



Master Thesis

submitted within the
UNIGIS MSc program Geographical Information Science & Systems
Interfaculty Department of Geoinformatics – Z_GIS
Paris Lodron University of Salzburg

on

Mapping social vulnerability to natural hazards

within the context of the
SOS Children's Village in Quito, Ecuador

by

Dipl.-Ing. Roman Breitfuss-Schiffer
104854, UNIGIS MSc 2017

Supervisor:

Dr. Stefan Kienberger

Thesis submitted in partial fulfilment of the requirements of the degree of
Master of Science (Geographical Information Science & Systems) – MSc (GIS)

Salzburg, 18.08.2019

Science Pledge

By my signature below, I certify that my thesis is entirely the result of my own work. I have cited all sources I have used in my thesis and I have always indicated their origin.

Place, Date

Signature

Acknowledgments

The successful writing of this thesis would not have been possible without the support and contribution of many people

First, I want to thank my supervisor Stefan Kienberger for providing me with the opportunity to be part of the cooperation between the Interfaculty Department of Geoinformatics (Z_GIS) and SOS Children's Village International and to contribute to the ongoing research in the field of risk and vulnerability assessment. In this context, I want to express my gratitude to Richard Resl and Marcelo Landivar from UNIGIS in Quito, who helped with data acquisition regarding the study area.

Furthermore, I want to especially thank Pablo Cabrera-Barona, who provided me with results of his study regarding deprivation and healthcare accessibility and supported me with the basic workflow of accessing and extracting Ecuadorean census data.

Abstract

Climate change is projected to increase risks from natural hazards such as heat stress, extreme precipitation, inland flooding, or landslides for people in urban areas due to population growth and poor planning and insufficient implementation of mitigation strategies (Pachauri et al., 2014). Billions of people are affected and threatened by natural and manmade disasters worldwide, while children are disproportionately affected (International Federation of Red Cross and Red Crescent Societies, 2018; SOS Children's Villages International, 2017a; Wallemacq and Below, 2018).

International organizations such as SOS Children's Villages International seek to tackle these threats and challenges and aim to minimize weather- and conflict-related risks for local communities (SOS Children's Villages International, 2017a). Risk and vulnerability assessment programs (RIVA) play an important role in the evaluation and strengthening of disaster preparedness and response capacities of local communities by developing target trainings, closing communication gaps and pro-positioning of vital resources (SOS Children's Villages International, 2017a).

Based on the aims of RIVA, this thesis focuses on the social vulnerability to natural hazards in an urban area and aims to quantify the social vulnerability through a composite index based on a theoretical risk and vulnerability framework. Furthermore, the spatial representation of the social vulnerability scores should enable the localization of hot spots and serve as a tool for risk management. The study area is the city of Quito.

Literature review was carried out to derive a set of preliminary socio-economic and demographic indicators and variables. After statistical and multivariate analysis and the derivation of statistically based weights through PCA/FA, the variables were aggregated to form a composite social vulnerability index. Hot and cold spot analysis (Getis-Ord G_i^* statistics) revealed neighborhoods of high interest in terms of social vulnerability. The approach proposed in this thesis made sure to be independent from third parties throughout the process of creation of the composite index, and therefore ruled out the possibility of delays caused by external factors.

The results show high social vulnerability scores mainly in the outskirts of the city of Quito. Especially in the outermost south-western and south-eastern neighborhoods high social vulnerability is concentrated. High values were also found in the outermost north-western part and along the western city limit.

The findings of this study serve as decision support for local authorities in terms of locating vulnerable neighborhoods regarding natural hazards and prioritizing intervention measures. Focusing on the revealed hot spot neighborhoods could lead to a better understanding of vulnerability itself in the local communities, raise awareness towards natural hazards and potentially change the behavior of people in case of an emergency. Furthermore, the results provide an important contribution towards developing an integrated risk management approach with the final goal of developing targeted risk mitigation strategies.

Table of contents

1.	Introduction and background.....	1
1.1	Defining vulnerability.....	1
1.1.1	Social vulnerability.....	1
1.2	Assessing vulnerability.....	3
1.2.1	Conceptual frameworks and models.....	3
1.2.2	Vulnerability indices.....	10
1.3	Aims and objectives	11
2.	Materials and methods.....	13
2.1	Study area	13
2.1.1	SOS Children’s Village in Quito	14
2.1.2	Natural hazards in Quito.....	14
2.2	Underlying data	16
2.2.1	Census data 2010.....	16
2.2.2	Hazard data	16
2.2.3	Other data	17
2.3	Conceptual framework	17
2.4	Constructing a composite index	19
2.4.1	Selection of indicators	19
2.4.2	Data transformation	22
2.4.3	Missing data and outliers.....	22
2.4.4	Normalization	25
2.4.5	Multivariate analysis.....	25
2.4.6	Final selection of indicators.....	31
2.4.7	Weighting	32
2.4.8	Aggregation	35
2.4.9	Hot and cold spot analysis.....	36
2.4.10	Visualization and mapping.....	36
3.	Results	37
3.1	Vulnerability variables	37
3.2	Social vulnerability to natural hazards in the city of Quito	40
4.	Discussion and outlook.....	48
5.	Summary and conclusion.....	50
6.	References	51
	Appendix A	57
	Appendix B	63

List of figures

Figure 1: Key spheres of the concept of vulnerability (Source: Birkmann, 2005).....	3
Figure 2: Bohle’s conceptual framework for vulnerability analysis (Source: Bohle, 2001).	5
Figure 3: The conceptual framework to identify disaster risk (Source: Bollin et al., 2003).	5
Figure 4: Vulnerability Framework defined by Turner et al. (Source: Turner et al., 2003).....	6
Figure 5: Pressure and Release (PAR) model: the progression of vulnerability (Source: Wisner et al., 2004).	6
Figure 6: Cardona and Barbat’s framework for holistic approach to disaster risk assessment and management (Source: Birkmann (2006a) based on Cardona and Barbat (2000)).	7
Figure 7: The BBC conceptual framework (Source: Birkmann (2006a) based on Bogardi and Birkmann (2004) and Cardona (2001 and 1999))......	8
Figure 8: Cutter’s hazard-of-place model (Source: Cutter, 1996).....	8
Figure 9: The MOVE framework (Source: Birkmann et al. (2013) based on concepts of Birkmann, 2006a; Bogardi and Birkmann, 2004; Cardona, 2001, 1999; Carreño et al., 2007a; IDEA, 2005; Turner et al., 2003).	9
Figure 10: Location map of the city of Quito, Ecuador.	13
Figure 11: Map of the city and study area of Quito, Ecuador.	13
Figure 12: Location of the SOS Children’s Village itself and other SOS CV premises in Quito. The district Quitumbe is highlighted as it is considered for future extension by SOS CV.	14
Figure 13: Adapted MOVE risk and vulnerability framework based on Birkmann et al. (2013) – The assessment is carried out on a subnational to local scale. The relevant domains are highlighted, while the exposure domain is excluded from the assessment.	18
Figure 14: Workflow for the composite index construction process (adapted from Hagenlocher et al., 2013)...	19
Figure 15: Box-and-whisker plots of the statistically problematic variables (excl. var. 10.3 & 14.1) with the 0.975 quantile marked in red.....	24
Figure 16: Visualization of correlation matrices with values of Pearson’s r for each of the two vulnerability domains (SUS – left, LoR – right).	26
Figure 17: Scree plots of eigenvalues from PCA for each of the two domains (SUS – left, LoR – right).....	28
Figure 18: Spatial distribution of the final selection of susceptibility (SUS) variables (min-max normalized values) within the study area with the assigned weight.	37
Figure 19: Spatial distribution of the final selection of lack of resilience (LoR) variables (min-max normalized values) within the study area with the assigned weight.	38
Figure 20: Social vulnerability to natural hazards in the city of Quito.	40
Figure 21: Distribution of social vulnerability to natural hazards in the city of Quito with the according mean value and standard deviation.	41
Figure 22: Hot and cold spots of social vulnerability (Getis-Ord G_i^* , fixed distance band, threshold distance 590.4 m).	41
Figure 23: Social vulnerability to natural hazards in the southern part of the city of Quito with locations of SOS CV premises and highlighting of the district Quitumbe.....	42
Figure 24: Relative contribution of the indicators to the social vulnerability composite index for three census blocks in the northern part of the city of Quito. Orange colors in the pie chart represent the SUS domain, purple colors represent the LoR domain.	43

Figure 25: Relative contribution of the indicators to the social vulnerability composite index for three census blocks in the district Quitumbe. Orange colors in the pie chart represent the SUS domain, purple colors represent the LoR domain. 44

Figure 26: Natural hazards (mass movements, floods, volcanic hazards, and forest fires) in the city of Quito with hot spot areas of social vulnerability (polygon data of mass movements and volcanic hazards from RIVA project, rest of the data from Quito Open Data). 46

List of tables

Table 1: Preliminary set/wish list of indicators with the according variables and domain (SUS – Susceptibility, LoR – Lack of Resilience). Sign indicates if a higher value increases (+) or decreases (-) vulnerability.	21
Table 2: Statistically problematic variables regarding potential outliers (skewness > 2.0, kurtosis > 3.5).	23
Table 3: List of variables included in the treatment of outliers; the column 97.5 perc. lists the value of the 97.5 percentile. The column > 97.5 perc. lists the percentage of values exceeding the 97.5 percentile.	24
Table 4: VIF values for each variable of the two vulnerability domains.	26
Table 5: Variables with critical values of high collinearity based on thresholds for Pearson's r and/or VIF.	27
Table 6: Results of the PCA for each of the two domains with eigenvalues and the according explained variance for each principal component.	28
Table 7: Component loadings of the retained first five principal components, loadings > ±0.30 are highlighted.	29
Table 8: Rotated factor loadings for individual variables (SUS) of the retained factors using varimax rotation, loadings > ±0.30 are highlighted.	30
Table 9: Rotated factor loadings for individual variables (LoR) of the retained factors using varimax rotation, loadings > ±0.30 are highlighted.	31
Table 10: Final set of indicators with the according variables and domain (SUS – Susceptibility, LoR – Lack of Resilience). Sign indicates if a higher value increases (+) or decreases (-) vulnerability.	32
Table 11: Rotated factor loadings for individual variables for each of the two domains, squared normalized factor loadings, the highest loading (absolute value) for each variable is highlighted.	33
Table 12: Indicators with the according variables, signs, and weights grouped by domain (SUS, LoR).	34

1. Introduction and background

1.1 Defining vulnerability

Generally speaking, the meaning of the term vulnerability differs regarding the context in which it is used (Miller et al., 2010). It has been applied as a core concept in various studies in different research fields (e.g. disaster risk studies or economics), which has also led to conceptual differences (Miller et al., 2010). Birkmann (2006a) states that there are more than 25 different definitions, concepts and methods to describe vulnerability. When focusing on the context of disaster risk, the ambivalence still remains as the term is widely spread and used with different meanings throughout distinct groups of interest, such as the academia, disaster management agencies, the climate change community, and development agencies (Villagran, 2006). Within the last decades, vulnerability assessment in the field of natural hazards and climate change has gained of importance (Birkmann et al., 2013).

Already in 1989, Chambers (1989) introduced an important concept in which vulnerability basically refers to “exposure to contingencies and stress, and difficulty in coping with them” (Chambers, 1989, p.1). He proposed an external and internal side of vulnerability, whereas the external side is related to risks, shocks and stress while the internal side is related to defenselessness and incapacity to cope with damaging loss (Chambers, 1989). Furthermore, Chambers (1989) argues that vulnerability should not be considered as equal to poverty but related.

In 2001, the IPCC Third Assessment Report describes vulnerability as “the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity and its adaptive capacity” (IPCC, 2001, p.6). This definition embodies the *starting point* interpretation where vulnerability is viewed as a general characteristic of societies generated by different social and economic factors and processes while the contrasting *end point* definition views vulnerability as the residual of climate change impacts minus adaption (the remaining segments of the possible impacts of climate change that are not targeted through adaptation) (Bogardi et al., 2005; Villagran, 2006). This shows once more the divergent meanings of the term vulnerability as well as the variations in the underlying concepts, even within the climate change community (Kelly and Adger, 2000).

The International Strategy for Disaster Reduction (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” (ISDR, 2004, p.16). In this approach vulnerability is classified in different components or factors (e.g. physical or social), which are again related to different factors itself (ISDR, 2004).

It is evident that the above-mentioned definitions and descriptions of vulnerability represent only a small extract of the different definitions in use. Nevertheless, it shows that the meaning of the term differs, even within the community of one single scientific field.

1.1.1 Social vulnerability

The predominant views on vulnerability in most of the studies up to a certain point, especially when focusing on climate change impact, concentrate on the physical dimensions of the issue (Adger, 1999). Birkmann (2006a) stresses the need for a paradigm shift from hazard analysis to identification and assessment of vulnerabilities, as the ability to measure vulnerability is increasingly being seen as a key step towards effective risk reduction and the promotion of a culture of disaster resilience.

As already mentioned in the title, this thesis focuses on social vulnerability, which is one of the key factors when describing vulnerability (Birkmann et al., 2013; ISDR, 2004). The problem of the vagueness of the term vulnerability also applies to the usage of the concept of social vulnerability, which means that different authors apply it differently (Birkmann, 2006a). Also Fatemi et al. (2017) point out, that there is still a lack of a comprehensive definition meeting the requirements of various social and humanistic disciplines.

Cannon et al. (2003) state that it is important to recognize “social vulnerability as much more than the likelihood of buildings to collapse or infrastructure to be damaged” (Cannon et al., 2003, p.5). They view social vulnerability as a person’s set of the following characteristics (Cannon et al., 2003, p.5):

- Initial well-being (nutritional status, physical and mental health)
- Livelihood and resilience (assets and capitals, income, qualifications)
- Self-protection (capability and willingness to build a safe home, use a safe site)
- Social protection (hazard preparedness provided by society more generally)
- Social and political networks and institutions (social capital, institutional environment)

In the definition of Cannon et al. (2003) it is evident that the processes and factors describing the vulnerability condition are quite distant from the impact of a hazard itself. In addition, Cannon et al. (2003) argue that social vulnerability is not equal to poverty, since poverty is a measure of current status, whereas vulnerability should involve a predictive quality. Nevertheless, all the vulnerability variables in their definition are inherently connected with peoples’ livelihoods and with poverty (Cannon et al., 2003).

Based on two decades of research on this issue, Downing et al. (2006) view social vulnerability characterized by six attributes. They argue that social vulnerability is (Downing et al., 2006, p.3)

- the differential exposure to stress experienced or anticipated by different exposure units,
- a dynamic process,
- rooted in the actions and multiple attributes of human actors,
- driven by social networks in social, economic, political and environmental interactions,
- constructed simultaneously on more than one scale,
- determined by multiple stresses.

In the definition of the ISDR (2004), the social factor of the vulnerability is characterized by multiple factors itself. Thus, social vulnerability is, i.a., linked to the level of well-being of individuals or communities, education, peace and security, access to human rights, social equity, gender, age, class or caste privileges, public health, handicaps of individuals, and basic infrastructure (e.g. water supply and sanitation) (ISDR, 2004, p.42).

In 2013, Birkmann et al. (2013) develop a holistic framework to systematize and assess vulnerability. Therein, Social vulnerability is defined as the “propensity for human well-being to be damaged by disruption to individual (mental and physical health) and collective (health, education services, etc.) social systems and their characteristics (e.g. gender, marginalization of social groups)” (Birkmann et al., 2013, p.200).

Apparently, social vulnerability relates to socio-economic factors and individual characteristics of people (e.g. age, gender, health etc.), but also to place inequalities, i.e. characteristics of communities and the built environment (e.g. level of urbanization, growth rates etc.) (Cutter et al., 2003). Consequently, the concept of social vulnerability is more broadly used than just for the estimation of traditional social aspects of vulnerability (e.g. gender, age, income etc.), but can include economic and physical aspects, provided they are the expressions of a socially constructed vulnerability (Birkmann,

2006a). Hence, social vulnerability should not be limited to the estimation of the direct impacts of a hazardous event, but it should be perceived as the estimation of the wider environment and social circumstances encompassing the coping capacity and resilience of the concerned people and communities (Birkmann, 2006a). The widening of the concept of vulnerability is illustrated in Figure 1 and it shows that starting from a general basic understanding, a process of broadening took place (Birkmann, 2005, 2006a).

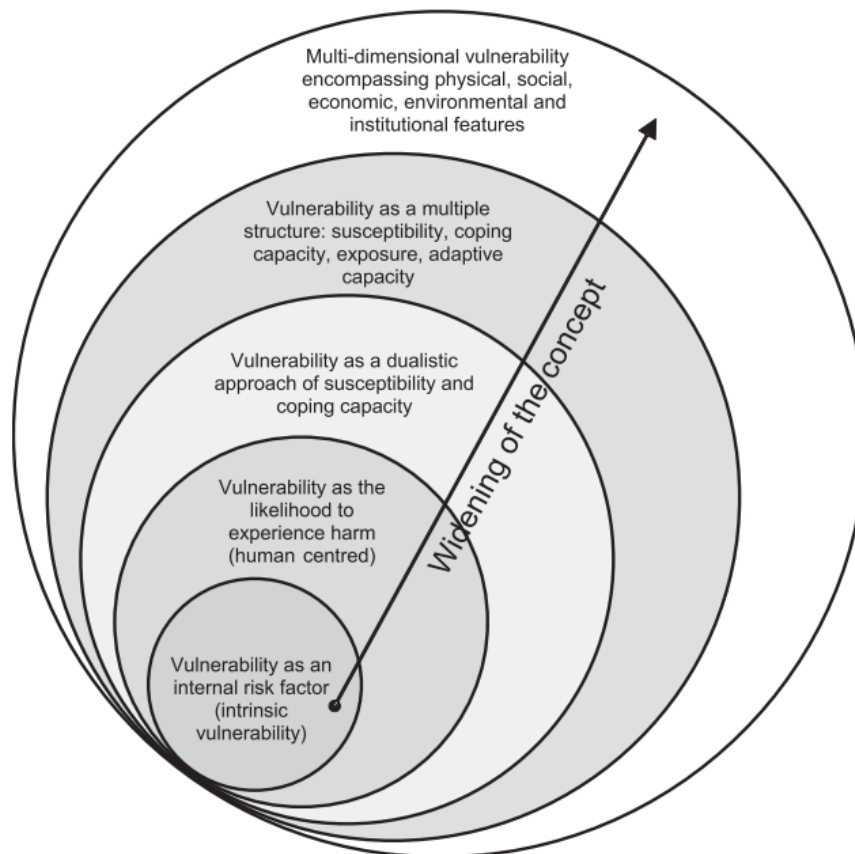


Figure 1: Key spheres of the concept of vulnerability (Source: Birkmann, 2005).

1.2 Assessing vulnerability

Birkmann (2006a) argues that when assessing vulnerability, we are still dealing with a paradox as we are aiming to measure vulnerability but cannot define it precisely (see 1.1). Nevertheless, “the ability to measure vulnerability is increasingly being seen as a key step towards effective risk reduction and the promotion of a culture of disaster resilience” (Birkmann, 2006a, p.9). In this regard, social vulnerability is of high importance as it is driven by socio-economic factors and individual characteristics of people that influence the capacity of the community to prepare for, respond to, and recover from disasters (Cannon, 1994; Cutter et al., 2003), and therefore helps to explain why different communities can experience the same hazardous event differently (Morrow, 2008). Yoon (2012) underlines that understanding the differential impact of hazard events is critical to reducing the negative impact of natural disasters.

1.2.1 Conceptual frameworks and models

The different spheres of the concept of vulnerability (Figure 1) are also reflected in the various analytical concepts and models of how to systematize vulnerability (Birkmann, 2006a). In addition, Downing (2004) stresses the importance of the relationship between the identification of relevant

indicators for vulnerability description and the underlying conceptual framework. In the following section, selected conceptual frameworks based on the listings of two different authors will be shortly discussed.

Birkmann (2006a, p.39) distinguishes six different schools of thought regarding conceptual frameworks systematizing vulnerability:

- The school of the double structure of vulnerability (Bohle, 2001; Chambers, 1989; Watts and Bohle, 1993)
- The conceptual framework of the disaster risk community (Bollin et al., 2003; Davidson and Shah, 1997)
- The analytical framework for vulnerability assessment in the global environmental change community (Turner et al., 2003)
- The school of political economy, which addresses the root causes, dynamic pressures and unsafe conditions that determine vulnerability (Wisner et al., 2004)
- The holistic approach to risk and vulnerability assessment (Cardona, 1999, 2001; Cardona and Barbat, 2000; Carreño et al., 2004, 2005, 2007a)
- The BBC conceptual framework, which places vulnerability within a feedback loop system and links it to the sustainable development discourse (based on work by Bogardi and Birkmann, 2004 and Cardona, 2001, 1999)

Cutter et al. (2008, p.601) lists three most often cited conceptual models for hazard vulnerability:

- Pressure and Release model (Wisner et al., 2004)
- Vulnerability/Sustainability framework (Turner et al., 2003)
- Hazard-of-place model of vulnerability (Cutter, 1996; Cutter et al., 2000)

Birkmann et al. (2013) identifies four distinct approaches to understanding vulnerability and risk rooted in different science fields:

- Political economy: pressure and release model (Wisner et al., 2004)
- Social-ecology: framework published by Turner et al. (2003)
- Vulnerability and disaster risk assessment from a holistic view: integrated explanation of risk (Barbat et al., 2011; Birkmann, 2006a; Birkmann and Fernando, 2008; Cardona, 2001, 1999; Carreño et al., 2012, 2007a, 2007b; IDEA, 2005)
- Climate change systems science: frameworks using the definition of vulnerability used by the IPCC (Füssel, 2007a, 2007b; IPCC, 2007, 2001; G. O'Brien et al., 2008; K. O'Brien et al., 2008)

The framework of the double structure distinguishes between an external and an internal side of vulnerability (Figure 2), where the external side refers to the exposure of shocks and stressors, while the internal side refers to coping and action to overcome the negative effects of those shocks (Bohle, 2001; Chambers, 1989).

The approach widely used in the disaster risk community (Birkmann, 2006a) sees vulnerability as a component within the context of hazard and risk, where disaster risk is determined by four different components: hazard, exposure, vulnerability, and capacity measures (Bollin et al., 2003; Davidson and Shah, 1997; Figure 3). According to this framework, and in contrast to the framework of the double structure mentioned above, vulnerability is separated from coping capacities and exposure.

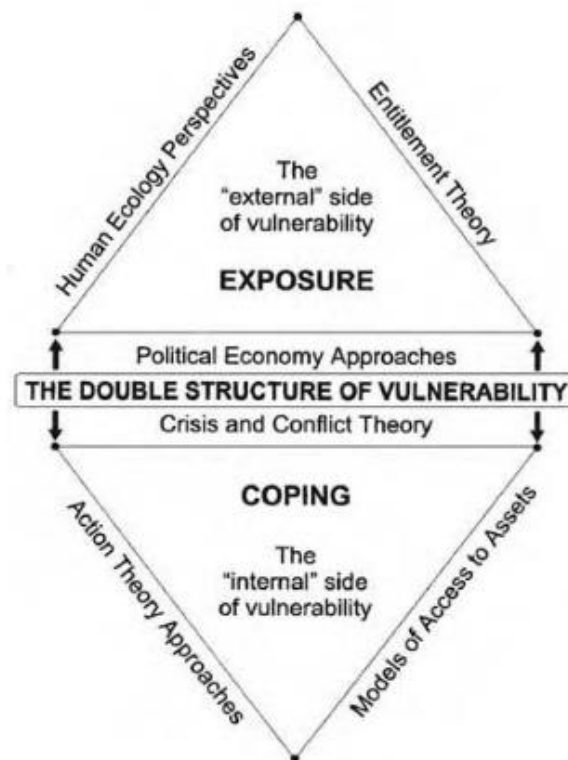


Figure 2: Bohle's conceptual framework for vulnerability analysis (Source: Bohle, 2001).

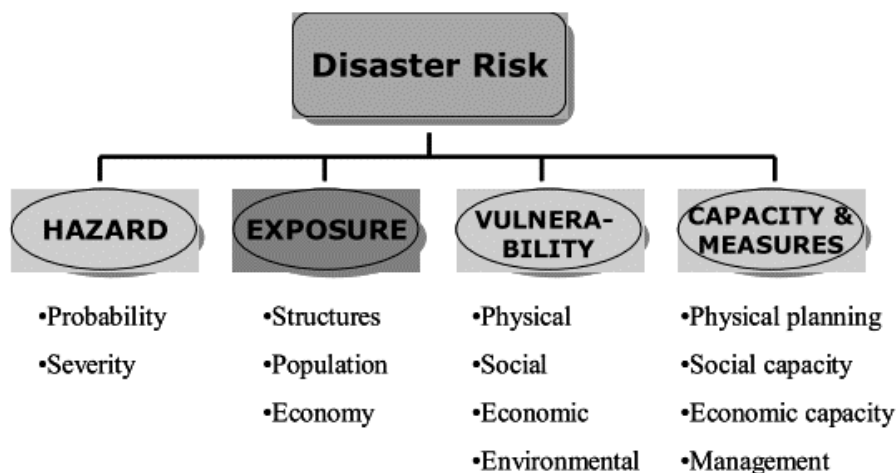


Figure 3: The conceptual framework to identify disaster risk (Source: Bollin et al., 2003).

The sustainability theme drives the attention to coupled human-environmental systems when dealing with vulnerability analysis and sees vulnerability in a broader sense (Turner et al., 2003). Several elements for inclusion in any vulnerability analysis are identified (Figure 4), while exposure, sensitivity, and resilience (coping response, impact response, adaptation response) is defined as parts of vulnerability (Turner et al., 2003). This is contrary to the above-mentioned disaster risk framework.

The pressure and release model (Wisner et al., 2004) argues that the risk faced by people must be seen as cross-cutting combination of vulnerability and hazard ($\text{Risk} = \text{Hazard} \times \text{Vulnerability}$). A disaster is the intersection of both opposing forces: those processes generating vulnerability on the one hand and the natural hazard event on the other (Wisner et al., 2004). In the model, the vulnerability and the development of a potential disaster is a process of increasing pressure for the affected people, while the reduction of vulnerability releases the pressure (Wisner et al., 2004).

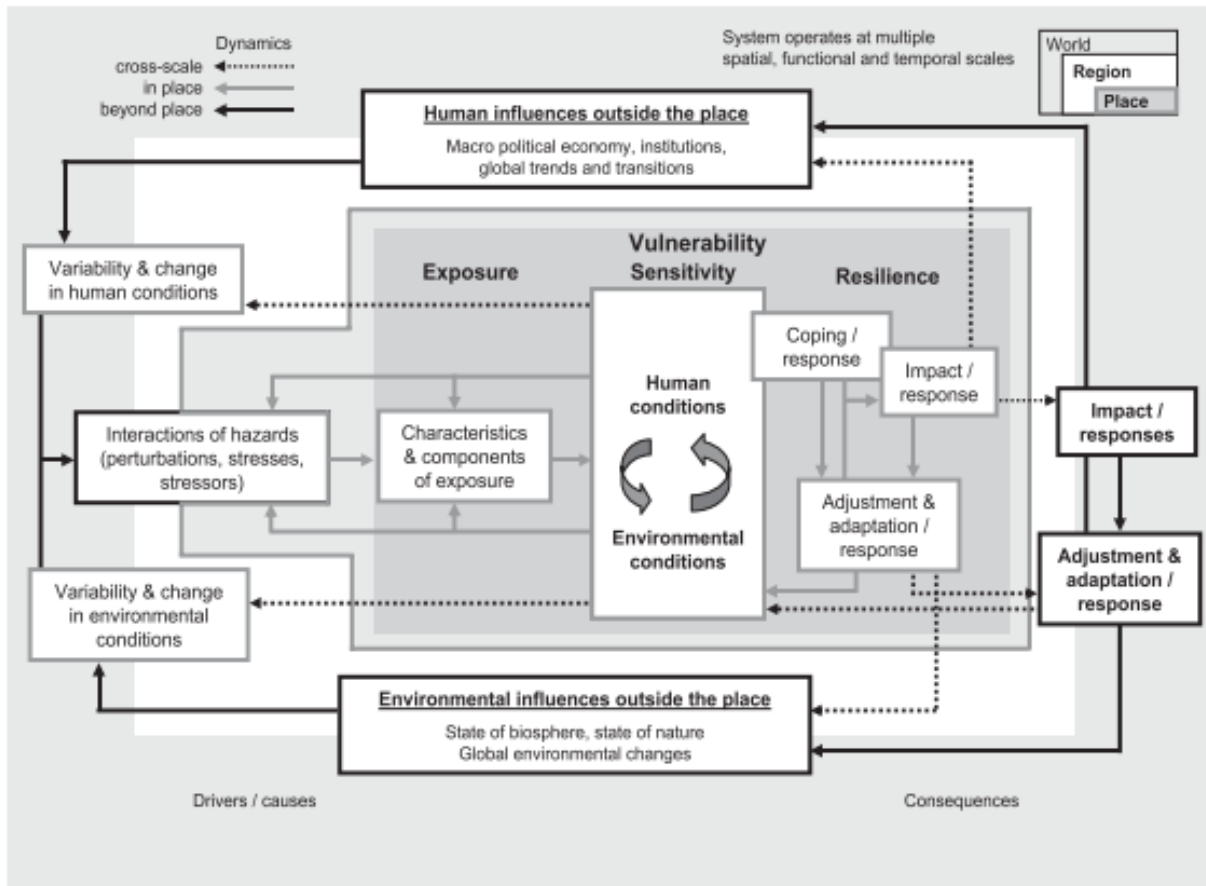


Figure 4: Vulnerability Framework defined by Turner et al. (Source: Turner et al., 2003).

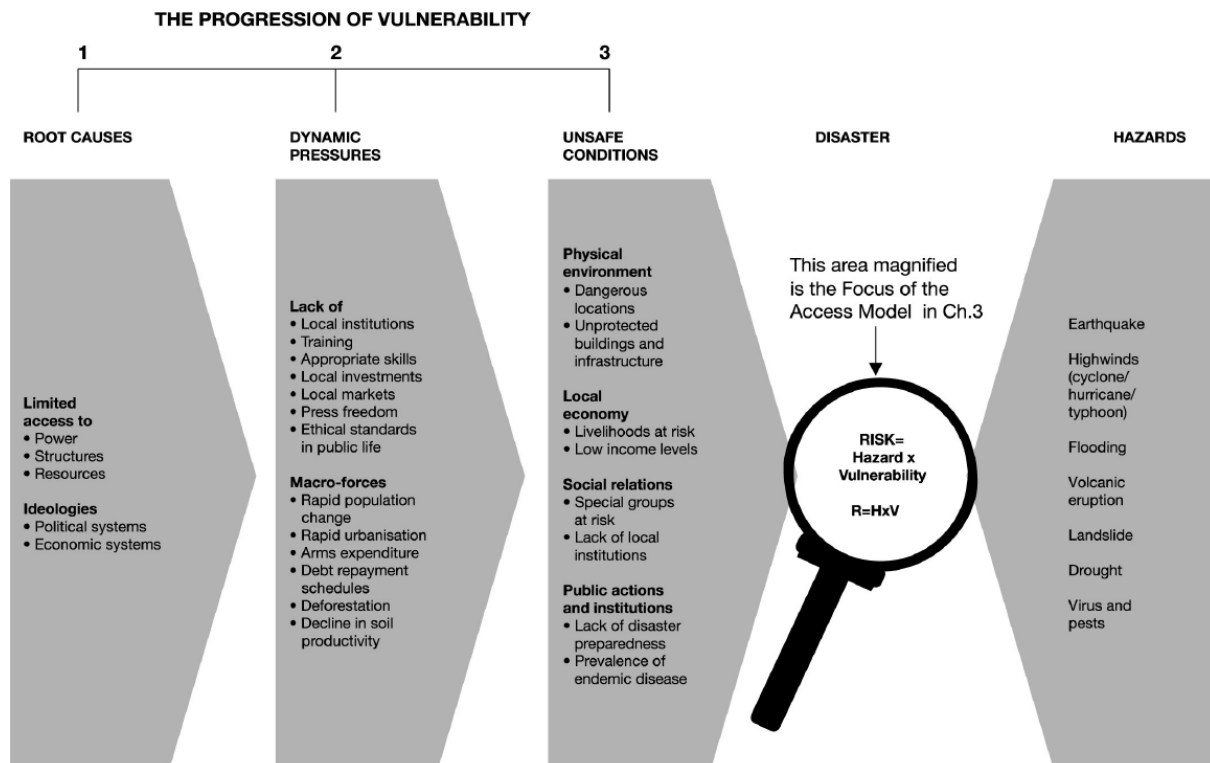


Figure 5: Pressure and Release (PAR) model: the progression of vulnerability (Source: Wisner et al., 2004).

In this context, the pressure and release model tracks the progression of vulnerability from root causes to dynamic pressures to unsafe conditions, which takes the connection of local risks to wider national and global shifts in the political economy of resources and political power into account (Birkmann, 2006a; Cutter et al., 2008).

Birkmann (2006a) and Birkmann et al. (2013) distinguish conceptual models with an holistic approach to vulnerability and risk, which differentiate exposure, susceptibility, and societal response capacities or the lack of resilience, and use complex system dynamics to represent risk management organization and action (Barbat et al., 2011; Birkmann, 2006a; Birkmann and Fernando, 2008; Cardona, 1999, 2001; Cardona and Barbat, 2000; Carreño et al., 2004, 2005, 2007b, 2007a, 2012; IDEA, 2005). Further, Birkmann et al. (2013) identify a feedback-loop system underlining that vulnerability is dynamic and that its assessment cannot be limited to the identification of deficiencies as a core element of these approaches (Figure 6).

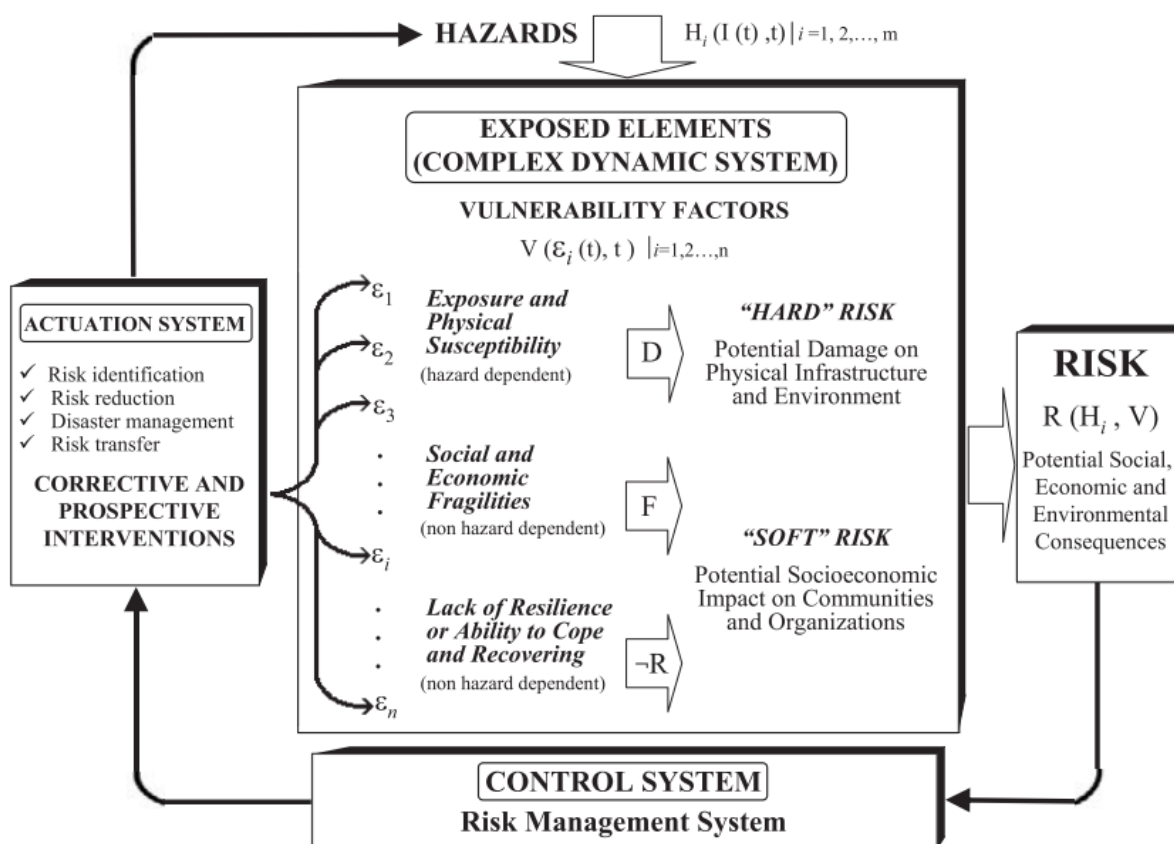


Figure 6: Cardona and Barbat's framework for holistic approach to disaster risk assessment and management (Source: Birkmann (2006a) based on Cardona and Barbat (2000)).

In this context the BBC conceptual framework (Figure 7), distinguished by Birkmann (2006a), can be seen, which is based on conceptual work done by Bogardi and Birkmann (2004) and Cardona (2001 and 1999) and links different elements of other frameworks (inclusion of sustainable development, holistic approach, development of causal framework) (Birkmann, 2006a). The BBC framework stresses the importance to focus on the different dimensions of vulnerability (social, economic and environmental) of the exposed elements, the coping capacity and the intervention tools to mitigate vulnerability, which is contrary to a risk analysis (Birkmann, 2006a).

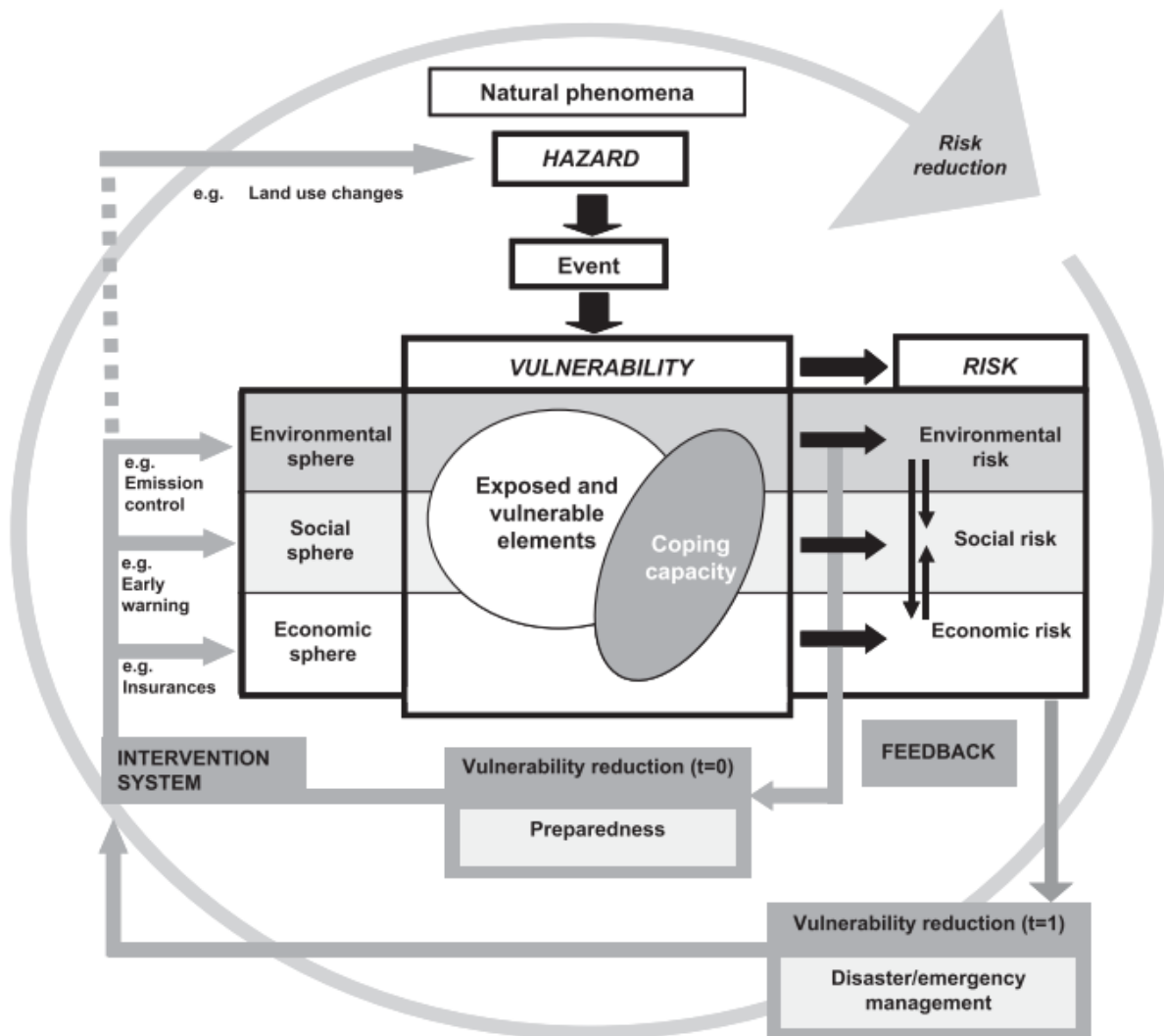


Figure 7: The BBC conceptual framework (Source: Birkmann (2006a) based on Bogardi and Birkmann (2004) and Cardona (2001 and 1999)).

The hazard-of-place model proposed by Cutter (Cutter, 1996; Cutter et al., 2000) tries to organize and combine the biophysical risk with the idea of social vulnerability (Figure 8) by tying them both to particular places, and thereby provide an opportunity to examine some of the underlying social and biophysical elements that contribute to vulnerability (Cutter et al., 2000).

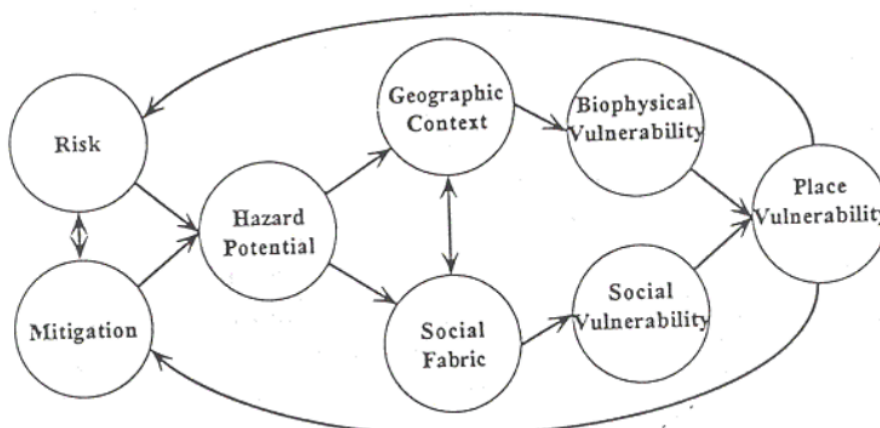


Figure 8: Cutter's hazard-of-place model (Source: Cutter, 1996)

In this model, risk and mitigation interact to produce a hazard potential, while the combination of biophysical and social vulnerability creates the place vulnerability (Cutter, 1996; Cutter et al., 2000).

Birkmann et al. (2013) distinguish another school of thought within the context of climate change adaptation research, in which most of the approaches focus on the definition of vulnerability used by the IPCC, according to which vulnerability is seen as a function of exposure, sensitivity, and adaptive capacities (Füssel, 2007b, 2007a; IPCC, 2007, 2001; G. O'Brien et al., 2008; K. O'Brien et al., 2008). These approaches take the rate and magnitude of climate change into account when calculating the vulnerability and therefore differ from the frameworks mentioned above (Birkmann et al., 2013).

Another holistic approach for assessing vulnerability is proposed by Birkmann et al. (2013) and is called the MOVE framework (Figure 9) which was developed within the context of the research project MOVE (Methods for the Improvement of Vulnerability Assessment in Europe) (Birkmann et al., 2013). The intention of the framework was to encompass the multiple dimensions of vulnerability by taking key factors into account such as exposure, susceptibility, lack of resilience (lack of societal response capacities) as well as the different levels of vulnerability (physical, social, ecological, economic, cultural, and institutional) (Birkmann et al., 2013). In addition, the concept of adaptation into disaster risk management is included in the model (Birkmann et al., 2013).

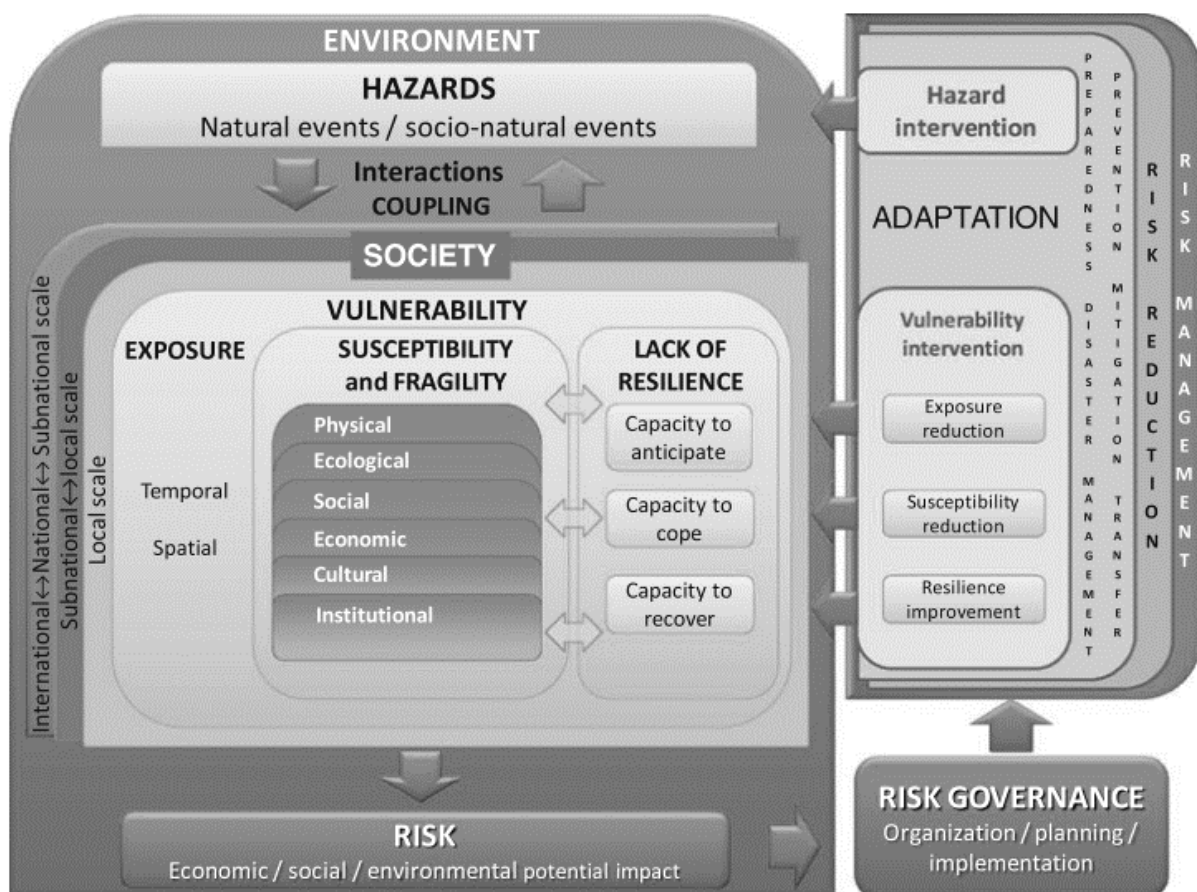


Figure 9: The MOVE framework (Source: Birkmann et al. (2013) based on concepts of Birkmann, 2006a; Bogardi and Birkmann, 2004; Cardona, 2001, 1999; Carreño et al., 2007a; IDEA, 2005; Turner et al., 2003).

1.2.2 *Vulnerability indices*

Within the above discussed conceptual frameworks by different authors, vulnerability is mostly quantified by indicators, which are key tools for identifying and measuring vulnerability (Birkmann, 2006b). The importance of their development to enable decision-makers to assess the impact of disasters was identified as a key activity by the international community on the World Conference on Disaster Reduction (WCDR) in the year 2005 (UN, 2005).

The use of indicators to assess and describe certain phenomena such as the GDP to describe a state's economic performance or the Dow Jones to measure the development of the US stock market is nowadays widely spread and commonly known. The development of social indicators emerged in the 1960s and 1970s (Cutter et al., 2003) followed by the development of environmental indicators in the 1970s connected to the formation of environmental policies (Birkmann, 2006b). The latest bigger thematic complex regarding indicator development was research associated with sustainability (Birkmann, 2006b).

Regarding social vulnerability, it is evident that this concept has multiple dimensions (Birkmann, 2006a; Miller et al., 2010; Villagran, 2006; Yoon, 2012), and therefore an adequate measure to quantify the multidimensional facet of vulnerability would be some sort of composite index (Adger et al., 2004; Barnett et al., 2008; Fatemi et al., 2017). Composite indicators are nowadays considered a useful tool for policy analysis, public communication, and decision-making and the number of indicators used is growing year after year (OECD, 2008), while Bandura (2008) lists nearly 180 composite indicators in existence around the world. However, as the concept of social vulnerability is multidimensional (Birkmann, 2006a; Miller et al., 2010; Villagran, 2006; Yoon, 2012), the development of indicators trying to quantify it will vary and therefore lead to the creation of different indicators (Fatemi et al., 2017; Yoon, 2012). This, of course, has also to do with the fact that every indicator is developed to serve a certain purpose (*indicandum*) and is related to certain goals (Birkmann, 2006b). Furthermore, the process of indicator development should be underpinned by an implicit conceptual model, which, of course, would influence the outcome of the corresponding vulnerability indicator (Downing, 2004).

Indicators can be differentiated on many levels. While the essential function of indicators is basically to quantify, an indicator could have either qualitative (nominal), ordinal (rank), or quantitative characteristics (Gallopín, 1997). Furthermore, as an indicator should always be developed in relation to a goal (Birkmann, 2006b), one can distinguish an indicator regarding its indicator-goal relations (Weiland, 1999). On the one hand, an indicator can focus on the direction a development is taking, which means that the development trend is used to evaluate e.g. vulnerability, while, on the other hand, an indicator can focus on a specific target that shows whether the state or the development has reached a defined value (Weiland, 1999). In addition, regarding social vulnerability Yoon (2012) distinguishes between a deductive and an inductive method used for assessment. The deductive approach, on the one hand, selects a limited number of variables to create a social vulnerability index based on a priori theory and knowledge from existing literature, while the inductive approach, on the other hand, includes all possible variables mentioned by literature and in a next step selects a set of variables based on probabilistic or statistical relationships (Yoon, 2012).

When developing an index, there are certain guidelines, which can be helpful throughout the development process. According to Maclaren (1996), ideally there are nine different phases (some of which already mentioned above) in the development of indicators relating to urban sustainability, which were applied to the development of vulnerability indicators by Birkmann (2006b, p.63).

1. Define goals: definition and selection of relevant goals
2. Scoping: identification of the target group and the associated purpose for which the indicators will be used
3. Choose indicator framework: identification of the underlying conceptual framework
4. Define selection criteria: definition of selection criteria for the potential indicators to meet certain defined standards in terms of viability and validity
5. Identify potential indicators: identification of a set of potential indicators, e.g. based on existing vulnerability studies
6. Choose a final set of indicators: Evaluation of the indicators and selection of a final set in regard of the defined selection criteria
7. Collect data & analyze indicator results: Collection of data for the chosen indicators to evaluate the applicability of the approach
8. Prepare and present report
9. Assess indicator performance

The Organization for Economic Co-operation and Development (OECD) (2008) lists ten different steps for building a composite indicator (OECD, 2008, p.20). While thematic overlaps do exist, those steps do not fully correspond with the above-mentioned nine phases according to Maclaren (1996).

1. Theoretical framework: provides the basis for the selection and combination of variables into a meaningful composite indicator
2. Data selection: should be based on analytical soundness, measurability, and relevance
3. Imputation of missing data: carried out in order to provide a complete dataset
4. Multivariate analysis: to study the overall structure of the dataset and derive subsequent methodological choices
5. Normalization: to render the variables comparable
6. Weighting and aggregation: according to the underlying theoretical framework and the data properties
7. Uncertainty and sensitivity analysis: to assess the robustness of the indicator in term of e.g. the choice of weights, the imputation of missing data etc.
8. Back to the data: to reveal the main drivers for an overall good or bad performance
9. Links to other indicators: to identify correlation and regressions linked to other existing indicators
10. Visualization of the results

It must be mentioned, that the nine phases according to Maclaren (1996) as well as the ten steps suggested by the OECD (2008) have to be considered as “ideal process” or “ideal sequence”, which in practice will be characterized by going back- and forwards (Birkmann, 2006b). Nevertheless, the distinction between different steps or phases can be helpful regarding structuring the process of indicator development as well as the analysis of current approaches and their development process (Birkmann, 2006b).

1.3 Aims and objectives

Climate change is projected to increase risks from natural hazards such as heat stress, extreme precipitation, inland flooding, or landslides for people in urban areas due to population growth and poor planning and insufficient implementation of mitigation strategies (Pachauri et al., 2014). Furthermore, Pachauri et al. (2014) point out that these risks are amplified for those people and communities lacking essential infrastructure and services or living in exposed areas. Billions of people

are affected and threatened by natural and manmade disasters worldwide, while children are disproportionately affected (International Federation of Red Cross and Red Crescent Societies, 2018; SOS Children's Villages International, 2017a; Wallemacq and Below, 2018). Supported by Allianz SE, the Emergency Preparedness Program of the SOS Children's Villages International seeks to tackle these threats and challenges and aims to minimize weather- and conflict-related risks for local communities (SOS Children's Villages International, 2017a).

Within the context of the Emergency Preparedness Program, a project called RIVA (Risk and Vulnerability Assessment) is conducted with the additional support of the Interfaculty Department of Geoinformatics (Z_GIS) (SOS Children's Villages International, 2017a). The main goal is to evaluate and strengthen disaster preparedness and response capacities of local communities by developing target trainings, closing communication gaps, and pre-positioning of vital resources (SOS Children's Villages International, 2017a). This assessment is carried out for ten different SOS Children's Villages worldwide (Allianz SE, 2017). While in a first step the assessment focuses on the SOS Children's Village itself, in a second step the assessment is extended to the surrounding area (SOS Children's Villages International, 2018). This findings will then be shared with local communities and NGOs (Ruep, 2017).

Typically, the impacts and the magnitude of damage (physical, psychological etc.) due to natural disasters are unevenly distributed among and within nations, regions, communities and groups of individuals (Yoon, 2012). However, spatial modelling of vulnerability is not always regarded as a central element (Kienberger et al., 2009) although vulnerability is strongly related to the specifics of a place (place-based) (Cutter et al., 2008; November, 2008). Thus, based on the aims of RIVA, this thesis focuses on the vulnerability of the inhabitants of the whole city of Quito in Ecuador in order to get to a better understanding of the social vulnerability to natural hazards in urban areas. The objectives are as follows:

- (1) Quantification of the social vulnerability by developing a composite index based on a theoretical risk and vulnerability framework
- (2) Mapping of the social vulnerability for the city area of Quito (census block scale)
 - a. Revealing of hot and cold spots
 - b. Supporting tool for risk management

2. Materials and methods

2.1 Study area

When carrying out an assessment of vulnerability it is essential to stress that we can only talk meaningfully about vulnerability of a specified system to a specified hazard or range of hazards (Brooks, 2003). Therefore, it is of high importance to set the study area in proper relation to the conducted vulnerability assessment study, as the conceptualization and the use of data or factors for creating an index for the social vulnerability depends heavily on the study area and the context and aim of the study carried out (de Loyola Hummell et al., 2016; Frigerio et al., 2016; Frigerio and De Amicis, 2016).

As mentioned above (see 1.3), within the context of the RIVA project the assessment is carried out on ten different SOS Children's Villages and their surrounding area, while this thesis focuses on the capital of Ecuador, the city of Quito (Figure 10 and Figure 11). This choice was made mainly since the quality of the underlying data as well as the abundance of the data is better or higher compared to the other case studies.



Figure 10: Location map of the city of Quito, Ecuador.

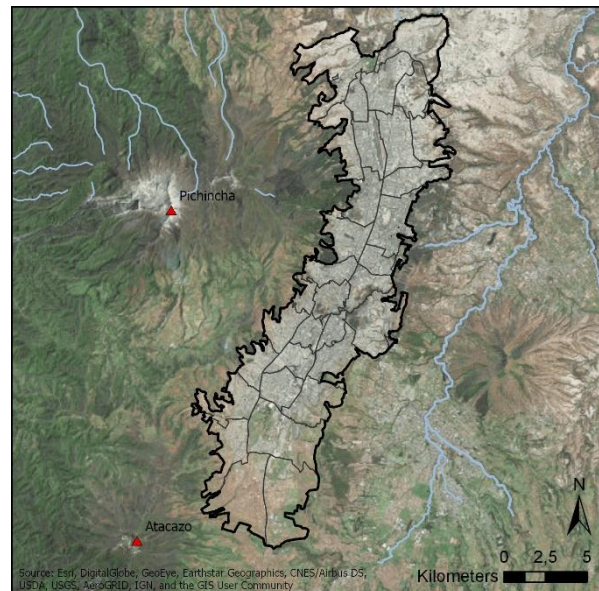


Figure 11: Map of the city and study area of Quito, Ecuador.

This thesis focuses on the assessment of social vulnerability in an urban area. While the metropolitan district of Quito, which is located in the Pichincha Province, is much bigger than the city itself, the study area is limited to the city of Quito and is related to the study area of the research study on deprivation and healthcare accessibility by Cabrera-Barona et al. (2018), who made the according data (e.g. shapefiles) available to the author. This approach also provides the possibility of a direct comparison of the results, which could be interesting as deprivation might be related to social vulnerability and show similar spatial patterns. The study area covers an area of around 195 km² with around 1.6 million inhabitants according to the 2010 Ecuadorean Population and Housing Census.

The city of Quito is located in a mountain valley of high altitude (around 2,850 m above sea level) in the northern part of Ecuador, close to the equator. The city is surrounded by several active and inactive volcanoes.

2.1.1 SOS Children's Village in Quito

SOS Children's Villages International is providing supportive care when children can no longer live with their families around the world (SOS Children's Villages International, 2017b). Further, its aim is to prevent family breakdown and to ensure that children's rights are met by working with children, families, communities and states (SOS Children's Villages International, 2017b). Especially the family strengthening programs help families to build capacities so that children are well cared for and families can stay together (SOS Children's Villages International, 2017b).

SOS Children's Villages has been working in Quito since 1963, supporting over 1,200 people with the family strengthening program throughout Quito (SOS Children's Villages International, 2017b). In the Children's Village itself ten families with a total of 70 children found a new home, while 42 staff members work in the village (SOS Children's Villages International, 2018). The Children's Village is located in a populous area underlined by the fact that a total number of around 49,000 people are living in the surrounding area (15 min walking time) (SOS Children's Villages International, 2018).

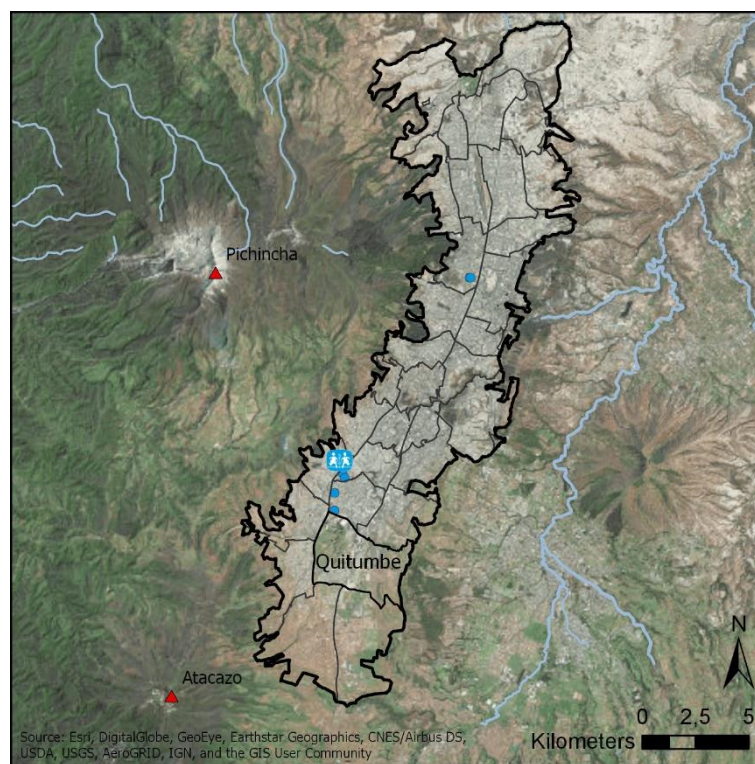


Figure 12: Location of the SOS Children's Village itself and other SOS CV premises in Quito. The district Quitumbe is highlighted as it is considered for future extension by SOS CV.

In the first step of assessment in the course of the RIVA project it was found that the village itself is highly exposed to volcanic hazards, while floods and new diseases (e.g. Zika, Chikungunya Fever) were characterized as emerging hazards (SOS Children's Villages International, 2018). Key vulnerabilities were detected in the domain of coping capacity as well as regarding the capacity to recover (SOS Children's Villages International, 2018). Quitumbe, a district in the south of Quito, is considered for further extension by SOS Children's Villages in the future.

2.1.2 Natural hazards in Quito

Ecuador finds itself in one of the zones of highest tectonic complexity, resulting in high seismic and volcanic activity (Municipio del Distrito Metropolitano de Quito, 2015). Additionally, it is located in the Intertropical Convergence Zone and is therefore exposed to hazards of hydrometeorological origin

such as floods, droughts, storms and frosts (Municipio del Distrito Metropolitano de Quito, 2015). Furthermore, due to the geomorphological conditions, processes of mass movement (e.g. landslides, mud flows, erosion) are supported (Municipio del Distrito Metropolitano de Quito, 2015). Those events of natural origin are periodically reoccurring throughout Ecuador, while Quito is no exception (Municipio del Distrito Metropolitano de Quito, 2015). In principle, these hazards are of natural origin, whereby, especially in the urban environment, human behavior, activities, and land use influence physical processes (Municipio del Distrito Metropolitano de Quito, 2015). In addition, climate change is projected to increase risks from natural hazards for people in urban areas due to population growth and poor planning as well as insufficient implementation of mitigation strategies (Pachauri et al., 2014).

Mass movements

Mass movements are displacements downhill from a mass of soil or rock whose movement occurs predominantly along a slip or shear surface (Municipio del Distrito Metropolitano de Quito, 2015). Those can be distinguished between the material type and the type of movement (Varnes, 1978). The most common events developing in the area of the city of Quito are landslides generated in the margins of the surrounding ravines, on the slopes of roads and on slopes generally steeper than 30° as well as mud and debris flows (Municipio del Distrito Metropolitano de Quito, 2015). The intensity, frequency, and occurrence of mass movement events are sometimes influenced by anthropogenic interventions and actions such as deforestation, infrastructure installation, water infiltration due to leaks in aqueducts and sewage systems, insufficiency of rainwater collection systems, and mining (Municipio del Distrito Metropolitano de Quito, 2015). The exposure of the city center itself to phenomena of mass movements is relatively low, while the threat is much higher in the outskirts in proximity to the areas of higher elevation (Municipio del Distrito Metropolitano de Quito, 2015).

Floods

Rainfalls in Quito are characterized by spatial and temporal irregularities (Pourrut and Leiva, 1989), and therefore strong, local rainfalls of short duration (rarely more than 1-2 hours) are leading to flooding of the urban areas as well as alongside the courses of rivers (Municipio del Distrito Metropolitano de Quito, 2015). Similar to the development of mass movements, flooding events are influenced or even caused by anthropogenic interventions such as the sealing of the soil and the insufficient rainwater collection systems, filling of natural drains, and deforestation (increasing runoff in higher elevated areas of the watershed) (Municipio del Distrito Metropolitano de Quito, 2015). The areas prone to flooding are more or less evenly distributed among the city area, while in the city center the danger of flooding tends to be a little bit higher (Municipio del Distrito Metropolitano de Quito, 2015).

Volcanic hazards

Volcanic activity leads to phenomena with local, regional, and global effects and the history of Ecuador is marked by several events of great magnitude causing environmental imbalances with sometimes long-term consequences (Municipio del Distrito Metropolitano de Quito, 2015). Quito is surrounded by several volcanoes such as the Guagua Pinchincha, Cotopaxi, Cayambe, Pululahua, Ninahuilca, or El Reventador, which had seriously affected the city of Quito throughout history (Municipio del Distrito Metropolitano de Quito, 2015). While pyroclastic flows are among the hazards with a very high destructive force, the city of Quito faces very limited exposure to pyroclastic flows (Municipio del Distrito Metropolitano de Quito, 2015). The city area is mostly exposed to ash fall and

flows of debris and mud (lahars), mostly caused by eruptions of Guagua Pichincha and Cotopaxi located in the west and in the south-east, respectively (Municipio del Distrito Metropolitano de Quito, 2015).

Seismic hazards

Ecuador is a tectonically active country with high seismic activity due to being located in the subduction zone of the Nazco oceanic plate under the continental plate of South America (Municipio del Distrito Metropolitano de Quito, 2015). The magnitude of seismic vibrations at a certain point of interest depends on several factors, such as the magnitude of the earthquake, the distance from the fault (fracture), and the “local effect”, which depends on soil types and thickness, relief, and topography (Municipio del Distrito Metropolitano de Quito, 2015). Crossed by a fault system, the city of Quito is located in an area of high seismic activity and has been affected by many intense earthquakes throughout history (Municipio del Distrito Metropolitano de Quito, 2015). Seismic micro zoning assessment studies show that the city center as well as the southern part of the city are exposed to a higher seismic hazard than the northern part of the city (Municipio del Distrito Metropolitano de Quito, 2015).

Forest fires

Forest fires bear a high destructive force, as their outbreak results in loss of infrastructure and environmental deterioration to a high degree (Municipio del Distrito Metropolitano de Quito, 2015). The inflammability and combustibility play an important role regarding the susceptibility to forest fires, while it is also influenced by other factors, such as e.g. accessibility (Municipio del Distrito Metropolitano de Quito, 2015). In the city of Quito itself, only a few areas are susceptible to forest fires, e.g. the forest running north-south in the central part of the district and forests in eastern parts of the city (Municipio del Distrito Metropolitano de Quito, 2015).

Solar radiation

Throughout the last couple of years, reports on very high solar (ultraviolet) radiation in whole Ecuador and in the city area of Quito itself became more frequent and the exposure to it is considered a serious health threat (CuencaHighLife, 2017; El Comercio, 2018; Parra et al., 2018; Serrano et al., 2014). Nevertheless, this hazard will not be considered in the indicator selection process.

2.2 Underlying data

2.2.1 Census data 2010

The 2010 Ecuadorean Population and Housing Census provides the socio-economic data for the creation of a social vulnerability index. The Population and Housing Census is carried out by the National Institute of Statistics and Censuses (Instituto Nacional de Estadísticas y Censos – INEC). The first census was carried out in 1950, while the last one was carried out in the year 2010 (INEC, 2014). The data is publicly available for free on the website of the National Institute of Statistics and Censuses at <http://www.ecuadorencifras.gob.ec/censo-de-poblacion-y-vivienda> (accessed on 31/08/2018).

2.2.2 Hazard data

There are two types of data available describing the different hazards in the study area: data of hazardous events and data describing the danger facing different types of hazards. As this thesis

focuses on the assessment of social vulnerability only and not on the exposure to natural hazards (see 2.3), the hazard data will not be included in the assessment itself. Nevertheless, this data might be useful in terms of visualization and interpretation of this thesis' results. This data is publicly available for free on the Quito Open Data website at http://gobiernoabierto.quito.gob.ec/?page_id=1105 and at <http://geo.quito.gob.ec:8080/geoserver/web/?wicket:bookmarkablePage=:org.geoserver.web.demo.MapPreviewPage> (accessed on 17/09/2018) in the shape file format.

Data of hazardous events

Point data represents different hazardous events i.e. floods and mass movements from 2005 to 2017.

Data of danger facing natural hazards

The danger facing natural hazards is represented by polygons referring to certain levels of danger facing mass movements, floods, volcanic hazards and forest fires.

2.2.3 Other data

Deprivation index, Healthcare accessibility

The results of the study regarding deprivation and healthcare accessibility of Cabrera-Barona et al. (2018) were made available to the author by Pablo Cabrera-Barona in the shape file format.

Data associated with the RIVA project

Various data associated with the ongoing RIVA project (see 1.3) and the assessment carried out in the first level of the project was provided by Stefan Kienberger. This data includes i.a. point data of different amenities (e.g. SOS CV, healthcare services, educational services, public transportation, security), line data of the street network, and line data of major and minor rivers. This data might be useful in terms of the interpretation of this thesis' results and their visualization but will not be included in the social vulnerability assessment itself.

In addition, the data includes point data of hazard events and polygon data of the danger facing volcanic hazards and mass movements. This data is mainly consistent with the above-mentioned data (2.2.2).

2.3 Conceptual framework

When carrying out a vulnerability assessment the underlying conceptual framework is of high importance, as it incorporates a certain vulnerability definition and therefore influences the development process of the corresponding vulnerability index (Downing, 2004; Maclaren, 1996; OECD, 2008). An overview of different vulnerability definitions and conceptual frameworks was given in chapter 1.1.1..

The underlying conceptual framework for the first level of vulnerability assessment regarding the RIVA project was the MOVE framework established by Birkmann et al. (2013). As this thesis is conducted in relation to the RIVA project, the same conceptual framework will be applied.

The framework has been developed within the context of the research project MOVE (Methods for the Improvement of Vulnerability Assessment in Europe) and is underlined by a multi-dimensional and holistic approach to vulnerability assessment that is understood as part of risk evaluation and risk management in the context of disaster risk management (DRM) and climate change adaptation (CCA)

(Birkmann et al., 2013). As already elaborated above, this thesis focuses specifically on the vulnerability domain of the framework and its social dimension only. Therefore, the exposure domain is excluded from the assessment as the potentiality of harm is independent from a hazard delineation, which is based on certain model assumptions with related uncertainties (Kienberger et al., 2014). Thus, this assessment will focus on localizing potential vulnerable areas based on their predispositions and general characteristics regarding the social dimension (Kienberger et al., 2014). Further, the subdomains of the “lack of resilience” domain were relabeled in the sense that the domain is coherent with the negative association regarding vulnerability (Kienberger et al., 2014). As already mentioned above (see 2.1), the study area is the city of Quito, which would relate to a subnational to local scale regarding the framework. The adapted framework is depicted in Figure 13.

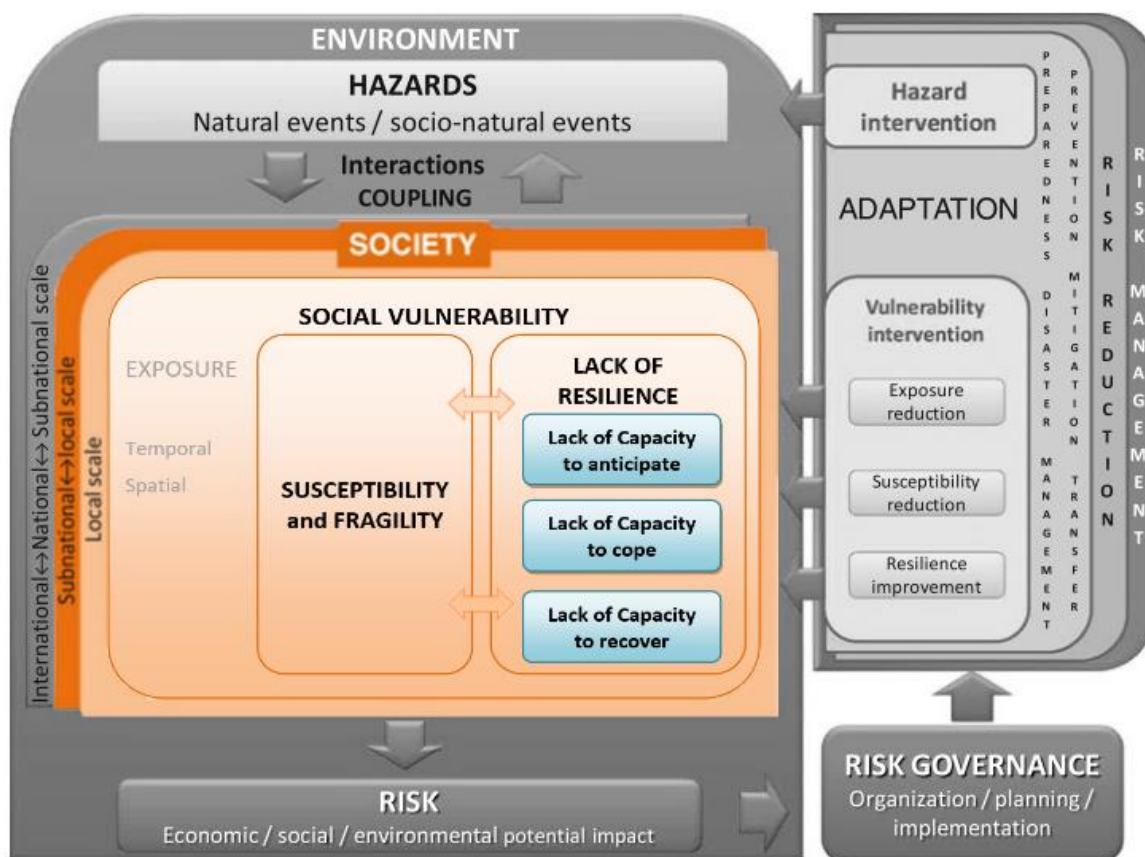


Figure 13: Adapted MOVE risk and vulnerability framework based on Birkmann et al. (2013) – The assessment is carried out on a subnational to local scale. The relevant domains are highlighted, while the exposure domain is excluded from the assessment.

Besides the key causal factors (exposure, susceptibility, lack of resilience), the MOVE framework incorporates different thematic dimensions of vulnerability such as physical, social, ecological, economic, cultural, and institutional dimensions (Birkmann et al., 2013). The social dimension of vulnerability within the framework is described as “propensity for human well-being to be damaged by disruption to individual (mental and physical health) and collective (health, education services, etc.) social systems and their characteristics (e.g. gender, marginalization of social groups) (Birkmann et al., 2013, p.200).”

Additionally, a core element of the underlying framework is the incorporation of a feedback-loop system (risk governance, adaptation) underlining that vulnerability and risk are part of various processes of a dynamic nature and therefore change over time (Birkmann et al., 2013).

2.4 Constructing a composite index

The following section describes the multi-step workflow for the construction of a composite index characterizing the social vulnerability for the study area. The workflow was adopted following OECD guidelines (OECD, 2008) as well as following an approach Hagenlocher et al. (2013) chose for a vulnerability study in Colombia. The chosen workflow made sure to be independent from third parties throughout the process of creation of the composite index, and therefore rule out the possibility of delays caused by external factors.

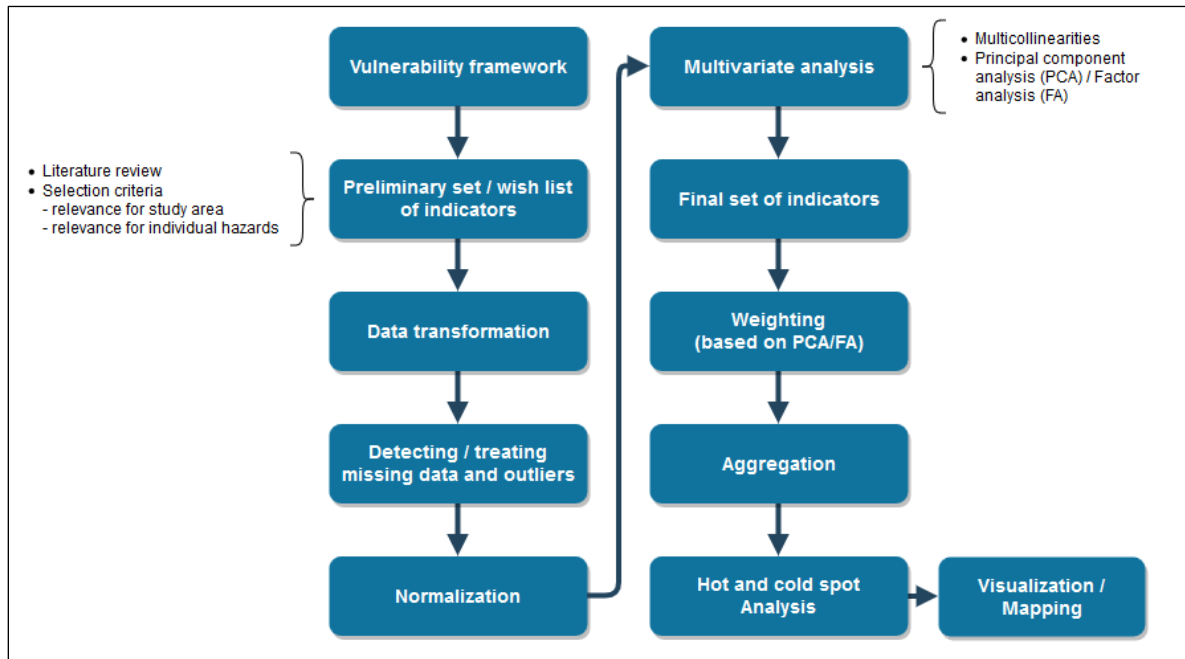


Figure 14: Workflow for the composite index construction process (adapted from Hagenlocher et al., 2013).

2.4.1 Selection of indicators

The selection of the different indicators/variables plays a key role in the development of a composite index as they account for the validity of the according vulnerability index, which means that the selected variables represent the underlying concept appropriately (Fatemi et al., 2017). When reviewing different studies measuring the social vulnerability, it is evident that there is no universal answer to the question of indicator selection, as every study serves a certain purpose or follows a certain goal (Fatemi et al., 2017; Yoon, 2012).

Nevertheless, the review of literature provides a fundamental approach for the identification of potential indicators (Fatemi et al., 2017; Kienberger et al., 2014; Yoon, 2012). Fatemi et al. (2017) carried out a systematic literature review including a total of 43 qualified scientific publications dealing with social vulnerability assessment and derived a list with around 30 classified indicators and related variables occurring in the reviewed studies (Fatemi et al., 2017). The main indicators are gender, age, education, language skills, employment, social status/income, physical and mental capacities, and access to public infrastructure (Cutter et al., 2003; de Loyola Hummell et al., 2016; Fatemi et al., 2017; Lee, 2014).

In most societies, a discriminatory surrounding towards women lead to gender inequalities resulting in higher vulnerability of the female population (Fatemi et al., 2017). Especially during recovery, women can be affected more severely by disasters due to sector-specific employment, lower wages, and family care responsibilities (Cutter et al., 2003; de Loyola Hummell et al., 2016).

Furthermore, the distribution of age groups in a society have an impact on the vulnerability. Especially extremes in the age spectrum may increase social vulnerability, as children and elders are dependent on others in terms of financial and physical support, in particular during and after disasters (Cutter et al., 2003; Fatemi et al., 2017; Kienberger et al., 2014).

Higher education is often linked to lower vulnerability because people with higher education have better access to resources (e.g. financial) and have a higher capability of accessing and understanding warning or recovery information (Cutter et al., 2003; Fatemi et al., 2017).

Immigration and the related social vulnerability is a widely discussed issue. Cutter et al. (2003) argue that language and cultural barriers could affect the access to financial help or funding in the post-disaster phase. Furthermore, immigrants, especially those who have recently moved to a new city, have less experience and knowledge regarding the local types of natural hazards leading to possibly wrong reactions during the disaster (de Loyola Hummell et al., 2016).

Employment and socio-economic status are related in most societies. The fact of being unemployed or being subjected to poverty may increase the social vulnerability as the ability to absorb losses and recover from disasters may decrease, while, on the contrary, wealth enables communities to deal with and recover from natural hazards more quickly (Cutter et al., 2003; de Loyola Hummell et al., 2016). Also, being employed in different sectors may lead to different levels of social vulnerabilities as sectors may be differentially affected by disasters (Kienberger et al., 2014). For instance, societies that are heavily dependent on agriculture, tourism-related activities, or extractive industries might be more vulnerable compared to others, while a strong public employment sector might decrease social vulnerability (Cutter et al., 2003; de Loyola Hummell et al., 2016; Kienberger et al., 2014).

Population with special needs (e.g. physically or mentally handicapped) are highly vulnerable and can be heavily affected by disaster, as they require special attention or infrastructure during a hazardous event, but also in the post-disaster phase (Cutter et al., 2003; de Loyola Hummell et al., 2016). Especially people residing in group quarters (e.g. nursing homes) have a particular vulnerability (Fatemi et al., 2017).

Accessibility of households to public infrastructures such as roads, water supply, electricity are of high importance regarding the social vulnerability (Cutter et al., 2003; Fatemi et al., 2017; Kienberger et al., 2014). Furthermore, the access to public services like early warning systems and healthcare infrastructure affect the level of social vulnerability (Fatemi et al., 2017; Kienberger et al., 2014).

As a first step, potential vulnerability indicators were identified from scientific publications (Cabrera-Barona et al., 2018; Cutter et al., 2003; de Loyola Hummell et al., 2016; Fatemi et al., 2017; Kienberger et al., 2014), while the main criteria to select the indicators were the relevance for the study area as well as the relevance for the individual hazards (Kienberger et al., 2014). The selection process led to a preliminary set or a wish list of indicators (Table 1) describing the social dimension of vulnerability in the study area to the natural hazards listed in chapter 2.1.2, excluding solar radiation. According to the adapted MOVE framework (Figure 13), the variables were assigned either to the lack of resilience (LoR) or the susceptibility (SUS) domain. Furthermore, a positive (+) or negative (-) sign indicates whether the social vulnerability increases or decreases with a higher value. This set of indicators is characterized as preliminary or as wish list because the availability of actual data to represent the individual indicators was not yet included in the selection process.

Mapping social vulnerability to natural hazards

Materials and methods

Table 1: Preliminary set/wish list of indicators with the according variables and domain (SUS – Susceptibility, LoR – Lack of Resilience). Sign indicates if a higher value increases (+) or decreases (-) vulnerability.

Nr.	Indicator	Variable	Domain	Sign
1.1	Female population	Percentage of females	LoR	+
1.2		Percentage of female headed households	LoR	+
1.3		Percentage of employed females in the labor force	LoR	+
2.1	Age structure	Median age	SUS	+
2.2		Percentage <5 years old	SUS	+
2.3		Percentage >64 years old	SUS	+
3.1	Family structure	Average number of people per household	SUS	+
3.2		Percentage of households with four or more persons per dormitory	SUS	+
4.1	Population characteristics	Population density	SUS	+
5.1	Race/Ethnicity & Minorities	Percent of minorities (e.g. indigenous people)	LoR	+
5.2		Percentage of population born in other states	LoR	+
5.3		Percentage of residents immigrating in the past 3-5 years	LoR	+
6.1	Quality of built environment	Percentage of households with no water infrastructure or well	LoR	+
6.2		Percentage of households with no sewer infrastructure	LoR	+
6.3		Percentage of households with no garbage collection services	LoR	+
6.4		Percentage of households with no electricity service	LoR	+
6.5		Percentage of population living in households with low quality external walls	LoR	+
6.6		Percentage of population living in households with low quality roofs	LoR	+
7.1	Housing unit status	Percentage of population living in rented households	LoR	+
8.1	Socioeconomic status/Income	Percentage of households with no phone (cell phone or landline)	LoR	+
8.2		Percentage of population living in households facing extreme poverty	LoR	+
8.3		Per capita income	LoR	-
9.1	Education	Percentage of illiterate population aged 15 and older	LoR	+
9.2		Percentage of population that completed middle school or with high school incomplete	LoR	-
9.3		Percentage of population that completed college degree	LoR	-
9.4		Percentage of population with no level of formal education or instruction	LoR	+
10.1	Employment	Percentage of population unemployed	SUS	+
10.2		Percentage of population employed in agriculture, mining, forestry production, livestock, and aquaculture	SUS	+
10.3		Percentage of population employed in extractive industry	SUS	+
10.4		Percentage of population employed in accommodation activities	SUS	+
10.5		Percentage of population employed in food service activities	SUS	+
10.6		Percentage of population employed in commerce	SUS	+
10.7		Percentage of population employed in public administration, defense and social security	SUS	-
10.8		Percentage of population employed in human health and social work services	LoR	-
10.9		Percentage of population that works in unpaid jobs	LoR	+
11.1	Occupation	Percentage of labor force with legal work registration	LoR	-
11.2		Percentage of labor force with no legal work registration	LoR	+
11.3		Percentage of subsistence workers in the labor force	LoR	+
12.1	Special needs population	Percentage of population with at least one type of deficiency	SUS	+
13.1	Healthcare accessibility	Index of Healthcare Accessibility (Cabrera-Barona et al., 2018)	LoR	-

Table 1 (continued)

Nr.	Indicator	Variable	Domain	Sign
14.1	Access to roads		LoR	-
15.1	Early warning systems		LoR	-

2.4.2 Data transformation

The raw data of the 2010 Ecuadorean Population and Housing Census was downloaded in the REDATAM format and the desired census variables were extracted for the study area with the freely available software *Redatam 7* (<https://www.cepal.org/en/topics/redatam/download-redatam>, accessed on 29/01/2019). The data extraction was based on a geographical selection criterion representing the study area (city of Quito) on the level of census blocks, while two census blocks, where no census data was available, were excluded. The census raw data was used to calculate most of the variables, while the data was transformed to render the variables better comparable. Hence, nearly all variables represent relative values in relation to the according subgroup of the population, the total numbers of households or the census block area. For example, the percentage of unemployed individuals was calculated in relation to the working population (i.e. excluding children, retired individuals etc.). the only variable not expressed as relative value is the median age. Due to unavailable representative data, some variables listed in Table 1 had to be dropped (8.2, 8.3, 9.2, 11.1, 11.2, and 15.1) and two variables had to be merged together (10.4 and 10.5). Detailed information about the calculation of the variables can be found in Appendix A.

As mentioned above (see 2.2.3), data of the study regarding deprivation and healthcare accessibility in the city of Quito of Cabrera-Barona et al. (2018) were made available to the Author by Pablo Cabrera-Barona. Thus, the healthcare accessibility data was included in the assessment of social vulnerability.

Data and statistical analysis were carried out using the software *RStudio* as well as *Microsoft Excel*. The script used in *RStudio* can be found in Appendix B.

2.4.3 Missing data and outliers

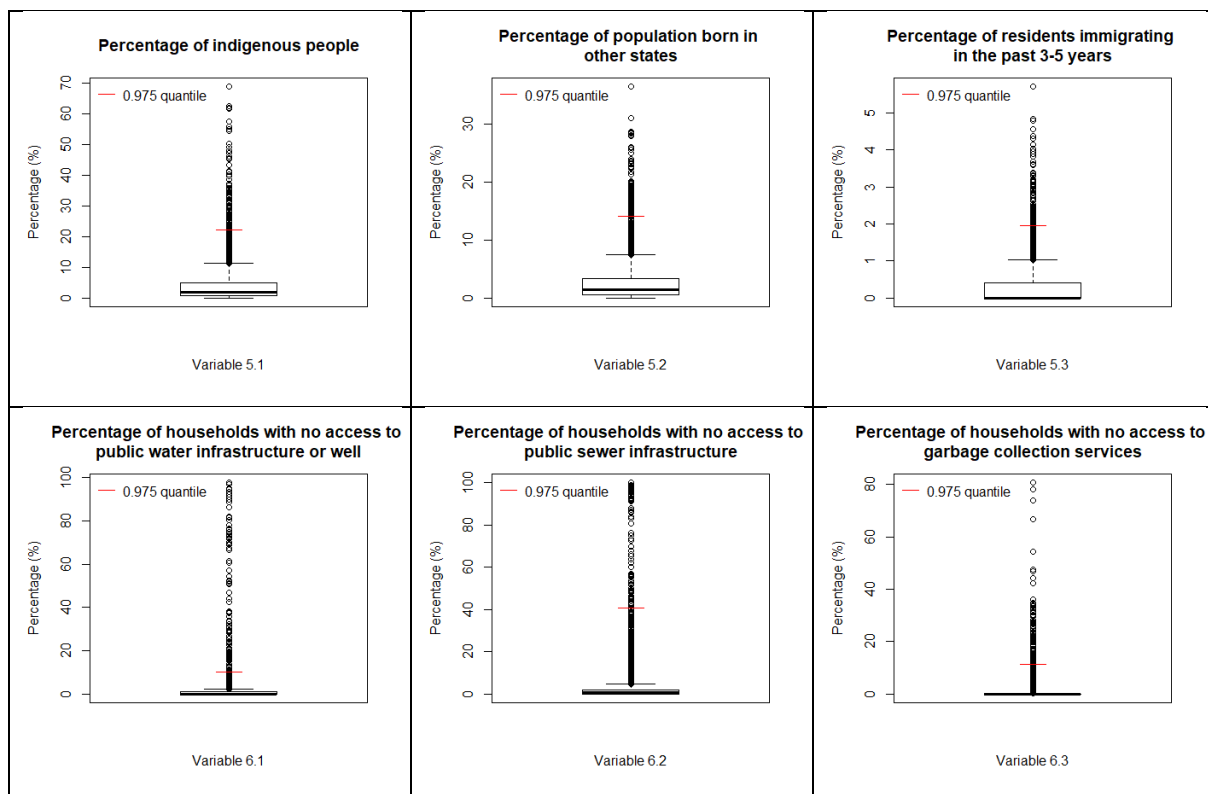
Descriptive statistical analysis was carried out to describe each variable. Following relevant literature (Groeneveld and Meeden, 1984; Hagenlocher et al., 2013; Saisana, 2012), variables with skewness > 2.0 and kurtosis (excess) > 3.5 were highlighted as statistically problematic with regard to potential outliers. These variables are listed in Table 2. To calculate the skewness and kurtosis in *R* the package *moments* was used.

In general, it is important to examine extreme values as they can become unintended benchmarks and further may influence subsequent steps in the process of building a composite indicator (OECD, 2008). One common way of treating outliers would be by limiting the variable distribution to certain percentile scores (e.g. 2.5 and 97.5) and winsorizing the data outside those limits accordingly (OECD, 2008; Saisana, 2012). Furthermore, transformations (e.g. logarithmic transformation) are widely spread to reduce the skewness of highly skewed data, while it should be kept in mind that the transformation would effect subsequent steps (e.g. normalization, aggregation) in the process of building a composite indicator (OECD, 2008; Saisana, 2012). It was decided to include variable 10.3 and 14.1 into the model without further treatment, as the skewness is exceeded only to a very small extent.

Table 2: Statistically problematic variables regarding potential outliers (skewness > 2.0, kurtosis > 3.5).

Nr.	Variable	Skewness	Kurtosis
5.1	Percentage of indigenous people	3.7	20.1
5.2	Percentage of population born in other states	3.1	12.8
5.3	Percentage of residents immigrating in the past 3-5 years	3.2	14.5
6.1	Percentage of households with no access to public water infrastructure or well	8.9	87.0
6.2	Percentage of households with no access to public sewer infrastructure	5.5	33.0
6.3	Percentage of households with no access to garbage collection services	8.2	93.5
6.4	Percentage of households with no access to public electricity service	9.5	134.8
10.2	Percentage of population employed in agriculture, forestry production, livestock, and aquaculture	3.5	26.1
10.3	Percentage of population employed in extractive industry	2.4	8.1
11.3	Percentage of subsistence workers in the labor force	3.7	21.4
12.1	Percentage of population with permanent disability for more than one year	13.2	328.6
13.1	Index of Healthcare Accessibility (Cabrera-Barona et al., 2018)	12.2	194.5
14.1	Percentage of households with access to paved roads	-2.2	3.9

The following figure (Figure 15) shows box-and-whisker plots of the further statistically problematic variables (excl. 10.3 & 14.1). It is evident that most variables are strongly distributed around close to zero. To explain this distribution pattern, one can argue that to a certain degree it is in the nature of things that in a city like Quito the vast majority of people has, for instance, access to public infrastructure like water, sewage, garbage collection services or healthcare services. In addition, when looking at the distribution of minority groups within the city’s population, obviously there will be a lot of values around close to zero. Furthermore, the box-plots show that most of the variables are characterized by a high number of outliers. To treat those outliers, the values are limited to the 97.5 percentile score (OECD, 2008).



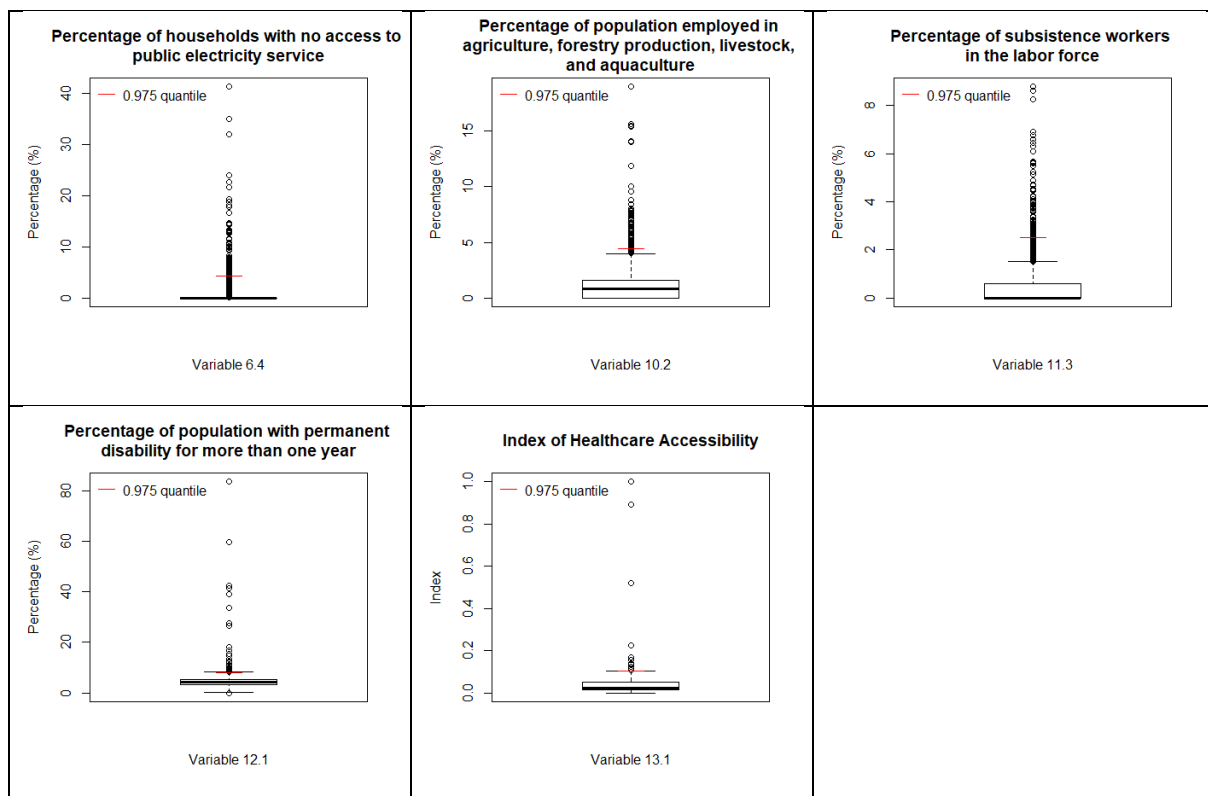


Figure 15: Box-and-whisker plots of the statistically problematic variables (excl. var. 10.3 & 14.1) with the 0.975 quantile marked in red.

For calculating the quantiles in *R*, the function *quantile* of the package *stats* was used, the boxplots were created with functions (*boxplot*, *segments*, *legend*) of the package *graphics*.

The limitation of the values to the 0.975 quantile led to reduced skewness and kurtosis and to the winsorization of 2,3 to 2,5 % of the variables’ values. The results of the outlier treatment are summarized in Table 3, while the updated skewness and kurtosis as well as the value of the 97.5 percentile and the percentage of the values exceeding the 97.5 percentile are listed. The winsorization was carried out in *R* by using the function *Winsorize* of the package *DescTools*.

Table 3: List of variables included in the treatment of outliers; the column *97.5 perc.* lists the value of the 97.5 percentile. The column *> 97.5 perc.* lists the percentage of values exceeding the 97.5 percentile.

Nr.	Variable	97.5 perc.	> 97.5 perc.	Skewness	Kurtosis
5.1	Percentage of indigenous people	22.18	2.50	2.1	4.0
5.2	Percentage of population born in other states	14.11	2.50	2.0	4.0
5.3	Percentage of residents immigrating in the past 3-5 years	1.96	2.50	2.0	3.5
6.1	Percentage of households with no access to public water infrastructure or well	10.01	2.50	3.4	12.2
6.2	Percentage of households with no access to public sewer infrastructure	40.75	2.50	3.7	13.5
6.3	Percentage of households with no access to garbage collection services	11.37	2.50	3.5	11.7
6.4	Percentage of households with no access to public electricity service	4.26	2.50	3.0	9.2
10.2	Percentage of population employed in agriculture, forestry production, livestock, and aquaculture	4.40	2.50	1.3	1.3
11.3	Percentage of subsistence workers in the labor force	2.52	2.48	1.9	3.2
12.1	Percentage of population with permanent disability for more than one year	7.91	2.50	0.3	-0.2
13.1	Index of Healthcare Accessibility (Cabrera-Barona et al., 2018)	0.10	2.30	0.8	-0.2

As the values of the skewness and kurtosis were decreased to an acceptable degree, the variables were included in the subsequent steps of the creation of the composite index.

No missing data was detected, as the census blocks with no available census data were already excluded in the geographical selection (see 2.4.2).

2.4.4 Normalization

To render the variables comparable, all variables were standardized using linear min-max normalization (equation 1) and z-score standardization (equation 2).

The min-max normalization results in values between 0 and 1 (OECD, 2008). Therefore, min-max normalization facilitates the aggregation of the variables to a composite indicator (Hagenlocher et al., 2013) and hence, was chosen as normalization method. However, it should be kept in mind that extreme values (or outliers) could distort the transformed variable (OECD, 2008).

$$v_i' = \frac{(v_i - v_{min})}{(v_{max} - v_{min})} * sign + 0.5 * (1 - sign) \quad (1)$$

v_i' normalized value

v_i actual value

v_{min} minimal value of variable distribution

v_{max} maximal value of variable distribution

$sign$ indication if variable contributes positively or negatively to vulnerability

Z-score standardization converts variables to a common scale with a mean of zero and standard deviation of one (OECD, 2008). Z-scores standardization values were calculated additionally as they are useful for subsequent statistical analysis (e.g. principal component analysis or factor analysis) (Hagenlocher et al., 2013).

$$v_i'' = \frac{(v_i - \bar{v})}{\sigma} * sign \quad (2)$$

v_i'' standardized value

v_i actual value

\bar{v} mean value of the data

σ maximal value of variable distribution

$sign$ indication if variable contributes positively or negatively to vulnerability

The min-max normalization and the z-score standardization were carried out in *R* by using the function *normalise_ci* of the package *Compind*.

2.4.5 Multivariate analysis

Multivariate analysis refers to any simultaneous analysis of more than two variables (Hair et al., 2010). More precisely, to be considered truly multivariate, all the variables must be interrelated in such ways that their different effects cannot meaningfully be interpreted separately (Hair et al., 2010). It aims to measure, explain and predict the degree of relationships among the variates (weighted combinations of variables) in the model (Hair et al., 2010).

Highly collinear variables within a domain (SUS, LoR) need to be detected and treated to ultimately reduce overall multicollinearities within the data, as they would influence principal component analysis and the overall output of the composite indicator (Hagenlocher et al., 2013; OECD, 2008; Saisana, 2012). Pearson's *r* as well as VIF (variance inflation factor) values were calculated for each

domain separately to exclude variables based on thresholds ($r > 0.8$, $VIF > 5.0$) (Hagenlocher et al., 2013; OECD, 2008; Saisana, 2012). Figure 16 and Table 4 give an overview of the calculated r and VIF values. Table 5 lists variables with critical values regarding the above-mentioned thresholds in terms of high collinearity. The values for Pearson's r were calculated in *R* using the function *cor* in the package *stats* while the visualization of the correlation matrices was created using the function *corrplot* of the package with the same name.

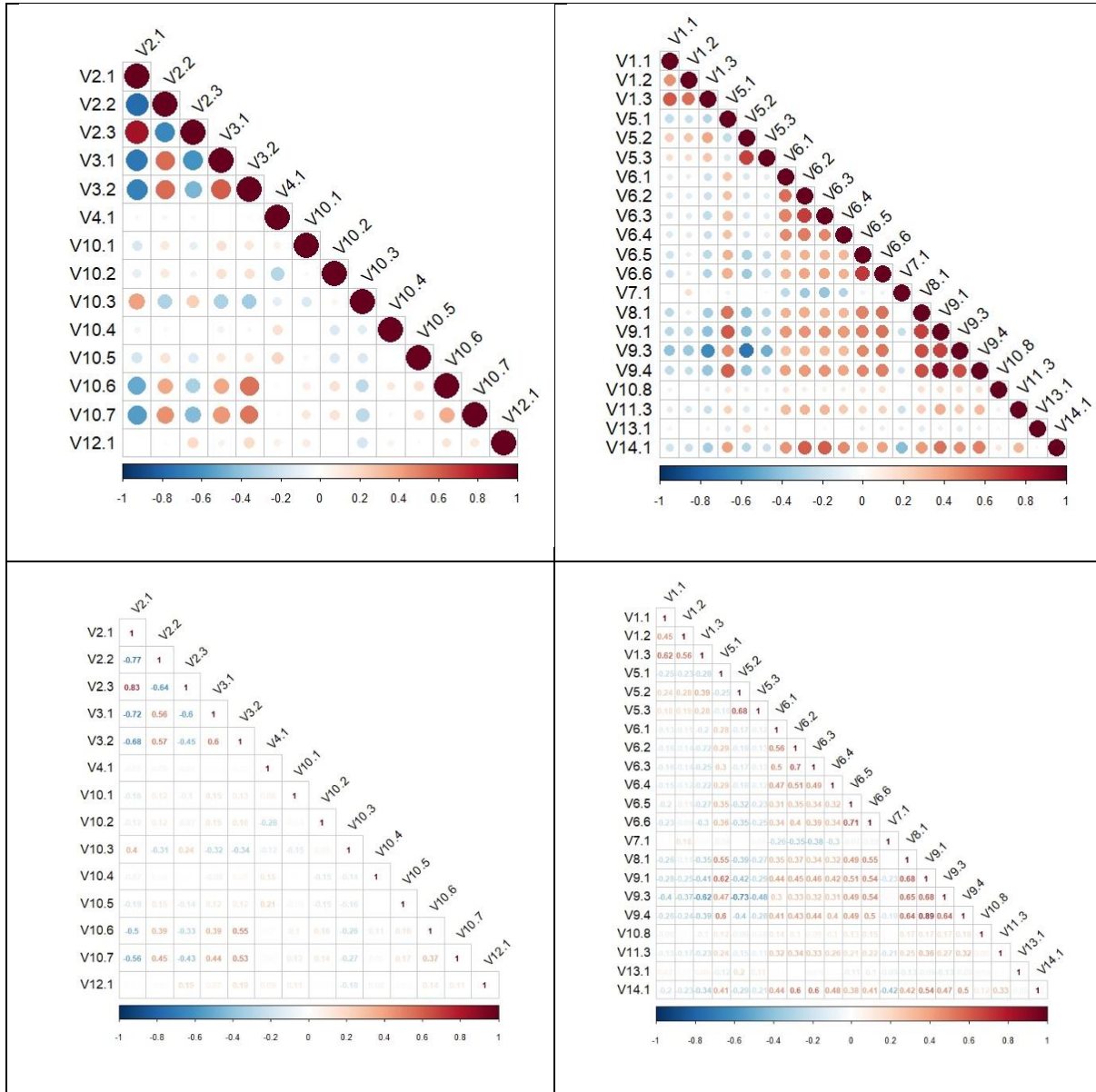


Figure 16: Visualization of correlation matrices with values of Pearson's r for each of the two vulnerability domains (SUS – left, LoR – right).

Table 4: VIF values for each variable of the two vulnerability domains.

<i>SUS</i>																					
Var.																					
Nr.	2.1	2.2	2.3	3.1	3.2	4.1	10.1	10.2	10.3	10.4	10.5	10.6	10.7	12.1							
VIF	8.0	2.5	4.1	2.3	2.5	1.2	1.1	1.2	1.3	1.1	1.1	1.6	1.6	1.2							
<i>LoR</i>																					
Var.																					
Nr.	1.1	1.2	1.3	5.1	5.2	5.3	6.1	6.2	6.3	6.4	6.5	6.6	7.1	8.1	9.1	9.3	9.4	10.8	11.3	13.1	14.1
VIF	1.7	1.7	2.6	1.8	3.3	1.9	1.7	2.5	2.3	1.6	2.1	2.4	1.6	2.5	6.4	5.3	5.2	1.1	1.2	1.1	2.3

Table 5: Variables with critical values of high collinearity based on thresholds for Pearson's r and/or VIF.

Nr.	Variable	Pearson's r (2 nd variable)	VIF
SUS			
2.1	Median age	0.83 (2.3)	8.0
2.3	Percentage >64 years old	0.83 (2.1)	4.1
LoR			
9.1	Percentage of illiterate population aged 15 and older	0.89 (9.4)	6.4
9.3	Percentage of population that completed college degree	-0.73 (5.2)	5.3
9.4	Percentage of population with no level of formal education or instruction	0.89 (9.1)	5.2

For the calculation of VIF values in R , a linear model (function *lm*, package *stats*) within each of the two domains was fitted to a matrix containing variables of the same values. The actual VIF values were calculated using the function *vif* contained in the package *car*.

To reduce collinearity between the variables, the variable 2.1 (Median age) and 9.1 (Percentage of illiterate population aged 15 and older) were eliminated. This decision was based on the respective correlation matrix and the VIF values of the according variables. After elimination, the VIF of variable 2.3 and 9.4 dropped to 2.3 and 2.6, respectively. The VIF of variable 9.3 (Percentage of population that completed college degree) dropped to 5.2, still exceeding the threshold of 5.0. Hence, the variable 9.3 was as well eliminated.

As mentioned above (Figure 14), the weighting of the components of the composite indicator will be based on weights derived from principal component analysis (PCA) and factor analysis (FA) to be independent from third parties, and therefore rule out the possibility of delays caused by external factors. Therefore, PCA and FA were conducted within each of the two domains to prepare the data for subsequent steps. Prior to PCA and FA, the data was normalized using z-score standardization, as regarding PCA, it helps to prevent one variable having an undue influence on the principal components and, regarding FA the normalization is required anyway (OECD, 2008).

The objective of PCA is to explain the variance of the observed data through a few linear combinations of the original data, which are uncorrelated and called principal components, and to select those principal components that represent a high amount of the overall variance of the original data (OECD, 2008). FA is similar to PCA, as it also aims to describe the original data with a smaller number of factors by highlighting the relationship between those factors (OECD, 2008). The question of how many factors should be kept in the model for further analysis without losing too much information is of high importance, while the most common method is PCA to extract the first principal components and to consider them as factors (OECD, 2008). For FA only a subset of principal components which account for the majority of the variance is retained and they are identified based on certain criteria (OECD, 2008). The most common standard practice is to choose factors that (OECD, 2008, p.89)

- have associated eigenvalues larger than one (Kaiser criterion),
- contribute individually to the explanation of overall variance by more than 10%,
- contribute cumulatively to the explanation of the overall variance by more than 60%.

An eigenvalue smaller one would mean that the according factor would explain less variance than is contained in one individual variable (OECD, 2008).

The results of the PCA for each of the two domains are summarized in Table 6, listing the eigenvalues with the according variance. In the SUS domain, the first principal component explains 29.0 % of the variance in all the variables (eigenvalue of 3.8), while the second principal component accounts for

12.4 % of the variance (eigenvalue of 1.6). Eigenvalues of 1 were calculated up to the fifth principal component, whereby the first five principal components account for 66.5 % of the variance in all the variables. Similar results are obtained in the LoR domain. The first principal component accounts for 32.1 % of the variance with an eigenvalue of 6.1, while the second principal component explains 11.1 % of the variance in all the variables (eigenvalue of 2.1). Again, eigenvalues of 1 were calculated up to the fifth principal component, whereby the first five principal components account for 62.4 % of the variance in all the variables. Figure 17 is a graphical representation of the eigenvalues in descending order (scree plot).

Table 6: Results of the PCA for each of the two domains with eigenvalues and the according explained variance for each principal component.

PC	Eigenvalue	Variance (%)	Cum. variance (%)	PC	Eigenvalue	Variance (%)	Cum. variance (%)
<i>SUS</i>							
1	3,8	29,0	29,0	8	0,7	5,1	82,9
2	1,6	12,4	41,4	9	0,6	4,8	87,7
3	1,3	9,7	51,1	10	0,5	4,1	91,8
4	1,0	7,9	59,0	11	0,4	3,2	95,0
5	1,0	7,6	66,5	12	0,4	2,9	97,9
6	0,7	5,8	72,3	13	0,3	2,1	100,0
7	0,7	5,5	77,8				
<i>LoR</i>							
1	6,1	32,1	32,1	11	0,5	2,8	85,6
2	2,1	11,1	43,1	12	0,5	2,5	88,1
3	1,6	8,2	51,3	13	0,4	2,2	90,3
4	1,2	6,1	57,4	14	0,4	2,0	92,3
5	1,0	5,0	62,4	15	0,3	1,8	94,1
6	0,9	4,9	67,3	16	0,3	1,6	95,7
7	0,9	4,5	71,8	17	0,3	1,5	97,2
8	0,8	4,1	75,9	18	0,3	1,4	98,6
9	0,7	3,8	79,8	19	0,3	1,4	100,0
10	0,6	3,0	82,8				

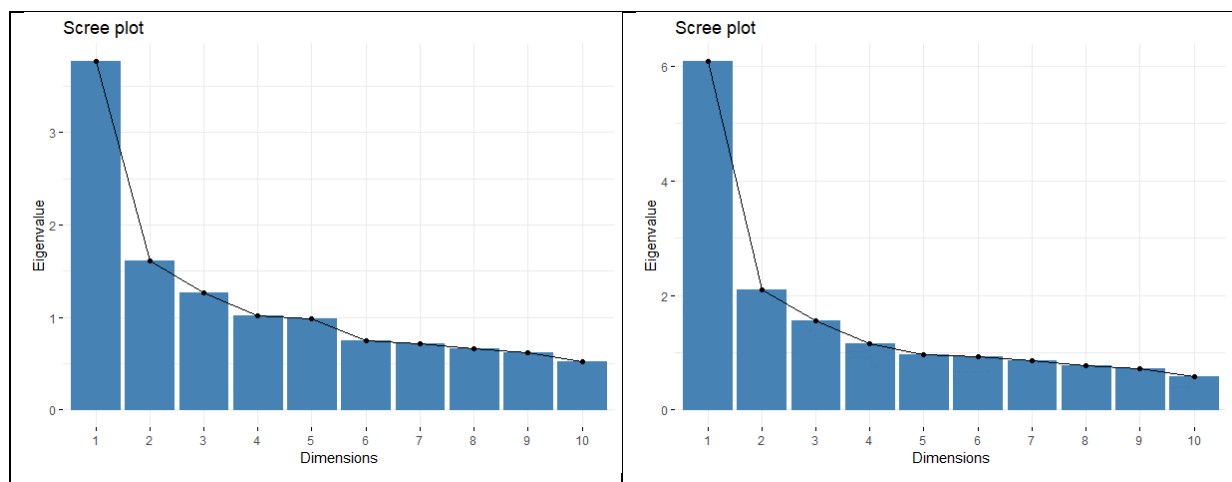


Figure 17: Scree plots of eigenvalues from PCA for each of the two domains (SUS – left, LoR – right).

The PCA was carried out in *R* by applying the function *prcomp* of the package *stats*. The eigenvalues were extracted with the function *get_eig* and the scree plots were generated using the function *fviz_eig*.

both included in the package *factoextra*. Based on the above-mentioned criteria for retaining principal components in the model, the first five principal components within each domain (eigenvalues larger than one and a cumulative contribution to the explanation of the overall variance by more than 60 %) were kept in the model for further analysis.

The correlation coefficients between the principal components and the variables are called component loadings, whereby the squared loading is the percentage of variance in that variable explained by the principal component (OECD, 2008). The loadings were calculated by multiplying the eigenvectors with the eigenvalues' square root values of the according principal component. The component loadings of the retained principal components for each of the two domains are listed in Table 7.

Table 7: Component loadings of the retained first five principal components, loadings $> \pm 0.30$ are highlighted.

Variable Nr.	PC1	PC2	PC3	PC4	PC5
<i>SUS</i>					
2.2	-0.79	0.06	-0.22	0.06	-0.10
2.3	0.73	-0.12	0.43	-0.14	0.12
3.1	-0.79	0.13	-0.07	0.11	0.10
3.2	-0.82	0.05	0.18	-0.10	-0.01
4.1	-0.05	-0.70	-0.19	0.11	0.10
10.1	-0.22	-0.16	0.27	0.81	0.04
10.2	-0.18	0.66	0.29	-0.17	0.02
10.3	0.51	0.36	-0.18	-0.04	0.02
10.4	-0.06	-0.47	0.14	-0.23	-0.77
10.5	-0.25	-0.42	-0.34	-0.37	0.50
10.6	-0.65	-0.02	0.21	-0.25	-0.06
10.7	-0.70	0.05	0.07	-0.09	0.02
12.1	-0.13	-0.30	0.76	-0.12	0.30
<i>LoR</i>					
1.1	0.43	-0.46	0.43	0.31	-0.03
1.2	0.38	-0.37	0.64	0.07	-0.01
1.3	0.56	-0.47	0.43	0.17	0.03
5.1	-0.61	0.11	0.14	-0.31	0.11
5.2	0.53	-0.52	-0.10	-0.52	0.05
5.3	0.41	-0.46	-0.08	-0.66	0.13
6.1	-0.61	-0.36	-0.02	0.02	-0.08
6.2	-0.70	-0.43	-0.08	0.08	0.03
6.3	-0.69	-0.42	-0.10	0.08	0.08
6.4	-0.61	-0.33	-0.04	0.04	0.01
6.5	-0.64	0.08	0.38	-0.14	0.08
6.6	-0.68	0.07	0.38	-0.12	0.05
7.1	0.33	0.49	0.38	-0.28	0.01
8.1	-0.70	0.17	0.34	-0.19	0.03
9.4	-0.78	0.07	0.16	-0.12	0.00
10.8	-0.22	0.03	0.18	-0.14	-0.86
11.3	-0.47	-0.17	-0.15	0.01	-0.05
13.1	0.13	-0.26	-0.27	-0.11	-0.40
14.1	-0.74	-0.26	-0.11	0.10	0.05

Regarding the assessment and interpretation of the loadings, Hair et al. (2010) suggest using practical significance as criteria. Thus, loadings in the range of ± 0.30 to ± 0.40 are considered to meet the minimal level for interpretation of structure, loadings ± 0.50 or greater are considered practically

significant, and loadings exceeding ± 0.70 are considered indicative of well-defined structure (Hair et al., 2010). However, the sample size strongly affects the threshold value for factor loadings considered significant (Hair et al., 2010). Therefore, factor loadings of ± 0.30 can already be considered significant with sample sizes of 350 (Hair et al., 2010), which would apply to this study, since the sample size for each variable is above 4000. The OECD (2008) considers loadings of ± 0.50 and greater as high and moderate loadings.

It is evident that for both domains most of the significant loadings are found in the first principal component, while significant loadings for all the variables can be found within the first five principal components. When looking at the SUS domain, one can see that five out of 13 variables are affected by cross-loadings. Regarding the LoR domain, most of the variables (14 out of 19) are affected by cross-loadings. In general, it is undesirable that variables relate significantly to more than one principal component, as difficulties for interpretation arise from such cross-loadings (Hair et al., 2010; OECD, 2008).

To improve the interpretability of the retained principal components (or factors), it is suggested to perform rotation, which is used to minimize the number of individual variables that have a high loading on the same factor (OECD, 2008). Ideally this would result in a structure in which each variable is loaded exclusively on one of the retained factors (OECD, 2008). As rotation method *varimax rotation* was chosen, since it is the most common rotation method in FA (OECD, 2008). The results of the rotation are listed in Table 8 (SUS) and Table 9 (LoR).

Table 8: Rotated factor loadings for individual variables (SUS) of the retained factors using varimax rotation, loadings $> \pm 0.30$ are highlighted.

Variable Nr.	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
<i>SUS</i>					
2.2	0.80	0.04	-0.20	0.05	0.01
2.3	-0.76	-0.07	0.43	-0.07	0.05
3.1	0.79	-0.03	-0.03	0.12	-0.17
3.2	0.81	-0.10	0.21	0.02	0.05
4.1	0.01	0.73	0.06	0.07	0.09
10.1	0.15	0.14	0.12	0.86	-0.09
10.2	0.21	-0.71	0.10	-0.10	-0.16
10.3	-0.47	-0.26	-0.28	-0.15	-0.17
10.4	0.05	0.17	0.04	-0.05	0.92
10.5	0.25	0.59	0.13	-0.47	-0.30
10.6	0.64	-0.08	0.26	-0.12	0.16
10.7	0.70	-0.05	0.13	-0.02	0.00
12.1	0.06	0.03	0.88	0.09	0.01
Eigenvalue	3.74	1.52	1.26	1.06	1.07
Explained variance	0.29	0.12	0.10	0.08	0.08
Cumulative variance	0.29	0.41	0.50	0.58	0.67

Applying the rotation (*varimax*) strongly enhanced the results in terms of cross-loadings. Furthermore, one can see that the individual eigenvalues have been affected, while the sum of the eigenvalues for the first five factors stayed the same. Regarding the SUS domain, the proportions of the explained variance stayed the same with a cumulative value of 67 %. Cross-loadings persist for the variables 2.3 (Percentage > 64 years old) and 10.5 (Percentage of population employed in commerce).

Table 9: Rotated factor loadings for individual variables (LoR) of the retained factors using varimax rotation, loadings > ±0.30 are highlighted.

Variable Nr.	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
<i>LoR</i>					
1.1	-0.22	-0.02	0.79	0.02	-0.01
1.2	0.06	-0.16	0.80	0.14	0.03
1.3	-0.24	-0.14	0.80	0.19	-0.05
5.1	0.64	0.21	-0.26	0.03	-0.02
5.2	-0.28	-0.09	0.22	0.83	0.03
5.3	-0.11	-0.09	0.12	0.90	-0.02
6.1	0.29	0.64	-0.02	-0.02	0.13
6.2	0.27	0.78	-0.04	-0.03	0.01
6.3	0.27	0.77	-0.06	-0.02	-0.04
6.4	0.28	0.64	-0.05	-0.03	0.04
6.5	0.72	0.22	-0.03	-0.14	0.00
6.6	0.73	0.26	-0.04	-0.16	0.03
7.1	0.24	-0.71	0.03	0.03	0.01
8.1	0.77	0.20	-0.14	-0.16	0.06
9.4	0.65	0.38	-0.22	-0.17	0.08
10.8	0.20	0.02	0.01	-0.11	0.88
11.3	0.16	0.46	-0.18	-0.04	0.07
13.1	-0.30	0.13	-0.04	0.23	0.41
14.1	0.31	0.71	-0.17	-0.14	-0.01
Eigenvalue	3.28	3.66	2.18	1.74	0.99
Explained variance	0.17	0.19	0.11	0.09	0.05
Cumulative	0.17	0.37	0.48	0.57	0.62

When looking at the LoR domain, one can see that the variance accounted for by the rotated factors is spread more evenly than prior to the rotation. The cumulative value of the explained variance stayed the same with 62 %. Cross-loadings persist for variables 9.4 (Percentage of population with no level of formal education or instruction), 13.1 (Index of healthcare accessibility (Cabrera-Barona et al., 2018)), and 14.1 (Percentage of households with access to paved roads).

According to Hair et al. (2010) variables with cross-loadings should be considered for deletion. As the conducted FA/PCA in this study serves as basis for deriving weights for the composite index and is not used for deriving explanatory factors for social vulnerability, the variables with cross-loadings are kept in the model.

2.4.6 Final selection of indicators

As outlined in the previous sections, some indicators/variables had to be dropped (8.2, 8.3, 9.2, 11.1, 11.2, and 15.1) or merged together (10.4 and 10.5) due to unavailable data. Additionally, three variables had to be eliminated due to high collinearity (2.1, 9.1, and 9.3).

The final set of indicators and variables is listed in Table 10 with the according domain (SUS, LoR) and sign, while a positive (+) or negative (-) sign indicates whether the social vulnerability increases or decreases with a higher value. The numbers assigned originally to the individual variables are left unchanged for overview and interpretability purposes.

Mapping social vulnerability to natural hazards

Materials and methods

Table 10: Final set of indicators with the according variables and domain (SUS – Susceptibility, LoR – Lack of Resilience). Sign indicates if a higher value increases (+) or decreases (-) vulnerability.

Nr.	Indicator	Variable	Domain	Sign
1.1	Female population	Percentage of females	LoR	+
1.2		Percentage of female headed households	LoR	+
1.3		Percentage of employed females in the labor force	LoR	+
2.2	Age structure	Percentage <5 years old	SUS	+
2.3		Percentage >64 years old	SUS	+
3.1	Family structure	Average number of people per household	SUS	+
3.2		Percentage of households with four or more persons per dormitory	SUS	+
4.1	Population characteristics	Population density	SUS	+
5.1	Race/Ethnicity & Minorities	Percentage of indigenous people	LoR	+
5.2		Percentage of population born in other states	LoR	+
5.3		Percentage of residents immigrating in the past 3-5 years	LoR	+
6.1	Quality of built environment	Percentage of households with no access to public water infrastructure or well	LoR	+
6.2		Percentage of households with no access to public sewer infrastructure	LoR	+
6.3		Percentage of households with no access to garbage collection services	LoR	+
6.4		Percentage of households with no access to public electricity service	LoR	+
6.5		Percentage of households with external walls in bad condition	LoR	+
6.6		Percentage of households with roofs in bad condition	LoR	+
7.1	Housing unit status	Percentage of rented households	LoR	+
8.1	Socioeconomic status	Percentage of households with no phone (cell phone or landline)	LoR	+
9.4	Education	Percentage of population with no level of formal education or instruction	LoR	+
10.1	Employment	Percentage of population unemployed	SUS	+
10.2		Percentage of population employed in agriculture, forestry production, livestock, and aquaculture	SUS	+
10.3		Percentage of population employed in extractive industry	SUS	+
10.4		Percentage of population employed in accommodation and food services activities	SUS	+
10.5		Percentage of population employed in commerce	SUS	+
10.6		Percentage of population employed in public administration and defense	SUS	-
10.7		Percentage of population employed in human health services	SUS	-
10.8		Percentage of population that works in unpaid jobs	LoR	+
11.3	Occupation	Percentage of subsistence workers in the labor force	LoR	+
12.1	Special needs population	Percentage of population with permanent disability for more than one year	SUS	+
13.1	Healthcare accessibility	Index of Healthcare Accessibility (Cabrera-Barona et al., 2018)	LoR	-
14.1	Access to roads	Percentage of households with access to paved roads	LoR	-

2.4.7 Weighting

As mentioned above (Figure 14), the weighting of the variables is based on weights derived from principal component analysis (PCA) and factor analysis (FA) to be independent from third parties. However, for the sake of completeness it should be mentioned that expert-based approaches for deriving weights, such as budget allocation process (BAP) or analytical hierarchy process (AHP), are widely spread in the field of vulnerability and deprivation science (Cabrera-Barona et al., 2018; Hagenlocher et al., 2013; Kienberger et al., 2014; Kienberger and Hagenlocher, 2014; OECD, 2008).

Mapping social vulnerability to natural hazards

Materials and methods

Table 11: Rotated factor loadings for individual variables for each of the two domains, squared normalized factor loadings, the highest loading (absolute value) for each variable is highlighted.

Variable Nr.	Rotated factor loadings					Squared normalized factor loadings				
	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
<i>SUS</i>										
2.2	0.80	0.04	-0.20	0.05	0.01	0.17	0.00	0.03	0.00	0.00
2.3	-0.76	-0.07	0.43	-0.07	0.05	0.15	0.00	0.14	0.00	0.00
3.1	0.79	-0.03	-0.03	0.12	-0.17	0.17	0.00	0.00	0.01	0.03
3.2	0.81	-0.10	0.21	0.02	0.05	0.17	0.01	0.04	0.00	0.00
4.1	0.01	0.73	0.06	0.07	0.09	0.00	0.35	0.00	0.00	0.01
10.1	0.15	0.14	0.12	0.86	-0.09	0.01	0.01	0.01	0.71	0.01
10.2	0.21	-0.71	0.10	-0.10	-0.16	0.01	0.33	0.01	0.01	0.02
10.3	-0.47	-0.26	-0.28	-0.15	-0.17	0.06	0.05	0.06	0.02	0.03
10.4	0.05	0.17	0.04	-0.05	0.92	0.00	0.02	0.00	0.00	0.80
10.5	0.25	0.59	0.13	-0.47	-0.30	0.02	0.23	0.01	0.21	0.08
10.6	0.64	-0.08	0.26	-0.12	0.16	0.11	0.00	0.06	0.01	0.02
10.7	0.70	-0.05	0.13	-0.02	0.00	0.13	0.00	0.01	0.00	0.00
12.1	0.06	0.03	0.88	0.09	0.01	0.00	0.00	0.62	0.01	0.00
Eigenvalue	3.74	1.52	1.26	1.06	1.07					
Explained variance	0.29	0.12	0.10	0.08	0.08					
Explained proportion	0.43	0.18	0.15	0.12	0.12					
	Sum of intermediate composite indicators					0.96	0.91	0.62	0.71	0.80
	Weighted sum with proportion of explained variance					0.42	0.16	0.09	0.09	0.10
<i>LoR</i>										
1.1	0.22	0.02	0.79	-0.02	0.01	0.01	0.00	0.29	0.00	0.00
1.2	-0.06	0.16	0.80	-0.14	-0.03	0.00	0.01	0.30	0.01	0.00
1.3	0.24	0.14	0.80	-0.19	0.05	0.02	0.01	0.29	0.02	0.00
5.1	0.64	0.21	0.26	0.03	-0.02	0.12	0.01	0.03	0.00	0.00
5.2	-0.28	-0.09	-0.22	0.83	0.03	0.02	0.00	0.02	0.40	0.00
5.3	-0.11	-0.09	-0.12	0.90	-0.02	0.00	0.00	0.01	0.46	0.00
6.1	0.29	0.64	0.02	-0.02	0.13	0.02	0.11	0.00	0.00	0.02
6.2	0.27	0.78	0.04	-0.03	0.01	0.02	0.17	0.00	0.00	0.00
6.3	0.27	0.77	0.06	-0.02	-0.04	0.02	0.16	0.00	0.00	0.00
6.4	0.28	0.64	0.05	-0.03	0.04	0.02	0.11	0.00	0.00	0.00
6.5	0.72	0.22	0.03	-0.14	0.00	0.16	0.01	0.00	0.01	0.00
6.6	0.73	0.26	0.04	-0.16	0.03	0.16	0.02	0.00	0.02	0.00
7.1	0.24	-0.71	-0.03	0.03	0.01	0.02	0.14	0.00	0.00	0.00
8.1	0.77	0.20	0.14	-0.16	0.06	0.18	0.01	0.01	0.01	0.00
9.4	0.65	0.38	0.22	-0.17	0.08	0.13	0.04	0.02	0.02	0.01
10.8	0.20	0.02	-0.01	-0.11	0.88	0.01	0.00	0.00	0.01	0.79
11.3	0.16	0.46	0.18	-0.04	0.07	0.01	0.06	0.01	0.00	0.01
13.1	-0.30	0.13	0.04	0.23	0.41	0.03	0.00	0.00	0.03	0.17
14.1	0.31	0.71	0.17	-0.14	-0.01	0.03	0.14	0.01	0.01	0.00
Eigenvalue	3.28	3.66	2.18	1.74	0.99					
Explained variance	0.17	0.19	0.11	0.09	0.05					
Explained proportion	0.28	0.31	0.18	0.15	0.08					
	Sum of intermediate composite indicators					0.75	0.88	0.88	0.86	0.96
	Weighted sum with proportion of explained variance					0.21	0.27	0.16	0.13	0.08

The variable weightings are calculated for each of the two domains separately and are derived from results of the factor analysis. The weights for the individual variables are constructed based on the factor loadings after rotation, whereby the squared factor loadings represent the proportion of the total unit variance of the variable which is explained by the factor (Nicoletti et al., 2000; OECD, 2008). The highest squared and normalized factor loadings for each individual variable are grouped into intermediate composite indicators each representing one factor (Nicoletti et al., 2000; OECD, 2008).

Table 12: Indicators with the according variables, signs, and weights grouped by domain (SUS, LoR).

Nr.	Indicator	Variable	Sign	Weight
SUS				
2.2	Age structure	Percentage <5 years old	+	0.09
2.3		Percentage >64 years old	+	0.08
3.1	Family structure	Average number of people per household	+	0.08
3.2		Percentage of households with four or more persons per dormitory	+	0.09
4.1	Population characteristics	Population density	+	0.07
10.1	Employment	Percentage of population unemployed	+	0.10
10.2		Percentage of population employed in agriculture, forestry production, livestock, and aquaculture	+	0.07
10.3		Percentage of population employed in extractive industry	+	0.03
10.4		Percentage of population employed in accommodation and food services activities	+	0.11
10.5		Percentage of population employed in commerce	+	0.05
10.6		Percentage of population employed in public administration and defense	-	0.06
10.7		Percentage of population employed in human health services	-	0.07
12.1	Special needs population	Percentage of population with permanent disability for more than one year	+	0.10
LoR				
1.1	Female population	Percentage of females	-	0.06
1.2		Percentage of female headed households	-	0.07
1.3		Percentage of employed females in the labor force	-	0.06
5.1	Race/Ethnicity & Minorities	Percentage of indigenous people	+	0.04
5.2		Percentage of population born in other states	+	0.07
5.3		Percentage of residents immigrating in the past 3-5 years	+	0.08
6.1	Quality of built environment	Percentage of households with no access to public water infrastructure or well	+	0.04
6.2		Percentage of households with no access to public sewer infrastructure	+	0.06
6.3		Percentage of households with no access to garbage collection services	+	0.06
6.4		Percentage of households with no access to public electricity service	+	0.04
6.5		Percentage of households with external walls in bad condition	+	0.05
6.6		Percentage of households with roofs in bad condition	+	0.05
7.1	Housing unit status	Percentage of rented households	+	0.05
8.1	Socioeconomic status	Percentage of households with no phone (cell phone or landline)	+	0.06
9.4	Education	Percentage of population with no level of formal education or instruction	+	0.04
10.8	Employment	Percentage of population that works in unpaid jobs	+	0.08
11.3	Occupation	Percentage of subsistence workers in the labor force	+	0.02
13.1	Healthcare accessibility	Index of Healthcare Accessibility (Cabrera-Barona et al., 2018)	-	0.02
14.1	Access to roads	Percentage of households with access to paved roads	-	0.05

Table 11 shows the rotated factor loadings and the squared normalized factor loadings for each of the two domains, while the highest loading for each variable is highlighted. Furthermore, the proportion of explained variance of each factor and the weighted sum of the intermediate composite indicators are listed. For deriving the weights for each individual variable, the corresponding highest factor loading is weighted according to the proportion of the explained variance of the factor in which the highest loading occurs and then normalized by the sum of weighted intermediate composite indicators (OECD, 2008).

Table 12 shows the indicators/variables grouped by domain with their according sign and derived weight. Note that the weights within each of the two domains sum up to one.

2.4.8 Aggregation

The normalized variables were aggregated within each of the two domains following equation 3 (Hagenlocher et al., 2013; OECD, 2008). While this aggregation method is widely spread, one has to keep in mind that the composite indicator depends on the quality of the underlying individual variables and that a condition for additive aggregation is that the individual variables are mutually independent (OECD, 2008). Hence, additive aggregation allows the assessment of the marginal contribution of each variable separately, which might be a rather unrealistic assumption for many phenomena (OECD, 2008). Therefore, the aggregation could result in a biased composite indicator, whereby the dimension and the direction of the error are not easily determined and an adjustment of the composite indicator cannot be carried out properly (OECD, 2008). Nevertheless, linear aggregation is by far the most widespread aggregation method (OECD, 2008), especially in the domain of vulnerability studies (e.g. Chen et al., 2014; de Loyola Hummell et al., 2016; Fatemi et al., 2017; Hagenlocher et al., 2013; Kienberger et al., 2014; Yoon, 2012), and therefore is chosen as aggregation method for this study. The aggregation of the two domains (SUS, LoR) to the composite indicator of social vulnerability was calculated following equation 4 taking into account specific weights for each of the two domains (Hagenlocher et al., 2013). The weights were derived from the number of variables in each domain in relation to the total number of variables resulting in a weight of 0.41 and 0.59 in the SUS domain (13 variables divided by 32 total variables) and in the LoR domain (19 variables divided by 32 total variables), respectively.

$$SUS/LoR = \sum_{i=1}^n w_i v_i' \quad (3)$$

SUS/LoR vulnerability domain
w_i weight of variable *i*
v_i' normalized value (min-max) of variable *i*

$$VU = \sum_{j=1}^n w_j X_j \quad (4)$$

VU composite index for social vulnerability
w_j weight of domain *j*
X_j normalized value (min-max) of domain *j*

To enhance and facilitate interpretation of the final composite index for social vulnerability, the index was scaled between 0.0 and 1.0 (min-max normalization), where 0.0 indicating a very low social vulnerability and 1.0 indicating a very high social vulnerability (Cabrera-Barona et al., 2018; Hagenlocher et al., 2013).

2.4.9 Hot and cold spot analysis

Hot and cold spot analysis was conducted on the composite index for social vulnerability to assess the degree of spatial correlation throughout the study area (Mazumdar and Paul, 2018). Getis-Ord G_i^* statistics were applied to display the spatial pattern in social vulnerability (Ord and Getis, 1995). Statistically significant z-scores are used for locating and making visible hot and cold spots (clustering of high and low values) for 99, 95 and 90 % confidence level (Anselin, 1995; Ord and Getis, 1995). The analysis was carried out with *ArcGIS Pro* (Tool *Hot-Spot Analysis (Getis-Ord G_i^*)*), while the fixed distance band option was used to conceptualize spatial relationships to ensure that each polygon will have at least one neighbor taken into account for the spatial analysis. A threshold distance of 590.4 m was calculated by applying the tool *Distance Band from Neighborhood Count*. Furthermore, false discovery rate (FDR) correction was applied, as it yields better results identifying local spatial clusters (Castro and Singer, 2006).

2.4.10 Visualization and mapping

The visualization and mapping of the composite index, the individual variables as well as the results of the hot and cold spot analysis were realized with the Software *ArcGIS Pro*. The figures are integrated in section 3 (Results).

3. Results

3.1 Vulnerability variables

After treating outliers and conducting multivariate statistical analysis (i.e. test for multicollinearities and PCA/FA), a total of 32 social vulnerability variables representing two vulnerability domains (SUS, LoR) were retained for the construction of the composite index. Overviews of the final set of variables with the according domains, signs and weights are provided in Table 10 and Table 12 (see 2.4.6 and 2.4.7). The visualization (Figure 18 and Figure 19) of the spatial distribution of the individual variables (min-max normalized values) gives a first impression of the city of Quito's socio-economic characteristics.

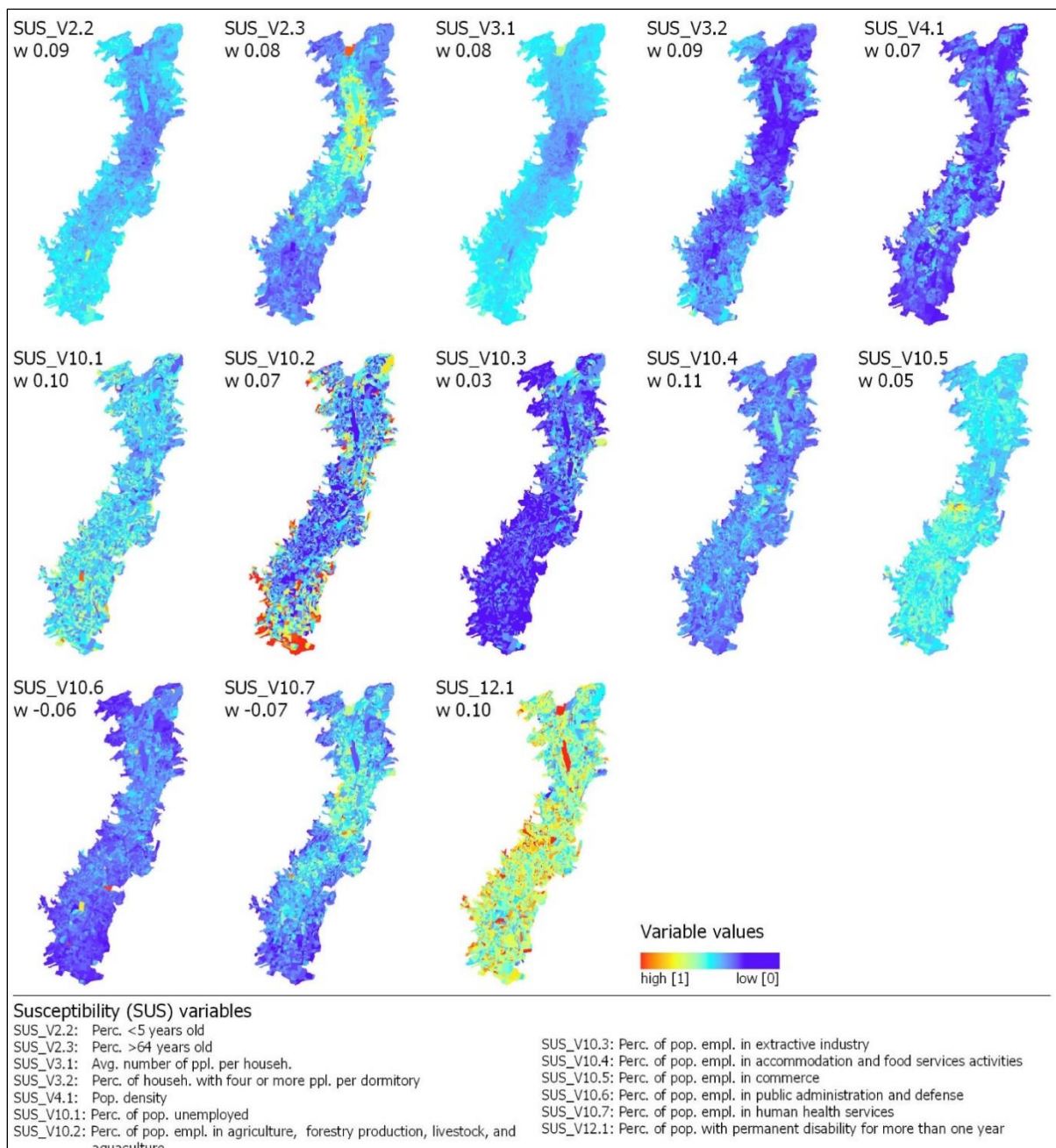


Figure 18: Spatial distribution of the final selection of susceptibility (SUS) variables (min-max normalized values) within the study area with the assigned weight.

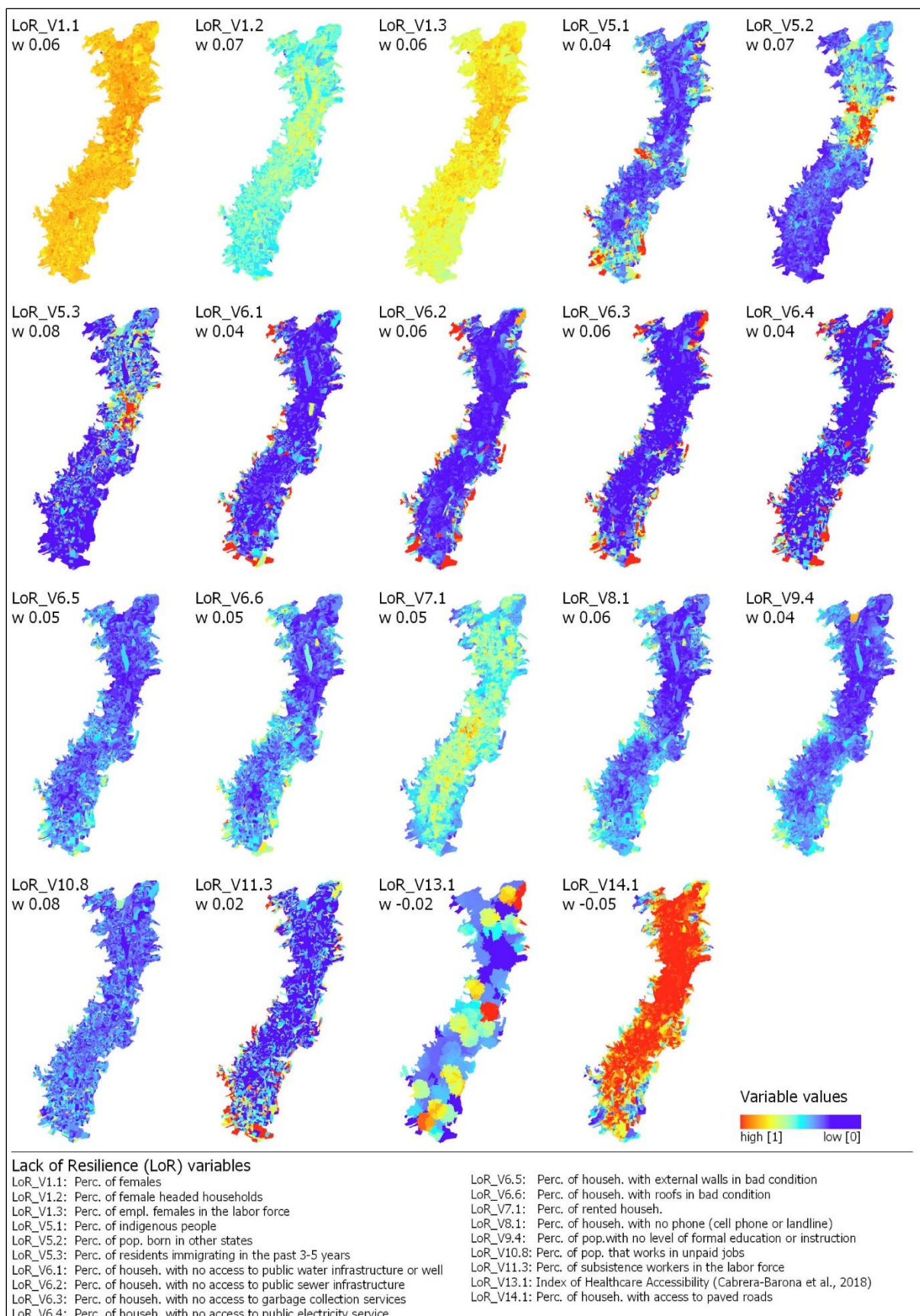


Figure 19: Spatial distribution of the final selection of lack of resilience (LoR) variables (min-max normalized values) within the study area with the assigned weight.

When interpreting the spatial distribution of the individual vulnerability variables, it must be kept in mind that since the values are normalized (min-max), they cannot be compared in terms of absolute value characteristics. Nevertheless, they give an impression of the spatial distribution of each variable itself.

Regarding the variables in the SUS domain, one can see that the percentage of children younger than 5 years (SUS_V2.2) is higher in the southern parts as well as in the northern outskirts of the city, while the variables related to the number of people living in the same household (SUS_V3.1 and SUS_V3.2) is characterized by a similar spatial distribution. The percentage of older people (SUS_V2.3) shows an inverse spatial distribution. The study area is more densely populated along the city center (SUS_V4.1). The percentage of unemployment (SUS_V10.1) is mainly evenly distributed, whereby tendencies of higher values are recognizable in the southern city parts. A higher percentage of people employed in agricultural and livestock related fields (SUS_V10.2) is identified in the outskirts of the city (especially in the southern region), while the highest values for the percentage of people working in extractive industry (SUS_V10.3) can be observed in the north. The percentage of people employed in accommodation and food service activities (SUS_V10.4) as well as the percentage of people employed in commerce (SUS_V10.5) are rather evenly distributed, while regarding the employment in human health services (SUS_V10.7), the distribution is characterized by a lower percentage in the southern and northern parts (mainly outskirts). Regarding population with permanent disability (SUS_V12.1), no clear spatial pattern is recognizable visually, while a slight tendency for lower values in the north can be observed.

Regarding the LoR domain, spatial patterns for some individual variables are as well identifiable visually. The variables regarding the role of females (LoR_V1.1, LoR_V1.2, and LoR_V1.3) are distributed similarly with lower values in the southern and northern city parts. The percentage of indigenous people (LoR_V5.1) is higher in the southern and northern outskirts, while the percentage of immigrants and expats (LoR_V5.2 and LoR_V5.3) is higher in the northern half of the city area with the highest values close to the city center. The variables regarding no access to infrastructure (LoR_V6.1, LoR_V6.2, LoR_V6.3 and LoR_V6.4), such as water, sewer, garbage collection, and electricity, are similarly distributed with high values in the city outskirts (especially in the south and north). The percentage of households with walls and roofs in bad condition (LoR_V6.5 and LoR_V6.6) is high mainly in the southern parts and the northern outskirts of the city. The percentage of people with no phone (LoR_V8.1) and no level of formal education (LoR_V9.4) follow a similar spatial distribution. Rented household (LoR_V7.1) are less frequent in the city outskirts (especially in the south and north). The distribution of the percentage of people working in unpaid jobs (LoR_V10.8) is fairly even, while tendencies for higher values in the southern city parts are recognizable. A higher percentage of subsistence workers (LoR_V11.3) are found mainly in the southern city outskirts. The distribution of the index of health care accessibility (LoR_V13.1, Cabrera-Barona et al., 2018) is characterized by patches, while higher values can be found throughout the study area. The access to paved roads (LoR_V14.1) shows an inverse spatial distribution compared to the variables regarding no access to infrastructure, i.e. lower values are found in the city outskirts (especially in the south and north).

Variable weights were derived based on PCA/FA statistics as described above (see 2.4.7). In Figure 18 and Figure 19, the weight for each variable is listed accordingly, while a negative value indicates a negative sign of the variable. The weights (absolute values) within each domain sum up to 1.0. In the SUS domain the weights range from 0.03 to 0.11, while the highest weights are found in the sector for employment and for population with special needs and the lowest weights are found in the sector of employment as well. It should be noted that the derived weight (0.11) for the variable displaying the

percentage of people working in accommodation and food service activities (SUS_V10.4) seems high compared to the other variable weights and in terms of the described phenomenon. Regarding the LoR domain, the distribution of weights is characterized by a narrower range from 0.02 to 0.08. The highest weights are found in the sectors of employment, female population and race, ethnicity and minorities, while the lowest weights are found in the sectors of occupation and healthcare accessibility.

3.2 Social vulnerability to natural hazards in the city of Quito

The variables were linearly aggregated following the above-described methodology (see 2.4.8). Figure 20 shows the spatial distribution of the composite index for social vulnerability to natural hazards in the study area. To facilitate spatial referencing, the district borders were added to the map (grey). Light red areas are indicating low values, while dark red areas are indicating high values of social vulnerability. The values of social vulnerability are close to normally distributed (Figure 21) with a mean value of 0.43, standard deviation of 0.12, skewness of 1.2, and kurtosis of 2.8.

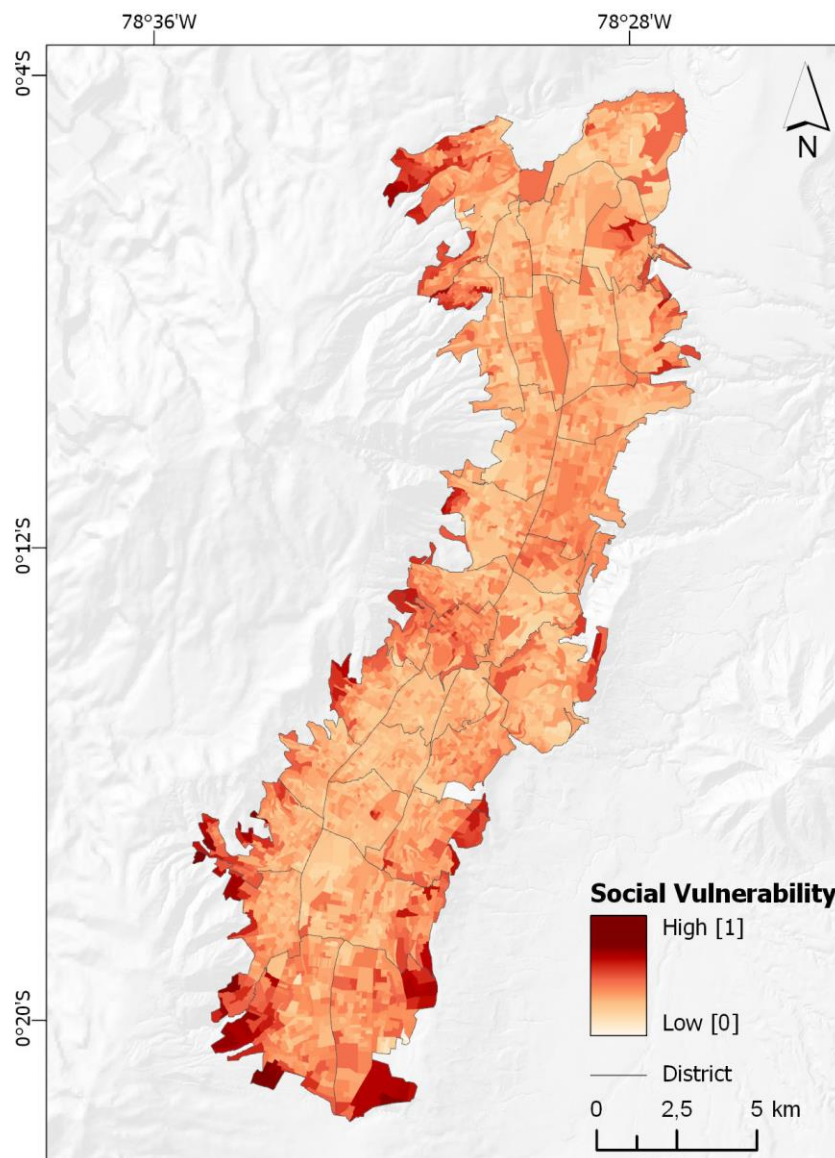


Figure 20: Social vulnerability to natural hazards in the city of Quito.

Looking at Figure 20, it is evident that some of the outskirts of the city are characterized by high social vulnerability. Especially in the outermost south-western and south-eastern neighborhoods, high social

vulnerability is concentrated. High values are also found in the outermost north-western part and along the western city limit.

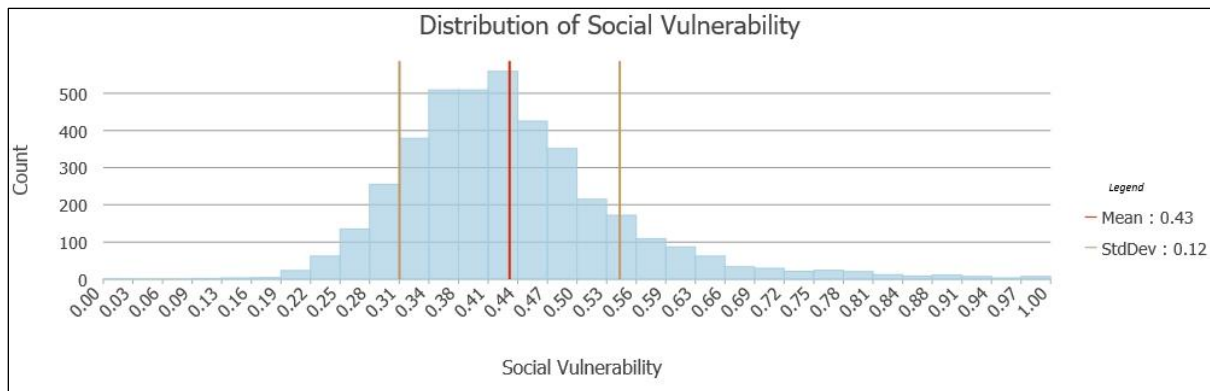


Figure 21: Distribution of social vulnerability to natural hazards in the city of Quito with the according mean value and standard deviation.

A similar pattern was already revealed by several variables of both domains (Figure 18 and Figure 19). Accordingly, these are neighborhoods with a higher percentage of people working in the agricultural sector (SUS_V10.2), with many children (SUS_V2.2) and with a higher number of people living in a household together (SUS_V3.1). Furthermore, these neighborhoods are characterized by bad access to essential infrastructure (LoR_V6.1-6.4, LoR_V14.1) and a low level of formal education (LoR_V9.4).

Spatial analysis in terms of localizing hot and cold spots of social vulnerability was carried out as described above (see 2.4.9).

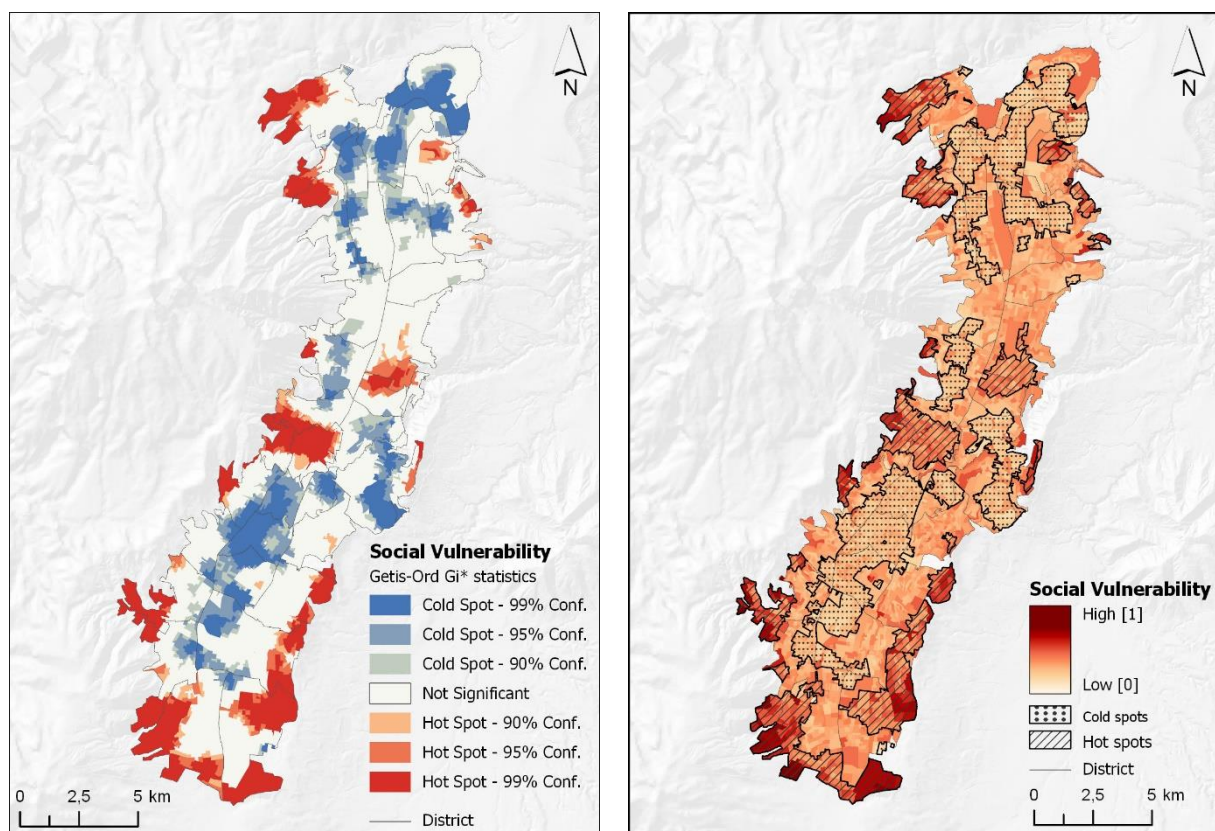


Figure 22: Hot and cold spots of social vulnerability (Getis-Ord G_i^* , fixed distance band, threshold distance 590.4 m).

Figure 22 shows the results of the hot and cold spot analysis, revealing areas of concentrated high (red) and low (blue) vulnerability levels at 99, 95 and 90 % confidence level in the left map. The map

on the right shows an overlay of the spatial distribution of the social vulnerability with the aggregated hot (line hatching) and cold spots (point hatching). The hot and cold spot analysis confirms the visually recognizable pattern with high levels of social vulnerability in the outskirts of the city of Quito. Around 22 % of the total study area are characterized as hot spots, while around 68 % of that area are revealed as hot spots at a 99 % confidence interval. The average score for the social vulnerability index within the hot spot neighborhoods is 0.54. Cold spots are revealed mostly along a band running from north to south in the city center. They account for around 26 % of the total study area, while around 42 % of the cold spot area is characterized by a confidence interval of 99 %. The average score for the social vulnerability index within the cold spots is 0.36. The remaining area, i.e. not significant in terms of hot and cold spot analysis has an average social vulnerability score of 0.43 which corresponds to the overall average.

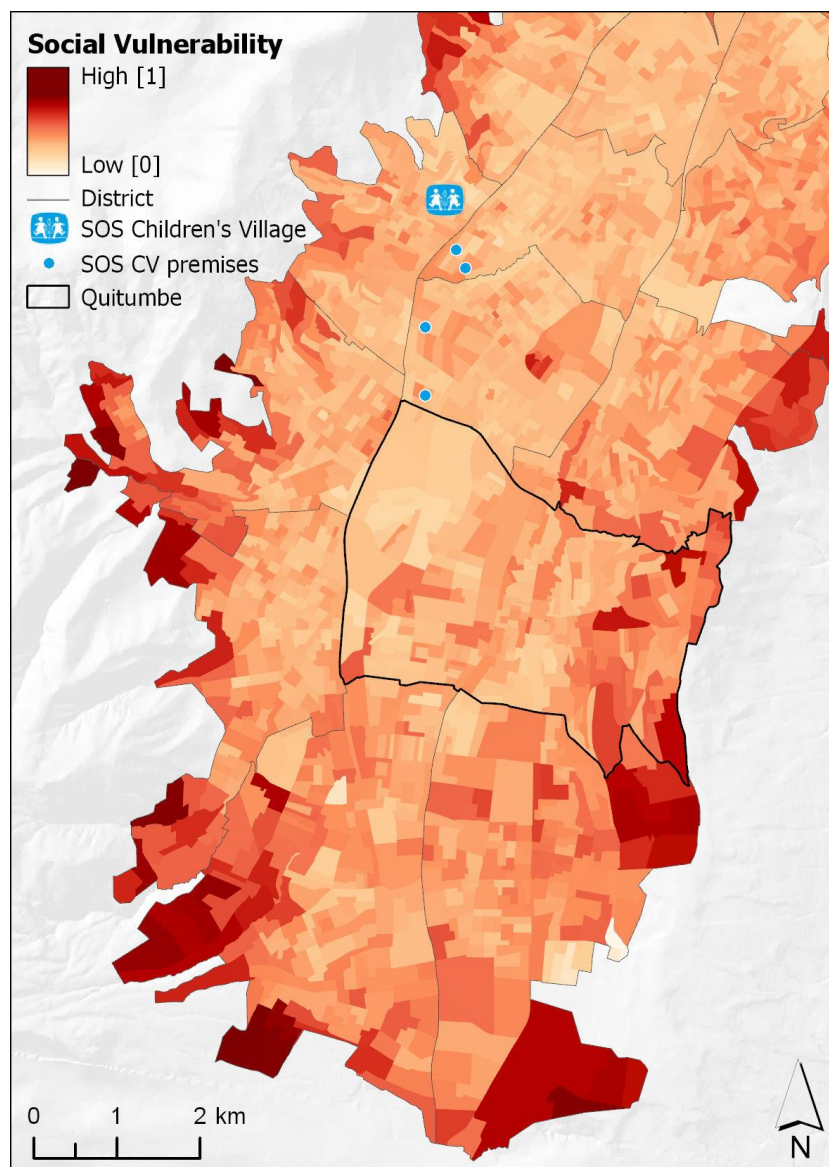


Figure 23: Social vulnerability to natural hazards in the southern part of the city of Quito with locations of SOS CV premises and highlighting of the district Quitumbe.

Figure 23 focuses on the southern part of the city of Quito where the SOS Children's Village itself and most of the other SOS CV premises are located. It is evident that in the neighborhoods of the SOS CV itself and its premises the social vulnerability to natural hazards is rather low. Accordingly, the neighborhoods are revealed as cold spots. Furthermore, the district Quitumbe is highlighted as this

district is considered for future extensions by SOS CV. It is characterized by low social vulnerability scores in most of the western part, while the uttermost north-western part is revealed as cold spot. Higher scores are concentrated in the eastern part of the district (hot spot).

To get a better understanding of the spatial variability of the underlying variables' relative contribution to the composite vulnerability index, exemplary census blocks representing hot and cold spots regarding the overall study area as well as regarding the district Quitumbe were selected for further analysis. For the purpose of clarity and better interpretation, the variables were summarized to the according indicators (Table 10). Note that the number of underlying variables is varying for different indicators. Nevertheless, the pie charts in Figure 24 and Figure 25 give a good impression of the relative contributions of the different indicators.

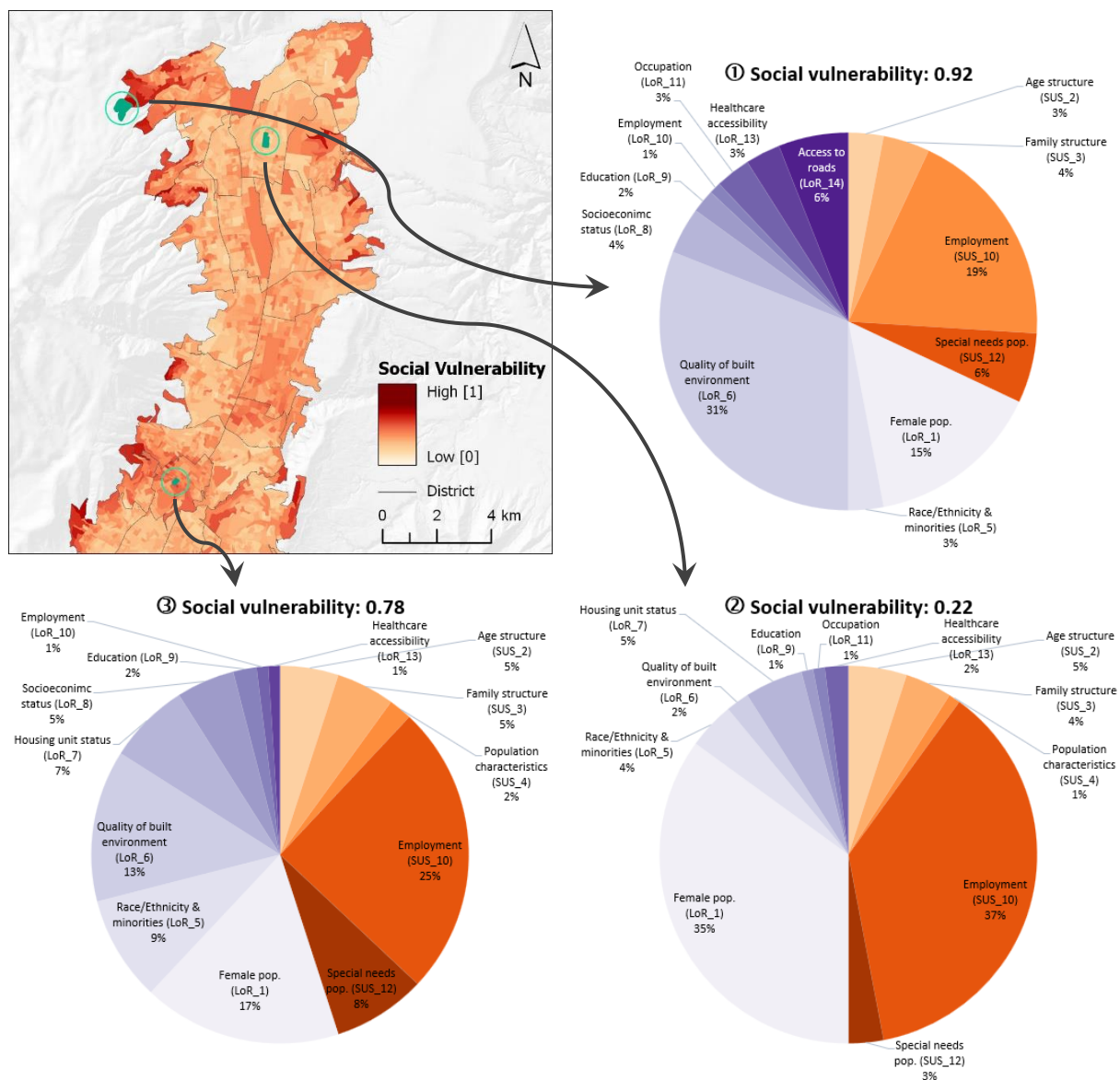


Figure 24: Relative contribution of the indicators to the social vulnerability composite index for three census blocks in the northern part of the city of Quito. Orange colors in the pie chart represent the SUS domain, purple colors represent the LoR domain.

Figure 24 shows the relative contribution of the indicators to the social vulnerability composite index of three census blocks, in a hot spot area in the northern outskirts, in a northern cold spot area, and in a hot spot in the center of the city area. The selection of census blocks was focused on the northern part

of the city of Quito, as the district Quitumbe in the southern part of the city is also subject to further analysis. The pie charts in Figure 24 show that the number of contributing indicators is high with 12 and 13, out of a total of 15 indicators. In both hot spot census blocks (pie chart 1 and 3), the LoR domain contributes more to the vulnerability score than the SUS domain with a share of 69 and 56 %, respectively. Regarding census block 1 (social vulnerability score of 0.92), the indicator describing employment (SUS_10; 19 %) is contributing the most in the SUS domain, while the quality of the built environment (LoR_6; 31 %) and the female population indicator (LoR_1; 15 %) have the biggest influence in the LoR domain. When taking a closer look at census block 3 (social vulnerability score of 0.78), it is again the employment indicator (SUS_10; 25 %) contributing the most in the SUS domain, while the indicator describing special needs population (SUS_12; 8 %) contributes the second most. Regarding the LoR domain, female population (LoR_1; 17 %), the quality of built environment (LoR_6; 13 %), and the indicator describing race/ethnicity & minorities (LoR_5; 9 %) are contributing the most. Regarding the cold spot census block (pie chart 2) with a social vulnerability score of 0.22, the employment indicator (SUS_10) accounts for 37 % in the SUS domain, while in the LoR domain the female population indicator (LoR_1) accounts for 35 %.

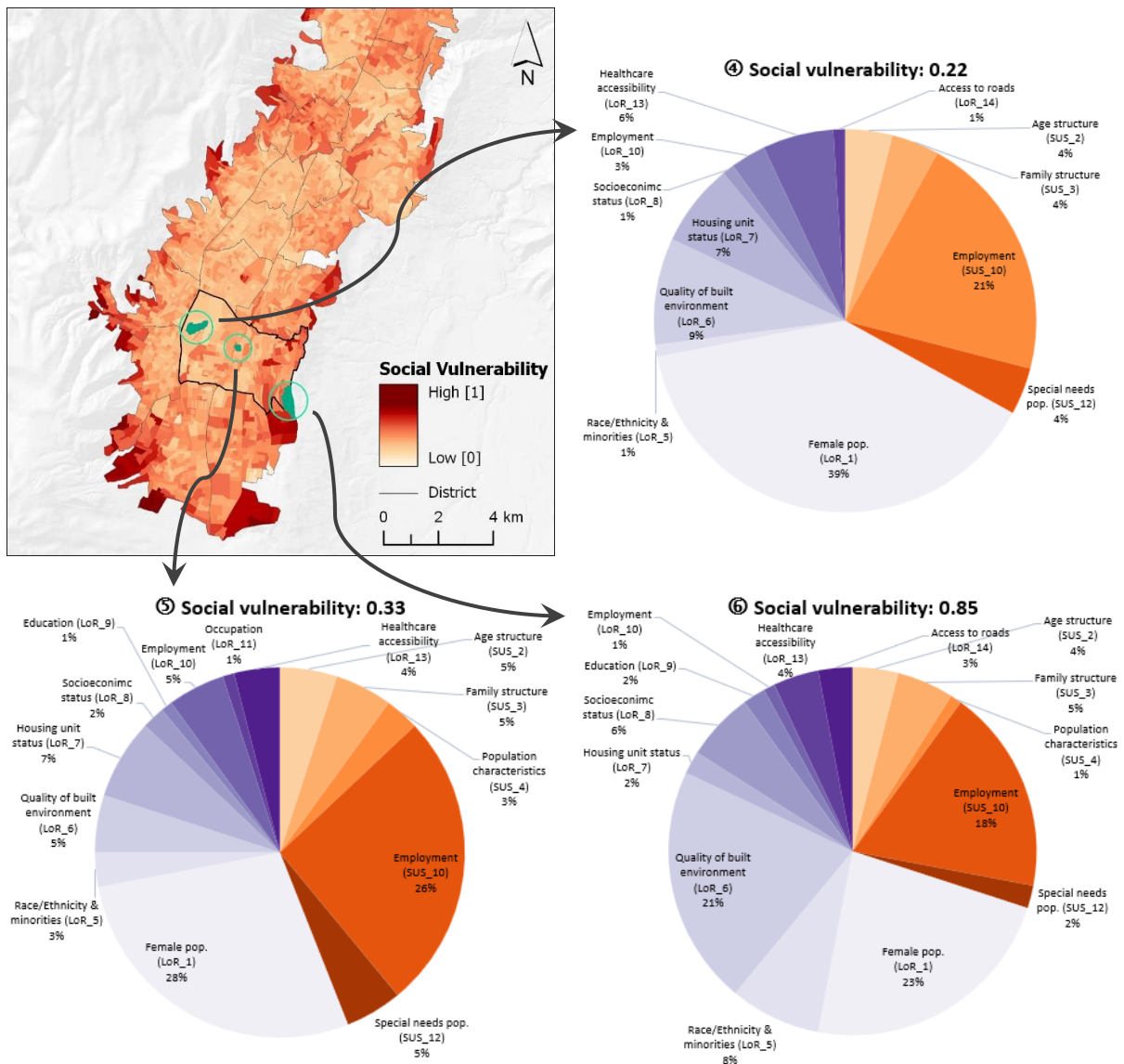


Figure 25: Relative contribution of the indicators to the social vulnerability composite index for three census blocks in the district Quitumbe. Orange colors in the pie chart represent the SUS domain, purple colors represent the LoR domain.

Figure 25 shows the relative contribution of the indicators to the social vulnerability composite index of three census blocks in the district Quitumbe. They are located in a cold spot area in the western part of district, in neither a cold nor hot spot area in the center of the district, and in a hot spot area in the eastern part of the district. The pie charts in Figure 25 show that the number of contributing indicators to the composite index of social vulnerability is also high in Quitumbe with 12 and 14, out of a total of 15 indicators. In all three census blocks (pie chart 4 to 6), the LoR domain contributes more to the vulnerability score than the SUS domain with a share of 67, 56 and 70 %, respectively. Regarding census block 4 in the cold spot area (social vulnerability score of 0.22), the employment indicator (SUS_10; 21 %) contributes the most in the SUS domain, while the indicator describing female population (LoR; 39 %) and the quality of built environment (LoR_6; 9 %) contribute the most in the LoR domain. A similar pattern can be recognized regarding the census block 5 with a social vulnerability score of 0.33. The employment indicator (SUS_10; 26 %) and the female population indicator (LoR_1; 28 %) contribute the most in the SUS and in the LoR domain, respectively. Regarding census block 6 in the hot spot area (social vulnerability score of 0.85), again, the employment indicator (SUS_10; 18 %) contributes the most in the SUS domain, while the indicator describing female population (LoR_1; 23 %), the quality of built environment (LoR_6; 21 %), and the indicator describing race/ethnicity & minorities (LoR_5; 8 %) contribute the most in the LoR domain.

In general, the indicators describing employment (SUS_10), female population (LoR_1), and quality of built environment (LoR_6 – access to public infrastructure, building condition of housing) account for the largest shares of contribution throughout all six exemplary census blocks. However, the contribution of the quality of built environment is higher in the outskirts (pie chart 1 and 6), while the indicator plays a minor role regarding the more central areas (pie chart 2, 4, and 5), where the overall social vulnerability score is lower. Also, the contribution of the female population indicator tends to be higher in the more central areas (pie chart 2, 4, and 5), where the overall social vulnerability score is lower. The employment indicator plays a major role in all six exemplary census blocks, while the contribution also tends to be higher in the areas located more central (pie chart 2, 3, 4, and 5).

Despite the assessment of exposure to natural hazards is not part of this thesis, Figure 26 gives an impression of the spatial distribution of natural hazards in the city of Quito such as mass movements, floods, volcanic hazards and forest fires. The danger of mass movements is low from north to south in the city center and tends to be higher along the city borders. The red dots represent different subtypes of hazardous events (landslides, sinking, mudflows and rock falls) recorded from 2006 to 2017, while landslides have the highest frequency. It is evident that the majority of the mass movement events were recorded in the southern half of the city. Flood prone areas (high and low danger) are located mostly along the minor rivers in the city area, while there is no river in close proximity to a larger flood prone area in the northern half of the city. The higher danger in this area probably results from a high degree of soil sealing and/or insufficient rainwater collecting systems (Municipio del Distrito Metropolitano de Quito, 2015). The red dots represent flood events recorded from 2005 to 2017. One can recognize a higher frequency of events along the areas prone to flood in the city center. Volcanic hazards pose low to high danger along the western city border and minor danger in the northern and southern uttermost outskirts. Obviously, the danger of forest fires is low along the city center and gets higher in the city outskirts as green areas are increasing. The highest danger is located in the uttermost north-eastern part of the city.

In addition to the spatial distribution of natural hazards in the city of Quito, Figure 26 shows hot spot areas of social vulnerability. This gives a first impression of the spatial distribution of areas characterized by high social vulnerability as well as an increased danger to natural hazards.

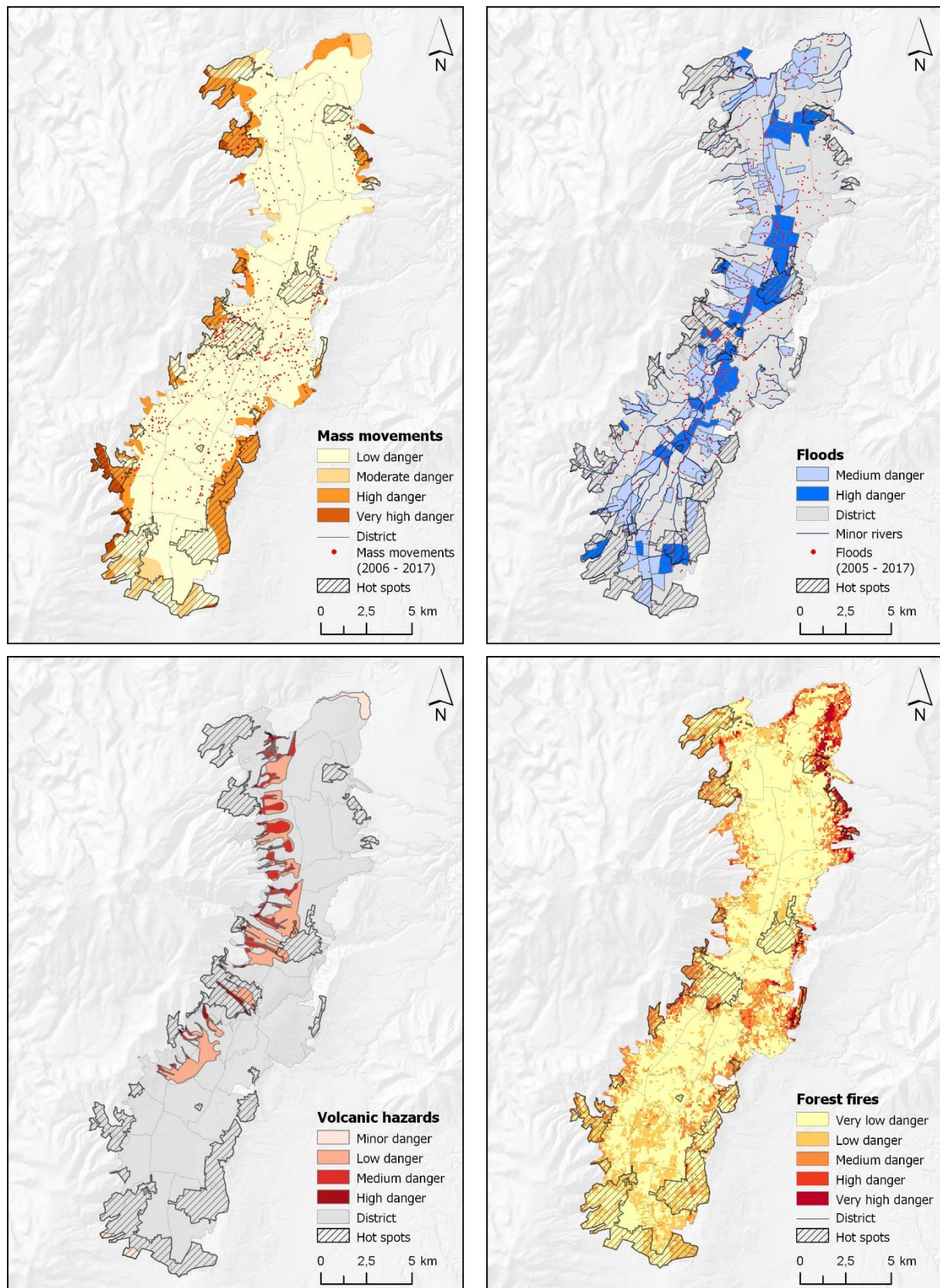


Figure 26: Natural hazards (mass movements, floods, volcanic hazards, and forest fires) in the city of Quito with hot spot areas of social vulnerability (polygon data of mass movements and volcanic hazards from RIVA project, rest of the data from Quito Open Data).

A large proportion of the area characterized by moderate to very high danger in terms of mass movements is also covered by social vulnerability hot spot areas. Flood prone areas are mostly located

along the city center, while vulnerability hot spots are mostly located among the city limits and in the city outskirts. Nevertheless, intersections between flood prone areas and vulnerability hot spots can be located in the city center and in the southern part of the city. Overlaps between areas with danger to volcanic hazards and vulnerability hot spots are rare and can be localized in the city center. Intersections between areas characterized by an increased danger to forest fires and social vulnerability hot spots can be localized mostly in the northern and southern outskirts as well as among the city borders in the central area of the city.

4. Discussion and outlook

The assessment of social vulnerability within this study was based on a holistic and integrative conceptual vulnerability framework. The chosen workflow led to the results presented in section 3 (Results) and successfully enabled the fulfillment of the thesis' objectives. However, throughout the study some challenges arose, which are partly rooted in the conceptualization of the workflow and the study design itself.

The chosen modeling approach is not spatially explicit as the underlying data is based on census block scale. This means that a potentially more appropriate spatial distribution is neglected which's boundaries would not be along administrative entities (Hagenlocher et al., 2013). A spatially explicit modeling approach would lead to the overcoming of the dependency on artificial boundaries and to the delineation of homogenous units of social vulnerability (Kienberger et al., 2009; Kienberger and Hagenlocher, 2014; Lang et al., 2014). Furthermore, the chosen modeling approach is not temporally explicit as the underlying data (e.g. census data, geospatial data, hazard data) corresponds to a particular point (snapshot) in time. Updates of the social vulnerability scores by including updated data are time consuming, as almost every step of the workflow would need to be carried out manually.

Sensitivity analysis is a method to assess the robustness of composite indicators regarding e.g. the mechanism for including and excluding variables, the weights, and the aggregation method as well as to identify all possible sources of uncertainty in the development of the composite indicator and to derivate uncertainty bounds (OECD, 2008). Despite the fact that sensitivity analysis is part of several vulnerability studies (e.g. Feizizadeh and Kienberger, 2017; Kienberger and Hagenlocher, 2014), it was not carried out within this thesis, mostly due to time restrictions. However, a sensitivity analysis would undoubtedly provide further insights in the robustness and structure of the composite indicator and would most likely lead to a more comprehensive result.

Unfortunately, data for the representation of certain variables included in the preliminary selection (Table 1), such as variables related to income and to work registration as well as the access to early warning systems, was not available. According to the *Atlas de amenazas naturales y exposición de infraestructura del distrito metropolitano de Quito*, there is an early warning system in place in the study area (Municipio del Distrito Metropolitano de Quito, 2015). Nevertheless, it was not possible to get representative data to add this aspect to the analysis accordingly, which is particularly unfortunate as access to early warning systems plays an important role in increasing the resilience and therefore was expected to have an increased impact on the results (Kienberger et al., 2014).

One key problem when assessing vulnerability is the fact that vulnerability itself cannot be measured in real world and therefore validation of the results remains a scientific challenge (Birkmann, 2006a; Hagenlocher et al., 2013; Kienberger et al., 2009). A comparison of this study's results to the findings of Cabrera-Barona et al. (2018) regarding deprivation shows similarities in the spatial pattern, with a concentration of deprivation in some outskirts such as in the uttermost north-west, the uttermost south-east and the uttermost south-west of the city of Quito. These similarities can be partly explained by the thematical overlap of vulnerability and deprivation resulting in the use of partly identical variables for analyzing the respective phenomenon (Cabrera-Barona et al., 2018). Furthermore, the underlying socio-economic data (2010 Ecuadorean Population and Housing Census) is the same for both studies (Cabrera-Barona et al., 2018). Thus, one can conclude that the results of Cabrera-Barona et al. (2018) are underlined by this thesis' results and vice versa.

Social vulnerability is one of several vulnerability domains and represents only one aspect of risk assessment and quantification (Birkmann et al., 2013). However, the localization of vulnerability hot

spots provides an important contribution towards the development of an integrated risk management approach for the local authorities. The findings of this study serve as decision support tool and could play an important role in the future risk management in the study area in terms of locating vulnerable neighborhoods regarding natural hazards and developing targeted mitigation strategies. Focusing on the revealed hot spot neighborhoods could lead to a better understanding of vulnerability in the local communities, raise awareness towards natural hazards and potentially change the behavior of people in case of an emergency. Subsequent steps towards an integrated risk assessment are the analysis of additional vulnerability domains and the assessment of exposure to different natural hazards in the study area (Birkmann et al., 2013). Additionally, further investigation of the spatial and statistical relationship between the findings of this thesis (e.g. through sensitivity analysis) and the occurring natural hazards themselves is necessary to gain deeper insights and a better understanding of ongoing processes in the study area.

5. Summary and conclusion

Based on the objectives of the RIVA project of SOS Children's Village (SOS Children's Villages International, 2017a), this thesis aimed to (1) quantify the social vulnerability through a composite index based on a theoretical risk and vulnerability framework and (2) to map the social vulnerability scores for the study area (city of Quito) on census block scale which would enable the (2a) revealing of hot and cold spots and (2b) would serve as a supporting tool for risk management.

The MOVE framework (Birkmann et al., 2013) served as theoretical risk and vulnerability framework. Review of scientific literature led to a preliminary selection of indicators and variables describing the social dimension of vulnerability in the study area to natural hazards, while the variables were assigned to one of two possible domains (susceptibility, lack of resilience). Socio-economic data for the representation of the according variables was extracted based on a geographical selection criterion from the raw data of the 2010 Ecuadorean Population and Housing Census. After applying outlier treatment by limiting the values of statistically problematic variables to the 97.5 percentile score, variables were normalized (min-max normalization, z-score standardization) to render them comparable for further analysis. Multivariate analysis (multicollinearities, PCA/FA) led to the final set of indicators and variables. Weights were derived from PCA/FA and were calculated for each of the two domains separately. The composite social vulnerability indicator was constructed by applying linear aggregation. Hot and cold spot analysis (Getis-Ord G_i^* statistics) revealed neighborhoods of high interest in terms of social vulnerability. The applied workflow made sure to be independent from third parties throughout the process of creation of the composite index, and therefore ruled out the possibility of delays caused by external factors. Data and statistical analysis were carried out using the software *RStudio* as well as *Microsoft Excel*, while the visualization and the hot and cold spot analysis were realized with the software *ArcGIS Pro*.

It was found that mainly outskirts of the city of Quito are characterized by high social vulnerability. Especially in the outermost south-western and south-eastern neighborhoods high social vulnerability is concentrated. High values were also revealed in the outermost north-western part and along the western city limit.

The study design and the applied methods enabled the successful fulfillment of the thesis' objectives and the findings serve thereby as decision support for local authorities in terms of locating vulnerable neighborhoods regarding natural hazards and prioritizing intervention measures. Furthermore, the results provide an important contribution towards developing an integrated risk management approach with the final goal of developing targeted risk mitigation strategies.

6. References

- Adger, W.N., 1999. Social Vulnerability to Climate Change and Extremes in Coastal Vietnam 27, 249–269. [https://doi.org/10.1016/S0305-750X\(98\)00136-3](https://doi.org/10.1016/S0305-750X(98)00136-3)
- Adger, W.N., Brooks, N., Bentham, G., Agnew, M., Eriksen, S., 2004. New indicators of vulnerability and adaptive capacity, Tyndall Centre for Climate Change Research Technical Report 7. Norwich, UK.
- Allianz SE, 2017. 2017 Allianz World Run [WWW Document]. URL <https://allianz-collection.com/results> (accessed 26.11.18).
- Anselin, L., 1995. Local Indicators of Spatial Association-LISA. *Geographical Analysis* 27, 93–115.
- Bandura, R., 2008. A Survey of Composite Indices Measuring Country Performance: 2008 Update. United Nations Development Programme, Office of Development Studies, New York, USA.
- Barbat, A.H., Carreño, M.L., Cardona, O.D., Marulanda, M.C., 2011. Evaluación holística del riesgo sísmico en zonas urbanas. *Revista International Métodos numéricos para cálculo y diseño en ingeniería* 27, 3–27.
- Barnett, J., Lambert, S., Fry, I., 2008. The hazards of indicators: Insights from the environmental vulnerability index. *Annals of the Association of American Geographers* 98, 102–119. <https://doi.org/10.1080/00045600701734315>
- Birkmann, J., 2006a. Measuring vulnerability to promote disaster-resilient societies: Conceptual frameworks and definition, in: Birkmann, J. (Ed.), *Measuring Vulnerability to Natural Hazards: Toward Resilient Societies*. United Nations University Press, Tokyo, JPN.
- Birkmann, J., 2006b. Indicators and criteria for measuring vulnerability: Theoretical bases and requirements, in: Birkmann, J. (Ed.), *Measuring Vulnerability to Natural Hazards: Toward Resilient Societies*. United Nations University Press, Tokyo, JPN.
- Birkmann, J., 2005. Danger need not spell disaster - But how vulnerable are we?. Research Brief (1). United Nations University. Tokyo, JPN.
- Birkmann, J., Cardona, O.D., Carreño, M.L., Barbat, A.H., Pelling, M., Schneiderbauer, S., Kienberger, S., Keiler, M., Alexander, D., Zeil, P., Welle, T., 2013. Framing vulnerability, risk and societal responses: The MOVE framework. *Natural Hazards* 67, 193–211. <https://doi.org/10.1007/s11069-013-0558-5>
- Birkmann, J., Fernando, N., 2008. Measuring revealed and emergent vulnerabilities of coastal communities to tsunami in Sri Lanka. *Disasters* 32, 82–105. <https://doi.org/10.1111/j.1467-7717.2007.01028.x>
- Bogardi, J.J., Birkmann, J., 2004. Vulnerability Assessment: The First Step Towards Sustainable Risk Reduction, in: Malzahn, D., Plapp, T. (Eds.), *Disaster and Society – From Hazard Assessment to Risk Reduction*. Logos Verlag, Berlin, GER, pp. 75–82.
- Bogardi, J.J., Villagran, J.C., Birkmann, J., Renaud, F., Sakulski, D., Chen, X., Affeltranger, B., Mensa, A., Kaplan, M., 2005. Vulnerability in the context of climate change. *Human Security and Climate Change. An International Workshop*. Oslo, NO.
- Bohle, H.-G., 2001. Vulnerability and Criticality: Perspectives from Social Geography. Update IHDP 2/01. Newsletter of the International Human Dimensions Programme on Global Environmental Change, 1–7.
- Bollin, C., Cárdenas, C., Hahn, H., Vatsa, K.S., 2003. Natural Disasters Network - Disaster Risk Management by Communities and local Governments. Inter-American Development Bank, Washington, D.C., USA.
- Brooks, N., 2003. Vulnerability, risk and adaptation: A conceptual framework. Tyndall Centre for Climate Change Research Working Paper No. 38, 1-16. Norwich, UK.

- Cabrera-Barona, P., Blaschke, T., Gaona, G., 2018. Deprivation, Healthcare Accessibility and Satisfaction: Geographical Context and Scale Implications. *Applied Spatial Analysis and Policy* 11, 313–332. <https://doi.org/10.1007/s12061-017-9221-y>
- Cannon, T., 1994. Vulnerability Analysis and The Explanation Of ' Natural ' Disasters, in: Varley, A. (Ed.), *Disaster, Development and Environment*. John Wiley & Sons Ltd, Chichester, UK, pp. 13–30.
- Cannon, T., Twigg, J., Rowell, J., 2003. *Social Vulnerability , Sustainable Livelihoods and Disasters*. Report to DFID Conflict and Humanitarian Assistance Department (CHAD) and Sustainable Livelihoods Support Office. Greenwich, UK.
- Cardona, O.D., 2001. Estimación Holística del Riesgo Sísmico utilizando Sistemas Dinámicos Complejos. Universidad Politécnica de Cataluña (UPC), Barcelona, ESP.
- Cardona, O.D., 1999. Environmental Management and Disaster Prevention: Two Related Topics: A Holistic Risk Assessment and Management Approach, in: Ingleton, J. (Ed.), *Natural Disaster Management*. Tudor Rose, London, Uk.
- Cardona, O.D., Barbat, A.H., 2000. El Riesgo Sísmico y su Prevención, Cuaderno Técnico 5. Calidad Siderúrgica, Madrid, ESP.
- Carreño, M.L., Cardona, O.D., Barbat, A.H., 2012. New methodology for urban seismic risk assessment from a holistic perspective. *Bulletin of Earthquake Engineering* 10, 547–565. <https://doi.org/10.1007/s10518-011-9302-2>
- Carreño, M.L., Cardona, O.D., Barbat, A.H., 2007a. Urban Seismic Risk Evaluation : A Holistic Approach. *Natural Hazards* 40, 137–172. <https://doi.org/10.1007/s11069-006-0008-8>
- Carreño, M.L., Cardona, O.D., Barbat, A.H., 2007b. A disaster risk management performance index. *Natural Hazards* 41, 1–20. <https://doi.org/10.1007/s11069-006-9008-y>
- Carreño, M.L., Cardona, O.D., Barbat, A.H., 2005. Sistema de Indicadores para la Evaluación de Riesgos. Monografías CIMNE. Technical University of Catalonia, Barcelona, ESP.
- Carreño, M.L., Cardona, O.D., Barbat, A.H., 2004. Metodología para la Evaluación del Desempeño de la Gestión del Riesgo. Monografías CIMNE. Technical University of Catalonia, Barcelona, ESP.
- Castro, M.C. De, Singer, B.H., 2006. Controlling the False Discovery Rate : A New Application to Account for Multiple and Dependent Tests in Local Statistics of Spatial Association. *Geographical Analysis* 38, 180–208. <https://doi.org/10.1016/j.matcom.2009.09.005>
- Chambers, R., 1989. Editorial Introduction: Vulnerability , Coping and Policy. *IDS Bulletin* 20.
- Chen, W., Cutter, S.L., Emrich, C.T., Shi, P., 2014. Measuring Social Vulnerability to Natural Hazards in the Yangtze River Delta Region , China. *International Journal of Disaster Risk Science* 4, 169–181. <https://doi.org/10.1007/s13753-013-0018-6>
- CuencaHighLife, 2017. Stay out of the sun, government warns: High levels of UV radiation reported in Quito and Cuenca [WWW Document]. URL <https://cuencahighlife.com/stay-out-of-the-sun-government-warns-high-levels-of-uv-radiation-reported-in-quito-and-cuenca/> (accessed 28.3.19).
- Cutter, S.L., 1996. Social Vulnerability to Environmental Hazards. *Progress in Human Geography* 20, 529–539. <https://doi.org/10.1177/030913259602000407>
- Cutter, S.L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., Webb, J., 2008. A place-based model for understanding community resilience to natural disasters. *Global Environmental Change* 18, 598–606. <https://doi.org/10.1016/j.gloenvcha.2008.07.013>
- Cutter, S.L., Boruff, B.J., Shirley, W.L., Cutter, S.L., Carolina, S., 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly* 84, 242–261.

- Cutter, S.L., Mitchell, J.T., Scott, M.S., 2000. Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. *Annals of the Association of American Geographers* 90, 713–737.
- Davidson, R.A., Shah, H.C., 1997. An Urban Earthquake Disaster Risk Index, The John A. Blume Earthquake Engineering Center, Department of Civil and Environmental Engineering, Report No. 121. Stanford University. Stanford, USA.
- de Loyola Hummell, B.M., Cutter, S.L., Emrich, C.T., 2016. Social Vulnerability to Natural Hazards in Brazil. *International Journal of Disaster Risk Science* 7, 111–122. <https://doi.org/10.1007/s13753-016-0090-9>
- Downing, T.E., 2004. What Have We Learned Regarding a Vulnerability Science?, in: *Science in Support of Adaptation to Climate Change. Recommendations for an Adaptation Science Agenda and a Collection of Papers Presented at a Side Event of the 10th Session of the Conference of the Parties to the UN Framework Convention on Climate Change*. Buenos Aires, ARG, pp. 18–21.
- Downing, T.E., Aerts, J., Soussan, J., Barthelemy, O., Bharwani, S., Ionescu, C., Hinkel, J., Klein, R.J.T., Mata, L.J., Martin, N., Moss, S., Purkey, D., Ziervogel, G., 2006. Integrating social vulnerability into water management. SEI Working Paper and Newater Working Paper No. 4. Oxford, UK.
- El Comercio, 2018. Quito Ecuador : ALERT – Ultraviolet Radiation Index Very High Levels [WWW Document]. URL <http://latinamericacurrentevents.com/quito-ecuador-alert-ultraviolet-radiation-index-very-high-levels39874-2/39874/> (accessed 28.3.19).
- Fatemi, F., Ardalan, A., Aguirre, B., Mansouri, N., Mohammadfam, I., 2017. Social vulnerability indicators in disasters: Findings from a systematic review. *International Journal of Disaster Risk Reduction* 22, 219–227. <https://doi.org/10.1016/j.ijdr.2016.09.006>
- Feizizadeh, B., Kienberger, S., 2017. Spatially explicit sensitivity and uncertainty analysis for multicriteria-based vulnerability assessment. *Journal of Environmental Planning and Management* 60, 2013–2035. <https://doi.org/10.1080/09640568.2016.1269643>
- Frigerio, I., De Amicis, M., 2016. Mapping social vulnerability to natural hazards in Italy: A suitable tool for risk mitigation strategies. *Environmental Science and Policy* 63, 187–196. <https://doi.org/10.1016/j.envsci.2016.06.001>
- Frigerio, I., Ventura, S., Strigaro, D., Mattavelli, M., De Amicis, M., Mugnano, S., Boffi, M., 2016. A GIS-based approach to identify the spatial variability of social vulnerability to seismic hazard in Italy. *Applied Geography* 74, 12–22. <https://doi.org/10.1016/j.apgeog.2016.06.014>
- Füssel, H.M., 2007a. Adaptation Planning for Climate Change : Concepts , Assessment Approaches and Key Lessons. *Sustainability Science* 2, 265–275. <https://doi.org/10.1007/s11625-007-0032-y>
- Füssel, H.M., 2007b. Vulnerability: A generally applicable conceptual framework for climate change research. *Global Environmental Change* 17, 155–167. <https://doi.org/10.1016/j.gloenvcha.2006.05.002>
- Gallopín, G.C., 1997. Indicators and their use: information for decision-making. Part One - Introduction, in: Moldan, B., Billharz, S. (Eds.), *Sustainability Indicators. A Report on the Project on Indicators of Sustainable Development*. SCOPE 58. Wiley, Chichester, UK.
- Groeneveld, R.A., Meeden, G., 1984. Measuring Skewness and Kurtosis. *Journal of the Royal Statistical Society* 33, 391–399. <https://doi.org/10.2307/2987742>
- Hagenlocher, M., Delmelle, E., Casas, I., Kienberger, S., 2013. Assessing socioeconomic vulnerability to dengue fever in Cali, Colombia: statistical vs expert-based modeling. *International Journal of Health Geographics* 12. <https://doi.org/10.1186/1476-072X-12-36>
- Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2010. *Multivariate Data Analysis*, 7th ed. Pearson Education Limited, Essex, GB.

- IDEA, 2005. Indicators of Disaster Risk and Risk Management - Main technical report. English and Spanish edition, National University of Colombia/Manizales, Institute of Environmental Studies/IDEA, Inter- American Development Bank, Washington, DC, USA.
- Instituto nacional de estadística y censos (INEC), 2014. Evolución de las variables investigadas en los censos de población y vivienda del Ecuador 1950, 1962, 1974, 1982, 1990, 2001 y 2010. Quito, ECU.
- International Federation of Red Cross and Red Crescent Societies, 2018. World Disasters Report 2018. Geneva, CH.
- IPCC (Intergovernmental Panel on Climate Change), 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution to the Working Group II to the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK.
- IPCC (Intergovernmental Panel on Climate Change), 2001. Climate Change 2001: Impacts, Adaptation, and Vulnerability. Contribution to the Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK.
- ISDR (International Strategy for Disaster Reduction), 2004. Living with Risk. A Global Review of Disaster Risk Initiatives. Geneva, CH.
- Kelly, P.M., Adger, W.N., 2000. Theory and Practice in Assessing Vulnerability to Climate Change and Facilitating Adaptation. *Climate Change* 47, 325–352.
- Kienberger, S., Contreras, D., Zeil, P., 2014. Spatial and Holistic Assessment of Social, Economic, and Environmental Vulnerability to Floods-Lessons from the Salzach River Basin, Austria, in: *Assessment of Vulnerability to Natural Hazards: A European Perspective*. pp. 53–73. <https://doi.org/10.1016/B978-0-12-410528-7.00003-5>
- Kienberger, S., Hagenlocher, M., 2014. Spatial-explicit modeling of social vulnerability to malaria in East Africa. *International Journal of Health Geographics* 13. <https://doi.org/10.1186/1476-072X-13-29>
- Kienberger, S., Lang, S., Zeil, P., 2009. Spatial vulnerability units - Expert-based spatial modelling of socio-economic vulnerability in the Salzach catchment, Austria. *Natural Hazards and Earth System Science* 9, 767–778. <https://doi.org/10.5194/nhess-9-767-2009>
- Lang, S., Kienberger, S., Tiede, D., Hagenlocher, M., Pernkopf, L., 2014. Geons-domain-specific regionalization of space. *Cartography and Geographic Information Science* 41, 214–226. <https://doi.org/10.1080/15230406.2014.902755>
- Lee, Y.J., 2014. Social vulnerability indicators as a sustainable planning tool. *Environmental Impact Assessment Review* 44, 31–42. <https://doi.org/10.1016/j.eiar.2013.08.002>
- Maclaren, V.W., 1996. Urban sustainability reporting. *Journal of the American Planning Association* 62, 184–202. <https://doi.org/10.1080/01944369608975684>
- Mazumdar, J., Paul, S.K., 2018. A spatially explicit method for identification of vulnerable hotspots of Odisha, India from potential cyclones. *International Journal of Disaster Risk Reduction* 27, 391–405. <https://doi.org/10.1016/j.ijdrr.2017.11.001>
- Miller, F., Osbahr, H., Boyd, E., Thomalla, F., Bharwani, S., Ziervogel, G., Walker, B., Leeuw, S. Van Der, Hinkel, J., Downing, T., Folke, C., Nelson, D., 2010. Resilience and Vulnerability: Complementary or Conflicting Concepts?. *Ecology and Society* 15.
- Morrow, B.H., 2008. Community Resilience: A Social Justice Perspective. Community and regional resilience initiative (CARRI) research report 4. Miami, USA.
- Municipio del Distrito Metropolitano de Quito, 2015. Atlas de amenazas naturales del Distrito Metropolitano de Quito: Segunda Edición. Quito, ECU.

- Nicoletti, G., Scarpetta, S., Boylaud, O., 2000. Summary Indicators of Product Market Regulation with an Extension to Employment Protection Legislation. OECD, Economics Department Working Papers No. 226, ECO/WKP(99)18.
- November, V., 2008. Spatiality of risk. *Environment and Planning A* 40, 1523–1527. <https://doi.org/10.1068/a4194>
- O'Brien, G., O'Keefe, P., Meena, H., Rose, J., Wilson, L., 2008. Climate adaptation from a poverty perspective. *Climate Policy* 8, 194–201. <https://doi.org/10.3763/cpol.2007.0430>
- O'Brien, K., Sygna, L., Leichenko, R., Adger, W.N., Barnett, J., Mitchell, T., Schipper, L., Tanner, T., Vogel, C., Mortreux, C., 2008. Disaster Risk Reduction , Climate Change Adaptation and Human Security. GECHS Report vol. 3. University of Oslo, Oslo, NOR.
- Ord, J.K., Getis, A., 1995. Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis* 27, 286–306. <https://doi.org/10.1111/j.1538-4632.1995.tb00912.x>
- Organisation for Economic Co-operation and Development, 2008. Handbook on Constructing Composite Indicators: Methodology and User Guide. <https://doi.org/10.1787/9789264043466-en>
- Pachauri, R.K., Allen, M.R., Barros, V.R., Broome, J., Cramer, W., Christ, R., Church, J.A., Clarke, L., Dahe, Q., 2014. Climate Change 2014: Synthesis Report, Contributino of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva, CH. <https://doi.org/10.1073/pnas.1116437108>
- Parra, R., Cadena, E., Flores, C., 2018. Poster: Maximum Ultraviolet Radiation Levels in Quito (Ecuador) During the Period 2010-2017 and Their Implications to Human Health. 30th Meeting of the Parties to the Montreal Protocol, Quito, ECU.
- Pourrut, P., Leiva, I., 1989. Las lluvias de Quito : características generales, beneficios y problemática, in: Peltre, P. (Ed.), Riesgos Naturales En Quito: Lahares, Aluviones y Derrumbes Del Pichincha y Del Cotopaxi. Corporacion Editora Nacional, Colegio de Geografas del Ecuador, Quito, ECU, pp. 33–44.
- Ruep, S., 2017. Geodaten sollen Kinderdörfer vor Katastrophen retten [WWW Document]. *Der Standard*. URL <https://derstandard.at/2000061147531/Geodaten-sollen-Kinderdoerfer-vor-Katastrophen-retten> (accessed 26.11.18).
- Saisana, M., 2012. A do-it-yourself guide in Excel for composite indicator development. European Commission, Joint Research Centre, Italy.
- Serrano, S., Diana, Z., Lema Puruncaja, C., 2014. Extreme Events of Solar Radiation in Quito : a Relation with Temperature and Climate Change. III International Conference on ENSO, Bridging the gaps between Global ENSO Science and regional processes, extremes and impacts, Guayaquil, ECU. <https://doi.org/10.13140/2.1.3136.8006>
- SOS Children's Villages International, 2018. Summary Factsheet Quito, Ecuador - RIVA Risk and Vulnerability Assessment.
- SOS Children's Villages International, 2017a. Resilient Future Generations - Addressing Local Risks through the Emergency Response Partnership [WWW Document]. URL https://www.allianz.com/content/dam/onemarketing/azcom/Allianz_com/sustainability/media-2017/Resilient_Future_Generations.pdf (accessed 26.11.18).
- SOS Children's Villages International, 2017b. SOS Children's Villages International Official Website [WWW Document]. URL <https://www.sos-childrensvillages.org/our-work> (accessed 28.11.18).
- Turner, B.L., Kasperson, R.E., Matson, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., Eckley, N., Kasperson, J.X., Luers, A., Martello, M.L., Polsky, C., Pulsipher, A., Schiller, A., 2003. A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences* 100, 8074–8079. <https://doi.org/10.1073/pnas.1231335100>

- United Nations, 2005. Hyogo Framework for Action 2005-2015: Building the Resilience of Nations and Communities to Disaster. World conference on Disaster Reduction, Kobe, JPN.
- Varnes, D.J., 1978. Slope movement types and processes, in: Schuster, R.L., Krizek, R.J. (Eds.), Special Report 176: Landslides: Analysis and Control. Transportation and Road Research Board, National Academy of Science, Washington D.C., USA, pp. 11–33.
- Villagran, J.C., 2006. Vulnerability: a conceptual and methodological review, Studies of the University: Research, Counsel, Education - Nr. 4. UNU Institute for Environment and Human Security, Bonn, DE.
- Wallemacq, P., Below, R., 2018. Economic Losses, Poverty & Disasters: 1998-2017. Centre for Research on the Epidemiology of Disasters (CRED), Brussels, BEL & United Nations Office for Disaster Risk Reduction (UNISDR), Geneva, CH.
- Watts, M.J., Bohle, H., 1993. Progress in Human Geography. Progress in Human Geography 17, 43–67. <https://doi.org/10.1177/030913259301700103>
- Weiland, U., 1999. Indikatoren einer nachhaltigen Entwicklung: vom Monitoring zur politischen Steuerung?, in: Weiland, U. (Ed.), Perspektiven Der Raum- Und Umweltplanung Angesichts Globalisierung, Europäischer Integration Und Nachhaltiger Entwicklung. Festschrift Für Karl-Hermann Hübler. Berlin, GER.
- Wisner, B., Blaikie, P., Cannon, T., Davis, I., 2004. At Risk: Natural hazards, people's vulnerability and disasters (Second edition). Routledge, London, UK.
- Yoon, D.K., 2012. Assessment of social vulnerability to natural disasters: A comparative study. Natural Hazards 63, 823–843. <https://doi.org/10.1007/s11069-012-0189-2>

Appendix A

List of calculation of the variables describing social vulnerability. The description of the calculation is held in *italic*, while most of the names of the used variables within the calculation are referring to the raw data of the 2010 Ecuadorean Population and Housing Census.

1 Female Population

1.1 Percentage of females

PERSONA.P01[2]/PERSONA.P01[Total]

P01 – Sex

P01[2] – Female

1.2 Percentage of female headed households

(PERSONA.P01[2] by PERSONA.P02[1])/HOGAR.NUMHOG[Total]

P01 – Sex

P01[2] – Female

P02 – Relationship to head of household

P02[1] – Head of household

1.3 Percentage of employed females in the labor force

(PERSONA.P01[2] by PERSONA.P02[1])/HOGAR.NUMHOG[Total]

P01 – Sex

P01[2] – Female

P02 – Relationship to head of household

P02[1] – Head of household

2 Age structure

2.1 Median age

MEDIAN(PERSONA.P03)

P03 – Age

2.2 Percentage <5 years old

SUM(PERSONA.GEDAD[1-2])/PERSONA.GEDAD[Total]

GEDAD – Age groups

GEDAD[1] – <1 year

GEDAD[2] – 1-4 years

2.3 Percentage >64 years old

PERSONA.GRANEDAD[3]/PERSONA.GRANEDAD[Total]

GRANEDAD – Large age groups

GRANEDAD[3] – ≥65 year

3 Family structure

3.1 Average number of people per household

AVERAGE(HOGAR.TOTPER)

TOTPER - Total persons in household

3.2 Percentage of households with four or more persons per dormitory

$SUM(VIVIENDA.PERDOR[4-5])/VIVIENDA.PERDOR[Total]$

PERDOR – Number of persons per dormitory

PERDOR[4] – 4-5 persons per dormitory

PERDOR[5] – ≥ 5 persons per dormitory

4 Population characteristics

4.1 Population density

$COUNT(PERSONA)/Shape_Area$

5 Race/Ethnicity & Minorities

5.1 Percentage of indigenous people

$PERSONA.P16[1]/PERSONA.P16[Total]$

P16 – Ethnicity

P16[1] – Indigenous

5.2 Percentage of population born in other states

$PERSONA.P11L[3]/PERSONA.P11[Total]$

P11L – Place of birth

P11L[3] – Other country

5.3 Percentage of residents immigrating in the past 3-5 years

$SUM(PERSONA.P11A[2005-2007])/COUNT(PERSONA)$

P11A – Year of arrival in Ecuador

6 Quality of built environment

6.1 Percentage of households with no access to public water infrastructure or well

$SUM(VIVIENDA.V07[3-5])/VIVIENDA.V07[Total]$

V07 – Origin of water

V07[3] – River, slope, ditch or channel

V07[4] – Distributor car

V07[5] – Other origin (Rain water/"albarrada" water)

6.2 Percentage of households with no access to public sewer infrastructure

$SUM(VIVIENDA.V09[2-6])/VIVIENDA.V09[Total]$

V09 – Type of hygiene service

V09[2] – Connected to septic tank

V09[3] – Connected to cesspit

V09[4] – Direct discharge in the sea, in a river, lake or stream

V09[5] – Letrine

V09[6] – None

6.3 Percentage of households with no access to garbage collection services

$SUM(VIVIENDA.V13[2-6])/VIVIENDA.V13[Total]$

V13 – Disposal of garbage

V13[2] – Dumping in the fallow or ravine terrain

V13[3] – Burning

V13[4] – Burrying

V13[5] – Dumping into a river, ditch or canal

V13[6] – Otherwise

6.4 Percentage of households with no access to public electricity service

$SUM(VIVIENDA.V10[2-5])/VIVIENDA.V10[Total]$

V10 – Source of electric light

V10[2] – Solar panel

V10[3] – Light Generator (Power Plant)

V10[4] – Other

V10[5] – None

6.5 Percentage of households with external walls in bad condition

$VIVIENDE.V04[3]/VIVIENDA.V04[Total]$

V04 – Conditions of the walls

V04[3] – Bad

6.6 Percentage of households with roofs in bad condition

$VIVIENDE.V02[3]/VIVIENDA.V02[Total]$

V02 – Conditions of the roof

V02[3] – Bad

7 Housing units status

7.1 Percentage of rented households

$HOGAR.H15[6]/HOGAR.H15[Total]$

H15 - Tenancy or ownership of the dwelling

H15[6] - Rented

8 Socio-economic status

8.1 Percentage of households with no phone (cell phone or landline)

$(HOGAR.H07[2] \text{ by } HOGAR.H08[2])/HOGAR.H07[Total]$

H07 - Conventional phone availability

H07[2] - No

H08 - Mobile phone availability

H08[2] – No

8.2 Percentage of population living in households facing extreme poverty

No data on income

8.3 Per capita income

No data on income

9 Education

9.1 Percentage of illiterate population aged 15 and older

$(PERSONA.P19[2] \text{ by } SUM(PERSONA.GRANEDAD[2-3]))/PERSONA.P19[Total]$

P19 - Capability of reading and writing

P19[2] - No

GRANEDAD - Large age groups

GRANEDAD[2] - 15-64 years

GRANEDAD[3] - ≥65 years

9.2 Percentage of population that completed middle school or with high school incomplete

No reliable reference on what value corresponds to middle or high school

9.3 Percentage of population that completed college degree

$PERSONA.P23[8-10]/PERSONA.P23[Total]$

P23 - Level of education attended

P23[8] - Post-Baccalaureate cycle/education

P23[9] - Superior/tertiary education

P23[10] - Postgraduate education

10 Employment

10.1 Percentage of population unemployed

$SUM(PERSONA.TIPOACT[6-7])/SUM(PERSONA.TIPOACT[1-7])$

TIPOACT - Type of activity

TIPOACT[1] - Worked at least 1 hour

TIPOACT[2] - Not worked but having a job

TIPOACT[3] - At least 1 hour in services or manufacture of products

TIPOACT[4] - At least 1 hour in a family business

TIPOACT[5] - At least 1 hour did agricultural work

TIPOACT[6] - Unemployed

TIPOACT[7] - Looking for a job for the first time

10.2 Percentage of population employed in agriculture, forestry production, livestock, and aquaculture

$PERSONA.RAMACT[1]/PERSONA.RAMACT[Total]$

RAMACT - Branch of activity

RAMACT[1] - Agriculture, livestock, forestry and fishing

10.3 Percentage of population employed in extractive industry

$PERSONA.RAMACT[2]/PERSONA.RAMACT[Total]$

RAMACT - Branch of activity

RAMACT[2] - Exploitation of mines and quarries

10.4 Percentage of population employed in accommodation and food services activities

$PERSONA.RAMACT[9]/PERSONA.RAMACT[Total]$

RAMACT - Branch of activity

RAMACT[9] - Accommodation and meal service activities

10.5 Percentage of population employed in commerce

$PERSONA.RAMACT[7]/PERSONA.RAMACT[Total]$
RAMACT - Branch of activity
RAMACT[7] - Wholesale and retail trade

10.6 Percentage of population employed in public administration and defense

$PERSONA.RAMACT[15]/PERSONA.RAMACT[Total]$
RAMACT - Branch of activity
RAMACT[15] - Public administration and defense

10.7 Percentage of population employed in human health services

$PERSONA.RAMACT[17]/PERSONA.RAMACT[Total]$
RAMACT - Branch of activity
RAMACT[17] - Human health care activities

10.8 Percentage of population that works in unpaid jobs

$PERSONA.P31[7]/PERSONA.P31[Total]$
P31 - Occupation category
P31[7] - Unpaid worker

11 Occupation

11.1 Percentage of labor force with legal work registration

No data on work registration

11.2 Percentage of labor force with no legal work registration

No data on work registration.

11.3 Percentage of subsistence workers in the labor force

$(PERSONA.P31[6] \text{ by } PERSONA.RAMACT[1])/PERSONA.P31[Total]$
P31 - Occupation category
P31[6] - Self-employed
RAMACT - Branch of activity
RAMACT[1] - Agriculture, livestock, forestry and fishing

12 Special needs population

12.1 Percentage of population with permanent disability for more than one year

$PERSONA.P08[1]/PERSONA.P08[Total]$

13 Special needs population

13.1 Index of Healthcare Accessibility

Secondary data (Cabrera-Barona et al. (2018))

14 Access to roads

14.1 Percentage of households with access to paved roads

(SUM(VIVIENDA.VAP[1-3])/VIVIENDA.VAP[Total]) by VIVIENDA.V15[1-2]

VAP - Main access to housing

VAP[1] - Paved (asphalted) or concrete street or road

VAP[2] - Paved street or road

VAP[3] - Ballasted or dirt street or road

V15 - Existence of households in the dwelling

V15[1] - One household

V15[2] - More than one household

15 Early warning systems

No data on early warning systems

Appendix B

The script used in *RStudio* for data and statistical analysis.

```

#Author: Roman Breitfuss-Schiffer
#Purpose: Mapping social vulnerability to natural hazards - Thesis
#-----

#Load libraries
library(moments)
library(dplyr)
library(xlsx)
library(DescTools)
library(data.table)
library(Compind)
library(corrplot)
library(car)
library(stats)
library(factoextra)
library(psych)

#Import data
ind=read.csv("C:/path/data.csv")

#Create subset of statistically problematic variables
#-3 to calculate the excess kurtosis (value of 0 for Gaussian normal distr.)
statprob<-ind[which(abs(skewness(ind))>2 & (kurtosis(ind)-3)>3.5)]

#Create subset to treat outliers
#Exclude variables with skewness exceeding 2 only by small extent
subset_sp1<-statprob
subset_sp1[ ,c('V10.3', 'V14.1')] <- list(NULL)

#OUTLIER TREATMENT
#-----
#Calculate quantiles for subset
quantile_0975<-stack(lapply(subset_sp1, quantile, prob=0.975))

#Create boxplots of the variables of the subset
boxplot(subset_sp1$V5.1,
        main = "Percentage of indigenous people",
        xlab = "Variable 5.1",
        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[1,"values"],
         x1 = 1.05, y1 = quantile_0975[1,"values"],
         col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
       bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V5.2,
        main = "Percentage of population born in \nother states",
        xlab = "Variable 5.2",
        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[2,"values"],
         x1 = 1.05, y1 = quantile_0975[2,"values"],
         col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
       bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V5.3,
        main = "Percentage of residents immigrating \nin the past 3-5 years",
        xlab = "Variable 5.3",

```

```

        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[3,"values"],
        x1 = 1.05, y1 = quantile_0975[3,"values"],
        col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
        bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V6.1,
        main = "Percentage of households with no access to \npublic water
        infrastructure or well",
        xlab = "Variable 6.1",
        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[4,"values"],
        x1 = 1.05, y1 = quantile_0975[4,"values"],
        col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
        bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V6.2,
        main = "Percentage of households with no access to \npublic sewer
        infrastructure",
        xlab = "Variable 6.2",
        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[5,"values"],
        x1 = 1.05, y1 = quantile_0975[5,"values"],
        col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
        bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V6.3,
        main = "Percentage of households with no access to \ngarbage collection
        services",
        xlab = "Variable 6.3",
        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[6,"values"],
        x1 = 1.05, y1 = quantile_0975[6,"values"],
        col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
        bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V6.4,
        main = "Percentage of households with no access to \npublic electricity
        service",
        xlab = "Variable 6.4",
        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[7,"values"],
        x1 = 1.05, y1 = quantile_0975[7,"values"],
        col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
        bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V10.2,
        main = "Percentage of population employed in \nagriculture, forestry
        production, livestock, \nand aquaculture",

```


Mapping social vulnerability to natural hazards

Appendix B

```
      xlab = "Variable 10.2",
      ylab = "Percentage (%)",
      col = "white",
      border = "black",
      boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[8,"values"],
         x1 = 1.05, y1 = quantile_0975[8,"values"],
         col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
      bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V11.3,
        main = "Percentage of subsistence workers \nin the labor force",
        xlab = "Variable 11.3",
        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[9,"values"],
         x1 = 1.05, y1 = quantile_0975[9,"values"],
         col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
      bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V12.1,
        main = "Percentage of population with permanent \ndisability for more than
              one year",
        xlab = "Variable 12.1",
        ylab = "Percentage (%)",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[10,"values"],
         x1 = 1.05, y1 = quantile_0975[10,"values"],
         col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
      bty = "n", lty = "solid", lwd = 1, col = "red")

boxplot(subset_sp1$V13.1,
        main = "Index of Healthcare Accessibility",
        xlab = "Variable 13.1",
        ylab = "Index",
        col = "white",
        border = "black",
        boxwex=0.75)
segments(x0 = 0.95, y0 = quantile_0975[11,"values"],
         x1 = 1.05, y1 = quantile_0975[11,"values"],
         col = "red", lwd = 1)
legend("topleft", legend = paste("0.975", "quantile"),
      bty = "n", lty = "solid", lwd = 1, col = "red")

#Calculate percentage of values above certain quantile which are winsorized
values_win<-lapply(subset_sp1, function(x) which(x>quantile(x,0.975)))
values_win1<-stack(lapply(values_win, length))/4037

#Winsorize values above certain quantile
win_0975<-lapply(subset_sp1,Winsorize,probs=c(0.0,0.975))
#Check skewness and kurtosis of winsorized data
stack(lapply(win_0975,skewness))
stack(lapply(win_0975,function(x) kurtosis(x)-3))
#Write in Excel
write.xlsx(stack(lapply(win_0975,skewness)), "C:/path/win_0975_skew.xlsx")
write.xlsx(stack(lapply(win_0975,function(x) kurtosis(x)-3)),
          "C:/path/win_0975_kurt.xlsx")
#Convert list to dataframe
win_0975_df<-data.frame(matrix(unlist(win_0975), ncol=length(win_0975)))
colnames(win_0975_df)=c("V5.1", "V5.2", "V5.3", "V6.1", "V6.2", "V6.3", "V6.4", "V10.2", "V
11.3", "V12.1", "V13.1")
```

Mapping social vulnerability to natural hazards

Appendix B

```
#Define dataframe to update
ind_update<-ind
win_0975_df<-cbind(win_0975_df,Nr=ind_update$Nr)
#Update dataframe with winsorized data
ind_update[ ,c("V5.1","V5.2","V5.3","V6.1","V6.2",
              "V6.3","V6.4","V10.2","V11.3","V12.1",
              "V13.1")] <- list(NULL)
ind_update<-merge(ind_update,win_0975_df,by="Nr")
ind_update <- ind_update[colnames(ind)]

#NORMALIZATION
#-----
#Normalize dataframe
polarity_norm<-c("POS","POS","POS","POS","POS","POS","POS","POS","POS","POS",
                "POS","POS","POS","POS","POS","POS","POS","POS","POS","POS",
                "POS","NEG","POS","POS","POS","POS","POS","POS","POS","NEG","NEG",
                "POS","POS","POS","NEG","NEG")
ind_minmax<-normalise_ci(ind_update,c(3:37),polarity_norm,method=2)
ind_zscore<-normalise_ci(ind_update,c(3:37),polarity_norm,method=1,z.mean=0,
                        z.std=1)
write.xlsx(ind_minmax,"C:/path/ind_minmax.xlsx",
          sheetName="ind_minmax")
write.xlsx(ind_zscore,"C:/path/ind_zscore.xlsx",
          sheetName="ind_zscore")
#Convert list to dataframe
ind_minmax_temp<-ind_minmax
ind_minmax_temp$norm_method<-NULL
ind_minmax_df<-data.frame(matrix(unlist(ind_minmax_temp), ncol=35))
colnames(ind_minmax_df)=c("V1.1","V1.2","V1.3","V2.1","V2.2","V2.3","V3.1","V3.2",
                        "V4.1","V5.1","V5.2","V5.3","V6.1","V6.2","V6.3","V6.4",
                        "V6.5","V6.6","V7.1","V8.1","V9.1","V9.3","V9.4","V10.1",
                        "V10.2","V10.3","V10.4","V10.5","V10.6","V10.7","V10.8",
                        "V11.3","V12.1","V13.1","V14.1")
remove(ind_minmax_temp)

ind_zscore_temp<-ind_zscore
ind_zscore_temp$norm_method<-NULL
ind_zscore_df<-data.frame(matrix(unlist(ind_zscore_temp), ncol=35))
colnames(ind_zscore_df)=c("V1.1","V1.2","V1.3","V2.1","V2.2","V2.3","V3.1","V3.2",
                        "V4.1","V5.1","V5.2","V5.3","V6.1","V6.2","V6.3","V6.4",
                        "V6.5","V6.6","V7.1","V8.1","V9.1","V9.3","V9.4","V10.1",
                        "V10.2","V10.3","V10.4","V10.5","V10.6","V10.7","V10.8",
                        "V11.3","V12.1","V13.1","V14.1")
remove(ind_zscore_temp)

#Divide dataframe in susceptibility and lack of resilience domain
ind_minmax_SUS<-select(ind_minmax_df,V2.1,V2.2,V2.3,V3.1,V3.2,V4.1,V10.1,V10.2,
                    V10.3,V10.4,V10.5,V10.6,V10.7,V12.1)
ind_minmax_LoR<-select(ind_minmax_df,V1.1,V1.2,V1.3,V5.1,V5.2,V5.3,V6.1,V6.2,V6.3,
                    V6.4,V6.5,V6.6,V7.1,V8.1,V9.1,V9.3,V9.4,V10.8,V11.3,V13.1,
                    V14.1)
ind_zscore_SUS<-select(ind_zscore_df, V2.1,V2.2,V2.3,V3.1,V3.2,V4.1,V10.1,V10.2,
                    V10.3,V10.4,V10.5,V10.6,V10.7,V12.1)
ind_zscore_LoR<-select(ind_zscore_df,V1.1,V1.2,V1.3,V5.1,V5.2,V5.3,V6.1,V6.2,V6.3,
                    V6.4,V6.5,V6.6,V7.1,V8.1,V9.1,V9.3,V9.4,V10.8,V11.3,V13.1,
                    V14.1)

#Write in Excel
write.xlsx(ind_minmax_SUS, "C:/path/ind_minmax_SUS.xlsx",
          sheetName="ind_minmax_SUS")
write.xlsx(ind_minmax_LoR, "C:/path/ind_minmax_LoR.xlsx",
          sheetName="ind_minmax_LoR")
write.xlsx(ind_zscore_SUS, "C:/path/ind_zscore_SUS.xlsx",
          sheetName="ind_zscore_SUS")
write.xlsx(ind_zscore_LoR, "C:/path/ind_zscore_LoR.xlsx",
          sheetName="ind_zscore_LoR")
```

Mapping social vulnerability to natural hazards

Appendix B

```
#MULTIVARIATE ANALYSIS
#-----
#Calculate correlation
write.xlsx(cor(ind_minmax_SUS), "C:/path/Corr/corr_minmax_SUS.xlsx",
           sheetName="corr_minmax_SUS")
write.xlsx(cor(ind_minmax_LoR), "C:/path/Corr/corr_minmax_LoR.xlsx",
           sheetName="corr_minmax_LoR")
write.xlsx(cor(ind_zscore_SUS), "C:/path/Corr/corr_zscore_SUS.xlsx",
           sheetName="corr_zscore_SUS")
write.xlsx(cor(ind_zscore_LoR), "C:/path/Corr/corr_zscore_LoR.xlsx",
           sheetName="corr_zscore_LoR")

#Plot correlation matrix
coll<-colorRampPalette(rev(c("#67001F", "#B2182B", "#D6604D", "#F4A582",
                           "#FDDBC7", "#FFFFFF", "#D1E5F0", "#92C5DE",
                           "#4393C3", "#2166AC", "#053061")))
corrplot(cor(ind_minmax_SUS), type="lower", col=coll(200), tl.col="black",
         tl.cex=1.2, tl.srt=45)
corrplot(cor(ind_minmax_LoR), type="lower", col=coll(200), tl.col="black",
         tl.cex=1.2, tl.srt=45)

corrplot(cor(ind_minmax_SUS), method="number", type="lower", col=coll(200),
         tl.col="black", tl.cex=1.2, tl.srt=45, number.cex=0.75)
corrplot(cor(ind_minmax_LoR), method="number", type="lower", col=coll(200),
         tl.col="black", tl.cex=1.2, tl.srt=45, number.cex=0.75)

#Calculate VIF
#Write in Excel
y<-data.frame("y"=rep(1,4037))
y<-as.matrix(y)

reg_minmax_SUS<-lm(y~V2.1+V2.2+V2.3+V3.1+V3.2+V4.1+V10.1+V10.2+V10.3+V10.4+V10.5+
                  V10.6+V10.7+V12.1,ind_minmax_SUS)
write.xlsx(vif(reg_minmax_SUS), "C:/path/Corr/VIF_minmax_SUS.xlsx",
           sheetName="VIF_minmax_SUS")
reg_minmax_LoR<-lm(y~V1.1+V1.2+V1.3+V5.1+V5.2+V5.3+V6.1+V6.2+V6.3+V6.4+V6.5+V6.6+
                  V7.1+V8.1+V9.1+V9.3+V9.4+V10.8+V11.3+V13.1+V14.1,ind_minmax_LoR)
write.xlsx(vif(reg_minmax_LoR), "C:/path/Corr/VIF_minmax_LoR.xlsx",
           sheetName="VIF_minmax_LoR")

reg_zscore_SUS<-lm(y~V2.1+V2.2+V2.3+V3.1+V3.2+V4.1+V10.1+V10.2+V10.3+V10.4+V10.5+
                  V10.6+V10.7+V12.1,ind_zscore_SUS)
write.xlsx(vif(reg_zscore_SUS), "C:/path/Corr/VIF_zscore_SUS.xlsx",
           sheetName="VIF_zscore_SUS")
reg_zscore_LoR<-lm(y~V1.1+V1.2+V1.3+V5.1+V5.2+V5.3+V6.1+V6.2+V6.3+V6.4+V6.5+V6.6+
                  V7.1+V8.1+V9.1+V9.3+V9.4+V10.8+V11.3+V13.1+V14.1,ind_zscore_LoR)
write.xlsx(vif(reg_zscore_LoR), "C:/path/Corr/VIF_zscore_LoR.xlsx",
           sheetName="VIF_zscore_LoR")

#Elimination of Variables with high collinearity (r>0.8, VIF>5.0)
ind_minmax_SUS_updatecorr<-ind_minmax_SUS
ind_minmax_SUS_updatecorr["V2.1"]<-NULL
ind_minmax_LoR_updatecorr<-ind_minmax_LoR
ind_minmax_LoR_updatecorr[,c("V9.1","V9.3")]<-list(NULL)
ind_zscore_SUS_updatecorr<-ind_zscore_SUS
ind_zscore_SUS_updatecorr["V2.1"]<-NULL
ind_zscore_LoR_updatecorr<-ind_zscore_LoR
ind_zscore_LoR_updatecorr[,c("V9.1","V9.3")]<-list(NULL)

#Plot correlation matrix
corrplot(cor(ind_minmax_SUS_updatecorr), type="lower", col=coll(200),
         tl.col="black", tl.cex=1.2, tl.srt=45)
corrplot(cor(ind_minmax_LoR_updatecorr), type="lower", col=coll(200),
         tl.col="black", tl.cex=1.2, tl.srt=45)

corrplot(cor(ind_minmax_SUS_updatecorr), method="number", type="lower",
         col=coll(200), tl.col="black", tl.cex=1.2, tl.srt=45, number.cex=0.75)
corrplot(cor(ind_minmax_LoR_updatecorr), method="number", type="lower",
         col=coll(200), tl.col="black", tl.cex=1.2, tl.srt=45, number.cex=0.75)
```

Mapping social vulnerability to natural hazards

Appendix B

```
#Calculate correlation
#Write in Excel
write.xlsx(cor(ind_minmax_SUS_updatecorr),
           "C:/path/Corr/update_corr_minmax_SUS.xlsx",
           sheetName="update_corr_minmax_SUS")
write.xlsx(cor(ind_minmax_LoR_updatecorr),
           "C:/path/Corr/update_corr_minmax_LoR.xlsx",
           sheetName="update_corr_minmax_LoR")
write.xlsx(cor(ind_zscore_SUS_updatecorr),
           "C:/path/Corr/update_corr_zscore_SUS.xlsx",
           sheetName="update_corr_minmax_SUS")
write.xlsx(cor(ind_zscore_LoR_updatecorr),
           "C:/path/Corr/update_corr_zscore_LoR.xlsx",
           sheetName="update_corr_minmax_LoR")

#Calculate VIF
#Write in Excel
reg_minmax_SUS_updatecorr<-lm(y~V2.2+V2.3+V3.1+V3.2+V4.1+V10.1+V10.2+V10.3+V10.4+
                             V10.5+V10.6+V10.7+V12.1,ind_minmax_SUS_updatecorr)
write.xlsx(vif(reg_minmax_SUS_updatecorr),
           "C:/path/Corr/update_VIF_minmax_SUS.xlsx",
           sheetName="update_VIF_minmax_SUS")
reg_minmax_LoR_updatecorr<-lm(y~V1.1+V1.2+V1.3+V5.1+V5.2+V5.3+V6.1+V6.2+V6.3+V6.4+
                             V6.5+V6.6+V7.1+V8.1+V9.4+V10.8+V11.3+V13.1+V14.1,
                             ind_minmax_LoR_updatecorr)
write.xlsx(vif(reg_minmax_LoR_updatecorr),
           "C:/path/Corr/update_VIF_minmax_LoR.xlsx",
           sheetName="update_VIF_minmax_LoR_")

reg_zscore_SUS_updatecorr<-lm(y~V2.2+V2.3+V3.1+V3.2+V4.1+V10.1+V10.2+V10.3+V10.4+
                             V10.5+V10.6+V10.7+V12.1,ind_zscore_SUS_updatecorr)
write.xlsx(vif(reg_zscore_SUS_updatecorr),
           "C:/path/Corr/update_VIF_zscore_SUS.xlsx",
           sheetName="update_VIF_zscore_SUS")
reg_zscore_LoR_updatecorr<-lm(y~V1.1+V1.2+V1.3+V5.1+V5.2+V5.3+V6.1+V6.2+V6.3+V6.4+
                             V6.5+V6.6+V7.1+V8.1+V9.4+V10.8+V11.3+V13.1+V14.1,
                             ind_zscore_LoR_updatecorr)
write.xlsx(vif(reg_zscore_LoR_updatecorr),
           "C:/path/Corr/update_VIF_zscore_LoR.xlsx",
           sheetName="update_VIF_zscore_LoR")

#Principle Component Analysis - Factor Analysis
#Write in Excel
PCA_SUS<-prcomp(ind_zscore_SUS_updatecorr)
summary(PCA_SUS)
eigenvalues_SUS<-get_eig(PCA_SUS)
loadings_SUS<-t(t(PCA_SUS$rotation)*sqrt(eigenvalues_SUS$eigenvalue))
write.xlsx(loadings_SUS, "C:/path/PCA/PCA_SUS.xlsx",
           sheetName="loadings_SUS")
write.xlsx(get_eig(PCA_SUS), "C:/path/PCA/PCA_SUS.xlsx",
           sheetName="eigen_SUS", append=TRUE)
fviz_eig(PCA_SUS, choice="eigenvalue")

PCA_LoR<-prcomp(ind_zscore_LoR_updatecorr)
summary(PCA_LoR)
eigenvalues_LoR<-get_eig(PCA_LoR)
loadings_LoR<-t(t(PCA_LoR$rotation)*sqrt(eigenvalues_LoR$eigenvalue))
write.xlsx(loadings_LoR, "C:/path/PCA/PCA_LoR.xlsx",
           sheetName="loadings_LoR")
write.xlsx(get_eig(PCA_LoR), "C:/path/PCA/PCA_LoR.xlsx",
           sheetName="eigen_LoR", append=TRUE)
fviz_eig(PCA_LoR, choice="eigenvalue")

#Varimax-rotation factors=5 based on eigenvalues >1.0 and total represented
Variance >60%
#Write in Excel
PCA_SUS_rotated<-principal(ind_zscore_SUS_updatecorr,rotate="varimax",nfactors=5,
                          scores=TRUE)
```

Mapping social vulnerability to natural hazards

Appendix B

```
write.xlsx(PCA_SUS_rotated$loadings[1:13,], "C:/path/PCA/PCA_SUS.xlsx",
  sheetName="varimax_SUS_loadings", append=TRUE)
write.xlsx(PCA_SUS_rotated$Vaccounted, "C:/path/PCA/PCA_SUS.xlsx",
  sheetName="varimax_SUS_Var", append=TRUE)

PCA_LoR_rotated<-principal(ind_zscore_LoR_updatecorr, rotate="varimax", nfactors=5,
  scores=TRUE)
write.xlsx(PCA_LoR_rotated$loadings[1:19,], "C:/path/PCA/PCA_LoR.xlsx",
  sheetName="varimax_LoR_loadings", append=TRUE)
write.xlsx(PCA_LoR_rotated$Vaccounted, "C:/path/PCA/PCA_LoR.xlsx",
  sheetName="varimax_LoR_Var", append=TRUE)

#Define final set of indicators/variables
#Normalized
ind_minmax_SUS_final<-ind_minmax_SUS_updatecorr
ind_minmax_LoR_final<-ind_minmax_LoR_updatecorr

ind_zscore_SUS_final<-ind_zscore_LoR_updatecorr
ind_zscore_LoR_final<-ind_zscore_LoR_updatecorr

#Write in Excel
write.xlsx(ind_minmax_SUS_final, "C:/path/Ind_minmax_SUS_final.xlsx",
  sheetName="ind_minmax_SUS_final")
write.xlsx(ind_minmax_LoR_final, "C:/path/Ind_final/Ind_minmax_LoR_final.xlsx",
  sheetName="ind_minmax_LoR_final")
write.xlsx(ind_zscore_SUS_final, "C:/path/Ind_final/Ind_zscore_SUS_final.xlsx",
  sheetName="ind_zscore_SUS_final")
write.xlsx(ind_zscore_LoR_final, "C:/path/Ind_final/Ind_zscore_LoR_final.xlsx",
  sheetName="ind_zscore_LoR_final")
```