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# An approach for measuring social vulnerability in context: The case of flood hazards in Muzarabani district, Zimbabwe



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## ABSTRACT

Understanding the complexity of vulnerability to disasters, including those triggered by floods, droughts and epidemics is at the heart of disaster risk reduction. Despite its importance in disaster risk reduction, there remains a paucity of approaches that contribute to our understanding of social vulnerability that is hidden in dynamic contextual conditions. The study demonstrates an accessible means to assessing the spatial variation of social vulnerability to flood hazards and related for the context of Muzarabani district in northeast Zimbabwe. The study facilitated local identification with residents of variables contributing to social vulnerability and used the principal component analysis (PCA) technique to develop a social vulnerability index (SoVI). Using ArcMap10.2 geographic information systems (GIS) tool, the study mapped composite SoVI at the ward level. The results showed that Muzarabani district is socially vulnerable to hazards. The social vulnerability is influenced by a variety of economic, social and institutional factors that vary across the wards. Quantifying and visualising social vulnerability in Muzarabani provides useful information for decision makers to support disaster preparedness and mitigation programmes. The approach shows how spatially distributed multivariate vulnerability, as grounded in interpretations at local level, can be quantitatively derived for contexts such as those of Muzarabani. The study findings can inform disaster risk reduction communities and cognate disciplines on quantitative assessments for managing hazard vulnerability where these have hitherto not been developed.

## 1. Introduction

Ever since Jean-Jacques Rousseau, Lowell Carr and Gilbert White, in their very different ways, opened up new avenues for disaster analysis, there has been a growing recognition of the vital links between hazards and social vulnerability, demonstrating that disasters were a manifestation of uneven political-economic relations rather than exceptional events to otherwise stable everyday life (Grove, 2013). For Rousseau, the catastrophes such as the 1755 Lisbon earthquake were in large measure a result of the social conditions of Portugal, where crowded urban patterns of the city and corruption made people more exposed to adversity (de Almeida, 2009). In a prescient argument Carr (1932) recognised that disasters were a result of a collapse in cultural norms that support society, while White (1945, p. 2) argued that floods “are acts of God” while losses “are acts of man”. All this has become familiar territory, particularly from the 1970s, when social scientists began to find ample evidence that natural hazards had varying impacts on different social groups.

In their seminal paper, *Taking the naturalness out of natural disasters*,

O’Keefe et al. (1976) argued for a focus on human vulnerability in contrast to the modernist orthodoxies which treated hazards as the precursors to disasters. In this vein, disaster causation has become inextricably intertwined with the social, political and ideological assumptions and practices that produce vulnerability and create entitlements based on such things as race, gender, and age, in addition to class relations (Bradshaw, 2015; Enarson, 1998). As such, disaster analyses can put less emphasis on natural hazards. Rather, much focus should be on the surrounding social environments in which vulnerability is (re) produced. These social processes determine the people who are most at risk from hazards; where they live and work, the kinds of settlements in which people live, their level of hazard preparedness, income, health, access to information and further details of their lives, which may be spatially expressed.

A better quantification of the multifaceted nature of social vulnerability is an important and long overdue addition to the hazard mitigation planning and implementation processes (Tate, 2013) especially in the context of climate change adaptation and disaster risk reduction strategies. Importantly, there has been an increasing appetite for

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measuring vulnerability, however defined, as reflected in a set of examples compiled by Birkmann (2006). Moreover, as governments are increasing their attention towards planning for, and responding to, natural hazards, especially those associated with climate change (Stafford and Abramowitz, 2017), social vulnerability data becomes a *sine qua non* element for decision-making. By extension, the assumption here is that the vulnerability data, including its spatial representation, will inevitably make it possible to better address socio-economic and attendant environmental challenges faced by communities. While numerous index designs have been put forward, we still know very little about their reliability (Tate, 2013). In a time when the United Nations Sendai Framework for Disaster Risk Reduction (SFDRR) (UNISDR, 2015) calls for all parts of the world to engage in better ‘understanding risk’, for which vulnerability is fundamental, researchers are slow to implement the means to doing this, particularly in rural areas of poorer regions.

To address this gap, this article seeks to measure social vulnerability to hazards, broadly defined, in Muzarabani district, Zimbabwe in a new application of an applied and locally grounded quantitative technique. The application of this technique demonstrates how social vulnerability analyses can be operationalised in economically poorer and more marginalised settings with low-level secondary data. By ‘vulnerability’ the study refers to the conditions determined by physical, social, economic and environment factors or processes that increase the susceptibility and an individual, a community, assets or systems to the impacts of hazards (O’Keefe et al., 1976; Wisner et al., 2004; Adger, 1999). Given the known high incidence of socio-economic poverty in the area, reasons for measuring social vulnerability and the use of vulnerability indicators were fourfold. They were to help define where the greatest likely need of vulnerability reduction is, set priorities by deriving knowledge about spatial social vulnerability patterns, monitor progress in vulnerability reduction, and measure the effectiveness of mitigation approaches against disasters. This methodologically derives from Susan Cutter and colleagues’ social vulnerability index, which they developed in the mid-2000s. The social vulnerability index (SoVI) uses principal component analysis (PCA) to measure social vulnerability to environmental change and natural disaster (Cutter et al., 2003). The PCA identifies common factors underlying an assortment of potential vulnerability indicators (Cutter et al., 2010; Stafford and Abramowitz, 2017).

While context-specific SoVI studies have been conducted, for example in Caribbean Island States (Boruff and Cutter, 2007), Brazil (de Hummell and Cutter, 2016), Zimbabwe, and most parts of Africa, currently lack integrated place-based assessments of disaster, risk, and vulnerability, particularly in spatially defined contexts of hazards, risks and disasters. The replication of the original SoVI in the Zimbabwean context also expands evidence of the workability of the algorithm in a different context of development, as a limited number of studies have used empirical approaches to develop indicators of vulnerability to hazards in Africa (Lawal and Arokoyu, 2015; Abson et al., 2012).

The study used field-based approaches to develop indicators of social vulnerability to hazards in the Muzarabani community. Also, as people in different environments do not necessarily share the same perceptions of risk and their underlying causes (Laursen, 2015), adapted and enhanced comparative studies help to develop appropriate and context-specific sets of indicators of social vulnerability (Hinkel, 2011). Here, the use of field-based approaches identified context-specific indicators of vulnerability in Muzarabani. Although there are a wide range of possible spatial scales for examining vulnerability, this study used the ward scale, this being lowest scale for which quantitative data is available to develop contextual and place-specific indicators in Zimbabwe.

The rest of the article is organized as follows. Sections two and three review the concept of vulnerability and how it is assessed in relation to disaster risk reduction. Section four geographically contextualises the study area, and the fifth section explains the data source and methods

used. Sections six, seven and eight present the major findings and discussion respectively, ending with a conclusion that contextual and place-specific indicators can be derived at the lowest level to enhance understanding of, and spatial approaches to, social vulnerability in contexts such as northeast Zimbabwe.

## 2. The construction of social vulnerability to hazards

The vulnerability concept has been in use for close to five decades, especially across disaster management, development, economics, sociology, anthropology, geography, health, global change, and environmental studies (Bergstrand et al., 2015; Cutter, 1996; O’Keefe et al., 1976; Timmerman, 1981). Although a large and growing literature has investigated the role of vulnerability, not least in disaster and climate change studies, the concept of vulnerability remains fuzzy, which makes measuring vulnerability complex. In his analysis of 24 definitions of vulnerability, Weichselgartner (2001) identifies many differences in the meanings of vulnerability, which arise from different epistemological orientations and subsequent methodological practices.

Simply defined, vulnerability to disasters means the potential for loss (Cutter et al., 2003). As often the case, such simplistic definitions do not sit well with scholarly definitions. The problem with this simplistic definition of vulnerability is the danger of synonymising it with the definition of risk, which can be a source of confusion when attempting to measure vulnerability. Despite vulnerability is a contested concept, a general view of what vulnerability means has emerged as: a ‘threat’ or ‘exposure’ to a hazard; the degree of potential for loss; propensity or predisposition to be adversely affected; or circumstances that put people at risk, and it is a result of historical, social, economic, political, technological, institutional, environmental conditions and processes (Adger and Brown, 2009; Bankoff, 2004; Cutter, 1996; Susman et al., 1983; Timmerman, 1981; Weichselgartner, 2001; Wisner et al., 2004). Any one of these definitions individually does not capture the varied dimensions of vulnerability in full in that, for example, defining vulnerability as exposure to hazards fails to acknowledge the role of socio-economic characteristics of the individuals or community at risk. That vulnerability is a complex concept as these definitions suggest, is not new; this complexity characterizes the vulnerability literature to date, which has had a significant influence on how vulnerability is measured. What is apparent, however, is that vulnerabilities vary geographically, over time, space and among different social groups (Cutter et al., 2003). The basic questions underlying vulnerability analysis tends to be; ‘how do natural hazards affect society?’, but in more detail can be expressed as what are the critical processes and outcomes of hazards risks and disasters in society? (Collins et al., 2015). Hazards cannot be totally eliminated or controlled (Solangaarachchi et al., 2012), but humans can reduce the risk associated with the hazard occurrence through a shift from the hazard to the vulnerability paradigm (Timberlake, 1984) to achieve disaster risk reduction. However, to date, in many regions there is limited effort profiling social vulnerability to hazards from a local level upwards in hazard affected places where socio economically poorer people live.

Profiling factors that are likely to influence vulnerability to a wide variety of hazards in different geographical and socio-political contexts is complex as vulnerability is multi-dimensional and differential (Birkmann, 2006; Solangaarachchi et al., 2012). Restated, vulnerability varies across physical space, among and within social groups. Vulnerability is also scale dependent (with regard to time, space and units of analysis such as individual, community or system) and dynamic as the characteristics and driving forces of vulnerability change over time (Fekete et al., 2009; Tapsell et al., 2010). As a result, one major challenge in vulnerability assessment is that not only societies are different, but their socio-economic conditions are changing continuously, both as individuals and as groups (Fuchs et al., 2012). This constant change interacts with the physical system to make hazard, exposure, and vulnerability all dynamic (Fuchs et al., 2012). These changes lead to the

postulate that only consideration of either structural or social vulnerability is not sufficient to assess vulnerability comprehensively from an integrative point of view. In contrast, dimensions of susceptibility also encompass institutional and socio-economic aspects. As such, any damage occurring might be considered as prerequisite for structural and economic susceptibility, while institutional susceptibility and social aspects provide the framework for vulnerability in general (Fuchs et al., 2012). In this way, multiple interactions between these conceptualisations of vulnerability exist. Considering the dynamic nature of vulnerability, there is a need for approaches that consistently review the vulnerability of communities to hazards *in situ*. This is needed not least since vulnerability studies that are conducted at national level often overlook context-specific variables that drive vulnerability at local levels.

Although vulnerability conceptualisations vary in emphasis, three forms stand out: vulnerability as hazard exposure; vulnerability as social response; and vulnerability of places (Cutter, 1996). Thus, there are biophysical, social and spatially expressed vulnerabilities. Biophysical vulnerability includes the spatial distribution of hazardous conditions, the human occupancy of hazardous zone(s) and the extent of loss associated with the occurrence of a particular hazard. Social vulnerability includes conditions rooted in historical, cultural and socio-economic processes that impinge on an individual's or society's ability to cope with disasters. Spatially expressed vulnerability can combine elements of biophysical and social vulnerability, but within specific geographical areas (where social groups and all the characteristics of a place are located). The emphasis with social space therefore may include those places that are most vulnerable (Cutter, 1996).

Armaş and Gavriş (2013) and Solangaarachchi et al. (2012) distinguish between social and physical vulnerability. Gain et al. (2015) and Kusenbach et al. (2010) view social vulnerability as the susceptibility of humans to shocks and stressors and the conditions necessary for their survival and adaptation; while physical vulnerability is seen as the extent to which a system such as a community is exposed to adverse effects of a hazard and is (un)able to adapt to such impacts. Much research has focused on physical vulnerability. For example, Paul and Routray (2010) compared flood proneness between two villages in Bangladesh. Risi et al. (2013) assessed flood risk for informal settlements in Tanzania. However, the analysis of social vulnerability to natural hazards is a relatively small but growing research area. One of the reasons why social vulnerability studies are relatively few is that it is difficult to quantify social losses in after-disaster cost/loss estimation reports because they are intangible because they are intangible, as such losses are not only difficult to represent using physical objects but also pose challenges in measuring them (Cutter et al., 2003; Solangaarachchi et al., 2012).

Social vulnerability has been considered as the institutional, demographic and socio-economic characteristics of an individual, community or system that reduce its capacity to prepare for, respond to and recover from the hazard or disaster (Solangaarachchi et al., 2012; Yoon, 2012; Siagian et al., 2014). From a developmental perspective people experiencing vulnerability may transition to well-being if the nature of the underlying and proximate influences are understood and interventions are targeted with the right people, timing and places (Collins, 2009). As such, Sherman et al. (2015) postulate that the degree to which communities are vulnerable to hazards is not solely dependent upon their exposure to hazards but also upon their demographic (for example, gender and age) and socio-economic characteristics. This is because the demographic and socio-economic conditions of a community are the ones that interact with a hazard, which may be natural, but resulting in a disaster (Armaş and Gavriş, 2013). A variation in characteristics of people determines a position of advantage or disadvantage regarding disaster outcomes.

That different societies live under varying social, economic, political, cultural and institutional settings can be independent of hazards that trigger adversity, but greatly influences their capacity to prepare

for, respond to and recover (Lee, 2014). This difference in capacity may explain why communities with similar levels of exposure may experience different impacts from a particular hazard (Cutter et al., 2009; Finch et al., 2010).

Disparities in vulnerability to natural hazards can arise from wide gaps in access to resources and capacities for risk reduction associated with low-incomes and socio-cultural stratification (Massmann and Wehrhahn, 2014). However, not all low-income earners are vulnerable: some have assets, including livestock, which can be liquidated into cash at any time to enable them to cope with hazards. Social vulnerability to disasters also differs as the hazard unfolds and impacts upon the social groupings (Chang et al., 2015). In Indonesia, Siagian et al. (2014) found that the generation mode of floods, their rate of onset, velocities and their temporal persistence in the environment affects population groups differently. It is also important for preparedness planning to consider that floods have both long and short lead-time in terms of reactions to the risks they present.

Physically unsafe places do not always intersect with vulnerable populations (Cutter et al., 2003). For example, in an area of high physical risk to flooding, economic losses might be large, but equally the population may have significant safety nets such as insurance to absorb the flood hazards. However, a moderate flood event can have a significant impact with a long time-span for recovery on socially vulnerable populations. One of the crucial aspects of the social construction approach is that it focuses upon representations of underlying structural causes of vulnerability, as opposed to the proximate causes. With such a focus, it is necessary to understand interrelating processes operating on local and wider scales and how this constitutes vulnerability relative to specific groups or communities in space and time.

### 3. Measuring social vulnerability to disasters

Before elaborating on social vulnerability measurement, it is crucial to identify what to measure. A general consensus has emerged over the decades on the major factors that influence social vulnerability. Mostly cited are lack of access to resources; limited access to political power and representation; connectedness with supporting people; beliefs and customs; building stock and age; frail and physically limited individuals; and type and density of infrastructure including energy supply and transportation routes (Bergstrand et al., 2015; Cutter et al., 2003; Cutter and Finch, 2008; Siagian et al., 2014; Wisner et al., 2004). While several methodologies are employed in assessing social vulnerability at different scales and systems, the indicator-based approach has been commonly applied in different countries addressing specific hazards (Armaş and Gavriş, 2013; Chang et al., 2015; Siagian et al., 2014). The social vulnerability indicators include age, race, health, poverty, income, type of dwelling unit and employment (Adger, 2006; Cutter et al., 2003; Kusenbach et al., 2010; Lee, 2014; McEntire, 2012).

There are still disagreements in the selection of indicators of social vulnerability. In their study on social vulnerability to natural hazards in Indonesia, Siagian et al. (2014) used age, gender, income, education, family structure, infrastructure and population growth as their variables. In another study on assessing social vulnerability to malaria in Rwanda, Bizimana et al. (2015) used population pressure, population movement, household size, livelihoods, poverty index, pregnancy, age, HIV and AIDS, malnutrition, education, housing condition, access to media, protection to measures, and access to health services. Table 1 shows some input variables ranging from 16 to 57 in 22 studies on social vulnerability.

The majority of the indicators are selected subjectively by authors who base their choice on reviews of related literature (Chang et al., 2015). A limited number of studies have used empirical approaches to develop locally derived indicators of vulnerability to hazard. The most important aspect in the selection of indicators is to ensure that the indicators address the research question and test the concepts under operationalisation. While an indicator is a quantitative or qualitative

**Table 1**  
Studies on measuring social vulnerability.

References	Hazard type	Spatial extent	Spatial granularity	# of input variables	Component retention	Component weighting	High-vulnerability criterion
Cutter et al. (2003)	General environmental	USA	County	42	Kaiser (Eigenvalue > 1)	Equal	> 1 SD above mean
Boruff et al. (2005)	Coastal erosion	USA	County	39	Eigenvalue > 0.95	Equal	> 1 SD above mean
Rygel et al. (2006)	Hurricane (storm surge)	Hampton Roads, VA	Census block group	57	Kaiser	None	> 1.5 SD above mean
Burton and Cutter (2008)	Flooding (levee failure)	Sacramento-San Joaquin River Valley, CA	Sub-county	36	Kaiser	Equal	None
Myers et al. (2008)	Hurricane Katrina, Hurricane Rita	US Gulf Coast	County	24	Unspecified	None	> 1 SD above mean
de Oliveira Mendes (2009)	General environmental	Centre Region, Portugal	Municipality	50	Kaiser	Equal	> 1 SD above mean
Burton (2010)	Hurricane Katrina	Mississippi Gulf Coast	Census tract	32	Kaiser	Equal	Top 20 percent of tracts
Finch et al. (2010)	Hurricane Katrina	Orleans Parish, LA	Census tract	29	Kaiser	Equal	> 0.5 SD above mean
Tate et al. (2010)	General environmental	Charleston, SC	Census block group	32	Kaiser	Unspecified	Unspecified
Wood et al. (2010)	Tsunami	Pacific Northwest USA	Census block	29	Kaiser	Variance weighting	> 1 SD above mean
Bjarnadottir et al. (2011)	Hurricane (storm surge)	Miami-Dade County, FL in 2050	Municipality	16	Kaiser	Expert-assigned	None
	Hurricane Katrina, Hurricane Rita	US Gulf Coast	County	24	Unspecified	None	> 1 SD above mean
	General environmental	Centre Region, Portugal	Municipality	50	Kaiser	Equal	> 1 SD above mean
	Hurricane Katrina	Mississippi Gulf Coast	Census tract	32	Kaiser	Equal	Top 20 percent of tracts
	Hurricane Katrina	Orleans Parish, LA	Census tract	29	Kaiser	Equal	> 0.5 SD above mean
	General environmental	Charleston, SC	Census block group	32	Kaiser	Unspecified	Unspecified
	Tsunami	Pacific Northwest USA	Census block	29	Kaiser	Variance weighting	> 1 SD above mean
Schmidlein et al. (2011)	Hurricane (storm surge)	Miami-Dade County, FL in 2050	Municipality	16	Kaiser	Expert-assigned	None
Solangaarachchi et al. (2012)	Seismic	Charleston, SC metropolitan area	Sub-county/census tract	26	Kaiser	Equal	None
	Bushfire	South-eastern Australia	Census Collection District	26	Kaiser	Variance	> 1.5 SD above mean
Wang and Yarnal (2012)	Hurricane	Sarasota, FL	Census block group	64	Kaiser	None	Individual components > 1.5 SD above mean
Armaş and Gavriş (2013)	Earthquake	Bucharest, Romania	Census tract	22	Kaiser	Equal	> 1 SD above mean
Cutter et al. (2013)	Flooding	South-eastern USA	Census tract	32 and 9	Unspecified	Unspecified	Unspecified
Holand and Lujala (2013)	General environmental	Norway	Municipality	37	Kaiser	Equal	> 1 SD above mean
Martinić et al. (2013)	Sea level rise	US coastal counties	Census tract	26	Unspecified	Equal	> 1.5 SD above mean
Toké et al. (2014)	Seismic	Los Angeles, CA	Census block group	20	Unspecified	Unspecified	None
Lawal and Arokoyu (2015)	Multiple hazards	Nigeria The South West Geopolitical Zone	Geopolitical Zone	18	Kaiser	Equal	Unspecified
	Flooding Resilience, not social vulnerability	South Africa, Southern Cape	Municipality	24	Kaiser	Equal	> 1.5 SD above mean
Mwale et al. (2015)	Flooding	Lower Shire Valley, Malawi	Area Development Committee District	44	Unspecified	Variance weighting	> 0.8
Hahn et al. (2009)	Livelihood vulnerability	Mabote & Moma districts, Mozambique	District	30	Unspecified	Equal	1

Some of the source are from Stafford and Abramowitz (2017), pp. 1093–1094.

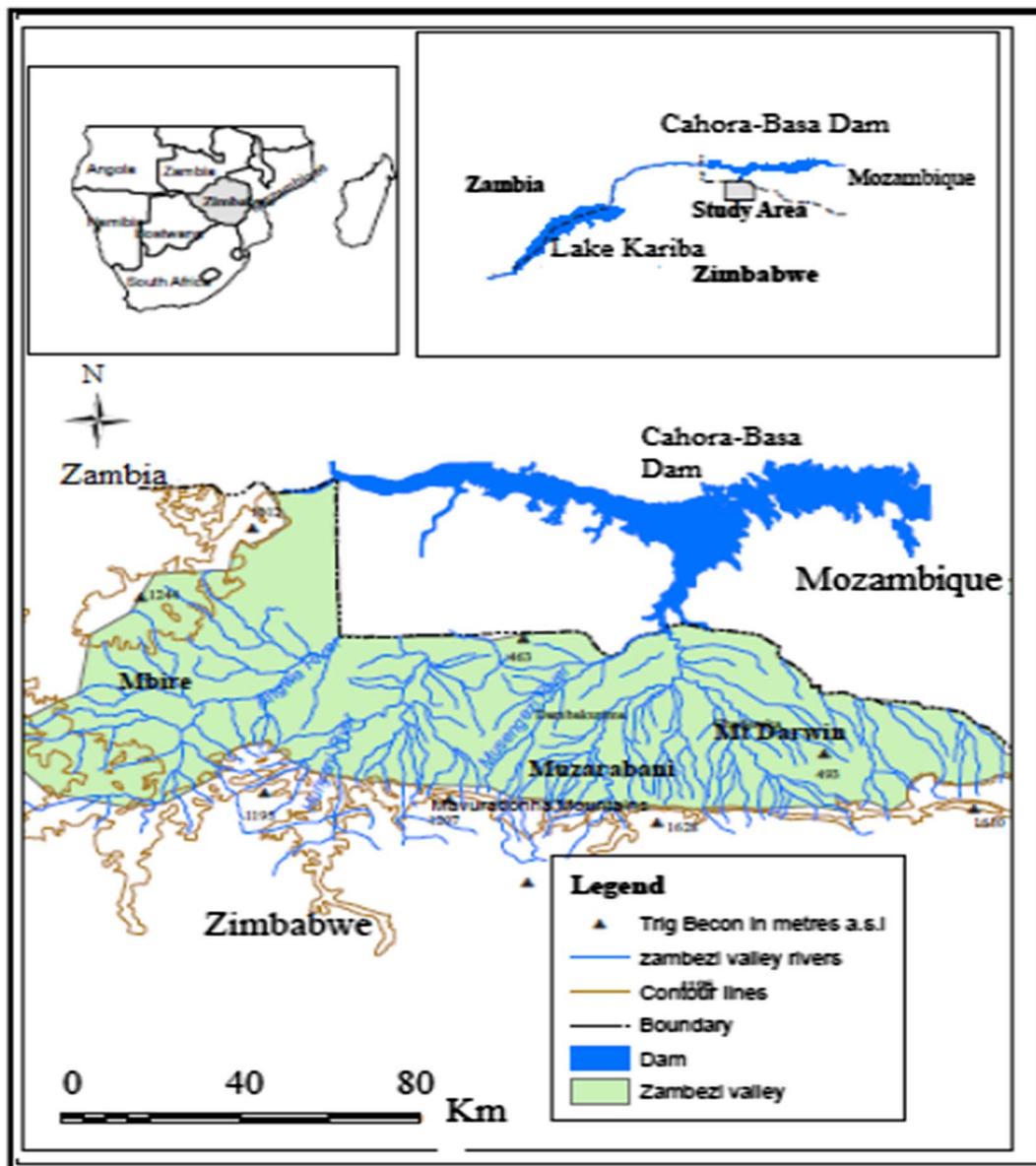


Fig. 1. Location of study area: Muzarabani.

measure derived from observed facts that simplify and communicate the reality of a complex situation, a composite indicator is the mathematical aggregate of individual variables or thematic sets of variables that represent different dimensions of a concept that cannot be fully captured by any individual indicator alone (Cutter et al., 2010). One of the main challenges of this study was to identify appropriate variables that represent susceptibility to hazards at the local level in Muzarabani. However, the concept of hazard - and context-specific, as opposed to generic determinants are useful when assessing vulnerability at community level. This is because generic indicators do not provide a complete description of vulnerability at local level where geographical and social differentiation are exhibited (Brooks et al., 2005).

The use of indicators also presents challenges in validating social vulnerability in that there are limits to quantification of social and mental states where these are not a directly observable phenomenon (Tate, 2012). The indicator approach may also fail to capture comprehensively the vulnerability conditions of a particular place. Despite this challenge, the indicator approach is ideal for comparative purposes of places (Chang et al., 2015). At local level, the indicator approach provides a more accurate estimation of baseline vulnerability which is

important for policy decision makers in disaster risk reduction. This should encourage progress in reducing the social inequalities generating the vulnerability conditions (Siagian et al., 2014).

Different methods to assess social vulnerability to hazards have evolved through ongoing research and practice in recent decades (Balica et al., 2013). In their review of the existing academic literature on the construction of quantitative social vulnerability indicators, Stafford and Abramowitz (2017), reveal that since its creation, social vulnerability index (SoVI) in particular, and principal component analysis (PCA)-based composite indexing more generally, have become one of the most common paradigms for quantitatively identifying social vulnerability to environmental hazards, such as hurricanes, storm surges, flooding, and coastal erosion.

Also, most of the studies (Table 1) tend to cover methods applicable pre- and post-hazard event including participatory, simulation models and indicator-based approaches that are applied to a great diversity of systems (Hinkel, 2011). On a macro scale, quantitative assessments using indicators are very common (Massmann and Wehrhahn, 2014). Approaches at the micro scale are both quantitative and qualitative, depending on research questions and data availability, being: (a)

deterministic modelling approaches and (b) parametric approaches using available data to build an impression of the vulnerability of a system (Balica et al., 2013).

The deterministic approach estimates the vulnerability of a particular place by assessing risk to life or damage based on physical vulnerability or by assuming a homogeneous vulnerability of the entire population (Lee et al., 2014). For example, Blanco-Vogt and Schanze (2014) assessed the flood susceptibility of buildings on a national scale in Colombia using remote sensing. The deterministic approach relies on a significant amount of detailed topographic, hydrographic and economic data in the area studied. It estimates vulnerability as a function of water depth, flood elevation and velocity. While the deterministic approach is by no means less important, it tends to neglect the social dimensions of risk and spatial variation (Koks et al., 2015).

The parametric approach generally consists of vulnerability metrics such as the Environmental Vulnerability Index (EVI), Global Risk and Vulnerability Index (GRVI), and the Climate Vulnerability Index (CVI), involving indicator selection and weight determination (Balica et al., 2013; Lee et al., 2014). Since its introduction in the 1980s by Little and Rubin (1983), the parametric approach has developed into four distinct versions (Balica et al., 2013). The first version of the parametric approach estimates the complete vulnerability value of a system by using only a few parameters relating to that system. The second parametric approach is used to estimate the imputation of non-observable values. Although there is a risk of getting assumptions wrong, here the observed parameters are used to model the non-observed ones. The third version of the parametric approach is what Little and Rubin (1987) call “parametric modelisation via maximum likelihood”. This is not a direct approach and is based on a large number of assumptions. The final approach is what Newey (1990, p. 99) calls a “semi-parametric approach”, where the functional form of some components is unknown, which allows modelling only of what is strictly necessary (Balica et al., 2013). The parametric approach can, in itself, have drawbacks that include an inevitable level of assumptions, the need for a sensitivity analysis, reliable sources and the subjective manner of interpreting the results. Previous social vulnerability studies have focused on assessing patterns of social vulnerability in a region (Angell and Stokke, 2014; Solangaarachchi et al., 2012) and the identification of socio-economic characteristics that can explain the social vulnerability of a population (Cutter et al., 2003; Siagian et al., 2014).

#### 4. The study area

This research took place in Muzarabani district, northern low-veld of Zimbabwe in Mashonaland Central Province (Fig. 1). Located about 250 km north of Harare, the capital city of Zimbabwe, and part of the Zambezi Valley basin, Muzarabani comprises an alluvial floodplain with deep sedimentary deposits formed by sediment flows from the Zambezi River and its tributaries. The Zambezi River flows from the Kalene Hills in Zambia generally in an easterly direction into the Indian Ocean and shared by seven countries: Angola, Namibia, Zambia, Botswana, Malawi, Mozambique and Zimbabwe (Madamombe, 2004). The Zambezi River also marks the boundary between Zimbabwe and Zambia as well as Mozambique.

Muzarabani is one of the disaster-prone districts in Zimbabwe. Disasters that are common in Muzarabani include floods, drought, malaria, and gastro-intestinal infections such as diarrhoea, typhoid and cholera. The term *muzarabani* in the local Shona language means flood plain, or an area frequently flooded. The soils over much of the district are sodic, and specialised vegetation communities have adapted to the highly mineralised soils. The vegetation that predominates is *Colophospermum mopane* (known as mopane woodlands). There are also pockets of ecologically important dry forests including *Acacia* spp., *Commiphora* spp. and baobab.

Two types of floods have affected the Muzarabani area for decades. The first and most frequent is the seasonal flood, which frequently

occurs in January or February, at the peak of the rainfall season. The second and not so frequent one is the cyclone-induced flood. In 2000, Cyclone Elin induced floods in Muzarabani and other eastern districts of Zimbabwe that left 120 people dead and over 250,000 people affected, with approximately US\$7.5 million in economic losses (Shumba, 2005). The floods caused great damage to houses, crops, electricity supply lines and food stocks and also promoted the spread of diseases such as malaria and cholera, among others. Economic activities were disrupted, thereby creating financial stress on already poor people.

Flooding in Muzarabani also relates to other hazards biological origin including malaria and gastro-intestinal tract infections (GTI) such as diarrhoea, typhoid and cholera. The unprecedented cholera outbreak in 2008/2009 resulted in about 100,000 cases and 4000 deaths being reported nationwide (Ministry of Health and Child Welfare and World Health Organisation, 2009). The 2008/9 cholera outbreak was the most severe on record and went beyond Zimbabwe's response capacity. This affected Muzarabani district although exact figures of deaths remain unpublished. With most of the underlying causes of the 2008/2009 cholera outbreak having not been addressed, the risk of GTIs remains high (Department of Civil Protection, 2012). Social gatherings such as funerals, religious and traditional ceremonies and practices commonly held in Muzarabani compound the risk of cholera.

Muzarabani is also a semi-arid to arid district located in agro-ecological region IV, which is characterised by low annual precipitation of 450–650 mm, seasonal droughts and severe intra-season dry spells. The rain season is unimodal, extending from mid-November up to the end of March. Mudavanhu et al. (2015) posit that the climate of Muzarabani district is largely controlled by global atmospheric circulation patterns, chief among them, the movement of the inter-tropical convergence zone (ITCZ) that determines the annual seasonality of precipitation across tropical Africa. Because of high temperatures during the summer season, convective rainfall is at times experienced. The frequency of these hazards has increased the risk of disasters in Muzarabani.

Results of the 2012 national population census show that Muzarabani district has a total population of 122,791 people (ZimStat, 2012), of which 61,160 (49.8%) are males and 61,631 (50.2%) are females. This population is relatively young; 45.3% being under 15 years of age. There are 26,928 households and an average household size of 4.5 persons. The households are spread over the 29 wards in the district. This is a predominantly rural population (97.1%), with only 2.9 percent living in the in the business centre being considered urban (ZimStat, 2012).

Mudavanhu et al. (2015) identify small-scale rain-fed agriculture as the main source of livelihood in Muzarabani district. Crops grown are maize, small grains, cotton and tobacco. In comparison with other parts of Zimbabwe, the crop yield levels are significantly low in Muzarabani especially during years of severe drought. In some cases, a little surplus is realised, which is then saved for other household needs. In response to the low yields, smallholder farmers diversify their sources of income by engaging in petty business. However, the livelihood security of smallholder farmers in Muzarabani district remains closely linked with the productivity levels of the local agro-ecological zones, which are hindered to a large extent by water availability (MEA, 2005; Stringer et al., 2009).

Commercial agriculture once flourished in Muzarabani district under the auspices of the Agricultural Rural Development Authority (ARDA) until the 1990s. ARDA was a parastatal that was running commercial farming in different districts of Zimbabwe. Today, following the collapse of ARDA activities resulting from Zimbabwe's socio-economic challenges during the 2000s, Muzarabani district is largely under smallholder crop production. Livestock rearing is also practised at the subsistence level (Madamombe, 2004). Most people in Muzarabani are poor smallholder farmers who have settled close to rivers. This exposes them and their livelihoods to river flooding. The majority of their houses, built of wooden poles and daga (clay) with thatched

roofs, are easily washed away in times of floods.

## 5. Methodology

### 5.1. Data source

This study is based on three data sources: interviews, focus groups and census reports. Twenty-five interviews were conducted in 2015 to identify and rank hazards, including socio-economic stressors that are common in Muzarabani, and to confirm the accuracy and validate social vulnerability indicators that were used in the corresponding metrics for the district. The interviewees were purposively selected from Muzarabani district. This included stakeholders whose roles are outlined in the Civil Protection Act of 1989, which provides the legal and institutional framework for disaster risk management in Zimbabwe. The key stakeholders included government officials, members of the National Civil Protection Organisation, local authority representatives, ward councillors, traditional leaders, villagers and representatives of NGOs in the district.

Two focus groups involving adults purposively selected from the villages and disaster institutions in Muzarabani were conducted between 2014 and 2015. The focus group participants discussed how indicators and variables reflected vulnerability to hazards in Muzarabani. The participants were invited through ward councillors and village heads. Each focus group was comprised of people who had been living in the villages for the past ten years or more. This criterion included participants with experiences related to the 2008 flood event which the community regarded as the highest magnitude floods since 2000. Each group's participants ranged between six and ten people whose ages were between twenty-four and sixty years. This age group was purposively chosen to include respondents who could have witnessed the 2008 flood events and were capable of narrating the story from an observant (emic) point of view. Seventeen (17) variables were selected by both interviewees and focus groups.

Data for the selected vulnerability variables was extracted from the 2012 Zimbabwe national census report. Census data for the whole population of Muzarabani was used because it accounted for every individual in the district. The PCA technique used in this study required comprehensive, not sampled population data to develop the social vulnerability metrics. Census data was highly relevant since it is considered reliable, being collected, using standardised questionnaires, by the government. The spatial scale of analysis in this study was the ward, because that was the smallest unit available with complete data. Often community-level disaster assessments are done at ward level (Armaş and Gavriş, 2013; Solangaarachchi et al., 2012). Where data for variables such as income were not available in the census report, data from the Poverty, Income Consumption, and Expenditure Survey of 2012 was used. This enriched the number of variables for input into the PCA. The next sub-section explains how census data was applied to the PCA technique to measure social vulnerability to hazards in Muzarabani.

### 5.2. Principal Component Analysis (PCA)

Guided by the approach developed by Cutter et al. (2003), this study developed context-specific social vulnerability variables (Table 2) that were identified by key informants from the community as relevant to the hazard events they had experienced (predominantly flood and related). Before being used in the PCA, each variable had to meet three conditions. First, qualitative interviews or focus groups conducted with residents of the Muzarabani district needed to identify the variable. Second, the variable needed support from literature on social vulnerability. Third, the variable needed quantitative data at ward level from the most recent national census. There were a few instances where identified variables, such as percentage of households without draught power, lacked quantitative data from the census reports. After all the variables mentioned by participants were discussed and agreed upon,

the social vulnerability metrics were developed to model the spatial variation of social vulnerability in Muzarabani district.

The social vulnerability data for all the 29 wards were normalised before conducting the statistical analysis. Table 2 gives a list of the 17 variables used to develop the social vulnerability index (SoVI) for the district, together with their descriptive statistics based on 116 cases. High standard deviation of variables  $X_{12}$ ,  $X_{13}$ ,  $X_{15}$ ,  $X_{16}$  and  $X_{17}$  indicates that the data were spread out over a large range of values. No values were missing in the dataset. Major changes from literature were on eight variables that were contextualised and added to the final list of the variables contributing to social vulnerability to hazards in Muzarabani. The variables include variable  $X_3$ ,  $X_4$ ,  $X_5$ ,  $X_9$ ,  $X_{12}$ ,  $X_{13}$ ,  $X_{14}$  and  $X_{17}$ . Variable  $X_9$  is unique in this study because it specifically considered rain-fed subsistence farming as a contextual vulnerability variable, not farming in general. This is because farming is a business in some areas, rather than at basic subsistence level, such that those farmers are more economically mobile and less vulnerable to disaster risks. Some larger commercial farms use irrigation all year round and harvest enough crops to enable them to mitigate the effects of droughts.

A composite index was developed using PCA. Solangaarachchi et al. (2012) view the PCA as a multivariate statistical technique that is used as a data reductionist method. The technique condenses an original set of variables into a smaller number of linear varieties by identifying patterns in high-dimensional data and revealing the underlying factors (principal factors) that best describe variations in the data through identification and clustering of variables that measure the same theme (Kazmierczak and Cavan, 2011). The use of this reductionist technique allowed for a robust and consistent set of variables that can be monitored over time to assess any changes in overall vulnerability in Muzarabani. The technique also facilitates replication of the variables at district, provincial and national level, as well as the monitoring of the variables over time to assess any changes in overall vulnerability (Cutter et al., 2003). The PCA worked well in this study because the distribution of variables varied across the 29 wards in Muzarabani district. This variation allowed mapping the SoVI scores at ward level to show the spatial variability of social vulnerability in the district. The PCA produced a set of uncorrelated components that represented a linear weighted combination of the initial set of variables. The resulting components were used to calculate a SoVI for each ward in Muzarabani district.

The Statistical Package for Social Sciences (SPSS), Version 22, was used to run the PCA. Varimax rotation was used to simplify the structure of the underlying dimensions and produce more independence among the factors. The varimax rotation also minimised the number of variables that loaded high on a single factor, thereby increasing the percentage variation between each factor (Armaş and Gavriş, 2013). The Kaiser criterion (eigenvalues  $> 1$ ) was applied for the component selection. This stepwise exclusion approach was carried out and repeated until the variables and components were stable and statistically robust. To check the robustness of the model, two statistical tests, the Kaiser-Meyer-Olkin (KMO) of sampling adequacy and the Bartlett's Test of Sphericity, were used. Components that increased vulnerability were considered positive, and those that reduced vulnerability were viewed as negative (Solangaarachchi et al., 2012). No variables loaded both positively and negatively on a component.

Then, a composite SoVI score was developed by adding all four component scores (factor loadings) for each ward. An additive model was chosen so as to make no a priori assumption about the importance of each factor in the overall sum (Cutter et al., 2003). In this way, each factor was viewed as having an equal contribution to the district's overall vulnerability the purpose here being on spatial variability and ultimately contributing to understanding of complexes of vulnerability explanations. This was the best option in the absence of a defensible method for assigning weights. After that, the final SoVI scores were classified using the standard deviation from the mean method, which provided a relative measure of deviation from the mean of each ward.

**Table 2**  
Descriptive statistics of selected variables used in developing SoVI for Muzarabani.  
Source: Authors.

Selected variables	N	Min	Max	Range	Mean	Std. dev	Variance
Percentage of people over 65 years (X <sub>1</sub> )	116	0.3	14.9	14.6	5.5	3.8	14.4
Percentage of population of people below 15 years (X <sub>2</sub> )	116	34.4	51.3	16.9	45.6	3.4	11.8
Percentage of households headed by females (X <sub>3</sub> )	116	16.5	37.7	21.2	29.0	5.4	29.3
Percentage of child headed households (X <sub>4</sub> )	116	1.0	9.3	8.3	2.7	2.4	5.5
Percentage of households headed by people above 65 years of age (X <sub>5</sub> )	116	1.0	19.3	18.3	12.4	4.7	22.5
Crude birth Rate (per 1000) (X <sub>6</sub> )	116	33.8	38.8	5.0	36.3	1.5	2.2
Average household size (X <sub>7</sub> )	116	3.9	4.8	0.9	4.6	0.2	0.0
Percentage of female population (X <sub>8</sub> )	116	47.3	53.0	5.7	50.3	1.1	1.3
Percentage of population entirely dependent on rain-fed smallholder farming (X <sub>9</sub> )	116	72.9	99.3	26.4	94.6	6.5	41.6
Percentage of population which has never been to school (X <sub>10</sub> )	116	0.4	7.4	7.0	4.0	1.5	2.2
Percentage of population attained primary education as highest (X <sub>11</sub> )	116	28.5	51.8	23.3	44.9	3.3	10.7
Percentage of Households without access to proper sanitation (X <sub>12</sub> )	116	19.0	98.0	79.0	93.2	9.7	93.0
Percentage of Households without access to safe water (X <sub>13</sub> )	116	2.0	88.0	86.0	44.4	22.9	522.0
Percentage of households dependent on wood fuel (X <sub>14</sub> )	116	36.0	98.0	62.0	93.2	7.3	53.5
Percentage of Households in traditional dwellings (X <sub>15</sub> )	116	4.0	81.0	77.0	52.5	17.1	292.7
Percentage of unemployment (X <sub>16</sub> )	116	54.0	99.0	45.0	90.7	10.8	115.8
Percentage of households without electricity (X <sub>17</sub> )	116	25.0	99.0	74.0	87.8	10.3	106.7
Valid N (listwise)	116						

NB: N: Number of cases used in the analysis; Min: minimum; Max: maximum; Std. Dev: standard deviation.

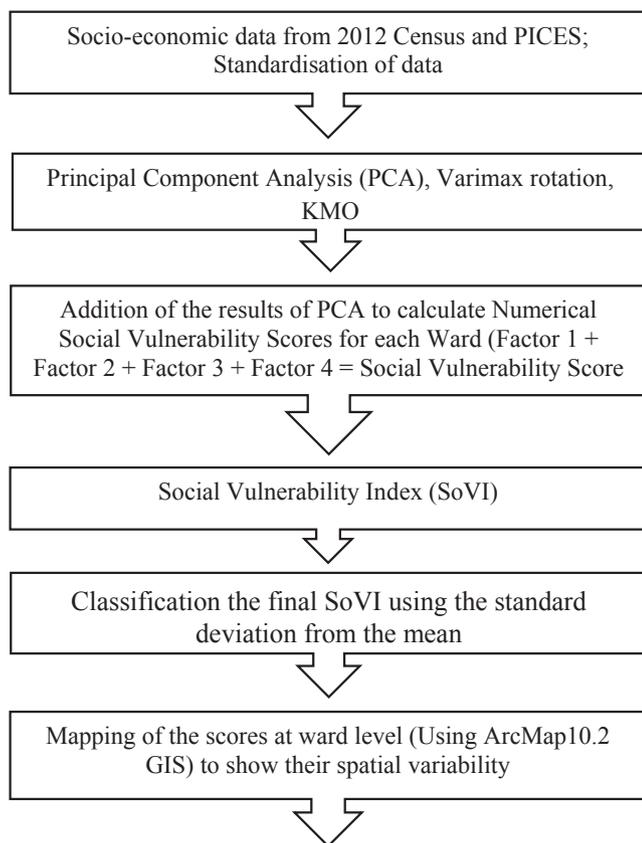


Fig. 2. Flow chart of constructing SoVI using PCA.

Using the ArcMap10.2 GIS tool, the results were mapped at the ward level to show their spatial variability. This enabled comparison of the level of social vulnerability across the 29 wards in the district. Fig. 2 below shows the flow chart in developing the SoVI using the PCA.

Although disaster vulnerability models can be validated by comparing their predictions with an independent set of data that includes measures of post-disaster outcomes (Fekete, 2009), this study was not validated in this way. The main reason is that there were no post-disaster data available at household level for this study. However, interviews with members of the National Civil Protection Organisation, local

authorities and community members were used to check if the SoVI's results were consistent with accounts of social vulnerability in terms of the living conditions across these areas (Armaş and Gavriş, 2013). To back this up, a focus group was convened, and each participant was asked to consider which key indicator they felt was the “most important” in terms of defining or predicting vulnerability, and then to rank the different indicators according to importance, based on their experience in different areas of the vulnerability assessment. This verification process led to the conclusion that the SoVI components broadly captured the level and type of spatial social vulnerability in the Muzarabani community, such as exposure to flooding.

## 6. Results

Communalities from the selected variables introduced in Table 2 were extracted and are shown in Table 3. The communalities refer to the proportion of each variable's variance that can be explained by the

**Table 3**  
Extracted Communalities from the selected variables of social vulnerability.  
Source: Authors.

Variable	Raw	
	Initial	Extraction
Percentage of population of people over 65 years (X <sub>1</sub> )	14.4	3.7
Percentage of population of people below 15 years (X <sub>2</sub> )	11.8	6.9
Percentage of households headed by females (X <sub>3</sub> )	29.38	20.6
Percentage of child headed households (X <sub>4</sub> )	5.5	0.2
Percentage of households headed by people above 65 years of age (X <sub>5</sub> )	22.5	10.3
Crude birth Rate (per 1000) (X <sub>6</sub> )	2.2	0.4
Average household size (X <sub>7</sub> )	0.04	0.1
Percentage of female population (X <sub>8</sub> )	1.3	0.7
Percentage of population entirely dependent on smallholder farming (X <sub>9</sub> )	41.6	40.5
Percentage of population which has never been to school (X <sub>10</sub> )	2.2	0.4
Percentage of population attained primary education as highest (X <sub>11</sub> )	10.7	7.3
Percentage of Households without access to proper sanitation (X <sub>12</sub> )	93	87.9
Percentage of Households without access to safe water (X <sub>13</sub> )	522	521.9
Percentage of households dependent on wood fuel (X <sub>14</sub> )	53.5	51.1
Percentage of Households in traditional dwellings (X <sub>15</sub> )	292.7	292.5
Percentage of unemployment (X <sub>16</sub> )	115.8	113.7
Percentage of households without electricity (X <sub>17</sub> )	106.7	97.7

**Table 4**  
KMO and Bartlett's test results.  
Source: Authors.

KMO and Bartlett's Test <sup>a</sup>			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			0.652
Bartlett's Test of Sphericity	Approx. Chi-Square		2293.894
	Df		136
	Sig.		0.000

<sup>a</sup> Based on correlations.

principal components. The extracted communalities are higher than 0.5 [ $h \geq 0.5$ ] (Siagian et al., 2014; Solangaarachchi et al., 2012) (Table 4). This means that all but one extracted component represented the selected variables well. The exception was X<sub>7</sub> whose value (0.013) was less than 0.5.

After extracting the communalities, a KMO statistical test was calculated. The KMO test was meant to measure the sampling adequacy and evaluate the correlations and partial correlations to determine if the data were likely to coalesce on components (i.e. some items highly correlated, and some did not). This KMO measure varies between 0 and 1, and values that are closer to 1 are adequate. A value of 0.6, a figure that is well above half of 1, is a suggested minimum (Fekete, 2012), i.e. KMO values should be greater or equal to 0.6. In this study, the KMO value was 0.65, which was above the recommended minimum. This indicated that the variables used were suitable for the PCA.

As a general rule, the Bartlett's Test of Sphericity was supposed to be significant ( $p < 0.05$ ). It tested the null hypothesis that the correlation matrix was an identity matrix. An identity matrix is one in which all of the diagonal elements are 1 and all off-diagonal elements are 0 (Fekete, 2012). This hypothesis needed rejection. In this study, the SPSS indicated that the correlation matrix (of items) was not an identity matrix. The Bartlett's Test statistic was highly significant ( $df = 136$ ; Sig. = 0.000), implying that the data were appropriate for component analysis. Taken together, both the KMO and the Bartlett's Test of Sphericity provided a minimum standard which was passed before conducting a PCA.

After having passed the KMO and Bartlett's Test of Sphericity, the PCA was then conducted. The PCA extracted four (4) components out of

**Table 5**  
Total variance explained of the seventeen selected variables.  
Source: Authors.

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative%	Total	% of Variance	Cumulative%
1	629.88	47.53	47.53	629.88	47.53	47.53
2	406.97	30.71	78.23	406.97	30.71	78.23
3	137.01	10.34	88.57	137.01	10.34	88.57
4	81.87	6.18	94.75	81.87	6.18	94.75
5	23.05	1.74	96.49			
6	14.30	1.08	97.56			
7	10.97	0.83	98.39			
8	6.07	0.46	98.85			
9	5.67	0.43	99.28			
10	3.61	0.27	99.55			
11	2.37	0.18	99.73			
12	1.84	0.14	99.87			
13	0.82	0.06	99.93			
14	0.58	0.04	99.97			
15	0.33	0.03	99.99			
16	0.06	0.01	99.99			
17	0.01	0.001	100			

seventeen (17) variables, which were then used in the analysis. The four components explained 94.8 percent of the total cumulative variance in social vulnerability (Table 5). The initial eigenvalues shown in the same table (Table 5) are the variances of the principal components. Because the PCA was conducted on the correlation matrix, the variables were standardised, which means that each variable had a variance of 1, and the total variance was equal to the number of variables used in the analysis; 17. The total column under the eigenvalues section contains the eigenvalues. The first component always accounts for the most variance (and hence has the highest eigenvalue) and the second component accounts for as much of the left-over variance as it can, and so on. Hence each successive component will account for less and less variance. The percentage of variance column simply contains the percent of variance accounted for by each principal component. The cumulative% column contains the cumulative percent of variance accounted for by the current and all the preceding principal components. In this study the first component (with the highest eigenvalue of 629.880) accounted for the most variance, 47.5 percent, and the second component accounted for as much as 30.7 percent. Thus, each successive component accounted for less and less variance. The extraction sum of squared loadings has three columns which exactly reproduced the values given on the same row of the left side of the table. The number of principal components (4) whose eigenvalues were 81 or greater determined the four rows reproduced in this study. A scree plot (Fig. 3) displays the information about the components' eigenvalues. The scree plot determined the number of components that adequately explained the correlations between the variables.

A SoVI score was developed by adding all four component scores (factor loadings) for each ward. The results are shown in Table 6. The positive numbers in the last column of Table 6 represent increased potential of social vulnerability to hazards, while the negative numbers show reduced potential of the same. Depending on the numbers, the extent of vulnerability could be very high or very low. In this analysis, the SoVI scores ranged from 2.7 (most vulnerable) to -8.0 (least vulnerable).

Benchmarking the SoVI scores is important in identifying wards with relatively high and low social vulnerability to hazards. Therefore, the SoVI scores were classified into five categories. These ranged from 5 (highly vulnerable) to 1 (very low vulnerability). Table 7 describes the final benchmarks for the SoVI scores based on the five levels.

Using the composite SoVI scores and the ArcMap10.2 GIS tool, the

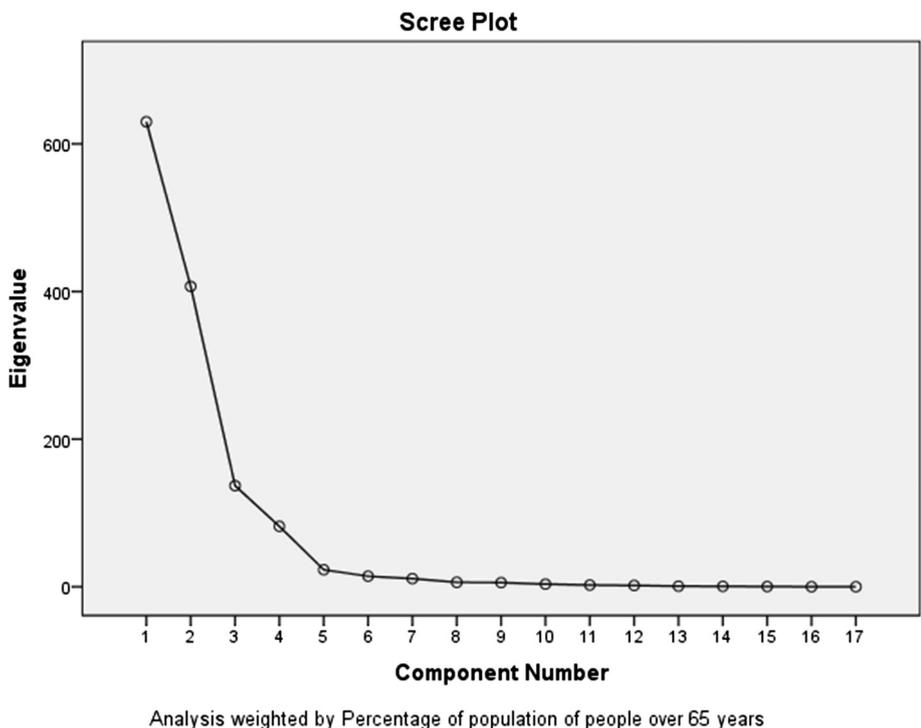


Fig. 3. Scree Plot of seventeen variables.

SoVI results were mapped at the ward level to show their spatial variability (Fig. 4). As shown in Fig. 4, the majority (20 out of 29, or 69.0%) of the wards in Muzarabani have a moderate to high level of social vulnerability. Twelve (12) of the 20 wards (60%) are located in the lower part of the district, where exposure to floods is high. Fig. 4 also confirms that every ward is at risk of hazards but with spatial variation. For example, Wards 15 and 13 are among the least vulnerable in Muzarabani.

The wards were then ranked according to their level of social vulnerability independent of physical location (Tables 8 and 9), as considered a reasonable reflection of a locally grounded conception of vulnerability in relation to overall disaster risk amongst the participants in Muzarabani. The 10 most vulnerable wards are then the potential hotspots of societal vulnerability to hazard, affected by floods drought and GTIs in this instance. This is consistent with the local and national view of the region that flooding, often from the Cahora Basa dam, is a

Table 6  
Composite SoVI scores for the twenty-nine wards in Muzarabani.  
Source: Authors.

Ward name	Ward no.	Factor 1	Factor 2	Factor 3	Factor 4	SoVI score
Chadereka	1	0.07715	0.29024	0.13996	-0.6896	-0.18225
Maungaunga	2	0.37794	-0.22002	0.94782	0.50228	1.60802
Machaya	3	0.56239	0.89153	-0.99808	-0.49443	-0.03859
Dambakurima	4	1.04752	0.20657	-1.40097	2.68423	2.53735
Kapembere	5	0.80473	0.57672	-0.80292	-0.49992	0.07861
Gutsa	6	-0.01946	0.05952	1.07785	-2.14217	-1.02426
Hwata	7	0.40211	0.09165	-1.65721	-0.81884	-1.98229
Muringazuva	8	0.15775	-0.71477	-1.36132	-1.56881	-3.48715
Chiwashira	9	0.283	0.1461	0.84635	-0.12947	1.14598
Chiweshe	10	-0.14143	-0.34513	0.33363	0.3115	0.15857
Chinyani	11	-0.25996	-0.27481	-0.3667	1.97724	1.07577
Botambudzi	12	-3.08995	-0.16152	-0.61584	-0.05802	-3.92533
Mawari	13	-2.63281	-0.6028	-0.12132	-0.63905	-3.99598
Nyamanetsa	14	-2.1635	0.30452	-0.15408	0.31438	-1.69868
Gatu	15	0.43391	-7.59078	-0.52626	-0.33818	-8.02131
Mukwengure	16	0.49192	0.33495	-1.74046	-1.52446	-2.43805
Hoya	17	0.14745	0.24666	1.11849	0.55889	2.07149
Mutemakangu	18	0.40924	0.32937	0.77078	0.77583	2.28522
Utete	19	0.64216	0.47231	0.00436	-0.18529	0.93354
Chawarura	20	-0.00139	0.02889	1.47709	-1.22974	0.27485
Runga	21	0.54973	-0.46189	-1.16996	0.78019	-0.30193
Chaona	22	0.10732	0.34411	-0.54987	0.27885	0.18041
Kairezi	23	0.07361	0.22043	1.60691	-0.08345	1.8175
Chiwenga	24	0.28308	-0.10041	1.58681	0.94233	2.71181
Mutuwa	25	-0.48161	-0.18307	-1.54556	1.60809	-0.60215
Mutute	26	-2.27412	-0.12813	-0.75123	1.10202	-2.05146
Museredza	27	0.79421	0.44565	-0.67835	-0.50146	0.06005
Chidikamedzi	28	-3.32382	0.61665	-0.66941	0.0994	-3.27718
Palms	29	-1.79736	0.46497	0.42673	1.24085	0.33519

**Table 7**  
Description of the benchmarks of the SoVI scores of Muzarabani.  
Source: Authors.

Category	SoVI Score	Description
5: Highly vulnerable	1.608021–2.711810	The community is highly vulnerable to flood hazards. There is need to urgently attend to the root causes and dynamic pressures causing fragile livelihoods and unsafe conditions.
4: Moderately vulnerable	0.335191–0.608020	The community has a moderate level of vulnerability to floods. Resources of the community are failing to sustain the basic needs of people; there is lack of effective institutions to address flood risk.
3: Vulnerable	–1.698679–0.335190	The community experiences critical thresholds in asset holdings that lead to tipping points between increased and reduced vulnerability to floods. A big push in initial investments is required so that the community can cross the critical threshold to higher standards of living where conditions reinforce economic growth.
2: Low vulnerability	–8.021309 to –1.698680	The community is lowly vulnerable to floods. There is need to continue building community socio-economic capitals and address flood risk.
1: Very low vulnerability	Less than –8.021310	The community's social fabric is exhibiting strengths in reducing flood risks. The community is close to relatively higher welfare equilibrium. There is a need to monitor the feedbacks to well-being for continued reinforcing of growth.

prime cause of disaster vulnerability in Muzarabani. This is likely to be a cyclical relationship whereby exposure to past effects of the hazards also makes residents of these areas more vulnerable to their recurrence. The study did not extend at this point to identifying how new socially vulnerable people may move from outside into the more hazardous

locations. It was neither here an aim to test underlying issues of governance, preparedness and response at the wider level; issues acknowledged as causes of vulnerability and addressed elsewhere by the authors, such as for example [Bongo and Manyena \(2015\)](#) in the case of Zimbabwe.

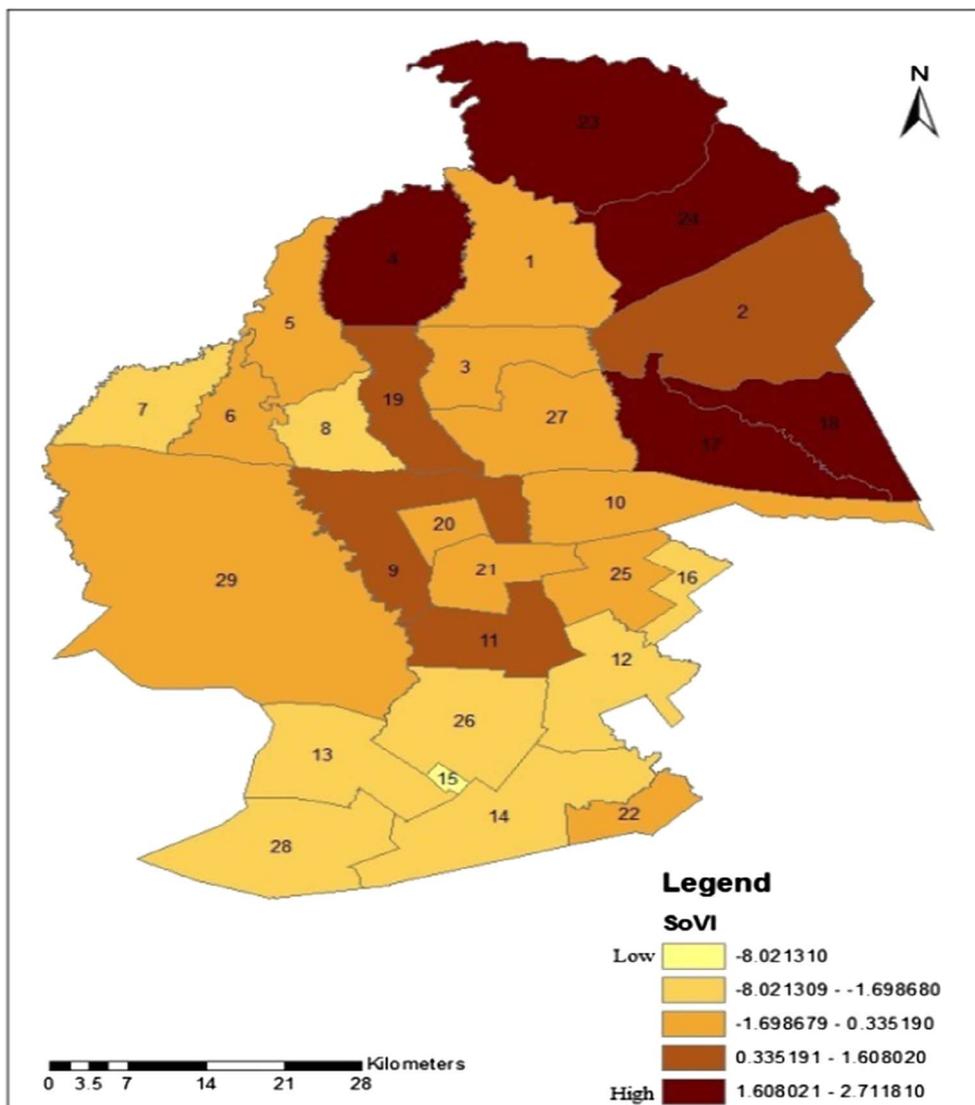


Fig. 4. Spatial variations in social vulnerability to floods in Muzarabani.

NB: The numbers inside the map represent the ward numbers.  
(Source: Authors)

**Table 8**  
The ten (10) most vulnerable wards in Muzarabani.  
Source: Authors.

Rank	Ward Name	Ward no.	Upper/Lower Muzarabani	SoVI
1	Chiwenga	24	Lower	2.71
2	Dambakurima	4	Lower	2.54
3	Mutemakangu	18	Lower	2.29
4	Hoya	17	Lower	2.07
5	Kairezi	23	Lower	1.82
6	Maungaunga	2	Lower	1.61
7	Chiwashira	9	Upper	1.15
8	Chinyani	11	Upper	1.08
9	Utete	19	Lower	0.93
10	Chawarura	20	Upper	0.27

NB: SoVI figures are rounded to 2 decimal places.

**Table 9**  
The ten (10) least vulnerable wards in Muzarabani.  
Source: Authors.

Rank	Ward Name	Ward no.	Upper/Lower Muzarabani	SoVI
1	Gatu	15	Upper	-8.02
2	Mawari	13	Upper	-4.00
3	Botambudzi	12	Upper	-3.93
4	Muringazuva	8	Lower	-3.49
5	Chidikamedzi	28	Upper	-3.28
6	Mukwenhure	16	Upper	-2.44
7	Mutute	26	Upper	-2.05
8	Hwata	7	Lower	-1.98
9	Nyamanetsa	14	Upper	-1.70
10	Gutsa	6	Lower	-1.02

NB: SoVI figures are rounded to 2 decimal places.

## 7. Discussion

### 7.1. Conceptual and methodological implications for understanding context-specific vulnerability

The selection criterion of social vulnerability variables is one of the most important advances made by this study. A participatory approach was triangulated with literature to come up with place-specific variables for Muzarabani. Key informants from the community were the first to identify the variables before being used in the PCA. Then each variable had to meet two other conditions: support from literature on social vulnerability and, quantitative data availability at the lowest level from the most recent national census. The social vulnerability indices revealed many wards with high levels of social vulnerability as being areas of floods and related hazards. The resultant map showed vulnerability hotspots that are likely to remain the same for some time unless policy interventions are made. The variation is not random, but rather is a result of the interacting conditions of geographical location and the economic vitality context of the ward communities. Some of the conditions are linked to the community's infrastructure, and others pertained to the social and demographic attributes of the smallholder farmers in Muzarabani. However, the most socially vulnerable wards are predominantly in the remote, lower part of the district, where physical exposure to flood hazards is very high and the socio-economic conditions are worse than other parts. The study demonstrates an accessible way of confirming this relationship quantitatively for one of the poorest parts of Zimbabwe and would be replicable in similar regions.

The major contribution in the use of the PCA technique, however, lies in the selection of the vulnerability variables. Expert and community opinions were sought to identify variables peculiar to Muzarabani. One of the variables unique to this study relates to the percentage population entirely dependent on rain-fed smallholder farming instead of the percentage of the population engaged in farming alone or extractive industries as suggested by Cutter et al. (2009) and Terti et al. (2015).

Farming and extractive industries are broad terms, and in some instances the two are lucrative businesses that may not make people vulnerable to disasters. Intensive farming under irrigation may reduce vulnerability. Therefore, this study specifically considered the percentage of smallholder farmers who depend on rainfall for their farming processes.

Chang et al. (2015) and Bergstrand et al. (2015) argue that the majority of social vulnerability studies are characterised by indicators that are selected subjectively by authors who base their choice on review of related literature. In contrast, this study used context-specific vulnerability variables that were identified by key informants from the community. This is because literature does not have all indicators and locally generated and verified vulnerabilities are context-specific.

This study has also demonstrated that sensitivity to hazards in Muzarabani associated with complex poor socio-economic conditions of the community. High unemployment, low levels of education, inadequate water, sanitation and hygiene (WASH) and medical services and over-reliance on rain-fed smallholder farming are some of the variables making Muzarabani socially vulnerable. These variables are also indirectly induced, if not created or reinforced, by hazards including flooding, drought and dry spells occurring in Muzarabani. About 92.5% of the population in Muzarabani is entirely dependent on rain-fed smallholder farming. This farming sector is closely linked to low productivity levels of the local agro-ecological zone IV. Dependency on rain-fed farming creates a form of economic vulnerability because Muzarabani district is characterised by high atmospheric evaporation and highly variable spatial and temporal precipitation that makes rain-fed farming a risky economic activity. Erratic rainfall, frequent droughts and floods wipe out the crops - the mainstay of the community's economy. As a result, many households fail to recover quickly from the disasters.

The employment statistics show that the majority of the population in Muzarabani *havashandi* (are not formally employed), causing them to be financially deprived. Low income in Muzarabani may also result from low educational levels and reliance on rain-fed farming. Flooding and drought that are the major natural hazards in Muzarabani, also cause low income by destroying the income sources of the community. In turn, low income leads to absence of modern flood-proofing, use of poor building materials for shelter, low productivity in farming and occupancy of non-insured homes. Low income prevents some households from accessing basic needs such as decent shelter, health, education and transport to service centres. It reduces the health seeking behaviour of the people. In times of disasters, smallholder farmers become vulnerable. *Hurombo* (poverty) plays an important role in determining households' vulnerability to hazards. Poor households are not with circumstances that enable them to develop effective disaster-coping strategies.

At a wider scale of analysis, many factors can influence low education in Muzarabani wards including low income, unemployment, poverty, flooding, drought, the Shona cultural values and low productivity in the farming sector. The Shona culture prioritizes educating the boy child, against the girls. This leads to poor WASH services among the households, gender imbalances that amplify women's vulnerability to hazards, over-dependence on rain-fed agriculture, and occupancy in hazardous floodplains. Some smallholder farmers are attracted to low-lying flood plains by flood-recession farming. Others do not have alternative arable land. High poverty levels among the households of Muzarabani wards are therefore both an effect and cause of low education level in the community. Low education level also influences negatively a person's knowledge and awareness of disaster risk management practices that may be possible even in the prone locations.

Sanitation refers to the principles and practice related to collecting, removing and disposing of human excreta, refuse, storm and waste water (Johannessen et al., 2014). The destruction of WASH services by floods and the general negligence of the sanitation sector in most wards increases the vulnerability of the community to risks associated with

unclean water. About 92% of the population in Muzarabani district do not have access to proper sanitation and safe tap water. Water system toilets are exclusively found in the small peri-urban area while households in rural areas rely on pit latrines or open defecating systems. Women who constitute half of the population and are culturally custodians of the household health and hygiene suffer the brunt. In addition to farming activities, women are expected to fetch water outside the home, prepare food and do all household chores. The deprivation in WASH services also perpetuates the existence of poverty when the smallholder farmers are forced to spend the limited income in seeking medical care against GTIs. This increases community vulnerability to the impact of hazards such as flooding.

## 7.2. Policy implication for social vulnerability reduction in conditions of disaster risk

Addressing social vulnerability to disaster risk requires first understanding risk in context, which usually also has a spatial expression. This helps guide reduction of the liabilities that the communities face and second, the building of capacities which deal effectively with the hazards. Liability reduction involves efforts to eliminate the variables leading to vulnerability while capacity building includes activities that help people mitigate the disaster's impact or react to them effectively *in situ*. The variables leading to vulnerability in Muzarabani includes high poverty levels, unemployment, low levels of education, inadequate water, sanitation and hygiene and medical service, and widespread reliance on rain-fed smallholder farming. It implies directing much effort at the material well-being of the smallholder farmers if the adverse impact upon them is to be curtailed. However, this might take time, considering the economic challenges the community is facing. Both liability reduction and capacity building are determined by human activities that have a bearing on the degree of disaster risk and susceptibility (McEntire, 2012).

For Zimbabwe, the first step is to develop a policy framework for an integrated place-based vulnerability assessment for spatially defined contexts of hazards, risks and disasters. Although Zimbabwe has made progress in disaster risk reduction following the implementation of the Hyogo Framework for Action 2005–2015 and has committed herself to the Sendai Framework for Action 2015–2030, hazard and vulnerability assessments are still centralised and tend to focus at the national level. Empirically applying the social vulnerability index (SoVI) at sub-national level, in this case, in the disaster-prone Muzarabani district, provides a rationale for measuring social vulnerability at context-specific spatial scales. As SoVI uses indicators to simplify complex phenomena and problems by identifying patterns in high-dimensional data and suggesting the underlying factors, it offers certain advantages to policy makers, including easy communication of problems (Birkmann, 2007).

By defining where the greatest need of vulnerability reduction is in situations such as Muzarabani, SoVI can support policy-makers, such as those at national governmental level, to prioritise wards that need development as well as humanitarian aid interventions. As in many parts of the world SoVI has not been applied in Zimbabwe. In this way, SoVI becomes one of the tools for informing poverty reduction initiatives. As this study demonstrates, poverty increases susceptibility to disasters in Muzarabani. Research has shown that people are best able to protect themselves and prepare for disasters when their incomes are above a poverty levels (Armaş and Gavriş, 2013; McEntire, 2012). If the adverse impact of disasters are to be curtailed, emphasis should be directed at improving the material well-being of the individuals and their households. Employment creation and diversification of livelihoods would go a long way in improving socio-economic conditions of the community. Assessments of the proximate and underlying influences on individual and household vulnerabilities can be supported by an accessible empirically based SoVI approach that draws from multivariate quantification and its spatial representation.

While it has become abundantly evident that social vulnerability assessments such as SoVI are critical in providing robust and precise information for local level decision-making, the absence of clear disaster risk reduction goals in Zimbabwe is one of the major challenges. The Civil Protection Act of 1989 which guides disaster risk reduction in Zimbabwe is outdated and therefore inadequate to guide social vulnerability assessments. This is a situation likely to be familiar in many low and middle-income countries. However, even in the absence of an updated policy framework, SoVI can provide a basis for discussing the root causes of risk and vulnerability, mitigation measures, preparedness and response planning and recovery. To broaden the discussion, the SoVI analysis is likely to be one of the useful inputs into other frameworks, such as the Zimbabwe Vulnerability Assessment and Analysis, which informs the government on the status of vulnerability to food insecurity.

Prevailing economic policies and disaster legislations should address social inequalities and their impacts on disaster risk management, including preparedness and response. SoVI can be used at any phase of the disaster management cycle (Solangaarachchi et al., 2012). At the mitigation and preparedness stage, SoVI can be used as a proactive tool to plan community-based disaster mitigation activities that support more vulnerable areas in order to enhance community resilience. At the response and recovery stages, it can be used as a reactive tool to design early warning and early action systems, evacuation and recovery needs. A SoVI can be used to capture the dynamics of the community over time. When new census data becomes available, a comparative analysis can be conducted to track the progress in reducing social inequalities generating vulnerability to hazards in regions such as these. Thus, SoVI analyses, that can be widened to multiple scales represent a useful policy tool for identifying, as well as tracking vulnerability trends in areas of concern (Abson et al., 2012). In addition to providing valuable tools for Zimbabwe's disaster management community in assessing vulnerability, including delineation of vulnerability hotspots, SoVI analysis will also guide investment decisions and efficient allocation of resources (Boruff and Cutter, 2007).

## 8. Conclusion

Social vulnerability to disasters is determined by households' socio-economic positions in society. It varies across impacted areas. Vulnerability is contextual, and place-specific indicators can enhance the understanding of social vulnerability at the lowest level. This study has developed place-based indicators for social vulnerability measurement in a region with a specific hazard context but relevant to other areas of low and middle-income nations in particular. The indicators can be incorporated into vulnerability models using community assessments and locales. This responds to the relatively few explicit sets of procedures within the existing literature that suggest how multivariate vulnerability should be quantified and measured in contexts of multi-shocks/stressors but where floods and related hazards are a trigger of the disaster. Such indices provide tangible scores that can be used by decision makers to guide disaster mitigation. From a practical perspective, this research has deepened the understanding of the way in which social vulnerability can be quantified in places where there is insufficient new data or only public level data at the lowest level, particularly in low income regions where data scarcity is a common phenomenon. Within this context, the study has offered a methodological approach for SoVI construction that accounts for the selection of place-based variables, standardisation and the reduction of uncertainties as they pertain to internally consistent data selections. While this study advances access to quantification of vulnerability in context, there is opportunity to validate for post-disaster data and for other settings or scales. This study proposes a reduction of the liabilities that rural communities face and the building of capacities which deal effectively with multiple hazards and the related "ratchet effect" (Chambers, 1996) in poverty and vulnerability, translating ultimately

to changes in baseline social vulnerability over time (Adger, 1999) Liability reduction of local and national authorities involves efforts to eliminate the variables leading to disaster vulnerability while capacity building includes activities that help people mitigate the hazards' impact or react to them effectively. Progress in understanding and responding in many more contexts than are hitherto engaged in spatially aware disaster risk reduction can be assisted by this location specific multivariate vulnerability analysis.

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