Multiple hazards risk profiling in West Africa

Assessment, Validation and Upscaling

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Dedication

This dissertation is dedicated to my two sons, Chief Kwabena Asare-Kyei and Ohene Amponsem Asare-Kyei. Your presence in this earth has been a source of boundless joy and strength to me.

Abstract

Disasters, particularly recurring small-scale natural disasters of floods and droughts have been affecting West African (WA) communities, impacting particularly weak households. These losses have been significantly high over the last decade due to increasing climate variability and inherently depressed socio-economic systems. However, to date, few studies have attempted to understand the risk and vulnerability profiles in West Africa to these multiple hazards across several scales, from rural communities and watersheds to districts and to regions. A considerable number of studies predict the impacts of droughts and floods hazards, but many do so at a very coarse scale and are unable to predict localized impacts. Despite many efforts put in vulnerability assessments, there has been limited success in simultaneously traversing scale and hierarchy and the need for upscaling risk indices is important to understand the effects of cross scale interactions. To address these gaps, this thesis (i) explored methods to involve at-risk populations in local communities in a bottom-up participatory process as opposed to the classical top-down, single scale approaches and (ii) assessed the risks from multi-hazard perspectives in a coupled Socio-Ecological System (SES). The thesis also (iii) explored appropriate methodologies that can reflect the spatial variability of flood hazard intensity at community level. Building on these investigations, the thesis finally (iv) introduced a novel risk index upscaling procedure to upscale risk and vulnerability indices across multiple scales.

The thesis used several methods ranging from rural participatory methods, statistical, Geographic Information System (GIS), remote sensing and introduced the innovative concept of Community Impact Score (CIS). The results show that more than half of the designated local level indicators and over two thirds of the macro scale indicators are rarely used in present risk assessments in the region. Additionally, although an indicator may be common to three countries, their differential rankings will result in differences in explaining the risks faced by people in different societies.

Empirical validation of a flood hazard map using the statistical confusion matrix and the principles of participatory GIS show that flood hazard areas could be mapped at an accuracy ranging from 77% to 81%. These high mapping accuracies notwithstanding, the flood index categories may change under conditions of very high rainfall intensities beyond the anomalies used to construct the model. To this end, studies that aim at understanding projected flood intensities under varying rainfall conditions beyond the anomalies used in this study are recommended. This is important to determine the trajectory of flood safe havens or hotspots across an entire study area. The study also develops two important indices, The West Sudanian Community Vulnerability Index (WESCVI) and The West Sudanian Community Risk Index (WESCRI). The underlying factors constituting the two indices are the elements of risk and vulnerability profiles of communities in West Africa. The WESCVI and WESCRI should help planners and policy makers to analyse and finally reduce vulnerability and risk. To evaluate the results of the risk indices, this thesis introduces a novel technique to validate the results of complex aggregation methods. Based on up to date knowledge, the CIS concept is the first in the available literature of risk assessment. The thesis also provides a theoretical concept to upscale risk and vulnerability indices from watershed to higher spatial scales. Further studies are however recommended to apply these theoretical

concepts. A conclusion of the thesis is that while it has neither been optimal to completely neglect classical approaches nor to take as an absolute fact opinion from local experts, more emphasis should be paid to the later in risk assessment that is supposed to serve the very people on whose behalf the assessment is done. Attempts should therefore be made in finding mechanisms where the two approaches could interact fruitfully and complement each other.

Zusammenfassung

Naturgefahren, wie beispielsweise Überflutungen und Dürren, bedrohen die Existenz von Gemeinden und insbesondere schwächeren Haushalten in West Afrika. Durch die zunehmende Klimavariabilität und den geschwächten Zustand der sozial-ökologischen Systeme haben die Verluste während der letzten Dekade ein besonders hohes Ausmaß erreicht. Bisher haben nur wenige Studien versucht, die unterschiedliche Zusammensetzung des Risikos im Hinblick auf mehrere Naturgefahren in Westafrika zu verstehen und über verschiedene Skalen hinweg, von ländlichen Gemeinden hin zu Wassereinzugsgebieten, Distrikten und Regionen zu analysieren. Eine signifikante Anzahl von Studien prognostiziert die zu erwarteten Schäden durch Naturgefahren wie Überflutungen und Dürren. Dies geschieht jedoch oftmals auf einem sehr groben Maßstab, wohingegen wenig über die lokalen Auswirkungen bekannt ist. Trotz mannigfaltiger Anstrengungen in Bezug auf Vulnerabilitätsassessments gab es bisher wenig Erfolg bei der Berücksichtigung verschiedener Skalen und Hierarchien. Die Hochskalierung von Risikoindizes ist jedoch nötig, um die Effekte über verschiedene Skalen hinweg zu verstehen.

Diese Forschungslücken werden in dieser Arbeit aufgegriffen und mit methodischen Verfahren über einen „Bottom-up“-Ansatz adressiert, der zunächst die gefährdete Bevölkerung involviert, um die Risiken gegenüber von mehrfachen Gefährdungen in einem sozio-ökologischen System (SES) zu untersuchen. Außerdem verwendet die Studie Methoden, die es ermöglichen, die räumliche Variabilität der Überflutungsintensität auf Gemeindeebene zu reflektieren. Aufbauend auf diesen Forschungsergebnissen stellt diese Arbeit eine neue Vorgehensweise vor, die es erlaubt Verwundbarkeits- und Risikoindizes über verschiedene Skalen hinweg hochzuskalieren. Der Methodenmix umfasst partizipative und statistische Ansätze sowie Methoden basierend auf Geographische Informationssystemen (GIS) und Fernerkundung. Des Weiteren schlägt die Arbeit ein innovatives Konzept zur Quantifizierung der Gefährdungsauswirkungen auf Gemeindeebene vor, den sogenannten „*Community Impact Score*“ (CIS).

Die Ergebnisse zeigen, dass etwas mehr als die Hälfte der in dieser Arbeit abgeleiteten Indikatoren auf Gemeindeebene und über zwei Drittel der Indikatoren auf Makroebene selten in den gegenwärtigen Risikoassessments der Region verwendet werden. Zudem wurde den Indikatoren, selbst wenn sie für alle drei Länder abgeleitet wurden, oftmals eine unterschiedliche Wichtigkeit zugesprochen. Die empirische Validierung der Hochwassergefährdungskarten mittels einer statistischen Konfusionsmatrix basierend auf einem partizipativen GIS zeigt, dass die durch Hochwasser gefährdeten Gebiete mit einer Genauigkeit von 77-81% kartiert werden konnten. Trotz dieser hohen Genauigkeit ist es jedoch möglich, dass sich die Hochwassergefährdungskategorien bei Anomalitäten, die über die modellierten Bedingungen hinausreichen, verändern. Dementsprechend werden weiterführende Studien, die eben diese Bedingungen untersuchen empfohlen. Dies ist zur Bestimmung von sicheren Zufluchtsorten oder Hotspots von großer Bedeutung.

In dieser Studie wurden außerdem zwei verschiedene Indizes entwickelt, der sogenannte „*West Sudanian Community Vulnerability Index*“ (WESCVI) und der „*West Sudanian Community Risk Index“*

(WESCRI). Die den Indizes zugrunde liegenden Faktoren bilden außerdem die Bestandteile der Risiko- und Vulnerabilitätsprofile für die Gemeinden Westafrikas. Sowohl der WESCVI als auch der WESCRI sollen Planern und politischen Entscheidungsträgern dabei helfen, die Vulnerabilität und das Risiko zu analysieren und zu reduzieren. Um die Ergebnisse der Risikoindizes zu evaluieren stellt diese Arbeit ein innovatives Konzept zur Validierung solch komplexer Aggregationsmethoden vor. Nach aktuellem Kenntnisstand ist das CIS Konzept das erste seiner Art in der erhältlichen Literatur zu Risikoassessments. Des Weiteren wurde ein theoretisches Konzept zur Hochskalierung von Risiko- und Vulnerabilitätsindizes von Wassereinzugsgebieten hin zu höheren Ebenen erarbeitet.Dieses theoretische Konzept bietet eine Basis für weiterführende Untersuchungen im Hinblick auf die Anwendung und Umsetzung.

Insgesamt unterstreicht diese Studie, dass weder die klassischen Ansätze allein noch das Gleichsetzen von lokalem Expertenwissen mit der absoluten Wahrheit als optimal erachtet werden können. Die Studie zeigt, dass man dem lokalen Expertenwissen in Risikoassessments mehr Gewicht beimessen sollte. Dementsprechend sollten Ansätze gefunden werden, bei denen sich beide Herangehensweisen erfolgreich ergänzen.

Résumé

Les catastrophes naturelles, particulièrement celles récurrentes aux échelles locales, liées aux inondations et aux sécheresses, ont affecté les communautés Ouest-Africaines, avec des répercussions sur les ménages particulièrement fragiles. Ces pertes ont été sensiblement élevées au cours de la dernière décennie en raison de la variabilité croissante du climat et des systèmes socio-économiques intrinsèquement en déclin. Cependant, à ce jour, peu d'études ont tenté de comprendre les profils des risques en Afrique de l'Ouest face à des risques nombreuses et multi-échelles, allant des communautés rurales et des bassins versants aux districts et aux régions. Un nombre considérable d'études prédisent l'impact des risques et aléas courants inhérents aux sécheresses et inondations, mais beaucoup le font à d’échelles très grossières, rendant impossible la prévision des impacts y relatifs de façon localisée dans l’espace. En dépit de nombreux efforts en matière d'évaluation de la vulnérabilité, peu de succès a été noté en parcourant simultanément l'échelle et la hiérarchie; et la nécessité d’effectuer un *upscaling* des indices liés aux risques est importante pour comprendre les effets croisés émanant des interactions d’échelles. Pour remédier à ces lacunes, cette thèse explore des méthodes prenant en compte les populations à risque à partir de plusieurs niveaux échelles et via un processus participatif ascendant, par opposition aux approches classiques du haut vers le bas et à échelle unique; et afin d'évaluer les risques à partir de perspectives Socio-Ecologiques Multi-Système (Socio-Ecological System - SES). La thèse explore aussi des méthodologies appropriées à même de refléter la variabilité spatiale de l'intensité du risque d'inondation au niveau communautaire. En s'appuyant sur ces investigations, la thèse introduit finalement une nouvelle procédure de *upscaling*, en vue mettre à niveau les indices risque et de vulnérabilité à travers de multiples échelles. La thèse utilise plusieurs méthodes allant des méthodes participatives ruraux, des statistiques, du Système d'Information Géographique (SIG), de la télédétection, et introduit également le concept novateur du concept de score d'impact de risque communautaire sur les dangers (Community Hazard Impact Score - CIS). Les résultats montrent que plus de la moitié des indicateurs locaux désignés et plus de deux tiers des indicateurs macroéconomiques sont rarement utilisés dans les évaluations actuelles des risques dans la région. De plus, quoiqu’un indicateur puisse être commun à trois pays, leur classement différentiel entraînera des différences dans l'explication des risques auxquels est confrontée la population dans les différentes sociétés.

La validation empirique d'une carte des risques d'inondation à l'aide de la matrice de confusion statistique et des principes du SIG participatif montre que les zones à risque d'inondation pourraient être cartographiées avec une précision allant de 77% à 81%. Malgré ces précisions cartographiques élevées, les catégories d'indice d'inondation peuvent changer dans des conditions d'intensité pluviométrique très élevée au-delà des anomalies utilisées pour construire le modèle. À cette fin, des études visant à comprendre les intensités d'inondation projetées dans des conditions pluviométriques variables au-delà des anomalies utilisées dans cette étude sont recommandées. Ceci est important pour déterminer la trajectoire des havres de sécurité des inondations ou des hotspots sur toute une zone d'étude. L'étude développe également deux indices importants: l'Indice de Vulnérabilité de la Communauté Ouest- soudanienne (West Sudanian Community Vulnerability Index - WESCVI) et l'Indice de Risque communautaire de l'Ouest-Soudanien (West Sudanian Community Risk Index - WESCRI). Les

facteurs sous-jacents constitutifs de ces deux indices sont les éléments des profils de risque et de vulnérabilité des communautés en Afrique de l'Ouest. Le WESCVI et WESCRI devraient aider les planificateurs et les décideurs politiques à analyser et de réduire la vulnérabilité et les risques. Pour évaluer les résultats des indices de risque, cette thèse introduit une nouvelle technique pour valider les résultats des méthodes d'agrégation complexes. À notre connaissance, le concept de CIS est le premier de la littérature disponible sur l'évaluation des risques. La thèse fournit également un concept théorique permettant d’effectuer un *upscaling* des indices de risque et de vulnérabilité du niveau du bassin versant à des échelles spatiales plus élevées. D'autres études sont cependant recommandées pour favoriser l’application des concepts théoriques. La conclusion de la thèse est qu’il n’est pas optimal de négliger complètement les approches classiques, ni de prendre comme fait absolu les opinions des experts locaux, néanmoins il conviendrait de mettre davantage l'accent sur les actions des seconds dans l'évaluation des risques; ces derniers étant censées servir les populations pour lesquelles ces évaluations sont effectuées. Des tentatives doivent donc être effectuées en vue de trouver des mécanismes où les deux approches peuvent interagir fructueusement et se compléter mutuellement. Nous espérons que la présente thèse fournira une bonne base pour les efforts dans ce sens.

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Abbreviations

AAP	Africa Adaptation Project
ABM	Agent Based Model
BMBF	German Federal Ministry of Education and Research
CCA	Climate Change Adaptation
CIS	Community Impact Score
DEM	Digital Elevation Model
DRI	Disaster Risk Index
DRR	Disaster Risk Reduction
EPA	Environmental Protection Agency
ESI	Environmental Sustainability Index
FAO	Food and Agriculture Organization
FAO GIEWS	Food and Agriculture Organization-Global Information and Early Warning System
FHI	Flood Hazard Index
GIS	Geographic Information System
GLADIS	Global Land Degradation Information System
HDI	Human Development Index
HWI	Human Welfare Index
HWSD	Harmonized World Soil Database
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
IRS	Indicator Reference Sheet
MEA	Millennium Ecosystem Assessment
MoFA	Ministry of Food and Agriculture
NADMO	National Disaster Management Organization
PGIS	Participatory Geographic Information System
PIV	Predictive Indicators of Vulnerability Index
PVI	Prevalence of Vulnerability Index
SES	Socio Ecological System
SOVI	Social Vulnerability Index
SSA	Sub-Sahara Africa

SVA	Index of Social Vulnerability to Climate Change in Africa
UNDP	United Nations Development Programme
UNFCCC	United Nations Framework Convention for Climate Change
UNISDR	United Nations Office for Disaster Risk Reduction
UNOCHA	United Nations Office for the Coordination of Humanitarian Affairs
USAID	United States Agency for International Development
VRIP	Vulnerability-Resilience Indicator Prototype
WA	West Africa
WARA	West Africa Risk Assessment
WASCAL	West Africa Science Service Centre on Climate Change and Adapted Land Use
WESCRI	West Sudanian Community Risk Index
WESCVI	West Sudanian Community Vulnerability Index
WRI	World Risk Index

1. General Introduction

Disasters, many of which are exacerbated by climate change are increasing in frequency and intensity…...e*vidence indicates that exposure of persons and assets in all countries has increased faster than vulnerability has decreased, thus generating new risks and a steady rise in disaster related losses, with a significant economic, social, health, cultural and environmental impact in the short, medium and long term, especially at the local and community levels. Recurring small-scale disasters and slow-onset disasters particularly affect communities, households and small and medium-sized enterprises, constituting a high percentage of all losses. All countries – especially developing countries, where the mortality and economic losses from disasters are disproportionately higher – are faced with increasing levels of possible hidden costs and challenges in order to meet financial and other obligations…….UNISDR (2015). The Sendai Framework for Disaster Risk Reduction, p. 9)*

1.1. Background and research problem

Presently, Africa is a continent under pressure from climate stresses and is highly vulnerable to the impacts of climate change (IPCC, 2014; UNFCCC, 2007). West Africa (WA) has been described as a hotspot of climate change (IPCC, 2014). The frequency of occurrence of extreme events is expected to increase and the interaction of climate change with non-climate stressors will aggravate vulnerability of agricultural systems in semi-arid Africa particularly, the West Sudanian Savanna region of Burkina Faso, Ghana and Benin (IPCC, 2014). The vulnerabilities are projected to worsen given a host of biophysical and human related stressors in the region including erosive rainfall, recurring drought, soil qualities and fertility, low input farming systems, decreased fallow period, deforestation, frequent bush fires, and overgrazing (USAID, 2011) as well as social conflicts, political upheavals and cultural stresses (Fields, 2005).

Though there are several uncertainties in climate change predictions models for West Africa (WA), the dominance of rain-fed agriculture in the region where 60% of the population is engaged in agriculture (FAO, 2012) makes its population vulnerable to climate change, particularly warmer temperatures and lowered rainfall. In this region, a temperature of 3-6°C above the late 20th century baseline is "very likely" to be realized within the 21st century and the fact that this projection is expected to occur one or two decades earlier than other regions (IPCC, 2014) contributes to making the region more vulnerable to climate change. There is also medium confidence that projected increase in extreme rainfall will "contribute to increases in rain-generated local flooding" (Kundzewicz *et al*., 2014:p.24). For WA, Sylla *et al.* (2015) projected a decrease in the absolute number, but an increase in the intensity of very wet events – leading to increased drought and flood risks towards the late 21st century.

Despite the major impact of floods on the livelihoods of the people living in this region, no attempt has been made to delineate the boundaries of flood hazard intensity at the community level and to identify areas most at risk of flooding. Mapping flood hazard zones is an important first step in the proper management of future flooding events. The use of flood hazard maps for managing disasters in West Africa is virtually non-existent. Disaster managers have for many years relied on traditional methods such as watermarks on buildings, local knowledge and media reports to identify possible affected areas during flood events (Nyarko, 2002). Lack of proper records on historical flood events, coupled with logistical and financial challenges have often resulted in a poor preparedness and response to flooding events. Consequently, fatalities have often been high (Braman *et al*., 2013; Levinson & Lawrimore, 2008).

The IPCC (2012) reported a medium confidence of the occurrence of a significant temperature increase of warmest days and coldest nights. Dry spell duration is reported to have increased between 1961 and 2000 with recent years characterized by a greater inter-annual variability than the past 40 years. Overall, there is evidence that the agriculture sector including fisheries, cocoa, cereals, and root crops, and water resources as well as human health and women's livelihoods will be negatively impacted by climate change; the poor being most vulnerable (Dasgupta *et al.*, 2009; World Bank, 2009a). Fields (2005) argues that the influence of multiple stressors such as natural disasters, infectious diseases, economic turbulence from globalization, resource privatization, and civil conflicts, combined with the lack of resources for adaptation, will present serious challenges for African communities struggling to adapt to climate change. Yet, comprehensive and quantitative understanding of the vulnerability and risk faced by WA communities to these multiple hazards, not even the common occurring hazards of floods and droughts are still lacking.

A considerable number of models predict the impacts of climate change on Socio-Ecological Systems (SES), but many do so at a very coarse scale and are also unable to predict localized impacts, which may typically differ from coarser scale assessments (Birkmann, 2007).

Research on risks and the accompanying vulnerabilities of the SES to climate change has largely addressed the expected impacts of climatic change on global, national, regional or sectoral scales but are largely unavailable at community level where risk outcomes are first materialized (Bollin & Hidajat, 2006). This is partly because of a non-universal applicability of existing indicator based vulnerability and risk assessment methods to areas such as the West African sub-region, implying that different and well-adapted methods need to be developed. Such methods should tackle complex settings of hazards occurrence as well as the dynamic socio-economic and environmental exposure; such methods needed to be spatially explicit and reflect the dynamic nature of the SES under study and be multi-scaled, allowing local based approaches and upscaling; They also need to be context specific, be able to capture all relevant processes shaping vulnerability and risk at various scales and, more importantly, still be applicable to local communities affected usually by multiple hazards (Adger *et al*., 2004; Africa Adapt, 2011). However, the available literature suggests that these important considerations have been missing in many risk assessments particularly, for the West African sub-region.

The assessment of risks from different hazards has normally been studied through independent analysis and dependencies between hazards sources are largely neglected (Marzocchi *et al*., 2009). The status quo has been a single hazard analysis and major questions remain. These questions include how to quantify risk across multiple hazards such as combined drought and floods; across multiple scales (local to regional to sub-regional); include indicators that also reflect external drivers of climate change and at the same time being useful for policy makers?

To date, few studies have attempted to understand the risk profiles of West African communities in the context of climate change through a set of indicators. The only study that comes close is a study conducted in Ghana in 2011 by the United States Agency for International Development (USAID, 2011).

Even in this study, the indicators were derived purely from literature and lack the important element of the participatory process from the vulnerable themselves. Other studies available in the area have either qualitatively assessed vulnerabilities (e.g. Trench *et al.*, 2007; Tschakert, 2007) or only looked at specific aspects such as vulnerability to food insecurity (Bacci et al., 2005; Barbier *et al.*, 2009), or focused on single hazards such as floods (e.g. Adelekan, 2011; Armah *et al*., 2011). Despite the large amount of knowledge available in local areas (Reed *et al*., 2008) most, if not all risk assessments in the WA region have been approached from classical methods[1] without tapping into the wealth of resources available at the local level. Moreover, little is known about the vulnerability profiles of rural WA communities particularly regarding risk to multiple hazards. Yet, it is acknowledged that risk and vulnerability identification and measurement before and after the occurrence of hazards are essential tasks for effective and long term Disaster Rik Reduction (DRR), (Birkmann, 2007b). There is an increasing need for a shift from global and regional assessments to sub-national and community level assessments because these are the scales where major decisions against risk are made and expected to be implemented.

Validation is an essential aspect of assessing the accuracy of the results of complex models. However, only statistical validation methods have been used in almost all risk assessment literature reviewed even though indicator development and subsequent modelling often involves several subjective decisions by the authors (Damm, 2010). Some have argued that conventional validation of vulnerability is impossible because vulnerability cannot be measured in the traditional sense and have concluded that validation still remains an open challenge in risk assessment (Damm, 2010). In this study, therefore, the concept of Community Impact Score (CIS) is introduced as an innovative validation technique for assessing the accuracy of complex risk assessment modelling.

Again, despite much efforts in vulnerability assessments, there has been limited success in ‘’simultaneously traversing scale and hierarchy from a lower scale to large scale and vice versa’’ (Cushman *et al.*, 2010). Moving upward (upscaling) in socio-ecological hierarchy and landscapes is an exigent task as the sampling cost in very large spatial areas such as a whole administrative region is prohibitive, and methods of combining these fine grain data to produce broad scale predictions are exciting (King, 1991; Rastetter *et al*., 1992; Schneider, 1994). In risk and vulnerability assessments, scale is important for two main reasons. SES and processes operate at a wide variety of scales and that across scales, they can change in their nature and sensitivity to various driving forces and so it cannot be assumed that results obtained at given scale will invariably be the same at another. The second reason is that cross-scale interactions exert a critical influence on outcomes at a given scale and that these interactions can be missed by focusing on a single scale (Kremen *et al*., 2000; McConnell, 2002). The underlying reasons, effects and specific interactions resulting from decisions from various stakeholders acting at different scales are poorly understood. For these reasons, Disaster Risk Reduction (DRR) practices need to be multi-hazard, multi-sectoral and inclusive in nature to make it efficient and effective (UNISDR, 2015). A good way to achieve this is to pursue inclusive risk assessment approaches that recognize the effects different stakeholder actions have on the mean risk of other at-risk

[1] Classical methods here mean traditional, top-down approaches where indicators are selected purely by researchers without involvement of stakeholders or at-risk populations.

populations. Yet, Effective disaster management demands a well-coordinated operation of complex, interacting human and technological systems (Dawson, 2011).

The combination of multiple hazards of drought and floods in increased magnitude and frequency impacting vulnerable communities and ecosystems in West Africa demands significant attention in research so as to pre-empt the worst. The impacts of climate risks are likely to magnify the uneven social and spatial distribution of risk in West Africa, and possibly amplify poverty in the region. It is therefore essential to understand the coping and adaptation strategies that could be potentially available to rural communities and to provide a means to reinforce them. The links between disaster risk and poverty — in a changing climate—means that reducing disaster risk can help reduce rural and urban poverty, promotes sustainable development and growth and improve adaptation to climate change (World Bank, 2009a). This can only be achieved by operationalizing risk assessments and analysis and providing policy makers with critical information on the dangers that populations face with respect to climate induced multiple hazards and providing scientific arguments to formulate proper alternative risk management and adaptation strategies.

1.2. Flood and drought disasters in West Africa

Major catastrophic natural disasters have been recorded in the region particularly, within the Sudanian Savanna zone which is being studied in this research. Above normal rainfall amounts at the peak of the rainy season in the Sudanian and Sahelian regions (*i.e.* July to September) frequently lead to severe floods, and cause many of the major rivers (e.g. Niger, Volta river systems, Senegal) to overflow their banks. In 2007, for example, a series of anomalous abundant rainfall events caused severe floods in West Africa (WA) and other parts of Sub-Saharan Africa (SSA) which affected more than 1.5 million people and resulted in the destruction of farm lands, loss of personal effects, destruction of infrastructure, outbreak of epidemic diseases and the loss of human lives (Armah *et al*., 2010; BBC, 2007; Braman et al., 2013; Levinson & Lawrimore, 2008; Paeth et al., 2011). Similar floods in 2009 affected an estimated 940,000 people across twelve countries in West Africa, killing about 193 people and destroying properties worth US$152 million (UNOCHA, 2009). In 2012, flooding along the river Niger, which is the principal river in West Africa, resulted in the death of 81 and 137 people in Niger and Nigeria, respectively, while displacing more than 600,000 people (IRIN News, 2012).

Drought has had a devastating impact on this ecologically fragile region and was the major driver for the founding of the United Nations Convention on Combating Desertification and Drought (Zeng, 2003). From the 19th century, the frequency and duration of drought in the region has increased dramatically. Droughts in the 1910, 1940, 1960s, 1970s and the 1980s have led to famines in the region (Zeng, 2003).

Under the realms of the German Federal Ministry of Education and Research (BMBF) funded WASCAL[2] project, three West African Countries of Ghana, Burkina Faso and Benin have been selected as the study areas for this study. Within these countries, three watersheds representative of the Sudanian Savanna ecological system will be used for in-depth local assessments. This section traces the history and impacts of floods and drought disasters in these countries in recent past, 1970 to 2012.

[2] West African Science Service Centre for Climate Change and Adapted Land use (www.wascal.org)

1.2.1. Flood and drought disasters in Ghana

Ghana ranks high amongst African countries most exposed to risks from multiple natural hazards occasioned by climate variability. Ghana is exposed to floods and droughts, particularly in the Northern Savannah belt (World Bank, 2009b). In 2007, floods followed immediately after a long period of drought and damaged the initial cereal harvest. This, per the World Bank (2009) is an indicative of the high variability in climate and hydrological flows in Northern Ghana. During this flood disaster, at least 20 people died and an estimated 400,000 people were affected, over 90,000 people were displaced and nearly 20,000 homes were damaged (BBC, 2007). The long-term and economic impacts on the regional economy are still not known but the World Bank (2009a) estimated the damage to be around US$130 million. Between 1991 and 2015 the country experienced seven major floods; the largest number of people affected being in 1991 and 2015. The floods in June 2015 led to a cascading hazard when flooding waters were combined with fuel station explosion, leaving some 200 people in the capital dead and thousands affected (NADMO, 2009, 2015). From 2007 to 2011, there has been a consecutive flood event (Figure 1-1) Heavy rains in southern Ghana in 2010 affected the south of the country. In the Eastern, Central and Volta regions large swathes of land were inundated and communities were isolated from the rest of the country. The flood in 2010 affected particularly the northern half of Ghana. Again in 2011, floods occurred in the Eastern Region of Ghana killing at least five people and displacing some 100,000 more (Africanspotlight, 2011; Ghanaweb, 2010).

According to Gall (2007), Ghana has experienced several droughts in recent history, in 1977, 1983, 1992 and 1998. It is estimated that 35% of the land area in Ghana (roughly 83,489 km2) is prone to desertification, with the Sudanian Savanna zone facing the greatest hazards. Drought and their attendant's desertification is said to be advancing inland at an estimated 20,000 hectares per year (USAID, 2011), with its concomitant destruction of farmlands and livelihoods. The major drought event in recent times was in 1983 where over 12.5million people were affected, most of them located in the Sudanian Savanna zone. As much as 76.9% of all people affected by any disaster in Ghana are due to drought[3].

1.2.2. Flood and drought disasters in Burkina Faso

In 2009 heavy rains in Burkina Faso forced officials to open the main gate of a hydroelectric dam in the Volta River basin, near the Ghana border, causing additional flooding in both countries. This is the sixth-time officials in Burkina Faso had open the reservoir's gate since its construction in 1994 (Esty *et al*., 2005). During this flood, Burkina's main hospital was closed. Whereas annual rainfall in Burkina Faso has been averaging 1,200mm, as much as 300mm occurred within one hour on September 1, 2009 and the Burkinabe Government estimated that it will cost US$152 million to face the consequences of the flooding. Again in 2010, torrential rains caused massive flooding that affected more than 133,000 people in many parts of the country. At least 13 provinces were flooded, with more than 16,000 households directly affected by the floods, and 14 people were reported dead. Villages were devastated with damage to shelters, livestock, properties, fields, roads and wells (Beck *et al*., 2012).

[3] http://www.preventionweb.net/english/countries/statistics/?cid=67. Retrieved March, 5, 2013-

The United Nations Office for Disaster Risk Reduction (UNISDR, 2014) reports in its database that, major drought events have occurred in Burkina Faso. Drought affected over 2.6million people in 1990, over 1.2million in 1980, 200,000 in 1988 and over 75,000 in 1995. The most severe drought event in recent times is the one in 2011 which caused the United Nations to organize an emergency meeting in Rome in a bid to avoid famine in the country. UNSIDR reports that the probability of drought occurring in Burkina Faso for a typical year is 0.19 and accounts for 84.8% of all people affected by any disaster in the country.

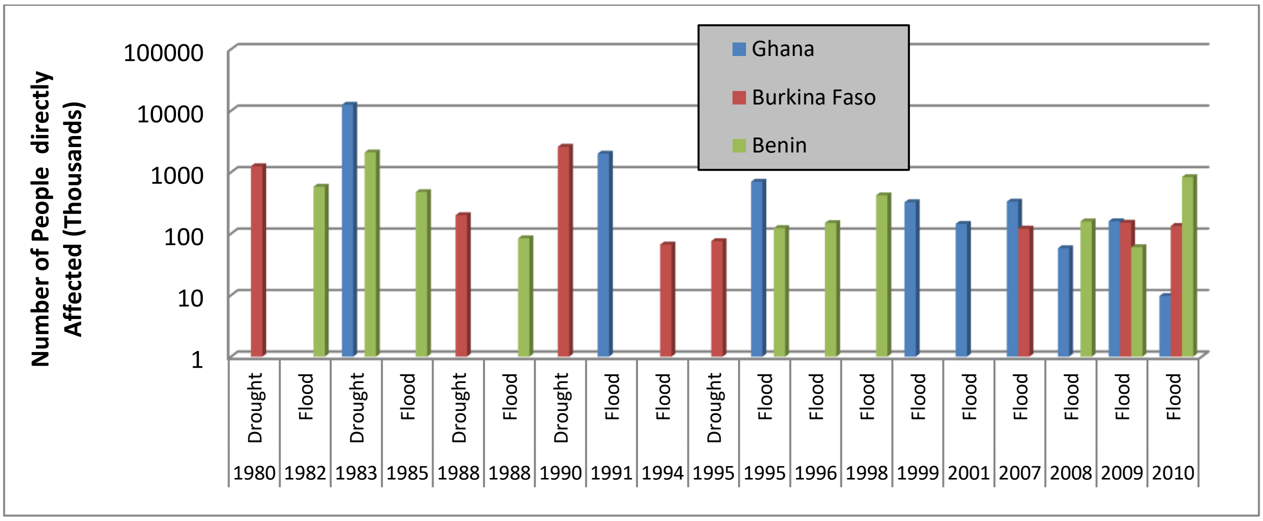

Figure 1-1: Statistics of major hydrological hazards in West Africa: 1980-2010.
Data source: www.preventionweb.net of UNISDR.

1.2.3. Floods and drought disasters in Benin

Benin has also not been spared of the hydrological hazards that have plagued the West African sub-region. The worst flood since 1963 occurred in September 2010 when heavy downpour and influx from the Niger River flooded 55 out of the 77 municipalities in the country. In this flood alone, over 680,000 people were affected, 800 cases of cholera were reported, 55,000 homes were destroyed and at least 56 people were killed (Forum, 2005).

Similar catastrophic events have been reported in 2008, 2011 and 2012. The 2011 floods in particular, resulted in heavy damages to poultry and livestock and thousands of hectares of farmland. Also in 2008, the flooding in Ouinhi and Za-Kpota areas torn down mud and straw homes and infrastructure, and polluted major rivers. The flooding in the Oueme river valley wiped out more than 25,000 hectares of cropland, killed about 30,000 animals, flooded 18,000 homes and affected almost 7,000 people.

The worst drought event to hit Benin in recent times is the one in 1983 where over 2.1million people were affected and faced severe famine. Droughts alone accounts for 40.2% of people affected by any type of disaster in the country.

1.3. Multi-hazard risk assessment, approaches and trends

Over the years, various attempts have been made to measure vulnerability to climate change at different scales from local to national assessments. Examples include (Birkmann, 2006b; Cardona, 2005; Damm, 2010; Dilley *et al.*, 2005; Mohan & Sinha, 2011; Renaud & Perez, 2010; UNDP, 2004b; USAID,

2011) and more recently by Beck *et al.* (2012); Garschagen *et al*. (2014); Welle *et al*. (2013). These studies have attempted to measure vulnerability, risk and resilience and using a variety of concepts, approaches and indicators.

Indicators have been widely used to measure vulnerability and to understand the risk patterns of societies from both natural and anthropogenic hazards. The Millennium Development Goals are a classical example of the use of indicators to monitor progress of set targets. The Hyogo Framework for Action 2005-2015 emphasized the need to “develop systems of indicators of disaster risk and vulnerability at national and sub-national scales that will enable decision-makers to assess the impact of disasters” (UNISDR, 2005, p.10). The Millennium Ecosystem Assessment (MEA) makes broad use of several indicators both, biophysical and socio-economic to analyse data in order to develop policy relevant actions for decision making (MEA, 2003). However, because of the complexity, multi-dimensional aspects (Birkmann, 2006a; Downing, 2004; Mohan & Sinha, 2011); copious (Thywissen, 2006) and sometimes confusing definitions of vulnerability and risk, it has become difficult and even impossible to define a methodology or reduce the concept of vulnerability to a single equation or model that has a universal application.

Despite these gaps in current knowledge on risk and vulnerability assessments, significant progress has been made regarding the development of conceptual vulnerability frameworks allowing the operationalization of this complex concept to some local conditions and the development of composite vulnerability indices. Examples of widely used frameworks include the SUST framework developed and piloted by Turner *et al*. (2003a) and later adapted to a sub national level in Germany by Damm (2010) and Fekete *et al*.(2009); as well as the BBC framework by Birkmann (2006b) and more recently the MOVE framework (Birkmann *et al*., 2013). Yet, no attempt has been made to operationalize these frameworks to the local West African conditions and spatially explicit multi-risk maps across multiple scales based on any of these frameworks still do not exist in the region. However, these models presented in Figure 1-2 and Figure 1-3 have been criticized for being complex and difficult to operationalize and only few studies have managed to implement them (Damm, 2010). Another drawback of the SUST model in particular, is the missing link relating to the concept of risk itself. Other models that developed after this SUST model such as the BBC and MOVE models (Birkmann, 2006b) emphasized the strong linkages between risk and vulnerability in disaster research. The SUST framework does not establish any

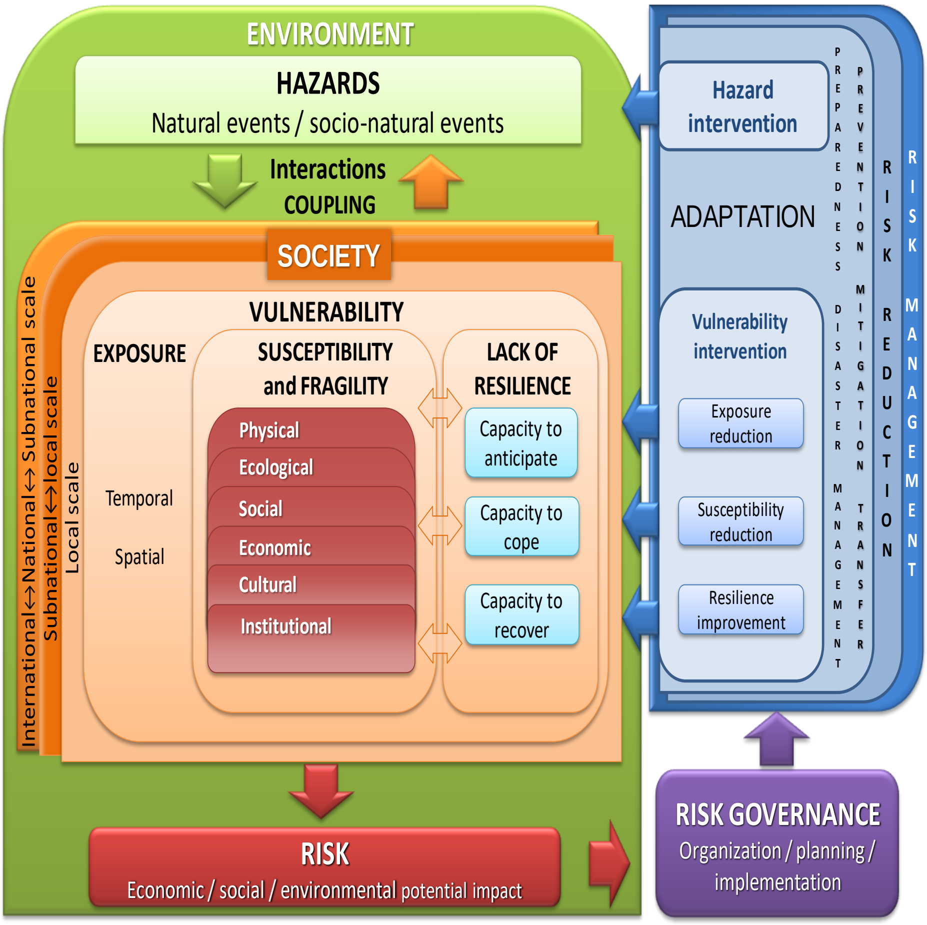

Figure 1-2: The MOVE framework (Birkmann, 2013).

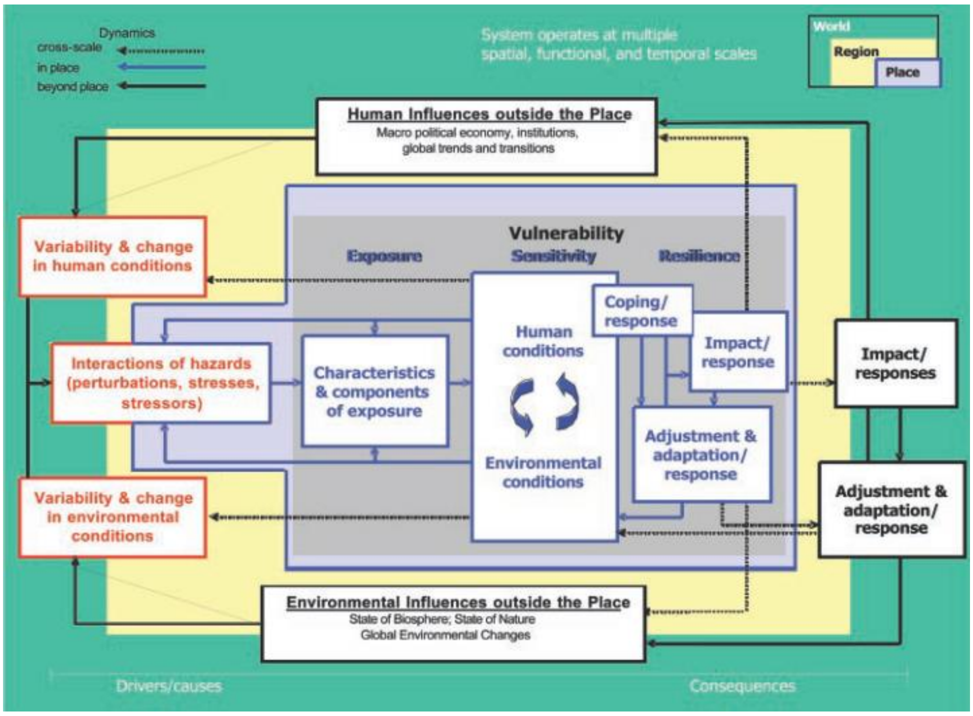

Figure 1-3: The SUST model (Turner *et al.*, 2003a).

relationship with risk whatsoever and does not outline how risk is conceptualize (Damm, 2010). Moreover, the concept of resilience has developed very rapidly since the model was introduced in 2003 rendering the original connotation of resilience by Turner *et al*. (2003) redundant. To Turner *et al*. (2003), resilience was viewed as an independent concept and was not seen as an integral part of vulnerability.

The MOVE framework (Figure 1-2) on the other hand refers to all four natural hazard responses of vulnerability, resilience, coping and adaptation and has an excellent linkage of risk and risk governance. The capacities to adapt, cope or recover by the element at risk are described in the MOVE framework as constituting its resilience.

To address these constraints Kloos *et al.* (2015) conducted an extensive review of existing risk assessment frameworks and proposed a hybrid framework customized for West African specific context. This hybrid framework is based on the key element, a social-ecological system (SES), reflecting the connections and feedbacks between the environmental and social sub-systems taking place at various spatial scales (local, sub-national and national). Kloos *et al.* (2015) proposed that risk is to be evaluated against hydro-climatic hazards and stressors, which may materialize as sudden shocks such as floods and/or heavy rainfall events, slow onset events such as droughts, late onset of the rainy season but also more gradual changes such as changes in variability or averages of rainfall. At the same time, an SES is affected by socio-economic drivers and stressors (see chapter 4, Figure 4-2) which may lead to environmental changes that can turn into stressors or hazards in themselves. Ecosystem services are essential components of SES and provide numerous monetary and non-monetary benefits to people living in the system. To account for the multi-hazard nature of hazards, Kloos *et al*. (2015) introduced to the framework, ‘H1’ and ‘H2’, and the combination of both hazards selected for the West Sudanian Savanna case, ‘H1+H2’. The first operationalization of this framework will be attempted in this study across multiple scales in three West African countries.

1.4. Research objectives

To address the gaps identified in the review above, the present study aims at exploring methods to involve at risk populations at multiple scales in a bottom-up participatory process as opposed to the classical top-down, single scale approaches; assess risk from multi-hazard perspectives in a coupled SES rather than single-hazard-decoupled risk assessments and finally assess risk using indicators relevant for rural communities across West Africa. The study will also explore appropriate methodologies that are able to provide the spatial variability of flood hazard intensity at community level under limited data conditions. The study also will aim at introducing a novel risk index upscaling procedure to upscale risk and vulnerability indices across multiple scales. The broad objective therefore is to develop multi-hazard risk maps across multiple scales in West Africa by operationalizing a hybrid risk and vulnerability assessment framework and to develop theoretical concepts to upscale the derived vulnerability and risk indices.

In view of the study objectives enumerated above, the study will strive to answer the following research questions.

i. How do we involve at risk populations in a bottom-up participatory process to develop indicators relevant for multiple hazard risk assessment across multiple scales?
ii. How do we develop an appropriate methodology that are able to provide the spatial variability of flood hazard intensity at community level and yet yields accurate results with limited data availability?
iii. How do we operationalize, adapt and integrate existing vulnerability and risk models to systematically analyse vulnerability and risk profiles for rural communities in West Africa?
iv. How do we upscale vulnerability and risk indices from a watershed scale to higher scales taking cognizance of cross scale interactions, actions and reactions of policy makers and feedback loops?

1.5. Research methods

The hybrid risk assessment framework proposed by Kloos *et al*. (2015) provided key inputs for a conceptual framework required for various components of the thesis. The four research questions outlined above constitute the four separate but related components of the thesis.
To answer the first research question, a multi-scale participatory process was used to extend the classical approach of indicator development for risk assessment in West Africa. The approach followed a step-wise procedure to develop an Indicator Reference Sheet (IRS) based on the conceptual risk assessment framework proposed by Kloos *et al*. (2015). This IRS was combined with knowledge of local experts iteratively selected through snowball approach. The local experts including at risk populations were constituted into technical working groups in a series of expert workshops, to elicit important processes shaping risks at multiple spatial scales. One expert workshop was held in each of the three study watersheds in Ghana, Burkina Faso and Benin. In addition, experts from the national capitals were engaged in a series of expert interviews and technical group discussions to illicit indicators relevant for national scale risk assessment. The results from these highly participatory, bottom-up processes were analysed and the final indicators presented. Details about this procedure and the comprehensive indicators have been presented in Chapter 2 of the thesis.

To answer the second research question, remote sensing and Geographic Information System (GIS) techniques were combined with hydrological and statistical models to delineate the spatial limits of flood hazard zones in selected communities in Ghana, Burkina Faso and Benin. The approach involves estimating peak runoff concentrations at different elevations and then applying statistical methods to develop a Flood Hazard Index (FHI). A unique approach is also proposed to use a bottom-up participatory method based on the principles of Participatory Geographic Information System (PGIS) (Carver, 2003; Craig, *et al*., 2002; Dunn, 2007) and coupled with robust empirical confusion matrix methods to evaluate the results of the modelling procedure.

To answer the third research question, this study quantifies and models risk and vulnerability of rural communities across West Africa to drought and floods. Risk is assessed using an indicator-based approach based on the results of research question one. A stepwise methodology is followed that combines on the one hand participatory approaches and on the other statistical, remote sensing and

GIS techniques to develop community level vulnerability index in three watersheds (Dano, Burkina Faso; Dassari, Benin; Vea, Ghana). The index is developed from ten working steps including:

(i) Operationalization of the context specific risk assessment framework proposed by Kloos *et al*. (2015).
(ii) The use of the results of the novel participatory indicator development approach as obtained from research question one.
(iii) Exploratory data analysis to understand the indicator data values
(iv) Construction of bivariate correlation matrices following the approach of Damm (2010).
(v) Normalization of indicators to scale the values to a range between 0 and 1 to allow for comparability of indicators of varying measuring units as applied in Welle *et al*. (2013).
(vi) Weighting of normalized indicators by converting expert judgment ranking to weights using rank to weight conversion model proposed by Al-Essa (2011).
(vii) Application of a three-tiered linear aggregation process as applied in Birkmann *et al*. (2011) and Welle *et al*. (2013) to develop the sub-indices of exposure, susceptibility and the three capacity sub-components to derive the composite vulnerability index.
(viii) Multi-hazard characterization and mapping using a flood hazard index developed in research question two and vegetation health index from FAO Global Information and Early Warning System on Food and Agriculture (FAO GIEWS, 2015) to denote drought severity. A drought severity index was developed in the process.
(ix) Integration of the developed vulnerability index and the multi-hazard index based on the framework to derive the final West Sudanian Community Risk Index (WESCRI). This index is then used to construct the multi-risk indices of the rural communities in GIS environment;
(x) The final work step is the introduction of a novel technique termed the 'Community Impact Score' (CIS) as vulnerability and risk validation procedure.

To answer the fourth and last research question, a decision tree is introduced to simulate the decisions and actions of the various actors involved in DRR and their interaction with the ecological sub-system. This is a novel risk index upscaling procedure that could allow for the application of tools such as an Agent-based model designed to assess the risk of socio-ecological system towards the impact of multiple hazards of floods and droughts across multiple scales in the western Sudanian savanna zone of Ghana, Burkina Faso and Benin. In this thesis, the theoretical concepts required to upscale risk indicators are presented.

1.5.1. Study area

This study forms part of the West African Science Service Centre for Climate Change and Adapted Land Use (WASCAL) project. Within this project, three countries in the region, Ghana, Burkina Faso and Benin were selected for detailed climate change related studies. In addition to differences in geopolitical contexts, the countries were selected due to the following reasons:

(i) more than two-thirds of the land area of these countries fall in the West Sudanian Savanna Ecological Zone, an area with a high agricultural production potential, but also noted for high climate variability and uncertainty;

(ii) The areas have good records of existing long-term historical socio-economic data are available; and

(iii) The areas have experienced more than one natural disaster over the last 10 to 15 years and major catastrophic natural disasters have been recorded in the region particularly, within the Sudanian Savanna zone which is being studied in this research.

Within these three countries, the WASCAL project has selected three watersheds for in-depth research. These watersheds are

i. The Vea-watershed in the Upper East region of Ghana
ii. The Dano watershed in the province of Sud-Ouest of Burkina Faso and
iii. The Dassari-watershed in the commune of Materi in North West Benin.

The study area shown in Figure 1-4 belongs to the Sudanian Savanna ecological zone and have a similar climate and are under varying forms of agricultural systems.

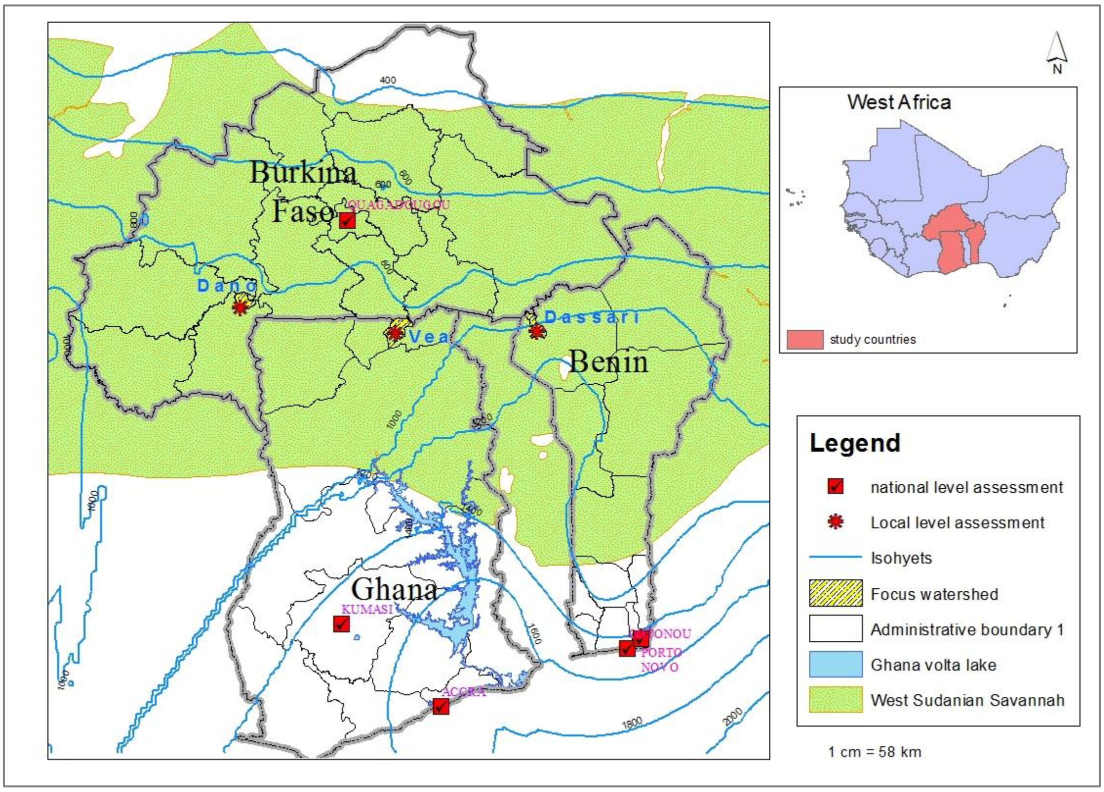

Figure 1-4: The study area in three West African countries.

Climatic factors show high variability and there is a high frequency of droughts and floods (Challinor *et al.* 2007). Three watersheds located in each country and their surrounding administrative districts were selected for local level assessment with households as the unit of analysis. In addition, consultations at the national capitals of all three countries were carried out for macro/national scale assessment, taking the perspective of experts working at the national scale. Finally, collection of additional information and expert interviews for both indicator development and triangulation purposes were carried out in Accra and Kumasi (Ghana), Ouagadougou (Burkina Faso) and, Porto Novo and Cotonou (Benin), all over a period of eight months (May to December 2013).

1.5.2. The three watersheds and community clustering

To be able to undertake community level assessment, the three watersheds or local scale study areas were further disaggregated down to the community level. In this study, the delineation into community clusters was based on Digital Elevation (DEM), river channel systems, populations in the communities as well as the operational plans which are used by local disaster managers to segregate and demarcate the areas for effective disaster management. Using this approach, the Vea study area (Figure 1-5) was delineated into 13 community clusters[4]. The largest of this cluster is the Kula River drain (Figure 1-5), named after the Kula river which is well known for causing many of the floods in the area. Other prominent community clusters are the Vea main drain and Kolgo/Anateem valley. These clusters are located at the downstream of the Vea and Kolgo Rivers and are also significantly exposed to floods.

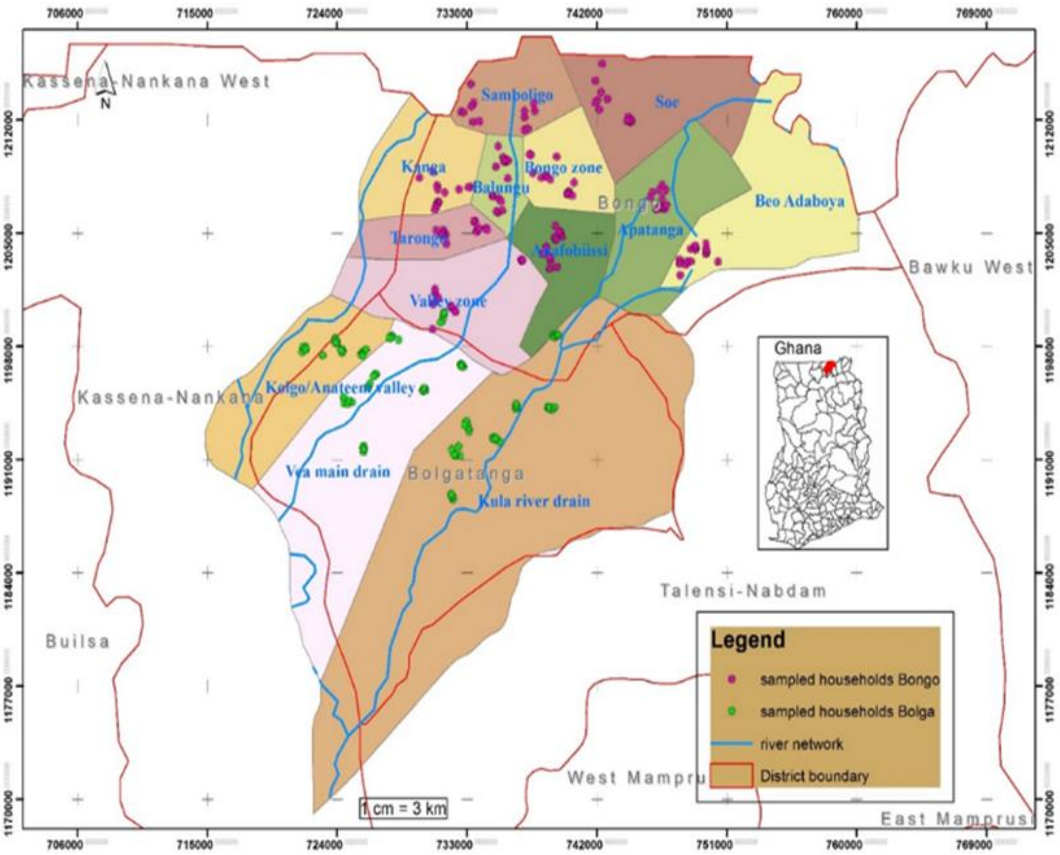

Figure 1-5: The Vea study area of Ghana.

The Vea area cuts across two districts in Ghana (second administrative units)—Bolgatanga and Bongo—and covers an area of 1037.8 km^2. The city of Bolgatanga, the capital of Upper East region is found in this area. This study site is the most urbanized of the three local study areas and has well developed road network, schools, market access, hospitals, irrigation dams and electricity. Consequently, it has a

[4] This is also referred to as sub-catchments in chapter 3.

relatively higher population density of about 104 persons per km^2. Hydrologically, it falls within the White Volta sub-basin, which extends from northern Ghana to mid Burkina Faso.

The area ranks high amongst areas most exposed to risks from multiple natural hazards occasioned by climate variability. Similar to other parts of West Africa, studies have shown that this area experiences high variability in climate and hydrological flows (Challinor *et al*., 2007; World Bank, 2009a). According to Oduro-Afriyie & Adukpo (2006), the area has frequently experienced floods in the past.

Similarly, the Dano study area of Burkina Faso has further been delimited into thirteen community clusters in relation to population, contours and river network. The Yo, Bolembar, Gnikpiere and Loffing-Yabogane clusters are prominent among them with extensive river system, smallholder agriculture and many scattered settlements and hamlets. The Dano study area shown in Figure 1-6 is essentially the third sub- administrative level in the province of Ioba of Burkina Faso and has an area of 633.8 km2. Population density in this study area is about 59 persons per km2. Hydrologically, it falls within the Black Volta sub-basin system, which forms the western part of the Volta basin.

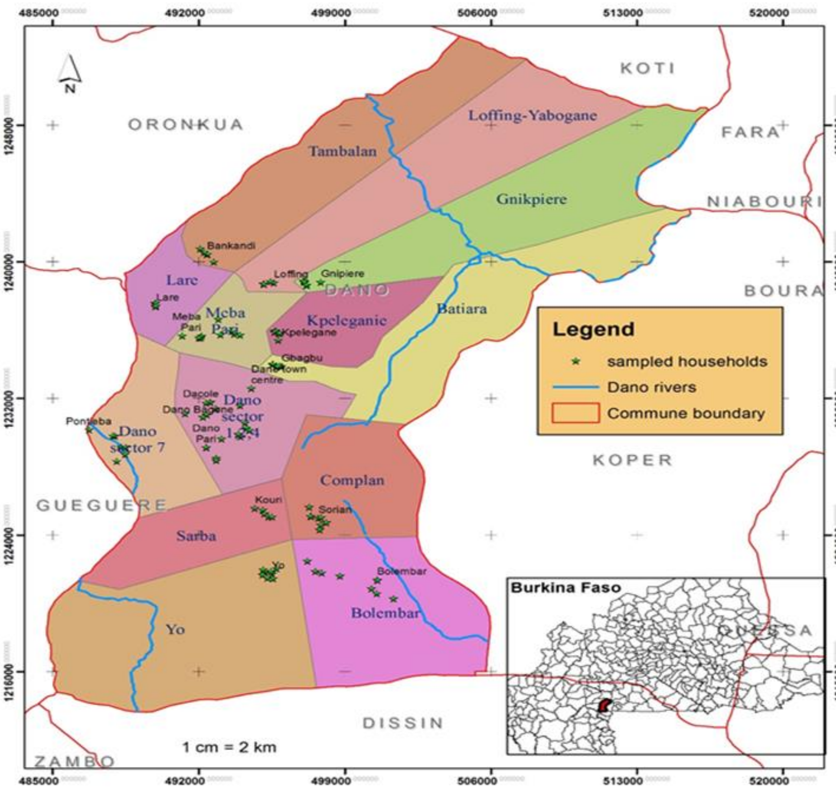

Figure 1-6: The Dano study area of Burkina Faso.

The Dassari area in Benin was also delineated into twelve (12) community clusters to reflect population, river network and local administrative management as described above. The Setcheniga, Porga and Nagassega clusters are most prominent as they are run through by a major river network that significantly exposes the area to flooding.

The Dassari study area shown in Figure 1-7 covers an area of 657.1 km^2. It falls in the third sub-national administrative level in Benin (known as the Arrondissement of Dassari) and has a population density of about 56 persons per km^2. In terms of hydrology, the study area falls within the Oti sub-basin of the Volta basin. The north-eastern corner of the study area forms part of the Pendjari national park in West Africa.

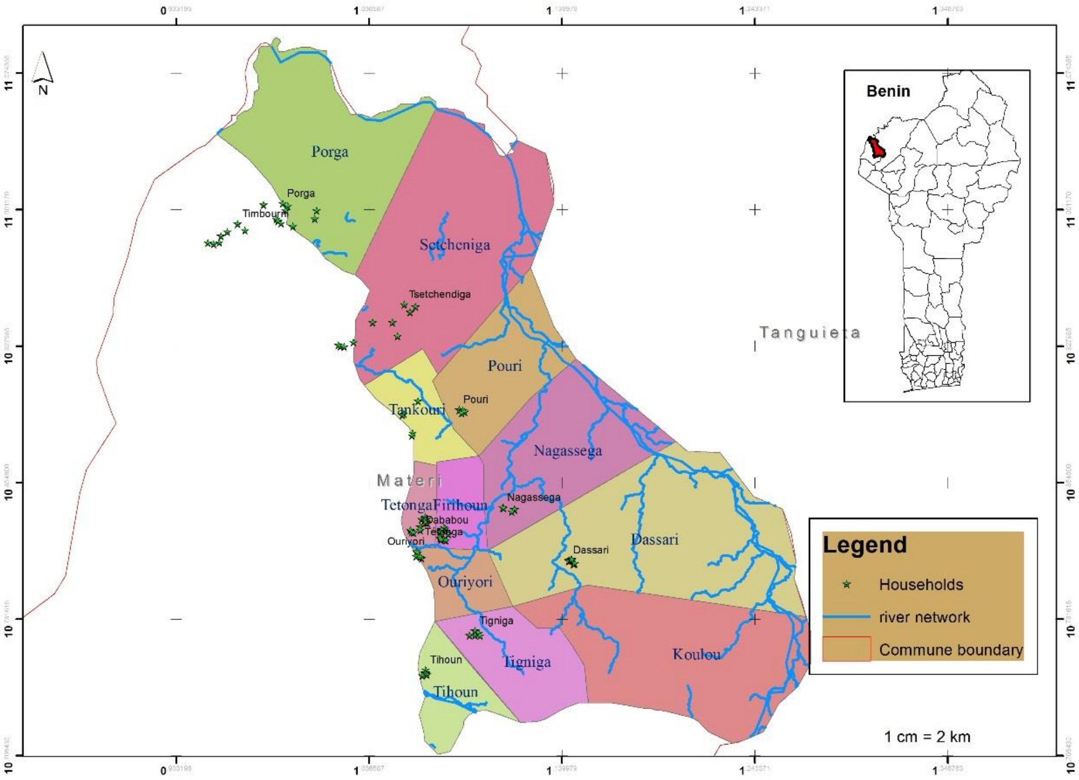

Figure 1-7: The Dassari study area of Benin.

1.6. Outline of the study

The rest of the thesis is structured into five main chapters that address the formulated research questions in section 1.4. Chapter two outlines a novelty in indicator development using a bottom-up participatory process to develop indicators relevant for multiple hazard risk assessment and across multiple scales. This chapter describes how at-risk populations were selected and involved in developing a comprehensive indicator set for West African risk assessment. It details the combination of classical indicator development approaches and participatory processes to select indicators and analyses how expert judgement was used to rank indicators in each vulnerability sub-component. All the indicators used in the subsequent chapters were drawn from the results of chapter 2. The chapter also makes use of a conceptual framework of vulnerability assessment developed by Kloos *et al*. (2015) and provided the basis for the next chapters of the thesis.

Chapter 3 of the thesis presents an approach involving the use of a simple hydrological model suitable for data scarce environments and integrated with statistical procedures in a GIS environment to map the spatial limits of flood hazard zones at a high spatial resolution. A unique approach is presented to use a bottom-up participatory method based on the principles of Participatory Geographic Information System (PGIS) (Carver, 2003; Craig *et al*., 2002; Dunn, 2007) and coupled with robust empirical methods to evaluate the results of the modelling procedure. The main motivation was to develop community level flood hazard maps at a fine spatial resolution that could allow for accurate delineation of flood hot spots and flood safe havens at the sub-district/community levels in Ghana, Burkina Faso and Benin.

Chapter 4 deals with how the results from Chapters two and three are applied to develop community risk indices from multiple hazards. The chapter addresses the gaps in classical methods of risk assessment and lack of comprehensive risk assessment for the West Africa region to conduct multiple hazard risk assessment through a bottom-up participatory process as opposed to the classical top-down, large scale approaches. It follows the perspective of a coupled Socio-Ecological System (SES) rather than single-hazard-decoupled risk assessments. Several methodologies were employed including the use of remote sensing and GIS methods to retrieve data for a number of biophysical indicators. The chapter also developed multi-hazard maps using inputs from Chapter two and Vegetation Health Index (VHI) datasets developed by (FAO GIEWS, 2015). An innovative concept termed, the Community Impact Score (CIS) was introduced to evaluate the results of a complex aggregation process. The chapter provides results that could support decision-makers with information to recognize and map risk hotspots in order to support priority setting for risk-reduction strategies.

Chapter 5 deals with an upscaling risk index from a watershed to higher spatial scale. It explores how multi-scale and cross scale interactions can contribute to decision making at various levels and how that affect the overall risk faced by people in nearby areas. This chapter lays the foundation for a possible application of multi-agent model such as an Agent Based Models (ABM) (Le *et al.*, 2008, 2012; Linghu et al. 2013) to simulate the decisions and actions of the different stakeholders in responding and adapting to natural hazards and how these decisions and actions feedback into risk and vulnerability of people in other scales. It lays the theoretical basis for upscaling risk indices and presents interesting theoretical concepts in the global discourse of risk assessment especially in the area of understanding the dynamic nature of risk and predicting future vulnerability and risk.

Chapter 6 finally concludes the thesis. It provides a summary of the key findings, relevant literature and policy implication of the findings and future research outlook.

2. Multi-scale Participatory Indicator Development Approaches for Climate Change Risk Assessment in West Africa[5]

2.1. Introduction

The dominance of rain-fed agriculture in West Africa where 60% of the population is engaged in agriculture (FAO, 2012) makes its population vulnerable to climate change and variability. The recent IPCC report (IPCC, 2014, p.3) reported with high confidence that the interaction of climate change with non-climate stressors will "exacerbate vulnerability of agricultural systems in semi-arid" Africa such as the West Sudanian Savanna region of Burkina Faso, Ghana and Benin. Vulnerabilities are shaped through a host of biophysical and human related issues in the region including rainfall-related soil erosion, recurring droughts, poor soil quality and fertility, low input farming systems, decreased fallow periods, deforestation, frequent bush fires, and overgrazing (FAO, 2012; USAID, 2011). Numerous studies exist worldwide that measured vulnerability to climate change at different scales from local to national assessments (see for example (Damm, 2010; Mohan & Sinha, 2011). Also, large-scale studies by (Birkmann, 2006b; Cardona, 2004; Dilley *et al*., 2005; UNDP, 2004a; USAID, 2011) have measured vulnerability, resilience and adaptation using a variety of concepts, approaches, and indicators. However, it is impossible to reduce the concept of vulnerability and risk to a single equation or model that has a universal application. This is due to inherent complexity of Social Ecological Systems (SES); the multi-dimensional nature of vulnerability and risk (Birkmann, 2006a; Downing, 2004; Mohan & Sinha, 2011) and a variety of concepts such as exposure, sensitivity, susceptibility, response, coping and adaptive capacity, robustness and resilience that are employed in order to measure vulnerability and that are defined in many different ways (Thywissen, 2006).

The factors outlined above result in a non-universal applicability of existing indicator based vulnerability and risk assessment methods to areas such as the West African sub-region, implying that different and well-adapted methods need to be developed. Such methods should tackle complex settings of hazards occurrence as well as the dynamic socio-economic and environmental exposure; They also need to be context specific, be able to capture all relevant processes shaping vulnerability and risk at various scales and, more importantly, still be applicable to local communities affected usually by multiple hazards (Adger *et al*., 2004; Africa Adapt, 2011). However, the available literature suggests that these important considerations have been missing in many risk assessments particularly for the West African sub-region. To date, no study has attempted to understand the risk patterns of West African rural communities in the context of climate change through a set of indicators. The only study that comes close is a study conducted in Ghana in 2011 by United States Agency for International Development (USAID, 2011). Even in this study, the indicators were derived purely from literature and lack the important element of the participatory process from the vulnerable themselves. Furthermore, this study only considered social

[5] A version of this paper has been published as: Asare-Kyei, D. K., Kloos, J., & Renaud, F. G. (2015). Multi-scale participatory indicator development approaches for climate change risk assessment in West Africa. *International journal of Disaster Risk Reduction, 11*, 13–34.

vulnerability to climate change and did not account for the ecological or biophysical aspects which are closely linked to the social processes. More importantly, this study conducted risk level assessment at the district level and not at the rural community level where risk outcomes are first materialized.
Other climate risk assessments studied in the region have either been conducted at the country level or looked at decoupled SES. Studies from Boko *et al*. (2007); Briguglio (2009); Challinor *et al*., (2007); Thornton *et al*. (2006); World Bank (2009a, 2011) aimed at country level comparisons of risk. On the other hand, studies such as Challinor *et al*. (2007) and IFPRI (2010) looked at decoupled SES and assessed narrow segments of it such as the vulnerabilities of agricultural sub-systems or the environmental sub-system. Most of the studies published in Africa Adapt (2011) fall into the latter category. It is often very difficult to link local level results to assessments made at higher scales and vice versa, hindering a potential downscaling and upscaling of results. Besides the USAID (2011) study in Ghana, Raschid (2011) undertook a water mediated climate impact assessment for urban areas based on indicators. In the three countries studied here, other risk assessment has been carried out at much smaller scales and on decoupled SES such as Arnold *et al.* (2012) in Burkina Faso; World Bank (2009) and IFPRI (2010) in Ghana, Benin and Burkina Faso. All these studies however, are based on classical risk assessment and did not involve the vulnerable themselves. More importantly, risk assessment was done only at single scales and for single hazards.

In other countries, Bollin & Hidajat (2006) developed a community based risk index for Indonesia based on indicators and showed how an indicator based approach could be implemented at the community level where risk outcomes are first materialized. In another example, on a more global level, the Alliance Development Works led by the researchers of the United Nations University Institute for Environment and Human Security has been publishing the World Risk Reports since 2011. The 28 global level indicators depicting current conditions underlying exposure to natural hazards, susceptibility, coping capacity and adaptive capacity were aggregated to generate the World Risk Index. This index allows for the identification of the low and high countries of world (Welle *et al*., 2013). These are also based on classical (top-down) approaches and aimed at country level comparisons. Despite the large amount of knowledge available in local areas (Reed et al., 2008) most, if not all risk assessments in the West African region have been approached from classical methods without tapping into the wealth of resources available at the local level. Moreover, many risk assessments in the region are mainly based on qualitative assessments without any attempt at combining them to quantitative data even though it has been recognized that risk assessment from both quantitative and qualitative (social, psychological, ecological) methods is required to deliver a more complete description of risk and risk causation processes (Cardona, 2004; Douglas & Wildavsky, 1982; Weber, 2006; Wisner *et al*., 2004).

In the present study, the points of departure from the studies reviewed above are to explore methods to involve at risk populations at multiple scales in a bottom-up participatory process as opposed to the classical top-down, single scale approaches; assess risk indicators from multi-hazard perspectives in a coupled SES rather than single-hazard-decoupled risk assessments and finally assess risk indicators relevant for rural communities across West Africa.

Indicator based risk assessment where the indicators have been selected from a rigorous scientific process involving active participation of populations at risk at different scales as well as the authorities governing these risks is a prerequisite in meeting these criteria. Although it is often impossible to involve large numbers of affected community members in evaluating a set of potential indicators, representatives of the main stakeholder groups (farmer representatives, disaster managers, etc.) should systematically be consulted. Additionally, to develop localized indicators of risk at both the local and sub-national levels, it is imperative to involve government officials and development experts from non-governmental organizations. This is because: (1) these officials have prolonged contact with vulnerable populations, (2) most of them live with them and have themselves been affected by the hazards, and (3) their professional training and experience have made them experts in their own right and (4) they have comprehensive perspectives of the processes shaping vulnerabilities.

2.2. Indicator functions and indicator based risk assessment

Like models, indicators are abstraction of reality and limit themselves to the realm of the measureable. Nardo *et al.* (2005) defined indicator as either quantitative or qualitative measures obtained from a series of observed phenomena with the ability to reveal relative positions in a given study area. We consider here Moldan & Dahl (2007) definition of indicators as being representations of certain construct or issue too complex to be measured by a unit variable.

Indicators have been widely used to measure vulnerability and to understand the risk patterns of societies from both natural and anthropogenic hazards. The millennium development goals are a classical example of the use of indicators to monitor progress of set targets. The Hyogo Framework for Action 2005-2015 emphasized the need to “develop systems of indicators of disaster risk and vulnerability at national and sub-national scales that will enable decision-makers to assess the impact of disasters” (UNISDR, 2005 p.10). The Millennium Ecosystem Assessment (MEA) makes broad use of several indicators both, biophysical and socio-economic to analyse data in order to develop policy relevant actions for decision making. Several examples abound in literature on the use of indicators to measure vulnerability, risk and resilience as shown in Table 2-1.

The IPCC (2014, p.5) summary report for policy makers defined risk as the “potential for consequences” where a valuable element is at stake and its outcome uncertain. It’s the product of the probability of occurrence of hazardous events and the impacts if these events were to occur (IPCC 2014). It is also defined as the “the probability of harmful consequences, or expected loss of lives, people injured, property, livelihoods, economic activity disrupted (or environment damaged) resulting from interactions between natural or human induced hazards and vulnerable conditions’’ (UNDP 2004, p.113). There are numerous conceptualizations of risk and vulnerability.

Table 2-1: Examples of indicator based vulnerability, risk and development indices.

Index		Concept	Reference	Sub-indices/components	Variables
HDI	Human Development Index	Quality of Life	Moldan & Dahl (2007)	1	4
HWI	Human Well-being Index	Quality of life	Prescott-Allen (2001)	5	33
ESI	Environmental Sustainability Index	Sustainable Development	Esty *et al*. (2005)	21	76
PVI	Prevalent Vulnerability Index	Social vulnerability	Cardona (2004)	3	24
SVA	Index of social vulnerability to climate change in Africa	Social vulnerability	Vincent (2004a)	4	8
DRI	Disaster Risk Index	Socio-ecological vulnerability	UNDP (2004)	3	10
SOVI	Social Vulnerability Index	Socio-economic vulnerability	Cutter *et al.* (2003)		42
PIV	Predictive Indicators of Vulnerability Index	Social vulnerability	Adger *et al*. (2004)	0	45
WRI	World Risk index	Socio-ecological vulnerability	Welle *et al*. (2013)	4	28
VRIP	Vulnerability-Resilience Indicator Prototype	Social ecological vulnerability and resilience	Moss *et al. (*2002)	2	17
	Climate Vulnerability Index	Social-ecological vulnerability	Sullivan & Meigh (2005)	6	21
	Livelihood Vulnerability Index	Social vulnerability	Hahn *et al.* (2009)	7	30

Adapted from (World Bank, 2010a) and Cutter *et al*. (2009)

In this paper, we follow UNDP (2004) which views risk as the result of interaction between vulnerability and hazard.

Development of indicators from participatory processes has long been used in sustainable development literature. It has been used extensively to involve communities to monitor progress towards achievement of goals in sustainable development and environmental management. Fraser *et al.* (2006) used the approach to study the United Kingdom's government effort to develop sustainability indicators to assess the socio-economic and environmental impacts of macro-economic changes. Reed *et al*. (2008) complemented participatory approaches with ecological and soil-based methods when they elicited environmental sustainability indicators from pastoralists in Botswana and found that the process results in more comprehensive lists of indicators than previous indicators published in the fields of rangelands, vegetation, soil and socio-economic studies. More importantly, Reed *et al*. (2008) concluded that a participatory process enhances community empowerment in situations where traditional approaches have failed.

Other studies have also used local experts in selecting indicators for risk assessment. Examples of such studies include Damm (2010), Adger *et al.* (2004), Brooks et al. (2005), Fekete & Birkmann, (2008); Purnomo, *et al.* (2011) where expert judgment was complemented with the results of correlation analyses and other statistical procedures to select most relevant indicators. Morgan (1996) asserted that expert focus group is commonly used to elicit, refine information and produce new data and understanding through interactions with stakeholders. However, this common approach asserted by Morgan (1996) only refers to using a core group of local experts and does not include iterative selection of other remote stakeholders and at multiple scales. Such studies also do not make any attempt to triangulate the findings from the local expert group with the opinions with national level experts. An original approach is presented in this paper that uses both local and national levels experts to develop indicators applicable at different scales to allow for a comparison to be made between the results coming from the different categories of expertise at different spatial scales.

It has been shown that participatory methods of developing indicators are an effective means of promoting dialogue about trade-offs and divergent views (Sayer *et al*., 2007). This study builds on this approach to encourage debate among vulnerable people as to what set of processes and system states influence risk in their communities. The present paper explores a participatory approach to develop local and national (macro) scales indicators for multi-hazard risk assessment for rural populations in the Sudan Savanna ecological zone of Ghana, Burkina Faso and Benin faced with frequent floods and droughts events. A key motivation is to develop locally and nationally validated sets of indicators that can be used to develop risk profiles at multiple scales in a coupled SES in subsequent studies.

2.3. Multiple hazard risk assessment frameworks

The first step in developing a set of indicators for risk and vulnerability assessment is the development or selection of an appropriate conceptual framework. It is critical to have a comprehensive and well-adapted conceptual framework that establishes clearly the relationships, interactions and feedback mechanisms that exist within the SES under investigation. The present study relies on an on-going effort to broaden the theoretical concepts underlying two commonly used models, the SUST model by Turner *et al*. (2003b) and the MOVE model by Birkmann *et al*. (2013). Most of the existing frameworks do not incorporate the concepts of risk and have been criticized for being complex and difficult to operationalize (Damm 2010). The analytic frameworks identified are considered as the most suitable to the West African context and the research objectives because combining them help bridge the gap between vulnerability and risk (Kloos et al., 2015). This proposed hybrid framework served as the conceptual basis to categorize the various dimensions of vulnerability. It recognizes the fact that vulnerability rests in a multifaceted coupled system with connections operating at different spatiotemporal scales and commonly involving stochastic and non-linear processes (Kloos *et al*., 2015; Turner *et al*., 2003b). The major components of the framework are Exposure, Susceptibility (of both social and ecological subsystems) and Capacities (coping and adaptive capacities as well as ecosystem robustness). This hybrid framework serves as a template for a reduced form of analysis allowing for the operationalization of the complex concept of vulnerability to a placed based assessment (Kloos *et al*., 2015).

2.4. Participatory indicator development

The development of the hybrid vulnerability framework followed with the participatory indicator development process. This study was based on a step-wise approach to indicator development where standard procedures were followed to select the indicators as shown in Figure 2-1. The first step is the preliminary indicator selection from literature, conceptual frameworks of risk causation processes combined with personal experience in the region and knowledge of the processes leading to vulnerability of rural farming communities to multiple hazards (droughts and floods). This first step consisted in a review of the status quo in risk assessment including of all global indices such as the World Risk Index (Welle *et al*., 2013) described in section 2.2. The standard indicators that resulted from this classical indicator development process were used to develop an Indicator Reference Sheet (IRS). The indicator reference sheet is a document detailing most commonly used indicators in the region that have been compiled from literature, conceptual frameworks and personal experience of the authors. The second step is the participatory selection of local experts based on the snowball principle. This is where a core group of local experts comprising people from local agricultural departments, farmer representatives, disaster managers, rural development experts and local government authorities were asked to recommend institutions involved in drought or flood prevention or are involved in supporting communities to reduce their vulnerabilities to floods and droughts.

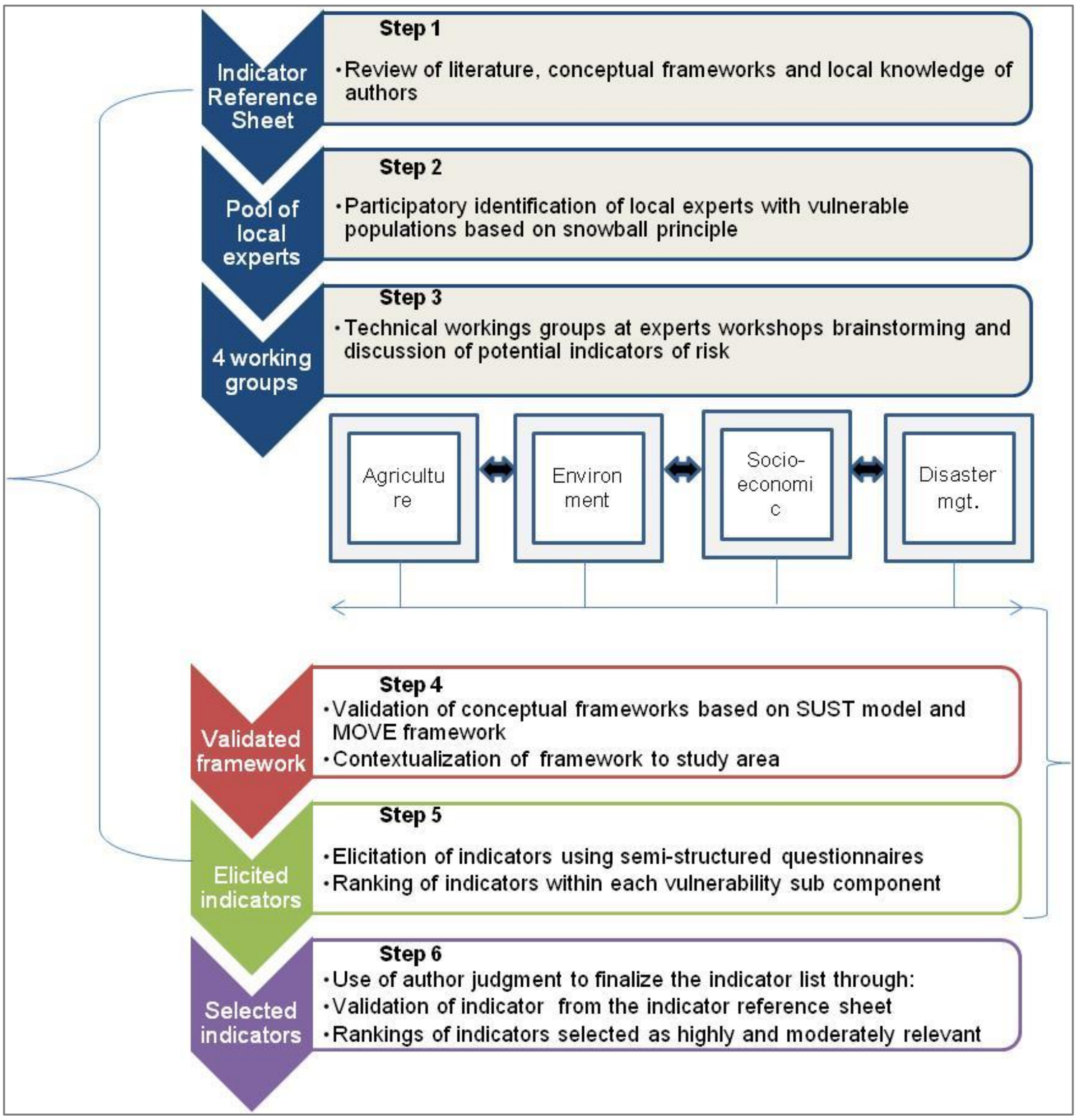

Figure 2-1: Adapted systematic procedure for participatory indicator development

This resulted in the selection of experts from the local departments in charge of agriculture, disaster management and local government authorities as well as farmer group leaders for both crop and livestock sub sectors. These first four groups served as the focal expert group. They were then asked to recommend other institutions in the area involved in any of the following thematic areas: agricultural development, rural development, disaster/emergency management, weather forecasting, health and social work. This provided a list of government institutions, local and international NGOs as well as development institutions operating in the area. Representatives of various farmer associations were asked to indicate their level of engagement with these institutions as far as their relevance in supporting, mitigating, preventing or providing technical assistance on floods, droughts, climate change and general socio-economic development are concerned. Equivalent institutions in adjoining districts and regional or provincial capitals were also invited to participate in the workshop. Twenty-five institutions were identified in both the Vea watershed in Ghana and the Dassari watershed in Benin whilst seventeen were identified in the Dano watershed of Burkina Faso. These local experts were then invited to a technical expert workshop (step 3).

2.4.1. Local level indicator elicitation and Indicator Reference Sheet

A day long technical workshop was held in each case study country at the local level. Participants were asked to indicate which of the four technical areas they had expertise and competences in. Four experts' groups were constituted to become the four 'technical thematic working groups'. These four-technical thematic working groups were:

- Agriculture
- Socio-economic and health matters e.g. rural development experts, health and development practitioners
- Disaster management/meteorology and
- Environment.

institutional support that help the people to cope and adapt to the multiple hazards.

The nature of the semi-structured questionnaire allowed for practical elicitation of relevant indicators of risk and vulnerability as participants actively discussed and debated among them before settling on a particular indicator. The same participatory process was also used to reassess and finalize the rankings. Each technical group provided rankings within each vulnerability sub-component which would later feed into the weighting of the selected indicators. As a result, all indicators were (supposed to be) presented in the order of the most important in terms of defining exposure, susceptibility and capacities of people living in the area

Table 2-2 summarizes the expert categories at the various workshops as well as experts engaged at the national level. As shown in the bottom half of Figure 2-1, and in steps four to six, three major tasks were assigned to each group. The fourth task was the validation of the proposed vulnerability and risk assessment framework. A conceptual framework of vulnerability was presented to the groups and they were asked to make comments regarding the various components of risks, impacts and perturbations within first, the context of the watershed and second, the surrounding areas within Savanna agro-ecological zone of the respective countries.

After this and in step five, a separate semi-structured questionnaire with questions ranging from indicators of exposure, coping and adaptive capacity to ecosystem robustness was presented to each technical group. For instance, those in the agriculture group discussed aspects of risk that are clearly linked to agricultural activities such as determinants of a farm exposure, indictors of susceptibility of the agricultural system, impacts of drought and floods on the agricultural system in the area and elements of farmers' coping and adaptation capacities to frequent floods and droughts, etc.

Those in the Disaster management/meteorology group were to discuss indicators of disaster preparedness, risk governance, impacts of disasters on human systems and the local economy. Those in the environment group discussed questions on the state of the environmental systems, ecological and soil properties, water systems etc. The socio-economic and health group were to focus on factors and conditions that predispose the people to be affected by floods and drought. They discussed poverty levels, housing conditions, food availability, household dependencies as well as social networks and institutional support that help the people to cope and adapt to the multiple hazards.

The nature of the semi-structured questionnaire allowed for practical elicitation of relevant indicators of risk and vulnerability as participants actively discussed and debated among them before settling on a particular indicator. The same participatory process was also used to reassess and finalize the rankings. Each technical group provided rankings within each vulnerability sub-component which would later feed into the weighting of the selected indicators. As a result, all indicators were (supposed to be) presented in the order of the most important in terms of defining exposure, susceptibility and capacities of people living in the area

Table 2-2: Number of participants and interviewed experts per working groups in the three research countries.

Working group	Ghana		Burkina Faso		Benin	
	Expert workshop-local level	National level experts	Expert workshop-local level	National level experts	Expert workshop-local level	National level experts
Agriculture	6	6	5	2	7	5
Socio-economic/health	4	5	4	3	5	6
Disaster management/climate change/meteorology	7	3	4	4	4	3
Environment	4	6	4	4	4	4

In step six as shown in Figure 2-1, the experts worked on two additional tasks. One was the validation of the indicators listed in the 'Indicator Reference Sheet' (IRS) and another was the ranking (weighting) of the validated Reference Sheet Indicators (RSI). Each group was given the IRS to determine their relevance for the present study. The experts determined the relevance of the given indicators within each vulnerability sub-component and had to choose between three options: highly relevant, moderately relevant, and irrelevant.

2.4.2. National level indicator elicitation and Indicator Reference Sheet

To get an understanding of what kind of indicators are deemed relevant by experts working in national capitals of the three countries, the same set of questionnaires used to elicit responses at the expert workshops were used in a combination with interviews, focus group discussions and mini-workshops in Accra, Ouagadougou and Cotonou. One-on-one interviews were carried out in cases where there was only one expert on climate change at a particular institution. Where there were more people involved in any of the thematic areas of the study (floods, droughts, disaster management, agriculture, climate change), the interview took the form of focus group discussions and mini workshops. Table 2-2 shows the number of experts at the national level that were interviewed. It is important to emphasize that the national level exercise was focused on developing a set of indicators relevant for macro scale risk assessment.

The indicators that are selected as either highly relevant or moderately relevant were ranked by the experts in decreasing order of importance within each vulnerability sub- component. Indicators were reclassified by the authors to ensure that they fall in the proper vulnerability sub-component (as determined by the vulnerability framework) and also to allow for comparison with the IRS. In selecting the final indicators from the two sources, elicited indicators and IRS, the former always takes precedence and preference was given to indicators directly elicited by the experts. The implication is that all technically sound elicited indicators were selected by the authors according to the ranking given by the experts. Within the same vulnerability sub-component, where the same indicator is chosen as relevant from the IRS and also appears on the elicited indicator list, the ranking from elicited indicator is used. In cases where a reference sheet indicator is described as highly relevant but not listed on the elicited list, author judgment was used to select and rank that indicator. This process is outlined in Figure 2-2.

Working with indicators and with the concept of vulnerability is a relatively novel approach and not all experts invited to the workshop understood clearly what constitute relevant indicators of risks and vulnerability. In some cases, experts could only describe the process affecting risk and were unable to

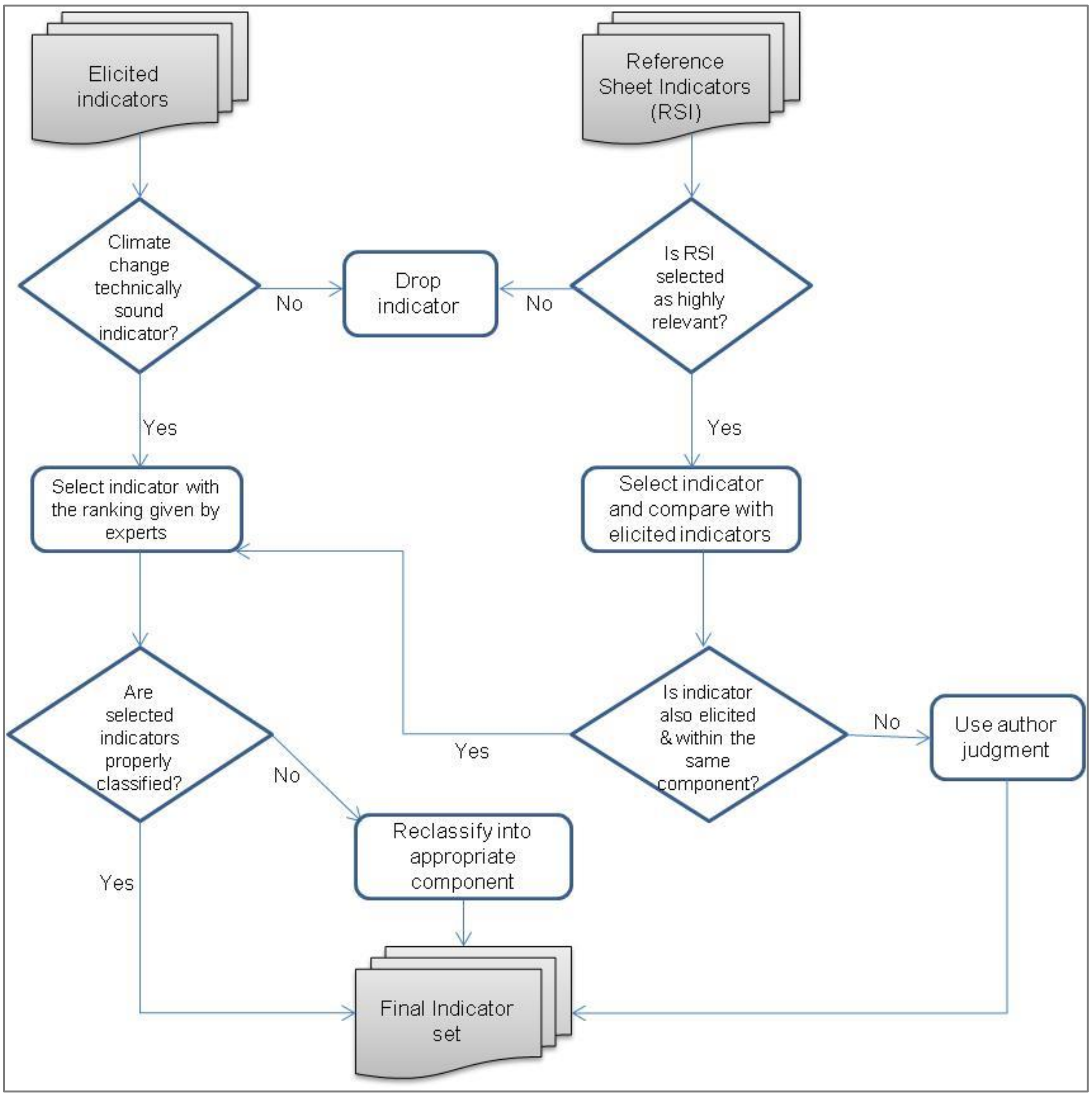

Figure 2-2 Selection of final indicators from the two sources

provide the technical names of the indicators or were unable to provide good proxies to describe the complex term of vulnerability and risk. The use of the IRS made it easier to match the terms used by the experts to the standard indicators on the reference sheet. Judgment from the authors was used in refining the indicator list from the local and national experts. Combining author judgment with participatory inputs has been found to result in robust indicator refinement (Reed & Dougill, 2003).

2.5. Results

2.5.1. Indicators of risk in West African social-ecological systems

At the local level, experts from Ghana validated and elicited a total of 37 indicators, those from Benin, 36 and Burkina Faso, 34. Similarly, at the national level, Ghana elicited 25, Benin, 25 whilst Burkina Faso named 22 indicators. Interestingly, as many as 12 indicators deemed to be important by the local level experts in all three countries were not selected by their counterparts at the national level. Of these, four belong to the vulnerability component, coping capacity whilst three belong to the component 'susceptibility of the social sub-system'. These local level unique indicators have been presented in Table 2-3.

Table 2-3: Summary of indicators relevant only at the local level.

Indicator	Vulnerability component
Distance to food market	Susceptibility of social sub-system
Prevalence of wasted children	Susceptibility of social sub-system
Demographic pressure	Susceptibility of social sub-system
Amount of surface run-off	Susceptibility of ecological sub-system
Normalized Difference Vegetation Index	Ecosystem robustness
Total soil nitrogen	Ecosystem robustness
Ability to survive crisis	Coping capacity
Presence of emergency management committee	Coping capacity
Local emergency funds as a percentage of local budget	Coping capacity
Access to national emergency funds and relief goods and services	Coping capacity
Declining labour availability	Adaptive capacity
Land ownership	Adaptive capacity

2.5.2. Unique indicators and differential rankings

Table 2-4 indicates that there are as many as eight indicators that were unique to only Ghana at the national scale, and five at the local level. Burkina Faso recorded only three unique indicators at the national level against six at the local level, whilst Benin recorded six indicators at the national scale compared to four at the local level. In the case of Ghana, it is important to note that four out of five local level unique indicators maintained their uniqueness to Ghana at the national level as no other national expert in the two other countries cited them. The remaining one, ‘crop type’, was cited by Benin national experts causing it to lose its uniqueness to Ghana at the national level. Also, Ghanaian national level experts cited three new indicators which had never been cited by any expert from the two other countries at any level. These are ‘land use planning’; ‘annual water balance’ and ‘access to purchased inputs’. National experts in Burkina Faso also cited a unique indicator, ‘siltation of bas fonds’, bringing again to the fore the differences that underline socio-ecological conditions determining the vulnerabilities of the different societies.

Besides the exclusivity of many indicators, there were a number of indicators that were common to all three countries, albeit with differences in their rankings. For instance, at the local level, whereas experts from Ghana ranked ‘prevalence of poverty’ (Figure 2-3) as the ninth most important determinant of susceptibility to droughts and floods out of a total of ten indicators (9 out of 10), their counterparts in Benin ranked the same indicator as the first most important (1 out of 8) and those in Burkina Faso ranked the same indicator also as the first most important (1 out of 7).

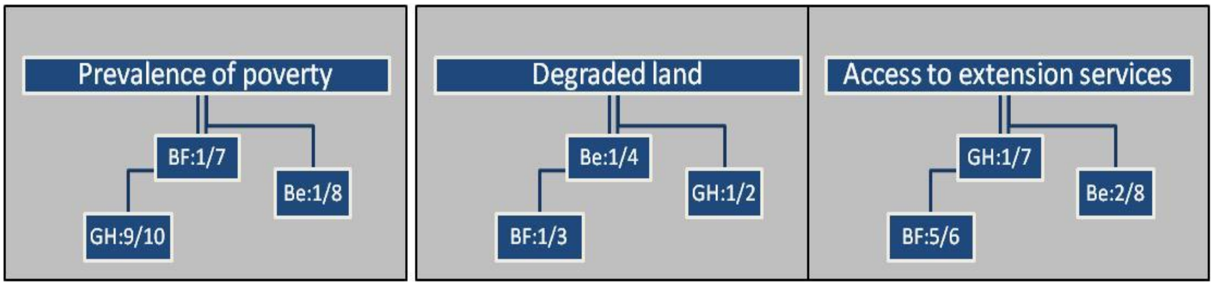

Figure 2-3: Differential ranking of indicators.

Table 2-4 Summary of indicators unique to each study country[6].

Ghana	Vulnerability component	Burkina Faso	Vulnerability component	Benin	Vulnerability component
Unique Indicators at the local level					
1 Crop type	SUS.ES	1. Household size	SUS.SS	1. Forested area	Eco. robust
2. Unimproved drinking water source	SUS.SS	2. Agroforestry cover	SUS.ES	2. Erosion rates	SUS.ES
3. Physical infrastructure	Exp. SS	3. Soil depth	SUS.ES	3. Land ownership	Adaptive capacity
4. Population density		4. Number of bas-fonds [7]	Eco. robust	4. Total soil nitrogen	Eco. Robust
5. Female headed households	SUS.SS	5. NDVI[8]	Eco. robust		
	SUS.SS	6. Early warning systems	Coping capacity		
Unique indicators at the national level					
1. Physical infrastructure	Exp-SS	1. Household size	SUS-SS	1. Stunting	SUS-SS
2. Population density	SUS-SS	2. Siltation of bas fonds	SUS –ES	2. Seasonal variability	SUS-ES
3. Unimproved drinking water source	SUS-SS	3. Dry season duration	SUS -ES	3. Infiltration rate	Eco. Robust
4. Female headed households	SUS-SS			4. Groundwater	Eco. Robust
5. Land use planning	SUS-ES			5. Local knowledge of disasters	Coping capacity
6. Annual water balance	Eco. robust			6. Leadership& management	Adaptive capacity
7. Gross margin	Adaptive cap				
8. Access to inputs	Adaptive cap				

[6] SUS.ES = susceptibility of ecological subsystem, SUS.SS =susceptibility of social subsystem, Exp.SS=exposure, social system, Eco.robust =ecological robustness: NDVI= Normalized Difference Vegetation index: Highlighted indicators for Burkina Faso are all drought related indicators

[7] Small reservoirs or dams used for agricultural purposes and animal feeding

[8] Normalized Difference Vegetation Index

2.5.3. New or rarely used indicators

A number of the indicators have either not been used or are rarely used in classical risk and vulnerability assessment literature in the region. Comparing the final indicator set with the RSI, there are 28 indicators at the local level and 29 at the national level that were not captured in the RSI. At the national level, they constitute 69% of all indicators deemed to be relevant in the context of the study countries whilst they represented 56% of all indicators at the local level. In some cases, proxies of these indicators have been used. For instance, a typical indicator used to express the exposure of people to droughts and floods is ‘Agricultural Employment’. This indicator measures the percentage of people in an area engaged in agricultural-related activities. Although it has been extensively used (see for example, USAID, 2011; Brooks *et al*., 2005; O’Brien *et al*., 2004b). Adger *et al*. (2004) criticized the use of such indicator as being “biased towards wage labour”. In this study, the experts agreed with the assertion of Adger *et al*. (2004) that the ‘Agricultural Dependent Population’ gives a more accurate depiction of people who may potentially be exposed to natural hazards since it accounts for all people directly or indirectly engaged in the climate sensitive sector of agriculture.

Indicators such as ‘insecure farms’ which measures the percentage of farm plots located in slopes of more than 5%, was reported at the local level in Ghana and Burkina Faso and shows the extent to which slope exposes the agricultural system to floods and droughts. Such farms were said to be extremely vulnerable to high episodes of rainfall through increased erosion whilst at the same time more prone to the impacts of droughts as a short dry spell leads to significant crop failures due to poor water infiltration rates. Other conspicuously missing indicators in the literature of existing risk assessment are ‘Number of herds per household’ and ‘Gross Margin per Hectare’. These indicators were found to be extremely important in influencing the adaptive capacities of farmers in all three countries. Gross margin per hectare was seen as far better indicator than crop production which is the one commonly used. This is because gross margin analysis incorporates all four aspects of productivity including area cultivated, production cost, yield and market prices. The keeping of livestock in the Sudanian region was also seen as a social safety net and offers diversified livelihoods especially in times of old age or crisis. Households with livestock are more likely to withstand hazards events than those who depend solely on crops for their livelihoods. The study found that major coping and adaptation capacities lie in the number of livestock owned by the households. It offers both the means of immediate liquidation to cope with a present disaster and also offers long term capacity to recover from a disaster.

2.5.4. Comprehensive indicator sets

Table 2-5to Table 2-11 **s**how the outcomes from the various technical groups working on indicators at both the local and at the national levels. The indicators are presented according to the various vulnerability components of the proposed framework. The indicators were presented in two parts. The first part, Table 2-5 to Table 2-10 details indicators which are rarely used in West African multi-hazard risk assessment. Two levels of assessment have been presented. These are the results from the local scale and those from the national level (macro scale). The ranking (which can subsequently lead to weights) of the indicators has also been presented according to each sub-component of the framework used. For example, in Table 2-5 the indicator ‘Agricultural Dependent Population’ is ranked at the Ghana local scale as the most important indicator out of three indicators (1/3) within the vulnerability sub-component ‘exposure of Social system’. That same indicator was not selected at the national/macro level in Ghana but was ranked as 1/2 in Burkina Faso within the same vulnerability sub-component. The tables also describe the relevance of the indicators for climate change research as stipulated by the experts and complemented with literature and knowledge of the authors.

The second part of the tables (Table 2-11) presents the other commonly used indicators in literature which have also been confirmed in this study. Together they form the ‘West African Comprehensive Indicator Set’ for flood and drought risk assessment in a coupled SES under climate change. The indicators have been grouped into the various components and sub-components of the framework. For example, Table 2-5 presents the indicators describing the exposure of the SES, Table 2-6 presents indicators describing the susceptibility of the social sub-system and Tables 2-7a and 2-7b shows the indicators describing the susceptibility of the ecological sub-system.

Table 2-5: Major indicators describing the exposure of the socio-ecological system to drought and floods.

Indicator	country reporting and rank within the sub-component		Definition of indicator	Studies using indicator or similar indicator
	local scale	macro scale		
Agricultural dependant population (ADP)	Ghana 1/3, Benin 1/2, Burkina Faso 2/2	Burkina 1/2, Benin 2/2	The percentage of the area's total population depending on agriculture related employment (including hunting, fishing and forestry)	Adger et al 2004, USAID (2011) and O'Brien *et al.*, 2004b). All these studies used the related indicator of Agricultural employment.
	Relevance for Climate Change Research: The experts believe that the higher the ADP, the more a district will be impacted by disruptions in production due to changing environmental conditions. High ADP suggest lack of other employment options and therefore in the event of crop failures, farmers and their dependants have few opportunities to earn additional income (Adger et al 2004, (O'Brien et al., 2004b). In addition, high ADP means that a higher percentage of people are exposed to a climate sensitive sector of agricultural particularly in the study areas where rain-fed agriculture predominates.			
Insecure settlement	Ghana 3/3, Benin 2/2, Burkina 1/2	Ghana 1/2, Burkina 2/2 Benin 1/2	Percentage of an area villages in high flood intensity zones	.
	Relevance for Climate Change Research: Hastily constructed settlements although generally inexpensive to build, are more physically vulnerable to hazards especially if located in high flood intensity zones. Adger *et al*. (2004) contend that People living in such settlement are less likely to adopt risk spreading measures such as insurance and will be less able to engage in post-disaster reconstruction			
Insecure farms	Ghana 3/3, Burkina Faso 2/2	Ghana 1/2 Benin 2/3	% of farms plots in an area located in slopes of more than 5%	
	Relevance for Climate Change Research: Farms located in slope of more than 5% are more prone to erosion in cases of extreme rainfall. Also, because they have less water infiltration rates, a short dry spell can lead to crop failure			

Table 2-6: Indicators describing the susceptibility of social sub-system to the hazards.

Indicator	country reporting and rank within the sub-component		Definition of indicator	Studies using indicator or similar indicator
	local scale	**macro scale**		
Prevalence of Stunted children	Ghana 7/10, Benin 2/8	Benin 4/4	Percent of children under 5 in an area who are stunted (have low height for their ages)	
	Relevance for Climate Change Research: Stunting, or low height for age (UNICEF 2013) is caused by long term intake of insufficient nutrients associated with frequent infections. It normally occurs before age two, and its effects are largely irreversible. Households having already stunted children will have aggravated nutrient deficiencies when drought cause food shortages especially for those engaged in rain-fed agriculture.			
Calorie intake per capita	Ghana 8/10, Benin 4/8, Burkina 2/7	Burkina 5/5, Benin 3/4	The dietary energy consumption per person is the amount of food, in kcal per day, for each individual in the total population.	Adger *et al*. (2004)
	Relevance for Climate Change Research: Poor nutrition is associated with poor general health and particularly after flooding due to a weakened immune system. Malnourished people or those close to malnourishment are less likely to survive food shortages caused by droughts [13]. Adger et *al*. [13] again indicated that although food prices are a better indication of food security, calorific intake is a more direct, and strongly related, measurement of nutritional status.			
Prevalence of poverty[9]	Ghana 9/10, Benin 1/8, Burkina 1/7	Burkina 2/5, Benin 1/4	Percent of people living on less than 1.25USD a day	Birkmann *et al*. (2011); Bollin & Hidajat (2006); Vincent (2004b)
	Relevance for Climate Change Research: Poverty is seen in all study countries as major determinant of vulnerability. Most experts believe that the effects of poverty on vulnerability are most felt in depressing farmer's adaptive capacity. Poor farmers are generally not able to adopt improved agricultural practices aimed at adapting to climate change.			
Household size	Burkina Faso 3/7	Burkina 3/5	Average number of people in a household with clearly identified household head	Bollin & Hidajat (2006) used a closely related indicator of dependency ratio, used also by Hahn *et al*. (2009).
	Relevance for Climate Change Research: The more people there are in a household, the more the household has to spread its thin resources in the event of hardships. Households with greater number of people invariably spend their food reserves faster than households with fewer people. This forces the household to quickly fall back on its other coping measures.			

[9] This indicator was reclassified from Adaptive capacity to susceptibility because the authors believe poverty actually pre-disposes a person to be adversary affected. It however, creates several feedback mechanisms that go on to affect his coping and adaptive capacities.

Table 2-7: Indicators describing the susceptibility of the ecological sub-system to floods and droughts and floods.

Indicator	country reporting and rank within the sub-component		Definition of indicator	Studies using indicator or similar indicator
	local scale	macro scale		
Land use planning	none	Ghana 1/2	Proportions of land within an area which has been properly zoned with clear demarcations as to the use of the land	
	Relevance for Climate Change Research: The experts in Ghana believe that areas with effective land use plans are able to meet the land needs of its people whilst protecting natural resources. In the event of hazard occurrence, areas without proper land use plans are more likely to suffer crop, buildings and other property damages than areas with effective land use plans.			
Siltation of dams	none	Burkina 3/4	This is measured as the depth of water in major irrigation dams in an area.	
	Relevance for Climate Change Research: Dams with shallow depths as a result of siltation dry faster under short dry spells. In the event of climate change, such dams are more likely to experience water shortages than low silted dams and thus farmers relying on such will be heavily impacted.			
Crop type	Ghana 2/2	Ghana 2/2, Benin 2/3	% of area under cultivation of drought and flood sensitive crops.	
	Relevance for Climate Change Research: Areas with greater share of drought and flood sensitive crops are more vulnerable than those growing drought and flood tolerant crop cultivars. A typical climate change adaptation among farmers in Ghana is the use of Drought and Flood ‘escape crops’ such as early millet".			
Dry season duration	Benin 4/4, Burkina 3/3	Burkina 4/4	Duration of dry season in days over the past 10 years.	
	Relevance for Climate Change Research: Climate change in the study area has mainly been experienced in the form of climate variability with increasing prolongation of the annual dry season. Farmers already experiencing longer dry season are at greater risk of suffering more under increasing climate variability.			

Table 2-8a: Indicators describing the robustness of the ecological sub-system to cope with floods and droughts.

Indicator	country reporting and rank within the sub-component		Definition of indicator	Studies using indicator or similar indicator
	local scale	macro scale		
Annual water balance	none	Ghana 4/6	This is the amount of water remaining in the watershed at the end of the rainfall season. It is evaluated using the general water balance equation given as $P=Q+E+\Delta S$ (Oosterban *et al*., 1996)[10].	Strzepek *et al*. (2011); Zhang *et al*., (2011)
	Relevance for Climate Change Research: Water balance is an important factor of irrigation requirements, runoff assessment and flood control. The Experts believe that areas with below average annual water balances are more prone to water shortages. In the event of climate change, such areas will be more impacted than areas having average water balance under normal rainfall conditions.			
Green vegetation cover	Ghana 5/5, Benin 5/6, Burkina 8/8	Burkina 4/4, Benin 7/7	Fractional cover of green vegetation during the dry season	Rojas *et al.* (2011)
	Relevance for Climate Change Research: Areas exposed to droughts and floods typically have no vegetation cover during the dry season, increasing the risks of water and wind erosions			
Soil depth	Burkina 3/8	Ghana 3/6, Burkina 2/4	The maximum rooting depth at which major crops can grow	
	Relevance for Climate Change Research: Deep, well drained soils are better able to infiltrate excess rain water before generating run-off to cause flooding. Shallow soils have several limitations in holding water and this has implications for flood and drought. Whilst shallow soils easily saturate and generate run-off, they also dry faster under short dry spells.			

[10] Where P is precipitation, Q is runoff, E is evapotranspiration and ΔS is change in storage

Table 2-8b: Indicators describing the robustness of the ecological sub system to cope with droughts and floods.

Indicator	country reporting and rank within the sub-component		Definition of indicator	Studies using indicator or similar indicator
	local scale	macro scale		
Agroforestry	Burkina 2/8	Ghana 2/6, Burkina 3/4	The percentage of total land in the area under agroforestry plantation or of secondary forest type	
	Relevance for Climate Change Research: Experts believe that areas with greater agroforestry share have improved micro climate that reduces the impacts of droughts and surface run-off. Farmers with agroforestry systems have alternative sources of income in periods of annual crop failure from drought or floods. The effects of increased climate variability will be felt more in areas with little or no dense vegetation.			
Soil organic carbon (SOC)	Ghana 1/5, Benin 1/6, Burkina 4/8	Ghana 1/6, Benin 1/7	The percent or mass of Soil Organic Carbon held per gram of all soil constituents	
	Relevance for Climate Change Research: Areas with substantial high levels of organic matter are expected to hold moisture effectively and be more fertile even in periods of droughts. In the region, low levels of organic carbon are usually associated with low supply of major nutrients [69]. This is worsened by burning of biomass in the prevailing-slash-and burn systems, frequent bush fires and high temperatures which lead to a rapid decomposition of organic matter [70]. Areas with low SOC are more likely to experience food shortage during droughts events.			
Conservation agriculture practice	none	Ghana 6/6, Benin 6/7	Percent of farmers in area who practice conservation agricultural practices. These practices include soil-water management regimes, use of cover crops, organic manure, stone bonding, terracing etc.	
	Relevance for Climate Change Research: Areas with a greater proportion of its agricultural land under conservation agricultural practices are better able to withstand drought conditions and flooding. A Study by Kloos and Renaud (2014) in Benin shows that organic cotton production using animal manure directly reduces the impacts of climatic risks and indirectly reduces economic risks and support women empowerment. Areas with apparent lack of any conservation agricultural practice are more likely to suffer from increasing climate variability.			

Table 2-8c: Indicators describing the robustness of the ecological sub system to cope with droughts and floods.

Indicator	country reporting and rank within the sub-component		Definition of indicator	Studies using indicator or similar indicator
	local scale	macro scale		
Ground-water level	Ghana 3/5, Benin 6/6	Benin 3/7	Average level at which most boreholes in the area reach water.	
	Relevance for Climate Change Research: Experts agreed that high groundwater reserves will enable the area to adapt to long term droughts by expanding its irrigation facilities. The ability of vulnerable people to adapt to climate change will largely be determined by the availability of natural resources (Adger *et al*., 2004) particularly water resources. Increases in mean land surface temperature will lead to an increase in evapotranspiration with a corresponding increase in irrigation demands. As more irrigation options are explored, Arid and semi-arid regions of West Africa might actually be drawing water from non-renewable aquifers which has been recharged in past episodes of high rainfall. Water availability will then be determined by a combination of water from present-day precipitation or runoff and water from aquifers.			
Bas-fonds	Burkina Faso 1/8	Burkina 1/4, Benin 2/7	The number Low-lying areas or depressions, for instance valley bottoms, which are seasonally waterlogged without a marked stream channel and hence can be inundated for several months during the rainy season.	
	Relevance for Climate Change Research: Bas-fonds play crucial role in the lives of people in Burkina Faso. Small reservoirs located in bas-fonds provide critical water resources during the dry season for vegetable gardening and drinking water. Areas with limited bas-fonds have little option to diversify their farm enterprises and are more likely to suffer from drought and crop failures.			
Water holding capacity	Ghana 4/5, Benin 3/6, Burkina 7/8	Ghana 5/6, Benin 4/7	Soil water holding capacity is the amount of water that a soil can hold and generally depends on the soil texture and the soil organic matter content.	
	Relevance for Climate Change Research: Soils in the area have low water holding capacities. Moreover, they are also highly susceptible to erosion and compaction [69]. Areas with low soil moisture under conditions of normal rainfall are expected to be less able to hold water during short dry spells.			

Table 2-9: Indicators describing the major coping capacities of the social sub-system.

Indicator	country reporting and rank within the sub-component		Definition of indicator	Studies using indicator or similar indicator
	local scale	macro scale		
Alternate food and income sources	Ghana 1/7, Benin 1/7, Burkina 7/7	Ghana 1/1, Benin 1/3	Percentage of population with additional food and income source other than agriculture.	Crop diversity, Percent of household's dependent solely on agriculture as a source of income [30].
	Relevance for Climate Change Research: Experts believe farmers with additional food and income sources are better able to cope with disasters. Other income sources include economic activities such as teaching, trading, driving carpentry, masonry, etc. whilst other food sources include those receiving or can receive food aid			
Local knowledge	Ghana 4/7, Benin 3/7, Burkina 3/7	Benin 2/3	The percentage of people with adequate understanding of local climate and local environmental issues and have benefited from emergency training programmes.	
	Relevance for Climate Change Research: Local knowledge and experience of the environment is as useful as a scientific understanding of climate hazards. This is because generally climatic forecasts and written information are unavailable to the most vulnerable members of the population who need it most [13]. In the study areas, farmers who have gained local understanding of the climate are better able to strategize and plan their production accordingly.			
Presence of emergency management committee	Ghana 6/7, Benin 7/7, Burkina 4/7	none	Annual meeting frequency of local emergency committees	Meeting frequency of risk management/emergency committee and Local risk management/emergency groups (Bollin & Hidajat 2006).
	Relevance for Climate Change Research: Household's ability to cope with disasters is determined largely by the effectiveness of the village and local disaster management committees. In all the three countries, there's no national budgetary allocation for disaster committees. In the case of Ghana, there is a 5% allocation of the district assembly's common fund for emergency management but the disbursement and application of this provision is vague and local disaster managers have no access to this fund.			
Local emergency funds	Ghana 7/7, Benin 5/7, Burkina 5/7	none	local emergency fund as a percentage of national budget	Note: the relevance of these two indicators for climate change research is the same as the one just above.

access to national emergency funds and relief items	Ghana 5/7, Burkina 6/7 Benin 4/7,	none	release period of national emergency funds and relief items	
community participation/social capital	Ghana 3/7, Benin 2/7, Burkina 1/7	Burkina 1/1, Benin 3/3	Communities with highly or adequate participation of people in communal activities	(Mechler, 2005)
	Relevance for Climate Change Research: This was seen as an important determinant of how community members can be mobilized in times of crisis. It also measures the strength of social cohesion and solidarity existing within the community. In the study areas, communal spirit was very strong and really support affected people to cope with crisis.			

Table 2-10a Indicators describing the major adaptive capacities of the social sub-system.

Indicator	country reporting and rank within the sub-component		Definition of indicator	Studies using indicator or similar indicator
	local scale	macro scale		
Extension service	Ghana 1/7, Benin 2/8, Burkina 4/5	Ghana 1/6, Burkina 3/4	Number of agricultural/ health extension officers/staff in an area	
	Relevance for Climate Change Research: Agricultural and health extension services were found to be highly important in creating awareness about current adaptation options and health related issues. Farmers with unhindered access to extension are better positioned to learn current developments in climate change adaptation. Also, mentioned as important is access to health advice by public health officers in the aftermath of disasters.			
Illiteracy	Ghana 3/7, Benin 4/8, Burkina 1/5	Ghana 6/6, Burkina 2/4	The percentage of an area's total population below 15 years that can neither read nor write	USAID (2011), Brooks *et al.*, (2005); Eriksen *et al.*, (2007b); O'Brien *et al.*, 2004b)
	Relevance for Climate Change Research: Education is closely linked with poverty and marginalization – the least educated and lower skilled members of a society are likely to be the most vulnerable to climate hazards in terms of livelihoods and geographical location. The least educated tend to depend more on climate sensitive sectors of employment such as agriculture including fishing, hunting and forestry. Brooks *et al*. [50] also indicated illiteracy can serve as a barrier to facilitating understanding of the complex nature of hazards and appropriate responses.			
No of herds per household	Ghana 4/7, Benin 3/8, Burkina 5/5	Ghana 3/6, Burkina 1/4, Ben 1/3	Number of herds of livestock owned by households. Herds include goats, sheep, cattle and donkeys if they are used for economic activities	
	Relevance for Climate Change Research: Households with livestock are more likely to withstand hazards events than those who depend solely on crops for their livelihoods. The study found that a major coping and adaptation capacity lie in the number of livestock owned by the households. It offers both the means of immediate liquidation to cope with a present disaster and also offer as long-term capacity to recover from a disaster.			

Table 2-10b: Indicators describing the major adaptive capacities of the social sub-system.

Indicator	country reporting and rank within the sub-component		Definition of Indicator	Studies using indicator or similar indicator
	local scale	macro scale		
Gross margin per hectare	Ghana 5/7, Benin 5/8	Ghana 4/6	This is the ratio of the difference between total revenue and variable production cost per hectare.	Bollin & Hidajat (2006)
	Relevance for Climate Change Research: This was seen as a better indicator than crop production. Gross margin analyses incorporate all four aspects of productivity including area cultivated, production cost, yield and market prices. Areas with already depressed gross margin from major commodities are more likely to suffer from drought and floods.			
good leadership and management	Ghana 6/7, Benin 6/8, Burkina 3/5	Benin 3/3	Percentage of communities within an area with well functional institutional network of well-respected chiefs and effective local government structures.	E.g. institutional capacity building and communication Bollin & Hidajat (2006)
	Relevance for Climate Change Research: Local leadership was seen as critical in enforcing rules and regulations as well as policies aimed at reversing the negative effects of climate change. Areas with failed leadership such as powerless tribal chiefs were said to be more vulnerable than those with well functional chiefs.			
Access to purchased inputs	none	Ghana 5/6	Proportion of farmers within an area with readily access to affordable purchased inputs.	
	Relevance for Climate Change Research: Farmers with readily access to affordable inputs are better to adopt improved agricultural practices and are thus better able to adapt to climate variability.			
Declining labour availability	Ghana 7/7 Benin 8/8	none	Percent of population without timely access to labour for major farm activities	
	Relevance for Climate Change Research: Agriculture is a labour-intensive activity and most adaptation options require labour to implement. Areas with limited labour supply are more likely to be unable to implement several adaptation options with the potential to increasing their resilience to future climate related hazards. In the study areas, especially Ghana, this was seen as a consequence of climate variability as more young people who could have provided farm labour have migrated to cities in the South of the country as a result of declining agricultural productivity.			

Table 2-11: Other indicators that are commonly used in the region –Part II indicators[11].

Vulnerability component	Indicator	country reporting and rank within the sub-component		Studies using indicator or similar indicator
		local scale	macro scale	
Exposure	Physical infrastructure	Ghana 2/3	Ghana 2/2	Bollin & Hidajat (2006)
	Agricultural area	Ghana 1/3, Burkina Faso 1/2, Benin 2/2	Burkina 1/1, Benin 1/3	(Mechler, 2005)
	protected area	Ghana 2/3, Benin 1/2	Ghana 2/2, Benin 3/3	Mechler (2005)
Susceptibility-social sub system	Dependent population	Ghana 1/10, Burkina 4/7	Ghana 5/5, Burkina 1/5	(Brooks et al., 2005; Cutter et al., 2003; Eriksen et al., 2007b)
	Population density	Ghana 2/10,	Ghana 2/5	Mechler (2005)
	Quality of housing	Ghana 3/10, Benin 5/8, Burkina 5/7	Ghana 1/5, Burkina 4/5, Benin 2/4	Bollin & Hidajat (2006)
	Distance to drinking water	Ghana 4/10, Benin 6/8	None	[USAID (2011), Adger *et al*. (2004), Brooks *et al*. (2005), Eriksen *et al*. (2007a)
	Distance to food market	Ghana 5/10, Benin 7/8	None	
	Unimproved drinking water source	Ghana 6/10	Ghana 4/5	USAID (2011), Brooks *et al*. (2005), O'Brien *et al*. (2004)
	Female headed households	Ghana 10 /10	Ghana 3/5	USAID (2011), Cutter *et al*. (2003), Hahn *et al*. (2009), Brooks *et al*. (2005) Eriksen *et al*. (2007a)
	Prevalence of Wasted children	Benin 3/8, Burkina 6/7	None	
	Demographic pressure	Benin 8/8, Burkina 7/7	None	Mechler (2005)
Susceptibility-ecological sub system	degraded land	Ghana 1/2, Benin 1/4, Burkina 1/3	Burkina 1/4, Benin 1/3	Mechler (2005)
	Surface run-off	Benin 3/4, Burkina 2/3	None	

[11] These are selected indicators which were also found to have been widely used in climate change risk assessment literature both in the region such as USAID (2011) and elsewhere Adger *et al*. (2004) Bollin & Hidajat (2006)

	erosion rates	Benin 2/4	Burkina 2/4, Benin 3/3	Bollin & Hidajat (2006)
Capacity-ecosystem robustness	Infiltration rate	Ghana 2/5, Benin 4/6, Burkina 6/8	Benin 5/7	
	Total soil nitrogen	Benin 2/6	None	
	NDVI	Burkina 5/8	None	Rojas *et al*. (2011)
Coping Capacity	Ability to survive crisis	Ghana 2/7 Benin 6/7	None	USAID (2011), Brooks *et al.* (2005), Eriksen *et al.* (2007a)
	Early warning system	Burkina 2/7	Burkina 5/5, Benin 2/3, Ghana 7/7	
Adaptive capacity	Household income	Ghana 2/7, Benin 1/8, Burkina 2/5	Ghana 2/6, Burkina 4/4	Per capita income Cutter *et al.* (2003)
	Land ownership	Benin 7/8	None	

2.6. Discussion and Conclusions

A participatory approach was followed to select indicators for both the quantitative and qualitative assessment of risks faced by people in West Africa under climate change. The objective was to determine the most important indicators that could be used to describe the vulnerability and risk to drought and floods under climate change. The methodology allowed for a representative participation of stakeholders (including farmers) dealing with climate related hazards of drought and floods. The study, as a first step, used a conceptual risk assessment framework being developed to categorize vulnerability components. The major outcomes are comprehensive sets of indicators grouped according to the components of the conceptual framework that can be used to assess the risk to flood and droughts in West African socio-ecological systems at various scales in the region. The scales range from the very local level (watershed and surrounding areas) to district and region within the Sudan Savanna zone and finally at the national level in the West African region. At the local level, a total of 50 indicators were selected in all three countries. At the national level, a total of 42 indicators were found. As much as 12 relevant indicators at the local level were not selected by any expert at the national level. These indicators which could determine the extent to which a household is vulnerable to a hazard or a combination of hazards could not have emerged without a local participatory process, underscoring the need to include local people in risk assessment. Local emergency funds, access to relief goods and services, or household's ability to survive crisis, for example, are extremely important in periods of disasters and only an engagement with people who have experienced a deficit in these services during an event can bring them to the fore. The obvious omission of these indicators at the national level in all three countries suggests the need to have sub-national risk assessment so as to truly capture the vulnerabilities of people experiencing hazards. One would have expected that the national level experts would actually be interested in relief goods and services and emergency funds as important indicators.

The reason why they did not mention them is unclear but could probably mean they underestimate the benefits of these services to the local people; a situation which might have led to the fact that in most cases it takes too long for victims of disasters to receive relief.

Differences in indicator types between local and national assessment is important and suggests that a simple country or regional level risk assessment could underestimate the risk in rural areas where risk outcomes are first materialized. These 12 indicators are important in determining the extent to which a household will be potentially impacted by a hazard. According to the vulnerability framework used; of the 12 indicators, as much as five describe the susceptibility of the SES whilst another six determine the coping and adaptive capacities available to the people (Table 2-3).

The study has shown that majority of the indicators (as much as 56% of the local level indicators and 69% at the national level) have either not been used or are hardly used in the literature related to West African multi-hazard risk assessment in the context of climate change. The World Development Report in 2010 reviewed two major vulnerability-driven indices –Disaster Risk Index, DRI (UNDP, 2004) and Index of Social Vulnerability to Climate Change for Africa, SVA (Vincent, 2004) and concluded that these indices created spatial patterns out of tune with development-driven indicators and consistently showed a pattern contradictory to expert knowledge (World Bank, 2010a). The results from the present study show that such contradictory results are expected because they ignore the salient indicators deemed to be relevant by the local populations. Studies in the region that ignore indicators such as number of herds per household, gross margin per hectare, insecure farms, could lead to conclusions that “contradict expert knowledge” as found by World Bank (World Bank, 2010a, p.12). It is important to note that the relevance and weights of such indicators can only be understood by engaging with the vulnerable people themselves. This study has therefore shown the potential disadvantages involved in using the same set of indicators for several countries and make comparisons between them. Even within the same country, different indicators and weightings apply depending on the scale of assessment. Besides the indicators that are unique to each country, differences in risk perceptions, socio-economic conditions and other factors will mean that even the same indicator will invariably be ranked differently by different societies.

The study found that unique indicators were very relevant practically. For example, five of the six local level unique indicators for Burkina Faso are all drought related (see highlighted section in Table 2-4 and show the importance of drought to the livelihoods of an ordinary rural person in that country. Data from United Nations office for Disaster Risk Reduction (UNISDR) archives indicates that the probability of drought occurring in Burkina Faso for a typical year is 0.19 and accounts for 84.8% of all people affected by any disaster in the country (UNISDR, 2014). In contrast, drought probability in Ghana and Benin is 0.03 and people affected are 40.2% in Benin and 76.0% in Ghana. The presence of unique indicators has wider implications for risk assessment that uses common indicators for several countries and makes an effort to derive relative vulnerabilities of those countries or make an effort to compare vulnerability levels across countries.

In the case of Ghana, the issue of land use planning and access to inputs have been topical issues in national debates. Most flood events have been linked to the absence of land use plans or unenforced building regulations, a situation that has led to many houses built over waterways and impeding run-off during rainstorms. There has been a series of politically and socially sensitive housing demolition exercises by local authorities. The emergence of land use planning as an important elicited indicator therefore reflects this underlying socio-political condition that successive governments have failed to address. Also, access to purchased inputs was elicited probably because of difficulties in Ghana's inputs subsidy programme. Ghana's fertilizer consumption had decreased from 21.9 kg/ha in 1978 to 8 kg/ha in 2006 (MoFA, 2008). In an attempt to address the situation, the Government in 2007 re-introduced fertilizer and seed subsidies. However, a study in two farming communities on the performance of the inputs subsidy programme by (Yawson *et al.*, 2010) revealed that operational and bureaucratic difficulties have led to about 82% of farmers in these two communities without access to fertilizers. Its potential impacts on a wider national crop production have led to debates on potential food insecurity problems especially under climate change conditions.

In Burkina Faso, 'siltation of bas-fonds' is a major issue as most farmers rely on small reservoirs for both on-season and off-season vegetable farming in this semi-arid environment. However, these small reservoirs are being silted from sand from erosive rainfall and windstorms. High deforestation rate, estimated at 107,000 ha per year (0.83% per annum), faster rate of land degradation, at 0.5 million ha per year and resulting soil erosion, bulldozing (conversion) of protected land for biofuel and commercial agriculture are the major causes (DGPEDD, 2012).

It can be seen from the above that national level experts rely heavily on processes of a wider national interest and derive their indicators from major challenges facing the whole country whilst the local level experts rely on indicators pertinent to households and the local economy. This is an important dimension of risk assessment that a participatory process can help bring to the fore.

The differential rankings of the indicators in each of the study countries will affect the weights that will be applied in the estimation of a composite vulnerability index and subsequently the community risk index. Thus, although, an indicator may be common to two countries, their differential rankings will result in differences in explaining the risks faced by people living in the two countries. This differential ranking arises from differences in perceptions of risks, as well as cultural, political and socio-economic disparities in different countries. For example, in Figure 4, Ghana ranked prevalence of poverty as 9/10 as against 1/7 in Burkina Faso and 1/8 in Benin. This is probably due largely to major economic gains Ghana has achieved over the last two decades becoming the first country in Sub-Sahara Africa to reduce poverty by half over the past 10 years (USAID, 2013) and achieving a per capita output twice as much as all the countries in West Africa combined except Nigeria (British Council, 2012; World Folio, 2013). From the foregoing discussions, it is clear that errors can be generated or uncertainties may be increased when assigning the same weights to indicators for different countries or when countries are treated with the same set of indicators ignoring obvious heterogeneity of factors. This could lead to policy interventions that do not reflect reality and ill-informed allocation of scare resources. Alternatively, sub-national risk comparisons from a participatory process at multiple scales could result in better identification of high and low risk areas and lead to better targeting of development resources.

Notwithstanding the many strengths of the approach presented above, the methodology is not without shortcomings. Reed *et al.* (2008) found that participatory approaches alone are not enough for objective identification of indicators and suggested a combination of methods to achieve high accuracy. Also, Bell and Morse (2003) as well as Freebairn & King (2003) added that more value is added when participatory process is used in combination with expert judgment. In this study, also, judgment from the authors had to be used on a number of occasions. First, an Indicator Reference Sheet (IRS) was used to provide examples of potential indicators to the experts. Second, the IRS was used to derive proper technical names of the indicators in cases where the experts could only describe their understanding of the indicator. Third, elicited indicators had to be reclassified to properly align them to a vulnerability sub-component. Fourth, author judgment was employed in assigning weights and rankings of reference sheet indicator which were selected as highly relevant but were not directly elicited by the experts.

It must be noted that this study has only succeeded in identifying the relevant indicators and corresponding weights to use for a multi-hazard risk assessment. In subsequent studies, the indicators will be subjected to pre-defined criteria such as representativeness, reliability and feasibility (MEA, 2003) and correlation analysis to determine which ones can be considered for computation of the proposed West Sudanian Savannah Risk index (WSSRI). The indicators developed at the local level will be used in an upscaling process to understand the risk faced by people in the district and regional levels within the Sudan Savannah zone in a subsequent study. The national level indicators could also be used for national scale multi-hazard risk assessment. The indicators will be assessed on their performance towards a trajectory of multiple scales in a novel upscaling of risk indices. In cases where an indicator cannot be measured quantitatively or described qualitatively, author judgment will be used to either drop the indicator or find a proxy variable.

Although this study has not quantified the actual risk faced by the people, the participatory indicator development has allowed for the recognition of multiple “stimuli beyond those related to climate” (Smit & Wandel, 2006 p.7) and revealed significant indicators that have never been used in traditional risk assessment in the region. The study has also provided a sound scientific basis to allow for risk quantification in a related study. It has highlighted that major attention should be paid to differences in risk perceptions, culture, political, institutional and socio-economic dynamics in assessing risk faced by people in different countries particularly, for West Africa. More importantly, the rigorous process followed has led to the identification of locally and nationally relevant indicator set that can be used in assessing the risk to floods and droughts even as the impact of climate change is projected to worsen in the region.

From the discussions above, it is clear that neither a standalone classical approach (top-down) nor a purely participatory process is sufficient in determining useful indicators for risk assessment. While it has, neither been optimal to completely neglect classical approaches nor to take as an absolute fact opinion from local experts, more emphasis should be placed on the later in risk assessment that is supposed to serve the very people on whose behalf the assessment is done. Attempts should therefore be made in finding mechanisms where the two approaches could interact fruitfully and complement each other. We hope the present paper provides a good basis for efforts in this direction.

3. Modelling Flood Hazard zones at the sub-district level with the rational model integrated with GIS and remote sensing Approaches[12]

3.1. Introduction

West Africa is prone to frequent floods and droughts due to high variability in rainfall patterns (Sylla *et al*., 2009). In the last three decades, the sub-region has witnessed a dramatic increase in flood events, with severe impacts on livelihoods, food security and ecological systems (Armah *et al*., 2010; Braman *et al*., 2013; Tall *et al*., 2012). Above normal rainfall amounts at the peak of the rainy season in the Sudanian and Sahelian regions (i.e. July to September) frequently lead to severe floods, and cause many of the major rivers (e.g. Niger Volta river systems, Senegal) to overflow their banks. In 2007, for example, a series of anomalous abundant rainfall events caused severe floods in West Africa (WA) and other parts of Sub-Saharan Africa (SSA) which affected more than 1.5 million people and resulted in the destruction of farm lands, loss of personal effects, destruction of infrastructure, outbreak of epidemic diseases and the loss of human lives (Armah et al., 2010; BBC, 2007; Braman et al., 2013; Levinson & Lawrimore, 2008; Paeth *et al*., 2011). Similar floods in 2009 affected an estimated 940,000 people across twelve countries in West Africa, killing about 193 people and destroying properties worth $152 million (UNOCHA, 2009). In northern Ghana, the impacts of these floods were exacerbated by the spillage of the Bagre dam in neighbouring Burkina Faso (Armah *et al*., 2010; Forkuo, 2011). In 2012, flooding along the river Niger, which is the principal river in West Africa, resulted in the death of 81 and 137 people in Niger and Nigeria, respectively, while displacing more than 600,000 people (IRIN News, 2012).

Considering the fact that in this region a temperature of 3–6 °C above the late 20th century baseline has a “very likely” prediction and the fact that the projection is expected to occur one or two decades earlier in West Africa than at the global time, West Africa has been described as a hotspot of climate change (IPCC, 2014). The frequency of occurrence of extreme events is expected to increase (Boko *et al*., 2007). There is also medium confidence that projected increase in extreme rainfall will “contribute to increases in rain-generated local flooding” (Kundzewicz *et al*., 2014 p. 24). This situation will have dire consequences for the sub-region’s agricultural sector and food security (Roudier et al., 2011).
Despite the major impact of floods on the livelihoods of the people living in this region, no attempt has been made to delineate the boundaries of flood intensity at the community level and to identify areas most at risk of flooding. Mapping flood hazard zones is an important first step in the proper management of future flooding events. Flood hazard maps depict areas (extent and depth) that may be at risk of flooding under extreme rainfall conditions (e.g., above normal rainfall). These maps have proven useful around the world, especially in the developed countries (De Moel *et al*., 2009) and have: (a) assisted in the early identification of populations and elements at risk; (b) served as a guide in spatial planning in

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order to avoid development in flood prone areas (Cantos, 2005; Zimmerman *et al.*, 2005). (c) served as information base for implementation of a flood insurance scheme (D'Haeseleer, *et al*., 2006) and (d) raised awareness among the public concerning flood prone areas (De Moel *et al.,* 2009).

The use of flood hazard maps for managing disasters in West Africa is virtually non-existent. Disaster managers have for many years relied on traditional methods such as watermarks on buildings, local knowledge and media reports to identify possible affected areas during flood events (Nyarko, 2002). Lack of proper records on historical flood events, coupled with logistical and financial challenges have often resulted in a poor preparedness and response to flooding events. Consequently, fatalities have often been high (Braman *et al*. 2008, Levinson & Lawrimore 2008).
In order to improve this situation, non-governmental organizations (NGOs) and other international bodies have, in recent years, introduced various initiatives, including flood hazard mapping, aimed at improving disaster management in the sub-region. For example, the World Health Organization (WHO) has produced flood hazard maps at national scale for most countries in SSA (Morjani, 2011). Other initiatives have also produced climate change hot spot maps at national, continental and global scales (Birkmann *et al*., 2011; Busby *et al*., 2014; Yohe *et al*., 2006) that show regions that are particularly vulnerable to current and future climate change impacts. However, these products suffer the limitation that they are only useful at the national, continental or global scales, and, thus, are of limited use and applicability at the local scale (e.g., district or community level) where small settlements are mostly the worst affected flood areas. Some researchers have reported the use of seasonal climate forecasts by international bodies (e.g., Red Cross and Red Crescent Society) to manage disasters in the sub-region (Tall *et al.* 2012). However, these forecasts are limited to specific years, and are unable to provide information on specific geographical locations that may be at risk of flooding. Other papers reviewed the vulnerability of some West African cities (e.g., Bobo-Dioulasso, Burkina Faso and Saint-Louis, Senegal) in the light of climate change (Silver *et al*., 2013), but made no efforts at mapping the spatial limits of the flood risk areas.

Development of flood hazard maps at the local level/scale (e.g., sub-district and community) can achieve a better targeting of rural communities that are vulnerable to floods than the national/global maps that currently exist. Unfortunately, local level flood hazard maps are rare in the Sudanian Savannah of West Africa. Some of the few that exist also lack the needed spatial variability (i.e. within the unit of mapping) required for an effective management of flood events. For example, in Ghana, Forkuo, (2011) integrated topographical, land cover and demographic data to derive a composite flood hazard index for all the districts (second administrative unit) in the Northern region of Ghana. The assignment of a composite flood index to each district greatly limits the use of these maps for identifying communities in the district that may be at risk of flooding. Recently, the Environmental Protection Agency (EPA) of Ghana, with the support of the United Nations Development Programs (UNDP) and the African Adaptation Program (AAP) have conducted flood risk mapping for five, out of the two hundred and sixteen, districts in Ghana (EPA, 2012). They integrated GIS layers of elevation, soil, rainfall, land use and proximity to water bodies to map flood risk areas in the five districts. Although this initiative produced high resolution flood hazard maps for the selected districts, it is extremely limited in extent (i.e., number of districts considered).

Moreover, many flood modelling approaches require complex calibration procedures and demand huge data as inputs, making them unsuitable in data scarce environments such as WA. There remains therefore an urgent need to explore appropriate methodologies that are able to provide the spatial variability at community level and yet yields accurate results with limited data availability.

In this study, an innovative approach involving the use of a simple hydrological model suitable for data scarce environments and integrated with statistical procedures in a GIS environment is proposed to map the spatial limits of flood hazard zones at a high spatial resolution. A unique approach is also proposed to use a bottom-up participatory method based on the principles of Participatory Geographic Information System (PGIS) (Carver, 2003; Craig *et al*., 2002; Dunn, 2007) and coupled with robust empirical methods to evaluate the results of the modelling procedure. The main motivation was to develop community level flood hazard maps at a fine spatial resolution that could allow for accurate delineation of flood hot spots and flood safe havens at the sub district/community levels in Ghana, Burkina Faso and Benin.

3.1.1. Contexts

To be able to identify the spatial extent of high and low flood hazard zones, the three focal sites were delineated to sub-catchments in a GIS environment. There are a number of approaches used to delineate an area into sub- catchments based on a digital elevation model (DEM). In an urban landscape, artificial drainage channels may be used in addition to natural water bodies in delineating the boundaries of the various catchments in an area. This method works relatively well in drainage areas where the slope of the landscape is primarily responsible for the path taken by runoff (Nyarko, 2002; Sanyal & Lu, 2006). However, very often in a highly-urbanized setting, control structures such as culverts and detention basins can control the boundaries of various sub-catchments (Kemper & Wagner, 2004).

In this study, the delineation into sub-catchments was based on Digital Elevation Model (DEM), river channel systems, populations in the communities as well as the operational plans which are used by local disaster managers to segregate and demarcate the areas for effective disaster management. Using this approach, the Vea study area was delineated into 13 sub-catchments. The largest of this sub-catchment is the Kula River drain (Figure 1-5), named after the Kula river which is well known for causing many of the floods in the area. Other prominent sub-catchments are the Vea main drain and Kolgo/Anateem valley. These sub-catchments are located at the downstream of the Vea and Kolgo Rivers and are also significantly exposed to floods. Similarly, the Dano study area has further been delimited into thirteen sub-catchments in relation to population, contours and river network. The Yo, Bolembar, Gnikpiere and Loffing-Yabogane sub-catchments are prominent among them with extensive river system, smallholder agriculture and many scattered settlements and hamlets. The Dassari area in Benin was also delineated into twelve (12) sub-catchments to reflect population, river network and local administrative structure. The Setcheniga, Porga and Nagassega sub-catchments are most prominent as they are run through by a major river network that significantly exposes the area to flooding. The size of the sub-catchment largely influences the volume of runoff past the outlet hence the larger the catchment size, the greater the potential amount of rainfall that can be captured and directed towards the catchment’s outlet (TxTDOT, 2009).

3.2. Methods

3.2.1. Overview of Flood Hazard Mapping

Development of flood hazard maps has often been through the integration of spatial layers representing flood causal factors (e.g., elevation, runoff, land use, etc.) in a Geographic Information System (GIS) environment (De Moel *et al*., 2009; Nyarko, 2002). In recent years, and with the advancement of satellite technology, a number of studies have explored the use of satellite images and GIS in developing flood hazard maps (Forkuo, 2011; Sanyal & Lu, 2006; Islam & Sado, 2000). Morjani, (2011) reviewed four major techniques for developing flood maps. These techniques include hydrological frequency analysis, hydraulic modelling, hydrological models and statistical methods.

1) In Hydrologic frequency analysis, historical flood data is used to estimate the probability and spatial extent of future floods events for different time intervals (Kjeldsen *et al*., 2002; Kroll & Vogel, 2002). The reliance of this method on historical data limits its usefulness because physical parameters that existed when the floods occurred will no longer remain the same for future floods (Morjani, 2011).
2) A hydraulic model such as the Engineering Centre's River Analysis System (HEC-RAS) developed by the Hydrologic Engineering Centre (HEC) of the US Army Corps of Engineers (USACE) estimates inundation extent, duration and changes in water depth and velocity using river steady flow measurements (USACE, 2001a, 2001b) This model produces highly accurate results for small catchments. However, it requires significant amounts of input such as high resolution Digital Elevation Models (DEMs), stream network model and detailed cross-sectional geometries of river channels.
3) In hydrological models, mathematical estimation procedures use a known or an assumed value for components of the hydrological cycle to model stream flow behaviour in specific study areas. There are two derivates of hydrological models. These are deterministic models that are based on physical parameters and processes whilst stochastic model allows for the probabilistic variability in both parameters and processes (Nyarko 2002; Al-Rawas *et al*., 2001; Mannaerts, 1996; Meijerink *et al*., 1994; Viessman & Lewis, 1996).
4) The last method used in determining flood prone areas is the statistical method which combines historical flood frequency and associated causal factors to estimate flooded areas. This method allows for the derivation of Flood Hazard Index (FHI) as applied in Islam and Islam (2000) and Morjani (2011).

The first two of the flood modelling approaches reviewed above require complex calibration procedures and demand large data inputs, making them unsuitable in data scarce environments like West Africa. In this study, the last two approaches were integrated with GIS and remote sensing techniques to develop a Flood Hazard Index at the community level.

3.2.2. Integration of Hydrological and Statistical Models in GIS

In this study, two flood modelling approaches—hydrological model and statistical procedures—were combined to map the spatial extent of flood hazard areas at a high spatial resolution at sub district level.

First, a modified version of the rational hydrological model (Mannaerts, 1996; Meijerink *et al.*, 1994; Viessman & Lewis, 1996) was used to estimate the runoff of the respective catchments based on rainfall intensity, the area of LULC type within catchments and a runoff coefficient. Thereafter, statistical procedures were adopted in a GIS environment to integrate the output of the hydrological model with other flood causal factors such as topography (DEM) to determine a flood hazard intensity map for the respective study areas. Flood hazard zones were eventually defined through a reclassification of the flood hazard intensity maps to derive the Flood Hazard Index (FHI) which determines the flood hazard zones of an area.

Morjani (2011) found that the use of statistical procedures in mapping flood hazards zones resulted in the following benefits:

a) There are reliable estimates of flood hazard zones because the integration of the statistical methods avoids the use of a purely empirical model.
b) There is ease of integration in Geographic Information System (GIS).
c) Is able to consider both the susceptibility of each small area to be inundated and flood emergency management. This could allow for delineating flood hazard zones at community level which then helps local disaster managers to effectively manage local disasters.
d) Allows the use of knowledge of flood causal factors which are readily available from local experts.

The uniqueness of this present study is the integration of the statistical methods which then allows a simple hydrological model to be applied in this data scarce environment. Statistical procedures were used at two different stages. The first stage is where various standardization methods were applied to develop the flood hazard index. The second stage is where statistical procedures were combined with PGIS principles to evaluate the results of the flood maps.

The methodological approach adopted has been diagrammatically summarized in Figure 3-1. As first step, the approach retrieves data values from all flood causal factors and then calculates peak runoff rates using the rational model. The causal factors for flood which have been elaborated in section 3.2.4 are land cover/use, soil type and texture, slope, elevation, rainfall and drainage area (Morjani, 2011). It then uses the statistical procedures to determine the peak runoff rates at different elevations before applying standardization methods to determine flood hazard zones.

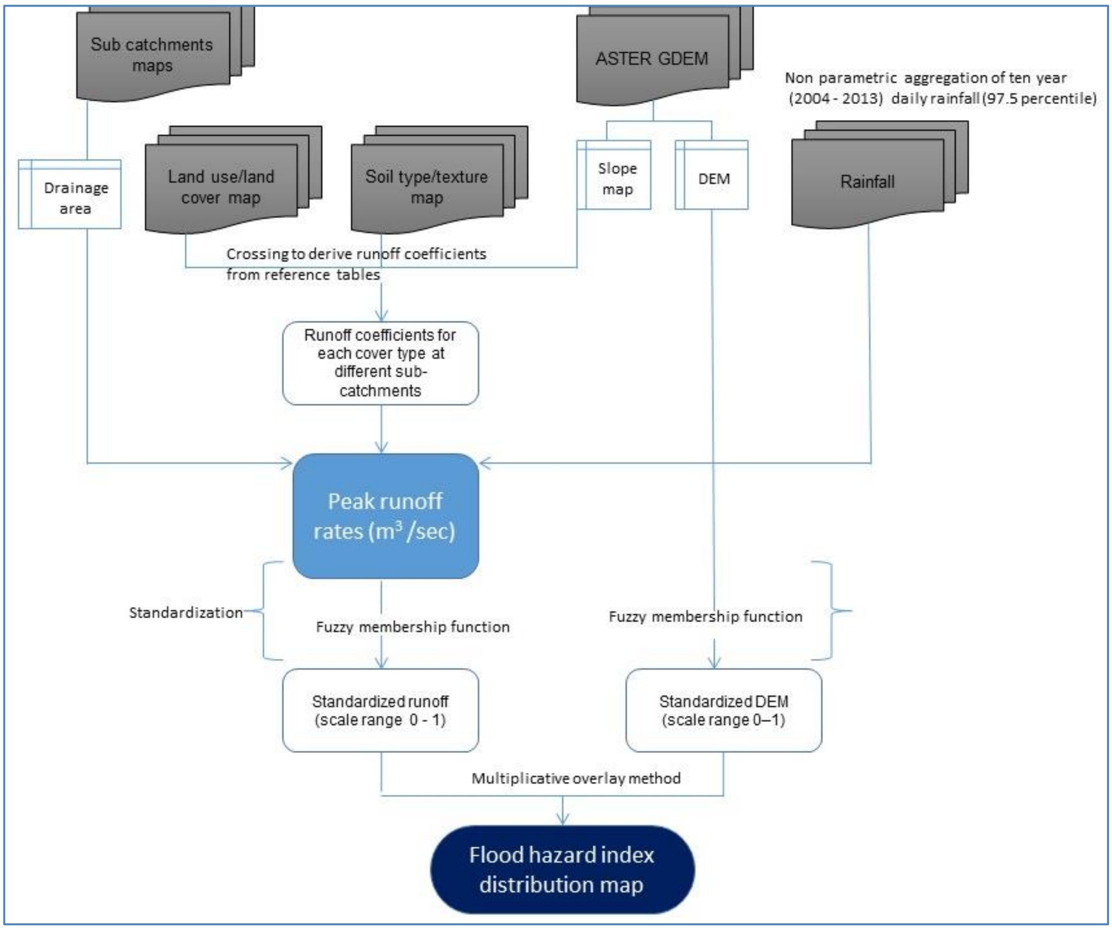

Figure 3-1: Integration of hydrological and statistical models with GIS.

3.2.3. Determination of Peak Runoff Using the Rational Model

The rational model (Mannaerts, 1996; Viessman, 1996) belongs to the group of lumped hydrological models which treats the unit of analysis (normally a catchment or sub-catchment) as a single element whose hydrological parameters (e.g., rainfall) are considered as average values (Díez-Herrero *et al.*, 2009). The strength of this model lies in its simplicity and the ease of implementation. Consequently, it has been widely used to calculate peak surface runoff rate for the design of a variety of drainage structures (Bengtson, 2010), study area modelling and flood hazard mapping (Nyarko, 2002). The rational model converts rainfall in a catchment into runoff by determining the product of the rainfall intensity in the catchment and its area, reduced by a runoff coefficient (C, between 0 and 1), which is a function of the soil, land cover and slope in the study catchment. The runoff coefficient, which is the most critical parameter in the rational model (ITC, 2014), provides an estimation of how much water (rainfall) is lost due to infiltration (soil), interception and evapotranspiration (land cover). Thus, the runoff coefficient of a catchment can be considered as the fraction of rainfall that actually becomes storm water runoff (Bengtson, 2010). Accurate determination of this parameter is, therefore, vital to the successful implementation of this method. The rational model operates on several assumptions including:

a) The entire unit of analysis is considered as a single unit.
b) Rainfall is uniformly distributed over the drainage area.

c) Predicted peak runoff has the same probability of occurrence (return period) as the used rainfall intensity (I).
d) The runoff coefficient (C) is constant during the rain storm.

The model is given by the equation:

$$Q_p = 0.28 \times C \times I \times A$$

Equation 3-1: The rational model for estimating peak runoff

Where,
Q_p = Peak runoff rate (m3/sec)
C = Runoff coefficient (-)
I = Rainfall intensity (mm/hr)
A = Drainage area (Km2)
The factor "0.28" is required to convert the original units in North American system (i.e., cubic feet per second—cfs) to an international system such as cubic meters per second (m3/s).

3.2.4. Flood Causal Factors and Retrieval Methodologies

In this study, spatial layers of land use and land cover, soil and slope were analysed to accurately determine the runoff co-efficient prior to the implementation of Equation 3-1. The sections below, 3.2.4.1 to 3.2.4.4 detail the source or the methodology used to derive each of the four datasets and the preliminary processing conducted on each.

3.2.4.1. Land Use/Land Cover (LULC)

The type of LULC in an area determines how much rainfall infiltrates the soil and how much becomes runoff. Impervious surfaces such as concretes have runoff coefficients approaching one while surfaces with vegetation to intercept rainfall and promote water infiltration have lower runoff coefficients (Bengtson, 2010; McCuen, 1998). There is a direct relationship between land cover and hydrological parameters of interception, infiltration, runoff and concentration which ultimately influence flooding (Nyarko, 2002; Islam & Sado, 2000; Bapalu & Sinha, 2005; Sarma, 1999; Todini *et al*., 2004).

In this study, LULC maps for the three study areas were generated by classifying high spatial resolution (5m) multi-temporal RapidEye images acquired between April and November 2013 (Forkuo *et al*., 2014). RapidEye provides data in five spectral channels (blue, green, red, red edge and near infrared). Table 3-1 provides details of all the satellite imagery used.

The images were atmospherically corrected with ENVI ATCOR2 (Richter & Schläpfer, 2012) prior to analysis. Classification was conducted to reveal five broad LULC classes. These are: (1) croplands (all crop classes); (2) forest (trees with a crown canopy of greater than 70%); (3) grasslands; (4) mixed vegetation (combination of grassland, herbs and shrubs) and (5) artificial surfaces (buildings, bare areas, tarred roads, etc.). Training and validation data for these classes were obtained from field campaigns conducted between July and October 2013. Training and validation samples for the classification were generated by overlaying the training and validation data (polygons) on the time-series satellite images and extracting the corresponding values.

Table 3-1: Satellite imagery used and their acquisition dates.

Study Area	Satellite Data Used	Acquisition Dates (DD/MM/2013)
Vea	RapidEye	01/04; 02/05; 03/06; 19/09; 02/10; 03/11
	TerraSAR-X	25/09; 21/10
Dano	RapidEye	01/04; 03/05; 30/09; 13/10
	TerraSAR-X	30/07; 10/08; 12/09; 15/10
	Landsat	12/06; 14/07; 03/11
Dassari	RapidEye	04/04; 02/05; 13/06; 19/09; 12/10; 15/11
	TerraSAR-X	15/05; 17/06; 20/07; 22/08

The Random Forest (RF) classification algorithm (Breiman, 2001) as implemented in the R statistical software (Liaw & Wiener, 2002) was used to classify the images of the respective study areas. RF generates a large set of independent classification trees, each trained on a bootstrapped sample (randomly selected) of the training samples. The training samples consist of a matrix of rows and columns, where the columns (also called predictors or variables) represent the individual spectral bands of the underlying image, while each row represents the corresponding values of a pixel in the spectral bands. RF's construction of a large number of classification trees overcomes the limitation of single decision trees, which often over fit the training data (Gislason *et al.*, 2006). Each classification results were independently validated with the validation samples. Overall classification accuracies of 88%, 95% and 97% were obtained for the Dano, Vea and Dassari catchments respectively.

As indicated in the introductory section, this study explores appropriate methods to map flood hazard at community level in the face of a daunting challenge relating to limited data availability. One effect of scarce data is on the images analysed. It did not spatially cover the studies areas, particularly the Dassari study area and to some extent the Vea study area. Consequently, a 500m resolution global LULC map produced from Moderate Resolution Image Spectroradiometer (MODIS)—MCD12Q1 (MODIS, 2014) was used to fill-in the areas that were not covered by the RapidEye and TerraSAR-X images. MCD12Q1 products are developed on an annual basis. Thus, to ensure consistency with the LULC map produced in this study, the 2013 version was downloaded and utilized. The MODIS product was resampled to the resolution of the RapidEye and TerraSAR-X images but some variations in spatial resolutions of the LULC can be seen at the affected areas (Figure 3-2). Figure 3-2 shows the final LULC maps of the respective watersheds.

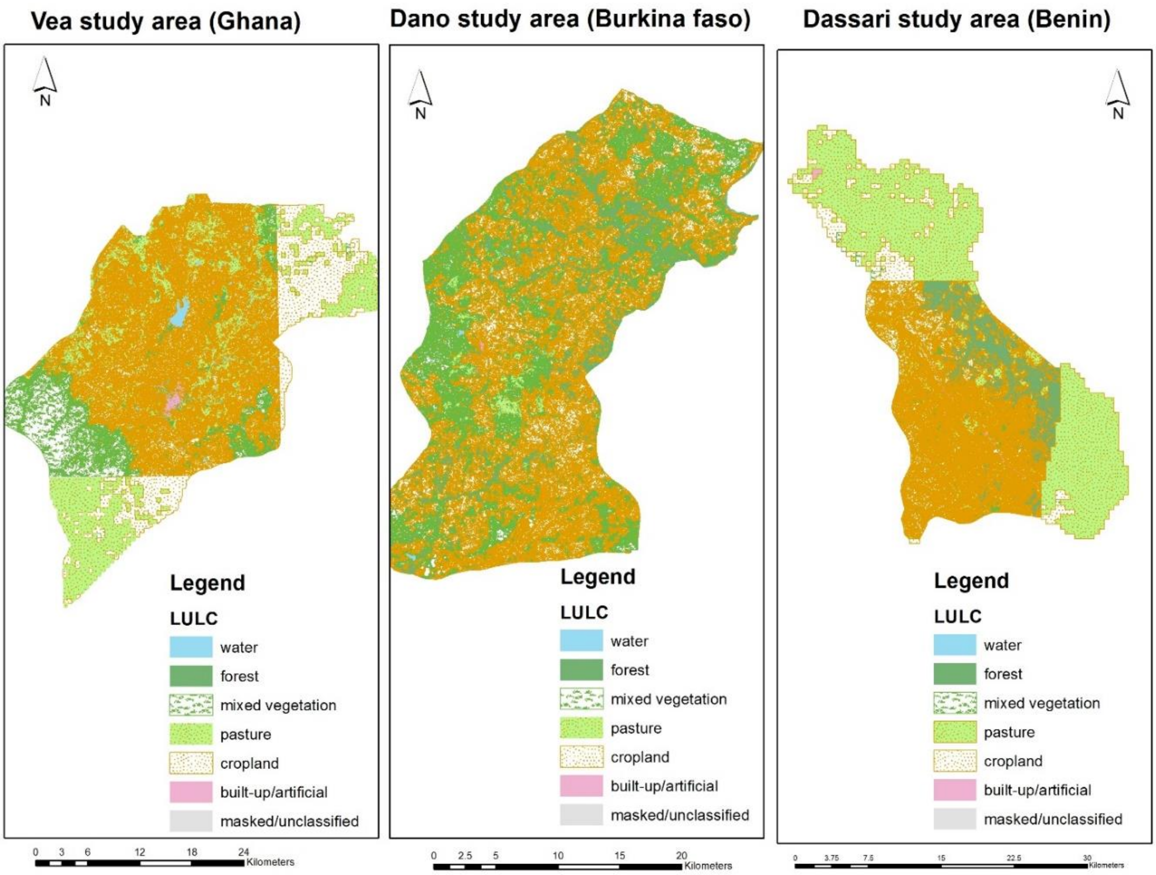

Figure 3-2: Land Use/Land Cover (LULC) maps of the study areas.

MODIS—MCD12Q1 product was used to fill in portions of the high resolution RapidEye and TerraSAR-X images for particularly the Dassari study area and to some extent the Vea study area. As can be seen, the southernmost and north-eastern portions of the Vea study area and in the case of Dassari, the north and southeastern portions were the main areas affected. The MODIS product was resampled to the resolution of that of the RapidEye and TerraSAR-X images.

3.2.4.2. Digital Elevation Model (DEM)/Slope

A study area with a greater slope will have more runoff and thus a higher runoff coefficient than a study area with a lower slope, Ceteris Paribus. The probability of a flood increases with decreasing elevation and hence is a strong indicator for flood susceptibility (Islam & Sado 2000; Al-Rawas *et al*. 2011; Peduzzi *et al*., 2005; Sanyal & Xi, 2003; Shrestha, 2004; UNDP, 2004b). The slope angle and topography are important factors of runoff. Probability of flooding increases when slope angle is below a critical value and then decreases logarithmically (EPA 2012). In this study, the Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) developed jointly by the Japanese Ministry of Economy, Trade and Industry (METI) and the United States National Aeronautics and Space Administration (NASA) was used to derive the slope maps for the respective study areas. The ASTER GDEM was produced by applying automated procedures to process the entire 1.5-million-scene ASTER archive, including stereo-correlation, cloud masking to remove cloudy pixels, stacking, removal of residuals and outliers, averaging and finally portioning into 1°-by-1° tiles. This ASTER GDEM which has spatial resolution of 1 arc second (approximately 30 m) grid was downloaded in

GeoTIFF format from ASTER GDEM webpage (Japan Space Systems, 2012). The data has a vertical accuracy of 20m at 95% confidence level (Fujisada *et al*., 2005). The downloaded DEM was converted to percent slope in a GIS application after all the sinks had been filled to remove small imperfections. In accordance with standardized tables for calculating runoff coefficient, the slope map was reclassified into three classes; (1) areas with slope less than 2%; (2) areas with slope between 2 and 6% and (3) areas with slope greater 6%. Besides the slope map that was obtained, the filled DEM layer was maintained and used later in the integration of peak runoff and elevation to determine runoff concentration at different elevations.

3.2.4.3. Soil Type and Texture

Soils that have a high clay content do not allow very much infiltration and thus have relatively high runoff coefficients, while soils with high sand content have higher infiltration rates and low runoff coefficients (Bengston, 2010; Mccuen, 1998). Nyarko (2002), Todini *et al*. (2004) found the important role played by soil type in influencing water infiltration, runoff and hence flood susceptibility. The texture of a soil influences its erodability, water retention capacity, crust formation and aggregate stability. The amount of water available for runoff is thus a function also of both soil texture and structure (EPA, 2012). The Natural Resource Conservation Service of the United States has classified four broad hydrological soil groups that provide useful information in determining study area runoff coefficients. Classification into any of these groups can either be on the basis of a description regarding soil texture or measured infiltration rates (Bengston, 2010). The study used the 1km resolution soil map from the Harmonized World Soil Database (HWSD) version 1.1 produced in 2009 by the International Institute for Applied System Analysis (IIASA). The HWSD is an image file linked to a comprehensive attribute database in Microsoft Access. This attribute information includes soil mapping units, soil texture for top and sub soils and several other soil properties. Details about this database can be found in FAO(2009). Based on the soil texture attribute information, the extracted soil maps of the study areas were reclassified into the four-main soil hydrological groups (A to D) defined by the United States Soil Conservation Service (USDA, 2007).

3.2.4.4. Rainfall

The probability of a flood increases with increasing rainfall within a specified time period (Nyarko, 2002; Morjani, 2011; Todini *et al*. 2004). We obtained daily data of precipitation at a resolution of about 11 × 11 km based on the African Rainfall Climatology, version 2 (ARC2), subsetted to our period of analysis (2004–2013) and study area in West Africa. This period was chosen because of increased occurrence of flood events recorded in the areas as mentioned in Section 2. These data were then further aggregated to capture long-term precipitation magnitude (97.5th percentile, median, and 2.5th percentile) and extremes (97.5th percentile). To capture long-term precipitation magnitude (97.5th percentile, median, and 2.5th percentile) and extremes (97.5th percentile), the time-series of records per grid are statistically considered as a population (rainfall records per grid, 2004–2013). The extreme (97.th percentile) for each grid was retained as input to the calculation of Peak Storm Water Runoff Rate. The rational for this non-parametric aggregation is found in the stochasticity of rainfall; a parametric aggregator (i.e., maximum or mean) would be sensitive to outliers and data errors. Called the African Rainfall Climatology, version 2 (ARC2), the underlying dataset is a revision of the first version of the ARC

(Novella & Thiaw, 2013) consistent with the operational Rainfall Estimation, version 2, algorithm (RFE2), ARC2 uses inputs from two sources:

- Three-hourly geostationary infrared (IR) data cantered over Africa from the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) and
- Quality-controlled Global Telecommunication System (GTS) gauge observations reporting 24-h rainfall accumulations over Africa.

The main difference with ARC1 resides in the recalibration of all Meteosat First Generation (MFG) IR data (1983–2005). Results show that ARC2 is a major improvement over ARC1. It is consistent with other long-term datasets, such as the Global Precipitation Climatology Project (GPCP) and Climate Prediction Centre (CPC) Merged Analysis of Precipitation (CMAP), with correlation coefficients of 0.86 over a 27-yr period. However, a marginal summery dry bias that occurs over West and East Africa is examined. Daily validation with independent gauge data shows RMSEs of 11.3, 13.4, and 14, respectively, for ARC2, Tropical Rainfall Measuring Mission Multi satellite Precipitation Analysis 3B42, version 6 (3B42v6), and the CPC morphing technique (CMORPH) for the West African summer season. The reconstructed Africa Rainfall Climatology (ARC2) offers a number of advantages compared to other long-term climatological rainfall datasets that are widely used. First, high resolution historical rainfall estimates on a daily basis would help not only to monitor precipitation associated with synoptic and mesoscale disturbances, but also to undertake studies of extreme events, wet and dry spells, number of rain days (i.e., rainfall frequency), and onset of the rainfall seasons. Second, a 0.1° (~11km) spatial resolution allows users to see rainfall phenomenon on local scales that cannot be captured by coarser climate datasets (Novella & Thiaw, 2013)

3.2.5. Development of Peak Runoff Maps

Within the study area, more than one land cover type, slope and soil group exists. In order to find representative runoff coefficients within a given land cover, sub-catchment runoff coefficient was determined using the areas of the different LULC type and then the hydrologic soil group, and slope complexes as weighting factors. The classical application of the rational model requires treating the entire sub-catchment as a single unit and thus, does not lead to spatial variability of the runoff and for that matter, flood risk within sub-catchments. In this study, however, a novel technique is introduced where the various classes of LULC types within the sub-catchments are used as the unit of analysis to ensure spatially explicit assessment of flood risk. This was required because the key purpose of this study is to explore methods to derive community level flood risk in a data scarce environment. Therefore, we sought to operationalize the rational model in a way that meets the objective of the study. It was realized that treating the whole sub-catchment as a single unit will not lead to a determination of the spatial variability of discharge within a sub-catchment which is required to understand community level flood risk. Therefore, instead of using the sub-catchment as the unit of analysis (which is the classic application of the rational model), the area of the different land use units was used as the unit of analysis. In other words, the area of the various LULC classes was computed and peak runoff estimated for each cover type. Although this approach has some limitation especially regarding catchment boundaries where a land use/cover type crosses the boundaries, it was found to be conceptually and operationally better than implementing the rational model in its raw form which can only give single peak runoff for each sub-catchment based on many averages (i.e., average coefficient, rainfall and total area).

A runoff coefficient map was first generated by vectoring the reclassified layers of LULC, slope and soil layers and overlaying them in a GIS. The overlay resulted in multiple polygons each having a unique LULC, soil and slope class. Based on Table 3-2, which specifies a runoff coefficient for a combination of LULC, soil type and slope, the attribute table of the resultant overlay layer was populated with the corresponding runoff coefficient number. This layer was eventually rasterized (30 m resolution) for subsequent analysis.

In order to allow for integration with the generated runoff coefficient map, the rainfall intensity map was resampled to a cell resolution of 30 m to correspond to the spatial resolution of the ASTER GDEM layer. A vector layer of the sub-catchment map containing the areas (in km2) of each LULC type within each sub-catchment was also rasterized into a 30m resolution raster. Once the raster layers of the runoff coefficient (C), rainfall intensity (I) and sub-catchment areas (A) was ready, the runoff peak layer was calculated by implementing Equation (1) in a GIS using raster algebra.

Table 3-2: Rational method runoff coefficients.

LULC	Runoff Coefficient											
	Soil Group A			Soil Group B			Soil Group C			Soil Group D		
Slope	<2%	2%–6%	>6%	<2%	2%–6%	>6%	<2%	2%–6%	>6%	<2%	2%–6%	>6%
Cropland	0.14	0.18	0.22	0.16	0.21	0.28	0.20	0.25	0.34	0.24	0.29	0.41
Forest	0.08	0.11	0.14	0.10	0.14	0.18	0.12	0.16	0.20	0.15	0.20	0.25
Grassland	0.15	0.25	0.37	0.23	0.34	0.45	0.30	0.42	0.52	0.37	0.50	0.62
Mixed vegetation	0.14	0.22	0.30	0.20	0.28	0.37	0.26	0.35	0.44	0.30	0.40	0.50
Artificial Surfaces	0.33	0.37	0.40	0.35	0.39	0.44	0.38	0.42	0.49	0.41	0.45	0.54

Source: (Knox County Tennessee, 2014).

3.2.6. Statistical Modelling

The generated peak runoff map was combined with the elevation layer to produce the flood hazard intensity map. However, prior to that, the two layers (peak runoff and elevation) were standardized. Due to the dissimilar units (i.e., m3/s for peak runoff and m for elevation), standardization was necessary to make any combination of the two layers meaningful. The fuzzy set theory (Malczewski, 2000) was used to standardize the layers into comparable scales prior to combining them. Compared to other methods (e.g., Boolean sets) that allow only binary membership functions (i.e., true (1) or false (0)—membership or no membership), the fuzzy set theory admit the possibility of a partial membership (Burrough & Rachel, 1998). This means that the transition between membership (1) and non-membership (0) of a location in the set is gradual, compared to sharp boundaries, in for example, Boolean sets (Malczewski, 2000). Fuzzy sets are, therefore, characterized by a membership grade that ranges from “0” to “1”, indicating a continuous increase from non-membership (0) to complete membership (1).

The fuzzy membership function implemented in ESRI’s ArcGIS was used to standardize the peak runoff and elevation layers. Due to the positive linear relationship between peak runoff and probability of flooding, the peak runoff layer was linearly rescaled between the minimum and maximum values using a linear membership type. This means the lowest peak runoff value in each study area was assigned a value of “0” (i.e., no membership or low probability of flooding) while the highest peak runoff value was assigned a value of “1” (full membership or high probability of flooding), with all other values in-between the two extremes rescaled between “0” and “1”. Thus, the lowest likelihood for a flood to occur in a given sub-catchment was rescaled as 0 with 1 for categories with the highest likelihood.

The reverse, however, was done for the elevation layer. Theoretical principle underlying the relationship between elevation and probability of flooding indicate a negative relationship. In other words, areas with low elevation have a higher probability of flooding than areas with high elevation values. Therefore, in rescaling the respective elevation layers, the lowest value was assigned a membership of “1” (i.e., high probability of flooding) while the highest value was assigned a membership of ‘0’ (low probability), will all other values in-between have been rescaled between “0” and “1”.

3.2.7. Developing Intensity Level of Flood Hazard Distribution Map

The standardized peak runoff and elevation layers were combined using the weighted linear combination method (Malczewski, 2000) to produce the flood hazard intensity map at different elevations. Equation 3-2 was implemented in a GIS to achieve this. The method permits the assignment of weights, which indicates the relative importance of a layer. The weights must add up to one. In this study, the two standardized layers were considered equally important, thereby assigning a weight of 0.5 each to the layers in Equation 3-2.

$FHI = \sum_{i=1}^{n} w_i x_i$ Or more simply as $FHI = \sum_{i=1}^{n} 0.5X(DEM) + 0.5X(\text{peak runoff})$

Equation 3-2: Model for integrating DEM and Peak runoff

3.3. Results and Discussion

3.3.1. Peak Runoff Rates

Maps of the peak runoff rates in cubic meters per second (M^3/s) have been produced for the three study areas and show the distribution of runoff within all the catchments in the three areas studied. These maps are presented in Figure 3-3.

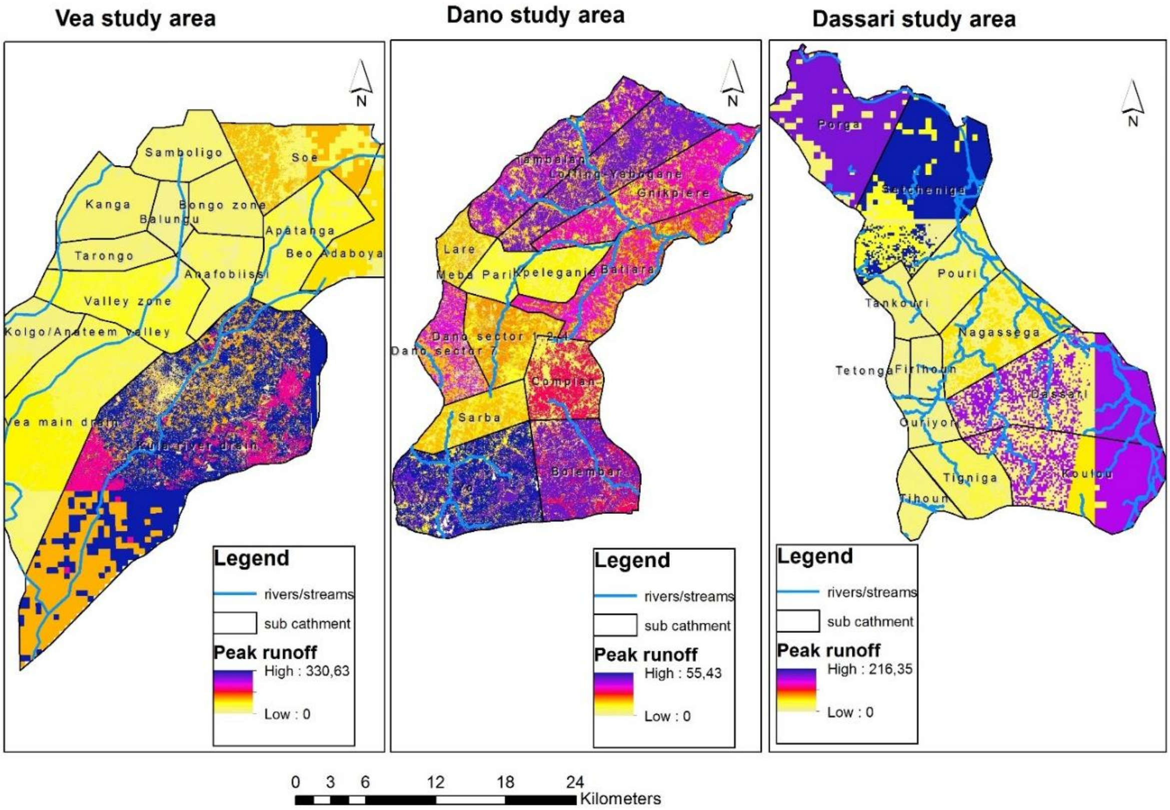

Figure 3-3 Peak runoff maps of the three study areas.

Table 3-3 presents the total amount of peak runoff generated within the various sub-catchments. In the Vea study area, the Kula river sub-catchment generates the highest amount of runoff in excess of 713.0 M3/s whilst the lowest amount was generated in the Balungu sub-catchment with an amount of 26.0 M3/s. In the Dano study area in Burkina Faso, the Yo sub-catchment recorded the highest peak runoff rate of 119.6 M3/s whilst the Meba Pari segment generates a meager 25.5 M3/s. In the Dassari study area in Benin, the Sétchindiga sub-catchment generates the highest amount of 290.5 M3/s as against the lowest amount of 13.6 M3/s generated in the Tetonga sub-catchment. Comparing the three study areas in the three countries, the Vea study area in Ghana generates an average of 155.7 M3/s per sub-catchment. This amount is higher than the average sub-catchment runoff of 113.11 M3/s in the Dassari study area and 69.0 M3/s in the Dano study area. High runoff is positively correlated with increased susceptibility of flood hazards. As reported in Islam and Sado, (2000); Todini *et al*. (2004); Bapalu and Sinha (2005), there is a direct relationship between hydrological parameters of interception, infiltration, runoff concentration and flooding. Although there is limited data available at the community level in Dano and Dassari study areas, available data collected during the field work shows that the Vea study area record more flood events and more people suffer from flood impacts than both Dano and Dassari study areas. Records from local authorities also show that the Dassari study area also reports more flood events than the Dano study area in conformity with the average runoff figures shown in this study. For instance, between the periods 2008 to 2012, over 294,000 people have been affected by floods in the Vea study area (NADMO, 2013) whilst 3600 were affected in the Dassari study area with Dano recording only 1130 people as affected. In addition, whilst the Dassari and Dano study areas have experienced three flood events between 2008 and 2012, there has been consecutive flood event in the Vea study area of Ghana over the same period.

Table 3-3: Results of total amount of peak-runoff generated within the various sub-catchments.

Vea Study Area (Ghana)		Dano Study Area (Burkina Faso)		Dassari Study Area (Benin)	
Sub Catchment	**Runoff (m^3/s)**	**Sub Catchment**	**Runoff (m^3/s)**	**Sub Catchment**	**Runoff (m^3/s)**
Balungu	26.0	Tambalan	100.3	Dassari	236.8
Beo Adaboya	191.0	Bolembar	86.1	Firihoun	25.8
Bongo zone	68.0	Dano sector 1,2&4	57.0	Nagassega	100.2
Anfobissi	82.4	Batiara	80.8	Ouriyori	27.5
Apatanga	128.6	Gnipiere	88.3	Porga	204.4
Kolgo/Anateem	107.7	Sarba	42.9	Pouri	71.5
Kula river channel	713.2	Kpeleganie	32.6	Sétchindiga Tankouri	290.5
Samboligo	60.3	Lare	34.2	Tetonga	32.1
Soe	201.6	Loffing-Yabogane	112.0	Tigniga	13.6
Valley zone	138.0	Meba Pari	25.5	Tihoun	63.7
Vea main drain	178.0	Dano sector 7	65.1	Koulou	34.0
Tarongo	54.2	Complan	52.2		257.3
Kanga	75.2	Yo	119.6		

3.3.2. Digital Elevation Model (DEM)

The map presented in Figure 3-4 show the DEM of the three study areas. In the Vea study area, high elevations values are concentrated in the Apatanga, Soe, Beo Adaboya and parts of Samboligo sub-catchments whilst the Kula River, Vea main drain and Kolga Anateem valley records very low elevation. Indeed, in the southernmost part of the Kula River, a low elevation of 89 m is found. From the peak runoff map, the Kula river sub-catchment simultaneously records high runoff generation. This area is therefore expected to fall in the category of high flood intensity zone) in the Flood Hazard Index (FHI).

In the Dano study area, high elevations values are found in Dano, Sarba and parts of Yo sub-catchments. In this study area, low elevation areas are found in the north-eastern part and largely correspond to the river networks in the area. These areas also generate significant amounts of runoff as can be seen in the maps. In the Dassari study area, high elevation values are found in the southern parts of Tigniga, Tihoun, Koulou, parts of Dassari and Ouriyori sub-catchments. Similar to the Vea study area and Dano study areas, areas in Dassari with low elevation values and hence high-risk areas for flooding also correspond to areas generating the largest amounts of runoff. These areas are the Sétchindiga and Porga sub-catchments and are thus expected to result in high flood risk zone.

Comparing the elevation maps of the three study areas, the Vea and Dassari study areas are generally more low-lying than the Dano study area in Burkina Faso. Average elevation in Vea is 196 m as against 379 m in Dano and 197.5 m in Dassari. This fact coupled with relatively high amounts of runoff generation will thus make the Vea more prone to flooding than the other two study areas.

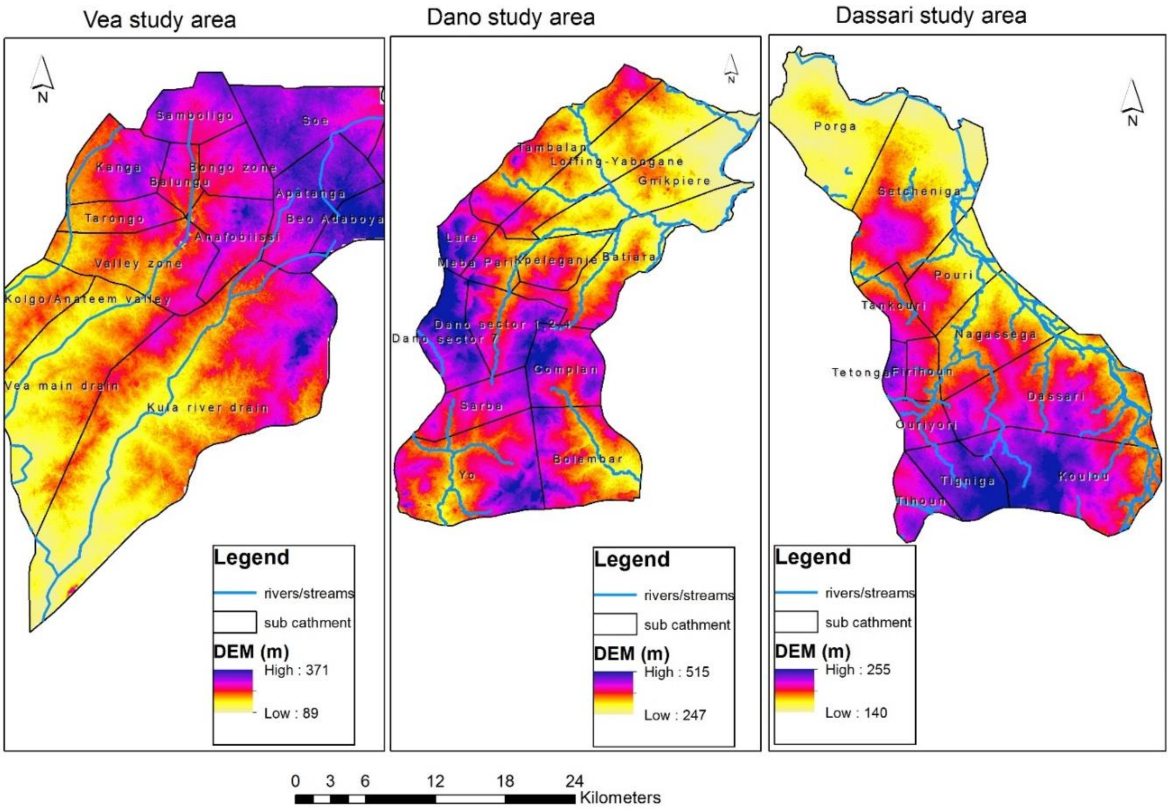

Figure 3-4: Digital Elevation Model (DEM) of the study areas.

3.3.3. Flood Hazard Intensity Levels and Flood Hazard Index

By combining the standardized peak runoff maps with the standardized DEM, the flood hazard intensity map was produced. This map was then classified using the Natural Break (Jenks) method into five classes to produce the Flood Hazard Index (FHI). The index ranges from 1 (very low flood hazard intensity) to 5 (very high flood hazard intensity). In Figure 8 below, the final Flood Hazard Index is represented in a graduated colour map.

Figure 3-5 presents the flood hazard intensity maps of the respective study areas. In the Vea study area of Ghana, the very high flood hazard intensity zone is concentrated in the Kula river sub-catchment. As indicated in Sections 3.3.1 and 3.3.2, this sub-catchment has the highest runoff of 330 M3/s and also has the lowest elevation of 89 m. Consequently, more than half of the sub-catchment falls into the very high flood hazard zone. This sub-catchment has the highest population density. The capital of the Upper East region, Bolgatanga, is found in this sub-catchment and it is the most urbanized and with good infrastructure. Records from the National Disaster Management Organization (NADMO) show that of the 702,000-people affected by floods in northern Ghana between 2010 and 2012, as much as 42% were from the Bolgatanga municipality (NADMO, 2013). This result of the Kula river sub-catchment having the highest flood risk correlates with the modelling result of Ghana’s Water Research Institute (WRC, 2012)] when it was found that up to 75 cm of runoff is added to the maximum water level at Pwalugu, an area at the southernmost part of the sub-catchment.

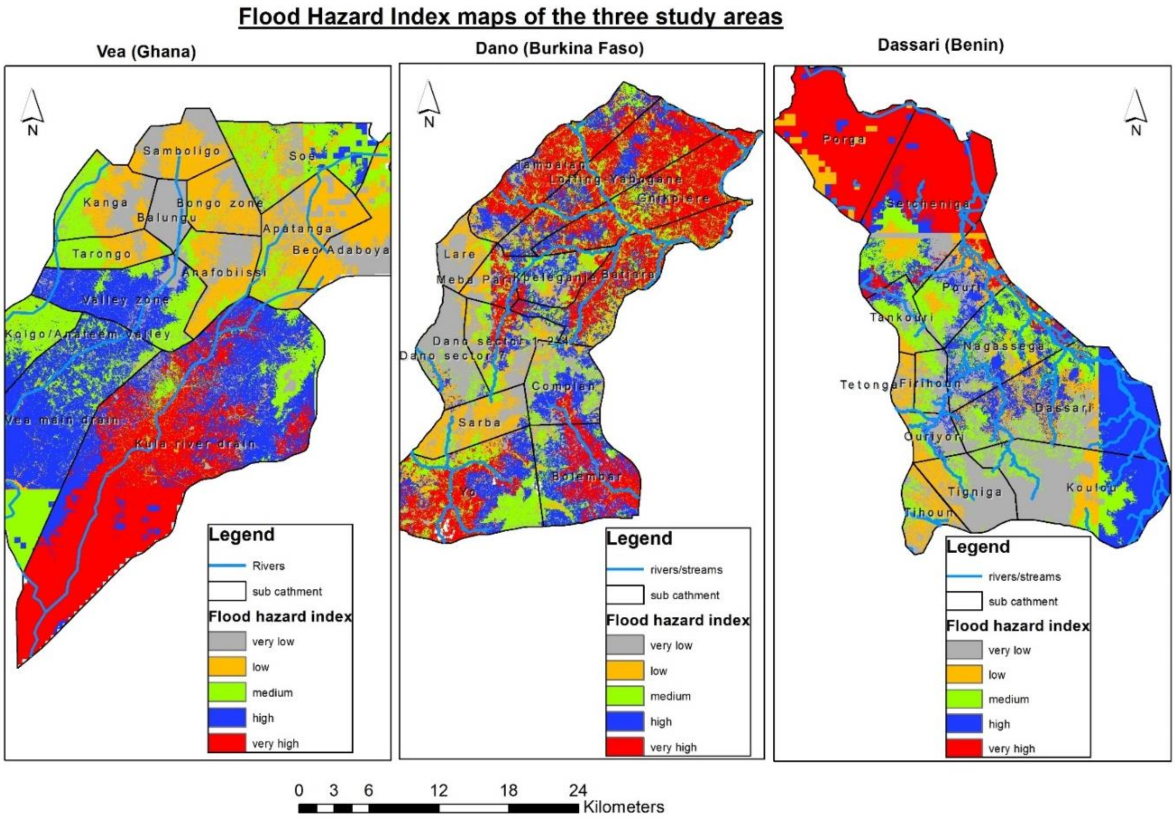

Figure 3-5: Flood Hazard Index

In addition, the Kolga Anateem valley and Vea main drain sub-catchments are found in the high flood hazard intensity zones. With the exception of the valley sub-catchment in Bongo district, none of the sub-catchments in Bongo are located in the very high flood intensity zone. However, there are pockets of high flood hazard intensity zones in the Soe sub-catchment. Almost all of Balungu and parts of Samboligo and Beo Adaboya sub-catchments fall in the very low flood intensity zone and are thus expected to pose no flood risk.

In the Dano study area, very high and high intensity flood hazard zones are distributed throughout the study area. However, the sub-catchments of Yo, Bolembar, Gnipiere, Loffing-Yabogana and Tambalan have significant areas classified as very high flood risk zones. Contrary to the Vea study area, the most populous area in this study area fall into the very low to medium flood hazard intensity zones. Therefore, the Dano township, the capital of the province with a projected population of 20,786 in 2010 (Yili, 2006) largely falls into low flood risk zone.

In the Dassari study area, two sub-catchments stand out in terms of flood risk. The Porga and Sétchindiga sub-catchments have very high flood hazard intensity. This is as a result of low elevation values coinciding with high runoff generation as explained in Sections 4.1 and 4.2. In addition, in this study area, significant parts of Koulou and Dassari fall in the high flood intensity zone. There are also pockets of high flood intensity zones in Nagessega, Ouriyori, and Firihoun and Tetonga sub-catchments.

From Table 3-4, more than half of the Dano study area (52.1%) falls in the two-high flood hazard intensity zones of very high and high. In addition, in the Vea and Dassari study areas, almost half of the entire study areas fall into the very high and high flood risk zone. It must be noted that, the data ranges for the FHI differ among all the study areas but they can all be translated into the five-qualitative classification scheme of very high (5), high (4), medium (3), low (2) and very low (1). This is the same procedure adopted by Beck *et al*. (2012) and Birkmann *et al*. (2011) in the World Risk Reports. In addition, important to note is that an area classified as very low flood hazard intensity in the Vea study area could be rendered a high-risk due to cross scale interactions. Flood risks from outside the sub-catchment area could lead to cascading hazards. For example, some of the flood events recorded in the Vea study area is as a result of the opening of the Bagre dam in nearby Burkina Faso.

Table 3-4: Proportions of areas under various flood intensity zones.

Flood Hazard Intensity Number	Flood Hazard Intensity Zone/Class	Percent of Study Area		
		Vea	Dano	Dassari
1	Very low	15.2	16.4	23.2
2	Low	18.8	11.2	13.3
3	Medium	19.5	20.3	16.7
4	High	28.2	18.1	22.1
5	Very high	18.42	34.0	24.7
Total High and Very High Risk Zone		**46.6**	**52.1**	**46.8**

These cascaded flood events are independent or partially independent of local rainfall in the Vea area and conditions of other flood causal factors. The implication is that an area classified as low or medium flood intensity zone in the Vea area as a result of the interactions of the factors considered in this paper could still experience significant flood episodes whenever overflow upstream in the Bagre dam is allowed to pass. At the same time, however, whenever this cross-scale influence coincides with high episodes of local rainfall anomalies, sub-catchments such as the Kula River which is already classified as very high flood intensity could experience catastrophic flood event. This is absolutely important for local disaster managers in the Vea area to constantly monitor the operations of dams upstream so as to prevent or minimize the impacts of this knock-on effect.

The study found most of the high flood hazard risk areas close to the major rivers in the area. This was the case in Kula River sub-catchment in Vea, Porga and Sétchindiga in Dassari as well as Yo, Gnikpiere etc. in the Dano study area. This finding is contrary to the assertion by Forkuo (2011) that high hazard zones are not necessarily located very near to river bodies.

3.3.4. Quantitative Validation of the Flood Hazard Index with PGIS and Confusion Matrix

The study introduced an innovative method of applying the principles of Participatory GIS (PGIS) to evaluate the flood map. The approach involves using local disaster managers, community leaders and local disaster volunteers to undertake field evaluation of the five flood categories. The team randomly visited known locations over 5 days in the Vea study area and 3 days in the Dano study area. At each location visited, the local experts were asked to classify the spot into the five flood hazard classes based on their knowledge of flood intensity at that particular location. A GPS receiver was then used to record the geographic coordinates of the location and its attributes. The objective was to construct a confusion matrix which will then allow for the quantitative validation of the flood map using statistical procedures.

Typically, the confusion matrix (Congalton & Green, 1999; Joshi *et al*., 2006; Stehman & Czaplewski, 1998) is used to display class membership of observations according to the map and according to field observations. The diagonal of the confusion matrix lists the correct classifications while off diagonal cells list errors. The overall accuracy quantifies the proportion of correctly classified pixels. Using this approach, the flood hazard of the Vea and Dano study areas have an overall accuracy of 77.62% and 81.41% respectively (Table 3-5 and Table 3-6).

Table 3-5: Confusion matrix in the Vea study area.

	Very High	High	Medium	Low	Very Low	Total	Accuracy (%)
very high	**34**	0	3	3	1	**41**	82.93
high	0	**15**	0	0	0	**15**	100.00
medium	0	0	**16**	0	1	**17**	94.12
low	2	1	0	**12**	0	**15**	80.00
very low	4	4	5	0	**13**	**26**	50.00
Total	40	20	24	15	15	114	81.41

An in-depth look at the errors in Table 3-5 and 3-6 (off-diagonals) show that some classes are frequently confused. For example, in the Vea study area, there are eight sites classified as very high intensity flood zones but in reality, there are low intensity flood zones.

Table 3-6: Confusion matrix in the Dano study area.

	Very High	High	Medium	Low	Very Low	Total	Accuracy (%)
very high	**34**	0	3	3	1	**41**	82.93
high	0	**15**	0	0	0	**15**	100.00
medium	0	0	**16**	0	1	**17**	94.12
low	2	1	0	**12**	0	**15**	80.00
very low	4	4	5	0	**13**	**26**	50.00
Total	40	20	24	15	15	114	81.41

The study applied the chi-square statistic to test the assumption that the errors associated with the flood modelling are coincidence or that the modelling procedure makes errors randomly. A null hypothesis stating that the frequency in the confusion matrix results from a random process assigning pixels to the five categories of flood hazard. The alternative hypothesis was then formulated that the frequencies are not random and that there is a systematic error in the confusion matrix. Based on this, we expect that 77.62% of ground truth observations in the Vea study area and 81.41% in the Dano study area in every class to be accurately classified while 22.38% (Vea) and 18.59% (Dano) would be randomly assigned to erroneous pixels in the column belonging to this class.

To predict the expected outcomes for the correct observations in the Vea study area, we expect that 77.62% of the 27 “Very high” intensity flood zones (20.96 records) to be classified as very high intensity zones. Table 3-7 shows in bold the expected number of accurately classified observations. The marginal values indicate the residual observations or errors for every row and column which are not yet distributed over the remaining pixels.

Table 3-7 shows that there are 5.69 observations which were "High" intensity zone which in reality remain to be classified. The proportion of this assigned to "very low" intensity zone would be 5.69 multiplied by the row total of 3.36 divided by the grand total of 18.57 less the row total for "High" intensity zone of 2.69. This is expressed as (5.69 × 3.36)/ (18.57 − 2.69) = 1.20. Using this approach, Table **3-8** is filled completely assuming that the errors are randomly distributed.

Table 3-7: Expected number of correct classifiers and total error margins in the Vea study area.

	Very High	High	Medium	Low	Very Low	Column Error
very high	**20.96**					6.04
high		**9.31**				2.69
medium			**13.97**			4.03
low				**8.54**		2.46
very low					**11.64**	3.36
row error	0.04	5.69	4.03	8.46	0.36	18.57

Table 3-8: Expected number of misclassified observations based on random error assumption.

	Very High	High	Medium	Low	Very Low
very high		2.16	1.67	3.17	0.14
high	0.01		0.74	1.41	0.06
medium	0.01	1.44		2.12	0.09
low	0.01	0.88	0.68		0.06
very low	0.01	1.20	0.93	1.76	
Total	0.04	5.69	4.03	8.46	0.36

Applying the Chi square, x^2 statistics given as

$$x^2 = \sum_{i=1}^{n} \left(\frac{O_i - E_i}{E_i}\right)^2$$

Where Oi indicates the observed frequency and Ei is expected frequency in pixel i. The difference between the observed and expected frequency in every pixel was squared and divided by the expected frequency. This was finally summed up as showed above to calculate the chi-square statistic.

In the Vea study area, the results showed that the observed chi square statistics of 1025.25 with 12 degrees of freedom (df) is much higher than the expected chi square at 5% significant level of 21.03. However, in the Dano study area, the observed x^2 was estimated to be 9.46 which is much lower than the expected x^2 of 21.03 with 12 df at 5% significant level.

Following these results and in the case of the Vea study area; we rejected the null hypothesis which stated that the frequencies in the table were the result of a random process assigning pixels to the five flood hazard classes. A conclusion was therefore made that the frequency of observed errors differs significantly from the frequency of errors expected under the randomness hypothesis and that the observed frequencies are unlikely to have resulted from a random process indicating a systematic error in the confusion matrix. However, in the case of the Dano study area, we fail to reject the null hypothesis stating that the errors are random and conclude that there is no systematic error or bias in the five hazard intensity zones as predicted by the modelling procedures introduced in this study (Chi square, $x^2 = 9.46$, df = 12, α = 5%, x^2(critical) = 21.03).

An in-depth look at Table 3-9 will explain which combinations of flood hazard categories contribute to the bias or systematic error in the confusion matrix for the Vea study area. In Table 9, the squared differences for "very high" intensity zone and "very low" intensity were quite large compared to the squared differences for the same combination of categories in the Dano study area (

Table 3-10). There could be several reasons why the confusion matrix of the Vea study area showed a systematic error. Besides the rapid rate of land use change as a result of high population density and intensive agricultural activities (Challinor *et al.*, 2007; Oduro-Afriyie & Dukpo, 2006), the subjective nature of classifying the various locations visited into the five hazard categories could also contribute to the element of bias. During the field evaluation in the Vea area, the relatively large number of local experts involved led to some instances where the local experts argued among themselves regarding the proper classification of a particular spot. Lessons learnt from the field evaluation in the Vea study was used to improve the Dano field evaluation and this serves as important lesson for PGIS techniques. There was therefore improved selection of local stakeholder participation as well as improved sampling of locations to be evaluated. The lesson here is, in using local experts to evaluate geographic information, it is important that the participation of community members is limited to few opinion leaders and local elders whose expertise, knowledge and day to day activities have a direct bearing on the topic under study. Expanding the list to include many interested parties could lead to unnecessary arguments and introduced some elements of subjectivity in the results.

Table 3-9: Squared deviances estimated based on observed and expected frequencies—Vea study area.

	Very High	High	Medium	Low	Very Low
very high		2.16	0.06	7.34	0.14
High	0.01		0.74	1.41	0.06
Medium	0.01	1.44		2.12	89.45
Low	119.75	0.02	0.68		0.06
very low	797.49	0.53	0.01	1.76	
Total	917.26	4.15	1.49	2.63	89.71

Table 3-10: Squared deviances estimated based on observed and expected frequencies —Dano study area.

	Very High	High	Medium	Low	Very Low
very high		3.23	0.39	2.95	−5.22
High	1.36		1.57	0.42	−1.05
Medium	1.54	1.34		0.48	−4.03
Low	0.30	0.03	1.57		−1.05
very low	1.14	1.87	1.90	0.73	
Total	4.35	6.46	5.44	4.58	−11.35

3.3.5. Qualitative Validation of the Flood Hazard Index with Historical Flood Events

The resulting FHI was also subjected to qualitative validation procedures to assess how the modelling outcome conforms to generally held knowledge and local opinion of flood hazard occurrence in the study areas. A similar approach has been successfully used in the region to validate the results of flood modelling. For example, EPA (2012) engaged beneficiary communities and local experts in a series of validation workshops to assess the results of a multi-criteria flood mapping approach.

In addition to statistical validation procedure, the present study also relied on local expert knowledge and four-year historical records of flood events in the Vea study area where significant historical data is available. In this study area, 19 communities showed in Figure 3-6 are generally known by local disaster managers, agriculture development officers and local people as highly prone to flood hazards. Consecutive flood events have been recorded in these communities since 2007 when local disaster managers started to systematically record flood events. In the qualitative validation process, these communities were plotted and then overlaid on the FHI map as shown in Figure 3-7. The results (Figure 3-7) show that, of the communities listed as "flood prone" in Figure 3-6, only 21% fall in the medium flood hazard intensity zone. The remaining 79% were all correctly classified by the flood modelling procedure used in this study as high flood prone communities. Of the communities that are classified as flood prone, 37% fall in the very high intensity whilst 42% fall in the high intensity zones.

BOLGATANGA MUNICIPAL AGRIC. DEV.UNIT

LIST OF FLOODY PRONE COMMUNITIES

STRETCH OF VALLEY	COMMUNITIES	OPERATIONAL AREA	AEA NAME
Kula river	Tindonshiew, Kumbosigo, Danwei, Tindonmolgo, Tindongsobiligo and Kalbeo	Zuarungu, Bolga Central and Kalbeo	Lambert, Maxwel and Iddrisu
Vea Main Drain	Nyariga, Yorogo, Zaare, Yikene, Sumburungu Azoribisi, Zobgo, Sherigu Kumbelingo, Yebongo, Kulbia	Nyariga, Zaare/Yorogo, Sumbrungu East	Adongo Victoria, Thomas Anobiga, John Asigre and Hamza Akurubila
Kolgo/Anatem Valley	Kolgo, Dazongo, Anateem, Kulbia	Sumbrungu East and Sumbrungu West	Thomas Anobiga and John Asigre

Figure 3-6: List of flood prone communities as listed by local agricultural authority.
Data source: District MoFA office, Bolgatanga, Ghana.

This suggests that the developed flood hazard index reasonably predicts areas likely to be flooded. It is interesting to note the result from the qualitative validation closely approximates the results achieved from the empirical validation process. In the Vea study area, the confusion matrix recorded a mapping accuracy of 77% and this is quite close to the 79% achieved with the qualitative validation with historical flood events.

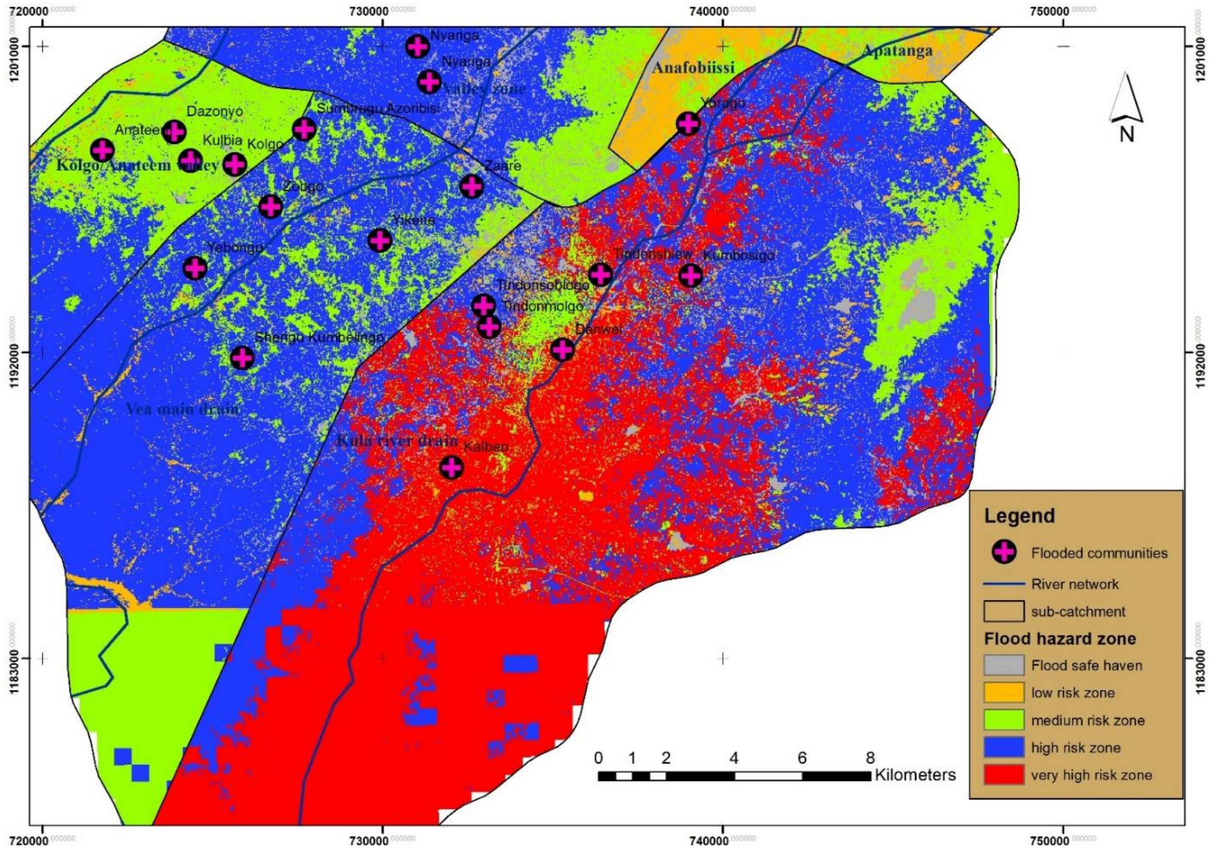

Figure 3-7 Qualitative validation of FHI with local expert knowledge.

3.3.6. Determining Flood Safe Havens

The 30m spatial resolution of the final flood hazard map could be one ingredient to allow for accurate determination of areas normally safe from floods at the community level. Such areas are critical in periods of severe hazard occurrence. They are needed for evacuation plans, temporal shelters and provision of general relief efforts. However, accurate derivation of evacuation plans requires access routes to and from the flood zones (Forkuo, 2011), which was not investigated in this study.

The results obtained in this study can contribute to the development of community-based sustainable flood risk management plans that can ensure prevention, protection and preparedness for flood events. For example, effective community based education could help community members to identify agricultural areas on the map that fall within the high flood hazard zones and to avoid cultivating such areas during certain periods of the year. This will translate into a reduction in the socio-economic and environmental related losses that are mostly associated with the occurrence of floods and enhance efforts at achieving sustainable development in West Africa. In Figure 3-8 for example, all the areas marked in green shades and classified as very low flood intensity zones could be considered as flood safe havens. In combination with field inspections with local people, these flood safe havens can be verified and marked as flood safe havens for the purpose of effective emergency management. Additionally, policy makers and development planners can, through an assessment of the flood hazard zones, develop appropriate policies and rules that will limit development in flood hot spots and consequently reduce the effects of flooding on the livelihoods of rural small holder farmers in the study watersheds.

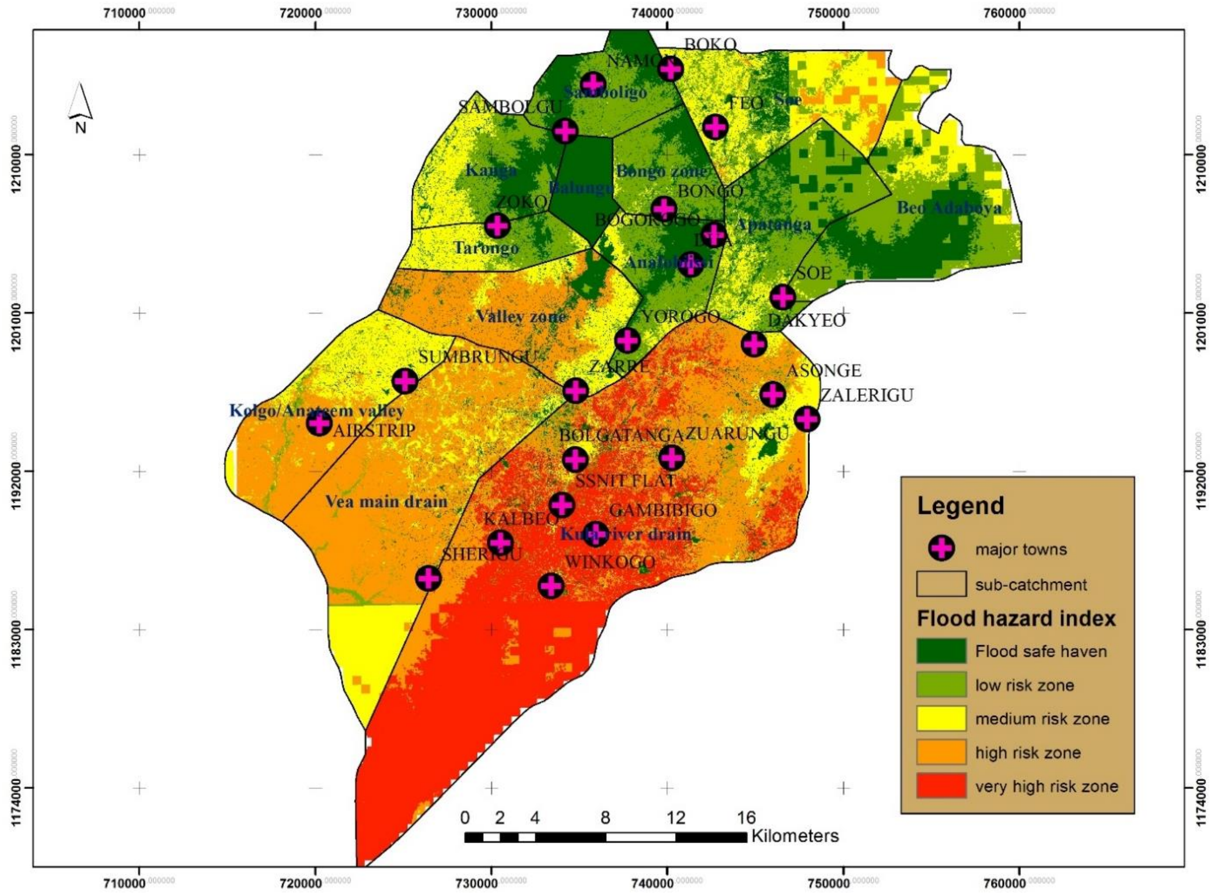

Figure 3-8: Flood safe havens in Vea study area.

3.4. Conclusions

The study has applied flood modelling approaches to demonstrate the feasibility of flood modelling in data scarce environments and limited resources. This study has drawn on the strengths of a simple hydrological model and statistical methods integrated in GIS to develop a Flood Hazard Index to an acceptable accuracy level. The flood hazard index shows that almost half of the study areas in Ghana and Benin falls into the “very high and high flood intensity zones” whilst more than half of the study area in Burkina Faso fall in high intensity flood zones.

The study also introduced an innovative flood modelling validation procedure using statistical and PGIS principles to evaluate the robustness of the methods used. Using the remote sensing technique of a confusion matrix, the overall accuracy of the flood hazard index was estimated at 77.62% in the Vea study area and 81.41% in the Dano study area.

The study also conducted qualitative validation of the results obtained for the Ghana site with local expert knowledge and found that the flood modelling methods accurately classified 79% of communities deemed to be highly susceptible to flood hazard and classified the remaining 21% into medium risk zone. The close similarity in the accuracy levels of the Vea flood Hazard index between the statistical-PGIS validation and qualitative assessment showed the robustness of the methods employed in mapping community flood hotspots.

Integration of the two approaches (hydrological and statistical) and combined with GIS and remote sensing techniques have shown the potential for diverse applications of the Flood Hazard Index. With this approach, flood risk of various land uses can be determined with a higher spatial resolution of 30 m. Such a high mapping scale could allow for accurate estimation of most flood risk elements and identification of flood safe havens.

However, although this approach has yielded an acceptable accurate Flood Hazard Index, it must be pointed out that under increased flood intensity occasioned by climate change, areas originally classified as flood safe havens under this model could offer protection, albeit only within the limits of the model inputs. For instance, an increase in rainfall intensity far beyond the anomalous (extreme) rainfall values used in this study could lead to the reclassification of these safe havens into another flood hazard intensity zone. This study also used a hydrological model which relied on globally available runoff coefficients to estimate the peak runoff values. These coefficients may not necessarily be exactly the same as those determined from field measurements in the study areas. In addition, the study did not investigate the contribution of flood inundation statistics such as flood depth, velocity, and progression as well as physical infrastructure which could also influence the intensity level of flooding. Again, lack of adequate data especially high resolution remote sensing imagery which necessitated the merging of courser resolution imagery for limited portions of the Dassari and Vea study areas should be taken into account in interpreting the results of the affected areas.

Flood risk is projected to increase with increasing exposure of populations and therefore effective flood management must include changes in the landscape that impacts the response to floods, locations of people and elements at risk (Kundzewicz et al., 2014). Using this community level flood hazard map could contribute to effective disaster management operations as recommended by Kundzewics *et al*. (2014) including prevention. For instance, in combination with high resolution satellite imagery, the FHI could help in rapid post-disaster assessments to estimate the economic impacts of flood disasters. This could be done by overlaying the maps of critical infrastructure in addition to detail land use maps.

Availability of “non-structural measures such as flood risk maps help in reducing flood risk in the area with relatively little investment” (WRC 2012, p. 5). In addition, the output from this approach will be very useful in the retrieval of socio-ecological indicators such as those identified in chapter two crucial for the assessment of risk and vulnerability in a coupled socio-ecological system in subsequent studies. The result of this study can be used by local disaster managers in Disaster Risk Reduction (DRR) and Health Emergency Preparedness and Response Programmes (HEPRP) and serve, among other things, “to build safer” public infrastructure, improve mass movement of “casualties during emergencies” (Morjani, 2011, p. 7) and help build more climate resilient rural communities.

4. Development and validation of risk profiles of West African rural communities facing multiple natural hazards[13]

4.1. Introduction

Africa is currently a continent under pressure from climate stresses and is highly vulnerable to the impacts of climate change (UNFCCC, 2007, IPCC, 2014). West Africa (WA) in particular, has been described as a hotspot of climate change (IPCC, 2014). In this region, a temperature of 3-6°C above the late 20th century baseline is "very likely" to materialize within the 21st century and the fact that this projection is expected to occur one or two decades earlier than other regions (IPCC, 2014) contributes to making the region more vulnerable to climate change. The frequency of occurrence of extreme events is expected to increase and the interaction of climate change with non-climate stressors will aggravate vulnerability of agricultural systems in semi-arid Africa such as the West Sudanian Savanna region of Burkina Faso, Ghana and Benin (IPCC, 2014). There is also medium confidence that projected increase in extreme rainfall will "contribute to increases in rain-generated local flooding" (Kundzewicz *et al*., 2014: p.24).

For West Africa, Sylla *et al*. (2015) projected a decrease in the absolute number, but an increase in the intensity of very wet events – leading to increased drought and flood risks towards the late 21st century. Increases in the frequency and intensity of extreme weather events constitute an immediate and damaging impact of climate change (DRDLR, 2013). This situation will have dire consequences for the sub-region's agricultural sector and food security (Roudier *et al*., 2011). The region's vulnerability to climate change is compounded by the reliance of much of the population (65%) on agriculture, particularly rain-fed agriculture (FAO, 2012). More than half of this people are women. This situation means that high vulnerability to climatic hazards particularly droughts, rainstorms, flood and other environmental factors is inevitable in the region (FAO, 2011). This makes it even harder to achieve sustainable development. On an annual basis, the Food and Agricultural Organization estimates countries within WA and the Sahelian sub-region to be adversely affected by natural disasters, such as droughts and floods, as well as transboundary animal diseases, economic crises and civil conflicts (FAO, 2011). Destructive floods particularly, since 2005 have weakened agriculture-based livelihoods and rendered local development efforts unsustainable (Armah *et al*., 2010, BBC, 2007, Braman *et al*., 2013). The severity on rural livelihoods is compounded by the exposure to one or multiple natural hazards which are predominantly hydro-meteorological and climatologically in nature (World Bank, 2010), a situation which according to Vincent (2004) has resulted in a growing interest on the inter-relationships between natural and human systems. This should lead to an acknowledgement of the nexus between Disaster Risk Reduction (DRR) and Climate Change Adaptation (CAA) but in this region, these inter-linkages are yet to be fully recognized by policy makers. Empirical evidence further shows that climatic change impacts will not evenly be borne across countries, communities and households; and also, the

[13] Asare-Kyei D, Renaud FG, Kloos J, Walz Y, Rhyner J (2017). Development and validation of risk profiles of West African rural communities facing multiple natural hazards. PLoS ONE 12(3): e0171921. doi: 10.1371/journal.pone.0171921.

capacity to respond effectively to climate change is differentiated, with poor rural communities often being the least equipped to respond (DRDLR, 2013).

Fields (2005) argues that the influence of multiple stressors such as environmental disasters, infectious disease, economic turbulence from globalization, resource privatization, and civil conflicts, combined with the lack of resources for adaptation, will present serious challenges for African communities struggling to adapt to climate change. Yet, comprehensive and quantitative understanding of the vulnerability and risk faced by WA rural communities to these multiple hazards, not even the common occurring hazards of floods and droughts are still lacking. The few studies available in the area have either qualitatively assessed vulnerabilities (e.g. Trench *et al*., 2007; Tschakert 2007) or only looked at specific aspects such as vulnerability to food insecurity (Bacci *et al*. 2005; Barbier *et al*., 2009), or focused on single hazards such as floods (e.g. Adelekan, 2011; Armah *et al*., 2010).

All these studies have measured vulnerability, resilience and adaptation using a variety of concepts, approaches, and indicators, however, important considerations such as applicability to local communities, methods to estimate localized risks, inclusion of at risk populations in developing the indicators themselves, use of multiple hazards and multiple scales were often missing. Studies such as Linstädter *et al*. (2016) assess the resilience of pastoral SES to droughts in South Africa whilst Martin *et al*. (2016) assessed livelihood loss to drought using a model based approach. Although these recent studies introduce new and interesting dimensions to resilience assessment in the context of droughts; using multidisciplinary approaches (Linstädter *et al*., 2016) and scenario comparison (Martin *et al*., 2016) they do not integrate multiple hazards occurrence, and limit their assessments to pastoral systems. For West Africa, chapter two indicated that, "no study has attempted to understand the risk patterns of rural communities in the context of climate change" through a set of participatory developed indicators. The only study that comes close is provided by the United States Agency for International Development (USAID, 2011) however, indicators were derived purely from literature without a participatory process with the vulnerable themselves. For more information of available risk and vulnerability indices, refer back to Chapter two of this thesis.

Studies such as Beckmann *et al.* (2011) and Welle *et al.* (2013) have also developed risk indices across countries and compared countries with high and low risk levels. However, it has been found that studies that use the same indicator set and make an effort to derive relative vulnerabilities across countries produce results that may be contradictory to expert knowledge (World Bank, 2010). The World Development Report in 2010 reviewed two major vulnerability-driven indices –Disaster Risk Index, DRI (UNDP, 2004) and Index of Social Vulnerability to Climate Change for Africa, SVA (Vincent, 2004) and concluded that these indices created spatial patterns out of tune with development-driven indicators and consistently showed a pattern contradictory to expert knowledge (World Bank, 2010). This contradictory result is expected because using the same indicators ignores the salient indicators deemed to be relevant by the local populations. In countries, even where the same indicators apply, they differ in their ranking and hence the weights that must be applied in estimating the final risk index. To this end, this study does not intend to use common indicators and make comparisons across countries but rather uses a participatory bottom-up approach where case study specific indicators are used.

A significant number of models predict the impacts of climate change, but many do so at a very coarse scale and are also unable to predict localized impacts, which may typically differ from coarser scale assessments. Research on risks and the accompanying vulnerabilities of the Social-Ecological Systems (SES) to climate change has largely addressed the expected impacts of climatic change on national, regional or sectoral scales but are largely unavailable at community level where risk outcomes are first materialized. In 2007, Birkmann (2007) indicated that a discussion has just begun as to whether and how global approaches and the associated indicators can be down-scaled to estimate localized risk and vulnerability and whether they provide appropriate and useful information. However, to date, little is known about the vulnerability profiles of rural WA communities particularly regarding risk to multiple hazards. Yet, it is acknowledged that risk and vulnerability identification and measurement before and after the occurrence of hazards are essential tasks for effective and long term DRR (Birkmann, 2007). There is an increasing need for a shift from global and regional assessments to sub-national and community level assessments because these are the scales where major decisions against risk are made and expected to be implemented.

4.1.1. Community level vulnerability and risk assessment

A study By USAID (2011) is the only study known to the authors that tried to assess risks by measuring social vulnerabilities to climate change in Ghana at the district level and recently the National Disaster Management Organization (NADMO) through the Community Resilience and Early Warning (CREW) project undertook extensive risk assessment of 10 flood and drought hotspots in Ghana as well as their early warning gaps (UNDP, 2015). However, the indicators used to construct the vulnerability index were derived solely from literature and lack the important element of the participatory process from the vulnerable populations themselves. Moreover, this study only measured social vulnerability to climate change and did not account for the ecological or biophysical aspects which are closely linked to the social processes. This study conducted risk level assessment at the district level and not at the rural community level as indicated in chapter one.

Douglas et al. (2008) carried out a study on participatory vulnerability analysis to ascertain the dimensions of flood problems in poor communities in the cities of Accra, Kampala, Lagos, Maputo and Nairobi. He assessed the perception of the local people on why floods occur and how they adjust to them. In another study, Antwi-Agyei *et al*. (2012) observed considerable differences between districts in terms of vulnerability which could only be partly explained by socioeconomic variables and stressed the importance of employing further community and household-scale research to explain the causes of differences in the observed vulnerability which their study did not look at. Moreover, many risk assessments in the region are mainly based on qualitative assessments without any attempt at combining them to quantitative data despite the fact that it has been recognized that risk assessment from both quantitative and qualitative (social, psychological, ecological) methods is required to deliver a more complete description of risk and risk causation processes (Cardona, 2004; Douglas and Wildavsky, 1982; Weber, 2006; Wisner *et al*., 2004). Other climate risk assessments in the region have either been conducted at the country level or looked at decoupled SES. Most of these studies have been reviewed in chapter two of this thesis and are more oriented towards vulnerability assessments and deal less with risk scenarios or multiple natural hazards.

Validation or model evaluation is an essential aspect of assessing the accuracy of complex model outcomes. Gall (2007) outlined six critical dimensions of model evaluation, of which validation is a key component. However, in almost all risk assessment studies reviewed, the only validation approach is based on statistical assessments of model intrinsic uncertainties. Damm (2010) observed that the development of indicators and subsequent modelling of composite risk indices has inherent uncertainties due to the many subjective decisions made by authors, yet “conventional validation of vulnerability is not possible as vulnerability cannot be measured in the traditional sense” and concluded that “validation still remains an open challenge” in risk assessment (Damm, 2010, p.17, 197). To this end, major risk assessments studies such as the World Risk Index (Beck *et al*., 2012; Birkmann *et al*., 2011; Depietri *et al*. 2013; Welle *et al*., 2013) used statistical Monte Carlo analysis and sensitivity analysis as validation tools. Other studies such as Adger & Vincent (2005) and Brooks *et al.* (2005) attempted to undertake indicator validation using mortality outcome. On the other hand, the difficulties with validating complex risk assessment models means that some studies don’t undertake any validation at all, (e.g. Antwi Adyei *et al.,* 2012). To address this open challenge in risk assessment, the study introduces the concept of community impact score (CIS) to validate the indicator-based risk and vulnerability modelling. The CIS is a novel and innovative approach to validate risk assessment and uses observed disaster impacts to validate the results of a complex indicator aggregation model. The results of this aggregation model are termed in this study as the West Sudanian Community Risk Index (WESCRI). The contributions of single constituent parameters to WESCRI describe the specific risk index of a community in terms of the main determinants of risk.

The present study therefore addresses the gaps noted above and in particular aims at (1) conducting multiple hazard risk assessment through a bottom-up participatory process as opposed to the classical top-down, large scale approaches; (2) assessing risk from the perspectives of a coupled SES rather than single-hazard-decoupled risk assessments; and (3) assess risk using indicators relevant for rural communities across West Africa. A key motivation for this study was to identify and support decision-makers with information to recognize and map risk hotspots in order to support priority setting for risk-reduction strategies. It is against this backdrop that this study develops vulnerability profiles of selected West African rural communities faced with multiple climate change related natural hazards. The study helps to provide a better understanding of the risks and vulnerabilities of rural communities in three West African countries. In so doing, the study helps differentiate communities in terms of the elements characterizing their risks and vulnerabilities. Studying risk and vulnerability profiles of rural communities also provides an insight on how to situate vulnerability, risk and climate change adaptation efforts within the context of the community’s sustainable development agenda and can help to develop appropriate, inclusive and well-integrated mitigation and adaptation plans at the local level.

4.2. Context

Within the structure of the West African Science Service Centre for Climate Change and Adapted Land use (WASCAL project), three study areas in three West African countries have been selected. These areas are (i) the Vea area in the Upper East region of Ghana (ii) the Dano area in the province of Sud-Ouest of Burkina Faso and (iii) the Dassari area in the Commune of Materi in North West Benin. In the study, these three watersheds are used for the community level risk profiling. Field observations and interactions with the people reveal that all these communities are frequently exposed to droughts and floods and life in these communities has been reduced to routine adaptation to these two hazards. The survival of a household's livelihood now depends on the household's ability to manage the impacts of droughts and floods events. Table 4-1 provide information on the physical characteristics of the study areas. Other details about these study areas are provided in section 1.5.2.

Table 4-1: Physical characteristics of the three watersheds.

Watershed	Average annual rainfall (mm/year)	Average peak runoff (M^3/sec)	Evapotranspiration (mm/year)	Mean slope (%)
Vea	980	155.70	1455	0.4
Dano	910	68.96	1747	0.5
Dassari	1000	113.11	1552	0.3

Data source: runoff data from Chapter three of this thesis, other data from Ibrahim et al. (2015).

4.3. Methods

The development of a common methodology to identify and measure risk and vulnerability to climatic hazards in order to define disaster risk reduction measures is still not sufficiently developed (Antwi-Agyei *et al*., 2012, Birkmann, 2007). To this end, participatory "bottom–up" methods are increasingly being employed to identify and document the processes that occur at a local level, involving decision-makers in communities and societies (Smit and Wandel, 2006; van Aalst *et al*., 2008; Yamin *et al*., 2005).

However, despite the growing acknowledgement of the necessity of enhanced community participation for sustainable disaster reduction, this has not been translated into actions to carry out participatory community based vulnerability and risk assessments in the West African sub region. In this study, a community based participatory method of assessing risk to multiple natural hazards based on indicators is introduced. A stepwise process (Figure 4-1) is followed, first to develop the community level vulnerability index and subsequently the West Sudanian Community Risk Index (WESCRI). As illustrated in Figure 4-1, the index is developed from ten work steps including:

1) Development of context specific risk assessment framework (Kloos *et al*., 2015)
2) A novel participatory indicator development approach as presented in chapter two.
3) Exploratory data analysis to understand the indicator data values.
4) Construction of bivariate correlation matrices following the approach of Damm (2010).
5) Normalization of indicators to scale the values to a range between 0 and 1 to allow for comparability of indicators of varying measuring units as applied in Welle *et al*. (2013).
6) Weighting of normalized indicators by converting expert judgment ranking to weights using rank to weight conversion model proposed by Al-Essa (2011).
7) Application of a three-tiered linear aggregation process as applied in Birkmann *et al*. (2011) and Welle *et al*. (2013) to develop the sub-indices of exposure, susceptibility and the three capacity sub-components to derive the composite vulnerability index.

8) Multi-hazard characterization and mapping using a flood hazard index developed inn n chapter three and vegetation health index from FAO Global Information and Early Warning System on Food and Agriculture (FAO GIEWS, 2015) to denote drought severity.
9) Integration of the developed vulnerability index and the multi-hazard index based on the framework to derive the final multi-risk index (WESCRI). This index is then used to construct the multi-risk indices of the rural communities in GIS environment;
10) The final work step is the introduction of a novel technique termed the 'Community Impact Score' (CIS) as vulnerability and risk validation procedure. The sections below present detail descriptions of these work steps.

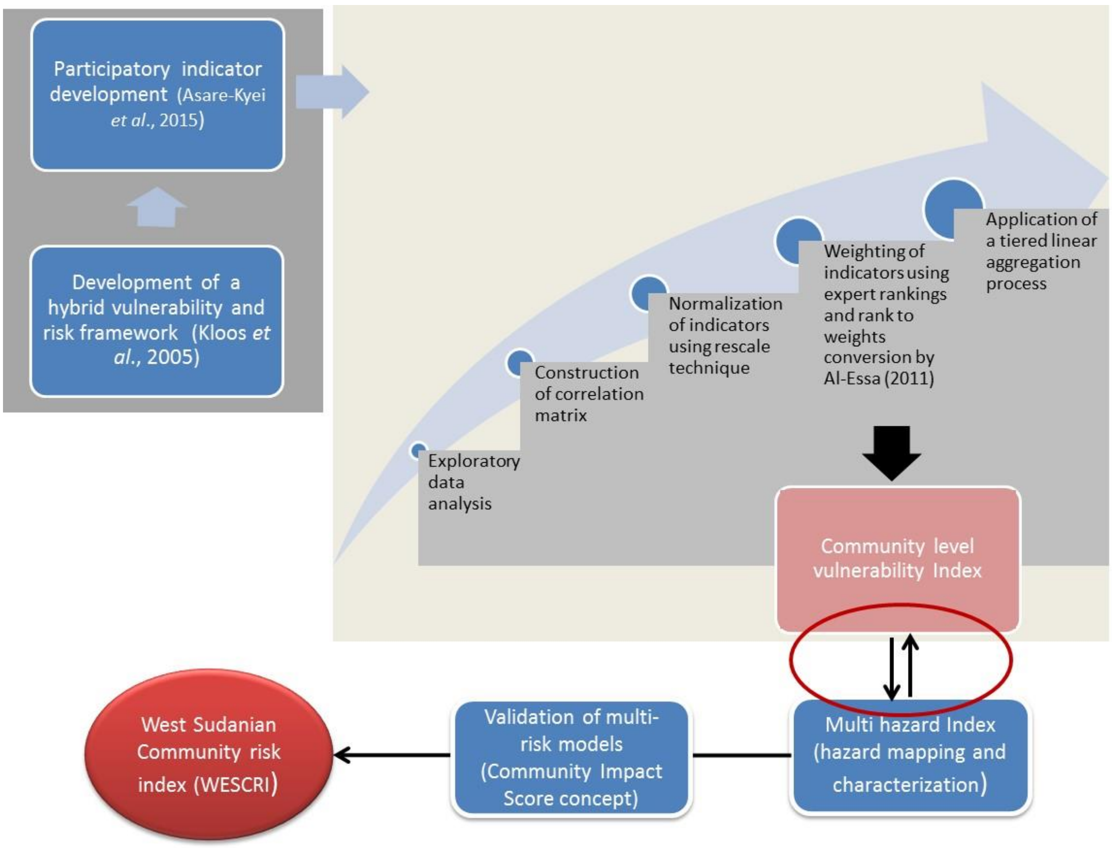

Figure 4-1: A stepwise process to quantify risk and vulnerability at the community level.

4.3.1. Development of a multi-hazard vulnerability and risk assessment framework

Although several frameworks have been developed to measure vulnerability and risk as reviewed in Birkmann *et al*. (2013) and Turner *et al*. (2003), most of these frameworks have several limitations making them difficult to use for risk assessment in a multi-hazard context and in a coupled Socio-Ecological System (SES) perspective (Kloos *et al.,* 2015). In developing an adapted framework suitable for multi-hazard (Figure 4-2) coupled SES studies in West African context, Kloos *et al*. (2015) provided an extensive overview of existing frameworks for assessing vulnerability and enumerated a number of shortcomings of these models. In this study, an attempt is made to conduct the first operationalization of the framework proposed by Kloos *et al*. (2015) at the community level in three West African countries.

The framework is based on the key element, a social-ecological system (SES), reflecting the connections and feedbacks between the environmental and social sub-systems taking place at various spatial scales (local, sub-national and national). Multiple temporal scales of different components of the framework are also covered by looking at the dynamics within the system.

Risk is to be evaluated against hydro-climatic hazards and stressors (Figure 4-2), which may materialize as sudden shocks such as floods and/or heavy rainfall events, slow onset events such as droughts, late onset of the rainy season but also more gradual changes such as changes in variability or averages of rainfall. At the same time, an SES is affected by socio-economic drivers and stressors (Figure 4-2) that may lead to environmental changes that can turn into stressors or hazards in themselves.

Ecosystem services are essential components of SES and provide numerous monetary and non-monetary benefits to people living in the system. To account for the multi-hazard nature, two hazards are introduced to the framework, 'H1' and 'H2', and the combination of both hazards selected for the West Sudanian Savanna case, 'H1+H2'. For details about the framework, see Kloos *et al*. (2015).

In this framework, vulnerability is characterized by exposure, susceptibility and the capacity of the coupled SES to cope and adapt to the impacts of either a single hazard or the combined effects of multiple hazards. Risk is a product of vulnerability and the characteristics of the hazard. Characteristics of the hazards in this study are construed to mean the intensity and frequency of occurrence of the two hazards, floods and droughts.

Studies such as Beck *et al.* (2012) and Welle *et al.* (2013) have included the exposure term in risk quantification and there have been debates as to whether exposure should be included in vulnerability component or the risk term (Birkmann, 2006b). In this study, however, the point of departure from the framework proposed by Kloos *et al*. (2015) is that exposure is only construed to mean the elements of the SES that are exposed to the multiple hazards, hence the term 'Exposure' as used by Kloos *et al*. (2015) is replaced with 'Exposed Elements'.

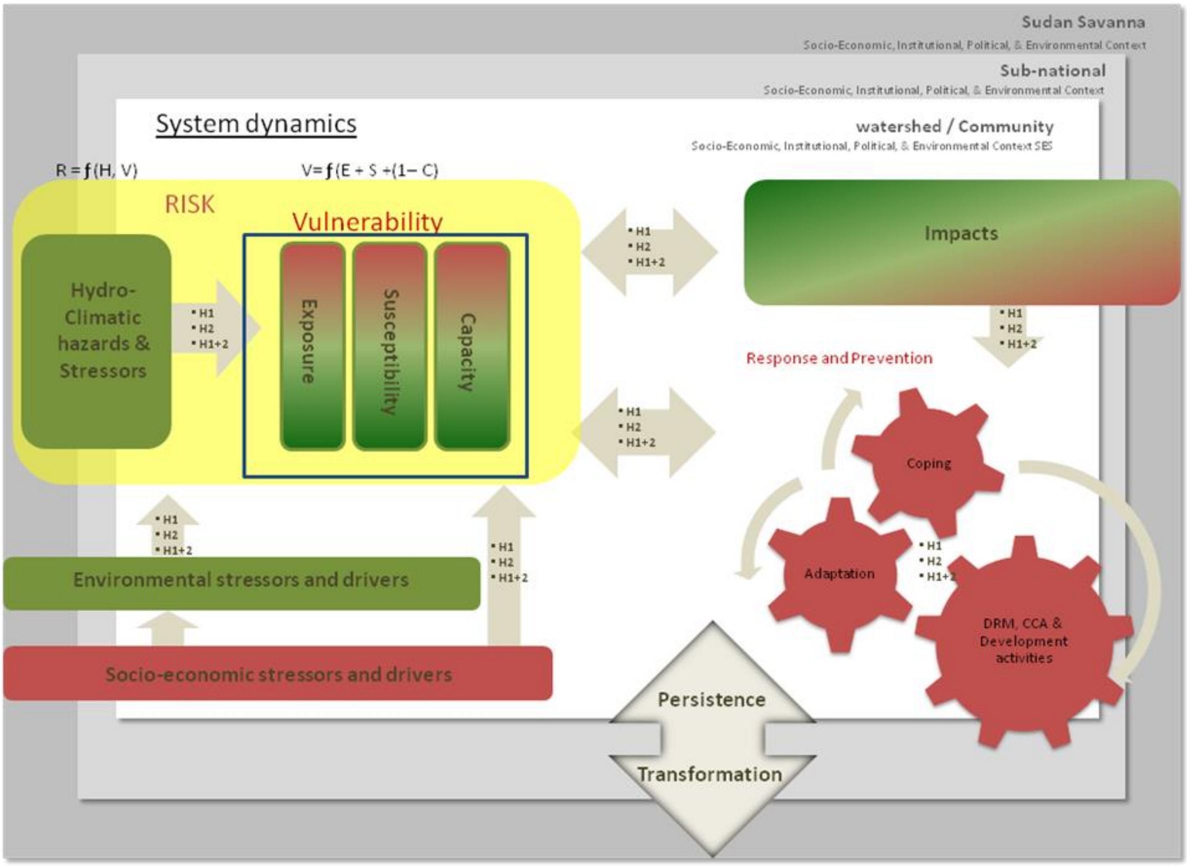

Figure 4-2: The proposed West Sudanian Savana Vulnerability framework by Kloos *et al*. (2015).

This conceptualization helps to provide an avenue to deal with the debate on whether exposure should be part of vulnerability or included in the risk term. According to Birkmann (2006b, p.38], “an element or system is only at risk if the element or system is exposed and vulnerable to the potential phenomenon”. Although exposure is often related to the hazard, excluding exposure from vulnerability assessment entirely makes such an analysis “politically irrelevant” (Birkmann 2006b, p.38). This is because once vulnerability is agreed to mean those conditions that intensify the susceptibility and decrease the capacity of the SES to the impact of the hazard, it also rests on the spatial dimension, by which the degree of exposure of the SES to the hazard is referred to (Birkmann, 2006b; Cardona 2004). This study is based on the assertion of Birkmann (2006b), that the location’s general exposure is essentially a component of the hazard whilst the degree of exposure of its critical elements such as farmlands, schools, houses etc. falling in hazard prone areas indicates the spatial dimension of vulnerability. In this study, therefore, this spatial dimension of vulnerability is termed as ‘Exposed Elements’ and shows that exposure is a partial characteristic of vulnerability. To this end, indicators used to describe the SES spatial dimension of vulnerability in this study include: agricultural areas in hazard zones, insecure settlements (share of the area’s settlement intersecting the hazard zones), protected areas in hazard zones, agricultural dependent population, etc.

From these conceptualizations, vulnerability (V) and risk (R) of the SES can be expressed as:

$$V_{ses} = EE_{ses} + S_{ses} + (1 - C_{ses})$$

Equation 4-1: Model to quantify vulnerability.

$$R_{ses} = V_{ses} \times M_H$$

Equation 4-2: Model to quantify risk from multiple hazards.

where *V* is the vulnerability of the SES, *EE* is the exposed elements within the SES indicating their degrees of exposure, *S* is the susceptibility of the SES, *C* is the capacity of the SES to cope, adapt and resist the hazard, *R* is the risk faced by the SES and M_H represents the characteristics of the multi-hazards (here intensity and frequency of droughts and floods). M_H represents the SES general exposure to the hazards under study. This conceptualization agrees with the IPCC summary report for policy makers (IPCC, 2014, p. 5), which defines risk as the *"potential for consequences*" where a valuable element is at stake and its outcome uncertain. This framework serves as a template for a reduced form of analysis allowing for the operationalization of the complex concept of vulnerability to a place based assessment. Note that all the quantities in Equation 4-1 are assessed by set of indicators which have been developed through participatory methods as described in chapter 2.

4.3.2. Participatory Indicator Development

In this study, the indicators developed in chapter two were used to construct the vulnerability and risk indices. The approach here followed a participatory approach to select indicators suitable for both quantitative and qualitative assessment of risks faced by people in WA under climate change. The methodology allowed for a representative participation of all stakeholder groups dealing with or affected by drought and floods. This was achieved through local stakeholder workshops where participants elicited indicators they considered as important in describing the risk they face revealing many new indicators which either have not been used or are rarely used in the literature related to West African risk assessment in the context of climate change.

A standardized questionnaire was developed to collect fine scale data for each applicable indicator identified in chapter two in three case studies. Table 4-2 shows the number of households sampled per study area. The selection of households was done with the use of a sampling frame received from the local authorities. The sampling frame contained information about communities frequently affected by floods and droughts, number of people affected, population as well as relief items provided by the local authorities. Almost all the communities affected by the hazards were sampled. Within each community, simple random sampling was used to select households usually affected by the hazards based on the sampling frame provided. The number selected from each community depended on total number of affected households, thus communities with higher affected populations received more representation. Unaffected households in these communities were also randomly selected to serve as basis for comparing the responses from affected households. In addition, 10 focus group discussions were held in the three study areas to capture the processes and impacts associated with droughts and floods and in situations where the two hazards occur in the same year.

Table 4-2: Households sampled for indicator data collection.

Study area	Number of households selected
Vea (Bolgatanga and Bongo districts, Ghana)	240
Dano (Burkina Faso)	100
Dassari (Benin)	92
Total	**432**

For indicators, which cannot be described by household data such as Green Vegetation Cover, soil organic matter, population density, etc., secondary data were used. While some of these secondary data came from local statistical reports, some were also retrieved from remote sensing through Geographic Information System (GIS) procedures. Appendix 2 describes the construction of the data values for each indicator. The household data was analysed with SPSS statistics Version 17.0.

4.3.3. Exploratory Data analysis

Exploratory data analysis is the next step after the data values have been retrieved for all the indicators. Here, the indicators were described by their minimum, range, mean, maximum and standard deviation. In the Vea study area, two indicators in the adaptive capacity component were removed from subsequent analysis after the statistical descriptive procedure. The indicator, 'access to national emergency funds' was removed for lack of data whilst the indicator 'local emergency funds as percentage of national budget' was removed due to lack of variability within the community clusters. Similarly, in the Dano study area, two indicators in the adaptive capacity component were removed from further analysis. The indicators, 'social capital' and 'early warning system' were removed for lack of variability within the community clusters. In the Dassari study area, four indicators were removed from further analysis. Two of the indicators, 'prevalence of stunted children under age five' and 'prevalence of wasted children under age five' which belong to susceptibility of the social system were removed for lack of community level data. Furthermore, one coping capacity indicator, 'local emergency funds as a percentage of local budget' and as well as one adaptive capacity indicator, 'Farm labour availability' were removed due to lack of variability within the datasets of the various community clusters.

4.3.4. Construction of correlation matrix

Following the approach of Backhaus *et al*. (2006) and Damm (2010), a bivariate correlation matrix was constructed to understand the strength and direction of the linear relationships between the indicators especially between those indicators in the same component of the framework. The Pearson correlation coefficient was estimated for indicators with absolute metric variables whilst the Spearman correlation coefficient was estimated for indicators with ordinal variables. Similar to the approach of Damm (2010), a rule of thumb was used where all relationships with a coefficient above a threshold value of r=0.65 were carefully scrutinized.

In the Vea study area, this approach resulted in the following correlation relationships:

1) The indicator 'Physical infrastructure' is significantly correlated with the indicator 'Insecure settlement' with r=0.9. Since both indicators belong to the same vulnerability sub-component

"exposure of social system", one of them is dropped. Physical infrastructure was dropped because the only data available to describe physical infrastructure within the community clusters was road network which could grossly underestimate the number and types of other infrastructure in the communities such as schools and markets.

2) The indicators 'Protected area' and 'Agricultural area' were significantly correlated (r=0.95). These two indicators belong to the same sub-component "exposure of ecological subsystem" and hence one is redundant and was removed. Protected Area was removed because its retrieval involved considerable uncertainty and thus could not meet the criteria of good data quality.
3) 'Unimproved drinking water source' has a significant correlation with two other indicators belonging to the same component. It correlates significantly with 'Number of dependents per household'(r=0.68) and 'Distance to drinking water' (r=0.78). This double correlation means that removing 'Unimproved water source' will help avoid redundancy.
4) Again, the indicator 'Prevalence of poverty' correlates strongly with 'Prevalence of stunted children' (r=0.9). These two indicators belong to the same vulnerability component, yet within this component, they fulfil different analytical purposes and also describe different factors that determines the extent to which a household or community is vulnerable to droughts and floods. Whilst 'Prevalence of poverty' belongs to 'Economic and dependencies' category of the social system, 'Children under age five who are stunted' is a health and nutrition factor. Since there are just two health and nutrition related indicators in the framework, the two indicators were kept. However, Prevalence of stunted children was weighted lower due to its inherent data quality.

In the Dano study area, the following correlation matrixes were observed:

5) The indicator 'Prevalence of poverty' exhibits significant correlation with two indicators. It has positive association with 'Caloric intake per capita' (r=0.77) and 'Population density' (r=0.73). Due to these double correlations exhibited by 'Prevalence of poverty', it was removed to avoid redundancy and doubling effects.

In the Dassari study area of Benin, observed relationships are outlined below:

6) 'Total soil nitrogen' correlates with 'Soil organic matter' (r=0.68). Since both indicators belong to the capacity sub-component' Ecosystem robustness', one of them is redundant and must be removed. 'Total soil nitrogen' was removed because of poor data quality.
7) Again, in this study area, 'Green vegetation cover' also has a strong correlation with 'Soil organic matter' with a coefficient of r = 0.84. Both indicators belong to the component 'Ecosystem robustness' and were all retrieved from remote sensing procedures. However, in terms of understandability of the two indicators among practitioners, 'Green vegetation cover' was found difficult to be understood and was thus removed from subsequent analysis.
8) Expectedly, 'Water holding capacity' and 'Infiltration rates' have a perfect positive relationship (r=1). Since both belong to the same component, 'Infiltration rates' which exhibited a lower variability within all community clusters were removed.

9) Finally, in this study area, 'Access to agricultural extension service' and 'Farm labour availability have a significant negative correlation of r =-0.77. Both belong to the adaptive capacity component and subsequently, 'Farm labour availability' was removed due to its rank within the sub-component.

It must be noted that varying degrees of significant correlations were found among other indicators in all the three study areas. However, since they belong to different components of the vulnerability, they are deemed to represent different causes and aspects of vulnerably and thus those relationships were neglected.

The final indicators used to construct the vulnerability indices for the three watersheds are presented in Figure 4-3 to Figure 4-5.

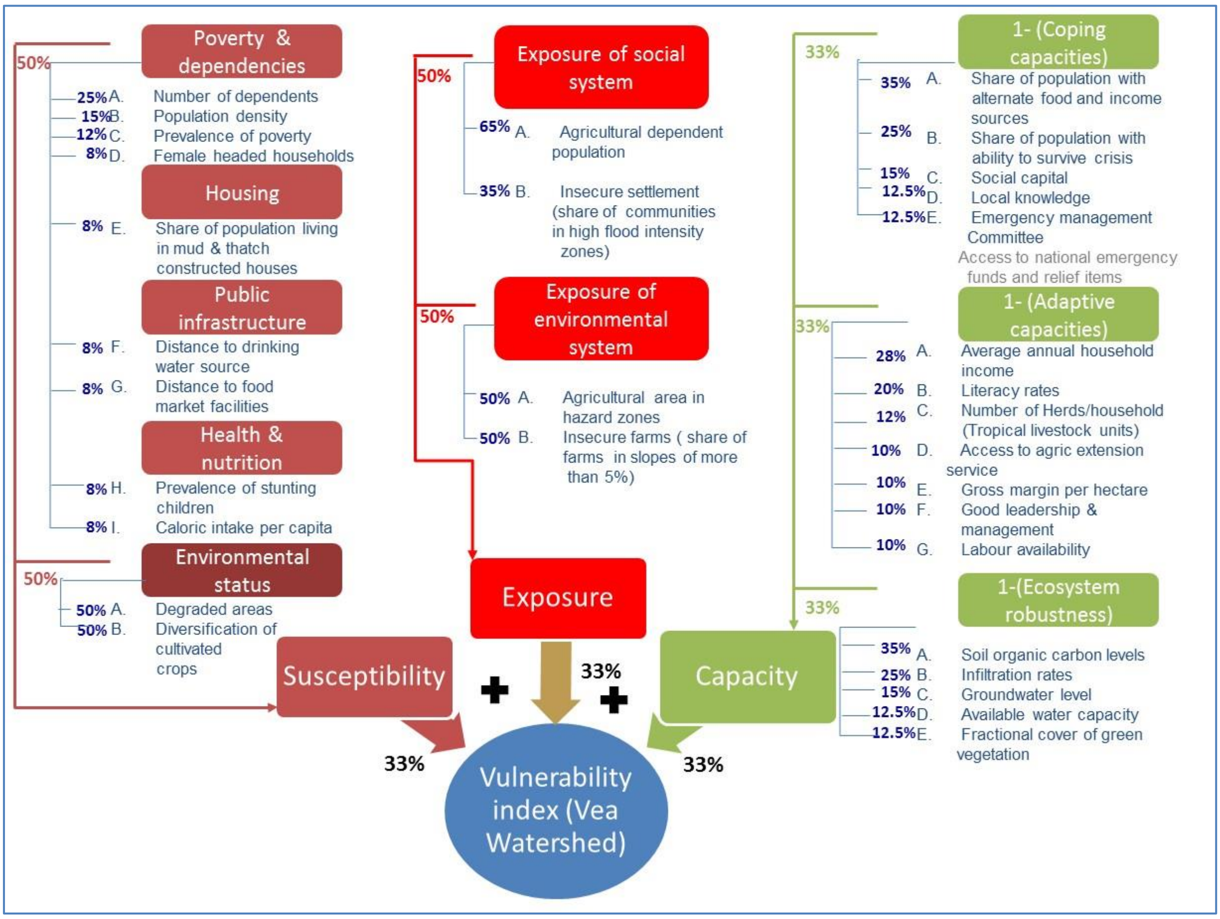

Figure 4-3: Development of West Sudanian Community vulnerability index in the Vea study area of Ghana

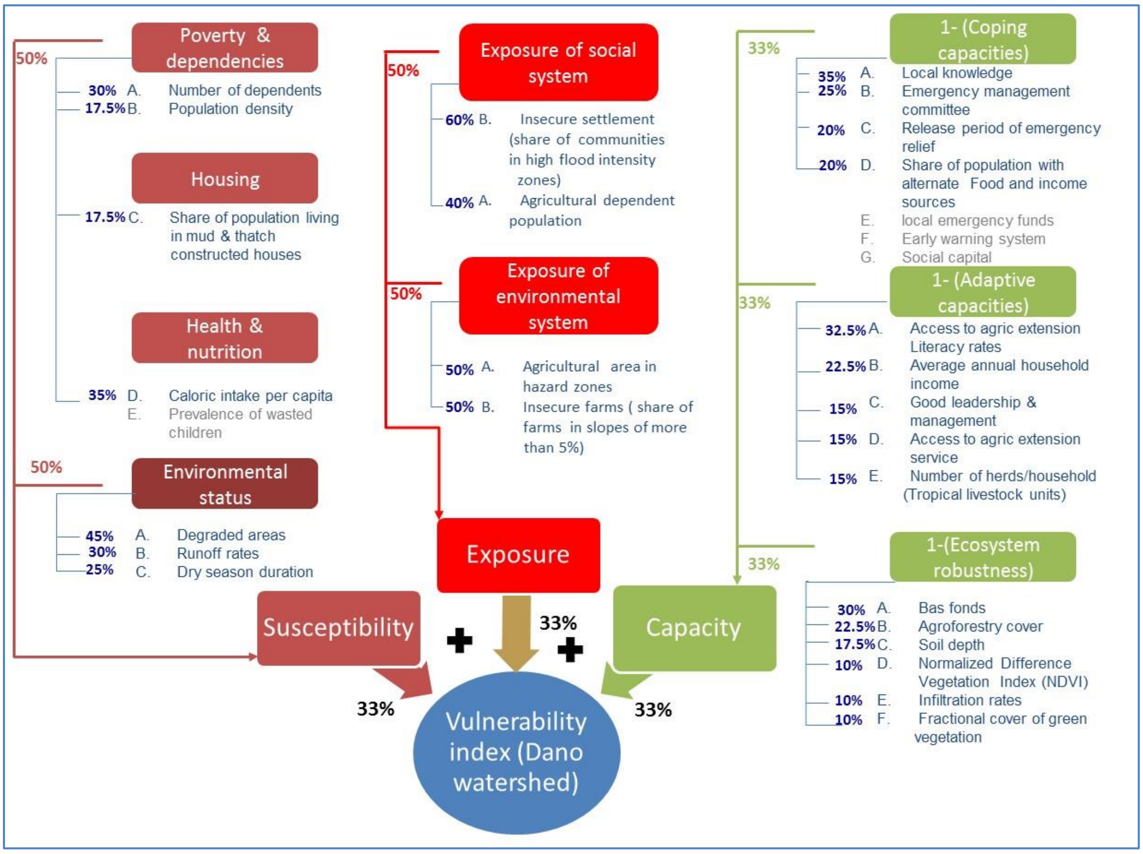

Figure 4-4: Development of community vulnerability index in the Dano area of Burkina Faso

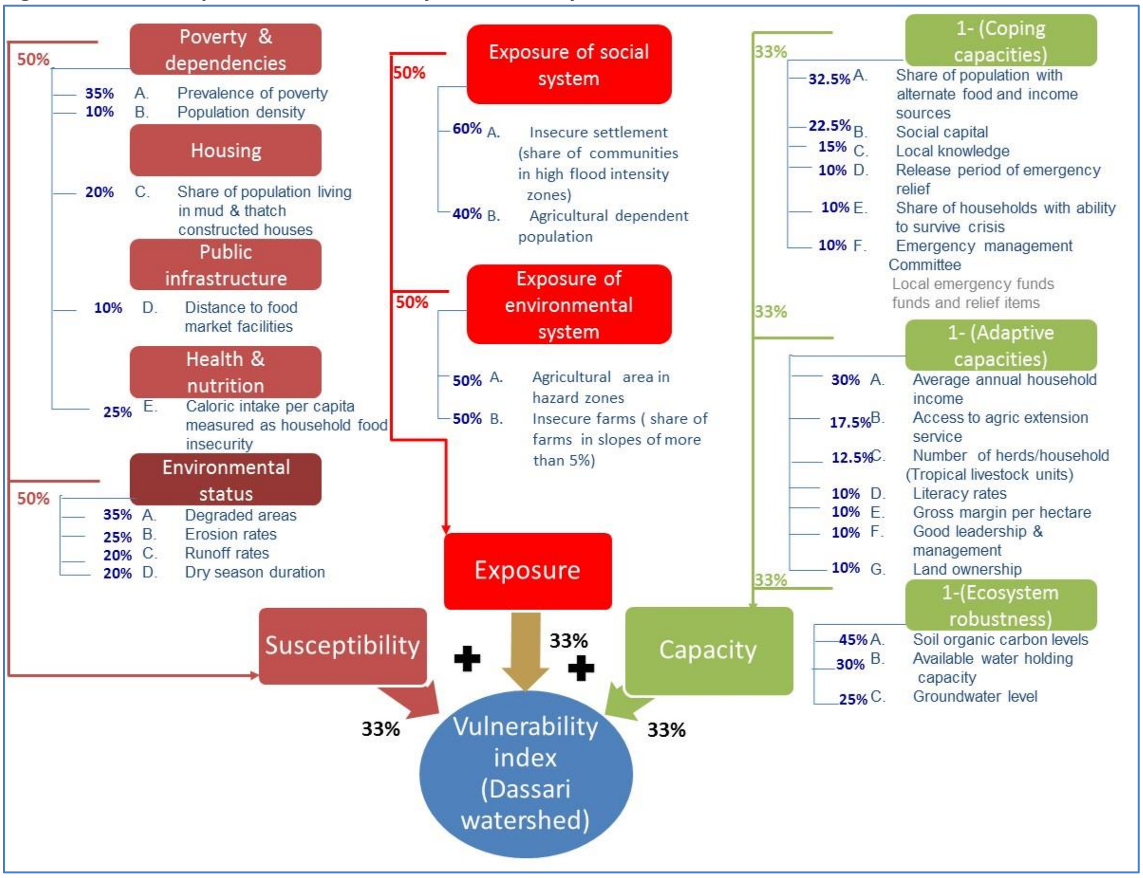

Figure 4-5: Development of community vulnerability index in the Dassari area of Benin.

4.3.5. Normalization and Weighting of indicators

The re-scaling normalization technique was applied to convert different measurement units into a dimensionless unit. This method (equation 3) normalizes indicators X to have an identical range between 0 and 1.

$$I_q = \frac{X_q - Min(X_q)}{Max(X_q) - Min(X_q)}$$

Equation 4-3: Normalization of indicators

Where I is the normalized indicator and q is each value/observation of the indicator.

The drawback of this approach is that outliers can distort the transformed indicator. To prevent this, the exploratory data analysis described above removed all extreme values (outliers) within the datasets based on statistical methods. The approach however, has an advantage of widening the range of indicators lying within a small interval and increases the effect on the composite indicator more than the z-score transformation which has been used by Damm (2010). The world risk report used this approach to develop the “WorldRiskIndex” (Birkmann *et al*., 2011, Welle *et al*., 2013).

After the indicators, have been normalized to have identical ranges, the indicators were weighted. There are several weighting methods ranging from statistical methods like factor analysis and data envelopment analysis, but also participatory methods such as budget allocation, analytical hierarchy process to a combination of statistical and expert judgment (Damm, 2010). In this study, an expert opinion approach was used to weigh indicators to better reflect policy priorities and at-risk populations’ understanding of important indicators that influence risk and vulnerability in the study area. As explained in chapter two, the experts provided rankings for all indicators within each vulnerability component. This ranking was converted to weights before the indicators were combined to develop the vulnerability index. The rank to weight conversion model developed by Al-Essa (2011) was used in this study. This model assumes that there is a consistent relationship between ranks provided by the experts and weight. This relationship is independent of the problem context. The slope is a function of the number of criteria, n and assumes a linear relationship with the model.

The model is given as:

$$Wr = 100 - Sn(r-1)$$

Where wr is the weight of the indicator, r is the rank, and Sn is the absolute value of the slope estimated by least squares regression when the number of indicators is equal to n. Using least-squares regressions to Sn versus n, Al-Essa (2011) obtained equation 5 which converts all the ranks provided by the experts into weights.

$$Wrn = 100 - \left(3.19514 + \frac{37.75756}{n}\right) \times (r-1)$$

Equation 4-4: Rank to weight conversion model

Where $1 \leq r \leq n$ and r and n are integer

However, the model was used to convert the first three highest ranked indicators. This is because there is some element of subjectivity when experts had to rank more than four indicators within a component of the framework. It was observed that when experts had to rank more than four indicators, the ranking becomes highly subjective after the fourth indicator. This fact coupled with the limitation imposed by the aggregation method which stipulated that the sum of all the weights in single vulnerability component must be equal to 100, or in this case 1, means that equal weights were used from the fourth indicator up to indicator n. See Figure 4-3 for the final weights applied in the Vea area. Those for Dano study area is in Figure 4-4 and Dassari study area is in Figure 4-5.

4.3.6. Aggregation to develop the composite vulnerability index

Applying the linear aggregation method, the normalized and weighted indicators were summed up to derive the composite vulnerability index. This approach has been applied in several studies such as Damm (2010) in mapping socio-ecological vulnerability to flooding in Germany, and by Beck *et al*. (2012), Birkmann *et al*. (2011) and Welle *et al*. (2013) in developing the World Risk Reports since 2011. Although there are other aggregation techniques, the linear aggregation technique proposed in this study is the most widespread aggregation method. This approach is basically the summation of weighted and normalized individual indicators.

This method imposes limitations on the nature of individual indicators. For example, to get a meaningful composite indicator (CI) is dependent on the quality of the underlying individual indicators and the measurements units. It also has implications for the interpretation of weights. This additive aggregation function works only if the individual indicators are mutually independent preferentially. This implies that the function allows the assessment of the marginal contribution of each indicator separately (OECD, 2008).

The linear aggregation technique applied in this study is given as

$$CI_c = \sum_{q=1}^{Q} w_q I_{qc}$$

Equation 4-5: Linear aggregation model for composite indicator development

With $\sum_q w_q = 1$ and $0 \leq w_q \leq 1$ for all $q = 1,..., Q$ and $c = 1,..., M$.

4.3.7. Developing the vulnerability and risk profiles – sub components aggregation

Using Equation 4-5, a three-tier aggregation process was followed to develop the West Sudanian Community Vulnerability Index (WESCVI). From the vulnerability framework presented in Figure 4-2, vulnerability is composed of three main components, exposure of the SES to droughts and floods, Susceptibility to these hazards and capacity of the SES to cope, adapt and resist the hazards.

To quantify vulnerability therefore means applying the weights to the data values of each variable and then adding them up. Before doing so, a sub-index for each component was developed (see Figure 4-3 to Figure 4-5). As shown in Figure 4-3 for the Vea study area, the weight applied to each indicator is indicated in percentages. It must be noted that the indicators within each component have been listed in order of the ranking provided by the experts. The ranks for the first three indicators have been converted to weights as described above and equal weights were applied for all remaining indicators. In cases where we have two indicators in a sub-component, weighting was influenced by inherent data quality and the indicators were either weighed equally or equation 5 was applied. For the exposure component, two indicators each for exposure of social system and ecological system exposure finally went to the computation of the exposure index after the bivariate correlation analysis (Indicators A, B and A, B).

There are four thematic areas within the susceptibility component of the social subsystem according to which the indicators have been structured. These are ‘poverty and dependencies’, ‘housing conditions’, ‘public infrastructure’ and ‘health and nutrition’. The further categorization of the indicators into these thematic areas will allow for the development of additional sub-indices if so desired and thus will be crucial for determining which social aspect is most or least important in influencing the vulnerability of the people living in the study areas.

Similarly, to calculate the susceptibility index, the weights assigned against each indicator were applied and summed up to derive the two sub-indices of social conditions (A to I indicators) and environmental status (A and B indicators). The sub-indices were then summed up by applying equal weights to derive the susceptibility index.

The capacity component has three sub-components, these are coping capacity, adaptive capacity and ecosystem robustness. An index was calculated for each of these sub-components by applying equation 6 before being combined into the capacity index. Each of these sub-components were given equal weights of 33%, thus giving the social system a higher weight of 66% compared to the 33% from the ecological system. The reason is that capacity to cope or adapt is more construed to be pertaining to the social system than more of the ecological system. Weighing them equally here will mean underestimating the inherent ability of social systems to respond through coping and adaptation measures to the impact of the hazards.

It must be noted that in quantifying the WESCVI, coping capacities are not considered but instead their lack thereof. This lack of coping capacity is estimated by subtracting the estimated coping capacity value from one. This approach which is also used in the estimating of the WorldRiskIndex (Birkmann *et al*., 2011, Welle *et al*., 2013) was used to calculate lack of adaptive capacity and lack of ecosystem robustness. In vulnerability analysis, susceptibility by definition is construed to mean all factors that increase vulnerability whilst Capacities does the opposite effect. Therefore, the negative variants of data values were used for susceptibility (e.g. distance of more than 30 minutes to water source) whilst positive variants of capacity indicators were used. E.g. Literacy levels instead of illiteracy levels.

In calculating lack of coping capacities, four main indicators (A to D) that support the reduction of negative impacts of droughts and floods induced by climate change were used. One indicator, access to national emergency funds and relief items could not be used due to lack of adequate data at the community level. However, due to the high relevance of this indicator as described in Asare-Kyei et al (2015a), they have been included in the final indicator set listed in Figure 6.

Also in calculating lack of adaptive capacities in the Vea study area, five indicators (A to G) that "describe the capacities for long-term adaptation of societies and SES" (Birkmann *et al.*, 2011) were used. The weights assigned to these indicators were multiplied by the normalized indicator data values to derive the lack of adaptive capacity index. In the same way, the index for lack of ecosystem robustness was calculated by using the indicators, M to Q. The weights assigned to these indicators were multiplied by the normalized indicator values. Finally, the lack of capacity index was estimated by applying equal weights (33%) to each of three sub-indices.

The West Sudanian Community Vulnerability Index (WESCVI) was finally estimated by combining the three indices describing exposure, susceptibility and (lack of) capacity. Equal weights were applied to each of the three indices. The vulnerability indices for the Dano (Figure 4-4) and Dassari (Figure 4-5) were estimated by using the same approach described above for the Vea study area.

4.3.8. Multi-hazard index development

The development of the multi-hazard index maps considered two components (Figure 4-6). The first part was the development of a flood hazard index map. This approach presented in detail in chapter three drew on the strengths of a simple hydrological model and statistical methods integrated in GIS to develop a Flood Hazard Index (FHI) to an acceptable accuracy level. The resulting FHI shows that almost half of the study areas in Ghana and Benin falls into the "very high and high flood intensity zones" whilst more than half of the study area in Burkina Faso falls in high intensity flood zones. This is a relative approach and one cannot assume equal flood intensity in the different catchments even if they fall in the same category. The FHI was validated with participatory GIS techniques using information provided by local disaster managers and historical data.

The second component involves the development of Drought Severity Index (DSI). The DSI is computed from Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) as explained in FAO GIEWS (2015). In this study, the final Vegetation Health Index (VHI) dataset was received from FAO Global Information and Early Warning System on Food and Agriculture (GIEWS) covering a period of 30 years (1984 to 2013). The mean VHI is an average of the decadal VHI values over the crop growing season to date and have non-cropland areas masked to cover only cultivated land. It is a good indicator of drought at pixel level (FAO GIEWS, 2015).

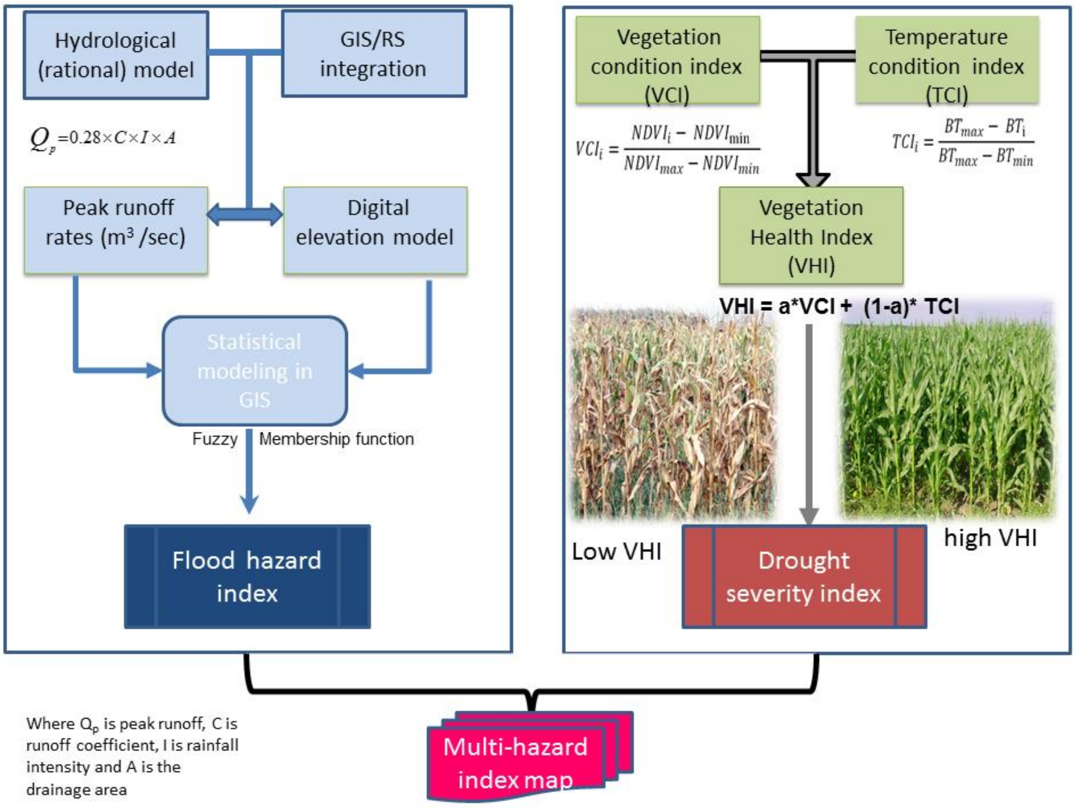

Figure 4-6: Development of multi-hazard index map. Symbols are explained in text below.
The figure on the left is a modified representation of the flood modelling approach introduced in chapter three whilst the right figure is a modified abstraction of FAO GIEWS (2015) illustrating the development of DSI as computed from the mean season one VHI. VCI is the scaling of maximum and minimum Normalized Difference Vegetation Index (NDVI) and TCI is the scaling of maximum and minimum Brightness temperature, BT estimated from thermal infrared band of AVHRR channel 4. The final VHI is derived by applying weight, "a" to the VCI and TCI. The end results of these two methods were combined in GIS to develop the multi-hazard map.

The mean VHI was temporally integrated for every major season from 1984 to 2013 to derive the seasonal mean VHI. Two main estimations pathways were followed to derive the DSI which measures both the magnitude (intensity) of the drought and its frequency. The intensity was measured by computing the thirty-year average VHI. Kogan (1995) developed a threshold value of 35% below which a pixel is described as having agricultural drought condition. This threshold value was set by correlating VCI with different crop yields and various ecological conditions. The result was a logarithmic fit between VCI and crop yields at r-square of 0.79 (Kogan, 1995, Rojas *et al*., 2011).

To estimate the frequency of droughts at each pixel, a routine was established in the program R that calculates the number of times within the 30-year period that a pixel registers a VHI value of less than 35%. Using this approach, the frequency of drought was established for every pixel over the entire study area (Figure 4-7). The highest frequency was found to be 10 indicating that those pixels have registered exceptional drought conditions in 10 out of the 30-year period. Table 4-3 presents the classification of the drought frequency and intensity into five classes corresponding to the categories of the FHI.

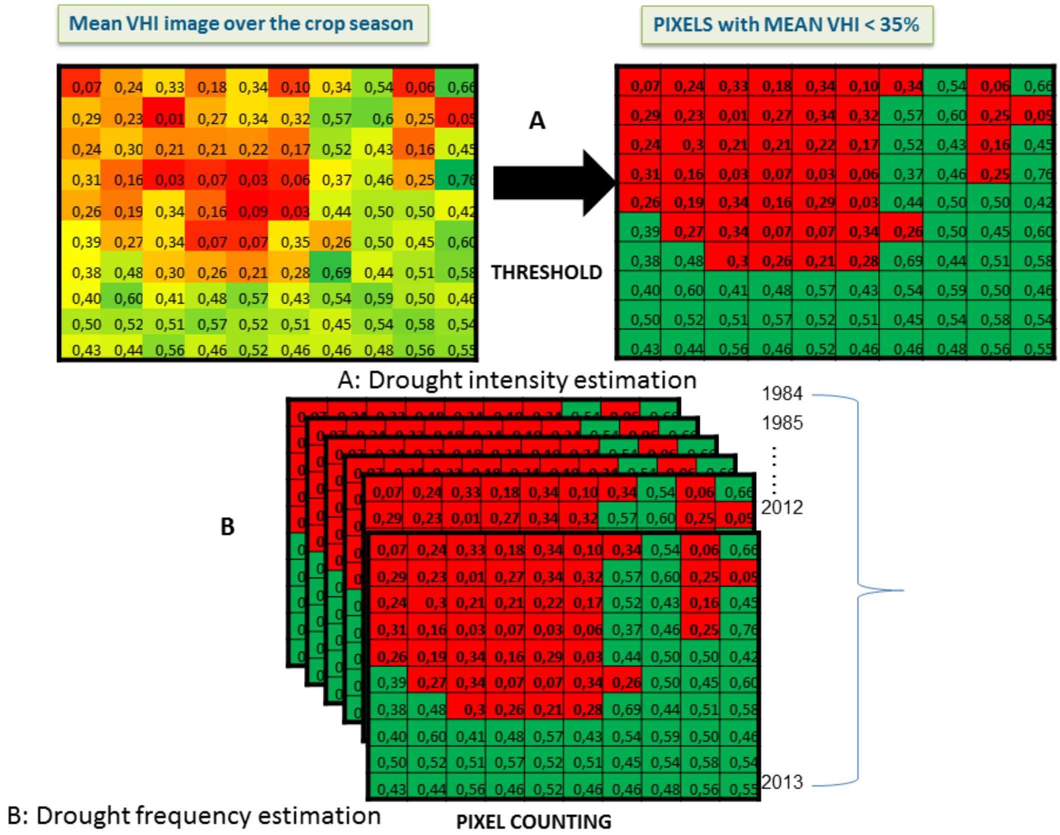

Figure 4-7: Conceptual basis for estimating the drought frequency over the 30-year period.
Adapted from Rojas et al. (2011) and FAO GIEWS (2015).

Table 4-3: Classification of drought frequency and intensity datasets.

Frequency	Drought category	Av. VHI (intensity)	DSI at pixel level
9- 10	Exceptional drought	<35	5
7 - **8**	Extreme drought	36 – 45	4
5 – **6**	Severe drought	46 – 55	3
3 – **4**	Moderate drought	56 – 65	2
1 – 2	abnormal drought	66 – 75	1
0	no drought	>75	1

Classification according to the Jenks method implemented in ESRI ArcGIS and as modified from FAO GIEWS (2015). VHI is Vegetation Health Index and DSI is Drought Severity Index.

The drought frequency and intensity were normalized between 0 and 1 and combined using the weighted linear combination method given in Equation 4-6 (Malczewski, 2000) to produce the Drought Severity Index (DSI) in a GIS. The method permits the assignment of weights, which indicates the relative importance of a layer. The weights must sum up to one. In this study, the two standardized layers were considered equally important, thereby assigning a weight of 0.5 each to the layers in Equation 4-6.

$$DSI = \sum_{i=1}^{n} 0.5X(av.VHI) + 0.5X(droughtfreq)$$

Equation 4-6: Derivation of Drought Severity Index.

Where i indicates the number of pixels or spatial units within each layer. This formulation then allowed the spatial combination of FHI and DSI to derive the multi-hazard index maps. Equation 4-6 was again applied to combine the DSI and FHI to derive the Multi-Hazard Index (MHI) map. It is important to mention that there are other approaches one could follow to combine the two hazards. Another example could be using the maximum function, in which case, a more than usual higher value in one quantity (hazard) could be rewarded. However, in this study, the weighted average function was found to be much simpler to implement. It therefore remains a possibility for subsequent studies to test the results of using different approaches of combining the two hazards. Note that the flood intensity (FHI) was also later normalized between 0 and 1 to allow for the spatial combination with the DSI.

4.3.9. Risk index approaches

Once the vulnerability and multi-hazard indices have been estimated, the multi-risk indices of all the communities can be estimated by implementing Equation 4-2. This is graphically represented in Figure 4-8.

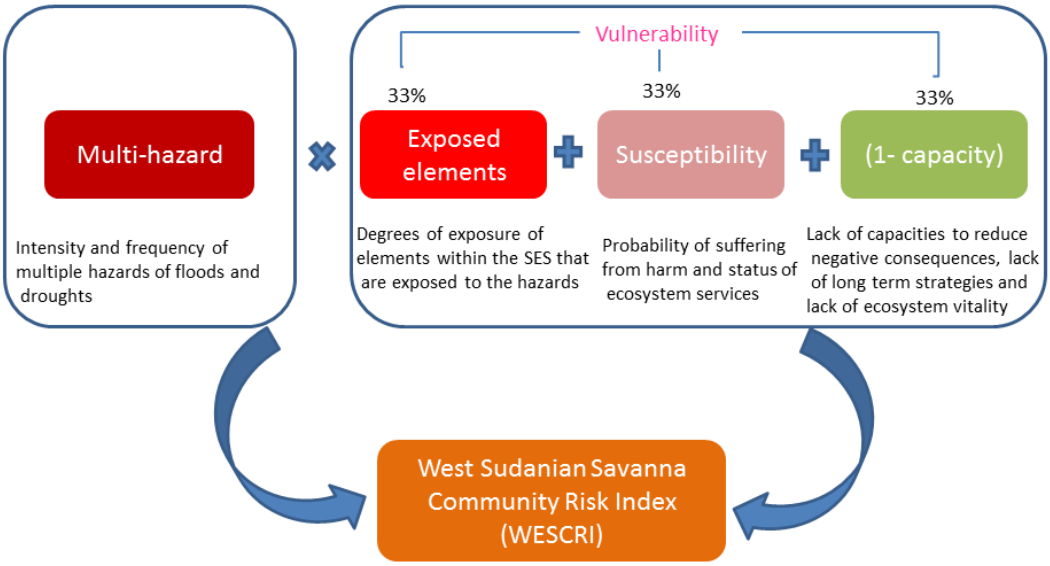

Figure 4-8: The modular structure of the community multi-risk index.

Populations exposed to the hazards were not intersected or overlaid with the quantity, M_H as this was already captured in the vulnerability estimation pathway where the degrees of exposure of the critical elements (people, farmlands, protected area etc.) were used. The quantity, M_H in Equation 4-2 measures a spatially explicit assessment of the SES general exposure to the two hazards of floods and drought.

4.3.10. Validation of risk and vulnerability indices

The robustness and the quality of the composite vulnerability indicator as well as the soundness of the risk indices in estimating the potential impacts of the hazards on the communities studied were further tested. In this study, two main approaches are presented to evaluate the results of the community level vulnerability and risk indices.

4.3.10.1. The Concept of Community Hazard Impact Score

A novel technique is introduced in this study that validates the underlying models and assumptions used to develop the community risk indices with real historical impact data collected from at risk populations. To do this type of risk model validation, which as far as available literature on risk assessment confirms has not been pursued, we introduce an approach to develop an impact score for each community cluster called 'Community Impact Score' (CIS). The CIS measures the cumulative impact of the occurrence of the multiple hazards over a period of five years. During the field work as described above, households were asked to recount the impact they have suffered over the last five years as result of the occurrence of drought, floods and multiple hazard occurrence. The impact assessment captured data on the following key variables.

1) Population affected by floods (%) by community cluster
2) Population affected by droughts (%) by community cluster
3) Population affected by floods and droughts in the same year (%) by community cluster
4) Average area of cropland affected per community (acres)
5) Average number of livestock affected/killed by hazards
6) Number of people killed by floods (human loss)
7) Number of housing units destroyed or partially damaged by floods
8) Economic value of properties (houses, personal effects etc.) destroyed by floods

The results of this detailed assessment are presented in appendix 1 (section 4.4.11). To develop the CIS, these impact variables were first standardized to make any combination meaningful. The linear interpolation method was applied to standardize the impact variables. This procedure results in standardized impact values on a scale of 1 to 4; with one being the lowest impact level and 4 for the categories with the highest impact levels. The linear interpolation scheme (Equation 4-7) as applied in Morjani (2011) was used to standardize all the variables. This procedure first involves the determination of minimum and maximum impact levels and then calculating the slope and intercepts of the impact level for each variable. The minimum and maximum values were used as the known variables in the horizontal axis whilst the scale range of 1 to 4 was used as the known variables in the vertical axis in the estimation of the slope and intercept. The resulting slope and intercept values of the respective variables were then applied to each impact variable value using Equation 4-7 below. This procedure resulted in standardized impact variables, which were then multiplied to derive the CIS.

$$IV_{st} = Integer([slope \times IV] + \mathrm{int} + 0.5)$$

Equation 4-7: Standardization of CIS variables

Where IV is the impact variable, IVst is the standardized impact variable and "int" is the intercept. The derived CIS was then scaled between 0 and 1 to correspond to the multi-risk index. Three statistical model validation tools were used to assess how well the risk model approximate actual disaster impacts. The Root Mean Square Error (RMSE), the Coefficient of determination (r^2) and the Nash-Sutcliffe efficiency (NSE) index (Nash & Sutcliffe, 1970; Walz *et al*., 2015) were used. The NSE index determines the relative magnitude of residual variance or noise compared to observed impact data variance and ranges between one and minus infinity.

$$NSE = 1 - \left(\frac{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_i^{pre}\right)^2}{\sum_{i=1}^{n} \left(Y_i^{obs} - Y^{mean}\right)^2} \right)$$

Where Yiobs is the ith observation (impact score) for the total number of community clusters, n, Yipre is the ith predicted value for the corresponding community cluster and Ymean is the mean value of the observed data, in this case, the mean impact score.

4.3.10.2. Sensitivity analysis

The vulnerability model was also validated with the use of a sensitivity analysis to examine the sources of variation in the model output and also to determine the input variables contributing to this variation. The study favoured the use of local sensitivity analysis which allows the influence of one varying variable to be studied while all the other variables are held constant. A local sensitivity analysis could reveal complementary information that have policy relevance, allowing policy makers to understand the variables which when intervened on could have significant impact on the overall vulnerability of the communities. This is important for the objective of this study which seeks to identify variables contributing to household's vulnerability so as to influence programmatic interventions at the community level. In this study, sensitivity was analysed by way of volatility of the variable to be changed in relation to its original state. In accordance with Damm (2010), OECD (2008) and Groh *et al*. (2007), volatility is measured by the standard deviation of community vulnerability index across all community clusters in each study area.

4.4. Results and Discussion

The results and discussion for all the sub-components including exposure (4.4.2), susceptibility (4.4.3) and Capacity (4.4.4) are presented in this section as well as the risk indices and profiles of vulnerability. The study also developed a framework for selecting relevant indicators for risk assessment in West Africa, results of which is presented first.

4.4.1. A framework for indicator selection

One objective of this research is to have a flexible indicator set to account for local circumstances. This was achieved through a bottom-up participatory indicator development process combined with expert judgement and validated in three case studies. A framework for this flexibility must be provided to allow other researchers in the West African sub-region or the wider African context to select indicators for similar studies. In the table below, we summarize the indicators for all three countries showing explicitly the cases where we have multiple possibilities and where a choice could be made between one indicator and the other. The aim is for example, for someone in Cote d'Ivoire who cannot do an in-depth participatory exercise as was done in chapter two to see what indicators are preferred by stakeholders but knows the region well, to be able to select some indicators on top of others.

Table 4-4: Indicator reference table for West Africa risk assessment.

Vulnerability sub component	Indicator	Ghana	Burkina Faso	Benin
Exposure of social system	Agricultural dependent population	√	√	√
	Insecure settlement	√	√	√
Exposure of environmental system	Agricultural area in hazard zones	√	√	√
	Insecure farms (cropland in high slopes areas)	√	√	x
	Protected area in hazard zones	x	x	√
Susceptibility of social system	Number of dependents	√	√	x
	Population density	√	√	√
	Quality of housing	√	√	√
	Distance to drinking water source	√	x	x
	Distance to food market	√	x	√
	Prevalence of stunted children	√	x	x
	Caloric intake per capita	√	√	√
	Prevalence of poverty	√	x	√
	Female headed households	√	x	x
Susceptibility of ecological system	Degraded areas	√	√	√
	Crop type (crop diversification practices)	√	x	x
	Runoff	x	√	√
	Dry season duration	x	√	√
	Erosion rates	x	x	√
Capacity ecosystem robustness	Soil organic matter	√	x	√
	Infiltration rates	√	√	x
	Groundwater level	√	x	√
	Water holding capacity	√	x	√
	Green vegetation cover	√	√	x
	Bas fonds	x	√	x

	Agroforestry cover	x	√	x
	Soil depth (distance to bedrock)	x	√	x
	Normalized Difference Vegetation Index	x	√	x
Coping capacity	Alternative food and income sources	√	√	√
	Ability to survive crisis	√	x	√
	Social capital	√	x	√
	Local knowledge	√	√	√
	Emergency management committee	√	√	√
	Relief period of emergency items	x	√	√
Adaptive capacity	Access to agric and health extension officers	√	√	√
	Average annual household income per capita	√	√	√
	Literacy levels	√	√	√
	Tropical livestock units (Number of herds)	√	√	√
	Gross margin per hectare	√	x	√
	Farm labour availability	√	x	x
	Access to farmland	x	x	√

4.4.2. Exposure of the rural communities to the multiple hazards

Exposure to hazards is an important dimension of the overall risks faced by a system or community. The implementation of an SES approach means that the exposure index represents both the exposure of the environmental sub-system to droughts and floods as well as the exposure of the social sub-system. In Table 4-5 below, the exposure of all the community clusters studied in the three countries have been presented. In the Vea study area (Ghana), the Kula river community cluster comes out on top as the most exposed community, followed by communities in the Vea main drain and Valley zone in that order. Communities in the Kanga cluster have the least exposure with an index value of just 0.13. Similarly, in the Dano study area (Burkina Faso), communities in the Loffing-Yabogane cluster are the most exposed to the multiple hazards followed by those in Batiara, Bolembar and Gnipkiere in that order. In this study area, Meba Pari has the lowest exposure index of 0.225%. Also in the Dassari study area (Benin), Porga cluster of communities are the most exposed followed by Tankouri and Sechendiga clusters.

Table 4-5: Community ranking of the exposure of SES to droughts and floods.

	Vea study area		Dano study area		Dassari study area	
Rank	Community cluster	Exposure index	Community cluster	Exposure index	Community cluster	Exposure (%)
1	Kula river drain	0.581	Loffing-Yabogane	0.591	Porga	0.405
2	Vea main drain	0.496	Batiara	0.585	Tankouri	0.269
3	Valley zone	0.349	Bolembar	0.554	Setchendiga	0.234
4	Balungu	0.341	Gnikpiere	0.551	Nagassega	0.224
5	Kolgo-Anateem	0.313	Yo	0.542	Ouriyori	0.222
6	Anafobiisi	0.299	Complan	0.535	Firihoun	0.192
7	Apatanga	0.297	Tambalan	0.523	Pouri	0.154
8	Samboligo	0.297	Dano sector 1,2,4	0.482	Tetonga	0.139
9	Soe	0.295	Kpeleganie	0.462	Tigniga	0.121
10	Tarongo	0.195	Lare	0.283	Tihoun	0.120
11	Beo Adaboya	0.193	Sarba	0.275	Dassari	0.113
12	Bongo zone	0.164	Dano sector 7	0.236	Koulou	0.044
13	Kanga	0.134	Meba Pari	0.225		

The results show that the mean exposure index is highest for communities in the Dano study area (0.45) as against a mean of 0.30% in Vea and only 0.19 in Dassari. Exposure of communities in Dano is also more variable within communities. The variability is estimated at 0.14 around the mean in Dano and 0.12 in Vea. The higher variability of the exposure index in Dano means significant differences exist between the communities in terms of exposure.

It is interesting to note that exposure of communities followed the same pattern of the Flood Hazard Index maps developed in chapter three where the distribution of flood hazard in the study areas was modelled. In their study, the Kula River and Vea main drain in Vea; Porga in Dassari and Loffing-Yabogone in Dano were reported to be falling in high flood intensity zones. This study reinforces this finding and showed that the exposure index followed the pattern of flood hazard intensity zones. Although, there are other determinants of exposure as can be seen in the indicators used to construct the index, this fact shows the strong effect proximity to hazards has on the overall SES exposure to floods. Another major driving factor influencing community exposure to multiple occurrences of drought and flood is the indicator measuring the share of the population engaged in agriculture. This indicator measures populations whose livelihood depends solely on agriculture and which have no other income or food sources. As expected, 72% of people in the Dano area belong to this category of 'Agricultural Dependent Population' (ADP), 42% in Dassari and Vea having the least number of people (35%) engaged in only agriculture. Although this indicator was ranked second in Dano and first in both Vea and Dassari, its effect on exposure is still significant.

4.4.3. Susceptibility of the communities to drought and floods

Susceptibility is measured as inherent conditions within the communities that predispose them to be adversely affected by the two hazards. The SES approach measures susceptibility for both the socio-economic and environmental sub-systems. Within the social-economic sub-system, four dimensions comprising 'poverty and dependencies', housing, public infrastructure and health and nutrition are considered. In Table 4-6 below provides details about the susceptibility indices of the communities.

Table 4-6: Community rankings in terms of susceptibility to the multiple hazards.

	Vea study area		Dano study area		Dassari study area	
Rank	**Community cluster**	**Susceptibility index**	**Community cluster**	**Susceptibility index**	**Community cluster**	**Susceptibility index**
1	Tarongo	0.693	Bolembar	0.534	Setcheniga	0.537
2	Samboligo	0.594	Yo	0.506	Tetonga	0.505
3	Balungu	0.525	Dano sector 7	0.398	Dassari	0.497
4	Bongo zone	0.473	Complan	0.395	Porga	0.494
5	Kula river drain	0.468	Loffing-Yabogane	0.379	Tigniga	0.476
6	Apatanga	0.438	Dano sector 1,2,4	0.375	Koulou	0.466
7	Beo Adaboya	0.406	Gnikpiere	0.368	Firihoun	0.446
8	Kanga	0.384	Lare	0.349	Tihoun	0.436
9	Anafobiisi	0.382	Sarba	0.334	Tankouri	0.404
10	Vea main drain	0.382	Batiara	0.318	Ouriyori	0.398
11	Valley zone	0.375	Meba Pari	0.302	Nagassega	0.383
12	Soe	0.345	Tambalan	0.290	Pouri	0.343
13	Kolgo-Anateem	0.219	Kpeleganie	0.234		
	Mean	*0.437*		*0.367*		*0.448*
	Standard deviation	*0.119*		*0.814*		*0.575*

In Table 4-6, the three most susceptible community clusters have been highlighted in grey. Interestingly, all the highly susceptible communities in the Vea area are in the Bongo district. In this study area, Tarongo has the highest susceptibility of 0.693 and Kolgo-Anateem clusters having the least susceptibility. Susceptibility indices in the Dassari area are generally higher with a mean of 0.44 and lower in Dano area with a mean of 0.37. However, there are sharp differences in susceptibility indices in the Vea area measured by the standard deviation of 0.12 while communities in the Dassari area record less variability (0.6) from each other.

4.4.4. Lack of capacity index

Community lack of capacity to cope and adapt to the hazards occurrence is an integral part of the overall vulnerability of the community. Total lack of capacity in this study has been computed from three sub-indices, lack of coping capacity, lack of ecosystem vitality and lack of adaptive capacity to respond to long-term hazards.

Table 4-7: Community rankings in terms of lack of capacity to cope, adapt and ecosystem vitality.

	Vea study area		Dano study area		Dassari study area	
Rank	**Community cluster**	**Lack of capacity (%)**	**Community cluster**	**Lack of capacity (%)**	**Community cluster**	**Lack of capacity (%)**
1	Samboligo	0.614	Loffing-Yabogane	0.600	Tankouri	0.616
2	Apatanga	0.613	Yo	0.586	Firihoun	0.658
3	Soe	0.606	Complan	0.582	Tetonga	0.595
4	Kolgo-Anateem	0.580	Tambalan	0.551	Ouriyori	0.587
5	Balungu	0.544	Batiara	0.524	Pouri	0.564
6	Bongo zone	0.534	Kpeleganie	0.499	Tihoun	0.497
7	Beo Adaboya	0.532	Sarba	0.495	Porga	0.495
8	Vea main drain	0.493	Gnikpiere	0.494	Tigniga	0.481
9	Anafobiisi	0.475	Lare	0.485	Nagassega	0.475
10	Valley zone	0.465	Bolembar	0.482	Koulou	0.449
11	Kanga	0.465	Dano sector 1,2,4	0.478	Dassari	0.438
12	Tarongo	0.422	Dano sector 7	0.432	Setcheniga	0.423
13	Kula river drain	0.399	Meba Pari	0.374		
	Mean	*0.519*		*0.506*		*0.519*
	Standard deviation	*0. 722*		*0.634*		*0.710*

Table 4-7 presents the lack of capacities existing within the three study areas. In the Vea area, Samboligo, Apatanga and Soe, all in the Bongo district are the three clusters with the least capacity to cope, adapt and have poor state of the environment. In Dano, Loffing-Yabogane, Yo and Complan are the top three communities with least capacity whilst Tankouri, Firihuou and Tetonga in Dassari area have the least capacity. In terms of capacity, there is no significant difference between the three study areas with mean lack of capacity. All of them are > 50% with minimal differences in variability. Lack of coping and adaptive capacities are major contributors to the total lack of capacity.

4.4.5. The West Sudanian Community vulnerability index (WESCVI)

Following the three tier-aggregation procedures, the sub-indices of exposure, susceptibility and lack of capacity were combined to develop the composite vulnerability index and mapped in GIS (Figure 4-9). This composite index measures the degree of vulnerability across all community clusters in the study areas. To illustrate the variability of vulnerability across the clusters, five classes of vulnerability have been developed using the Quantile Classification system implemented in ESRI ArcGIS.

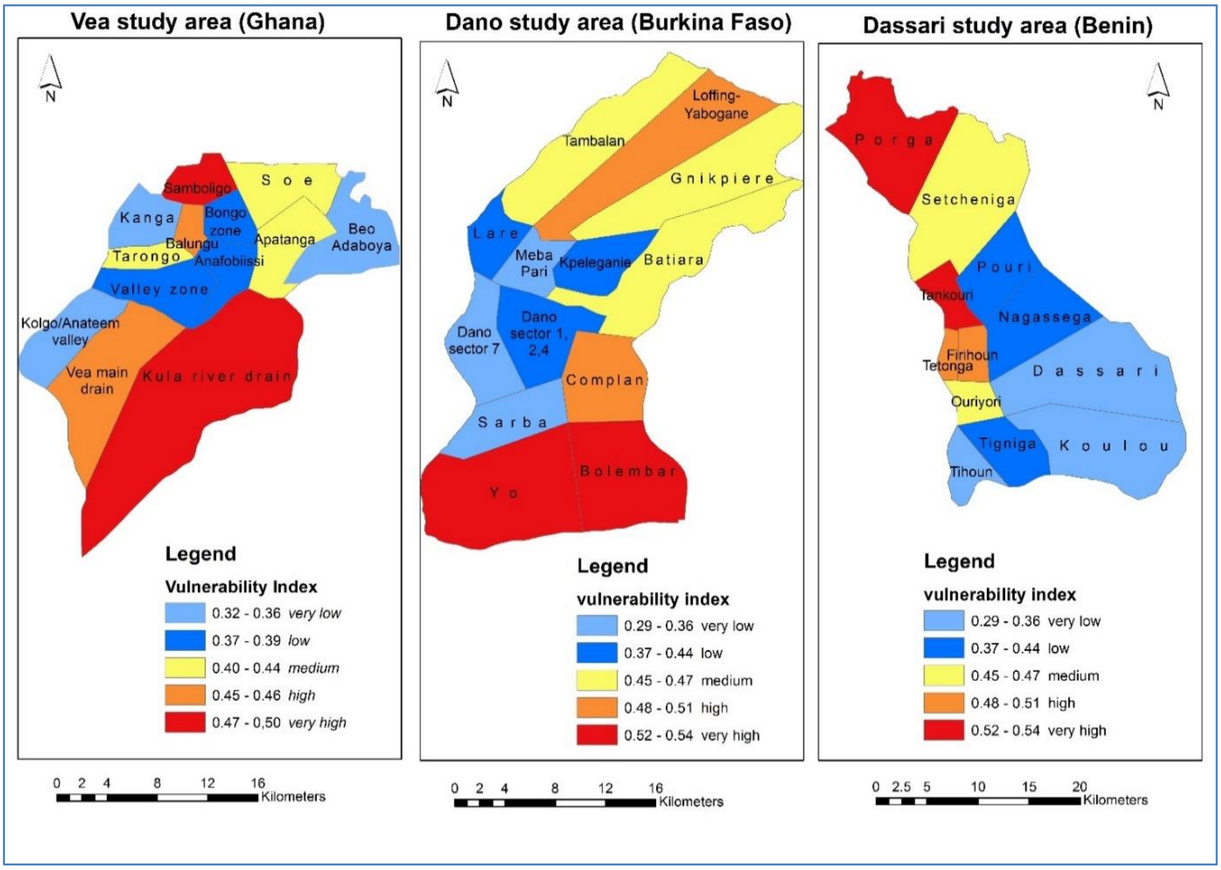

Figure 4-9: The composite community vulnerability index.
Note that the class ranges for the three maps differ because each represents a distinct study area. The vulnerability indices for the study areas are presented together here just to conserve space and they are not intended for comparisons.

Results show that in the Vea study area, the Samboligo community cluster is the most vulnerable area with a vulnerability score of 0.50. It is followed by communities in the Kula River drain (0.478) and Balungu (0.460). In this context, the level of exposure of these communities explains the high vulnerability. For instance, although the Kula River communities have the highest capacity to cope and adapt to changing climate pattern (see Table 4-7) and relatively moderate level of susceptibility, its high level of exposure (Table 4-5) affects its overall vulnerability score. Contrary, in the case of Samboligo, high levels of susceptibility and weakened capacity to cope and adapt make it highly vulnerable even though its exposure to the hazards is significantly lower. Balungu's high vulnerability status results from moderate to high levels score recorded for all three vulnerability components. It has moderate levels of rankings of 4, 3 and 5 out of 13 community clusters for exposure, susceptibility and lack of capacity respectively. This means that in vulnerability analysis, a consistent moderate ranking of an area or system will ultimately put the community or system into a high vulnerability class. In the Vea area, Samboligo emerges as the hotspot of vulnerability due its lowest level of coping capacity, poor adaptive capacity and generally poor state of its ecosystem. It is also highly susceptible to droughts and floods as results of inherent poverty and high dependency ratios, poor housing and lack of infrastructure. The results of the household survey show, that as much as 93% of its inhabitants have poor housing conditions living in primarily mud and thatch houses which are easily damaged by flash floods and torrential rains. On the other hand, the Beo-Adaboya, Kolgo Anateem and Kanga are clusters with the least vulnerable levels. In the Kanga area, moderate levels of susceptibility are mitigated by low exposure (13.4% in Table 4-5), high coping and adaptive capacities and generally robust ecosystems.

In the Dano study area, the hotspots of vulnerability are the Yo, Bolembar and Loffing-Yabogane community clusters. The Yo area remains the highest vulnerable area due its high susceptibility to the hazards and weak capacities. It also has moderate exposure ranking 5 out of 13 clusters. The vulnerability of the Yo communities results mainly from its low levels of coping and adaptive capacities. Only 37% of its inhabitants have adequate local knowledge regarding droughts and floods coping strategies, DRR measures, etc. This coupled with a meagre percentage of households having access to alternate food and income sources (12.5%) and an absolute illiteracy levels makes the Yo area a hotspot of vulnerability in the commune of Dano of Burkina Faso.

In the Dassari study area, Porga, Tankouri and Firihoun are the three top vulnerability hotspots with Tihoun, Dassari and Koulou being the least vulnerable areas. The high level of exposure in the Porga area counteracts its moderate levels of susceptibility and capacity, making it the most vulnerable area in the Dassari arrondissement of Benin. This high exposure results primarily from two indicators, ‘insecure settlement’ and ‘agricultural area in hazard zones’. All the settlements in the area (100%) are located in high flood and drought intensity zones whilst over 33% of their agricultural land is also found in high flood intensity zone. The study found a common destruction of settlements by wild fires due to prolonged drought conditions and flash floods. As much as 90% of all houses are made of mud and thatch and are of poor quality. These houses are hastily constructed after each disaster. These settlements may be inexpensive to build but are more physically vulnerable to hazards such as floods and increase the risk to physical injury to those who live in them (Adger *et al.,* 2004).

4.4.6. Community vulnerability profiles in the West Sudanian Savannah zone

In Figure 4-10 to Figure 4-12, the detail vulnerability profiles of two community clusters each in the Vea, Dano and Dassari study areas are presented and show the main causative factors to vulnerability in the area. In the Vea study area (Figure 4-11), the two community clusters all fall into the high vulnerability index category and a look into the indicators contributing to this high vulnerability class show that both clusters have similar underlying vulnerability profiles. In both cases, exposure is the highest causative factor to total vulnerability, contributing 38.32% in the Kula River drain cluster and 34.66 in the Vea main drain cluster. There are also similar profiles at the sub-component level, exposure in both clusters are more influenced by agriculture area in hazard zones, ADP and insecure farms whilst Alternate Food and Income Sources (AFIS) is the main cause of communities’ lack of capacity. However, the Dano community clusters present different vulnerability profile scenarios. Although both clusters, Sarba and Meba Pari fall in a low vulnerability category, their vulnerability profiles are markedly different from each other. Exposure contributes far less to risk (24.4%) in the Sarba area and far more to vulnerability in the Dano Meba Pari (34.81%). Whist three indicators, Dry Season Duration (DSD), Caloric Intake per Capita (CIPC) and housing are the main drivers of susceptibility in the Sarba cluster, only CIPC and population density have a significant contribution to susceptibility in the Meba Pari cluster.

These result show that different communities can be in the same vulnerability category but the underlying factors defining their vulnerability and subsequently their risk levels can be fundamentally different from each other. It's therefore incumbent on policy makers and practitioners to understand the detail causative factors of vulnerability so as to deploy interventions that effectively targets the principal factors affecting vulnerability in a given area.

Maximum vulnerability level for all community clusters studied is in the Yo area of Dano whilst the Meba Pari cluster of communities has the least vulnerability levels. Also, communities in the Kula River drain registered significant high vulnerability level of 40.30%.

The statistically significant vulnerability risk faced by people in the Dano area results from poor socio-economic systems, high exposure to droughts and rainstorms. The household survey found several cases of collapsed buildings due to flash floods and generally poor living standards as evident in the high vulnerability scores estimated.

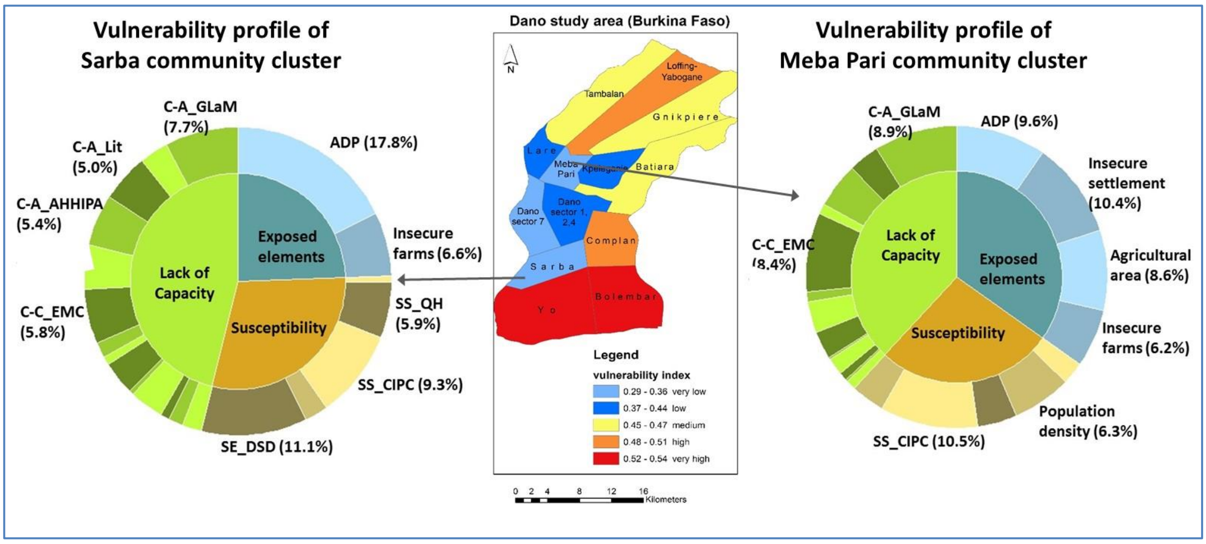

Figure 4-10: Detail vulnerability profiles of two community clusters in the Dano study area.

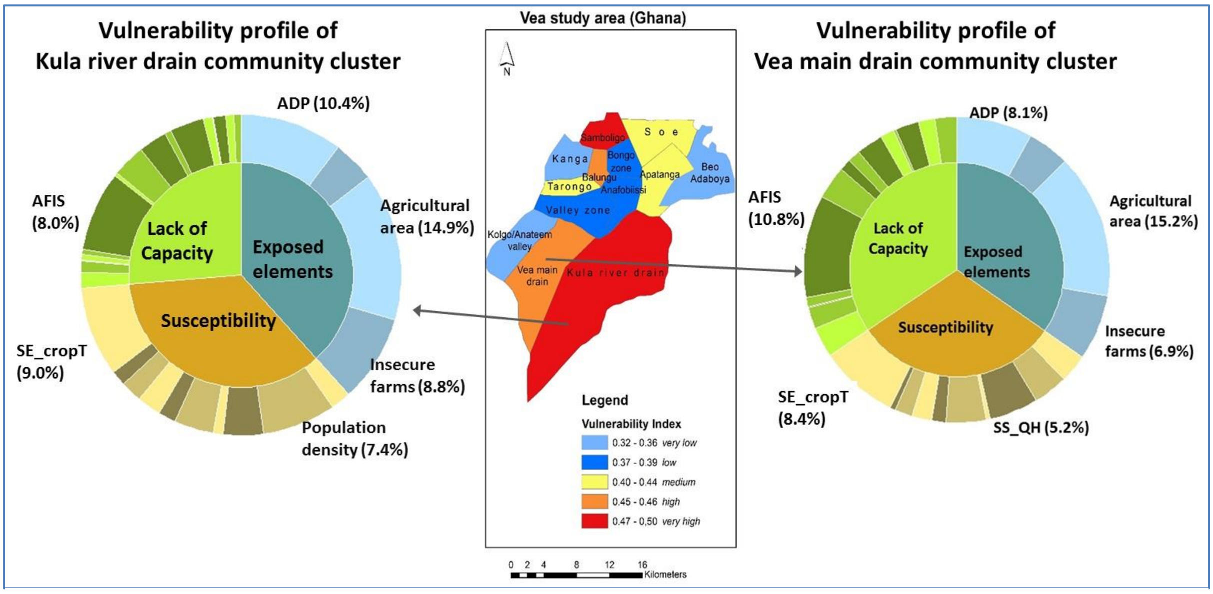

Figure 4-11: Detail vulnerability profiles of two community clusters in the Vea study area.

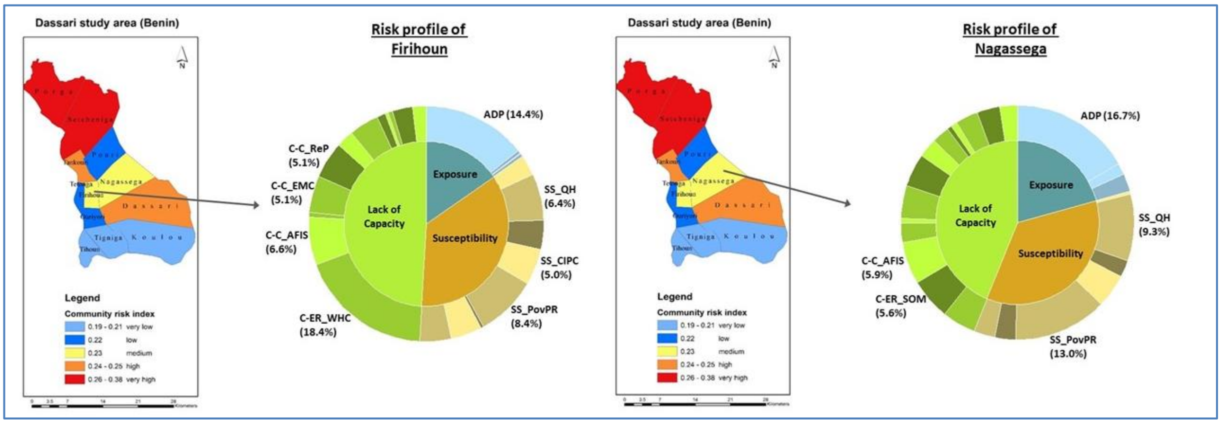

Figure 4-12: Detail vulnerability profiles of two community clusters in the Dassari study area.
In these figures, two levels of factors contributing to final community vulnerability level are presented. The first is the three major components of vulnerability, which are exposure, susceptibility and lack of capacity. The second level shows the relative contribution of each indicator to first, the sub-component such as exposure and then to final vulnerability. Only indicators contributing to more than 5% of the vulnerability risk are shown. Major contributory factors to vulnerability are: AFIS = Access to Alternative Food and Income Sources; SE-CropT = Crop type or the proxy of crop diversification practices; ADP = Agricultural Dependent Population; SS-QH = Quality of Housing; SE-DSD = Length of Dry Season Duration; CC-EMC = presence of Emergency Management Committee; C-A AHHIPA = Annual household income; CA-Lit= Literacy levels of adult population above age 15; CA-GLaM = Good leadership and Management at the community level and CIPC= Caloric Intake per Capita, C-ER SOM= soil organic matter; SS-PovPR = prevalence of poverty.

4.4.7. Risk indices from multiple hazards

By combining the vulnerability and the multi-hazard indices through the arithmetic multiplicative function in GIS (Equation 4-2**Error! Reference source not found.** implementation), the multi-risk indices of all communities in the study area were developed. This multi-risk index represents the combined effect of the occurrence of multiple hazards and their interaction with vulnerable SES. It measures the extent to which households within the communities will be impacted by floods, droughts and a combination of them. In Figure 4-13, the results of the West Sudanian Community Risk Index (WESCRI) are presented and show contrasting levels of risk among community clusters.

In the Vea study area, the Kula River drain and Vea Main drain remain the hotspot of risk to droughts and floods. Communities in these areas are characterized by high exposure to floods and droughts and at the same time have the highest levels of vulnerability. The study shows the strong effect of exposure to overall risk faced by a community. This is evident from the relatively good scores recorded by the two clusters in the vulnerability sub-components of susceptibility and capacity to cope, adapt and state of ecosystem.

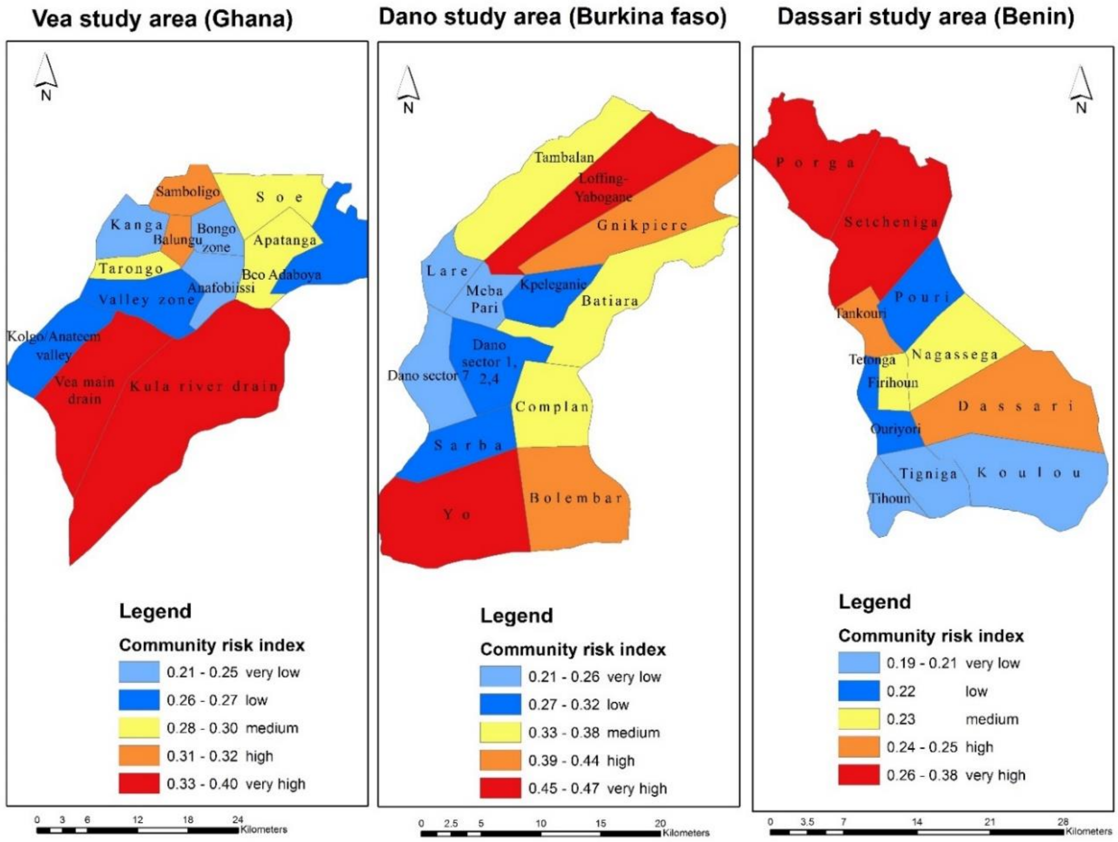

Figure 4-13: The West Sudanian Community Risk Index (WESCRI) in the study areas.
***Following the approach in the WorldRiskIndex (Beck et al., 2012, Birkmann et al., 2011). The risk indices have been translated into five qualitative classification schemes of very high (5), high (4), medium (3), low (2) and very low (1). Classification algorithm employed is the Quantile method*.**

Kula River drain in particular has the highest capacity in the Vea area, yet it has the highest vulnerability and subsequently is amongst the high-risk areas due primarily to its exposure to floods and droughts. This means that an area will still be classified as having significantly high multiple risk levels when unusually high exposure levels are combined with moderate levels of susceptibility, no matter how strong its capacity to cope and adapt to the hazards might be. The reverse is also true. However, poor state of inherent conditions and lack of capacity could still place an area in high risk zone although its exposure to the hazards is low. This is the case of Samboligo where its low exposure index of 0.297 could not mitigate the high negative scores in susceptibility (0.594) and lack of capacity (0.614). Balungu cluster of communities shows reverse situation where elevated levels of vulnerability (Figure 4-9) are mitigated by very low levels of multiple hazards occurrence.

In the Dano study area, Yo, Loffing-Yabogane as well as Bolember and Gnipiere are the hotspots of risk. These areas also are the hotspots of vulnerability. However, in the Complan community cluster, vulnerability is comparatively lower because of low levels of multiple hazards occurrences pushing the communities in the area into a medium risk class. The high levels of risk in these community clusters are due to underlying poor socio-economic conditions. Only 37% of its inhabitants have adequate local knowledge regarding droughts and floods coping strategies, DRR measures etc. This coupled with a meagre percentage having access to alternate food and income sources (12.5%) and an absolute illiteracy level in most clusters (100%) makes the area a hotspot of vulnerability and risk.

In the Dassari study area, Porga, Sétchindiga followed by Dassari and Tankouri are the risk hotspots. The medium vulnerability profile of Sétchindiga was not enough to mitigate the effects of high multiple hazards occurrence and, as can be seen in Figure 4-9, pushes the communities in the area to high risk levels. Similarly, Dassari has a significant lower level of vulnerability (Figure 4-9); yet high occurrence of multiple hazards eventually increases its overall risk to droughts and floods.

4.4.8. Results and discussion of the CIS validation concept

The CIS estimated above was compared with the simulated risk index to determine the robustness of modelling procedures. In the Vea study area, the RMSE was estimated relatively low at 0.29, r^2 was found to be 0.45 whilst the NSE index was estimated at -0.04. In the Dano study, RMSE was found to be 0.29, r^2 was estimated at 0.76 and NSE index was -0.05. These results present an interesting dimension to the validation of complex aggregation models. Although the RMSE was a bit higher for both studies, the multi-risk model closely approximates the observed impacts of the hazards. In the Dano study area, as much as 76% of the variance in observed impact of hazards was explained by the risk model whilst 45% of the variability in observed hazard impact in Vea study area was explained by the multi-risk modelling procedures (Figure 4-14). These levels of variance are considered relatively high against the background of uncertainties associated with the observed impact data. The impact data as recounted by at risk populations were derived from memory and there were no systematically documented records of the impacts of the hazards. Most of the respondents were able to recount only the high intensity or magnitudes of the hazards and small impacts events were generally not recalled. In the Dassari study area, the responses were found to be highly inconsistent and were subsequently discarded. Therefore, no validation based on reported impacts was possible. Figure 4-14 shows the strong linear relationship between the observed disaster impact and the modelled output of multi-risk index. As can be seen from this graphic, despite the difficulties in recounting disaster impacts from memory, communities with high simulated disaster risk generally follows areas with high observed disaster impacts. This shows the robustness of the vulnerability and risk models in predicting high and low risk areas in the study areas.

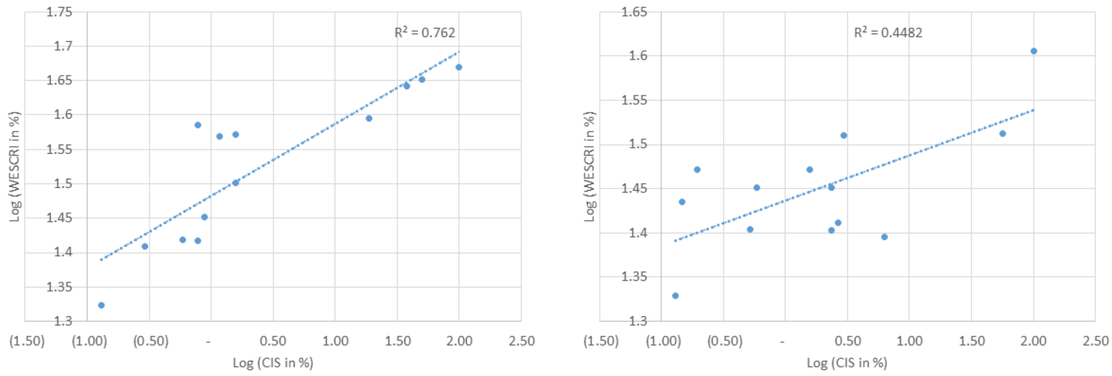

Figure 4-14: Relationship between simulated risk index and observed disaster impacts.
Left chart represents the Vea study area with the trendline, LogWESCRI = 0.1045*LogCIS+1.4828.
The right chart shows the Dano study area with the trendline, LogWESCRI = 0.0511*LogCIS + 1.4367.

Moreover, the NSE indices for both study areas closely approximate positives. Although the NSE indices are relatively lower than those achieved in other studies such as in Walz (2014) which recorded only positive values of NSE for disease risk suitability studies in Burkina Faso, yet the close to positive values obtained in this study means that in predicting high and low disaster risk areas, the approach presented in this study will yield accurate results than simply averaging the observed impact data and using that to represent the risk indices for all communities in question.

4.4.9. Results of the sensitivity analysis

In this study, six scenarios based on observed relationship between the input variables (indicators) and the vulnerability composite have been carried out to understand which inputs account more to a community's vulnerability profile.

Table 4-8: Mean volatility between 6 different vulnerability scenarios.

	Scenario	Mean volatility		
		Vea	Dano	Dassari
1	Equal weights of all indicators	0.050	0.071	0.048
2	Excluding Agricultural Dependent population	0.046	0.075	0.036
3	Excluding insecure settlement, population density, Soil organic carbon (Basfonds for Dano), Ability to survive crisis (alternate food % income source for Dano) and access to extension	0.049	0.051	0.036
4	Increased Agricultural Dependent population by 10%	0.056	0.074	0.043
5	A. Increased by 10% Agriculture area, population density, Caloric Intake per Capita and B. decrease by 10% SOC (Bas fonds in Dano & Dassari) and annual household income	0.057	0.076	0.043
6	Excluding number of dependents (Dano & Dassari, Vea) and distance to market (Vea)	0.047	0.066	0.039
	Minimum	0.046	0.051	0.036
	Maximum	0.057	0.076	0.048

Table 4-8 presents the mean volatility of the six different scenarios compared to the original vulnerability estimations. In accordance with Damm (2010), OECD (2008) and Groh *et al.* (2007), volatility is measured by the standard deviation of community vulnerability index across all community clusters in each study area. In the Vea study area, volatility ranges from 0.046 to 0.057. Overall, the mean volatilities for all three study areas are found to be very low indicating that the sensitivity of the composite vulnerability index to the varied or excluded indicator is negligibly low. This means the aggregation technique introduced, the weighting system applied as well as the modelling procedure followed resulted in robust estimates and that the final indices are largely unaffected by changes in single indicators.

4.4.10. Conclusion

The aim of this study was to carry out a multi-hazard risk assessment in a bottom-up participatory process at the community level to derive community vulnerability profiles in marked departure from the classical top-down, large scale approaches. The study also aims to develop a new concept for quantitative validation of risk assessment and followed the perspectives of a coupled SES rather than single-hazard-decoupled risk assessments. The study used three sets of indicators from three case studies that have been verified by at risk population as highly relevant for multiple hazard risk assessment in their respective communities. The study sought to develop approaches that could support practitioners and policy makers by informing them about vulnerability and risk profiles at the community level. A key motivation for this study was to identify high risk communities by mapping risk hotspots in the study areas.

The study found that community's exposure to the multiple hazards follow the same pattern of flood hazard intensity and as expected exposure is logically a key determinant of vulnerability. Although, there are other determinants of exposure, the study found the strong effects proximity to hazards has on an SES overall exposure to droughts and floods. Besides this proximity effect, a major driving factor influencing community exposure is the indicator measuring the share of the population engaged in agriculture. This finding confirms the assertions by Adger *et al*. (2004) and O'Brien *et al*. (2004) that high Agricultural Dependent Population (ADP) means that a higher percentage of people are exposed to a climate sensitive sector of agriculture. In the study areas, rain-fed agriculture predominates further aggravating people's exposure to irregular rainfall. High ADP suggest lack of other employment options and therefore in the event of crop failures, farmers and their dependents have few opportunities to earn additional income (Adger *et al*. 2004, O'Brien *et al*. 2004).

The study found that an area will still be classified as having significantly high-risk levels when unusually high exposure levels are combined with moderate levels of susceptibility, no matter how strong its capacity to cope and adapt to the hazards might be. The reverse is also true. However, poor state of inherent conditions and lack of total capacity could still place an area in elevated risk zone although its exposure to the hazards is low.

Using five-year historical impact data collected from at risk populations, a novel technique was introduced to validate the underlying models and assumptions used to construct the vulnerability profiles. The concept of Community Impact Score (CIS) was thus introduced and measures the cumulative impact of multiple hazard occurrences in the study areas. Three statistical validation models were used to assess how well the risk model approximate actual disaster impacts. Against the background of large uncertainties associated with the observed impact data, this study found relatively high levels of variance explained, 76% for the Dano study area and 45% for the Vea study area.

The study also employed local sensitivity analysis to reveal complementary information that may have significant impact on the overall vulnerability of the communities. Six scenarios based on the observed relationship between the input variables (indicators) and the vulnerability composite were implemented to understand which inputs account more to a community's vulnerability profile. The results show that the mean volatilities for all three study areas were very low indicating that the sensitivity of the composite indicator is relevant for policy makers and could allow them to understand the variables which when intervened could affect vulnerability index. For instance, the vulnerability profiles shown in Figure 4-10 to Figure 4-12 showed that varying agricultural areas in hazard zones in two community clusters (Kula river drain and Vea main drain) will have significant effect in the level of vulnerability and overall risk faced by the SES in those areas. Policy makers could therefore implement interventions aimed at reducing cropland areas in high hazard zones.

In an attempt to deal with the on-going scientific debate on whether to include the exposure component in vulnerability assessment, this study provided an alternative approach where the degrees of exposure of elements in the SES (spatial dimension of exposure) are considered as contributing to the SES total vulnerability, rather than using the SES's general exposure as part of vulnerability or rather than excluding the exposure term altogether. This procedure therefore eliminates a key drawback of the summation conceptualization of vulnerability which could place a community in a high vulnerability class although its exposure may be zero. To counter this effect, indicators that indirectly measure exposure such as Agricultural Dependent Population were used to describe the exposed elements to the hazards. The point is that, in reality, people are still vulnerable even though they may not be exposed to any hazard due to inherent and depressed socio-economic conditions. This phenomenon is very common in the study areas where existing socio-economic conditions in most cases is very dire and leaves people vulnerable even though there are no obvious physical exposure. In the final risk assessment, however, where there's no hazard, risk will be zero even though Vulnerability could be high. This is the upside of the multiplicative effect which was finally used to estimate the risk index. This area of risk assessment where a system could be still be vulnerable even though there may not be obvious linkages to physical hazards requires further studies.

The study provides a framework for conducting risk assessment for multiple cultural and social contexts spanning three countries using indicators developed from a bottom-up participatory process. Unlike risk assessment from classical approaches, the differential risks from these three study areas therefore uniquely represents actual risks faced by its SES as identified by the at-risk populations. At the same time, the study sets the pathway for conducting risk assessment using a unified indicator set if so desired by practitioners or policy makers. The details of this framework are presented in Table 4-4. It must be noted however that, practitioners or policy makers desiring to conduct multiple hazard risk assessment based on the methodologies presented in this study need to have several scientific competencies to be able to follow all the approaches outlined here.

The validation procedure has shown the relative robustness of the models in predicting low and high-risk areas despite the uncertainties in the validation dataset. The present study helps to provide a better understanding of the risks and vulnerabilities of rural communities in three West African countries as well as the differential impacts of climatic hazards in the communities studied. Studying risk and vulnerability profiles of rural communities also provides an insight on how to situate vulnerability, risk and climate change adaptation efforts within the context of the community's sustainable development agenda and can help to develop appropriate, inclusive and well-integrated mitigation and adaptation plans at the local level. To cope with climate change and achieve poverty reduction, it is essential to pursue actions at sector and community levels (Armah *et al.* 2011) and we believe the present study contributes greatly to efforts in this direction. Another key output is development of comprehensive methods allowing practitioners to conduct similar community level assessment and to continue to update the vulnerability profiles. Generally, vulnerability and risk assessment are rarely verified against impact data. This is because such impact data are rarely available in the level of detail and/or spatial scale required. We attempted here to validate the computed risks by introducing the novel and pioneering concept of CIS which remains improvable but can allow for a first estimation of the validity of risk indices in global scientific studies of risk assessment under climate change context.

4.4.11. Appendix 1: Variables used to construct the Community Impact Score

Community cluster	Study area	P-droughts	P-floods	P-multi	Human loss	Housing	Eco-value	cropland	livestock	impact score
Anafobiisi	Vea	100.00	92.86	40.00	-	30.00	10,541.00	88.50	323.00	1,536.00
Apatanga	Vea	100.00	50.00	42.86	2.00	11.00	8,420.00	78.00	81.00	384.00
Balungu	Vea	100.00	20.00	50.00	-	43.00	4,050.00	102.00	47.00	48.00
Beo Adaboya	Vea	100.00	93.33	30.00	2.00	24.00	9,430.00	58.00	31.00	128.00
Bongo zone	Vea	100.00	82.35	52.94	-	15.00	32,949.00	110.50	159.00	576.00
Kanga	Vea	100.00	20.00	20.00	1.00	25.00	15,728.00	51.00	51.00	32.00
Kolgo-Anateem	Vea	100.00	6.00	60.00	4.00	80.00	20,110.00	25.00	141.00	648.00
Kula river drain	Vea	100.00	100.00	87.10	6.00	120.00	10,499.00	129.75	200.00	24,576.00
Samboligo	Vea	93.33	80.00	60.00	4.00	86.00	2,050.00	85.00	12.00	729.00
Soe	Vea	100.00	6.67	60.00	-	118.00	25,951.00	58.50	91.00	576.00
Tarongo	Vea	92.86	40.00	28.57	-	75.00	7,891.00	51.50	134.00	144.00
Valley zone	Vea	84.62	76.92	53.85	-	25.00	11,040.00	57.50	52.00	36.00
Vea main drain	Vea	100.00	100.00	80.00	3.00	104.00	9,399.00	85.00	225.00	13,824.00
Batiara	Dano	71.43	100.00	57.14	-	17.00	278,571.43	13.00	-	96.00
Bolembar	Dano	90.00	100.00	78.00	-	27.00	353,125.00	59.00	34.00	4,608.00
Complan	Dano	62.50	75.00	25.00	-	18.00	308,333.33	44.00	35.00	144.00
Dano sector 1,2,4	Dano	100.00	83.33	41.67	-	13.00	379,166.92	20.00	4.00	192.00
Dano sector 7	Dano	92.86	100.00	33.00	1.00	10.00	83,923.08	16.00	12.00	96.00
Gnikpiere	Dano	83.33	100.00	78.00	-	24.00	150,000.00	66.80	37.00	2,304.00

Kpeleganie	Dano	90.00	80.00	60.00	-	17.00	150,000.00	16.50	13.00	108.00
Lare	Dano	90.00	66.00	40.00	-	3.00	150,000.00	47.50	10.00	36.00
Meba Pari	Dano	100.00	60.00	33.00	-	8.00	148,285.71	9.75	12.00	16.00
Sarba	Dano	80.00	80.00	80.00	3.00	6.00	172,500.00	9.00	1.00	72.00
Tambalan	Dano	100.00	100.00	66.67	-	12.00	185,000.00	16.00	11.00	192.00
Loffing-Yabogane	Dano	95.00	80.00	100.00	-	27.00	275,000.00	59.50	31.00	6,144.00
Yo	Dano	100.00	100.00	100.00	1.00	22.00	1,115,875.00	35.40	32.00	12,288.00
N=26										

4.4.12. Appendix 2: Construction of indicator data values and data sources

Vulnerability Component: Exposure			
Indicator: rank & applicable study area	**Definition and Measuring unit**	**Indicator construction and limitation of indicator**	**Data source**
Agricultural dependent population Vea 1/3[14]; Dano 2/2 and Dassari ½	The percentage of the area's total population depending on only agriculture related employment (including hunting, fishing and forestry). The number of people with only agriculture as their source of livelihood was divided by the total number of sampled households and scaled from 0 to 1	The survey instrument sought to know if the respondents are engaged in only agricultural activities and has no other source of livelihood. This indicator is valid as several experts believe it gives a better description of people depending on agriculture (Adger 2004).	Own household survey
Insecure settlement: Vea 3/3; Dano 1/2 and Dassari 2/2	Percentage of communities within the cluster which are located in high hazard intensity zones.	Using the flood hazard intensity map developed by Asare-Kyei *et al.* (2015b), in GIS environment, the very high and high intensity flood zones were considered. The process begun by intersecting the three vector layers, the flood index map, land cover and slope to determine land cover types under two intensity zones. After intersecting, a new field is added and area in hectares was calculated. The community cluster maps were used to clip the intersected features to allow for community level analysis. Then the total area occupied by each community cluster was estimated using the summarize tool in ArcGIS. Then,	Asare-Kyei *et al.* *(2015b)*

[14] These numbers represent the rank of the indicator within the vulnerability sub-component. In this case, Agricultural dependent population is ranked as the first out of three indicators in the Vea study area.

		the flood intensity zone field was sorted in descending order and the very high and high zones were selected. The summarized tool was again used to calculate the area of the respective land covers that fall in the two hazard intensity zones.	
Physical infrastructure Vea 2/3	Number of physical infrastructure in an area. Such as irrigation dams, hospitals, schools, food markets and major bridges located in floodplains	Physical infrastructure was estimated using road network map of Ghana. Each community cluster was used to extract the very high and high areas of the flood intensity map and then also the road network map. The clipped flood intensity map and road network map were intersected in GIS to determine the percentage of the road network in a community cluster that falls within the two high flood intensity zones. Lack of local level data means only road network could be used to describe the physical infrastructure located in flood plains.	Results from chapter 3 *and Road network map from Ghana base maps*
Insecure Farms Vea 3/3; Dano 2/2	Percentage of cropland within the community cluster located in slopes of more than 5%.	Retrieval of data values for these indicators follow the approach used to construct the data values for the indicator “Insecure settlement” describe above.	From 30m spatial resolution Global Digital Elevation Model developed jointly by the Japanese Ministry of Economy, Trade and Industry (METI) and the United States National Aeronautics and Space Administration (NASA).

Agricultural Area Vea 1/3; Dano 1/2; Dassari 2/2	Percent of total land used for agricultural activities in an area located in flood plain. This includes arable land and pastures in flood plains		LULC maps for the three study areas were generated by classifying high spatial resolution (5m) multi-temporal RapidEye images developed by (Forkuor et al., 2014). Flood map from Asare-Kyei *et al*. (2015b).
Protected Area Vea 2/3; Dassari ½	Percent of area of land that are protected including national parks, forest reserves, watersheds etc. located in flood plains		Same as above

Vulnerability Component: Susceptibility of social system			
Indicator:	**Definition and Measuring unit**	**Indicator construction and Validity/limitation of indicator**	**Data Source**
Number of dependents : Vea 1/10, Dano, 4/7	Average number of household members below the age 15 and above the age of 65.	This is retrieved from household survey data where the number of household members below the age of 15 and above 65 years were added and divided by the total number of households sampled in a community cluster. High number of dependents population per household denotes high vulnerability as such individuals rely on family members or social services for financial services and other support.	From own household survey
Population density: Vea 2/10, Dano 7/7, Dassari 8/8	This is the number of people per square kilometer in the inhabited area of the study areas. In Dano and Dassari study areas, the original indicator, Demographic pressure was replaced with the population density. High population density increases vulnerability.	Population density data at 100m resolution estimated in 2013 for the year 2015 was retrieved. The data has been adjusted for UN national population estimates. This data was extracted as ESRI shapefile and overlaid on the community cluster maps. Geoprocessing techniques were used to estimate average population density per community cluster.	Secondary data from Africa Population database (AFRIPOP) was used. Details about can be found at: http://www.worldpop.org.uk/data/summary/?contselect=Africa&countselect=Ghana&typeselect=Population
Quality of Housing: Vea 3/10, Dano 5/7, Dassari 5/8	Percentage of households within a cluster living in houses prone to flood damage and or bushfires. Higher percentage increases vulnerability.	This is also termed percent of poor housing. Poor housing includes mud and thatch with no concrete and proper roofing system. The percentage of people living in mud and thatch house or mud with aluminum roofing sheets was computed.	From own household survey data

Distance to water: Vea 4/10	Percentage of total households within a community cluster that travel more than 30 minutes for drinking water. Higher percentage increases vulnerability.	Respondents were asked about the time spent in getting to the nearest water source.	From own household survey data
Distance to food market: Vea 5/10, Dassari 7/8	Percentage of households within a community cluster that travels for more than 30 minutes to reach the nearest food market. High percentage increases vulnerability.	Respondents were asked about the time spent in getting to the nearest food market to either sell farm produce or buy foodstuffs.	From own household survey data
Prevalence of stunted children: Vea 7/10	Percent of children under 5 in a community cluster who are stunted (have low height for their ages). Higher percentage denotes higher vulnerability.	The USAID METSS project conducted a Population Based Survey (PBS) of key socio-economic variables. The data is available at the district scale and was thus downscaled to the community clusters. Prevalence of poverty was assumed to directly affect stunting and therefore poverty scores in the clusters were used as weighting factors to derive stunting values from the district stunting data.	From secondary data, which has been collected by United States Agency for International Development (USAID) funded METSS project in Ghana

Caloric intake per Capita: Vea 8/10, Dano 2/7, Dassari 4/8	The dietary energy consumption per person is the amount of food, in kcal per day, for each individual in the total population. The study couldn't directly measure this indicator in the field and so Household food insecurity was used as a proxy. High percentage denotes higher vulnerability	Following the approach of World Food Program (WFP, 2012), household food insecurity is measured as a percentage of households classified as severely food insecure and moderately food insecure. Using non-food income, total crop production from all crops produced by the household and Tropical Livestock Unit (TLU), each of these variables were ranked and divided into quintiles (5 equal parts). The scores were subsequently multiplied and the final total score divided into 4 parts. This means the households have been classified into 4 food security levels. Households with severe and moderate food insecurity were computed for each cluster (WFP, 2012).	Data source for estimating household food insecurity is from own household survey.
Female headed households : Vea 10/10	Percentage of total households in a community cluster that is headed by a female. High percentage denotes high vulnerability.	Respondents were simply asked to indicate the head of the household by sex.	From own Household survey data
Prevalence of poverty: Vea 9/10, Dassari 1/8	Percentage of households living below the national absolute poverty line. High percentage increases vulnerability.	Household equivalent scale was used as weighting factor for household size. Then all income sources including non-farm income and farm income were added. Absolute national poverty line estimated by Ghana Statistical Service (GSS) in 2014 as Ghc3.6/person per day was used for the Vea study and national absolute poverty line in Benin estimated in 2003 ass FCFA82, 672 was used for the Dassari study area. The percentages of poverty levels in Dassari are relatively low probably because the national poverty line is outdated.	Household survey data
Household size: Dano 3/7	Average number of total household members in a community cluster	From household survey data. Respondents were asked to indicate the total number of people in the household.	From own Household survey data

Vulnerability Component: Susceptibility of ecological sub-system			
Indicator:	**Definition and Measuring unit**	**Indicator construction and limitation of indicator**	**Data sources**
Degraded areas: Vea 1/2, Dano 1/3, Dassari 1/4	Percentage of land in the community cluster that is degraded or deserted.	The land degradation classes 'map shows the complete status in provision of biophysical ecosystem services and the processes of declining biophysical ecosystem services by considering the combined value of each biophysical axis' (FAO LADA). The land degradation dataset in Geotiff format was imported into ArcGIS for analysis. Of the eight classes listed in the GLADIS database, five were used to compute the percent degraded area per community cluster. These classes are: a) low status, medium to strong b) high status, medium to strong c) low status, weak degradation d) low status improving and e) Bare lands. A key limitation of the datasets is its spatial resolution. At a spatial resolution of 9km, the dataset is not ideal for local scale assessment but no better dataset could be found.	Data was obtained from FAO LADA project hosted at the Global Land Degradation Information System (GLADIS) database. For details see LADA (2011), http://www.fao.org/nr/lada/gladis/glad_ind/

Runoff rates: Dano 2/3, Dassari 3/4	Surface runoff measured in mm/hour is the flow of water that occurs when the soil is infiltrated to full capacity and excess water from rain flows over the land. Higher runoff increases vulnerability of ecological system.	Runoff was estimated by applying the rational model integrated with remote sensing and GIS techniques	Data source from Asare-Kyei *et al*. (2015b).
Crop type: Vea 2/2	This indicator was originally defined in Asare-Kyei et al (2015a) as percent of community cluster under cultivation of drought and flood sensitive crops. However, this was difficult to operationalize and hence the variable "lack of crop diversification" was used as a proxy. Higher percentage increases vulnerability.	Lack of crop diversification measures the percentage of households in a community cluster having three or less different crops under cultivation in any farming season. This was estimated by counting the number of different farm plots of different crops cultivated by sampled farmers and deriving the average per cluster. Relationship between crop diversification and adaptive capacity/vulnerability can be found in (Tarleton, M., & Ramsey, D. 2008; Ngigi 2009).	From own household survey

Dry season duration: Dano 3/3, Dassari 4/4	The average duration in days of the dry season over the last decade. This was operationalized by using the frequency of irregular rainfall events. Higher occurrence or irregular rainfall events increases vulnerability.	This was operationalized with the frequency of irregular rainfall recorded over the period, obtained from household surveys. Responses were converted to categorical variable as follows: a) 6 represents irregular rainfall event every year b) 5 represents irregular rainfall occurrence once every two years c) 4 is once in three years irregular rainfall d) 3 is once in four years irregular rainfall e) 2 is once in five years and f) 1 represents once in more than 5 years. This sort of measures of the return period of drought events -	From own household survey
Erosion rates: Dassari 2/4	Amount of water erosion recorded in each community cluster measured in tons/ha/year. High erosion rates increase vulnerability	This dataset was retrieved from FAO LADA project database (GLADIS) as described above.	Data was obtained from FAO LADA project hosted at the Global Land Degradation Information System (GLADIS) database. For details see LADA (2011), http://www.fao.org/nr/lada/gladis/glad_ind/

Vulnerability Component: Capacity, ecosystem robustness			
Indicator:	**Definition and Measuring unit**	**Indicator construction and /limitation of indicator**	**Data source**
Soil Organic Matter (SOM): Vea 1/5, Dano 4/8, Dassari 1/6	The amount of Soil Organic Carbon held per unit area of land per year. Soil organic carbon content (fine earth fraction) in 2.5cm (mean estimate) depth (topsoil) was used. Higher SOM levels decreases vulnerability.	SoilGrids1km provides a collection of updatable soil property and class maps of the world at a relatively coarse resolution of 1 km. This data is derived from state-of-the-art model-based on statistical techniques including “3D regression with splines for continuous soil properties and multinomial logistic regression for soil classes”. In this study, the SOM was sub-setted and extracted into GIS and the areas of the various community clusters were intersected to determine the average amount of SOM per square km in each cluster. This dataset has a limitation of limited spatial accuracy and contain artefacts and missing pixels. However, they presented the best options of readily accessible data in this category in the study areas. For details see ISRIC (2013).	This data was obtained from SoilGrids1km which is a global soil data product generated at ISRIC - World Soil Information (http://soilgrids1km.isric.org).
Water holding capacity: Vea 4/5, Dano 7/8, Dassari 3/6	This is the amount of 'Water in Millimeters stored in or at the land surface and available for evapotranspiration' (IPCC, 2012). High water capacity reduces vulnerability.	Available water capacity from regridded HWSD is used here. Categorical values use is indicated below: a) 7 = 150mm b) 6 = 125mm c) 5 = 100mm d) 4 = 75mm e) 3 = 50mm f) 2 = 15mm g) 1 = 0mm	Data taken from rigridded Harmonized World Soil Database (HWSD) (FAO, 2009)
Bas Fonds: Dano 1/8	The number of reservoirs and water bodies (bas-fonds) located in the study area. Operational definition adopted here is the percentage of the cluster's total area suitable for bas-fonds management. Higher percentage reduces vulnerability.	This is derived from International Water Management Institute (IWMI) bas fonds management suitability maps, Category one on the map representing areas highly suitable for bas fonds management was extracted and used. This is expressed as a percentage of the total land area within the cluster that are described as highly suitable for bas fonds management.	Details about this are found at FAO (2012).

Infiltration rate: Vea 2/5, Dano 6/8	The rate measured in Millimeters per hour at which soil absorbs rainfall or irrigation water. This indicator could not be measured in the field due to time constrains and a proxy, Drainage class was used. High drainage class values denote reduced vulnerability.	The study used Drainage class as proxy. This is a 1km resolution soil map from the Harmonized World Soil Database (HWSD) version 1.1 produced in 2009 by the International Institute for Applied System Analysis (IIASA). The HWSD is an image file linked to a comprehensive attribute database in Microsoft Access. This attribute information includes soil mapping units, soil texture for top and sub soils and several other soil properties including Drainage. There are 7 drainage classes in this database. In this study, the 7 classes were converted to categorical values as follows: a) very poor, excessive = 1 b) poor = 2 c) Imperfectly, somewhat excessive = 3 d) moderately well = 4 e) well = 5 Details about this database can be found in FAO (2009).	This is a 1km resolution soil map from the Harmonized World Soil Database (HWSD) version 1.1 produced in 2009 by the International Institute for Applied System Analysis (IIASA).
Green Vegetation Cover (GVC): Vea 5/5, Dano 8/8	Fractional cover of green vegetation during the dry season. Higher GVC reduces vulnerability.	Green Vegetation was computed from 1 km MODIS-based Maximum Green Vegetation Fraction. These data describe annual maximum green vegetation fraction (MGVF), and are based on 12 years (2001-2012) of Collections of 5 MOD13A2 Normalized Difference Vegetation Index (NDVI) data. The data is based on the annual maximum NDVI and linear mixing models that describe green vegetation fraction (vs. non-vegetated area) for each land cover class for each year. Generation of these data is described in Broxton et al., 2014b. The data has been re-gridded from the MODIS sinusoidal grid to a regular latitude-longitude grid. Details at: Broxton *et al*. (2014). Average GVC for each community cluster was computed with geostatistical techniques in GIS.	Details at: Broxton *et al*. (2014).

Groundwater level (GWL): Vea 3/5, Dassari 6/6	Average level at which most boreholes in the area reaches water. This is measured in meters below ground level. Lower GWL denotes reduced vulnerability	The WRI conducted Hydro-geological Assessment Project to monitor the water levels of 37 observation boreholes throughout the three northern regions since 2005. Using the mean water level in cm recorded between 2005 and 2011, the 37 observation points were interpolated with Kriging method in GIS to obtain data for all community clusters. To follow the general trend of data in this vulnerability sub-component, the GWL data have to be ranked. Ranking was done by sorting the GWL data in descending order. The area with the highest GWL was given a lowest value of 1 and the area with the lowest GWL was given a highest value of 13. This is based on theoretical understanding that areas with lower groundwater levels offer more water access to communities in times of climate change and these will have more capacity to cope or adapt (less energy required to extract water, less costs to dig wells). Data values are categorical values representing meters below ground level (mbgl) as follows: a) 1 = >250 b) 2= 100 to 250 c) 3 =50 to 199 d) 4 = 25 to 50 e) 5 = 7 to 25 and f) 6 = 0 to 7. The higher the categorical score the better in terms of access to groundwater and thus increases community capacity to cope with limited access in the face of climate change. Thus, a community with a score of 6, means depth to groundwater is relatively shallow, depth range 0 to 7 mbgl and will normally has access to more water in the event of drought.	In the Vea study area of Ghana, GWL data was obtained from the Water Research Institute (WRI) of Ghana. In the Dassari study area, the GWL data was obtained from the British Geological Survey of Africa wide groundwater mapping project (Macdonald et al., 2012).

Agroforestry cover: Dano 2/8	The percentage of total land in the community cluster under agroforestry plantation or of considerable tree density.	Where respondents were asked to indicate if they practice agroforestry system. Farming practices where 10 or more/acre economic trees such as Shea and Baobab are purposely left in the farms were also counted as agroforestry system.	From own household survey
Soil depth: Dano 3/8	The maximum rooting depth at which major crops can grow. This is operationalized as the depth to bedrock in centimeters.	This data is obtained from ISRIC-World Soil Information as described above.	From ISRIC-World Soil Information as described above.
Normalized Difference Vegetation Index (NDVI): Dano 5/8	Normalized difference vegetation index during peak crop growth	This follows the computational description of Green Vegetation Cover described above.	

Vulnerability Component: Capacity, Coping capacity			
Indicator:	**Definition and Measuring unit**	**Indicator construction and /limitation of indicator**	**Data source**
Alternate food and income source: Vea 1/7, Dano 7/7, Dassari 1/7	Percentage of population in a community cluster with additional food and income source other than agriculture. Higher percentage increase capacity and reduces vulnerability	This is from household survey data and it's computed as percent of households with alternate food and income sources. Computed by adding percent with alternate income sources and percent with outside family support.	From Household survey
Ability to survive crisis: Vea 2/7, Dassari 6/7	The percentage of total households within a community cluster that is able to survive crisis. Higher percentage reduces vulnerability.	From household survey data. Respondents were asked about their sense of security. Household who feel insecure or somewhat insecure are not able to survive crisis. Households that feel either "somewhat" or "very" insecure about their ability to withstand any hardships have low coping capacity.	From household survey
Social capital: Vea 3/7, Dassari 2/7	Percentage of communities within a cluster with highly or adequate participation of people in communal activities such as clean-up campaigns, village meetings etc. Higher ordinal score increases coping capacity and reduces vulnerability.	This is from household survey and focus group discussion. Community leaders were asked to rank the level of participation of community members in communal activities. Four ordinal classes were used: a) total apathy of community members =1 b) barely adequate participation = 2 c) adequate participation =3 d) highly participatory =4	From household survey
Local knowledge: Vea 4/7, Dano 3/7, Dassari 3/7	The percentage of people in a community cluster with good knowledge of climate variability, local environmental issues and have taken part in any disaster risk reduction education in the last five years. Higher percentage reduces vulnerability.	From household survey data. Households were asked to indicate their knowledge on local environmental issues, disaster risk reduction, climate change adaptation and awareness of climate variability. Households who described their knowledge level as high and very high were computed as having adequate understanding of local climate change issues.	From own household survey

Emergency management committee (EMC): Vea 5/7, Dano 4/7, Dassari 7/7	Annual meeting frequency of local emergency committees in the community cluster. Higher meeting frequencies reduces vulnerability	From household surveys and focus group discussion. It was difficult for the disaster volunteers to estimate the number of times they meet in a year and therefore an operational definition of the indicator was found. The indicator was operationalized as a binary variable with two indicating the presence of emergency committees and 1 representing absence thereof. In a cluster of communities, the dominant response was used. For instance, in a cluster of 7 communities, if 5 out of the 7 communities indicate they that they have EMC, that average response was used to represent the cluster.	From own household survey
Relief period of emergency items: Dano 6/7, Dassari 4/7	The length of time in days it takes for disaster managers to provide relief items and emergency support services to affected people. Relief items could include medicines, temporal shelters, blankets, food aid etc. in times of emergencies. High categories increase coping capacity and reduce vulnerability.	This indicator from field surveys measures access to national emergency funds and relief items. Relief response is the response time that disaster managers takes to provide relief to affected people. It is stated in days and converted into categorical variables as values: a) 6 = 1 to 7 days after disaster b) 5 =8 to 15 days after disaster c) 4 = 16 to 30 days after disaster d) 3 = 31 to 60 days after disaster e) 2 = 61 to 300 days after disaster f) 1 = beyond 300 days after disaster	From own household survey

Vulnerability Component: Capacity, Adaptive capacity			
Indicator:	**Definition and Measuring unit**	**Indicator construction and limitation of indicator**	**Data sources**
Access to agricultural extension service: Vea 1/7, Dano 4/5, Dassari 2/8	Average number of agriculture extension officers per community in the cluster. High number increases adaptive capacity and reduces vulnerability.	From household survey	
Household income per annum: Vea 2/7, Dano 2/5, Dassari 1/8	Average household income per annum in the community cluster. Higher income decreases vulnerability.	From household survey data. All income sources from all farm plots cultivated by the households, income from sales of livestock and poultry, non-farm income from activities of all economically active household members as well as remittances and support received from friends and family were computed.	From own household survey
Literacy rates: Vea 3/7, Dano 1/5, Dassari 4/8	The percentage of the cluster's household heads that can read and write. Higher percentage increases adaptive capacity and decrease vulnerability.	From field surveys: Initially, the illiteracy rates computed from percentage of household's heads who can neither read nor write was estimated from people without any education both formal and informal. This was subsequently subtracted from one to give an indication of percent literate.	From own household survey

Number of herds per household: Vea 4/7, Dano 5/5, Dassari 3/8	Average number of herds of livestock owned by households. Herds include goats, sheep, poultry, cattle and donkeys if they are used for economic activities. Higher herds per household increases adaptive capacity and reduces vulnerability.	From household surveys. The number of all livestock and poultry including cattle, sheep, goats, pigs, chicken, guinea fowls, ducks, dogs and donkeys were recounted by households. These absolute numbers were converted to a common scale to allow for comparison using the Tropical Livestock Units indicated below: a) Cattle = 0.8 b) Sheep, goats = 0.1 c) Pigs = 0.3 d) Chicken, guinea fowl, ducks = 0.007 e) Donkey = 0.5	From own household survey
Gross margin per hectare: Vea 5/7, Dassari 5/8	This is the ratio of the difference between total crop revenue and variable production cost per hectare. Higher Gross margin increases adaptive capacity and reduces vulnerability.	From household surveys. Production information for all crops produced by the household was collected. This information included area cultivated per crop, yield/ha, market prices of the commodities and production cost. Gross margin was estimated as total crop revenue less the variable cost of production. Variable cost for gross margin estimation is the sum of all inputs which cost constitutes more than 5% of the total production cost. Sum of gross margins from three most important crops in terms of area under production were then estimated to derive the Gross margin/ha.	From own household survey

Good leadership & management: Vea 6/7, Dano 3/5, Dassari 6/8	Percentage of communities within a cluster with well functional institutional network comprising well respected chiefs and effective local government structures. Higher categorical values increase adaptive capacity and reduce vulnerability.	This is from field surveys. Community members were asked to indicate the level of effectiveness of local government structures and tribal chiefs in managing the affairs of the community especially in times of emergencies. Four ordinal variables were ranked. These are classified as follows: a) 1 is nonfunctional local leadership b) 2 is ineffective local leadership c) 3 is effective local leadership and d) 4 is highly effective local leadership	From own household survey
Access to farm labour: Vea 7/7	Percent of households within a cluster with timely access to labour for major farm activities. Higher percentage increases adaptive capacity and reduces vulnerability	This is from household surveys. Respondents were asked to indicate whether they have immediate access to labour for major farm operations in a situation where funding is not a constraint.	
Access to land or land ownership: Dassari 7/8	Percentage of households within a cluster with unhindered access to land. Higher percentage increases adaptive capacity and reduces vulnerability.	From household surveys. Respondents were asked to indicate whether they own their farmlands or have readily access to farmland to rent especially in settler communities where the people do not own land.	From own household survey

5. From Communities to Nations: Upscaling risk and vulnerability Indices – Theoretical concepts

5.1. Introduction

O'Brien *et al*., (2004), observed that for people to cope with actual and potential changes in climate and climate variability, it is important to recognize climate vulnerabilities at the regional and local scales, and to address them accordingly and that multi-scale assessment are important for a comprehensive understanding of global change impacts. According to the MEA (2003), results obtained from a given scale are invariably influenced by interactions of ecological, socio-economic, and political factors from other scales and that relying on a single scale is likely to lead to missing interactions which are important for our understanding of ecosystem determinants and their effects on human well-being. For example, local non-codified knowledge or information systems of marginalized people are often overlooked in larger spatial scale assessment or higher levels of aggregation (MEA, 2003). An important prerequisite therefore is to explore how multi-scale and cross scale interactions can contribute to decision making at various levels and how that affects the overall risk faced by people in nearby areas. This can help in the visualization of complex patterns (UNDP, 2004) and can also help to identify important dynamics of the system that might otherwise be discounted. Trends that take place at much larger scales according to MEA (2003), although can be expressed at a local scale, could go undetected in purely local-scale assessments. Yet, the global risk assessment literature and discourse lack this perspective and normally assesses risk at single scales and also to single hazards. Little is known about upscaling risk and vulnerability indices from a local scale to larger spatial scales and studies that take into consideration the effects of the interactions among various decision makers on the overall risk in other scales are lacking.

In this chapter, a conceptual basis for conducting risk upscaling at higher spatial hierarchies is outlined. This conceptual approach allows for a unified risk assessment at higher spatial scale which is required to support comparative assessment of risk across equivalent spatial scales in different countries. This approach is referred to as upscaling and it involves combining the different indicators from all three study areas, investigated in the preceding chapters, into a unified indicator set without losing the fine details from local scale experts. In this chapter, the fundamental principle to upscale the information per indicator in a relevant manner for the next hierarchical scale is outlined. This upscaling process is seen as a tightrope walk between achieving comparability for a regional based risk assessment but at the same time carrying all relevant information from the specific watershed sites. This then allows for multi scale risk assessment and also multi-location comparison. This indicator upscaling principle then lays the foundation for a more quantitative risk assessment by future researchers across multiple spatial scales.

In this study, disaster risk upscaling is defined as the indicator-based determination of disaster risk at higher spatial scale using results of current risk indicators at lower spatial scale. The disaster risk determined at the higher spatial scale is not simply scaling up the lower risk indices but it takes into account the interactions and cross-scale influences from different actors acting independently to reduce disaster risk at that scale. The lower spatial scale can be a watershed or the community level where the principle of participatory approaches has been used to develop indicators to determine the risk faced by the SES in chapter two of this thesis.

In vulnerability and risk assessments, scale is important for two main reasons. SES and processes operate at a wide variety of scales and across scales, they can change in their nature and sensitivity to various driving forces and so it cannot be assumed that results obtained at a given scale will invariably be the same at another. Focusing on single scale can lead to missing these interactions (Kremen *et al*., 2000, McConnell, 2002). This is observed in the recent World Risk Report 2014 (Garschagen *et al*., 2014) issued by the United Nations University-Institute for Environment and Human Security and the Alliance Development Works where it was found that some parts of West Africa, particularly Ghana and Mali are classified as having very high national-level risk, yet the urban risk in these countries fall in the very low risk category (Garschagen *et al*., 2014). Among the many causes of this phenomenon is the huge dependency on climate sensitive sectors in the rural areas but probably also, as a result of cross-scale interactions resulting from decisions from various stakeholders acting at different scales. However, the underlying reasons and specific interactions of such phenomenon are poorly understood. For these reasons, disaster risk reduction practices need to be multi-hazard, multi-sectoral and inclusive in nature so as to make it efficient and effective (UNISDR, 2015). A good way to achieve this is to pursue inclusive risk assessment approaches that recognize the effects different stakeholder actions have on the mean risk of other at-risk populations at different scales.

In

Figure 5-1 below, the different stakeholders acting at different scales are shown. It shows that several stakeholders operate at different scales and in most cases the actions of these stakeholders operating at different scales leave unintended results which affect the risk or increases the exposure of the people and the SES in adjoining scales.

Nelson *et al*., (2010) outlined the steps and scales of mainstreaming (

Figure 5-1) needed to integrate Climate Change Adaptation (CAA) and Disaster Risk Reduction (DRR) and indicated that for the integration to be effective and to mitigate these cross-scale interactions, there is a need to create “comprehensive integration and interweaving of climate change and DRR issues combined with environmental and socio-economic themes and dealing with the trade-offs in the decision making” (Nelson *et al*. 2010, p.28). These trade-offs can be assessed when the nature of these interactions is better understood, an area that is not covered in current risk assessment discourse.

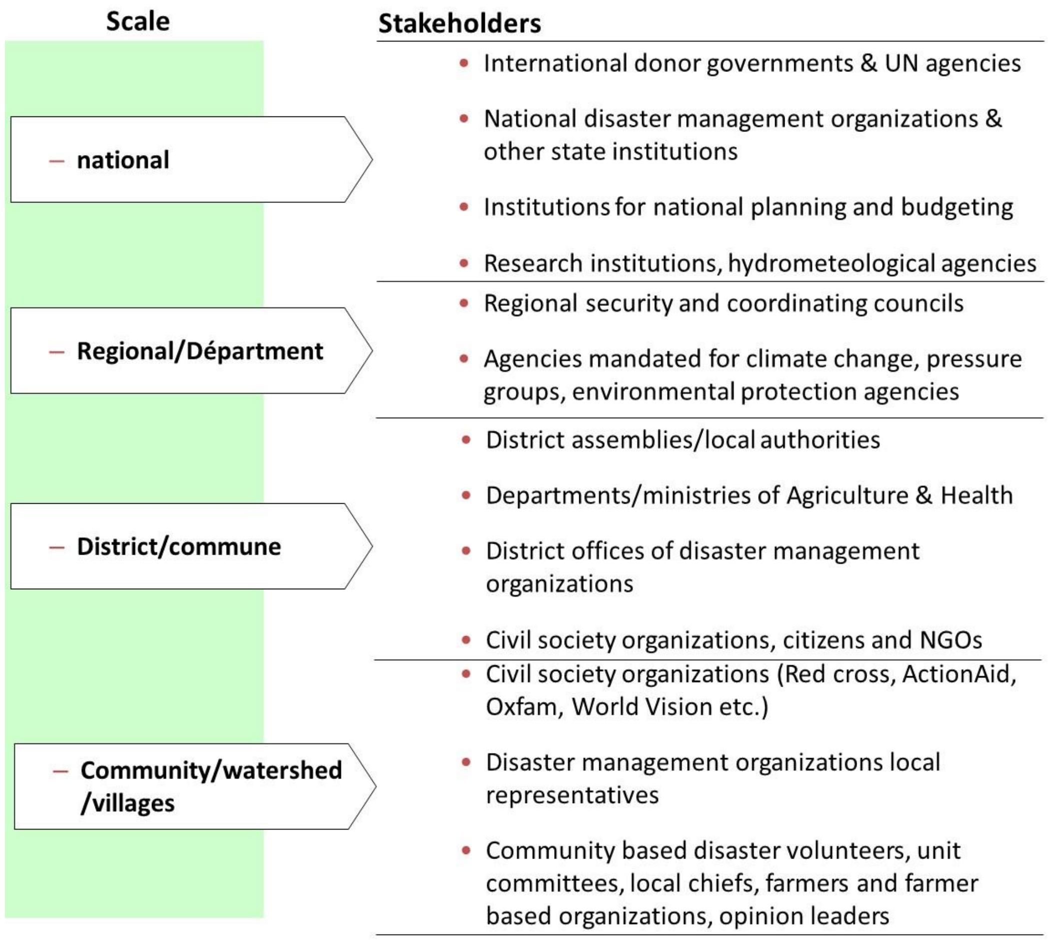

Figure 5-1: Level of mainstreaming climate change adaptation into DRR.
Adapted from Nelson et al., (2010).

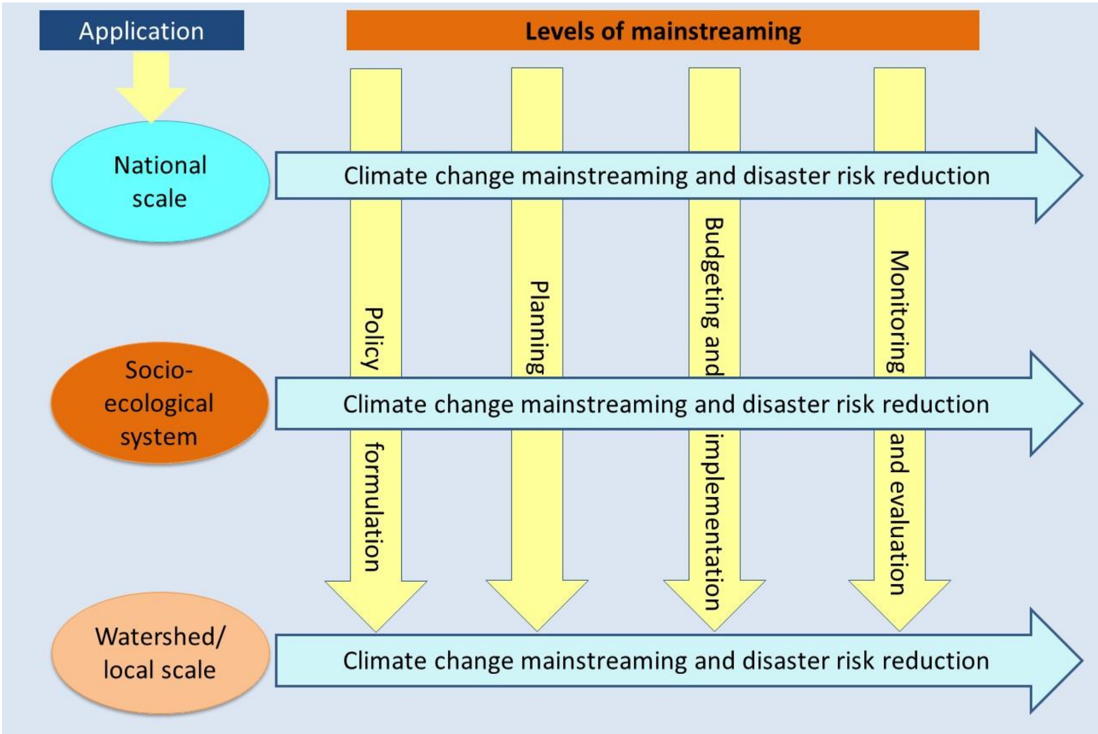

Figure 5-2: Typical stakeholders and their interactions for DRR in the three case study countries. ***Data derived from UNDP (2012).***

2. The concept of indicator upscaling in risk assessment

Upscaling, according to (MEA, 2003, p.129) is "essentially an aggregation challenge, complicated by the fact that simply adding smaller-scale values can give misleading results" as the data may fail to meet established sampling methods or may not take account of stochastic variability in processes and interactions among different stakeholders as well as decisions and actions emanating from the many actors".

5.2. Upscaling levels

The three levels to upscale the risk index derived at the watershed scale is proposed (Figure 5-3). These spatial levels are:

- Sub-national (refers to 2nd sub-national administrative levels of districts or communes or county or province depending on the terminology used in the country under study)
- National (Refers to 1st sub-national administrative level of regions or departments or state as used in the country under study)
- Regional (refers to sub-continental groupings such as ECOWAS or continental grouping such as Africa or Europe).

The basis for upscaling is the watershed scale where fine scale data were collected from both primary and secondary data sources including remotely sensed estimated biophysical parameters. Here the unit of analysis is the household. Community vulnerability profiles relating to multiple hazards of floods and droughts have been developed and presented in chapter four. The vulnerability index developed at the watershed scale will be upscaled to several administrative hierarchies (Figure 5-3) within the West African sub-region as a case study. The first upscaling level will be the sub-national administrative level of districts; the second is national level of regions and provinces whilst the third could extend the framework to allow for the index to be upscaled to the national or regional level. Beyond the administrative scales herein proposed for upscaling, the concepts of upscaling can also be applied based on agro-ecological zones or climatic zones to assess if different agro-ecological zones which are largely determined by climate and geomorphology exhibit differences in disaster risks.

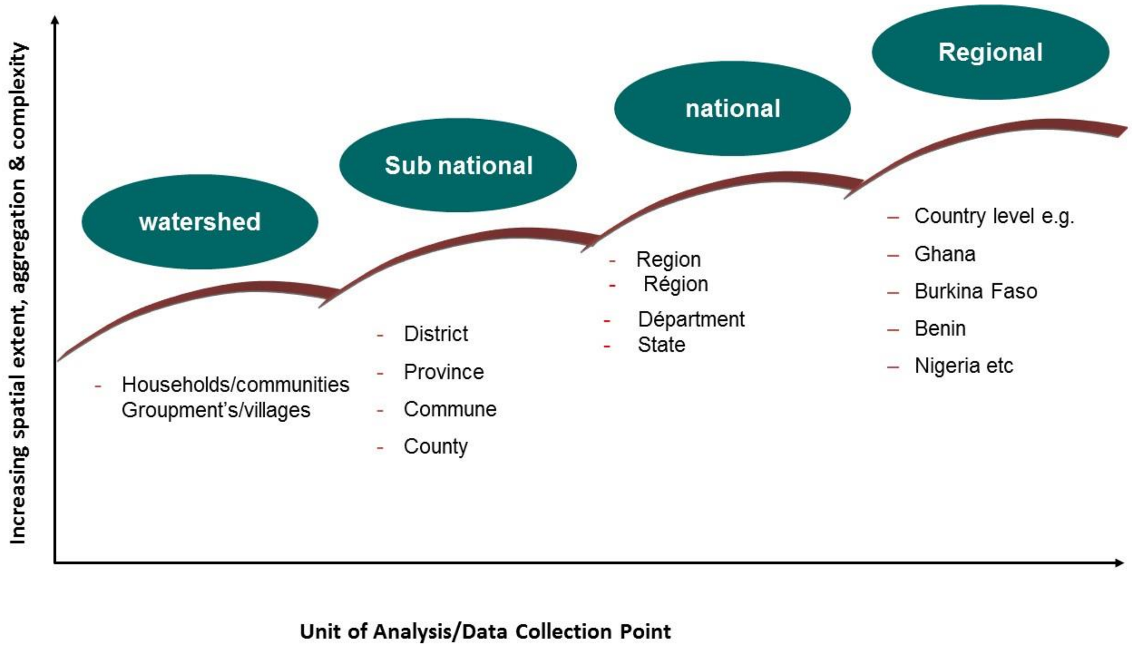

Figure 5-3: Different scales for upscaling risk index.
Note that, as a case study, the risk and vulnerability indices have already been developed at the basis scale (the watershed level and presented in Chapter 4. In the present study, the next upscaling level, the sub-national with administrative districts as the unit of analysis will be assessed under autonomous conditions. The indices will then be upscaled to the national level where the unit of analysis is the administrative region/province.

5.2.1. Upscaling indicators of drought and flood vulnerability of a socio-ecological system in West Africa– conceptual basis

In chapter two, a set of indicators for quantifying the vulnerability and risk to flood and drought hazards were developed from participatory methods. The approach followed a step-wise procedure to develop Indicator Reference Sheet based on conceptual risk assessment framework developed by Kloos *et al*. (2015) and combined with knowledge of local experts iteratively selected through a snowball approach. These indicators, which differed from each study area, have been used to construct community level vulnerability profiles for the three case study areas, Vea in Ghana, Dano in Burkina Faso and Dassari in Benin. In the present study, an approach is presented to upscale indicators to the next higher spatial scale in a unified manner without losing important features. This is important to scale-up essential information gathered from the lower scale assessment to a higher spatial scale. As can be seen in Figure 5-3, upscaling risk indices from lower scale at multiple locations to higher spatial scales has inherent complexity and aggregation as one transcends the higher scales and it's therefore essential to reduce this complexity through for example, a unified indicator approach for all the multiple locations.

To do this, a tiered upscaling process is conducted to allow indicators within each component to be upscaled from the watershed scale to the next scale which would be districts or regional scales (at the sub-national level). A grid-based upscaling procedure is proposed allowing each study area to retain the original ranking and then by extension the weights that were assigned to that particular indicator as described in chapter two. In the indicator development process described in chapter two, each study area provided the ranking indicating the relative importance of each indicator for that study area. To be able to use this ranking at higher spatial scales and without compromising this important location specific indicator ranking system, a grid-based upscaling process is introduced. The grid size to be used for the next upscaling level depends on data availability and the need to reduce model complexity but generally a 1 km grid could be used for sub-national spatial levels. The use of uniform grid-based approach allows risk assessment from a watershed level to be upscaled to any desired spatial scale. The boundary criterion is then defined by the research interest and this could range from administrative boundaries to climatic zones to agro-ecological zones or any boundary layer defined by research interest.

In this study, the MEA (2003) approach of indicator categorization was combined with author judgement and literature to upscale indicators from the watershed scale to the next higher scale. Indicators are then categorized as either (i) scale dependent with known scaling rules or (ii) scale independent or (iii) non-scalable.

Scale-dependent indicators that have a known or potentially knowable translation rules are scalable and can be expressed in smaller or larger aggregated units. Usually the scaling rules are complex and nonlinear. These variables tend to follow nonlinear or discontinuous scaling rules for reasons such as spatial or temporal interactions, organizational scope and the limits of institutional authority as one transcends to a higher scale, and high heterogeneity or changes in the nature of the regulating factors as the scale changes (MEA, 2003).

The second category of scale-independent variables can be scaled rather simply by addition or proportionality. They show conservation of mass or value and have no or little spatio-temporal interdependencies. Simply dividing the numerical values of such variables by their measurement unit such as per square meter or per year will render such variables scale independent. A typical example is population density where the number of people is divided by the land area.

Variables or processes whose meanings are defined only at particular scales are described by MEA, (2003) as non-scalable. For instance, the process of decision-making within a household cannot be scaled up to the nation as different principles apply. Such variables can only be “qualitatively scaled” by placing them in clusters with conceptually related variables at different scales.

Combining this theory and that of author knowledge, a decision tree is developed and shown in Figure 5-4 below that forms the conceptual basis for upscaling indicators from a lower spatial scale to a higher spatial and multiple scales. The upscaled indicator from the watershed level is then assumed to be relevant for all higher spatial hierarchies beyond the watershed/local scale. This is the upside of using a grid based approach for the upscaling.

In the decision tree below (Figure 5-4), all indicators are subjected to four fundamental questions and three sub-*questions resulting* in a total of seven questions during the upscaling process. Four of the seven total questions are terminal questions. This means if an indicator fails that particular question; it’s immediately dropped from further analyses and does not go through the upscaling process. These questions are described below:

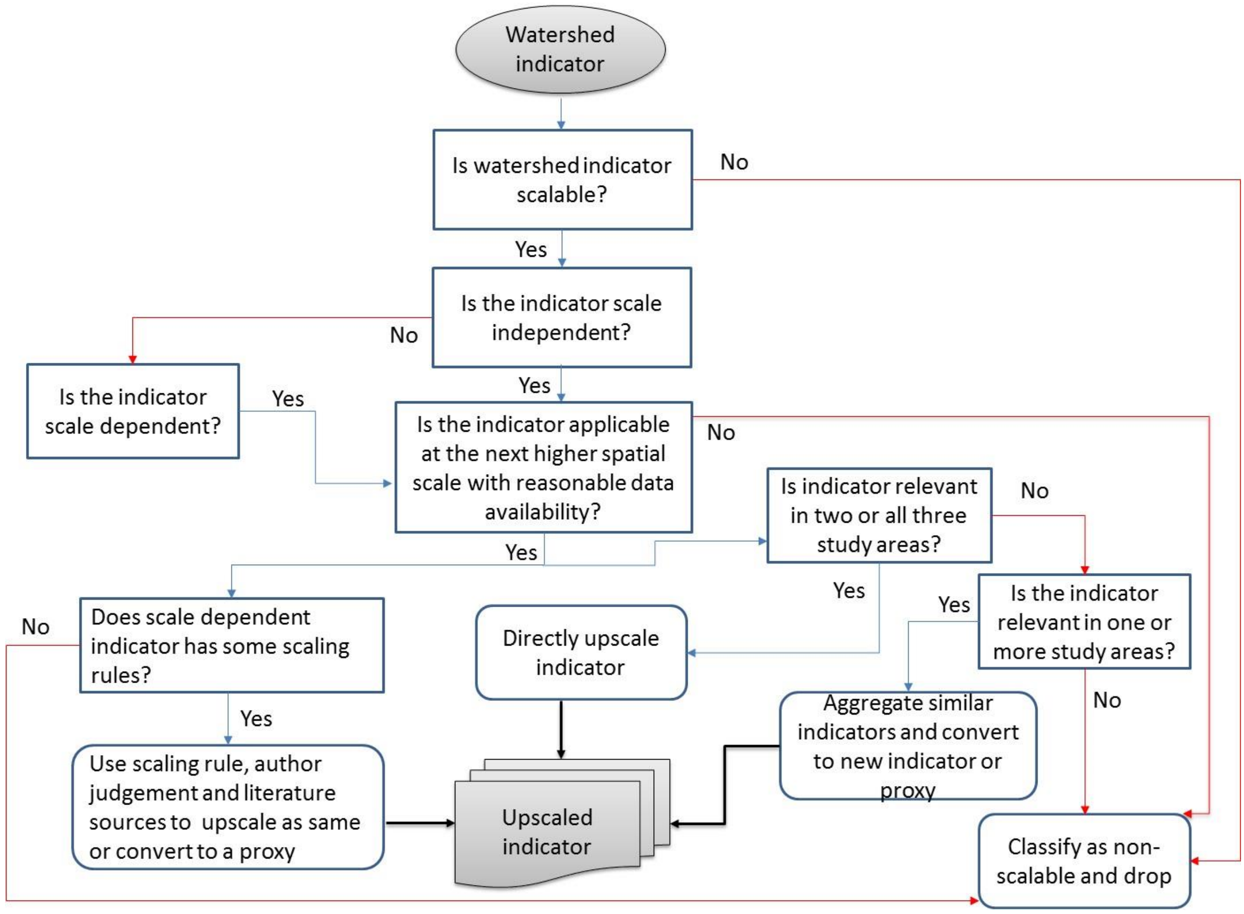

Figure 5-4: Decision tree for upscaling indicators from a lower spatial scale to higher scale.

[1] Is watershed indicator scalable? This is the first fundamental question that an indicator must satisfy before being subjected to the next criteria. If an indicator is not scalable, it's immediately dropped from subsequent analysis. Scalable indicators can either be scale dependent or scale independent.

[2] ***Is the indicator scale independent?*** If an indicator is scale independent, that indicator is upscaled based on the principle of scale independent upscaling by simply dividing the numerical values of such variables by their measurement unit such as per square meter or per year. For instance, the indicator 'Population density' in the susceptibility component is upscaled to the next spatial hierarchical scale of say, a district by dividing the number of people who live in that district by the total land area defined by the district boundary.

[3] ***Is the indicator scale dependent?*** If a group of indicators are relevant in one or more local scale study areas and are scale dependent, the next sub-question is whether that indicator has some known scaling rule, if that is true, then that indicator is upscaled by using the scaling rule and author judgment. If not, it's classified as non-scalable. For example, indicators 'Bas fonds' and 'Agroforesty area' are scale dependent but with the application of remote sensing techniques, those indicators can be upscaled to the next spatial hierarchy. Similarly, Indicators 'Runoff rates' and 'Soil erosion' are scale dependent but have scaling rules. These indicators can be upscaled with the application of runoff and erosion models

such as the rational hydrological model and universal soil loss equations to upscale them to the next higher spatial hierarchy. Again, in this category, if an indicator has no known scaling rules, that indicator is described as non-scalable and is therefore dropped from subsequent analysis. For example, the indicator 'Local knowledge' in the coping capacity component has no known scaling rule and was thus dropped. In sum, there are two basic criteria for upscaling scale dependent indicators. These are:

a) Indicators with potentially known scaling rules. Here the scaling rule is combined with author/expert knowledge and then the indicator is upscaled.

b) Practical relevance of the indicator for the next spatial hierarchy in the context of multi-hazard risk assessment. This is described below:

[4] ***Is indicator or its proxy applicable at the next higher spatial scale with reasonable data availability?*** This an important sub-question below both the scale independent and scale dependents criteria that seeks to confirm whether the indicator if upscaled will be applicable at the next higher spatial scale. This is also another terminal sub-question. If an indicator will be irrelevant at higher scales either because it doesn't apply or lacks reasonable course scale data or a proxy variable cannot be found, that indicator is classified as non-scalable and is dropped. Such indicators are not relevant for climate change risk assessment at the next spatial scale and are thus also classified as non-scalable. For example, the indicator, 'Female headed households' has no practical relevance for risk assessment in urban areas since vulnerability in urban centres is neutral to whether the household is headed by a female or not, whereas, in rural areas, access to economic resources such as land has important gender dimensions.

Scale independent indicators are further subjected to two other sub-criteria described below:

a) I***s the indicator relevant at the local scale in two or all the three case study areas? Note the use of word "two or more study areas".*** If so, that indicator is directly upscaled to the next spatial scale. Direct upscaling relies on the principle that simply using proportions, additions or averaging the pixel values within each spatial unit provides a data value for the upscaled indicator at the next higher spatial scale. For instance, the indicator, 'Caloric intake per capita' in the susceptibility component is directly upscaled to the next higher spatial hierarchy by averaging the calories consumed per capita from all pixels that constitute the spatial unit. At the district upscaling level, this spatial unit is the boundary layer of the district.

b) The next sub-question under the scale independent category is whether an indicator or group of closely related indicators in the same vulnerability sub-component is/are relevant at the local level in one or more study areas? If this question cannot be satisfied, the indicator under consideration is dropped. If the question is affirmed, the group of scale independent indicators are typically aggregated and converted to a closely related variable or proxy. This aggregation of indicators is based on observed relationships between the indicators from literature and authors knowledge. This indicator reductionist approach is required to minimize model complexity in subsequent analysis needed to estimate risk index at higher spatial scales and also to aggregate fine scale information obtained at a lower spatial scale to higher scale with less detailed information. For example, in the susceptibility component, two indicators, ‘Number of dependents’ and ‘Household size’ are aggregated and converted into ‘Dependent Population’ since the two Indicators measure the similar phenomenon in climate change risk assessment. The converted indicator ‘Dependent population’ at the next upscaled level is derived by averaging people above age 65 and below age 15 for all households in the spatial unit.

It must be noted however, that, directly upscaling indicators described in category [4a] are also scale independent indicators just as those as described in category [4b]. They show conservation of mass or value, can be scaled by addition or proportionality and have little or no spatio-temporal interdependencies, the main difference between the two in this study is that, indicators in category [4b] are typically aggregated and converted into a proxy variable whereas indicators in category [4a] are “directly upscaled” without any translation or conversion. Moreover, for an indicator to belong to category [4a] and be directly scaled, it must be relevant in at least two watershed case study areas whilst category [4b] indicators need to be relevant in one or more watershed case study areas.

The results of the application of this upscaling have been presented in accordance with the risk assessment framework adopted for this study. These results are presented in the section below.

5.2.2. Illustration of indicator upscaling concept

To upscale indicators that describe the exposed elements in the social sub-system, two indicators, ‘Agricultural Dependent Population’ and ‘Insecure settlements’ are combined to form ‘critical elements in hazard zones’ during the upscaling process. This is because both indicators describe the exposure of elements within the SES, in this case including people and settlements. The relevance of this broad category in risk assessment is that the higher the proportion of critical elements in hazard zones, the more an area will be impacted by disruptions in production system due to changing environmental conditions (Adger *et al*. 2004, O’Brien *et al*, 2004).

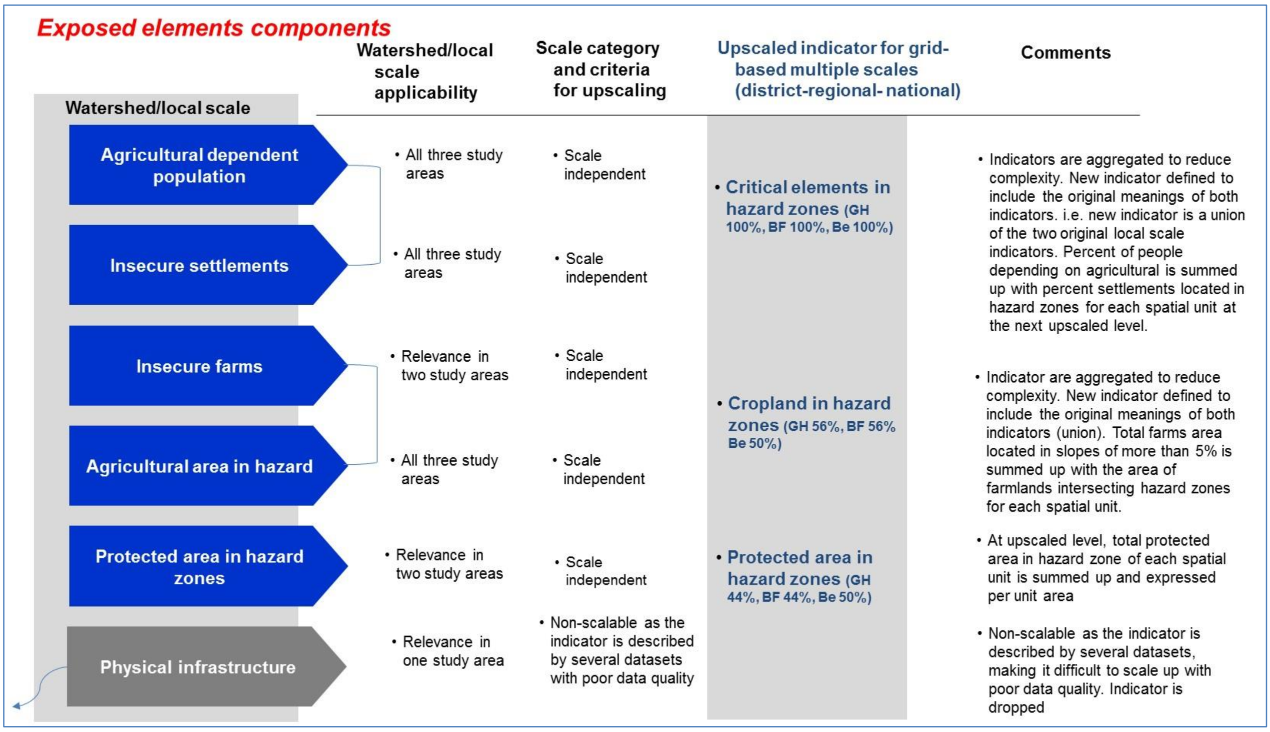

Figure 5-5: Procedure for upscaling exposed elements indicators.

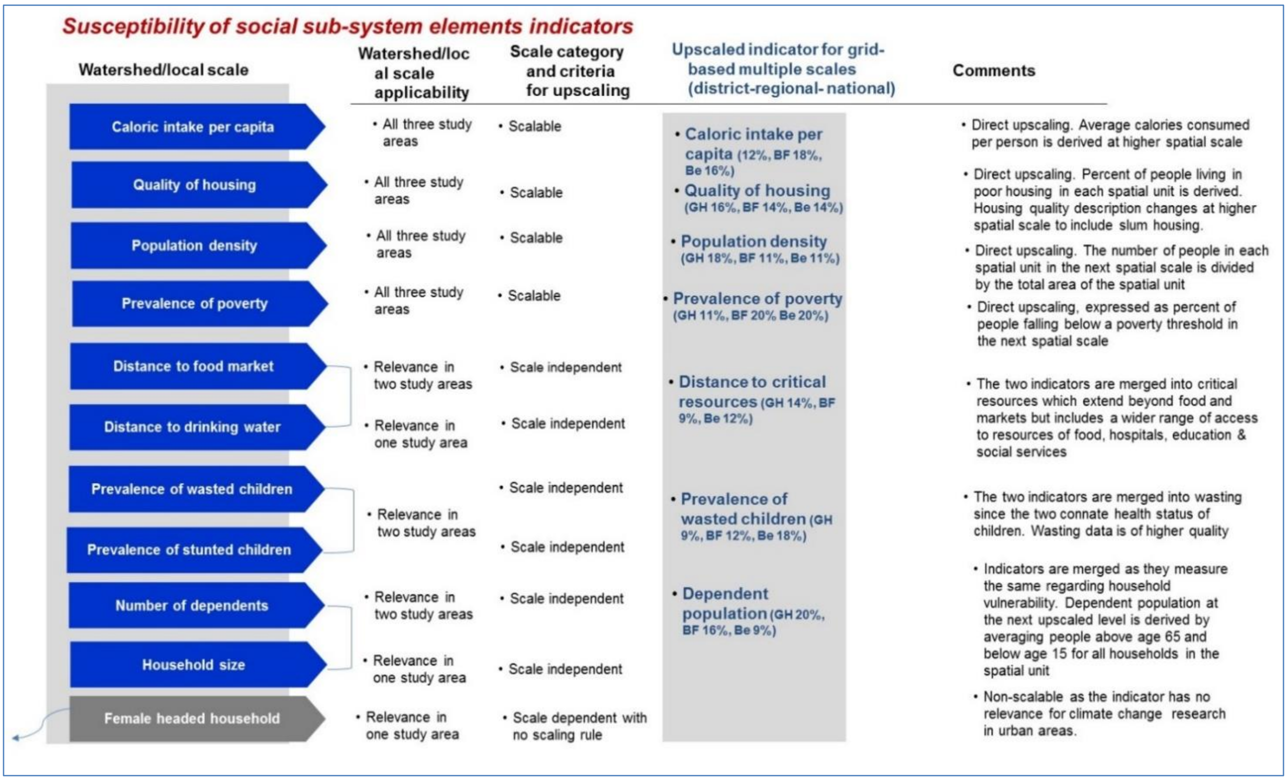

Figure 5-6a**: Procedure for upscaling social system susceptibility indicators**

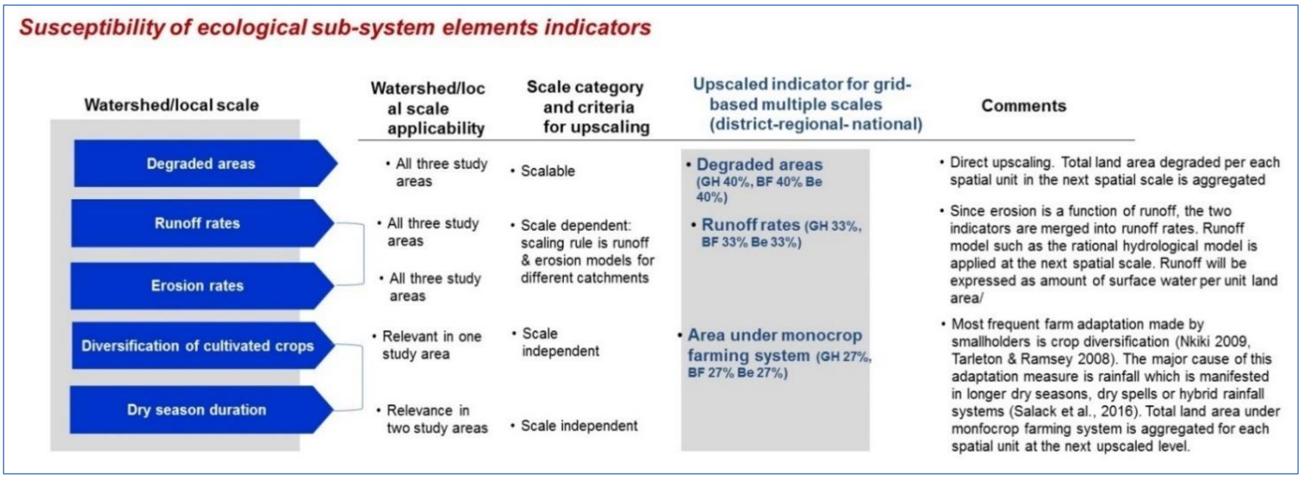

Figure 5-7b**: Procedure for upscaling ecological system susceptibility indicators.**

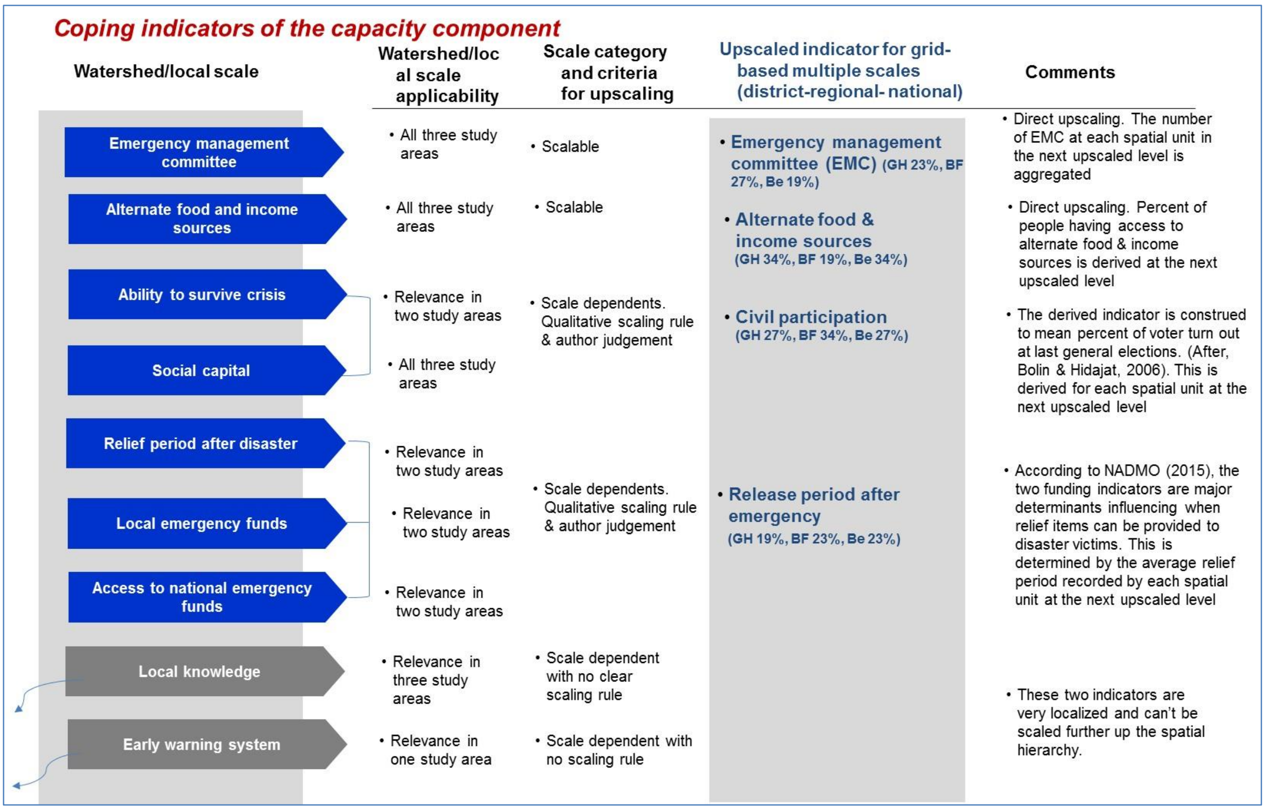

Figure 5-8: Procedure and results for upscaling coping capacity indicators

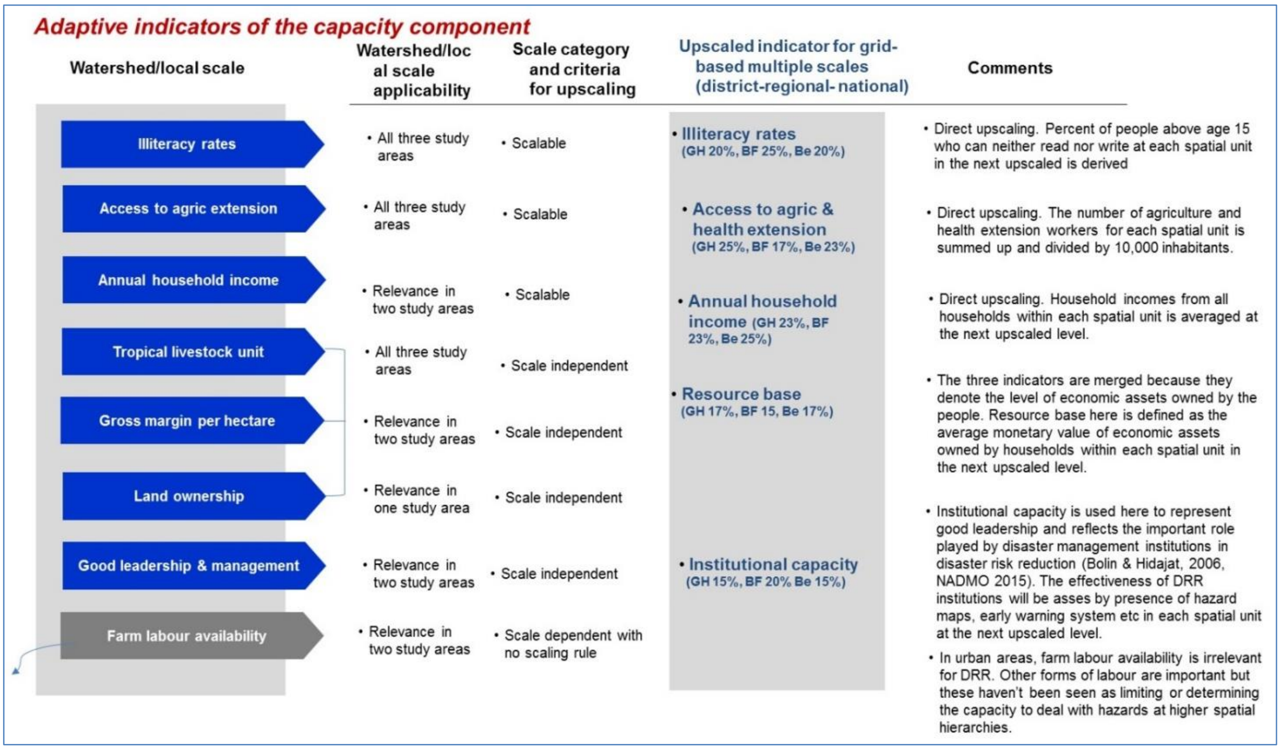

Figure 5-9: Procedure and results for upscaling adaptive capacity indicators.

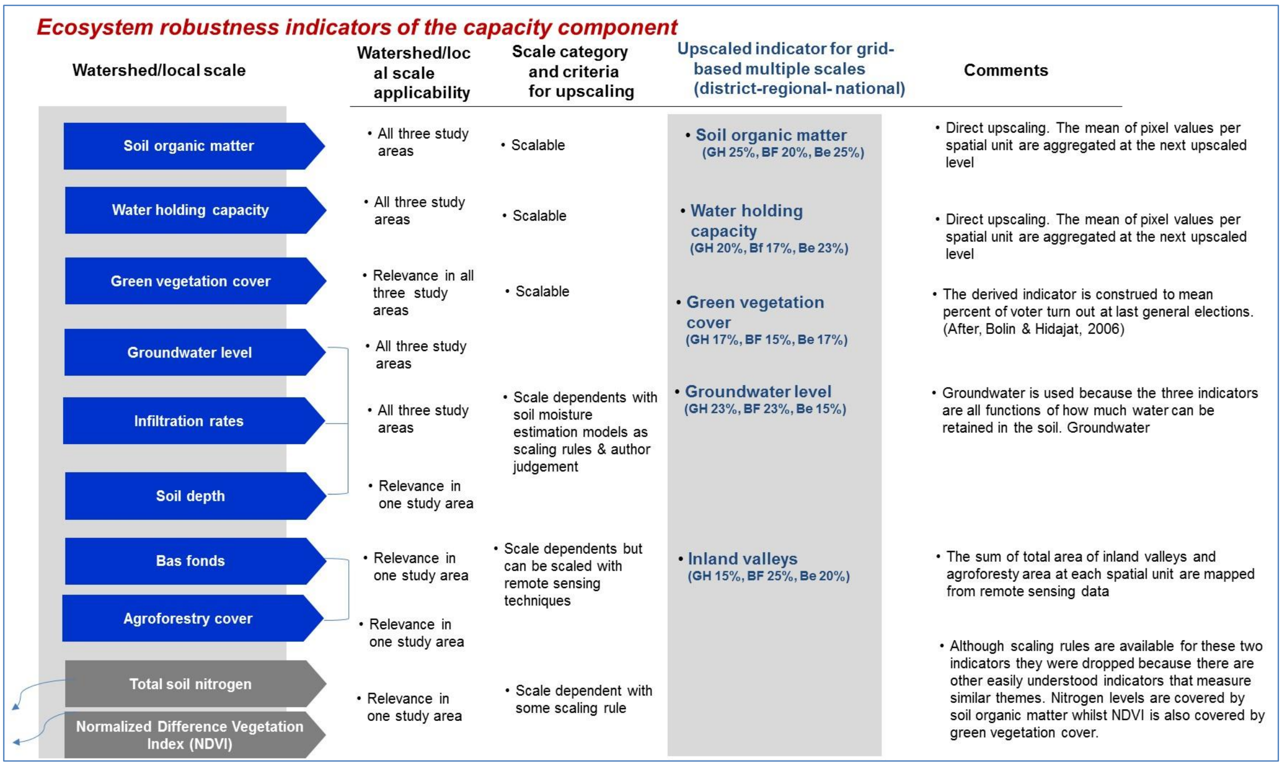

Figure 5-10: Procedure and results for upscaling ecosystem robustness indicators.

5.3. Weighting of indicators in the upscaling process

To determine the aggregate weight of the upscaled indicator, the original rank of that indicator in the applicable study area was converted to weights by using the Al-Essa (2011) model presented in Equation

4-4. Then the average weights of the indicator across all applicable study areas within the same sub-component are computed. Within that sub-component, the indicators are ranked in ascending order based on the derived weights. The new ranking is then used to determine the new weights of the indicator in the unified system by using the Al-Essa model. The final weight is determined as an average of the weightings of all indicators in a sub-component. This is finally converted to percentages to ensure the sum of all weights in a sub-component adds up to 100.

5.4. Conclusions

The results of this approach in the context of the present research shows that there is a total of 27 indicators to be used for upscaling risk indices from the watershed scale to the next spatial scale. This is a clear example of indicator reductionist approach where as one transcends higher scales; the number of indicators and detail information are reduced due to increasing level of aggregation. For instance, the lower scale Vea study area used a total of 32 indicators to determine the risk index at that scale. This type of indicator aggregation theory agrees with the assertion of Cushman *et al*., (2010) that up-scaling usually involves changes in the organizational-level of observation and inference. Moving across organizational levels changes the grain and extent of observations in space and time, together with the entities observed, variables measured and the processes underlying the phenomena.

In this chapter, the theoretical concepts have been formulated to provide the foundation to upscale disaster risk index from watershed to numerous administrative units. In order to evaluate risk across equivalent administrative units in a number of countries, it's important to have unified indicators. A grid-based conceptual framework is therefore proposed and introduced to upscale the indicators from a watershed scale to higher scale. This approach allows the application of complex models such as Agent Based Model (ABM) to be applied in further studies to understand the interactions and feedbacks loops that influence risk outcomes particularly, in higher spatial scales. The thesis has also introduced a useful concept of risk index upscaling. These theoretical concepts although could not be operationalized and quantified in this thesis due to time constraint, provides an interesting shift in the scientific discourse of risk assessment. Lack of appropriate approaches has limited the assessment of climate change impacts to regional or global levels. In some cases, attempts have been made to downscale these courser scale assessments to a local level. This thesis therefore provides the theoretical basis to enable a reverse assessment i.e. from lower spatial level such as watershed level to a higher spatial level such as administrative regions or country level. This is absolutely important as it allows policy makers, practitioners and in particular disaster managers to better understand the effects of their interventions across a trajectory of spatial scales and to institute inclusive and well-integrated adaptation strategies so as to sustainably reduce disaster impacts.

6. Synthesis and outlook

Disasters, particularly recurring small-scale disasters and slow-onset natural disasters have been affecting communities, impacting inherently weak households and small and medium-sized enterprises (UNISDR, 2015).

This constitutes a high percentage of all losses and impedes sustainable development. In West Africa, these losses have been significantly high over the last decade due to increasing climate variability and inherently depressed socio-economic systems. The region has been described as a hotspot of climate change as all climate projections indicate a marked departure from historical weather phenomenon. Of particular importance is rainfall which Sylla *et al*. (2015) projected a decrease in the absolute number, but an increase in the intensity of very wet events – leading to increased drought and flood risks towards the late 21st century. The reliance on rain-fed agriculture by over 65% of the population means that vulnerability to climatic hazards such as droughts, rainstorms and floods will continue.

However, till date, no study has attempted to understand the risk and vulnerability profiles in West Africa to these multiple hazards across several scales; from rural communities and watersheds to districts to regions and to the national levels. Few studies in the region and across the world that have assessed risks to natural hazards have done so at single scales and used indicators from literature, therefore lacking an important element of a participatory process that could allow at risk populations to be involved in determining what factors (indicators) characterise their own risks. Another drawback of these existing studies is sectorial risk assessment where either only the social sub-system or only the ecological sub-system are assessed and also using single hazards.

A significant number of studies predict the impacts of climate change, but many do so at a very coarse scale and are also unable to predict localized impacts, which may typically differ from coarser scale assessments. Research on risks and the accompanying vulnerabilities of the Social-Ecological Systems (SES) to climate change has largely addressed the expected impacts of climatic change on national, regional or sectoral scales but are largely unavailable at community level where risk outcomes are first materialized. There is an increasing need for a shift from global and regional assessments to sub-national and community level assessments because these are the scales where major decisions against risk are made and expected to be implemented.

There have been arguments that conventional validation of vulnerability and risk is impossible because vulnerability cannot be measured in the traditional sense and a conclusion that validation still remains an open challenge in risk assessment has been made (Damm, 2010). To this end, the risk assessment literature commonly uses statistical methods such as Monte Carlo analysis, sensitivity analysis etc. as the only validation tools although actual evaluation of complex model outcome against real data is an integral part of risk assessment.

Also, despite the major impact of floods on the livelihoods of the people living in this region, no attempt has been made to delineate the boundaries of flood intensity at the community level and to identify areas most at risk of flooding. The use of flood hazard maps for managing disasters in West Africa is uncommon and disaster managers have for many years relied on traditional methods such as watermarks on buildings, local knowledge and media reports to identify possible affected areas during flood events (Nyarko, 2002).

Again, despite much efforts in vulnerability assessments, there has been limited success in ‘’simultaneously traversing scale and hierarchy from a lower scale to large scale and vice versa’’ (Cushman *et al*., 2010). The underlying reasons, effects and specific interactions resulting from decisions from various stakeholders acting at different scales are poorly understood. There is an urgent need to pursue inclusive risk assessment approaches that recognizes the effects different stakeholder actions have on the mean risk of other at-risk populations.

This thesis therefore purports four main objectives to address the gap outlined above:

[1] To develop indicators using both local and national levels experts at different scales to allow for a comparison to be made between the results coming from the different categories of expertise at different spatial scales. To do this, the study followed a step-wise procedure to develop Indicator Reference Sheet based on conceptual risk assessment framework and combined with knowledge of local experts iteratively selected through snowball approach.

[2] To develop community level flood hazard intensity maps at high spatial resolutions to aid local disasters manages to effectively manage flood disasters. To achieve this, remote sensing and Geographic Information System (GIS) techniques were combined with hydrological and statistical models to delineate the spatial limits of flood hazard zones in selected communities in Ghana, Burkina Faso and Benin. The study also employed empirical validation methods using statistical confusion matrix and the principles of Participatory GIS to evaluate the results of the flood hazard intensity zones.

[3] To conduct multiple hazard risk assessment through a bottom-up participatory process as opposed to the classical top-down, large scale approaches; assessing risk from the perspectives of a coupled SES rather than single-hazard-decoupled risk assessments; and assess risk using indicators relevant for rural communities across West Africa. The study also aims to explore appropriate validation approaches to evaluate the results of a complex risk assessment. Several methodological procedures including statistical, GIS and remote sensing approaches were followed to develop community vulnerability and risk indices.

[4] To simulate the decisions and actions of the different stakeholders in responding and adapting to natural hazards and how these decisions and actions feedback into risk and vulnerability of people in other scales through a novel indicator upscaling concept.

6.1. Conclusions at a glance

The key findings of the thesis are:

In Chapter 2:

- The study developed comprehensive list of indicators relevant for multi-sectorial, multi-hazard and spanning three watersheds in three countries. The study has systematically produced comprehensive indicator set that now could support policy makers, researchers and practitioners in West Africa and across the world with a set of indicators ready to be used for risk and vulnerability assessment in the context of climate change, multi-hazard scenarios and when a coupled SES approach is desired.
- The methodology allowed for a representative participation of at risk populations facing multiple hazards of drought and floods and then developed indicators for both the quantitative and qualitative assessment of risk.
- The study showed that majority of the indicators have either not been used or are hardly used in the literature related to West African multi-hazard risk assessment in the context of climate change. Different study areas or cultures have specific indicators that were unique to its socio-economic context.
- However, even among common indicators, there are differential rankings across different countries and this differential ranking indicates the relative importance of the indicator in other socio-economic and environmental settings.
- The study showed that the relevance and weights of indicators can only be properly understood by engaging with the vulnerable people themselves.
- However, participatory approaches were not without shortcomings. This has been collaborated by Bell & Morse (2003; Freebairn & King, (2003) and Reed *et al*. (2008).
- In some cases, classical approaches were combined so as to derive the best results. This chapter concludes that neither standalone classical approaches (top-down) nor a purely participatory process is sufficient in determining useful indicators for risk assessment and that appropriate mechanism must always be sought to strike a balance.

In chapter 3:

- The study demonstrated the feasibility of flood modelling in data scarce environments and mapped flood hazard intensity zones at community levels.
- The study introduced an innovative flood modelling validation procedure using statistical and PGIS principles to evaluate the robustness of the methods used.
- Using the remote sensing technique of a confusion matrix, the overall accuracy of the flood hazard index was estimated to be 77.62% in the Vea study area and 81.41% in the Dano study area.
- The flood modelling method introduced in this study delineated hotspots of flooding and showed areas within the three watersheds which are generally free from flood risk.

- These so-called flood safe havens are extremely important in times of emergencies. They support effective disaster management operations as recommended by Kundzewicz *et al*. (2014) and allow for the preparation of evacuation plans (Morjani, 2011).
- These high mapping accuracies notwithstanding, the flood index categories may change under conditions of very high rainfall intensities beyond the anomalies used to construct the model. Under such situations, areas previously classified as flood safe havens may fail to offer protection.
- To this end, further studies aimed at understanding projected flood intensities under varying rainfall intensities beyond the anomalies used in this study will be very important to determine the trajectory of flood safe havens across the study areas.

In chapter 4:

- The study also developed the vulnerability profiles of communities in the three study countries using a multi-hazard context and an SES orientation.
- The study developed two important indices, The West Sudanian Community Vulnerability Index (WESCVI) and The West Sudanian Community Risk Index (WESCRI).
- The underlying factors constituting the two indices were then taken as constituting the risk and vulnerability profiles of communities in West Africa.
- These vulnerability profiles are significantly important and provide the main pointers to policy makers to reduce vulnerability and risk.
- For instance, the results show that sharp differences in vulnerability among communities in the Vea study area of Ghana is due to huge disparities in the socio-economic profiles of the people.
- The results went further to show that a low exposure level can mitigate moderate levels of susceptibility and subsequently help reduce vulnerability and risk.
- Policy makers can then deploy interventions that reduce exposure levels to help bring down vulnerability and risk.
- Similarly, the study found that an area will still be classified as having significantly high risk levels when unusually high exposure levels are combined with moderate levels of susceptibility, no matter how strong its capacity to cope and adapt to the hazards might be. This finding is important and has several implications for policy makers and development practitioners striving to undertake only adaptation measures without the commensurate efforts to reduce people's exposure to obvious physical hazards.
- However, this must not be misconstrued as over-emphasizing the importance of exposure reduction.
- Because the study also found that poor state of inherent conditions and lack of total adaptive capacity could still place an area in high risk zone although its exposure to the hazards is low.
- Therefore, it's absolutely important to pursue development activities and Climate Change Adaptation (CCA) interventions that are well integrated, inclusive and address all facets of vulnerability and development.

- The community level risk and vulnerability profiles fulfils an increasing need for a shift from global/regional assessments to community level where major decisions against risk are actually made and implemented.
- To evaluate the results of the vulnerability and risk indices, this thesis introduced a novel technique to validate the results of complex aggregation methods.
- The Community Impact Score (CIS) which measured the cumulative impact of the occurrence of multiple hazards over five years in a community is the first in the available literature of risk assessment.
- The CIS uses several variables to determine the aggregated impact of multiple hazards and compare this result with simulated risk index.
- This is a significant contribution to scientific knowledge in this field and opens new frontiers in the search for appropriate methods to evaluate the results of complex aggregation methods.
- Several notably studies in this area including the WorldRiskIndex, index of social vulnerability to climate change in Africa, Social Vulnerability Index and many others (Cutter *et al*., 2003; Esty *et al*., 2005; Prescott-Allen, 2001; UNDP, 2004b; Vincent, 2004a; Welle *et al*., 2013) have tried to evaluate the robustness of their indices using only pure statistical methods such as Sensitivity analysis and Monte-Carlo analysis and could not compare the simulated index to real impact data.
- This failure to link simulated complex aggregated index to real data on the ground is in most cases due to lack of disaggregated primary data.
- It must be noted that this thesis was able to pursue actual evaluation of the indices because of the scale at which the indices were developed. At higher spatial scales, it may be impractical to collect actual impact data from the ground or such data may simply be unavailable.
- A key drawback with the methodologies used to develop the community vulnerability profiles is the concept of summation used to describe vulnerability.
- This approach means that in some cases, a community could still be highly vulnerable although its exposure may be zero. This is counterintuitive to the basic definition of vulnerability which determines that a system must be exposed to a known hazard in order to be said to be vulnerable.
- To counter this effect, the thesis used indicators that indirectly measure exposure such as Agricultural Dependent Population to describe the elements within SES that are exposed to the hazards.
- It introduced two variants of exposure. These were ‘Exposed Elements’ measured by indirect indicators of exposure and ‘General Exposure’, measured by intensity and frequency of hazards under study.
- These definitions of exposure allowed for much better interpretation and avoided the debate in risk assessment literature about whether to include exposure term in either vulnerability or risk component.

- In reality, however, people are still vulnerable as a result of inherent depressed socio-economic conditions although there may not be any obvious hazard to which they are exposed to.
- This calls for a new definition of vulnerability to be proposed especially in West Africa where people are still severely vulnerable in the face of no physical hazard.
- In the final risk assessment, however, where there's no hazard, risk will be zero even though Vulnerability could be high. This is the upside of the multiplicative effect which was finally used to estimate the risk index.
- This area of risk assessment where a system could still be vulnerable even though there may not be obvious linkages to physical hazards requires further studies.

In Chapter 5:

- The thesis has also introduced a pioneering concept of risk index upscaling. A grid-based conceptual framework was proposed to upscale the indicators from a watershed scale to higher scale.
- This approach can then allow the application of complex models such as Agent Based Model (ABM) to be applied in future studies to understand the interactions and feedbacks loops that influence risk outcomes across multiple scales. Studies that can apply ABMs to understand the cross-scale interactions and feedbacks are needed.
- These theoretical concepts of risk index upscaling, represent an interesting shift in the scientific discourse of risk assessment.
- Lack of appropriate approaches has limited the assessment of climate change impacts to regional or global levels. In some cases, attempts have been made to downscale these courser scale assessments to a local level. This thesis therefore provides the theoretical basis to enable a reverse assessment i.e. from lower spatial level such as watershed level to a higher spatial level such as administrative regions or country level.
- This is absolutely important as it allows policy makers, practitioners and in particular disaster managers to better understand the effects of their interventions across a trajectory of spatial scales and to institute inclusive and well-integrated adaptation strategy so as to sustainably reduce disaster impacts.
- The thesis has also provided a framework for conducting risk assessment relevant for multiple cultural, political and institutional contexts.
- The indicators were developed from a highly participatory process. The strength of this approach lies in the fact the risk and vulnerability profiles developed can be said to represent actual risk and vulnerability of the people living in the SES. The same cannot be said of risk and vulnerability profiles developed from classical approaches since the foundation of such an approach (indicators from literature) are in most cases of abstract nature and do not uniquely represent the SES under study.
- At the same time and as key outlook, the study sets the pathway for conducting risk assessment using a unified indicator set if so desired by practitioners or policy makers. It lays

the foundation for researchers interested in an emerging field of study discovered in this thesis in the area of risk index upscaling.

- There is an urgent call for more research, investment in fine scale data generation and real-time transmission; as well as interventions to better understand risk to multiple hazards beyond droughts and floods across multiple scales.
- It must be noted however that, practitioners or policy makers desiring to conduct multiple hazard risk assessment based on the methodologies presented in this study need to have several scientific competencies to be able to follow all the approaches outlined in this study.
- This thesis has however, provided the basic methodologies that have been lacking in the West African region in particular, and in the global risk assessment literature in general, and show how multiple hazard risk and vulnerability profiles could be assessed, validated and upscaled across several scales. We believe the present study contributes to efforts to finding innovative approaches in understanding climate change impacts to rural communities affected by multiple hazards.

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