MASTERARBEIT | MASTER'S THESIS

Titel | Title

Mapping Social Vulnerability at the local level. Methods, Challenges, Ethical considerations.

verfasst von | submitted by

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angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 855
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Geography: Global Change and Sustainability
Betreut von | Supervisor:	Dr. Marion Borderon MSc

Acknowledgments

First, I’d like to thank my supervisor Dr. Marion Borderon MSc for her continuous support and guidance throughout the whole process of this Master’s Thesis.

Then, I want to thank my mother and my sister for their continuous support, too, and their patience, generally, and, particularly, during the working process of this thesis.

Abstract English

In the context of growing harmful impacts by global climate change, particularly on the poorest populations, vulnerability assessments allow to guide policies aimed at reducing these impacts. Following recent critics of the concept of 'Vulnerability' and possible negative effects for the investigated populations, this thesis aims to conduct an integrated vulnerability assessment on the local scale, guided by ethical considerations. Using the case study of Kersa, Ethiopia, a drought-prone area, multidimensional socioeconomic characteristics serve as a proxy for social vulnerability at the face of potential drought events. The results of a Multidimensional Socioeconomic Index (MSEI) are mapped on the local level, allowing for identification and localization of socioeconomic inequalities, while preserving privacy and avoiding the risk of misrepresentation. Acknowledging the value of quantitative vulnerability assessments, propositions are made to reduce the risks of harmful effects of the concept, emphasizing the central role of transparency and communication of limitations and uncertainties related to vulnerability assessments.

Keywords

Climate change, Social Vulnerability, Local scale, Ethiopia, Mapping, Ethical considerations, Droughts, Socioeconomic inequalities

Abstract Deutsch

Vor dem Hintergrund der zunehmenden schädlichen Auswirkungen des globalen Klimawandels, insbesondere auf die ärmsten Bevölkerungsschichten, ermöglichen Vulnerabilitätsbewertungen eine Orientierung für politische Maßnahmen zur Verringerung dieser Auswirkungen. In Anlehnung an jüngste Kritiken am Konzept der "Vulnerabilität" und den möglichen negativen Auswirkungen auf die untersuchten Bevölkerungsgruppen, zielt diese Arbeit darauf ab, eine integrierte Vulnerabilitätsbewertung auf lokaler Ebene durchzuführen, die von ethischen Überlegungen geleitet wird. Anhand der Fallstudie von Kersa, Äthiopien, einem dürregefährdeten Gebiet, dienen multidimensionale sozioökonomische Merkmale als Indikator für die soziale Vulnerabilität angesichts möglicher Dürreereignisse. Die Ergebnisse eines mehrdimensionalen sozioökonomischen Index (MSEI) werden auf lokaler Ebene kartiert, was die Identifizierung und Lokalisierung sozioökonomischer Ungleichheiten ermöglicht, wobei die Privatsphäre gewahrt bleibt und das Risiko einer falschen Darstellung vermieden wird. In Anerkennung des Wertes quantitativer Vulnerabilitätsbewertungen werden Vorschläge zur Verringerung der Risiken schädlicher Auswirkungen des Konzepts gemacht, wobei die zentrale Rolle der Transparenz und der Kommunikation von Einschränkungen und Unsicherheiten im Zusammenhang mit Vulnerabilitätsbewertungen betont wird.

Schlagwörter

Klimawandel, soziale Vulnerabilität, Lokale Ebene, Äthiopien, Kartieren, ethische Aspekte, Dürren, sozioökonomische Ungleichheiten

List of abbreviations

CC	-	Climate Change
ENSO	-	El Nino- Southern Oscillation
HDSS	-	Health & Demographic Surveillance System
IPCC	-	Intergovernmental Panel on Climate Change
(IPCC) AR6	-	(IPCC) Assessment Report 6
LMIC	-	Low- or Middle-Income Country
MSEI	-	Multidimensional Socioeconomic Index
M-K Test	-	Mann-Kendall Test
NA	-	Not available (missing data)
n.d.	-	no date
SoVI	-	Social Vulnerability Index (Cutter et al., 2003)
SPEI	-	Standardized Precipitation and Evapotranspiration Index
SVA	-	Social Vulnerability Assessment
SVI	-	Social Vulnerability Index

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1. Introduction

1.1. Context

It is widely recognized that global Climate Change (CC) will have harmful impacts on many regions and communities across the world, particularly on the most disadvantaged and poorest (Füssel, 2012). The Intergovernmental Panel on Climate Change (IPCC) Assessment Report 6 (AR6) states with high confidence that "approximately 3.3 to 3.6 billion people live in contexts that are highly vulnerable to climate change", and that vulnerabilities to climate change differ substantially among and within regions (IPCC, 2022b: 5). 'Who are the most vulnerable?', 'Where are the most vulnerable?' and 'What are they vulnerable to?' are frequently asked and important questions in the face of growing CC impacts, as they potentially guide policy implications and prioritize important funding (de Sherbinin et al., 2018). Broadly defined as "the potential for loss" (Cutter et al., 2003: 242), vulnerability is often used as a straightforward (Brown, 2011) and self-explanatory concept (Gilodi et al., 2022). However, the concept of vulnerability is highly complex and interdisciplinary, and has been discussed and developed over the past four decades (Birkmann, 2013). Over time, the concept has evolved from considering human vulnerability as an outcome of exposure to environmental stressors, to considering and focusing on the social dimensions of vulnerability, which are investigated under the umbrella term 'Social Vulnerability'. Varying social, economic, political, cultural and institutional settings greatly influence how different societies and communities prepare for, respond to and recover from climatic and environmental shocks (Mavhura et al., 2017). Focusing on social vulnerability can reveal local patterns of vulnerability and explain why some regions, communities, households, or individuals are more vulnerable than others, despite facing the same exposure to potential stressors. Generally, so-called integrated vulnerability assessments combine exposure and social vulnerability of an investigated area or population. Targeted policies based on scientific evidence and recommendations can reduce inequalities and various vulnerabilities by reducing sensitivity and increasing adaptive capacity and resilience to climatic variabilities and environmental changes. To visually interpret vulnerability patterns, it is a common procedure to map the results of the vulnerability assessment of a given area, presenting a given population. These so-called vulnerability maps are used to direct attention to specific regions or areas of differing scale, where, according to the vulnerability analysis, impacts of a certain stressor are expected to be greatest. This directed attention to certain regions, areas, or communities should guide policies aimed at reducing the detected vulnerabilities.

This thesis investigates the Kersa district in the East Hararghe Zone, Oromia region, Ethiopia, as a case study, conducting an integrated vulnerability assessment with a particular focus on local social vulnerabilities. Ethiopia has a history of drought events and has recently been hit by a devastating drought in three successive years, between 2015-2017 (Mera, 2018) as well as the current, ongoing multi-year drought. Drought conditions and intensities differ at the sub-national scale, especially in a country the size of Ethiopia. Hence, local analyses are meaningful to analyse exposure to climatic and environmental hazards, such as droughts. In the context of social vulnerability, the Ethiopian economy has traditionally been characterized by "subsistence farming that is highly dependent on rainfall and extremely vulnerable to all kinds of shocks" (Admassie & Abebaw, 2014: 269). It is generally assumed that CC will more severely impact countries where "agriculture has a large share in the gross domestic product and the labour force" (Füssel, 2012: 12), which makes Ethiopia an appropriate case study for the investigation of local social vulnerabilities. On the local scale, detecting and localizing differentiated social vulnerabilities at the household level can guide precise policies or future research aiming at reducing these vulnerabilities.

1.2. Relevance of the thesis and Knowledge gaps

In the context of growing CC effects, identifying populations that are at risk of being most severely affected is crucial to guide policy recommendations aiming at reducing these vulnerabilities. Typically, the poorest countries are most severely affected by climate change impacts, as they have lower coping – and adaptation capacity. In 2019, 8 out of the 10 countries most affected by the impacts of extreme weather events have been low- to lower-middle income countries, and 5 out of the 10 are situated on the African continent (Eckstein et al., 2021). In AR6, the IPCC (2022: 1320) states that "the differential impacts of climate change and adaptation options available to vulnerable groups in Africa are a critical knowledge gap. More research is needed to examine the intersection of different dimensions of social status on climate change vulnerability in Africa (…)." This research gap is mainly linked to the lack of (reliable) data, both for environmental as well as socioeconomic factors. To identify effects of changing climates on socioeconomic conditions, multiple surveys over time are needed (IPCC, 2022). However, in Africa, from 2000 to 2010, 25 countries conducted only one nationally representative poverty survey, while 14 conducted none over this period (Jean et al., 2016). Most studies on climate change impacts in Africa "rely on evidence from global studies that use data largely from outside Africa" (IPCC, 2022: 1298). In this context, local studies that enable to analyze vulnerability, exposure and adaptive capacity in Africa, within one country or on the local level, are scarce.

Parallel to the need for vulnerability assessments, there are critical reflections coming up questioning the ethical appropriateness of the 'vulnerability' concept. As "the meaning, framing and assessment of vulnerability remains contested terrain" (Birkmann, 2013: 9), researchers should be careful when labelling individuals, households, or communities as 'vulnerable', as this label can mean very different things to different readers (Brown, 2011). The interdisciplinary, dynamic, and context-specific nature of 'vulnerability' poses considerable challenges in accurately measuring (social) vulnerability, which ultimately leads to concerns over harmful labelling and misrepresentation of populations and communities. This risk is even greater when conducting a vulnerability assessment on the local scale, investigating communities, households or even individuals. In this context, it is particularly imperative to assure privacy of the investigated populations, in order to minimize the risk of identifying specific households labelled as 'vulnerable'.

Other than surrounding the appropriateness of the vulnerability concept in general, ethical considerations should also guide visualizations of so-called vulnerability patterns through so-called vulnerability maps, where particular attention must be paid to assuring privacy of the investigated populations. As climate change vulnerability is the subject of research and policy priorities, "it is imperative to develop a better understanding of suitable approaches to vulnerability mapping across a range of scales, regions, climate hazards, and thematic foci" (de Sherbinin et al., 2018: 2), especially as "literature explicitly discussing vulnerability mapping is relatively sparse" (Cutter et al., 2009: 24).

1.3. Research Questions and Research Goals

The main research goal of this Master's Thesis is to identify local patterns of social vulnerability and find adequate mapping techniques to visualize these local patterns, both guided by ethical considerations. Moreover, when conducting a vulnerability assessment on the local scale, there are considerations to be made regarding privacy issues, especially when the results are mapped. These issues lead to the central research question of this thesis:

How can we develop a quantitative assessment and mapping of social vulnerability to climate change at the local scale that ensures the privacy of individuals and safeguards communities against harmful labelling or misrepresentation?

This research question incorporates multiple dimensions. First, the quantitative assessment of social vulnerability on the local scale, constitutes an initial, major part of the research. Here, a first sub-question is defined:

- Which methodologies and indicators effectively measure social vulnerability on the local scale?

As (social) vulnerability can't be measured in a direct way, researchers need to find methodologies and indicators that can accurately serve as a proxy to describe (social) vulnerability. This step greatly influences the outcome of the social vulnerability assessment and therefore needs to be handled with careful consideration. The choice of indicators used to measure or be used as a proxy for social vulnerability is essential and of great importance concerning the aspect of misrepresentation and harmful labelling. Choosing inappropriate, not enough, or too many indicators can inaccurately describe the investigated populations as vulnerable. Hence, the choice of appropriate methods and context-specific indicators are essential and should be handled with careful consideration.

The second part of the central research question refers to the mapping of social vulnerability on the local scale. As already described, a map is often the most effective, and most used way to disseminate the results of a (social) vulnerability assessment. The aim of this thesis is to find ways to map local vulnerability patterns while conserving privacy and minimizing the risk of harmful labelling and misrepresentation of the populations under investigation. Here, more sub-questions arise:

- How can local vulnerability patterns be mapped to maximise information while assuring privacy?
- What strategies can be applied to minimize the risk of misrepresentation and harmful labelling of the populations under investigation?
- How can researchers assure transparency and effectively communicate the limitations and uncertainties inherent in assessing and mapping climate change vulnerability at the local level?

These questions all contribute to a local social vulnerability assessment that is guided by ethical considerations. By finding answers to these research questions, this thesis aims at proposing methods assuring that future quantitative vulnerability assessments are ethically appropriate and do not misrepresent or harmfully label investigated populations.

Additionally, as this thesis aims for an integrated vulnerability assessment, incorporating both social vulnerability as well as exposure, the following sub-question will also be considered in the frame of this study:

- What is the investigated population vulnerable to?

This question focusses on the main environmental and/or climatic hazards faced by the population in Kersa, Ethiopia.

1.4. Data and Methodology

To investigate the described research questions, this thesis utilizes Health and Demographic Surveillance System (HDSS) Data from Kersa, Ethiopia. The Kersa HDSS Site is part of the INDEPTH Network, which currently observes 49 HDSS field sites which represent over 3.8 million people under surveillance in 19 LMICs in Africa, Asia, and Oceania (INDEPTH Website, n.d.). Other than health- and demographic-related data, HDSS data provide longitudinal geolocalized socioeconomic data on a dynamic cohort in a defined area. In Kersa, after a baseline census in 2007, the survey has been conducted every 6 months (Assefa et al., 2015). In 2010, global positioning system (GPS) coordinates have been taken for each household in the HDSS (Assefa et al., 2015), which form the basis of this study. The dataset covers 12787 households distributed across the 12 Kebeles. This thesis utilizes data from 2014, where socioeconomic conditions were first collected. More information on HDSS data, and, specifically, the Kersa HDSS, can be acquired at the INDEPTH Network website (INDEPTH Website, n.d.).

The HDSS data is used to construct a composite indicator, describing multidimensional socioeconomic characteristics of the Kersa population, which is used as a proxy for social vulnerability. The spatial patterns of the created composite indicator are visualized through maps for each Kebele (smallest administrative unit of Ethiopia) in Kersa.

To investigate exposure, Standardized Precipitation and Evapotranspiration Index (SPEI) High-Resolution (HR) data was used to analyze drought events in the Kersa region for the time period 1981 - 2016 (36 years). The SPEI-HR dataset covers the whole of Africa at a monthly temporal resolution and 5 km spatial resolution, allowing local analysis. Different accumulation periods (1 - 48 months) to calculate the SPEI facilitate the diagnosis of different types of drought events, having different durations, from meteorological to hydrological droughts (Peng et al., 2020). The analysis consists in detecting drought frequencies in Kersa for the investigated time period as well as visualizing local drought patterns in the Kersa region. The high-resolution SPEI dataset is publicly available from the Centre for Environmental Data Analysis (CEDA).

Since 2018, the University of Vienna and the Haramaya University in Eastern Ethiopia share an Agreement on Academic Collaboration, aiming 'to develop joint research activities on the topics of migration and demography in the Kersa region (University of Vienna, n.d.). More information on this agreement can be found at the University of Vienna website (University of Vienna, n.d.).

1.5. Structure of the Thesis

After presenting the context of the study, the scientific relevance with related research gaps, the formulation of the research questions and the research goals, and the data and methodology used in the study, the thesis will proceed to present conceptual and methodological developments of Social Vulnerability. Chapter 2.1. describes the concept and its evolution from Vulnerability to Social Vulnerability, while Chapter 2.2. discusses methodologies and related challenges in measuring Social Vulnerability, as well as the link between vulnerability and poverty. In Chapter 2.3., recent critics of the Vulnerability concept are presented and discussed. In Chapter 3, Kersa, Ethiopia, is presented as a case study of this thesis, elaborating social, economic and demographic as well as climate change and drought patterns in Ethiopia in general, before specifically presenting the Kersa region and the 12 Kebeles under investigation. Here, an SPEI analysis serves as 'Exposure' investigation and allows for identification of local drought patterns over the time period 1986 - 2016. Chapter 4 presents the methodological index construction of a Multidimensional Socioeconomic Index (MSEI), which serves as a proxy for social vulnerability. Here, sub-chapters (4.1. - 4.3) treat presentation of the data, variable selection, data preparation, normalization, weighting, aggregation, validation and mapping of the MSEI. Chapter 5 presents the results of the visualized local patterns of the constructed MSEI within the 12 Kebeles of the Kersa. The results are mapped separately for each Kebele and subdivided according to MSEI scores. Chapter 6 then specifically discusses transparency, limitations and uncertainties regarding the social vulnerability assessment (SVA), which represent important issues, especially when the work is guided by ethical considerations. Chapter 7 discusses the main results, findings and implications of the thesis, before Chapter 8 concludes.

2. Theoretical Framework: Vulnerability

2.1. From Vulnerability to Social Vulnerability

The concept of vulnerability has its roots in geography and natural hazards research (Füssel, 2012) and has been on research agendas of different disciplines since the late 1970s (Marino & Faas, 2020). This interdisciplinary approach, which draws insights from geography, sociology, environmental science, economics, and other disciplines, is crucial in comprehending the complex interactions between biophysical and social factors that shape vulnerability to environmental hazards. However, different backgrounds contribute to different conceptualizations and definitions of vulnerability. According to Birkmann (2013: 20) “the current literature encompasses more than 30 different definitions, concepts and methods to systematize vulnerability”, highlighting the complexity, multidisciplinarity and growing popularity of the concept.

Until the early 2000s, human vulnerability was primarily understood in relation to the physical damages caused by climatic and environmental stressors. Therefore, differentiated vulnerabilities and impacts among a population or different areas were linked to the degree of exposure to adverse events and therefore explained by geographical and climatic characteristics of the affected area (Cappelli, 2023). Then, it was recognized that some suffer more than others from climatic or environmental stressors, which shifted the focus to human systems and their ability to respond to the experienced impacts, which can either mitigate or increase their harm (Cappelli, 2023). Today, vulnerability is primarily conceived as a “social construction” (Cappelli, 2023: 3) and assessment of social vulnerability is recognized as “critical to understanding natural hazards risks and developing effective response capabilities” (Tate, 2012: 326). However, this should not deny the possibility of disasters where the natural event dominates and differential social vulnerabilities do not play a major role, which is, however, considered as rare (Wisner et al., 2004).

The evolution of the IPCC’s definition of vulnerability shows a similar pathway. While, until the 2007 IPCC report, exposure remained to be a focal point in defining vulnerability, from the 2014 report on, the sole focus was on sensitivity and adaptive capacity (Cappelli, 2023). This evolution in the understanding of vulnerability allows for "a shift in focus from responding to the disaster event toward an understanding of disaster risk" (Cardona et al., 2012: 71), i.e. from an ex post to an ex ante approach. In the IPCC's most recent Assessment Report (AR6) from 2022, vulnerability is defined as:

> *"The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt"* (IPCC, 2022: 2927).

This definition highlights sensitivity and adaptive capacity as the two main dimensions determining vulnerability. Both concepts are interlinked and influence each other, high adaptive capacity can reduce sensitivity to environmental and climatic stressors, while low adaptative capacity can increase sensitivity.

Adaptive capacity is defined as "the ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities or to respond to consequences" (IPCC, 2022: 2899). According to Cappelli (2023: 5), adaptive capacity refers to "critical system-specific attributes" inherent in a system, such as irrigation systems in agriculture or crop rotation for soil regeneration. These attributes enable the system to mitigate and respond to hazards effectively. Conversely, vulnerability tends to increase in systems lacking adaptive capacity or due to 'maladaptation' (Cappelli, 2023: 5).

In AR6, sensitivity is defined as "the degree to which a system or species is affected, either adversely or beneficially, by climate variability or change. The effect may be direct (e.g., a change in crop yield in response to a change in the mean, range, or variability of temperature) or indirect (e.g., damages caused by an increase in the frequency of coastal flooding due to sea level rise)" (IPCC, 2022: 2922). Cappelli (2023: 4) explains that high sensitivity of a human system is "the result of context-specific and intrinsic conditions of the system itself". Thus, sensitivity accounts for "the weaknesses that make the system predisposed to suffer damages from the occurrence of a hazard" (Cappelli, 2023: 4). Importantly, as elaborated, "such a damage may be prevented or at least mitigated if the system is endowed with adaptive capacity" (Cappelli, 2023: 4), highlighting the interrelation between both concepts.

Exposure, meanwhile, is regarded as a separate, although linked concept to vulnerability, and is defined as “the presence of people; livelihoods; species or ecosystems; environmental functions, services, and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected” (IPCC, 2022: 2908). Depending on sensitivity and adaptive capacity, a system can be highly exposed to climatic and environmental stressors but not be vulnerable to these, and, vice versa, a system can be not exposed to climatic and environmental stressors but still be highly vulnerable if they were to occur. A system, a community, or an individual is seen as vulnerable when they are potentially exposed to climatic or environmental stressors, are sensitive to those stressors, and have limited adaptive capacity to prepare, react or adapt to these events.

According to the shift in focus from the biophysical factors and exposure to socioeconomic, cultural, demographic, and political factors, researchers use the term social vulnerability to “separate the biophysical from the human dimension of natural hazards” (Otto et al., 2017: 1652). Several authors have proposed a definition on social vulnerability. Cutter and Finch (2008: 2301) define social vulnerability as “a measure of both the sensitivity of a population to natural hazards and its ability to respond to and recover from the impacts of hazards”, while Füssel (2012: 11) defines the concept as “the (lack of) capability of individuals, groups or communities to cope with and adapt to any external stress placed on their livelihoods and well-being” and further states that this is “determined by the availability of resources and by the entitlement of individuals and groups to call on these resources” (Füssel, 2012: 11). These definitions emphasize the role of adaptive capacity and sensitivity, as described above. More detailed, Cutter et al. (2009: 2) describe social vulnerability as explicitly focusing on “those demographic and socioeconomic factors that increase or attenuate the impacts of hazard events on local populations, in other words who is at risk and the degree to which they can be harmed”. The focus on social vulnerability allows researchers to identify inequalities among investigated populations that lead to differentiated vulnerabilities at the face of potential climatic and environmental stressors. The question now is what demographic and socioeconomic factors contribute to sensitivity, adaptive capacity, and, ultimately, social vulnerability. This aspect will be discussed in the following Chapter 2.2.

2.2. Measuring Social Vulnerability

2.2.1. Challenges in measuring Social Vulnerability

The concept of social vulnerability represents a "latent" variable, "something inherent to a person or a place but not directly observable" (Spielman et al., 2020: 419). A latent variable "can only be measured indirectly through statistical procedures (…) with sufficient information about things that can be directly measured" (Spielman et al., 2020: 419). Hence, in order to measure social vulnerability, a composite indicator, or index, needs to be created. In general, an indicator is "a quantitative or a qualitative measure derived from a series of observed facts that can reveal relative positions (e.g. of a country) in a given area" (OECD, 2008: 13). More precisely, a composite indicator "is formed when individual indicators are compiled into a single index on the basis of an underlying model" (OECD, 2008: 13). Composite indicators are created for multidimensional concepts that cannot be described or measured by one single indicator. Social vulnerability, as discussed in the previous chapter (2.1.) is indeed a perfect example of a multidimensional, complex concept which cannot be measured by a single indicator, as the concept encompasses multiple aspects, ranging from economic and demographic to social, structural and cultural dimensions. *Table 1* presents Pros and Cons of composite indicators as described by the Composite Indicator Handbook by the OECD (2008).

Pros:	**Cons:**
• Can summarise complex, multi-dimensional realities with a view to supporting decision-makers. • Are easier to interpret than a battery of many separate indicators. • Can assess progress of countries over time. • Reduce the visible size of a set of indicators without dropping the underlying information base.	• May send misleading policy messages if poorly constructed or misinterpreted. • May invite simplistic policy conclusions. • May be misused, *e.g.* to support a desired policy, if the construction process is not transparent and/or lacks sound statistical or conceptual principles. • The selection of indicators and weights could be the subject of political dispute.

• Thus make it possible to include more information within the existing size limit. • Place issues of country performance and progress at the centre of the policy arena. • Facilitate communication with general public (*i.e.* citizens, media, *etc.*) and promote accountability. • Help to construct/underpin narratives for lay and literate audiences. • Enable users to compare complex dimensions effectively.	• May disguise serious failings in some dimensions and increase the difficulty of identifying proper remedial action, if the construction process is not transparent. • May lead to inappropriate policies if dimensions of performance that are difficult to measure are ignored.

Table 1: Pros and Cons of Composite Indicators (OECD, 2008: 13-14)

Although less numerate than the Pros, the Cons for composite indicators as described by the OECD (2008) are essential and particularly true for the concept of vulnerability. As the concept of vulnerability aims to guide policy recommendations, it is very important to consider limitations of composite indicators, such as, e.g., the risk of misinterpretation or simplistic conclusions. These factors are discussed in Chapter 2.3.

As Tate (2012) outlines, vulnerability indices can be structured in various ways. First, there are deductive designs, where typically less than ten indicators are normalized and aggregated to the index. Then, there are hierarchical designs, which typically include ten to twenty indicators, which are separated into different groups, such as e.g. socioeconomic status or demographic structure, which are then aggregated into the final vulnerability index. Finally, there are inductive designs, which begin with larger sets of variables, which are reduced by conducting statistical methods such as Principal Component Analysis (PCA), to then build the index using uncorrelated latent factors. This last approach has been popularized by Cutter et al.'s (2003) Social Vulnerability Index (SoVI), and now forms the basis for the majority of social vulnerability indices (Tate, 2012).

Over the last two decades, a number of social vulnerability indicators came up from scientific research. The Human Development Index (UNDP, 2010) or the Disaster Risk Index (UNDP, 2004) are amongst well known indices at the global and regional scale (Tate, 2012). On the sub-national scale, the most widespread social vulnerability indicator is the Social Vulnerability Index (SoVI) as presented by Cutter et al. (2003). Originally applied as an analysis of social contributions to natural hazard or disaster vulnerability at the county level in the United States for 1990, the SoVI has since been replicated in a considerable number of studies in various geographic settings, spatial scales and time periods (e.g., Muyambo et al., 2017; Dintwa et al., 2019; Mavhura et al., 2017; Holand & Lujala, 2013). However, recently, there have been critics of the SoVI as proposed by Cutter et al. (2003). Spielman et al. (2019), found critical shortcomings in the index's internal and theoretical consistency and therefore "question if the SoVI provides a defendable or reliable approach for understanding place vulnerability to guide risk-reduction efforts" (Spielman et al., 2019: 433). Rufat et al. (2019) also investigated the empirical validity of a range of models of social vulnerability. Their empirical analysis from Hurricane Sandy raises questions about the SoVI construct validity. Although the SoVI is the most widespread vulnerability indicator, it is important to note that there are many other widely used indicators, such as the SVI by Flanagan et al. (2011). As Cutter et al. (2009: 13) argue, "developing a universal metric or measurement tool for vulnerability assessments across all disciplines is challenging given the ever-present definitional ambiguity along with the dynamic nature and changing scale of analysis (temporal and spatial)". Hence, it is important to adapt and contextualize the SoVI (or any other Social Vulnerability Indicator (SVI)), rather than replicate it when applying it to a new setting (Holand & Lujala, 2013). In this context, Schmidtlein et al. (2008) further stress the importance of coupling quantitative social vulnerability assessments with qualitative expert recommendations to ensure that the vulnerability assessment is "reasonable and consistent with locally based geographic knowledge of the study area" (Schmidtlein et al., 2008: 1112). This need for qualitative expert recommendations further highlights the challenges in constructing a quantitative SVI that accurately 'measures' vulnerability patterns in a given context.

However, there is a general consensus within the literature about some major factors influencing social vulnerability. These include different dimensions such as "poverty, social marginalization and powerlessness, demography, social networks, education, health, and well-being" (Birkmann, 2013: 26). Disagreements arise when choosing concrete variables to measure these broader concepts (Cutter et al., 2003). In the literature, age, gender, race and socioeconomic status are among the generally accepted characteristics influencing social vulnerability (Cutter et al., 2003). Apart from these general indicators which should be applicable in most contexts, there are always region-, place- and hazard-specific indicators that should be included in a social vulnerability assessment, corresponding to the already elaborated need to adapt SVIs to new contexts. For instance, in the context of drought assessments in LMIC's, it is reasonable to integrate type of and distance to main drinking water sources. Generally, the selection of variables for vulnerability indexes is a subjective process (Holand & Lujala, 2013). As Mah et al. (2023: 9) state, "there are many ways to choose social factors in an index, from theory driven to data availability to community consultations; however, there is no gold standard". *Table 2* sums up the variables that have been used most often in SVI's, as identified in Mah et al.'s (2023) review of social vulnerability indices. This list further highlights the wide range of variables which can be selected when constructing an SVI. However, these findings also show that, "despite differing fields, purposes and applications of the 121 original SVIs" included in the review, the authors identified "seven domains of social factors that were used in the composition of over half of the SVIs: at risk populations, education, micro (i.e., individual, family or household) level markers of socioeconomic status, household composition, employment, housing, and population health statistics" (Mah et al., 2023: 8). Ultimately, it is the researcher's choice on which indicators he, she, or they choose as being the most appropriate proxies for social vulnerability or on what aspects they choose to focus on.

Besides the difficulties in picking the right variables for a specific context, picking the right number of variables can also be a challenge. As Badmos et al. (2017: 2265) note, "too many indicators may create noise that can be tricky to explain", while "insufficient indicators may limit the extent of the understanding of vulnerability". The challenge of determining the optimal number of variables to incorporate into a SVI is also highlighted in the review of social vulnerability indices by Mah et al. (2023), which notes that the number of indicators used varies widely, from as few as four to as many as sixty.

As already noted (Chapter 1.2.), another important aspect when selecting specific variables in developing countries is the inadequacy or non-availability of secondary data. Often, "data on good indicator(s) may be imperfect or limited whereas data on weak indicator(s) may be readily available" (Badmos et al., 2017: 2265). Most researchers relied on census (Dintwa et al., 2019), surveys (Muyambo et al., 2017; Badmos et al., 2017) or mixed data sources (e.g. interviews, focus groups and census reports (Mavhura et al., 2017)) as a data source when conducting vulnerability assessments in LMICs (in these cases, in Sub-Saharan Africa). Data insufficiency and/or non adequacy often plays a major role and determines which indicators and how many indicators are included in a SVI.

Domains and Items in > 50% of SVIs	Domains and Items in 20–50% of SVIs	Domains and Items in < 20% of SVIs
At risk populations (76.0%)	**Gender or Sex (49.6%)**	**Disaster Preparedness (19.0%)**
Older Adults	**Density (47.1%)**	Access to Internet, Phone or Radio
Children	Population Density	Community Disaster Resources
Dependents	Urban or Rural	First Responders
Institutionalized	Building Density	**Marital Status (18.2%)**
Child Laborers	**Micro Level Socioeconomic Status (42.1%)**	**Land Use (17.4%)**
Teen Pregnancy	Community Poverty or Standard of Living	General Land Use
Victims of Domestic Violence	Gross Domestic Product or Community Finances	Farming or Soil Use
Education (74.4%)	Trade	Forest
Micro Level Socioeconomic Status (66.1%)	**Healthcare Infrastructure (40.5%)**	Green Space
Income or Wealth	Healthcare Facilities	Ecological Land Use
Income Assistance	Medical Staff	**Social Engagement (15.7%)**
Land Size	Health Insurance	Clubs or Community Centers
Savings or Debt	Public Health	Golf, Physical Leisure or Walking
Food Insecurity	Basic Services	Church or Religion
Access to Banking	Health Expenditure	Amount of Social Engagement
Household Composition (62.0%)	Avoidable Hospital Admissions	Volunteering
Size of Household	**Transport (33.1%)**	Feelings Towards Social Engagement
Single Parent or Female-Headed Household	Transport Infrastructure	Activities Around the Home (e.g., gardening)
Lives Alone	Road Infrastructure	Cards or Games
Child-Headed Household	Access to Railways, Roads or Transit (Community)	Hobby, Project or Further Education
Employment (61.2%)	Able to Get Places (Individual)	Pets
Unemployment	**Ethnicity or Race (32.2%)**	**Power Sources (15.7%)**
Occupation	**Water and Waste (26.4%)**	Power and Electricity Infrastructure
Housing (56.2%)	Water Infrastructure & Safety	Biomass
Housing Materials or Condition	Waste Infrastructure and Collection	**Personal Attitudes and Expectations (10.7%)**
House Ownership	**Social connection and capital (21.5%)**	Control
House Without Necessities	Relationships with Family	Expectations of Self and Others
Housing Type	Relationships with Friends	Satisfaction with Life
Housing Price	General Relationships	Attitude Towards Life
Housing Vacancy	Emotional Support Available	Self Worth or Self Esteem
Group Housing	General Support Available to Help	Major Life Events
Homelessness	Relationships with Neighbours	Hope for the Future
Population Health Statistics (55.4%)	Telephone Use	**Industry (10.7%)**
Migration	Ability to Give	Tourism or Hospitality
Average Age	Specific Task Support Available	Specific Industries (e.g. Cotton)
Population Growth	Help Available in a Crisis	General Industries (e.g. Primary)
Total Population	Relationships with Children	**Environment and Climate Events (10.7%)**
Birth Rate	Community Social Support	Flood
Mortality Rate	Loving Support Available	Extreme Weather
Life Expectancy	Relationships with Community	Rainfall or Drought
	Relationships with Spouse	Landslides
	Individual Communication (20.7%)	**Government Aptitude and Investments (7.4%)**
	Ability to Communicate (Oral or Written)	School Infrastructure
	Sensory Problems	Capacity for Governance
		Corruption
		Research and Development Infrastructure
		Isolation or Loneliness (6.6%)
		Health Conditions (6.6%)
		Chronic Health Conditions or their Risk Factors
		HIV / AIDS
		Poor Mental Health
		Specific Disease Incidence
		Specific Disease after Flood
		Adherence to Medical Advice
		Political Stability (5.0%)
		Refugees Displaced
		Political Armed Conflict
		Noise or Air Pollution (2.5%)

Table 2: Variables used across 121 different original SVI's (Mah et al., 2023: 7)

2.2.2. Link between Poverty and Social Vulnerability

It is generally accepted that there is a relationship between poverty and vulnerability, with the poor often described as the most vulnerable to climate change. Evidence has shown that "the poor are more vulnerable at all stages - before, during, and after - of a catastrophic event" (Flanagan et al., 2011: 2). Individuals with limited financial assets and resources face greater challenges in adapting to or mitigating the impacts of climate or environmental changes (Füssel, 2012; Leichenko & Silva, 2014; Cutter et al., 2009). Further, poor peoples' livelihoods are "more likely to depend on climate sensitive sectors (e.g., agriculture, forestry, fishing, pastoralism)" (Leichenko & Silva, 2014: 542), making them more vulnerable to climate variabilities and changes. To refer to the IPCC's (2022) definition of vulnerability, poverty limits adaptive capacity and increases sensitivity to climatic and environmental stressors. Then, research has shown that poorer households and communities tend to live in areas facing a higher risk, i.e. higher exposure, to environmental hazards (Brouwer et al., 2007; Winsemius et al., 2018). However, the causal relationship between poverty and exposure may go in both directions: Poor people may tend to settle in flood- and drought-prone areas, while households affected by these environmental hazards have a higher risk of falling into poverty (Winsemius et al., 2018). In addition to the geographic exposure to environmental stressors, "poor people are more likely to live in substandard housing, which can be a major disadvantage when disasters occur" (Cutter et al., 2009: 20). Generally, climatic and environmental hazards have the potential to exacerbate poverty patterns in direct, e.g. through food prices or agricultural production, and indirect, more complex ways. Further, climate change and climatic or environmental hazards have the potential to create or exacerbate so-called poverty traps, which are defined as "self-reinforcing mechanisms that create significant barriers to escaping poverty" (Leichenko & Silva, 2014: 547).

Similar to vulnerability, there are many different conceptualizations, definitions and ways to measure poverty. Economic indicators, like e.g. income, have traditionally been and are still the predominant measure for poverty. However, since the 1970s, non-monetary considerations have been integrated into poverty literature and have become increasingly important (Leichenko & Silva, 2014). Today, it is widely acknowledged that poverty is multidimensional and incorporates low income, but also a wide range of other disadvantages that are “related to, but not entirely dependent upon” monetary aspects (Leichenko & Silva, 2014: 540). For example, in the context of rural African communities, the number of livestock owned, possession of a radio, and quality of residential homes are frequently used indicators of wealth (Deressa et al., 2008).

However, it is not simply ‘being poor’ that makes a person vulnerable, but, rather, it’s a “combination of many dimensions of poverty, including income, social exclusion, lack of assets and capabilities, as well as a range of contextual factors and external stresses” (Leichenko & Silva, 2014: 542) that increases a person’s vulnerability to climate change, which again points at the multidimensional nature of poverty, but also its’ multidimensional relationship to vulnerability.

It is important to note that poor individuals and communities can be “highly resilient” and “display significant capacity to learn from extreme events and take steps to reduce future vulnerability” (Leichenko & Silva, 2014: 543). Hence, it would be wrong to claim that everyone who is considered as poor is necessarily more vulnerable than others. Although poverty plays a significant role in contributing to (social) vulnerability, there are a lot of other factors influencing (social vulnerability), as elaborated in Chapter 2.2.2.

2.3. Criticism of Vulnerability concept

While vulnerability has been a widely used concept, not only in scientific research, but also in policymaking and political debates, recent discussions question its continued relevance and ethical implications. The term has become a ‘buzzword’ (Brown et al., 2017) and is often used as a self-explanatory phenomenon (Gilodi et al., 2022). However, recent critics argue that “vulnerability is neither conceptually straightforward nor as morally and politically neutral as its popularity may suggest” (Gilodi et al., 2022: 2), illustrated by the fact that there is no “common and systematic understanding” of the notion, “with conceptualizations and definitions varying enormously not only across fields of research but at times also within them” (Gilodi et al., 2022: 1-2).

What does it mean to label communities as vulnerable?

Could it have indirect negative effects?

In their literature review of the “contested” concept of vulnerability, Virokannas et al. (2018: 336) state that, while some authors find vulnerability “useful and promising”, there is a significant discourse on its potential to “stigmatize, label, marginalize, and objectify, denying the agency and voice of those seen as vulnerable”. The risk of denying the agency and voice of those labelled as vulnerable is particularly great when researchers conduct quantitative vulnerability assessments without conducting in-depth qualitative investigations on local circumstances, e.g. through interviews or group discussions, enabling the investigated populations to describe their situation themselves. Assessing vulnerability based on quantitative secondary data risks neglecting indigenous knowledge of populations that have been living in their environments over multiple generations. In this sense, Marino and Faas (2020: 33) argue that labelling populations as vulnerable “discursively nullifies the everywhere-visible “resilience,” toughness, and genius that exist in communities that are habitually exposed to risk and hazards”. The risk of misinterpretation or simplistic conclusions is generally inherent to composite indicators, as discussed in Chapter 2.2., which is particularly important to consider when investigating a concept as sensitive as vulnerability. Acknowledging the “deficit-oriented nature” of the term and its “association with stigma”, Brown, too, underscores the need to understand how individuals labeled as 'vulnerable' perceive such categorizations, which is essential for policies aimed at protecting the vulnerable to gain legitimacy among those they intend to help (Brown, 2011).

Vulnerability, according to Brown (2011: 318) “should be handled with care”, as the concept seems to be value-free, but in fact is value-laden and can be seen as “paternalistic and patronizing”. In this sense, the concept of vulnerability, potentially considers those labelled as vulnerable as being “less capable, less autonomous, less rational, less competent, etc.” (Gilodi et al., 2022: 11) as opposed to ‘normal’, i.e. capable, autonomous, rational and competent populations, contributing to a discourse of ‘Othering’. Similarly, the concept has an exclusionary potential (Gilodi et al., 2022), as it suggests some may need help rather than others, or some peoples’ vulnerabilities are more important than others.

Going further, Marino and Faas (2020) suggest that labeling communities or locations as vulnerable can mistakenly put focus on the experiences of the designated communities, and neglect the broader dimensions of actors and institutions “engaged in the (re)production, distribution, and contestation of risk, resources, and possible futures” (Marino & Faas, 2020: 34), which ultimately shape so-called vulnerability patterns. Marino and Faas (2020) further assert that what is often deemed as vulnerable results from complex historical events, notably influenced by factors such as colonialism, white supremacy, and patriarchy, shaping a sociohistorical production of vulnerability. Hence, Marino and Faas (2020) describe the risk of ‘addressing the affects rather than the causes’. They start from the assumption that vulnerability is not a trait that has always been inherent in populations, but rather has developed due to certain causes, and argue that many vulnerability assessments overlook these causes. While it is necessary to mitigate the direct harms faced by at-risk communities, this approach can inadvertently overshadow the need for systemic changes. This idea goes in hand with Brown’s critical publication on vulnerability, where she argues that the concept can focus on either the individual or the structural reasons, and here, most often, structural vulnerability is neglected (Brown, 2011; Virokannas et al., 2018). Generally, Brown calls for a reevaluation of the research agenda on vulnerability, urging scholars to move beyond viewing it as a pre-existing and easily measurable concept.

Generally, I argue that, given that (social) vulnerability is a concept that can’t be directly measured (see Chapter 2.2.1.), and further given the highly complex, interdisciplinary, context-specific, and dynamic nature, it will always remain a challenge to gain a comprehensive image on (social) vulnerability, especially when the assessment is based on secondary, quantitative data. Therefore, a (social) vulnerability assessment does not truly determine who is more vulnerable than others, but, rather, who tends to be more vulnerable than others based on some selected indicators believed to represent reality as accurately as possible. However, this remains a biased approach as the vulnerability assessment is influenced by the researchers’ decisions concerning variable selection and index construction. Further, it remains extremely challenging to consider every factor contributing to either in- or decreasing social vulnerability, especially on the local level, due to the high complexity of vulnerability, but also due to data availability. Hence, recent critics are right to question the ethical appropriateness of the concept. Apart from its potential to “stigmatize, label, marginalize, and objectify, denying the agency and voice of those seen as vulnerable" (Virokannas et al., 2018: 336) described above, SVAs risk to misrepresent the investigated populations by not accurately and comprehensively analyzing local patterns, especially when the assessment is done on a quantitative basis, without in-depth qualitative research. Due to these reasons, I have decided in this thesis not to label communities or households as 'vulnerable' but rather, try to identify those that, based on relevant literature, tend to be, but not necessarily are, more vulnerable than others. This assessment will be based on a set of socioeconomic indicators, due to the close links between poverty and 'vulnerability', described in Chapter 2.2.2. Hence, the methodology will consist in constructing a multidimensional socioeconomic index, which is used as a proxy for social vulnerability, while recognizing that socioeconomic indicators are not the only factors influencing social vulnerability. The use of 'vulnerability' in this thesis should not simplify the realities of the investigated communities, neither neglect their resilience efforts. Rather, generally, quantitative assessments of social vulnerability should navigate and direct future, qualitative, in-depth research to some regions or populations that are expected to be severely affected by climate change impacts. While, in this context, proven useful, quantitative assessments should be aware of their risks of misrepresenting, harmful labeling and limitations, and transparently communicate those to the end-user.

3. Case study Kersa, Ethiopia

3.1. Social, economic and demographic development

Ethiopia, formally known as the Federal Democratic Republic of Ethiopia, is a landlocked nation situated in the Horn of Africa region of Eastern Africa. It shares its borders with Eritrea to the north, Djibouti to the northeast, Somalia to the east and southeast, Kenya to the south, South Sudan to the west, and Sudan to the northwest. As of 2022, Ethiopia is inhabited by approximately 123,379,924 people (World Bank Open Data, 2020), making it the 12th-most populous country globally, the second-most populous in Africa after Nigeria, and the most densely populated landlocked country on the planet.

Over the last 15 years, the country has experienced an average annual economic growth rate of close to 10%, ranking among the highest in the world (World Bank, 2023). This consistently high economic growth led to poverty reduction in both urban and rural areas. While in 2011, 30% of the population lived below the national poverty line, this share decreased to 24% in 2016, with human development indicators improving as well (World Bank, 2023). However, compared to other countries with similar fast growth rates, “gains are modest” and “inequality has increased in recent years” (World Bank, 2023). Also, economic growth “has dropped significantly as a result of the COVID-19 pandemic and due to violent conflict within the country”, as well as “the increase in world market prices for food, agricultural inputs and energy caused by Russia's war of aggression against Ukraine” (BMZ, 2023).

Agriculture forms the basis of Ethiopia’s economy, representing about 33.88% of the country`s GDP (Wendimu, 2021) and employing some 79% of the population (Diriba, 2020). Ethiopia’s agricultural sector is largely characterized by “traditional farming systems and low production and productivity” (Wendimu, 2021: 21), making it sensitive to climate variabilities and climate change effects such as increased temperatures and reduces rainfalls. In addition, the country is largely characterized by arid and semiarid regions which are highly prone to desertification and drought events (Gezie, 2019). The country is known for regular food shortages, which occur, among other factors, due to recurrent drought events (Wendimu, 2021).

3.2. Climate Change and Droughts in Ethiopia

Despite being one of the lowest contributors to greenhouse gas emissions causing climate change, Africa has “already experienced widespread losses and damages attributable to human-induced climate change, including biodiversity loss, water shortages, reduced food production, loss of lives and reduced economic growth” (IPCC, 2022: 1289). Climate change affects climatic patterns in East Africa and Ethiopia in many different ways, and these effects are subject to regional and temporal variabilities. However, it was found that, in East Africa, since 2005, drought frequency “has doubled from once every six years to once every three years” (Gebremeskel Haile et al., 2019: 147). In Ethiopia, the recurrence frequency of droughts shortened from one in ten years during the earlier periods of the last 50 years to between every 3-5 or 6-8 years three decades ago, depending on regional differences (Mera, 2018).

Ethiopia has a history with drought events. According to the World Bank (2023), "frequent severe weather events alongside long-term impacts of climate change undermine agriculture and pastoral livelihoods as well as food security" in Ethiopia. Droughts, specifically, have "impacted nearly every sector in the past, including agriculture (loss of crops and livestock), water resources (increased evaporation and decreased availability of fresh water, resulting in water stress), insufficient water for industry, (and) reduced electricity production (from hydropower)" (Bogale & Bekeko, 2022: 474). Recently, Ethiopia has been hit by a devastating drought in three successive years, between 2015-2017 (Mera 2018) as well as the current, ongoing multi-year drought. According to The World Bank (2023), "the 2022 drought is the worst in forty years, severely affecting millions in the southern and eastern parts of the country. Overall, more than 20 million persons are facing severe food insecurity in 2023".

In its AR6, the IPCC (2021: 1570) defines droughts as "periods of time with substantially below-average moisture conditions, usually covering large areas, during which limitations in water availability result in negative impacts for various components of natural systems and economic sectors". Hence, droughts are a combination of natural factors, such as precipitation deficiencies or excessive evapotranspiration, and human factors, such as water use demands and water distribution and management (Wang et al., 2016). Droughts occur over varying time periods and different area extents and involve "numerous interacting climate processes and various land-atmosphere feedback" (Wang et al., 2016: 2).

In Ethiopia, the main rainfall season, Kiremt, ranges from June to September (Teshome & Zhang, 2019). This season accounts for "50–80% of the total annual rainfall (…), covers a large proportion of the country" (Mera, 2018: 25) and is "crucial to Ethiopia's water resource and agriculture operations" (Korecha and Barnston, 2007: 628). Hence, the most severe droughts in Ethiopia are "usually related to a failure of the Kiremt rainfall to meet the agricultural and water resource needs" (Korecha and Barnston, 2007: 628). It is widely accepted that the El Nino - Southern Oscillation (ENSO) influences rain patterns in Ethiopia (Korecha and Barnston, 2007; Mera, 2018). Generally, it has been observed that, during the Kiremt rain season, "suppressed rainfall has been observed to accompany El Niño over much of Ethiopia, often with economic catastrophe" (Korecha and Barnston, 2007: 633), while La Nina is associated with enhanced summer rainfalls.

3.3. Droughts in Kersa

This thesis focusses on the Kersa district, located in the East Hararghe Zone, Oromia region. The study site includes 12 sub-districts, called Kebeles. *Figure 1* shows the location of the Kersa district within Ethiopia, as well as the location of the 12 included Kebeles within the Kersa district. Further, it shows elevations in meters across the Kersa district.

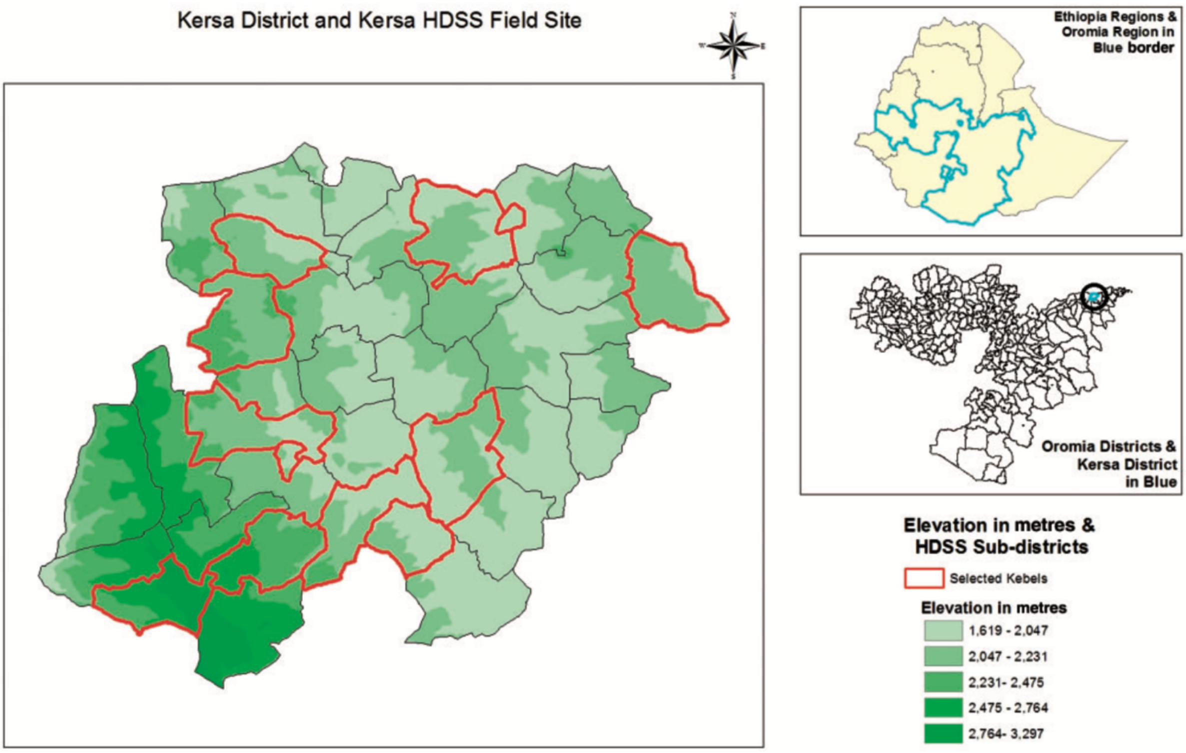


Figure 1: Location of the Kersa district with selected Kebeles (Assefa et al., 2015: 95)

When conducting a comprehensive vulnerability assessment, it is important to consider and understand exposure patterns of the investigated area. As elaborated in Chapter 2.1., exposure is regarded as a separate, although linked concept to vulnerability and hence has a 'raison d'être' in a comprehensive vulnerability assessment. Also, as de Sherbinin (2018: 11) note, "vaguely defined maps of 'vulnerable populations' are unlikely to lead to concrete policy or implementation responses" compared to more concrete vulnerability assessments investigating a specific environmental or climatic stressor and its impact on the investigated population.

Following a literature review, drought emerged as the predominant climatic stressor in Ethiopia. This chapter delves into the examination of drought patterns specifically within the study area of Kersa, focusing on the local scale.

To investigate drought patterns in the study area, this study uses Standardized Precipitation Evapotranspiration Index (SPEI) data. SPEI is a drought index that combines precipitation and potential evapotranspiration to monitor dry and wet conditions. The dataset covers the whole African continent for a time period of 36 years, ranging from 1981 to 2016. For the analysis, the dataset was reduced to the study area, the Kersa district. The dataset allows for local analysis, with a spatial resolution of 5km. Different accumulation periods, ranging from 1 to 48 months, facilitate the diagnosis of different types and durations of drought events (Peng et al., 2020). The SPEI analysis described in this chapter has been conducted in RStudio.

To analyse drought patterns in Kersa, SPEI-03, -06 and -12 served as proxies for short-, medium-, and long-term droughts, respectively. These different SPEIs have respective accumulation periods of 3, 6 and 12 months. Also, SPEI-04 values for September are utilized to analyze conditions in the main rainfall season, Kiremt, which ranges from June to September.

First, Mann-Kendall (M-K) trend tests for SPEI-03, -06 and -12 were conducted for the 36-year period between 1981 and 2016. Here, SPEI-03 and SPEI-06 showed no statistically significant trend. This suggests that there has been no consistent pattern of increasing or decreasing moisture conditions for these timeframes. For SPEI-12, meanwhile, the Mann-Kendall test has indicated a statistically significant trend with a tau value of 0.0913 and a p-value of 0.0051522. The positive tau value suggests a slight upward trend, meaning that, on an annual basis, moisture conditions are becoming wetter in Kersa.

After analysing trends among the data, the 36-year period was investigated for each SPEI-03, -06 and -12, to look for drought conditions in the Kersa region. The analysis consisted in finding each month of the total 432 months where the SPEI value indicated a drought event. Here, the classification in *Table 3* differentiated between different degrees of severity of the drought event. Typically, an SPEI value of -1 is indicative of drought conditions, with increasingly negative values signalling greater drought intensity.

SPEI	Category
2 and above	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
−0.99 to 0.99	Near Normal
−1.0 to −1.49	Moderately dry
−1.5 to −1.99	Severely dry
−2 and less	Extremely dry

Table 3: SPEI values and related moisture categories (Peng et al., 2020: 755)

Figures 2, 3 and *4* show the results of the analysis. Each plot shows the total frequencies of drought events over the 36-year period for SPEI-03 (short-term drought), SPEI-06 (medium-term drought) and SPEI-12 (long-term drought), while differentiating between moderate, severe and extreme droughts.

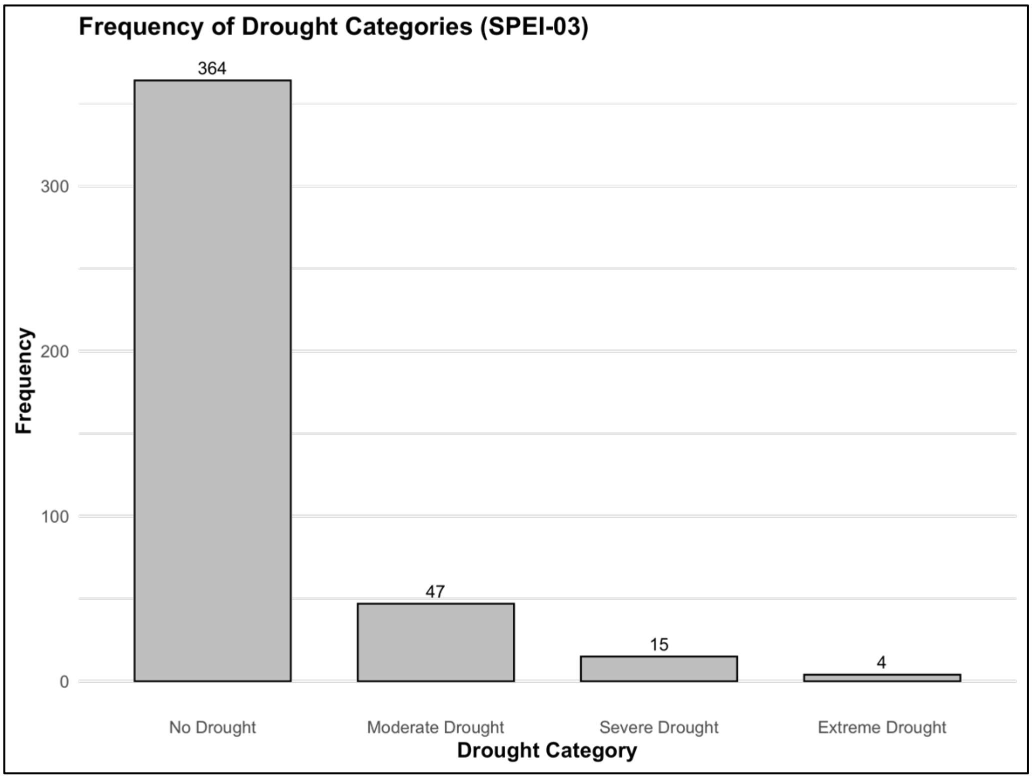


Figure 2: Frequencies of different drought events for SPEI-03 (1986-2016)

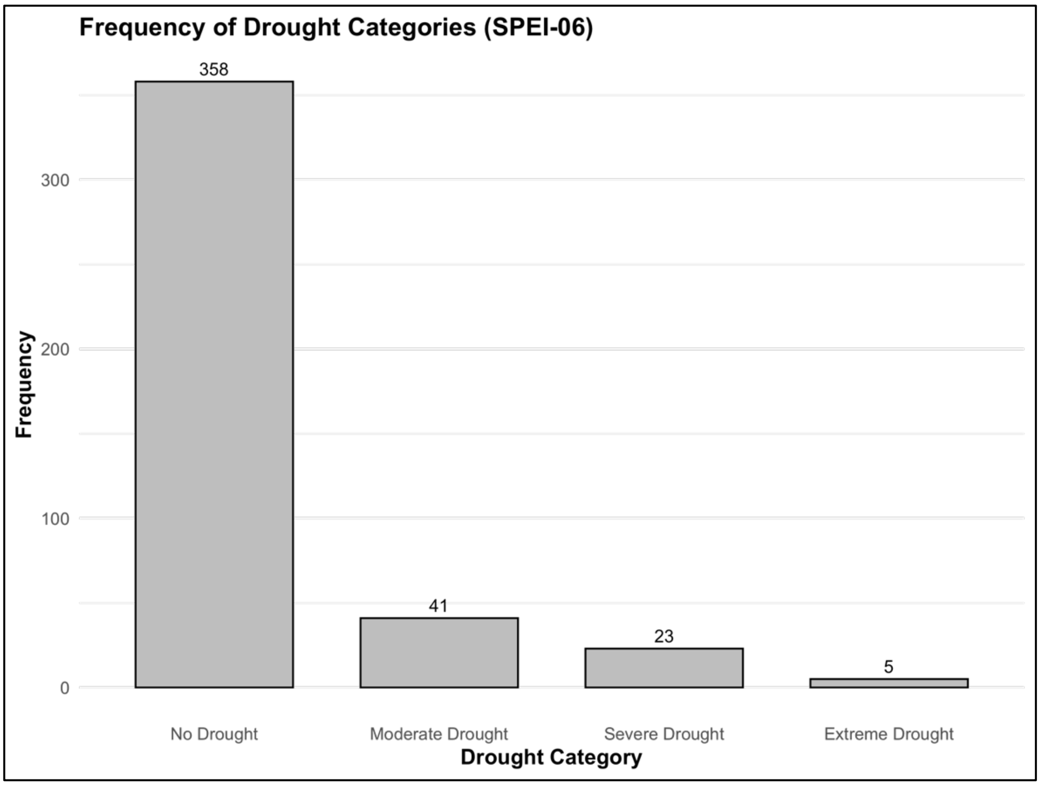


Figure 3: Frequencies of different drought events for SPEI-06 (1986-2016)

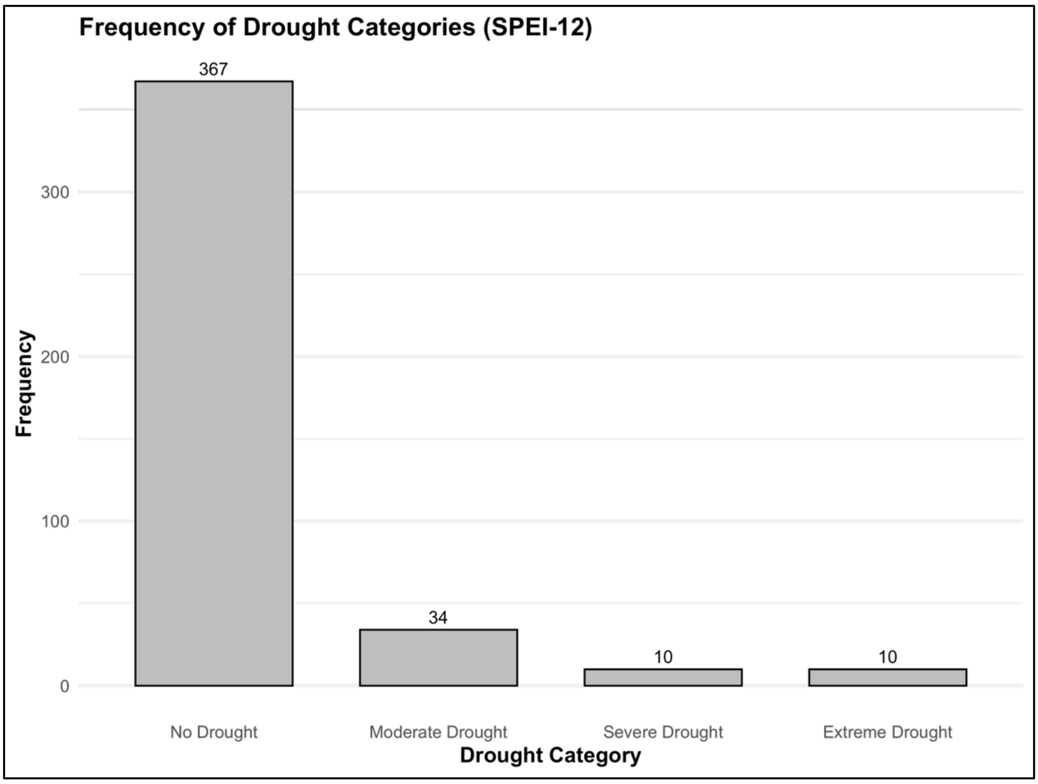


Figure 4: Frequencies of different drought events for SPEI-12 (1986-2016)

For SPEI-03, investigating short-term droughts, there were drought conditions for 66 months during the 36-year period, representing 15,28 %, or 1,83 months per year with an SPEI-03 indicating at drought conditions. Most often, these were ‘moderate’ droughts (47), while there were also 15 ‘severe’ and 4 ‘extreme’ droughts.

For SPEI-06, analyzing medium-term droughts, there were a total of 69 months were there were drought conditions within the Kersa district, representing 15,97 % of the total months. Out of these 69, 41 were considered ‘moderate’, 23 ‘severe’ and 5 as ‘extreme’.

For SPEI-12, which considers long-term droughts, a total of 54 months has been found hinting at drought conditions. 34 were considered ‘moderate’, 10 as ‘severe’, and, notably, 10 were considered ‘extreme’.

In summary, the prevalence of moderate droughts was highest across all categories, but severe and extreme droughts also significantly impacted the region, indicating an area prone to drought that varies by duration and intensity.

In a next step, the analysis focused on the main rain season, Kiremt. Here, SPEI-04 (accumulation period June to September) values for September gave good insights into the conditions of the Kiremt seasons for each year of the investigation period.

Again, as a first step, a M-K Trend Test was conducted for each September SPEI-04 value over the period of investigation, meaning 36 values representing each year of the investigated period. The test result found a statistically significant trend, with a p-value of 0.022925 and a tau value 0.267, indicating an increase in moisture patterns for the Kiremt season over the 36-year period. This supports the findings of the overall positive trend detected for SPEI-12.

Then, again, drought frequencies were investigated for the Kiremt season for each year. *Figure 5* shows the results, again differentiating between different drought classifications.

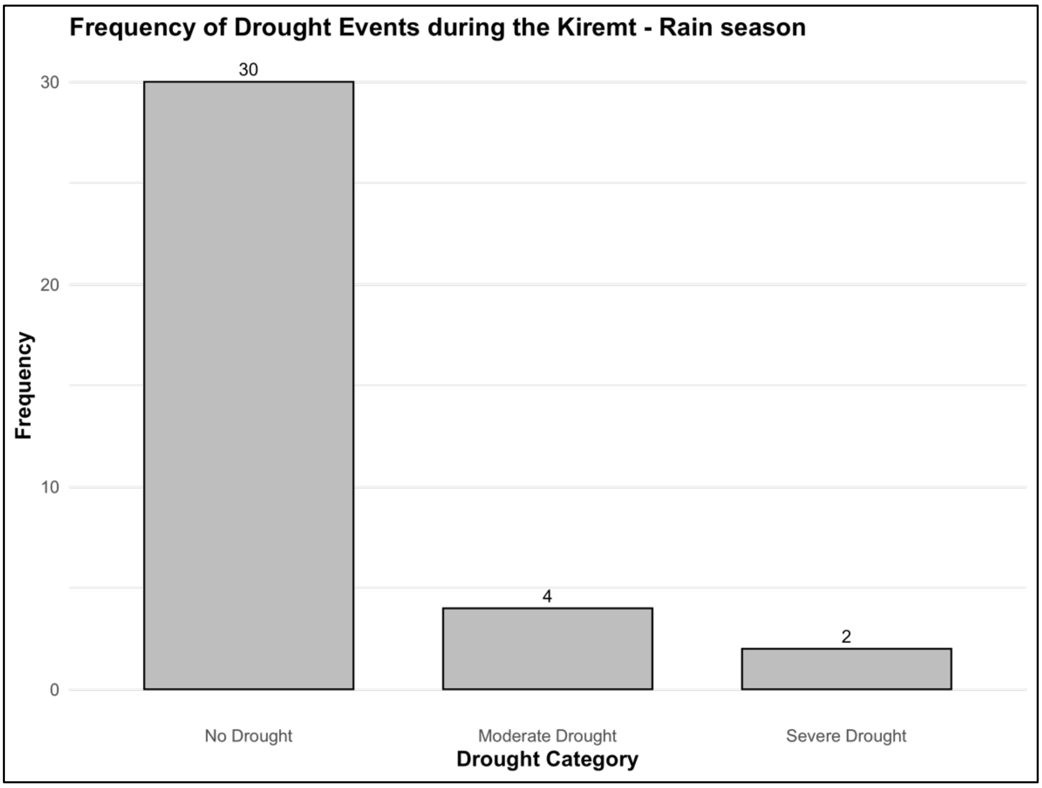


Figure 5: Frequencies of different drought events during the Kiremt season (1986-2016)

For the Kiremt period, 6 of the investigated 36 years showed drought conditions. While 4 years showed ‘moderate’ drought conditions during the Kiremt season, 2 showed ‘severe’ droughts, which took place in 1987 and 2015. Mera (2018) supports these finding by describing two major droughts in 1987 and 2015. Drought occurrences during the main rainfall season are particularly devastating for affected populations, due to the already described reliance on this period for general water supply and agricultural production. For this thesis, I decided to analyze the 2015 severe drought in Kersa on the local scale, given its temporal proximity to the data used to analyze social vulnerability patterns within Kersa, which has been collected in 2014.

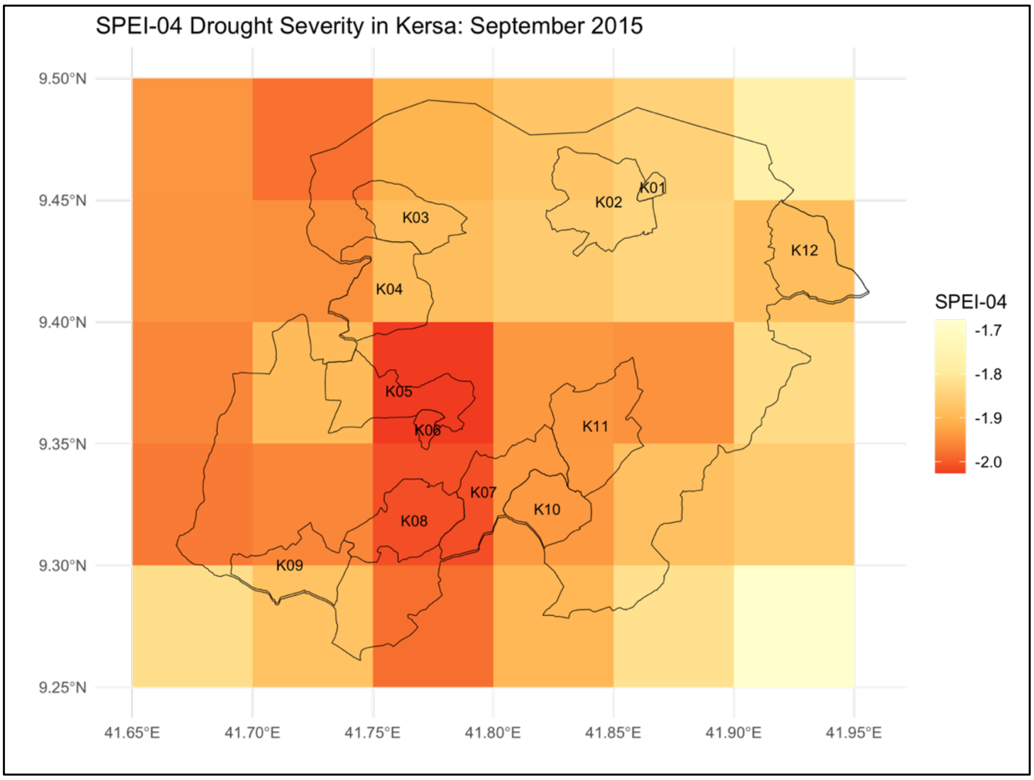


Figure 6: *Local spatial patterns of the 2015 drought over Kersa*

Figure 6 shows a local visualization of the 2015 drought over Kersa, with each cell representing 5x5km. During the Kiremt season in 2015, the Kebeles K05 and K06, i.e. Meda Oda and Weter Town, were most severely hit by drought conditions, with SPEI-04 values lower than -2, representing extreme drought conditions. Overall, the SPEI values vary from around -1.7 to -2 across the Kersa district, meaning that the whole region has been hit by 'severe' or even 'extreme' drought according to the SPEI drought classification.

Based on the analysis and findings from the SPEI data over the 36-year period, it can be concluded that the study site, the Kersa district, is susceptible to droughts across different temporal scales. Although the M-K trend test suggested positive trends for annual SPEI-12 values and explicitly for the Kiremt season, the occurrence of drought conditions in 66 months (SPEI-03), 69 months (SPEI-06), and 54 months (SPEI-12) during the 36-year period indicates that droughts are indeed a recurrent environmental challenge in the area. The frequency of drought conditions represented by SPEI-03 and SPEI-06 findings, which account for approximately 15.28% and 15.97% of the months respectively, suggests that droughts, especially those of moderate severity, are relatively common occurrences on both short-term and medium-term scales. The presence of severe and extreme drought conditions, although less frequent, particularly at the long-term scale as indicated by SPEI-12, underscores the potential for significant impacts on water resources, agriculture, and ecosystems over time. Analysis on drought patterns during the main rainfall season, Kiremt, further supported these findings, with drought conditions detected in 6 out of 36 years for this crucial period. Local analysis showed that for a ’severe’ drought year, the entire Kersa region is at risk of being impacted.

However, these findings need to be regarded with caution. Droughts are a complex phenomenon and assessments based on a single indicator have their limitations. In order to “fully characterize drought magnitude, spatial extent, and potential impacts”, drought assessments should integrate “multiple climate, water, vegetation, and soil parameters, as well as socioeconomic information retrieved from different sources” (Wang et al. 2016: 2).

4. Methodology: Multidimensional Socioeconomic Index (MSEI)

Given the strong association between poverty and social vulnerability outlined in Chapter 2.2.2, alongside concerns over the potential negative consequences of labeling groups as ‘vulnerable’ elaborated in Chapter 2.3., this thesis proposes the creation of a Multidimensional Socio-economic Index (MSEI) to investigate social vulnerabilities at the face of potential drought events. This index serves as a proxy for social vulnerability, while acknowledging its limitations in fully capturing the complexities of vulnerability in the context of climatic and environmental challenges.

4.1. Data

This thesis uses HDSS data to analyze local socioeconomic characteristics in the Kersa district, Ethiopia. In the context of scarce socioeconomic data in Africa (IPCC, 2022), HDSS data provide a valuable data source, with a particularly significant possibility for longitudinal monitoring of socioeconomic conditions in a given area. HDSS sites provide detailed socioeconomic data on the local scale in Low-or Middle-Income countries (LMIC). One strength of HDSS data is the collection of data on whole communities over a period of time. HDSS data does not allow for country-wide representation; however, it offers unique insights on the local scale into certain areas where every household is included in the sample. Further, this allows the data to be geolocalized on the local level, which enables analyzing spatial patterns and visualizations through maps.

4.2. Index Construction

In the next chapters (4.2.1 – 4.2.6), each step in the construction of the index is described, beginning with the selection of relevant variables, data preparation, which includes handling of NAs and recoding of variables, normalization, weighting, aggregation, and finally, index validation. The analysis is conducted in RStudio.

4.2.1. Variable Selection

The first step in the index construction is the selection of relevant variables. This selection is guided by relevant literature, which has been discussed in Chapters 2.2.1 and 2.2.2, and adjusted to the Ethiopian context. The study uses a hierarchical structural design, as described in Chapter 2.2.1. After analyzing the available HDSS data, I decided to construct the index around 3 major dimensions:

- Household Assets and Living Conditions
- Housing conditions
- Education

The HDSS dataset offers a broad set of socioeconomic variables that potentially depict multidimensional poverty in a comprehensive way. The first dimension, 'Household Assets and Living Conditions' groups many of these socioeconomic variables which greatly influence both sensitivity and adaptive capacity to natural hazards. This first dimension, due to being very broad, is the best represented within the dataset, as it includes the most variables, and therefore, contributes the most to the MSEI. The next dimension, 'Housing conditions', is closely linked to living conditions, but is here described as a separate major dimension due to its detailed representation through numerous variables within the HDSS dataset. Housing conditions influence a household's sensitivity to natural hazards. The last dimension, 'Education', is the least well represented in the dataset, with only two variables describing the alphabetization of household head and members. However, this offers a good first indication of the household's education and is important in the context of disaster adaptation or preparation. Higher education can be seen as empowering for households, enabling them to prepare for potential hazards as well as cope with and adapt to natural hazards. Education offers possibilities to absorb information, influences decision-making and potentially offers possibilities for livelihood diversification. However, if not well educated, a household might be more limited regarding adaptation options to natural hazards, as well as being more sensitive to be severely affected, e.g. through non-adequate preparation or information assimilation.

These 3 dimensions were also found to be among the most selected in the scoping review of social vulnerability indices by Mah et al. (2023) (*Table 2*). Among 118 original SVI's, 74.4% included variables related to education, 66.1% related to 'Microlevel socioeconomic status' and 'Employment', which are both, amongst others, represented in the 'Household Assets and Living Conditions' and 56.2% related to 'housing' conditions.

Following a hierarchical structure, the dimensions are further subdivided into several sub-dimensions. The first dimension, 'Household Assets and Living Conditions', is subdivided into 4 subdimensions: 'Livelihood and Assets', 'Water Source and Accessibility', 'Livestock', 'Access to information and Communication'. The 'Housing conditions' dimension is subdivided into 'Condition and Material of the house' and 'Assets of the house'. The last dimension, 'Education' is not subdivided, as it contains only 2 variables.

Overall, 22 variables have been selected to describe multidimensional socioeconomic characteristics for the case study in Kersa. *Table 4* summarizes the selected variables with the related categories per variable. The table shows the final variables and categories, after data preparation, which is described in the following chapter (4.2.2).

Dimensions	Sub-dimensions	Variables	Categories
Household Assets & Living conditions	Livelihood & Assets	Type of occupation	Occupation related to agricultural activities
			Occupation from secondary and tertiary sectors
			Dependant Population
		Any member of the household has an account with a bank/credit association/micro finance	yes
			no
		Does any member have any mean of transportation (bicycle, motorbike, car)	yes
			no
		Does any member of the household own a watch	yes
			no
	Water Source & Accessibility	Main source of drinking water	Piped water
			Protected water source
			Unprotected tube or bore well or water in the nature
		Location of main source of drinking water	in own dwelling
			in own compound
			elsewhere
		Distance to drinking water (in minutes)	5
			5 - 14
			15 - 29
			30 - 59
			>= 60
	Livestock	Number of working animals	0
			1
			2 - 5
			more than 5
		Number of animals for consumption	0
			1 - 10
			11 - 20
			more than 20
	Acces to Information & Communication	Any member of the household owns a mobile telephone	yes
			no
		Household owns a radio	yes
			no
		Household owns a television	yes
			no
Housing conditions	Condition & Material of the house	In what condition is the main house?	in good shape
			requires some repair
			in bad shape
		The floor of the house is made of	Finished floor / cemented
			Wood or bamboo floor
			Natural floor / earth / sand & mud
		The roof of the house is made of	Corrugated iron
			Plastic sheet
			Thatched / Leaf
			Other
		Main material of the wall of the house	Bricks / Cement
			Trunks with mud
			Stone with mud
			Bamboo / Wood
			Other
	Assets of the house	Household has a bed	yes
			no
		House has rooms used only for sleeping	yes
			no
		Type of toilet facilities of the household	Ventilated improved pit latrine
			Traditional pit latrine
			No latrine
		Household has electricity	yes
			no
Education		Literacy of head of household	yes
			no
		No. of adults aged 14 and over in the household who are literate	0
			1
			2 or 3
			more than 3

Table 4: Dimensions, Sub-dimensions, Variables and Categories included in MSEI

4.2.2. Data preparation

First, household data with socioeconomic information is combined with geolocalized household data. Here, 11931 out of the initial 12787 remain, as some households are not geolocalized, are duplicates, or have had some other issues in data collection. Ultimately, this means that 6,7% have been lost and the dataset contains geolocalized socioeconomic information of 93,3 % of the total population of the 12 Kebeles.

4.2.2.1. Handling NA's

The next step is to analyze and handle NAs (Not Available; i.e. missing data) within the dataset. Out of the 24 selected variables, 6 include missing values, as shown in *Table 5.*

Variable name	N of NAs
Type of occupation	100
Any member of the household has an account with a bank/credit association/micro finance	115
Distance to drinking water in min.	1027
Material of the floor of the house	10
Type of toilet facilities of the household	58
Literacy of head of household	1154
No. of adults aged 14 and over in the household who are literate	177

Table 5: Variables with NAs and Number (N) of NAs

For the variable 'Distance to drinking water in min.', missing values were compared with the variable 'Location of main source of drinking water'. This comparison showed that out of the 1027 NAs, 830 were located 'elsewhere', 197 'in own compound' and 0 'in own dwelling'. This shows that the NAs do not correspond to '0' or a very small number of minutes to get to the source of drinking water, as most NAs are households with water sources located outside of their compound. Also, the NAs were distributed randomly across the different Kebeles. Therefore, these NAs were handled by imputation, using the mean of 'Distance to drinking water in min.' per kebele for the respective kebele. *Table 6* shows the mean values for 'Distance to drinking water in min.' for each kebele. As these means show, there are large differences between the different kebeles, particularly for the low means of K01 and K06, which are the urban areas. These differences among the kebeles support the decision to impute means per kebele.

Kebeles	Minutes
K01	5.67
K02	20.7
K03	29.2
K04	65.3
K05	24.4
K06	5.73
K07	35.6
K08	13.6
K09	21.3
K10	93.6
K11	30.5
K12	26.1

Table 6: Average minutes per kebele to get to main drinking water source

The variable 'Literacy of head of household' was compared to the variable 'No. of adults aged 14 and over in the household who are literate'. Those NAs where the response in 'No. of adults aged 14 and over in the household who are literate' was '0', were also assigned the value '0' for the variable 'Literacy of household', assuming that when there are 0 literate adults in the household, the head of that household is illiterate, too. For those households that counted 1 or more adults aged 14 and over in the household who are literature, I assigned the value '1' to 'Literacy of head of household', assuming that the head of household was either the one, or one of the adults being literate. For those households that had NA in both variables, which was the case for 177 observations, I assigned '0' to both, assuming that the head and all adults of that household are illiterate. For the variable 'No. of adults aged 14 and over in the household who are literate', every NA within the dataset corresponded to an NA for the variable 'Literacy of head of household'. Therefore, as already declared in the previous section, both were assigned '0'.

For the remaining variables ‘Type of occupation’, ‘Any member of the household has an account with a bank/credit association/micro finance’, ‘Type of toilet facilities’ and ‘Material of the floor of the house’, there was no reasonable way to impute the missing data. Therefore, due to the small numbers of NA observations in these 4 variables (N= 100, 115, 58 and 10, respectively), it was decided to exclude observations with missing data. In total, 282 observations were excluded (1 overlap), which represents about 2,4 % of the data. Hence, the total number of observations decreases from 11931 to 11649.

4.2.2.2. Recoding variables

First, the following variables have been recoded in prior work in the context of the Agreement on Academic Collaboration between the University of Vienna and the Haramaya University in Eastern Ethiopia. These variables have mainly been recoded to summarize certain categories into fewer groupings.

- Type of occupation
- Main source of drinking water
- Material of the floor of the house
- Material of the roof of the house
- Material of the wall of the house

Then, quantitative variables have been recoded to transform them into categorical variables.

The variable ‘Distance to main water source in min.’ has been recoded into 5 categories ranging from less than 5 minutes to more than 1 hour. The categories and respective distributions of the households can be seen in *Figure 7*.

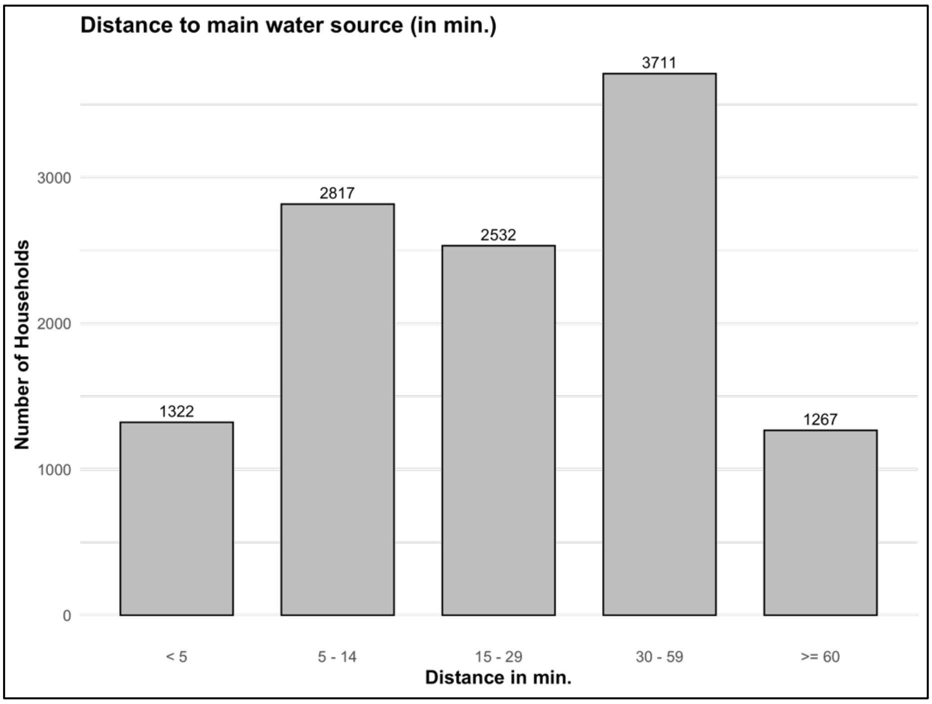


Figure 7: Frequencies of recoded variable 'Distance to main water source (in min.)'

The four variables 'How many oxen / horses / mules / donkeys does this household have?' have been recoded and grouped into one variable called 'working animals'. This was decided as these animals all represent working animals that help the household, e.g. on the agricultural land or in matters of transportation, rather than contribute to consumption. Due to the small numbers in the observations (max. of summed up variable 'working animals' = 12), it seemed reasonable to sum up the 4 variables. Then, the new variable 'working animals' has been subdivided into 4 categories, ranging from '0' working animals to '3 or more' working animals. The distributions of the households among the different categories can be seen in *Figure 8.*

Similarly, the four variables 'how many cows / goats / sheep / chicken does this household have?' have also been recoded and grouped to one variable called 'animals for consumption'. Contrary to the 'working animals' these animals are held to contribute to the household's consumption through different ways. Here, the households in the Kersa site show higher numbers of property compared to 'working animals'. The categories have been constructed ranging from '0' to 'more than 10' animals for consumption. The distributions of the households among the different categories can be seen in *Figure 9.*

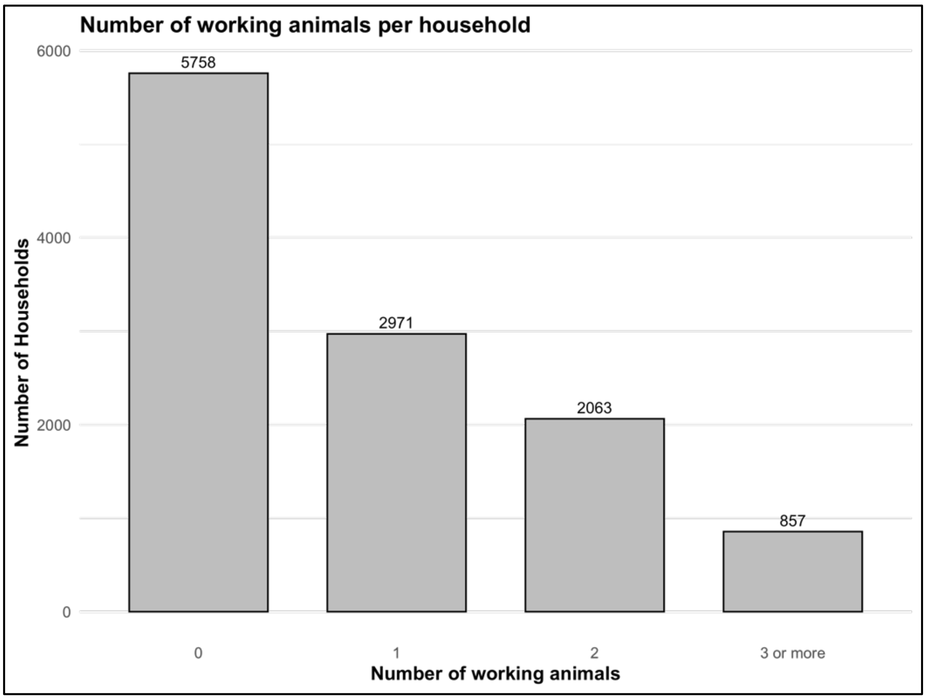


Figure 8: Frequencies of recoded variable 'Number of working animals per household'

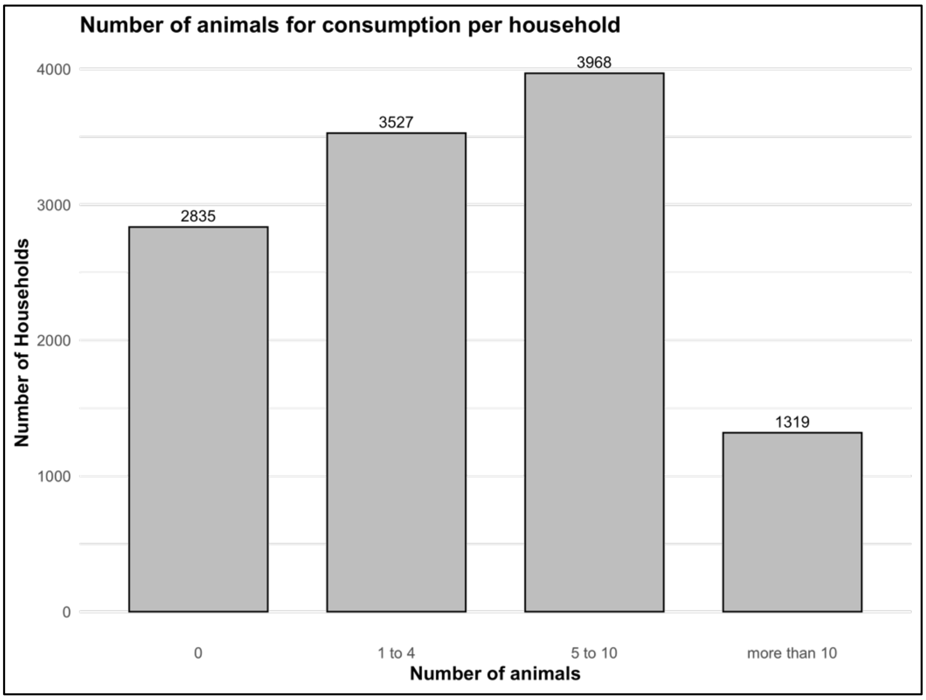


Figure 9*:* Frequencies of recoded variable 'Number of animals for consumption per household'

The last variable to be recoded from numerical to categorical is 'No. of adults aged 14 and over in the household who are literate'. Categories were constructed ranging from '0' to 'more than 3' literate adults per household. The distributions of the households among the different categories can be seen in *Figure 10.*

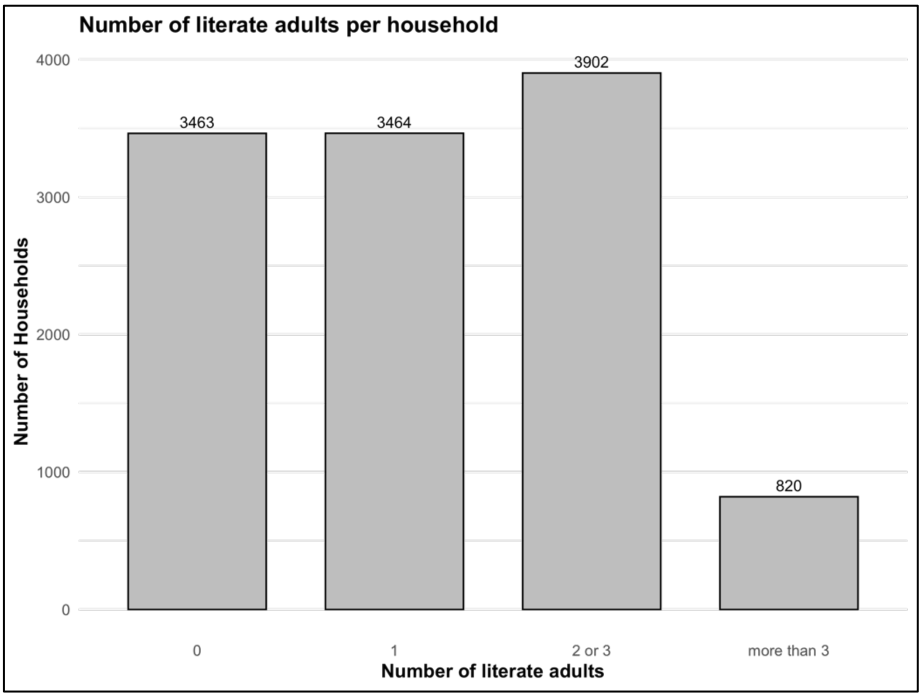


Figure 10*: Frequencies of recoded variable 'Number of literate adults per household'*

4.2.3. Normalization

"Normalization is performed to place all indicators, into a common and dimensionless measurement scale" (Tate, 2012: 329). To normalize the categories, scores between 0 and 1 were assigned for each category of each variable, which can be seen in *Table 7*. The scores reflect a gradation from the least desirable condition (scored as 0) to the most desirable (scored as 1), with intermediate values for variables which have more than 2 categories.

For most variables, the scores reflect a binary system, with 0 and 1 scores. Here, most often, it is straightforward which condition is the less desirable, and which is desirable. For some variables with 3 or more categories, the scoring system is also straightforward, e.g. the continually lower scores with higher minutes required to get to the main drinking water source, higher scores for more literature adults per household, or higher scores for higher numbers of animals owned in the variables 'working animals' and 'animals for consumption'.

Some other category scores require justification. For example, type of occupation is divided in 3 categories, where secondary and tertiary sectors are ranked as the most desirable (1), the agricultural sector as less desirable (0.5) and dependent populations as the least desirable condition (0). Here, the reasoning is that, at the face of drought exposure, the agricultural sector is more sensitive, e.g. through reduced yields, as the secondary or tertiary sectors. For the materials of the roof and wall of the house, MSEI scores were attributed according to the durability of the material.

Variables	Categories	MSEI Score
Type of occupation	Occupation related to agricultural activities	0.5
	Occupation from secondary and tertiary sectors	1
	Dependant Population	0
Any member of the household has an account with a bank/credit association/micro finance	yes	1
	no	0
Does any member have any mean of transportation (bicycle, motorbike, car)	yes	1
	no	0
Does any member of the household own a watch	yes	1
	no	0
Main source of drinking water	Piped water	1
	Protected water source	0.5
	Unprotected tube or bore well or water in the nature	0
Location of main source of drinking water	in own dwelling	1
	in own compound	0.5
	elsewhere	0
Distance to drinking water (in minutes)	5	1
	5 - 14	0.75
	15 - 29	0..5
	30 - 59	0.25
	>= 60	0
Number of working animals	0	0
	1	0.33
	2 - 5	0.66
	more than 5	1
Number of animals for consumption	0	0
	1 - 10	0.33
	11 - 20	0.66
	more than 20	1
Any member of the household owns a mobile telephone	yes	1
	no	0
Household owns a radio	yes	1
	no	0
Household owns a television	yes	1
	no	0
In what condition is the main house?	in good shape	1
	requires some repair	0.5
	in bad shape	0
The floor of the house is made of	Finished floor / cemented	1
	Wood or bamboo floor	0.5
	Natural floor / earth / sand & mud	0
The roof of the house is made of	Corrugated iron	1
	Plastic sheet	0.5
	Thatched / Leaf	0
	Other	0.5
Main material of the wall of the house	Bricks / Cement	1
	Trunks with mud	0.33
	Stone with mud	0.66
	Bamboo / Wood	0
	Other	0.5
Household has a bed	yes	1
	no	0
House has rooms used only for sleeping	yes	1
	no	0
Type of toilet facilities of the household	Ventilated improved pit latrine	1
	Traditional pit latrine	0.5
	No latrine	0
Household has electricity	yes	1
	no	0
Literacy of head of household	yes	1
	no	0
No. of adults aged 14 and over in the household who are literate	0	0
	1	0.33
	2 or 3	0.66
	more than 3	1

Table 7: MSEI scores assigned to each category for Normalization

4.2.4. Weighting

For the calculation of the index, a weighting scheme was put in place, as elaborated in *Table 8*. Weighting approaches are helpful to value indicators according to their significance and importance (Kienberger et al., 2016). There are numerous expert-based and statistical approaches, such as Principal Component Analysis (PCA), to assign differential indicator weights, but "by far the most common approach is the use of equal weights" (Tate, 2012: 33).

The cumulative weighting scheme used in this study is designed to ensure that each sub-dimension has an equal overall impact on the final index, despite the different number of variables within each sub-dimension. Each sub-dimension contributes 1/7 to the overall measurement, and the weights within each sub-dimension are distributed equally among the respective variables. Cutter and Finch (2008: 2305) state that, for SVIs, there is no "theoretical justification for assuming the relative importance of one factor over another", which supports the decision to assign equal weights across the 7 sub-dimensions.

Hence, the 3 main dimensions 'Household Assets and Living Conditions', 'Housing conditions' and 'Education' are not represented equally within the index. 'Socioeconomic status and Assets' represents 4/7, 'Housing conditions' 2/7 and 'Education' 1/7, which is justified by the number of sub-dimensions and related variables contributing to each dimension. Hence, the 'Household Assets and Living Conditions' dimension contributes the most to the MSEI by containing the most sub-dimensions and variables.

Sub-dimension	Variable	Weighting	
Livelihood & Assets	Type of occupation	1/28	1/7
	Any member of the household has an account with a bank/credit association/ micro finance	1/28	
	Does any member have any mean of transportation (bicycle, motorbike, car)	1/28	
	Does any member of the household own a watch	1/28	
Water Source & Accessibility	Main source of drinking water	1/21	1/7
	Location of main source of drinking water	1/21	
	Distance to drinking water (in minutes)	1/21	
Livestock	Number of working animals	1/14	1/7
	Number of animals for consumption	1/14	
Access to information & communication	Any member of the household owns a mobile telephone	1/21	1/7
	Household owns a radio	1/21	
	Household owns a television	1/21	
Condition & Material of the house	Condition of the main house	1/28	1/7
	Material of the floor of the house	1/28	
	Material of the roof of the house	1/28	
	Material of the wall of the house	1/28	
Assets of the house	Household has a bed	1/28	1/7
	House has rooms only for sleeping	1/28	
	Type of toilet facilities of the household	1/28	
	Household has electricity	1/28	
Education	Literacy of the head of the household	1/14	1/7
	No. of adults aged 14 and over in the household who are literate	1/14	

Table 8: Weighting scheme used for MSEI

4.2.5. Aggregation

"In the aggregation stage, the weighted normalized indicators are combined to form the index. The summing of indicators to compute the arithmetic mean (additive aggregation) is nearly universally applied" (Tate, 2012: 330).

Aggregation is conducted by adding the score assigned to each category, multiplied by the assigned weight for this category, for each variable for every observation (household). This results in a number between 0 and 1, which represents the calculated MSEI for a specific household. 0 represents the lowest possible multidimensional socioeconomic status, while 1 represents the highest possible. After this stage, each household across the 12 Kebeles in Kersa is assigned a MSEI value.

4.2.6. Index Validation / Comparative Analysis

To validate the MSEI, it is compared to the variable ‘declared income of the household’, expressed in Birr. This variable has also been collected within the HDSS program and is part of the dataset used in this thesis. Generally, declared incomes need to be treated with caution, as it is a sensitive information and is often underreported or inaccurately reported, especially in rural areas in the Global South where informal economies are prevalent. However, it can be regarded as a proxy for socioeconomic status, and it is appropriate to compare the declared income of a household to the calculated MSEI for validation purposes.

The Spearman rank correlation coefficient is an appropriate choice as it does not assume that the data are normally distributed and is less sensitive to outliers and skewed distributions, which is the case for the ‘declared income’ variable. The Spearman's rho is 0.50, which suggests a moderate positive association between declared income and the MSEI. This means as one variable increases, the other variable tends to increase as well, but not perfectly. The p-value is less than 2.2e-16, which is very close to zero, and hence smaller than 0.05, which indicates that the correlation is statistically significant, and it's very unlikely that this strong correlation is due to random chance.

Figure 11 shows the scatter plot of the ‘declared income’ variable and the calculated MSEI. The plot shows a positive trend, as indicated by the upward slope of the regression line, which is consistent with the Spearman's rank correlation result. There's a high concentration of data points at the lower end of the income scale, which suggests that a large proportion of the dataset consists of households with lower declared income. The scatter plot and the regression line suggest that while there is a positive relationship between the MSEI and ‘declared income’, the relationship may not be linear across all income levels. Generally, there are high variabilities around the regression line.

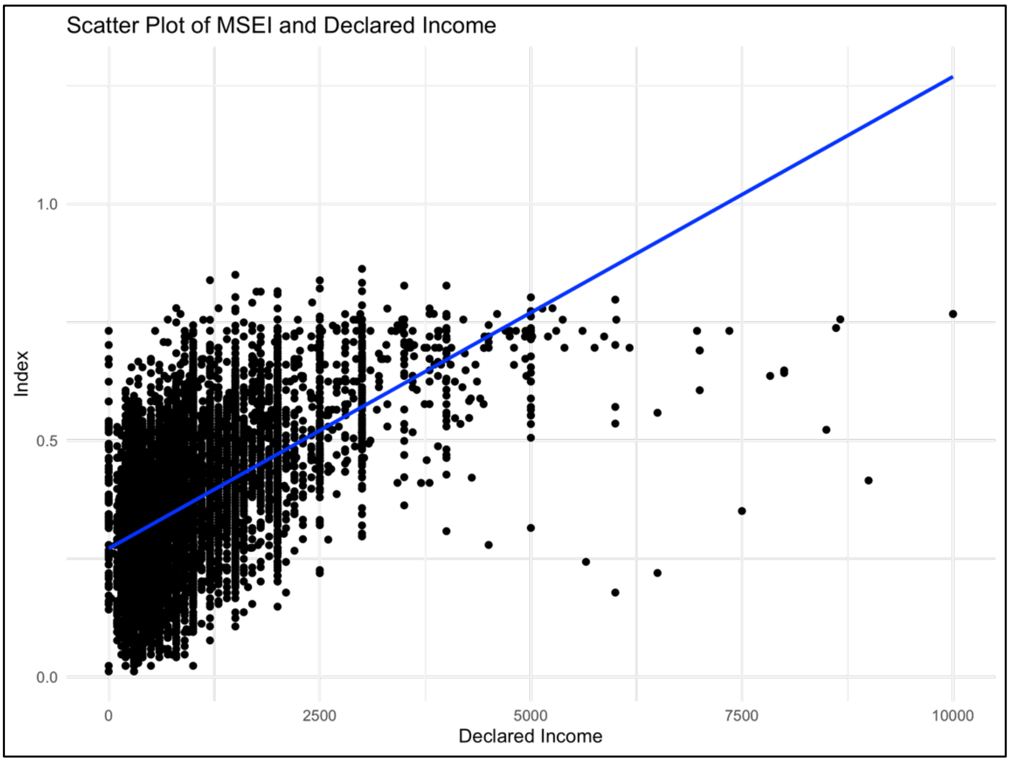


Figure 11: Scatter Plot of MSEI and ‚declared income' correlation pattern

In summary, this correlation demonstrates evidence of a statistically significant moderate positive relationship between declared income and MSEI. The MSEI is constructed to capture a comprehensive spectrum of socioeconomic factors, going beyond monetary wealth. Hence, while a positive correlation between the MSEI and declared income was anticipated - given that income is a significant aspect of socioeconomic status - this relationship was not expected to be perfectly linear. The relationship indicates that the MSEI successfully captures elements of socioeconomic status that extend beyond mere income, affirming its multidimensional design.

4.3. Mapping

As 'the map' is often the final outcome of an in-depth, complex analysis, trying to resume all the relevant information, and consequently the product of the research that is given most attention to by the end-user, it should be given careful consideration, both regarding the methods used to visualize the results, as well as cartographic aspects.

After describing various stages of index construction and calculation in detail in the preceding chapters, this chapter focusses on mapping and visualizing the spatial patterns of the MSEI in Kersa. The process of mapping, just like the overall construction of the MSEI, was carried out using RStudio.

After calculating the MSEI on the household level, it was clear that the 11649 households could not be mapped in a way where they are all represented individually. This is due to two major reasons. First, the map would be overcrowded with too many points due to the large dataset, which would make it unreadable and minimize the information the map is intended to deliver. Second, mapping each household with their exact coordinate position would not be appropriate due to privacy reasons. The map should not allow to identify specific households, especially when assigning an index score on households, due to the potential of misrepresenting and stigmatizing households and individuals.

Due to these two important reasons, the data points must be aggregated. The aggregation process will aim at providing as detailed information as possible without breaching confidentiality. To this goal, the 12 Kebeles in Kersa considered in this study were overlayed with a hexagonal grid, with each hexagon summarizing information of the households located in it. This method, called 'hexagonal binning', allows for local analysis, while keeping the map readable, assuring efficient information deliverance, and preserving privacy and ethical considerations.

There are a number of things to consider in the binning process. The main issue here is the choice in the size of the hexagons. It is important to find the right balance of cell sizes that:

1) includes not too few and not too many households,
2) does not allow to localize individual households,
3) assures readability and optimizes the presentation of information,
4) allows for local analysis.

The issue of finding a balance between not too few and not too many households within a hexagon has turned out to be complex. As hexagon sizes within one Kebele need to be consistent to allow coverage of the whole area, it was inevitable that some hexagons contain very few households. Therefore, to maintain privacy, categories representing a range of households were constructed to inform the end-user on the number of households per hexagon. The lowest category encompasses hexagons containing between 1 and 10 households, effectively preventing the identification of individual households or hexagons with merely 1 or 2 households. The highest category encompasses hexagons containing between 50 and 99 households. This approach not only ensured privacy protection but also enabled data simplification and enabled more effective mapping.

To enhance readability and optimize the presentation of data, hexagons were tailored to reflect the distinct characteristics of rural and urban areas. In rural regions of Kersa, the extensive surface areas and lower population densities necessitate larger hexagon sizes. Conversely, the urban areas, with their smaller surface areas and higher population densities, are represented by smaller hexagons. This approach ensures that the spatial distribution of households is accurately and effectively communicated, respecting the varying densities and scales of different regions. Specifically, the dimensions of hexagons have been set to 0.002 degrees for rural settings and 0.001 degrees for urban locales. In rural regions, this translates to hexagons measuring roughly 222 meters in the north-south axis and 219 meters along the east-west axis. Meanwhile, in urban areas, the hexagons are smaller, approximately 111 meters in height (north-south) and 110 meters in width (east-west). These hexagon sizes, containing 1-99 households, allow for local analysis while preserving privacy and assuring readability.

A number of maps have been created to visualize the results. First, to gain a general overview, one first map shows the Kersa district with all the investigated Kebeles and their respective average MSEI per Kebele. Then, to enable local analysis, each Kebele is mapped separately, with two maps per Kebele showing 1) the spatial distribution of households, and 2) the spatial distribution of MSEI scores within the Kebele. Both of these maps are constructed through the 'Binning' method and have the same hexagonal structure. This way, the end-user can identify individual cells, and determine both their MSEI value as well as the number of households within these cells. When constructing these maps (in total, N=25), a number of aspects need to be considered. When creating multiple maps, it is important to have consistency in the choice of colors and the ranges that these colors represent to ensure that the different maps can be compared to each other in an intuitive and straightforward way. For the MSEI distributions within the Kebeles, to facilitate orientation, basic spatial reference information, like e.g. major rivers and roads (Source: OpenStreetMap) have been included. For the maps on household distributions, coordinate system lines have been included, to include one more information and avoid duplicating information compared to the associated MSEI map. In general, the two maps per Kebele are designed to be complimentary to each other and maximize information for the end user.

5. Results

Preliminary analyses indicate that Kebeles in Kersa vary in their socioeconomic characteristics, both in comparison with each other and within the Kebeles. The spatial visualization through maps enables to localize socioeconomic inequalities between households and communities on the local scale. At the face of potential drought events, which has been identified as the main climatic or environmental stressor in the region, this analysis enables to identify, based on multidimensional socioeconomic characteristics, different degrees of potential vulnerabilities. However, socioeconomic characteristics shape vulnerabilities to other climatic and environmental stressors, too, and hence generally serve as important information for future research or policy recommendations.

First, *Figure 12* shows the number of households per Kebele included in the analysis. It shows that each Kebele contains a minimum of 400 households and a maximum of 1500 households, meaning there are considerable demographic differences across different Kebeles. *Table 9* indicates the Kebele's names, their assigned code for analysis used in this thesis, as well as their rural or urban nature and their topography. The HDSS Site is principally rural with two small towns, Kersa Town and Weter Town.

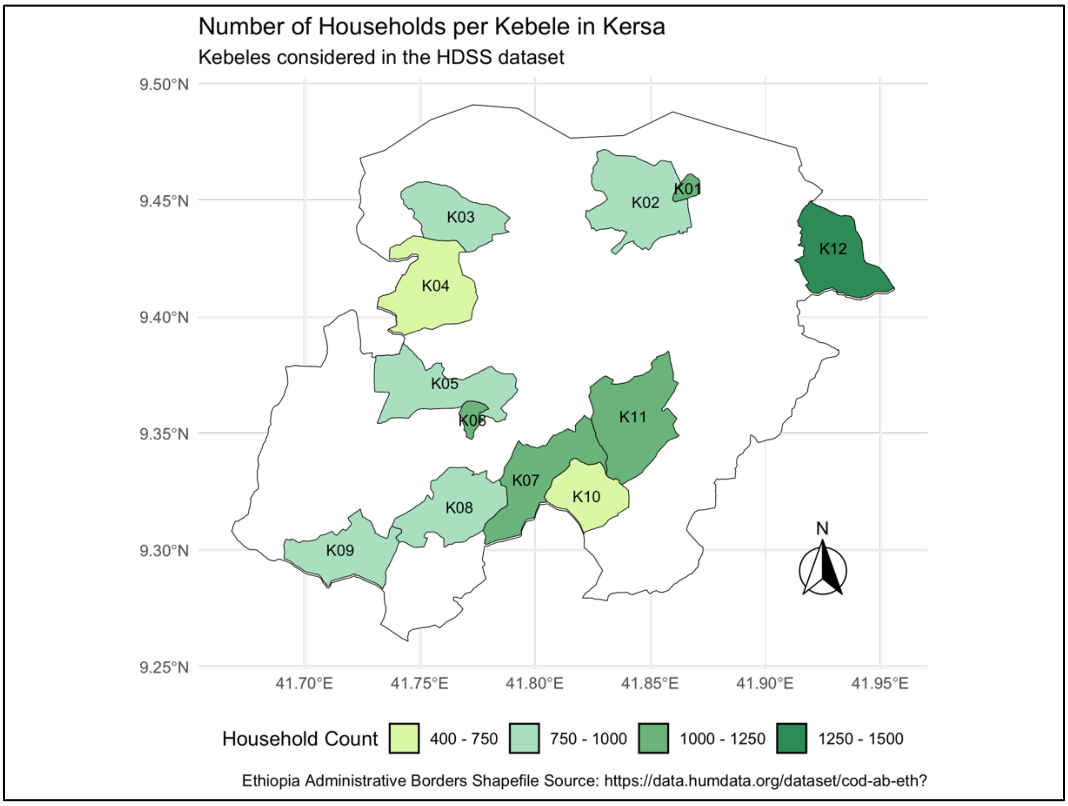


Figure 12*:* Households per Kebele included in the Kersa HDSS Dataset

Kebele Name	Code	Nature	Topography
Kersa Town	K01	Town	Mid land
Metekoma	K02	Rural	Mid land
Yabeta Lenicha	K03	Rural	Mid land
Efa Jalela	K04	Rural	Mid land
Meda Oda	K05	Rural	Mid land
Weter Town	K06	Town	Mid land
Handuhura Kosum	K07	Rural	Mid land
Tola	K08	Rural	High land
Gola Belina	K09	Rural	High land
Bereka	K10	Rural	Low land
Walitaha Bilisuma	K11	Rural	Low land
Adele BeyiKey	K12	Rural	Mid land

Table 9: Names of the Kebeles, assigned Code for Analysis and Characteristics

Figure 13 shows the average MSEI values per Kebele. The MSEI average values range from 0.27 (K07) to 0.54 (K01). In general, the two urban Kebeles (K01 and K06) have the highest average MSEI scores, meaning they have the highest multidimensional socioeconomic status, based on the calculated index. In this sense, the urban areas are expected to be less vulnerable to CC impacts such as drought events. K02, K09 and K12 have very similar MSEI (0.39 – 0.40) and are, here, classified as having 'moderate' MSEI scores. The remaining Kebeles were found to have 'lower' MSEI scores, ranging from 0.27 - 0.32.

Kersa district, 12 Kebeles	Average MSEI: 0.36 Urban and rural areas, 11462 Households		
Livelihood & Mobility	0.26	Condition & Material of house	0.49
Water Source & Accessibility	0.35	Assets of house	0.24
Livestock:	0.36	Education:	0.54
Access to information & Communication	0.25		

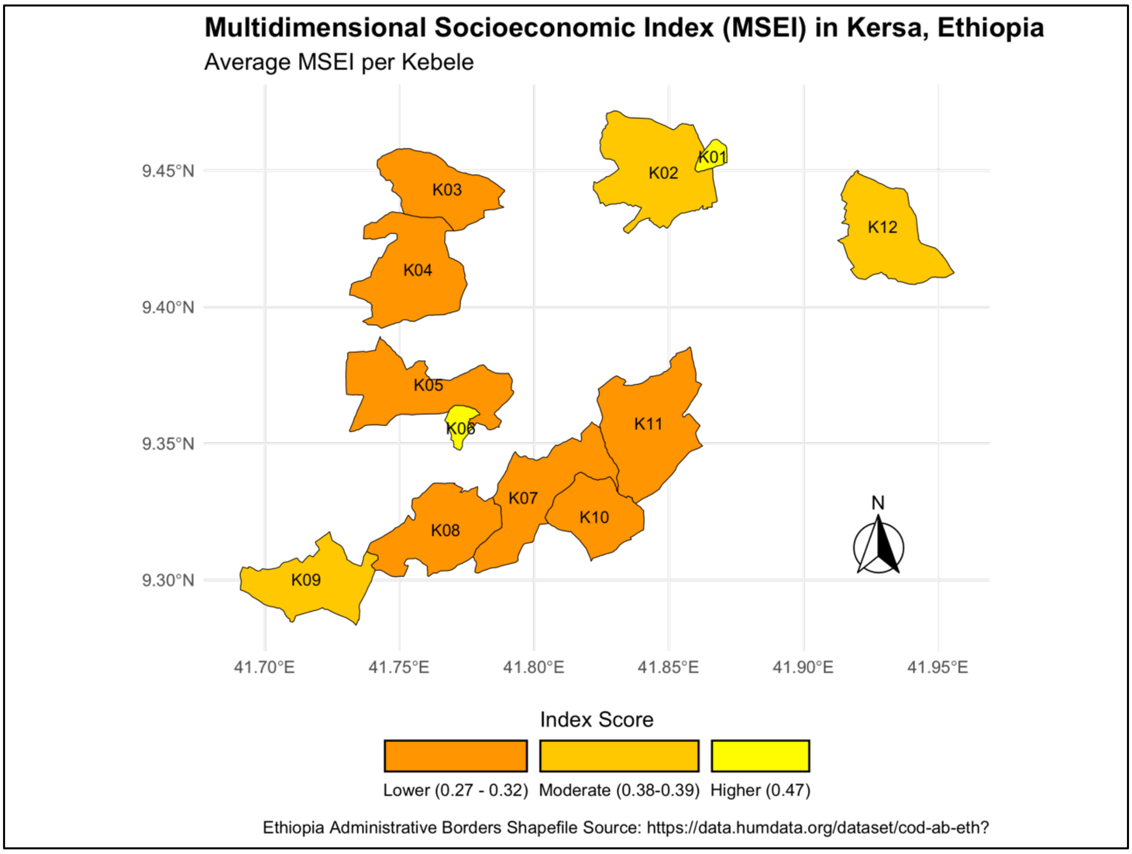
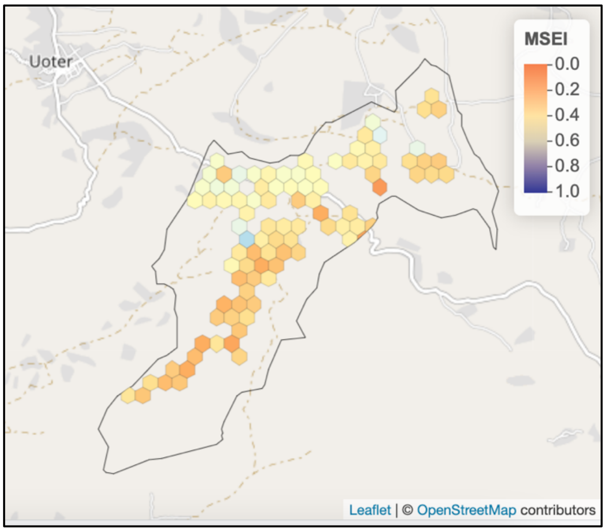


Figure 13: Overview of average MSEI scores per Kebele in Kersa.

In the following Chapters 5.1. – 5.3, MSEI patterns are visualized on the local scale, with a zoom and focus on each Kebele. Here, as elaborated in Chapter 4.3., two maps with a hexagonal grid are presented for each Kebele, showing 1) average MSEI values per hexagon and 2) the number of households per hexagon. In addition to the spatial patterns of the MSEI, the text box above the Kebele maps represents important information for the end-user. First, it delivers basic information regarding the visualized Kebele, i.e. by specifying the rural or urban nature, as well as the number of households per Kebele. Moreover, providing the individual MSEI sub-dimension scores allows for a better understanding of what factors in- or decrease a Kebele's MSEI, limiting the risk of misrepresentation. For the sub-dimension scores, it's important to compare them with the Kersa averages, as indicated above *Figure 13*. In the next chapters (5.1. – 5.3.), the Kebeles are ordered according to their average MSEI rating, beginning with the Kebele having the lowest MSEI (K07).

5.1. Kebeles with lower MSEI scores

Kebele 07 (K07): Handuhura Kosum	Average MSEI: 0.27 Rural area, 1214 Households		
Livelihood & Assets	0.16		
Water Source & Accessibility	0.11	Condition & Material of house	0.45
Livestock:	0.27	Assets of house	0.21
Access to information & Communication	0.17	Education:	0.51



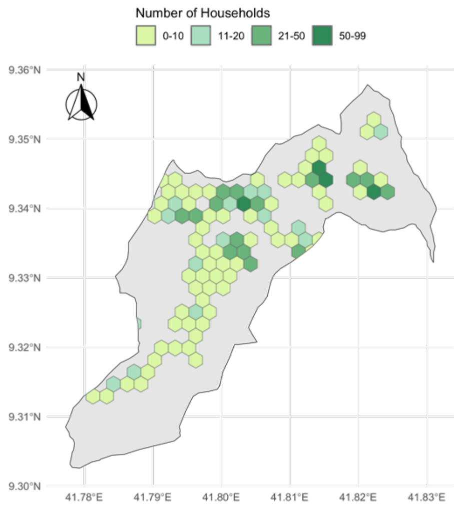
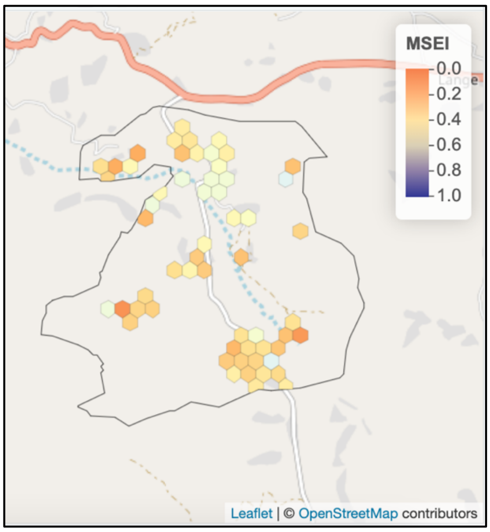


Figure 14: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K07

Kebele 04 (K04): EFA JALELA	Average MSEI: 0.28 Rural area, 489 Households		
Livelihood & Mobility	0.20		
Water Source & Accessibility	0.08	Condition & Material of house	0.45
Livestock:	0.39	Assets of house	0.14
Access to information & Communication	0.19	Education:	0.51



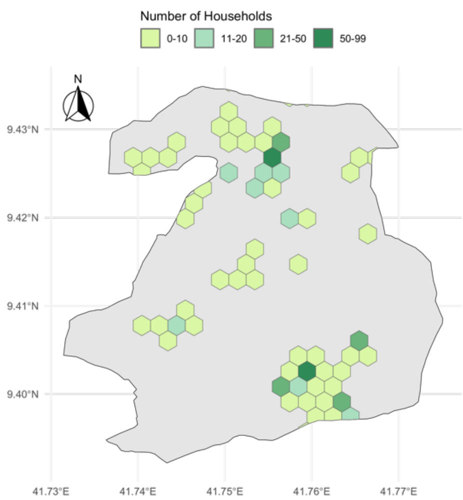


Figure 15: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K04

Kebele 10 (K10): Bereka	Average MSEI: 0.30 Rural area, 607 Households		
Livelihood & Mobility	0.30		
Water Source & Accessibility	0.01	Condition & Material of house	0.51
Livestock:	0.36	Assets of house	0.27
Access to information & Communication	0.23	Education:	0.40

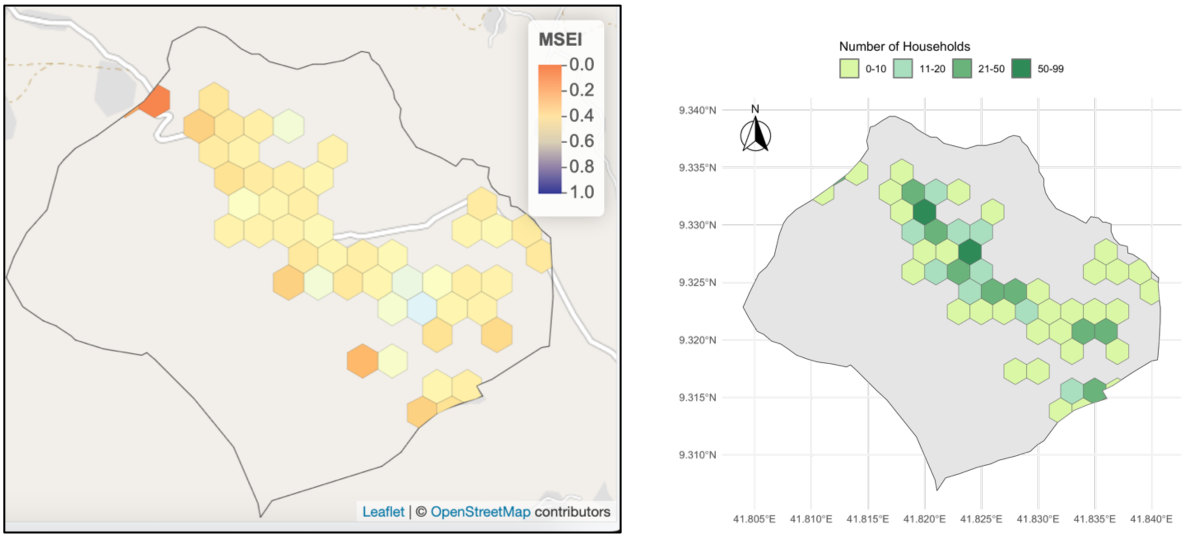


Figure 16: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K10

Kebele 05 (K05): Meda Oda	Average MSEI: 0.30 Rural area, 871 Households		
Livelihood & Mobility	0.14		
Water Source & Accessibility	0.34	Condition & Material of house	0.40
Livestock:	0.49	Assets of house	0.16
Access to information & Communication	0.07	Education:	0.49

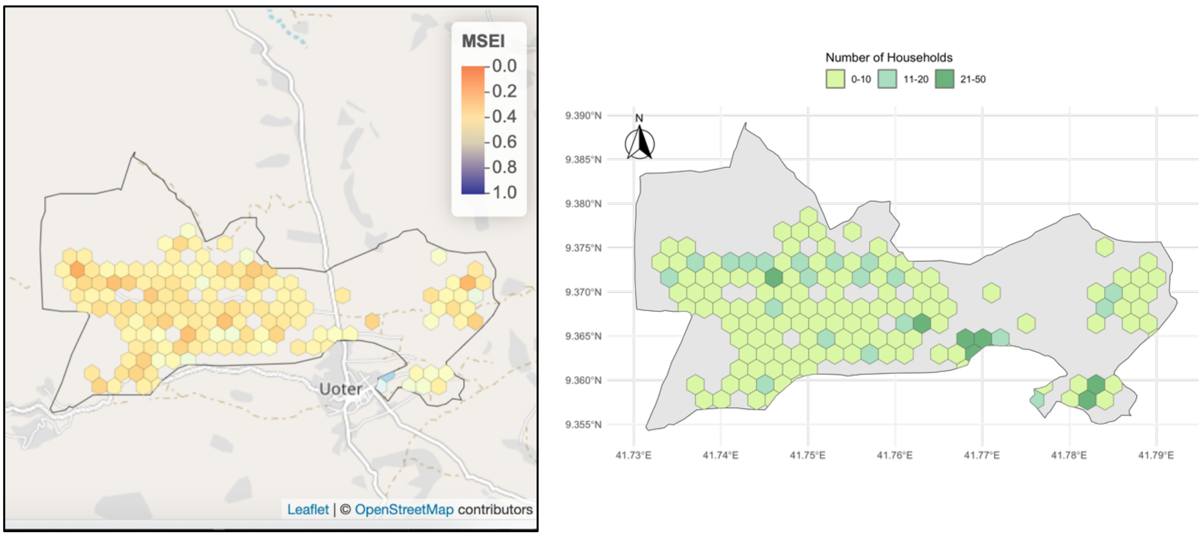


Figure 17: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K05

Kebele 11 (K11): Walitaha Bilisuma	Average MSEI: 0.30 Rural area, 1154 Households		
Livelihood & Mobility	0.23		
Water Source & Accessibility	0.40	Condition & Material of house	0.45
Livestock:	0.40	Assets of house	0.02
Access to information & Communication	0.17	Education:	0.42

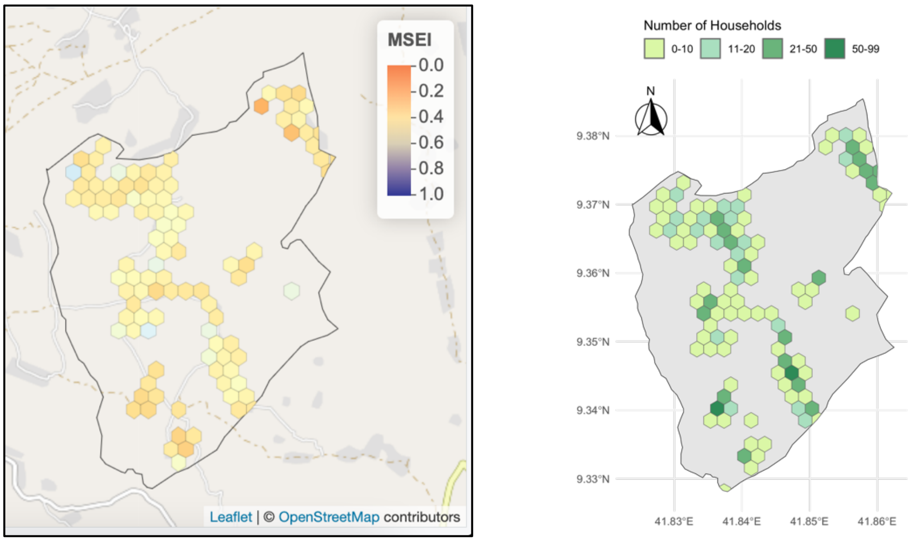


Figure 18: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K11

Kebele 08 (K08): Tola	Average MSEI: 0.31 Rural area, 970 Households		
Livelihood & Mobility	0.21		
Water Source & Accessibility	0.46	Condition & Material of house	0.41
Livestock:	0.32	Assets of house	0.10
Access to information & Communication	0.16	Education:	0.49

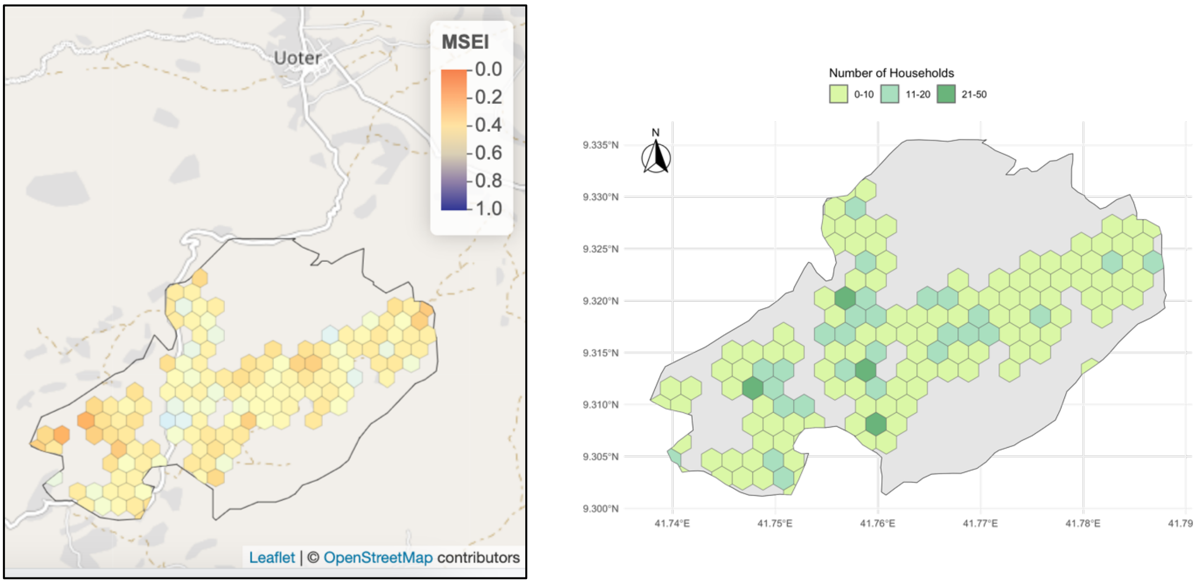


Figure 19: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K08

Kebele 03 (K03): Yabeta Lenicha	Average MSEI: 0.32 Rural area, 853 Households		
Livelihood & Mobility	0.28		
Water Source & Accessibility	0.42	Condition & Material of house	0.41
Livestock:	0.44	Assets of house	0.01
Access to information & Communication	0.15	Education:	0.52

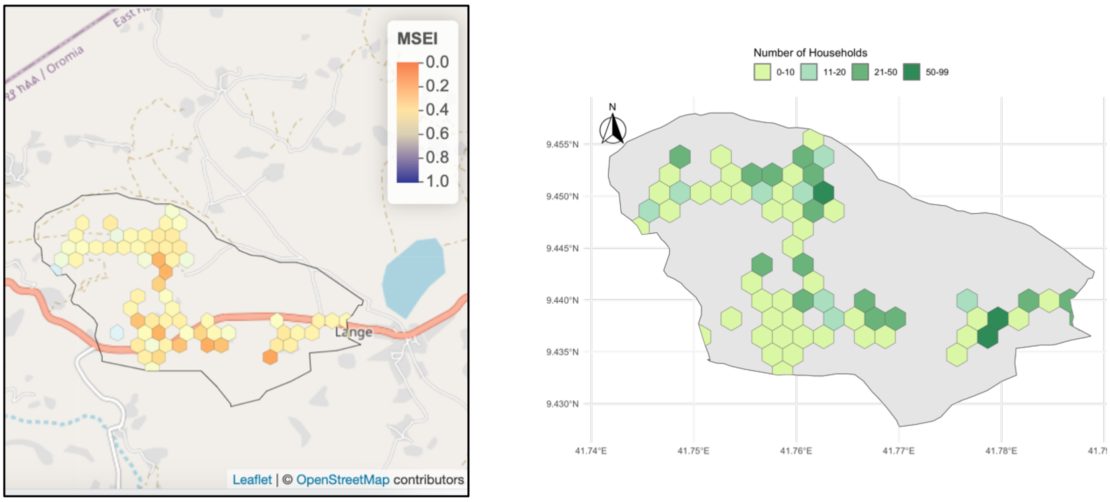


Figure 20: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K03

The Kebeles presented in this chapter represent the lowest MSEI scores in the study. Specifically, their MSEI scores range from 0.27 to 0.32. In this chapter, the aim is to analyze and possibly identify local spatial patterns of MSEI scores within the Kebeles. Generally, (dark)orange colors point at low MSEI scores, while (dark)blue colors point at higher MSEI scores. In the 7 Kebeles visualized in this chapter, orange colors are clearly dominant, reflecting poor socioeconomic characteristics. However, most Kebeles show scattered light blue hexagons, pointing at better socioeconomic characteristics. Overall, the color distributions inside each Kebele, with the presence of both orange and blue hexagons inside each Kebele, points at spatial heterogeneity, reflecting socioeconomic inequalities at the local scale.

However, some spatial patterns can be identified. For example, in Kebele 7 (*Figure 14*), households located near the main road leading to Weter Town, and, generally, near the town, seem to have better socioeconomic characteristics than those located more remotely. The same can be observed in the south-east of Kebele 5, albeit to a lesser extent (*Figure 17*). Hence, with proximity to urban areas, socioeconomic conditions seem to increase.

The text boxes above each specific Kebele delivers valuable information. For example, regarding the 'Assets of the house', Kebeles 3, 8 and 11 show particularly low scores, which means that policies could target support regarding toilet- and sleeping facilities, as well as electricity supply for these Kebeles. In this category, Kebele 4 and 5 can also be considered as having a low score. Contrary, regarding the condition and material of the house, there seem to be no big differences between the Kebeles, with the lowest (K05: 0.40) and highest score (K10: 0.51) not far from the Kersa average (0.49). As the MSEI was initially created as a proxy for social vulnerability at the face of potential drought events, the 'Water Source and Accessibility' dimension is particularly important. Here, Kebele 04, 07 and 10 have the lowest scores, by some distance. Hence, these Kebeles have, on average, the most difficulties regarding water source and accessibility, which is measured in minutes to get to the main water source, and could hence be prioritized by potential policies aiming to reduce the impacts of drought events.

5.2. Kebeles with moderate MSEI scores

Kebele 09 (K09): Gola Belina	Average MSEI: 0.39 Rural area, 806 Households		
Livelihood & Mobility	0.29		
Water Source & Accessibility	0.25	Condition & Material of house	0.56
Livestock:	0.48	Assets of house	0.32
Access to information & Communication	0.18	Education:	0.65

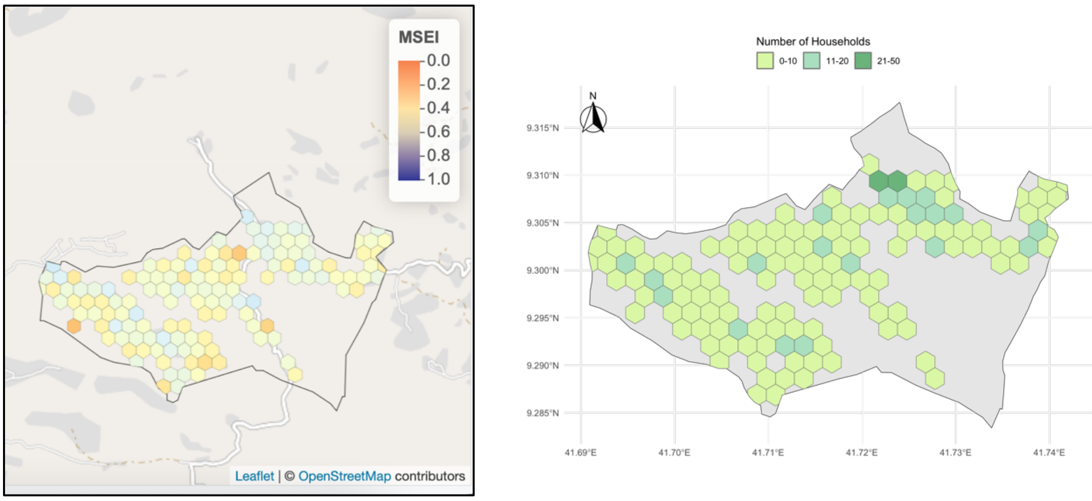


Figure 21: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K09

Kebele 02 (K02): Metekoma	Average MSEI: 0.39 Rural area, 844 Households		
Livelihood & Mobility	0.34		
Water Source & Accessibility	0.40	Condition & Material of house	0.56
Livestock:	0.59	Assets of house	0.10
Access to information & Communication	0.20	Education:	0.53

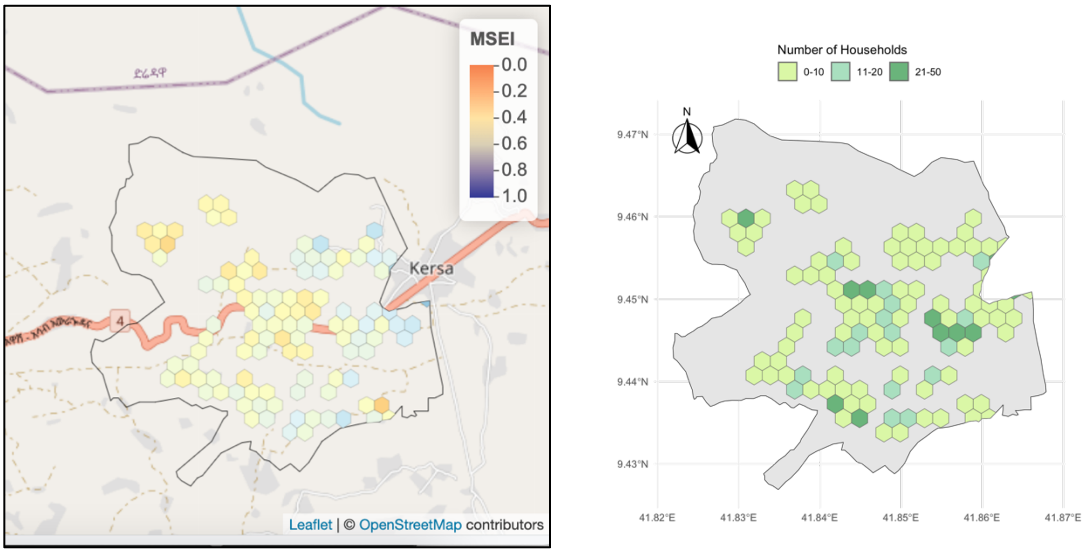


Figure 22: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K02

Kebele 12 (K12): Adele Beyikey	Average MSEI: 0.40 Rural area, 1485 Households		
Livelihood & Mobility	0.26		
Water Source & Accessibility	0.31	Condition & Material of house	0.47
Livestock:	0.39	Assets of house	0.47
Access to information & Communication	0.31	Education:	0.59

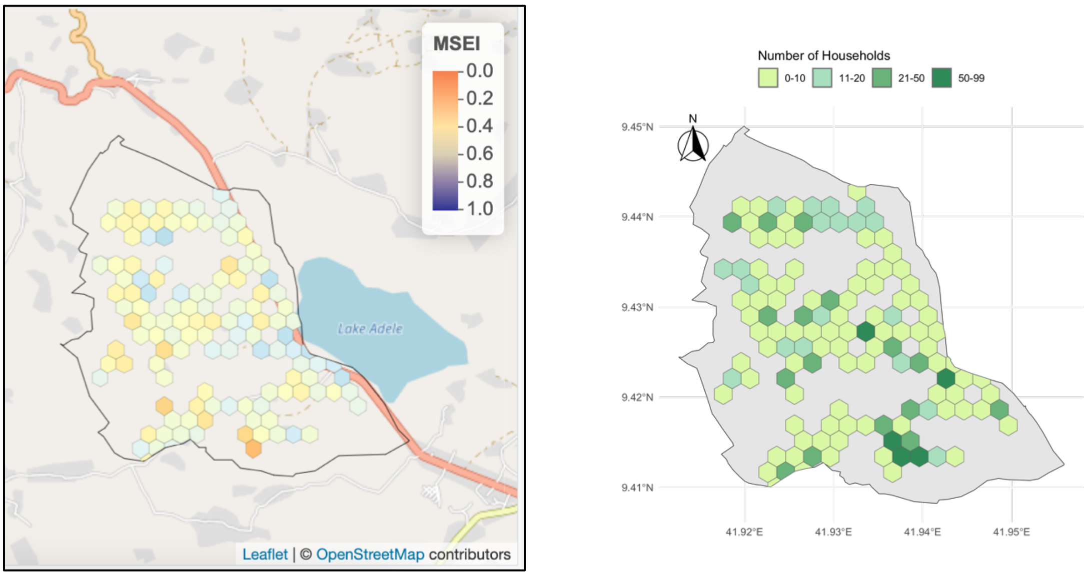


Figure 23*: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K12*

In this Chapter, Kebeles 02, 09 and 12 represent moderate MSEI scores, with very similar scores, ranging from 0.39 to 0.40. Overall, the 3 Kebeles visualized in this chapter show a more balanced color scheme compared to the Kebeles visualized in the previous Chapter. Blue colors, representing higher socioeconomic characteristics, are more common, while orange hexagons remain largely present. Here, again, spatial heterogeneity, and, hence, inequalities regarding socioeconomic characteristics are very significant, and patterns are, again, difficult to identify.

However, here, again, one local spatial pattern that can be identified is, for Kebele 02 (*Figure 22*), which is situated next to the main town of the Kersa district, Kersa Town, households situated near the town show higher socioeconomic characteristics compared to those households that are situated more remotely. This supports similar findings for Kebele 05 and 07 described in Chapter 5.1.

Regarding the MSEI sub-dimensions, it can be noted that Kebele 02 shows a low score in 'Assets of the house', hinting at deficiencies regarding sleeping- or toilet facilities and/or electricity supply. Due to the importance of the 'Water Supply and Accessibility' sub-dimension, it can be noted that Kebele 09 shows a value considerably lower than the Kersa average, while Kebele 12 shows a value slightly lower than the Kersa average. Other than that, the sub-dimensions do not hint at a significant weakness in either of the 3 Kebeles visualized in this chapter.

5.3. Kebeles with higher MSEI scores (urban areas)

Kebele 06 (K06): Weter Town	Average MSEI: 0.47 Urban area, 1158 Households		
Livelihood & Mobility	0.29		
Water Source & Accessibility	0.66	Condition & Material of house	0.59
Livestock:	0.14	Assets of house	0.46
Access to information & Communication	0.49	Education:	0.68

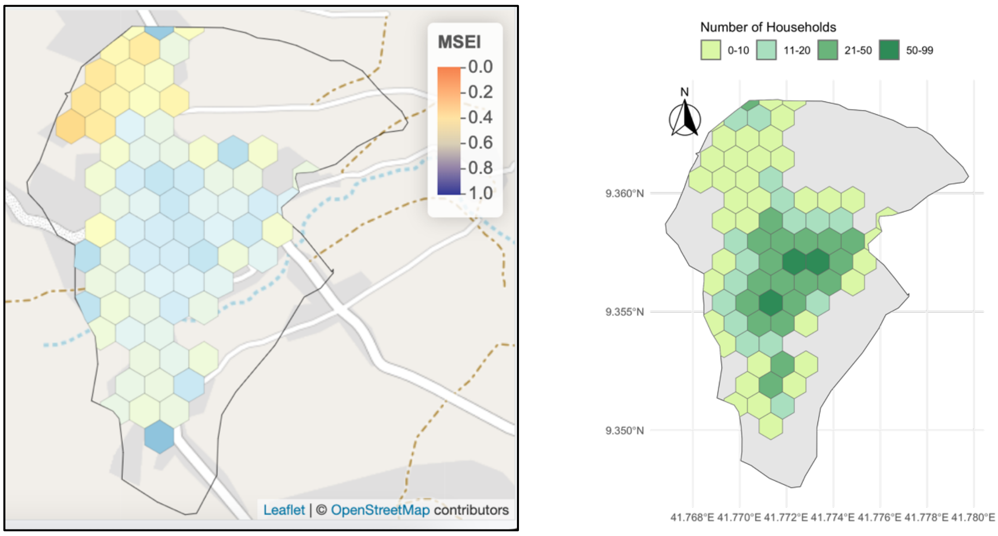


Figure 24: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K06

Kebele 01 (K01): Weter Town	Average MSEI: 0.54 Urban area, 1158 Households		
Livelihood & Mobility	0.46		
Water Source & Accessibility	0.71	Condition & Material of house	0.59
Livestock:	0.10	Assets of house	0.57
Access to information & Communication	0.65	Education:	0.68

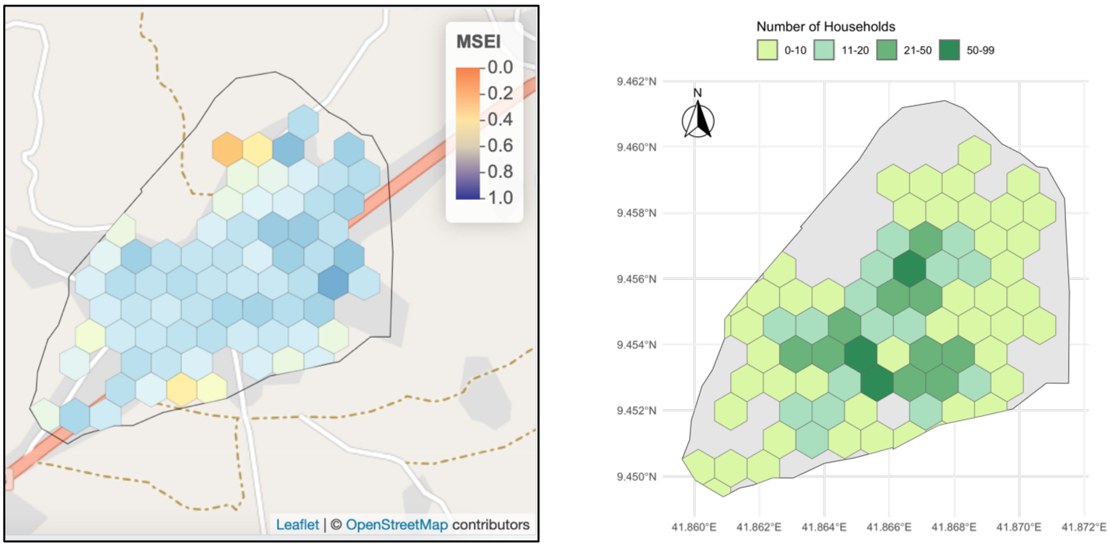


Figure 25: Local patterns of MSEI (left), households (right) and MSEI sub-dimensions (top) for K01

In this chapter, the Kebeles showing the highest MSEI scores, i.e. the urban areas, are visualized. For both urban areas, Weter Town and Kersa Town, it can be noted that, contrary to the Kebeles visualized in previous chapters, blue colors, representing higher socioeconomic characteristics, are clearly dominant. Overall, spatial heterogeneity, representing socioeconomic inequalities, seems to be lower for both urban Kebeles compared to the rural Kebeles. However, it can be noted that, for both towns, households situated on the outskirts of the town show lower socioeconomic characteristics compared to the center of the town. For the two towns, the center of the town, representing tendentially higher MSEI values, are also the most densely populated areas.

Regarding the sub-dimensions for both towns, it can be noted that both have low scores, considerably lower than the Kersa average, for the ‘Livestock’ dimension. This was expected as the population in the towns do not possess nor rely on as much livestock as the rural population. For every other sub-dimension, the urban Kebeles show values above Kersa-average. Noteworthy, the urban areas have, compared to the other Kebeles, the highest values for the sub-dimension ‘Water Source and Accessibility’ which is of particular interest due to the exposure to drought events.

Overall, while Chapter 5.1. to 5.3 showed first findings and possible spatial patterns of the local socioeconomic characteristics, each of the 12 Kebeles should be analyzed separately, as the local analysis allows to identify small scale areas with particularly low MSEI scores, which in turn allows precise place-based local policy recommendations and interventions or further research priorities. Generally, the analysis visualized spatial heterogeneity, corresponding to socioeconomic inequalities within the Kersa district and within Kebeles.

6. Transparency, Limitations and Uncertainties

Guided by ethical considerations, this study emphasizes on the importance of ensuring transparency and clearly communicating limitations and uncertainties of a social vulnerability assessment. As vulnerability is a complex, multidimensional and dynamic concept that can be interpreted differently according to context, place, population under investigation and expertise of the researcher, it is imperative to assure transparency across the entire assessment. Especially for the construction of composite indicators representing vulnerability, it is imperative to assure transparency throughout the whole process, as composite indicators are the result of multiple choices made by the researcher at multiple stages. Therefore, index construction and all related steps need to be documented carefully and presented appropriately (Chapter 4).

When it comes to hierarchical composite indices, one good practice to assure transparency is to deliver as much information as possible on the individual contributions of the different sub-dimensions contributing to the overall index. Understanding why a certain unit of analysis has an either high or low index value through the presentation of the sub-dimensions gives a far more comprehensive and understandable information to the end-user. This is particularly easy to implement when assigning equal weights between sub-dimensions. Moreover, it is valuable to include this information, as has been done in this thesis, next to the map as the main output of a social vulnerability assessment, as this emphasizes the importance of the individual sub-dimension contributions (Chapter 5).

However, transparency is not limited to index construction, visualization and presentation, but is also essential concerning the limitations and uncertainties of the study. Limitations and uncertainties are inherent to every social vulnerability assessment, due to the simple fact that social vulnerability can't be measured in a direct way (Chapter 2.2.). There are numerous ways to minimize limitations and uncertainties related to the measurement of social vulnerability, including sensitivity analysis, uncertainty analysis, and index validation. Due to the potential harmful effects of the concept of 'vulnerability', it is imperative to attribute special attention to limitations and uncertainties of the study, which will be addressed in the following two chapters.

6.1. Limitations

While the MSEI was built according to relevant literature and proved to correlate with declared income patterns of the Kersa region, there are considerable limitations to this study, which need to be made aware to the end-user and potential decision-makers or researchers.

First, while HDSS data proved to be useful in creating a multidimensional socioeconomic index, considering place-based assets combined with geolocalized household information, it is limited when used as a proxy for social vulnerability. While, as described in Chapter 2.2.2., poverty and socioeconomic characteristics play a vital role when determining vulnerability, there are many other factors contributing to people's social vulnerability at the face of environmental and climatic stressors. For example, demographic variables, such as age, gender and structure of the household or indicators on health, have not been considered in this thesis, although they contribute to and determine a household's vulnerability. Also, other factors such as irrigation potential for the agricultural sector or proximity to health centres are of great importance when assessing vulnerability to natural hazards such as droughts, but have not been considered in this thesis. Another important limitation of the study is that it does not investigate structural and political circumstances in Ethiopia and Kersa. As elaborated in Chapter 2.3, recent critics describe the risks of ignoring structural issues and the role of institutions when conducting an SVI, potentially missing out on the root causes of a region's or a population's so-called 'vulnerability'. Similarly, any SVA based on quantitative secondary data is at risk of misrepresenting the investigated populations as it potentially ignores important local circumstances, such as indigenous knowledge, or other important factors that can't be captured in quantitative data. Hence, while this study focused on socioeconomic characteristics as one important factor contributing to social vulnerability, this analysis is far from comprehensive. To gain a more comprehensive understanding of a region's or a population's vulnerability at the face of climatic or environmental hazards, qualitative in-depth investigations are needed.

Further, when it comes to variable selection, no multivariate data analysis, such as Principal Component Analysis (PCA) or Multiple Correspondence Analysis (MCA) has been conducted. Multivariate analyses are commonly used among many SVAs, e.g. Cutter et al. (2003)'s widely used SoVI, as a data reduction strategy to avoid correlated variables. Hence, in the constructed MSEI of this thesis, it is possible that some variables are correlated, potentially leading to redundancy, and possibly skewing the vulnerability assessments to overemphasize certain dimensions. Recognizing the significance of this limitation, this research underscores the necessity for future studies to incorporate advanced multivariate techniques early in the variable selection process. Such analyses can refine the variable set to ensure that each contributes unique, valuable information to the vulnerability assessment, thereby enhancing the precision and reliability of the findings.

Similarly, another limitation of this study is the absence of statistical uncertainty and sensitivity analysis. This issue is discussed in the next section (Chapter 6.2.) The methodological choice to leave out statistical procedures such as Multivariate Data Analysis and uncertainty and sensitivity analysis might affect the robustness and interpretability of the results. The decision to exclude statistical analyses from this thesis is due to its focus on the ethical dimensions of social vulnerability and its mapping at a local scale, which renders extensive statistical exploration beyond the intended scope.

6.2. Uncertainties

Preston et al. (2011: 190) state that, unfortunately, "the tendency within vulnerability assessments is to neglect the issue of uncertainty almost entirely". De Sherbinin et al (2018: 10) found that only 40% of studies included in their review addressed uncertainty, with "20% providing textual discussion only (and) 18% providing additional quantitative assessment". While it should be imperative to minimize uncertainties or shortcomings in index construction, authors should at least be aware of the latter and communicate them to the end user. This chapter acknowledges and addresses the various sources of uncertainty that inherently affect the SVA presented in this thesis. Each step in the process of constructing the MSEI, from initial data selection to final aggregation, is a potential source of uncertainty, as it includes choices made by the researcher, which impact the results. According to de Sherbinin et al. (2018: 10), the main sources for uncertainty are "data processing decisions made throughout the vulnerability mapping process, such as inclusion/exclusion of datasets and/or indicators, imputation of missing values (or lack thereof), spatial interpolation of data (to fill gaps), data normalization or scaling and the choice of weighting and aggregation schemes". As elaborated, in this thesis, no statistical uncertainty and sensitivity analysis were conducted, hence, no quantitative measurement of uncertainty is presented. Instead, uncertainties are textually discussed.

First, the in- or exclusion of indicators greatly influences the results of the SVA. While this process was guided by relevant literature, it is limited by data availability and there is potential to leave out some, while including other variables from the HDSS dataset, particularly when investigating a concept as broad as multidimensional socioeconomic characteristics. The data selection process has been described and justified in Chapter 4.2.1. Then, while data gaps, i.e. NAs, represent a potential source of uncertainty, the choices to either handle NAs by imputation or omit observations were described and justified in Chapter 4.2.2.1. The process of recoding some variables (Chapter 4.2.2.2.) from quantitative to qualitative is another source of uncertainty, as the categories and the chosen thresholds potentially influence the results. Here, the categories have been chosen according to frequencies inside the data, aiming at assigning meaningful thresholds inside the categories. However, here, there is no 'best-practice' and the thresholds could've been chosen in different ways, possibly resulting in different outcomes. Then, in the normalization process described in Chapter 4.2.3., different 'index scores' for different categories potentially influence the results. Here, again, although the choices have been described and justified in Chapter 4.2.3., other choices for the index scores could've yielded different results. The weighting scheme (Chapter 4.2.4.) is the last source of uncertainty. However, as described, most SVAs apply equal weights, as there is no theoretical justification for assuming some indicators are more important than others in a SVA (Cutter and Finch, 2008). Due to these numerous sources of uncertainty, providing detailed transparency across the whole index construction process is particularly important. Other than assuring transparency, validation methods contribute to minimizing uncertainties related to composite indicators, as done in Chapter 4.2.6.

Given the limitations and uncertainties identified, the quantitative SVA developed in this thesis should act as a preliminary guide for more detailed, qualitative inquiries. The findings should inform, but not solely determine, policy decisions. It's important for policymakers to understand that, while the SVA provides valuable insights into socioeconomic factors influencing vulnerability, it doesn't encompass the full scope of the local realities. Hence, qualitative studies are essential to capture the nuanced experiences of affected communities, ensuring that policies are not only data-driven but also contextually informed and sensitive to the diverse needs of populations at risk.

7. Discussion

This thesis conducted an ethically guided integrated vulnerability assessment on the local level using the case study of Kersa, Ethiopia. While the focus of the study was on social vulnerability, it is important to include an analysis on what the investigated population is potentially vulnerable to. In this thesis, droughts were identified as the main environmental and climatic stressor the population in Kersa is facing. Starting from literature on drought patterns in Ethiopia, this study analyzed the local Kersa context by investigating SPEI patterns from 1981 - 2016. The analysis showed that, during the investigated time period, the Kersa district has been affected on numerous occasions by drought events of differing degrees and durations. The drought analysis contributed to an integrated vulnerability assessment in this thesis by investigating 'exposure', a separate, although linked concept to vulnerability. However, due to the multidimensional relationship between poverty and vulnerability, elaborated in Chapter 2.2.2., the MSEI, reflecting multidimensional socioeconomic patterns, represents potential vulnerability not only at the face of potential drought events, but also other climatic and environmental stressors.

The results of the ethically guided local SVA conducted in this thesis are diverse. Having elaborated the challenges related to the quantitative measurement of social vulnerability in

Chapter 2.2.1., one research question of this thesis concerned the adequate measurement of social vulnerability on the local scale. In this context, it is a common procedure to create a composite index, grouping different variables that are suspected to contribute to vulnerability patterns of the investigated population and assigning values to areas or communities, representing different degrees of vulnerability. However, given the multidimensional, complex and dynamic nature of vulnerability, there's a risk of misrepresenting and harmful labeling of the investigated populations. In particular, the concept was found to have the potential to "stigmatize, label, marginalize, and objectify, denying the agency and voice of those seen as vulnerable" (Virokannas et al., 2018: 336). Therefore, researchers need to be careful when conducting a so-called vulnerability assessment and should be guided by ethical considerations at every stage of the assessment.

In this context, this thesis proposes several ways to minimize the potential negative effects of vulnerability. Generally, assuring transparency along the whole research is of extreme importance to minimize potential harmful effects and avoid misrepresentation. Indicators to be included in the index should be clearly based on and justified by relevant literature and, ideally, supported by local experts. Then, each step of the index construction should be described and documented, enabling reproducibility of the analysis. The results should be validated by external sources. Uncertainty and sensitivity analysis enable to quantitatively assess the robustness of the index. In the absence of statistical procedures, uncertainties and limitations should be textually discussed. The aspect of uncertainties and limitations of a SVA are particularly important in the context of potential harmful labelling and misrepresentation of the concept. Another important aspect concerning transparency is the clear communication of what the constructed index precisely measures. By accurately naming the index, such as e.g. Multidimensional Socioeconomic Index (MSEI) instead of 'Vulnerability Index', the end-user has a clearer idea on what aspects of vulnerability are investigated. Further, one important contribution is the clear presentation of what factors contribute in what ways to the final index. Information on what factors in- or decrease the final index give a more comprehensive and clear understanding of the local context and avoids labelling and possibly misrepresenting the investigated populations as 'vulnerable' when this term is potentially misleading. As Schmidtlein et al. (2018: 1112) state, "we must be careful when employing numerical vulnerability indices to realistically represent the underlying vulnerability, and not other hidden or related phenomena”. The index’s sub-dimensions have the potential to shed light on hidden (spatial) patterns of the index and allow for more nuanced and detailed results. This thesis demonstrated how including this information next to the map(s), as the central outcome of the SVA, highlights the importance of the respective contributions of different indicators within the index, and hence effectively communicates this information to the end-users.

Another focus of this thesis was on visualizing the results of the SVA on the local scale while preserving the investigated populations’ privacy. Here, (hexagonal) binning proved to be an appropriate method. By summarizing a group of households into one hexagon, individual households can’t be traced or precisely localized, which assures privacy for the investigated population. By adjusting the hexagon sizes according to population density and size of the investigated area, information can be maximized while assuring that privacy is upheld.

In this thesis, the focus has been on the link between poverty and vulnerability, as described in Chapter 2.2.2., which is why it was decided to construct a multidimensional socioeconomic index (MSEI) to capture local context-specific circumstances. While socioeconomic characteristics greatly contribute to and influence social vulnerability, other researchers can focus on very different aspects when measuring social vulnerability, e.g. demographic or health patterns, which is equally as important. Generally, social vulnerability can mean very different things to different researchers and end-users (Brown, 2011). Hence, it is important for researchers to describe and justify what aspects of vulnerability they are focusing on.

The results have shown that socioeconomic characteristics differ considerably among and within the 12 investigated Kebeles in the Kersa district. Generally, urban areas were found to have higher scores and less spatial heterogeneities, i.e. less socioeconomic inequalities, compared to rural areas. Hence, it could be concluded that urban areas are, based on socioeconomic characteristics, less vulnerable to potential environmental or climatic stressors. Also, sub-dimension scores have shown that urban areas have, compared to the rural areas, better water sources and accessibilities to those, which is particularly important in the context of potential drought events. However, the Kebeles need to be investigated separately and in-detail to gain insights into local patterns and explore the full potential of the visualization at the local level. The analysis and visualization through maps allow for local identification of more or less 'poor' households, i.e. more or less local socioeconomic inequalities, which are expected to influence vulnerabilities at the face of potential drought events or other environmental or climatic stressors.

Generally, in the context of scarce socioeconomic data in many African regions, the 37 HDSS sites in Africa have proven to be valuable for future research aiming to understand the intersection between socioeconomic inequalities and climate change vulnerability. Here, the SPEI data used to investigate exposure to drought events can be valuable, too, especially when the analysis is conducted on the local level.

Finally, composite indicators "must be seen as a means of initiating discussion and stimulating public interest" (OECD 2008, 13). In the context of vulnerability, they can provide valuable first insights into local patterns of an investigated area, however, they do not replace the need for cooperation with local experts and communities to identify, understand and overcome potential vulnerabilities to climate change. As Schmidtlein et al. (2008: 1112) state, "in-depth qualitative analysis, such as case studies, often proves indispensable in providing the context necessary for successful application of quantitative index constructions". In this sense, quantitative SVIs can be seen as "useful guides for the selection of study areas in which more intensive, qualitative analyses may be conducted" (Schmidtlein et al. 2008: 1112).

8. Conclusion

After recent critics of the concept of 'Vulnerability', this thesis aimed at conducting an integrated quantitative vulnerability assessment which is guided by ethical considerations. Using the case study of Kersa, a drought-prone district in Ethiopia, a Multidimensional Socioeconomic Index (MSEI) was constructed, which served as a proxy for social vulnerability. By integrating socioeconomic characteristics through HDSS data with local environmental and climatic stressors, notably droughts, through SPEI data, this study contributes an integrated assessment of vulnerability within a highly specific context. Key findings highlight significant variabilities in socioeconomic characteristics across and within different Kebeles in Kersa, with urban areas displaying higher socioeconomic characteristics compared to their rural counterparts. On the local scale, socioeconomic inequalities, which influence differentiated vulnerabilities at the face of climatic and environmental stressors, were detected and localized, which can potentially guide future research or policies.

However, ethical considerations demand for a re-evaluation of common quantitative SVAs. As long as vulnerability potentially misrepresents and harmfully labels investigated populations, the term should be used with caution. This thesis has proposed some ways to conduct a quantitative SVA in an ethically guided way. Ensuring transparency through each step of the index construction, presenting the limitations and uncertainties associated with the index, and specifying how different indicators or sub-dimensions contribute to the final index is essential for minimizing the risk of misrepresenting the populations under investigation. Further, regarding the dissemination of the results, (hexagonal) binning proved to be an appropriate mapping method, conserving privacy of the investigated populations while maximizing information for the end-user.

Overall, quantitative assessments of (social) vulnerability remain challenging and critics need to be heard about whether or not the term 'vulnerability' is suited and ethically appropriate. Ideally, quantitative SVAs should inform future qualitative, in-depth research, leading to policy recommendations that encompass a broader and more comprehensive understanding of local vulnerabilities in the face of climatic and environmental stressors.

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