Contemporary Disaster Management Framework Quantification of Flood Risk in Rural Lower Shire Valley, Malawi

Faidess Dumbizgani Mwale

Submitted for the degree of Doctor of Philosophy

Heriot-Watt University

School of Energy, Geoscience, Infrastructure and Society

December 2014

Abstract

Despite floods and droughts accounting for 80% and 70% disaster related deaths and economic loss respectively in Sub-Saharan Africa (SSA), there have been very few attempts in SSA to quantify flood-related vulnerability and risk, especially as they relate to the rural poor. This thesis quantifies and profiles the flood risk of rural communities in SSA focusing on the Lower Shire Valley, Malawi. Given the challenge of hydro-meteorological data quality in SSA to support quantitative flood risk assessments, the work first reconstructs and extends hydro-meteorological data using Artificial Neural Networks (ANNs). These data then formed the input to a coupled IPCC-Sustainable Development Frameworks for quantifying flood vulnerability and risk. Flood risk was obtained by integrating hazard and vulnerability. Flood hazard was characterised in terms of flood depth and inundation area obtained through hydraulic modelling of the catchment with Lisflood-FP, while the vulnerability was indexed through analysis of exposure, susceptibility and capacity and linked to social, economic, environmental and physical perspectives. Data on these were collected through structured interviews carried out with the communities and stakeholders in the valley and later analysed. The implementation of the entire analysis within a GIS environment enabled the visualisation of spatial variability in flood risk in the valley. The results show predominantly medium levels in hazardousness, vulnerability and risk. The vulnerability is dominated by a high to very high susceptibility component largely because of the high to very high socio-economic and environmental vulnerability. Economic and physical capacities tend to be predominantly low but social capacity is significantly high, resulting in overall medium levels of capacity-induced vulnerability. Exposure manifests as medium. Both the vulnerability and risk showed marginal spatial variability. Given all this, the thesis argues for the need to mainstream disaster reduction in the rather plethoric conventional socio-economic developmental programmes in SSA. Additionally, the low spatial variability in both the risk and vulnerability in the valley suggests that any such interventions need to be valley-wide to be effective.

Publications

1. Mwale, F.D., Adeloye A.J. & Rustum, R. (2012) Infilling of missing rainfall and streamflow data in the Shire River basin, Malawi – A self-organizing map approach. Physics and Chemistry of the Earth, 50–52, 34–43.

2. Mwale, F.D., Adeloye A.J. & Rustum, R, (in press) Application of SOM and MLP-ANN for streamflow and water level forecasting in data poor catchments - The case of the Lower Shire Floodplain, Malawi. Hydrology Research, doi:10.2166/nh.2014.168.

3. Mwale, F.D., Adeloye A.J. & Rustum, R L.Beevers (submitted). Quantifying vulnerability of rural communities to flooding in SSA: a contemporary disaster management perspective – The case of the Lower Shire Valley, Malawi. Journal of Disaster Risk Reduction.

4. Mwale, F.D and Adeloye A.J. (2014) Quantifying exposure, susceptibility and capacity of rural communities to the flood hazard in Sub Saharan Africa – The case of the Lower Shire Valley. In: Proceedings of the Infrastructure and Environment Scotland 2nd Postgraduate Conference, University of Edinburgh, September 2014, Edinburgh, pp 93-100.

Presentations

1. Mwale, F.D, Infilling of missing rainfall and streamflow data in the Shire River basin, Malawi. BHS 11th National Hydrology Symposium. Hydrology for a Changing World, Dundee, 9-11 July 2012.

2. Mwale, F.D, Quantifying exposure, susceptibility and capacity of rural communities to the flood hazard in Sub Saharan Africa – The case of the Lower Shire Valley. Infrastructure and Environment Scotland 2nd Postgraduate Conference, University of Edinburgh, 2nd September, 2014.

Dedication

To my father, John Benson Chirwa, who never lived to see his dream come true.

Acknowledgement

First and foremost, my profound thanks go to the Government of Malawi through the Department of Human Resource and Management for funding my study.

I will forever be indebted to my husband for being a mother to our three children in the years the study separated us. His love and unwavering support made this achievement possible.

I am highly indebted to my primary supervisor, Dr. Adeloye, who supported me throughout this work whilst allowing me to learn and work independently. His unprecedented instant feedback will forever be memorable. My gratitude extends to Dr Grant Wright and Dr. Lindsay Beervers who co-supervised this work.

I am thankful to so many people too numerous to mention. In particular, I will forever be indebted to Dr Rabee Rustum for his help with data driven models, a field completely new to me. While so far, he was so close. I thank Dr Guy Schumann (University of Bristol) and Sam Jamieson for the help with Lisflood-FP model.

In Malawi, my gratitude goes to Mr Piasi Kaunda of the Ministry of Irrigation and Water Development who provided the hydrological data for the Shire River Basin. I am extremely grateful to Mr Osborne Shela who augmented this hydrological data and whose years of experience on the Shire Basin provided a valuable benchmark to the theoretical hydrological outputs from this research. I further thank Mr Adams Chavula (Department of Climate Change and Meteorological Services of Malawi), Mr James Chiusiwa (Department of Disaster Management Affairs), Mr. Kumbukani Mhango (Evangelical Association of Malawi), Mr. Tawachi Kaseghe (Eagles Relief and Development Programme), Mr Chrispin Chikwama (Illovo), Mr. Abel Chigunduru and Mr. Blessings Mlowoka (Plan International) – all for the assistance with data. Special thanks go to Mr Humphrey Magalasi and Mr. Anthony Mchawa who facilitated my working with communities in Nsanje and Chikwawa respectively.

I thank amazing friends I met in school: Pooja Shrestha, Rajaa Assaad, Ogechi Ileme, Sana, Judith Montford, Nwarwaz, Gilbert Kasangaki and Prince Boateng. The laughs, the sharing of experiences all made me strong in what transpired to be the most difficult moment of my life. I thank Pastor Justice Kwawu and Mama Patience Kwawu and the congregation of the Embassy of the Word of God for the spiritual support.

I will forever be indebted to my sisters Annastacia, Magreth and Victoria for keeping an eye on my children and my household.

Finally, I thank my father and mother for prayers, blessings and words of encouragement that never departed their mouths.

Declaration

ACADEMIC REGISTRY
Research Thesis Submission

Name:	Faidess Dumbizgani Mwale		
School/PGI:	School of Energy, Geoscience, Infrastructure and Society		
Version: *(i.e. First, Resubmission, Final)*	Final	Degree Sought (Award **and** Subject area)	PhD

Declaration

In accordance with the appropriate regulations I hereby submit my thesis and I declare that:

1) the thesis embodies the results of my own work and has been composed by myself
2) where appropriate, I have made acknowledgement of the work of others and have made reference to work carried out in collaboration with other persons
3) the thesis is the correct version of the thesis for submission and is the same version as any electronic versions submitted*.
4) my thesis for the award referred to, deposited in the Heriot-Watt University Library, should be made available for loan or photocopying and be available via the Institutional Repository, subject to such conditions as the Librarian may require
5) I understand that as a student of the University I am required to abide by the Regulations of the University and to conform to its discipline.

* *Please note that it is the responsibility of the candidate to ensure that the correct version of the thesis is submitted.*

Signature of Candidate:		Date:	18th December, 2014

Submission

Submitted By *(name in capitals)*:	
Signature of Individual Submitting:	
Date Submitted:	

For Completion in the Student Service Centre (SSC)

Received in the SSC by *(name in capitals)*:			
Method of Submission *(Handed in to SSC; posted through internal/external mail)*:			
E-thesis Submitted (mandatory for final theses)			
Signature:		Date:	

Table of Contents

Abstract I

Publications II

Dedication III

Acknowledgement IV

Declaration VI

Table of Contents VII

Chapter 1 Introduction 1

1.1 Introduction 1

1.2 Aim and objectives 5

1.3 Thesis outline 5

Chapter 2 Literature Review 8

2.1 Vulnerability, hazard and risk – some definitions 8

2.2 Theoretical frameworks for 'vulnerability analyses' 10

2.2.1 The hazard framework 10

2.2.2 The social framework 12

2.2.3 Contemporary frameworks 15

2.2.4 Summary 21

2.3 Approaches to measuring risk 22

2.3.1 A broader overview to measuring vulnerability 23

2.3.2 Measuring flood hazardousness, vulnerability and risk in SSA 31

2.4 Flood risk assessment and management in Malawi – perspectives from the Lower Shire Valley 36

2.4.1 Pathways to flood risk 36

2.4.2 Measuring flood risk and flood management 52

2.4.3 Hydrological data issues 57

2.4.4 Summary 59

Chapter 3 Methodology 60

3.1 Methodology overview....60
3.2 Scale of assessment....60
3.3 Quantifying the flood hazard and forecasting....64
3.3.1 Hydro-meteorological data and collection....64
3.3.2 Hydrological analyses – Artificial Neural Networks (ANN)....68
3.3.2.1 Self-Organizing Maps (SOM) as a basis for data reconstruction....69
3.3.2.2 Multi-layer Perceptron ANN (MLP-ANN) as a basis for forecasting....78
3.3.2.3 ANN evaluation....81
3.4 Hazardousness determination....82
3.4.1 Model choice....82
3.4.2 Data inputs....86
3.4.3 Flood hazardousness parameters....87
3.4.4 Model calibration and evaluation....87
3.5 Measuring vulnerability....88
3.5.1 Vulnerability factors....88
3.5.2 Conceptual framework for vulnerability analysis....94
3.5.3 The vulnerability index....95
3.5.4 Data collection....104
Chapter 4 Data Analysis....107
4.1 SOM application....107
4.2 MLP-ANN application....109
4.2.1 Input gauge stations....109
4.2.2 Data inputs....110
4.2.3 Network development....110
4.2.4 Network parameters....114
4.3 Lisflood-FP application....115
4.3.1 Data inputs....115
4.3.2 Mode of application....117
4.3.3 Model calibration and evaluation....117
4.3.4 Hazard severity ranking....118

4.4 The community vulnerability index 119

4.4.1 Vulnerability parameters 119

4.4.2 Vulnerability ranking 122

4.5 Risk analysis 122

Chapter 5 Results and Discussion 124

5.1 SOM quality analysis 124

5.2 Performance on flow, water level and rainfall 125

5.3 Flood hazardousness of the Lower Shire Valley 143

5.3.1 Model performance 143

5.3.2 Hazardousness magnitudes, areal extent and spatial variation 146

5.3.3 Average community hazardousness 151

5.4 Flow and water level forecasting 155

5.4.1 1-day ahead forecasting 155

5.4.2 Flow and water level forecasting for 2 to 5 day leads 161

5.5 The vulnerability profile of the Lower Shire Valley 163

5.5.1 Vulnerability magnitudes 163

5.5.2 Spatial trends 174

5.6 The flood risk of the valley 177

5.6.1 Risk magnitudes and profile 178

5.6.2 Spatial trends of risk 182

5.7 Policy implications and caveats 183

5.7.1 Introduction 183

5.7.2 Policy implications 183

5.7.3 Limitations of the study 184

Chapter 6 Conclusions and Recommendations for Future Research.. 186

6.1 Conclusions 186

6.2 Recommendations for Future Research 189

References 191

Appendices 213

Appendix A: Manning's Roughness Coefficient based on Chow (1959).................214
Appendix B: Questionnaire used for the CBDRI in Chikwawa and Nsanje Districts.. 215
Appendix C: Community responses to the questionaire 221

List of Figures

Figure 2.1: Sustainable Livelihood Framework. 13

Figure 2.2: The PAR model 14

Figure 2.3: A hazard of place framework 16

Figure 2.4: The BBC model 17

Figure 2.5: ISDR framework for disaster risk reduction ((ISDR, 2004) 19

Figure 2.6: Vulnerability framework based on Turner et al.'s (2003) model 20

Figure 2.7: Geographical location of the Lower Shire Valley 37

Figure 2.8: Variation in rainfall across the Shire River Basin 38

Figure 2.9: Annual hydrographs at selected stations on the Shire River and at Sinoya on the Ruo 40

Figure 2.10: Soils of the Lower Shire Valley. 42

Figure 2.11: Landuse and landcover in the Shire Basin (a) based on Department of Surveys data and (b) FAO classification by Palamuleni et al. (2010) 43

Figure 2.12: LULC changes in four classes in Lake Malawi basin between 1982 and 1995 based on AVHRR imagery. 44

Figure 2.13: Landuse and landcover changes between 1982 and 2002 in the upper Shire catchment 45

Figure 2.14: A 100-year flood as modelled by (a) World Bank (2010b) and (b) Atkins (2012). 56

Figure 3.1: Methodology overview 61

Figure 3.2: The architecture of SOM 72

Figure 3.3: Prediction of missing components of the input vector using SOM. 77

Figure 3.4: Configuration of feedforward three layer ANN. 78

Figure 3.5: Schematic diagram of node. 78

Figure 3.6: The vulnerability web for Malawi. Source: (Malcomb et al., 2014) 93

Figure 3.7: Conceptual framework for vulnerability analysis 95

Figure 4.1: The gauging network in the Shire Valley assessed for forecasting at Chiromo 109

Figure 4.2: ACF on (a) Chiromo water levels with the dashed lines representing the 95% confidence bound; and (c) Chiromo flows; PACF on (b) Chiromo water levels; and (d) Chiromo flows. 111

Figure 4.3: Cross correlations of (a) Chikwawa and Sinoya levels with Chiromo water levels and (b) Chikwawa and Sinoya flows, and rainfall with Chiromo flows. 112
Figure 4.4: Hydrographs of Shire River flows at Liwonde, Chikhwawa and Chiromo following a test run at Liwonde barrage upstream in 1981. 112
Figure 4.5: Flow hydrographs at Chikwawa and Sinoya in the 2008 flood season. 116
Figure 4.6: Flood frequency distribution at Chikwawa based on EV1 116
Figure 5.1: Component planes of flow, water level and rainfall from case 1 (F= flow, L = water level and R = rainfall 127
Figure 5.2: Component planes for flow and water level (a) and rainfall (b) resulting from Case 2. 129
Figure 5.3: Component planes for rainfall clusters 1 (a), 2 (b) and 3 (c) 131
Figure 5.4: A comparison of observed and predicted data on (a) flows, (b) daily water levels and (c) rainfall 133
Figure 5.5: A time series comparison of SOM –predicted and observed water levels 136
Figure 5.6: A time series comparison of SOM –predicted and observed flow 137
Figure 5.7 Time series comparison of observed and predicted values for all the 28 stations 139
Figure 5.8: Time series comparison of SOM- predicted data and observed rainfall 141
Figure 5.9: (a) Observed inundation extent from the 7-2-1 MODIS image, (b) Modelled flood extent and (c) a comparison of the two. 148
Figure 5.10: Flood inundation extent in the Lower Shire Valley by severity. 149
Figure 5.11: Flood inundation extent across communities 150
Figure 5.12: Flood extents across communities in the Lower Shire Valley 151
Figure 5.13: Spatial variation in flood hazardousness in the Lower Shire Valley.. 154
Figure 5.14: Model performance with increasing number of hidden neurons 156
Figure 5.15: A scatter plot comparison between observed and forecasted 1-day ahead data for selected ANN structures 158
Figure 5.16: A 1-day ahead time series comparison of observed and forecasted data on the selected ANN structures 160
Figure 5.17: ANN performance when trained on raw data and SOM features. 161
Figure 5.18: Aggregate vulnerability across communities in the Lower Shire Valley 168

Figure 5.19: Vulnerability magnitudes from exposure, susceptibility and a lack of capacity across communities. 168
Figure 5.20: Vulnerability of the Lower Shire from Sustainable Development Framework 169
Figure 5.21: Vulnerability profile from a coupled IPCC-Sustainable Development Framework 169
Figure 5.22: Resilience to climate change based on assets, access and livelihoods .. 173
Figure 5.23: Spatial variation in community vulnerability arising from exposure, susceptibility and capacity 175
Figure 5.24: Spatial variability in community vulnerability - a social, economic, environment and physical perspective 176
Figure 5.25: Quantified risk to climate change in Malawi 180
Figure 5.26: Spatial variation in flood risk across the valley 182

List of Tables

Table 2.1: Dimensions of social vulnerability 25
Table 2.2: Soil type and distribution across the Lower Shire Valley 43
Table 2.3: Areal extent of LULC classes (in Km^2) and lake level (meters above sea level) in Lake Malawi drainage basin 44
Table 3.1: Implications of spatial scales for spatial vulnerability assessments: 62
Table 3.2: Rating equations at main stations in the Shire River Basin 64
Table 3.3: Gauge and meteorological stations used for flood risk analysis 66
Table 3.4: Social-economic indicators of vulnerability in natural disasters 90
Table 3.5: Vulnerability indicators to climate change in Malawi based on Malcomb et al. (2014) 93
Table 3.6: Vulnerability indicators in Hahn et al.'s (2009) study 94
Table 3.7: Examples of natural disaster-related vulnerability indices 97
Table 3.8: Vulnerability factors in the CBDRI 105
Table 3.9: Communities under study 106
Table 4.1: Hydro-meteorological variables infilled with SOM 107
Table 4.2: Flood severity designation 118
Table 4.3: Vulnerability by social, economic, environmental and physical dimensions 121
Table 4.4: Risk rating 123
Table 5.1: Trained SOM characteristics 124
Table 5.2: SOM performance based on Case 1 125
Table 5.3: SOM performance based on Case 2 128
Table 5.4: SOM performance on clustered rainfall 130
Table 5.5: A basic static comparison of SOM- predicted data and observed data over analysis period 141
Table 5.6: Lisflood-FP performance with respect to floodplain friction (nfp) 143
Table 5.7: Lisflood-FP performance with varied Manning's coefficient 144
Table 5.8: Flood depth and associated hazard index 152
Table 5.9: Average community flood hazardousness in the Lower Shire Valley 152
Table 5.10: Performance of the three models in the testing phase 157
Table 5.11: Comparison of raw and SOM-trained 2-3-2 MLP-ANN for forecasting 162
Table 5.12: Perceived importance of variables in contributing to vulnerability 165

Table 5.13: Scores and associated weights as allocated by communities 166
Table 5.14: Risk to flooding across the Lower Shire Valley....................................178

Chapter 1 Introduction

1.1 Introduction

The frequency, severity and damage costs of natural disasters are on the increase (Adikari and Yoshitani, 2009). This has been linked to a number of factors: population growth, urbanization and climate change and variability (Mathur, 2006; WMO, 2009). The significant increase has been in water-related natural disasters, particularly in floods and windstorms (Adikari and Yoshitani, 2009). Between, 1980 and 2006, floods have been the most recurrent water-related natural disaster. Floods have also accounted for the highest proportion of people affected by natural disasters. They have come second to windstorms in accounting for disaster-related economic damages and ranked second to droughts in accounting for natural disaster-related fatalities (Adikari and Yoshitani, 2009).

The increase in frequency, severity and associated damage costs in natural disasters in general, has spurred the call for sustainable disaster management strategies. This is exemplified in the agenda of international initiatives such as the International Decade for Natural Disaster Reduction (IDNDR, 1990 - 1999), the Second World Summit on Sustainable Development in Johannesburg in 2002 and the World Conferences on Disaster Reduction in Kobe, Japan in 2005.

A shift in conceptualization and methodological approach in assessing risk to natural hazards has been one key outcome. In particular, there has been an emphasis on integrated and multi-dimensional assessments coupled with the use of metrics (ISDR, 2005; Luers, 2005; Nelson et al., 2010; WMO/GWP, 2009). The Hyogo Framework for Action (HFA) 2005-2015 (ISDR, 2005) underscores this in the following statement:

> "*the starting point for reducing disaster risk and for promoting a culture of disaster resilience lies in the knowledge of the hazards and the physical, social, economic and environmental vulnerabilities to disasters that most societies face, and of the ways in which hazards and vulnerabilities are changing in the short and long term, followed by action taken on the basis of that knowledge*".

The framework goes on to underscore the need for metrics:

> *"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 on social, economic and environmental conditions and disseminate the results to decision-makers, the public and populations at risk".*

The increasing support for such methodological approaches stems from their usefulness in supporting decision making and policy in ways pertinent to sustainable risk reduction. Several researchers (Gall, 2007; Luers, 2005; Nelson et al., 2010; Vincent, 2004) assert that metric-based assessments allow identification of relative vulnerabilities of specific people and specific places. In this way, metric-based assessments support targeting of interventions and allocation of scarce resources, an important aspect for resource strapped developed countries. Besides, such approaches allow the monitoring of policy interventions. Cinner et al., (2012) have also argued in favour of dimensioning vulnerability or risk observing that specific dimensions demand different policy measures and therefore such an approach would lead to the institution of appropriate interventions. This has been echoed by Fussel (2007) who cites the example of social vulnerability being important for the design of adaptation policies but limited in informing mitigation policy.

Adoption of such approaches in vulnerability or risk assessments has been considerable in many parts of the world (Balica et al., 2012; Cutter and Finch, 2008; Cutter et al., 2000; Dinh et al., 2012; Vincent, 2004). In contrast, in Sub-Saharan Africa (SSA) where floods alongside droughts are the dominant natural hazards accounting for 80% and 70% of disaster related mortality and economic losses respectively (World Bank, 2010a), assessing risk from this contemporary perspective has been limited and confined to climate change studies (Gbetibouo and Ringler, 2009; Hahn et al., 2009; Sullivan and Meigh, 2005; Vincent, 2004).

Studies on flood risk in SSA have mainly been qualitative, addressing vulnerability in isolation by focussing on the identification of causal factors, impacts and coping strategies (Adelekan, 2010; Armah et al., 2010; Campion and Venzke, 2013; Douglas et al., 2008; Khandlhela and May, 2006; Maheu, 2012; Nethengwe, 2007). Even in a few studies that have departed from this usual descriptive approach by adopting quantitative methods, the tendency has been to emphasise the social dimension (Kienberger, 2012; Musungu et al., 2012) or, to a small extent, the biophysical dimension (Ologunorisa, 2004; Yahaya et al., 2010) without efforts to understand their confounding effects.

A bias towards understanding vulnerability may stem from calls for vulnerability reduction at household and community level and a culture of building resilience (Birkmann, 2006). It follows the recognition that complete flood protection by structural measures (addressing the hazard) is an illusion due to cost implications, the inherent uncertainty in floods and a limitation with what may be achieved in modifying the hazard in comparison to modifying human behaviour (Cardona, 2004; Kundzewicz and Takeuchi, 1999). There are also concerns of sustainability of structural measures (Birkmann, 2006). Environmental concern is another factor (WMO, 2009).

The bias towards vulnerability assessments has particularly been underscored for developing countries (Lumbroso et al., 2008). It is observed that cost implications from focussing on the hazard have more bearing on developing countries, as these countries face competing investment demands such as food and health (Herath et al., 2002). The beneficial side of flooding, though not confined to developing countries, has also been another drive for focussing on addressing vulnerability other than the hazard. It is estimated that about one billion people (one sixth of the world population), the majority of them being among the world's poorest people, live on floodplains (WMO-UNESCO, 2007). Floodplains provide them with deep fertile alluvial soils, space for development, and water availability for agriculture, navigation and recreation purposes besides sustaining ecosystems. However, a vulnerability emphasis discounts the hazard (Cardona, 2004). Cardona (2004) argues that without the hazard which is a triggering phenomenon, even if vulnerability is quantified, there is no risk and thus no possible future disaster.

Thus, research on flood risk in SSA has been deficient in some ways. Not only has it consistently ignored the interplay between hazard and vulnerability; it has also paid little attention to their quantification. A vulnerability emphasis has downplayed the physical factors that contribute to the risk of a system. Similarly, flood hazard studies, though few, have disregarded the wider political, social and economic struggles that intensify vulnerability and ultimately the impact of a hazard (Birkmann, 2007; Cutter et al., 2009). In either case, a narrow view of risk results.

The above deficiencies have implications for flood risk management considering the increasing need to link disaster assessment to decision making (Cardona, 2004; Nelson et al., 2010; Ribot, 2010). They impinge, in particular on appropriateness and adequacy of interventions, and on aspects of comparison, targeting and monitoring as earlier highlighted.

Given the current direction of flood risk research in SSA, how vulnerability and ultimately flood risk for rural communities in SSA manifest in magnitudes and along different dimensions, particularly so within a contemporary disaster management discourse, remain unknown. There is therefore need for improved understanding of the flood risk problem in SSA. Focusing on the Lower Shire Valley, Malawi, the thesis first sets out to characterise vulnerability and ultimately risk to flooding of rural communities in the Lower Shire Valley, Malawi.

The study contributes on two fronts. It proposes a methodology for reconstructing hydro-meteorological data, a major hindrance to water management in general in SSA and, hazard quantification in particular for complete risk analysis in this thesis. It further assesses the feasibility of such data for flood risk management through forecasting and warning. While hydrological data quality issues are not uncommon, the problem is more marked in developing countries; the extent of which may be unsuitable for application of traditional methods. The thesis further contributes, backed by a quantitative basis, through advancing the understanding of the flood risk of rural communities in SSA beyond the listing of causes, impacts, perceptions and coping strategies. It measures and profiles vulnerability and risk in respect of broader dimensions within the contemporary discourse of disaster management.

1.2 Aim and objectives

The aim of the thesis is to enhance understanding of vulnerability and risk to flooding of rural communities in the Lower Shire floodplain, Malawi for the purpose of supporting decision making for effective flood risk management. The objectives are to:

- Develop an approach to augment and extend hydro-meteorological data in data poor catchments for the support of hydrological and hydraulic modelling.

- Develop, verify and validate AI –based forecasting models for flow and water levels.

- Quantify the hazard, vulnerability and risk, as well as their dimensions, and determine how these manifest themselves spatially.

- Make recommendations on flood mitigation and adaptation strategy for flood risk management.

1.3 Thesis outline

Chapter 1 provides a background and objectives of the study. It also outlines the structure of the thesis.

Chapter 2 is a review of literature. It provides definitions with regard to hazard, vulnerability and risk as linked to different disciplines. It then draws attention to the different theoretical frameworks historically and contemporarily used in disaster management and highlights their weaknesses and strengths. The chapter goes on to outline approaches used in measuring risk in general and the trends exhibited in SSA. The chapter also brings the Lower Shire Valley in to context; highlighting flood risk factors, previous attempts to measure flood risk in this valley and flood risk management in general. It further discusses the quality of hydrological data in the broader context of developing countries and how this impinges water management including flood assessment and mitigation.

In Chapter 3, the methodological approach for the thesis is presented. Risk as a convolution of the hazard and vulnerability is distinguished. The chapter identifies the spatial unit of analysis. It describes and justifies data to be used in defining hazardousness, vulnerability and ultimately risk. Alongside the data needs, methods for collecting this data are presented. Finally, the chapter presents tools for the reconstruction of the data and forecasting, and for the analysis of the hazard, vulnerability and risk. The methods used for data reconstruction have not hitherto been done for Malawi and in general not for data poor catchments in SSA. Neither have the IPCC framework been coupled with the Sustainable Development Framework for better understanding of vulnerability. These therefore constitute principal claims of the thesis to making an original contribution.

Chapter 4 dwells in detail on how data was analysed. It details the exact data inputs used in the tools identified in chapter 3. It further presents parameters, thresholds and rankings used to give a degree of severity of hazardousness, vulnerability and consequently risk. The chapter also outlines means for validation where applicable.

Chapter 5 outlines and discusses the results. This is with regard to the performance of developed ANN models in reconstructing data as well as in forecasting in such data-poor environments. Further, the chapter provides magnitudes and spatial patterns of hazardousness, vulnerability and risk, across communities in the valley. The determinants of vulnerability to flooding on the basis of dimensions other than factors are identified. Likewise, the determinant of flood risk for these rural communities vis-à-vis vulnerability or the hazard is also established. The chapter concludes with policy implications of the findings and limitations of the study.

Chapter 6 concludes the thesis and recommends areas for further research in order to promote evidence-based policy decision making in flood risk management.

Chapter 2 Literature Review

2.1 Vulnerability, hazard and risk – some definitions

Hazard

A hazard has been defined as a dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage (ISDR, 2009). Hazards are often classified based on origin. In this regard therefore, hazards are classified as natural (floods, droughts, earthquakes, landslides, volcanoes), technological (explosions, spills, release of toxic chemicals) and social or human-induced hazards (wars, terrorism) (ISDR, 2004; Villagran de Leon, 2006). Natural hazards that are triggered or aggravated by a combination of natural events and human intervention are sometimes distinguished. These are referred to as socio-natural hazards (Villagran de Leon, 2006) and constitute hazards such as floods, landslides and bush fires.

Vulnerability

Vulnerability is a term that carries different and often contested meanings across disciplines. Nonetheless, in the natural hazard or the human-environment disciplines, the definitions accorded are normally not mutually exclusive; it is a matter of language (Adger, 2006; Brooks, 2003).

In general, vulnerability has been linked to the weakness of a system in the face of a hazard. The International Strategy for Disaster Reduction (ISDR) (2004) defines vulnerability as the conditions determined by physical, social, economic, and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards. According to Cardona (2004), vulnerability is an internal risk factor of the subject or system that is exposed to a hazard and corresponds to its intrinsic predisposition to be affected or to be susceptible to damage. Adger, (2006) looks at vulnerability as the state of susceptibility to harm from exposure to stresses associated with environmental and social change and from the absence of capacity to adapt. The Inter-Governmental Panel on Climate Change (IPCC) (IPCC, 2012) defines vulnerability as the propensity or predisposition to be adversely affected.

Whilst vulnerability has the general connotation of weakness, the inclusion of coping capacities also underlies most definitions. Therefore, vulnerability is a phenomenon also associated with such terms as *coping capacity, coping, adaptive capacity, adaptation, resistance and resilience* besides *susceptibility*, *sensitivity* and *exposure* (Adger, 2006; Birkmann et al., 2013; Fussel, 2007; IPCC, 2001; Smit and Wandel, 2006).

Risk

The term risk is associated with potential loss for a particular place and time, arising from the interactions of vulnerable conditions and the hazard. The ISDR (2004) for example defines risk as the probability of harmful consequences, or expected losses (deaths, injuries, property, livelihoods, economic activity disrupted or environment damaged) resulting from interactions between natural or human-induced hazards and vulnerable conditions. The term has been operationalized as:

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \qquad \text{(ISDR, 2004)} \tag{2.1}$$

$$\text{or as Risk} = \text{Probability} \times \text{Consequence} \qquad \text{(IPCC, 2012).} \tag{2.2}$$

The use of the terms *vulnerability* or *risk* is largely a function of the discipline. In social sciences, environmental hazards and climate change studies, the term of use is *vulnerability.* However, the social sciences discipline e.g. Blaike et al. (1994) reduces *vulnerability* to structural factors i.e. social, economic, political and institutional, that make the human system susceptible to harm. In contrast, in climate change studies, *vulnerability* is an all-encompassing term that besides social factors also includes biophysical factors such as rainfall, sea level rise, temperature etc. (Allison et al., 2009; Cutter et al., 2000; Hahn et al., 2009; Sullivan and Meigh, 2005).

Similarly, as with the climate change community, the natural hazard discipline (Bollin et al., 2003; Cardona, 2004; ISDR, 2004) is also cognisant of both social factors and biophysical factors. However, unlike in the climate change literature where the term vulnerability is used, the all-encompassing term used in the natural hazard discipline is *risk*. Thus risk in natural hazards discipline is synonymous to vulnerability in climate change literature with v*ulnerability* in the natural hazard discipline being an integral component of risk, along with the hazard. Vulnerability in the natural hazard discipline has been limited to the intrinsic disposition of a system to harm; independent of the hazard (Birkmann et al., 2013; Brooks et al., 2005)

In a classification scheme of 'vulnerability' to climate change by Fussel (2007), Fussel (2007) identifies four categories: *internal social vulnerability* (e.g. household income, social networks, access to information), external *social vulnerability* (national policies, international aid, economic globalization), *internal biophysical vulnerability* (topography, environmental conditions, land cover) and *external biophysical vulnerability* (severe storms, earthquakes, sea level rise). Based on this classification, in environmental hazards and climate change studies, all four categories constitute vulnerability. In natural hazards however, only internal and external social vulnerability and, internal biophysical vulnerability define vulnerability; external biophysical vulnerability is a hazard

2.2 Theoretical frameworks for 'vulnerability analyses'

An extensive review of literature on 'vulnerability' has been given by Brooks (2003), Vincent (2004), Adger (2006), Eakin and Luers, (2006), Birkmann (2006), Fussel (2007) and Cutter et al. (2009) amongst others. It emerges from these reviews that 'vulnerability' is polarised between two distinctive frameworks: a natural hazard framework and the social science frameworks. Other frameworks tend to be hybridizations. The two frameworks are synonymous to what has been referred to as "end point" and "start point" vulnerability (Kelly and Adger, 2000); "biophysical" and "social" vulnerability (Brooks, 2003) or "outcome" and "contextual" vulnerability . (O'Brien et al., 2007).

2.2.1 The hazard framework

The hazard framework focuses on the hazard. Until recently, this framework has been the domain of natural hazard and climate change scientists (Brooks, 2003; Fussel, 2007). The vulnerability of concern in this framework is that of the elements at risk (population, physical infrastructure, places, sectors, activities) by virtue of their exposure to the hazard. Ultimately, the focus is the impacts of the hazard in terms of loss of life and property and hazard characteristics (Brooks, 2003; Cutter, 1996; Eakin and Luers, 2006). According to Cutter (1996), magnitudes, frequency, duration, impact and rapidity of onset of the hazard are characteristics of interest. Thus in this framework, ‘vulnerability’ is an outcome following the occurrence of the hazard and the occupancy of hazardous zone (floodplains, coastal zones, seismic regions etc). Summed up by Eakin and Luers (2006), the hazard framework addresses the following questions: what are we vulnerable to? what consequences might be expected? where and when will those impacts occur?

Evaluation of vulnerability or risk from this perspective in many ways is advantageous. According to Dilley and Boudreau (2001), it allows monitoring of causal factors and predictions of impacts thereby creating opportunities for anticipating for them. Consequently, it enables the determination of the type of intervention needed, the location, timing, target population and level of effort needed to counter the impacts.

The framework is nonetheless without flaws. Its major criticism has been on undermining political, social and economic struggles that intensify vulnerability and ultimately the impact of a hazard (Adger, 2006; Cutter et al., 2009; Turner II et al., 2003). While the framework addresses *to what*, *where, when* and the consequences of the hazard, it does not address the *why* of vulnerability (Ribot, 2010). Another problem arises from treating the exposed system as uniform; without accounting for differences that result in differential impacts of the hazard (Birkmann, 2006; Turner II et al., 2003).

Furthermore, from a flood risk management point view, viewing ‘vulnerability’ as a sole function of exposure to the hazard carry costly implications: the tendency is to take away the flood from people through predominantly structural mitigation measures (Nelson et al., 2010). Herath et. al. (2002), Plate (Plate, 2007) and Lumbroso et al. (2008) amongst others have all drawn attention to the aspect of costs and the inherent unsustainability of structural measures for developing countries in the face of numerous competing socio-economic developmental demands for the available meagre resources.

2.2.2 The social framework

In contrast to the hazard framework, social frameworks place the burden to explain ‘vulnerability’ within the social system (Ribot, 2010). Vulnerability in this framework is attributed to historical, cultural, socio, economic and political processes that make people vulnerable (Adger, 2006; Eakin and Luers, 2006; Ribot, 2010). Consequently, as opposed to the hazard framework where vulnerability is an outcome, Eakin and Luers (2006) note that vulnerability in this framework is a state or condition of being moderated by existing inequities in resource distribution and access, the control individuals can exert over choices and opportunities, and historical patterns of social domination and marginalization. The framework identifies who precisely is vulnerable, why they are vulnerable and how they are vulnerable (Cutter et al., 2009; Eakin and Luers, 2006).

The social theoretical framework has been exemplified in a number of theories: the entitlement theory (Sen, 1981), sustainable livelihoods theory (DFID, 1999) (Figure 2.1) and to some extent in the Pressure and Release (PAR) model (Blaikie et al., 1994; Wisner et al., 2004) (Figure 2.2). The Entitlement theory explains vulnerability as a consequence of failure in means or avenues, both real and potential, of access to resources. The framework refers to these avenues as entitlements. Vulnerability variables of focus are the social realm of institutions, well-being, class and social status (Adger, 2006).

In the Sustainable Livelihood Framework, two elements are important: livelihoods and sustainability (Birkmann, 2006). Chambers and Conwal (1992) defined livelihoods as capabilities, assets (including both material and social resources) and activities required for a means of living. They observed that a livelihood is sustainable when it can cope with and recover from stresses and shocks, maintain or enhance its capabilities and assets, while not undermining the natural resource base.

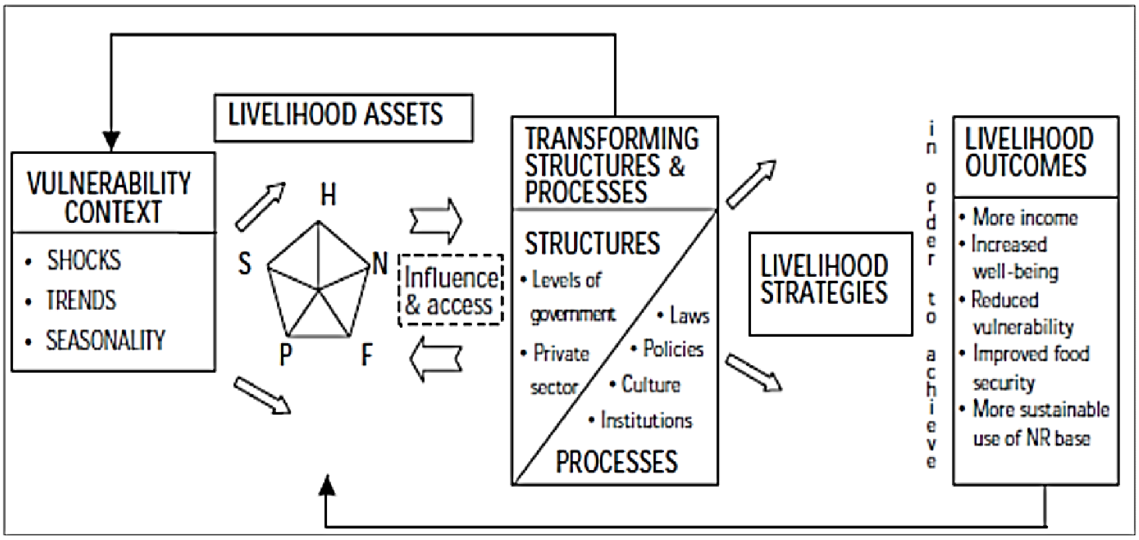


Figure 2.1: Sustainable Livelihood Framework.
H=human capital, N=natural capital, F=financial capital, P=physical capital, S=social capital. Source: (DFID, 1999)

Typically in this framework, the livelihoods are human capital (health, nutrition, education, knowledge and skills, capacity to work, capacity to adapt), natural capital (land and produce, water and the aquatic resources, biodiversity, trees and forest products, environmental services and wildlife); social capital (neighbours and kinship, mutual trust, formal and informal groups, common rules and sanctions, collective representation, mechanism for participation in decision making, leadership); physical capital (infrastructure - roads, vehicles, secure shelter and buildings, water supply and sanitation, communication and; tools and technology and financial capital (savings, credit/debts (formal and informal, non-governmental organizations), remittances, pensions and wages) (DFID, 1999). The Sustainable Livelihood Framework therefore conceptualizes vulnerability as failure to access and maintain livelihoods. The failure is often linked to transforming structures in the government system and private sectors and respective processes (laws, policies, culture, institutions) (Adger, 2006; Birkmann, 2006).

The PAR model (Figure 2.2) rather adopts a historical approach; it conceptualizes vulnerability as shaped by historical processes; from some ‘root causes’, intensified by some ‘dynamic processes’ which result in ‘unsafe conditions’ (vulnerability) Nonetheless, unlike other social models, the PAR model is cognisant of a disaster being a compounding function of the hazard and vulnerability.

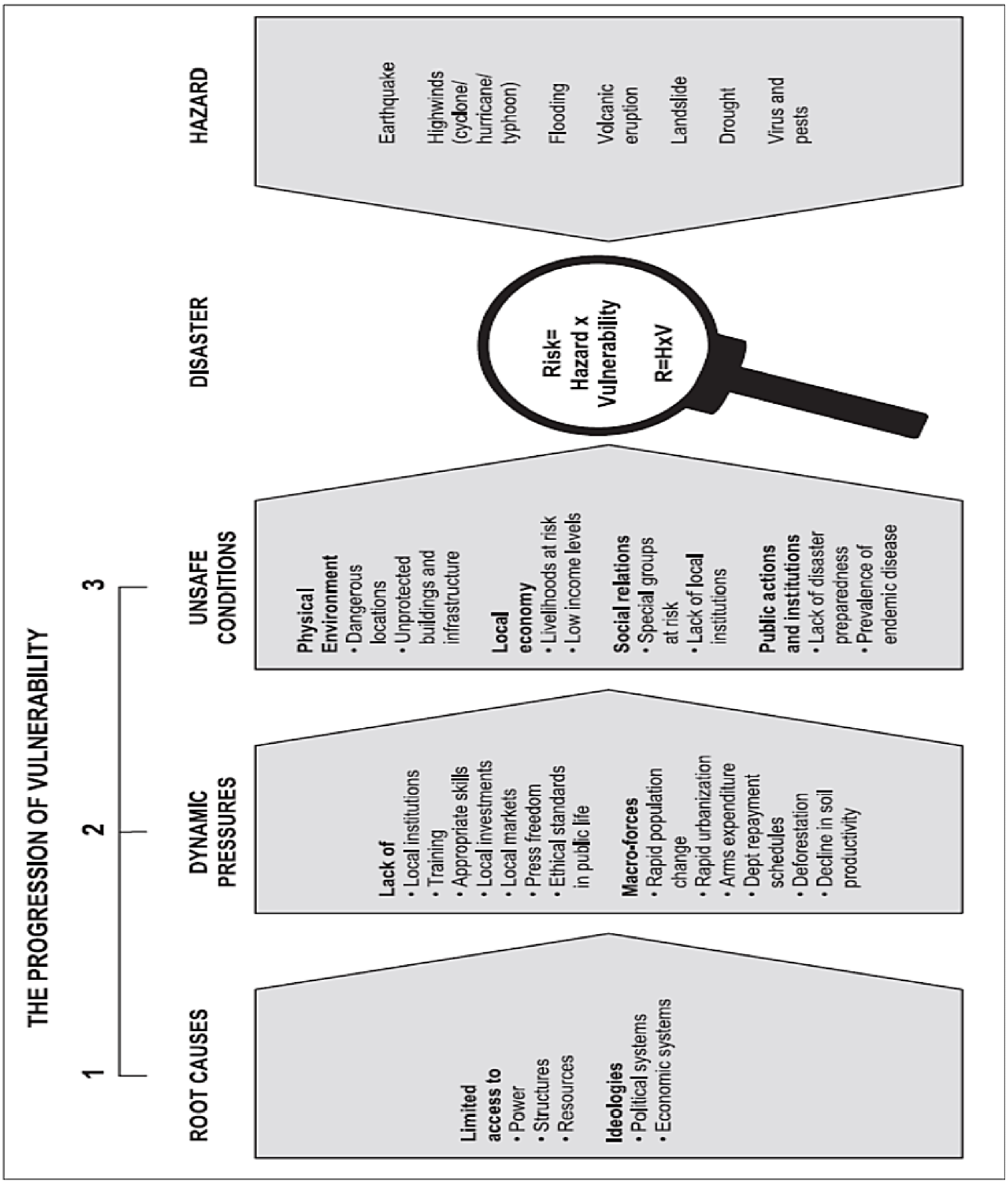


Figure 2.2: The PAR model

Source: (Wisner et al., 2004)

As with the hazard framework, a social framework has its own strengths. In identifying who precisely is vulnerable, why they are vulnerable and how they are vulnerable, the strength of these frameworks lies in revealing social differentiation in causes and outcome of vulnerability (Adger, 2006). Knowing *why* people are vulnerable helps design and modify interventions (Fussel, 2007; Ribot, 2010). In addition, the perception of vulnerability as being a structural outcome has implications for vulnerability redress that is less costly and therefore more befitting developing countries. Dunno (2011) points out that because impacts are contingent upon society rather than nature in this framework, when people are in danger, an important aspect becomes their coping strategies rather than the severity of a damaging agent, and when disasters do occur, the focus is especially upon who is affected and their ability to withstand, mitigate and recover from damage.

In spite of these advantages, the social framework has also not escaped criticisms. The human-centric element in this framework presents a major weakness; it ignores the physical processes that work to amplify vulnerability (Adger, 2006). There are other weaknesses. Eakin and Luers (2006) for example note that social frameworks sometimes fail to provide clearly defined vulnerability outcomes which, they observe, has produced in some research, generic descriptions of inequities in resource distribution and opportunity without demonstrating ties to differential susceptibility to harm. Wisner et. al (2004) also considers the framework emphatic of people's weakness and limitation and therefore treats human beings as dormant members incapable of taking preventive and adaptive measures.

In tandem with the growing recognition that social and human systems are integral to influencing 'vulnerability', 'vulnerability' research has in recent decades, also evolved.

2.2.3 Contemporary frameworks

'Vulnerability' research has in recent decades witnessed the emergence of theoretical frameworks that give a comprehensive and broader perspective of vulnerability to hazards (Adger, 2006). Their origins can be traced to the mid 90's (Cutter et al., 2009). In his review of vulnerability, Adger (2006) makes the following observations about these contemporary frameworks: they are characterized by the recognition of the coupled human and environment system in the analysis of vulnerability; they analyse elements of a bounded system; analysis is scale-linked; there is explicit linkage to other factors and processes beyond the scale of analysis; and they do not only treat exposure and sensitivity, they are also cognisant of responses of the communities (coping, adaptation, resilience). A further characteristic of contemporary frameworks is a shift from qualitative to quantitative assessments. Consequently, there is emphasis on linking ‘vulnerability’ analysis to decision making in practice (Adger, 2006; Cutter et al., 2009; Gall, 2007).

Contemporary conceptualization of ‘vulnerability’ is, to varied extents, exemplified in a number of models. The hazard-of-place framework (HOP) (Cutter, 1996; Cutter et al., 2000) shown in Figure 2.3 is an archetype of these frameworks. The HOP is integrative of both the social framework and the biophysical framework but with emphasis on a specific geographic domain.

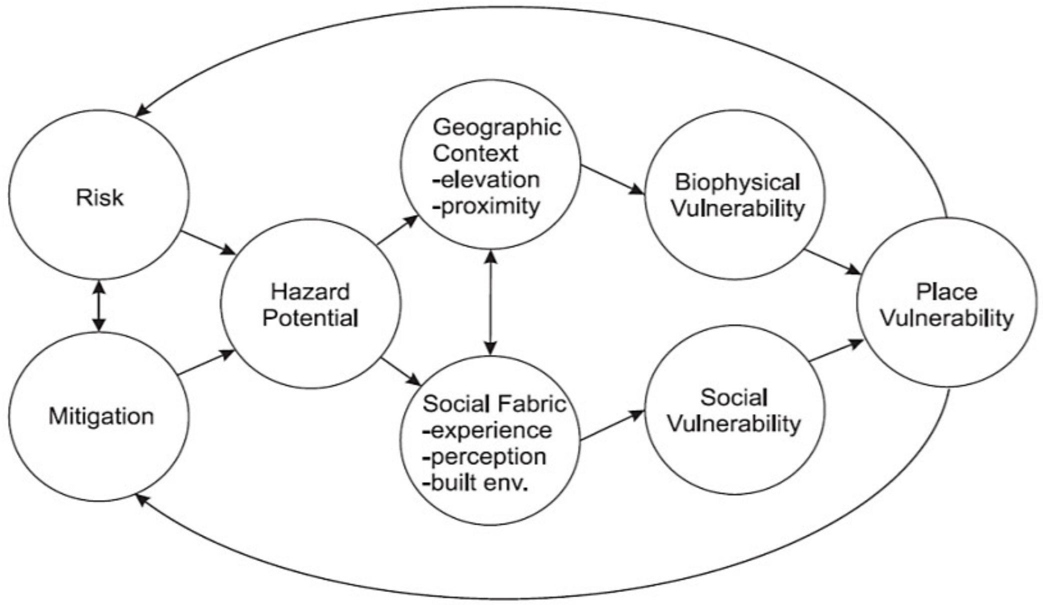


Figure 2.3: A hazard of place framework
Source: (Cutter et al., 2003)

The framework views the hazard potential as an outcome of risk (the likelihood of a hazard) and mitigation measures (measures to reduce risk or its impacts). The hazard potential is then filtered through the geographic context (site and situation, proximity) to produce biophysical vulnerability. The hazard potential is also filtered through the social fabric (socioeconomic conditions, risk perception, ability to respond). This generates social vulnerability. The overall ‘vulnerability’ for a place is the intersection of biophysical and social vulnerability. This further provides feedback loop to both risk and mitigation which may enhance or ameliorate the hazard potential. The HOP framework has mainly been used in the USA (Chakraborty et al., 2005; Cutter and Finch, 2008; Wu et al., 2002) but is applicable anywhere.

More recent integrative frameworks include the BBC (Bogardi and Birkmann, 2004; Cardona, 1999; Cardona, 2001) framework (Figure 2.4), the ISDR (2004) framework (Figure 2.5), and Turner II et al.'s (2003) model (Figure 2.6).

The BBC framework (Figure 2.4) underscores a risk analysis that goes beyond the estimation of deficiencies and disaster impacts; it rather stresses a dynamic process that simultaneously and continuously focuses on vulnerabilities and interventions to reduce vulnerability whilst accounting for the hazards and potential events that

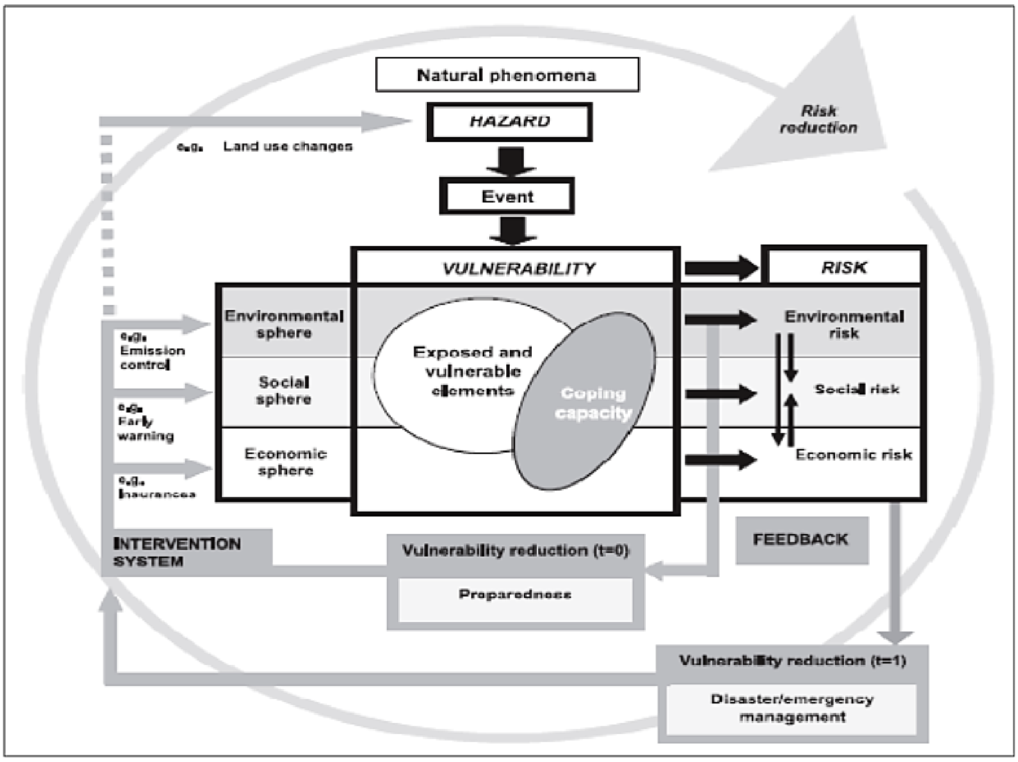


Figure 2.4: The BBC model
Source: (Birkmann, 2006)

the society is vulnerable to, the interaction with which leads to risk (Birkmann, 2006). The framework conceptualises vulnerability as a function of exposure, susceptibility and coping capacities. Besides, it underscores sustainable development elements. In this regard, it analyses vulnerability from a social, economic and environmental perspective. The incorporation of interventions to reduce vulnerability, both ext-ante and ex-post, and those to reduce hazard magnitudes and frequency makes the framework risk reduction-oriented (Birkmann, 2006).

Like the BBC framework, the ISDR (2004) framework (Figure 2.5) conceptualises vulnerability as independent of the hazard and therefore recognises risk as arising from vulnerability and the hazard. Its conceptualisation of vulnerability as having four dimensions: social, economic, environmental and physical. The framework is emphatic on disaster risk reduction processes i.e. hazard and vulnerability analysis, risk assessment and response (awareness, knowledge development, public commitment, application of risk reduction measures, early warning and preparedness).

Turner II et al.'s (2003) model (Figure 2.6), like the HOP, is a place-based model that emphasizes coupled human-environmental systems. Unlike in the BBC and ISDR frameworks where vulnerability is retained for the social system, 'vulnerability' in Turner II et al.'s (2003) model, as with the HOP, is inclusive of the biophysical component. Vulnerability is defined in terms of exposure, susceptibility and responses (coping responses, impact responses and adaptation responses). Specifically, a system's vulnerability to hazards in this framework consists of (i) linkages to the broader human and biophysical (environmental) conditions and processes operating on the coupled system in question; (ii) perturbations and stressors/stresses that emerge from this conditions and processes; and (iii) the coupled human – environment system of concern in which vulnerability resides, including exposure and responses (i.e. coping, impacts, adjustments, and adaptation) (Turner II et al., 2003). Unlike the HOP therefore, Turner et al's model links place vulnerability to in-place, beyond place and cross scale factors.

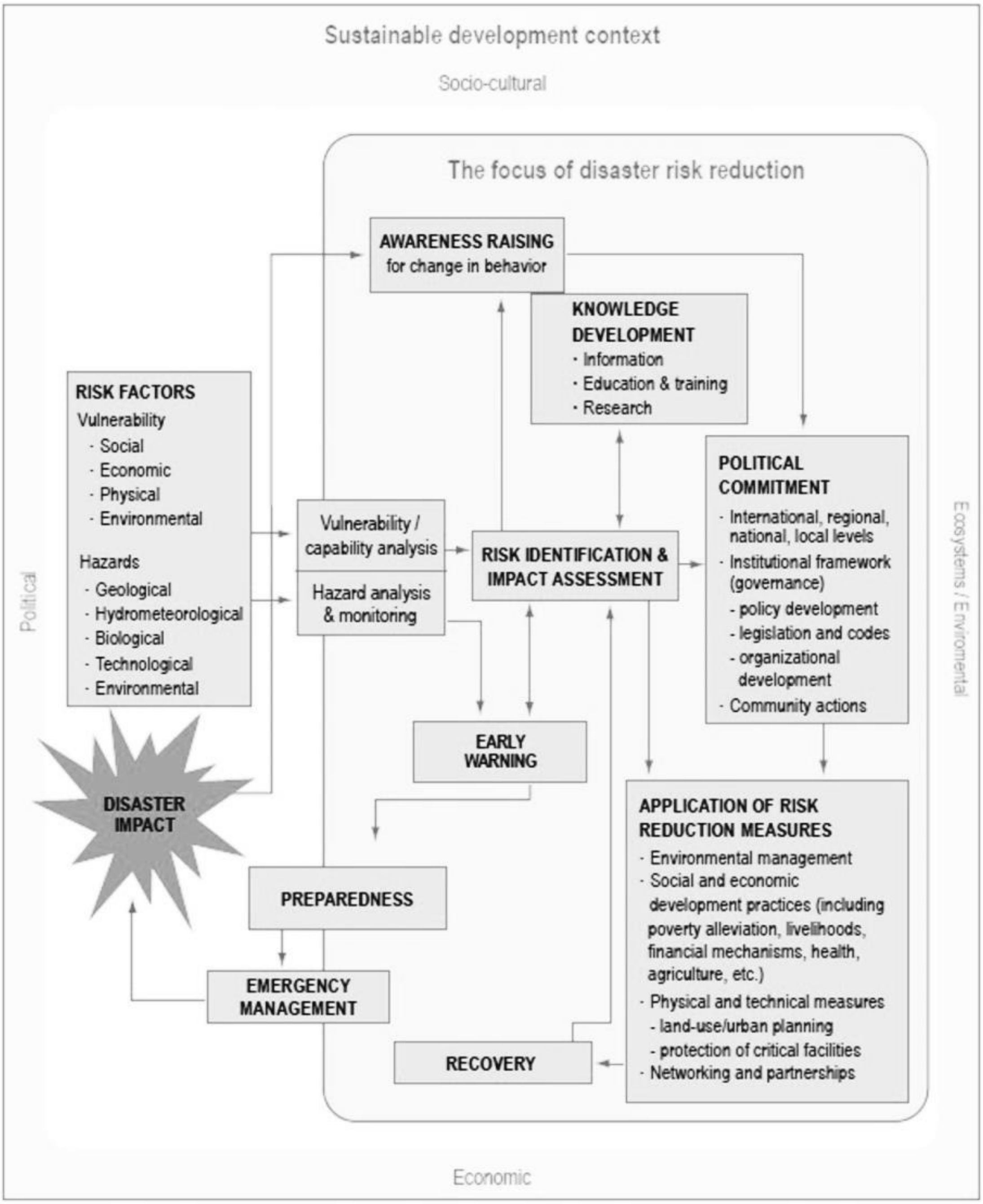


Figure 2.5: ISDR framework for disaster risk reduction ((ISDR, 2004)

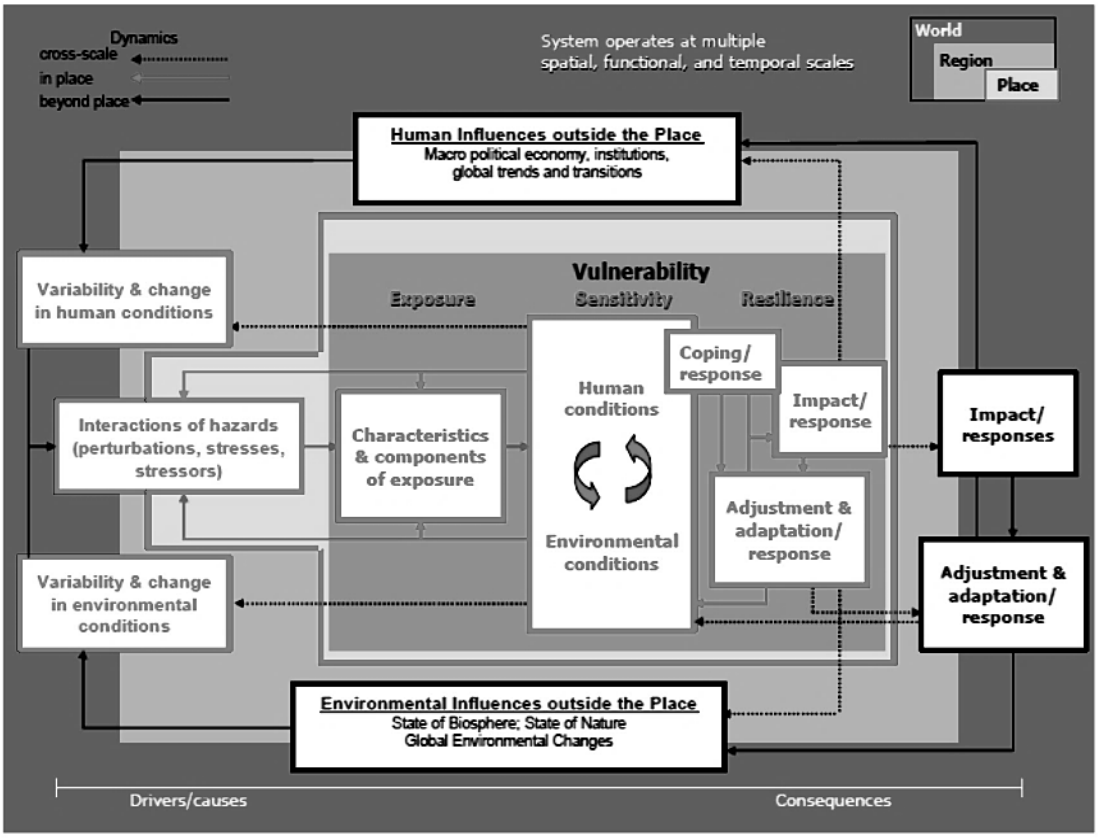


Figure 2.6: Vulnerability framework based on Turner et al.'s (2003) model

Despite being conceptually appealing, these contemporary frameworks are not without shortfalls. For instance, the HOP model (Figure 2.3) does not provide a causal explanation of the vulnerability; rather variables are adopted as is. Because it focuses on place-based interactions between biophysical and social systems, it also excludes the larger contexts within which such vulnerability exists (Cutter et al., 2009).

In the case of Turner II et al.'s model, Gall (2007) argues it is theoretical and lacks specificity. She specifically questions what in the model constitutes human and environmental conditions that construct vulnerability and the mechanisms that cause variability and change in both systems.

Similarly, the ISDR (2004)'s conceptualisation of vulnerability does not link vulnerability and preparedness response system and therefore is not explicit on how vulnerability and risk can be reduced (Birkmann, 2006).

Ultimately, the most important limitation of contemporary frameworks is the methodological difficulty of translation of some concepts into practice. For example, positing social and environmental processes within nested scales is one such difficulty in Turner‘s model (Eakin and Luers, 2006; Gall, 2007). In this regard, Gall (2007) argues against the generalizability of the cross-scale aspect observing that cross-scale integration would be more appropriate for global climate change studies.

Indeed, cross-scale integration has been exemplified in global climate change studies e.g. O’Brien et al. (2004a). O’Brien et al. (2004a) assessed the vulnerability of agriculture in India not only in the context of climate change taking place in India but also due to global market forces. However, the cross interaction is not elaborate. Eakin and Luers (2006) argues that in O’Brien et al. (2004a), the nature of the cross scale interaction between the two stressors, the relative importance of each at any given time, and the possible nonlinear responses of a system to multiple stressors study are elusive.

As is the difficulty of integration of spatial scale, the incorporation of different links that exist between factors is also a difficulty that has also been elusive in most studies (Chakraborty et al., 2005; Cutter and Finch, 2008; Cutter et al., 2003).

Besides these challenges, Eakin and Luers (2006) also observe that capturing the full dynamics of vulnerability in these contemporary models, would entail larger interdisciplinary teams and huge amount of financial resources which is a challenge in resource scarce areas.

2.2.4 Summary

Vulnerability, hazard and risk are terms associated with different disciplines. Vulnerability is a term more associated with the social sciences and climate change discipline although they carry different connotations. Risk on the other hand is used in the natural hazard literature and refers to the convolution of the hazard and vulnerability. Nonetheless, vulnerability in climate change is synonymous to risk in the natural hazards discipline.

Assessing risk to natural disasters has evolved in numerous ways. Among them is a shift from a traditional sole biophysical or social emphasis, to the integration of both systems. Further, contemporary disaster management accounts not only for exposure or sensitivity but is also inclusive of the adaptation capacity at hand. Associated with the paradigm shift in conceptualization, is also an emphasis on the quantification. This has been viewed as one of the pathways to sustainable disaster management as quantification informs policy and decision making. Despite advances in theoretical frameworks, not all contemporary frameworks are amenable to practical applications.

This thesis draws largely from the disaster risk community. Hence, it adopts a natural hazard nomenclature where vulnerability and hazard are integral to risk. Drawing from Fussel's (2007) classification, vulnerability in this study is confined to predisposition of a system to harm defined by internal and external socio-economic conditions including internal biophysical characteristics e.g. topography, soil. External biophysical such was flow depth, velocity, frequency constitute a hazard in this study. Due to methodological challenges, it disregards the links and synergies between factors. Further, the study is place-based - confined to factors as determined by the geography of the Lower Shire floodplain.

2.3 Approaches to measuring risk

Birkmann (2006) describes measuring risk as "translating the abstract concept of risk into practical tools to be applied in the field". According to Birkmann, measuring risk is both quantitative and qualitative.

The issue of measuring risk has steadily gained attention. In the face of increasing frequency and severity of disasters in recent years, measuring risk is increasingly seen as key to disaster reduction (Birkmann, 2006; Luers, 2005; Nelson et al., 2010). It provides a sound basis for risk reduction (Victoria et al., 2014): it enables the adoption of appropriate policies, the monitoring of such policies of what they may achieve over time and stirs the mobilization of local synergies for resilience building (Fussel, 2010; Luers, 2005; Victoria et al., 2014). Brown et al. (2011) view measuring risk as important for targeted adaptation efforts and hence optimal allocation of resources; a prerequisite for countries with scarce resources, notably developing countries. It has also been viewed as a step towards sustainable development, poverty alleviation and achieving Millennium Development Goals (Birkmann, 2006; Mathur, 2006) and this cannot be over emphasized for developing countries.

2.3.1 A broader overview to measuring vulnerability

A plethora of methods has been applied to measuring risk.

Measuring vulnerability

Measuring vulnerability objectively is difficult (Smith, 2013). The complexity of the human-ecological interactions, the multiple stressors to which a system is subjected, the multiple outcomes manifested by vulnerability, the dynamic nature of the different components in a system, the inclusiveness of variables, the qualitative nature of social variables, the need for thresholds and the difficulty of setting them all add to the difficulty of measuring vulnerability (Luers, 2005; Vincent, 2004).

Despite the above measurement issues, using indicators has emerged as a prominent trend in the measurement of vulnerability risk in contemporary disaster management (Gall, 2007; Luers, 2005; Nelson et al., 2010); more particularly in social and integrated frameworks. Tate (2012) defines indicators as "quantitative variables intended to represent a characteristic of a system of interest". They can be single e.g. income or composite (index) e.g. GDP.

Quite common to the use of indices is the use of a dimensionless number to represent vulnerability e.g. the Social Vulnerability Index (Vincent, 2004), the Environmental Sustainability Index (Esty et al., 2005), the Prevalent Vulnerability Index (Cardona, 2005) and the Climate Vulnerability Index. A variant is to equate variables deemed to influence vulnerability to a proxy variable of vulnerability, often mortality or economic damages, through some equation (Brooks et al., 2005; Fekete, 2009). The identification of the equation in the later follows some statistical analyses such as regression analysis and principal component analysis

Advantages of indicators as tools for measuring vulnerability are well documented by Vincent (2004), Gall (2007), Birkmann (2007) and Tate (2012) amongst others. These authors highlight a number of strengths. They note that indicators summarize complexity in simple figures, therefore, argue that indicators are relatively easy for understanding to non-experts making them attractive to stakeholders, practitioners and decision makers. They opine that indices use a diverse range of variables which encapsulate various dimensions of vulnerability, and therefore afford the opportunity to identify the root causes of vulnerability. They also argue that indicators can be used as a basis for setting targets for risk reduction. Furthermore, they also point out that indicators allow monitoring of changes over time and over different areas of what might have been achieved as a result of policy interventions or investments made. In general, measuring vulnerability with indicators is viewed as a systematic approach to discussing and addressing the various features of vulnerability and therefore a sound basis for sustainable management (Birkmann, 2006; Birkmann and Fernando, 2008; ISDR, 2004; Nelson et al., 2010).

In spite of these advantages and the associated increasing use, indicator-based vulnerability assessments are also not without criticism. From a methodological perspective, they suffer from subjectivity in terms of actual indicators used, definitions and units assigned, weightings used, aggregation process employed and thresholds set among other factors (Birkmann, 2007; Cutter et al., 2009; Esty et al., 2005; Gall, 2007; Vincent, 2004).

This is exemplified in a number of studies. For example, the Social Vulnerability Index (SoVI) (Cutter et al., 2003) has been widely used in the USA but with different thresholds for vulnerability ranking. The SoVI first identifies dominant vulnerability factors from a large set of social vulnerability factors using principal component analysis. Factor loadings (correlations) of the variables selected are then scaled to ensure that those that increase vulnerability are positive and those that work to reduce vulnerability are negative. In case of ambiguous factors, absolute factors are used. The SoVI score for a place is a sum of scaled factors. For comparisons, quartiles or standard deviations are used.

In measuring social vulnerability of the whole USA at county level with the SoVI, Cutter et al. (2003) identified 11 dominant factors shown in Table 2.1.

Table 2.1: Dimensions of social vulnerability

Factor	Name	Percent variation explained	Dominant variable	correlation
1	Personal Wealth	12.4	Per capita income	0.87
2	Age	11.9	Median age	-0.9
3	Density of the built	11.2	No commercial	0.98
4	Single-sector	8.6	%employed in	0.8
5	Housing stock and	7	%housing units that	-0.75
6	Race-African	6.9	%African American	0.8
7	Ethnicity-Hispanic	4.2	%Hispanic	0.89
8	Ethnicity-Native	4.1	%Native American	0.75
9	Race-Asian	3.9	%asian	0.71
10	Occupation	3.2	%employed in	0.76
11	Infrastructure	2.9	%employed in	0.77

The mean SoVI score from all 3141 USA counties was 1.54 and the standard deviation σ, 3.38. A threshold of $<-1\sigma$ was used for the least vulnerable counties and $+1\sigma$ for the most vulnerable. In contrast, Cutter and Finch (2008) used $\geq +2\sigma$ for high vulnerability and $\leq -2\sigma$ as low vulnerability for the purpose of determining spatial and temporal patterns of social vulnerability in USA over the period 1960 to 2008.

Similarly, while most studies (Allison et al., 2009; Balica and Wright, 2010; Cutter and Finch, 2008; Cutter et al., 2003) have avoided attaching weights to the variable or components arguing there is yet no real understanding of the relative value and nature of interaction amongst components, others have used weights to underline differential importance of variable in accounting for vulnerability. Sometimes the basis has been elusive. An example in question is the social vulnerability index to climate change, in particular for water availability (equation (2.3)), developed by Vincent (2004) for African countries.

$$SVI = I_i W_i + I_{ii} W_{ii} + I_{iii} W_{iii} + I_{iv} W_{iv} + I_v W_v \qquad (2.3)$$

where I = sub-component and W = sub-component weight. Specifically,

I_i = *economic well-being and stability* sub-component = 0.8 *poverty indicator* +0.2 *percentage urban growth.* $W_i = 0.2$

I_2 = *demographic structure* sub-component = *dependent population* + *proportion of working population with HIV/AIDS,* $W_{ii} = 0.2$

I_3 = *institutional stability and strength of public infrastructure* sub-component = 0.8 *health expenditure* + 0.2 *the number of telephones per 1000 population*, $W_{iii} = 0.4$

I_4 = *global interconnectivity* sub-component, $W_{iv} = 0.1$

I_5 = *natural resources* sub-component, $W_v = 0.1$

In this index, indicators are first standardised based on min-max standardization scheme before application of equation (2.3). For a second version of this index, corruption is accounted for and I_3 = *institutional stability and strength of public infrastructure* = 0.6 *health expenditure* + 0.2 corruption index +0.2 *the number of telephones per 1000 population*. In applying these weights to this index, both at indicator aggregation level and at sub-component level, the basis is unclear.

While the choice of the variables in Vincent (2004) as in others such as Hahn et. al (2009) is informed by a deductive framework (a rigorous conceptual understanding of vulnerability or adaptive capacity (Nelson et al., 2010)), others have used an inductive approach whereby statistical techniques are applied on an initial large number of factors to isolate only those factors that are statistically significant. For example, Cutter et al. (2003) as illustrated in Table 2.1 and Fekete (2009) have both used Principal Component Analysis (PCA) to identify important variables. Factors in the Disaster Risk Index (UNDP, 2004) and the flood vulnerability index by Connor and Hiroki (2005) arise from application of linear regression. Likewise, factors in the flood vulnerability index by (Balica and Wright, 2010) follow application of three reducing techniques on the initial index (Balica et al., 2009): the differentiation method, a questionnaire and then a correlation method. Thus ultimately, the factors used in an index either with deductive or inductive underpinnings are at the discretion of the researcher and are not exhaustive.

The other challenge in the index-based approach to measuring vulnerability also arise from the difficulty of defining and quantifying indicators which may sometimes lead to some indicators being left out in the analyses thus compromising on the efficacy of the model (Birkmann, 2007; Dinh et al., 2012; Fekete, 2009). Vincent (2004) highlights other limitations of index-based measurements. She observes that because indicators are a snapshot in time, they are limited to represent dynamic processes. She also points out that indicators do not account for feedbacks, non-linearities and synergies that may exist in real systems amongst indicators. In aggregating indicators to reduce complexity, Vincent (2004) opines that more room for subjectivity is created resulting in higher demand for critical appraisal although King and MacGregor (2000) have argued otherwise.

The lack of a means for validation after the index has been developed is another big challenge and source of uncertainty for indices (Gall, 2007; Vincent, 2004). Even inductive models cannot remove subjectivity completely (Brooks et al., 2005). In fact, equating vulnerability factors to some proxy variable to validate vulnerability or risk, has attracted a lot of criticism. Commonly used proxy variables for validation are mortality or economic flood damages. In this case therefore, mortality or economic flood damages represent vulnerability. Most criticism has centred on quality of data. Researchers observe that disaster-related mortality figures are not systematically recorded and quite often are under-recorded, even in developed countries (Birkmann, 2007; Downton and Pielke, 2005; Gall, 2007; Guha-Sapir and Below, 2002). Birkamann (2007) also argues that some regions may be highly exposed, have high poverty levels and subject to repeated and catastrophic floods and hence by virtue of these characteristics are highly vulnerable. Yet, he observes, these regions may not register significant deaths. Another point of contention is that damages may also arise from other factors other than the hazard in question e.g. typhoons in the event of a flood (Birkmann, 2007; Connor and Hiroki, 2005).

Birkmann (2007) further draws attention to the aspect of thresholds. In international databases e.g. the Emergence Events Database (EM-DAT) maintained by the Center for Research on the Epidemiology of Disasters (CRED), which is a data source often for most global, regional and national studies, thresholds such as 10 deaths and/or 100 people affected and/or a call for international assistance are used. Birkmann (2007) observes that such thresholds underestimate chronic, creeping or low impact disasters. Gall (2007) further argues that since mortality and damage figures arise from actual events, using such proxy therefore measures actual vulnerability; potential vulnerability is therefore disregarded.

Despite limitations of indices, they present a common and an increasingly used method for vulnerability in contemporary disaster management due to their relevance in informing decision-making and policy. Their weakness is downplayed on the basis that they are not an end in themselves but a means to the end; a pointer to more significant issues and approximate rather than absolute (Bollin et al., 2003; Esty et al., 2005; King and MacGregor, 2000).

Community based assessments (CBA) have increasingly recently found a niche in vulnerability. Van Aalst (2008) describes CBA as assessments that use active participation of local communities in identifying the hazards, vulnerabilities and risks through such methods as transect walks, risk mapping, asset inventories, livelihood surveys, focus group discussions or key informant interviews. They have been particularly used in developing countries by Non-Governmental Organisations (NGO) as a means to foster their relationships with communities and as a basis for the design and operation of their projects (Izumi and Shaw, 2012; van Aalst et al., 2008). Outputs from CBA have also been used in index-based vulnerability assessments e.g. Kienberger (2012).

Strong arguments for CBA have been that hazards, vulnerabilities, risks and associated adaptive measures are better identified and ranked by own communities and therefore results are likely to be more representative of situation. Consequently, CBA have been viewed as a means of instilling empowerment and a sense of ownership and therefore, a sustainable way towards disaster reduction (Guarin et al., 2005; van Aalst et al., 2008; Zhang et al., 2013).

Despite their popularity, CBA have limitations. CBA can be resource intensive in terms of time and human resource requirement. This arise from the need for large areas of investigation if results are to be meaningful (van Aalst et al., 2008; Zhang et al., 2013). The other challenge arises from the tendency of communities to incorporate factors unrelated to the hazard under investigation (van Aalst et al., 2008). In particular, Van Aalst (2008) notes that communities may prioritise issues related to everyday lives such as livelihoods over the hazard being investigated. Finally, CRA's success depends on winning community participation (Shaw, 2014; Zhang et al., 2013) and to a certain extent, on the relationship between the government and community (Shaw, 2014).

Measuring risk

From a hazard framework perspective, where the focus is on impacts, risk has often been equated to mortality or economic damage costs (Buchele et al., 2006; Dilley et al., 2005; Dutta et al., 2003; UNDP, 2004).

It is common practice (Buchele et al., 2006; Dutta et al., 2003; World Bank, 2010b) to estimate the hazard (water depth, inundation area, velocity, duration and frequency) through models and overlay with the elements at risk i.e. population, roads, buildings etc. The resulting damage costs from this intersection constitute risk. The availability of spatial data on elements at risk made readily available through GIS has easily afforded risk measurement in this way. Guarin et al. (2005) notes that while good at depicting spatial and temporal dimensions of hazards, models are demanding in terms of data, technical expertise and capital costs, requirements often challenged in developing nations.

Remote sensing has been another technique widely used in the hazard framework. In the context of measuring flood risk, it is ideal for sparsely gauged or ungauged areas (Khan et al., 2011; Sanyal and Lu, 2004) and therefore an alternative to data demanding models where flow, rainfall, topography, landuse, river channel sections and other data sets may be required. Besides, the availability of some satellite imagery at no cost e.g. Landsat and Moderate-resolution Imaging Spectroradiometer (MODIS) affords countries that suffer from resources constraints i.e. technology, and infrastructure chance to conduct flood risk assessments (Ramirez-Herrera and Navarrete-Pacheco, 2013). In the case of floods, for example, remote sensed imagery has advantage of capturing large flood inundation extents in a very cost effective way (Sanya and Lu, 2004). It is also an ideal technique for rapid assessments, a critical factor for damage assessments, rescue operations and reconstruction efforts soon after the flood event (Ramirez-Herrera and Navarrete-Pacheco, 2013).

Despite these advantages, the use of remote sensing for measuring risk is also subject to a number of limitations. Optical remote sensing imagery is the most widely used due to prohibitive costs associated with radar imagery. Yet optical imagery can be impeded by cloud cover (Leauthaud et al., 2012; Sanya and Lu, 2004). Therefore, the efficacy of remote sensed imagery for risk assessment depends on the availability of suitable imagery.

The difficulty of determination of inundation depths, in the case of the flood hazard, from optical satellite imagery further arise; only visual judgment of depths can normally be made (Sanyal and Lu, 2005). The need for high spatial resolution imagery to determine the elements at risk and the inability of remote sensing to reveal characteristics of those elements, makes remote sensing unsuitable for vulnerability assessment (Lowe, 2010) and thus impinging on risk assessments. Consequently remote sensing has largely been confined to flood extent determination and for validation purposes on outputs from models (Islam et al., 2010; Khan et al., 2011; Schumann et al., 2013).

As with vulnerability assessments, employing indices for the measurement of risk is not uncommon (Bollin and Hidajat, 2006; Chakraborty et al., 2005; Dinh et al., 2012; Gbetibouo and Ringler, 2009; Hahn et al., 2009) though in climate-related studies such as Hahn et al. (2009) and Gbetibouo and Ringler (2009), this is referred to as measuring vulnerability. Again, as with vulnerability measurement, risk is also proxied on mortality or economic damage through an equation whose variables are deemed to influence risk (Brooks et al., 2005; Connor and Hiroki, 2005; Dilley et al., 2005; UNDP, 2004). Measuring risk with indices or with mortality and damage costs does not escape criticisms raised in the previous section against similar measurements for vulnerability.

CBA have also been used in risk assessment, though widely applied in building community resilience and therefore in addressing vulnerability rather than risk. For risk assessment, community's past memory is used to reconstruct the flood hazard. Similarly, their knowledge of their social and geographical environment is used to construct vulnerability and ultimately risk (Guarin et al., 2005; Hahn et al., 2009).

The strengths and weaknesses associated with CBA, earlier raised also apply to measuring risk with CBA. In using CBA for risk quantification though, other aspects emerge. In data scarce regions, notably in developing countries where hydrological and meteorological data are a challenge, CBA may be the only form of risk assessment (Guarin et al., 2005). On the other hand, hazard information with CBA suffers distortion, incompleteness in accounts and, differences in the accounts among different people due to memory loss (van Aalst et al., 2008). Consequently, because hazard memories fade with time, CBA have been described as unsuitable for assessments of historically distant events. They are also unsuitable for the prediction of future risk and quantitative risk assessments in general (Guarin et al., 2005; van Aalst et al., 2008).

2.3.2 Measuring flood hazardousness, vulnerability and risk in SSA

Research in the domain of measuring flood risk in SSA is limited in several aspects: few studies have been conducted; the studies have largely addressed vulnerability and not risk and more so, they have strived to understand vulnerability characteristics in terms of causative factors, impacts, perceptions and coping capacities at hand. While understanding factors is important, it offers very little in terms of decision-making on targeting of scarce resources, comparison of risk across specific people and places and monitoring of interventions as earlier highlighted.

The large body of literature on causes of vulnerability in the context of rural communities in SSA identifies causes as emanating from their socio-economic disadvantage (Aboagye et al., 2013; Armah et al., 2010; Khandlhela and May, 2006; Nethengwe, 2007; Nyakundi et al., 2010). Whilst cognisant of heavy rainfall, these studies report that rural people have very low access to assets (land, livestock, farm equipment, income generating equipment) and basic services (water, sanitation); their incomes are very low because income generating activities tend to be informal; and illiteracy is high. Gwimbi (2009) adds, using the case of Zimbabwe, that the vulnerability of the rural people in SSA is a result of their livelihoods being intricately linked to natural resources, a factor that makes them more exposed to the flood hazard as they settle in flood prone areas.

In certain contexts, these factors have been traced to issues of marginalisation. In Milaboni and Dzingahe villages in Thulamela Municipality of the Limpopo province of South Africa, Nethengwe (2007) using a political ecology framework found that vulnerability to flooding of rural households was socially constructed through the historical apartheid system that had resulted in differential access to household resources including land, income and housing quality.

On impacts, the studies unanimously report loss of lives, destruction of property mainly loss of crop and livestock, food and water shortages, disease incidence, loss of income and psychological trauma. The studies also report a number of coping strategies exhibited by rural people. According to Armah et al (2010), Khandlhela and May (2006) and Nyakundi et al (2010), coping strategies to the flood hazard for rural people in SSA tend to be short-term and include modification to consumption behaviour, diversification to non-agricultural livelihoods, premature harvest of crops, social networks, relief items, remittances from migrant relatives, borrowing, minimization of expenditure, selling of assets and temporary migration. Nyakundi et al (2010) also reports of use traditional knowledge as anticipatory strategy. In Nyando district, Kenya, they found that old people's bones aching, a large number of cow egrets, loud persistent croaking of frogs, domestic animals making loud distraught noises, movement of ants to higher ground were forms of an early warning system. Nyakundi et al (2010) however noted that such strategies were underutilised.

In the urban context, causes of flooding have been reported as lack of drainage systems, poor drainage systems where existent, wanton solid waste disposal, unplanned and unregulated developments, weak housing, the hazardous nature of geographical locations the urban poor occupy, over-population and government indifference to their problems amongst other factors (Adelekan, 2010; Campion and Venzke, 2013; Douglas et al., 2008; Sakijege et al., 2012). In the informal neighbourhoods of Malika and Keur Massar districts in Dakar, Senegal, Maheu (2012) has also reported of differential access to knowledge as a dominant vulnerability determinant.

Impacts for the urban poor have been found to include disease incidence, lack of portable water, smelly environments, blocked accessibility, diminished opportunities for economic activities, seasonal displacement and, ultimately mental stress (Adelekan, 2010; Campion and Venzke, 2013; Douglas et al., 2008; Sakijege et al., 2012).

As in the rural context, the urban poor vulnerable to flooding employ a number of coping strategies but these strategies are also short-term (Sakijege et al., 2012). According to the these studies, coping strategies for the urban poor include moving valuable items to higher heights in homes, use of water proof materials, bailing water out, digging trenches around the houses, blocking water at doors and treatment of water. Further, social relations, government and religious organizations act as important coping strategy for the urban poor.

With climate change projections pointing to several parts of Africa being likely to be affected (IPCC, 2007), though with uncertainty, causation of vulnerability and flood risk has also been investigated in the context of climate change. In this regard, studies (Adeloye and Rustum, 2011; Campion and Venzke, 2013; Di Baldassarre et al., 2010) suggest that causal factors are anthropogenic (concentrated populations in hazardous regions through urbanization, a failure in the urban planning system and poverty) and may be exacerbating by the climate forcing.

In both rural and urban settings, the disaster management process has also been perceived to contribute to vulnerability (Mpofu, 2011; Nyakundi et al., 2010; Roth and Becker, 2011; Shela et al., 2008; Tempelhoff et al., 2009; World Bank, 2010a). According to these studies, effective disaster risk management in SSA is hampered by weak institutional frameworks that are characterised by lack of coordination, lack of preparation, poor stakeholder participation and more particularly inadequate resources i.e. financial, human and technical.

Such qualitative understanding of causation, impacts, coping strategies in place and challenges provides a rich insight into the vulnerability and the risk problem. This, however, is only pertinent to the design of adaptation but not mitigation measures (Fussel, 2007). The lack of quantitative measurement in these kinds of studies is a limitation to supporting decision making and policy in aspects of comparisons across different people and different places, optimization of resources, targeting of interventions, monitoring of progress that may accrue from such interventions and setting of targets (Luers, 2005). The list of factors identified, rather than an aggregation to some common bracket, is also a practical challenge to work with in disaster management (Chakraborty et al., 2005).

Quantitative approaches to measuring vulnerability or risk, perceived to address this gap, are few in SSA and often characterised by a social or a biophysical emphasis. Kienberger (2012) for example mapped the vulnerability to flooding of Buzi district of Mozambique on a scale of 0 – 1 with 1 denoting the most vulnerable. However, the assessment was limited to social and economic variables (access to health services, education, water services, capacity to anticipate, distance to rescue centres, distance to conflict points, access to local markets, road infrastructure and cities; crop density and ecosystem services).

Similarly, in the informal settlement of Graveyard Pond in Cape Town, South Africa, Musungu et al. (2012) digitised shack outlines from aerial photographs and linked them to socio-economic information of the occupants, sourced through a questionnaire. The result was a spatial map of vulnerability for each of the four variables (type of exposure, mitigation mechanism, disease type suffered and employment type) and of aggregate vulnerability - all linked to social vulnerability.

To quantify the vulnearbility to flooding of the Hadejia-Jama'Are River basin in Nigeria, Yahaya et al. (2010) also used multicriteria evaluation techniques, specifically Boolean method, ranking method and pairwise comparison. The data used was annual rainfall, basin slope, drainage network, landcover and type of soil. Associated weights were found to be 33.9%, 25.5%, 19.7% 15.2% and 5.7% respectively. The result was a vulnerability map for Hadejia-Jama'Are River basin. As demonstrated by the choice of factors used, the study has a biophysical emphasis.

Ologunorisa (2004) determined flood risk (R) in 18 settlements of the Niger Delta region of Nigeria based on the following relationship:

$$R = w_1 \times w_2 \times w_3 ....w_n \tag{2.4}$$

$R < 100$ =Low, $100 < R < 600$=medium, $R > 600$ =high.

$w_1, w_2,.........w_9$ are the scores equal to 1 (low), 2 (medium) or 3 (high) scored by a settlement on a variable. n = 9 and is the total number of variables investigated i.e. depth of flooding, duration of floods, perceived frequency of hazard flood occurrence, extent of damage, percentage deviation of seasonal rainfall from normal average, relief above sea level, proximity to hazard, perceived adequacy of flood control and dominant landuse or economic activity. The result was a map of spatial variation in risk, concentrated in the medium and high classes. While Ologunorisa (2004) claims to have measured flood risk of the Niger Delta region of Nigeria, the factors used clearly excludes the social dimension.

Despite quantification of vulnerability in these studies i.e. Kienberger (2012), Musungu et al. (2012), Yahaya et al. (2010) and Ologunorisa (2004) little attention has been paid to integration and multi-dimensioning.

2.4 Flood risk assessment and management in Malawi – perspectives from the Lower Shire Valley

The National Adaptation Programmes of Actions (NAPA) (Governement of Malawi, 2006) for Malawi lists natural hazards facing the country as intense rainfall, floods, seasonal and multi-year droughts, dry spells, cold spells, strong winds, thunderstorms, landslides, hailstorms, mudslides and heat waves. However, NAPA (2006) also highlights floods and droughts as the most prevalent natural hazards facing Malawi, an observation in line with the World Bank's (2010a) assertion that floods and droughts are the most important natural hazards that face SSA.

The Lower Shire Valley forms the basis of this study. It is the most affected region in the country in terms of severity and frequency of floods when compared to other five river systems affected by flooding in Malawi namely: Likangala/Thondwe, Limphasa/Luweya, Bwanje/Livulezi, Songwe and Linthipe (Malawi National Contingency Plan: 2009–2010, 2009; Nilson et al., 2010).

2.4.1 Pathways to flood risk

The flood risk in this valley stems from a complex web of factors; both physiological as and socio-economical as outlined in the sections below.

Physical factors

Location and topography

The Lower Shire Valley, located on the lower section of the Shire River in the southern region of Malawi (Figure 2.7), sits on the Great East African Rift Valley. It is an elongated plain with a width of 8 to 40km at an elevation of between 30 and 150 meters above sea level (masl) (Phiri and Saka, 2009) (Figure 2.7). The valley falls in two administrative districts: Chikwawa and Nsanje. At Chikwawa Boma, the valley is at an elevation of about 107 masl and at 61masl at Nsanje Boma (SVADD, 1975). Beyond Nsanje to the confluence with the Zambezi River, relief fluctuates around 30 – 40 masl (Shela et al., 2008). Slopes are gentle: 0.437m/km from below Chikwawa escarpments

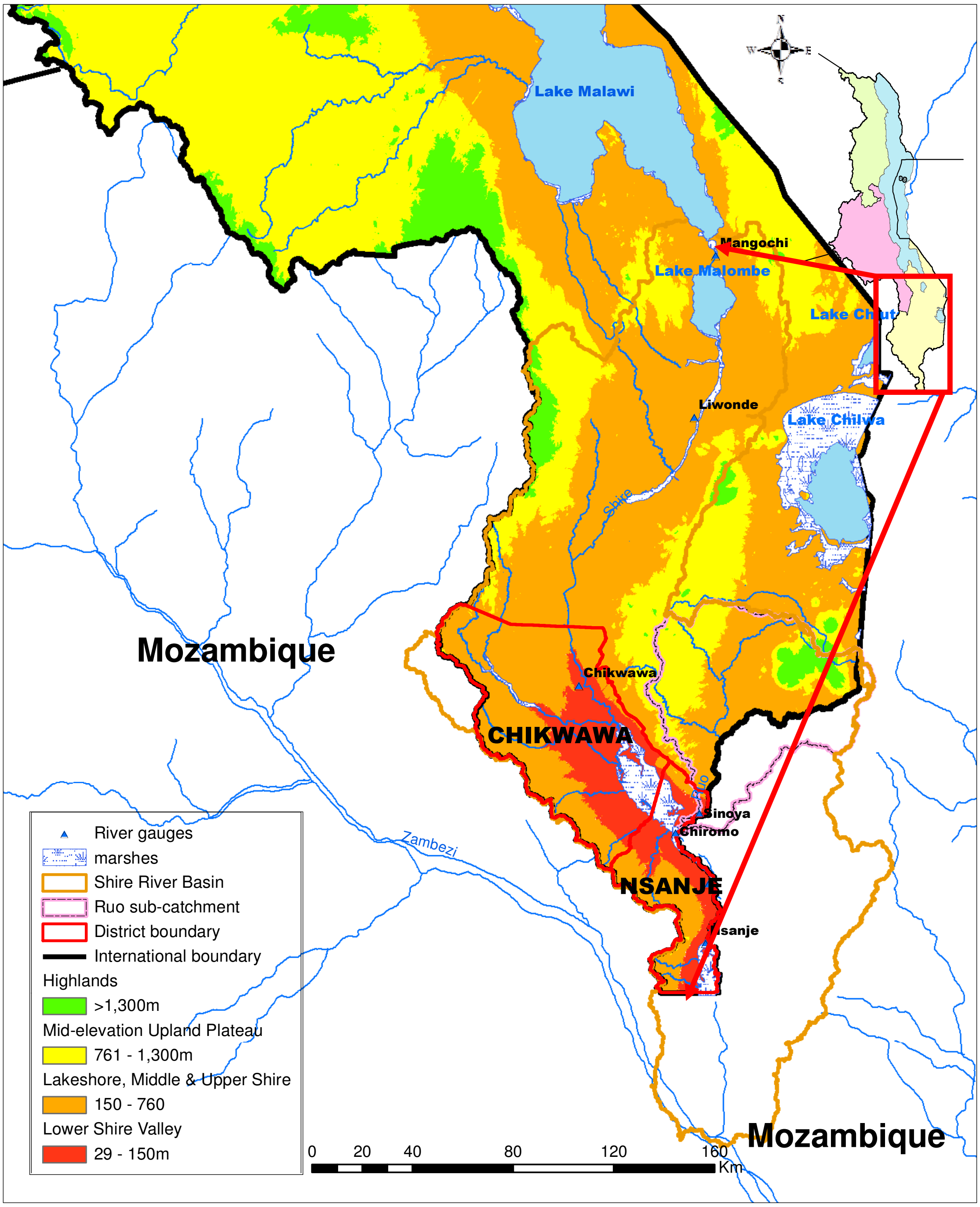


Figure 2.7: Geographical location of the Lower Shire Valley (adapted from Saka and Phiri (2009))

to Chiromo and 0.125m/km from Chiromo to the confluence; making it very susceptible to flooding (Shela, 2000). The Lower Shire Valley is part of the Shire Basin, which extends into Mozambique and is drained by the only outlet of Lake Malawi, the Shire River with its tributaries.

Rainfall

Rainfall amount in Malawi is a function of relief with highlands and windward sides receiving very high rainfall (Russell et al., 2008). The low relief of the Lower Shire Valley therefore translates into low rainfall of 400 – 700mm annually (Phiri and Saka, 2009) and is the lowest in Malawi. However, the valley is bordered by escarpments and highlands to the east, north and west. Therefore despite its dryness, the valley receives much runoff from upper and middle sections of Shire River and from the Ruo, its sub catchment in the east (Figure 2.8). According to Shela et al. (2008), rainfall amounts to about 900 mm annually in the upper and middle section of the Shire River and exceeds 2000 mm in the Ruo sub catchment.

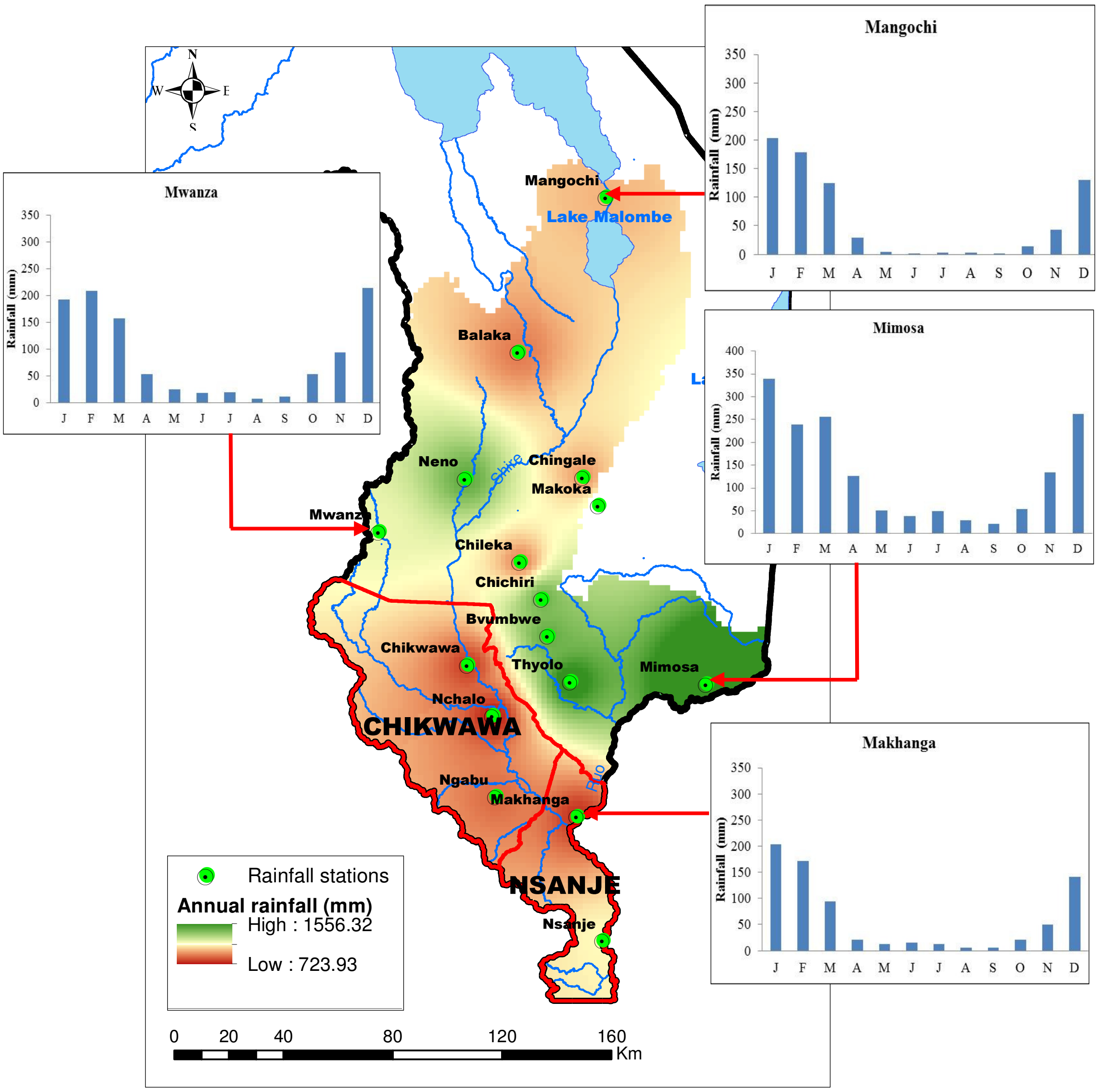


Figure 2.8: Variation in rainfall across the Shire River Basin

The country receives early rains (between October and November) due to orographic effects on moist south east air masses producing convective thunderstorms as the air passes over the highlands and escarpment zones (Pike and Remington, 1965). The main rainfall type for Malawi however is the Inter-Tropical Convergence Zone (ITCZ) rainfall system, a convergence of moist air brought about by the South Easterly winds, the North Monsoon Easterlies and the North West Zaire winds (Pike and Remington, 1965). Therefore the dominant type of rainfall received in the Lower Shire Valley, as is the case with the whole country, is the heavy convective rainfall. In some years, this has been intensified by cyclonic activity in the Mozambique Channel in the Indian Ocean (Pike and Remington, 1965). Rains occurring between April and May due to the moist south east trades that get re-established after the ITCZ has moved up north are light.

Besides rainfall type, the distribution of rainfall over the year has implications for flood risk in the Lower Shire valley. Whilst the rainfall season stretches between November and April, 90% of the total rainfall is concentrated between December and March (Figure 2.8) when also much of the flooding occurs.

Hydrology

The Shire Basin is drained by the Shire River, the only outlet of Lake Malawi. The river is divided into three sections: the upper Shire, from the Mangochi to Matope; the middle Shire from Matope to Maganga and the Lower Shire from Maganga to the confluence with Zambezi River (Shela, 2000). The upper section of the river is characterized by low lying sand banks (Chimatiro, 2004). The middle section, 80 km long, is the steepest characterized by gorges, waterfalls and cataracts and has therefore been exploited in hydropower generation. The Lower Shire stretches 200 km from below Chikwawa escarpment to the confluence with Zambezi (Shela, 2000).

Flow in the basin increases downstream towards the confluence with Zambezi (Figure 2.7, 2.9). According to Shela (2008), average annual flow of the Shire River from the upper catchment measured at Matope is 450m^3/s. At Maganga, which marks the boundary between the middle and lower section of the Shire River, the average annual flow estimated at Chikwawa gauge station just below Maganga is 550m^3/s. At Chiromo gauge station, some 60 km below Maganga, average annual flow is 460m^3/s increasing to 520 m^3/s at the border town of Marka further downstream.

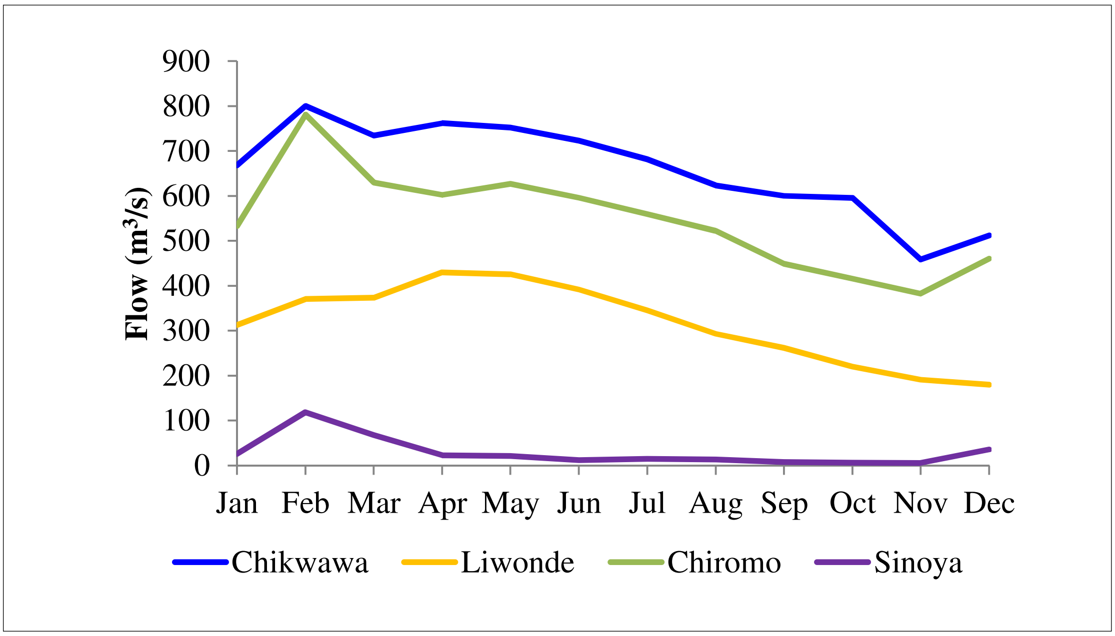


Figure 2.9: Annual hydrographs at selected stations on the Shire River and at Sinoya on the Ruo

The low average flow at Chiromo in comparison to the flow at Chikwawa (Figure 2.9) is due to the attenuating effect of the Elephant Marsh between them (see Figure 2.7). Just below Chiromo gauge station, the Shire River is joined from the eastern side by its major tributary, the Ruo River whose average annual flow is 54m^3/s measured at Sinoya.

While average daily flows measured at Chiromo and Sinoya are 460m^3/s and 54m^3/s respectively, flood flows in the Shire/Ruo River system can be extremely high. A list of flood events documented by Shela (2008) shows that historical flows measured at Chiromo and Sinoya have been as high as 1430 m^3/s and 5400 m^3/s respectively.

Soils

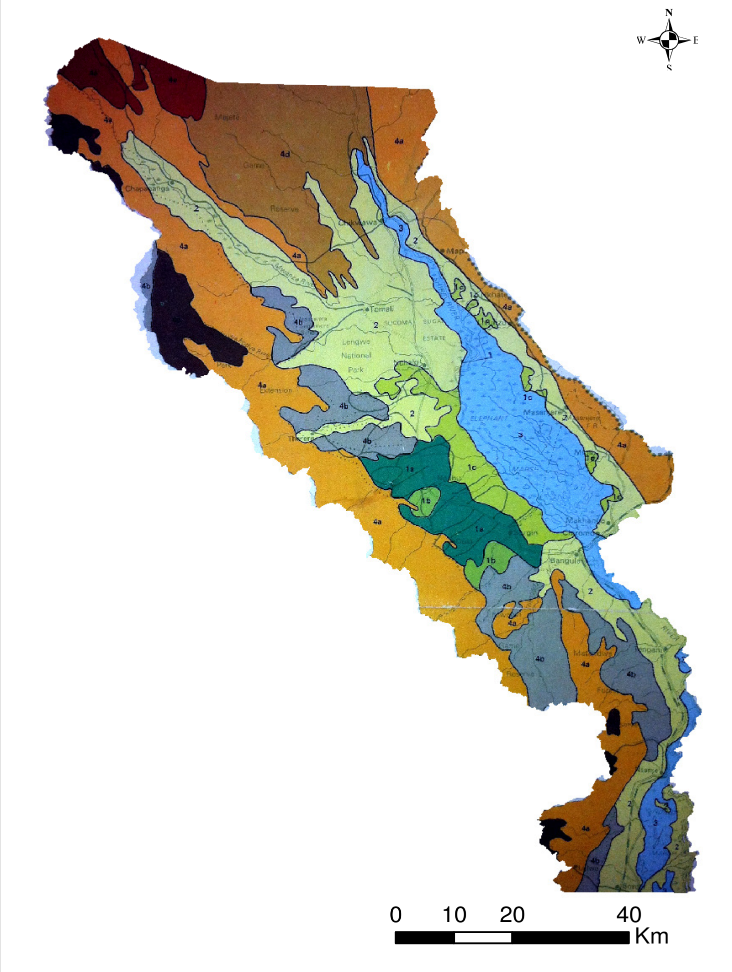
The two districts of Chikwawa and Nsanje are associated with five broad land classes (SVADD, 1975): marsh, floodplain, makande plain, drift plain and uplands (Figure 2.10). According to Monjerezi (2012), marshes, which are permanently under water, consist of hydromorphics. The floodplain on the other hand, which is land seasonally flooded, is associated with stratified alluvium with varying proportions of sandy and heavy grey-black clays soils. Makande plains are associated with vertisols whilst drift plains consist of alluvial carcimorphic soils. Lithosols characterise uplands. The predominant soil types in the Lower Shire Valley (land less than 150masl) however are the alluvial carcimorphic soils and hydromorphics (Table 2.2) which account for 44.2% and 24.6% respectively of valley area. The fertile alluvial soils attract settlements in floodprone areas (Nilson et al., 2010) thus increasing exposure. The presence of hydromorphic soils also implies poor soil drainage thereby exacerbating the flooding problem.

Landuse and landcover

Land use and land cover (LULC) of the Shire Basin based on data obtained from the Department of Surveys of Malawi is shown in Figure 2.11(a). However, a standard classification based on the Food and Agriculture Organisation (FAO) Land Cover Classification System (LCCS) by Palamuleni et al. (2010) in the upper Shire River (between Mangochi and Liwonde gauge stations) identified eight land classes i.e. woody closed, woody open, savanna shrubs, grasslands, marshes, cultivated/grazing areas, built-up areas and fresh water (Figure 2.11)(b)).

Like the rest of eastern, central and southern Africa, Miombo woodlands form the dominant vegetation cover (Desanker et al., 1997). However, several studies (Palamuleni et al., 2010; Place and Otsuka, 2001; Walkers and Peters, 2007) point to a declining forest cover in Malawi. This is attributed to a number of factors including expansion of land mainly for subsistence agriculture, charcoal selling, uncontrolled fire, tobacco curing, population density and growth, land tenure system, poverty, weak institutions, nature of political regime etc. However, the main cause of the declining vegetal cover in Malawi is the conversion to agricultural land (Chavula et al., 2011;

Mkwara and Marsh, 2009; Palamuleni et al., 2010; Place and Otsuka, 2001; Walkers and Peters, 2007). Chavula et al (2011) investigated LULC changes between 1982 – 2005 in the Lake Malawi basin (upstream of Shire River basin) using both Advanced Very High Resolution Radiometer (AVHRR) imagery and Moderate Resolution Imaging Spectroradiometer (MODIS) imagery.



1. MAKANDE PLAIN
(a) Lithomorphic vertisols
(b) Shallow lithomorphic Vertisols/lithosols
(c) Topovertisols

2. DRIFT PLAIN
Alluvial carcimorphic soils

3. FLOOD PLAIN and MARSH
Hydrophorphics

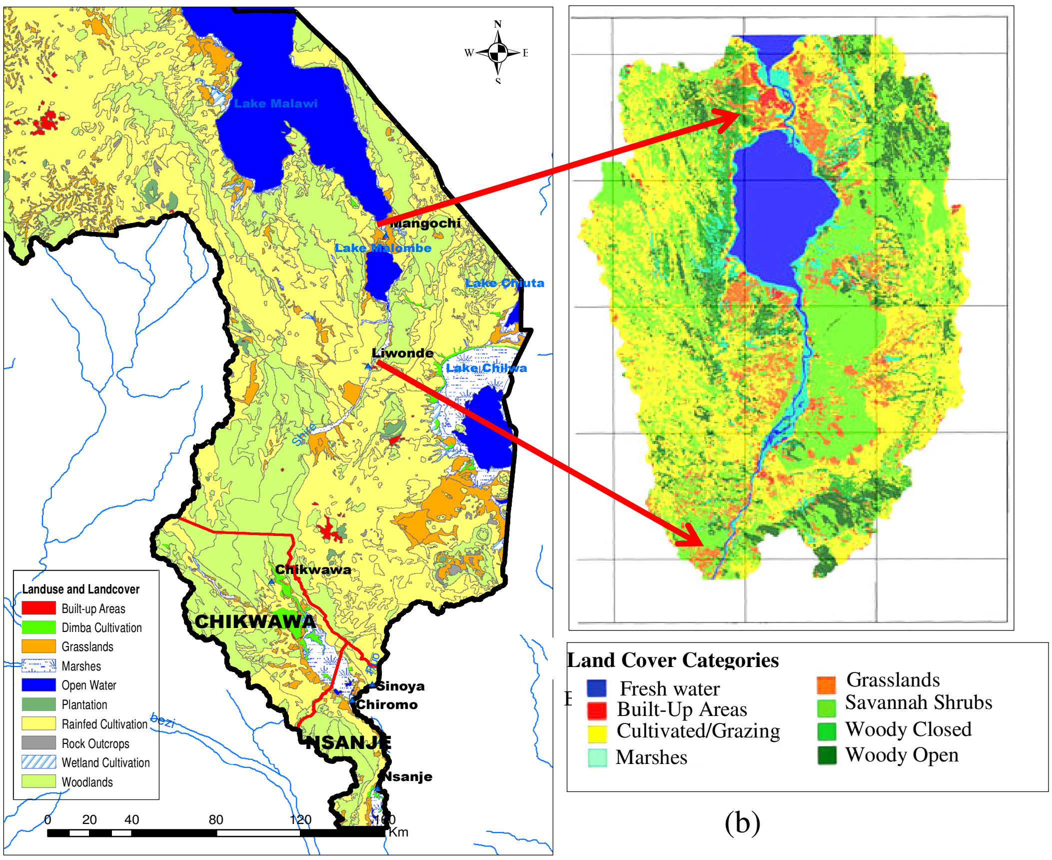
4. UPLANDS
(a) Lithosols
(b) Shallow grey brown earths
(c) Ferrallitic soils, lithosols and intergrades
(d) (Shallow) ferruginous soils and lithosols
(e) Intergrades

Figure 2.10: Soils of the Lower Shire Valley.

Source: (SVADD, 1975)

Table 2.2: Soil type and distribution across the Lower Shire Valley

Land class	Soil type	Total area in Chikwawa and Nsanje districts (km^2)	Area in the valley (km^2)	Proportion in the valley (%)
Floodplain and Marsh	Hydromorphics	736	720.0	24.6
Makande	Lithomorphic vertisols	263.1	220.4	7.5
	Shallow lithomorphic vertisols/lithosols	56.4	43.6	1.5
	Topovertisols	238.5	238.0	8.1
Drift plains	Alluvial calcimorphic soils and grey brown earths	1588	1293.7	44.2
Uplands	(Shallow) ferruginous soils and lithosols	741	42.3	1.4
	Ferrallitic soils, lithosols and intergrades	266	-	-
	Intergrades	190	-	-
	Lithosols	2101	161.3	5.5
	Shallow grey brown earths	713	207.0	7.1



(a) (b)

Figure 2.11: Landuse and landcover in the Shire Basin (a) based on Department of Surveys data and (b) FAO classification by Palamuleni et al. (2010)

Based on AVHRR imagery which was available for a longer period than MODIS imagery, they found that from an initial coverage of 43,681km^2 in 1982, the area of savanna, shrubs and woodland had decreased by 87.8% by 1995 (Table 2.3), with significant changes (75.6%) taking place between 1982 and 1985. Cropped area had almost doubled for the same period; again with drastic changes (88.6%) taking place in the period 1982 – 1985. However, thereafter, cropped area remained almost constant. The changes are visually illustrated in Figure 2.12.

Table 2.3: Areal extent of LULC classes (in Km^2) and lake level (meters above sea level) in Lake Malawi drainage basin

Year	Imagery	Forest	Cropland	Water Bodies	SSW[1]	Lake Level
1982	AVHRR	26741	45738	29040	43681	476.05
1985	AVHRR	20086	86273	28193	10648	475.17
1990	AVHRR	22264	87846	29403	5687	475.42
1995	AVHRR	24442	83490	31944	5324	473.66
2001	MODIS	33800	46408	29707	20091	474.51
2005	MODIS	32739	40545	29799	26921	474.83

[1] savannah/shrubs/woodlands. Source: (Chavula et al., 2011)

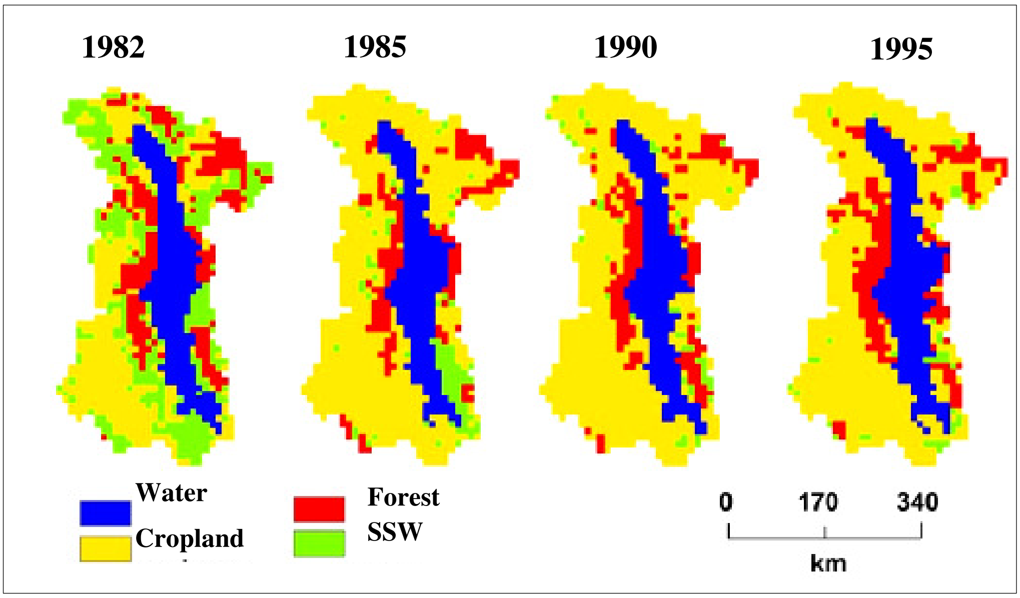


Figure 2.12: LULC changes in four classes in Lake Malawi basin between 1982 and 1995 based on AVHRR imagery.
Source: (Chavula et al., 2011)

Similarly, Palamuleni et al. (2010) investigated LULC in the Shire River basin, between 1989 – 2002 focusing on the upper Shire section (Figure 2.13). They found that as of 2002, cultivated/grazing area was the largest class accounting for 25.7% of landuse. Their findings show an increase in cultivated/grazing area by 23% and a decrease in closed forests by 52% over this period. Both studies are unanimous on the increase in cropland at the expense of woodland.

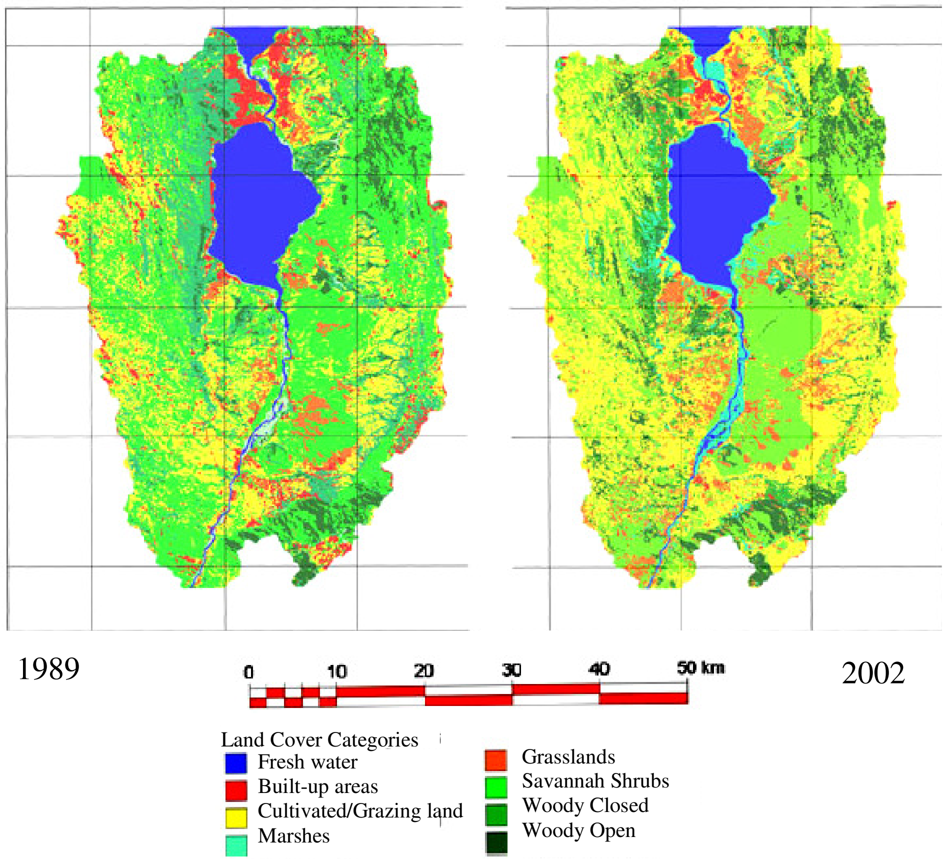


Figure 2.13: Landuse and landcover changes between 1982 and 2002 in the upper Shire catchment

Source: (Palamuleni et al., 2010)

These findings are not unexpected considering the predominance of a poor rural population in the basin. While findings on the rural poverty-land degradation nexus have been mixed, studies in developing countries and in Sub-Saharan Africa in particular, according to Nkonya et al. (2008), point to a general positive correlation between the two. A number of factors are identified. Barbier (2000) observes that rural poor farmers in Africa abandon land in the face of declining productivity and open new land; a cycle which repeats itself. In addition, Barbier observes that the prices of crops normally grown by these farmers are very low. Consequently, input use (irrigation, fertilizer application) in these countries is also very low resulting in an agriculture system that is not highly productive and therefore a disincentive to invest in inputs and viable land management and cropping systems. Barbier (2000) also note that the situation is exacerbated by the policy environment. In this regard, Barbier (2000) draws attention to the Malawian example where price increases for more erosive, monocropped crops (maize, tobacco, cotton) throughout the 80's meant less growing of less-erosive and nitrogen fixing crops (pulses and legumes).

Nkonya et al. (2008) also point out that high population growth rates, occupation of marginal lands, weak institutions and policies associated with poverty are pathways to land degradation. A contrast is however drawn to a success story in Africa on land management – the Machakos Distrct in Kenya. According to Barbier (2000), farming in the Machakos is market other than subsistent oriented with crops grown including coffee, cotton, fruit and horticulture. He observes this has also gone hand in hand with adoption of new and affordable technologies and agricultural practices with the most striking land improvement being the terracing of 200,000 hectares of land.

In the Shire basin, proximity to cities has been identified as another factor on land degradation as woodlands have been exploited to meet the demand for firewood and construction materials in the nearby cities of Zomba and Blantyre (Palamuleni et al., 2010).

The decrease in vegetal cover in the basin has no doubt had impacts on the flooding problem. In terms of flow responses, Palamuleni (2009) found that land use and land cover changes that had taken place in the upper Shire basin between 1989 and 2002 had altered surface runoff significantly. Her simulations of flow between 1979 and 1981 under the 1989 and 2002 LULC at Liwonde gauge station (the upper Shire catchment outlet) (Figure 2.7), suggested an increase in maximum daily surface flows from 83m^3/s to 154 m^3/s; an increase in minimum daily surface flows from 1 m^3/s to 3 m^3/s and a general increase in average daily surface flows from 19 m^3/s to 30 m^3/s. While there is dearth of studies on the measurement of soil loss and sediment yield in the Shire basin, evidence from quantitative studies in other catchments and observation within the basin suggests there are substantial soil loss and sedimentation taking place. Sediment load and yield are sensitive to the degree of agricultural land use with high levels being associated with extensive agricultural activities (Hecky et al., 2003) which is the case in the Shire basin (Palamuleni et al., 2010).

Further, Bojo (1996) characterized Malawi as one of the countries with the highest soil erosion rates in Sub-Saharan Africa. A crude national level estimate by the World Bank (1992) put the average annual soil loss rate due to water-induced erosion in Malawi at 20 tons/ha. In the Linthipe catchment, Mkanda (2002) estimated soil loss rates to be in the order of medium (3.1 – 12.7 tons/ha/year) to very severe magnitudes (19.1 – 29 tons/ha/year). These rates surpass the maximum permissible soil loss rate of 12.7 tons/ha/year that can be balanced by soil formation (Shaxson, 1970). Considering that adoption of soil conversation technologies by smallholder farmers in Malawi is low (Mangison, 2009; Mkanda, 2002), present soil loss rates in Malawi may actually be higher than these figures and the Shire Basin is no exception.

The increased soil loss is intensifying sedimentation in the rivers leading to reduced carrying capacity of the channels. A report by the Ministry of Irrigation and Water Development in Malawi in 2003 (MoIWD, 2003) attests to increased sediment load in the rivers in the basin. The report observes that the zero gauge level at Sinoya river gauge station on Ruo tributary had moved from 54.428 masl in 1985 to 57.973 masl in 2003 suggesting a loss of depth to silt of 3.545m in 18 years. Thus landuse and landcover practices in the basin have undoubtedly reduced the thresholds for flooding.

Socio-economic factors

Demographic factors

According to the 2008 national census report (National Statistical Office, 2009), Chikwawa has a population of 438,895 and Nsanje, 238,089. Forty percent of the population in Chikwawa and 90% of that in Nsanje are affected by floods (Atkins, 2012).

Besides physical exposure through population concentrations in the floodplain, noteworthy is also the susceptibility of this population. The female population in Chikwawa and Nsanje is 50.3% and 51.5% respectively. These proportions are not different from the rest of the country. However, Nsanje is one of the districts in Malawi with a high Female-Headed Household (FHH) population at 32% compared to the national average of 27%. The FHH in Chikwawa is 27.3%, also slightly higher than the national average. Besides, the dependency ratio of Nsanje i.e. the proportion of people outside the economically active age in a household (less than 15-year olds and greater than 65 years) to the economically active (15-64 year olds) is among the highest. Based on the 2008 population and housing data (National Statistic Office, 2009), Chikwawa had a dependency ratio of 1.03 and Nsanje 1.10, implying that there is an almost equal number of dependants for every economically active group.

Literacy rates for Chikwawa and Nsanje stand at 53% and 52% respectively against a national average of 64% (National Statistic Office, 2009). Fertility rates of the two districts are above the national average of 6 with Nsanje at 6.8, making it one of highest rates in the country, and Chikwawa at 6.2 (National Statistical Office, 2009). Infant mortality rates are 84 per 1000 births for Nsanje and 85 per 1000 births in Chikwawa just below the national average of 87 deaths per 1000 births. UNICEF (2009) reported the nutritional status of the two districts as being the worst in comparison to any livelihood zone in Malawi. UNICEF (2009) also reported the two districts to be among districts worst affected by HIV/AIDS with prevalence greater than 30% against a national average of 12.4%.

Access to basic services

Platt (1995) defined lifelines as networks that provide for the circulation of people, goods, services and information upon which the health, safety, comfort and economic activity depend. Both districts are among those with the lowest access to phones; at 19.6% in Chikwawa and 17.8% in Nsanje (National Statistical Office, 2012). Data obtained from Department of Surveys in 2010 showed that Chikwawa had only 83.6km of asphalted road from a total road network of 3323.4 km and Nsanje 88.9 km from a total of 1057.5 km.

Access to safe water in the two districts, in terms of proportion of people having safe water is however significantly higher than the national average. In Chikwawa, access to safe water is at 83.6% and 81% in Nsanje (National Statistical Office, 2012). This high rate is attributed to boreholes drilled by non-governmental and international organizations in the 90's when both districts played host to Mozambican refugees (Shela et al., 2008). Like the rest of the country, boreholes account for the highest proportion of safe water source (National Statistical Office, 2012). However, as noted by Shela et al. (2008), the actual level of access to potable water in the Lower Shire may be lower than reported due to abandonment of boreholes as a result of vandalism, damage caused by floods, lack of maintenance, improper siting of the borehole and salinity issues.

The assertion by Shela et al.'s (2008) on the level of access has been supported by Kuotcha et al. (2012), who measured the level of access to basic facilities (water, schools, health centres, markets, mills and religious centres) of villages in Chikwawa based on distance. They found that most villages were located beyond recommended threshold distances to services. Based on straight line distance, (which assumes that people take footpaths to services and hence the shortest distance), 68% of villages were located beyond a 1 km distance threshold for the water service. On the basis of road network distance, the deprivation was higher at 92%.

In consideration of access to improved sanitation (flush toilets, ventilated pit latrines and roofed traditional latrines), access in the Shire Valley is very low; the lowest in the country. In Chikwawa, access is at 32.6% and 27.5% in Nsanje against a national average of 72.4% (National Statistical Office, 2012). The low level of sanitation is explained by floodplain conditions: high water tables and poor soils (Shela et al., 2008). The level of accessibility to health centres is also low; 60% of the villages are outside the 6km threshold. When straight line distance is used however, only 38% are deprived (Kuotcha et al., 2012). Accessibility to schools is the highest with only 23% of the villages located outside the threshold distance of 3km based on straight line distance. However, the figure rises to 65% when calculated based on road network (Kuotcha et al., 2012).

In view of Kuotcha's results and taking into account that the roads are impassable during the rainy season compounded by the nature of soils, deprivation of access to basic services in the lower Shire is likely to be very high and a concern for vulnerability.

Livelihoods

Like the rest of the country, the livelihood base in the Lower Shire valley is very narrow. With the exception of few sugarcane and cotton small holder farmers, the majority of farmers are smallholder subsistence farmers who account for 90% of the agricultural sector (Tchale, 2009) and cultivate on less than a 1 hectare of land (World Bank, 2007). With population densities being higher in the southern region (National Statistical Office, 2009), land pressure is more pronounced in the south.

Besides small land size, productivity on these farms is also low (Tchale, 2009). Tchale attributes this to low adoption and less intensive use of productive agricultural technologies, unreliable rainfall, production inefficiencies and poor soils. Tchale (2009) exemplifies this on hybrid maize, the main staple food of Malawi, whose potential yield is 5 to 8 tons/hectare but points out actual yields are only 1.5 to 2.5 tons/hectare and rarely exceeded.

While the irrigation potential of the two districts is high and has been promoted by government and Non-Governmental Organisations (NGOs), productivity of existing irrigation schemes is also very low due to problems of siltation and flooding, failure to invest in operational and maintenance cost, land disputes, ownership and leadership wrangles (Shela et al., 2008). Therefore, as observed by Shela et al. (2008), success remains confined to large scale commercial farms owned by the Illovo Group, the largest in the country, and Kasinthula Irrigation Scheme, a large scale irrigation scheme supported by the government.

There are other forms of livelihoods. These include fishing (Donda and Njaya, 2007; Hatlebakk, 2012) and livestock farming. However, fishing is mainly artisanal (Donda and Njaya, 2007). Cattle rearing is also limited to the few well-off; the majority poor rear goats and chicken (Malawi National Vulnerability Assessment Committee, 2005). Casual labour, popularly known as *ganyu* is also an important livelihood mainly for the poor and accounts for 20% of their income source (Malawi National Vulnerability Assessment Committee, 2005). However, it is a livelihood source that deprives them of the necessary labour on own farm (Casale et al., 2008) trapping them in a cycle of food insecurity and poverty.

Besides being narrow, livelihoods in the Lower Shire also tend to be fragile and face a number of stressors prevalent in the region, leading to a further decline in productivity. Traditional agriculture in the uplands is subject to droughts and loss of soil fertility (Casale et al., 2008; Chidanti-Malunga, 2011). Farming in the low wetland areas, used as a coping strategy against droughts, also repeatedly faces flooding (Casale et al., 2008; Chidanti-Malunga, 2011). High livestock morbidity and mortality and stock theft are other major stressors that face the Lower Shire and impacts on people's resilience. According to Casele et al. (2008), Chikwawa has the highest prevalence of livestock diseases; the most prevalent being Foot and Mouth Disease, Trypanosomiasis and Tick borne disease (Malekano, 2000). While petty theft of cattle is not uncommon, stock theft in this region can be massive with examples of a family losing 27 cattle in a night and 100 cattle in a month. Consequently, affected families may eventually sell off the remainder of cattle to pre-empt further theft (Malekano, 2000); stripping them of what is considered as the most important asset in this region.

The role of this complex web of socio-economic factors in exacerbating vulnerability in the Lower Shire valley is summed up in the poverty profile. Poverty rates in the two districts (calculated with respect to 37,002 Malawi Kwacha poverty line which is equivalent to US$0.40 per person per day as of 2012) are the highest in the country at over 80% (National Statistical Office, 2012), significantly exceeding the national average of 50.7%. The two districts also have the highest ultra-poverty rates; over 55% in comparison to the national average of 24.5% (measured against a food consumption poverty line of 22, 956 Malawi Kwacha; equivalent to US$0.25 per person per day as of 2012).

2.4.2 Measuring flood risk and flood management

Despite a general consensus, based on observations, that the Lower Shire is highly hazardous and vulnerable to floods, flood studies in this region have been scarce. In the few studies available, trends in the approaches to risk assessments are those exemplified in studies in SSA. While touching on both vulnerability and the hazard, flood risk studies in the Lower Shire are largely confined to the identification of causes, impacts, institutions in place, mitigation measures and their effectiveness. More so, the work remains largely descriptive; elusive of quantitative underpinnings.

The most comprehensive studies in these aspects are those by Shela et al. (2008) and Nilson et al. (2010). In their analysis of the flood risk of the Lower Shire, Shela et al. (2008) reviewed the causes, impacts of floods, flood risk management and proposed risk reduction measures. They found that flooding in the Shire valley arose from a number of factors: heavy rainfall in the upper catchments sometimes compounded by cyclone movement, physiography of the floodplain, environmental degradation leading to siltation of rivers, high poverty levels pushing people to settle in marginal lands for livelihoods thus exacerbating environmental degradation; weak housing, low access to basic services (sanitation, schools, health centres), a high prevalence of such diseases as cholera, dysentery and HIV/AIDS and poor infrastructural services.

Shela et al. (2008) further observed that flood risk in the valley was exacerbated by weak disaster management. They noted that flood management was characterised predominantly by relief and rehabilitation. Long-term mitigation and adaptation measures were low. In this respect, they observed inadequate and lack of properly designed structural measures (dams, levees) for flood mitigation. They found that only a manual warning system existed, based on which crude warnings were made, leading to false or late warnings or no warnings at all. They also found that government institutions were weak, characterised by a lack of financial resources and technical expertise for flood management. Consequently, government institutions were unable to implement disaster plans and had to rely on donors and NGOs.

The activities towards flood risk reduction implemented by NGOs according to Shela et al. (2008) were community education, sustainable livelihood enhancement via food security and agriculture, provision of clean water and sanitation facilities, and provision of flood related infrastructure works (dykes, levees). Nonetheless, Shela et al. (2008) found that NGOs equally lacked technical knowhow resulting in flimsy structural measures that lacked design where these structures had been implemented.

Community behaviour was another impediment to flood risk management. Shela et al. (2008) observed that while community mobilization and education had been fairly high, communities in the Lower Shire valley had a dependency inclining; always expecting freely provided items thus retarding resilience-building towards floods.

With respect to impacts, Shela et al. (2008) found that floods had devastating impacts on the communities in the valley. These included: loss of crops and livestock, decreased crop production and loss of farmland leading to loss of incomes and livelihoods; destruction of houses, loss of infrastructure (rail, roads, bridges, schools; irrigation systems, telephone lines, boreholes, electricity infrastructure), interrupted education system due to repeated shut down of schools, disease incidence and displacement of people.

Other studies e.g. Kaonda (2009), Mijoni and Izadkhah (2009) and Nilson et al. (2010) have also undertaken descritpive studies in which they determine causes, impacts, community perceptions, coping and adaptation strategies. By and large, they also report same findings. Nilson et al. (2010) nonetheless draw attention to additional factors. They note that flood risk also arise from settlements along floodplains due to fertile soils that support agriculture, livestock production and fisheries; a subsistent type of agruclture with no tangible industries to provide employment and a general resistence by communities towards relocation. Nilson et al. (2010) further note that flood risk management faces other challenges besides a lack of resources. They observe that the Department of Disaster Management Affairs (DoDMA) is highly centralised at national level and only supported at district and sub-district levels with Civil Protection Committees (CPCs). These committees, they observe, have neither operational funds nor staff management to implement disaster risk reduction activities. Neither are responsibilities pinned to particular members. There is limited availability of operational procedures. Nilson et al. also observe duplication of effort, conflicting policy and limited awareness on existing plans and procedures for flood risk management by all stakeholders at different levels. They also report of a general lack of scientific flood risk assessments to support mitigation and adaptation, observing that any flood managment is based on observations.

Quantitative assesmments of flood risk are very limited in this valley. The study by World Bank (2010b) and Atkins (2012) are probably the most comprehensive towards flood risk assessment in this valley. The World Bank measured the flood risk of the Lower Shire floodplain by intersecting elements at risk (population, households, roads, railway lines and agriculture (maize and tobacco)) and with flood inundation extents from 2, 5, 10, 20, 50, 100, 200 and 500 year floods. The flood inundation extents were derived with the 1D hydraulic model, HEC-RAS.

The World Bank study provides two outputs: flood hazard maps for these return periods and Average Annual Loss (AAL), the latter representing flood risk. In respect of these annual losses, the World Bank study reports that flooding in combination with droughts in this valley accounts for a countrywide annual loss in GDP of 0.7%. It further indicates that flood-induced poverty due to crop losses to climatological shocks in the Shire Valley amounts to 17.4% for a 50-year flood event.

Similarly, using the 1D-2D Infoworks software, Atkins (2012) derived flood hazard maps for the Lower Shire valley for different return periods i.e. 5, 10, 50,100 and 500 including flood depths at critical villages. Unlike the World Bank that assessed damages, Atkins identified and assessed mitigation measures (height and length of defence structures and impact of catchment improvement) on flood depths at critical villages. In this regard, they found that catchment improvement would have more impact in the Mwanza catchment with reduction in flood heights at critical villages in the range of 30mm to 290mm. Little or no effect on flood heights in the Ruo catchment was found which the study attributed to proximity of the villages to the confluence.

Provision of storage for flood waters was adjudged impractical considering that a 10 year flood already required enomous storage that was difficult to provide in tems of physical provision of diversion, storage and release facilities.

Whilst the World Bank study measures flood hazardouness by extent and depth and Atkins (2012), besides extent, uses a severity factor that incorporates velocity and debris factor based on Defra and Environmental (2006) guidelines, these studies seem to agree on the spatial extent of flooding in the Lower Shire Valley (Figure 2.14(a), (b)). However, hazard severity between the two studies is incomparable quantitaively given that in both cases results were lmited to the visual display in a map.

Approaches of this kind carry with them various well known limitations earlier presented. Both studies limit vulnerability to exposure – what is in the harm's way. They do not account for the wider socio, economic, cultural and institutional factors that may work to intensify or ameliorate vulnerability. In this regard, the approach attracts mitigation measures that are structural and therefore deficient of more transformative and holistic opportunities to adapt (Nelson et al., 2010), an aspect already evident in Atkin's (2012) study. The cost and sustainability implications of such measures for developing countries, is also something that have also been brought to attention e.g. Lumbroso et al. (2008). Besides, use of damages as a proxy for risk in the World Bank's (2010b) is likely to underestimate risk. Credibility of damage data as earlier discussed is another concern.

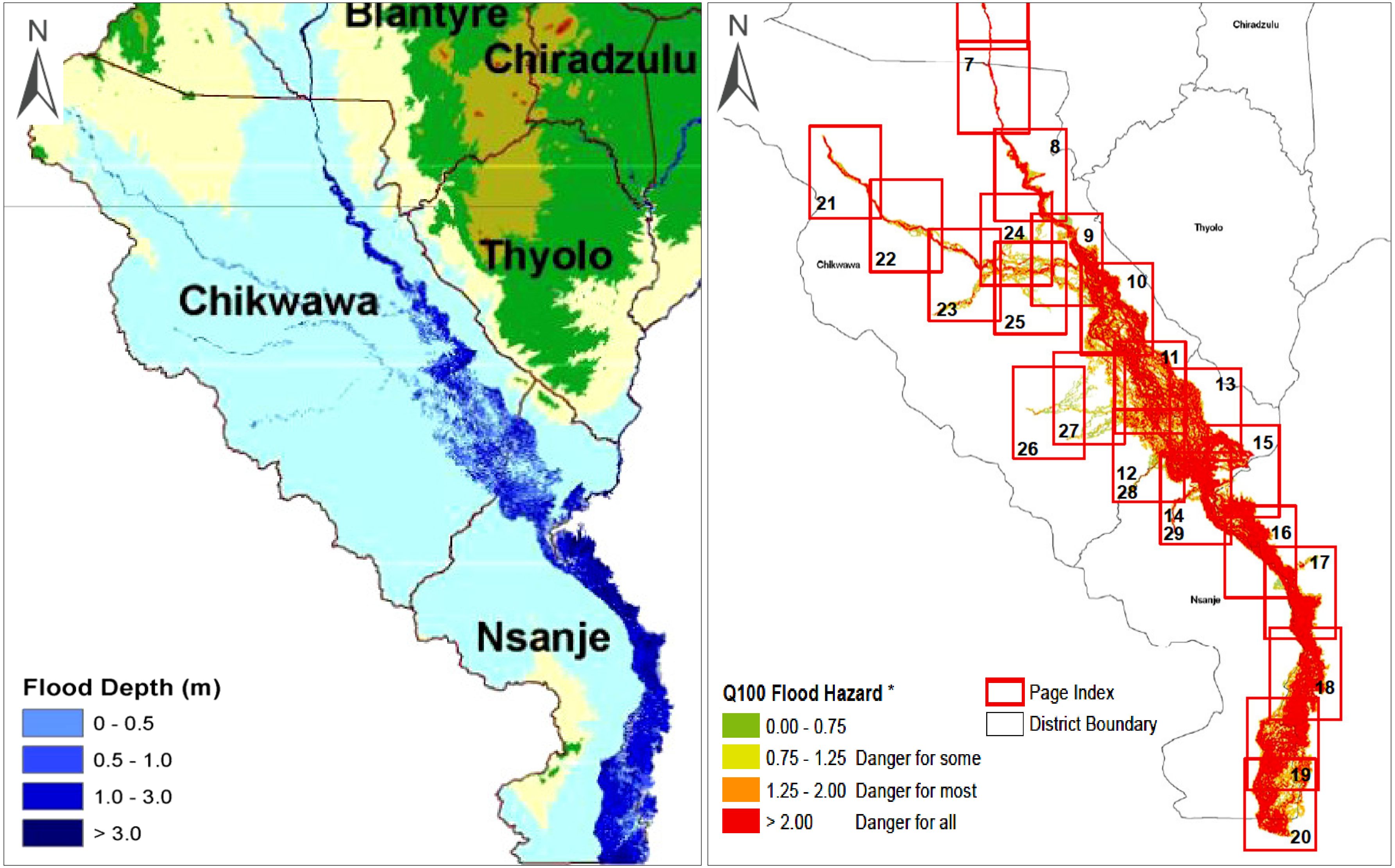


Figure 2.14: A 100-year flood as modelled by (a) World Bank (2010b) and (b) Atkins (2012).

Linking risk assessments to appropriate scales and institutions is paramount for effective disaster risk reduction as risk reduction strategies are developed, promulgated and implemented through institutions (Ribot, 2010). Both studies are indifferent to the spatial scale of disaster management decision making, a deficiency for effective risk reduction and a gap addressed in this thesis. Because the whole Shire Valley forms the unit of analysis in the two studies, application of results for disaster risk reduction are limited in a number of aspects such as comparisons across places and people and targeting of resources and interventions.

2.4.3 Hydrological data issues

Hazards stem from different processes and agents; flood hazards in particular arise from the geomorphological and hydro-meteorological conception (Alca´ntara-Ayala, 2002). While quantifying vulnerability relies on socio-economic data that are richly available, the availability and quality of hydro-meteorological data in most developing countries are an impediment to flood hazard severity estimation and water management in general. Hydro-meteorological data in these developing nations are characterised by gaps, short durations and dubious quality (Adeloye, 2011; Dastorani et al., 2010; Gyau-Boake and Schultz, 1994; Ilunga and Stephenson, 2005).

The above deficiencies of hydrological and meteorological data arise from several factors. For example, observational networks for both hydrological and meteorological data have been declining over the decades globally (Smakhtin and Wichelns, 2009) but the decline is more marked for SSA (Giles, 2005). In their review of the operational status of observational points installed under the SADC HYCOS (Southern Africa Development Community – Hydrological Cycle Observation System) project, Houghton-Carr and Fry (2006) found that of the 48 data collection platforms installed between 1998 - 2000, only 7 were working by 2006 due to broken sensors, vandalism, theft, electrical and transmission faults, a general lack of maintenance and unavailability of resources.

Recently, Phalira (2012) reviewed the capacity of weather stations in providing meteorological data in the Lake Chilwa basin in Malawi. They found that only 14 out of the 20 stations investigated were operational and only 7 out of the 14 operational stations had standard equipment. There was also lack of trained personnel, limited equipment, inadequate or no funding resulting in failure to maintain or buy new equipment, failure to recruit and pay skilled labour and in some cases resulting in total closure of the station. Phalira further found that only secondary stations stored data electronically; primary stations stored data manually limiting retrieval and hence utilisation of data in the later and also leading to data loss. He observed that electronic databases were equally prone to loss due to computer viruses. Quality checks were also rarely carried out.

In view of the above, hydrological data constitute a major problem to water management studies in developing countries. In their analysis of rainfall and flow variability in SSA, Conway et al. (2009) had to combine data from international data bases and national bases. Even then, the number of gauging stations used in some basins in the analyses is very small. For example, only two stations are used for the whole Zambezi River basin: Victoria Falls on the Zambezi and Mohembo on the Okavango, raising concerns over the reliability of their results.

In her assessment of hydrological impacts of climate change and variability at sub basin scale in the Zambezi Basin, Tirivarombo (2012) is also confronted with ungauged basins and basins with sparse stations whose data is characterised by short durations and extensive gaps. Consequently, the work is significantly supported by global data sets: the Climate Research Unit (CRU TS2.1) rainfall of the University of East Anglia and flow from the Global Runoff Data Center (GRDC) (The Global Runoff Data Center, 2003). While very important, global data sets may not always be available at a time resolution or spatial unit of analysis required.

Due to unavailability of instantaneous flow values in some countries, Mkhandi et al. (2000) derived regional flood frequency distributions for 11 countries in Southern Africa (Angola, Botswana, Lesotho, Malawi, Mozambique, Namibia, South Africa, Swaziland, Tanzania, Zambia and Zimbabwe) based on annual maximum daily discharges. From 44 delineated regions, Mkhandi et al. (2000) found that 33 regions failed the homogeneity test and attributed this to a large variance from short samples of data in these regions.

The Lower Shire Valley in Malawi is no exception to hydrological data deficiencies. Due to hydrological data issues among other factors, the existing flood warning system is manual, dependant on manual observation of gauge readings and rainfall in the Shire and Ruo catchments (Nilson et al., 2010). The system has been described as inefficient and unreliable sometimes leading to false, late or no alert at all (MoIWD, 2003; Nilson et al., 2010; Shela et al., 2008). There have been efforts towards automated real time flood warning system. An automated system installed in the 1990's failed due to vandalism, lack of maintenance, and lack of local support (Nilson et al., 2010). However, in the status report on flood warning and forecasting by the Ministry of Irrigation and Water Development (MoIWD, Undated), the report also points to hydrological data challenges that could not support the Hydrologiska Byråns Vattenbalansavdelning (HBV) conceptual model for forecasting.

2.4.4 Summary

It emerges from the foregone sections that patterns exhibited in flood risk studies in SSA are not atypical to the Lower Shire Valley. Previous work in the valley has been dominated by vulnerability assessments that have strived to understand causation, impacts, perceptions and coping strategies qualitatitively. It is also clear that availability and quality of the hydrological data is also a challenge to water resources assessments including flood risk assessments. Ultimately, several aspects on the flood risk of the rural subsistent people in the Lower Shire Valley and in SSA at large remain unknown. In particular, from a contemporary disaster management perspective, it emerges that the degree of vulnerability, hazardousness and ultimately risk and the broader dimensions rather factors driving these components have not been brought empirically into a strategic picture for disaster management.

Chapter 3 Methodology

3.1 Methodology overview

The whole methodological process is summarised in Figure 3.1 below. It specifies the scales of analysis, data needs and collection methods. It highlights the treatment of hydrological data and the subsequent analysis of both hydrological and socio-economic data for hazardousness and vulnerability and hence risk quantification. These aspects are discussed in fuller details in the following sections.

3.2 Scale of assessment

Vulnerability and hence risk, is a scale-dependant variable determined by spatial scale (individual, household, community, sub-national, national or regional) and specificity of a place, and time scale (over a period of time or for a specific moment in time) (Kienberger et al., 2013). Hence scale has methodological and practical implications.

Vulnerability tends to be more conspicuous with micro scale (Fekete et al., 2010; O'Brien et al., 2004b; Queste and Lauwe, 2006). O'Brien et al. (2004b), for example, found that while Norway in the global context would be classified as a resilient nation to climate change and variability, vulnerability was quite marked in some regions and certain places at local levels.

In addition, vulnerability and risk assessment outcomes at different scales serve different purposes. Global or regional scale assessments have national resolution (Cardona, 2005; Dilley et al., 2005; UNDP, 2004) that allow comparisons across nations, which is useful for flagging to aid and development agencies, prioritization of resources at global scale and also for bench marking purposes (Birkmann, 2007; Fekete et al., 2010). Similarly, sub-national scales and national scales are important for planning and distribution of resources (Queste and Lauwe, 2006).

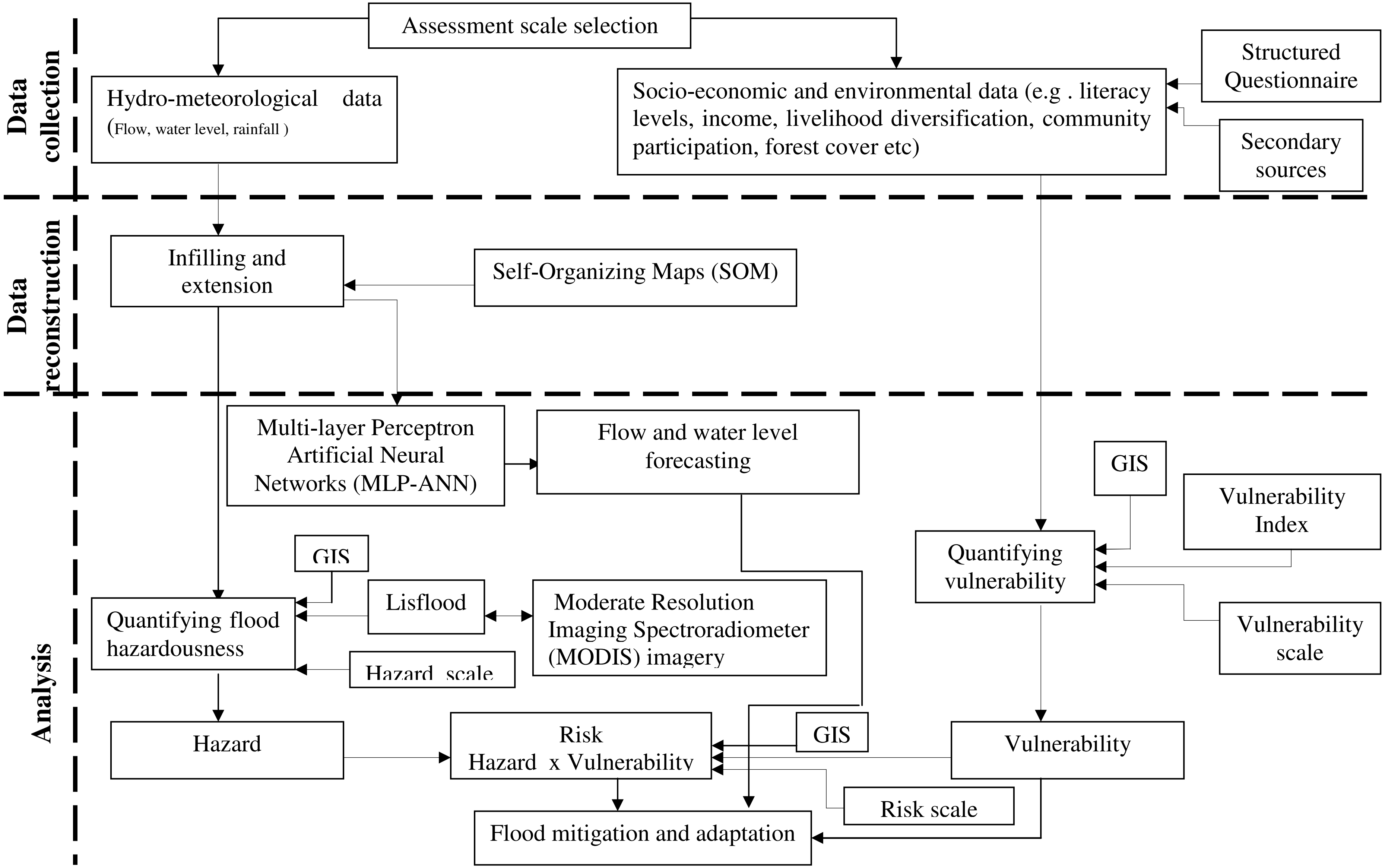


Figure 3.1: Methodology overview

In contrast, the local scale is more important for the design of disaster risk reduction because it is a scale of disaster occurrence and thus an appropriate scale of unmasking vulnerability (Queste and Lauwe, 2006).

Furthermore, it is important that assessment scale is matched with the scale of jurisdiction of decision making on disaster management (Ribot, 2010). According to Ribot (2010), disaster reduction measures are developed, promulgated and implemented through institutions.

The implication of scale in the context of local, national and regional assessments as observed by Hagenlocher et al (2014) is shown in Table 3.1.

Table 3.1: Implications of spatial scales for spatial vulnerability assessments:

	Local scale	National scale	Regional scale
Data availability	●	●●	●●●
Data collection	●	●●	●●●
Uncertainity in the data	●	●●	●●●
Level of spatial detail	●	●●	●●●
Identification of root causes of vulnerabilityy	●	●●●	●●●
Availability/reliability of expert knowledge	●	●●	●●
Validation	●	●●	●●

(●) barely pose a challenge, (●●) pose medium challenge (●●●) pose major challenge
Source: (Hagenlocher et al., 2014)

In view of the above, the selection of scale is a crucial step in this study. Kienburger et al. (2013) describes four types of scale:

- Intrinsic scale - scale at which the pattern/process typically operates and is defined by pattern/process itself.

- Observational scale – the scale of measurement and sampling of the phenomena. Ideally, the observational scale is closely linked to the intrinsic scale, but may be adjusted if appropriate.

- Modelling scale - scale level at which the analysis is carried out. Data derived from the observational scale may be scaled to the appropriate modelling scale in a valid manner.

- Policy scale - scale level for which policies (such as laws and regulations) are valid and implemented.

Driven by a strong support for policy and decision making, selection of spatial scale of analysis of risk in this thesis follows the institutional framework for disaster management in Malawi. At national level, the Department of Disaster Management Affairs (DoDMA) coordinates and directs implementation of disaster management activities. The department is supported at the lower level by other local government structures: the District Level, Area Level and Group Village Level. The Lower Shire Valley falls into two district level units: Chikwawa with an area of 4755 km^2 and Nsanje with an area of 1942 km^2. Chikwawa District has 11 Area Development Committee levels (ADCs) and Nsanje 9, with each ADC corresponding to the area under the jurisdiction of a chief (Traditional Authority, TA). Further Chikwawa comprises 79 Village Development Committees (VDC) and 593 villages. Nsanje on the other hand has 82 VDCs and 790 villages. The number of VDCs and villages in both districts are actually higher than these figures given the continual promotion of tradition leaders to chiefs and senior chiefs through political will. Each VDC level is a conglomerate of several villages. The basis for a number of villages making a VDC is elusive and explains the unexpected higher figures in Nsanje than Chikwawa despite Nsanje's size.

The district as the ultimate scale of analysis of risk was adjudged too large to unmask risk at a local scale. Conversely, while the VDC and village units would have provided a more representative picture of risk, the associated costs proved prohibitive. The ADC was therefore chosen as a working scale, also referred to as *community* in this study.

For the vulnerability component, the ADC as a modelling scale has the added advantage of data availability. Socio-economic data gathered through nationwide surveys e.g. Population and Housing Census and Integrated Household Surveys are readily available at this scale. In furtherance, developmental work in Malawi through NGOs, donor community or government is also much tied to administrative boundaries of TAs (Malcomb et al., 2014). For the purpose of reconstructing hydro-meteorological data, on the other hand, the Shire River Basin is used as the modelling scale. This takes advantage of multi-variate relationships that exist between hydro-meteorological data within hydrological boundaries. However, for the ultimate quantification of the hazard and risk, the Lower Shire Valley is the modelling scale as flooding is confined to the valley. Results are then linked to the associated ADC through GIS.

3.3 Quantifying the flood hazard and forecasting

3.3.1 Hydro-meteorological data and collection

Hydro-meteorological data of particular interest to the study were flow, water levels and rainfall. All data were secondary. Flow and level data were collected from the Ministry of Irrigation and Water Development (MoIWD). Rainfall data on the other hand were sourced from the Department of Climate Change and Meteorological Services (DCCMS). Both institutions are government agencies. The MoIWD collects water levels manually using staff gauges. The water levels are then converted to flow using rating equations, some of which are shown in Table 3.2.

Table 3.2: Rating equations at main stations in the Shire River Basin

Station	Equation	Period relevant	Level covered
Mangochi	$Q = 41.454(h - 3.379)^{1.817}$	1-Nov-1981-31-Oct-2007	Up to 8.3m
Liwonde	$Q = 153.666(h - 2.986)^{1.3}$	1-Nov-1989- 31-Oct-2009	6.31m
Chikwawa	$Q = 438.2(h - 1.4)^{1.3}$	1 December 1983-31st October, 1984	Up to 4.93m
	$Q = 114.563(h - 1.2)^{1.3}$	1 April 1985-31 October, 2010;	Up to 8.03m
Chiromo	$Q = 152.43(h - 0.025)^{1.494}$	1 November 1981-31 October 2010	Up to 3.9m
Sinoya	$Q = 22.828(h - 2.172)^{2.8}$	10 August 1979 - 3 November, 1981	Up to 15m
	$Q = 10.333(h - 2.004)^{2.8}$	4 November 1981-15 September, 1986	Up to 15m
	$Q = 51.936(h - 3.987)^{2.8}$	16-Sep-1986- 31-Oct-2001	Up to 15m

The Shire River basin is a gauged basin but with poor quality hydrological data. While the adequacy of station density could not be ascertained, it is apparent from data made available to the study (Table 3.3) that hydro-meteorological data on tributaries in recent years has declined significantly.

In addition, not all stations on the main river are calibrated for flow measurement; Tengani and Nsanje gauge stations have been calibrated for only water level measurement. Further, characteristic of stations in this basin in general is the significant proportion of missing data. The size of discontinuities, not evident from the table, can be in the order of some years. Besides these issues, due to resource constraints, the update of rating curves is rarely done (Shela et al., 2008).

As with hydrological data, the DCCMS also collects rainfall data manually using manual rainfall gauges. However, in contrast to water levels and flows, rainfall series (Table 3.3) are long and the proportion of missing values and size of discontinuities are much lower.

Determined by the recency of data at most stations at the start of the study, the study investigated the 2008 flood for the flood hazardousness of the valley. Consequently, gauge stations used were those on the Shire River; all indicated in Table 3.3. Due to the importance of Sinoya station as the most downstream on Ruo catchment, the later being very important in the flooding of the valley (Shela et al., 2008), the station was also included despite the shortness of the series, notably on flow data. All rainfall stations in the table were included.

Table 3.3: Gauge and meteorological stations used for flood risk analysis

Station	Catchment size (km^2)	Variable	Record length (daily data)	Proportion of missing values	Min	Max	Mean	Standard Deviation
Shire River Stations*								
Mangochi	126,500	Water level (m)	1953-2009	6.4	0.2	9.5	7.1	0.8
Liwonde	130,250		1970-2010	1.6	0.9	4.7	2.2	0.6
Chikwawa	138,600		1977-2009	14.0	0.9	5.9	2.5	0.7
Chiromo	149,500		1970-2009	14.4	2.2	7.9	4.7	1.09
Tengani	150,000		1970-2006	23.4	0.7	5.9	3.25	1.32
Nsanje	154,000		1960-2005	41.4	0.6	8.1	4.8	1.67
Mangochi		Flow (m^3/s)	1956-2008	7.1	118.8	1096	492.5	178.9
Liwonde			1948-2010	1.9	0.2	1073	378.3	191.9
Chikwawa			1977-2009	18.3	53	2286	593.2	295.5
Chiromo			1953-2009	6.0	0.8	2142	459.4	257.7
Tributary Stations								
Mwanza at Tomali	1650	Flow (m^3/s)	1970-2008	31	0.001	437.7	1.78	7.8
Mkulumadzi at Mlongora	586		1980-2008	33	0.001	205	5.4	7.7
Mwamphazi at Mpokonyola	311		1956-2001	11	0.01	86.1	7.2	10.2
Chisombezi at Midima Rd	76.4		1962-2000	5	0.001	291.9	1.3	7.7
Ruo at M1 Bridge	193		1956-2004	4	0.01	571	10.2	19.5
Nswadzi at Chipungu	380		1956-2002	9	0.01	2144	14.3	07.3
Nkhate at Irrigation works	1		2006-2008	3	0.03	20.4	0.89	1.59
Ruo at Sinoya	4530		1980-1990	23.0	0	3683.4	92.4	196.9
		Water level (m)	1962-2002	21,1	0.8	10.2	4.74	1.57

*Catchment area on stations on the Shire River includes Lake Malawi Basin area (126,500km^2) upstream of the Shire River Basin

Table 3.4 (continued)

Station	Variable	Record length (daily)	Proportion of missing values (%)	Minimum	Maximum	Mean	Standard Deviation
Nsanje	Rainfall (mm)	1973-2009	3.1	0	164.9	2.8	10.3
Makhanga		1953-2010	4.7	0	138.5	2.0	8.1
Ngabu		1981-2010	1.4	0	165.0	2.2	8.4
Chikwawa		1979-2010	10.8	0	145.7	2.2	8.4
Nchalo		1981-2010	3.8	0	100.4	2.0	7.4
Neno		1980-2009	15.9	0	161.4	3.4	10.8
Mwanza		1935-2006	17.7	0	150.9	3.0	9.6
Mimosa		1958-2010	0.8	0	127.7	3.2	9.5
Thyolo		1962-2010	0.0	0	169.5	2.4	8.5
Bvumbwe		1953-2010	0.0	0	126.0	3.1	9.4
Chileka		1961-2010	0.6	0	147.0	2.8	9.1
Chichiri		1981-2010	15.7	0	182.5	2.8	9.4
Makoka		1981-2010	1.4	0	144.7	2.4	9.1
Chingale		1952-2010	0.0	0	153.0	2.0	7.5
Balaka		1981-2010	4.4	0	185.2	4.5	12.5
Mangochi		1961-2010	0.3	0	177.3	3.4	10.1

3.3.2 Hydrological analyses – Artificial Neural Networks (ANN)

Traditionally, hydrological modelling for water management has employed traditional models i.e. blackbox models (Dutta et al., 2012; Yawson et al., 2005), conceptual models (Primožič et al., 2008; Rahman et al., 2012) and physically based models (Liu et al., 2005; Sahoo et al., 2006; Thielen et al., 2009).

Blackbox models transform inputs to outputs using e.g. regression without reference to the internal physical processes controlling the transformation. Physically based models at the other extreme try to replicate the natural system using the basic mathematical representation of the flow at a point based on the principles of conservation of mass, momentum and energy. Conceptual models are those relying on a simple arrangement of a relatively small number of interlinked conceptual elements (the most common elements being storage elements), each representing a segment of the land phase of the hydrological cycle (Jain, 1993).

These models have challenges. Physically-based models have been associated with complexity, long computational times, problems related to scale on the application of physical laws, extensive data demands and hence cost (O' Connor, 2005; Toth and Brath, 2007a). Whilst conceptual and simple blackbox models are more widely used in comparison to physically-based models, data requirements in conceptual models are still high and in many occasions, these data are unavailable or expensive and time consuming to collect (Chau et al., 2005; Singh, 2005). Traditional linear, blackbox models offer simplicity and sometimes parsimony, but they reduce the complex non-linear system to a linear system and may thus inadequately represent the system.

The above challenges with traditional modelling paradigms have resulted in increased attention towards data-driven models, with Artificial Neural Networks (ANN) being the most widely used data-driven techniques in water resources management. ANN are computational techniques that mimic the functioning of neural biological system of the human brain (Haykin, 1999). Their appeal has been well documented e.g. Thirumalaiah and Deo (1998), Dawson and Wilby (1998), Kneale et al. (2004), Lekkas et al. (2004), Minns and Hall (2004) and stems from their ability to: model complex nonlinear patterns; work without a priori knowledge of the underlying process; self-adjust; to be speedy and be robust to the existence of missing data during training or calibration.

ANNs have been used in water resources and environmental management for rainfall forecasting (Hung et al., 2009), rainfall-runoff modelling (Wu and Chau, 2011), flow forecasting (Aquil et al., 2007; Wu et al., 2009), water level forecasting (Alvisi et al., 2006), reservoir parameters prediction (Adeloye and De Munari, 2006), groundwater level prediction (Nayak et al., 2006), sediment load estimation (Cigizoglu, 2004), water quality parameter prediction (Baxter et al., 2001; Diamantopoulou et al., 2005; Panda et al., 2004; Rustum and Adeloye, 2012), land use/land cover classification (Yuan et al., 2009), land use and land cover change prediction (Ito and Murata, 2009), and land use/land cover change impact on water resources (Isik et al., 2013).

Like traditional models, ANNs are also not without difficulties either. One of the limitations of ANN has been their poor performance outside the calibration range; they therefore cannot be reliably used in situations where significant events outside the calibration range are important. Further, they are not transparent because their structure is hidden in computer code, which means they are less comprehensible to practitioners (Solomantine and Price, 2004). However, these limitations pale into insignificance when compared to its merits especially in data-poor catchments where the needed data and information for calibrating and validating traditional models do not exist. Consequently this study had adopted the ANN for hydrological modelling specifically for data reconstruction and the forecasting of river flows and levels.

3.3.2.1 Self-Organizing Maps (SOM) as a basis for data reconstruction

Numerous techniques of estimating missing values have been used. Their application depends on a number of factors: the length of the gaps, the availability of hydro-meteorological data from neighbouring stations, the season of missing values, the climatic region under consideration, the knowledge and expertise of the person responsible for correcting data, length of existing data record, the importance of prediction and hence consideration of the performance of the model to be used for infilling (Gyau-Boake and Schultz, 1994; Khalil et al., 1998; Rees, 2008).

Simple arithmetic averages (Dinpashoh et al., 2011; Linacre, 1992) and linear interpolation techniques (Yawson et al., 2005) have normally been used when dealing with an auto-series (data from a station for which in-filling is to be made). However, it is probably more common to use other surrounding stations acting as donor sites. In this case, linear regression e.g. Abatzoglou et al. (2009) and weighted averages based on such variables as distance and correlation coefficient (Dastorani et al., 2010; Roudier et al., 2012) are often used. While most of these traditional methods offer simplicity, there are not without challenges which tend to be more profound in context of the quality of data in developing countries. Rees (2008) observes that serial interpolation techniques are only suitable in stable periods i.e. periods having neither flood events nor significant rainfall. In addition, their application is also limited to short lengths of the gap (Hydrology Project, 1999).

For periods with variable flows and longer sequences of missing data, regression analysis and other forms of hydrological modelling are recommended (Hydrology Project, 1999; Rees, 2008). Regression analysis, however, demands a relatively long and reliable data set – a requirement not easily met in developing countries. Since augmentation by regression assumes that the predictor variables are always available, based on data from neighbouring stations, the approach will break down if the independent variable is also missing as noted by Adeloye (2009). Besides, classical regression methods normally analyse for one predictand; thus for a large number of variables requiring infilling, developing different predictive regression equations for each can be time consuming (Rustum, 2009).

While hydrological modelling-based infilling offers accurate estimates, the challenge of data availability for calibration and validation as earlier highlighted are a challenge to data-poor catchments, making ANN a powerful alternative. In particular, several recent studies e.g. Rustum and Adeloye, (2007) and Kalteth and Hjorth (2009) have found that SOM, an unsupervised ANN, performed better than the most widely used Multi-Layer

Perceptron Artificial Neural Networks (MLP-ANNs) in water resources. SOMs are also very robust to missing data during its training (Malek et al., 2008) whereas MLP-ANNs will require a complete data set for its training. Thus, if data are missing, an off-line pre-processing to provide estimates of the data in the input space is mandatory before the training of MLP-ANNs can proceed (Rustum and Adeloye, 2007).

Common to hydrological and meteorological data available in the Shire Basin and developing countries in general, is the considerable proportion of missing data which would naturally preclude the use of MLP-ANNs or other regression-based methods. As a result of the above attributes of SOM, this study uses the SOM for augmenting data in the Shire basin.

Self-Organizing Maps

Self-organizing maps (SOM) are a competitive, unsupervised form of artificial neural networks pioneered by the Finnish professor, Professor Teuvor Kohonen (Kohonen et al., 1996). They provide a means of compressing data from multi-dimensions to lower dimensions discrete map, usually two dimensions, although higher dimensions are possible but not as common (Haykin, 1999). They also cluster input patterns in such a way that similar patterns are represented by the same output neurons or by one of its neighbours. The information in a SOM is stored in such a way that any topological relationships within the training set are maintained. This implies that the SOM translates the statistical dependencies between the data into geometric relationships, therefore maintaining the most important topological and metric information contained in the original data (Rustum, 2009).

Basics of SOM

The SOM (also called feature map or Kohonen map) is one of the most widely used artificial neural networks algorithms (Kohonen et al., 1996). It is usually presented as a dimensional grid or map whose units (nodes or neurons) become tuned to different input data patterns. Its algorithms are based on unsupervised competitive learning, which means that training is entirely data driven and the neurons or nodes on the map compete with each other (Alhoniemi et al., 1999). The principal goal of the SOM is to transform an incoming signal pattern of arbitrary dimension into a two-dimensional discrete map. It involves clustering the input patterns in such a way that similar patterns are represented by the same output neurons, or by one of its neighbours (Back et al., 1998). In this way, the SOM can be viewed as a tool for reducing the amount of data by clustering, thus converting complex, nonlinear statistical relationship between high dimensional data into simple relationship on low dimensional display (Kohonen et al., 1996). This mapping preserves the most important topological and metric relationship of the original data elements, implying that not much information is lost during the mapping.

The SOM consists of two layers: the multidimensional input layer and the competitive or output layer; both of these layers are fully interconnected as illustrated in Figure 3.2.

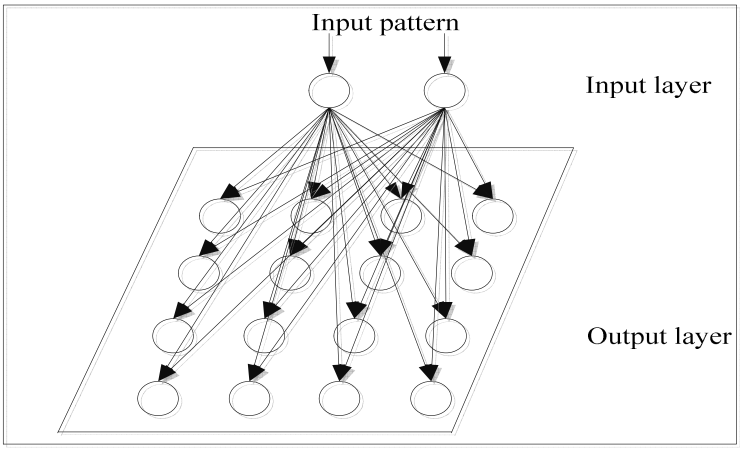


Figure 3.2: The architecture of SOM

The output layer consists of M neurons arranged in a two-dimensional grid of nodes. Each node or neuron i ($i = 1,2,...,M$) is represented by an n-dimensional weight or reference or code vector $W_i = [w_{i_1}, ..., w_{i_n}]$, where n is the dimension of each input vector, i.e. the maximum number of variables in the input vector. In other words, each neuron in the output layer of the SOM contains exactly the same set of variables contained in the input vectors and thus, unlike the MLP-ANNs, variables in the SOM are not partitioned into input or output variables.

Garcia and Gonzalez (2004) offer guidance on determining the optimum number of neurons, which is:

$$M = 5\sqrt{N} \tag{3.1}$$

where N is the total number of data samples or vectors. Once M is known, the number of rows and columns in the SOM can be determined. A guideline by Garcia and Gonzalez (2004) on the dimensions of M is that:

$$\frac{l_1}{l_2} = \sqrt{\frac{e_1}{e_2}} \tag{3.2}$$

where l_1 and l_2 are the number of rows and columns respectively, e_1 is the biggest eigenvalue of the training data set and e_2 is the second biggest eigenvalue.

Training the SOM

The multi-dimensional input data is first standardized by deducting the mean and then dividing the result by the standard deviation. To start, the neurons in the output layer are seeded with randomly generated, standardized values. A standardized input vector is then chosen at random and presented to each of the individual neurons of the SOM for comparison with their code vectors in order to identify the code vector most similar to the presented input vector. The identification uses the Euclidian distance, which is defined as:

$$D_i = \sqrt{\sum_{j=1}^{n} m_j \left(x_j - w_{ij}\right)^2} \qquad i = 1,2........ M \tag{3.3}$$

where D_i is the Euclidian distance between the input vector and the code vector i; x_j is the j th element of the current input vector; w_{ij} is the j th element of the code vector i; n is the dimension of the input vector; and m_j is the so called ''mask'' which is used to include in $(m_j = 1)$, or exclude from $(m_j = 0)$, the calculation of the Euclidian distance, the contribution of a given element x_j of the input vector. This is very useful where the input vector contains missing elements because all that needs to be done is to set the mask (m_j) to zero for such elements. In this way, the SOM is able to handle missing values in the input vector without any problem. The neuron whose vector most closely matches the input data vector (i.e. for which the D_i is minimum) is chosen as a winning node or the best matching unit (BMU). The code vectors of this winning node and those of its adjacent neurons are then adjusted to match the input data using equation (3.4), thus bringing the code vectors further into agreement with the input vector (Vesanto et al., 2000).

$$w_i(t+1) = w_i(t) + \alpha(t)h_{ci}(t)[x(t) - w_i(t)] \tag{3.4}$$

where t denotes time, $\alpha(t)$ is the learning rate at t, $h_{ci}(t)$ is the neighbourhood function centred in the winner unit c at time t and all the other variables are as defined previously. In this manner each node in the map internally develops the ability to recognize input vectors similar to itself. This characteristic is referred to as *self-organizing*, because no external information is supplied to lead to a classification (Penn, 2005). The process of comparison and adjustment continues until the optimal number of iteration is reached or the specified error criteria are attained.

Both the learning rate and the neighbourhood function affect the learning effectiveness of the SOM and must be chosen carefully. In particular, the learning rate decreases monotonically with increased number of iterations as in the following equations:

$$\alpha(t) = \alpha_0 \left(1 - t/T\right) \tag{3.5}$$

$$\alpha(t) = \alpha_0 (0.005/\alpha_0)^{t/T} \tag{3.6}$$

$$\alpha(t) = \frac{\alpha_0}{\left(1 + 100\, t/T\right)} \tag{3.7}$$

where α_0 is the initial learning rate and T is the training length or the number of iterations (Vesanto et al., 2000), thus forcing the weight vector to converge. In general, best results are obtained by setting $T = 250 / N^{0.5}$ (SOM toolbox for Matlab 5 – see http://www.cis.hut.fi). The neighbourhood function is normally chosen to be Gaussian centred in the winner unit c, such that:

$$h_{ci}(t) = \exp^{\left(-\|r_c - r_i\|^2 / \left(2\sigma^2(t)\right)\right)} \tag{3.8}$$

where r_c and r_i are the positions of nodes c and i on the SOM grid and $\sigma(t)$ is the neighbourhood radius. Like the learning rate $\alpha(t)$, $\sigma(t)$ also decreases monotonically as the number of iterations increases.

A variant to the sequential training algorithm above is the batch training algorithm where all data are presented to the SOM and their winning neuron identified before adjustments take place. In this regard, the update takes the form:

$$w_i(t+1) = \frac{\sum_{j=1}^{N} h_{ic}(t) x_j}{\sum_{j=1}^{N} h_{ic}(t)} \tag{3.9}$$

where c is the index of the BMU of the data sample x_j.

In this study, the batch algorithm was used as it has been known to be significantly more computationally efficient in terms of speed than the sequential training algorithm (Pölzlbauer, 2004). Besides, it does not require a learning rate to converge thus eliminating the potential source of poor convergence (Silva and Marques, 2007).

SOM quality measures

The quality of the trained SOM is measured in many ways but two properties widely assessed are vector quantization and topology preservation (Pölzlbauer, 2004). Pölzlbauer (2004) describes vector quantization as finding a suitable subset that describes and represents a larger set of data. Topology preservation on the other hand relates to neighbourhood preserving (Van-Hulle, 2011). To assess the quality of SOM in this study, two widely used measures were adopted: the total average quantization error and total topographic error respectively. The quantization error is given by:

$$q_e = \frac{1}{N}\sum_{i=1}^{N} \| X_i - W_c \| \tag{3.10}$$

where q_e is the quantization error, X_i is the ith data sample or vector, W_c is the prototype vector of the best matching unit for X_i and ||.|| denotes the Euclidian distance (equation (3.3)). The topographic error is given by:

$$t_e = \frac{1}{N}\sum_{i=1}^{N} u(X_i) \tag{3.11}$$

where $u_i(.)$ is a binary integer such that it is equal to 1 if the first and second best matching units for X_i are not adjacent units; otherwise it is zero. Thus a value of zero depicts total topology preservation (Pölzlbauer, 2004).

Use of SOM for prediction

Once the SOM has been fully and effectively trained as described above, it is now ready to be used for prediction. The application of the SOM for data record infilling is illustrated in Figure 3.3 (see also (Rustum and Adeloye, 2007)). As evident in Figure 3.3, there can be more than one variable needing to be predicted in a single input vector. In fact as illustrated in Figure 3.3, there are three variables of the input vector that need to be predicted.

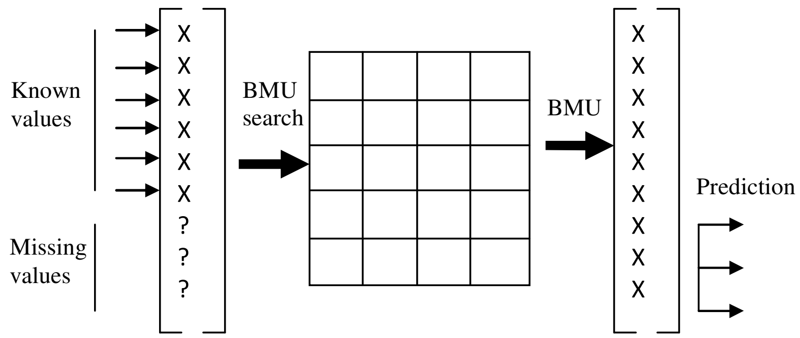


Figure 3.3: Prediction of missing components of the input vector using SOM.
Source: (Rustum and Adeloye, 2007)

This ability to simultaneously predict multiple variables is what makes the SOM a much more versatile tool than classical regression. The multivariate prediction using the SOM proceeds as follows:

i. Decide on the variables needing prediction in the input vector. These will be variables that are unavailable because they are actually missing (e.g. missing river stage and discharge) resulting in a depleted input vector. In the schematic of

Figure 3.3 the input vector has three variables missing, which are represented by ‘‘?’’

ii. Determine the Euclidian distance, D_i, of the depleted vector from each of the nodes of the output layer of the trained SOM using equation (3.3). In doing this, the mask, m_j, of each of the unavailable variables will be set to zero while m_j will be set to unity for all the other variables in the input vector.

iii. Examine all the D_i's for the minimum and hence isolate the SOM's BMU for the depleted input vector. It should be noted that while the input vector in step (i) above is depleted, i.e. has variables missing, the BMU identified here is a node of a trained SOM and hence has the full complement of variables.

iv. Replace the missing values of the input vector by their corresponding values in the BMU identified in step (iii) above.

3.3.2.2 Multi-layer Perceptron ANN (MLP-ANN) as a basis for forecasting

The feedforward MLP-ANN) (Figure 3.4) remains the most widely used ANN in water resources and more exclusively so in predictions and forecasting (Maier and Dandy, 2000; Maier et al., 2010).

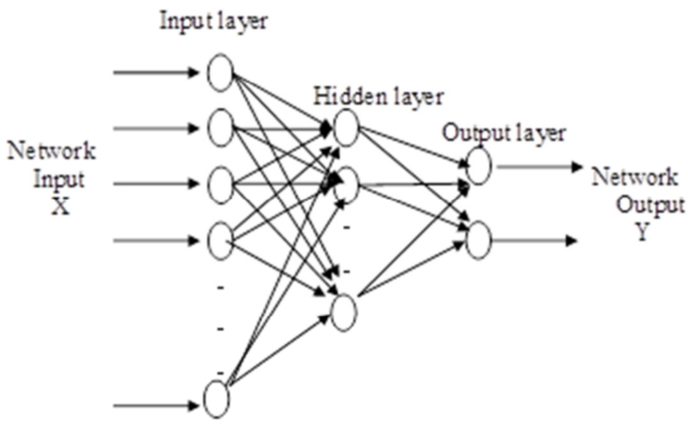


Figure 3.4: Configuration of feedforward three layer ANN.

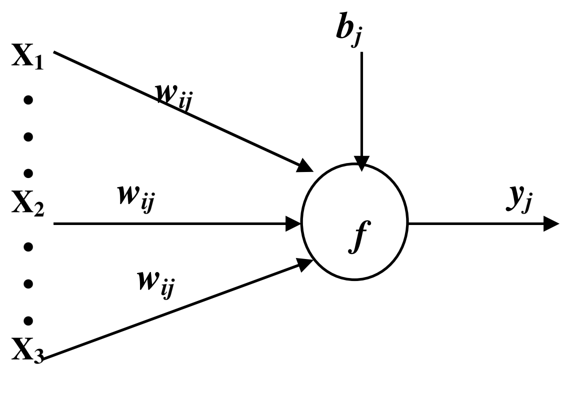


Figure 3.5: Schematic diagram of node.
Source: (ASCE, 2000)

MLP-ANN consists of several layers: an input layer, one or more hidden layers and an output layer. Each layer has one or more nodes arranged in parallel and connected to other nodes (not in the same layer) through weight vectors (Figure 3.4).The number of nodes in the input layer and output layers are problem-dependent being equal to the independent and dependent variables respectively. The number of neurons in the hidden layer is subject to several propositions but the trial-and-error approach remains widely used method for establishing this (Maier et al., 2010). The use of one hidden layer in hydrological studies involving ANN is not atypical and has been considered complex enough to simulate non-linear patterns exhibited in hydrological problems (Demuth et al., 2009). In feedforward MLP-ANN, information flows in one direction i.e. from input side to the output side and therefore output information at a given node (Figure 3.5) is a function of weighted inputs from preceding nodes in a previous layer and the activation function in the node. The output signal at a given node is mathematically expressed as:

$$y_j = f\left(X.W_j - b_j\right) \tag{3.12}$$

where y_j is the output at node j, f is the activation function, X is the input vector of inputs $\left(x_1,.....x_i,...x_n\right)$, W_j is the weight vector $\left(w_{1j},.....w_{ij},......w_{nj}\right)$ and w_{ij} is the weight connection from the ith node in the preceding layer to node j. b_j is the threshold value also called a bias which must be exceeded before the network can be activated (ASCE Task Committee, 2000). Non-linear activation functions such as the log or tan sigmoid transfer functions are normally used in the hidden layer as they are known to capture both linear and non-linear function (Demuth et al., 2009). In contrast, the output layer may contain either linear or non-linear activation functions. The commonly used activation function is the sigmoid function below with its popularity linked to the simplicity of its derivative which is used during the training process.

$$f\left(n\right) = \frac{1}{1+e^{-n}} \qquad 0 < f\left(n\right) < 1 \tag{3.13}$$

Knowledge is acquired through training, also known as learning; a process by which connection weights are adapted continuously to minimise the error function so as to generate an output that is as close as possible to the target vector (ASCE Task Committee, 2000). The back-propagation training algorithm tends to be the most widely used in water resources problems. It is a computationally efficient mechanism for weight adjustments in feedforward networks (Maier and Dandy, 2000; Maier et al., 2010). As illustrated earlier (see equation (3.12)), in the forward pass, the information at a particular node is a weighted sum of signals from the previous nodes plus a bias term calculated through a predetermined activation function. The network output is compared to the target and the error calculated. The error is propagated backwards through the network to each node. In this backward pass, weights are adjusted. Training continues until a predetermined level of error is reached or when no further changes are observed in the error. A trained ANN ought to give reasonable results given new inputs. A comprehensive description of ANN can be found in several publications including Haykin (1999), Maier and Dandy (2000), ASCE Task Committee (2000), Dawson and Wilby (2001), Maier et al. (2010).

While ANN has been widely and successfully applied for various studies, application in data-poor African catchments is sparse. It is also faced with the challenge of data quality. MLP-ANN requires data that is complete. The presence of gaps therefore has to be addressed before MLP-ANN can be applied. Also, because MLP-ANN characterise systems response from data presented through training (Toth and Brath, 2007a), small data sets, often the case in these data poor catchments, will lead to inadequate learning due to reduced degrees of freedom available for parameter estimation (Khamis et al., 2006).

For example, in the application of MLP-ANN for the determination of sediment load transfer under different agricultural and land management practices in Bvumbwe, Mindawi I, Mindawo II and Mphezo areas of Malawi (Abrahart and White, 2001), controlled random noise had to be added to the small training set to increase data size and thus reduce the uncertainties in the parameter estimation.

Similarly, Mazvimavi (2003) used MLP-ANN to predict flow characteristics from catchment characteristics in selected catchments of Zimbabwe. He estimated mean annual flow, baseflow index, annual hydrograph, mean monthly flows and flow duration curves using mean annual precipitation, lithology, slope, mean annual potential evaporation, land cover and drainage density as inputs. Due to data availability problems, Mazvimazi's work was limited to flow stations with a minimum of ten years of data; an aspect that may impact on the learning process.

It is important, therefore, to recognise that catchments in developing countries pose a unique challenge in the sense that most are either ungauged or if gauged, have poor quality data characterised by gaps and short durations (Adeloye and Rustum, 2012;

Mazvimavi, 2003; Saliha et al., 2011). Thus while the competence of MLP-ANN has been widely assessed in flow prediction, the Lower Shire floodplain of Malawi presents a unique situation in terms of data quality and availability. As noted above, much of this problem was overcome by using the SOM to infill and thus extends the available patchy data records.

3.3.2.3 ANN evaluation

It is important that the model represents as closely as possible the transformation of the input into output (Kachroo, 1992). A number of criteria has been used to evaluate ANN performance and take the form of visual inspection of graphical comparisons (scatter plots, times series) and statistical indices (ASCE, 1996). Visual inspection allows a quick assessment of model fit, capabilities and sensitivity to parameters something that may not be apparent in some statistical measures. On the other hand, visual inspection may be limited for example in ranking when performance of different models is nearly the same (Jain and Sudheer, 2008). Thus combination of both measures is important.

Commonly used statistical indices in ANN are the squared errors (the sum of squared errors (SSE), root mean square error (RMSE) and the Nash Sutcliffe efficiency (NS)), absolute errors (total sum of absolute deviations (TSAD), mean sum of absolute deviations (MSAD), total bias (TBIAS), mean bias (MBIAS)), relative error metrics (the average absolute relative error (AARE), the normalized root mean square error (NRMSE) and those based on correlation e.g. the Pearson correlation coefficient (R) (Maier et al., 2010). Squared errors provide a good measure of goodness of fit at high magnitudes; relative errors on the other hand provide a more balanced perspective moderate flows (Dawson and Wilby, 2001). While absolute errors provide magnitudes of the error, they are limited in providing information regarding under and over prediction (Maier et al., 2010).

Error statistics used in this study are the Nash–Sutcliffe index, NS (Equation (3.14)); the correlation coefficient, R (equation (3.15)); and the mean squared relative error, MSRE (equation (3.16)). In these equations, n is the number of observations, $\hat{Q}_i$ is the predicted value, Q_i represents observed flow and $\overline{Q_i}$ denotes the mean of the observed values.

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(Q_i - \hat{Q}_i\right)^2}{\sum_{i=1}^{n}\left(Q_i - \overline{Q_i}\right)^2} \tag{3.14}$$

$$R = \frac{n\sum Q_i \hat{Q}_i - \sum Q_i \sum \hat{Q}_i}{\sqrt{\left[n\sum Q_i^2 - \left(\sum Q_i\right)^2\right]\left[n\sum \hat{Q}_i^2 - \left(\sum \hat{Q}_i\right)^2\right]}} \tag{3.15}$$

$$MSRE = \frac{\sum_{i=1}^{n}\frac{\left(Q_i - \hat{Q}_i\right)^2}{Q_i^2}}{n} \tag{3.16}$$

The NS is different from the R in that, unlike R, it quantifies the proportion of the observed variance that is explained by the model but in doing this, it does not assume *a priori* a linear relationship between the inputs and outputs. For a simple regression model, NS is the same as the square of R. Additionally, following recommendations against relying on a single measure of accuracy (Dawson and Wilby, 2001; Jain and Sudheer, 2008; Legates and McCabe, 1999), MSRE was also used. The relative error measure was preferred to the absolute error because it removes any distortion that could result due to differences in units of output variables (Maier et al., 2010). Finally, time series plots and scatter plots were produced to confirm the relative efficacies of the different models.

3.4 Hazardousness determination

3.4.1 Model choice

As discussed in the literature review, the flood hazard has been measured in a variety of ways notably by hydraulic modelling, remote sensing techniques and community based approaches; often with the integration of GIS. Each of these methods has advantages and disadvantages already discussed.

The present analysis used hydraulic modelling for flood hazard determination. Hydraulic modelling was considered appropriate given estimation of flood hazardousness in this study was based on a historic flood event, i.e. the 2008 flood event. The choice of the 2008 flood event follows the availability of hydrological data in basin which was mostly up to 2008 at the time of the research. The hydraulic model approach also allows objective quantification of the hazard in terms of flood depths, a difficult aspect to achieve if satellite imagery or community based approaches were to be used.

Hydraulic models can be data intensive and quite complex requiring expert skill, requirements often not met in developing countries. A parsimonious hydraulic model is therefore paramount for the Lower Shire floodplain. A number of flood inundation models are available. These include one dimensional models such as MIKE II (DHI, 1993), ISIS (ISIS, 1995) , HEC-RAS (HEC-RAS, 2002). These models consider flow to be longitudinal, thus approximating the domain as a series of cross sections perpendicular to flow. They are computationally very efficient (Hunter et al., 2007) and well suited to parameterization using traditional field surveys (Bates and De Roo, 2000; Horritt and Bates, 2001). However, these models fail to approximate the domain as a surface but rather use a series of cross section. Hence, they are also unable to simulate the lateral diffusion of the flood wave (Hunter et al., 2007). Areas between cross section are not explicitly represented (Bates and De Roo, 2000). Besides, the cross sections are under the subjectivity of location and orientation (Hunter et al., 2007).

On the other extreme end are the 2D full Saint Venant equations- based models e.g. TELEMAC-2D (Bates and Anderson, 1993), MIKE 21 (DHI, 1996). These offer a better approximation of known hydraulic processes and require no secondary treatment to determine flood inundation as they are integrated for use with available satellite imagery. Despite these advantages, their computational costs and data requirements are high (Bates and De Roo, 2000).

Models from simplified full Saint Venant equation that neglect different aspects of the momentum equations have increasingly been used. Given typically available non-error free data used in model construction and validation, mathematically rigorous models may not be justified (Hunter et al., 2007). Such models include the volume spreading models such as the Rapid Flood Spreading Method (RFSM) (Gouldby et al., 2008) and dynamic models such as JFLOW (Bradbrook et al., 2004) and RFSM-EDA (Jamieson et al., 2012)

Lisflood-FP (Bates and De Roo, 2000) is also one of the simplified versions of full Saint Venant equations. It simulates channel flow with kinematic or diffuse approximation of one dimensional St Venant equations while floodplain inundation is approximated with a 2D diffusion wave using Manning's law and a storage cell concept applied over the raster grid (Bates and De Roo, 2000). A mathematical description of the model as given by Horritt and Bates (2001) is outlined below.

Channel flow in Lisflood-FP is described by continuity and momentum equations:

Continuity $$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = q \qquad (3.17)$$

Momentum $$S_o - \frac{n^2 P^{\frac{4}{3}} Q^2}{A^{\frac{10}{3}}} - \left[\frac{\partial h}{\partial x}\right] = 0 \qquad (3.18)$$

where Q is the volumetric flow rate in the channel, A the cross-sectional area of the flow, x is the distance between cross sections, q the flow into the channel from other sources (i.e. from the floodplain or possibly tributary channels), S_o the down-slope of the bed, n is the Manning friction coefficient distinguished as n_c for channels and n_{fp} for floodplains, P is the wetted perimeter of the flow, and h is the flow depth. The term in brackets is the diffusion term, which according to Horritt and Bates (2001) forces the flow to respond to both the bed slope and the free surface slope, and can be switched on and off in the model, to enable both kinematic and diffusive wave approximations to be tested. The channel parameters required to run the model are its width, bed slope, depth (for linking to floodplain flows) and Manning's n value and these can be varied spatially along the reach.

Over the floodplain, flows are also derived from the continuity and momentum equations applied to a grid of square cells. A cellular approximation is given by:

$$\frac{dh^{i,j}}{dt} = \frac{Q_x^{\ i-1,j} - Q_x^{\ i,j} + Q_y^{\ i-j,j} - Q_y^{\ i,j}}{\Delta x \Delta y} \tag{3.19}$$

Where $h_{i,j}$ is the water free surface height at the node (i, j), Δx and Δy are the cell dimensions, Q_x and Q_y describe the volumetric flow rates between floodplain cells. From the various flow equations available that would be equally applicable, Lisflood-FP uses Manning's equation.

$$Q_x^{\ i,j} = \frac{h^{\frac{5}{3}}{}_{flow}}{n} \left(\frac{h^{i-1,j} - h^{i,j}}{\Delta x} \right)^{\frac{1}{2}} \Delta y \tag{3.20}$$

Q_y is treated analogous to Q_x. The flow depth, h_{flow} represents the depth through which water can flow between two cells, and is defined as the difference between the highest water free surface in the two cells and the highest bed elevation. The model simulates the time evolution of water depth in each model grid cell at each time step in response to main channel flood waves and represents the simplest physical representation capable of simulating dynamic floodplain inundation (Wilson et al., 2007)

A number of advantages have been associated with Lisflood-FP. It models floods with minimum representation of floodplain hydraulics often demanded in typical hydraulic models. Yet results from Lisflood-FP have been found to be comparable with those from other models including full St Venant based models. On their application on the 35km stretch of the River Meuse in The Netherlands, for example, Bates and De Roob (2000), found that Lisflood-FP outperformed both the simpler planar approximation to the free surface based on a linear interpolation of maximum water surface elevations recorded at two gauge stations, and the steady state simulation with a two dimensional finite element model. Lisflood-FP and TELEMAC-2D also achieved similar results in terms of fit and mass balance error over a 40km stretch on River Thames, UK with Lisflood-FP further emerging computationally efficient on speed (Horritt and Bates, 2001). Fewtrell et al.(2009) compared Lisflood-FP with SOBEK, a fully 2D hydrodynamic model, in the prediction of the flood inundation on the River Thames in Greenwich, UK. Flood extent from the two models was comparable.

In addition, Lisflood-FP results are easily compared to typically available hydraulic data such as flow, stage data and satellite imagery; it requires relatively little hydraulic modelling expertise and is more computationally efficient than full St Venant models (Bates and De Roo, 2000; Fewtrell et al., 2009; Neal et al., 2012).

Furthermore, Lisflood-FP has been applied to a diverse set of conditions. It is applicable to fluvial, coastal and estuarine flooding and is executable in 1D, coupled 1D/2D and 2D (Neal et al., 2012). It has been extensively tested including in topographically complex regions, very large catchments and data scarce regions e.g. in the Amazon (Wilson et al., 2007), the Niger River (Neal et al., 2012) and the Ob (Biancamaria et al., 2009).

While JFLOW is very similar to Lisflood-FP (Bradbrook et al., 2004), Lisflood-FP is used in this study owing to its wider applicability in African catchments (Coulthard et al., 2013; Phanthuwongpakde, 2011; Zahera et al., 2011) where data availability and quality pose a bigger challenge. For a detailed discussion of Lisflood-FP, one is referred to Bates and De Roob (2000); Neal et al. (2012) amongst others.

3.4.2 Data inputs

Lisflood-FP is a parsimonious hydraulic model, a further advantage over its use and pertinent to data-poor catchments. At minimum, Lisflood-FP requires only an input flow hydrograph at the upstream boundary, topographic data, being readily available from remotely sensed topographic data, and flow resistance defined in the model by Manning's coefficient (Bates and De Roo, 2000). An estimate of flow resistance can be made from widely available literature such as those published by Chow (1959)

(Appendix A). Therefore, these three data sets were used. The downstream boundary condition was defined as a free uniform surface.

3.4.3 Flood hazardousness parameters

Analysis and understanding of hazards is based on certain characteristics. Literature on the flood hazard (Hamilton et al., 2004; Islam and Sado, 2002; Lung et al., 2013; Mosquera-Machado and Ahmad, 2007; Sanyal and Lu, 2005; Tingsanchali and Karim, 2010) identify flood depth, inundation area, frequency of occurrence, flow velocity, duration and rate of rise of water level as characteristics that can be used to measure flood hazardousness of an area. This study employs *flood inundation extent* and *depth*, the most widely used parameters in literature (Hamilton et al., 2004; Mosquera-Machado and Ahmad, 2007; Pelletier et al., 2005; Sanyal and Lu, 2004).

3.4.4 Model calibration and evaluation

The only variant used in the calibration process was the Manning's floodplain friction factor (nfp). As stated in the foregone section, Lisflood-FP results are easily compared to typically available hydraulic data such as flow, stage data and satellite imagery. Evaluation of inundation extent in this study was done by comparison to inundations in the satellite imagery using the degree of fit $Fit(\%)$ (equation (3.21)) as suggested by Bates and De Roo (2000).

$$Fit(\%) = \frac{A_{obs} \cap B_{\mathrm{mod}}}{A_{obs} \cup B_{\mathrm{mod}}} \tag{3.21}$$

where A_{obs} is the observed inundation area from the satellite image and B_{mod} is the modelled area, $\cap$ is the intersection and $\cup$ is the union. The fit is 100% for an exact match.

Validating flood depths on the other hand was constrained by lack of quality data, a challenge also faced in previous studies in the valley i.e. World Bank (2010b) and Atkins (2012). As earlier stated, water levels are manually collected. The collection of data during flooding is in most cases unlikely or intermittent. On the other hand, the Lower Shire Valley is rural and largely unobstructed by structural flood mitigation measures (Shela et al., 2008). In this regard, as discussed by Hunter et al (2007), a satisfactory match between observed and modelled inundation extent is a reasonable indicator of the match between observed and modelled water levels.

3.5 Measuring vulnerability

3.5.1 Vulnerability factors

Vulnerability is affected by social, economic, cultural and institutional factors. Cutter et al. (2003) and Collins et al. (2009) reviewed a number of literature on social vulnerability factors. They found that social vulnerability had been defined by such variables as age, gender, race; socioeconomic status (income, power, prestige); whether the population is rural or urban; special-needs population and minorities (the physically or mentally challenged, immigrants, the homeless, transients, and seasonal tourists); livelihoods, family structure, education, population growth and densities, access to medical services, access to information, institutional capacity, quality of human settlements in terms of housing type and construction and, infrastructure, and lifelines. The relationship between these factors and vulnerability according to Cutter et al. (2003) and Collins et al. (2009) is summarised in Table 3.4.

While developed and developing countries share many typical vulnerability characteristics, developing countries are also unique in some ways. For example, some factors in Table 3.4 also exhibit other pathways to vulnerability for developing countries. A dependency on the primary sector (agriculture, fisheries and forestry) for example by the predominantly rural population in SSA has implications on settlement patterns. People settle in marginal lands (where the livelihood is) making their physical exposure high (Gwimbi, 2009; Wisner et al., 2004). Their dependence on natural resources also undermines the environmental integrity of the land.

Further, the very narrowness of their livelihood base, undermines their resilience to hazards as they cannot draw on other resources should their livelihoods be under the shock of a hazard (Adger, 2000; Vincent, 2004).

Higher vulnerability for the young and the elderly does not only arise from physiological susceptibility and inability to render service to others as indicated in Table 3.4. These groups have impaired livelihoods and lack resources due to absence of social grants and inability of the elderly to significantly contribute income generating activities (van Riet, 2006). Thus the groups have few resources if any, to anticipate and cope with hazards. This carries a societal impact too. Vincent (2004) observes that as the young and the elderly draw on the resources of the working class, they reduce societal resilience.

In recent times, HIV/AIDS has become another humanitarian crisis for SSA, whose incidence increases population susceptibility and also reduces societal resilience. People living with HIV/AIDS in SSA account for 70% of those infected worldwide (UNAIDS, 2000). The impacts of HIV/AIDS on vulnerability are well documented. Van Riet (2006) and FANRPAN (2007) draw attention to the following impacts:

- an increase in widow-headed families and orphanhood and hence an increase in dependency
- Financial strain through medical bills, funerals and absenteeism from work
- Diminished access to resources due to stigmatization that limits social linkages and networks
- Lack of labour to maintain livelihoods and productive activities as the disease is debilitating.

Table 3.4: Social-economic indicators of vulnerability in natural disasters

Basic concept	Influence on vulnerability
Socio-economic status (income, political power and prestige)	Wealth enables communities to absorb and recover from losses more quickly due to insurance, social safety nets, and entitlement programs.
Gender	Women may lack resources to cope due to discrimination, sector-specific employment, lower wages and family care responsibilities. Female headed households also face a myriad of challenges to providing familial security as well as preparing for and recovering from hazards events.
Race and ethnicity	Processes of marginalisation, language and cultural barriers reduce their access to resources for coping with hazards, and inhibit their ability to recover from disasters.
Age	Mobility for the very young and very old is difficult which impinges on their evacuation. This age group has to be cared for; children depend on decisions made by others for survival and the elderly have limited income.
Commercial and industrial development	The value, quality, and density of commercial and industrial buildings provides an indicator of the state of economic health of a community, and potential losses in the business community, and longer-term issues with recovery after an event.
Employment loss	The potential loss of employment following a disaster exacerbates the number of unemployed workers in a community, contributing to a slower recovery from the disaster.
Rural/urban	Rural residents may be more vulnerable due to lower incomes and more dependent on locally based resources extraction economies (e.g. farming, fishing). High-density areas (urban) complicate evacuation out of harm's way.
Residential property	Expensive homes are costly to replace; mobile homes are easily destroyed and less resilient to hazards.
Access to information	The ability to receive radio and television broadcasts or telephone alerts can facilitate resilience by helping people make better-informed decisions.
Infrastructure and lifelines	Loss of infrastructure may place an insurmountable financial burden on smaller communities that lack the financial resources to rebuild.

Table 3.4 (continued)

Renters	People that rent often lack financial resources and access to financial aid information. Without property insurance, they are likely to be displaced without recovering any of their losses. Sometimes, they may be left without shelter altogether.
Occupation	People in certain jobs such as self-employed fishing, agriculture, low-skilled service jobs such as housekeeping, childcare, and gardening are severely impacted by a hazard; they may lack the physical and financial capital to resume the work soon after a disaster.
Family structure	Families with large numbers of dependents or single-parent households have to juggle work responsibilities and care for family members, which affect the resilience to and recovery from hazards.
Education	Low educational attainment result in lower earnings. It also constrains the ability to understand warning information and access to recovery information.
Population growth	Rapid population growth may outstrip provision of housing and other basic services. Immigrants are the most likely to be affected by bureaucracies for obtaining relief or recovery information.
Medical services	Lack of readily available medical services may prolong recovery from disasters.
Social dependence	A high social dependence reflects a community already marginalised economically and socially and thus a need for additional support.
Special needs populations	Special needs populations (infirm, institutionalised, transient, homeless) are disproportionately affected during disasters and mostly ignored during recovery. Like the very young and old, the survival of special needs population depend on decisions made by others.
Institutional capacity	The capacity of institutions to provide social support to its residents will affect the degree of susceptibility and recovery.

Source: Cutter et al. (2003) and Collins et al. (2009)

- Selling of productive assets which impairs future productivity
- Abandonment of school by children as they shoulder adult responsibilities
- Food insecurity
- Malnutrition
- Poverty

Furthermore, while according to Cutter et al. (2003) and Collins et al. (2009), destruction of public infrastructure exerts insurmountable financial pressure on small communities towards rebuilding, for developing countries, this impact is not necessarily confined to small communities; it is ubiquitous. In addition, in these countries, the failure of infrastructure or lack thereof is also much of a reflection of the weakness of institutions in terms of preparedness and coping capacity (Vincent, 2004).

In vulnerability studies of rural communities to climatological hazards in SSA in particular, vulnerability has been found to be a complex web of factors related to poverty, health, AIDS, mortality, livelihoods, food, water and environmental degradation. This is exemplified in Malcomb et al.'s (2014) study conducted Malawi (Figure 3.6, Table 3.5). Similarly, in measuring vulnerability to climate change in Mozambique, Hahn et al. (2009) draw indicators from five dimensions: Social demographic factors, livelihoods, health, social networks, food and water, shown in Table 3.6.

It is evident that vulnerability arises from a number of factors. These factors are often linked. Nonetheless, as several authors point out (Gall, 2007; Tate, 2012; Vincent, 2004), what factors ultimately go into measuring vulnerability is a function of several aspects: the objective of the assessment, the scale of analysis, the relative ease of measurement of an indicator, data availability, validity of the variable and methodological approach in building the index i.e. whether deductive, hierarchical or inductive.

The factors used in measuring the vulnerability to flooding in the study area are broadly classified as social, economic, environmental and physical. They draw from vulnerability literature as discussed in the above section. The actual variables ultimately used however depend on the vulnerability index to be used, identified in the section below.

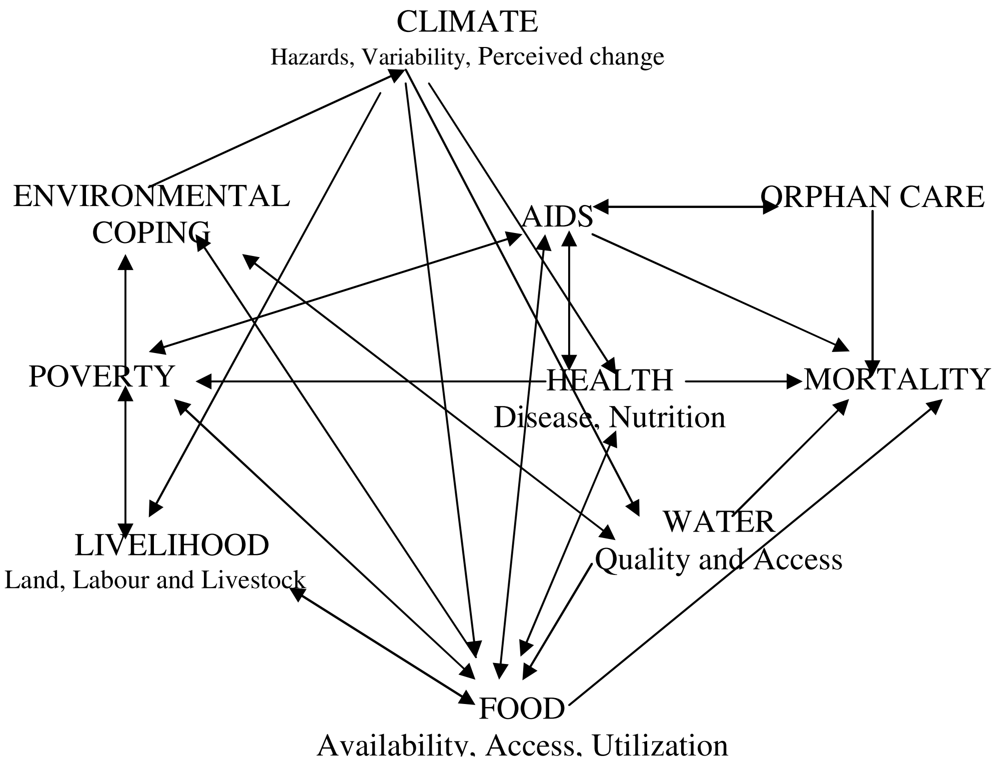


Figure 3.6: The vulnerability web for Malawi. Source: (Malcomb et al., 2014)

Table 3.5: Vulnerability indicators to climate change in Malawi based on Malcomb et al. (2014)

Theory	Indicator
Asset	
Arable Land	Amount of Arable land per HH
Livestock	Number of Animals per HH (by type)
Money	Wealth index (based on owned assets)
Good Health	Sick in the past 12 mos
Orphan Care	Number of orphans or vunerable children
Access	
Access Basics	Electricity (Y/N) Cooking fuel type Water(time to source)
Market access	Rural, peri-urban
Technology sharing	Own radio (Y/N)
Media and information	Own a cellphone (Y/N)
Power and decision making	Female-headed HH (Y/N)
Livelihood sensitivity	
Income source	% Poor income from labor
Ability to meet food needs	% Food intake from personal farm
Cash crop exposure	% Non-food crop (cotton, tobacco, tea)
Ecological coping effect	Access to alternative forms of income
Biophysical exposure	
Floods and rain variability	Flood events
Drought and dry spells	Drought indices

Table 3.6: Vulnerability indicators in Hahn et al.'s (2009) study

Major	Sub-component
Socio- demographic profile	Dependency ratio
	Percent of female-headed households
	Percent of households where head of family has not attended school
	Percent of households with orphans
Livelihood	Percent of households with family member working in a different community
	Percent of households dependent solely on agriculture as a source of income
	Average Agricultural Livelihood Diversification index
Health	Average time to health facility
	Percent of households with family member with a chronic illness
	Percent of households where a family had to miss work or school in the last 2 weeks due to illness
	Average malaria exposure prevention index
Social Networks	Average Receive: Give ratio (range: 0 – 15)
	Average Borrow: Lend Money (range: 0.5-2)
	Percent of households that have not gone to their local government for assistance for the past 12 months
Food	Percent of households dependent on family farm for food
	Average number of months households struggle to find food (range: 0-12)
	Average crop diversity index (range: >0-1)
	Percent of households that do not save crops
	Percent of households that do not save seeds
Water	Percent of households reporting water conflicts
	Percent of households that utilize a natural water source
	Average time to water source (minutes)
	Percent of households that do not have a consistent water supply
	Inverse of the average number of litres of water stored per household (range:>0-1)

3.5.2 Conceptual framework for vulnerability analysis

This study draws from the natural hazard community, (Bollin et al., 2003; ISDR, 2004), also referred to as the disaster risk discipline (Birkmann et al., 2013). Therefore vulnerability herein is limited to the intrinsic disposition of a system to harm; independent of the hazard (Birkmann et al., 2013) and is also inclusive of internal biophysical factors i.e. topography, forest cover, soil etc (Bollin et al., 2003). Dimensional components used are *exposure*, *susceptibility* and *capacity/resilience* perspectives as championed in the IPCC framework and disaster risk community (Birkmann et al., 2013; IPCC, 2012). The following definitions are used:

- *exposure* - the presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social and cultural assets in places that could be adversely affected.

- *susceptibility* - the predisposition of elements at risk to suffer harm.

- *resilience* - the ability of a system and its components to anticipate, absorb, accommodate, or recover from the effects of a hazardous event (Birkmann et al., 2013; IPCC, 2012). Resilience is a term also used synonymously to capacity (Birkmann et al., 2013). Consequently, the two are used interchangeably in this study.

Characterising the disaster risk framework are sustainable development concepts (Birkmann et al., 2013). Therefore *exposure*, *susceptibility* and *resilience* components in this study are further examined within four major thematic sustainable development dimensions: *social*, *economic, environment* and *physical* (ISDR, 2004*)*. This is illustrated in Figure 3.7.

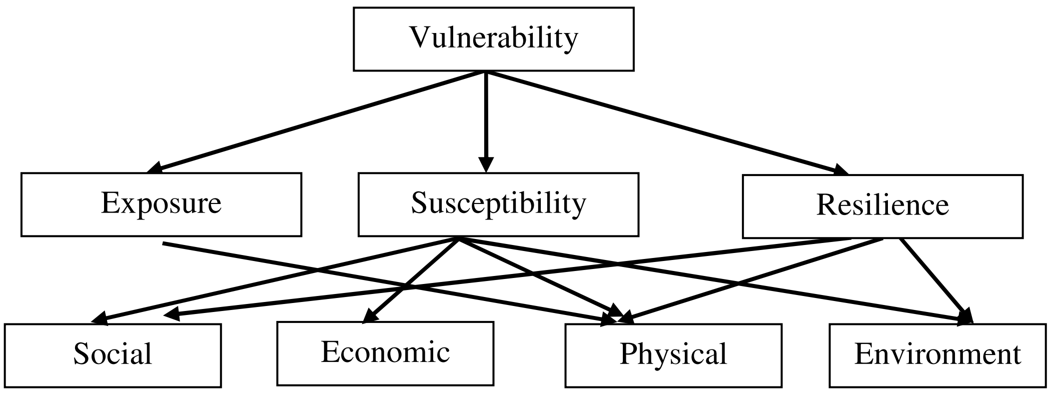


Figure 3.7: Conceptual framework for vulnerability analysis

3.5.3 The vulnerability index

The study adapts an existing index from the plethora of indices used in the measurement of vulnerability. Some vulnerability indices are outlined in Table 3.7 . Indices such as the Disaster Risk Index (UNDP, 2004), the Hot spot project index (Dilley et al., 2005), the Predictive Indicators of Vulnerability (Adger et al., 2004; Brooks et al., 2005) and the Environmental Sustainability Index (Esty et al., 2005) have a global focus though with a national resolution, which precludes their application to the study. Similarly, other indices are regional. For example, the Environment Vulnerability Index (Pratt et al., 2004) was specifically developed for Small Islands Developing States (SIDS); the Prevalent Vulnerability Index (Cardona, 2005) for 12 Latin American states and the Social Vulnerability Index for African nations (Vincent, 2004). While advantageous in various aspects such as bench marking or flagging to the international development or aid community, these global or regional assessments at a national resolution masks the micro-level factors, an interest in this study, which are very pertinent to vulnerability and hence risk reduction.

A number of indices developed address climate change and hence this aspect precludes their application to this study irrespective of resolution of scale. Such indices include the Climate Vulnerability Index (Sullivan and Meigh, 2005), the Social Vulnerability Index (Vincent, 2004) and Predictive Indicators of Vulnerability (Adger et al., 2004; Brooks et al., 2005), the Livelihood Vulnerability Index (Hahn et al., 2009).

Few indices have been flood-specific. Connor and Hiroki (2005), through a multi-variate analysis, developed a basin scale flood vulnerability index (FVI) for Japan where the vulnerability is measured in terms of mortality (FVI_H) and economic loss (FVI_M) as below.

$$FVI_H = \frac{y}{x_{pop}} = -0.38140x_1 - 42.96608x_2 - 0.34078x_3 + 16.73267x_4 + 0.14879x_5 - 57.92870 \quad (3.22)$$

$$FVI_M = \frac{z}{x_{pro}} = -0.00029x_1 - 0.0007926x_2 + 4.55142\times10^{-6}x_5 + 11.20716x_6 + 0.0215 \quad (3.23)$$

$$0 \le FVI \le 1$$

where y = total casualties in millions, x_{pop} = total population in the floodplain in millions, x_1 = TV penetration rate (%), x_2 = investment amount (Y100 million) in flood control infrastructure, x_3 = advancement rate in % of people completing high school,

Table 3.7: Examples of natural disaster-related vulnerability indices

Index	Definition
Prevalent Vulnerability Index (PVI) (Cardona, 2005)	$PVI = PVI_{ES} + PVI_{FS} + PVI_{LR}$ ES , FS , LR correspond to Exposure and Susceptibility, Socio-economic Fragility and Lack of Resilience. $PVI^{t}_{c(ES,FS,LR)} = \frac{\sum_{i=1}^{N} w_i I_{ic}{}^{t}}{\sum_{i=1}^{N} w_i} \mid_{(ES,SF,LR)}$ where, w_i is the weight assigned to each indicator, derived by Analytic Hierarchy Process (AHP), $I_{ic}{}^{t}$ corresponds to each normalized indicator as in the equations below. These represent the conditions of vulnerability for each situation (ES, FS, LR) respectively. $I^{t}_{ic} = \frac{x^{t}_{ic} - \min\left(x^{t}_{i}\right)}{rank\left(x^{t}_{i}\right)}$, for (ES,FS) and $I^{t}_{ic} = \frac{\max\left(x^{t}_{i}\right) - x^{t}_{ic}}{rank\left(x^{t}_{i}\right)}$ for LR x^{t}_{ic} is the original data for the variable for country *c* during time period *t*, and x^{t}_{i} is the variable considered jointly for all countries. x^{t}_{M} is the maximum value defined for the variable at *t* period, x^{t}_{m} is the minimum value defined for the variable at *t* period, x^{t}_{i} rank is the difference between the maximum and minimum value $\left(x^{t}_{M} - x^{t}_{m}\right)$ at *t* period. The indicators in the sub-components are:

	PVI_{ES} = Population growth, avg. annual rate (%), Urban growth, avg. annual rate (%), Population density, people/5 Km^2; Poverty-population below US$ 1 per day PPP; Capital stock, million US$ dollar/1000 km^2; Imports and exports of goods and services, % GDP; Gross domestic fixed investment, % of GDP; Arable land and permanent crops, % land area. PVI_{FS} =Human Poverty Index, HPI-1; Dependents as proportion of working age population, Inequality as measured by the Gini coefficient, Unemployment, as % of the total labour force, Annual increase in food prices (%), Share of agriculture in total GDP growth (annual %), Debt service burden as a % of GDP, Soil degradation resulting from human activities (GLASOD). PVI_{LR} = Human Development Index, HDI [Inv], Gender-related Development Index, GDI [Inv], Social expenditure; on pensions, health, and education, % of GDP [Inv], Governance Index (Kaufmann) [Inv], Insurance of infrastructure and housing, % of GD [Inv], Television sets per 1000 people [Inv], Hospital beds per 1000 people [Inv], Environmental Sustainability Index, ESI [Inv]. [Inv] = inverse.
Predictive Indicators of Vulnerability (PVI) (Adger et al., 2004; Brooks et al., 2005)	Vulnerability (V) = country score on 11 socio-economic indicators i.e. population with access to sanitation, literacy rate of 15-24year olds, maternal mortality, literacy rate of over 15 year olds, calorie intake, voice and accountability, civil liberties, political rights, government effectiveness, literacy ratio (female to male) and life expectancy at birth.

	$V = \frac{\sum_{i=1}^{11} x_i w_1}{N}$, $1 < V < 55$ where x is a score, ranging from 1 to 5, that a country scores on a particular vulnerability variable, w is weight allocated to the variables determined by a group of experts and ranges from 1 (least important, corresponding to the last ranking variable) to 11 (most important, corresponding to the first ranking variable) and $N = 11$.
Climate vulnerability index (CVI) (Sullivan and Meigh, 2005),	$CVI = \frac{r_r R + r_a A + r_C C + r_e E + r_g G}{r_r + r_a + r_C + r_e + r_g}$ R, A, C, E and G refer to resource, access, capacity, environment and geospatial component. r is a factor representing the relevance of a component in a specific place obtainable through expert opinion or stakeholder consultations.
Livelihood Vulnerability Index (LVI) (Hahn et al., 2009).	$M_d = \frac{\sum_{i==1}^{n} index}{n}$, $LVI = \frac{\sum_{i=1}^{7} w_{M_i} M_{d_i}}{\sum_{i=1}^{7} w_{M_i}}$, $0 < LVI < 0.5$, M_d= one of the seven major components i.e. Social Demographic Profile (SDP), Livelihood Strategies (LS), Social Networks (SN), Health (H), Food (F), Water (W), Natural Disasters and Climate Variability (NDCV), *index*= normalized indices that make up each major component, n= number of indicators in each major component, w_{M_i} =weight of each major component and is equal to n.
Social Vulnerability Index (Vincent, 2004)	$SVI = 0.2I_i + 0.2I_{ii} + 0.4I_{iii} + 0.1I_{iv} + 0.1I_v$ where $I_i, I_{ii}, I_{iii}, I_{iv}., I_{5v}$ are the dimensionless sub-components corresponding to Economic wellbeing and stability, Demographic structure, Institutional stability and strength of public infrastructure, Global connectivity, and Natural Resource Dependence respectively as explained in section 2.3.1

x_4 = proportion of elderly population (%) and x_5 = specific discharge (m^3/s/100km^2), z = damage amount (Y1 million), x_{pro} = total property in the floodplain (Y1 million), x_6 = frequency of heavy rainfall (number of days per year receiving more than 100 mm precipitation).

The success of Connor and Hiroki's (2005) FVI in Japan was only confined to the national scale; replication at basin level was sub-optimal (coefficient of determination = 0.46) calling for an improvement in the equation (Connor and Hiroki, 2005). The poor performance may be attributed to the empirical nature of the equation. Empirical equations are subject to boundary conditions under which they were developed and therefore application to basin level from a national scale is likely to violate boundary conditions resulting in sub-optimal performance. Besides, as an inductive approach, it is also sensitive to scale of application. Tate (2012) tested the robustness of deductive, hierarchical and inductive indices. He found that results from inductive models were highly influenced by scale of analysis unlike deductive and hierarchical models. These aspects aside, equating vulnerability to mortality or damage costs has serious weaknesses earlier discussed.

Another flood specific index is one by Balica et al (2009); subsequently improved (Balica and Wright, 2010) to achieve parsimony. Unlike the FVI by Connor and Hiroki's (2005), Balica et al (2009) developed several FVIs; each for a specific scale i.e. basin FVI, the sub-catchment FVI, urban FVI and coastal FVI. This addresses the issue of scale encountered in Connor and Hiroki's (2005). Consequently, it has been widely applied to river basins, urban units and coastal areas (Balica et al., 2014; Balica et al., 2009; Balica et al., 2013; Balica and Wright, 2010; Balica et al., 2012; Dinh et al., 2012). The index is also the basis for the automated web-based interface (http://unescoihefvi.free.fr/vulnerability.php) for vulnerability assessment managed by UNESCO IHE Institute of Water Education.

Besides addressing the issue of scale to a certain extent, the derivation of Balica and Wright's (2010) FVI has the advantage that it is not linked to mortality or damage estimates. Further, the index dimensions vulnerability by social, economic, environmental and physical components and conceptualises vulnerability as arising from exposure (E), susceptibility (S) and resilience (R). Thus in this regard, the FVI by Balica and Wright's (2010) is more in sync with contemporary disaster management than one by Connor and Hiroki.

Despite the scale-specificity advantage and its conformity to contemporary approaches to measuring vulnerability, depending on context, the spatial resolution of a sub-catchment may still be large to capture micro-level vulnerability. Besides, hydrological boundaries are not always units of disaster management, as is the case in the Lower Shire Valley. The mathematical construction of the index also raises some issues. Using the sub-catchment FVI for discussion purposes, variables in each sub-component are first normalised based on the maximum of the variable from n spatial units under consideration (equation (3.24)):

$$NV_i = \frac{RV_i}{Max_{i=1,n}(RV_i)} \tag{3.24}$$

where NV_i = normalized value of the indicator i; RV_i = raw value of the indicator i and $Max_{i=1,n}(RV_i)$ = maximum value from a set of n raw values for the indicator under consideration and n is equal to number of sub-catchments. The sub-component vulnerability $(FVI_{sub-component})$, i.e. social, economic, environmental and physical, is calculated for each sub-catchment based on equation (3.25). All exposure and susceptibility variables appear in the numerator and all resilience factors in the denominator as the vulnerability is directly proportional to exposure and susceptibility and inversely proportional to resilience.

$$FVI_{sub\_component} = \frac{NV_E \times NV_S}{NV_R} \tag{3.25}$$

where $N_E = \prod_{i=1}^{a} NV_{i_e}$, $N_S = \prod_{i=1}^{b} NV_{i_s}$ $N_R = \prod_{i=1}^{c} NV_{i_r}$; a, b, c are the number of exposure, susceptibility and reliance factors in the sub-component.

The $FVI_{sub-componenet}$ resulting from equation (3.25) can be any number. Therefore, the values are normalised again (equation (3.26)) to get a final normalized sub-component score i.e. $NFVI_{social}$, $NFVI_{economic}$, $NFVI_{environment}$ and $NFVI_{physical}$ whose value is between 0 and 1.

$$NFVI_{sub-component} = \frac{FVI_{sub-compoent}}{Max_{i=1,n}\left(FVI_{sub-componet}\right)} \tag{3.26}$$

The overall vulnerability for a given sub-catchment is a dimensionless simple arithmetic average of the four standardised components as below:

$$FVI_{average} = \frac{1}{4}\left(NFVI_{social} + NFVI_{economic} + NFVI_{environment} + NFVI_{physical}\right) \tag{3.27}$$

$$0 < FVI_{average} < 1$$

It is observed that the multiplicative model in equation (3.25) is subject to the nullity problem. If the exposure or susceptibility factor is a zero, then the outcome is a zero. If the resilience factor is a zero, the outcome is indeterminate. Besides, the multiplicative model skews the outcome heavily towards the indicator with the smallest score. In addition, the second normalization (equation (3.26)), undertaken to ensure that the sub-component vulnerability is between 0 and 1, always leads to a sub-component vulnerability of 1 (very high vulnerability) for a catchment having the maximum multiplicative score from equation (3.25). This mathematical weakness and the spatial resolution issue led to its exclusion for potential use in this study.

In view of pro-local vulnerability and risk assessment in contemporary disaster management (Lumbroso et al., 2008; Malcomb et al., 2014; Nelson et al., 2010) and cognisant of the context of vulnerability in developing countries, the Livelihood Vulnerability Index (LVI) by Hahn et. al. (2009) and the Community Based Disaster Risk Index (CBDRI) by Bollin et al. (2003) presented potential indices for the Shire Valley. The LVI by Hahn et. al. (2009) however has been specifically developed for measuring vulnerability with respect to climate change and variability. The CBDRI on the other hand, though not specific to flooding, is an index that can be applied to any hazard. Though developed for risk measurement, its additive form as shown in equation (3.28) makes it possible to disaggregate the index into hazard and vulnerability components and thus vulnerability can be extracted. The index has been used in developing countries e.g. Guatemala (Bollin et al., 2003) and Indonesia (Bollin and Hidajat, 2006). The CBDRI was therefore adopted for the Lower Shire Valley.

The CBDRI

Bollin et al. (2003) operationalizes the CBDRI by equations (3.28) and (3.29).

$$CBDRI = v(H + E + S - C) \tag{3.28}$$

$$H = \sum_{i=1}^{h} w_i x_i \, , \quad E = \sum_{j=1}^{q} w_j x_j \, , \qquad S = \sum_{k=1}^{r} w_k x_k \, , \qquad C = \sum_{y=1}^{z} w_y x_y \tag{3.29}$$

where *H*, *E*, *S* and *C* are the *hazard*, *exposure, susceptibility* and *capacities* sub-components with a range from 0 to 100; $v = 0.33$. This factor keeps the final value of risk within 0 and 100. x is a score allocated to the variable in the sub-component and is equal to either 1 (low), 2 (medium) or 3 (high). w is the weight attached to the variable reflecting its significance in contributing to the sub-component and h, q, r, z are the total number of variables in the hazard, exposure, susceptibility and capacity components respectively.

It is also important to note that the CBDRI in Bollin et al. (2003) rather uses *vulnerability V* in place of *susceptibility S* in equation (3.28); suggesting exposure and capacity are independent of vulnerability. However, an examination of variables in this sub-component in Table 3.8 (labelled accordingly as (*S*)) shows that the variables essentially describe susceptibility. In a common conceptualisation of vulnerability in contemporary disaster management (Adger, 2006; Birkmann et al., 2013; Fussel, 2007; Smit and Wandel, 2006), exposure, susceptibility and capacities underlie vulnerability. In this study therefore, susceptibility *S* is used in equation (3.28), as vulnerability is an all-encompassing term that includes exposure, susceptibility and capacity.

3.5.4 Data collection

Vulnerability data for this study is defined by the data needs of CBDRI shown in Table 3.8. Community opinion formed the basis for this study. It follows strong arguments for community disaster management that vulnerabilities and associated adaptive measures are better identified and ranked by own communities (van Aalst et al., 2008; Zhang et al., 2013). Data were sourced through a structured questionnaire (Appendix B).

The questionnaire was administered to a group of experts and knowledgeable people as recommended by Bollin et al. (2003). In this case, the Area Development Committee (ADC) was used as the knowledgeable group. The ADC draws membership from the Area Executive Committee (AEC), the Area Civil Protection Committee (ACPC), Non-Governmental Organisations (NGOs), Community Based Organisations (CBO) and ordinary people.

The AEC is a technical arm of the ADC. It consists of government extension workers notably from Forestry Department, Ministry of Agriculture, Ministry of Health, Ministry of Education, Community Development and Police. The ACPC on the other hand is a sub-committee of the ADC with the mandate over disasters. Ordinary members include chiefs and members of the community.

Some data (*population density*, *population growth rate*, *access to water services* and *literacy levels*) could not be obtained from administering the questionnaire and were obtained from the 2008 Population and Housing Census data (National Statistical Office, 2009) and the third Integrated Household Surveys (National Statistical Office, 2012). The *percentage of forested area* for a given community on the other hand was derived with GIS from Malawi land cover database (FAO, 2013).

Table 3.8: Vulnerability factors in the CBDRI

Component	Indicator Name	Indicator
EXPOSURE		
Structures	(E1) Number of housing units. (E2) Lifelines	Number of housing units % of homes with piped drinking water
Population	(E3) Total resident population	Total resident population
Economy	(E4) Local gross domestic product	Total locally generated GDP in constant currency
SUSCEPTIBILITY		
Physical / Demographic	(S1) Density. (S2) Demographic pressure. (S3) Unsafe settlements. (S4) Access to basic services	People per km2. Population growth rate. Homes in hazard prone areas (ravines, river banks, etc). % of homes with piped drinking water.
Social	(S5) Poverty level. (S6) Literacy rate. (S7) Attitude. (S8) Decentralisation. (S9) Community participation	% of population below poverty level. % of adult population that can read and write. Priority of a population to protect against a hazard. Portion of self generated revenues of the total budget. % of voter turn out at last commune elections.
Economic	(S10) Local resource base. (S11) Diversification. (S12) Stability. (S13) Accessibility	Total available local budget in US$. Economic sector mix for employment. % of businesses with fewer than 20 employees. Number of interuption of road access in last 5 years
Environmental	(S14) Area under forest. (S15) Degraded land. (S16) Overused land	% Area of the commune covered with forest. % Area that is degraded/eroded/desertified. % of agricultural land that is overused.
CAPACITY & MEASURES		
Physical planning and engineering	(C1) Land use planning. (C2) Building codes. (C3) Retrofitting/maintenance. (C4) Preventive structures. (C5) Environmental management.	Enforced land use plan or zoning regulations. Applied building codes. Applied retrofitting and regular maintenance. Expected effect of impact-limiting structures. Measures that promote and enforce nature preservation.
Societal capacity	(C6) Public awareness programs. (C7) school curricula. (C8) Emergency response drills. (C9) Public participation. (C10) Local risk management groups	Frequency of public awareness programmes. Scope of relevant topics taught at school. Ongoing emergency response training and drills. Emergency committee with public representatives. Grade of organisation of local groups.
Economic capacity	(C11) Local emergency funds. (C12) Access to local emergency funds. (C13) Access to international emergency funds. (C14) Insurance market. (C15) Mitigation loans. (C16) Reconstruction loans. (C17) Public works.	Local emergency funds as % of local budget. Release period of national emergency funds. Access to international emergency funds. Availability of insurance for buildings. Availability of loans for disaster risk reduction measures. Availability of construction credits. Magnitude of local public works programmes.
Management and institutional capacity	(C18) Risk management committee. (C19) Risk map. (C20) Emergency plan. (C21) Early warning system. (C22) Institutional capacity building. (C23) Communication.	Meeting frequency of a commune committee. Availability and circulation of risk maps. Availability and circulation of emergency plans. Effectiveness of early warning systems. Frequency of training for local institutions. Frequency of contact with district level risk institutions.

In total, 14 communities (ADCs) were initially considered for assessment: Ngabu, Katunga, Chapananga, Maseya, Makhuwila, Ngowi and Lundu in Chikwawa District and Mbenje, Mlolo, Tengani, Ngabu, Malemia, Ndamela and Nyachikhadza in Nsanje District. These communities comprised 7 of the 11 ADCs in Chikwawa and 7 of the 9 ADCs in Nsanje (Table 3.9).

Table 3.9: Communities under study

District	Community
Chikwawa	Ngabu
	Katunga
	Chapananga
	Maseya
	Makhuwila
	Ngowi
	Lundu
Nsanje	Mbenje
	Mlolo
	Tengani
	Ngabu
	Malemia
	Ndamela
	Nyachikhaza

Community selection was done with the help of personnel from the respective District Assembly who confirmed flooding in the ADCs chosen. Ngowi was subsequently dropped as it acted as a pilot ADC, leaving only 13 communities. The exclusion of the other six followed resource constraints. The number of participants in each group varied between 10 and 16. The questionnaire administered is shown in Appendix B.

Chapter 4 Data Analysis

4.1 SOM application

The analysis period of hydro-meteorological data was taken as 1978–2008. As shown earlier in Table 3.3, available data had different record lengths. This period was selected on the basis of substantial overlap of data. The variables infilled are shown in Table 4.1

Table 4.1: Hydro-meteorological variables infilled with SOM

Hydrological data		*Rainfall*
Mangochi	Flow	Nsanje
	Water level	Makhanga
Liwonde	Flow	Ngabu
	Water level	Chikwawa
Chikwawa	Flow	Nchalo
	Water level	Neno
Chiromo	Flow	Mwanza
	Water level	Mimosa
Sinoya	Flow	Thyolo
	Water level	Bvumbwe
Tengani	Flow	Chileka
Nsanje	Flow	Chichiri
		Makoka
		Chingale
		Balaka
		Mangochi

Before SOM application, data were arranged in columns with each column representing a variable to be infilled e.g. Mangochi rainfall, Chikwawa flow, etc. Each row constituted an input vector. In this exercise, there were 28 variables (shown in Table 4.1) in a single input vector. In total, there were 11231 such vectors corresponding to the number of daily observations (complete and incomplete) in the record. Entries without data were recorded as NaN (Not a Number) to meet Matlab requirements.

The SOM tool box developed at the Laboratory of Information and Computer Science (CIS) at Helsinki University of Technology (http://www.cis.hut.fi/projects/somtoolbox) was used in MATLAB environment by Mathworks Inc. A batch training algorithm was adopted.

Based on the multivariate relationship that exist between rainfall and runoff data, all data i.e. flow, water level and rainfall data for all stations constituting 28 variables were first trained together. This was referred to as Case 1. However, Kalteth and Berndtsson (2007) investigated the ability of SOM to interpolate rainfall data in a region with high spatial and temporal variability in Iran. They found that SOM performance was influenced by the homogeneity of data in question. Therefore, two more scenarios were investigated and these were called Cases 2 and 3 respectively. In Case 2 flow and water level data were trained separate from rainfall data. This resulted in two sets of data for independent training: 12 variables of flow and level data with 11231 input vectors and; 16 variables of rainfall having 11231 vectors. Case 3 only dealt with rainfall. In this scenario, rainfall stations were split into three clusters.

The clusters used were those established by Ngongondo et al. (2011b). According to Ngongondo et al.(2011a), rainfall in Malawi is highly variable with spatial correlations being highest only within 20 km of a station. In the southern region, in which the study area falls, three homogeneous rainfall regions can be found according to Ngongondo et al. (2011b). The regions are the predominantly semi-arid low lying Shire valley that occupies the southern arm of the Malawi Rift Valley with an average altitude of 84 m above sea level (cluster 1), the southern highlands with an altitude of above 1000 m above sea level (cluster 2), and areas along Lake Malawi, the upper Shire River basin and the surrounding medium altitude and plain areas with average altitude of 632 m above sea level (cluster 3).

Based on the information in Table 4.1, Cluster 1 comprised Nsanje, Makhanga, Ngabu, Chikwawa, Nchalo stations. Stations in cluster 2 were Neno, Mwanza, Mimosa, Thyolo, Bvumbwe, Chileka, Chichiri, Makoka while Chingale, Balaka and Mangochi fell in cluster 3.

As indicated in Chapter 3, SOM quality was evaluated on the basis of quantization and topographic errors. Its predictive ability was further assessed through the coefficient of correlation R, the Nash Sutcliff index NS and the visual inspection of scatter and time series plots.

4.2 MLP-ANN application

4.2.1 Input gauge stations

Gauge stations in Lower Shire Valley along the Shire and Ruo Rivers are Chikwawa, the most upstream; Chiromo just upstream of the confluence; Sinoya, on the Ruo just before the confluence and, Tengani and Nsanje below the confluence Figure 4.1.

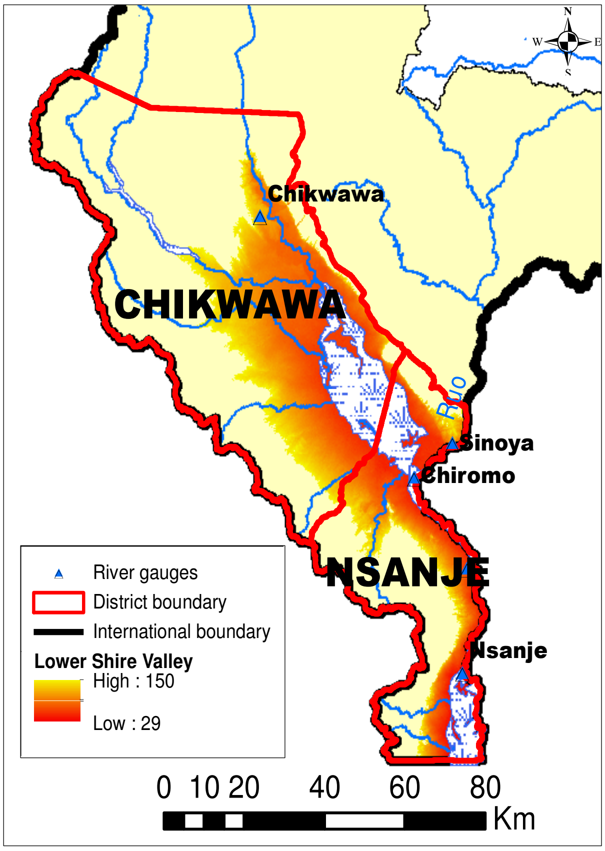


Figure 4.1: The gauging network in the Shire Valley assessed for forecasting at Chiromo

Upstream of Chikwawa station are Liwonde station and Mangochi stations. The greatest impact on water levels in the floodplain, measured at Chiromo, has been found to be from the Ruo River $(r^2 = 0.9)$ and Chikwawa station $(r^2 = 0.5)$ (Chimatiro, 2004).

Therefore, stream flow and water level were modelled for Chiromo gauging station using Chikwawa station upstream and Sinoya station on the Ruo.

4.2.2 Data inputs

MLP-ANN was applied on data that had been reconstructed with SOM. Determining the right inputs to an ANN model is an important exercise as not all inputs are equally informative: some inputs may be correlated, others may be noisy or may actually have no relationship to the output being modelled (Bowden et al., 2005). In flow, water level or rainfall runoff modelling, normally model inputs tend to be flow, stage or rainfall and their corresponding lagged inputs. Therefore these were the variables used.

The hydrological year in Malawi starts in November and ends in October. Thus data used for prediction in MLP-ANN was data from November 1978 and not January 1978 as used in SOM. Therefore, for the period November 1978 to August 2008, a total of 10,891 daily data records were available for training.

4.2.3 Network development

It follows from section 4.2.1 that water levels at Chiromo and their corresponding flows are correlated with current and lagged levels and flow respectively at Chikwawa, and levels and flows at Sinoya on the tributary. Catchment rainfall becomes another variable as flooding in this catchment arises from rainfall. Input rainfall was taken as average basin rainfall calculated by Thiessen Polygon method on stations shown in Figure 2.8.

The number of lagged inputs to include were determined through autocorrelation (acf), partial correlation (pacf) and cross-correlation (ccf) functions as suggested by Sudheer et al. (2002). The acf for Chiromo levels and flows (Figure 4.2(a) and (c)) shows dominant autoregressive processes in both. The pacf (Figure 4.2(b) and (d)) nonetheless revealed that only six lags of water levels are statistically significant at 95% confidence level. Similarly, only five day lags on flow series are statistically significant. Therefore, from Chiromo, a total number of 11 lags were used.

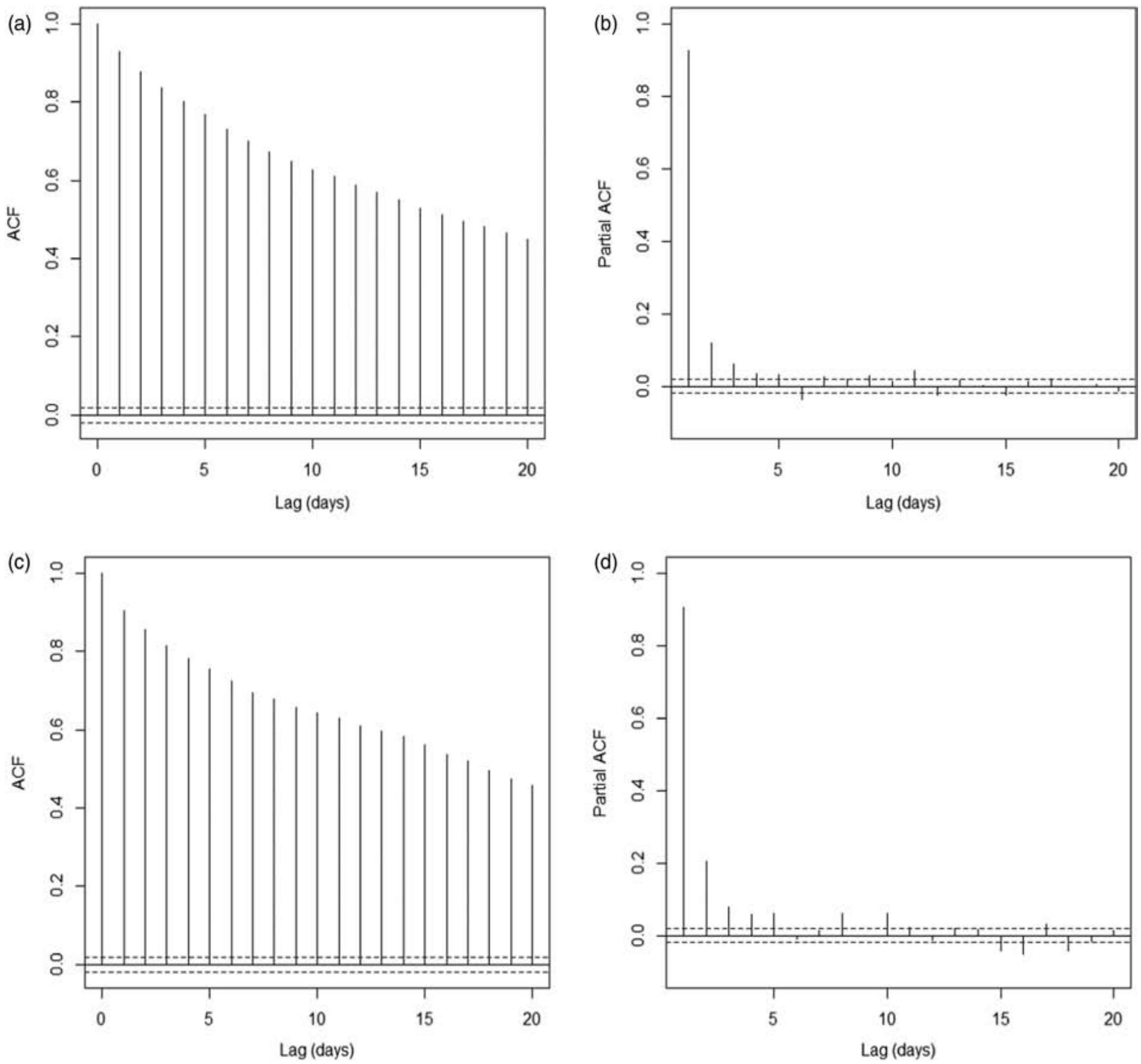


Figure 4.2: ACF on (a) Chiromo water levels with the dashed lines representing the 95% confidence bound; and (c) Chiromo flows; PACF on (b) Chiromo water levels; and (d) Chiromo flows.

As for exogenous variables, that is, flows and levels at Chikwawa and Sinoya and catchment rainfall, their lagged inputs were identified through ccf with Chiromo station flow and water level series and the appropriate number of lags identified as those up to the maximum cross-correlation (Figure 4.3). This approach has been used by Solomantine & Dulal (2003), Teschl & Randeu (2006) and Wu & Chau (2011). Lags corresponding to maximum correlation have been equated to travel times to the point of interest in the catchment. Figure 4.3 reveals that the maximum cross-correlations for both Chikwawa and Sinoya with Chiromo levels (Figure 4.3(a)) and Chiromo flows (Figure 4.3(b)) occur at zero lag. Thus only the current day's flow and water level from both Chikwawa and Sinoya were incorporated. As for rainfall, the maximum cross-correlation with Chiromo flows (Figure 4.3(b)) corresponded to a maximum of 18 days suggesting a concentration time of about 18 days. This is in agreement with results from a test carried out by the MoIWD in 1981 (Figure 4.4) which suggest a travel time of 17 days between Liwonde, 87 km from the river source, and Chiromo. The long concentration time is attributed to the Elephant marsh between Chikwawa and Chiromo

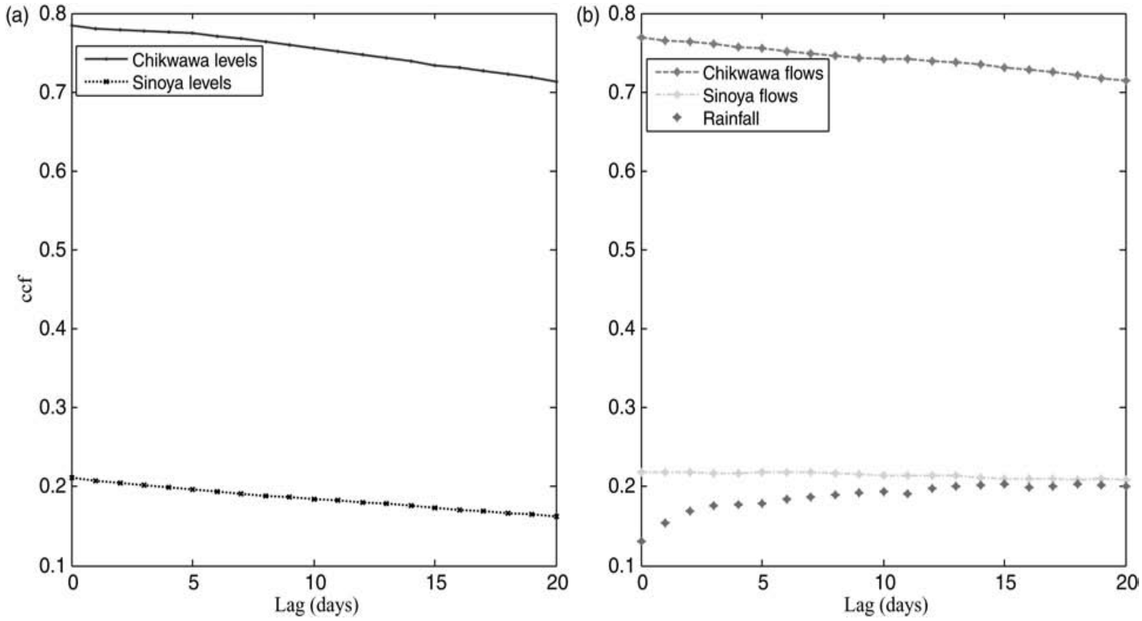


Figure 4.3: Cross correlations of (a) Chikwawa and Sinoya levels with Chiromo water levels and (b) Chikwawa and Sinoya flows, and rainfall with Chiromo flows.

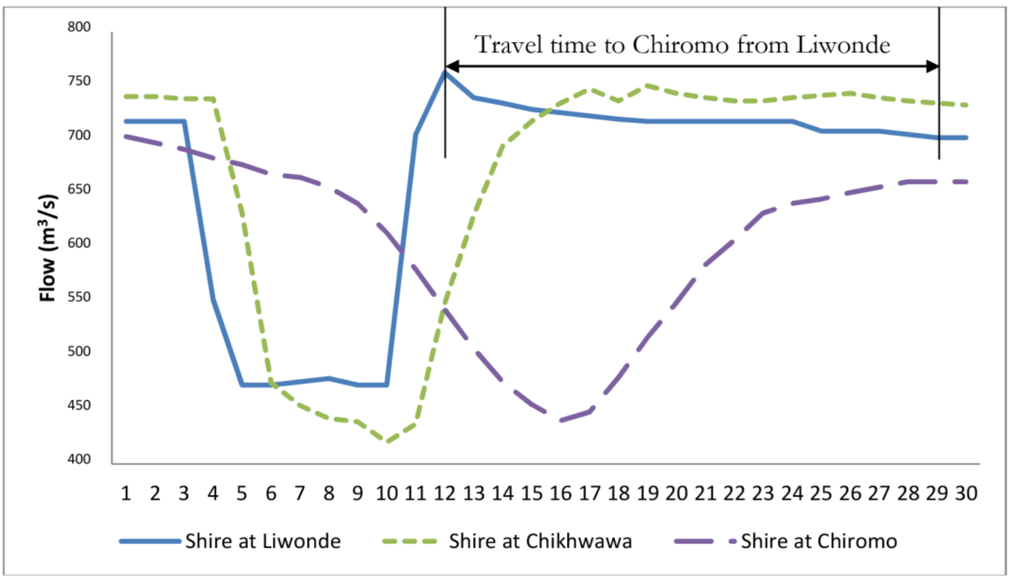


Figure 4.4: Hydrographs of Shire River flows at Liwonde, Chikhwawa and Chiromo following a test run at Liwonde barrage upstream in 1981.
Source: MoIWD.

Nonetheless, as earlier indicated, flooding at Chiromo is more influenced by Ruo River flows and therefore the concentration time of Ruo catchment is more relevant than that from the headwater catchments. The average slope of the Ruo catchment, derived with GIS, is 9.64%. The river has a total length of 130 km. An estimate of concentration time of the Ruo catchment at the confluence with Shire River with the Kirpich equation (Kirpich, 1940) yields a value of 6.9 hours validating the general view that flooding from Ruo is flash flooding. Since data used is available at a daily time step, no lag was applied to the rainfall and the day's rainfall was thus used.

Based on this analysis therefore, the total number of inputs to the ANN model for flow and level forecasting at Chiromo was determined as 18 (a day's flow at Chiromo and flow on each of previous 5 days: sub-total = 6; a day's water level at Chiromo and the water level on each of previous 6 days: sub-total = 7; a day's flow and water level at both Chikwawa and Sinoya: sub-total = 4; and a day's average catchment rainfall: sub-total = 1). The model had two outputs; the next day's water level and flow at Chiromo. Thus mathematically, the model is defined by the following equation:

Model 1:

$$\left(CRL_{t+1}, CRF_{t+1}\right) = f\left(CRL_t, CRL_{t-1} \ldots\ldots CRL_{t-6}, CRF_t, CRF_{t-1}, \ldots\ldots CRF_{t-5}, CKL_t, CKF_t, SL_t, SF_t, R_t\right) \quad (4.1)$$

where CR= Chiromo, CK = Chikwawa, S = Sinoya; L, F and R are water level, flow and rainfall, respectively. t is the point in time at which forecasting is being made and $t-1$, $t-2$ etc are the lags.

In search of a parsimonious model, further investigations were carried out. PACF on both flow and water level data at Chiromo (Figure 4.2(b) and (d)) show that over 90% of the variance in both variables are explained by their 1-day lag, which is not unexpected. Therefore a second model (Model 2) with only one lag for both flow and water level from the Chiromo series was investigated. Inputs from Chikwawa and Sinoya were excluded. Rainfall was retained as prediction accuracy has been found to be better when rainfall is included other than when flow is modelled solely on flow variable (Toth and Brath, 2007a; Wu and Chau, 2011)

Model 2: $$(CRL_{t+1}, CRF_{t+1}) = f(CRL_t, CRL_{t-1}, CRF_t, CRF_{t-1}, R_t) \quad (4.2)$$

On the same basis of parsimony, it was further investigated whether Chiromo levels and flows can be modelled with just 'today's' variables. This model is referred to as Model 3.

Model 3 $$(CRL_{t+1}, CRF_{t+1}) = f(CRL_t, CRF_t, R_t) \quad (4.3)$$

As justified earlier, the MLP feedforward neural network with three layers was used, i.e. with just one hidden layer. The tan-sigmoid transfer function was used in the hidden layer. A major criticism of ANN has been their failure to generalise beyond the calibration range and it has been suggested that the use of a linear function in the output layer circumvents this problem to a certain extent (Maier and Dandy, 2000; Solomantine and Dulal, 2003). A linear transfer function was therefore used in the output layer.

4.2.4 Network parameters

The training adopted the early stop approach (Maier et al., 2010) and to achieve this, the 10891 daily data record was partitioned in the ratio of 60%, 20% and 20% for training, validation and testing, respectively. Thus, 6,535 samples were used for training, 2,178 for validation and 2,178 for testing. Random sampling was applied for the partitioning to ensure representative data was used for training. In early stopping, errors on both the training and validation sets are monitored during network training and training is stopped when the validation error starts increasing following a period of continuous fall. In this way, over-fitting is avoided.

The Levenberg–Marquardt backpropagation algorithm was chosen as the training algorithm. The traditional backpropagation training algorithm has been associated with problems of lengthy training processes and possibilities of getting trapped in a local minima (ASCE Task Committee, 2000). In contrast, the Levenberg–Marquardt backpropagation training algorithm has performed better than the standard backpropagation algorithms: it is more accurate, faster and more reliable (Adeloye and De Munari, 2006; Aquil et al., 2007; Okkan, 2011).

To identify the best architecture for each of the three models, the number of neurons in the hidden layer was progressively increased from 2 to 15 at a time step of one hidden neuron and the best architecture in terms of the hidden neurons was picked based on best performance on test data using the performance indices discussed in section 3.3.2.

4.3 Lisflood-FP application

4.3.1 Data inputs

With limited resources for high resolution DEM, developing countries rely on freely available global data sets (Fan, 2002). These DEMs contain errors that arise from acquisition technology and processing technology with respect to particular terrain and landcover type. Model outputs are therefore dependant on the amount of error in the DEM (Mukherjeea et al., 2013). In low relief terrain such as floodplains, the Shuttle Radar Topography Mission (SRTM) DEM has been found to outperform other open source DEMs in terms of accuracy. In the Lower Limpopo basin of Mozambique which has similar terrain as the Lower Shire Valley as both are part of the Lower Zambezi Basin, Karlssom and Arnberg (2011) reported better vertical accuracy in the STRM DEM than in HYDRO1K DEM. Similarly, in a comparison between SRTM DEM and Advanced Spaceborne Thermal Emission Reflection Radiometer (ASTER) DEM in Zaria and Kajuru in Northern Nigeria, vertical accuracy was higher in the SRTM DEM over the flat terrain town of Zaria (Isioye and Yang, 2013). The STRM DEM was therefore used for Lisflood-FP application in this study. The STRM DEM is a 90m DEM. It was however resampled to 270m resolution for this study. Resampling improves surface representation cognisant of the errors in the DEM; it also reduces computational time of the model (Schumann et al., 2013).

Incoming flows into the model domain were taken as flows at Chikwawa station on Shire River. This data is available as average daily data. The hydrograph at the station from November 2007 to May 2008 is shown in Figure 4.5. Wolman and Leopold (1957) have shown that bankful flow has a return period of 1-2 years. A regional flood frequency analysis in the Shire basin (World Bank, 2010b) based on Extreme Variate Type 1 (EV1) distribution suggests that a 2 year flood at Chikwawa gauge station is 932m^3/s (Figure 4.6). Therefore this value was taken as bankfull flow and subtracted from flows. The maximum flood flow reached (1483m^3/s) in this year suggests a 4-5 year flood event.

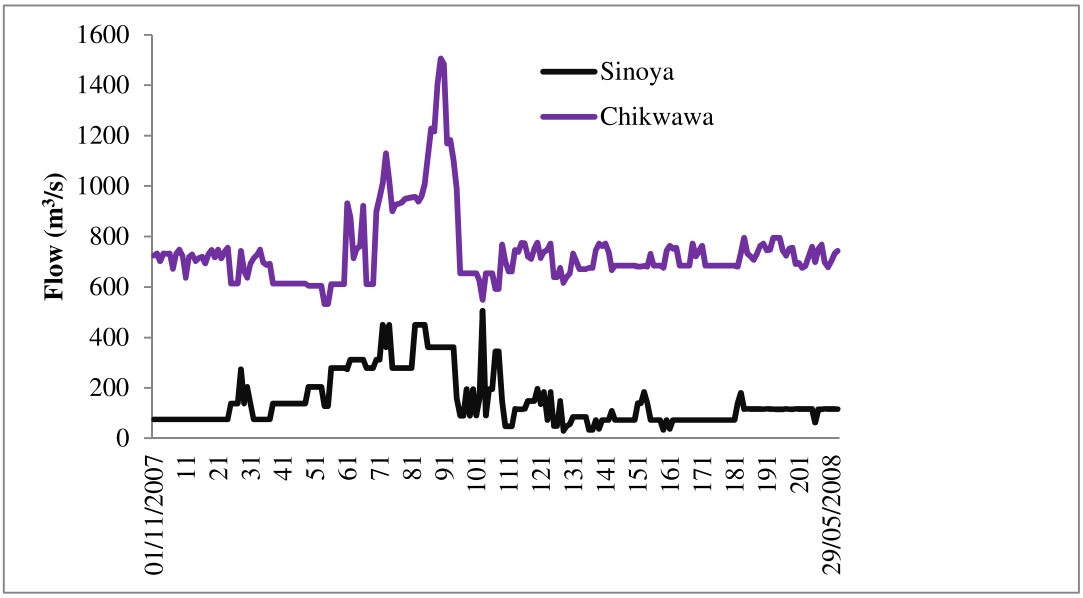


Figure 4.5: Flow hydrographs at Chikwawa and Sinoya in the 2008 flood season

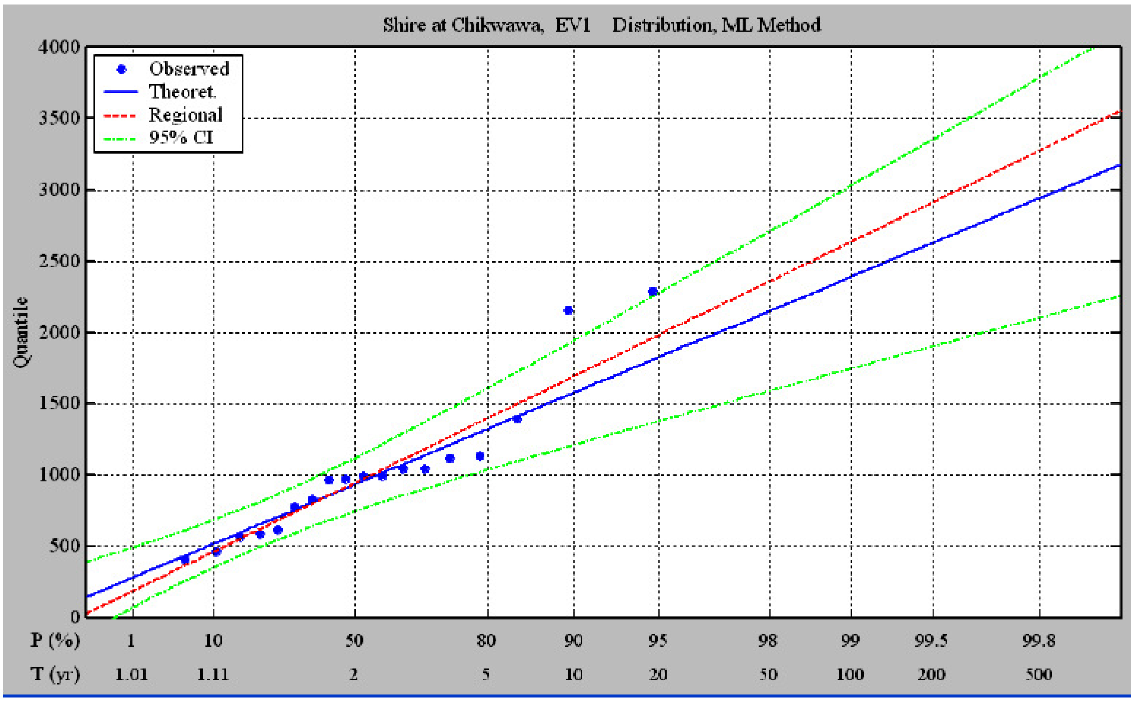


Figure 4.6: Flood frequency distribution at Chikwawa based on EV1

While flows from the Ruo catchment are dominant in the flood regime of the Lower Shire valley (Chimatiro, 2004; Shela et al., 2008), flow data at Sinoya gauge station were below bankful levels during the 2008 rainy season, estimated as 822m^3/s using the

Extreme Value Type 1. Consequently, input flows into Lisflood-FP were limited to Chikwawa data.

4.3.2 Mode of application

Cross sectional data on both the Shire and Ruo Rivers are elusive. Only recently did Atkins commission some limited cross sectional surveys on the Shire and Ruo Rivers for the Shire Integrated Flood Risk Management Project under World Bank funding (Atkins, 2012). Nonetheless, the cross sections cover only a distance of 5km upstream of the confluence on the Ruo, at 200m spacing and, a distance of 12.5km on the Shire at 500m spacing. Even then, the surveys on the Ruo do not extend into the Mozambican territories. Yet the valley is about 150km in length (Shela et al., 2008).

To reduce further introduction of uncertainty into the model due to data challenges of the river channel, Lisflood-FP in this study was applied in 2D mode. Schuman et al. (2013) recently also applied Lisflood-FP to the Lower Zambezi of which the Lower Shire Valley is part, for a large scale flood forecasting system. However, only the area from Chiromo and downstream was covered by this exercise, thus excluding a significant portion of the Lower Shire floodplain i.e. between Chikwawa and Chiromo. The application of Lisflood – FP in this study covers the whole Lower Shire Valley: from Chikwawa gauge station to some arbitrary boundary just beyond Malawi-Mozambique border within Malawian territories (see Figure 4.1).

4.3.3 Model calibration and evaluation

A uniform coefficient was assumed for the whole domain, for a given simulation. Land cover in the region consists of savannah, herbaceous and degraded vegetation, and agricultural fields (Fernandes et al., 2006). Therefore Manning's values used fell in the range of 0.025 to 0.07 based on published values of Chow (1959) (Appendix A). For a given Manning's n, Lisflood-FP was run for five months, from 1st December 2007 to 30th April, 2008.

The imagery used for evaluation was the 250m 7-2-1 terra Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. In this band combination, water appears black and the sediments dark blue. The image used was acquired on the 4th February, 2008. This date provided the best cloud free image for the 2008 flood season. MODIS is an instrument aboard Aqua and Terra satellites that orbit around the earth and managed by the United States National Aeronautics and Space Administration (NASA). The cost issue limits studies in developing countries to freely available optical imagery, notably MODIS and Landsat. While Landsat has the advantage of high resolution i.e. 30 m, in comparison to MODIS (250m – 1km), the orbital repeat cycles for Landsat is much lower (16 days). MODIS has a frequent overpass (1 to 2 days) making it ideal for flood inundation studies (Leauthaud et al., 2012). The flooded area in MODIS imagery was manually digitised.

4.3.4 Hazard severity ranking

Flood hazard ranking was based on the designation by Dinh et al. (2012) shown in Table 4.2. Dinh et al. (2012) combines degree of property damage and difficulty to daily lives to define flood hazard severity.

Table 4.2: Flood severity designation

Flood Depth (m)	Hazard zone	Definition of hazard zone
0 - 0.2	Very low	This is the case in which the damage to property is expected to be very low
0.2 - 0.5	Low	This is the case in which the number of casualties due to floods, interms of death or injuries, is insignificant, and the damage to property is expected to be relatively low. Moreover, in this case, vehicles transport is affected, but wading is safe.
0.5 - 1.0	Medium	This is the case in which casualties, interms of death and injuries, are considerable, relative to the number of people living in the area under study. Moreover, the peoperty damage is expected to be high. Vehicle transport and wading are not safe
1.0 - 2.0	High	This is the case in which damage to property is quiet extensive and the probability of having dead and injured people is high. The social disruption is also very high
> 2.0	Very high	This is the case in which, at all levels, severe damages are expeted. Buildings and houses are the most affected and nothing is safe any longer

Source: (Dinh et al., 2012)

4.4 The community vulnerability index

4.4.1 Vulnerability parameters

As justified earlier in Chapter 3, this study used the CBDRI for vulnerability. Details of the CBDRI were given in Chapter 3 (see equations (3.28) and (3.29)) and Table 3.10. However, for the current study, the *Number of housing units* and *total resident population* in the exposure sub-component were not used due to the difficulty of thresholds given the differences in community size. *Total Gross Domestic Product* was replaced with *average per capita income per day*. In the susceptibility sub-component, *unsafe settlements* was not accounted for due to the challenge of thresholds. Similarly, *degraded land* and *overused land* were not included due to the difficulty of definitions. Thus environmental susceptibility was limited to *amount of forest cover*.

As the name implies, CBDRI was developed to measure risk directly; however, its additive form as shown in equation (3.28) makes it possible to disaggregate the index into hazard and vulnerability components. The adaptation of the index carried out in the current study was to quantify the vulnerability from the E, S and C components. Thus, to measure vulnerability in this study, *E, S* and *C* were first calculated using equation (3.29).

The CBDRI uses a weighting scheme to reflect differential importance of indicators towards risk. Therefore, besides measuring the variable by a score of 1, 2 or 3, the community also weights the variables in the sub-component. The weights used in the study ranged from 1 to 10 with 10 being very important. For example, lack of *building codes* gets a score (x) of 1 signifying low capacity with respect to this variable. The community may feel nonetheless *building codes* is a very important indicator in contributing to the overall capacity in anticipating floods. In this case they would give the indicator *'building codes'* a weight (w) of 9. Similarly, incorporation of disaster studies in the school curriculum in all grades may attract a 1 signifying low contribution to susceptibility. However, the community may weight the indicator with a 4 signifying it is not a very important variable in contributing to their societal capacity. Given that 13 communities were assessed for the Lower Shire as explained earlier in section 3.5. 4, there are 13 weights for a given variable. To attach a common perception to a given variable for comparison purposes, the weight for a particular variable is the mode of 13 weights.

The CBDRI was developed to ensure that the total sum of weights in each sub-component equal 33 (so that the final sub-component value is between 0 and 100). Therefore, a final weight *w* for the variable in a given sub-component used in equation (3.29) is one derived by a simple proportion on 33. For example, if the sum of weights in the capacities sub-component is 80, then the weight of indicator *'building codes'* is 9/80*33 = 4 assuming 9 was the mode.

The aggregate vulnerability (V) was then estimated using the widely used arithmetic aggregation scheme (Allison et al., 2009; Cardona, 2005; Hahn et al., 2009) as follows:

$$V = \frac{1}{3}\left[E + S + (1 - C)\right] \tag{4.4}$$

where (1-C) represents lack of capacity or lack of resilience

A second adaptation to the CBDRI follows the fact that while *exposure*, *susceptibility* and *capacities* are directly measured through equation (3.29), the CBDRI does not provide a direct measure of *social*, *economic*, *environment* and *physical* vulnerability despite variables being identified as such (see Table 3.10). To dimension vulnerability by the *social, economic, environment* and *physical* dimensions, variables in the exposure, susceptibility and capacities sub-components in Table 3.10 were rearranged into social, economic, environment and physical sub-components as shown in Table 4.3. Vulnerability by social, economic, environment and physical characteristics was then measured by equations (4.5).

Table 4.3: Vulnerability by social, economic, environmental and physical dimensions

Factor component		Indicator Name	Indicator
PHYSICAL			
Exposure	Structures	(E2) Lifelines	% of homes with piped drinking water
	Economy	(E4) Economy	Total locally generated GDP in constant currency
Physical susceptibility		(S1) Density	People per km2.
		(S2) Demographic pressure	Population growth rate (%)
		(S4) Access to basic services	% of homes with piped drinking water.
Physical capacity		(C1) Landuse planning	Enforced land use plan or zoning regulations.
		(C2) Building codes	Applied building codes.
		(C3) Retrofitting/Maintenance	Applied retrofitting and regular maintenance.
		(C4) Preventive measures	Expected effect of impact-limiting structures.
		(C5) Environmental management	Measures that promote and enforce nature preservation.
SOCIAL			
Social susceptibility		(S5) Poverty level	% of population below poverty level
		(S6) Literacy	% of adult population that can read and write.
		(S7) Attitude	Priority of a population to protect against a hazard.
		(S8) Decentralization	Portion of self generated revenues of the total budget.
		(S9) Community participation	% of voter turn out at last commune elections.
Societal capacity		(C6) Public awareness programs	Frequency of public awareness programmes.
		(C7) School curriculum	Scope of relevant topics taught at school.
		(C8) Emergency response drills	Ongoing emergency response training and drills.
		(C9) Public participation	Emergency committee with public representatives.
		(C10) Local risk management/emergency	Grade of organisation of local groups.
Management and Institutional Capacity		(C18) Risk management/emergency	Meeting frequency of a commune committee.
		(C19) Risk map	Availability and circulation of risk maps.
		(C20) Emergency plan	Availability and circulation of emergency plans.
		(C21) Early warning system	Effectiveness of early warning systems.
		(C22) Institutional capacity building	Frequency of training for local institutions.
		(C23) Communication	Frequency of contact with district level risk institutions.
ECONOMIC			
Economic susceptibility		(S10) Local resource base	Total available local budget in US$.
		(S11) Diversification	Economic sector mix for employment.
		(S12) Stability	% of businesses with fewer than 20 employees.
		(S13) Accessibility	Number of interuption of road access in last 5 years
Economic capacity		(C11) Local emergency fund	Local emergency funds as % of local budget.
		(C12) Access to national emergency fund	Access to international emergency funds.
		(C13) Access to international emergency	Release period of national emergency funds.
		(C14) Insurance market	Availability of insurance for buildings.
		(C15) Mitigation loans	Availability of loans for disaster risk reduction measures.
		(C16) Reconstruction loans	Availability of reconstruction credits.
		(C17) Public works	Magnitude of local public works programmes.
ENVIRONMENTAL			
Environmental		(S14) Environmental	% Area of the commune covered with forest.

$$V_j = \left[\left(V_{E_j} + V_{S\,j} + \left(1 - V_{C\,j}\right)\right)\right]/3 \qquad (4.5)$$

where

$$V_{E_j} = \sum_{i=1}^{m}\left[x_i\left(33\frac{w_i}{\sum_{i=1}^{m} w_i}\right)\right]$$

$$V_{S_j} = \sum_{i=1}^{n}\left[x_i\left(33\frac{w_i}{\sum_{i=1}^{n} w_i}\right)\right]$$

$$V_{C_j} = \sum_{i=1}^{p}\left[x_i\left(33\frac{w_i}{\sum_{i=1}^{p} w_i}\right)\right]$$

V_{E_j}, V_{S_j} and V_{C_j} are the vulnerability due to exposure(E_j), susceptibility (S_j), and capacities(C_j), within the newly defined social, economic, environmental and physical sub-component V_j as per the rearranged variables in Table 4.3; x_i and w_i are the score and weight respectively as originally allocated to the variable i in equation (3.29); m, n and p are the number of variables in the exposure(E_j), susceptibility (S_j), and capacities(C_j) respectively of the sub-component V_j. As in equation (3.29), V_{E_j}, V_{S_j} V_{C_j} and V_j range from 0 to 100 or alternatively 0 and 1.

4.4.2 Vulnerability ranking

Once the vulnerability was quantified dimensionally (exposure, susceptibility, resilience, social, economic, environmental, physical) and aggregately, the quintile scale was used: *0 – 0.2 = very low*, *>0.2– 0.4 = low*, *>0.4 – 0.6 = medium, >0.6 – 0.8 = high and >0.8 – 1.0 = very high.*

4.5 Risk analysis

Underpinned by the conceptualization from the disaster risk community, risk (R) in this study is expressed as a convolution of the hazard (H) and vulnerability (V) through equation (4.6). A critical aspect in the equation is that even in the presence of a high magnitude hazard, there can only be risk when there is a vulnerable population. Conversely, a vulnerable population will only experience risk when faced with a hazard (Cardona, 2004; Wisner et al., 2004).

$$R = H \times V \tag{4.6}$$

In this study, risk is measured on a scale of 0 to 1. Since the hazard (m) and vulnerability (dimensionless) carry different dimensions, flood depths were first standardised to a scale of 0 to 1, commensurate with the vulnerability scale before calculating risk. The hazard scale (Table 4.2) was divided by 3.3 m, the maximum inundation depth simulated with LisFlood-FP. Classes of risk severity were then defined by multiplicative scores on corresponding hazard and vulnerability classes, an approach also shared by Tingsanchali and Karim (2005), Mimi and Assi (2009) and Dinh et al. (2012). This is shown in Table 4.4.

Table 4.4: Risk rating

Class	Vulnerability (dimensionless)	Hazard (m)	Hazard (dimensionless)	Risk (dimensionless)
Very low	0.0 – 0.2	0.0 – 0.2	0.0-0.06	0.00 – 0.012
Low	0.2 – 0.4	0.2 – 0.5	0.06 – 0.15	0.012 – 0.06
Medium	0.4 – 0.6	0.5 – 1.0	0.15 – 0.3	0.06 - 0.180
High	0.6 -0.8	1.0 – 2.0	0.3 – 0.61	0.18 – 0.50
Very high	0.8-1.0	>2	0.61-1.0	0.50 - 1.0

Chapter 5 Results and Discussion

5.1 SOM quality analysis

As indicated in the methodology section, SOM was used to reconstruct hydro-meteorological data (flow, water level and rainfall) given the enormity of gaps, discontinuities and short durations in the data; an aspect that precluded the use of traditional techniques (weighted averages, regression techniques). Besides, the amount of data involved, (daily data from 28 variables over a period of 30 years), would have been time consuming with traditional techniques.

The batch training algorithm was used. The initial neighbourhood radius was set to $\max(l_1, l_2)/4$ where l_1 and l_2 are the dimensions of the map determined through equation (3.2). The parameters and quality of the output map are shown in Table 5.1.

Table 5.1: Trained SOM characteristics

Data	Map size $(l_1 \times l_2)$	Map size, M (Number of neurons)	Final quantization error (QE)	Final topographic error (TE)
Case 1				
Flow, water levels and rainfall	25 x 21	525	1.803	0.093
Case 2				
Flow and water level	35 x 16	560	0.520	0.093
All rainfall	35 x 15	525	0.801	0.085
Case 3				
Cluster 1 rainfall	35 x 16	560	0.027	0.035
Cluster 2 rainfall	37 x 15	555	0.551	0.067
Cluster 3 rainfall	32 x 17	544	0.097	0.340

Table 5.1 shows that actual map sizes used in the SOM training are slightly different from an estimate based on Garcia and Gonzalez' (2004) suggestion i.e. $M = \sqrt{N}$ (equation (3.1)) where N in this case is 10891. Such a difference arises from

adjustments on map size in the SOM toolbox that ensures that M is exactly $l_1 x l_2$. The values of both quantization and topographic errors on all four maps are small suggesting a properly adapted SOM to the training data. This is further examined in the sections below.

5.2 Performance on flow, water level and rainfall

Case 1

Performance of the SOM for Case 1 in which all 28 variables (flow, water level and rainfall) are trained together is summarized in Table 5.2. On observation of Table 5.2, it is evident when flow, water levels and rainfall are trained together, SOM predictions are only fairly strong on flow and water level data but unsatisfactory on rainfall data.

Table 5.2: SOM performance based on Case 1

Station	Variable	R	NS	Station	Variable	R	NS
Mangochi	Water level	0.93	0.87	Nsanje	Rainfall	0.59	0.35
Chikwawa		0.93	0.88	Makhanga		0.68	0.44
Liwonde		0.95	0.91	Ngabu		0.73	0.55
Chiromo		0.90	0.82	Chikwawa		0.72	0.53
Nsanje		0.94	0.90	Nchalo		0.77	0.61
Tengani		0.93	0.90	Neno		0.66	0.46
Sinoya		0.89	0.82	Mwanza		0.76	0.73
Mangochi	Flow	0.94	0.89	Mimosa		0.65	0.42
Chikwawa		0.93	0.86	Thyolo		0.77	0.59
Liwonde		0.95	0.90	Bvumbwe		0.78	0.60
Chiromo		0.94	0.90	Chileka		0.71	0.49
Sinoya		0.68	0.87	Chichiri		0.74	0.55
				Makoka		0.69	0.48
				Chingale		0.64	0.47
				Balaka		0.72	0.50
				Mangochi		0.67	0.43

All gauge stations, except Sinoya, register coefficient of correlation values equal or above 0.9. Sinoya flow has a value of 0.68. Corresponding NS values all exceed 0.8 pointing to very good SOM predictions. In contrast, the *R* values for rainfall data range from 0.59 to 0.78. Associated NS values fall in the range of 0.35-0.76. Moriasi et al. (2007) rated as *very good* a model with 0.75<NS≤1.0; *good* for 0.65<NS ≤0.75; *satisfactory* for 0.5<NS≤0.65 and unsatisfactory for NS≤0.5. *R* values of ≤0.35 are

generally considered to represent low or weak correlations, 0.36 to 0.67 modest or moderate correlations, and 0.68 to 1.0 strong or high correlations with *R* coefficients ≥ 0.90 very high correlations (Taylor, 1990). While *R* values on rainfall suggest good predictions, it is evident from corresponding NS values that SOM performance on rainfall was largely unsatisfactory.

An examination of component planes of flow, water level and rainfall data shows little or no correlation between flow/water level and the rainfall data in Case 1(Figure 5.1). A component plane shows the values of one variable as determined by each unit in the map (Vesanto et al., 2000) and therefore each component plane can be thought of as a slice of a SOM (Adeloye et al., 2011). Component planes are color or gray shaded in a two dimensional lattice. Thus component planes help to visually identify relationships, in terms of correlations, between the variables involved in the analysis. For example, if the color gradients of two planes are parallel, that is an indication of high positive correlation; anti-parallel gradients imply negative correlation between variables.

From Figure 5.1, it can be observed that the coloration of flow and water level component planes is similar except for Sinoya flow suggesting all gauge stations are correlated except for the latter. This is expected as all stations lie on the Shire River whilst Sinoya is a gauge station on Shire's tributary, the Ruo. Similarly, rainfall component planes are distinct from flow/water level planes suggestive of little or no correlation between rainfall and flow/water levels in the basin.

The outcome of the SOM on case 1 as noted earlier (see Table 5.2) where the rainfall was relatively poorly simulated is therefore to be expected and agrees with the earlier findings by Kalteth and Berndtsson (2007) that showed that the predictive ability of SOM was affected by the correlation in the data set. For the purpose of reconstruction of data in this study therefore, results obtained particularly on rainfall would be unsuitable.

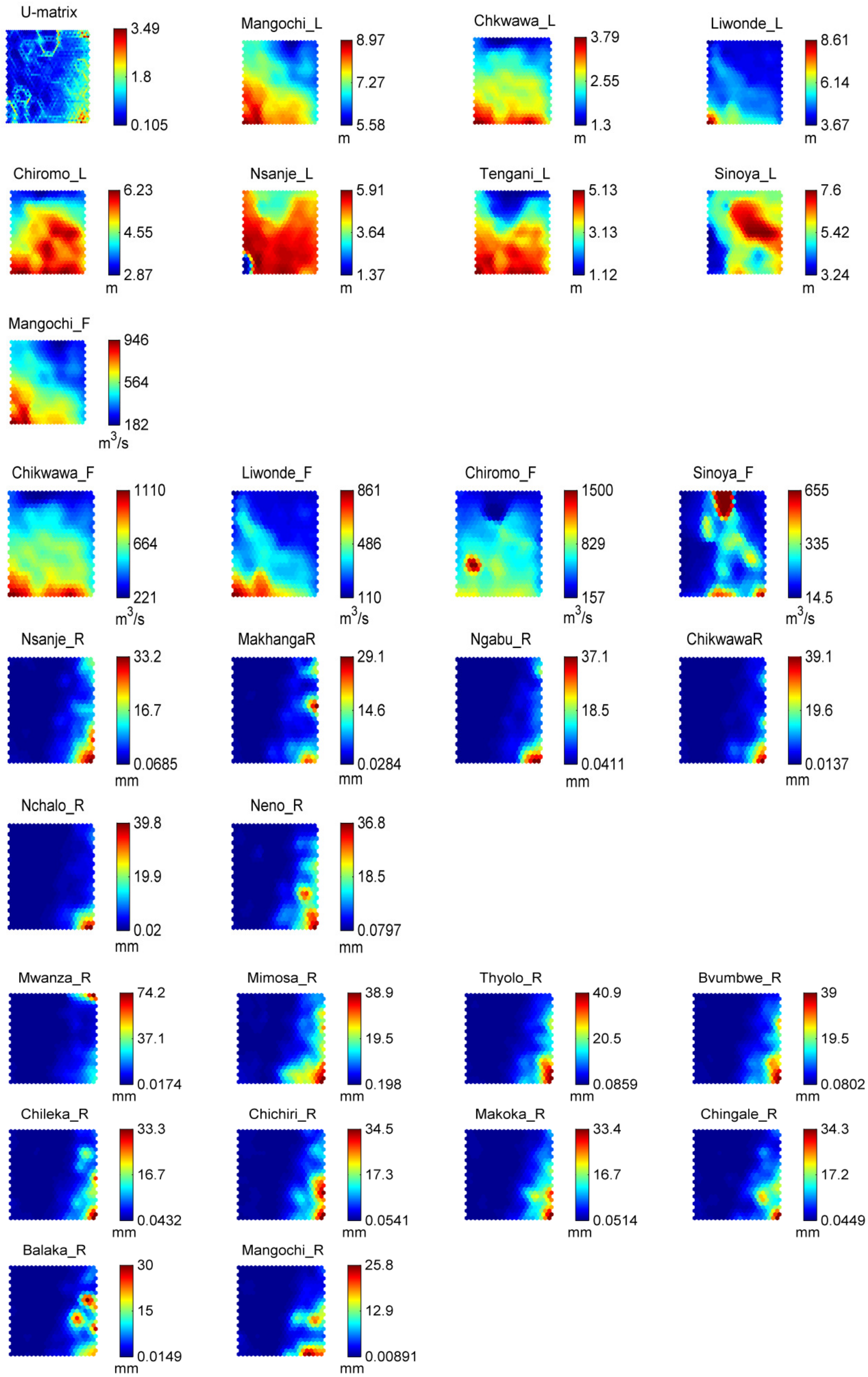


Figure 5.1: Component planes of flow, water level and rainfall from case 1 (F= flow, L = water level and R = rainfall

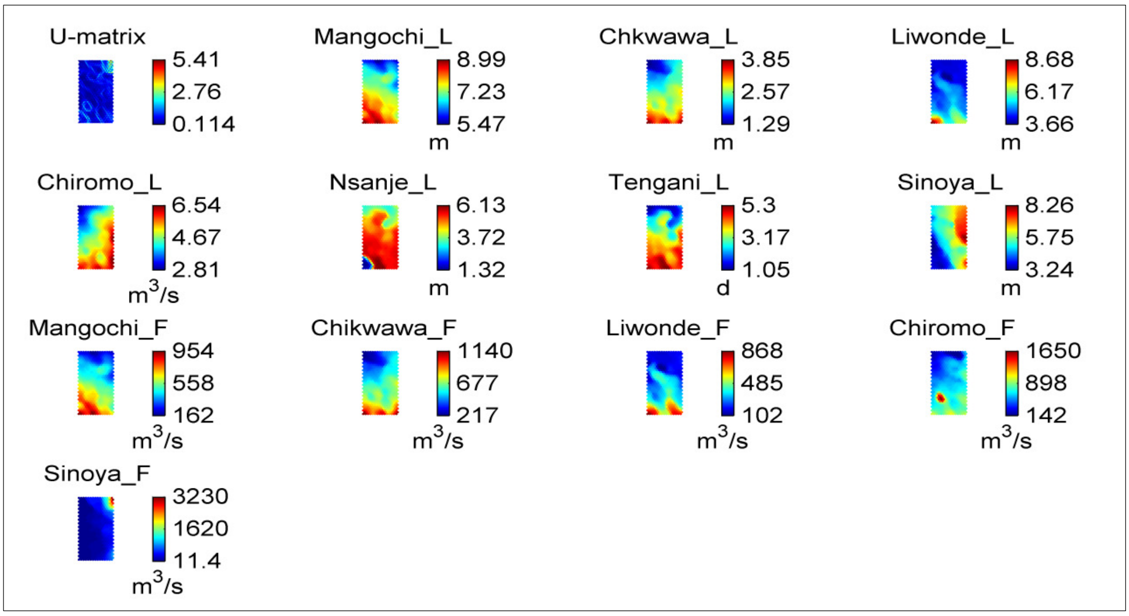
Case 2

SOM performance when flows and levels are trained separately from rainfall is summarized in Table 5.3.

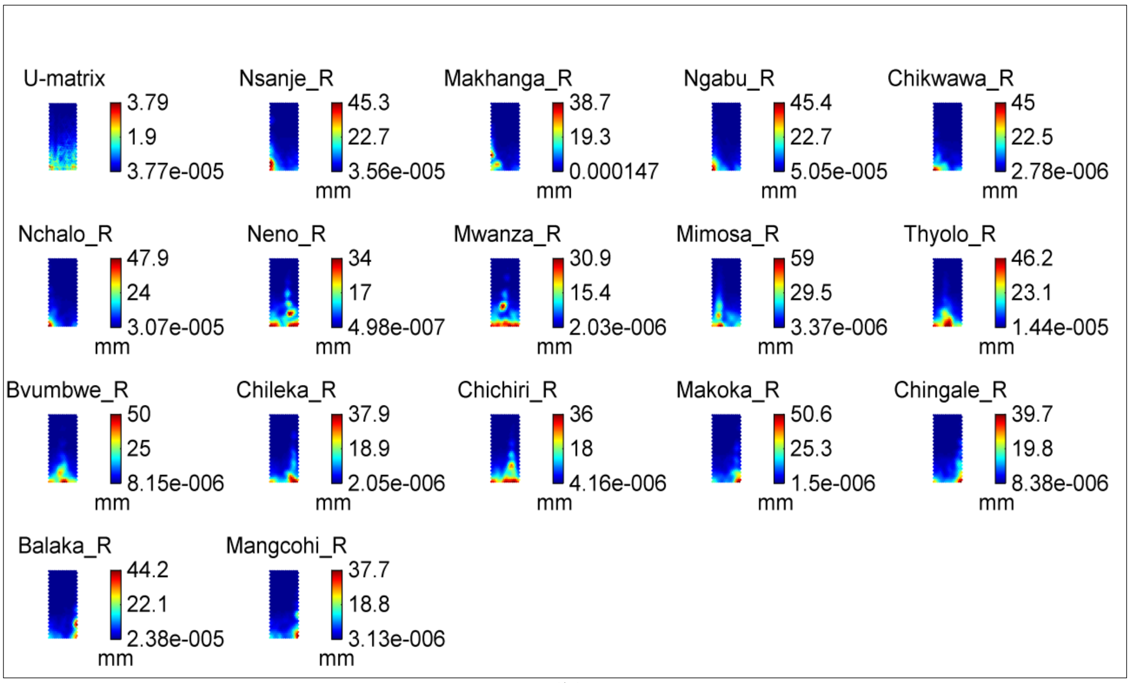
Table 5.3: SOM performance based on Case 2

Station	Variable	R	NS	Station	Variable	R	NS
Mangochi	Water level	0.98	0.99	Nsanje	Rainfall	0.72	0.52
Chikwawa		0.98	0.99	Makhanga		0.79	0.61
Liwonde		0.98	0.96	Ngabu		0.75	0.58
Chiromo		0.97	0.94	Chikwawa		0.75	0.56
Nsanje		0.97	0.98	Nchalo		0.80	0.67
Tengani		0.98	0.98	Neno		0.71	0.53
Sinoya		0.98	0.99	Mwanza		0.73	0.63
Mangochi	Flow	0.98	0.97	Mimosa		0.79	0.62
Chikwawa		0.98	0.96	Thyolo		0.83	0.68
Liwonde		0.97	0.98	Bvumbwe		0.84	0.71
Chiromo		0.97	0.97	Chileka		0.79	0.62
Sinoya		0.97	0.99	Chichiri		0.78	0.63
				Makoka		0.83	0.63
				Chingale		0.68	0.51
				Balaka		0.80	0.64
				Mangochi		0.76	0.56

Table 5.3 shows that there is a significant improvement in the predictive capacity of SOM on both flow/level and rainfall. The range of R on flow and water levels jumps from 0.89 - 0.95 in Case 1 to 0.97 - 0.98. Similarly, R on rainfall, moves from 0.59 – 0.78 to 0.68 – 0.84. The improvement is also reflected in NS values. The results further accords with Kalteth and Berndtsson’s (2007) findings and are strongly supported by a marked distinction in component planes of flow and water levels (Figure 5.2 (a)) and rainfall (Figure 5.2 (b)). Similarities between some component planes are more conspicuous. For example, flow and water levels at Mangochi and Liwonde appear strongly related. Similarly, Nsanje, Makhanga, Ngabu, Chikwawa and Nchalo rainfall stations are correlated and different from the rest.



(a)



(b)

Figure 5.2: Component planes for flow and water level (a) and rainfall (b) resulting from Case 2.

Ultimately, SOM results in predicting flow and water levels when trained separate from rainfall are very good. In contrast, while SOM show an improvement from the previous case, based on NS, the overall SOM prediction on rainfall is just satisfactory. This is despite similarity in component planes.

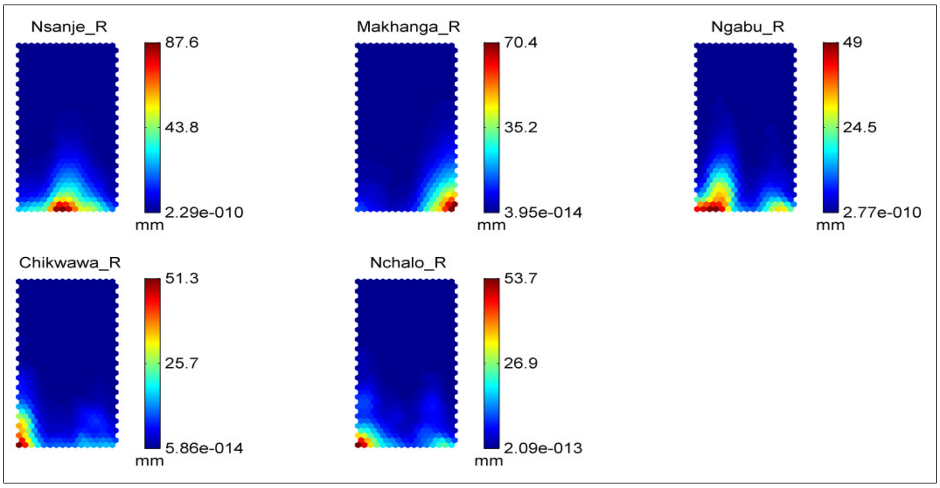
Case 3

Table 5.4 shows results when SOM is applied on clustered rainfall (Case 3) from which it is apparent that rainfall results improve with clustering. R values now range from 0.81 - 0.96; an improvement from 0.68 – 0.84. Similarly, NS values improve from largely satisfactory to good and very good. The modelling skills of SOM are the most satisfactory in cluster 3 with stations attaining R in excess of 0.9. This may suggest much correlation in this cluster though not evident in Figures 5.3 (a) – (c).

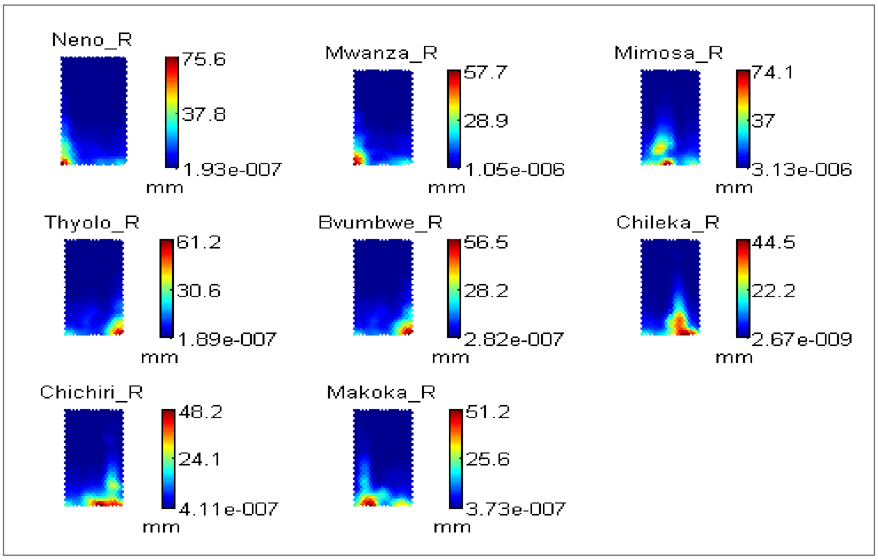
Table 5.4: SOM performance on clustered rainfall

Station	R	NS	Cluster
Nsanje	0.93	0.85	Cluster 1
Makhanga	0.95	0.90	
Ngabu	0.91	0.82	
Chikwawa	0.87	0.77	
Nchalo	0.88	0.78	
Neno	0.84	0.71	Cluster 2
Mwanza	0.81	0.74	
Mimosa	0.87	0.74	
Thyolo	0.88	0.76	
Bvumbwe	0.89	0.79	
Chileka	0.88	0.76	
Chichiri	0.87	0.76	
Makoka	0.87	0.76	
Chingale	0.95	0.91	Cluster 3
Balaka	0.96	0.92	
Mangochi	0.96	0.92	

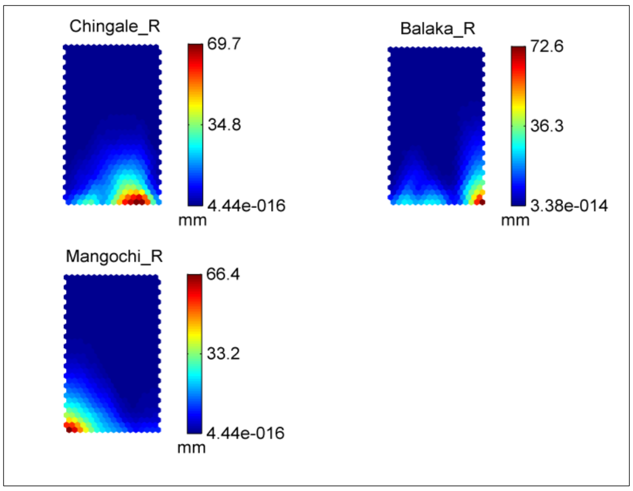
Despite good predictions on rainfall following clustering, the predictive capacity of SOM on hydro-meteorological data in the Shire remains superior on flow and water level data in comparison to rainfall.



(a)



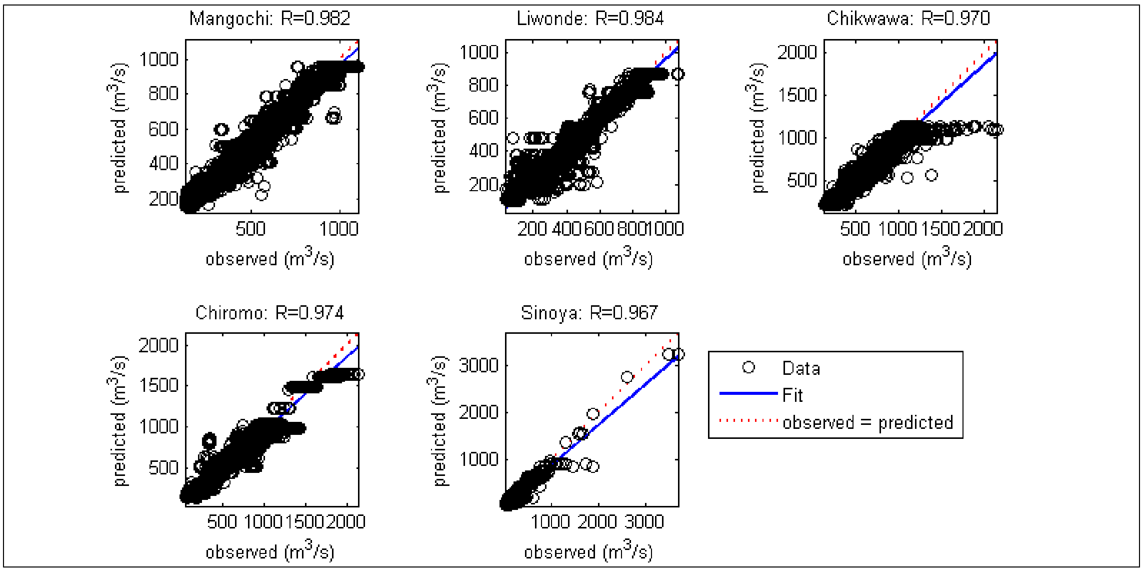
(b)



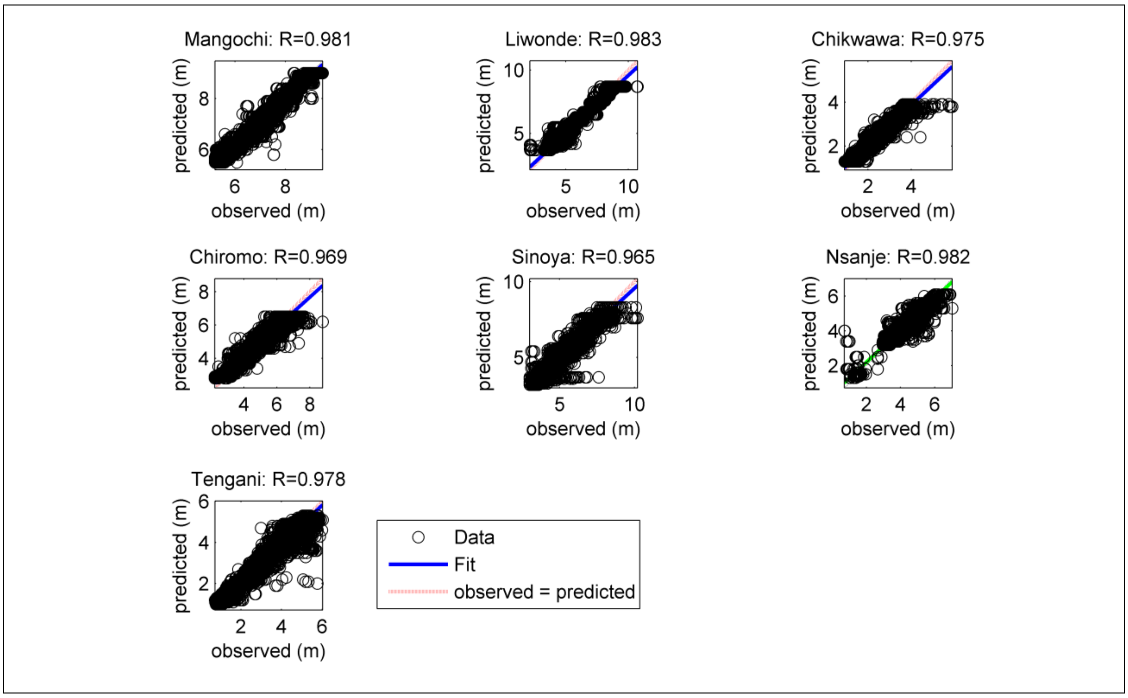
(c)

Figure 5.3: Component planes for rainfall clusters 1 (a), 2 (b) and 3 (c)

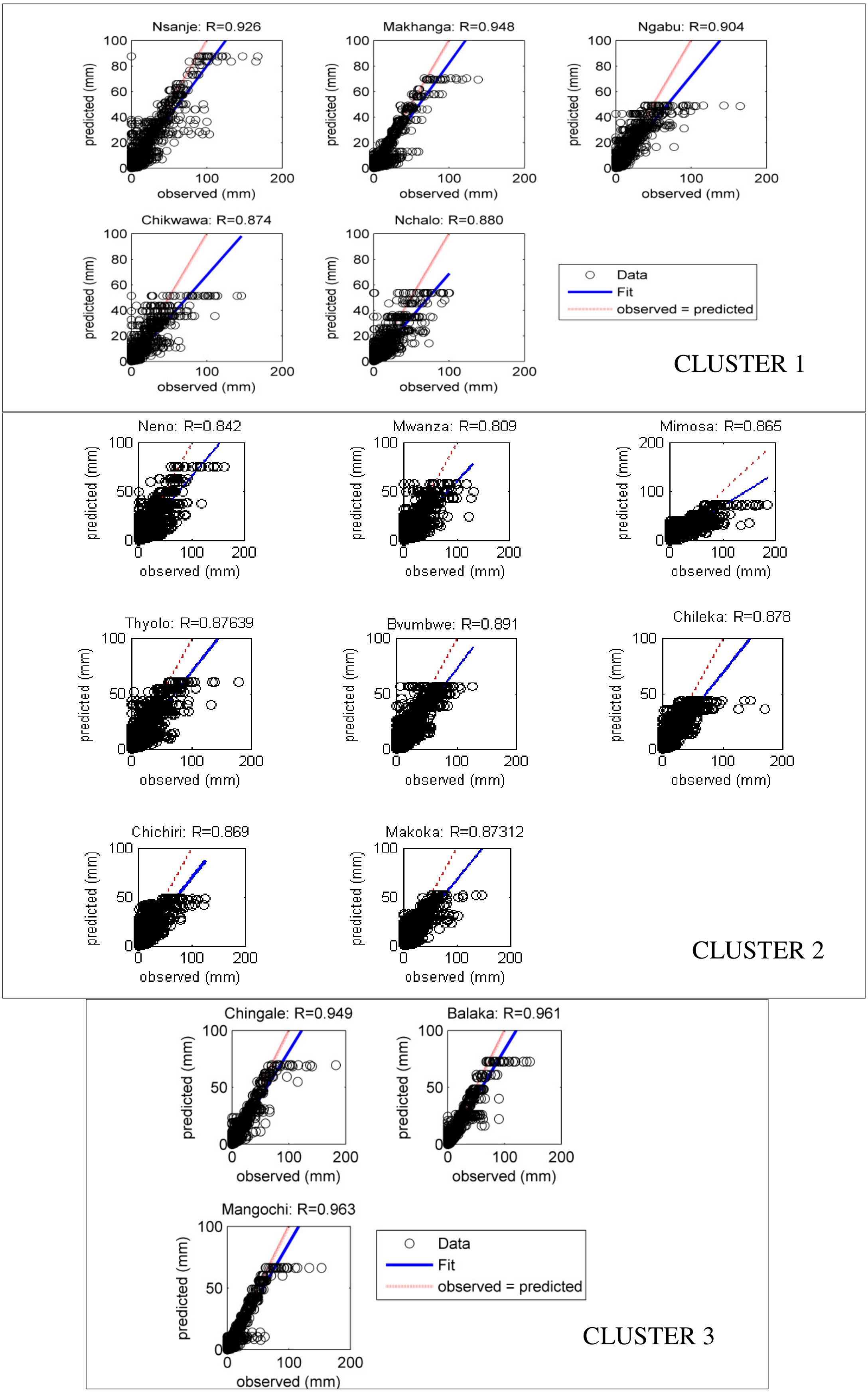
Given that cases 2 and 3 presented the best SOM prediction for flow and water level, and rainfall data respectively, they provided the basis for reconstructing gaps and discontinuities in flow and water level data, and rainfall data respectively. The quality of SOM predictions on the basis of Cases 2 and 3 is further visually shown in Figure 5.4(a), (b) and (c).



(a) – Flows



(b) – Water levels



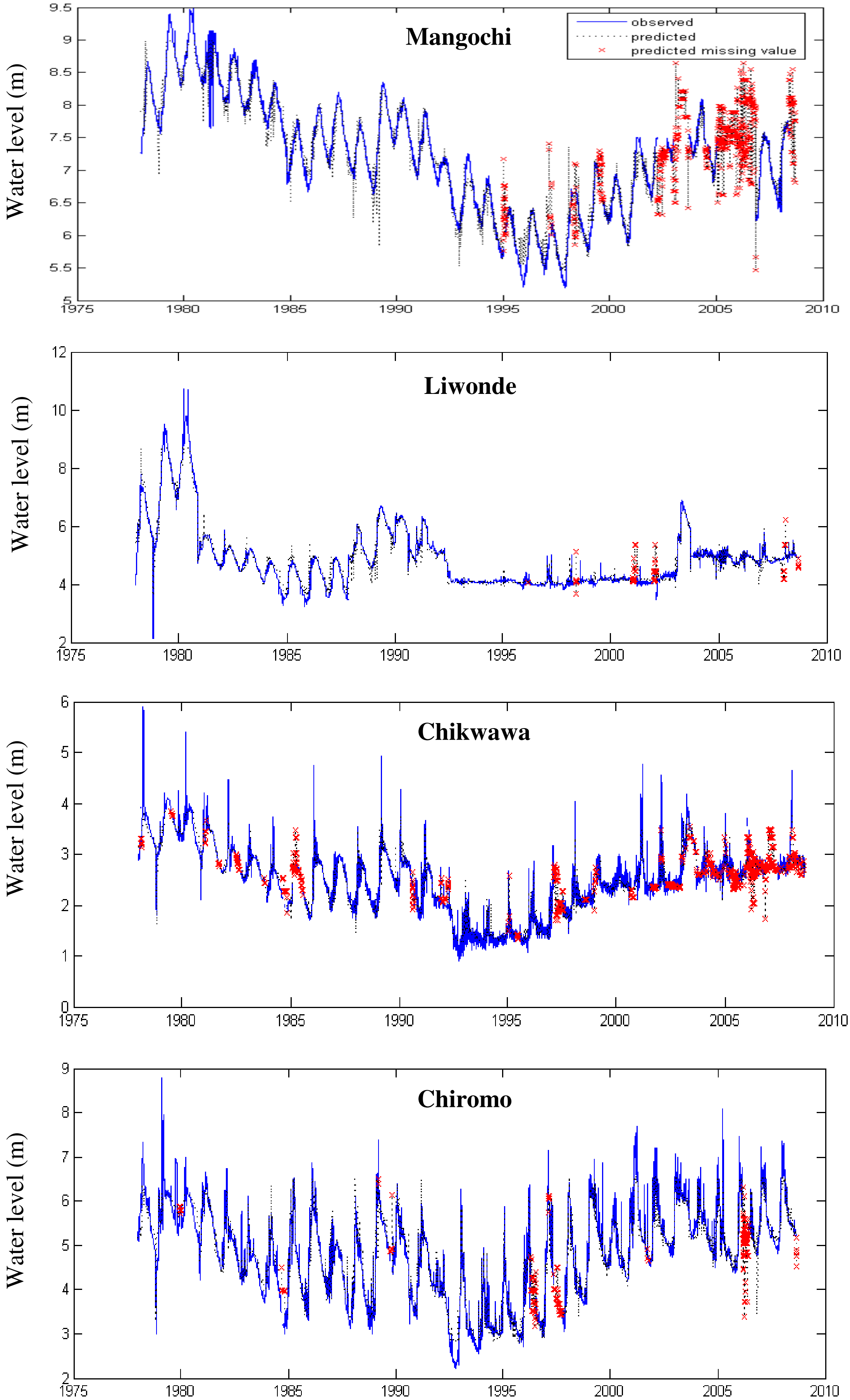
(c)

Figure 5.4: A comparison of observed and predicted data on (a) flows, (b) daily water levels and (c) rainfall

As shown in Figure 5.4, the degree of scatter about the best fit axis is low in both cases. Correlation coefficients (R) are also high: about 0.98 for flow and water levels and 0.8 – 0.96 for rainfall. This shows a strong relationship between SOM predicted values and observed values; further underscoring the high predictive capacity of SOM. However, with Figure 5.4, is becomes apparent that SOM ability is limited at high values. The deficiency is more pronounced on rainfall data (Figure 5.4 (c)).

A further analysis with time series plots (Figures 5.5, 5.6 and 5.7) shows that SOM predictive ability is also high in respect of reproducing trends in flows, water levels and rainfall respectively. In addition, predicted missing values interpolate well within the original series. As noted earlier, while peak flow and water values are reasonably replicated, high rainfall values (Figure 5.7) are overly under-predicted.

The basic statistics in consideration of predicted and raw data (Table 5.5) are also evidential of the powerful predictive ability of SOM. This is demonstrated in the means, standard deviations and in the prediction of low values. Its failure on high values notably on rainfall is also confirmed. The general under-performance exhibited in rainfall in comparison to hydrological data is in support of Ngongondo et. al's (2011a) findings of high variability of rainfall in Malawi even within shortest distances. According to Ngongondo et al., spatial correlations in rainfall are only observable within 20km of a station.



Mangochi
observed
predicted
predicted missing value
Water level (m)
Liwonde
Water level (m)
Chikwawa
Water level (m)
Chiromo
Water level (m)
1975
1980
1985
1990
1995
2000
2005
2010

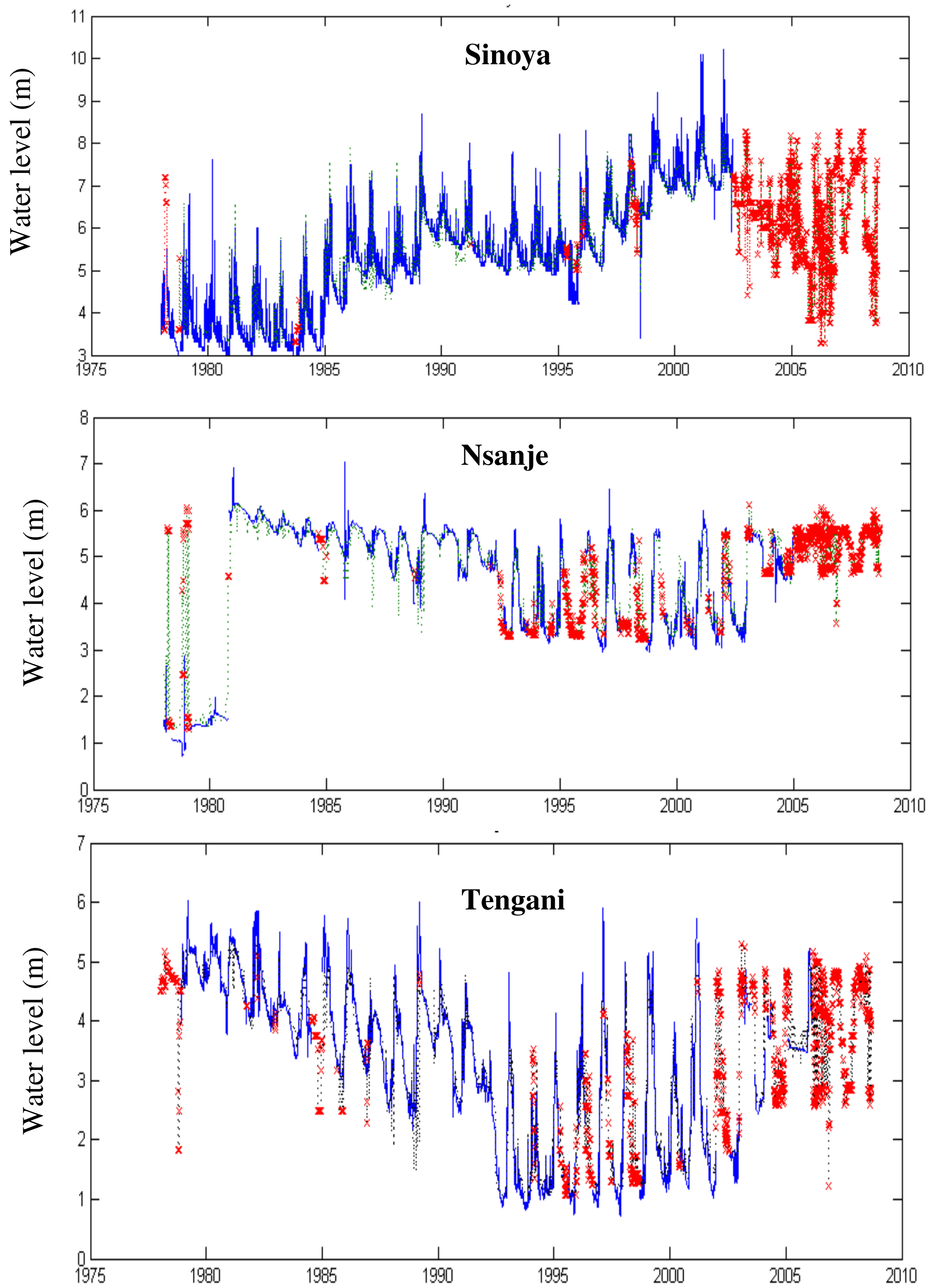


Figure 5.5: A time series comparison of SOM –predicted and observed water levels

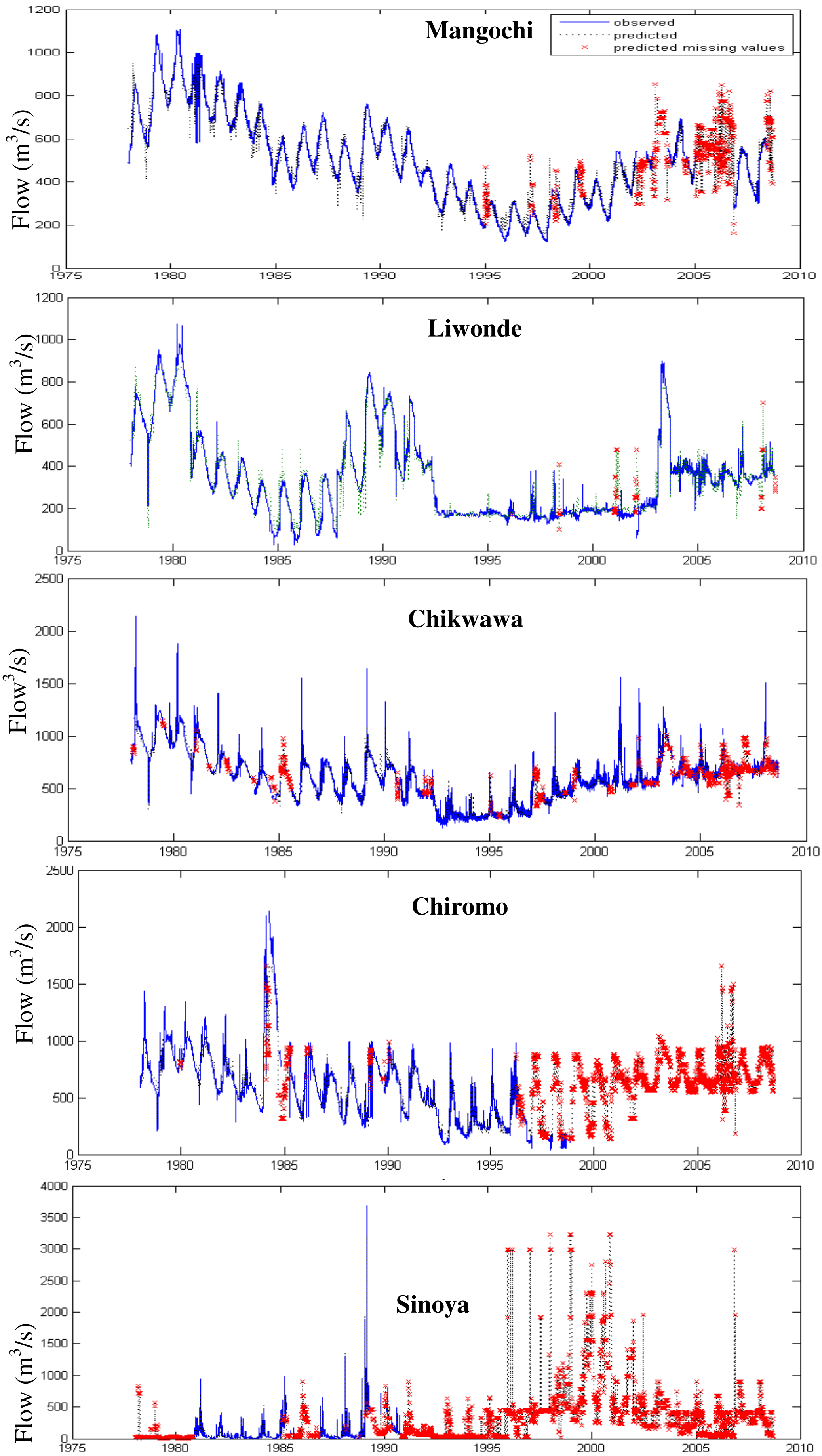
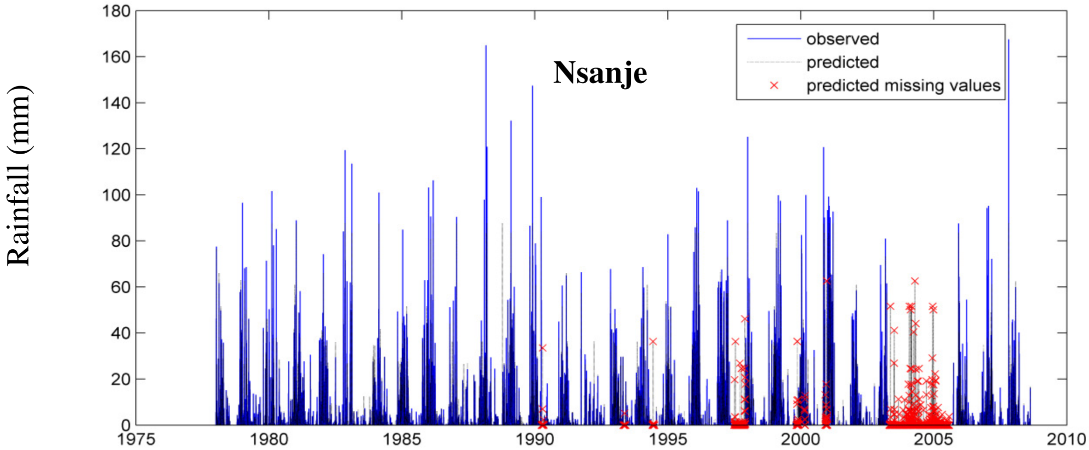
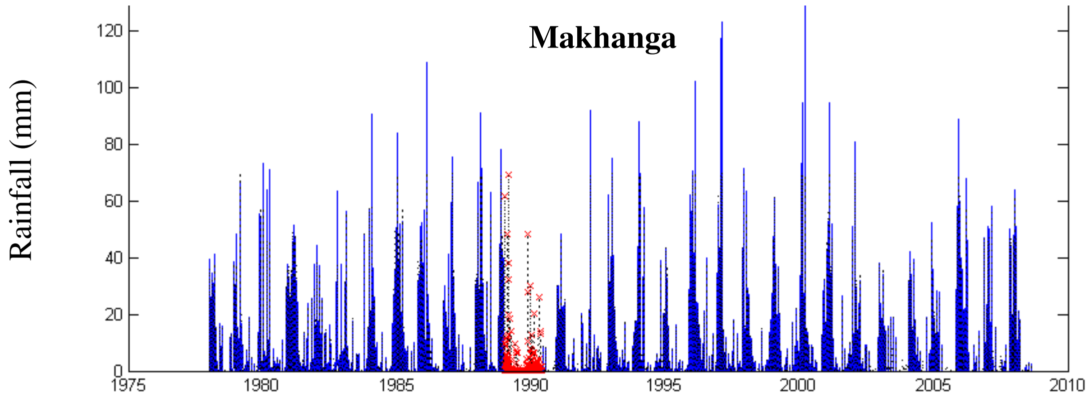
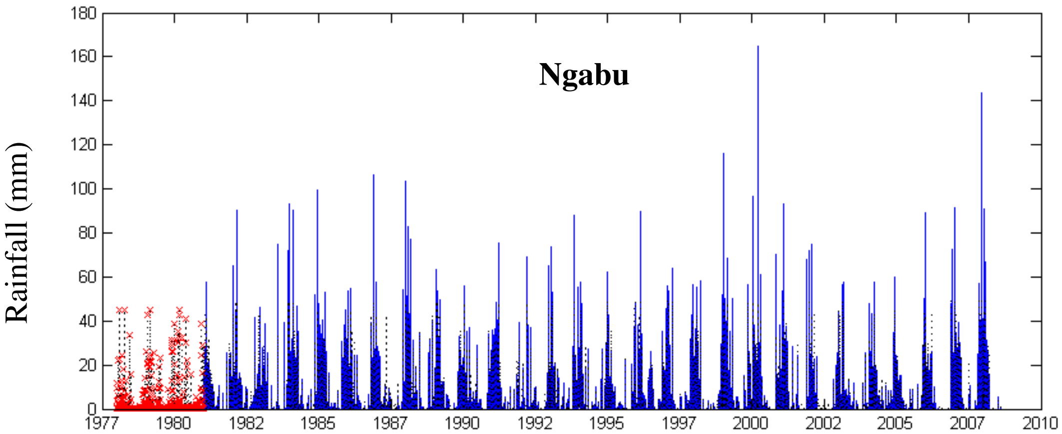
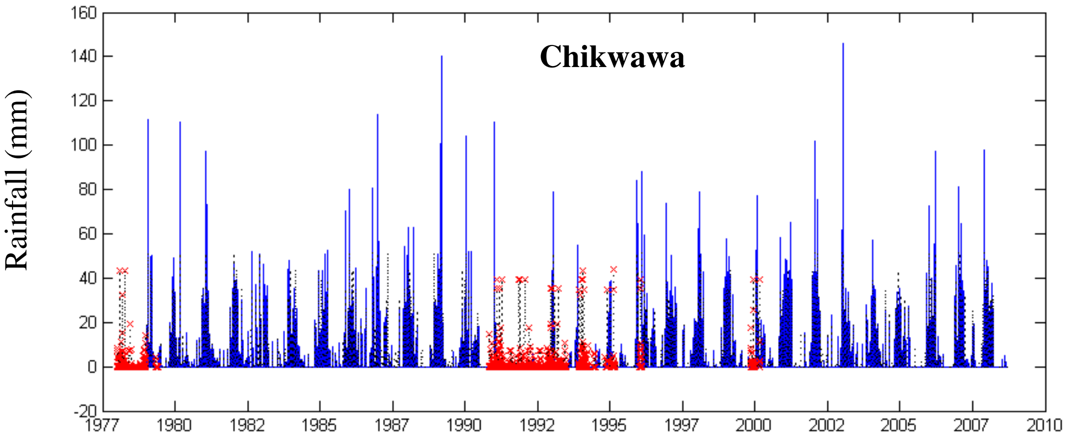


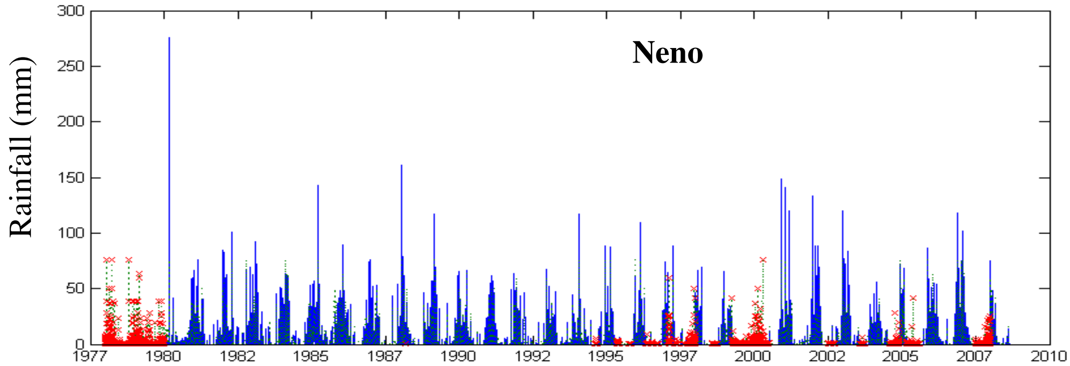
Figure 5.6: A time series comparison of SOM –predicted and observed flow

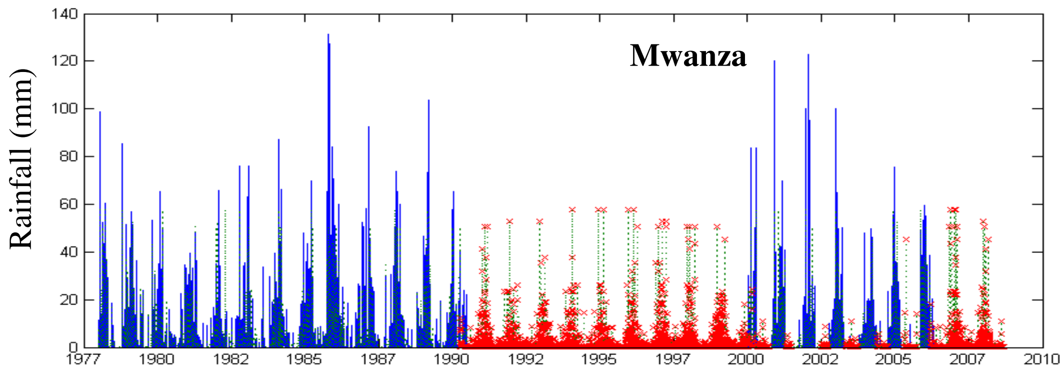

Nsanje
observed
predicted
predicted missing values
Rainfall (mm)
180
160
140
120
100
80
60
40
20
0
1975
1980
1985
1990
1995
2000
2005
2010

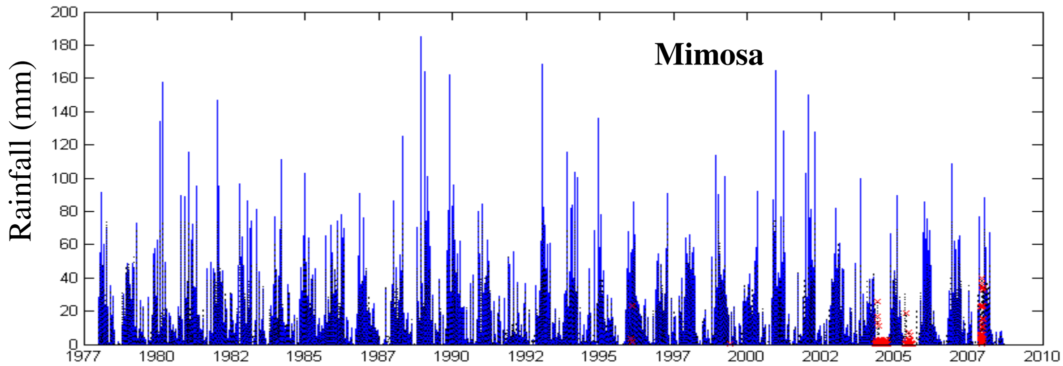

Makhanga
Rainfall (mm)
120
100
80
60
40
20
0
1975
1980
1985
1990
1995
2000
2005
2010

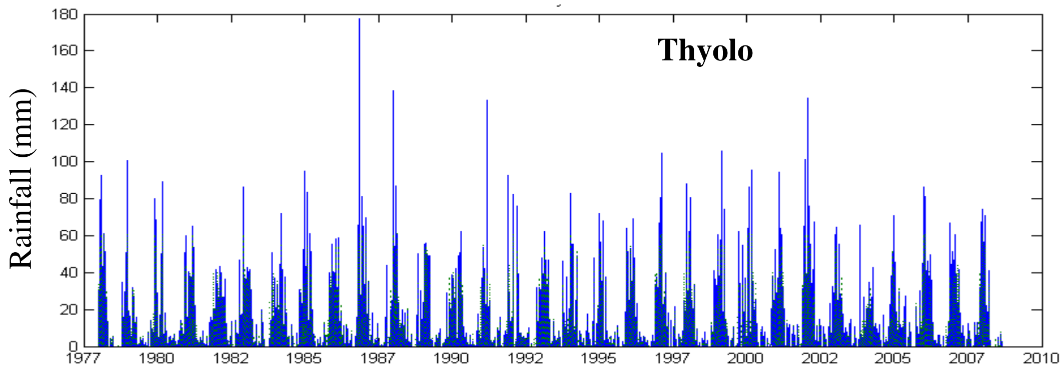

Ngabu
Rainfall (mm)
180
160
140
120
100
80
60
40
20
0
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010

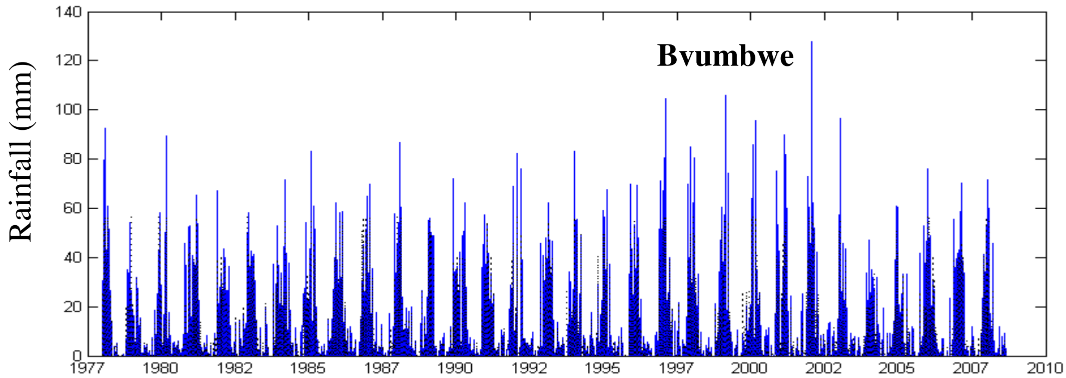

Chikwawa
Rainfall (mm)
160
140
120
100
80
60
40
20
0
-20
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010

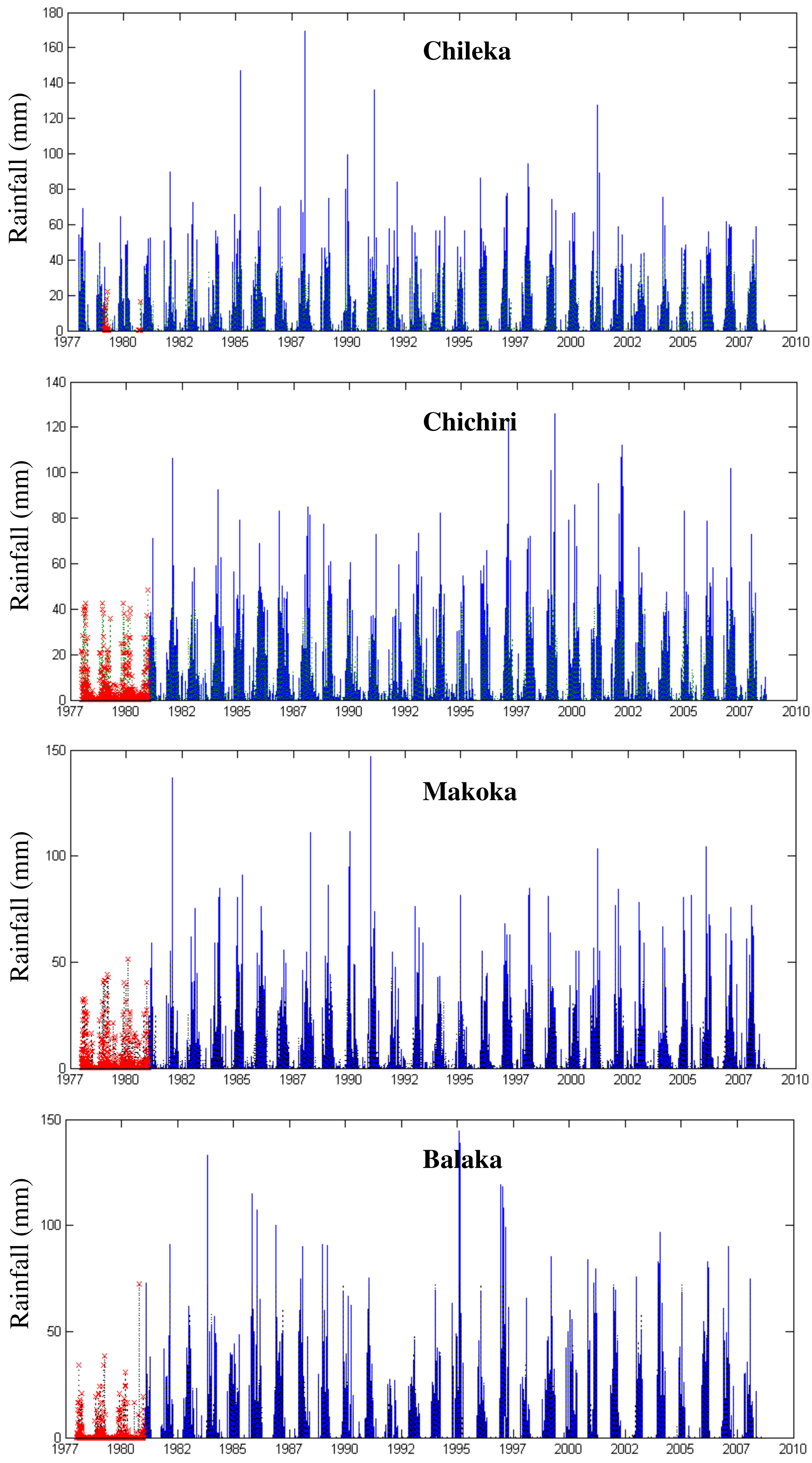

Neno
Rainfall (mm)
0
50
100
150
200
250
300
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010


Mwanza
Rainfall (mm)
0
20
40
60
80
100
120
140
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010


Mimosa
Rainfall (mm)
0
20
40
60
80
100
120
140
160
180
200
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010


Thyolo
Rainfall (mm)
0
20
40
60
80
100
120
140
160
180
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010


Bvumbwe
Rainfall (mm)
0
20
40
60
80
100
120
140
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010


Chileka
Rainfall (mm)
0
20
40
60
80
100
120
140
160
180
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010
Chichiri
Rainfall (mm)
0
20
40
60
80
100
120
140
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010
Makoka
Rainfall (mm)
0
50
100
150
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010
Balaka
Rainfall (mm)
0
50
100
150
1977
1980
1982
1985
1987
1990
1992
1995
1997
2000
2002
2005
2007
2010

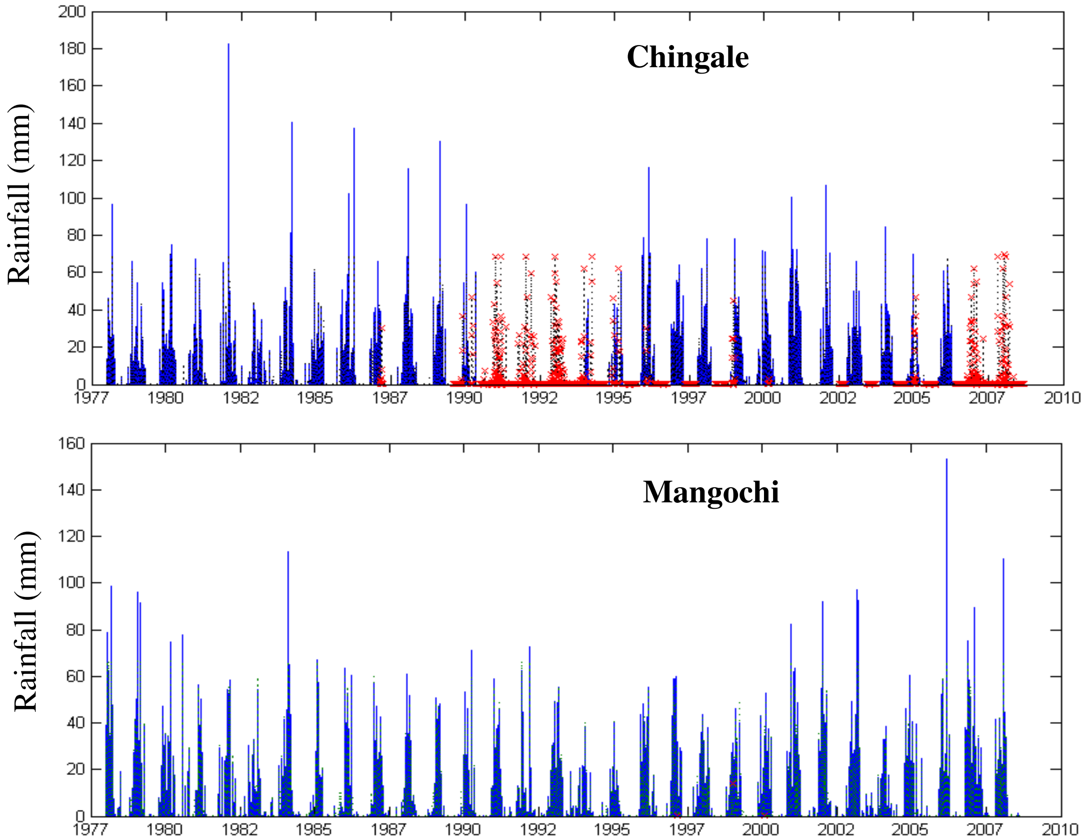


Figure 5.8: Time series comparison of SOM- predicted data and observed rainfall

Table 5.5: A basic static comparison of SOM- predicted data and observed data over analysis period

Flow and Water levels

Variable	Minimum		Maximum		Mean		Standard Deviation	
	Raw	SOM	Raw	SOM	Raw	SOM	Raw	SOM
Mangochi_L	5.2	5.5	9.5	9.0	7.3	7.3	0.9	0.8
Chkwawa_L	0.9	1.3	5.9	3.9	2.5	2.5	0.7	0.6
Liwonde_L	2.1	3.7	10.7	8.7	4.9	4.9	1.1	1.0
Chiromo_L	2.2	2.8	8.8	6.5	4.8	4.8	1.1	1.0
Nsanje_L	0.7	1.3	7.0	6.1	4.5	4.5	1.4	1.2
Tengani_L	0.7	1.0	6.0	5.3	3.3	3.3	1.3	1.3
Sinoya_L	3.0	3.2	10.2	8.3	5.3	5.5	1.4	1.3
Mangochi_F	123.1	162.3	1107.3	953.6	505.8	510.4	210.9	192.5
Chikwawa_F	127.1	216.8	2139.2	1136.5	598.2	602.2	246.7	222.0
Liwonde_F	27.2	101.9	1073.0	868.4	344.8	345.3	204.7	193.4
Chiromo_F	41.5	142.0	2142.0	1653.1	583.6	611.3	315.9	264.7
Sinoya_F	3.0	11.4	3683.4	3230.5	94.3	280.4	198.2	417.6

Table 5.5 (continued)

Station	Rainfall							
	Minimum		Maximum		Mean		Standard Deviation	
	Raw	SOM	Raw	SOM	Raw	SOM	Raw	SOM
Nsanje	0	0	167.5	87.6	2.8	2.8	10.6	8.9
Makhanga	0	0	138.5	70.4	2.0	1.9	8.0	6.9
Ngabu	0	0	165.0	49.0	2.2	2.1	8.4	6.7
Chikwawa	0	0	145.7	51.3	2.1	2.0	8.3	6.3
Nchalo	0	0	100.4	53.7	1.9	1.8	7.4	5.6
Neno	0	0	276.1	75.6	3.4	3.0	11.1	7.9
Mwanza	0	0	131.5	57.7	3.3	2.7	10.2	6.9
Mimosa	0	0	185.2	74.1	4.5	4.5	12.6	9.7
Thyolo	0	0	177.3	61.2	3.3	3.1	9.9	7.8
Bvumbwe	0	0	127.7	56.5	3.2	3.0	9.3	7.5
Chileka	0	0	169.5	44.5	2.4	2.3	8.5	6.5
Chichiri	0	0	126.0	48.2	3.1	3.0	9.3	7.2
Makoka	0	0	147.0	51.2	2.8	2.7	9.1	6.8
Chingale	0	0	182.5	69.7	3.1	2.4	9.9	7.9
Balaka	0	0	144.7	72.6	2.4	2.2	9.1	7.6
Mangochi	0	0	153.0	66.4	2.1	2.0	7.8	6.9

In general, results show that the SOM is a powerful predictive tool that handles large data sets and high proportions of missing values. However, as indicated by Kalteth and Berndtsson (2007), the quality of prediction depends on the correlation of data in the training set. In this study, the predictive capacity of SOM in this catchment is better on flow and water level data in comparison to rainfall data. Nonetheless, the fact that flow prediction has been better with the SOM is to be welcome because although flow data are the preferred ones to have for effective water resources assessment, they are also the most difficult and expensive to measure. They are thus the ones most likely to be missing and the result of the study reported here offers a significant re-assurance for data sparse regions of the world.

Similar work however, conducted by Adeloye and Rustum (2012) in the Osun basin of south west Nigeria, whereby runoff and rainfall were trained together yielded very good results, warranting no further clustering. They confirm the effectiveness of SOM in predictions, which can be much improved if the variables exhibit low spatial variability and/or high correlations, which was the case for the Osun basin (Adeloye and Rustum, 2012). Where this is not the case, e.g. with the rainfall data for the Shire catchment analyzed, working with clusters of homogeneous regions proves useful in improving the predictability of the SOM.

5.3 Flood hazardousness of the Lower Shire Valley

5.3.1 Model performance

Table 5.6 shows Lisflood-FP performance in modelling the flood hazard of the Shire Valley based on the 2008 flood season and using SOM-reconstructed flow data. The match between modelled flood extent and that observed from MODIS ranges from 64% to 71%. The results are acceptable (Bates and De Roo, 2000) for a greater proportion of Manning's coefficient tested (nfp >0.04). However, the steady improvement in fit with increase in floodplain friction in the results is surprising.

Table 5.6: Lisflood-FP performance with respect to floodplain friction (nfp)

nfp	0.025	0.030	0.035	0.040	0.045	0.050	0.055	0.060	0.065	0.070
$F(\%)$	64.3	65.4	66.5	67.6	68.6	68.9	69.70	69.7	70.6	71.1

Higher Manning's nfp reduces velocity, resulting in flow accumulation and increase in flood inundation extent (Biancamaria et al., 2009). Results therefore indicate that the fit improves on the basis of increase in flood extent from flow accumulation. Flood water accumulation is more likely for the Lower Shire Valley given the presence of the Elephant marsh, in between Chikwawa and Chiromo and the Ndindi marsh southward of Nsanje Boma. The increase in fit with increase in flood extent may also be attributable to the higher flood extent in the imagery than in Lisfood-FP as the latter did not account for tributary flows.

Therefore to determine a representative floodplain frictional factor and therefore a more representative flood inundation extent, unobtainable in Table 5.6 due to the gradual increase, the model was re-calibrated with two different frictional coefficients for any given simulation: one assigned to the Elephant marsh and the other to the rest of the domain. The degree of fit for the variable-friction model is shown in Table 5.7. The values are also compared to those obtained from a uniform friction model in Table 5.6.

As Table 5.7 shows, the degree of fit is generally higher when the presence of the marsh is accounted for, underscoring the influence of the marsh. However, for a given uniform floodplain Manning's nfp, the differences in the values of fit between the two models tend to be small except for $n = 0.025$. Mason et al.'s (2003) made similar observations on the River Severn in UK. They found that flood extents from spatially varied and uniform Manning's coefficients differed marginally.

Table 5.7: Lisflood-FP performance with varied Manning's coefficient

Floodplain friction	wetland friction									Fit (%) with uniform floodplain friction
	0.04	0.045	0.05	0.055	0.06	0.065	0.075	0.085	0.1	
0.025	67.5	67.6	67.4	68.7	69.1	69.5	70.1	70.5	70.2	64.3
0.035	67.9	68.3	68.1	69.4	69.8	69.0	70.2	70.3	71.6	66.5
0.045	68.2	68.5	69.2	70.5	70.2	71.3	71.0	71.3	72.8	68.6
0.055	68.4	68.6	68.7	69.0	70.1	70.3	70.9	71.4	72.2	69.0
0.065	69.2	69.0	70.2	70.7	70.4	70.6	71.8	71.7	73.0	70.6

The varied-friction model does not address the vagaries of trends observed in fit values in a constant-friction model. As in constant-friction model, the degree of fit also increases with increase in wetland friction. Therefore, the gradual increase in the degree of fit with increase in Manning's nfp observed in this study may largely be due to other issues discussed below, other than the presence of the wetland.

Flood extent determination

The actual extent of the flooded area in this study is determined by digitizing the MODIS image, guided by visual inspection. This is in consideration of uncertainty also associated with thresholds in using spectral water indices e.g. the Normalized Difference Water Index (NDWI) (McFeeters, 1996) or Normalized Difference Vegetation Index (NDVI), indices often employed in extracting the observed flood extents from satellite images (Khan et al., 2011; Schumann et al., 2013; Wang et al., 2003). NDVI for water bodies is less than zero and greater than zero for other surfaces. With the NDWI, water features have a NDWI of greater than zero (McFeeters, 1996). However, Ji et al. (2009) have shown that the thresholds defining water features are not static but dependent on the relative proportion of soil and vegetation with respect to water.

Therefore, in manually digitizing the flood extent, the flood extent digitized is larger in comparison to one modelled by Lisflood-FP. This could be a true reflection of flood extent given that MODIS imagery is inclusive of tributary flows; uncounted for in Lisflood-FP due to the unavailability of hydrological data on tributary stations in recent years. On the other hand, the visual inspection in digitizing the spatial extent could over-estimate the flood extent.

Flow data

The study uses flow data as input into the domain. As pointed out earlier, flows in this basin are derived from water levels through rating curves. Water levels are manually collected with staff gauges and therefore quality of the data is subject to human error. The rating curve also presents another source of errors. Shela et al. (2008) has reported siltation issues in the basin but as Shela et al. (2008) notes, there has been no re-calibration on rating curves over the years due to lack of resources. Another aspect is the availability of this data in average form; instantaneous hydrographs are not available. Very high values are therefore likely to be missed.

Topographical data

Developing countries lack national digital elevation models data sets and have to rely on global data sets (Fan, 2002). The DEM adopted in the study is a global data set; the widely used (Neal et al., 2012; Schumann et al., 2013; Zahera et al., 2011) 90m STRM DEM. According to Karlsson and Arnberg (2011), globally available data sets have quality issues that can lead to an under-estimation or over-estimation of modelled results. Over the Lower Limpopo in Mozambique, which is close to this study area, Karlsson and Arnberg (2011) found that the SRTM DEM had a vertical mean error of

1.95m. Although they found that flood modelling over this DEM led to a reasonable representation of flooding, they also observed that flood extent and depths were over or under estimated in some areas.

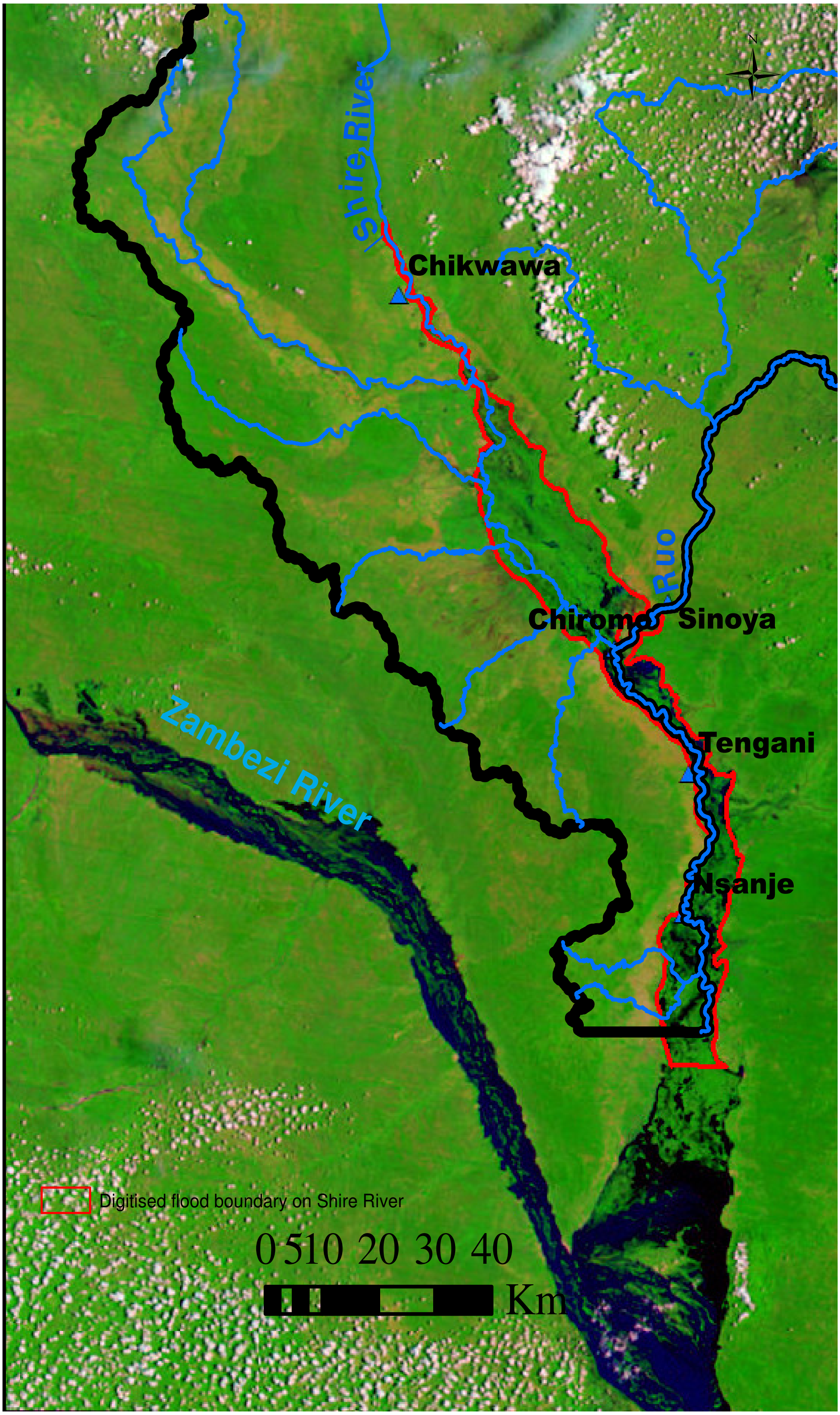
In the face of these factors, errors in the results are likely which impacts on Manning's nfp estimation. Therefore, the choice of floodplain frictional factor in this study follows the value found by Schumann et al.'s (2013). Schumann et al.'s (2013) found that a value of 0.05 better represented this region. Schumann et al. (2013) used the European Centre for Medium-Range Weather Forecasts (ECMWF) data in the VIC (Variable Infiltration Capacity) hydrological model for flow generation at Lisflood-FP's upstream boundary stations. Besides the degree of fit as an evaluation measure, Schumann et al. (2013) also evaluated model results using distance between modelled flood edge cells and Landsat flood edge points taken off the flooded area perimeter. Therefore, the 0.05 floodplain friction might be more representative.

5.3.2 Hazardousness magnitudes, areal extent and spatial variation

A valley perspective

Adopting a uniformly distributed Manning's coefficient of 0.05, the fit of the predicted flood inundation extent was 69% (Table 5.6). The resulting simulated flood extent, the observed extent from 7-2-1 MODIS imagery and a comparison of the two are shown in

Figure 5.9 (a), (b) and (c) respectively. A quantified distribution of hazardousness based on the maximum flood levels reached during the flood event is shown in Figure 5.10. The highest proportion of the flooded land in the Lower Shire Valley (38%) falls under the *medium hazardous depths* (0.5-1.0m). The *high* class (1.0-2.0m) and the *low* class (0.2-0.5m) follow at 30% and 23% respectively. The *very low* hazard zone (<0.2m) and the *very* high hazard zones (>2.0m) are the smallest segments of the valley constituting 7.5% and 1.7% respectively.


Shire River
Chikwawa
Ruo
Chiromo
Sinoya
Tengani
Nsanje
Zambezi River
Digitised flood boundary on Shire River
0 5 10 20 30 40
Km

(a)

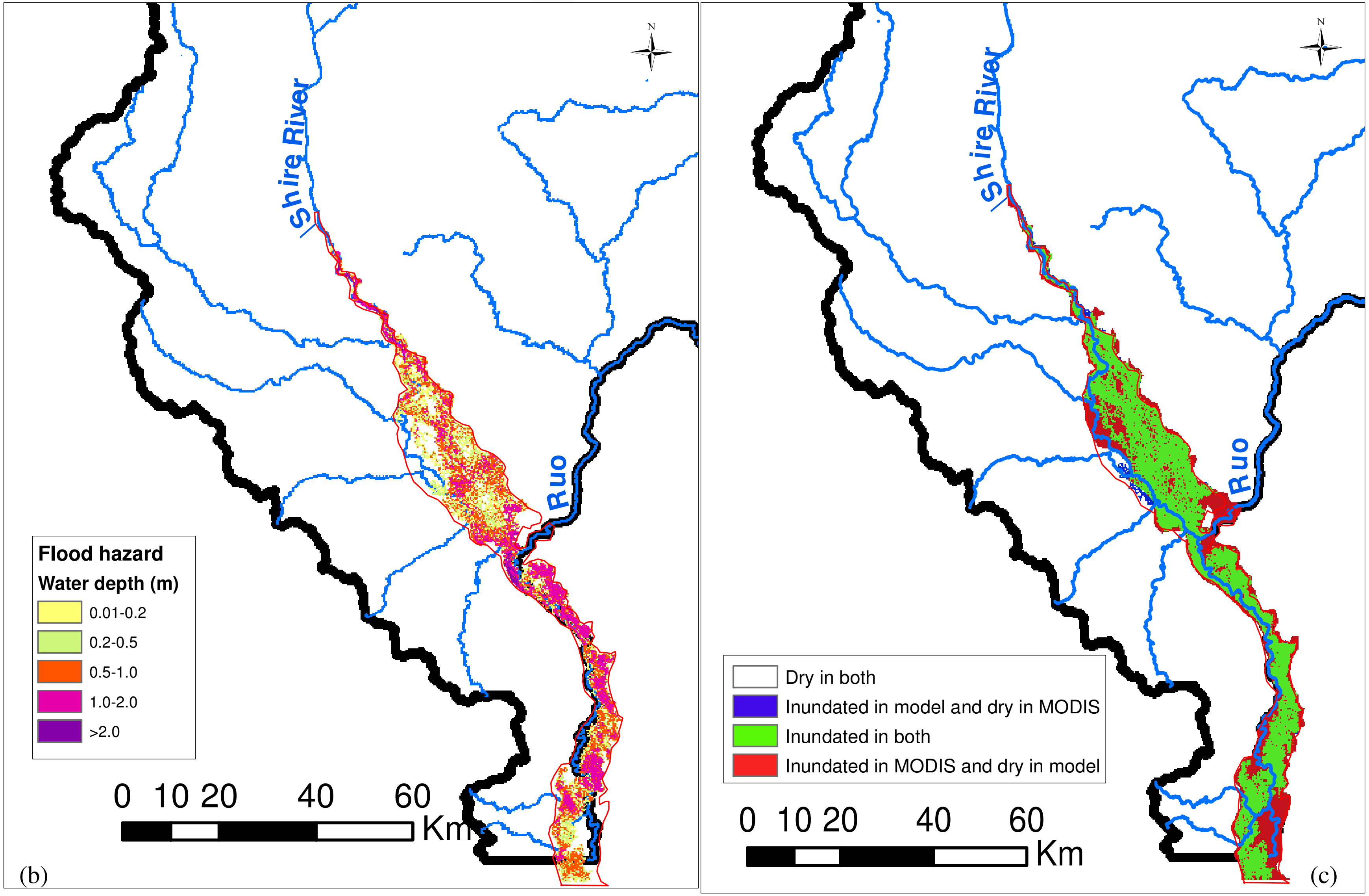


Figure 5.9: (a) Observed inundation extent from the 7-2-1 MODIS image, (b) Modelled flood extent and (c) a comparison of the two.

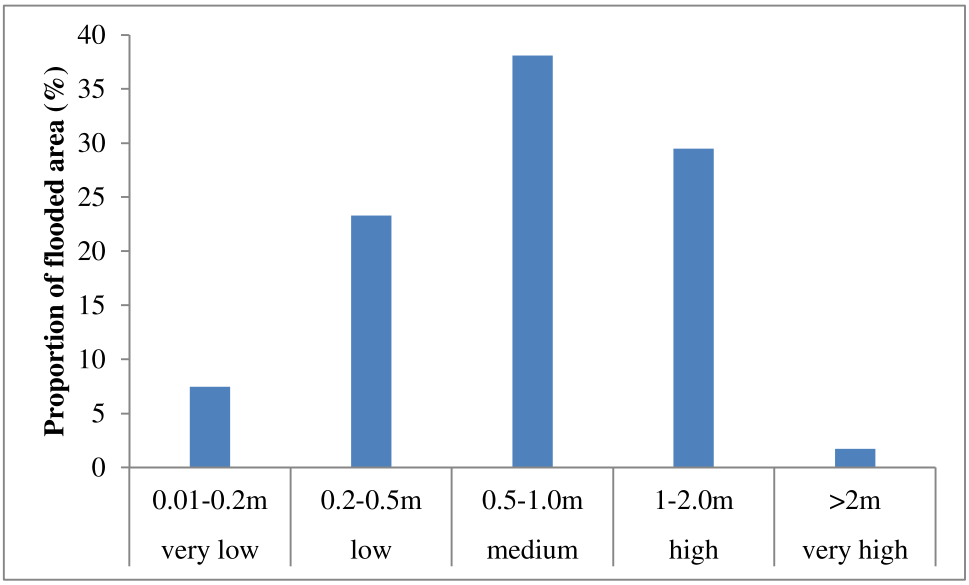


Figure 5.10: Flood inundation extent in the Lower Shire Valley by severity.

The results therefore suggest that the Lower Shire is a region predominantly affected by low to high flood levels but with a dominance of medium levels. However, the flood levels may however actually be higher than found, given that flooding from tributaries, were not accounted for in this study.

Below Chikwawa to just beyond the border with Mozambique (Figure 5.9(b)), flooding affects about 708 km^2 of land area. About 553 km^2 of the flooded area falls inside Malawi territory, accounting for about 78% of the flooded area.

While the three flood classes i.e. *very low, low* and *medium* occur throughout the valley; *very high* hazard areas (>2m) tend to cluster around the confluence at Chiromo. Concentrations of high hazard levels on the other hand occur just upstream of the confluence and just downstream indicative of more severe flood hazard around the confluence and downstream (Figure 5.9(b)), corroborating the perceived degree and locations of the most severe flooding on the Shire Ruo/River System (Shela et al., 2008).

While the flood hazard of the Lower Shire Valley has also been quantitatively highlighted in two World Bank studies, one by World Bank (2010b) and the other by

Atkins (2012), the two studies lack depth in the description of flood depths and extent affecting the Shire Valley; flood extents and depths in their findings are only visually interpreted.

A community perspective

When viewed through the community lens (Figure 5.11), Makhuwila and Mlolo alone account for 59% of the total flooded area in the Lower Shire valley. Makhuwila has the highest proportion of the flooded area (38.7%). It is followed by Mlolo (20%), Nyachikhadza (7.5%) and Mbenje (7.4%). The rest of the communities account for less than 5% of the flooded area each with Malemia being the least affected (0.7%).

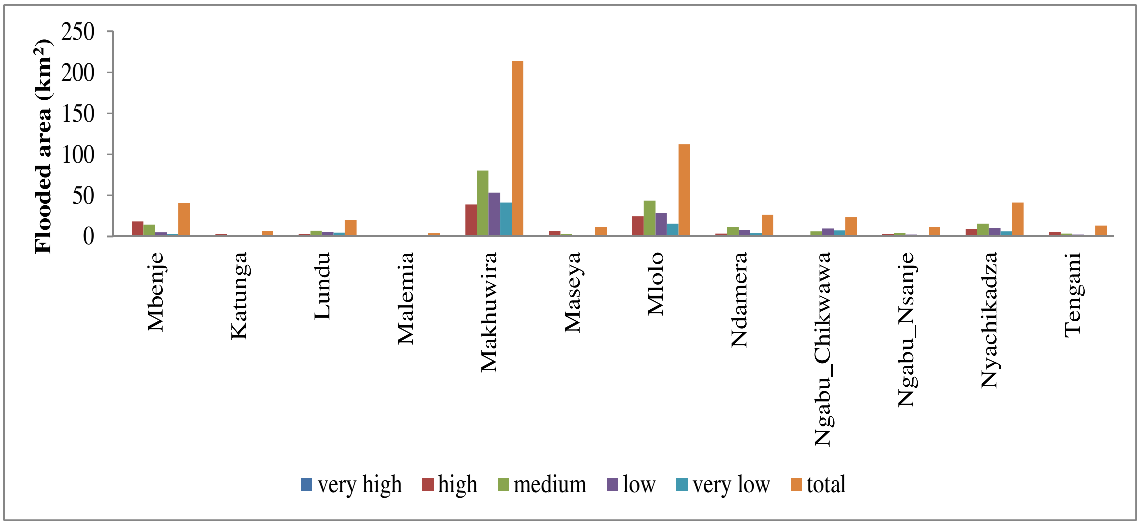


Figure 5.11: Flood inundation extent across communities

The dominance of Makhuwila, Mlolo, Nyachikhadza and Mbenje in the proportion of area affected correlates with geographical location of the Elephant marsh, the Shire/Ruo confluence and the Ndindi marsh. Makhuwila covers the biggest portion of the Elephant marsh, which extends from below Kapichira Falls to the Shire/Ruo confluence. The size of the marsh under normal dry conditions is approximately 500 km^2 but may swell to 90km in length and 30km in width during flooding (Tweddle et al., 1978). The marsh also falls into Mlolo and Mbenje.

Mlolo and Mbenje are further affected by the back-flow effect of Ruo on Shire at the confluence. Flow in Ruo can be a multifold of the flow in the main river during flooding. As pointed out earlier, Shela et al. (2008) reports historical flood flows in the Ruo being as high as 5400m^3/s, in contrast to the maximum flood flows of 1430 m^3/s recorded in the Shire. They further point to flow in the 1952 flood, one of the worst flood episodes, being only 850m^3/s in the Shire River upstream of the confluence and 2000 m^3/s on the Ruo resulting in a flow downstream of the confluence of about 2850 m^3/s. Nyachikhaza is an island community on Ndindi Marsh. Thus a spatial concentration of the flooded area with these communities is not unlikely.

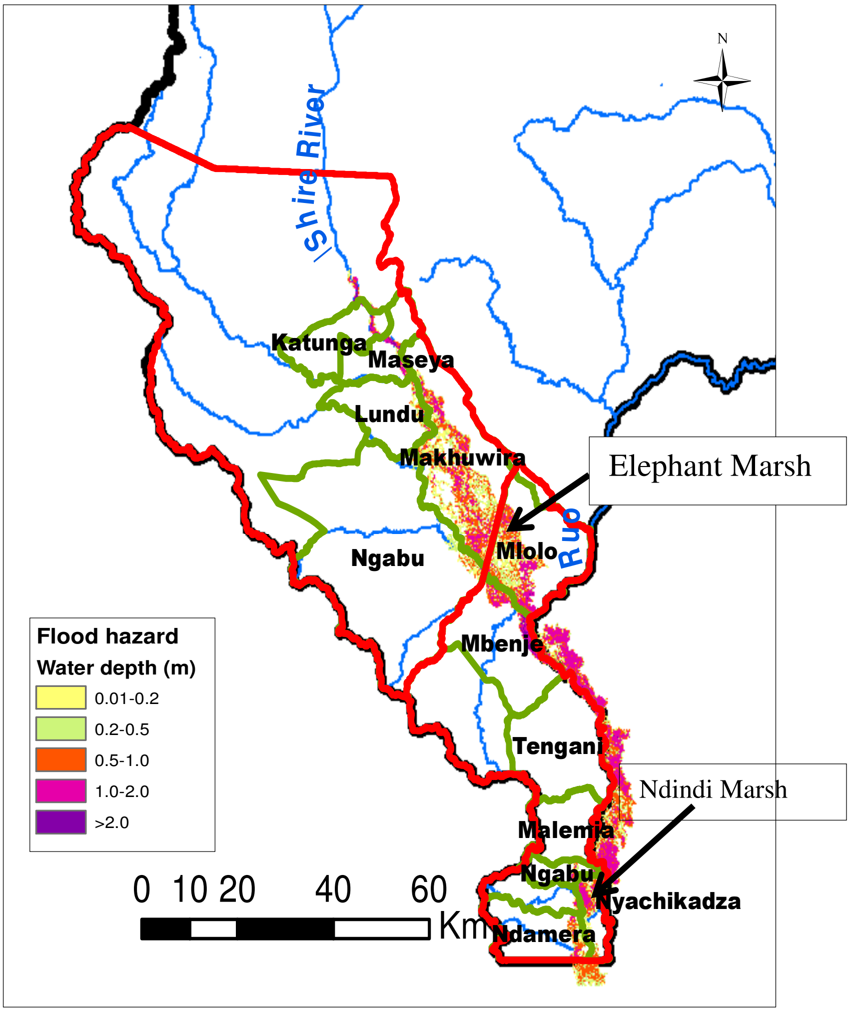


Figure 5.12: Flood extents across communities in the Lower Shire Valley

5.3.3 Average community hazardousness

As observed in Figure 5.11, a given community will have several flood hazard classes with each class having a particular areal extent. Therefore an average hazard index (AHI) is used to define the average flood hazard severity of a community. The AHI accounts for areal extent of a given flood depth and is calculated based on equation (5.1).

$$AHI = \frac{\sum_{i=1}^{n} (HI)_i A_i}{\sum_{i=1}^{n} A_i} \qquad (5.1)$$

where A_i is the land area (km^2) in a community under the flood hazard class HI_i (meters); n=5 and is the number of hazard categories. For the purpose of this calculation, the hazard classes HI_i was taken as the average depth in a hazard class as shown in Table 5.8

Table 5.8: Flood depth and associated hazard index

Flood depth, D (m)	**Hazard index level**	**Average hazard depth (HI) (m)**
D<0.2	Very low	0.1
0.2<D<0.5	Low	0.35
0.5<D<1.0	Medium	0.75
1.0<D<2.0	High	1.5
>2	Very high	2.1

The average hazard index (AHI- estimated according to equation (5.1)) is shown in Table 5.9.

Table 5.9: Average community flood hazardousness in the Lower Shire Valley

Community	AHI (m)	Designation
Maseya	1.12	H
Mbenje	1.06	H
Katunga	1.08	H
Tengani	1.03	H
Ngabu_Nsanje	0.9	M
Ndamera	0.77	M
Nyachikadza	0.94	M
Mlolo	0.86	M
Malemia	0.99	M
Lundu	0.82	M
Makhuwira	0.84	M
Ngabu_Chikwawa	0.68	M

Viewed against the classes in Table 5.8, results reveal a predominance of AHI concentrations in the medium to high flood hazardousness. Nonetheless, medium hazardousness tends to dominant. Of the 12 communities affected by Shire flooding, there are eight communities in the medium class and four in the high class.

Communities accounting for higher proportions of the flooded area (Figure 5.11), are not necessarily the most hazardous. In examining Figure 5.11, Makhuwila, Mlolo and Nyachikhadza, the most affected in terms of areal extent come out in the medium range on average flood hazardousness (Table 5.14). Except for Maseya, characteristic of all communities in the Lower Shire valley is the significant proportion (>50%) of their flooded area falling in the very low to medium category of hazardousness. In particular, all but Mbenje, Katunga and Malemia have 70-98% of flooded area in the very low to medium zones with Mbenje, Katunga,and Malemia scoring 55%, 54% and 51% respectively. The proportion is the highest in Ngabu (Chikwawa) (93%) explaining its overall low average hazardousness

As shown in Table 5.9, community hazardousness in the Lower Shire Valley is one characterised by relative homogeneity. However, the geographical distribution of medium and high hazardousness differs (Figure 5.13). Medium hazardous communities are ubiquitous across the valley. In contrast, high hazardous communities tend to be localized: around the confluence in Nsanje and in Katunga and Maseya in Chikwawa.

A dearth on studies in this valley that have attempted to attach a metric to flood severity and more so, within the scale of decision making for flood risk management, prevents a critical analysis of the results. In the World Bank (2010b) and Atkins (2012) studies, due to the confinement of results to visual interpretation, the severity of hazardousness within scales of disaster management in the two studies cannot be ascertained.

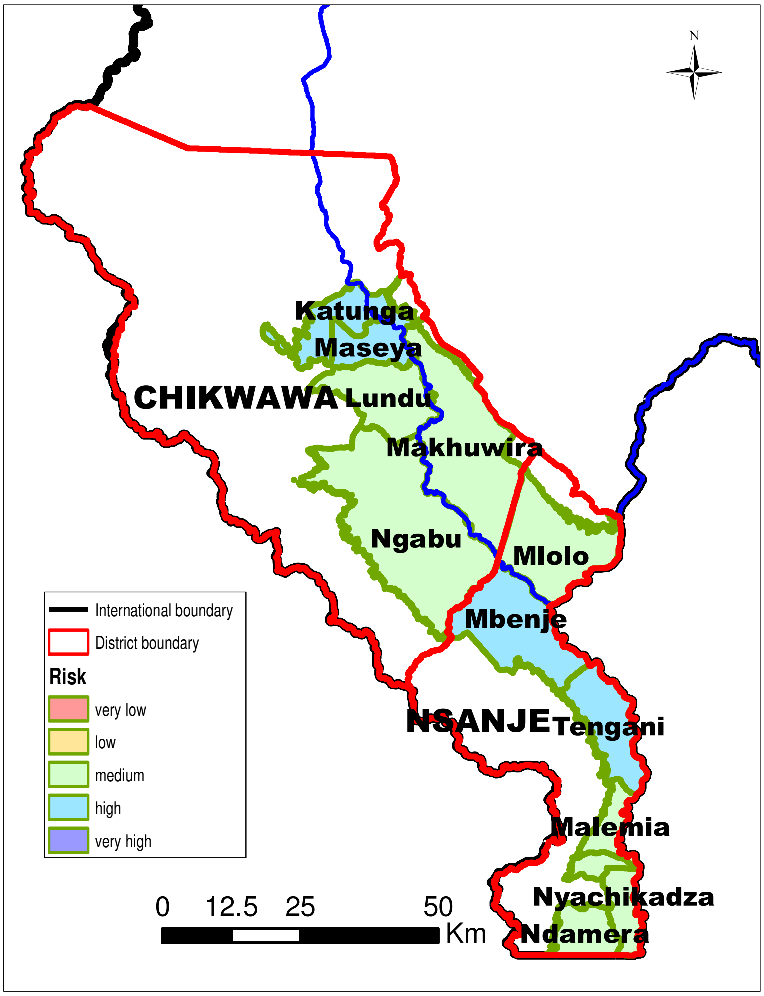


Figure 5.13: Spatial variation in flood hazardousness in the Lower Shire Valley

This study attaches magnitudes to the flood hazardousness of the Lower Shire Valley. It also determines the geography of this hazardousness as linked to community scale, a scale of disaster management decision making. These aspects have not been addressed in World Bank (2010b) and the other by Atkins (2012). The resulting degree of flood severity and the associated geography are nonetheless subject to data used and modelling assumptions made. The study relies on manually collected hydrological data whose quality is further compromised by a significant proportion of gaps and discontinuities. This is nonetheless addressed with powerful data driven models. Also, flow values used are average daily values other than the instantaneous values and therefore actual maximum flows reached are likely to be missed. Further, velocity is disregarded in the hydraulic model on the basis of the flatness of the valley and simplicity. However, flash flooding has been reported on the Ruo/Shire confluence area

(Shela et al., 2008). This is therefore likely to underestimate hazardousness for some communities.

5.4 Flow and water level forecasting

Besides use for flood hazardousness estimation, SOM-reconstructed data were also used for the development of a flood forecasting MLP-ANN model given increasing attention towards non-structural measures for flood mitigation but also cognisant of the data challenges in developing countries to support traditional forecasting models. Results are outlined in the sections below.

5.4.1 1-day ahead forecasting

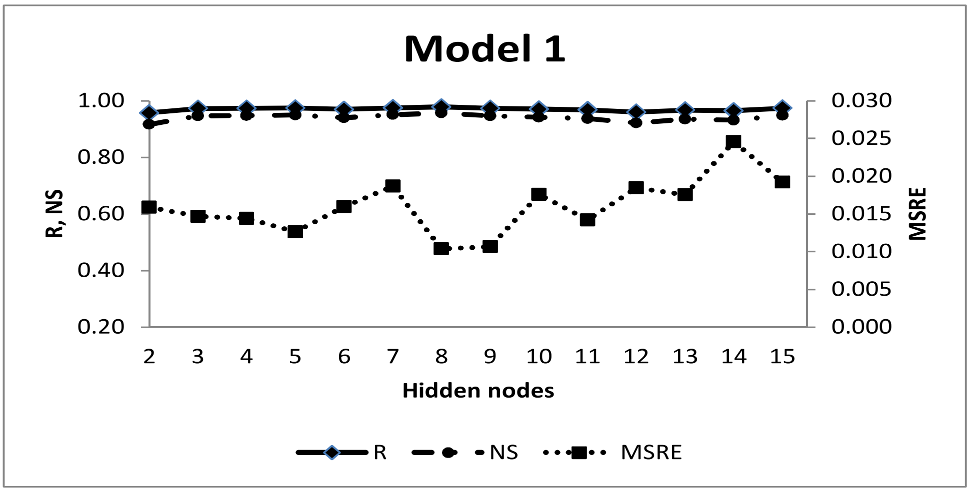
As noted in section 4.2, forecasting models were developed using ANN. These models are:

Model 1 – this forecasts flow and water levels at Chiromo based on average catchment rainfall, endogenous flows and water levels, including lagged inputs, and flows, water levels and their lagged inputs from Chikwawa upstream, and Sinoya on the tributary.

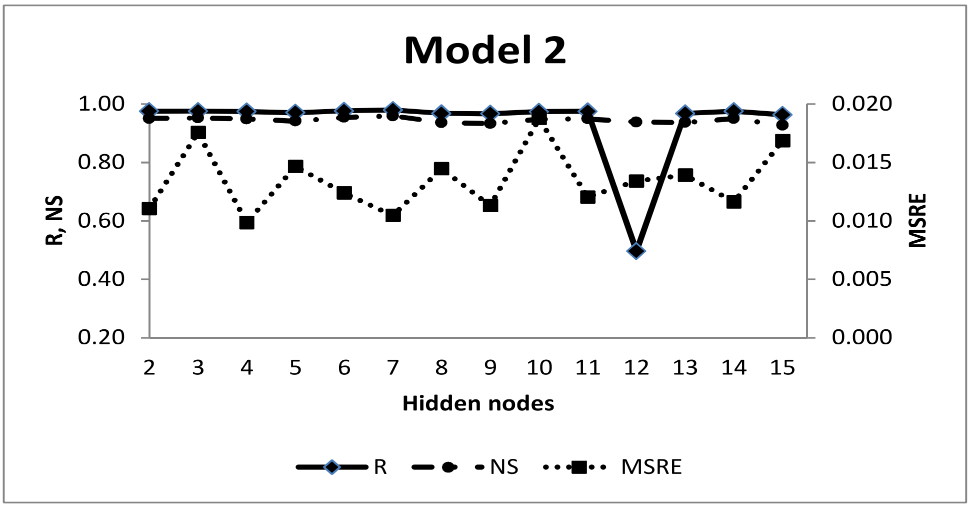
Model 2 – this forecasts flow and water levels at Chiromo based on average catchment rainfall and flow and water level including lagged inputs from only Chiromo station.

Model 3 – this replicates Model 2 but with the exclusion of lagged inputs from flow and water levels.

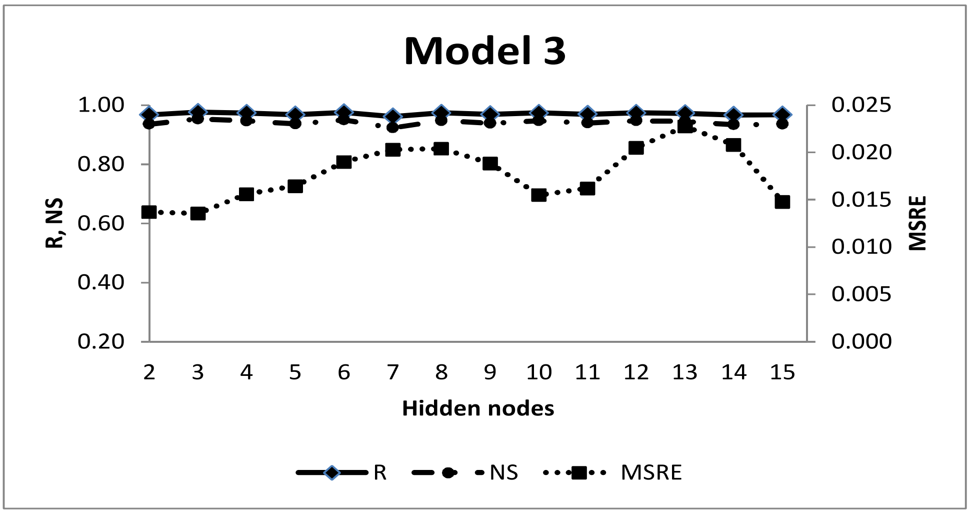
It was observed that the MSRE, in comparison to NS and R, was more sensitive to the number of hidden neurons in the MLP-ANN model (Figure 5.14 (a), (b), (c)). Consequently, the selection of best MLP-ANN structure in terms of hidden neurons was based on MSRE. Average MSRE values from flow and water level were used. The selected optimal ANN structures, from each of the three models assessed, are shown in Table 5.10. Figure 5.15 and Figure 5.16 show corresponding scatter plots and time series.



(a)



(b)



(c)

Figure 5.14: Model performance with increasing number of hidden neurons

Table 5.10: Performance of the three models in the testing phase

Model	Best architecture	Water level			Flow			Average values		
		MSRE	R	NS	MSRE	R	NS	MSRE	R	NS
1	18-8-2	0.0018	0.9818	0.9638	0.0189	0.9746	0.9498	0.0104	0.9782	0.9568
2	5-7-2	0.0019	0.9801	0.9604	0.0190	0.9784	0.9572	0.0104	0.9793	0.9588
3	3-3-3	0.0029	0.9732	0.9472	0.0242	0.9797	0.9596	0.0136	0.9765	0.9534

As shown in Table 5.10, all three models selected exhibit high performance in modelling both flow and water levels at Chiromo with respect to all the three statistics. Besides guidance on R and NS given in section 5.2, Moriasi et al. (2007) also rated as very good a model with a relative error of <± 10%, 'good' for ±10–15%, 'satisfactory' for ±15–25% and 'unsatisfactory' for >± 25%. In all the three models, R and NS are above 0.9 and the maximum value of the average MSRE is below 2%. Similarly, high and low flows in the time series plots (time series plots are based on the whole data set) are well reproduced in all models.

A comparison of the models (Table 5.10) shows nonetheless that Model 2 performs better than the other two based on the average values of three statistics. Nonetheless, the differences are small, an aspect also reflected in the scatter plots (Figure 5.15) and time series plots (Figure 5.16). Therefore, on the basis of parsimony, model 3 presents the best model and is chosen.

Model 3 shows that remarkably good forecasts of the following day's water level and flow can be obtained at Chiromo with a parsimonious MLP-ANN model using only three inputs on a particular day: flow, water level and catchment rainfall. Forecasts of water levels are generally better compared with flows. This could be related to the quality of data.

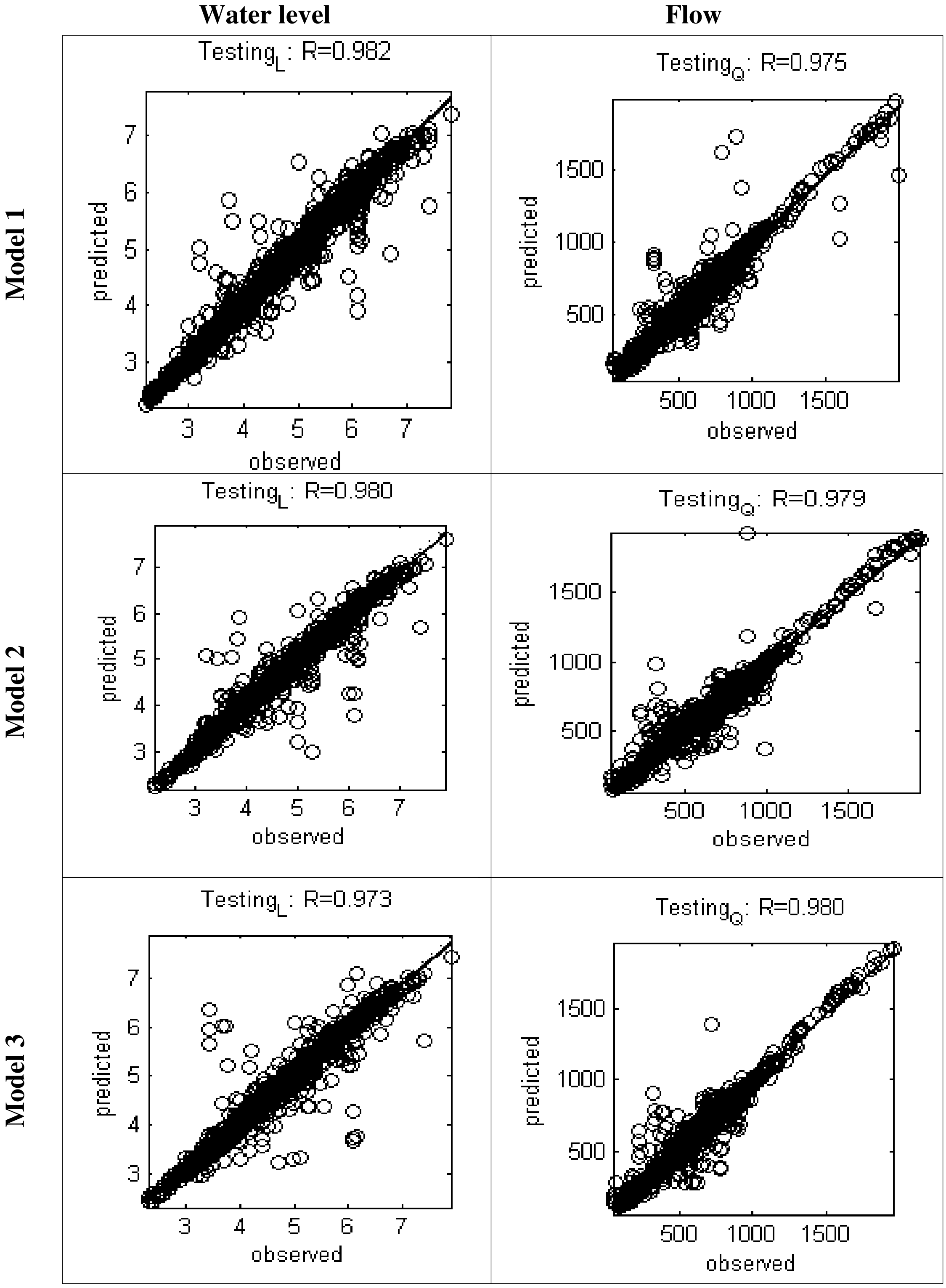
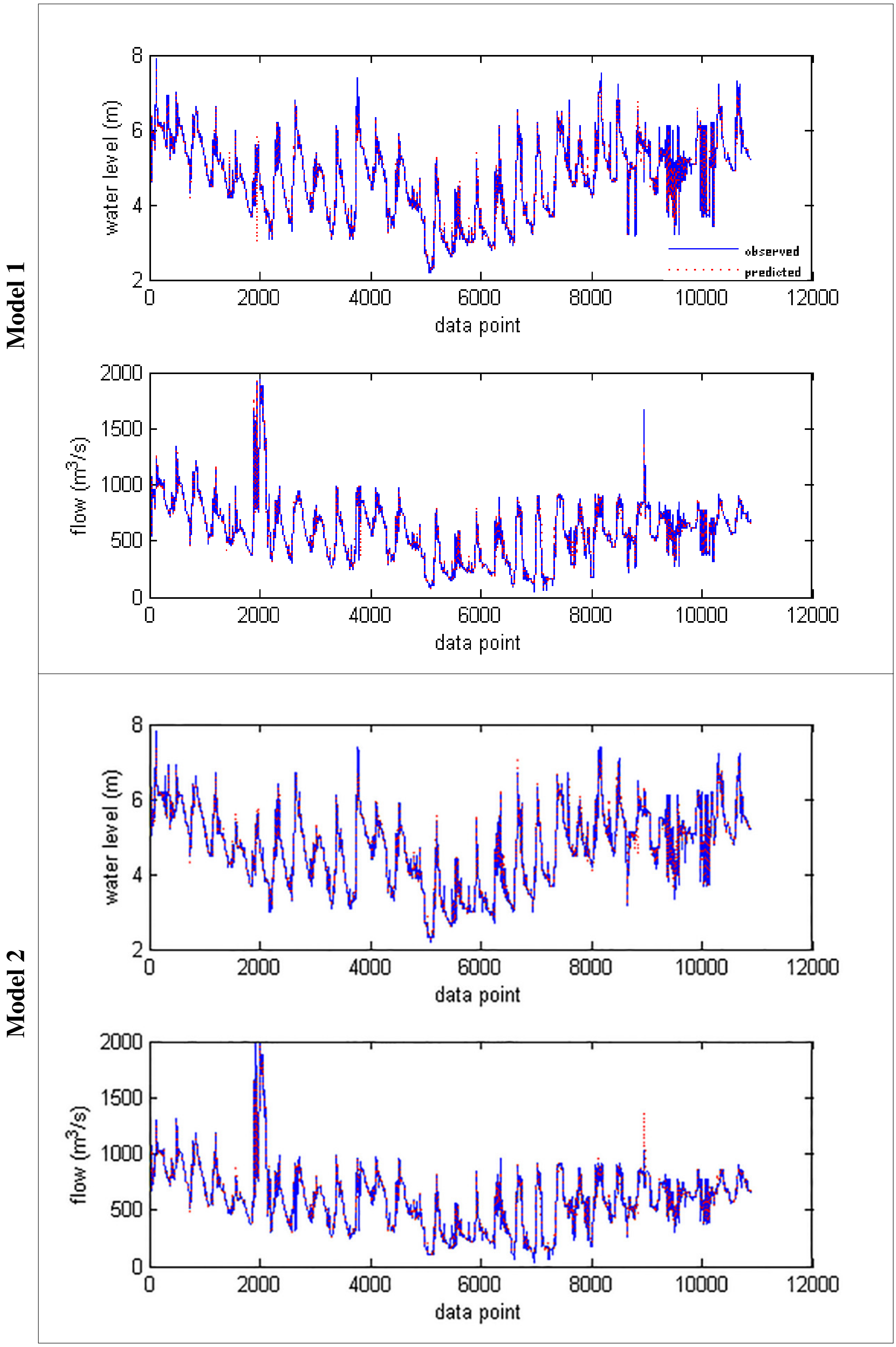


Figure 5.15: A scatter plot comparison between observed and forecasted 1-day ahead data for selected ANN structures


Model 1
Model 2
water level (m)
flow (m3/s)
data point
observed
predicted
0
2000
4000
6000
8000
10000
12000
2
4
6
8
500
1000
1500

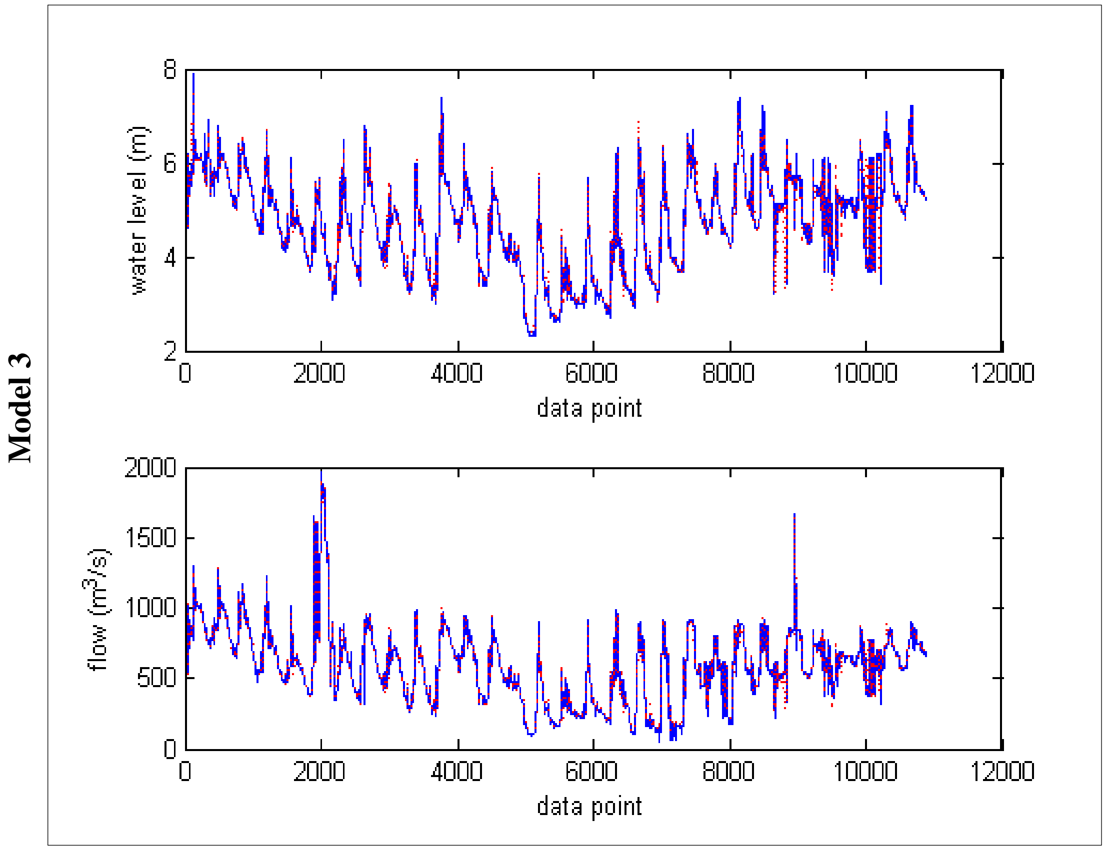


Figure 5.16: A 1-day ahead time series comparison of observed and forecasted data on the selected ANN structures

In the light of considerable noise that characterise hydrological data from data-poor catchments, Model 3 (the best model identified in the previous section was also tested for forecasting but based on features (SOM predicted values) as training data. With three inputs and two outputs as before, the number of hidden neurons was also systematically increased from 2 to 15 at a step of one.

Results are shown in Figure 5.17. ANN's prediction accuracy significantly improves with feature data. With MSRE, results are mixed; in some cases ANN trained on SOM features emerges as better, in other cases ANN is superior on raw data. Nevertheless, both R and NS show the modelling skills of ANN are enhanced when trained on feature data, supporting findings by Rustum & Adeloye (2012). This is important for data-poor areas where data is characterised by noise. By using SOM to first pre-process the data to obtain the error-free features, which are then used to drive the MLP-ANN, results can be enhanced.

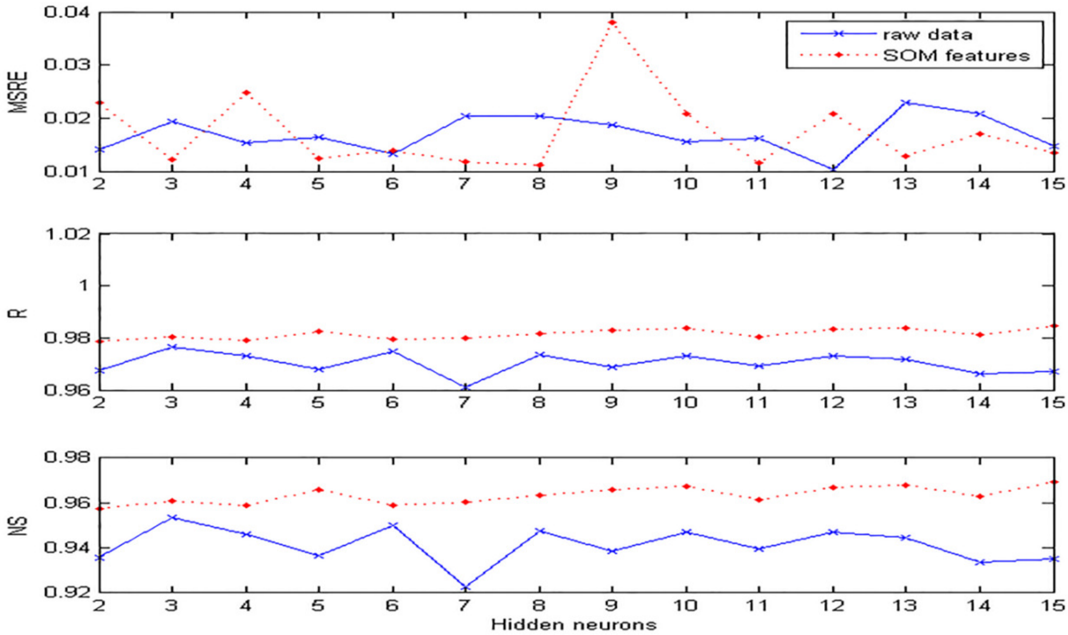


Figure 5.17: ANN performance when trained on raw data and SOM features.

5.4.2 Flow and water level forecasting for 2 to 5 day leads

While a day's forecast is good, a longer lead prediction would be far more important for flood warning. The results on the 1-day ahead forecasts presented in the previous section confirmed that Model 3, with just the day's level, flow and rainfall will give satisfactory forecasts. This is an indication that for longer lead times, there is no need to consider longer memory models. Consequently, further ANNs were trained to forecasts 2–5 days ahead levels and flows at Chiromo using the day's measurement of two of the same inputs employed for model 3 for the 1-day lead forecasts. The input variable excluded was the catchment rainfall on the day. This was because, although the inclusion of rainfall as an input has been found to improve flow predictions (Toth and Brath, 2007b; Wu and Chau, 2011), Wu & Chau (2011) observed that including rainfall in the input space only improved the results for lead times within the concentration time of a catchment. Otherwise, the impact of rainfall was insignificant. Since the time of concentration of Ruo catchment at Chiromo is less than a day, the day's rainfall was omitted and a series of 2-3-2 ANN models were trained on both raw data and the SOM features as before for 2 to 5 days' lead. The forecasts are mathematically expressed as follows:

2 day lead $$\left(CRL_{t+2}, CRF_{t+2}\right) = f\left(CRL_t, CRF_t\right) \tag{5.2}$$

3 day lead $$(CRL_{t+3}, CRF_{t+3}) = f(CRL_t, CRF_t) \tag{5.3}$$

4 day lead $$(CRL_{t+4}, CRF_{t+4}) = f(CRL_t, CRF_t) \tag{5.4}$$

5 day lead $$(CRL_{t+5}, CRF_{t+5}) = f(CRL_t, CRF_t) \tag{5.5}$$

Both the raw data and SOM features were used. The results are summarized in Table 5.11. It is clear from Table 5.11 that in general, model performance decreases with increasing lead time. The MSRE on both raw and feature data increases with increasing lead time. Similarly, R and NS decrease with increasing lead. This behaviour is not unexpected. According to Solomantine & Dulal (2003) as the lead time increases, the inputs used are the remotest and, therefore, do not contain the recent information.

Table 5.11: Comparison of raw and SOM-trained 2-3-2 MLP-ANN for forecasting

Lead time (days)	MSRE					
	Water level		Flow		Average	
	Raw	SOM	raw	SOM	raw	SOM
2	0.0039	0.0029	0.0286	0.0223	0.0163	0.0126
3	0.0055	0.0030	0.0443	0.0275	0.0249	0.0153
4	0.0068	0.0038	0.0542	0.0334	0.0305	0.0186
5	0.0079	0.0044	0.0675	0.0394	0.0377	0.0219
Lead time (days)	**NS**					
	Water level		Flow		Average	
	Raw	SOM	raw	SOM	raw	SOM
2	0.9214	0.9523	0.9244	0.9577	0.9229	0.9550
3	0.8873	0.9507	0.8723	0.9494	0.8798	0.9501
4	0.8779	0.9329	0.8723	0.9268	0.8751	0.9299
5	0.8393	0.9176	0.8469	0.9099	0.8431	0.9138
Lead time (days)	**R**					
	Water level		Flow		Average	
	Raw	SOM	raw	SOM	raw	SOM
2	0.9599	0.9759	0.9615	0.9787	0.9607	0.9773
3	0.9420	0.9750	0.9343	0.9744	0.9382	0.9747
4	0.9370	0.9660	0.9363	0.9627	0.9367	0.9644
5	0.9162	0.9580	0.9203	0.9540	0.9183	0.9560

As before, there is a significant improvement in forecast accuracy when ANN is trained on feature data. SOM features also increases lead time. With raw data, remarkably good forecasts were obtained up to two days ahead (based on the worst indicator, NS) with fairly satisfactory 3, 4 and 5-day forecasts. In contrast, with ANN trained on features, very satisfactory results for short-term forecasts of up to five days are attained.

The availability and quality of data in developing countries poses a big challenge for hydrological modelling; data-driven models such as ANN present alternatives. While most hydrological studies have stalled due to data demands posed by traditional models, coupling SOM and MLP-ANN offers an alternative for these data-scarce countries. SOM is quite robust to missing data and can therefore infill for large gaps, something that would be impossible with traditional infilling methods, thus presenting a relatively long series needed for hydrological modelling. With most of the data characterised by noise, SOM filtered data also present an alternative way of enhancing results. In this study, flows and water levels at Chiromo are reproduced to a high accuracy with a parsimonious MLP-ANN model. When SOM features are used, not only are forecasts very good for short lead times, the results are enhanced for longer lead times.

5.5 The vulnerability profile of the Lower Shire Valley

As underscored by Cardona (2004), the hazard is one determinant of risk whose sole occurrence does not translate to risk. Only when the hazard intersects in space with vulnerability is risk realised. This section provides results of the vulnerability component.

5.5.1 Vulnerability magnitudes

As described in the methodology section, the measurement of vulnerability was based on the combination of scores and weights. A score gave the actual measure of the variable. The weights on the other hand, gave the importance of the variable in contributing to exposure, susceptibility or capacity.

The perceptions of communities as to the importance of the variables in contributing to vulnerability, on a scale of 1 – 10, (with 10 being very important) are shown in Table 5.12. As expected, there are differences in weights accorded to the variables by communities. However, for the majority of variables and for a given variable, the differences between weights tend to be insubstantial suggesting similar perceptions for a given variable. Further, results suggest that communities perceive the variables captured by the CBDRI as being very important in contributing to their vulnerability. Of the 38 variables used, 34 had a mode in the range of 7-9 (Table 5.12). A similar pattern emerge when mean values are considered.

It nonetheless emerges from the results that while perceived important; some indicators of the CBDRI are not applicable to the Lower Shire Valley and probably to most developing countries. These indicators are notably those economic in nature, e.g. *access to national emergence fund, access to international emergency fund, existence of an insurance market* and *existence of mitigation* and *reconstruction loans*. Further, in a region where businesses are mainly small-scale and family-run, the indicator measuring economic stability i.e. *the proportion of businesses with a workforce of less than 20 employees* is the same across the valley. This would call for substitution with more befitting indicators.

In the context of Lower Shire Valley and with regard to economic capacity, the magnitude of public works by direct labour proves a more appropriate indicator instead. Although not used, access to relief and rehabilitation is also ideal. Nevertheless, in such a country where public works pay MK300 per day (less than 1USD per day as of 2013) and is delayed to coincide with the planting season and where relief and response trickle in much later after the flood has stricken (appendix C), the use of such variables would not alter the magnitude of economic incapacity associated with rural people in the Lower Shire anyway. Besides, the indicators used in the adapted CBDRI are those likely to be readily available in other countries with different spectra of vulnerability conditions thus making the wider implementation of the CBDRI much more feasible.

With the CBDRI as implemented in this study, the ultimate weights for the variables and the corresponding scores are shown in Table 5.13; resulting calculated levels of total vulnerability are shown in Figure 5.18. Figure 5.19 on the other hand shows vulnerability by exposure, susceptibility and lack of capacities.

Table 5.12: Perceived importance of variables in contributing to vulnerability

Factor component	Indicator Name	Indicator	Mbenje	Mlolo	Tengani	Ngabu	Malemia	Ndamela	Nyachikhaza	Ngabu	Katunga	Chapananga	Maseya	Makhuwila	Lundu	MODE	AVERAGE
EXPOSURE																	
Structures	(E1) Lifelines	% of home with potable water	3	7	7	8	5	2	2	3	2	3	5	4	7	3	4
Economy	(E2) Economy	average income per capita/day	8	8	8	8	8	7	8	7	8	7	6	7	10	8	8
SUSCEPTIBILITY																	
Physical	(S1) Density	People per km^2	8	5	5	10	8	7	8	9	8	9	9	5	6	8	7
	(S2) Demographic pressure	Population growth rate	6	5	5	10	8	7	8	8	8	9	9	5	6	8	7
	(S3) Access to basic services	% of home with potable water	4	7	2	5	5	4	10	10	4	5	7	5	4	4	6
Social	(S4) Poverty level	% of population below poevrty line	7	9	7	10	8	9	9	9	8	8	7	3	9	9	8
	(S5) Literacy	% of people that can aread and write	5	9	7	8	7	7	8	10	8	8	8	6	9	8	8
	(S6) Attitude	priority of population to protect against a hazard	2	9	5	6	8	2	7	10	9	7	7	7	7	7	7
	(S7) Decentralization	proportion of self geranated revenue of total budget	9	10	9	9	8	6	7	9	9	9	8	8	9	9	8
	(S8) Community participation	% of voter turnout at at last commune elections	2	8	9	9	8	2	2	10	7	3	5	3	4	2	6
Economic	(S9) Local resource base	Total available budget	8	10	9	8	7	7	7	10	9	9	8	8	9	8	8
	(S10) Diversification	Economic sector for employment	5	8	7	8	7	7	7	10	9	9	8	8	9	8	8
	(S11) Stability	% business with fewer than 20 employees	7	8	8	7	7	7	7	9	4	9	8	8	9	7	8
	(S12) Accessibility	Number of interruption of roads in the last 2 years	5	9	5	4	4	7	9	10	4	4	6	7	9	4	6
Environmental	(S13) Environmental	Area under forest	5	4	7	8	8	9	9	10	7	7	8	6	9	7	7
CAPACITIES AND MEASURES																	
Physical capacity	(C1) Landuse planning	Enforced landuse planning or zoning regulations	7	9	9	9	7	9	9	10	10	9	8	7	8	9	9
	(C2) Building codes	Applied building codes	7	9	9	9	7	9	9	10	10	9	8	7	8	9	9
	(C3) Retrofitting/Maintenance	Applied retroffiting and regular maintenance	7	9	8	9	8	9	9	10	10	9	6	7	8	9	8
	(C4) Preventive measures	Expected effect of impact-limiting structures	6		8	9	8	9	9	10	9	9	8	7	10	9	9
	(C5) Environmental management	Maesures that promote and enforce nature conservation	9	9	8	9	8	9	9	10	9	9	8	6	10	9	9
Societal capacity	(C6) Public awareness programs	Frequency of public awareness programs	8	10	8	9	10	9	9	10	8	9	8	9	10	9	9
	(C7) School curriculum	Scope of relevant topics taught at school	7	7	8	7	8	4	9	10	8	9	8	7	10	7	8
	(C8) Emergency response drills	Ongoing emergency response training and drills	8	10	8	8	8	9	9	9	8	9	8	8	10	8	9
	(C9) Public participation	Emergence committee with public representatives	9	10	7	9	10	9	9	10	8	9	7	9		9	9
	(C10) Local risk	Grade of organisation of local groups	8	10	9	8	10	9	9	9	9	9	8	9	9	9	9
Economic capacity	(C11) Local emergency fund	Local emergency fund as % of local budget	9	10	9	9	10	9	9	9	9	9	8	9	10	9	9
	(C12) Access to national	Release period of national emergency fund	5	10	9	9	10	9	9	9	9	9	8	9	10	9	9
	(C13) Access to international	Access to international emergency funds	7	10	9	8	10	9	9	9	9	9	8	9	10	9	9
	(C14) Insurance market	Availability of loans for disaster risk reduction measures	8	10	9	9	10	9	9	9	9	9	8	9	10	9	9
	(C15) Mitigation loans	Availability of loans for disaster risk measures	8	10	7	8	10	9	9	9	9	9	8	9	10	9	9
	(C16) Reconstruction loans	Availability of reconstruction credit for affected households	9	10	7	9	10	9	9	9	9	9	9	9	10	9	9
	(C17) Public works	Magnitude of local public works programm	7	10	9	9	10	9	9	9	10	9	9	9	10	9	9
Management and Institutional Capacity	(C18) Risk management/emergency	Meeting frequency of a community committee	9	9	9	9	10	9	9	10	10	8	9	9	10	9	9
	(C19) Risk map	Availability and circulation of maps	7	9	9	8	7	8	9	10	10	8	9	8	10	9	9
	(C20) Emergency plan	Availability and circulation of emergency plans	5	9	9	9	9	8	9	10	10	9	8	8	3	9	8
	(C21) Early warning system	Effectiveness of early warning system	9	10	9	9	8	8	9	9	10		8	7	5	9	8
	(C22) Institutional capacity building	Frequency of training of local institutions	6	10	9	9	8	9	10	10	10	9	8	8	10	10	9
	(C23) Communication	Frequency of contact with district level institutions	7	10	9	9	8	9	8	10	10	10	8	9	10	10	9

Table 5.13: Scores and associated weights as allocated by communities

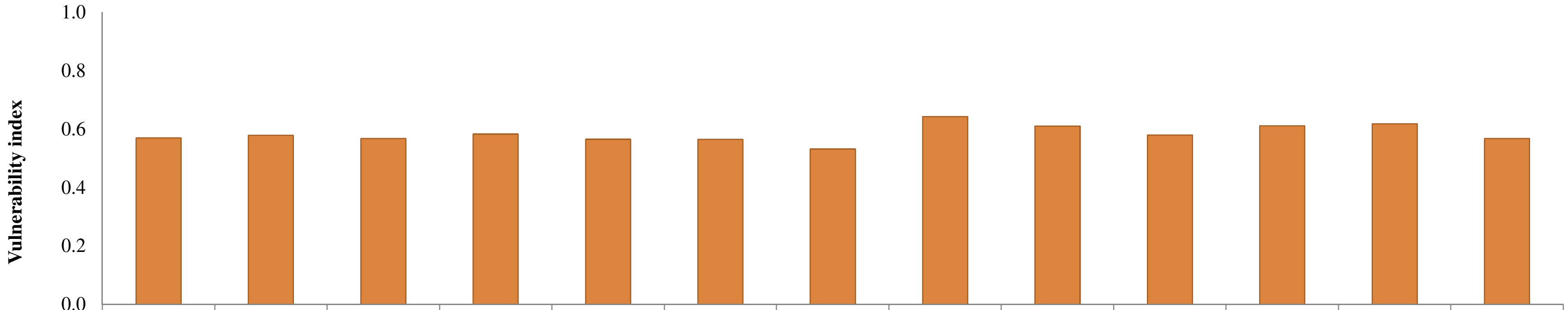
Factor component	Indicator Name	Mbenje		Mlolo		Tengani		Ngabu		Malemia		Ndamela		Nyachikhaz		Ngabu		Katunga		Chapananga		Maseya		Makhuwila		Lundu	
EXPOSURE		score	w*	score	w	score	w	score	w	score	w	score	w	score	w	score	w	score	w	score	w	score	w	score	w	score	w
Structures	(E1) Lifelines	3	9	3	9	3	9	3	9	3	9	3	9	1	9	3	9	3	9	2	9	3	9	3	9	3	9
Economy	(E2) Economy	1	24	1	24	1	24	1	24	1	24	1	24	1	24	1	24	1	24	1	24	1	24	1	24	1	24
SUSCEPTIBILITY																											
Physical	(V1) Density	2	3	2	2	1	2	1	2	2	2	2	2	1	2	2	2	2	2	1	2	2	2	2	2	1	2
	(V2) Demographic pressure	2	3	2	3	2	3	2	3	1	3	1	3	1	3	2	3	3	3	2	3	2	3	1	3	1	3
	(V3) Access to basic services	2	1	1	2	1	2	1	2	1	2	1	2	3	2	1	2	1	2	2	2	1	2	1	2	1	2
Social	(V4) Poverty level	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	(V5) Literacy	2	3	2	3	2	3	2	3	2	3	2	3	3	3	2	3	2	3	2	3	2	3	2	3	1	3
	(V6) Attitude	2	3	1	3	1	3	2	3	2	3	2	3	2	3	3	3	3	3	3	3	3	3	3	3	1	3
	(V7) Decentralization	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	(V8) Community participation	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	2	1	1	1	1	1	1	1	1	1
Economic	(V9) Local resource base	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	(V10) Diversification	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	(V11) Stability	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	(V12) Accessibility	3	1	3	2	2	2	3	2	3	2	3	2	3	2	3	2	2	2	3	2	2	2	3	2	3	2
Environmental	(V13) Environmental	1	3	3	3	1	3	2	3	1	3	1	3	3	3	2	3	2	3	1	3	1	3	3	3	3	3
CAPACITIES & MEASURES																											
Physical capacity	(C1) Landuse planning	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C2) Building codes	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C3) Retrofitting/Maintenance	1	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C4) Preventive measures	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1
	(C5) Environmental management	1	2	2	1	3	1	1	1	1	1	1	1	2	1	2	1	3	1	2	1	2	1	2	1	2	1
Societal capacity	(C6) Public awareness	3	2	3	1	1	1	2	1	2	1	2	1	2	1	1	1	3	1	1	1	3	1	2	1	2	1
	(C7) School curriculum	3	1	3	1	3	1	3	1	3	1	3	1	1	1	3	1	3	1	3	1	3	1	3	1	3	1
	(C8) Emergency response drills	3	1	3	1	1	1	2	1	3	1	3	1	3	1	1	1	1	1	2	1	1	1	2	1	2	1
	(C9) Public participation	3	2	3	2	3	2	3	2	3	2	3	2	3	2	3	2	3	2	3	2	3	2	3	2	3	2
	(C10) Local risk management/emergency groups	3	1	3	1	3	1	3	1	3	1	3	1	3	1	3	1	3	1	3	1	3	1	3	1	3	1
Economic capacity	(C11) Local emergency fund	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C12) Access to national	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C13) Access to international	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C14) Insurance market	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C15) Mitigation loans	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C16) Reconstruction loans	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C17) Public works	1	1	1	1	1	1	3	1	3	1	3	1	2	1	2	1	3	1	1	1	1	1	1	1	1	1
Management and Institutional Capacity	(C18) Risk management/emergency	2	1	2	1	2	1	2	1	3	1	2	1	3	1	1	1	1	1	1	1	2	1	1	1	3	1
	(C19) Risk map	2	1	1	1	1	1	3	1	3	1	3	1	3	1	1	1	1	1	1	1	1	1	1	1	1	1
	(C20) Emergency plan	3	1	1	1	1	1	2	1	3	1	3	1	3	1	1	1	1	1	1	1	1	1	1	1	3	1
	(C21) Early warning system	1	1	2	1	1	1	2	1	1	1	1	1	3	1	1	1	2	1	3	1	1	1	2	1	1	1
	(C22) Institutional capacity	1	2	2	2	1	2	1	2	2	2	2	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
	(C23) Communication	3	2	3	2	2	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	3	2	2	2

Total vulnerability scores for communities fall in the range of 0.53 - 0.64 suggesting that the Lower Shire Valley is a region in the medium to high category of vulnerability to flooding. Surprisingly, results show a predominance of medium aggregate vulnerability levels.

Susceptibility, quite marked from exposure and capacities, manifests as high (0.6-0.8) to very high (0.8-1.0) and has the greatest contribution to the vulnerability. It is followed by exposure and capacity-related vulnerability in the medium range (0.4 – 0.6).

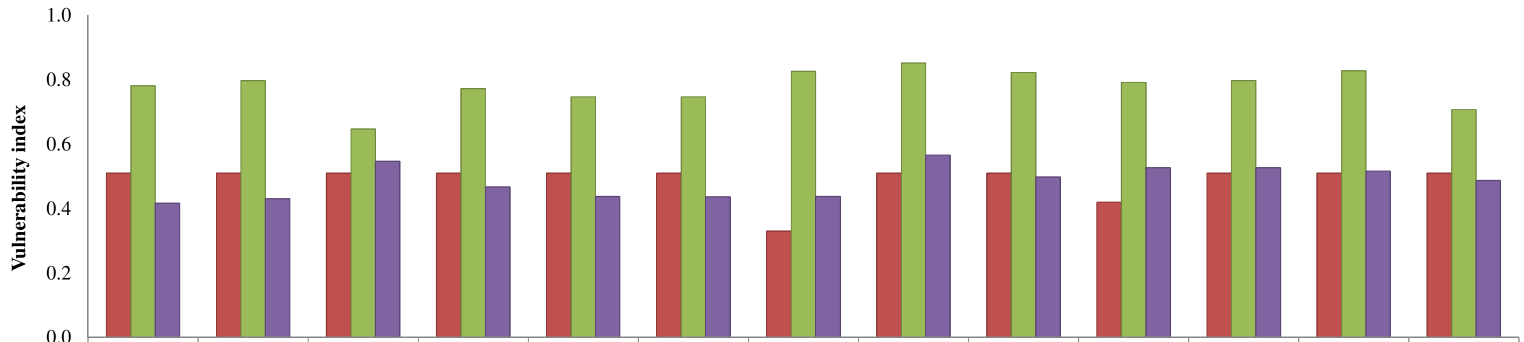
From a Sustainable Development Framework (Figure 5.20) i.e. a social, economic, environmental and physical perspective, the economic sub-component, manifesting as high to very high, emerges, in general, as a dominant component. Either physical or social vulnerability tend to follow in the medium to high ranges. Environmental vulnerability can be the least contributing component in some communities; it may also surpass other dimensions in other communities.

When viewed from a coupled IPCC and Sustainable Development Framework perspective (Figure 5.21), it is apparent that high susceptibility levels observed are driven by economic and social susceptibilities and to a considerable extent by environmental susceptibility. Physical susceptibility is the lowest contributing dimension to susceptibility. In particular, economic susceptibility is predominantly very high linked to factors such as a lack of economic resources, an undiversified economy and lack of employments opportunities (appendix C). Social susceptibility falls in the high to very high levels linked to factors of poverty and literacy levels. Environmental susceptibility is also predominantly high to very high but manifest as low in certain communities. Physical susceptibility manifests as medium to high.



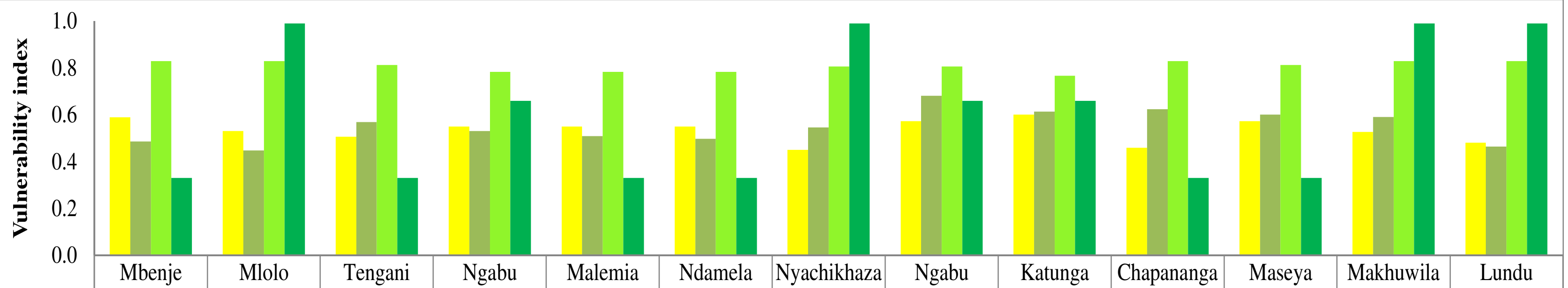
	Mbenje	Mlolo	Tengani	Ngabu	Malemia	Ndamela	Nyachikhaza	Ngabu	Katunga	Chapananga	Maseya	Makhuwila	Lundu
CoV	0.57	0.58	0.57	0.58	0.56	0.56	0.53	0.64	0.61	0.58	0.61	0.62	0.57

Figure 5.18: Aggregate vulnerability across communities in the Lower Shire Valley (CoV= Community Vulnerability)



	Mbenje	Mlolo	Tengani	Ngabu	Malemia	Ndamela	Nyachikhaza	Ngabu	Katunga	Chapananga	Maseya	Makhuwila	Lundu
E	0.51	0.51	0.51	0.51	0.51	0.51	0.33	0.51	0.51	0.42	0.51	0.51	0.51
S	0.78	0.80	0.65	0.77	0.75	0.75	0.83	0.85	0.82	0.79	0.80	0.83	0.71
LoC	0.42	0.43	0.55	0.47	0.44	0.44	0.44	0.57	0.50	0.53	0.53	0.52	0.49

Figure 5.19: Vulnerability magnitudes from exposure, susceptibility and a lack of capacity across communities. (LoC =Lack of capacity)



	Mbenje	Mlolo	Tengani	Ngabu	Malemia	Ndamela	Nyachikhaza	Ngabu	Katunga	Chapananga	Maseya	Makhuwila	Lundu
Physical	0.59	0.53	0.51	0.55	0.55	0.55	0.45	0.57	0.60	0.46	0.57	0.53	0.48
Social	0.49	0.45	0.57	0.53	0.51	0.50	0.55	0.68	0.61	0.62	0.60	0.59	0.47
Economic	0.83	0.83	0.81	0.78	0.78	0.78	0.81	0.81	0.77	0.83	0.81	0.83	0.83
Environmental	0.33	0.99	0.33	0.66	0.33	0.33	0.99	0.66	0.66	0.33	0.33	0.99	0.99

Figure 5.20: Vulnerability of the Lower Shire from Sustainable Development Framework

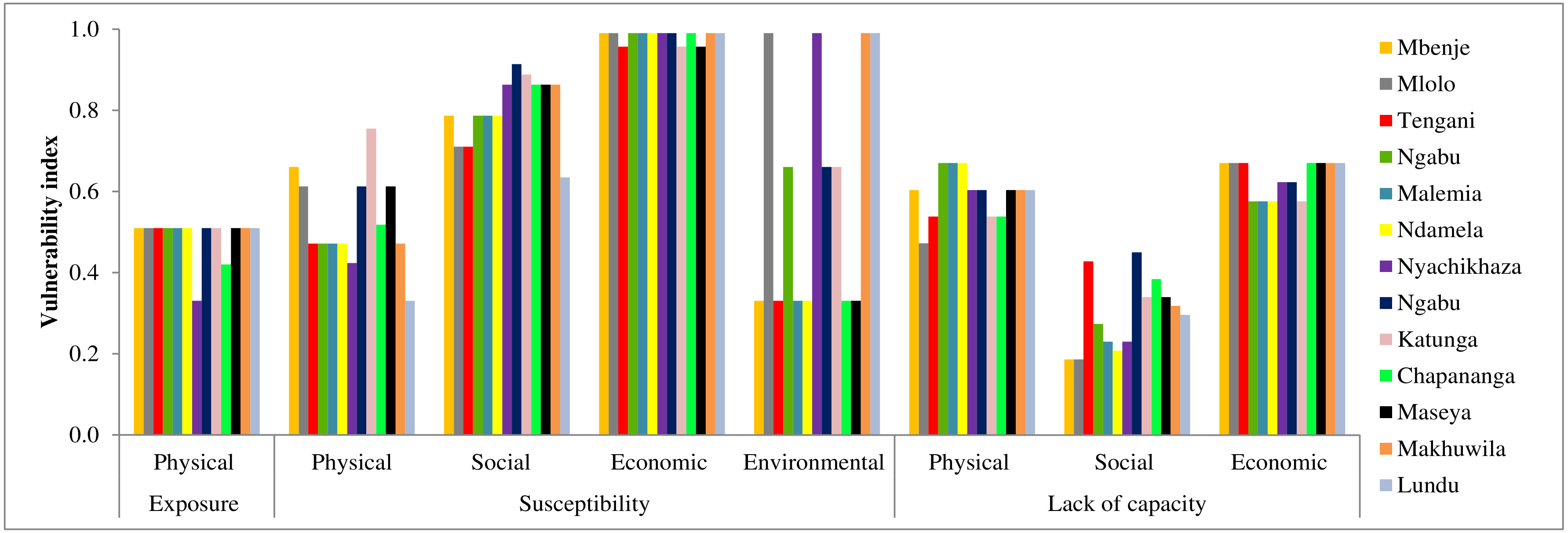


Figure 5.21: Vulnerability profile from a coupled IPCC-Sustainable Development Framework

In examining capacity-induced vulnerability, results show that capacity-related vulnerability is determined by high limitations in economic and physical capacities, both of which tends to be medium to high. In other words, economic and physical capacities are low. Viewed against appendix C, local emergency funds, access to national funds, loans for mitigation or reconstruction are non-existent. In addition, as with many developing countries an insurance market does not exist. In contrast, social capacity including management and institution surprisingly manifests as high resulting in low social capacity-related vulnerability (Figure 5.21) which, undoubtedly has an attenuating effect on overall capacity-induced vulnerability observed in Figure 5.19. A low capacity-related social susceptibility emanates from what comes out as substantial public awareness, public participation, existence of disaster-mandated local institutions, existence of non-conventional warning flood systems (whistling, drumming, use of text messages) and substantial coordination amongst local institutions (appendix C). These institutions called Civil Protection Committees (CPC) exist at all levels: at district level (DCPC), area level (ACPC) and at group village level (VCPC).

The context-specific nature of vulnerability, coupled with the differences in the indices used and a dearth in general on studies that have attempted to quantify vulnerability to flooding in SSA, limits a discussion of these results in the wider context. Nonetheless, the findings on the vulnerability to flooding presented in this study mirrors, in several aspects, findings of other studies on the vulnerability of the rural population in SSA to other climatological hazards.

While measurement of vulnerability from a social, economic, environmental and physical perspective is elusive, the predominance of environmental vulnerability magnitudes in the high and very high categories is consistent with the state of the environment not only in the region but also in the country. The dominant driver of landcover change in SSA has been agriculture and much of the changes has taken place in the Zambezia region, a region covering the study area (Brink and Eva, 2009). A study by Bandyopadhyay et al. (2011) confirms Malawi is a country in biomass distress with the southern region where the study area falls, being the most stressed. In fact, Minde et al. (2001) earlier observed that in the southern region of Malawi, there is little forest left outside forest reserves. Further, given the demand of forest products placed on the Shire

Basin due to its proximity with the city of Blantyre (Palamuleni et al., 2010), the levels of environmental vulnerability found in communities in this study most which fall in Chikwawa, are not unexpected. It is however difficult to explain from this study the low levels of environmental vulnerability observed in other communities such as Maseya and Chapananga in Chikwawa and, Mbenje, Tengani, Malemia and Ndamela in Nsanje. This may require an in-depth analysis.

In general, the vulnerability of communities in SSA to climatological hazards has been perceived as high. According to World Bank (2010a), SSA lacks fiscal resources to commit to disaster risk management. The economy is largely driven by rainfed agriculture and therefore highly vulnerable to climatological shocks. Infrastructure is poor. This does not only make SSA very prone to damage, it also impinges on relief and recovery. Institutional and policy frameworks and knowledge base in general are weak. The situation is exacerbated by population pressure in marginal lands (Di Baldassarre et al., 2010; World Bank, 2010a). Thus measured vulnerability to flooding in this study supports this perception.

Studies that have attempted to quantify vulnerability to other climatological hazards, notably climate change, albeit with different indices, have also reached similar conclusions of medium to high vulnerability for the rural communities in SSA. Gbetibouo and Ringler's (2009) found that in comparison to more developed provinces (Western Cape, Gauteng), provinces characterised by a rural subsistent and agriculture-dependent population, high unemployment and high illiteracy (Limpopo, KwaZulu Natal and Eastern Cape) exhibited a sensitivity (susceptibility) level that fell in the 'high' category in contrast to a 'low' level for the developed provinces. They also found that adaptive capacity in the provinces of Limpopo, KwaZulu Natal and Eastern Cape was 'low'. Reference to exposure is eluded as their exposure variables are analogous to the hazard in this study, the incorporation of which would constitute risk.

In Mozambique, Hahn et al. (2009) measured the vulnerability to climate change of two districts: Moma and Mabote. While they also measured vulnerability by exposure, sensitivity and adaptive capacity, a lack of categorization on the severity of vulnerability from this perspective prevents insightful comparisons. However, on the basis of Livelihood Vulnerability Index (LVI) alternatively used and on account of its five components deemed vulnerability components in the context of this study i.e. Socio-Demographic Profile (SDP), Livelihood Strategies (LS), Social Networks (SN), Health (H), Food (F) and Water (W), the scores found, in general, did not reflect low vulnerability. On a scale of 0 - 0.5, aggregate vulnerability scores were 0.316 and 0.306 respectively. Further, except for the Socio-Demographic Profile in Moma and the Water component in Mabote that measured 0.175 and 0.099 respectively, the rest of the dimensions fell in the range of 0.25 – 0.48 suggesting medium to high vulnerability.

While the results in both studies ought to be treated with caution as the values were relative amongst the provinces and districts investigated, the population in both studies was rural and therefore may be representative of other rural communities in SSA including the Shire Valley.

In a recent study on the vulnerability to climate change covering the whole Malawi, Malcomb et al. (2014) measured vulnerability from the equation: *Adaptive Capacity + Livelihood Sensitivity - Physical Exposure* with *Adaptive Capacity* and *Livelihood* according to the authors constituting *resilience*. As with Gbetibouo and Ringler's (2009), the exposure element in Malcomb et al.'s study is disregarded for vulnerability discussion, on the basis it constitutes a hazard component. Their resilience map is shown in Figure 5.22 from which it is apparent that while resilience is variable across the Lower Shire Valley, it falls on the lower end of the resilience scale, pointing to vulnerability that is high.

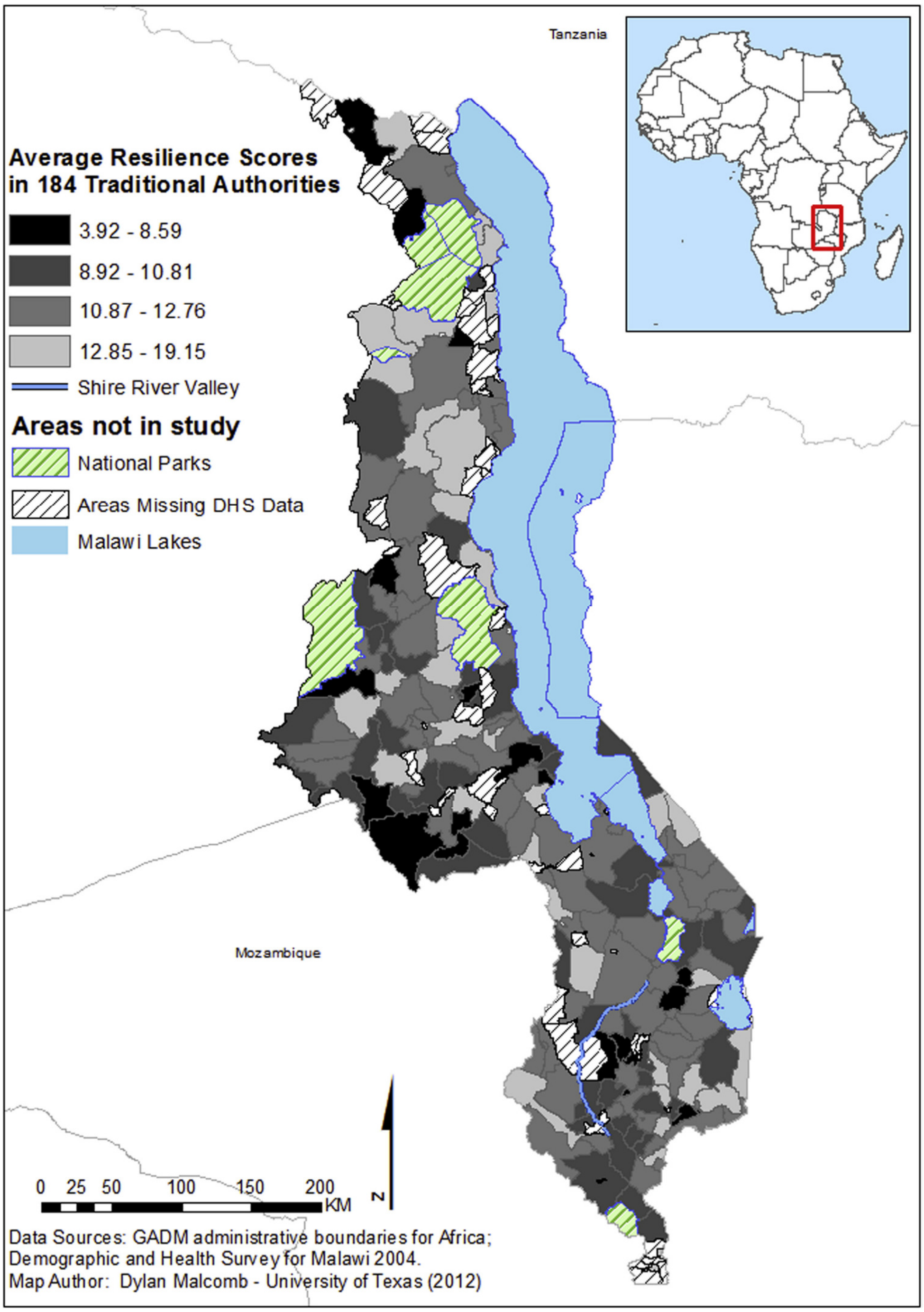


Figure 5.22: Resilience to climate change based on assets, access and livelihoods
Source: (Malcomb et al., 2014)

While vulnerability magnitudes found in this study are in tandem with other studies in SSA highlighted above, in coupling exposure, susceptibility and capacity to sustainable developments elements, the study brings to light significant results. Results show the low capacity associated with rural communities in SSA is economic and physical in nature; societal capacity, often unaccounted for in these studies (Gbetibouo and Ringler, 2009; Malcomb et al., 2014) tends to be substantially higher.

5.5.2 Spatial trends

Spatial trends are shown in Figure 5.23 and Figure 5.24. While there are differences in actual vulnerability scores (Figure 5.19), there is a general pattern of homogeneity in the levels of vulnerability across communities suggesting insubstantial differences between communities. The pattern is observed in aggregate community vulnerability, exposure, susceptibility and capacity related vulnerability. It also manifests when vulnerability is viewed as social, economic and physical. Environmental vulnerability however is the exception; it presents the most spatially differentiated dimension of vulnerability.

In spite of a relative uniform degree of vulnerability for a given dimension, there is a clear trend of extreme ends of vulnerability being concentrated in Chikwawa. Very high susceptibility levels are associated more with communities in Chikwawa than Nsanje. In the same way, few communities that emerge as highly vulnerable on aggregate vulnerability are also found in Chikwawa. A possible explanation is the spatial distribution of environmental vulnerability whereby high and very high levels of aggregate vulnerability tend to be concentrated in Chikwawa.

The concentration of environmental vulnerability in Chikwawa, amongst many factors, stem from its proximity to the city of Blantyre. Severity of deforestation in the Shire Basin has been linked to distance from urban centres (Palamuleni et al., 2010) with cities providing a lucrative market for charcoal and wood to meets the energy needs of the urban poor, and the urban masses in general in the face of constant power cuts. The impact of household energy needs in cities on the deforestation of outskirt areas have been also reported in Masvingo city in Zimbabwe (Mapira and Munthali, 2011).

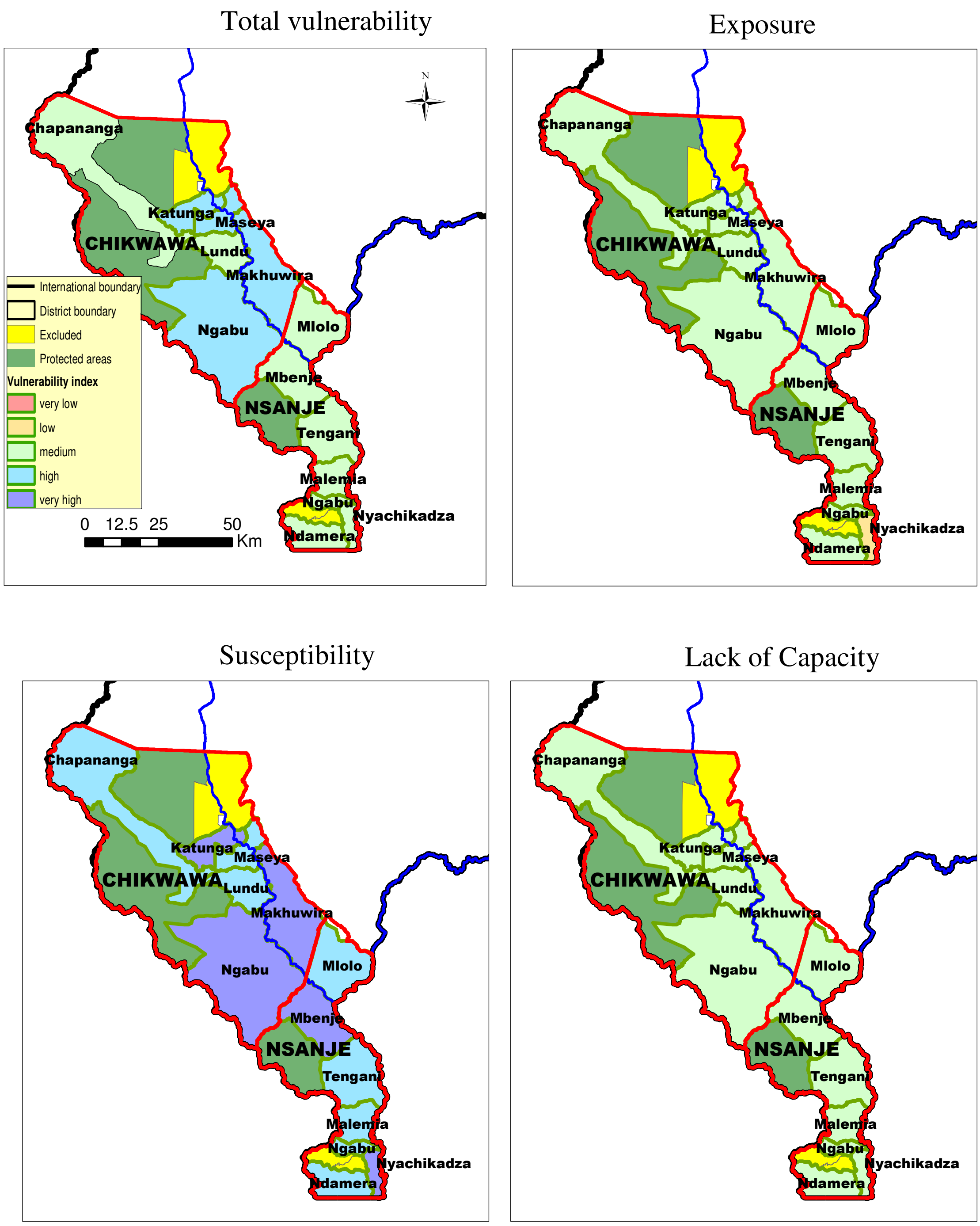


Figure 5.23: Spatial variation in community vulnerability arising from exposure, susceptibility and capacity

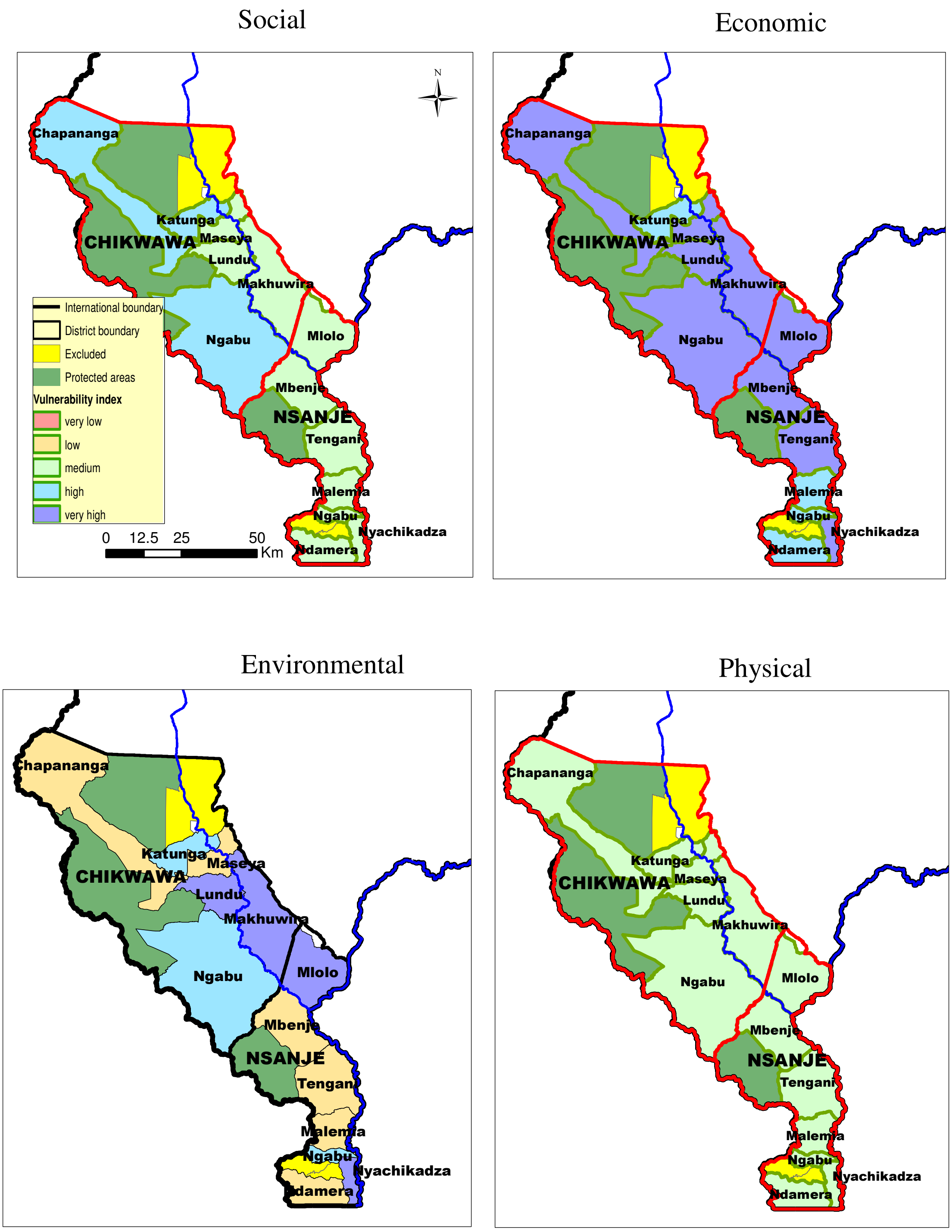


Figure 5.24: Spatial variability in community vulnerability - a social, economic, environment and physical perspective

Vulnerability is a spatially differentiated variable. Except for the environmental vulnerability, this is generally not supported for the Lower Shire Valley in this study. There are several possible explanations. Vulnerability is a scale-dependent variable that become more conspicuous with fineness in scale. Differences in vulnerability in the Lower Shire Valley may operate at a much smaller scale such as a village or at household level. The spatial scale used of the ADC level used therefore may be too big to unmask heterogeneity in vulnerability across the valley. Again, the scores used from 1 to 3 to define what is low, medium or high may too coarse to differentiate markedly between communities.

On the other hand, homogeneity in vulnerability for communities in the Shire Valley is somewhat not unexpected. Nsanje and Chikwawa are very similar districts in their social and economic profile as summed up in their poverty levels, which also happen to be the highest in the country (National Statistical Office, 2009; National Statistical Office, 2012). This is further evident in the raw data presented in appendix C where it can be seen that most respondents are on below 1USD per day. In addition, their economic capacity for disaster management in general is similar: both are served with non-governmental organisations and like the rest of the country, with local government decentralised institutional structures. In this respect, vast diversity in vulnerability in the Lower Shire valley at this scale is unexpected.

A lack of vast diversity in vulnerability amongst clusters of rural communities has also been observed in other parts of SSA though notably with respect to climate change. In Gbetibouo and Ringler's (2009) study in the Republic of South Africa, the differences in susceptibility and capacities (considered to constitute vulnerability in this study) was only marked between the predominantly rural provinces (Limpopo, KwaZulu Natal and Eastern Cape) and the economically developed provinces i.e. Western Cape and Gauteng, on the other end. However, amongst the predominantly rural provinces, the outcome was similar for both components. Similarly, in Hahn et al.'s (2009) study, the difference between for Moma (0.316) and Mabote (0.306) was marginal. Thus, the lack of differences across rural communities in the Shire Valley is not unlikely. Nonetheless, this study does highlight marked differentiation in environmental susceptibility with those communities on the high end of the spectrum being very close to the city.

5.6 The flood risk of the valley

Previous sections in this study have so far examined the hazard and vulnerability in isolation. As emphasised by Cardona (2004) and Collins et. al (2009) amongst others, understanding and attempting to remediate risks to environmental hazards demands a consideration of the biophysical and social contexts that place people and property in harm's way. This underscores the fact that flood risk is much a hazard problem as a vulnerability issue. To measure the flood risk, a multiplication of hazard and vulnerability scores (Table 4.4) was used.

5.6.1 Risk magnitudes and profile

Table 5.14 shows the results of the flood risk of the Lower Shire floodplain. As shown in the table, risk to flooding in the Lower Shire Valley is in general in the medium to high categories of the risk spectrum. However, it is predominantly medium as demonstrated by the higher proportion (67%) of communities in the medium risk class in comparison to 33% in the high class.

Table 5.14: Risk to flooding across the Lower Shire Valley

Community	AHI (m)	Standardised AHI	Vulnerability	Risk	Risk rating
Maseya	1.12 (H)	0.34	0.61 (H)	0.21	H
Mbenje	1.06 (H)	0.32	0.57 (M)	0.18	H
Katunga	1.08 (H)	0.33	0.61 (H)	0.20	H
Tengani	1.03 (H)	0.31	0.57 (M)	0.18	H
Ngabu-Nsanje	0.92 (M)	0.28	0.58 (M)	0.16	M
Ndamera	0.77 (M)	0.23	0.56 (M)	0.13	M
Nyachikadza	0.94 (M)	0.28	0.53 (M)	0.15	M
Mlolo	0.86 (M)	0.26	0.58 (M)	0.15	M
Malemia	0.99 (M)	0.30	0.56 (M)	0.17	M
Lundu	0.82 (M)	0.25	0.56 (M)	0.14	M
Makhuwira	0.84 (M)	0.25	0.62 (H)	0.16	M
Ngabu-Chikwawa	0.68 (M)	0.21	0.64 (H)	0.13	M

H = High, M = Medium, L=Low

From the table, four patterns describe the flood risk of the Lower Shire valley: high hazard-medium vulnerability combination, high hazard-high vulnerability combination, combinations of medium hazard and medium vulnerability, and lastly, medium hazard-high vulnerability combinations. Communities exposed to medium hazard/ medium vulnerability combinations are the most prevalent (Ngabu of Nsanje, Ndamera, Nyachikhadza, Mlolo, Malemia and Lundu) accounting for 50% of the communities studied. High hazard-medium vulnerability pattern is associated with 16.7% of the communities (Mbenje and Tengani). A further 16.7% is exposed to medium hazard-high vulnerability combination (Makhuwila, Ngabu of Chikwawa). Similarly, only 16.7% exhibit a profile of high hazardousness intersecting with high vulnerability (Maseya, Katunga). It therefore follows that neither process, hazardousness nor vulnerability, is noticeably dominant in the risk profile for a significant proportion of communities in the Lower Shire Valley.

The dominant medium magnitudes of flood risk in the Lower Shire brought to light in this study are unanticipated in consideration of historic flood flow magnitudes on both the Shire and the Ruo documented by Shela et al. (2008) and also in respect of the poor socio-economic indicators of the region highlighted in many studies (Kaonda, 2009; Nilson et al., 2010; Shela et al., 2008). This may be mainly explained by the hazard component. The level of hazardousness measured might have been under-estimated given that tributary flows were not accounted for as flow data available suggest below-bankfull flows at Sinoya gauge station for the 2008 rainy season. Similarly velocity was not accounted for on the basis of flatness of the Shire valley.

The overall findings are nonetheless consistent with both perceived and quantified risk of other studies in the valley and more particularly those of the rural population at large in SSA though measured to other climatological hazards. In the Lower Shire valley, the level of flood risk has always been perceived as ‘high’ though in general, with no link to quantification (Governement of Malawi, 2006; Shela et al., 2008)

In a more similar study in Malawi of Malcomb et al.’s (2014), although measured with respect to climate change, Malcomb et al. also place the risk (referred in their study as vulnerability) of the Lower Shire in the low to high categories (Figure 2.5).

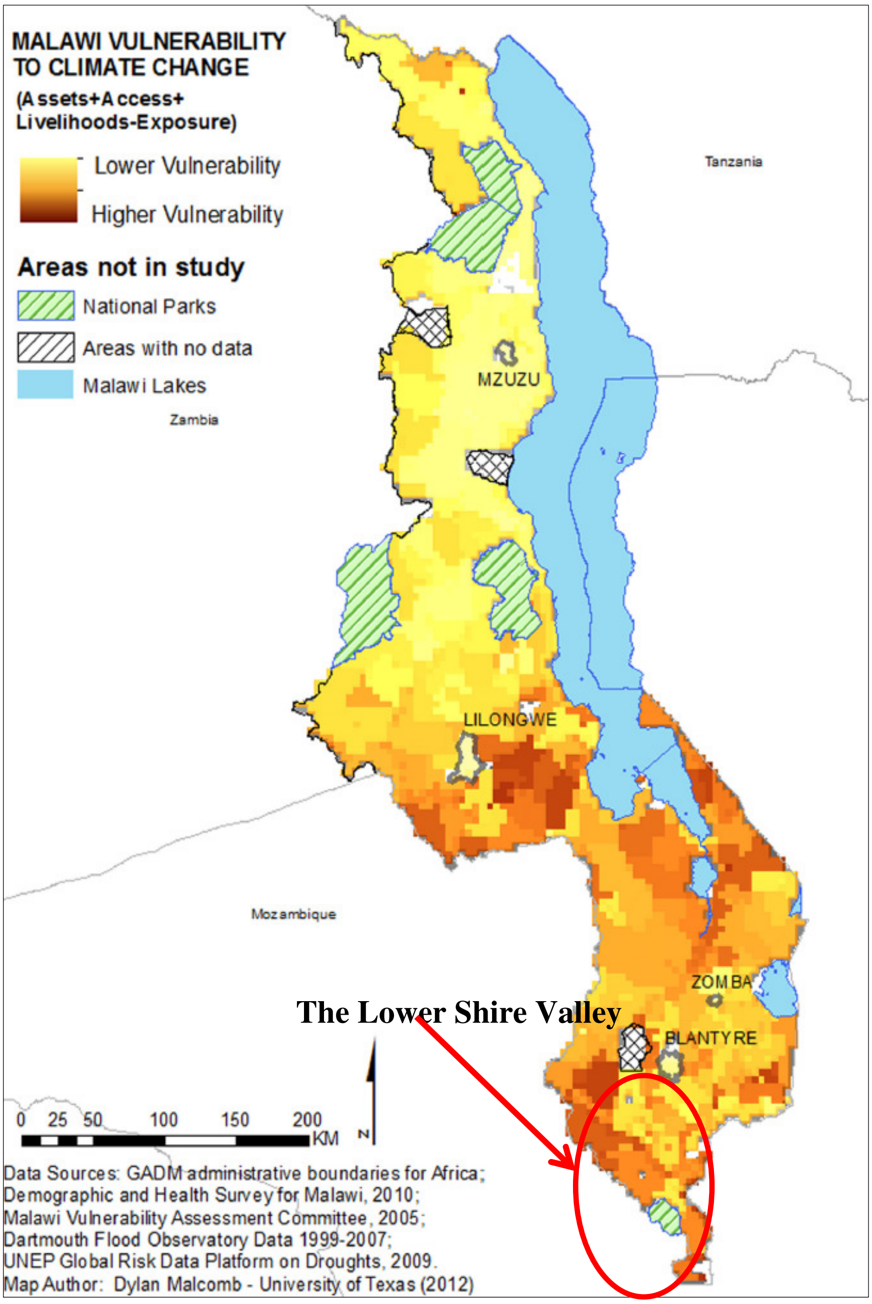


Figure 5.25: Quantified risk to climate change in Malawi

Source: (Malcomb et al., 2014)

Elsewhere in SSA where climatologigcal risk has been measured in this way, it has also been found to be predominantly medium to high. In South Africa, Gbetibouo and Ringler's (2009) found that all predominantly rural provinces (Kwazulu Natal, Eastern Cape and Limpopo) were associated with medium to high risk (referred to in their study as vulnerability). Similarly, in measuring risk to climate change in Moma and Mabote districts in Mozambique, (also referred to in their study as vulnerability), on the basis of fragility of livelihoods and health systems, people's capacity to alter the strategies and the actual climatic exposures, Hahn et al. (2009) found risk values of 0.316 and 0.326

respectively (on a scale of 0 to 0.5). Although Hahn et al. (2009) do not attach severity to the magnitudes, the values suggest medium to high risk to climate impacts.

Besides magnitudes, the risk profile to the flood hazard found in this study is also consistent with the risk profile of rural communities in SSA to climate change. Gbetibouo and Ringler's (2009) found that the coastal rural provinces of South Africa (Kwazulu Natal and Eastern Cape) were associated with risk that was defined by a combination of high levels of social vulnerability (low adaptive capacity and high sensitivity) and a high level exposure (synonymous to the hazard in this study). Limpopo, the inland province on the other hand exhibited risk that was characterized by medium exposures (hazard in this study) and high social vulnerability. Besides, they also found that areas of high hazardousness to flooding were not necessarily areas of high vulnerability.

In Hahn et al.'s (2009) study, sub-components used were not explicitly classified as either vulnerability or hazard. However, the Socio-Demographic Profile, Livelihood Strategies, Social Networks, Health, Food and Water define the intrinsic disposition of the system to harm and therefore constitute *vulnerability*. Aggregate values for two districts measured on the basis of these components as earlier indicated were 0.316 and 0.306 respectively. The Natural Disasters and Climate Variability component on the other hand included factors of frequency of floods, droughts and cyclone and statistical values of temperature and rainfall, factors exogenous to the system. In this respect, the component constituted the *hazard*. Associated values were 0.312 and 0.409 respectively. On this basis and in respect of the 0-0.5 scale used, their results also suggest that risk to climatic impacts in rural Mozambique is defined by medium to high value combinations of hazardousness and vulnerability.

Nonetheless, while the flood risk profile in this study is consistent with risk profiles in the above two studies, the smaller number of rural units involved in these two studies (3 rural provinces in Gbetibouo and Ringler's (2009) study and 2 districts in Hahn et al. (2009)) precludes establishing a dominant profile of risk to climate change. This study however finds that in the context of flood risk, for medium risk affecting the majority of communities, risk is much a function of the hazard as it is for vulnerability. However, at high risk, hazardousness is dominant.

5.6.2 Spatial trends of risk

The degree of risk is spatially illustrated in Figure 5.26. The illustration is confined to parts of the assessed ADCs that fall in the valley (150 – 30masl).

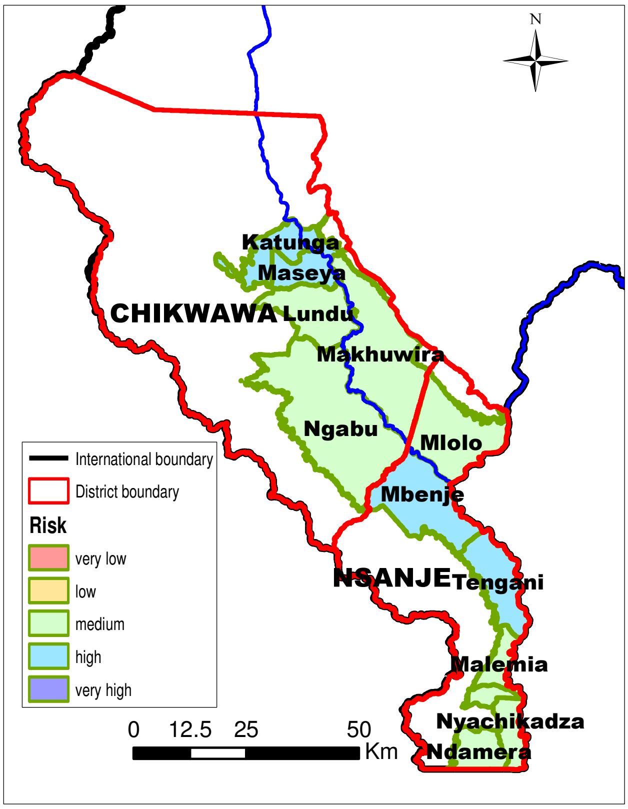


Figure 5.26: Spatial variation in flood risk across the valley

It is apparent from Figure 5.26 that communities exhibiting high risk occur both in Chikwawa and Nsanje. However, they are localised: concentrated in Katunga and Maseya and around the Shire/Ruo confluence and downstream (Mbenje and Tengani). Medium risk on the other hand is ubiquitous across the valley, an indication of relative homogeneity in flood risks in the communities. High risk geographically intersects with areas of high hazardousness (Figure 5.13) thus being associated with hazardousness dominance.

Results in general, as with the spatial variation in hazardousness and vulnerability, show little differentiation in risk indicating relative similarities across communities.

5.7 Policy implications and caveats

5.7.1 Introduction

As evident in the foregoing sections, this study has successfully implemented an index-based approach to quantify flood risk in Malawi despite the challenges faced by the paucity of hydro-meteorological data. Such challenges are common in SSA and the relative success recorded in this particular case study is therefore a ray of hope that better policy interventions, informed by objective and quantitative assessments, to contain the menace of floods and other natural hazards, are possible in SSA. Some of the policy implications and their associated caveats are summarized in the following sub-sections.

5.7.2 Policy implications

The Lower Shire is one of the poorest parts of the country. There have been numerous efforts in the region towards conventional developmental projects and flood risk reduction programs, notably by Non-Governmental Organizations and donor partners. The levels of socio-economic and environmental susceptibility (high to very high) uncovered highlight the critical need for mainstreaming flood risk reduction measures into the plethora of conventional developmental programs. This, to some extent, also addresses the issue of economic incapacity that arises from implementing lone flood risk reduction programs.

Given relatively similar influence of the hazard and vulnerability in defining this risk for greater section of the valley (67%), a significant proportion (16.7%) of communities in the valley falling on the high end of the risk spectrum for which hazardousness is dominant and an equal 16.7% of the communities exhibiting vulnerability dominance, there is need for broad-based approaches that integrate both mitigation and adaptation. In this regard, reducing physical vulnerability through exposure reduction (such as relocation) is likely to prove challenging given communities derive their livelihoods from the floodplain an observation also made by Gwimbi (2009) in Zimbabwe.

Forecasting with MLP-ANN offers an alternative to data demanding traditional models for a macro scale flood warning system.

As evidenced by the results, despite a limited economic capacity, communities exhibit higher level societal capacity in diverse forms. These include availability of decentralised institutions, considerable coordination amongst institutional structures, public participation and awareness and to a smaller extent, the existence of unconventional warning systems such as drumming, whistling, and using of text messages. Therefore, programs that expand and strengthen this societal capacity will provide the much needed leverage for risk reduction.

Hazardousness, vulnerability and consequently risk are variables that are spatially differentiated – linked to a differentiation in socio-economic and biophysical conditions. A general homogenous pattern exhibited in these components in the Shire Valley does not justify targeted interventions; it calls for universally applied interventions to all floodprone areas in the basin. Chikwawa in the Shire Valley nevertheless offers a leverage point in vulnerability reduction through environmental responses.

5.7.3 Limitations of the study

A number of caveats need to be noted regarding the study. The estimation of the hazard in this study focussed on water depth and spatial extent as hazard parameters. Consideration of other parameters such as velocity (assumed very low in this study due to flatness of the area) and duration may yield different results. Further, the study was limited to flooding from the Shire River; incorporation of tributary flows, may also possibly reveal much higher hazard values than found. The flood depths found were not validated due to lack of quality hydrological data. Nonetheless, the match between observed and modelled inundation extent provides reasonable agreement between modelled and observed depths given that the Lower Shire Valley remains largely unimpeded by structural measures.

Vulnerability data is also a source of weakness. Primary data sourced from communities through a structured questionnaire is potentially subjective. In addition, some secondary data used in the vulnerability index are data recorded at different points in time. The study used 2008 as a reference year, determined by the record length of hydrological data available at the start of the research. However, other data sets occur at different points in time. For example, forest cover data used is based on satellite imagery from LANDSAT ETM sensor for 2010-2011 (FAO, 2013); population density on the other hand was based on 2008 population census. Interviews were conducted in 2012. This may misrepresent vulnerability as vulnerability is a dynamic phenomenon. Nonetheless, most vulnerability factors are structural; significant change over a 2-3 year period over which the data span is unlikely as exemplified by a meagre 1.4% decline in poverty between 2005 and 2011 (National Statistical Office, 2012).

Further, indices are subject to a number of shortfalls despite their relevance and popularity in decision making. Among them, the outcome is dependent on the variables used, the thresholds set, the aggregation processes applied and the scale of application. Besides, there are no means for validation. Use of validly different indices and threshold may reveal a different picture. This is a problem nonetheless shared by all index-based vulnerability and risk analyses.

Chapter 6 Conclusions and Recommendations for Future Research

6.1 Conclusions

Before concluding this thesis, it is important to first review the aim and objectives with a view to ascertaining the extent to which they have been achieved. The aim of the project as stated in Chapter 1 was to enhance the understanding of vulnerability and risk to flooding of rural communities in SSA, particularly from the perspectives of contemporary disaster management. Specifically, the thesis had the following objectives:

(i) Develop an approach to augment and extend hydro-meteorological data in data scarce catchments for the support of hydrological and hydraulic modelling.

(ii) Develop, verify and validate AI–based forecasting models for flow and water levels.

(iii) Quantify the hazardousness, vulnerability and risk, as well as their dimensions, and determine how these manifest themselves spatially.

(iv) Make recommendations on flood mitigation and adaptation strategy for flood risk management.

The first objective was achieved in sections 3.3.1, 3.3.2.1, 3.3.2.3 (Chapter 3), section 4.1 (Chapter 4) and sections 5.1 and 5.2 (Chapter 5). The second objective was achieved in sections 3.3.2.2, 3.3.2.3 (Chapter 3), 4.2 (Chapter 4) and 5.4 in Chapter 4. The third objective was covered by sections 3.2, 3.3.3, 3.4 (Chapter 3), 4.3, 4.4, 4.5 (Chapter 4), and 5.3, 5.5 and 5.6 (Chapter 5). Finally, the last objective was covered in section 5.7.2 of Chapter 5.

It is therefore clear that all of the objectives have been achieved. Based on the entire work, the following conclusions have emerged:

6.1.1 Hydro-meteorological data were reconstructed using data driven models, in particular, SOM. This follows the limitation of traditional infilling methods in the face of large gaps and short durations that characterise hydro-meteorological data in the catchment and not uncommon in developing countries. The study shows that SOM is a powerful technique for infilling and extension in the prevalence of large gaps, discontinuities and short durations. It has a further advantage of handling large data sets. The magnitudes of the coefficient of correlation R were in excess of 0.97 for water levels and flows and 0.8 - 0.96 for rainfall.

However, the modelling ability of SOM is highly dependent on the homogeneity in the data in question as observed herein, with the performance being highest on flow and water level in comparison to rainfall data; the latter being quite uncorrelated in the Shire River basin.

6.1.2 MLP-ANN was used for water level and flow forecasting on SOM reconstructed-data. Coupling SOM and MLP-ANN proves to be powerful strategy in such data-poor catchments. Results were very satisfactory with both the Nash–Sutcliffe index and coefficient of correlation being in excess of 0.9 for lead times of up to 2-days. This is to be welcome in the face of increasing focus on non-structural measures for risk reduction and the potential of flood forecasting as one such non-structural measure. The use of traditional conceptual models in such data-poor environments is limited. Even when the data has been reconstructed, it is still subject to noise, an aspect quite prevalent in hydrological data in developing countries. Using SOM features (SOM-predicted data) other than raw data improves the predictive capacity of the model thus allowing accurate predictions, an important element in forecasting. In the present analysis, with forecasting based on SOM filtered data other than the reconstructed raw data, very satisfactory forecasts (NS>0.9) are obtained up to 5 days from 2 days.

6.1.3 Based on SOM reconstructed data and hydraulic modelling with Lisflood-FP, results show that the Lower Shire is a region in the medium (0.5 – 1m) to high

(1-2m) levels of hazardousness but with a predominance of a medium hazard class. High hazardous communities were found to be Mbenje, Maseya, Katunga and Tengani. Medium hazardous communities were Ngabu (Nsanje), Ndamera, Mlolo, Makhuwila, Nyachikhadza, Malemia, Lundu and Ngabu (Chikwawa). In Nsanje, spatial mapping shows concentration of high hazardous communities around the confluence, affirming to some extent, long standing perceptions of the location of most severe flooding in the Lower Shire floodplain. In Chikwawa, high hazardousness is concentrated in Katunga and Maseya. It should be pointed out that such magnitudes pertain to the 4-5 year flood event investigated. For more rare events, higher magnitudes in hazardousness and consequently risk are expected.

6.1.4 The study finds the vulnerability to flooding of rural communities in the Lower Shire Valley to be medium (0.4-0.6) to very high (0.8 – 1.0) but with a predominance of medium to high levels. In particular, aggregate vulnerability emerges as medium to high but surprisingly predominantly medium. Susceptibility manifests as high (0.6-0.8) to very high (0.8-1.0) and exerts a dominant influence on overall vulnerability, reflecting fragility of communities in the Lower Shire from several angles: health, literacy, poverty, livelihoods, access to basic services, employment opportunities etc. Exposure tends to be medium (0.4-0.6) which the study links to limited infrastructure in the floodplain. Similarly, capacity-induced vulnerability manifests as medium.

From a sustainable development framework perspective, magnitudes of social, economic and to a large extent, environmental vulnerability are predominantly high to very high. Physical vulnerability generally tends to be medium.

Viewed from a coupled IPCC and Sustainable Development perspective, it becomes evident that susceptibility has a strong socio-economic and environmental dimension, all manifesting predominantly as high to very high. Capacity-induced vulnerability on the other hand has a strong economic and physical bearing, both falling in the high categories. Surprisingly societal capacity emerges as high, attenuating the overall capacity-induced vulnerability to medium levels. For any given dimension except environmental vulnerability, the study finds marginal differences in magnitudes across communities, an indication of relative homogeneity in vulnerability in the communities.

6.1.5 On the question of risk, the intersection of the hazard and vulnerability, results show flood risk is medium to high, but predominantly medium. It is characterized by high and medium combinations, medium and medium combinations and high and high combination from the two components. Patterns of medium hazardousness combining with medium vulnerability are the most predominant, pointing to a relative similar role of both hazardousness and vulnerability in the risk profile. However, at high risk, hazardousness tends to be dominant. In general, vulnerability, hazardousness and risk all tend to be marginally differentiated across the communities

6.2 Recommendations for Future Research

Beyond describing the causes, impacts, perceptions and coping strategies, vulnerability to flooding and associated risk in SSA is a subject that has not been addressed from a quantitative perspective, particularly within a contemporary disaster management discourse. While this thesis set out to provide a comprehensive quantitative overview of risk in consideration of both the hazard and vulnerability, and of vulnerability dimensions, it limited hazard parameters to water depths and inundation extent and to flooding emanating from the main river, the Shire. To provide more comprehensive and robust findings of flood hazard severity in the valley, future research should incorporate other hazard parameters such as velocity and duration and should account for tributary flows, though the challenge of flow data is likely to remain given the paucity of data on tributary gauge stations.

6.2.1 The paucity and quality of hydrological data in SSA is an impediment to robust risk assessments. The need for investment in hydrometry in SSA to support holistic and sustainable flood risk management advanced in contemporary disaster management cannot be over-emphasised.

6.2.2 Vulnerability in this study was dimensioned on the basis of exposure, susceptibility and capacities and in further consideration of social, economic, physical and environmental underpinnings. This was informed by the discourse in contemporary disaster management. Further research in SSA should also examine the vulnerability profile of rural communities along sectoral dimensions i.e. land/forest, water, agriculture, health, education etc. A sectoral approach will link vulnerability directly to responsible institutions and therefore offers another platform for evidence-based policy making, especially that although disaster management institutions exist, they have no budgets for implementation of any activity.

6.2.3 While the thesis found little heterogeneity in vulnerability dimensions and risk, except for environmental vulnerability, the findings do not offer conclusive evidence. The thesis used an Area Development level as a unit if analysis. This is the next level below the district level in the hierarchy of decentralized institutional structure. This level may be coarse to uncover micro-scale vulnerability. A much smaller unit such as Group Village Headman (GVH) level or Village level should be considered in future work. It would be of policy relevance to uncover any spatial differentiation in vulnerability and risk.

6.2.4 In furtherance, given the importance of this region in the disaster profile of Malawi and the findings herein that suggest some aspects of flood risk in this valley e.g. susceptibility remains relatively high despite a number of interventions from notably NGOs and other development partners, it would be of policy relevance to institute interventional studies and assess vulnerability and risk dynamics over a longer period of time.

References

Abatzoglou, J. T.; Redmond, K. T. and Edwards, L. M. (2009) 'Classification of Regional Climate Variability in the State of Califonia', *Journal of Applied Meteorology and Climatology,* 48(8), 1527-1541.

Aboagye, D.; Dar, T. and Koomson, J. (2013) 'Risk Perception and Disaster Management in the Savannah Region of Ghana', *International Journal of Humanities and Social Sciences,* 3(3), 85-96.

Abrahart, R. J. and White, S. M. (2001) 'Modelling Sediment Transfer in Malawi: Comparing Backpropagation Neural Network Solutions Against a Multiple Linear Regression Benchmark Using Small Data Sets', *Physics and Chemistry of the Earth, Part B,* 26(1), 19-24.

Adelekan, I. O. (2010) 'Vulnerability of poor urban coastal communities to flooding in Lagos, Nigeria', *Environment and Urbanization,* 22(2), 433-450.

Adeloye, A. J. (2009) 'The Relative Utility of Multiple Regression and ANN Models for Rapidly Predicting the Capacity of Water Supply Reservoirs', *Environmental Modelling and Software,* 24(10), 1233-1240.

Adeloye, A. J. (2011) 'Reducing the Uncertainity Associtated with Water Resources Planning in a Developing Country Basin with Limited Runoff Data through AI Rainfall-Runoff Modelling' in *Proceedings of the Symposium HS03 - Risk in Water Resources Management.*, Melbourne, Australia. IAHS, 121-126.

Adeloye, A. J. and De Munari, A. (2006) 'Artificial Neural Network Based Generalized Storage-Yield-Reliability Models using Levenberg-Marquardt algorithm', *Journal of Hydrology,* 362, 215-230.

Adeloye, A. J. and Rustum, R. (2011) 'Lagos (Nigeria) flooding and urban planning', *Proceedings of the ICE - Urban Design and Planning,* 164(3), 175-187.

Adeloye, A. J. and Rustum, R. (2012) 'Self-Organising Map Rainfall-Runoff Multivariate Modelling for Runoff Reconstruction in Inadequately Gauged Basins', *Hydrology Research,* 43(5), 603-617.

Adeloye, A. J.; Rustum, R. and Kariyama, I. D. (2011) 'Kohonen Self Organizing Map Estimator for Reference Crop Evapotranspiration', *Water Resources Reseach,* 47(WO8523), doi:10.1029/2011WR010690.

Adger, W. N. (2000) 'Social and ecological resilience: are they related?', *Progress in Human Geography,* 24(3), 347-364.

Adger, W. N. (2006) 'Vulnerability', *Global Environmental Change,* 16(3), 268-281.

Adger, W. N.; Brooks, N.; Bentham, G.; Agnew, M. and Eriksen, S., (2004) *New indicators of vulnerability and adaptive capacity*, Norwich, UK: Tyndall Centre for Climate Change Research.

Adikari, Y. and Yoshitani, J., (2009) *Global Trends in Water-Related Disasters: an insight for policymakers* Paris, France: UNESCO.

Alca´Ntara-Ayala, I. (2002) 'Geomorphology, natural hazards, vulnerability and prevention of natural disasters in developing countries', *Geomorphology,* 47, 107-124.

Alhoniemi, E.; Hollmén, J.; Simula, O. and Vesanto, J. (1999) 'Process Monitoring and Modeling using the Self-Organizing Map.', *Integrated Computer-Aided Engineering,* 6(1), 3-14.

Allison, E. H.; Perry, A. L.; Badjeck, M. C.; Adger, W. N.; Brown, K.; Conwal, D.; Halls, A. S.; Pilling, G. M.; Reynolds, J. D.; Andrew, N. L. and Dulvy, N. K. (2009) 'Vulnerability of national economies to the impacts of climate change on fisheries', *Fish and Fisheries,* 10(2), 173-196.

Alvisi, S.; Mascellani, G.; Franchini, M. and Bardossy, A. (2006) 'Water level forecasting through fuzzy logic and artificial neural network approaches', *Hydrology and Earth System Sciences,* 10(1), 1-17.

Aquil, M.; Kita, I.; Yano, A. and Nishiyama, S. (2007) 'Neural Networks for Real Time Catchment Flow Modeling and Prediction', *Water Resources Management,* 21(10), 1782-1796.

Armah, F. A.; Yawson, D. O.; Yengoh, G. T.; Odoi, J. O. and Afrifa, E. K. A. (2010) 'Impact of Floods on Livelihoods and Vulnerability of Natural Resource Dependent Communities in Northern Ghana', *Water,* 2(2), 120-139.

ASCE (1996) *Hydrology Handbook,* ASCE, New York.

ASCE Task Committee (2000) 'Artificial Neural Networks in Hydrology. I: Preliminary Concepts', *Journal of Hydrologic Engineering,* 5(2), 115-123.

Atkins, (2012) *Shire Integrated Flood Risk Management Volume II - Action Plan*, Lilongwe: World Bank.

Back, B.; Sere, K. and Hanna, V. (1998) 'Managing Complexity in Large Database using Self Organising Map.', *Accounting Management and Information Technologies,* 8(4), 191-210.

Balica, S.; Dinh, Q.; Popescu, I.; Vo, T. Q. and Pham, D. Q. (2014) 'Flood impact in the Mekong Delta, Vietnam', *Journal of Maps,* 10(2), 257-268.

Balica, S. F.; Douben, N. and Wright, N. G. (2009) 'Flood vulnerability indices at varying spatial scales', *Water Science and Technology,* 60(10), 2571-2580.

Balica, S. F.; Popescu, I.; Wright, N. G. and Beevers, L. (2013) 'Parametric and physically based modelling techniques for flood risk and vulnerability assessment: A comparison. ', *Environmental Modelling and Software,* 41, 84-92.

Balica, S. F. and Wright, N. G. (2010) 'Reducing the complexity of Flood Vulnerability Index', *Environmental Hazards,* 9(4), 321-339.

Balica, S. F.; Wright, N. G. and Van Der Meulen, F. (2012) 'A flood vulnerability index for coastal cities and its use in assessing climate change impacts', *Natural hazards,* 64(1), 73-105.

Bandyopadhyay, S.; Shyamsunda, P. and Baccini, A. (2011) 'Forests, biomass use and poverty in Malawi', *Environmental Economics,* 70(12), 2461–2471.

Barbier, E. B. (2000) 'The economic linkages between rural poverty and land degradation: some evidence from Africa', *Agriculture, Ecosystems and Environment,* 82, 355-370.

Bates, P. D. and Anderson, M. G. (1993) 'A two dimensional finite element model for river flood inundation', *Proceedings of the Royal Society of London,* 440, 481-491.

Bates, P. D. and De Roo, A. P. J. (2000) 'A simple raster-based model for flood inundation simulation', *Journal of Hydrology,* 236, 54-77.

Baxter, C. W.; Zhang, Q.; Stanley, S. J.; Shariff, R.; Tupas, R. T. and Stark, H. L. (2001) 'Drinking water quality and treatment: the use of artificial neural networks', *Canadian Journal of Civil Engineering,* 28(S1), 26-35.

Biancamaria, S.; Bates, P. D.; Boone, A. and Mognard, N. M. (2009) 'Large-scale coupled hydrologic and hydraulic modelling of the Ob river in Siberia', *Journal of Hydrology,* 379, 136-150.

Birkmann, J. (2006) 'Measuring vulnerability to promote disaster-resilient societies:conceptual frameworks and definitions', in Birkmann, J. (ed.) *Measuring vulnerability to natural hazards: Towards Disaster-Resilient Societies*, Tokyo, New York, Paris: United Nations University Press, 9-54.

Birkmann, J. (2007) 'Risk and vulnerability indicators at different scales: Applicability, usefulness and policy implications', *Environmental Hazards,* 7(1), 20-31.

Birkmann, J.; Cardona, O. D.; Carren˜O, M. L.; Barbat, A. H.; Pelling, M.; Schneiderbauer, S.; Kienberger, S.; Keiler, M.; Alexander, D.; Zeil, P. and Welle, T. (2013) 'Framing vulnerability, risk and societal responses: the MOVE framework', *Natura Hazards,* 67(2), 193-211.

Birkmann, J. and Fernando, N. (2008) 'Measuring revealed and emergent vulnerabilities of coastal communities to tsunami in Sri Lanka ', *Disasters,* 32(1), 82-105.

Blaikie, P.; Cannon, T.; Davis, I. and Wisner, B. (1994) *At Risk: Natural Hazards, People's Vulnerability and Disasters,* Routledge, London.

Bogardi, J. and Birkmann, J. (2004) 'Vulnerability Asssement: The First Step Towards Sustainable Risk Reduction', in Malzahn, D. & Plapp, T. (eds). *Disaster and Society - From Hazard Assessment to Risk Reduction*, Berlin: Logos Verlag Berlin, 75-82.

Bojo, J. (1996) 'The cost of land degradation in Sub-Saharan Africa', *Ecological Economics,* 16(2), 161-173.

Bollin, C.; Cardenas, C.; Hahn, H. and Vasta, K. S. (2003) *Natural Disasters Network: Comprehensive Risk Management by Communities and Local Governments,* Inter-American Development Bank, Washington D.C.

Bollin, C. and Hidajat, R. (2006) 'Community-based disaster risk index: pilot implementation in Indonesia', in Birkmann, J. (ed.) *Measuring Vulnerability to*

Natural Hazards—Towards Disaster Resilient Societies., Tokyo, New York, Paris: UNU-Press, 271-289.

Bowden, G. J.; Dandy, G. C. and Maier, H. R. (2005) 'Input Determination for Neural Network Models in Water Resources Applications. Part 1—Background and Methodology.', *Journal of Hydrology,* 301, 75-92.

Bradbrook, K.; Lane, S.; Waller, S. and Bates, P. (2004) 'Two dimensional diffusion wave modelling of flood inundation using a simplified channel representation', *International Journal of River Basin Management,* 2(3), 211-223.

Brink, A. B. and Eva, H. D. (2009) 'Monitoring 25 years of land cover change dynamics in Africa: A sample based remote sensing approach', *Applied Geography,* 29(4), 501-512.

Brooks, N., (2003) *Vulnerability, Risk and Adaptation: A Conceptual Framework*: Tyndall Centre.

Brooks, N.; Neil Adger, W. and Mick Kelly, P. (2005) 'The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation.', *Global Environmental Change,* 15(2), 151-163.

Brown, C.; Meeks, R.; Hunu, K. and Yu, W. (2011) 'Hydroclimate risk to economic growth in sub-Saharan Africa', *Climate Change,* 106(4), 621-647.

Buchele, B.; Reibich, H. K.; Kron, A.; Thieken, A.; Ihringer, J.; Oberle, P.; Merz, B. and Nestmann, F. (2006) 'Flood-risk mapping: contributions towards an enhanced assessment of extreme events and associated risks', *Natural Hazards and Earth System Sciences*, 6, 6485-503.

Campion, B. B. and Venzke, J. (2013) 'Rainfall variability, floods and adaptations of the urban poor to flooding in Kumasi, Ghana', *Natural Hazards,* 65(3), 1895-1911.

Cardona, O. D. (1999) 'Environmrntal Management and Disaster Prevention: Two Related Topics: A Hollistic Risk Assessment and Management Approach', in Ingleton, J. (ed.) *Natural Disasters Management*, London: Tudor Rose,

Cardona, O. D., (2001) *Estimancion Hollistica del Riesgo Sismico Utilizando Sistemas Dinamicos Complejos*, Barcelona, Technical University of Catalonia.

Cardona, O. D. (2004) 'The Need for Rethinking the Concepts of Vulnerability and Risk from a Hollistic Perspective: A Necessary Review and Criticism for Effective Risk Mangement', in Bankoff, G., Frerks, G. & Hilhorst, D. (eds). *Mapping Vulnerability: Disasters, Development and People*, London: Earthscan, 37-51.

Cardona, O. D., (2005) *Indicators of disaster risk and risk management: Summary Report*, Washington D.C.: Inter-American Development Bank.

Casale, M.; Scott, D.; Stuart, G.; Suneetha, K.; Paul, M.; Tim, Q. and Gina, Z., (2008) *Experiencing vulnerability in southern Africa: The interaction of multiple stressors.*, 6, Washington, D.C.: IFPRI.

Chakraborty, J.; Tobin, G. A. and Montz, B. E. (2005) 'Population Evacuation: Assessing Spatial Variability in Geophysical Risk and Social Vulnerability to Natural Hazards', *Natural Hazards Review,* 6(1), 23-33.

Chamber, R. and Conway, G., (1992) *Sustainable rural livelihoods: practical concepts for the 21st century*, IDS Discussion Paper 296, Brighton: IDS.

Chau, K. W.; Wu, C. L. and Li, Y. S. (2005) 'Compariosn of Several Forecasting Models in the Yangtse River', *Journal of Hydrologic Engineering,* 10(6), 485-491.

Chavula, G.; Brezonik, P. and Bauer, M. (2011) 'Land Use and Land Cover Change (LULC) in the Lake Malawi Drainage Basin, 1982-2005', *International Journal of Geosciences,* 2(2), 172-178.

Chidanti-Malunga, J. (2011) 'Adaptive strategies to climate change in Southern Malawi.', *Physics and Chemistry of the Earth, Parts A/B/C,* 36, 1043-1046.

Chimatiro, S. K. (2004). *The Biophysical Dynamics of the Lower Shire Floodplain Fisheries in Malawi.* PhD thesis, Rhodes University.

Chow, V. T. (1959) *Open channel hydraulics* Mc-Graw Hill New York.

Cigizoglu, H. K. (2004) 'Estimation and forecasting of daily suspended sediment data by multi layer perceptrons.', *Advances in Water Resources,* 27(2), 185-195.

Cinner, J. E.; Mcclanahan, T. R.; Graham, N. a. J.; Daw, T. M.; Maina, J.; Stead, S. M.; Wamukota, A.; Brown, K. and Bodin, O. (2012) 'Vulnerability of coastal communities to key impacts of climate change on coral reef fisheries', *Global Environmental Change,* 22(1), 12-20.

Collins, T. W.; Grineski, S. E. and Aguilar, M. (2009) 'Vulnerability to environmental hazards in the Ciudad Jua´ rez (Mexico)–El Paso (USA) metropolis: A model for spatial risk assessment in transnational context ', *Applied Geography,* 29(3), 448-461.

Connor, R. F. and Hiroki, K. (2005) 'Development of a method for assessing flood vulnerability', *Water Science and Technology,* 51(5), 61-67.

Conway, D.; Persechino, A.; Ardoin-Bardin, S.; Hamandawana, H.; Dieulin, C. and Mahé, G. (2009) 'Rainfall and Water Resources Variability in Sub-Saharan Africa during the Twentieth Century', *Journal of Hydrometeorology,* 10(1), 41-59.

Coulthard, T. J.; Ramirez, J. A.; Barton, N.; Rogerson, M. and Brucher, T. (2013) 'Were Rivers Flowing across the Sahara During the Last Interglacial? Implications for Human Migration through Africa', *PLoS ONE,* 8(10), doi:10.1371/journal.pone.0074834, 2013.

Cutter, S. and Finch, C. (2008) 'Temporal and spatial changes to social vulnerability to natural hazards', *PNAS,* 105(7), 2301-2306.

Cutter, S. L. (1996) 'Vulnerability to Environmental Hazards', *Progress in Human Geography* 20(4), 529-539.

Cutter, S. L.; Boruff, B. J. and Shirley, W. L. (2003) 'Socio Vulnerability to Environmental Hazards', *Social Science Quarterly,* 84(2), 242-261.

Cutter, S. L.; Emrich, C. T.; Webb, J. J. and Morath, D., (2009) *Social Vulnerability to Climate Variability Hazards: A Review of the Literature*: Oxfam America.

Cutter, S. L.; Mitchell, J. T. and Scott, M. S. (2000) 'Revealing the vulnerability of people and places: the case study of Georgetown county, South Carolina', *Annals of the Association of American Geographers,* 90(4), 713-737.

Danish Hydraulic Institute, (1996) *MIKE21: User Guide and Reference Manual*, Horsholm, Denmark: Danish Hydraulic Institute.

Danish Hydraulics Institute, (1993) *Danish Hydraulics Institute, MIKE11, User Guide & Reference Manual*, Horsholm, Denmark: Danish Hydraulics Institute.

Dastorani, M. T.; Moghadamnia, A.; Piri, J. and Rico-Ramirez, M. (2010) 'Application of ANN and ANFIS Models for Reconstructing Missing Flow Data', *Envirnmental Monitoring and Assessment,* 166, 421-434.

Dawson, C. W. and Wilby, R. (1998) 'An Artificial Neural Network Approach to Rainfall Runoff Modelling', *Hydrological Sciences,* 43(1), 47-66.

Dawson, C. W. and Wilby, R. L. (2001) 'Hydrological Modelling Using Artificial Neural Networks', *Progress in Physical Geography,* 25(1), 80-108.

Defra and Environmental Agency, (2006) *Flood Risks to People - Phase 2 Project Record*, FD2321 R&D Technical Report 1, London: Defra.

Demuth, H.; Beale, M. and Hagan, M., (2009) *Neural Network Toolbox™ 6 User's Guide*.

Desanker, P. V.; Frost, P. G. H.; Justice, C. O. and Scholes, R. J., (1997) *The Miombo Network: Framework for a Terrestrial Transect Study of Land-Use and Land-Cover Change in the Miombo Ecosystems of Central Africa*, IGBP Report 41, Stockholm: IGBP.

DFID, (1999) *Sustainable Livelihoods Guidance Sheets*, London: DFID.

Di Baldassarre, G.; Montanari, A.; Lins, H.; Koutsoyiannis, D.; Brandimarte, L. and Blöschl, G. (2010) 'Flood fatalities in Africa: From diagnosis to mitigation', *Geophysical Research Letters,* 37(22), doi:10.1029/2010GL045467.

Diamantopoulou, M. J.; Antonopoulos, V. Z. and Papamichail, D. M. (2005) 'The use of neural network technique for the prediction of water quality parameters of Axios River in Northern Greece', *European Water,* 11/12, 55-62.

Dilley, M. and Boudreau, T. E. (2001) 'Coming to terms with vulnerability: a critique of the food security definition', *Food Policy,* 26(3), 229-247.

Dilley, M.; Chen, R. S.; Deichmann, U.; Lerner-Lam, A. L.; Arnold, M.; Agwe, J.; Buys, P.; Kjekstad, O.; Lyon, B. and Yetman, G., (2005) *Natural Disaster Hotspots: A Global Risk Analysis*, Washington D.C.: World Bank.

Dinh, Q.; Balica, S.; Popescu, I. and Jonoski, A. (2012) 'Climate Change Impact on Flood Hazard, Vulnerability and Risk of the Long Xuyen Quadrangle in the Mekong Delta', *International Journal of River Basin Management,* 10(1), 103-120.

Dinpashoh, Y.; Jhajharia, D.; Fakheri-Fard, A.; Singh, V. P. and Kahya, E. (2011) 'Trends in Reference Crop Evapotranspiration over Iran', *Journal of Hydrology,* 399, 423-433.

Donda, S. and Njaya, F., (2007) *Fisheries co-management in Malawi: An analysis of the underlying policy process*, Cairo: World Fish Center.

Douglas, I.; Alam, K.; Maghenda, M.; Mcdonnell, Y.; Mclean, L. and Campbell, J. (2008) 'Unjust waters: climate change, flooding and the urban poor', *Environment and Urbanization,* 20(1), 187-205.

Downton, M. W. and Pielke, R. A. (2005) 'How Accurate are Disaster Loss Data? The Case of U.S. Flood Damage', *Natural Hazards,* 35(2), 211-228.

Dunno, C. H. (2011). *Measuring Social Vulnerability To Natural Hazards: An Examination Of The United States Virgin Islands.* PhD thesis, The University of North Carolina at Greensboro.

Dutta, D.; Herath, S. and Musiakec, K. (2003) 'A mathematical model for flood loss estimation', *Journal of Hydrology,* 277, 24-49.

Dutta, D.; Welsh, W. D.; Vaze, J.; Kim, S. S. H. and Nicholls, D. (2012) 'A Comparative Evaluation of Short-Term Streamflow Forecasting Using Time Series Analysis and Rainfall-Runoff Models in eWater Source', *Water Resources Management,* 26(15), 4397–4415.

Eakin, H. and Luers, A. L. (2006) 'Assessing the vulnerability of social-environmental systems', *Annual Review of Environmental Resources,* 31, 365-394.

Esty, D. C.; Levy, M.; Srebotnjak, T. and De Sherbinin, A., (2005) *2005 Environmental Sustainability Index: Benchmarking National Environmental Stewardship*, New Haven: Yale Center for Environmental Law & Policy.

Fan, H., (2002) *Development of the Mozambican Geoid Model MOZGEO 2002*, Geodesy Research Report No. 1058., Stockholm: Royal Institute of Technology

FANRPAN, (2007) *Household Vulnerability Index (HVI) for Quantifying Impact of HIV and AIDS on Rural Livelihoods* Pretoria: FANRPAN.

FAO (2013) Land cover and land cover change of Malawi (1990-2010). Lilongwe, Malawi.

Fekete, A. (2009) 'Validation of a social vulnerability index in context to river-floods in Germany', *Natural Hazards and Earth System Sciences,* 9(2), 393-403.

Fekete, A.; Damm, M. and Birkmann, J. (2010) 'Scales as a challenge for vulnerability assessment', *Natura Hazards,* 55(3), 729–747.

Fernandes, E. C. M.; Gillison, A. N.; G., A. and Richey, J., (2006) *Lower Zambezi River Basin: Baseline Data On Landuse, Biodiversity, And Hydrology. GEF - Zambezi Valley Market Led Smallholder Development Project* Draft Report, Washington, D. C.

Fewtrell, T. J.; Bates, P. D.; De Wit, A.; Asselman, N. and Sayers, P. B. (2009) Comparison of varying complexity numerical models for the prediction of flood inundation in Greenwich, UK. *In:* Samuels, P., Huntington, S., Allsop, W. & Harrop, J. (eds.) *Flood Risk Management - Research and Practice.* London: Taylor and Francis Group.

Fussel, H.-M. (2007) 'Vulnerability: A generally applicable conceptual framework for climate change research', *Global Environmental Change,* 17(2), 155-167.

Fussel, H. M., (2010) *Review and quantitative analysis of indices of climate change exposure, adaptive capacity, sensitivity, and impacts*, Washington D.C.: World Bank.

Gall, M. (2007). *Indices of social vulnerability to national hazards: a comparative evaluation.* Phd thesis, University of South Carolina.

Garcia, H. and Gonzalez, L. (2004) 'Self-organizing Map and Clustering for Wastewater Treatment Monitoring', *Engineering Application of Artificial Intelligence,* 17(3), 215-225.

Gbetibouo, G. A. and Ringler, C., (2009) *Mapping South African Farming Sector Vulnerability to Climate Change and Variability - A Subnational Assessment*, IFPRI Discussion Paper 00885: IFPRI.

Giles, J. (2005) 'Solving Africa's climate data problem', *Nature,* 435, 862-863.

Gouldby, B.; Sayers, P.; Mulet-Marti, J.; Hassan, M. and Benwell, D. (2008) 'A methodology for regional-scale flood risk assessment', *Proceedings of the Institution of Civil Engineers-Water Management* 161(3), 169-182.

Governement of Malawi, (2006) *Malawi's National Adaptation Programs of Action (NAPA) Under the United Nations Framework Convention on Climate Change (UNFCCC)*, Lilongwe: Environmental Affairs Department.

Guarin, P. G.; Van Westen, C. J. and Montoya, A. L. (2005) 'Community - based flood risk assessment using GIS for the town of San Sebastian, Guatemala.', *Journal of human security and development,* 1(1), 29-49.

Guha-Sapir, D. and Below, R., (2002) *The quality and accuracy of disaster data - a comparative analysis of three global data sets*: World Bank.

Gwimbi, P. (2009) 'Linking rural community livelihoods to resilience building in flood risk reduction in Zimbabwe', *Journal of Disaster Risk Studies,,* 2(1), 71-79.

Gyau-Boake, P. and Schultz, G. A. (1994) 'Filling Gaps in Runoff Time Series in West Africa', *Hydrological Sciences,* 39(4), 621-636.

Hagenlocher, M.; Kienberger, S.; Lang, S. and Blaschke, T. (2014) 'Implications of Spatial Scales and Reporting Units for the Spatial Modelling of Vulnerability to Vector-borne Diseases', in Vogler, R., Car, A., Strobl, J. & Griesebner, G. (eds). *GI_Forum 2014. Geospatial Innovation for Society*, Berlin: Wichmann Verlag, VDE VERLAG GMBH, 197-206.

Hahn, M. B.; Riederer, A. M. and Foster, S. O. (2009) 'The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique', *Global Environmental Change* 19(1), 74-88.

Hamilton, S. K.; Sippel, S. J. and Melack, J. M. (2004) 'Seasonal inundation patterns in two large savanna floodplains of South America: the Llanos de Moxos(Bolivia) and the Llanos del Orinoco (Venezuela and Colombia) ', *Hydrological Processes,* 18(11), 2103–2116.

Hatlebakk, M. (2012) 'Fishery as a livelihood strategy in Malawi - Analysing a small LSMS sub-sample', *Journal of International Development,* 24(1), 77-87.

Haykin, S. (1999) *Neural Networks: A Comprehensive Foundation,* Second edition, Prenticee Hall, New Jersey.

HEC-RAS, (2002) *HEC-RAS, River Analysis System User's Manual Engineers*, Califonia: Hydrological Engineering Center.

Hecky, R. E.; Bootsman, H. A. and Kingdom, M. L. (2003) 'Impact of Land Use on Sediment and Nutrient Yields to Lake Malawi/Nyasa (Africa)', *Journal of Great Lakes Research,* 29(Supplement 2), 139-158.

Herath, S.; Jha, R. and Dutta, D. (2002) Assessing Lead Time in Flood Forecasting for Better Emergency Response. *US-Japan Cooperative Research of Urban Earthquake Disaster Mitigation: Comparative Study on Urban Earthquake Disaster Management.* Kobe: Research Center for Disaster Reduction Systems, Disaster Prevention Research Institute, Kyoto University.

Horritt, M. S. and Bates, P. D. (2001) 'Predicting floodplain inundation: raster-based modelling versus the finite-element approach', *Hydrological Processes,* 15(5), 825-842.

Houghton-Carr, H. and Fry, M. (2006) 'The decline of hydrological data collection for development of integrated water resource management tools in Southern Africa' in *Climate variability and change: hydrological impacts. Proceedings of the fifth FRIEND World Conference*, Havana, Cuba. International Association of Hydrological Sciences, 51-55.

Hung, N. Q.; Babel, M. S.; Weesakul, S. and Tripathi, N. K. (2009) 'An artificial neural network model for rainfall forecasting in Bangkok, Thailand', *Hydrology and Earth System Sciences,* 13(8), 1413–1425.

Hunter, N. M.; Bates, P. D.; Horritt, M. S. and Wilson, M. D. (2007) 'Simple spatially-distributed models for predicting flood inundation: A review ', *Geomorphology,* 90, 208-225.

Hydrology Project, (1999) *Training Module (SWDP) #39: How to Correct and Complete Discharge Data*, 39, New Delhi, India.

Ilunga, M. and Stephenson, D. (2005) 'Infilling Streamflow Data using Feed-Forward Back-Propagation (BP) Artificial Neural Networks: Application of Standard BP and Pseudo Mac Laurin Power Series BP Techniques', *Water SA,* 31(2), 171-176.

IPCC (2001) *Climate Change 2001: Impacts, Adaptation and Vulnerability, Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change,* Cambridge University Press, Cambridge, UK, and New York, USA.

IPCC (2007) *The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* Cambridge University Press Cambridge, United Kingdom and New York, USA.

IPCC (2012) *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change* Cambridge University Press, Cambridge, UK, and New York, NY, USA.

ISDR, (2004) *Living with risk: A global review of disaster reduction initiatives*, Geneva: UNISDR.

ISDR, (2005) *Hyogo Framework for Action 2005 - 2015: Building the Resilience of Nations and Communities to Disasters*, A/CONF.206/6, Geneva: UNISDR.

ISDR, (2009) *Terminology on Disaster Risk Reduction*, Geneva: UNISDR.

Isik, S.; Kalin, L.; Schoonover, J. E.; Srivastava, P. and Lockaby, B. G. (2013) 'Modeling effects of changing land use/cover on daily streamflow: an artificial neural network and curve number based hybrid approach', *Journal of Hydrology,* 485, 103 - 112.

Isioye, O. A. and Yang, I. C. (2013) 'Comparison and validation of ASTER-GDEM and SRTM elevation models over parts of Kaduna State, Nigeria' in *SASGI 2013 - Geospatial Solutions for National Development Planning*, Gauteng, South Africa. SASGI.

ISIS, (1995) *ISIS Flow User Manual*, Wallingford, UK: Hallcrow & HR Wallingford.

Islam, A. S.; Bala, S. K. and Haque, M. A. (2010) 'Flood inundation map of Bangladesh using MODIS time-series images', *Journal of Flood Risk Management,* 3(3), 210-222.

Islam, M. and Sado, K. (2002) 'Development Priority Map for Countermeasures by Remote Sensing Data with Geographic Information System', *Journal of Hydrologic Engineering,* 7(5), 346-355.

Ito, F. and Murata, A. (2009) 'Artificial neural network model estimating land use change in the Southwestern Part ofNagareyama City, Chiba Prefecture.', in Asami, Y., Sadahiro, Y. & Ishikawa, T. (eds). *New Frontiers in Urban Analysis* Boka, Rato: CRC Press, 65-79.

Izumi, T. and Shaw, R. (2012) 'Role of stakeholders in disaster risk reduction under Hyogo Framework for Action: An Asian Perspective', *Asian Journal of Environmental Disaster Management,* 4(2), 164-182.

Jain, S. K. and Sudheer, K. P. (2008) 'Fitting of Hydrological Models: A Close Look at the Nash-Sutcliffe Index', *Journal of Hydrologic Engineering,* 13(10), 981-986.

Jamieson, S. R.; Lhomme, J.; Wright, G. and Gouldby, B. (2012) 'A highly efficient 2D flood model with sub-element topography', *Proceedings of the Institution of Civil Engineers Water Management,* 165, 581-595.

Ji, L.; Zhang, L. and Wylie, B. (2009) 'Analysis of Dynamic Thresholds for the Normalized Difference Water Index', *Photogrammetric Engineering & Remote Sensing,* 75(11), 1307-1317.

Kachroo, R. K. (1992) 'River Flow Forecasting. Part 1. A Discussion of Principles', *Journal of Hydrology,* 133, 1-15.

Kalteh, A. M. and Hjorth, P. (2009) 'Imputation of Missing Values in a Precipitation–Runoff Process Database', *Hydrology Reaserch,* 40(4), 420-432.

Kalteth, A. M. and Berndtsson, R. (2007) 'Interpolating Monthly Precipitation by Self Organizing Map (SOM) and Multilayer Perceptron (MLP)', *Hydrological Sciences,* 52(2), 305-317.

Kaonda, A., (2009) *Nsanje Floodplain Analysis*, Lilongwe: GOAL Malawi.

Karlsson, J. M. and Arnberg, W. (2011) 'Quality analysis of SRTM and HYDRO1K: a case study of flood inudation in Mozambique', *International Journal of Remote Sensing,* 32(1), 267-285.

Kelly, P. M. and Adger, W. N. (2000) 'Theory and practice in assessing vulnerability to climate change and facilitating adaptation', *Climate Change,* 47(4), 325-352.

Khalil, M.; Panu, U. and Lennox, W. (1998) Estimation of Missing Streamflows: A Historical Perspective. *Annual Conference of the Canadian Society for Civil Engineering.* Halifax, Nova Scotia.

Khamis, A.; Ismail, Z.; Haron, K. and Mohammed, A. T. (2006) 'Neural network model for oil palm yield modelling', *Journal of Applied Sciences* 6(2), 391-399.

Khan, S. I.; Hong, Y.; Wang, J.; Yilmaz, K. K.; Gourley, J. J.; Adler, R. F.; Brakenridge, G. R.; Policelli, F.; Habib, S. and Irwin, D. (2011) 'Satellite Remote Sensing and Hydrologic Modeling for Flood Inundation Mapping in Lake Victoria Basin: Implications for Hydrologic Prediction in Ungauged Basins', *IEEE Transactions on Geoscience and Remote Sensing,* 49(1), 85-95.

Khandlhela, M. and May, J. (2006) 'Poverty, vulnerability and the impact of flooding in the Limpopo Province, South Africa', *Natural Hazards,* 39(2), 275-287.

Kienberger, S. (2012) 'Spatial modelling of social and economic vulnerability to floods at the district level in Buzi, Mozambique', *Natural Hazards,* 64(3), 2001-2019.

Kienberger, S.; Blaschke, T. and Zaidi, R. Z. (2013) 'A framework for spatio-temporal scales and concepts from different disciplines: the 'vulnerability cube'', *Natural Hazards,* 68, 1343-1369.

King, D. and Macgregor, C. (2000) 'Using social indicators to measure community vulnerability to natural hazards', *Australian Journal of Emergency Management,* 15(3), 52-57.

Kirpich, Z. P. (1940) *Time of Concentration from Small Agricultural Watersheds*, 362.

Kneale, P. E.; See, L. M. and Abrahart, R. J. (2004) 'Why Use Neural Networks?', *Neural Networks for Hydrologic Modelling*, Leiden: Balkema.

Kohonen, T.; Oja, E.; Simula, O.; Visa, A. and Kangas, J. (1996) 'Engineering Application of the Self Organizing Map' in *IEEC Proceedings*. 1358-1384.

Kundzewicz, Z. W. and Takeuchi, K. (1999) 'Flood Protection and Management: Quo vadimus?', *Hydrological Sciences-Journal,* 44(3), 417-432.

Kuotcha, W. S.; Ferguson, N. S.; De Langen, M.; Kululanga, G. and Grimason, A. M. (2012) 'Identifying villages with multiple dimensions of access deprivation: the case of Chikwawa District in rural Malawi', *Transport Policy and Practice Journal,* 18(1), 12-24.

Leauthaud, C.; Duvail, S.; Belaud, G.; Moussa, R.; Grünberger, O. and Albergel, J. (2012) 'Floods and wetlands: combining a water-balance model and remote-sensing techniques to characterize hydrological processes of ecological importance in the Tana River Delta (Kenya)', *Hydrology and Earth System Sciences,* 9(10), 11267-11318.

Legates, D. R. and Mccabe, G. J. (1999) 'Evaluating the Use of Goodness-of Fit Measures in Hydrologic and Hydroclimatic Model Validation', *Water Resources Research,* 35(1), 233-241.

Lekkas, D. F.; Onof, C.; Lee, M. J. and Baltas, E. A. (2004) 'Application of Articial Neural Networks in Flood Forecasting', *Global Nest,* 6(3), 205-211.

Linacre, E. (1992) *Climate Data and Resources - A Reference Guide,* Routledge, London and New York.

Liu, Z.; Martina, M. L. and Todini, E. (2005) 'Flood forecasting using a fully distributed model:application of the TOPKAPI model to the Upper Xixian Catchment', *Hydrology and Earth System Sciences,* 9(4), 347-364.

Lowe, C. J. (2010). *Analyzing vulnerability to volcanic hazards: Application to St. Vincent.* PhD thesis, University College London.

Luers, A. L. (2005) 'The surface of vulnerability:An analytical framework for examining environmental change', *Global Environmental Change,* 15(3), 214–223.

Lumbroso, D.; Ramsbottom, D. and Spaliveiro, M. (2008) 'Sustainable flood risk management strategies to reduce rural communities' vulnerability to flooding in Mozambique', *Journal of Flood Risk Management,* 1(1), 34-42.

Lung, T.; Lavalle, C.; Hiederer, R.; Dosio, A. and Bouwer, L. M. (2013) 'A multi-hazard regional level impact assessment for Europe combining indicatorsof climatic and non-climatic change', *Global Environmental Change,* 23(2), 522-536.

Maheu, A. (2012) 'Urbanization and Flood Vulnerability in a Peri-Urban Neighbourhood of Dakar,Senegal: How can Participatory GIS Contribute to Flood Management?', in Filho, W. L. (ed.) *Climate Change and the Sustainable Use of Water Resources*: Springer, Belin.

Maier, H. R. and Dandy, G. C. (2000) 'Neural Networks for the Prediction and Forecasting of Water Resources Variables: A Review of Modelling Issues and Applications', *Environmental Modelling and Software,* 15(1), 101-124.

Maier, H. R.; Jain, A.; Dandy, G. C. and Sudheer, D. (2010) 'Methods used for the development of neural networks for the prediction of water resource variables in river systems: Current status and future directions', *Environmental Modelling & Software,* 25(8), 891-909.

Malawi Governement (2009) Chikwawa District Assembly: District Strategic Investment Plan for Water, Sanitation and Hygiene 2008 - 2015. Chikwawa: Chikwawa District Assembly.

Malawi National Contingency Plan: 2009–2010 (2009). Government of Malawi.

Malawi National Vulnerability Assessment Committee (2005) Malawi Baseline Livelihood Profiles. Lilongwe, Malawi.

Malcomb, D. W.; Weaver, E. A. and Krakowka, A. R. (2014) 'Vulnerability modeling for sub-Saharan Africa: An operationalized approach in Malawi', *Applied Geography,* 48, 17-30.

Malek, M. a. H., S.; Shamsuddin, S. M. and Mohamad, I. (2008) 'Imputation of Time Series Data via Kohonen Self Organizing Maps in the Presence of Missing Data', *World Academy of Science, Engineering and Technology,* 41, 501-506.

Malekano, L. B. (2000) The social-economic impact of stock-theft and diseases in the Lower districts of Malawi. *International Conference on Historical and Social Science Research in Malawi.* Zomba, Malawi.

Mangison, J. H. (2009) *Farm-Level Economics Of Soil-Conservation Practices In The Zomba Rural Development Project of Malawi,* OSSREA, Addis Ababa.

Mapira, J. and Munthali, A. (2011) 'Household Energy Demand: Woodfuel Consumption and Peri-urban Deforestation in the city of Masvingo (Zimbabwe)', *Journal of Sustainable Development in Africa* 13(5), 264-279.

Mason, D. C.; Cobby, D. M.; Horritt, M. S. and Bates, P. D. (2003) 'Floodplain friction parameterization in two-dimensional river flood models using vegetation heights derived from airborne scanning laser altimetry', *Hydrological Processes,* 17(9), 1711-1732.

Mathur, V. K. (2006) 'Sustainable Development through Integrated Flood Management', *WMO Bulletin,* 55(3), 164-169.

Mazvimavi, D. (2003). *Estimation of Flow Characteristics of Ungauged Catchments: Case Study in Zimbabwe.* PhD thesis, Wageningeni University.

Mcfeeters, S. K. (1996) 'The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features', *International Journal of Remote Sensing,* 17(7), 1425-1432.

Mijoni, P. L. and Izadkhah, Y. O. (2009) 'Management of Floods in Malawi: Case Study of the Lower Shire River Valley', *Disaster Prevention and Management,* 18(5), 490-503.

Minde, I. J.; Kowero, G.; Ngugi, D. and Luhanga, J. (2001) 'Agricultural Land Expansion and Deforestation in Malawi', *Forests, Trees and Livelihoods,* 11(2), 167-182.

Minns, A. A. and Hall, M. J. (2004) 'Rainfall - Runoff Modelling', in Abrahat, R. J., Kneale, P. E. & See, L. M. (eds). *Neural Networks for Hydrological Modelling*, Leiden: Balkema, 157-175.

Mkanda, F. X. (2002) 'Contribution by farmers' survival strategies to soil erosion in the Linthipe River Catchment: implications for biodiversity conservation in Lake Malawi/Nyasa', *Biodiversity and Conservation,* 11(8), 1327-1359.

Mkhandi, S. H.; Kachroo, R. K. and Gunasekara, T. a. G. (2000) 'Flood Frequency Analysis of Southern Africa II: Identification of Regional Distributions', *Hydrological Sciences,* 45(3), 449-464.

Mkwara, B. and Marsh, D., (2009) *The Links between Poverty and the Environment in Malawi*, Working Paper 09/10, Hamilton: University of Wakaito.

MoIWD, (2003) *Report on leveling survey for upgrading flood forecasting stations in the Lower Shire Valley*, WD/H/139, Lilongwe, Malawi: Mnistry of Irrigation and Water Development.

MoIWD, (Undated) *Flood Forecasting and Warning Sytem for Lower Shire Valley Project Status Report*, Lilongwe, Malawi: Ministry of Irrigation and Development.

Monjerezi, M. (2012). *Groundwater Salinity in lower Shire River valley (Malawi): Hydro-chemical and isotope constraints on sources and evolution.* PhD thesis, University of Oslo.

Moriasi, D. N.; Arnold, J. G.; Van Liew, M. W.; Bingner, R. L.; Harmel, R. D. and Veith, T. (2007) 'Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations.', *Transaction of the ASABE,* 50(3), 885-900.

Mosquera-Machado, S. and Ahmad, S. (2007) 'Flood hazard assessment of Atrato River in Colombia', *Water Resources Management,* 21(3), 591-609.

Mpofu, T. P. Z. (2011) 'An evaluation of the effectiveness of flood disaster mitigation measures in the city of Adigrat, Tigray region, Ethiopia', *Jamba: Journal of Disaster Risk Studies,* 3(2), 384-400.

Mukherjeea, S.; Joshib, P. K.; Mukherjeea, S.; Ghoshb, A.; Gargc, R. D. and Mukhopadhyayd, A. (2013) 'Evaluation of vertical accuracy of open source Digital Elevation Model (DEM)', *International Journal of Applied Earth Observation and Geoinformation,* 21, 205-217.

Musungu, K.; Motala, S. and Smit, J. (2012) 'Using Multi-criteria Evaluation and GIS for Flood Risk Analysis in Informal Settlements of Cape Town: The Case of Graveyard Pond', *South African Journal of Geomatics,* 1(1), 77-91.

National Statistical Office, (2009) *Malawi Population and Housing Census 2008 : Main Report*, Zomba, Malawi.

National Statistical Office (2012) Integrated Household Survey 2010-2011 - Household Socio-economic Characteristics Report. Zomba, Malawi.

Nayak, P. C.; Rao, S. Y. R. and Sudheer, K. P. (2006) 'Groundwater Level Forecasting in a Shallow Aquifer Using Artificial Neural Network Approach', *Water Resources Management,* 20(1), 77-90.

Neal, J.; Schumann, G. and Bates, P. (2012) 'A subgrid channel model for simulating river hydraulics and floodplain inundation over large and data sparse areas.', *Water Resources Research,* 48(11), doi: 10.1029/2012WR012514.

Nelson, R.; Kokic , P.; Crimp, S.; Meinke, H. and Howden, S. M. (2010) 'The vulnerability of Australian rural communities to climate variability and change: Part I—Conceptualising and measuring vulnerability', *Environmental Science and Policy,* 13(1), 8-17.

Nethengwe, N. S. (2007). *Integrating Participatory GIS and Political Ecology to study Flood Vulnerability in the Limpopo Province of South Africa.* PhD thesis, West Virginia University.

Ngongondo, C.; Xu, C.-Y.; Gottschalk, L. and Alemaw, B. (2011a) 'Evaluation of Spatial and Temporal Characteristics of Rainfall in Malawi: A Case of Data Scarce Region', *Theoretical an Applied Physics,* 106, 79-93.

Ngongondo, C. S. X., Chong-Yu.; Tallaksen, L. M.; Alemaw, B. and Chirwa, T. (2011b) 'Regional Frequency Analysis of Rainfall Extremes in Southern Malawi using the Index Rainfall and L-Moments Approaches', *Stochaistic Environmental Research and Risk Assessment,* 25(7), 939-955.

Nilson, A.; Shela, O. N. and Chavula, G., (2010) *Flood Risk Management Strategy: Mitigation, Preparedness, Response and Recovery*, Lilongwe, Malawi: Department of Disaster Management Affairs.

Nkonya, E.; Pender, J.; Kaizzi, K. C.; Kato, E.; Mugarura, S.; Ssali, H. and Muwonge, J., (2008) *Linkages between Land Management, Land Degradation, and Poverty in Sub-Saharan Africa - The Case of Uganda*, Washington D.C.: IFPRI.

Nyakundi, H.; Mogere, S.; Mwanzo, I. and Yitambe, A. (2010) 'Community perceptions and response to flood risks in Nyando District, Western Kenya', *Jamba: Journal of Disaster Risk Studies,* 3(1), 346-366.

O' Connor, K. M. (2005) 'River Flow Forecasting', in Knight, D. W. & Asaad, S. (eds). *River Basin Modelling for Flood Risk Mitigation*, London: Taylor & Francis 197-213.

O'brien, K.; Sygna, L. and Haugen, J. E. (2004b) 'Vulnerable or Resilient? A Multi-Scale Assessment of Climate Impacts and Vulnerability in Norway', *Climate Change,* 64, 193-225.

O'brien, K. L.; Eriksen, S.; Nygaard, L. and Schjolden, A. (2007) 'Why different different interpretations of vulnerability matter in climate change discourses', *Climate Policy,* 7, 73-88.

O'brien, K.; Leichenko, R.; Kelkar, U.; Venema, H. A., G.; Tompkins, H.; Javed, A.; Bhadwal, S.; Barg, S.; Nygaard, L. and West, J. (2004a) 'Mapping vulnerability to multiple stressors: climate change and globalization in India', *Global Environmental Change* 14(4), 303-313.

Okkan, U. (2011) 'Application of Levenberg-Marquardt Optimization Algorithm Based Multilayer Neural Networks for Hydrological Time Series Modeling', *An International Journal of Optimization and Control: Theories and Applications,* 1(1), 53-63.

Ologunorisa, T. E. (2004) 'An assessment of flood vulnerability zones in the Niger Delta, Nigeria', *International Journal of Environmental Studies,* 61(1), 31-38.

Palamuleni, L. G. (2009). *Land Cover Change and Hydrological Regimes in the Shire River Catchment, Malawi.* PhD thesis, University of Johannesburg.

Palamuleni, L. G.; Annegarn, H. J. and Landmann, T. (2010) 'Land cover mapping in the Upper Shire River catchment in Malawi using Landsat satellite data', *Geocarto International,* 25(7), 503–523.

Panda, S. S.; Garg, V. and Chaubey, I. (2004) 'Artificial Neural Networks Application in Lake Water Quality Estimation Using Satellite Imagery', *Journal of Environmental Informatics,* 4(2), 65-74.

Pelletier, J. D.; Mayer, L.; A, P.; Pearthree; Hous, P. K.; Demsey, K. A.; Klawon, J. E. and Vincent, K. R. (2005) 'An integrated approach to fl ood hazard assessment on alluvial fans using numerical modeling, field mapping, and remote sensing', *Gelogical Society of America Bulletin,* 117, 1167-1180.

Penn, B. S. (2005) 'Using Self-Organising Maps to Visualize High Dimensional Data.', *Computers and Goesciences,* 31(5), 531-544.

Phalira, W. (2012) *Climate Data Capture and Management in the Lake Chilwa Basin: Status, Challenges and Opportunities.* [Online] Available from: https://weadapt.org/knowledge-base/using-climate-information/climate-data-management-in-the-lake-chilwa-basin-malawi. [Accessed: 20th September, 2013].

Phanthuwongpakde, N. (2011). *Mapping flood hazard for Mozambique: Calibration and flood forecasting of LISFLOOD-FP inudation model on the lower Zambezi basin during the 2007 Mozambican flood event.* MSc thesis, University of Bristol.

Phiri, M. G. I. and Saka, R. A. (2009) 'The Impact of Changing Environmental Conditions on Vulnerable Communities in the Shire Valley, Southern Malawi', in Lee, C. & Schaaf, T. (eds). *The Future of Drylands*, The Netherlands: Springer, 545-559.

Pike, G. J. and Remington, G. T. (1965) *Malawi: A Geographical Study,* Oxford University Press, London, UK.

Place, F. and Otsuka, K. (2001) 'Population, Tenure, and Natural Resource Management: The Case of Customary Land Area In Malawi', *Journal of Environmental Economics and Management,* 41(1), 13-32.

Plate, E. J. (2007) 'Early Warning and Flood Forecasting for Large Rivers with the Lower Mekong as an Example', *Journal of Hydro-Environment Research,* 1(2), 80-94.

Platt, R. (1995) 'Lifelines: an emergency management priority for the United States in the 1990s', *Disasters,* 15(2), 172-176.

Pölzlbauer, G. (2004) 'Survey and Comparison of Quality Measures for Self-Organizing Maps ' in *Proceedings of the Fifth Workshop on Data Analysis (WDA'04)*, Sliezsky dom, Vysoké Tatry, Slovakia. Elfa Academic Press, 67-82.

Pratt, C.; Kally, U. and Michell, J. (2004) Manual: How to Use the Environmental Vulnerability Index (EVI). *UNEP/SOPAC Technical Report 38.3* [Online] Available from: http://www.sopac.org/sopac/evi/EVI_References.htm. [Accessed: 12th June, 2012].

Primožič, M.; Kobold, M. and Brilly, M. (2008) 'The implementation of the HBV Model on the Sava River Basin' in *XXIVth Conference of the Danubian Countries*, Bled, Slovenia. IOP Publishing, doi:10.1088/1755-1307/4/1/012004.

Queste, A. and Lauwe, P. (2006) 'User needs: why we need indicators', in Birkmann, J. (ed.) *Measuring Vulnerability to Natural Hazards: Towards Disaster Resilient Societies,* First ed, Tokyo, New York, Paris: UNU Press, 103-114.

Rahman, M.; Goel, N. and Arya, D. (2012) 'Development of the Jamuneswari Flood Forecasting System: Case Study in Bangladesh.', *Journal of Hydrologic Engineering,* 17(10), 1123–1140.

Ramirez-Herrera, M. T. and Navarrete-Pacheco, J. A. (2013) 'Satellite Data for a Rapid Assessment of Tsunami Inundation Areas after the 2011 Tohoku Tsunami', *Pure and Applied Geophysics,* 170, 1067-1080.

Rees, G. (2008) 'Hydrological Data', in Gustard, A. & Demuth, S. (eds). *Manual on Low-flow Estimation and Prediction. Operational Hydrology Report No. 50*: WMO,

Ribot, J. C. (2010) 'Vulnerability does not just Fall from the Sky: Toward Multi-scale Pro-poor Climate Policy', in Mearns, R. & Norton, A. (eds). *Social Dimensions of Climate Change: Equity and Vulnerability in a Warming World*, Washington D.C.: The World Bank,

Roth, A.-S. and Becker, P. (2011) 'Challenges to Disaster Risk Reduction: A study of stakeholders' perspectives in Imizamo Yethu, South Africa', *Jamba: Journal of Disaster Risk Studies,* 3(2), 443-452.

Roudier, P.; Sultan, B.; Quirion, P.; Baron, C.; Alhassane, A.; Traoré, S. B. and Muller, B. (2012) 'An ex-ante evaluation of the use of seasonal climate forecasts for millet growers in SW Niger ', *International Journal of Climatology,* 32(5), 759-771.

Russell, A. J. M.; Grötz, P. A.; Kriesemer, S. K. and Pemsl, D. E., (2008) *Recommendation Domains for Pond Aquaculture. Country Case Study: Development and Status of Freshwater Aquaculture in Malawi.*, Studies and Reviews1869, Panang: World Fish Centre.

Rustum, R. (2009). *Modelling Activated Sludge Wastewater Treatment Plants Using Artificial Artificial Intelligence Techniques (Fuzzy Logic and Neural Networks).* PhD thesis, Heriot Watt University.

Rustum, R. and Adeloye, A. J. (2007) 'Replacing Outliers and Missing Values from Activated Sludge Data Using Kohonen Self-Organizing Map', *Journal of Environmental Engineering,* 133(9), 909-916.

Rustum, R. and Adeloye, A. J. (2012) 'Improved Modelling of Wastewater Treatment Primary Clarifier Using Hybrid Anns', *International Journal of Computer Science and Artificial Intelligence,* 2(4), 14-22.

Sahoo, G. B.; Ray, C. and De Carlo, E. H. (2006) 'Calibration and validation of a physically distributed hydrological model, MIKE SHE, to predict streamflow at high frequency in a flashy mountainous Hawaii stream', *Journal of Hydrology,* 327, 94-109.

Sakijege, T.; Lupala, J. and Sheuya, S. (2012) 'Flooding, flood risks and coping strategies in urban informal residential areas: The case of Keko Machungwa, Dar es Salaam, Tanzania', *Jamba: Journal of Disaster Risk Studies,* 4(1), 46-56.

Saliha, A. H.; Awulachew, S. B.; Cullmann, J. and Horlacher, H. (2011) 'Estimation of flow in ungauged catchments by coupling a hydrological model and neural networks: case study', *Hydrology Research,* 42(5), 386-400.

Sanyal, J. and Lu, X. X. (2004) 'Application of Remote Sensing in Flood Management with Special Reference to Monsoon Asia: A Review', *Natura Hazards,* 33(2), 283–301.

Sanyal, J. and Lu, X. X. (2005) 'Remote sensing and GIS-based flood vulnerability assessment of human settlements: a case study of Gangetic West Bengal, India', *Hydrological Processes,* 19(18), 3699–3716.

Schumann, G. J. P.; Neal, C.; Voisin, N.; Andreadis, K. M.; Pappenberger, F.; Phanthuwongpakdee, N.; Hall, A. C. and Bates, P. D. (2013) 'A first large-scale flood inundation forecasting model', *Water Resources Research,* 49(10), 6248–6257.

Sen, A. (1981) *Poverty and Famines: An Essay on Entitlement and Deprivation,* Oxford University Press, Oxford.

Shaw, R. (2014) 'Disaster Risk Reduction and Community Approaches', in Shaw, R. (ed.) *Community Practices for Disaster Risk Reduction in Japan*, Japan: Springer, 3-20.

Shaxson, T. F. (1970) 'Conservation for survival', *The Society of Malawi Journal,* 23(1), 48-57.

Shela, O. N. (2000) Naturalisation of Lake Malawi Levels and SHire River Flows: Challenges of Water Resources Research and Sustainable Utilisation of the Lake Malawi-Shire River System. *1st WARFSA/WaterNet Symposium: Sustainable Use of Water Resources.* Maputo, Mozambique.

Shela, O. N.; Thompson, G.; Jere, P. and Annandale, G., (2008) *Analysis of Lower Shire Floods & A Flood Risk Reduction and Recovery Programme Proposal for the Lower Shire Valley*, Lilongwe: Department of Disaster Management Affairs.

Silva, B. and Marques, N. (2007) 'A hybrid parallel SOM algorithm for large maps in data-mining', in Neves, J., Santos, M. F. & Machado, J. (eds). *New Trends in Artificial Intelligence*, Guimar˜aes: Portugal Associac¸ ˜ao Portuguesa para a Intelig^encia Artificial (APPIA).

Singh, R. D. (2005) 'Real-Time Flood Forecasting- Indian Experiences' in *International G-WADI Modelling Workshop*, Roorkee, India.

Smakhtin, V. and Wichelns, D. (2009) Hydrometeorological data collection and sharing: the global challenge. *World Water Forum.* Istanbul, Turkey.

Smit, B. and Wandel, J. (2006) 'Adaptation, adaptive capacity and vulnerability', *Global Environmental Change,* 16(3), 282–292.

Smith, K. (2013) *Environmental Hazards - assessing risk and reducing disasters,* Sixth Edition, Routledge, Oxon.

Solomantine, D. P. and Dulal, K. N. (2003) 'Model Trees as an Alternative to Neural Networks inRainfall—Runoff Modelling', *Hydrological Sciences Journal,* 48(3), 399-411.

Solomantine, D. P. and Price, R. K. (2004) 'Innovative Approaches to Flood Forecasting using Data Driven and Hybrid Modelling' in Liong, S. Y., Phoon, K. K. & Babovic, V., eds. *6th International Conference on Hydroinformatics* Singapore. World Scientific Publishing Company.

Sudheer, K. P.; Gosain, A. K. and Ramasastri, K. S. (2002) 'A Data-driven Algorithm for Constructing Artificial Neural Network Rainfall-Runoff Models', *Hydrological Processes,* 16(6), 1325-1330.

Sullivan, S. and Meigh, J. (2005) 'Targeting attention on local vulnerabilities using an integrated index approach: the example of the climate vulnerability index', *Water Science and Technology,* 51(5), 69-78.

SVADD, (1975) *An atlas of the Lower Shire Valley, Malawi.*, Blantyre, Malawi.

Tate, E. (2012) 'Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis', *Natural hazards,* 63(2), 325-347.

Taylor, R. (1990) 'Interpretation of the Correlation Coefficient: A Basic Review', *JDMS,* 1, 35-39.

Tchale, H. (2009) 'The efficiency of smallholder agriculture in Malawi', *AFJARE,* 3(2), 101-121.

Tempelhoff, J.; Niekerk, D. V.; Eeden, E. V.; Gouws, I.; Botha, K. and Wurige, R. (2009) 'The December 2004-January 2005 floods in the Garden Route region of the Southern Cape, South Africa', *Jamba: Journal of Disaster Risk Studies,* 2(2), 93-112.

Teschl, R. and Randeu, W. L. (2006) 'A Neural Network Model for Short Term River Prediction', *Natural Hazards and Earth Systems Sciences,* 6, 629-635.

The Global Runoff Data Center. (2003). Koblenz, Germany. [Online] Available: http://www.eea.europa.eu/data-and-maps/data-providers-and-partners/global-runoff-data-centre-grdc

Thielen, J.; Bartholmes, J.; Ramos, M. H. and De Roo, A. (2009) 'The European Flood Alert System – Part 1: Concept and development', *Hydrology and Earth System Sciences,* 13 125-140.

Thirumalaiah, K. and Deo, M. C. (1998) 'Real Time Flood Forecasting using Neural Networks', *Computer-Aided Civil and Infrastracture Engineering,* 13(2), 101-111.

Tingsanchali, T. and Karim, F. (2010) 'Flood hazard assessment and risk based zoning of a tropical floodplain: case study of the Yom River, Thailand', *Hydrological Sciences,* 55(2), 145-161.

Tingsanchali, T. and Karim, M. F. (2005) 'Flood hazard and risk analysis in the southwest region of Bangladesh', *Hydrological Processes,* 19(10), 2055-2069.

Tirivarombo, S. (2012). *Climate Variability and Climate Change in Water Resources Management of the Zambezi River Basin* PhD thesis, Rhodes University.

Toth, E. and Brath, A. (2007a) 'Multistep ahead streamflow forecasting: Role of calibration data in conceptual and neural network modelling', *Water Resources Research,* 43 doi:10.1029/2006WR005383.

Turner Ii, B. L.; Kasperson, R. E.; Matson, P. A.; Mccarthy, J. J.; Corell, R. W.; Christensen, L.; Eckley, N.; Kasperson, J. X.; Luers, A.; Martello, M. L.; Polsky, C.; Pulsipher, A. and Schiller, A. (2003) 'A framework for vulnerability analysis in sustainability science.' in *Proceedings of the National Academy of Sciences*. 8074–8079.

Tweddle, D.; Hastings, R. E. and Jones, T. (1978) 'The Developmemnt of a Floodplain Fishery: Elephant Marsh, Malawi', in Welcomme, R. L. (ed.) *Symposium on river and floodplain fisheries in Africa, Bujumbura, Burundi, 21 November - 23 November 1977. Review and experience papers*: FAO,

UNAIDS, (2000) *Report on Global HIV/AIDS Epidemic*, Geneva: UNAIDS.

UNDP, (2004) *Reducing disaster risk - a challenge for development*, New York: United Nations Development Programme (UNDP), Bureau for Crisis Prevention and Recovery (BCPR).

UNICEF, (2009) *UNICEF Humanitarian Action Report 2009*.

Van-Hulle, M. (2011) 'Self-organizing maps', in Rozenberg G, B. & T, K. J. (eds). *Handbook of natural computing: theory, experiments, and applications*, Berlin: Springer, 1-45.

Van Aalst, M. K.; Cannon, T. and Burton, I. (2008) 'Community level adaptation to climate change: The potential role of participatory community risk assessment', *Global Environmental Change,* 18(1), 165-179.

Van Riet, G. (2006) 'Incorporating HIV/AIDS Considerations into Vulnerability Assessments for Disaster Risk Reduction', *Jamba: Journal of Disaster Risk Studies,* 1(1), 45-53.

Vesanto, J.; Himberg, J.; Alhoniemi, E. and Parhankangas, J., (2000) *Self Orgnizing Map (SOM) Toolbox for Matlab 5*, Report no A57, Helsink, Finland: Helsinki University of Technology.

Victoria, L.; Cruz, L. D. and Balgos, B. (2014) 'CSOs and the Challenges in Risk and Vulnerability Assessment ', in Shaw, R. & Izumi, T. (eds). *Civil Society Organization and Disaster Risk Reduction Disaster Risk Reduction: The Asian Dilemma*, Japan: Springer, 59-77.

Villagran De Leon, J. C., (2006) *Vulnerability – A conceptual and methodological review*, No.4/2006, Bohn: UNU-EHS.

Vincent, K., (2004) *Creating an index of social vulnerability to climate change in Africa* Norwich.

Walkers, P. A. and Peters, P. E. (2007) 'Making Sense in Time: Remote Sensing and the Challenges of Temporal Heterogeneity in Social Analysis of Environmental Change - Cases from Malawi', *Human Ecology,* 35(1), 69-80.

Wang, Q.; Watanabe, M.; Hayashi, S. and Murakami, S. (2003) 'Using NOAA AVHRR Data to Assess Flood Damage in China', *Environmental Monitoring and Assessment,* 82(2), 119-148.

Wilson, M.; Bates, P.; Alsdorf, D.; Forsberg, B.; Horritt, M.; Melack, J.; Frappart, F. and Famiglietti, J. (2007) 'Modeling large-scale inundation of Amazonian seasonally flooded wetlands', *Geophysical Research Letters,* 34 DOI : 10.1029/2007GL030156.

Wisner, B.; Blaikie, P.; Cannon, T. and Davis, I. (2004) *At Risk: natural hazards, people's vulnerability and disasters,* Second edition, Routledge, New York.

WMO/Gwp, (2009) *Integrated Flood Risk Management Concept Paper*, WMO-No. 1047, Geneva, Switzerland: WMO/GWP.

Wolman, M. G. and Leopold, L. B., (1957) *River Flood Plains: Some observations on their formation*, Geological Survey Professional Paper 282-C, Washington DC: US Geological Survey.

World Bank, (1992) *Malawi Economic Report No. 9888-MA1 on Environmental Policy*, Washington DC: World Bank.

World Bank (2007) Malawi: Poverty and vulnerability assessment – Investing in our future. Lilongwe, Malawi.

World Bank, (2010a) *Disaster Risk Reduction in Sub-Saharan Africa*, Washington D.C.

World Bank, (2010b) *Malawi: Economic Vulnerability and Disaster Risk Assessment*: World Bank.

Wu, C. L. and Chau, K. W. (2011) 'Rainfall–runoff modeling using artificial neural network coupled with singular spectrum analysis', *Journal of Hydrology,* 399, 394-409.

Wu, C. L.; Chau, K. W. and Li, Y. S. (2009) 'Methods to improve neural network performance in daily flows prediction', *Journal of Hydrology,* 372, 80-93.

Wu, S.; Yarnal, B. and Fisher, A. (2002) 'Vulnerability of coastal communities to sea-level rise: a case study of Cape May County, New Jersey, USA ', *Climate Research,* 22(3), 255-270.

Yahaya, S.; Ahmad, N. and Abdallah, R. F. (2010) 'Multicriteria Analysis for Flood Vulnerable Areas in Hadejia-Jama'are River Basin, Nigeria', *European Journal of Scientific Research,* 42(1), 71-83.

Yawson, D. K.; Kongo, V. M. and Kachroo, R. K. (2005) 'Application of Linear and Nonlinear Techniques in River Flow Forecasting in the Kilombero River Basin, Tanzania', *Hydrological Sciences,* 50(5), 783-796.

Yuan, H.; Van Der Wiele , C. F. and Khorram, S. (2009) 'An Automated Artificial Neural Network System for Land Use/Land Cover Classification from Landsat TM Imagery', *Remote Sensing,* 1(3), 243-265.

Zahera, S. S.; Di Baldassarre, G. and Balekelayi, C. N. (2011) 'Modelling Seasonally Flooded Wetlands in the Semi-arid Sahelian Zone', *Nile Basin Water Science & Engineering Journal,* 4(2), 83-93.

Zhang, X.; Yi, L. and Zhao, D. (2013) 'Community-based disaster management: a review of progress in China', *Natural Hazards,* 65(3), 2215-2239.

Appendices

Appendix A: Manning's Roughness Coefficient based on Chow (1959)

B. Flood plains (adjacent to natural streams):

1. Pasture, no brush:
   a. Short grass .... 0.030 - 0.035
   b. High grass .... 0.035 - 0.050
2. Cultivated areas:
   a. No crop .... 0.030 - 0.040
   b. Mature row crops .... 0.035 - 0.045
   c. Mature field crops .... 0.040 - 0.050
3. Heavy weeds, scattered brush .... 0.050 - 0.070
4. Light brush and trees:
   a. Winter .... 0.050 - 0.060
   b. Summer .... 0.060 - 0.080
5. Medium to dense brush:
   a. Winter .... 0.070 - 0.110
   b. Summer .... 0.100 - 0.160
6. Dense willows, summer, not bent over by current .... 0.150 - 0.200
7. Cleared land w/ tree stumps, 100-150 per acre:
   a. No sprouts .... 0.040 - 0.050
   b. With heavy growth of sprouts .... 0.060 - 0.080
8. Heavy stand of timber, a few down trees, little undergrowth:
   a. Flood depth below branches .... 0.100 - 0.120
   b. Flood depth reaches branches .... 0.120 - 0.160

Appendix B: Questionnaire used for the CBDRI in Chikwawa and Nsanje Districts

This questionnaire is part of a study undertaken for the purposes of measuring vulnerability and subsequently risk, in the Lower Shire Floodplain of Malawi. The overall objective of the study is to establish quantitatively the degree of vulnerability to the flood hazard and how this is disaggregated along exposure, susceptibility and capacity dimensions and further from a social, economic, economic and physical perspective. The study goes on to determine how such characteristics manifest spatially across the floodplain. The questionnaire in particular serves to elicit the community's ratings and weightings on vulnerability indicators indicated in the table below. The information provided is solely for academic purposes.

Date and Time of meeting……………………………………………………………

Place……………………………………………………………………………………

ADC
Name…………………………………………………………………………………..

2. EXPOSURE			
	STRUCTURES		
2.1	**(E1) Lifelines**		
	% of homes with piped drinking		
	<20%	Low	
	20%-50%	Medium	
	>50%	High	
2.2	**Economy**		
	(E2) average income per capita/day		
	<$2.8	Low	
	$2.8 - $11	Medium	
	>$11/capita/day	High	
3. SUSCEPTIBILITY			
3.1	**Physical/demographic**		
	(S1) Density		
	How many people per km^2 live in the		
	<100	Low	
	100-500	Medium	
	>500	High	
	(S2) Demographic pressure		
	Population growth rate		
	<2%	Low	
	2-4%	Medium	
	>4%	High	
	(S3) Access to basic services		
	% of homes with piped drinking water		
	>50	Low	
	20-50	Medium	
	<20	High	
3.2	**Social**		
	(S4) Poverty level		
	Percent of population below poverty level (1USD/day)		
	<10%	Low	
	10-30%	Medium	
	>30%	High	
	(S5) Literacy		
	Percentage of adult population able to read and write		
	>70%	Low	
	40-70%	Medium	
	<40	High	

	(S6) Attitude		
	What priority does the general population give the protection against a threat from a hazard		
	High priority. Protection against a hazard	Low	
	Concerned, but only if a disaster has hit.	Medium	
	Not concerned. Other issues (food, work etc are much more important)	High	
	(S7) Decentralization		
	What is the portion of self generated revenues of the total available budget		
	>50%	Low	
	20 - 50%	Medium	
	<20%	High	
	(S8) Community participation B53		
	% voter turnout on last commune elections		
	>70%	Low	
	50-70%	Medium	
	<20%	High	
3.3	**Economic**		
	(S9) Local resource base		
	Does the community have a budget	**yes/no**	
	Enough to help the most affected	Low	
	Insufficient	High	
	(S10) Diversification		
	Source of livelihood comes from one, two or three sectors?		
	Mix of 3 sectors	Low	
	Mix of 2 sectors	Medium	
	More than 80% in 1 sector (e.g. agriculture)	High	
	(S11) Small business		
	Percentage of businesses with fewer than 20 employees		
	<50%	Low	
	50-80%	Medium	
	>80%	High	
	(S12) Accessibility		
	How often in the last 5 years was the commune isolated through interruption of access roads for more than 2 days		
	0 - time	Low	
	1-5 times	Medium	
	>5 times	High	
3.4	**Environmental**		
	(S13) Area under forest		
	How much of the total territory of the commune is covered with forest?		
	>30%	Low	
	10-30%	Medium	
	<10%	High	

4. CAPACITIES AND MANAGEMENT				
4.1	**Physical planning and engineering**			
	(C1) Landuse planning		**Their enforcement is**	**Evaluation**
	Does a land use plan or zoning regulations exists that keeps local production and housing out of hazardous areas?	**YES/NO**	Low	Low
			High	High
	(C2) Building codes	**Percent of buildings in threatened area complying to code/standards**		
	Do building codes, design standards, and performance specifications for facilities exist that guarantee the use of flood resistant methods, techniques and material building codes?	**YES/NO**	<30%	Low
			30-70%	Medium
			>70%	High
	(C3) Retrofitting/Maintenance		**Measures implemented**	
	Are existing infrastructure (e.g. bridges, roads) and buildings (schools, hospitals etc) retrofitted to withstand flooding and /or are regular maintenance carried out (River dredging, flood canals etc)	**YES/NO**	Few	Low
			Some	Medium
			Many	High
	(C4) Preventive measures		**Expected effect on damage:**	
	Do flood exposure- limiting mechanisms/ structures exist (dykes, retaining walls, dams, barrages, rock fall barriers, terraces, drainage)?	**YES/NO**	Low	Low
			Medium	Medium
			High	High
	(C5) Environmental management		**Number of activities and projects**	
	Are there activities to promote and enforce conservation of natural resources in risk areas (e.g. protection of water reserves , natural resources, desertification control techniques, reafforestation)	**YES/NO**	Few	Low
			Some	Medium
			Many	High
4.2	**Societal measures**			
	(C6) Public awareness programs		**Frequency (annual)**	
	Are public awareness programs executed?	**YES/NO**	once	Low
			Sometimes	Medium
			regular	High
	(C7) School curriculum		**The topics are taught at:**	
	Are risk, disaster, environment and development topics part of taught lessons at school?	**YES/NO**	one grade only	Low
			2-3 grades	Medium
			all grades	High
	(C8) Emergency response drills		**Drills take place:**	
	Is emergency response training and drills at multiple levels ongoing?	**YES/NO**	One level	Low
			2 levels	Medium
			all levels	High
	Level 1: administration			
	Level 2: relevant response institutions (civil defence, police, fire brigade, emergence health)			
	Level 3: the public (hospitals, schools, large buildings etc			

	(C9) Public participation		**It is composed of**	
	Is the public represented as member in the risk management/emergency committee?	**YES/NO**	only level 1	Low
			2 levels	Medium
			mix of 3 levels	High
	Level 1: administration (mayor's office, planning department			
	Level 2: relevant response institutions (police, fire brigade, education, emergence health)			
	Level 3: the public (business, civil society, NGO'S)			
	(C10) Local risk management/emergency		**% of villages at risk with local emergency group.**	
	Do local groups exist, that have organized members with specific tasks (e.g. emergency response?	**YES/NO**	<30%	Low
			30 - 60%	Medium
			>60%	High
4.3	**Economic measures (Risk Transfer)**			
	(C11) Local emergency fund		**Fund as % of local budget:**	**Evaluation**
	Does a local fund for emergency exist?	**YES/NO**	<10%	Low
			10-50%	Medium
			>50%	High
	(C12) Access to national emergency fund		**How fast can it be released/received**	
	Is there access to a national/district emergency fund?	**YES/NO**	>7 days	Low
			3-5 days	Medium
			< 3 days	High
	(C13) Access to international		**Access to funds is:**	
	Is there access to international emergency funds?	**YES/NO D180**	Difficult	Low
			Easy	High
	(C14) Insurance market		Use	
	Is disaster risk insurance coverage for buildings available?	**YES/NO**	Not common	Low
			common	High
	(C15) Mitigation loans		**Use**	
	Do private banks (including micro-credit institutes) or the government offer loans or subsidies for disaster risk	**YES/NO**	not common	Low
			common	High
	(C16) Reconstruction loans			
	Are there reconstruction credits for affected households?	**YES/NO**	With collateral	Low
			Without	High
	(C17) Public works		**Magnitude:**	
	Do local public works programs (e.g. food for work) exist to support risks reducing measures (retrofitting, preventive structures, reconstruction)?	**YES/NO**	Low	Low
			Medium	Medium
			High	High

4.4	**Management and institutional measures**			
	(C18) Risk management/emergency		**Meeting frequency:**	
	Does a community risk management or emergency committee exist, that deals with prevention, mitigation, preparedness and response?	**YES/NO**	only during emergency	Low
			once a year	Medium
			at least quarterly	High
	(C19) Risk map		**The map is available at different levels:**	
	Does a risk map exist?	**YES/NO D107**	only level 1	Low
			also at level 2	Medium
			also at level 3	High
	Level 1: administration (mayor's office, planning department)			
	Level 2: relevant response institutions (police, fire brigade, education, emergence health)			
	Level 3: the public (business, civil society, NGO'S)			
	(C20) Emergency plan		**Availability of maps at different levels:**	
	Is there a worked out and circulated emergency plan?	**YES/NO**	One	Low
			few	Medium
			many	High
	(C21) Early warning system		Does it work	
	Is an early warning system in place?	**YES/NO**	Low	Low
			Medium	Medium
			High	High
	(C22) Institutional capacity building			
	Do local institutions (administration, police, fire brigade, hospitals, building sector) receive training on risk management?	**YES/NO**	Sometimes	Low
			Often	Medium
			Constant	High
	(C23) Communication			
	Is there coordination with national level risk management organizations (national committees, government etc.)?	**YES/NO**	Sometimes	Low
			Often	Medium
			Constant	High

Shaded data were sourced from third Integrated Household Surveys (National Statistical Office, 2012), the 2008 population and housing census data (National Statistic Office, 2009) and the Malawi land cover database (FAO, 2013).

Appendix C: Community responses to the questionaire

Factor component	**Indicator Name**	**Indicator**	Mbenje	Mlolo	Tengani	Ngabu	Malemia	Ndamela	Nyachikhaza	Ngabu	Katunga	Chapananga	Maseya	Makhuwila	Lundu
EXPOSURE															
Structures	(E1) Lifelines	% of home with potable water	97.5	90.5	97.9	62.5	100	56.3	0	89.8	100	34.4	71.9	96.9	100
Economy	(E2) Economy	average income per capita/day	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1	<US$ 1
SUSCEPTIBILITY															
Physical	(S1) Density	People per km^2	136	169	100	189	125	141	47	138	153	103	183	135	232
	(S2) Demographic pressure	Population growth rate (%)	2.7	2.2	3.8	2.3	1.3	1.3	1.7	3.1	5.0	3.3	3.9	0.7	0.3
	(S3) Access to basic services	% of home with potable water	97.5	90.5	97.9	62.5	100	56.3	water sourced from swamp, no boreholes	89.8	100	34.4	71.9	96.9	100
Social	(S4) Poverty level	% of population below poverty line	many	many	many	many	many	many	many	many	many	many	many	many	many
	(S5) Literacy	% of people that can read and write	41.7	46.9	41.7	46.9	50.0	50.0	very few	50.0	46.9	40.6	46.9	42.0	79.2
	(S6) Attitude	priority of population to protect against a hazard	medium	high priority, people relocating at own will	High priority	concerned but mainly when disaster hits	concerned but mainly when disaster hits	concerned but mainly when disaster hits	concerned but mainly when disaster hits	not concerned, other issues very important	not concerned, other issues very important	not concerned, other issues very important	high priority	not concerned, other issues very important	high priority
	(S7) Decentralization	proportion of self- generated revenue of total budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget
	(S8) Community participation	% of voter turnout at last commune elections	>70%	>70%	>70%		many, but mostly motivated by incentives	>70%	>70%	<20%	medium, people participate mainly if there are benefits	>70%	<50%	>70%	>70%
Economic	(S9) Local resource base	Total available budget	no budget	no budget	no budget, poverty levels very high	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget	no budget
	(S10) Diversification	Economic sector for employment	agriculture	agriculture	agriculture	agriculture	agriculture	agriculture	agriculture	agriculture	agriculture	agriculture	agricultu re	agriculture	agricultu re
	(S11) Stability	% business with fewer than 20 employees	most	most	most	most	most	most	most	most	most	most	most	most	most
	(S12) Accessibility	Number of interruption of roads in the last 2 years	every year	every year	every year	every year	every year	every year, high	every year	every year	medium	every year	medium	every year	every year
Environmenta l	(S13) Environmental	Area under forest (%)	34.9	2.3	58.9	10.7	57.4	44.2	0.0	11.8	10.8	30.5	33.4	5.3	2.8

Factor component	Indicator Name	Indicator	Mbenje	Mlolo	Tengani	Ngabu	Malemia	Ndamela	Nyachikhaza	Ngabu	Katunga	Chapananga	Maseya	Makhuwila	Lundu
CAPACITIES AND MEASURES															
Physical capacity	(C1) Landuse planning	Enforced landuse planning or zoning regulations	forest reserves, low enforcement	yes, related to agriculture and forestry	yes, low	yes, but settlements and cultivation in flood-prone areas, low enforcement	yes, forestry reserve, no cultivation along river banks, low enforcement	yes, targets rivers, low	none	none	none	none	yes, low	yes, low	yes, low
	(C2) Building codes	Applied building codes	none	none	none	none	none	none	none	none	none	none	none	none	none
	(C3) Retrofitting/ Maintenance	Applied retrofitting and regular maintenance	yes, few	yes, many	yes, few	yes, limited to minor works, few	yes, supported by NGOs, few	very few	none	none	none	yes, few	yes, few	yes, applied to boreholes, few	yes, few
	(C4) Preventive measures	Expected effect of impact-limiting structures.	yes, desiltation, afforestation, medium	yes, earth dykes, medium	no measures	yes, NGO or public works supported, low quality, low impact	yes, low	yes, but small activities, low	yes, low	yes, low	yes, low	yes, medium	none	yes, earth embarkments, low impact	yes, medium
	(C5) Environmental management	Measures that promote and enforce nature preservation.	yes, few	yes, tree planting, some	many, project based	yes, few	yes, few	yes, few	yes, many	yes, some	yes, many	yes, by NGOs, few	yes, some	yes, some	yes, some
Societal capacity	(C6) Public awareness programs	Yearly frequency of public awareness programs	yes, regular	yes, regular	yes, few, once	yes, sometimes	yes, sometimes	yes, assisted with NGOs, sometimes	yes, sometimes	yes, once	yes, regular	yes, once	yes, regular	yes, sometimes	yes, sometimes
	(C7) School curriculum	Scope of relevant topics taught at school.	taught in most grades of primary school	taught in most grades of primary school	taught in most grades of primary school	taught in most grades of primary school	taught in most grades of primary school	Taught in most grades of primary school	there is no school	taught in most grades of primary school	taught in most grades of primary school	taught in most grades of primary school	taught in most grades of primary school	taught in most grades of primary school	taught in most grades of primary school
	(C8) Emergency response drills	On-going emergency response training and drills	yes, all levels	yes, all levels, with help of NGOs	no	yes, supported by NGOs, at 2 levels	yes, all levels	yes, all levels	yes, all levels	no drills	yes, at 2 levels	yes, at 2 levels	yes, all levels	yes, one level, local level	yes, up to 2 levels
	(C9) Public participation	Emergence committee with public representatives	mix of all levels	Mix of all levels	mix of all levels	mix of all levels	mix of all levels	mix of levels	mix of all levels	mix of all levels	mix of all levels	mix of all levels	mix of all levels	mix of all levels	mix of all levels
	(C10) Local risk management/ emergency groups	Grade of organisation of local groups	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels	local risk groups exist at district, ADC and VDC levels

Factor component	Indicator Name	Indicator	Mbenje	Mlolo	Tengani	Ngabu	Malemia	Ndamela	Nyachikhaza	Ngabu	Katunga	Chapananga	Maseya	Makhuwila	Lundu
Economic capacity	(C11) Local emergency fund	Local emergency fund as % of local budget	no fund	no fund	no fund	no funds, but relief items, come after 4 months from flood occurrence	no fund	no fund	no fund	no fund	no fund	no fund	no fund	no fund	no fund
	(C12) Access to national emergency fund	Release period of national emergency fund	no access to funds	no access to funds	no access to funds	no access to funds	no access to funds	no access to funds but relief items. However, take long	no access to funds but relief, takes very long to arrive	no access to funds	no access to funds	no access to funds	no access to funds	no access to funds	no access to funds
	(C13) Access to international emergency funds	Access to international emergency funds	no access	no access	no access	no access	no access	no access	no access	no access	no access	no access	no access	no access	no access
	(C14) Insurance market	Availability of insurance for buildings	no insurance	no insurance	no insurance	no insurance	no insurance	no insurance	no insurance	no insurance	no insurance	no insurance	no insurance	no insurance	no insurance
	(C15) Mitigation loans	Availability of loans for disaster risk reduction measures	not available	not available	not available	not available	not available	not available	not available	not available	not available	not available	not available	Not available	not available
	(C16) Reconstruction loans	Availability of reconstruction credit	not available	not available	not available	not available	not available	not available	not available	not available	not available	not available	not available	not available	not available
	(C17) Public works	Magnitude of local public works programs	yes, low	yes, low	yes, K300 per day, low	yes, high	yes, high	yes, low	yes, medium	yes, medium	yes, targets afforestation, high	yes, low	yes, low	yes, low	yes, towards road reconstruction, low
Management and Institutional Capacity	(C18) Risk management /emergency committee	Meeting frequency of a community committee	yes, once a year	yes, only during emergence	yes, once a year	meet but not regularly	yes, at least quarterly	yes, at least quarterly	yes, at least quarterly	yes, only during emergency	yes, only during emergency	yes, only during emergency	meet, once a year	yes, meet only an emergency	yes, at least quarterly
	(C19) Risk map	Availability and circulation of maps	yes, only level 1	yes, only level 2	no map	yes, many levels	yes, also level 3	yes, also level 4	yes, also at level 3	no maps	no maps	no maps	yes, also at level 3	none	yes, only level 1
	(C20) Emergency plan	Availability and circulation of emergency plans	yes, many	yes, one	yes, one	yes, many	yes, many	yes, many	yes, many	no plans	yes, one level	no plans	no plans	none	yes, many
	(C21) Early warning system	Effectiveness of early warning system	yes, traditional systems, low	yes, medium	yes, only on Shire River, works sometimes	yes, weather forecasting, river gauges, phones, drumming, whistles, medium	yes, low	yes, whistles, drums, staff gauges, low impact	yes, radios, drums, whistle	no system	yes, from meteorological department, sometimes	yes, high	yes, low impact	yes, radio, medium	yes, phones, ,staff gauges, drums, low
	(C22) Institutional capacity building	Frequency of training of local institutions	yes, sometimes,	yes, sometimes, organised by NGOs	yes, sometimes	yes, sometimes	yes, often	yes, sometimes	yes, sometimes	no	yes, sometimes	yes, sometimes	no training	yes, sometimes	yes, offered by NGOs, sometimes
	(C23) Communication	Frequency of contact with district level institutions	yes, constant	yes, constant	yes, often	yes, often	yes, sometimes	yes, constant	yes, often	yes, often	often, but during rainy season	yes, often	yes, often	yes, constant	yes, often