap water. The latter source is less sensitive to local water availability conditions and hence more reliable under dry conditions. Thus, households that strongly depend on unreliable, often traditional water sources show a higher water source dependence and hence a higher drought sensitivity. For a more in-depth description of the seasonal ranking scheme and the sensitivity results (see section 6).

IND6: Food source dependence

The same mechanism described in the previous paragraph is applicable to *IND6 food source dependence*. While traditional, subsistence food systems such as rain-fed grain farming, fruit trees and wild-food collection often rely on local green water flow, food systems such as local markets and supermarkets are based on a larger network of suppliers and hence less sensitive to local water conditions. Though price fluctuations occur in times of water scarcity, the results from the sensitivity analysis clearly show that supra-regional supply systems as well as food relief via the extended family network tend to be more reliable than traditional, subsistence-based food systems (see section 6).

7.3.2.3 Coping capacity

As part of the vulnerability concept, coping capacity seeks to capture the capabilities of an affected societal entity to overcome a threatening situation. Multiple studies operationalized vulnerability and coping capacity in particular, often via secondary data on larger spatial scales (Alcamo et al., 2008; Carrão et al., 2016; Fang et al., 2016; Naumann et al., 2014a; Shahid and Behrawan, 2008) and less often in combination with primary empirical data on a finer scale (Babel et al., 2011; Pandey and Bardsley, 2015). This study builds upon the indicators selected in previous studies and sub-divides the coping capacity dimension into an external and internal sub-dimension. While the first sub-dimension characterizes a geographical area in terms of the coping-opportunities it offers to households, the second sub-dimension considers a household's internal capital endowment (Khayyati and Aazami, 2016). The latter explicitly adopts Amrita Sen's insights into entitlement and deprivation (Sen, 1981), captured in the Sustainable Livelihoods Approach (DFID, 1999), which was frequently taken up, particularly by developing organizations.

IND7: Infrastructural endowment

Infrastructure generally serves multiple purposes, e.g. to provide an area with energy, water, mobility and communication, among others. In the case of a drought situation, infrastructure is one key for a household to meet basic needs of water and food but also to generate income and receive support in health and security issues. Against the background of limited spatial data availability in the study area, two variables are chosen to represent the infrastructural endowment. First, the distance of a household to the nearest tap water system is calculated to explicitly cover the aspect of reliable water provision as a backup resource. Second, the distance of a household to the nearest road is regarded as an important proxy, as mobility is essential for the population to meet basic needs, in particular via local market and supermarkets and governmental drought relief programs (Republic of Namibia, 1997). Both variables narrow down their perspective on the spatial availability of infrastructural components. They deliberately leave aspects of access out of the focus, as these, such as monetary resources, are incorporated into the capital indicators that characterize the internal constitution of a household.

IND8: Institutional endowment

Institutions are understood as societal rules and norms. These can take the shape of formal physical institutions of governmental agencies and security bodies or informal community and/or traditional rules that shape people's daily lives (Casson et al., 2010), as in the specific case of local water management (Schnegg and Bollig, 2016). Institutions are relevant in times of drought on both the formal and informal level. For the purpose of quantifying this aspect of formal and informal institutions in the current study, two variables are selected. First, as the official governmental drought relief program is organized via regional and local office structures (Republic of Namibia, 1997), the distance of a household to the nearest community center was regarded as an important proxy. The second variable considers the overall population density, assuming that more densely populated areas provide a household the opportunity to maintain a social network which provides support in crisis situations. Households that live isolated in rural areas do have limited opportunities to receive support from neighbors, relatives and governmental relief measures.

IND9: Social capital

The capacity of households to deal with drought situations builds upon multiple kinds of capital. Therein, social capital is a contested approach with a variety of conceptual meanings. It basically assumes that people are embedded into a social environment/network of mutual trust, reputation and reciprocity. These interpersonal relationships of bonding and bridging ties enable people/households to withstand crisis situations (Adger, 2003; Pelling and High, 2005). While institutional indicators, such as the number of civil society organizations are often used as indicators for larger scale assessments, in the study area, social capital is primarily characterized by local support from neighbors and relatives (section 3). Neighborly support is common in both urban and rural communities and helps to receive support (e.g. in kind). Though, this kind of assistance cannot be overstrained since donors and receivers find themselves in a similar situation, it is a common social norm that is based on mutual respect and trust. While other studies operationalize social capital with rather generic indicators such as mobile phone ownership and internet usage (Khayyati and Aazami, 2016), this study assesses social capital with a stronger focus on the actual findings from the qualitative research phase. Hence, the first variable covers the relationship of a household with its neighbors, assuming that those people who are better integrated into the local social environment are more likely to receive assistance. Likewise, the second variable assesses the support from relatives, as kinship relations via the extended family are stronger and more reliable than relations to neighbors and friends. Both variables were assessed using the questions 35 – 38 of the structured questionnaire with answer categories on an ordinal scale (Annexes 2 & 3).

IND10: Human capital

While social capital is context specific, particularly the way it is measured, established metrics for measuring human capital are available that capture the "*productive wealth embodied in labor, skills and knowledge*" (OECD, 2001; Tan, 2014). The educational level is most often used as a proxy (Rahut et al., 2017). In this study, this perspective is expanded by using both the educational level and the household workforce. The first variable focuses on the workforce available to a household and hence its physical ability to act. In this regard the proportion of members able to work at ages between 15 and 59 to those members that require care at ages below 14 and above 60 was calculated. The more workforce is available, the better a household's human capital. The second variable considers the highest level of education. In this regard, the highest educational level among all household members was assessed rather than the educational level of a household's head. Kinship relations are a strong traditional component of the Namibian and Angolan society and hence, well-educated children and relatives with higher incomes support the family.

IND11: Financial capital

Financial means are essential for a household do deal with a drought situation. It enables them to purchase necessary quantities of food and water and access mobility/transport and health services. Since measuring income or wealth in quantities of money is a difficult task (e.g. Seaman et al., 2014), the financial situation of a household was assessed in two complementing ways. First, essential fields of expenditures were identified and second the dependence on drought-sensitive income sources was assessed. For both purposes, the seasonal ranking scheme from section 6.3.4 was adopted in questions 15 – 19 of the structured questionnaire (Annexes 2 & 3). The seasonal change of expenditures from the rainy to the dry season reveals, for which purposes a household spends its limited amount of money. Those fields of expenditure that are even served under stress situations in dry periods are regarded as essential (e.g. hygiene, basic consumption items). If households however, are not able to fulfill these essential obligations, their financial capital is regarded as limited. In order to support this first measure of financial capital, the income source types are classified according to their reliability in dry periods, again assessed via the seasonal change pattern. Households that depend on unreliable income sources (e.g. salary from agricultural sector, selling own agricultural products), do only have limited financial means available in crisis situations. Both metrics are combined to provide a more comprehensive measure of financial capital.

IND12: Physical capital

The fourth kind of capital regarded as important in this study is the physical capital as a measure of wealth that is less liquid than *IND11 financial capital*. Again, two variables are selected, being the availability of specific assets and the housing quality. With regard to the asset ownership of a household, a standardized list of asset items was adopted from the Namibian census survey (NSA, 2011) in question 47 of the structured questionnaire (Annexes 2 & 3). Based on the sample itself, assets were identified that are of high value, as they are only owned by a small number of households. From this frequency distribution, a level of wealth could be estimated for each household. The second variable of interest was assessed using the questions 41 – 43 in the structured questionnaire (Annexes 2 & 3). Several housing quality standards such as the material of walls, roofs and floors were assessed. Households with higher quality materials used for construction are regarded as more wealthy and hence have more physical capital available.

IND13: Natural capital

The population of the Cuvelai-Basin is strongly linked to its natural environment. Natural capital a household possesses is thus an important sign of wealth. Though a clear distinction to the previous indicator *IND12 physical capital* may be controversial, natural capital as defined in this study focuses on natural items of importance to people's livelihoods. Two variables are chosen in this regard, being the type and number of livestock a household owns and the property size. Livestock is essential for a large share of the population in financial, in kind and traditional perspectives. Thus, the livestock characteristics were assessed as large stock units (LSU) (Chilonda and Otte, 2006) using question 48 of the structured questionnaire (Annexes 2 & 3). The more LSU a household owns, the wealthier it is. As a second variable, the property size a household owns was selected, assuming that the larger a property, the more potential a household has to sell part of it or to use the ecosystem components located on the pasture. The property size was assessed via both question 44 of the structured questionnaire (Annexes 2 & 3) and satellite imagery, as land property is normally fenced off by the households and hence visible on spatial images (Google, 2015).

7.3.3 Structured household survey

The primary data assessment tool to acquire the relevant socio-economic data for the above-mentioned indicators was a structured questionnaire (Annexes 2 & 3). This tool was carried out amount 461 households in Angola and Namibia. The survey assessed key variables of the households to calculate the sensitivity (section 6) and coping capacities scores. The specific setup of the questionnaire and relevant aspects concerning pre-testing, sampling, field work, interviewer training and quality control are outlined in section 6.3.2.

7.3.4 Validation of coping capacity scores

The purpose of household surveys that try to measure societal phenomena such as vulnerability, sensitivity or coping capacity do necessarily only measure proxies, that are assumed to be relevant to describe the phenomenon. Validating the results of respective assessments is focus of ongoing research but yet, no satisfactory solutions were found.

One approach is to conduct a media analysis on reported drought crisis in a particular area and compare the events found with the vulnerability scores (Tänzler et al., 2008). This approach however, is only applicable if vulnerability metrics are available for a longer period of time. As the focus of this study is to provide a snapshot on drought vulnerability, the approach cannot be followed. Another promising approach was presented by Notenbeart et al. in 2013. They conducted vulnerability assessments using standard socio-economic indicators to derive an overall vulnerability score (Notenbaert et al., 2012). Simultaneously, they asked the households to compare themselves with their neighbors with respect to their personal ability to cope with hazard situations. From this, they derived subjective measures of how households view themselves, relative to their neighbors. Notenbeart et al. (2013) compared these estimates on the community level with conventional vulnerability indicators and found that only 9 out of 26 indicators they tested fitted the self-evaluation of the households (Notenbaert et al., 2012). This approach was incorporated into this study in the form of the validation questions 22 – 24 that were part of the structured questionnaire (Annex 2 & 3). The households were hence asked, if they were more or less affected by drought events, compared to their neighbors and if they required food or water aid during the last drought situation. The answers of being more or less affected by drought were used as a benchmark to determine, if the estimated coping capacity scores are reliable on the community level.

7.3.5 Data analysis and interpretation

The collected data from the remote sensing products and the empirical surveys were processed before entering the composite indicator. The following sub-sections provide information on the imputation of missing data, the normalization and aggregation scheme, the uncertainty analysis and the transfer of the sample results to administrative units via regression analysis.

7.3.5.1 Imputation of missing data

Missing data is a common feature of household surveys due to a variety of reasons (e.g. response denial, false value, illegibility) (Leeuw, 2001). Deleting entire sample cases due to selective missing values reduces the sample size and hence weakens the survey's representativeness. Thus, missing data positions need to be filled with appropriate information taken from the remaining cases that show structural similarities. For this purpose, several methods are available (Leeuw, 2001; OECD, 2008). This study applies the unconditional mean imputation procedure. Therein, the sample mean/median of a variable, depending on the scale of measurement, is used as information to fill the data gaps in the sample. The following equation was used (OECD, 2008):

$$\hat{x}_q = \frac{1}{m_q} \sum_{observed} x_{q,c} \tag{13}$$

where $x_{q,c}$ being the observed value of variable q with case c = 1,…, M. Let m be the number of available values on x_q and $M - m_q$ the number of missing values. Thus, equation 13 gives the unconditional mean or median value to be entered in every data gap of x in sample Q (OECD, 2008). In the case of data that is available on an ordinal scale, the median value of the sample was used for imputing data gaps.

7.3.5.2 Aggregation and normalization

The variables selected in Table 10 have different measuring units as they represent specific environmental and socio-economic characteristics of drought risk on the household level. The HDRI however, requires a common unit to combine the individual variables, indicators and components, respectively. Therefore, a certain normalization and aggregation scheme was required. First, each parameter was calculated for all sample households, for example the first human capital variable *education*. This variable was measured on an ordinal scale from 1 (no education) to 4 (university degree). Hence, each household will receive a value from 1 to 4, while the second human capital variable *workforce* has an interval measuring scale from 0 (no workforce) to 1 (all household members are able to work). The first step for combining these two variables is a normalization procedure. Several normalization techniques are available such as z-transformation and Min-Max normalization, among others (OECD, 2008). The linear Min-Max transformation procedure is widely applied in composite indicator construction and particularly in environmental risk assessments (Naumann et al., 2014a; OECD, 2008). Therefore, each variable was normalized on a common scale from 0 to 1 with values close to 0 indicating bad/unfavorable conditions and values close to 1 pointing to good/favorable conditions according to equation 12. This normalization technique offers the opportunity to combine the variables in an additive way. The results are again normalized and combined on the next level from variables to indicators and dimension up to the final HDRI. If required, data transformation is performed to better fit the assessed data to the Gaussian normal distribution. Here, several techniques were applied such as logarithmic, exponential, inverse sine or square root transformations, based on the respective skewedness of the distribution ranges.

7.3.5.3 Weighting, uncertainty and statistical sensitivity

The normalization and aggregation procedure outlined above implicitly assumes an equal weighting scheme of the final dimensions hazard, sensitivity and coping capacity when combining them to the $HDRI_{equal}$, irrespective of any underlying properties of the data. The number of indicators and the statistical characteristics of each dimension however, can be accounted for in the final HDRI. In order to account for these data properties, two more weighting schemes were applied. First, the dimensions were combined, proportional to the number of indicators they entail. This means, that the normalized dimensional scores were weighted with the number of indicators they are composed of, following the equation:

$$HDRI_{prop} = h * w_1 + s * w_2 + c * w_3, \quad (14),$$

with $HDRI_{prop}$ being the HDRI-score from proportional weighting, h, s and c being the hazard, sensitivity and coping capacity scores and w_1 to w_3 are the weights applied to the dimensions. The $HDRI_{prop}$ was subsequently normalized according to equation 12.

Going one step further and not just accounting for the number of indicators within each dimension, a weighting scheme was applied that takes into account the statistical properties of the data. For this purpose, a Principal Component Analysis (PCA) was applied on the indicator level. Since the PCA is essentially a technique to reduce the number of indicators, it will identify underlying principal components that capture most of the initial indicators' variances. The number of principal components was determined by their respective eigenvalues with components being selected if their eigenvalues were larger than 1. The indicators were grouped into these components on the basis of their specific loadings (OECD, 2008). The resulting $HDRI_{pca}$-score was subsequently calculated similar to equation 14, where the components' weights are the sum of variance they explain, following the equation:

$$HDRI_{pca} = p_1 * v_1 + p_2 * v_2 + \cdots + p_n * v_n \quad (15),$$

with $HDRI_{pca}$ being the HDRI-score from PCA weighting, p_1 being the first principal component that is multiplied by the aggregated variance v_1 it explains. As a result, every sample household receives an HDRI-score from equal, proportional and PCA weighting with values ranging from 0 (bad/unfavourable conditions) to 1 (good/favourable conditions). The different weighting schemes then allowed the analysis of uncertainty in the final HDRI-scores. For this purpose, the arithmetic mean of the three HDRI-scores was taken and set into reference to the minimum and maximum values of the three weighting schemes. The range of uncertainty was attributable to the aggregation scheme and provides insights into the robustness of the theoretically derived composition of the HDRI.

Besides this uncertainty among the final HDRI scores, their statistical sensitivities to the underlying indicators is an important benchmark, in particular when influential control parameters need to be identified that should be altered to reduce overall drought risk. Among the diverse range of analysis techniques (Saltelli et al., 2008), variance-based sensitivity analyses are commonly employed in the context of composite indicators (OECD, 2008; Saisana et al., 2005). The method developed by Ilya Meyerovich Sobol and the derivatives that emerged subsequently assess the explanatory power of input variables with respect to a specific output variable. In this regard, the first order effect can be assessed as the explained variance by single input variables. In addition, the total effect acknowledges interactions among the diverse variables included in a respective model to explain the variance of an output variable. The first order effect s_i of a particular indicator x_i can be formally written as

$$s_i = \frac{v_{x_i}(e_{x_{-i}}(HDRI|x_i))}{v(HDRI)} = \frac{v_i}{v(HDRI)} \quad (16),$$

where v_i is the conditional variance and $v(HDRI)$ being the unconditional variance of the HDRI as the output variable. Likewise, second and higher order effects can be calculated to account for the interactions among the variables. Adding up these first and higher order effects reveals the total effect s_{t_i} that is formally written as,

$$s_{t_i} = \frac{e_{x_{-i}}(v_{x_i}(HDRI|x_{-i}))}{v(HDRI)} \quad (17).$$

7.3.5.4 Spatial drought risk

The knowledge on drought risk on the household level is important to structurally identify vulnerable people. It serves to answer the questions on why people are at risk of drought. The question remains however, where people at risk live. Decision-makers require information on both, why and where in order to efficiently design short-term emergency responses and carry out long-term adaptation strategies in the most important areas among the most vulnerable people. Hence, the HDRI sample results are projected onto the administrative units within the Cuvelai-Basin to receive a first approximation of spatial drought risk hot-spots.

For part of the HDRI indicators, spatial data is available. The hazard dimension builds upon remote sensing data to calculate the BDI and its key characteristics. Each administrative unit hence receives a hazard score as the spatial average of BDI frequency, severity and duration. Likewise the indicators *IND7 infrastructural endowment* and *IND8 institutional endowment* build upon spatial socio-economic parameters. Again, the values are averaged for the administrative units for the variables distance to road network, distance to tap network, distance to community centers and population density.

Only the dimension sensitivity and the capital indicators within the coping capacity dimension do not primarily build upon spatially available data. Therefore, a transfer of results to the spatial scale is required. Estimating statistical characteristics of certain areas or societal groups is one of the central motivations in quantitative social sciences. Sample surveys are commonly designed to reveal estimates for the entire statistical population, targeted. Thus, the results are only valid on this level. For the purpose of estimating statistical characteristics of areas or domains smaller than the targeted ones, large standard errors occur due to small or even non-existent sample sizes in the sub-entities (Ghosh and Rao, 1994). For this reason, methodologies were developed to make reliable estimates on small areas and domains (Brackstone, 1987). The methods can be grouped together under the term of Small Area Estimation (SAE) (Ghosh and Rao, 1994), with several sub-groups available (Noble, 2010). Basically, the results of sample surveys borrow strength from similar or related surveys (i.e. census) to reduce the sampling error. Auxiliary data plays a critical role, since this data is used to interpolate sample results (Noble, 2010). In this study, the questionnaire intentionally contained a number of variables that overlap with available census information. These overlapping variables were used to predict the sensitivity and the aggregated capital indicators for the administrative units on the constituency/communal level. The basic assumption herein is that the patterns surveyed in the sample are applicable in the other areas. The multiple linear regression models follow the equation:

$$\hat{d}_a = \widehat{ß}_0 + \widehat{ß}_1 x_1 + \widehat{ß}_2 x_2 + \cdots + \widehat{ß}_n x_n + \in \quad (18).$$

Herein, $\hat{d}_a$ is the estimated value of the dimension sensitivity or the aggregated capital indicators in the administrative unit a, $\widehat{ß}_0$ is the intercept and $\widehat{ß}_n$ the slope coefficients of the n-th auxiliary variable x from the census while $\in$ is the error term (James et al., 2013).

The results for each administrative unit from both direct spatial measurements and the regression analysis were combined based on the normalization scheme outlined above. Since the census data from Angola, even the micro dataset (INE, 2017) were not available on the communal level as compared to Namibia, only the provincial results could be used (INE, 2014). These values were projected onto the communes under the assumptions that conditions are equal. This is a drawback for the interpretation of the spatial results. As soon as the census results become available on the communal level, data can be updated to reveal more detailed results.

7.4 Results

The study results are presented in the following sub-sections. First, key sample variables are shown and compared to available census information to elaborate on the representativity of the chosen sample households. Second, the drought risk results are illustrated with special emphasis on the indicator and dimensional results. Third, the effect of different weighting schemes on the uncertainty of the final HDRI scores and the sensitivity analysis are presented. Finally, the spatial drought risk estimates derived from an exploratory regression analysis are shown.

7.4.1 Descriptive statistics

The entire statistical population in the Cuvelai-Basin is approximately about 350,000 households (INE, 2016, p. 159; NSA, 2013, p. 16-20) of which 461 were selected in the survey sample. Against the background of the envisaged sample size to undercut a certain Relative Standard Error and against the project constraints (time, funds and accessibility), this sample size is regarded as reasonable to represent the living conditions of a large share of the population. In this regard, Table 11 presents key socio-economic variables of the households, distinguished into groups of nationality and settlement type (complete data available in Digital Annex 3). The values are measured against data from the recent censuses, obtained from respective micro-datasets (INE, 2017; NSA, 2014) to compare the arithmetic means of metric variables and proportions of nominal/ordinal values.

The comparison of sample and census values reveals heterogeneous results. While significant deviations are observable among certain variables, some group estimates such as the household size of urban Namibians, the number of household members between the ages 15 to 59 and the gender ratios show a good fit.

Table 11: Descriptive statistics for key variables obtained from the socio-economic household survey. Comparison of sample (n = 461) and sampled census mean values (two-sided t-test) and proportions. All values are compared based on groups of nationality and settlement type.

	Namibia				Angola			
	Urban [98]		Rural [212]		Urban [67]		Rural [84]	
Variables	Sample	Census	Sample	Census	Sample	Census	Sample	Census
Household size	4.82 (3.27)	4.42 (8.67)	***8.00 (4.36)	5.49 (4.22)	***7.04 (4.33)	4.97 (3.27)	***10.44 (5.36)	5.60 (3.40)
No. of household members < 14	***1.48 (1.63)	2.39 (1.74)	*2.70 (1.97)	3.03 (1.95)	3.02 (2.45)	3.06 (1.86)	***4.56 (2.55)	3.18 (1.93)
No. of household members 15 – 59	3.29 (2.22)	2.95 (8.06)	***4.73 (3.12)	2.53 (2.52)	***3.95 (2.89)	2.54 (1.64)	***5.32 (4.19)	2.52 (1.75)
No. of household members > 60	***0.05 (0.26)	1.74 (1.26)	***0.62 (0.72)	1.95 (0.84)	***0.12 (0.37)	1.15 (0.39)	***0.43 (0.61)	1.27 (0.53)
Household gender ratio [M/F]	0.82 (0.84)	0.85 (1.73)	1.02 (0.86)	0.99 (0.96)	1.06 (0.96)	1.14 (1.03)	1.08 (0.99)	1.10 (1.00)
Marital status: Head married [%]	29.60	31.24	50.33	46.49	50.97	52.83	48.25	54.17
Energy: Wood for cooking [%]	70.50	34.66	94.74	88.68	53.59	18.13	100.00	96.92
Sanitation: No toilet [%]	34.61	33.56	86.06	78.39	92.81	82.25	100.00	99.36
Ethnic group: Kwanhama [%]	58.21	---	30.30	---	53.72	32.80	79.87	58.55

Significance levels for deviations in sample mean from sampled census mean (*p < 0.1, **p < 0.01, ***p < 0.001). Squared brackets indicate the sample sizes while standard deviations of the means are given in round brackets. "---" indicates that no data is available in the census micro-dataset. The census parameters were obtained from official census micro-datasets (INE, 2017; NSA, 2014). The relative standard error (RSE) of the given metric variables is 12% on average.

Likewise, the discrete variables of marital status, energy utilization, sanitation and ethnic groups and in particularly the relative proportions between the groups are again, well reproduced. Only the energy utilization in urban Namibian and urban Angolan areas overestimates the utilization of firewood as an energy source for cooking. In general, the sample shows low shares of missing values per variable of about 4% on average and a low non-response rate (households rejecting to participate) of less than 5%. Overall, the sample is regarded as adequate for further processing and the intended purpose of approximating the HDRI indicator values.

The variables served to populate the 13 indicators of the HDRI for each household of the sample, based on their specific location (hazard, infrastructural and institutional indicators) and assessed socio-economic setting (survey data). Figure 31 presents histograms of the indicators, after their skewed distributions were transformed, using exponential, inverse sine and square root transformations, based on the direction and intensity of prior skewedness. Though not perfect, the transformations enhanced the fit to the Gaussian normal distribution, as quantitatively indicated by the test statistics of the Shapiro-Wilk test (Shapiro and Wilk, 1965) and the W/S normality test (Kanji, 2006) as well as the visual comparison with the hypothetical normal distribution (red line, Figure 31).

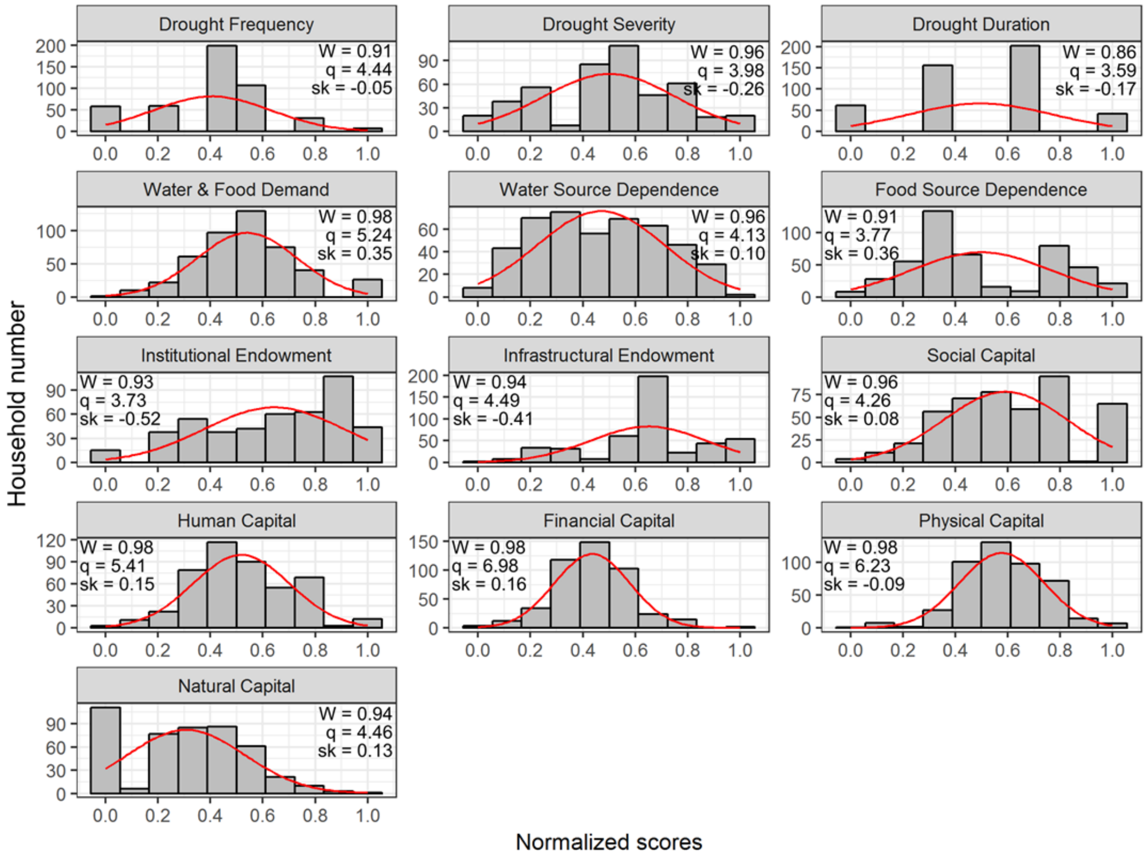

Figure 31: Histograms of HDRI-indicators and targeted normal distributions (n = 461).
Data of indicators was transformed prior to further processing (exponential function, square root and inverse sine transformation) to better fit the Gaussian normal distribution. Red line indicates the Guassian normal distribution, if the mean and standard deviation of the respective data is used. "W" = Shapiro Wilk test statistic, "q" = W/S normality test (quotient of data range and standard deviation), "sk" = Skewedness of distribution.

7.4.2 Household drought risk

As the previous section found the assessed variables and the derived indicators as suitable for further processing, this section elaborates on the signals that the individual indicators and the aggregated dimensions show. Figure 32 presents radar charts that depict the average indicator scores and the final HDRI scores of rural and urban households in Angola and Namibia. Therein, smaller sectors represent smaller score values and hence indicate unfavourable conditions, while larger sectors show rather better conditions. Differences are observable especially between rural Angolan and urban

Namibian households. Here, the orange sector, representing the average HDRI scores, is significantly larger among urban Namibian inhabitants which is primarily attributable to less sensitivity (blue sectors) and better infrastructural and institutional endowment (light green sectors). In terms of social, human and financial capital, both groups are rather equal, while differences are apparent when considering the physical capital (e.g. assets) and natural capital (property, livestock). While urban Namibians have a higher physical capital stock, their natural capital is rather non-existent. Here, the Angolan rural population can fall back on larger properties and in particular higher numbers of livestock. Nevertheless, urban inhabitants are still connected to the conditions in rural settings, as they maintain kinship relations and provide financial resources to their relative and/or receive in-kind support from the villages.

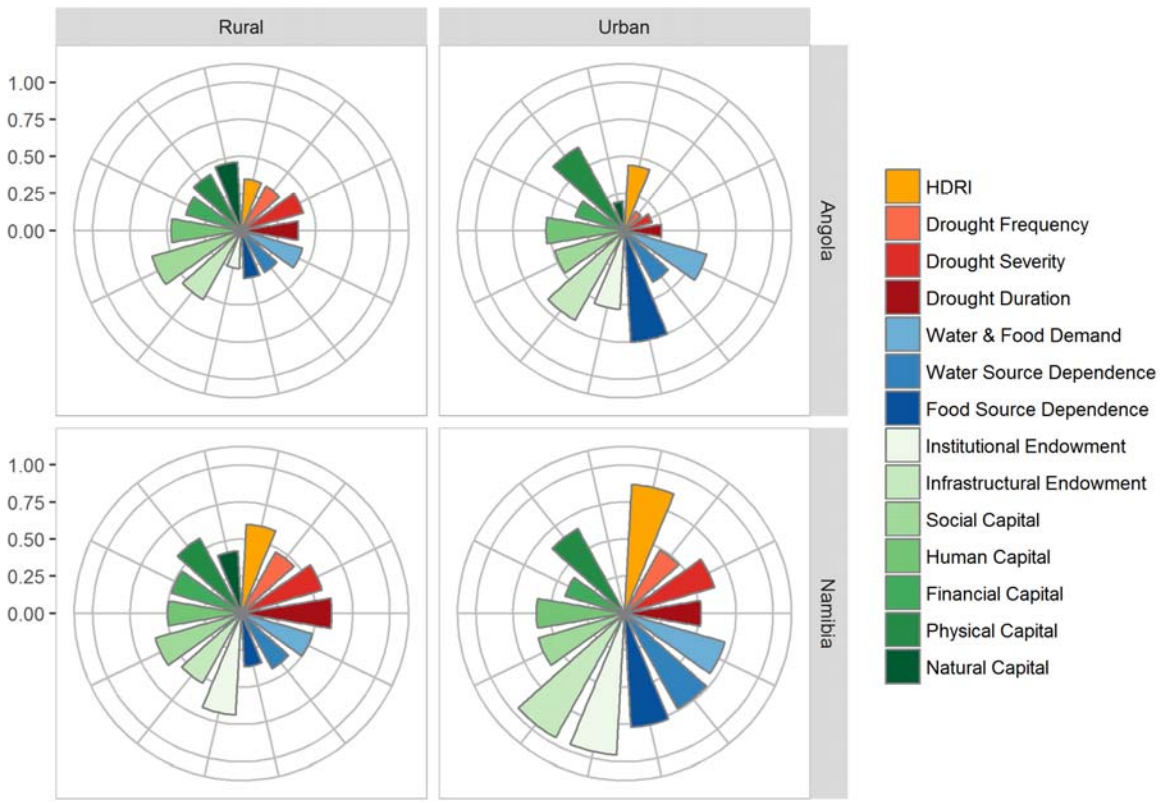

Figure 32: Indicator scores of rural and urban households in Angola and Namibia (n = 461).
The scores range from 0 (bad / unfavourable conditions) to 1 (good / favourable conditions). The HDRI score is added to the radar charts.

Urban inhabitants have better sensitivity conditions, in general, as they can access more reliable water and food source types. This is true for both countries, while in Angola, only major urban agglomerations show a good coverage with tap water, for instance. Another obvious difference exist in the hazard conditions when comparing Angola to Namibia.

Especially the urban Angolan households experience rather unfavourable environmental conditions, while these are better in rural areas in particularly in Namibia.

Analyzing the indicators among different groups gives detailed insights into the drought risk conditions for specific households, in particular when considering the socio-economic setup of them. As implied by the colors in the previous Figure, the indicators can be grouped into the dimensions proposed by the HDRI structure: hazard, sensitivity and coping capacity. This offers the opportunity to evaluate the indicators' combined signals and retrieve an aggregated measure of drought risk.

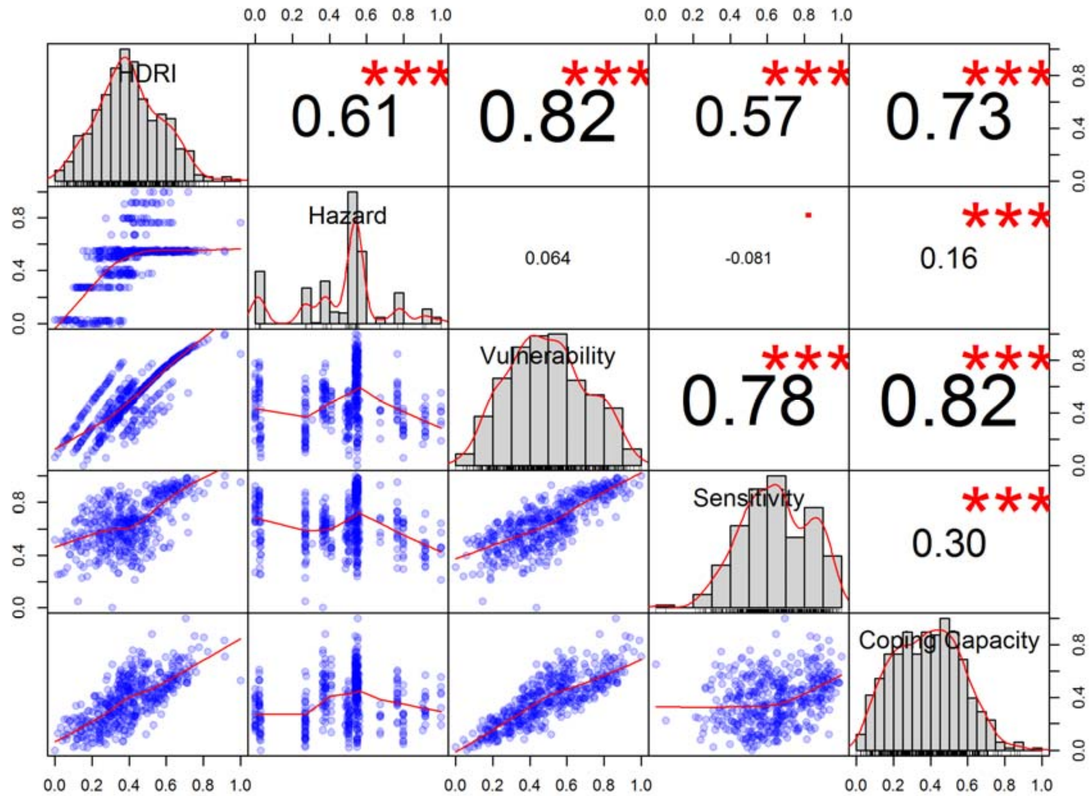

Figure 33: Correlations among the HDRI and its dimensions for the entire household sample (n = 461).
The lower panel presents the individual scatter plots between two individual dimensions, the diagonal plots present the dimensions' histograms and the upper panel shows the Pearson correlation coefficients with their statistical significance levels (*p < 0.1, **p < 0.01, ***p < 0.001).

Figure 33 shows, how the dimensions correlate to one another and with the final HDRI value. On the one hand, it is important to note that the hazard dimension does not correlate with the socio-economic dimensions of sensitivity and coping capacity. This is an important asset, as it confirms their statistical independence and indicates that they indeed measure different aspects of drought risk. On the other hand, sensitivity and coping capacity show a medium strength correlation to one another. This is reasonable, as the socio-economic conditions in people's consumption patterns (sensitivity) and their internal constitution (coping capacity) is necessarily linked. When combining only the latter two dimensions, a measure of vulnerability is available, that also shows a clear distinction to the hazard dimension.

The HDRI scores and the underlying dimensional and indicator level results can be explored further with respect to group specific features. Figure 34 presents several group variables that were assessed during the structured household survey in addition to the variables required for the indicator construction. The Figure shows the differences between the arithmetic mean vulnerability scores of households when grouped according to settlement type, sanitation conditions, nationality, marital status, household size, ethnic group and energy use for cooking. Of particular interest is the question, if the mean values differ significantly from one another. This is true for all but one of the investigated groups. While no significant difference can be found when Kwanhama households are compared to other ethnic groups, strong differences exist when considering the settlement type and the sanitation conditions. Some of the groupings are also available in the census surveys in both countries and hence, they serve the purpose of constructing linear multiple regression models to derive spatial drought risk estimates in the following section.

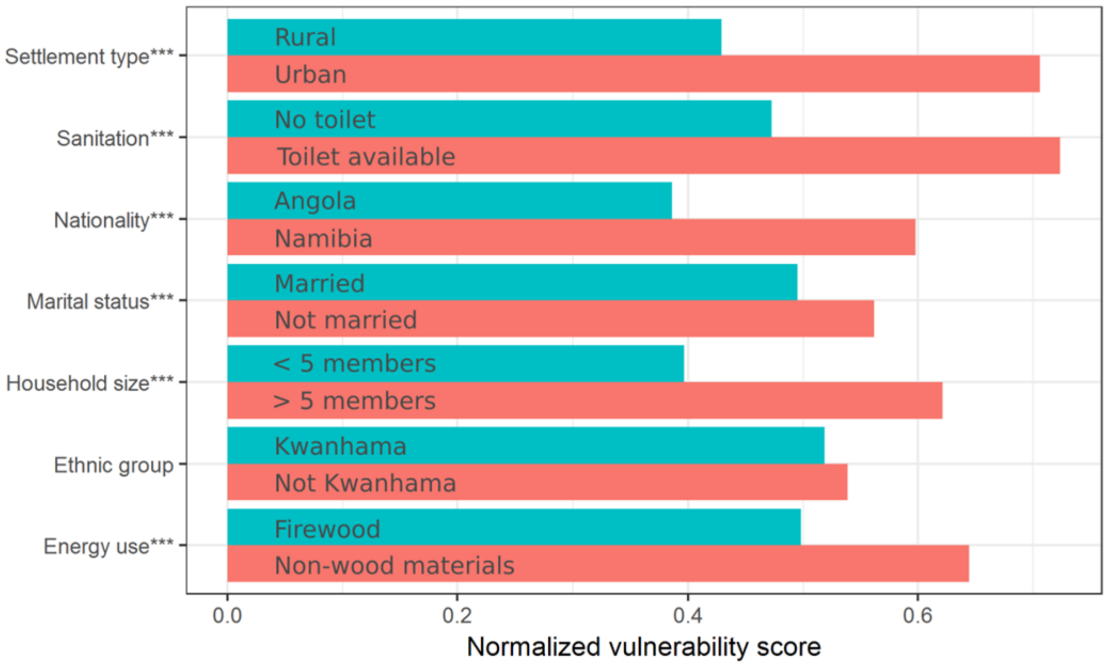

Figure 34: Comparison between vulnerability scores of selected socio-economic groups.
Differences among the groups are statistically significant at levels of *p < 0.1, **p < 0.01, ***p < 0.001.

7.4.3 Uncertainty and sensitivity of HDRI scores

The final HDRI scores are the result of aggregating the three dimensions hazard, sensitivity and coping capacity. The uncertainty attached to these HDRI scores is made explicit by applying different weighting schemes when aggregating the dimensions. While the primary method implicitly assumes an equal weighting of the dimensions, two more schemes on the dimensional level are considered being proportional (weights according to the number of indicators the dimensions entail) and PCA weighting (weights obtained from principal component analysis).

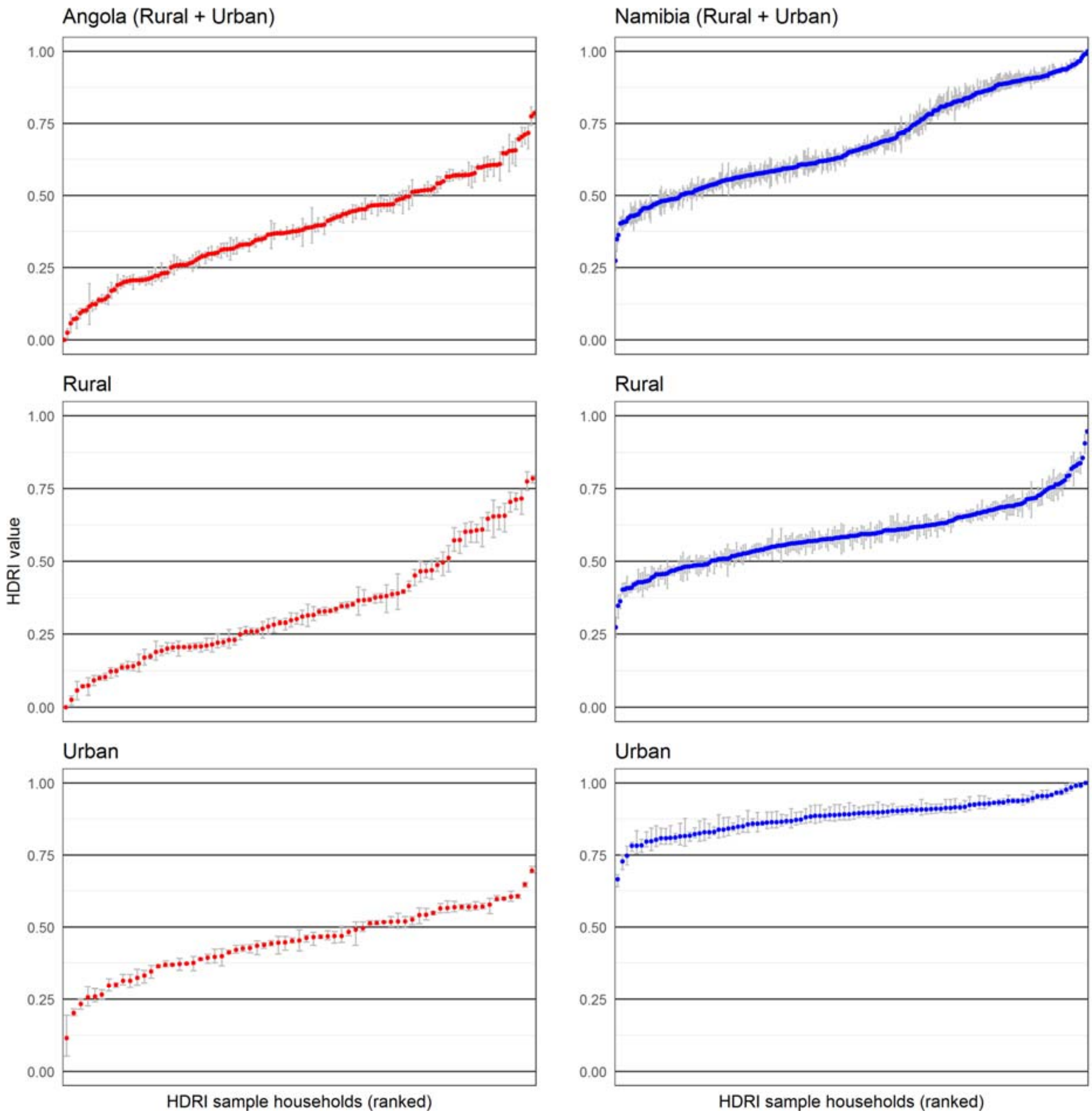

Figure 35: HDRI score comparison and variation among households in different groups (n = 461).
Three weighting schemes are applied prior to aggregation being equal, proportional and PCA weighting. The full-coloured points indicate the mean scores from the weighting schemes and the error bars show the minimum and maximum scores. Households are afterwards ranked from lowest (bad conditions) to highest (good conditions) mean HDRI scores.

Figure 35 presents the households' HDRI scores as the arithmetic mean of the three weighting schemes with values closer to 0 representing unfavorable/bad conditions and values closer to 1 indicating good/favorable conditions. The respective minimum and maximum scores that derive from the other weighting schemes are depicted as error bars. The individual plots show the distribution of HDRI scores in the countries as well as the settlement types rural and urban, respectively. The sequence of full-colored points gives an impression of how drought risk is distributed among households of different groups. For instance, most of the urban Namibian households show HDRI scores of above 0.75 while all of their Angolan counterparts score below this threshold. Similar patterns are observable among rural households. Rural Namibian households are generally worse-off than their urban neighbors, but better-off in comparison to their Angolan counterparts. Combining these two settlement types gives the aggregated picture for Angola and Namibia. Therein, Namibian citizens have lower drought risk levels (higher HDRI scores) than Angolan citizens. When considering the error bars among the full-colored points in Figure 35, it becomes apparent that the weighting schemes have a limited influence on the final results. Therefore, the primary method of aggregating the dimensions with equal weights is regarded as a statistically robust estimation of drought risk levels in the present case.

Table 12: Sensitivity results for the HDRI scores based on Sobol's sensitivity analysis.
First order and main effects are presented for the thirteen indicators.

Indicator / Dimension	First order (S_i)	Total effect (S_{Ti})	S_{Ti} - S_i
IND01: Drought frequency	0.01	0.09	0.08
IND02: Drought severity	0.02	0.10	0.08
IND03: Drought duration	0.01	0.07	0.06
IND04: Water and food demand	0.08	0.19	0.11
IND05: Water source dependence	0.08	0.18	0.11
IND06: Food source dependence	0.05	0.16	0.11
IND07: Infrastructural endowment	0.02	0.15	0.13
IND08: Institutional endowment	0.01	0.09	0.08
IND09: Social capital	0.02	0.10	0.08
IND10: Human capital	0.04	0.14	0.10
IND11: Financial capital	0.03	0.14	0.11
IND12: Physical capital	0.02	0.10	0.09
IND13: Natural capital	0.01	0.08	0.07
Indicator sum	**0.40**	**1.60**	**1.20**

The importance of individual indicators for the final HDRI scores can be analyzed via a variance-based sensitivity analysis. Table 12 presents the results of the Sobol global sensitivity analysis that reveals both first order (S_i) and total effect (S_{Ti}) of the indicators on the HDRI scores. When the explanatory power of the individual indicators is considered with respect to their ability to explain the variance in the target value, *IND4 Water and food demand* and *IND5 Water source dependence* have the largest first order effects. The sum of variance all indicators explain adds up to about 40%. Hence, the remaining 60% of variance is explained by interactions among the indicators. With regard to the indicator's total effects that incorporates the interactions among them, in particular the sensitivity indicators still show the strongest signal. In addition, human capital and financial capital as well as infrastructural endowment gain importance, compared to their respective first order effects.

7.4.4 Validation of coping capacity scores

The validation of the coping capacity scores is performed using three questions of the structured questionnaire. Two of them encouraged the respondents to self-reflect upon their performance within the last drought period. They stated if they would have been able to sustain the last drought period with or without food or water aid/donations. Table 13 presents the results when comparing the households' answers to the calculated scores of the coping capacity sub-dimension. The validation only considers the coping capacity sub-dimension, as this specifically reflects the capability of a household, people can evaluate. Table 13 indicates that for the presented sub groups of rural and urban settlements in Namibia and Angola, positive correlations are apparent. In particular the urban Namibian citizens and the urban Angolan citizens show stronger positive correlation, while the other groups only present weak correlations between the calculated scores and their self-reported ability. The fit between the scores to the water aid/donations people obtained is weaker than when considering the use of food relief.

Table 13: Spearman correlation coefficients for self-evaluation. Coefficients between the coping capacity scores and the households' self-reported ability to cope with or without food or water aid.

Group	Sub-group	Food aid	Water aid	Cases
Namibia	Rural	*0.13	0.00	
	Urban	**0.48	-0.08	
Angola	Rural	0.11	-0.12	
	Urban	**0.42	***0.45	

Significance levels: *p < 0.1, **p < 0.01, ***p < 0.001.

The third question asked the respondents to self-evaluate their performance in the last drought period in comparison to their friends and neighbors in the same community. They stated if they performed best, better, equal, less good or worse in the community. This metric was again compared to the calculated coping capacity scores of each household, relative to the other households within the community. Table 14 presents the results of the comparison by showing the Spearman correlation coefficients on the community level. The results show positive correlations of varying strengths. While strongly positive and statistically significant correlations are apparent in Namibian communities such as Etayi, Opononа, Oshandja and Outapi, only weak correlations are recorded in the Angolan communities, except of Oshitumba. Nevertheless, most communities show positive correlations between the calculated scores and their self-evaluation. The results on the community-level have to be interpreted with caution however, as the individual sample sizes are partly small.

Table 14: Spearman correlation coefficient of self-evaluation.
Coefficients are depicted between community-level self-evaluation of households' relative performance in drought periods compared to their neighbours.

Country	Community	r	Cases
Angola	Chiede	0.03	41
	Ehoko	NA	6
	Ohamukuyo	-0.10	40
	Okadweya	NA	15
	Ombala Sede	0.00	20
	Onepolo	0.00	14
	Oshitumba	0.23	15
Namibia	Etayi	*0.36	28
	Ikelo	0.12	9
	Ohamaala	0.28	19
	Olukekete	0.04	25
	Omanghwi	0.08	24
	Onaushe	0.21	28
	Oponona	*0.26	23
	Oshandja	*0.36	30
	Oshimumu	-0.10	26
	Oshoopala	0.11	54
	Outapi	*0.41	44

Significance levels: *p < 0.1; NA: no data.

Overall, the validation questions provide the opportunity to evaluate the performance of the calculated scores against an independent measure of the respondents' self-reflection. Though the correlation coefficients are heterogeneous and often weak, the results of questions one and two confirm the calculated scores, in particular when comparing these results with other studies in the field (Notenbaert et al., 2012). Question three also shows heterogeneous results, specifically in the difference between Angola and Namibia. When only considering the Namibian results, the coping capacity scores confirm the self-evaluation, though on a low level of weak to medium correlation strength. The reason for the poorer fit in Angola is speculative but maybe attributable to differences in perception of the question or translation problems.

7.4.5 Spatial drought risk hot-spots

While it is important to understand the causes and effects of drought risk on the household level, it is essential for authorities and non-governmental actors to identify spatial hot-spots. To provide a first approximation of the spatial patterns of drought risk, the sample results are made spatially explicit using both, primary spatial data and regression model estimates.

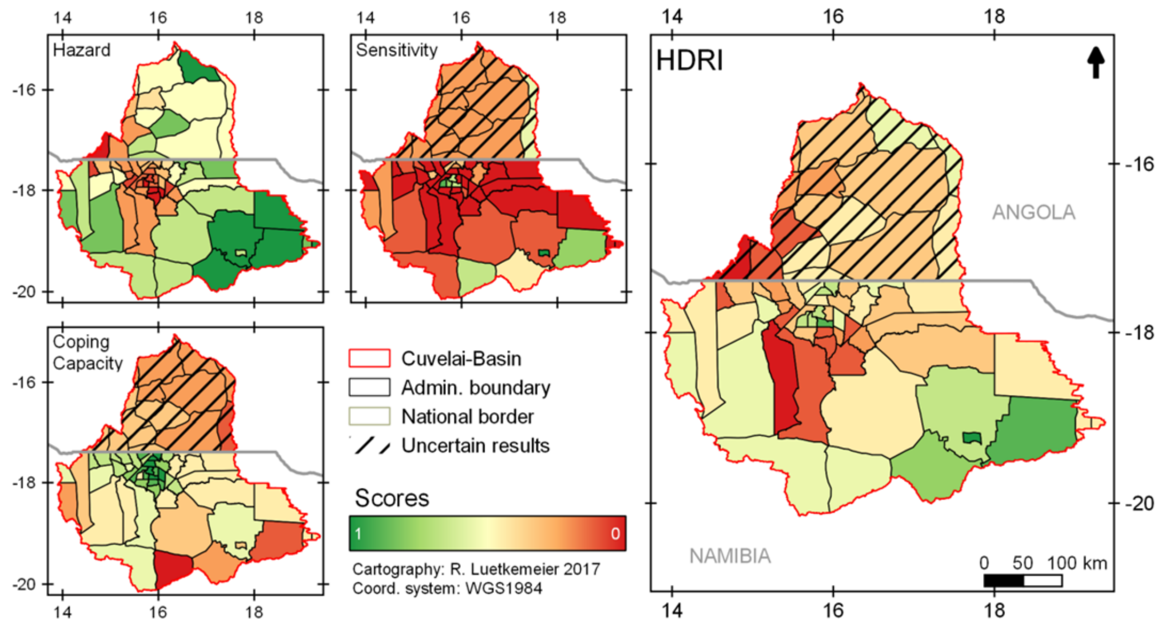

Figure 36: Spatial estimates of drought risk and the underlying dimensions.
The depicted maps build upon primary spatial data and regression model results. The hatched areas indicate uncertain results due to low resolution census data in Angola.

Figure 36 depicts the spatial HDRI scores on a scale from 0 (bad conditions/high risk) to 1 (good conditions/low risk) and presents the spatial configuration of the underlying dimensions. The highest HDRI risk levels are found in the southern part of central-northern Namibia and along the Kunene River in the west of the Angolan part. These regions are characterized by stronger hazard impacts and higher levels of sensitivity, particularly in Namibia. Although the coping capacity is regarded as good in Namibia, it cannot compensate the negative influences of the first two dimensions. The areas of lowest drought risk are found in the south and southeast of the basin and the central administrative units that are rather urbanized. Though hazard levels are still high, households located in these constituencies have better coping capacities and less sensitive consumption patterns. Considering the underlying dimensions in more detail, it becomes obvious that the spatial patterns vary from dimension to dimension. While the hazard is found to be most severe in the central and north-western administrative units, sensitivity shows a rather heterogeneous pattern with rural constituencies in Namibia having the highest sensitivity, due to critical water and food consumption patterns. Coping capacities are rather good in the central areas of northern Namibia, where water and food infrastructures are well available. In Angola, coping capacities are lower, as the entire area is less developed and households are less well capital endowed.

Overall, the spatial drought risk estimates can only be regarded as a first approximation, as the sensitivity and coping capacity dimensions partly build upon regression estimates. In this regard, linear multiple regression models were constructed to populate the capital-indicators of the coping capacity dimension and the entire sensitivity dimension, as these variables are not readily available from census surveys. Therefore, overlapping variables between the sample and the census were used to construct regression models and estimate the required parameters. Several variables were tested for suitability in the regression models as they were found to reveal significant differences between HDRI scores (Figure 34). As a result, the best-performing model to estimate sensitivity is composed of the parameters settlement type, marital status of the household's head and sanitation conditions which provides an explanatory power of 52% (R^2: 0.52). With respect to the aggregated capital indicators, the best-performing model included settlement type, sanitation conditions, marital status and energy type used for cooking being able to explain about 14% (R^2: 0.14) of the data's variance.

The results for sensitivity and coping capacity are less detailed for the Angolan administrative units, since census information to perform the regression analysis is only available on the provincial level. Results on the communal level are linearly interpolated and hence do not (sensitivity) or only slightly (coping capacity) show deviations.

7.5 Discussion

The discussion section will shed light on three major areas of interest. First, the results will be critically reflected with regard to the advantages of an integrated perspective on drought risk. Second, the methodology in terms of indicator selection and construction as well as validation and regression analysis will be discussed. Third, the potential to transfer the study design to other areas of interest is considered in the last sub-section.

7.5.1 Reflection on results

The consideration of societal and environmental aspects to describe and analyze drought risk on the household level is essential. If only the hazard dimension would have been considered to identify people at risk, different areas/households would have come into the focus, compared to a purely sociological perspective. In other words, if the hazard dimension would be narrowed down to low precipitation alone, Namibian inhabitants would be regarded as most affected by drought since mean precipitation conditions improve from south to north (section 4). On the contrary, if a broad vulnerability perspective would be taken that considers the overall development status, Angolan households would be found most at risk. Bringing these perspectives together reveals new insights into drought risk and helps to understand specific options for adaptation.

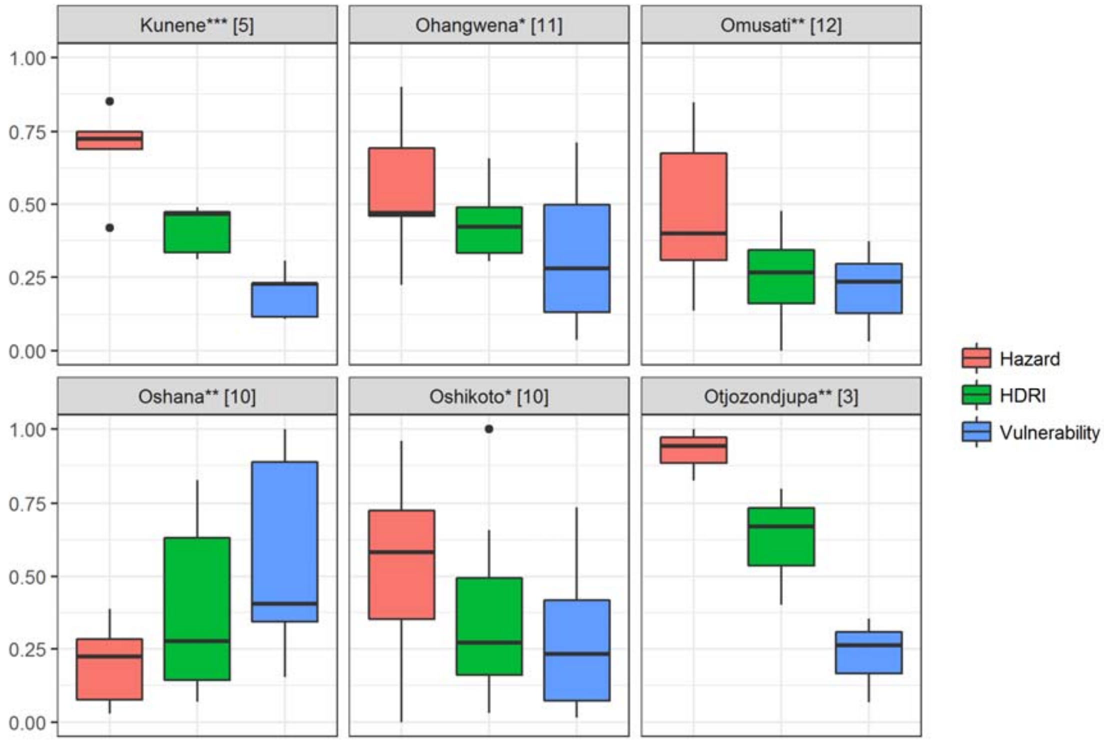

Figure 37: Comparison between HDRI, hazard and vulnerability scores among Namibian regions.
Data is based on the spatial estimates of the dimensions on the constituency level. Numbers in brackets indicate the number of constituencies included in the calculation, while the "*" indicates whether the means between the hazard and vulnerability scores are statistically different (*p < 0.1, **p < 0.01, ***p < 0.001). The Kavango region was excluded as only one constituency falls into the Cuvelai-Basin.

Figure 37 presents a boxplot diagram to compare the aggregated HDRI scores with the dimensional scores of hazard and vulnerability (combined sensitivity and coping capacity). Both the median values and the distributional ranges of each score show that considering either the environmental hazard side or the sociological vulnerability side in isolation reveals different results. The HDRI accounts for both perspectives but also offers the opportunity to review the individual dimensional results and even the underlying indicator scores to explore the reasons for drought risk levels of specific groups.

Overall, urban inhabitants are less affected by drought situations as their coping capacities are higher and sensitivities are lower. This is particularly driven by higher coping capacities, in terms of better infrastructural and institutional endowment as well as less sensitive consumption patterns. When considering the sensitivity of the final HDRI scores to its underlying indicators, it turns out from a statistical perspective that the infrastructural endowment of a region and human as well as financial capital are of greater importance than the other indicators.

The results in terms of both the socio-economic groups and the spatial approximation of drought risk offer entry points to reduce drought risk on the household level. From a spatial perspective, the densely populated rural areas in both countries are most at risk of drought, as the environment shows signs of degradation and the infrastructural endowment is limited. Urban centers however, offer rather favorable conditions to the inhabitants with more reliable water and food source types and better opportunities to for coping.

7.5.2 Reflection on methodology

This study makes an attempt to quantify the drought risk phenomenon by populating the HDRI's indicator set with measurable variables that are either readily available from remote sensing products, spatial socio-economic data or the conducted structured household survey. Though the qualitative insights put the HDRI on a well-founded basis (section 3), the selection and construction of the individual indicators can be subject to improvements. In particular the accuracy of *IND9 Social capital* hat focuses on support from neighbors and relatives can be enhanced, since the answers only show little variance. Further investigations into people's embeddedness into local level organizations or their responsibilities they take over in these may be a promising way to go (Bahta et al., 2016; van Rijn et al., 2012). Nevertheless, the overall approach of selecting targeted variables is regarded as a more feasible approach than relying on generic variables used in other studies (e.g. Khayyati and Aazami, 2016). In addition, the spatial variables used to populate *IND8 Institutional endowment* might be revisited as well to include relevant aspects of political institutions and traditional authorities as well as the role of churches. Respective data on this level however, was not readily available to this study. Furthermore, *IND11 Financial capital* used a new methodology of seasonal ranking to estimate the financial means available to a household at a sub-annual level. While the metrics obtained are consistent they have to be measured against conventional estimates of financial means to explore their suitability.

The task of validating the coping capacity scores is still a challenging task. The technique taken up in this study revealed heterogeneous results in terms of correlation directions and strengths but confirms the estimated scores to a large extent. Further research into this way of validating societal phenomena is however required. One further option might be a targeted household survey during the next drought period when the population requires food relief items. Those households that obtain food relief at the governmental offices throughout the regions may be surveyed in detail, so that their socio-economic characteristics and the hazard conditions they are confronted with can be assessed.

In general, the use of a composite indicator approach is regarded as reasonable as it is a common tool within development cooperation and research and thus well-known to practitioners and politicians (OECD, 2008). It offers good opportunities to combine data of different measuring regimes, even from the natural and the social sciences. As a promising alternative, Bayesian Belief Networks (BBN) gained momentum in the recent decades as ready-to-use software tools are available that facilitate their application for instance in a spatially explicit context (Landuyt et al., 2015). While they are applied in many fields, in particular the topics of ecosystem (services) and water management (e.g. Landuyt et al., 2013; McCann et al., 2006; Phan et al., 2016) and recently in the African context with respect to food security and climate-driven migration (Drees and Liehr, 2015; Kleemann et al., 2017b), BBN-based models are capable of handling different types of data, even expert judgments can be incorporated and processed.

The estimation of spatial drought risk within the Cuvelai-Basin borrows strength from the most recent censuses in both countries. Nevertheless, a regression approach always depends on the suitability of the data to reveal valid estimates. In this regard, the low spatial detail of the census data in Angola prohibits a more detailed description of the spatial patterns in capital endowment and the sensitivity dimension. Furthermore, the small number of variables available to perform the regression also limits the overall reliability of the regression models. If more census data become available even on finer spatial scales such as electoral districts, the HDRI estimates may be transferred and reveal better insights into drought risk, especially in the Cunene province.

7.5.3 Transferability

The HDRI should not be reduced to the final composite indicator value but should rather be regarded as a social-ecological drought risk assessment procedure that includes different stages. Therein, the qualitative exploratory research phase is inevitable to understand the provisioning system and the internal linkages between nature and society. It reveals, how spatio-temporal water scarcity impacts on the environment, how this impact is transmitted to society and which second-order effects occur. Subsequently, appropriate quantifiable indicators need to be identified to capture key aspects of both the environmental and societal domain. These have to be assessed, statistically processed and evaluated for their suitability to populate the final composite indicator. If the HDRI is perceived this way, as a holistic assessment procedure, it is capable of capturing the multifaceted impact of drought in a specific social-ecological system.

The exploratory research phase primarily served the purpose to gain system knowledge. Ecosystem services need to be identified, that decline in times of drought and result in impaired benefits people can obtain from nature and hence reduced human well-being. In the present study, water and food provision were found to be critical ecosystem services in the subsistence society of the Cuvelai-Basin. These services are essential to meet basic needs and support the economic development in this area but they respond quickly to drought conditions. Nevertheless, other ecosystem services might come into focus in other regions that show a different configuration of the social-ecological system. For instance in cases such as Gaborone in Botswana, where the population's energy supply depends on hydropower (Farrington, 2015) or the case of drought prone energy production in Mozambique (Uamusse et al., 2017), the qualitative pilot study might rather reveal that the HDRI's indicator set should focus on energy provision rather than water and food supply. The context-specific setup of the HDRI to capture the characteristics of the social-ecological system under consideration is a key task when performing a holistic drought risk assessment.

Against this background, the HDRI explicitly links to the Water-Energy-Food Nexus debate (Chirisa and Bandauko, 2015; Conway et al., 2015). In sub-Saharan Africa, water is a fundamental resource that is connected to multiple sectors such as the agricultural and the energy sector. Spatio-temporal reductions in quantity and/or quality of water have impacts on these sectors. Droughts hence manifest in declining food and water resources but also in impaired energy supply or associated services. The HDRI should be seen as a reconfigurable tool to capture the interlinkages between water and other sectors against the background of drought propagation and the specific sensitivities and coping capacities of people in a particular area (Vicente-Serrano et al., 2012).

7.6 Conclusion

This study approaches the challenge of drought risk assessment in a semi-arid environment in sub-Saharan Africa, the Cuvelai-Basin and seeks to capture its multifaceted impact on the social-ecological system in a quantitative manner. Against the background of the six principles presented in the Windhoek Declaration, three major conclusions can be drawn from the HDRI study to provide recommendations for drought risk analysis, monitoring and strategic mitigation.

First, from an analytical perspective, the overall HDRI procedure serves the purpose of analyzing drought risk in an integrated way. It offers the opportunity (i) to understand the underlying causes of drought impacts (qualitative pilot study), (ii) to assess household's internal coping capacities and sensitivities as well as (iii) the spatial hazard conditions. This enables the researchers, practitioners and politicians to perform targeted analyses of key determinants for risk reduction strategies.

Second, for monitoring purposes, part of the HDRI methodology should be taken up into larger scale surveys to continuously monitor drought risk among the population. In this regard, the seasonal ranking scheme and the assessment of household capital endowment should be focused and applied to even finer spatial scales of e.g. the electoral district level.

Third, in terms of short-term emergency responses and long-term adaptation strategies, as requested by the Windhoek Declaration, key recommendations are the following: While the alteration of precipitation conditions is beyond the scope of the Cuvelai-Basin's population, particularly vegetation and soil moisture conditions can by improved e.g. via targeted ecosystem restoration or reforestation activities and improvements in livestock management (Klintenberg and Verlinden, 2008). In order to reduce sensitivity, the households have to be enabled to switch their consumption patterns to less drought-sensitive source types. In this regard, the positive experiences in Namibia with regard to the centralized tap water system (Schnegg and Bollig, 2016) may serve as a blueprint for the Angolan part, when respective shortcomings in the institutional setup are adequately addressed (Hossain and Helao, 2008; Polak, 2014; Werner, 2007). Besides the centralized infrastructure, decentralized solutions of improved wells and boreholes as well as rain and floodwater harvesting techniques can be promising ways to go, in particular when combined with water-saving irrigation techniques for agricultural production or groundwater recharge (Kluge et al., 2008; Woltersdorf et al., 2014). Furthermore, infrastructure to enhance mobility among the population and to provide access to local markets has to improve in order to enable people to purchase and sell food items. Coping capacities can be enhanced by fostering local level community-based approaches, in combination with targeted support of households via capacity development measures. Co-knowledge production among rural smallholders and agricultural extension officers (Newsham and Thomas, 2011), the training of young professionals for construction and technical maintenance of RFWH facilities as well as the empowerment of women to run agricultural businesses (Woltersdorf et al., 2018) are regarded as promising ways to go.

8 Discussion

Synthesis of results and critical reflection on theory and methodology

8.1 Synthesis of results

This thesis approaches the complex challenge of drought risk in the Cuvelai-Basin from an interdisciplinary perspective in the sense of a mixed method approach from both physical and human geography. The entire research process is divided into several phases that consecutively build upon each other's insights to proceed in the social-ecological drought risk assessment as outlined in section 2.2.

While the individual phases already provide discussions of their specific results, this section will serve to conflate key results of the phases and discuss them against the background of the introductory research questions, presented in section 1.4. While the RQs 1-3 examine the results of the qualitative and quantitative assessments and reflect them against the scientific literature, RQ4 provides a more holistic perspective and presents opportunities for drought risk reductions on the household level.

8.1.1 RQ1: Drought impact and potential measurements

The thesis's first RQ sheds light on drought impact and how it can be measured. The answers provided particularly fall back on the results of section 3 in which the qualitative research phase explored this issue to gain a first-hand understanding. The specific wording of RQ1 is as follows:

RQ1: How does drought impact on the livelihoods of the population in the Cuvelai-Basin and how can this impact be measured?

The exploration's results (section 3) show how local livelihoods are impacted by drought events. The interpretation of the qualitative results in terms of the social-ecological system (section 3.5.1) reveals that droughts primarily alter local green and blue water flows and hence reduce the provision of ecosystem services households can utilize to maintain their well-being in the field of nutrition. The respondents stated that they are challenged to sustain water and food secure conditions on the household level as specific water and food sources fail (section 3.4.2). While the causal link between drought and reduced food availability is typically being found in sub-Saharan Africa and the Global South in general (e.g. Belle et al., 2017; Green, 2016), the adverse effect on water supply is a less prominent aspect in rural, subsistence economies. This issue only receives attention when larger urban areas are affected and media interest rises, as recently in the case of Cape Town (Loon, 2018). The exploration however, confirms that water supply impairments are an important problem for the population. This is specifically relevant in Angola, as a reliable backup resource such as tap water or improved, decentralized sources are rarely available. In addition, the interviews highlight that the quality of water quickly deteriorates under drought conditions as the few available sources that are used for multiple purposes are prone to contamination e.g. due to livestock interference. This critical susceptibility of traditional water supply systems in the study area is confirmed by geo-hydrological studies that assessed the pathogenic contamination of water sources (Wanke et al., 2018, 2014).

The above-mentioned primary impact of drought leads to second-order effects in the societal domain. The respondents emphasized negative consequences such as higher workloads, social conflicts and crime as well as mental and physical health problems that corrupt their well-being and deteriorate a household's capacities for coping (section 3.4.3). These qualitative insights indicate that consecutive hazardous events may constantly reduce people's coping capacities if recovery periods are too short. This will hence increase people's vulnerability to the next hazardous event and result in a more severe disaster. The identified adverse effect on social life and the decline of capacities are in line with findings on the number of social conflicts and cases of violence in SSA, triggered by drought events in rain-fed farming systems (von Uexkull, 2014). The results also point to links with the resilience concept (focus on resistance and recovery) as well as the necessity to consider the evolution of vulnerability over time (specifically coping capacity) in future research.

While the interviewed households were found to be sensitive to drought events due to their critical water and food consumption patterns that are strongly bound to local hydro-climatic conditions, they can employ short-term mechanisms to cope with these situations as also found in other areas of SSA (Bahta et al., 2016; Hänke and Barkmann, 2017). The fallback on more reliable water and food sources such as the tap water system and local markets and supermarkets turns out to be one major strategy as indicated by the respondents (section 3.4.3). Though access to the latter is monetarily restricted and markets are subject to price fluctuations under drought conditions (Wossen et al., 2018), food purchases are an important backbone for the households for both income generation (smallholder traders) and food acquisition (consumers). This major coping strategy is accompanied by the use of informal social networks either based on neighbours and friends or relatives in the sense of an extended family who give support in kind or via cash transfers. This latter finding is an important hint towards the consideration of the institutional setup in the communities in contrast to solely technological interventions to improve the living conditions. The importance of social networks under stress conditions was also found elsewhere (e.g. Chaudhury et al., 2017) though their respective importance is controversial (e.g. Bahta et al., 2016).

Since conventional drought assessments rather consider environmental parameters and identify affected people just from the spatial configuration of the hazard, this thesis adopted a social-ecological approach (section 2.2). One way to measure the impact of drought in this sense is the construction of a composite indicator to capture the multi-layered phenomenon. This kind of tool is well-known to scientists, practitioners and the general public and frequently used in the field of drought risk and vulnerability assessments (e.g. Naumann et al., 2014a; Plummer et al., 2012). Section 8.2.3 provides a brief review on alternative approaches to conflate respective data, for instance via Bayesian Belief Networks.

8.1.2 RQ2: Environmental determinants and their manifestation

The answers given to the previous RQ open the floor to approach drought risk from a social-ecological perspective. Hence, RQ2 considers the environmental dimension of the drought hazard, with the specific wording as follows:

RQ2: What are key environmental determinants of the drought hazard and how do these manifest spatially and temporally?

As depicted in sections 4 and 5, the drought hazard itself can be regarded as a climatic threat that originates from beyond the system's boundaries as inter-annual rainfall variability is regarded as the primary driver. Though, water availability may be locally influenced by the discharge of the Iishana river network, precipitation is the main control variable for rain-fed grain farming and the traditional water systems that provide drinking water (Hiyama et al., 2014; Mendelsohn and Weber, 2011). Based on the qualitative insights, this thesis confined its perspective on the drought hazard as an exogenous threat to the basin. Future research might assess the degree to which the population aggravates the drought situation (e.g. via upstream-downstream conflicts) as for instance found in other semi-arid regions (e.g. van Oel et al., 2010) or assumed for human-dominated environments, worldwide (Van Loon et al., 2016).

As the qualitative research phase identified the green and blue water flows to be critical for the population (section 3.4.2), environmental parameters were identified to depict the drought impact in these two domains. Since the evaluation of available ground measurements on key environmental parameters such as precipitation (section 4.3.1) shows limited data availability, remote sensing data products were preferred in the current case (section 5.3.1). The decision however, which product to choose for the analysis is difficult as the thesis's evaluation of available rainfall products revealed large differences (section 4.4.2). This is still true if the RPs were calibrated to rarely available station time series and particularly relevant when using them as input for modelling purposes (section 4.4.4). The thesis performed the evaluation for rainfall products but future research may proceed in this regard to evaluate remote sensing products for further environmental parameters. In addition, the need for ground truth data in the study area is required to assess the validity of widely used remote sending products.

Besides precipitation, which is most often used for drought assessments (Mishra and Singh, 2011, 2010), evapotranspiration, soil moisture and vegetation activity are incorporated into the thesis's analysis (section 5.3.1). Though the four proxies are necessarily interlinked, precipitation and evapotranspiration served to derive a simple water balance for the Cuvelai (SPEI) and are thus primarily perceived as a proxy for drought-affected blue water availability while soil moisture (SSI) and vegetation activity (VCI) rather provide insights into the drought-affected green water flow. Combining drought indicators to capture multiple effects is a common approach (Hao et al., 2016) that enables an analysis of drought frequency, severity and duration in both spatial and temporal terms. The applied copula-based technique is regarded as the state of the art in current drought assessment research (Chang et al., 2016; Saghafian and Mehdikhani, 2014). The derived Blended Drought Index (section 5.3.1.5) well reproduces drought events that were recorded in the period from 1980 up to now and correlates well with official yield data, outperforming the underlying conventional indicators.

Overall, the BDI is intended to depict the average hazard conditions in the basin on a data basis with a reasonable time series length. It is not primarily intended to serve as a drought forecasting tool, though the underlying assumption of monitoring and conflating more than just one parameter (often precipitation) may be transferable to forecasting systems. In this regard, seasonal climate forecasts, as provided by the Climate Service Centre of SADC or regionally confined by the South African Weather Service may be considered for model-based estimates of the resulting soil moisture and vegetation patterns. Respective results could be considered by the BDI and help to make drought forecasts for the basin. Further improvements of the BDI may focus on other important characteristics of droughts such as its onset or evaluate further indicators to complement or even replace some of the BDI indicators. One of the promising indicators to capture the drought impact in terms of surface water availability may be the Surface Water Supply Index (SWSI) (Mizuochi et al., 2014; Shafer and Dezman, 1982). In addition, remote sensing products or ground data may be used that provide a higher spatial resolution than the currently available datasets, like in the case of the soil moisture data processed.

8.1.3 RQ3: Socio-economic determinants and vulnerable groups

Analogous to the aforementioned RQ, within the context of the third RQ the findings of the socio-economic survey are discussed to shed light on the vulnerability of households. The specific wording of RQ3 is as follows:

RQ3: How are the key determinants of sensitivity and coping capacity distributed among the population and which societal groups are most vulnerable to drought?

The answers to this RQ directly link to the answers given to RQ1, as the qualitative research phase condensed its insights on drought impact on local livelihoods into key socio-economic indicators for sensitivity and coping capacity (section 3.5.2). While this knowledge is a relevant scientific end in itself due to the qualitative reasoning it builds upon, it can be regarded as a hypothesis on vulnerability to drought and how it can be measured using the proposed set of indicators. Taking the HDRI and its indicators as the starting point, the sections 6 and 7 explore the opportunities to populate the proposed indicators with relevant variables. These are supposed to capture the households' sensitivities and their coping capacities against the background of data availability and feasibility to assess them via a structured household survey. The latter constitutes the primary data assessment tool which is a common technique to obtain socio-economic information as found in other studies with a similar focus (e.g. Keshavarz and Karami, 2014; Pandey and Bardsley, 2015).

As one of the two vulnerability sub-dimensions, sensitivity is captured by considering the seasonal changes of water and food consumption patterns to identify those households who depend on unreliable water and food sources (e.g. shallow wells, rain-fed grain farming) to a large extent. The thesis's results show statistically significant changes in consumption patterns between dry and wet conditions (section 6.4.1), enabling to classify the source types according to their reliability in dry situations (section 6.4.2). The analysis revealed that modern, supra-regional sources (e.g. tap water, markets) are more reliable under dry conditions than traditional sources. It is interesting to note that these estimates solely stem from a socio-economic assessment procedure, not taking any further classification systems into account. Hence, the proposed ranking scheme (section 6.3.2.1) may be suitable to complement water point mappings (e.g. Welle, 2010) and conventional hydro-geological surveys (Wanke et al., 2018, 2014). Finally, drought sensitivity is derived from both, the sources' reliabilities and the household's dependencies on respective sources. The sensitivity results show that urban households follow less critical consumption patterns than their rural neighbours, while water source dependence is however, a major problem in urban Angolan areas (section 7.4.2). Though the tap water network is rather well developed in rural Namibian areas, their water source dependence is only marginally better than the one of rural Angolan people. In general, rural areas show critical levels of food source dependence as no reliable sources are available. This kind of sensitivity assessment is a new approach, taking up recent criticism on simplified techniques of assessing water and food consumption in countries of the Global South (Elliott et al., 2017). Further research into the sensitivity of households to drought may evaluate, if the proposed method provides results that are reproducible with conventional assessments of food and nutrition (e.g. 24-h recall and observed-weighted food records (Fiedler, 2013)) as well as water consumption quantities (Dagnew, 2012). In addition, a higher temporal resolution in the assessment of consumption patterns, following e.g. a seasonal calendar approach, may provide more detailed insights on local water availability conditions.

The second sub-dimension of vulnerability, the coping capacity is assessed by combining an external perspective on the spatial infrastructural and institutional endowment with an internal perspective on a household's capital setup (section 7.3.2.3). The latter perspective builds upon insights from Amrita Sen with regard to people's entitlement and deprivation (Sen, 1981) and further work on the Sustainable Livelihood Approach (DFID, 1999). The thesis's results show that Namibia outperforms Angola in terms of its infrastructural and institutional endowment. This is not surprising as the Angolan part of the basin remains less developed due to destroyed infrastructure and the displacement of the population during the 1975 to 2002 civil war (section 1.3). Hence, less favourable boundary conditions for the Angolan population were expectable. In contrast to this, the internal perspective on the capital endowment of the household does not reveal larger differences between Namibian and Angolan households. Herein, fine-grained variations become apparent between socio-economic groups, in particular when considering the physical capital endowment (asset ownership and living conditions) as well as natural capital (livestock ownership and property) (section 7.4.2). While the first one is larger among urban households, the latter is only available to rural households. Social, human and financial capitals are rather equally distributed among the households, independent of nationality or settlement type. The patterns observable on the indicator level however, may change if considering the underlying variables. For instance, the human capital indicator is composed of the educational level and the workforce of a household. Both variables make up human capital but capture different aspects of it. In this regard, Angolan households have a higher workforce in general (section 7.4.1), while their educational level is lower. In this thesis, both variables were regarded as equally important and hence, mathematically both may substitute each other. The bottom line is that further research may explore, if the specific roles of the underlying variables may be incorporated in more detail. One option to alleviate this common drawback of indicator approaches (OECD, 2008) would be to lift the variables into the position of indicators, so that their specific information is not hidden within aggregates, though the number of indicators increases and reduces the tool's clarity.

Overall, when conflating the sensitivity and coping capacity, the thesis's results reveal that the vulnerability scores vary according to a number of socio-economic characteristics (section 7.4.2). The rural-urban gradient was found to be a clear distinction among the sampled households as confirmed by other studies (Crush and Caesar, 2017). However, the qualitative research phase indicates that even urban inhabitants are linked to drought conditions in the rural areas, as in particular food items are obtained from the extended family domain and obligations have to be fulfilled like cash remittances or commitments to work in the field. Furthermore, the difference between an average Angolan and an average Namibian household is also statistically significant with the latter being less vulnerable. The quantitative data also indicate that the overall characteristics of sanitation conditions and energy utilization are statistically significant estimators for drought vulnerability, while no significant differences were found between ethnic groups (section 7.4.2).

The spatial estimates of overall drought vulnerability and risk, as provided in section 7.4.5, highlight areas north of the Etosha pan and along the Kunene River as hot-spot areas. In contrast to the hazard perspective, the urban constituencies in Namibia show lower risk levels, when the vulnerability estimates are included in the consideration. This is an important indication of the thesis as risk estimates may significantly change when expanding the perspective from an environmental focus to the specific sensitivities and coping capacities of the population in the exposed area. The spatial results however, have to be interpreted with care as they partly build upon regression estimates and coarse socio-economic data, in particular in Angola. Census results that were used to transfer the sample results onto the communes and constituencies are not publicly available on finer spatial scales. If the respective national agencies make data available on smaller scales, more detailed estimates on vulnerability can be derived.

With regard to the hypothesis on drought vulnerability as proposed by the indicator set from the qualitative research phase, the thesis attempted to obtain rather objective measures of drought affectedness to validate the indicator scores. While vulnerability validation is an ongoing scientific challenge (Notenbaert et al., 2012; Tänzler et al., 2008), two techniques that build upon self-reflective answers of the interviewed households were followed in this thesis. The results are heterogeneous with weak to medium strength correlations between the households' self-evaluation and the theoretically calculated indicator scores for their coping capacities (section 7.4.4). Nevertheless, the developed indicators can be regarded as a good first approximation of the vulnerability conditions in the basin, as for most communities visited, the validation task revealed promising results against experiences with respective methods in other settings (Notenbaert et al., 2012).

8.1.4 RQ4: Options for drought risk reduction

While the previous RQs addressed the individual research phases, the fourth RQ provides a rather conclusive perspective on the thesis's results and how these can contribute to developing interventions and strategies to reduce drought risk on the household level. The specific wording of RQ4 is as follows:

RQ4: Which interventions can serve to reduce drought risk among the population from a social-ecological perspective?

The thesis's results reveal that a reduction of drought risk among the population requires a focus on interventions to reduce sensitivity and enhance coping capacities, as the drought hazard itself is beyond the system's boundaries. Based on the qualitative research findings (section 3) and in particular the statistical analysis (section 7.4.3), Figure 38 provides an overview on a certain set of interventions that are grouped into the five key fields of action, *Water*, *Food*, *Infrastructure*, *Community* and *Education*.

The thesis is not intended to provide an in-depth policy analysis to identify the most suitable entry points for institutional adaptations in both countries, but the following paragraphs will highlight some interventions that might be suitable in the Cuvelai to improve the vulnerability situation. The interested reader is referred to authors like Werner (2007) and Polak (2014) who shed light in particular on local level water governance and its challenges in the context of Namibia.

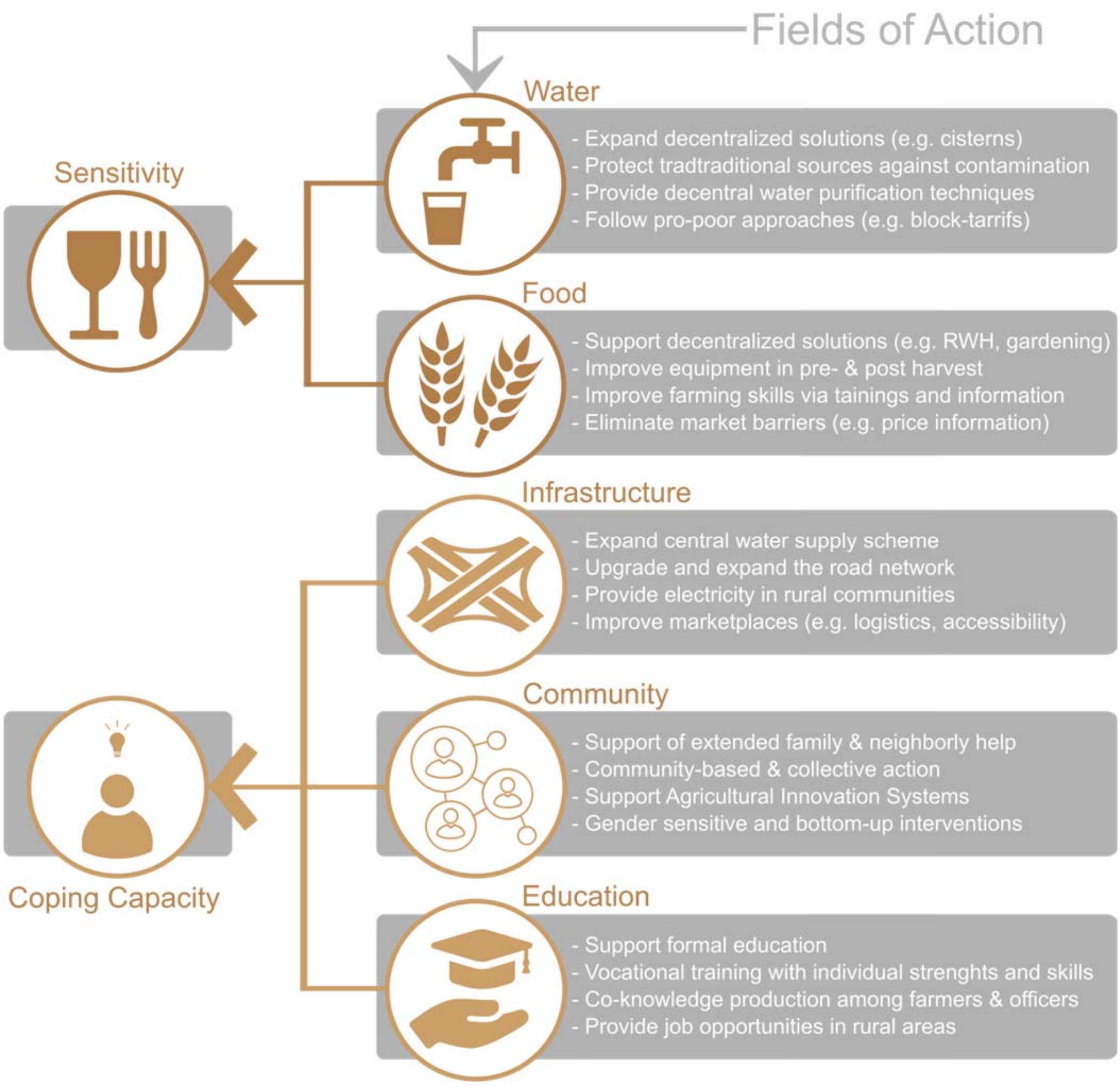

Figure 38: Proposed interventions to reduce sensitivity and enhance coping capacity.
The proposed interventions are grouped into five fields of action and connected to the HDRI-dimensions.

Field of action: Water

The qualitative research results reveal that water consumption patterns of households are critical to determine the sensitivity to drought (section 3). Traditional water sources are often unreliable under dry conditions as proven by the quantitative analysis (section 6). They either provide not enough quantity or only minor quality during dry periods. Against this background, local blue water buffers require upgrades.

The existing, decentralized infrastructure of traditional and improved well systems as well as boreholes, especially in rural areas, is a valuable asset that can provide sustainable water supply to the communities if certain upgrades are carried out. In the case of Angola, cisterns are available in several communities that are filled with water from the Protecção

Civil in stress situations. Potential upgrades of these tanks to fill them with flood or rainwater may be a feasible solution with little effort and might even reduce costs (e.g. for truck supply). Traditional water sources are often prone to contamination. Hence they require upgrades (e.g. groundwater protection, covered deep wells) to provide the population with reliable, quality-controlled water (Wanke et al., 2014). In addition, the latter may be provided by small scale treatment facilities that are cost effective and capable of filtering out major pathogens and suspended matter (Mwabi et al., 2013). Overall, if respective water supply schemes are implemented, a pro-poor approach in the sense of a suitable tariff system (e.g. block tariff) should be taken to not exclude those who only have little monetary means available (Angel and Loftus, 2017).

Field of action: Food

Analogous to the water consumption patterns, the qualitative results specifically highlight traditional food sources, such as from subsistence agriculture and natural wild food products, to be critical under dry conditions (section 6.3.5). As these food sources are however, an essential component of people's livelihood, the specific practices of producing these food items require improvements.

Small to medium scale rain and floodwater harvesting, partly including water-saving irrigation schemes for agricultural production and gardening were already tested successfully in northern Namibia (Kluge et al., 2008; Woltersdorf et al., 2014). They provide the opportunity for the population to generate high value and nutrient dense crops that serve for income generation and better nutrition (Dile et al., 2013; Rockström et al., 2002) as well as the empowerment of women. In addition, smallholders are required to enhance their pre- and post-harvest management. Better technical equipment is required with regard to field preparation, harvesting, storage and processing, in combination with access to capital and financing mechanisms (e.g. micro credits) (Collier and Dercon, 2014). The above-mentioned aspects all require capacity development in terms of practical training on key farming, horticulture and husbandry skills as well as new and in time information on e.g. weather patterns and market prices. Furthermore, logistics and trading opportunities require improvements to enhance the capacity of local market structures to supply the population. Better access for both consumers and smallholder traders is needed. Market barriers need to be reduced (Barrett, 2008; Ferris et al., 2014) via adequate infrastructure and the setup of market information systems as already proposed in Namibia's Food and Nutrition Policy (Republic of Namibia, 1995).

Both above-mentioned fields of actions make a contribution to reduce the households' sensitivities to drought. They come however, not without any costs. As experiences from project implementation in northern Namibia reveal, household financial means to cover respective investments costs are limited (e.g. Woltersdorf et al., 2018). Hence, support from third parties, in particular from governmental agencies is required to put respective measures into practice e.g. via subsidizing investment costs.

Field of action: Infrastructure

As provided by the answers of the respondents during the qualitative research phase, the infrastructural endowment of an area is relevant for the overall coping capacities during drought periods (section 3). In this regard, multiple infrastructural aspects require upgrades, specifically in Angola, where the lack of these assets is larger than in Namibia.

The tap water network in Namibia was found to be an important backup and complementary resource for the population (sections 3 and 6). As the Angolan side of the basin does only have limited access to this technology, the attempts made to expand the network in the Cunene Province under the Kunene Transboundary Water Supply Project (Kunene RAK, n.d.) should be accelerated. In this regard, a critical reflection of experiences gained in northern Namibia when it comes to the establishment of community water committees is required as drawbacks in the institutional design of respective community-based approaches exist (Hossain and Helao, 2008; Polak, 2014; Werner, 2007). If these shortcomings can be adequately addressed, this infrastructure and the associated institutional setup might serve as a promising blueprint to enhance the water security situation in Angola. The availability of services such as a road network, electricity, sanitation and small markets are similarly essential for people's coping capacities. In particular the Angolan part of the basin requires infrastructural development to lift its population into a similar situation as the Namibian neighbours. This difference between both regions is primarily driven by the civil war conditions in Angola that lasted until 2002 and prevented the overall development (Udelsmann Rodrigues, 2017; Unruh, 2012). Enhanced mobility services, electricity supply, sanitation provision and market infrastructures enable households to gain access to health services, educational programmes and water and food supply. This initiates feedback mechanisms that enhance their capital endowment and hence reduces the overall vulnerability. An opportunity found to be promising in water-scarce urban environments to provide sanitation services and thus contribute to better health conditions are water reuse technologies. Waste water collected from sanitation facilities may be used for gardening purposes and can thus make a contribution to sanitation supply, water savings and income generation (Woltersdorf et al., 2018).

Field of action: Community

In addition to the previous fields of action that rather consider technological and infrastructural enhancements, this field of action explicitly highlights the necessity of an adequate institutional setup. Therein, the importance of communities and the associated family and neighbourly networks should not be underestimated as revealed during the qualitative research phase (section 3).

Though social capital does not rank among the most influential indicators for drought risk in the statistical analysis (section 7.4.3), the qualitative research phase carved out its importance for the population to cope with drought. In particular the support from neighbours, friends and relatives – the extended family network – should not be underestimated as a rather informal way of coping. Hence, efforts should be directed towards a strengthening of social networks. Though, community-based approaches have to be treated with caution, as the top-down implementation of institutions that are unknown to people is critical (Hossain and Helao, 2008; Polak, 2014; Werner, 2007), they may strengthen people's self-responsibility if adequately implemented. In this regard, small-scale subsistence agriculture may serve as a valuable entry point for collective-action approaches (e.g. co-operatives, producer groups or machinery syndicates). Therein, Agricultural Innovation Systems (AIS) have great potential to trigger agro-economic growth and improve rural incomes if set up in a gender-sensitive and bottom-up way (Rajalahti et al., 2008).

Field of action: Education

Technological and infrastructural improvements as well as community innovations are all relevant aspects to reduce vulnerability. Capacity development is however, an important backbone when interventions are carried out.

The human and financial capitals were found to be relevant for the households to cope with drought situations (section 7.4.3). Therefore, the need for medium to long-term enhancement of educational levels and job opportunities is critical. Formal education must be supported in combination with capacity development options for advanced/vocational training for adults. The latter is especially required in rural areas to enhance living conditions and thus reduce the speed of urbanization and the pressure on fast growing towns. This medium-term strategy may focus on the fields of action presented above to reduce overall sensitivities in the villages. Capacity development efforts should target personal strengths and talents by enhancing farming and livestock management techniques as well as building capacity in the construction and operation of decentralized water harvesting and irrigation techniques. Co-knowledge production among rural smallholders and agricultural extension officers in northern Namibia was found to contribute to enhanced adaptive capacities and might serve as a blueprint for further collaborations (Newsham and Thomas, 2011). Similar experiences were gained in the CuveWaters project with the training of young professionals for construction and technical maintenance of RFWH facilities as well as in empowering women to run agricultural businesses (Woltersdorf et al., 2018).

8.2 Reflection upon theory and methodology

In addition to the research phases' discussions, the following sub-sections will reflect upon the overall theory and methodology of the entire thesis. In this regard, (i) the social-ecological risk assessment is critically considered, (ii) the combination of qualitative and quantitative methods is discussed and (iii) prospects for further validation of the vulnerability results are presented.

8.2.1 Social-ecological risk assessment

The thesis's theoretical foundation on SRN (section 2) served to highlight the relations between societal actors and specific ecosystem compartments that require deeper consideration. Since the societal system in the Cuvelai-Basin basically builds upon a subsistence economy, the relations between households and their environment are rather direct and visible. Thus, their depiction in the SES model (Figure 10) is rather straight forward and easy to reproduce by other scientific disciplines and practitioners. It hence serves as an applicable boundary object to gain a common understanding of key processes in the area on a qualitative basis. Especially the green and blue water consumption patterns serve as a valuable entry point to analyse the social-ecological structures and processes (knowledge, practices, institutions and technologies) – being the key elements of the SES – that are relevant for the provisioning system to function. Actors, their management, affected ecosystem functions and subsequently altered ecosystem services are identified, so that the impact of the drought hazard can be well reproduced and the SES model hence basically serves to gain and structure system knowledge.

Despite the positive experiences gained with the SES model in the current thesis setting, the following two issues may point to important aspects to be considered when applying the model. First, as elaborated upon in section 2.1.1, the SRN theory and the SES as its operationalization constitute an anthropocentric perspective with a focus on how actors meet their basic needs or maintain their well-being by managing and utilizing nature. This is purposeful when the effect on people's livelihood is of central interest in a research setting but when ecosystem impacts are to be considered in more detail, the SES model remains superficial. It might even suggest a certain degree of substitutability among ecosystem components (e.g. species) as long as ecosystem services are provided. The strength of the SES perspective is rather in the field of understanding certain management and utilization schemes of society rather than to gain an in depth understanding of ecosystem processes. Second, the question remains if the model is capable of providing system knowledge when the complexity of interactions between society and nature increases. This is particularly true when system boundaries are set differently or cross-scale linkages are incorporated that result in more potential control variables. As an example, the source of the tap water in northern Namibia was considered as an external, unaffected resource in this thesis that is reliable in a drought period. The water is however, abstracted from the Kunene River outside the basin and may likewise be prone to drought and hence create risk among the users of this resources. Correspondingly, the analysis would become more complex if larger scale political (e.g. employment, welfare policies) and economic developments (e.g. price fluctuations, international trade) are considered. This increase in complexity might overstrain the SES's capability of providing a suitable boundary object for inter- and transdisciplinary teams to structure their system knowledge.

Besides the SES model, the risk concept plays a major role in this thesis. It encompasses the hazard dimension and the vulnerability sub-dimensions sensitivity and coping capacity and provides the opportunity to condense key components of the SES that control the risk of the actors' well-being. This way, an understanding of the system functioning and critical components could be achieved. When considered from the perspective of disaster risk management, the thesis's recommendations to reduce sensitivity and enhance coping capacities constitute medium to long-term interventions for households to adapt to more intense drought events in the future. This primarily makes a contribution to the pre-disaster preparatory phase of the risk management cycle (Taubenböck et al., 2008). Nevertheless, the thesis's findings provide insights that are relevant for short-term emergency responses as well. The developed drought indicator can regularly be updated to provide a snapshot of current drought conditions throughout the basin. This enables authorities and/or NGOs to identify the most threatened regions. In combination with the produced knowledge on the characteristics of households which are most vulnerable and a first approximation on where those households are located in the basin, more targeted relief measures can be carried out. Hence, in combination with the system knowledge gained via the SES model, the risk concept provides orientation and transformation knowledge for stakeholders to adjust current practices.

One aspect that requires further consideration in this regard is the role of exposure. While this thesis captured the households' exposure via the spatial characteristics of the drought hazard, exposure may receive more attention if system boundaries are set differently, as already mentioned above and further outlined in section 9.2. If drought risk is considered on larger scales, telecoupling effects may be plausible as drought events in a confined area may alter the provisioning conditions in a remote region due to trade relations, for instance. Hence, it is not just the population in the direct vicinity of the drought hazard that is exposed but rather the people that depend on certain ecosystem services (e.g. indirectly via food trade or long distance water transfers) from this area.

8.2.2 Qualitative and quantitative research design

The interdisciplinary approach followed in this thesis in the sense of a methodological combination of qualitative and quantitative techniques (e.g. mixed-method) is regarded as a suitable research setup to approach a complex social-ecological problem context. Though not always termed as mixed methods or applying qualitative and quantitative techniques, numerous studies exist in the larger field of development studies that combine methods of different academic backgrounds for specific purposes. Positive experiences were gained for instance, when exploring the decision making processes of farmers under drought conditions in Iran (Keshavarz and Karami, 2014) or in the context of a multi-layered risk conglomerate in India (Singh et al., 2016). These studies rather apply a mixed methods approach that remains in the social science domain. Other studies go one step further by assessing and combining data from different disciplinary backgrounds, such as in the case of the investigation of land use change drivers in Ghana (Kleemann et al., 2017a) or the assessment of household decision making in livestock herding in South Africa using agent-based models (Rasch et al., 2016). This range of interdisciplinary studies expands into the field of risk assessments and in particular drought risk assessments with a strong bias on indicator-based approaches that take data from the socio-economic domain and the natural science domain and combine these in a single measure of e.g. drought risk (e.g. Naumann et al., 2014a; Shahid and Behrawan, 2008). These latter approaches partly suffer from being rather conceptual as they make use of existing secondary statistics on larger spatial scales. Against this background, two aspects should be highlighted that render the current thesis as rather unique:

First, the entire research builds upon primarily collected, qualitative data from the exploratory research phase. It hence does not infer assumptions from other regions but can build the insights and the subsequent research stages upon collected data and insights from the study area. This is regarded as an asset, making the overall results more reliable than purely statistical approaches. In this context it must be noted that the potential of exploratory research is often overlooked. Exploration offers a range of techniques to approach a certain research objective without having too narrowly framed pre-assumptions (Stebbins, 2001). This is particularly useful when attempting to describe and analyze a phenomenon that is locally and traditionally shaped as in the case of water use patterns.

Second, studies in the field of drought risk often have to fall back on secondary statistics to populate their developed indicators. Hence, the design and fit of an indicator for a specific phenomenon can be controversial. In this respect, the current thesis partly developed own indicators that focus specifically on the phenomenon to be assessed. Here, the best examples are the sensitivity indicators of food and water source dependences. These provide detailed insights into a household's consumption patterns to extract valuable information on drought sensitivities. In addition, these specific indicators take up recent criticism directed towards simplified assessments of water consumption that primarily ask for main water sources (Elliott et al., 2017). One drawback however, when developing study-specific indicators is their limited comparability with other studies. This trade-off between accuracy of fit and wider comparability is a critical question, in particular when working in regions with limited socio-economic data availability. Nevertheless, from an academic perspective, the development and examination of new indicators is an important task to highlight current limitations and guide larger scale indicator monitoring schemes such as the one decided upon in pursuit of the SDGs (UN, 2016).

8.2.3 Potential methodological advancements

In the following, some methodological aspects are highlighted that may be subject to improvements in future research studies, namely (i) the evaluation of alternatives to the use of composite indicators, (ii) further elaboration of uncertainties attached to environmental parameters assessed via remote sensing techniques and (iii) the challenge of developing suitable methods for validating risk and vulnerability estimates.

In the field of drought risk assessments, composite indicators are a common tool, in particular when integrated approaches are followed for combining environmental and socio-economic data (Babel et al., 2011; Naumann et al., 2014a; Pandey et al., 2010; Shiau and Hsiao, 2012; Sullivan, 2011). Even in other scientific and practical fields, composite indicators are a well-established method resulting in high popularity among researchers, policy-makers and the general public. They serve to summarize complex phenomena into a small set of variables that are easy to interpret and hence facilitate the communication to non-specialists. These strengths however, come not without any disadvantages. In particular the selection and weighting of indicators as well as their aggregation may be politically biased or poorly carried out, leading to simplistic or inappropriate policies (OECD, 2008). Their basic advantage for integrated research approaches is their ability to combine data of different measuring units and hence varying scientific disciplines. As an example for a promising alternative, Bayesian Belief Networks gained momentum in the recent decades as ready-to-use software tools are available that facilitate their application for instance in a spatially explicit context (Landuyt et al., 2015). While they are applied in many fields, in particular the topics of ecosystem (services) and water management are important (e.g. Landuyt et al., 2013; McCann et al., 2006; Phan et al., 2016) as well as recently in the African context with respect to food security and climate-driven migration (Drees and Liehr, 2015; Kleemann et al., 2017b). BBN-based models are capable of handling different types of data, even expert judgments can be incorporated and processed. They offer the opportunity to build decision-tree like conceptual models that visually show how input data lead to specific effects in the output variables. This advantage in terms of understandability is accompanied by their ability to explicitly handle the propagation of input data uncertainty. Further research may hence evaluate if BBN-models serve as suitable environments to assess drought risks and use it for knowledge organization, data integration and processing as well as communication tools, in particular when an inter- and transdisciplinary approach is followed (Zorrilla et al., 2010).

The second topic addressed in this sub-section is the use of remote sensing data of environmental parameters in a data scarce region such as southern Africa. As ground measurements on key environmental parameters are often unavailable, the utilization of remote sensing products is often the only feasible solution to perform environmental analyses. This thesis focused on four environmental parameters that are relevant for the drought hazard in the Cuvelai-Basin and conflated them to obtain a single measure of the drought hazard. The uncertainty of the underlying data however, was only explored in the case of precipitation (section 4) due to time constraints. The results of this single evaluation show that though the products present consistent spatial and temporal patterns on aggregated levels (e.g. overall spatial rainfall pattern and monthly to annual rainfall distribution), significant differences are apparent when it comes to smaller scale characteristics such as dry spells, rainy days and daily rainfall intensities. Similar differences are likely to be observable among other data products that provide information on evapotranspiration (e.g. Khan et al., 2018), soil moisture (e.g. Kumar et al., 2018; Wang and Qu, 2009) and vegetation (Tarnavsky et al., 2008), among others. Hence, future research on drought may consider a critical reflection of quality aspects when using remote sensing products.

As a third aspect, the challenge of validating risk or vulnerability estimates should be highlighted. The thesis provided new knowledge on drought impact from a social-ecological risk perspective. It measured the effect on the household level and hence enables to identify those people who are most at risk. Nevertheless, the challenge of validating the results remains. Few approaches exist to perform respective validations as for instance via post-disaster media analyses (Tänzler et al., 2008). As this approach was not feasible in the current case, this thesis incorporated validating questions in the sense of self-evaluation to check the vulnerability metrics (Notenbaert et al., 2012). Their application in the current case revealed heterogeneous results but further efforts into developing more targeted self-evaluation questions might be a feasible attempt. Furthermore, validation of risk estimates might be performed when the next drought event occurs, or in other words, when drought risk manifests and the disaster occurs. In this case, households that request drought relief at local institutions (e.g. administrative offices) can be surveyed on their sensitivities and coping capacities as proposed in this thesis. Assuming that the HDRI is a suitable measure of drought risk, these households that request drought relief should show according risk and vulnerability scores.

9 Conclusion

Recommendations for policy and science

9.1 Policy-brief: Integrated responses to drought risk[11]

Droughts threaten millions of people in sub-Saharan Africa, leading to famines, water shortages, migration and casualties. Climate change will exacerbate the devastating consequences as exceptional droughts are expected to become the new normal (Niang et al., 2014; Shongwe et al., 2009). Conventional drought risk assessments however, do not provide adequate tools, as they often limit their focus to environmental parameters, ignoring social vulnerabilities. Integrated strategies are required to carry out holistic drought risk assessments that serve to find adapted technological and institutional solutions to ensure water and food security (Pulwarty and Sivakumar, 2014).

Latest research results from SASSCAL task016 in the Cuvelai-Basin present a social-ecological technique to carry out environmental drought hazard assessments, coupled with socio-economic vulnerability estimations. The risk results clearly show drought hotspots and affected social groups in Angola and Namibia. Enhanced water use efficiencies and increased water buffers via large scale and decentralized infrastructures go hand in hand with institutional innovations on the community level to enhance coping capacities of the population, reduce sensitivities and thus adapt to future droughts. This will support the achievement of the Sustainable Development Goals 1 "*No Poverty*" and 2 "*Zero Hunger*" (UN, 2016).

[11] This sub-section is under final preparation to be published as an ISOE Policy-Brief (Luetkemeier and Liehr, forthcoming).

9.1.1 Key findings and recommendations

- The Cuvelai-Basin requires an integrated, transnational Drought Information System, potentially operated by the Cuvelai Watercourse Commission (CUVECOM) that incorporates both natural hazard data (e.g. precipitation, vegetation) and the social vulnerability domain (sensitivity and coping capacities). Only a coupled analysis enables governmental bodies to design suitable relief and adaptation measures.

- Water use efficiencies and local water buffers must be enhanced, in particular on the Angolan side of the border. The targeted implementation and further development of Multi-Resources-Mix technologies (e.g. rainwater harvesting, water reuse) can reduce the population's drought vulnerability. Larger scale infrastructural developments go hand in hand with decentralized solutions to enhance water and food security.

- Local community solidarity is an important institutional backbone for the population to cope with drought and adapt to future changes. In particular rural development efforts are required that go beyond technological interventions and support community-building and collective-action in both water management and agricultural production to decouple livelihoods from local rainfall.

- Climate, environment and society are continuously evolving in the Cuvelai-Basin and southern Africa, in general. Continuous monitoring of key drought risk parameters from both the natural hazard side (e.g. hydro-meteorological measurements) as well as the societal dimension (e.g. census surveys) are critical for successful drought mitigation and adaptation.

9.1.2 Background: Exceptional droughts become the new normal

Drought is a critical threat to the development opportunities of societies in sub-Saharan Africa. In the younger past, severe continental droughts occurred in the early 1970s, the mid 1980s and the early 1990s (Spinoni et al., 2014) with failed harvests, dead livestock and water shortages, leading to economic damages, health issues, migration and even casualties. In total, between 1900 and 2013 estimates show that almost 850,000 people died and more than 350 Million people were affected by numerous drought events on the African continent (Masih et al., 2014). The prevailing drought situations in the east African region (e.g. Somalia) and South Africa (e.g. Cape Town) aggravated by the 2015/2016 El Niño event are two of the most recent and most severe drought situations that result in ongoing humanitarian crises (Baudoin et al., 2017; Maxwell et al., 2016).

Angola and Namibia could not escape the negative impacts from droughts, either. Both countries experienced severe events in the early 1990s and 2000s as well as a multi-year drought from 2012 to 2015 recently where around 450,000 people were found to be food insecure in Namibia alone (20% of Namibia's population) (DDRM, 2013; UN-OCHA, 2012). The population of both countries, in particular in the transnational Cuvelai-Basin at the border between the Cunene-Province in Angola and the northern regions of Namibia, suffers tremendously as most people follow a subsistence economy that is closely connected to the hydrological conditions (Newsham and Thomas, 2011).

The exceptional drought events that were recorded in the past are likely to become the new normal in the near future as climate change will trigger more extreme hydro-meteorological events (Hoffman and Vogel, 2008). As a consequence, the Intergovernmental Panel on Climate Change emphasizes that droughts will become stronger and more frequent (Niang et al., 2014) and will hence challenge the growing population of the Cuvelai-Basin to sustain water and food security in the long-term (Reid et al., 2008). This policy brief builds upon recent research results from SASSCAL task016 to provide knowledge for the disaster risk management departments and development commissions in Angola (e.g. Protecção Civil Angola) and Namibia (e.g. Namibian Directorate for Disaster Risk Management) that seek to reduce drought risk and hence adapt to future conditions. Special emphasis is given to the role of the recently established Cuvelai Watercourse Commission, seated in Ondjiva, Angola. It may play a particular role in designing transnational strategies that make use of synergies from both countries' efforts and thus contribute to achieving the Sustainable Development Goals.

9.1.3 Towards better knowledge: Integrated drought risk assessments

The integrated drought risk assessment performed by the SASSCAL task016 research team in the Cuvelai-Basin identified the rural constituencies in the north of Namibia as well as the rural communes along the Kunene River in Angola to be most threatened by drought.

Standard drought hazard assessments typically focus on one or two hydro-meteorological parameters such as precipitation and evapotranspiration (Mishra and Singh, 2010). These few parameters however, do often only tell part of the story as the drought-sensitive population is connected to its environment in a multitude of ways, requiring a more comprehensive representation of the drought hazard. The Blended Drought Index was specifically developed by the research team for the Cuvelai-Basin to combine relevant drought indicators on precipitation, evapotranspiration, soil moisture and vegetation conditions. The BDI combines these aspects into a single indicator to temporally and spatially identify areas that are exposed to multiple characteristics of drought events. These drought characteristics culminate in a drought hazard map (Figure 23) to identify administrative units in the central north of Namibia (constituencies) and along the western border of the Cuvelai-Basin in Angola (communes) as being highly exposed to drought.

This environmental hazard perspective is indispensably accompanied by the sensitivities of households to drought and their capacities to cope with water scarce periods. Therein, qualitative and quantitative socio-empirical techniques were applied by the team of researchers to understand and quantify key socio-economic control variables that determine the vulnerability of a household. One of the key elements therein are a set of capitals, a household can employ during drought periods, such as social, human, financial, physical and natural capital. The final drought risk estimation builds upon the three risk dimensions (hazard, sensitivity, coping capacity) to provide national and regional development and relief agencies (e.g. Namibian Directorate for Disaster Risk Management and the Protecção Civil Angola) with comprehensive and consistent information on drought risk for incorporation into existing strategies.

9.1.4 Towards improved technologies: Promotion of a Multi-Resources-Mix

The SASSCAL task016 research on drought risk indicates that higher water use efficiencies can create local water buffers and therewith reduce the dependence on critical water and food sources. For this purpose, the combined strengths of both large-scale and decentralized water and food supply systems can serve as an efficient solution in the long-term for reducing drought risk if they are adapted to the environmental and societal preconditions.

The key challenges for households during drought periods are failing water and food sources. These undermine a household's ability to provide essential nutrition and drinking water to the family which results in second-order effects of e.g. mental and physical illness, social conflicts and crime. In order to prevent the traditional water and food provisioning systems to fail, large-scale and decentralized infrastructures and technologies are required that go hand in hand to support the population. In Namibia, the tap-water system constitutes an important backup resource for households. This pipeline network and its operation may serve as a blueprint for the Angolan side, as the expansion of the existing tap water network is planned under the Kunene Transboundary Water Supply Project (Kunene RAK, n.d.). With respect to establish food secure conditions, the logistics and trading opportunities for smallholders must be improved to enhance the capacity of local market structures to supply the population. Improved access for both consumers and smallholder traders is needed. Market barriers need to be reduced via adequate infrastructure and the setup of market information systems.

Figure 39: Improved borehole in the dense woodland of northern Namibia, east of Eenhana.
The covered surface prevents contamination of the well water and provides high quality drinking water even during the dry season (Photo: Luetkemeier 2014).

Complementary to these centralized solutions, decentralized technologies for remote areas with desalinated groundwater, improved boreholes (Figure 39) and purified rainwater are suitable opportunities. These techniques make use of local water resources that are captured during the rainy period and made available during the dry season. Adequate storage technologies, purification techniques and protection mechanisms against contamination are available and have to be implemented. The investment and operating costs for decentralized techniques require suitable financing schemes either via subsidized loans or in combination with business cases. The latter may even contribute to enhanced food security with the support of subsistence agricultural activities e.g. via water-saving irrigation systems and gardening activities as well as improved pre- and post-harvest management via upgrades of grain storage facilities.

9.1.5 Towards strengthened institutions: Support on the community level

Besides infrastructural and technological improvements, local community solidarity in both the rural and urban environments is an essential backbone of households' coping capacities. The social network of households, in particular neighborly support and kinship/extended family relations play an important role when drought conditions appear.

In-kind support in terms of drinking water and food provision is a typical feature in northern Namibia and southern Angola. This traditional community solidarity must be preserved and even supported by both governmental bodies and traditional authorities to strengthen the resilience of the Cuvelai people. Knowledge on suitable mechanisms to support communities is already available. In Namibia, for instance, positive experiences were gained with the setup of local water committees to manage community taps. The lessons learned in the institutional design of these committees might serve as a promising blueprint to enhance water security in Angola, when the tap network is expanded (Polak, 2014; Werner, 2007). These activities should always take a pro-poor approach in the sense of suitable tariff systems (e.g. block tariffs) to not exclude those who only have little monetary means available.

In addition, small-scale subsistence agriculture serves as a valuable entry point for collective-action approaches. Forms of collective-action (e.g. co-operatives, producer groups or machinery syndicates) as the core component of Agricultural Innovation Systems have great potential to trigger agro-economic growth and improve rural incomes if set up in a gender-sensitive and bottom-up way (Rajalahti et al., 2008). Recent research findings show that these kinds of resilient agricultural co-operatives need to incorporate five essential factors for long-term success:

- *Membership:* Mutual trust to reinforce norms and ensure cohesion among members.
- *collective skills:* Social learning and knowledge-sharing to build capacities,
- *networks:* Link with external peer-groups or actors/experts for knowledge sharing and guidance,
- *innovation:* Build adaptive capacities to improve productivity, quality and competitiveness and
- *governance:* Adequate institutional structures providing support and acknowledgement.

The CuveWaters project (Liehr et al., 2018) revealed interesting results with regard to small-scale agricultural practices in the support of female community members (Figure 40) for managing small-scale greenhouse gardens and running small businesses to generate income for the employees and providing high-value food items on local markets to the population (Woltersdorf et al., 2014).

Figure 40: Female villagers that are part of a community-driven gardening project.
The group produces high-value vegetables for local markets (Photo: CuveWaters Project, 2011).

9.1.6 Continuous monitoring of drought risk conditions

The social-ecological conditions in the Cuvelai-Basin are continuously evolving and never constant. While climate change will bring about more intense extreme events, the population will continue to grow, alter their natural environment and societal, agricultural and economic developments will continue. Hence, this research from SASSCAL task016 provides a first integrated assessment of drought risk, but both the environmental and socio-economic conditions will change in the future. It is essential to continuously monitor key environmental and societal variables to update drought risk estimates. Both qualitative and quantitative assessments carried out by natural and social scientists and practitioners are needed to fulfil this task.

The social-ecological drought risk assessment procedure developed in this research project should be taken up by national agencies responsible for drought vulnerability and drought risk adaptation as well as drought relief measures. In this regard, the national statistics agencies (Namibian Statistics Agency and Instituto Naciobal de Estatística de Angola) can update the regular census or thematic surveys with specific questions to assess the sensitivities and coping capacities of the population. Furthermore, both meteorological services (Namibian Meteorological Service and Office National de la Météorologie) may consider multiple and integrated environmental drought indicators in line with the proposed BDI. In addition, national bodies for drought relief and long-term adaptation (e.g. Namibian Directorate for Disaster Risk Management and Protecção Civil Angola) may consider integrating the outlined risk analysis into their existing assessment procedures.

Overall, the Angolan and Namibian population in the Cuvelai-Basin closely interact across the national border. Likewise water does not care about national borders and thus has to be managed in an integrated way by all members of society. Hence, SASSCAL task016 research supports the establishment of the Cuvelai Watercourse Commission to not just enhance water management in the basin, but to collaborate closer in infrastructural development and drought mitigation and adaptation. SASSCAL may well support this process via application-oriented research for long-term drought risk reduction and adaptation.

9.2 The missing link for Drought Information Systems

Drought risk was conceptualized as a social-ecological challenge in the present thesis. The Cuvelai-Basin served as a first case study example to apply the proposed risk assessment guideline and perform both qualitative and quantitative socio-economic and environmental assessments to capture the drought impact on society. While the focus in the Cuvelai-Basin was found to be the local water sector, closely interlinked with the food sector, this is not necessarily the only potential impact drought events might have on society. Generalizing the potential impacts droughts can have on society, the Water-Energy-Food Nexus approach might serve as a suitable framework. Along impacts in the water and food sectors, droughts can impact on energy production if e.g. water reservoirs for hydropower generation run dry. Hence, the WEF approach might be a suitable way forward in order to capture the way droughts impact on a provisioning system.

Furthermore, the locally applied drought risk assessment performed in the Cuvelai-Basin that takes into account both the environmental hazard and the societal sensitivities and coping capacities is applicable in other regions of similar challenges as well as on larger spatial scales, for instance on regional to national levels. In this regard, integrated Drought Information Systems can serve as tools for governance and decision-making. They build upon reliable risk assessments and early warning sub-systems that can provide a comprehensive way to address the multi-layered challenges drought imposes on the society (Pulwarty and Sivakumar, 2014). However, the development of DIS is still in its infancy, superimposed by a focus of researchers and practitioners on sophisticated EWS such as the African Drought Monitor, the Famine Early Warning System Network and the Global Information and Early Warning System on Food and Agriculture, among others. Though EWS provide up to date forecasts on regional drought hazard conditions and give valuable information for international aid organizations, governments and local agencies to implement drought relief programmes, they constitute only part of DIS. The information they provide needs to be linked to the local vulnerabilities of the water, energy and food sectors in order to provide profound information for effective governance of drought risk and prevent potential trade-offs (Vicente-Serrano et al., 2012).

The existing EWS only focus on the natural hazard side of the problem by considering common drought indicators based on e.g. rainfall variability, vegetation response, soil moisture, discharge variability and many more hydro-climatic parameters. As a result, risk maps are created for the entire continent, to show the probability of crop failures and water shortages (Pulwarty and Sivakumar, 2014). These conditions might have an impact on the population but the question remains, if the risk estimates that are solely derived from environmental parameters, are relevant for a particular societal system at a specific location. In order to determine the spatio-temporal drought risk, the vulnerabilities of the water, energy and food sectors need to be considered, individually and in a combined fashion in order to prevent trade-offs. Vulnerability research shows that neither a natural hazard approach nor a sociological approach alone, but rather an integrated perspective should be taken (Birkmann, 2006). Societal systems differ strongly in terms of their sensitivity to drought due to the specific configurations of their supply systems. Moreover, societal systems have capacities available to cope with and adapt to drought hazards but again, this differs significantly from one place to another. Modern societies for instance, do not solely depend on locally acquired/produced water, energy and food but rather purchase respective products from distant places via pipelines, markets and transport systems as well as high-voltage power lines. Thus, drought risk is not necessarily determined by local hydro-climatic conditions but rather by the drought conditions at the origin of the products. In subsistence economies, like rural communities of sub-Saharan Africa, the sensitivity to drought is more localized due to weaker interdependencies to distant areas. Nevertheless, telecoupling between societies and environments becomes an important control parameter (Schröter et al., 2018). Furthermore, multi-year drought conditions and economic and political processes are capable of deteriorating societal capacities to cope with drought events, in particular due to increases in commodity prices, like for staple food products. All these processes shape the combined vulnerability of water, energy and food supply systems. Research is required to combine these aspects with common EWS in order to build integrated DIS on a supra-regional level as a tool for coherent governance strategies.

10
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11
Annexes

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Digital annex on the enclosed electronic data carrier

Digital annex 1: Socio-economic data from the qualitative household survey
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Digital annex 3: Socio-economic data from the structured household survey
Digital annex 4: Research permits from the Angolan and Namibian administrative bodies

Annex 1: Qualitative interview guideline

Institute for Social-Ecological Research

EXPLORATIVE SURVEY ON WATER USE STRATEGIES
Namibia

SASSCAL Southern African Science Service Centre for Climate Change and Adaptive Land Management

DATE: …………………………………………. CODE: …………………………………..

REGION: ………………………………………

CONSTITUENCY: …………………………….

VILLAGE: ………………………………………

INTERVIEWER: ………………………………

TRANSLATOR: ……………………………….

HOUSEHOLD CHARACTERISTICS

Age of respondent (& household-head)	
Number of household-members	
Number of part-time / seasonally household-members	
Household-members under 14	
Head's marital status	
Head's level of education	
Highest level of education among household-members	
Head's main job	
Main source of income	
Tenure status	
Household's main source of energy for cooking	
Type of housing unit	
Number of dwelling units	
Number of sleeping rooms	
Material of walls, roof and floor	
Main toilet facility	
Disposal of waste	
Electricity	
Household assets (radio, fixed phone, TV, car)	
Household's agricultural activity	
Livestock	

WATER USE STRATEGY

RAINY SEASON

ACTIVITY / SOURCE	In-house tap	Public tap	Borehole	Hand-dug well	Surface water	Bottled water	…
QUALITY							
DISTANCE							
Drinking							
Cooking							
Personal hygiene							
Dishes							
Cleaning							
Laundry							
Livestock							
Horticulture							
Orcharding							
Brick making							
Cooking for selling							
Dust prevention							

DRY SEASON

ACTIVITY / SOURCE	In-house tap	Public tap	Borehole	Hand-dug well	Surface water	Bottled water	…
QUALITY							
DISTANCE							
Drinking							
Cooking							
Personal hygiene							
Dishes							
Cleaning							
Laundry							
Livestock							
Horticulture							
Orcharding							
Brick making							
Cooking for selling							
Dust prevention							

DROUGHT

E X P O S U R E

1.1. What are your concerns when you think of you, your family, your household and your community?

- *Hazards (drought, flood, heavy rain, heat, pests, etc.)*
- *Concerns (food, water, harvest, pollution, job, money, health, relatives, education, crime, lack of electricity, etc.)*
- *Ranking (importance of threats)*
- *History (past change of threats)*

S E N S I T I V I T Y

1.2. What is a good life?

- *Human Well-Being (security, basic material for a good life, health, good social relations, freedom of choice and action)*
- *Basic Goods (security, respect, personality, harmony with nature, friendship, health, leisure)*

1.3. How does drought affect you, your family, your household and your community?

- *Physical (food shortage, water shortage, harvest loss, livestock loss, health, etc.)*
- *Social (health, conflicts, marriage, psychologically/emotionally, etc.)*
- *Economic (income opportunities, workload, etc.)*

C O P I N G   C A P A C I T Y

1.4. How do you and your family get along with this situation?

- *Preparation (recognition of drought, insurance, income diversification, storage of water, storage of Mahangu, etc.)*
- *Handling (selling of livestock, selling of fruits, selling of Mahangu, selling of baskets, support from relatives/friends, support from neighbours, drought relief programme, reuse of water, seasonal/final migration (urbanisation/relatives), transhumance, eat and drink less, buy/borough food and water)*
- *Aftermath (buy new livestock, higher workload, payback debts, buy new plants, etc.)*

1.5. Please compare your situation to the situation of your neighbours.

- *Perception (more/less vulnerable, reasons, neighbour's activities, etc.)*
- *Reasons (job, income, field size, etc.)*

E N D

1.6. Is there anything else you would like to tell me?

Annex 2: Structured questionnaire (English)

ISOE

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HDRI Survey Task 16

SASSCAL Southern African Science Service Centre for Climate Change and Adaptive Land Management

Cuvelai Household Drought Risk Survey

Date		Constituency / Commune	
Questionnaire no.	(filled in by supervisor)	Community name	
Name of interviewer		Coordinates SOUTH	
Country	☐ Namibia ☐Angola	Coordinates EAST	

Ongepi Meme / Ongepi Tate,
My name is............................. and I work for............................., the international research project SASSCAL and the German Institute for Social-Ecological Research (ISOE). I would like to ask some questions about the way you use water and how you deal with drought situations.
Of course, all your answers will be anonymized and treated absolutely confidential.

1. **Which water sources do you use for domestic purposes in the rainy season? (Tick boxes)**
2. **If two or more sources are used, please rank (R:) them according to the amount of water withdrawn.**

	CATEGORY	SOURCES	CODE	RAINY SEASON		DRY SEASON
WATER (DOMESTIC)	Modern sources	Private tap	[01]	☐ R:	3. Different in dry season? If yes, please fill in here →	☐ R:
		Public tap	[02]	☐ R:		☐ R:
		Bottled water	[03]	☐ R:		☐ R:
		Borehole	[04]	☐ R:		☐ R:
		Water vendor	[05]	☐ R:		☐ R:
		Canal	[06]	☐ R:		☐ R:
		Improved deep well	[07]	☐ R:		☐ R:
	Traditional sources	Unimproved deep well	[08]	☐ R:		☐ R:
		Shallow well	[09]	☐ R:		☐ R:
		Earth dam	[10]	☐ R:		☐ R:
		Oshana / Lake / Pan	[11]	☐ R:		☐ R:
		Rainwater	[12]	☐ R:		☐ R:
	Other:...		[13]	☐ R:		☐ R:
	Comments:...					

4. **What is the most reliable water source during a drought year?**

[CODE] Other:........................

5. **How long does it take to walk to the most reliable water source (one-way)?**

.... Minutes

6. **Do you use water for any business activities?**

☐ Yes
☐ No

7. **If yes, for which activities?**

A)..
B)..

8. **Which water source does your livestock use during...**

... the rainy season? [CODE] Other: ....
... the dry season? [CODE] Other: ....
☐ No livestock

9. **Is tap water available in your neighborhood (e.g. public or private taps)?**

☐ Yes
☐ No

10. **If yes, would you financially be able to cover all your domestic water needs with tap water?**

☐ Absolutely
☐ Rather yes
☐ Rather no
☐ Not at all

11. Where does your household normally receive food from in the rainy season? (Tick boxes)
12. If two or more food sources are used, please rank (R:) them according to the amount of food received.

	CATEGORY	SOURCES	CODE	RAINY SEASON		DRY SEASON
FOOD	Own production	Field / grain basket	[01]	☐ R:	13. Different in dry season? If yes, please fill in here →	☐ R:
		Garden / fruit trees	[02]	☐ R:		☐ R:
		Livestock (meat, milk, eggs)	[03]	☐ R:		☐ R:
		Self-collected wild food	[04]	☐ R:		☐ R:
		Self-caught fish	[05]	☐ R:		☐ R:
		Self-hunted bush meat	[06]	☐ R:		☐ R:
	Markets	Local market	[07]	☐ R:		☐ R:
		Supermarket	[08]	☐ R:		☐ R:
	Social network	Relatives	[09]	☐ R:		☐ R:
		Neighbors	[10]	☐ R:		☐ R:
	Donations	Church	[11]	☐ R:		☐ R:
		Government	[12]	☐ R:		☐ R:
	Other:...		[13]	☐ R:		☐ R:
	Comments:...					

14. What is the most reliable food source during a drought year?

[CODE] Other:........................

15. Where does your household normally receive income from in the rainy season? (Tick boxes)
16. If two or more income sources used, please rank (R:) them according to the amount of cash received.

	CATEGORY	SOURCES	RAINY SEASON		DRY SEASON
INCOME	Own production	Selling products from own agriculture	☐ R:	17. Different in dry season? If yes, please fill in here →	☐ R:
		Selling handicraft products	☐ R:		☐ R:
		Selling bricks	☐ R:		☐ R:
		Other non-agricult. business activities	☐ R:		☐ R:
	Employment	Salaries from agriculture	☐ R:		☐ R:
		Salaries from non-agriculture	☐ R:		☐ R:
	Government	Old-age pension	☐ R:		☐ R:
		Orphan's grant	☐ R:		☐ R:
		Disability grant	☐ R:		☐ R:
	Relatives	Cash remittances	☐ R:		☐ R:
	Other:...		☐ R:		☐ R:
	Comments:...				

18. On which items/services does your household normally spend money in the rainy season? (Tick boxes)
19. If two or more expenditures exist, please rank (R:) them according to the amount of money spent.

	CATEGORY	OPTIONS	RAINY SEASON		DRY SEASON
EXPENDITURE	Domestic	Food for human consumption	☐ R:	20. Different in dry season? If yes, please fill in here →	☐ R:
		Water for human consumption	☐ R:		☐ R:
		Clothing & footwear	☐ R:		☐ R:
		Education (e.g. school fees)	☐ R:		☐ R:
		Health care (e.g. medication, hospital)	☐ R:		☐ R:
		Transport (e.g. fuel for car, taxi)	☐ R:		☐ R:
		Communication (e.g. Unitel)	☐ R:		☐ R:
		Energy (e.g. wood, gas, charcoal)	☐ R:		☐ R:
		Accommodation (e.g. rent)	☐ R:		☐ R:
	Agriculture / Livestock	Fodder for animal consumption	☐ R:		☐ R:
		Water for animal consumption	☐ R:		☐ R:
		Fertilizer / Pesticides	☐ R:		☐ R:
		Animal medication	☐ R:		☐ R:
	Other:...		☐ R:		☐ R:
	Comments:...				

21. How long does it take to walk to the nearest gravel / asphalt road (one-way)?

.... Minutes

22. Is your household more or less affected by drought, compared to your neighbors?

- ☐ Most
- ☐ Rather more
- ☐ Equal
- ☐ Rather less
- ☐ Least
- ☐ Don't know

23. During the last drought situation, would have you been able to survive without governmental drought relief?

- ☐ Absolutely
- ☐ Rather yes
- ☐ Rather no
- ☐ Not at all
- ☐ There is no drought relief
- ☐ Don't know

24. During the last drought situation, did your household depend on water donations from friends, relatives or neighbors?

- ☐ Absolutely
- ☐ Rather yes
- ☐ Rather no
- ☐ Not at all

25. Which ethnic group do you belong to?

☐ Ndonga	☐ Kolonkadhi
☐ Kwambi	☐ Kwanhama
☐ Ngandjera	☐ Mbadja
☐ Kwaluudhi	☐ Nyaneca-humbi
☐ Mbalanhu	☐ Muhanda
☐ Other:	

26. How many persons belong to the household (persons who stay in the house for more than 6 months per year)?

….. Female ….. Male = ….. Total

27. How many household members do stay away from the homestead for 1 to 6 month per year?

….. Persons

28. How many persons have any kind of disability or limitation that requires intensive care or prevents their engagement in economic activities?

….. Persons

29. How many household members belong to the age classes?

….. <= 14

….. 15 – 59 = ….. Total

….. >= 60

30. What is the household head's marital status?

☐ Never married	☐ Divorced
☐ Married with certificate	☐ Widowed
☐ Married traditionally	☐ Separated
☐ Consensual union	☐ Don't know

31. What is the respondent's relation to the head of the household?

- ☐ Identical ☐ Spouse
- ☐ Other: ....

32. What is the respondent's sex?

- ☐ Male
- ☐ Female

33. What is the respondent's age?

.... Years

34. What is the highest level of education one of the household members completed?

☐ Primary school	☐ University degree
☐ High school	☐ None
☐ Vocational training	
☐ Other:	

35. Would you say this neighborhood is a place where neighbors look after each other?

- ☐ Absolutely
- ☐ Rather yes
- ☐ Rather no
- ☐ Not at all
- ☐ Don't know

36. How often do you talk to your neighbors?

- ☐ On most days
- ☐ Once or twice per week
- ☐ Once or twice per month
- ☐ Less often than once a month
- ☐ Never

37. How close do your relatives live nearby?

- ☐ In this village
- ☐ In a neighboring village
- ☐ In the next town
- ☐ Far away
- ☐ Very far away
- ☐ No relatives

38. If relatives exist, how often do you meet them?

- ☐ On most days
- ☐ Once or twice per week
- ☐ Once or twice per month
- ☐ Less often than once a month
- ☐ Never

39. What is the type of housing unit?

- ☐ Detached house
- ☐ Semi-detached house / Town house
- ☐ Apartment
- ☐ Traditional dwelling
- ☐ Improvised housing unit
- ☐ Other: ....

40. How many rooms does the dwelling consist of?

….. Rooms

41. What is the main material used for the roof of the dwelling?

- ☐ Corrugated iron / zinc
- ☐ Thatch
- ☐ Asbestos
- ☐ Slate / brick tiles
- ☐ None
- ☐ Other: ....

42. What is the main material used for the walls of the dwelling?

- ☐ Cement blocks / bricks / stones
- ☐ Burnt bricks
- ☐ Corrugated iron / zinc
- ☐ Wooden poles, sticks and grass
- ☐ Sticks, mud, clay and / or cow-dung
- ☐ Asbestos
- ☐ None
- ☐ Other: ....

43. What is the main material used for the floor of the dwelling?

- ☐ Sand
- ☐ Concrete
- ☐ Mud, clay and/or cow dung
- ☐ Wood
- ☐ Other: ....

44. How much land do own?

☐	< 1 ha	☐	2 – 5 ha
☐	1 – 2 ha	☐	> 5 ha
☐	None	☐	Don't know

45. What is the main source of energy for cooking?

- ☐ Electricity from mains
- ☐ Electricity from generator
- ☐ Gas
- ☐ Paraffin
- ☐ Wood or wood charcoal
- ☐ Coal
- ☐ Animal dung
- ☐ Solar energy
- ☐ None
- ☐ Other: ....

46. What is the main toilet facility?

- ☐ Private flush connected to main sewer
- ☐ Shared flush connected to main sewer
- ☐ Private flush connected to septic/cesspool
- ☐ Shared flush connected to septic/cesspool
- ☐ Pit Latrine with ventilation pipe
- ☐ Covered Pit Latrine without ventilation pipe
- ☐ Uncovered Pit Latrine without ventilation pipe
- ☐ Bucket toilet
- ☐ No toilet facility
- ☐ Other: ....

47. Does anyone of the household members own any of the following assets? (Multiple choice)

☐	Radio	☐	Motor vehicle
☐	Stereo / HiFi	☐	Motor cycle
☐	Television	☐	Donkey-cart
☐	Satellite TV (e.g. DStv)	☐	Plough
☐	Telephone (landline)	☐	Tractor
☐	Cell telephone	☐	Wheelbarrow
☐	Refrigerator	☐	Grinding mill
☐	Stove: gas, elect., paraf.	☐	Bicycle
☐	Microwave oven	☐	Computer
☐	Freezer	☐	Generator
☐	Washing machine	☐	None
☐	Other:		

48. How much livestock do you own?

…..	Cattle	…..	Horses
…..	Goats	…..	Game
…..	Donkeys	…..	Poultry (Chicken)
…..	Sheep	…..	Ostrich
…..	Pigs	…..	Cats
…..	Dogs	☐	None
…..	Other:		

Annex 3: Structured questionnaire (Portuguese)

ISOE

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HDRI Pesquisa Task 16

SASSCAL
Southern African Science Service Centre for Climate Change and Adaptive Land Management

Pesquisa sobre a vulnerabilidade da seca no agregado familiar de Cuvelai

Data		Distrito / Comuna	
Questionário no.	(filled in by supervisor)	Nome da vila	
Nome do entrevistador		Coordenadas SUL	
Pais	☐ Namibia ☐ Angola	Coordenadas LESTE	

Prezado Senhor / Prezada Senhora,
Meu nome é............................ trabalho para.................................., para o projeto de pesquisa SASSCAL e para o Instituto Sócio-Ecológico de Pesquisa (ISOE). Gostaria de fazer algumas perguntas sobre a maneira que você utiliza a água e de como você lida com as situacões de seca.
Todos os dados fornecidos permanecerão anônimos e serão estritamente confidencial.

1. **Qual são as fontes de água que você utiliza para fins domésticos na estação chuvosa? (marque nos caixa)**
2. **Se duas ou mais fontes são usadas, classifique-as (C:) de acordo com a quantidade de água retirada.**

	CATEGORIA	FONTE	CODIGO	ESTAÇÃO CHUVOSA	3. È diferente na estração seca? Se sim, por favor preencha aqui →	ESTAÇÃO SECA
ÁGUA (DOMÉSTICA)	Fontes modernas	Torneira particular	[01]	☐ C:		☐ C:
		Torneira pública	[02]	☐ C:		☐ C:
		Agua engarrafada	[03]	☐ C:		☐ C:
		Poço / Sonda	[04]	☐ C:		☐ C:
		Vendedor de água	[05]	☐ C:		☐ C:
		Canal	[06]	☐ C:		☐ C:
		Poço profundo de boa qualidade	[07]	☐ C:		☐ C:
	Fontes tradicionais	Poço profundo de baixa qualidade	[08]	☐ C:		☐ C:
		Poço raso / Cassimba	[09]	☐ C:		☐ C:
		Açude / Chimpaca	[10]	☐ C:		☐ C:
		Oshana / Lago / Panela	[11]	☐ C:		☐ C:
		Água de chuva	[12]	☐ C:		☐ C:
	Outras:...		[13]	☐ C:		☐ C:
	Comentários:...					

4. **Qual é a fonte de água mais confiável durante a seca?**

[CÓDIGO] Outras:.......................

5. **Quanto tempo se leva para caminhar até esta fonte de água (mão única)?**

.... Minutos

6. **Você utiliza a água para fins comerciais?**

☐ Sim
☐ Não

7. **Se sim, para quais actividates?**

A)..
B)..

8. **Qual a fonte de água o seu gado faz uso...**

... estação chuvosa? [CÓDIGO] Outras: ....
... estação de seca? [CÓDIGO] Outras ....
☐ Não temos gado

9. **Há água da torneira disponível no seu bairro (ex. torneira púplica ou particular)?**

☐ Sim
☐ Não

10. **Se sim, você seria capaz de cobrir todos os seus gastos de água da torneira?**

☐ Absolutamente sim
☐ Mais para sim
☐ Mais para não
☐ Absolutamente não

11. De onde sua família normalmente obtém comida na estação chuvosa? (Marque nos caixa) 12. Se duas ou mais fontes são utilizadas, classifique-as (C:) de acordo com a quantidade de alimento						
ALIMENTO	CATEGORIA	FONTE	CODIGO	ESTAÇÃO CHUVOSA	13. È diferente na estração seca? Se sim, por favor preencha aqui →	ESTAÇÃO SECA
	Produção própria	Campo / Celeiro	[01]	☐ C:		☐ C:
		Hortas / Árvores frutíferas	[02]	☐ C:		☐ C:
		Criações de animais (carne, leite, ovos)	[03]	☐ C:		☐ C:
		Alimento selvage	[04]	☐ C:		☐ C:
		Própria pesca	[05]	☐ C:		☐ C:
		Própria caça	[06]	☐ C:		☐ C:
	Mercados	Mercado local	[07]	☐ C:		☐ C:
		Supermercado	[08]	☐ C:		☐ C:
	Rede sociais	Parentes	[09]	☐ C:		☐ C:
		Vizinhos	[10]	☐ C:		☐ C:
	Doações	Igreja	[11]	☐ C:		☐ C:
		Governo	[12]	☐ C:		☐ C:
	Outras:...		[13]	☐ C:		☐ C:
	Comentários:...					

14. Qual é a fonte de alimento mais confiável num ano de seca?	
[CÓDIGO]	Outras:.......................

15. De onde sua família normalmente tira dinheiro na estação chuvosa? (Marque nos caixa) 16. Se duas ou mais rendas são utilizadas, classifique-as (C:) de acordo com a quantidade de dinheiro					
RENDA	CATEGORIA	FONTE	ESTAÇÃO CHUVOSA	17. È diferente na estração seca? Se sim, por favor preencha aqui →	ESTAÇÃO SECA
	Produção própria	Vendendo alim. processados da agric. própria	☐ C:		☐ C:
		Venda de produtos artesanais feito em casa	☐ C:		☐ C:
		Venda de produção de tijólos própria	☐ C:		☐ C:
		Outra atividade comercial não agrícola	☐ C:		☐ C:
	Emprego	Remuneração agrícola	☐ C:		☐ C:
		Remuneração não agrícola	☐ C:		☐ C:
	Governo	Pensão para idosos	☐ C:		☐ C:
		Pensão de orfandade	☐ C:		☐ C:
		Pensão de invalidez	☐ C:		☐ C:
	Parentes	Remessas em dinheiro	☐ C:		☐ C:
	Outras:...		☐ C:		☐ C:
	Comentários:...				

18. Quais são as coisas que a sua familia normalmente gasta dinheiro na estação chuvosa? (Marque caixa) 19. Se dois ou mais gastos existirem, classifque-os (C:) de acordo com a quantidade de dinheiro gasto.					
DESPESAS	CATEGORIA	FONTE	ESTAÇÃO CHUVOSA	20. È diferente na estração seca? Se sim, por favor preencha aqui →	ESTAÇÃO SECA
	Domestíca	Comida para o consumo humano	☐ C:		☐ C:
		Água para o consumo humano	☐ C:		☐ C:
		Clothing & footwear	☐ C:		☐ C:
		Educação (ex. taxa de escola)	☐ C:		☐ C:
		Assistência médica (ex. medicatio, hospital)	☐ C:		☐ C:
		Transporte (ex. combustível para o carro)	☐ C:		☐ C:
		Comunicação (ex. Unitel)	☐ C:		☐ C:
		Energia (ex. madeira, gás, carvão, eléct.)	☐ C:		☐ C:
		Alojamento (ex. arrendar)	☐ C:		☐ C:
	Agricultura / Pecuária	Forragem para uso animal	☐ C:		☐ C:
		Água para uso animal	☐ C:		☐ C:
		Fertilizante / Pesticida	☐ C:		☐ C:
		Medicamento animal	☐ C:		☐ C:
	Outras:...		☐ C:		☐ C:
	Comentários:...				

21. Quanto tempo leva para caminhar até a Estrada asfaltada / atalho mais próxima (mão única)?

.... Minutos

22. Seu domicílio é mais ou menos afetado pela seca se comparado com seus vizinhos?

- ☐ Muito mais
- ☐ Mais
- ☐ Igual
- ☐ Menos
- ☐ Muito menos
- ☐ Não sei

23. Durante a última seca, sua família teria conseguido sobreviver sem a ajuda do governo?

- ☐ Absolutamente sim
- ☐ Mais para sim
- ☐ Mais para não
- ☐ Absolutamente não
- ☐ Não há alívio para seca
- ☐ Não sei

24. Durante a última seca, sua família dependeu de doações de água?

- ☐ Absolutamente sim
- ☐ Mais para sim
- ☐ Mais para não
- ☐ Absolutamente não

25. Qual grupo étnico você pertence?

☐	Ndonga	☐	Kolonkadhi
☐	Kwambi	☐	Kwanhama
☐	Ngandjera	☐	Mbadja
☐	Kwaluudhi	☐	Nyaneca-humbi
☐	Mbalanhu	☐	Muhanda
☐	Other:		

26. Quantas pessoas têm na sua casa (pessoas que ficam em casa por mais de 6 meses por ano)?

….. Mulheres ….. Homens = ….. Total

27. Quantos membros da família ficar longe da herdade por 1 a 6 meses por ano?

….. Pessoas

28. Quantas pessoas têm algum tipo de deficiência ou limitação que requer cuidado intensivo ou tem qualquer impedimento de se envolver em actividades económicas?

….. Pessoas

29. Quantos membros da família pertencem a classe de idade?

….. <= 14

….. 15 – 59 = ….. Total

….. >= 60

30. Qual é o estado civil do chefe da família?

☐	Nunca se casou	Divorciado
☐	Casado com certidão	Viúvo
☐	Casado tradicionalmente	Separado
☐	União consensual	Não sei

31. O que é a relação do intrevistado com o chefe da família?

- ☐ Idêntico — Cônjuge
- ☐ Outros: ....

32. O que é o sexo do intrevistado?

- ☐ Masculino
- ☐ Feminino

33. O que é a idade do intrevistado?

.... Anos

34. Qual é o nivel de educação mais alto de um dos membros do agregado familiar?

☐	Escola primária	Diploma universitário
☐	Ensino médio	Nenhum
☐	Formação profissional	
☐	Outras:	

35. Você diria que essa vizinhança é um lugar onde os moradores cuidam uns dos outros?

- ☐ Absolutamente sim
- ☐ Mais para sim
- ☐ Mais para não
- ☐ Absolutamente não
- ☐ Não sei

36. Com que frequência você conversa com seus vizinhos?

- ☐ Quase todos os dias
- ☐ Uma ou duas vezes por semana
- ☐ Uma ou duas vezes por mês
- ☐ Menos de uma vez por mês
- ☐ Nunca

37. Quão perto moram os seus parentes?

- ☐ Nesta vila
- ☐ Na vila vizinha
- ☐ Na próxima cidade
- ☐ Longe
- ☐ Muito longe
- ☐ Não tenho parentes

38. Se existem parentes, com que frequência vocês se encontram?

☐ Quase todos dias
☐ Uma ou duas vezes por semana
☐ Uma ou duas vezes por mês
☐ Menos de uma vez por mês
☐ Nunca

39. Qual é o tipo de unidade habitacional aqui?

☐ Casa separada
☐ Casa geminada
☐ Apartamento
☐ Construção tradicional
☐ Moradia improvisada
☐ Outras: ....

40. Quantos cômodos têm a habitação?

..... Cômodos / Compartimentos

41. De que consiste o material principal utilizado no telhado da moradia?

☐ Folhas de zinco / ferro
☐ Capim
☐ Amianto
☐ Ardósia / Tijolo cerâmico
☐ Nenhum
☐ Outros: ....

42. Qual é o material principal usado nas paredes da moradia?

☐ Blocos de cimento / tijólos / pedras
☐ Tijólos queimados
☐ Placas de ferro / zinco
☐ Colunas de madeira, varas e capim
☐ Varas, lama, barro e / ou esterco de vaca
☐ Amianto
☐ Nenhum
☐ Outras: ....

43. Qual é o material principal usado no chão da moradia?

☐ Areia
☐ Concreto
☐ Lama, barro e / ou esterco de vaca
☐ Madeira
☐ Outros: ....

44. Quanto de terra você possui?

☐ < 1 ha	☐ 2 – 5 ha
☐ 1 – 2 ha	☐ > 5 ha
☐ Nenhum	☐ Não sei

45. Qual é a fonte principal de energia para cozinhar?

☐ Electricidade da rede eléctrica
☐ Electricidade a partir de gerador
☐ Gás
☐ Parafina
☐ Madeira ou carvão vegetal de madeira / lenha
☐ Carvão
☐ Esterco de animais
☐ Energia solar
☐ Nenhuma
☐ Outras: ....

46. Qual é a principal instalação sanitária?

☐ Sanitário privado conectado ao coletor principal
☐ Sanitário comunitário conectado ao coletor principal
☐ Sanitário privado conectado ao esgoto
☐ Sanitário comunitário conectado os esgoto
☐ Fossa com tubo de ventilação
☐ Fossa coberta sem tubo de ventilação
☐ Fossa descoberta sem tubo de ventilação
☐ Balde sanitário
☐ Sem nenhum sanitário
☐ Outras: ....

47. Existe algum membro da família que possui algum dos seguintes bens? (Múltipla escolha)

☐ Rádio	☐ Veículo a motor
☐ Aparelho de som/HiFi	☐ Motocicleta
☐ Televisão	☐ Carroça de burro/boi
☐ Televisão por satélite	☐ Arado / Xarrua
☐ Telefone fixo	☐ Trator
☐ Telefone celular	☐ Carrinhão de mão
☐ Geladeira / Geleira	☐ Moinho
☐ Fogão: gás, eléct.	☐ Bicicleta
☐ Microondas	☐ Computador
☐ Congelador / Arca	☐ Gerador
☐ Máquina de lavar	☐ Nenhum
☐ Outros:	

48. Qual a quantidade de animais que você possui?

.....	Gado	.....	Cavalos
.....	Bodes /	.....	Caça
.....	Burros	.....	Aves / Galinha
.....	Ovelhas	.....	Avestruz
.....	Porcos	.....	Gatos
.....	Cães	☐	Nenhum
.....	Outros:		

Annex 4: List of publications

Peer-reviewed publications

Luetkemeier, R., Liehr, S., under review. Household drought risk index (HDRI): Social-ecological assessment of drought risk in the Cuvelai-Basin. Journal of Natural Resources and Development (JNRD).

Luetkemeier, R., Stein, L., Drees, L., Müller, H., Liehr, S., 2018. Uncertainty of rainfall products: impact on modelling household nutrition from rain-fed agriculture in southern Africa. Water 10, 499. https://doi.org/10.3390/w10040499

Luetkemeier, R., Liehr, S., 2018. Drought sensitivity in the Cuvelai-Basin: Empirical analysis of seasonal water and food consumption patterns, in: Revermann, R., Krewenka, K., Schmiedel, U., Olwoch, U., Helmschrot, J., Jürgens, N. (Eds.), Climate Change and Adaptive Land Management in Southern Africa – Assessments, Changes, Challenges, and Solutions, Biodiversity & Ecology. Klaus Hess Publishers, Göttingen & Windhoek.

Taubenböck, H., Müller, I., Geiß, C. & R. Luetkemeier (2018) Risk Management – A conceptual foundation, in: Revermann, R., Krewenka, K., Schmiedel, U., Olwoch, U., Helmschrot, J., Jürgens, N. (Eds.), Climate Change and Adaptive Land Management in Southern Africa, Biodiversity & Ecology. Klaus Hegg Publications, Windhoek, Namibia.

Luetkemeier, R., Stein, L., Drees, L., Liehr, S., 2017. Blended drought Index: Integrated drought hazard assessment in the Cuvelai-Basin. Climate 5, 51. https://doi.org/10.3390/cli5030051

Luetkemeier, R., Liehr, S., 2015. Impact of drought on the inhabitants of the Cuvelai watershed: A qualitative exploration, in: Alvarez, J., Solera, A., Paredes-Arquiola, J., Haro-Monteagudo, D., van Lanen, H. (Eds.), Drought: Research and Science-Policy Interfacing. CRC Press, Leiden, Netherlands, pp. 41–48.

Further publications

Luetkemeier, R., Liehr, S., forthcoming. Integrated responses to drought risk in southern Africa, Policy Brief. ISOE - Institute for Social-Ecological Research, Frankfurt am Main.

Liehr, S. & R. Luetkemeier 2018: Abschlussbericht SASSCAL Task016.

Kampfl, S., Luetkemeier, R. & S. Liehr 2017: Impact of household decisions on grazing pressure in northern Namibia: Modelling approach for sustainable livestock management. In: SASSCAL NEWS 2(2), June.

Luetkemeier, R. & S. Liehr 2017: Drought in the Cuvelai-Basin. Integrated tool for drought hazard assessment. In: SASSCAL NEWS 2(3), September.

Luetkemeier, R. 2016. Certainly uncertain! Do satellites help to monitor food security in Africa? In: Climate snack Blog. URL: https://www.scisnack.com/2016/04/22/certainly-uncertain-do-satellites-help-to-monitor-food-security-in-africa/ (22.04.2016).

Conference presentations

Luetkemeier, R. & S. Liehr 2018. Drought risk in southern Africa: The need for integrated local and regional risk assessments. In: SASSCAL Science Symposium, 16.04.2018 – 20.04.2018, Lusaka, Zambia.

Luetkemeier, R., Stein, L., Drees. L., Müller, H. & S. Liehr 2018. Uncertainty of rainfall products: Impact on modelling household nutrition from rain-fed agriculture in southern Africa. In: SASSCAL Science Symposium, 16.04.2018 – 20.04.2018, Lusaka, Zambia.

Luetkemeier, R. 2016. The missing link in drought information systems – water-energy-food nexus approach to account for multi-sector vulnerabilities. In: Water-Energy-Food Nexus Academy, 04.10.2016 – 07.10.2016, Trier, Germany.

Luetkemeier, R. & S. Liehr 2015. Sozial-ökologische Forschung im Südlichen Afrika CuveWaters, OPTIMASS & SASSCAL. In: Tagung der Afrikagruppe deutscher Geowissenschaftler (AdG), 26.06.2015 – 27.06.2015, Universität Frankfurt, Frankfurt, Germany.

Luetkemeier, R. 2015. Impact of drought on the inhabitants of the Cuvelai watershed: A qualitative exploration. In: "International Conference on Drought: Research & Science Policy Interfacing", 10.03.2015 - 13.03.2015, Valencia, Spain.

Luetkemeier, R. 2015. Drought vulnerability in Namibia and Angola: Current state of PhD-research project in the Cuvelai-Basin. In: Volkswagen Foundation summer school, 19.09.2015 – 12.10.2015, Ethiopia.

Luetkemeier, R. & S. Liehr 2015. Food security in the Cuvelai-Basin: Uncertainty analysis of satellite-rainfall products. In: 5th Zambia Water Forum and Exhibition (ZAWAFE) conference, 02.11.2015 – 03.11.2015, Lusaka, Zambia.

Luetkemeier, R. 2014. SASSCAL Task016: Wasserbezogene Vulnerabilität - Aktueller Stand der Forschung. In: Jahrestreffen der Afrikagruppe deutscher Geowissenschaftler (AdG), 28.06.2014, Universität Köln, Cologne, Germany.

Luetkemeier, R. 2013. TASK 16: Determination of water-related vulnerabilities and risk-based on water demand analyses. In: SASSCAL Thematischer Workshop des Forschungsbereichs Wasser, 08.10.2013 – 11.10.2013, Livingstone, Zambia.

Poster presentations

Luetkemeier, R., Stein, L., Drees. L., Müller, H. & S. Liehr 2018. Uncertainty of rainfall products: Impact on modelling household nutrition from rain-fed agriculture in southern Africa. In: SASSCAL Science Symposium, 16.04.2018 – 20.04.2018, Lusaka, Zambia.

Drees. L., Liehr, S. & **R. Luetkemeier** 2018. Coupling models to assess the use of water sources in southern Africa. In: SASSCAL Science Symposium, 16.04.2018 – 20.04.2018, Lusaka, Zambia.

Kampfl, S., **Luetkemeier, R.** & S. Liehr 2017: Impact of household decisions on grazing pressure in northern Namibia. In: Jahrestreffen der Afrikagruppe deutscher Geowissenschaftler (AdG), 23.06.2017 – 24.06.23017, Berlin, Germany.

Luetkemeier, R. & S. Liehr 2017: Household drought risk index. Integrated drought risk assessment in the Cuvelai-Basin, In: Water Security and Climate Change Conference (WSCC), 18.09.2017 – 21.09.2017, Cologne, Germany.

Drees, L., Liehr, S. & **R. Luetkemeier** 2017. Coupling models to assess the use of water sources in southern Africa. In: Geobiodiversity. An integrative approach expanding Humboldt's vision. International Conference, Senckenberg Gesellschaft für Naturforschung, 01.10.2017 – 03.10.2017, Frankfurt, Germany.

Luetkemeier, R. 2016. Household drought vulnerability: Social-ecological approach for an integrated vulnerability analysis. In: Volkswagen Foundation summer school, 21.02.2016 – 15.03.2016, Kenya.

Stein, L., **Luetkemeier, R.** & S. Liehr 2015. Blended drought index (BDI): Estimating drought exposure in the Cuvelai-Basin using multiple satellite datasets. In: Arbeitskreis Subsaharisches Afrika, 27.11.20.15 – 28.11.2015, Berlin, Germany.

Luetkemeier, R. & S. Liehr 2014. Vulnerability to water scarcity – Drought challenges Namibian smallholders. In: WASCAL-Konferenz "Climate Change in Africa. Negotiations, translations and socio-political implications", 10.09.2014 – 12.09.2014, Bonn, Germany.