Characterizing the spatio-temporal dynamics of social vulnerability in Burkina Faso

A comparison of Principal Component Analysis with Equal Weighting

Lotte Savelberg

Delft University of Technology

Characterizing the spatio-temporal dynamics of social vulnerability in Burkina Faso. A comparison of Principal Component Analysis and Equal Weighting

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CHARACTERIZING THE SPATIO-TEMPORAL DYNAMICS OF SOCIAL VULNERABILITY IN BURKINA FASO. A COMPARISON OF PRINCIPAL COMPONENT ANALYSIS AND EQUAL WEIGHTING

A thesis submitted to the Delft University of Technology in partial fulfillment
of the requirements for the degree of Master of Science in Engineering and Policy Analysis

by
Lotte Savelberg: (2022)

The work in this thesis was made at the:

The Data and Digital Initiative of
The Netherlands Red Cross
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EXECUTIVE SUMMARY

RESEARCH BACKGROUND AND RESEARCH QUESTION

Global climate change has resulted in a higher frequency of extreme disaster events and is therefore a serious challenge in disaster impact management. Disasters impact the livelihood of humans all over the world. The impacts of these disaster are becoming more prominent in countries outside the Walled World because of inadequate preparedness, adaptation and mitigation strategies.

Disaster risk is composed of several components, such as vulnerability, susceptibility, exposure, and the probability of occurrence and intensity of a hazard. Vulnerability has become a topical issue due to the major role it plays in disaster risk reduction strategies (Dintwa et al. 2019). The Hyogo Framework and Sendai Framework emphasize that understanding vulnerability is the key for disaster management and mitigation (SENDAI 2015; UN, General Asembly 2005). That is because the studies on vulnerability unveil the factors that cause a hazard to turn into a disaster. It reveals the specific indicators that are most fragile, and thus provides relevant information for disaster mitigation strategies Chen and Lin (2021). Vulnerability assessments thus play an important role in (multi-) hazard risk assessments. It portrays the variety of social, economic, physical, cultural environmental and institutional characteristics which influence the susceptibility of the exposed elements to hazards (Birkmann 2007; Moreira et al. 2021b).

Hence, this research focuses on the development of a method to understand the dynamics of vulnerability. The study area comprises Burkina Faso. Over the years, Burkina Faso has been challenged by a variety of hazards such as floods, droughts and conflicts. This has currently led to a situation with over one million Internally Displaced Persons (IDPs), of whom 60% are children. In total, almost three million people are in need of humanitarian support. Burkina Faso faces repetitive societal problems caused by the increased frequency of extreme rainfall as a consequence of climate change. On top of that conflict is increasing, leading to additional migration. The country is facing a variety of complex problems, that challenge the humanitarian needs of its inhabitants. Combining this, has led international organisations to conclude that Burkina Faso is facing 'by far the largest protection crisis in the Central Sahel (FAO 2021). Both, natural hazard events and the conflicts contribute to the vulnerability of the Burkinabé and leading them to leave their houses and become displaced in their own country. Considering the demand for a better understanding of flood vulnerability, and the rising humanitarian needs in the flood prone areas of Burkina Faso it is interesting to assess the change in vulnerability indicators over the years of conflict that have occurred. This is translated into the following research question:

> How to calculate a social vulnerability index for Burkina Faso that characterizes the spatial and temporal dynamics of social vulnerability?

APPLYING PRINCIPAL COMPONENT ANALYSIS

Previous social vulnerability studies and risk assessments executed by the The Netherlands Red Cross (NLRC) have always been executed with the use of a hierarchical structural design. In this thesis the usefulness of an inductive structural design for social vulnerability studies in the humanitarian field was assessed. Even tough the method works, it is useful the balance the pros and cons of both methods before concluding which method is most suitable. The Principal Componant Analysis (PCA) approach is part of statistically based inductive methods, whereas the hierarchical processes, also called Analytical Hierarchy Process (AHP) are part of participatory or expert-based methods.

This research shows large differences between the outcome of the social vulnerability assessments. Both in the absolute outcome of the social vulnerability score and in the ranking of the communities. When choosing a construction method, it is thus important to make deliberate methodological decisions. For this, understanding the qualitative meaning of the methods is required. Additional research is recommended for this.

On top of this, it is necessary to understand the fundamental benefits and drawbacks of both approaches. Hierarchical approach tend to be simpler, and have a hierarchical structure that is more inline with the structure of social vulnerability frameworks. This makes the understanding simpler and more straightforward. However, the method derives no insights into the relationships between the indicators and is thus sensitive for double counting. Furthermore, the biased weighting scheme makes it impossible to consider the internal dynamics of social vulnerability.

On the other hand, a PCA is a more objective, statistical approach of understanding social vulnerability. It is assumed that all indicators shape social vulnerability. Using the PCA reduces the risks of double counting, and classifies ungrouped indicators together. However the dimensions of the outcome are unpredictable, and the weights may differ from reality. Nevertheless, the method is more precise, and thus more suitable for comparing multiple years with each other.

The most important benefit of PCA relates to the understanding of the vulnerability dynamics. Due to the statistical approach, many insights are developed into the composition of social vulnerability. Understanding the contribution to the variance of the indicators, and comparing different results with each other will deliver insight in which indicators changed over the years and additionally how this contributed to an increased or decreased social vulnerability.

However, an important drawback of the PCA is that a high data resolution is required. This makes the method less suitable for sub–national and country level assessments of (social) vulnerability. It also emphasizes the need for a higher data resolution in countries outside the Walled world. Better data gathering mechanisms are required if more social vulnerability research is to be executed. These have to be set–up by the national Census offices.

A last remark that must be made with regard to the PCA related to the methodological decisions that are made within the construction of the algorithm. While construction the algorithm, at three points a variety of methods can be applied: the number of components, the type of rotation and the weighting scheme. To determine how sensitive the result is for these decisions a three–way ANOVA test is executed. The outcome of the analysis, is again very sensitive to these methodological decisions. Further research, should focus on the qualitative relation between those decisions and the problem the index aims to present. Such a research will focus on semantic discussions.

SOCIAL VULNERABILITY IN BURKINA FASO

The above insights of the PCA approach are derived from applying the method to a case study in Burkina Faso. Both a spatial assessment and a temporal assessment were executed.

The spatial assessment was executed on community level and provides useful results for humanitarian decision making. The assessment was executed with use of the PCA, in which the number of components was based on 90% explained variance, a varimax rotation was applied and the sum of all component scores was used as the weighting scheme. High vulnerable areas are identified in the Centre-Nord and the Sahel, areas that are also prone to many conflict events. The composition of the index in these areas also shows, that the social vulnerability is mainly caused by, the presence of IDPs, hazards, conflict events and undernourishment. There are also some high vulnerable areas in the Haute Bassins. However in these areas the high score is mainly cased by the prevalence of HIV and Elderly.

When zooming in on the spatial pattern, the spatial autocorrelation analysis Moran's I and LISA are used. This showed a positive correlation is found, that identifies that high vulnerable areas are surrounded with other high vulnerable communities. These clusters are found in the Sahel– Centre-Nord cluster, the Western Haute Bassins cluster and the East Haute Bassins – Centre-Ouest cluster. Furthermore low vulnerability clusters are identified in the East, the Capital, and the Sahel – South-East cluster. For policy decisions the outliers of these clusters are important.

The outlier communities identified with the spatial autocorrelation deserve special attention in risk-reduction strategies and further research. Since there is high human mobility in Burkina Faso, two things deserve better understanding. The HL areas, might need less external help with the risk reduction strategies, because the surrounding communities are relatively strong and can assist the community with high vulnerability in gaining more resilience. On the contrary the LH communities might face more IDPs in the short feature. Since the circumstances in these communities are relatively good, they might be attractive to move to when displacement occurs in the high vulnerable surrounding communities.

It is complicated to derive clear patterns between the social vulnerability score and the context related indicators: number of people affected by conflict, natural hazards and the number of IDPs in a commune. The research shows that the top ten vulnerable communes score high on these indicators. Which suggests an interaction between the social vulnerability score and the presence of hazards, conflict and **idps!** (idps!). However, when comparing the results for all communes, no patterns can be identified.

Secondly, the temporal assessment was executed. Originally, this was done with the PCA method. However, since not enough data was available to execute the analysis on community level, it had to be executed on sub-national level. This proved not valid due to low KMO-values. Therefore, the temporal dynamics were assessed with the results from the Disaster Risk Management Knowledge Center, EC (2022). Which is a hierarchical approach and thus does not provide insight into the internal dynamics. The temporal dynamics are assessed with the use of a simple linear regression. It did show a general increasing pattern in social vulnerability in all regions in Burkina Faso. Especially Boucle du Mouhoun, the Nord and the Centre-Nord showed a statistically significant increase over the last seven years.

This temporal analysis emphasized the lack of insight created into the composition of the social vulnerability score when using the hierarchical approach. Meanwhile it showed that this is the only valid approach when low data availability occurs.

RECOMMENDED FURTHER RESEARCH

This research showed a good first attempt in understanding the dynamics of social vulnerability over time. It developed a suitable method to assess the internal and external dynamics in further research. For this it is necessary to understand the semantic relation between the method that is used and the social vulnerability research. Furthermore, applying scenario discovery methods on the input data, will provide insights in the margin of manoeuvre of the results. It will then also be important to develop a strong indicator selection method. This could be verified with a simple correlation assessment between the input indicators and historical impact data. With doing so, a better understanding of the relative importance of each indicator can be developed. This could also be used to guide the weighting scheme.

ACKNOWLEDGEMENTS

The Hague, August 2022

Dear reader,

Nine years ago, the big Delft adventure started for me, in front of you lies my MSc thesis, with which I end these wonderful years. After several workarounds, my interests and capacities blended in very well in the Engineering and Policy Analysis program.

My interests in the humanitarian field were sparked during my time in Bolivia, and finally came in place when the freedom was given to choose a these project. I am very grateful that 510 offered the possibility to combine the climate knowledge I gained during my BSc civil engineering, together with the understanding gained of conflict during my minor Conflict and Peace studies at the Vrije Universiteit, and the data and policy interplay of which knowledge was developed in the EPA program.

Delivering a successful thesis usually seems to be an individual process, however I would not have been able to do this alone. First of all, I would like to thank the EPA community. Furthermore, I want to thank Tina for her guidance during the start of this project, and later on for the endless amount of critical questions that steered this research to a higher level.

Furthermore, I would like to thank Marc, for his patience with my enthusiasm that some times leads to decisions that were too inconclusive. Thanks to your scientific approach, and continuous flow of new literature and information my ad hoc ideas and analysis are finally combined in to a thorough storyline and insights for the disaster risk reduction field.

On a last professional note, I would like Ylenia and Jazmin. Ylenia, thanks a lot for the endless discussions we held on PCA and how to apply that in this research. These discussions provided the basis for my understanding of the method, and the insights it has delivered for the scientific field. Jazmin, I want to thank you very much for your keen interest, and endless support and motivational words in our biweekly meetings. Your trust provided a basis for me to trust my own work and not get to stressed during the last couple of months.

On a more personal note, I want to thank my parents. As all moms and daughters, and fathers and daughters, it was sometimes a bumpy road. However, your critical eyes and encouragement to follow my heart gave me the confidence, trust and drive I needed to find out how I see myself in this world, and in which way I can contribute to the society and to our family. And of course Jelle, moving in together might seem stupid to some people in a stressful time like we had over the last months. However, every bit of it is great! Your jolly behavior to get me in a better mood after a day of python errors, the thoughtful conversations we have had on the question 'what is next?', and the perfect dinners and weekend to keep thesis work limited from 9 - 17. I am sure a lot more of this will come, and we will both enjoy the most of it! So many more people have functioned as a relief mechanisms the last months, my sisters, friends and sport buddies. Now it is time for me to thank you for your patience and support.

Lotte

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1 INTRODUCTION

1.1 INTERNATIONAL ROLE OF DISASTER RISK REDUCTION

Global climate change has resulted in a higher frequency of extreme disaster events and is therefore, a serious challenge in disaster impact management. Disasters impact the livelihood of humans all over the world. The impacts of these disasters are becoming more prominent in countries outside the Walled World[1] because of inadequate preparedness, adaptation and mitigation strategies.

Disaster risk is composed of several components, such as vulnerability, susceptibility, exposure, and the probability of occurrence and intensity of a hazard. Vulnerability has become a topical issue due to the major role it plays in disaster risk reduction strategies (Dintwa et al. 2019). The Hyogo Framework and Sendai Framework - two important official documents on global disaster reduction - emphasize that understanding vulnerability is the key for disaster management and mitigation (SENDAI 2015; UN, General Asembly 2005). That is because the studies on vulnerability unveil the factors that cause a hazard to turn into a disaster. It reveals the specific indicators that are most fragile, and thus provides relevant information for disaster mitigation strategies Chen and Lin (2021). Vulnerability assessments thus play an important role in (multi-) hazard risk assessments. It portrays the variety of social, economic, physical, cultural environmental and institutional characteristics which influence the susceptibility of the exposed elements to hazards (Birkmann 2007; Moreira et al. 2021b).

1.2 INTRODUCTION TO CASE STUDY: BURKINA FASO

This thesis focuses on social vulnerability against flood hazards in Burkina Faso. Over the last years, Burkina Faso (BFA) has been challenged by a variety of hazards such as floods and conflicts. This has currently led to a situation with over one million IDPs, of whom 60% are children. In total, almost three million people are in need of humanitarian support. The ministry of Humanitarian Action of Burkina Faso asks for more attention for the risks of floods - which aligns with the calls for action from the Hyogo and Sendai frameworks. Floods are specifically a problem from June to September, when the country suffers from increased rainfall as a consequence of climate change. In 2020 and 2021, IDPs struggled with the consequences of the floods (Alexandru 2021; UNICEF et al. 2020). Burkina Faso faces repetitive societal problems caused by the increased frequency of extreme rainfall as a consequence of climate change. On top of that conflict is increasing, leading to additional migration. The country is facing a variety of complex problems, that challenge the humanitarian needs of its inhabitants.

1 Term introduced by Khan et al. (2022), it illustrates how 14% of the world's population hides behind a fortress or a wall which denies entry to the world outside it based on wealth. This is clear from the physical walls that have come up across the world such as in the Palestinian Occupied Territories and even Trump's 'border wall' between Mexico and the USA. It also signifies the political barriers created by for instance, 'Fortress Europe' to keep migrants and refugees from entering the continent.

1.2.1 The geographics of Burkina Faso

Burkina Faso is a land-locked country in West-Africa with an estimated population of 21 million. Livelihoods are very vulnerable due to changes in the natural environment. That is enhanced by the fact that over 80 % of the community is employed in agriculture, making them fragile to natural hazard events. Furthermore, recent spikes of conflict add to the vulnerability of the people. Since 2016, BFA is home to armed Islamist groups, which leads to increasing security incidents. Burkina Faso ranks 158th on the ND-GAIN index that shows the extreme vulnerability of the country for shock events such as natural hazard and conflict (The Notre-Dame Global Adaptation Initiative (ND-GAIN) 2020). The United Nations Development Program (UNDP) identified four major challenges facing the country: deforestation, desertification, low rainfall, and extreme weather conditions such as floods, droughts, high winds and extreme variation between wet and dry seasons. All contribute to the country's vulnerability (Global Facility for Disaster Reduction and Risk (GFDRR) 2011). The climate predictions for Burkina Faso are summarized by the Red Cross Climate Centre (RCCC) and visualized in table 1.1. This research focuses on the social vulnerability of flood events. Since floods present 28% of the hazards that occurred in the last 30 years, and there is a strong call from the practitioners working with IDPs to understand the flood risk better. This research often refers to the different levels of administrative units. In Burkina Faso there are 13 administrative units at admin 1 level (adm1). These refer the to sub-national regions in the country. Additionally, there are 45 provinces, which is referred to as admin 2 level (adm2). Lastly there are 351 communities in Burkina Faso, to which I refer as admin3 (adm3) regions.

Table 1.1: Climate change in Burkina Faso. *Source: Climate Fact Sheet BF RCCC*, (Red Cross Climate Centre (RCCC) 2021)

Historical Climate	Projected Climate
Temperature	
Since 1975 the annual average temperature have been observed to increase by 0.6 °C (USAID 2012). There has been an increase in the average yearly temperatures of approximately 0.10 °C per decade from 1901 - 2013 (USAID 2012). Reports suggest a warming of 0.26 °C per decade over the last 30 year (USAID 2012).	By 2050, a 1.4 - 1.6 °C rise in temperature is expected in Burkina Faso (United Nations Develpment Porgram (UNDP) 2020). Temperature is projected to increase by 3 - 4 °C in the period of 2080 - 2099, this is substantially higher than the global average (World Bank 2021). Temperature increases vary across the country, with higher temperatures expected in the North, the South-West and in the dry season (Potsdam Institute 2020; World Bank 2021).
Precipitation	

Observations from weather stations recorded since 1902 depict an expansion of the dry zone, which has been moving southward over the last century Global Facility for Disaster Reduction and Risk (GFDRR) (2011). Droughts are a regular occurrence and some argue northern Burkina Faso has been in a ”quasi drought” since 1970 (Crawford et al. 2016). Flooding events are increasing. Between 1991 and 2009, Burkina Faso saw 11 major floods which impacted 380.000 people and took 93 lives Global Facility for Disaster Reduction and Risk (GFDRR) (2011).

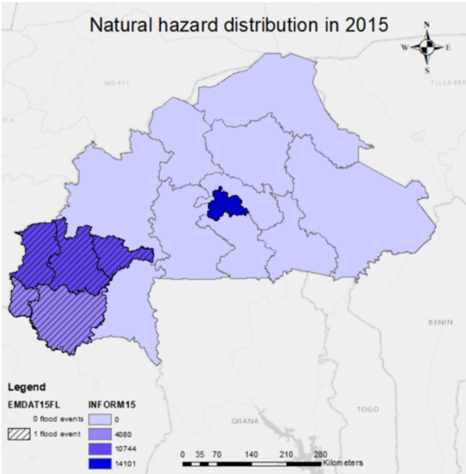
A high level of uncertainty exists regarding projections on precipitations in the region. Projections range from a decline of 10% to an increase in 16% of precipitation by 2100 (Crawford et al. 2016). IPCC estimates show a potential increase in rainfall in the West African region under a high emissions scenario of 1% by 2035, 2% by 2065, and 5% by 2100 (Crawford et al. 2016). Despite little projected change in annual precipitation sums, ’future dry and wet periods are likely to become more extreme’(Potsdam Institute 2020)

Consequently of these climate changes, Burkina Faso is suffering a variety of natural hazards. The natural hazard events that took place from 2015 – 2021 are mapped in figure 1.1. From this, it can be derived that the intensity of the events has increased over the years. Despite the many hazardous events in table 1.1, one of the major consequences of climate change of which the Burkinabé are suffering are floods. A wave of flood events occurred during the rainy seasons of the last two years, particularly August and September are wet. During 2020, an average of 70 mm of water per day was recorded during these months. In 2020, according to Government’s Council for Emergency Relief and Rehabilitation (CONASUR) 71.341 people were affected, of whom 33.675 are women and 35.919 are children. Over 3.347 houses were completely destroyed and 1.656 partly damaged. Furthermore IDPs have lost over 1790 emergency shelters. The most affected regions are the Sahel, the Centre-North, the North, The East and the Central Plateau, where 85% of the affected people live. The CONASUR estimates that 50.000 people are affected by floods and seasonal rains each year (Internal Displacement Monitoring Centre 2021). An overview of the floods from 2015 – 2020 is presented in figure 1.1.

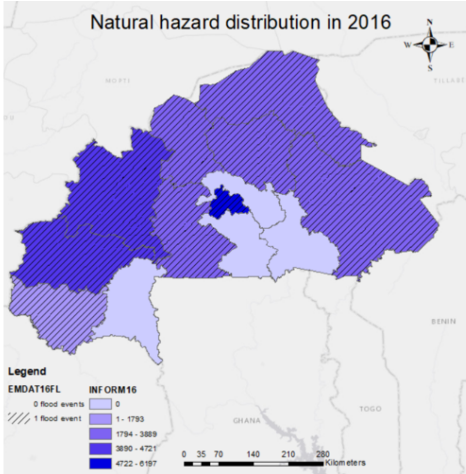
Conflict Type	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Battles	7	15	35	80	212	243	303
Explosions / Remote Violence	0	0	5	21	52	76	357
Protests	61	46	68	85	136	77	146
Riots	39	30	27	30	27	19	49
Strategic Developments	5	4	23	63	109	125	340
Violence Against Civilians	4	9	47	123	335	335	655
Total	**116**	**104**	**205**	**402**	**891**	**875**	**1850**

Table 1.2: Security incidents in Burkina Faso

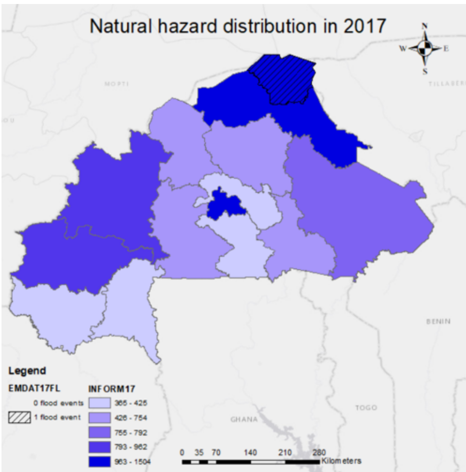
In addition to the natural hazard events, security incidents are spiking. In 2014, the events started with a popular uprising against a constitutional review proposed by president Blaise Compaoré. As a consequence, he had to resign after 27 years in power. Since 2016, BFA has seen inter communal conflict that is increasingly leading to armed group attacks (Red Cross Climate Centre (RCCC) 2021; Raleigh et al. 2010). A visualization of the increase of security incidents is given in table 1.2 and figure



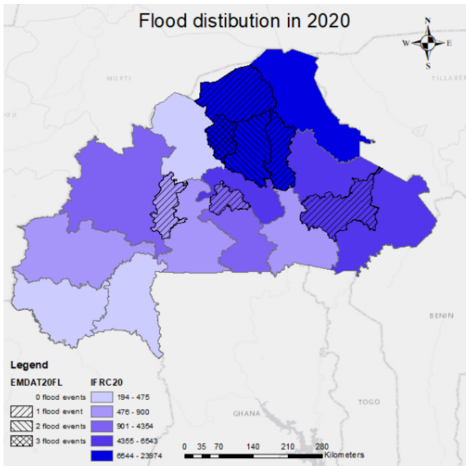
(a) 2015: One major riverine flood affecting a total of 28,925 people of which 54 became injured. In Cascades, Centre and Hauts-Bassins. Different information was registred by INFORM and EMDAT



(b) 2016: One major riverine flood affecting a total of 34,893 people contributing to 7,032 of them becoming homeless and 35 to be injured. In Centre, Hauts-Bassins and Boucle du Mouhoun.



(c) 2017: A Dengue epidemic affected a total of 9,029 people. A flood event impacted the province Oudalan affecting another 882 people. In Centre, Hauts-Bassins, Boucle du Mouhoun and Sahel.

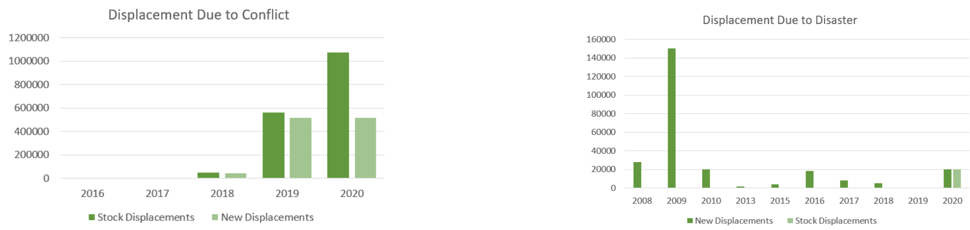


(d) 2020: 3 Flood events affected 110,365 people, 23,500 became homeless and 111 injured. In Centre-North, Sahel, Plateau-Central and Est. Furthermore a drought affecting 2,900,000 people in entire country.

Figure 1.1: The open source information on natural hazards that took place in Burkina Faso between 2015 and 2020. The blue shade shows the amount of people affected by the natural hazard according to Disaster Risk Management Knowledge Center, EC (2022), additionally the shades show the amount of hazard events according to EM-DAT, CRED / UCLouvain (2022).

1.3. Furthermore, figure 1.3 shows the spread of conflict and conflict related deaths.

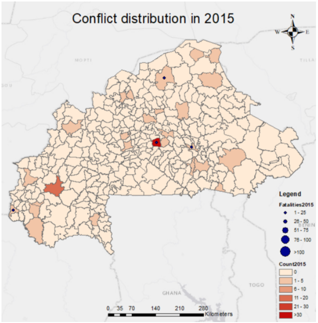
Due to the conflicts and natural hazards the number of IDPs increased as well. From 2019 – 2020, the number of IDPs increased from 50.000 to 750.000, and currently the number is over a million (UN OCHA 2021; World Bank 2020). The International Displacement Monitoring Centre (IDMC) expects an average number of 10.096 additional displacements each year due to floods (Internal Displacement Monitoring Centre 2021). The reasons behind displacement are shown in figure 1.2. The growth in displacement per community is visualized in figure 1.4. Combining this, with the natural hazards, has led international organisations to conclude that Burkina Faso is facing 'by far the largest protection crisis in the Central Sahel (FAO 2021). Both, natural hazard events and the conflicts contribute to the vulnerability of the Burkinabé and leading them to leave their houses and become displaced in their own country.



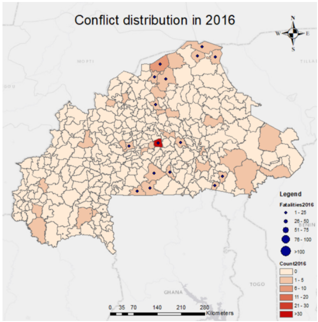
(a) IDPs due to conflict

(b) IDPs due to natural hazards

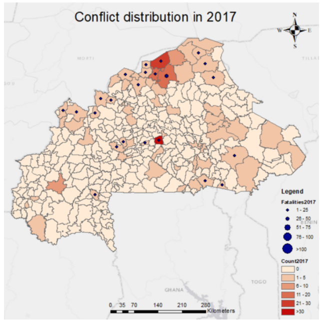
Figure 1.2: Reason for migration of IDPs in Burkina Faso, ***Source:*** ***(Internal Displacement Monitoring Centre 2021)***



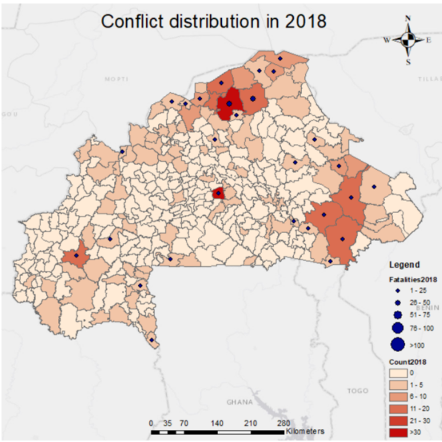
(a) 2015



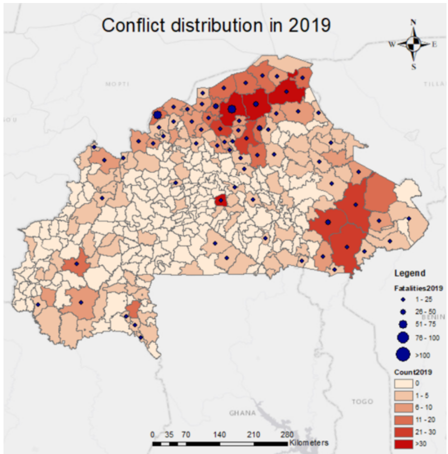
(b) 2016



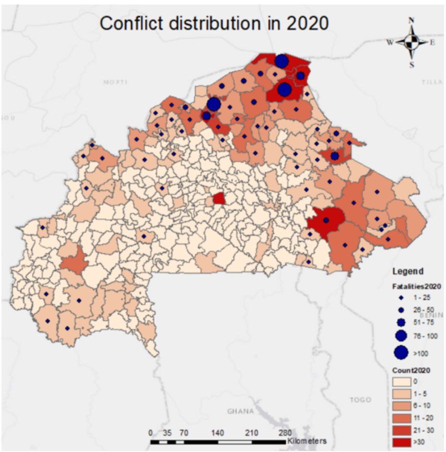
(c) 2017



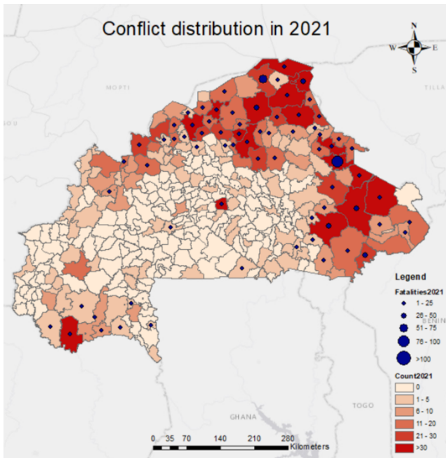
(d) 2018



(e) 2019

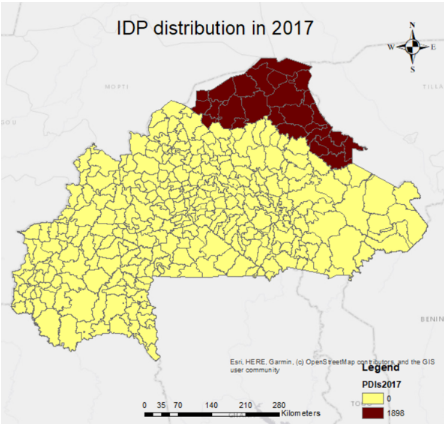


(f) 2020

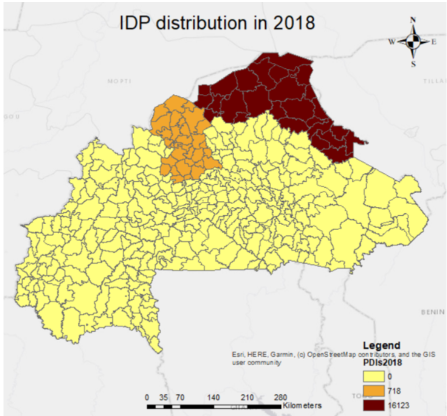


(g) 2021

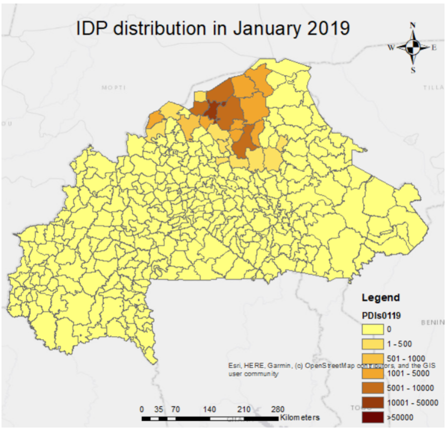
Figure 1.3: The open source information on conflict incidents that took place in Burkina Faso between 2015 and 2021. The darker the community, the more conflict events took place. The blue dots show the fatalities, e.g. the amount of people that died due to the conflict.



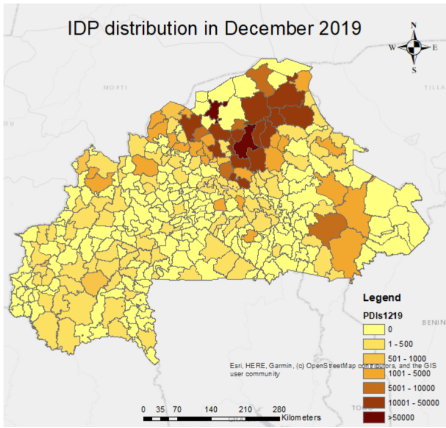
(a) 2017



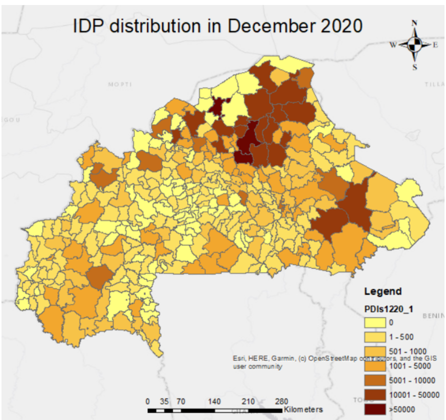
(b) 2018



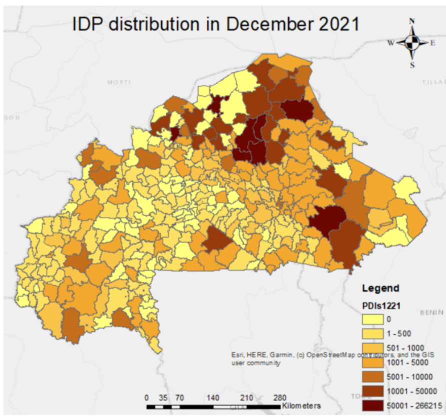
(c) January 2019



(d) December 2019



(e) December 2020



(f) December 2021

Figure 1.4: The open source information on Internally Displaced Persons in Burkina Faso between 2017 and 2021. The graphs show the total amount of IDPs in each community.

1.3 CALL FOR ACTION BETTER UNDERSTANDING (SOCIAL) VULNERABILITY

Considering the increasing number of security incidents and natural hazards leading to disasters in the country, it is tempting to draw direct and explicit correlations between these two. Nevertheless, local researchers are reluctant with drawing these conclusions (Ibrahim 2020). It can however be concluded that the violence is partly driven by a changing climate. The increased desertification, and decreased access to water and arable land are amplifying tensions between farmers and pastoralists (Web 2021). Additionally, the regions where conflict occurs, are also the regions suffering the most from climate shocks. Widespread poverty, enables the armed groups to misuse already existing tensions and play off of scarcity fears (Web 2021; Red Cross Climate Centre (RCCC) 2021).

Considering the demand for a better understanding of flood vulnerability, and the rising humanitarian needs in the flood prone areas of Burkina Faso, it is interesting to assess the change in vulnerability indicators over the years of conflict that have occurred. This understanding is not just important as a contribution to scientific knowledge. It is also essential for the people in BFA. Understanding the composition of vulnerability can contribute to understanding the dynamics between all different hazards taking place in BFA. Furthermore, the results will help the the International Committee of the Red Cross and Red Crescent Movement (ICRC) and the Burkina Faso Red Cross (BFRC) to improve their interventions around Water, Sanitation and Hygiene (WASH), habitat and anticipatory action, and thus improve the preparedness, adaptation and mitigation strategies. Therefore, this research is executed in close collaboration with ICRC and BFRC and focuses on the dynamic changes in social vulnerability against floods and the contribution of migration and conflict to vulnerability for floods.

Social sciences have long recognized the non-static nature of vulnerability (Cutter et al. 2003; Collins et al. 2009; de Ruiter and Van Loon 2022). However, assessing this dynamic behavior is not yet standardized in disaster risk research. In both drought vulnerability and flood vulnerability research, dynamic behavior is hardly ever assessed (Moreira et al. 2021a; Hagenlocher et al. 2018). Dynamic behavior of social vulnerability becomes especially interesting in long-duration hazards such as drought, pandemic and conflict and in multi-hazard settings (de Ruiter and Van Loon 2022). Given that vulnerability is often considered as a static risk dimension and conflict is not often included in the social vulnerability assessments, the dynamic insights developed in this research will create novel insights from a scientific and social point of view. This has led to the construction of the following research question for this thesis: *How to calculate a social vulnerability index for Burkina Faso that characterizes the spatial and temporal dynamics of social vulnerability?*

2 LITERATURE REVIEW

To understand the context and scientific knowledge gaps, a literature review is executed. This literature review focuses on (section 2.1) understanding the concept of disaster risk, (section 2.2) understanding the different aspects of vulnerability and (section 2.3) understanding the knowledge gaps that exist in vulnerability index construction research. Furthermore, section (2.4) highlights which indicators are usually used in social vulnerability indices. Lastly, section 2.5 introduces the often used INFORM model to calculate vulnerability.

For this literature review Web of Science, Scopus and Google scholar are used. Additionally, gray literature was retrieved from the Red Cross, as well as from a variety of departments of the United Nations and the World Bank. However, the focus is on scientific literature. In addition to the database search, literature has been identified through the means of *snowballing*[1].

2.1 CONCEPTS IN DISASTER RISK REDUCTION

Disaster Risk Reduction (DRR) aims to reduce the negative consequences of (natural) hazards. It therefore focuses on the prevention and mitigation of (natural) hazards, strengthening the capacities to cope with (natural) hazards and lastly, reduces the vulnerabilities to hazards (Wisner et al. 2012). "Disaster risk reduction is the concept and practice of reducing disaster risks through systematic efforts to analyse and reduce the causal factors of disasters. Reducing exposure to hazards, lessening vulnerability of people and property, wise management of land and the environment, and improving preparedness for adverse events are all examples of disaster risk reduction"(UNISDR 2004). The concept of disaster risk reduction entails three major phrases that need more in depth explanation before using them on a wide scale, *Hazards, Vulnerability and Risk* (United Nations Office for Disaster Risk Reduciont (UNISDR) 2017).

Theoretical research develops definitions are used by the UN office for Disaster Risk Reduction (UNDRR) to develop glossaries that standardize vocabulary for policy and practice. These definitions are established based on the work of fundamental scientific research. Where after applied (scientific) research, uses the definitions established by the UNDRR to develop models that test possible policy interventions.

2.1.1 Risk

The latest UNDRR glossary, defines *disaster risk* as "The potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society or a community in a specific period of time, determined probabilistically as a function of hazard, exposure, vulnerability and capacity." (United Nations Office for Disaster Risk Reduciont (UNISDR) 2017). The current definition that is used in the field forces science into quantification of risk. This is not entirely in line with wider

1 Snowballing is tracking down references (or citations) in documents. The snowball method is a way of finding literature by using a key document on your subject as a starting point. Consult the bibliography in the key document (book or journal article) to find other relevant titles on your subject.

literature regarding the definition of risk. In earlier scientific literature, two calculation categories were defined. The first, considers disaster risk as a function of hazard x vulnerability. This function designed by Wisner et al. (2014), is considered as a pseudo-equation, which suggests that the equation is used as a pattern rather then a quantitative equation of which the outcome can be considered as an absolute and meaningful value (Kelman 2018). The second category, combines risk with the probability of an event and the consequences of that event, which was applied by Hurley et al. (2015). Smith (2013) concatenates the two definitions to: "the likely consequence ... the combination of the probability of a hazardous event and its negative consequences." Despite the lacking coherence with scientific literature, applied research often uses the definition defined by the UNDRR and shown in equation 2.1. It is well understandable, and useful as long as Wisner's side note - consider it as a pseudo-equation - is taken into account.

$$Risk = Probability \quad of \quad Hazard * Vulnerability \tag{2.1}$$

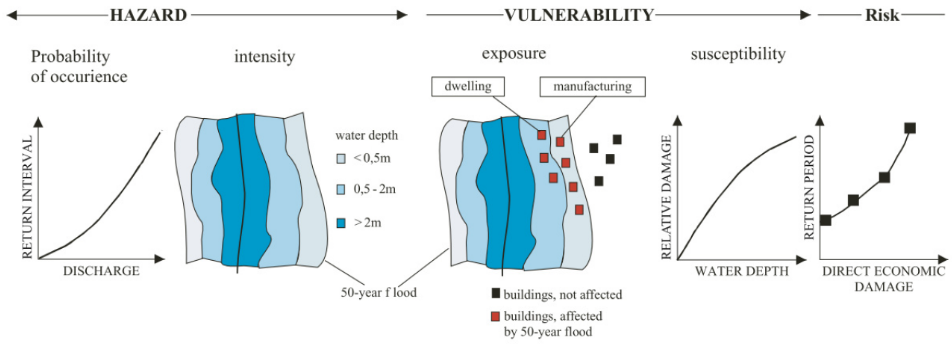


Figure 2.1: The interplay between hazard and vulnerability for estimating flood risk. ***Source:* *(Merz et al. 2007).***

2.1.2 Hazards

The most recent glossary is published in 2017 (United Nations Office for Disaster Risk Reducion (UNISDR) 2017; Kelman 2018), the definition of hazards stated here is: "A process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation." (United Nations Office for Disaster Risk Reducion (UNISDR) 2017; SENDAI 2015). It is important to note, that within this definition hazards can be dynamic through time and space. Meanwhile it can be triggered by nature, human activity or a combination of the former (Kelman 2018). Recognition of the human role in hazards happened with the establishment of the 2015 glossary (Kelman 2018). This shift challenged the former emphasis on hazard in the basic definitions of disaster risk and enabled for better understanding of vulnerability, exposure and risk in the DRR equation. Despite the note that hazards can be dynamic through time and space, most risk assessments are considered from a static perspective (de Ruiter and Van Loon 2022; Hagenlocher et al. 2018; Moreira et al. 2021b).

2.1.3 Vulnerability

The UNDRR glossary defines vulnerability as: "The conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards." (United Nations Office for Disaster Risk Reduciont (UNISDR) 2017). In 2017, exposure and vulnerability were considered as separate terms for the first time (Kelman 2018). This emphasises that exposure can be complementary to vulnerability, in that exposure describes *what* could be harmed by a hazard, while vulnerability explains *why* it is in harm's way (Kelman 2018). Vulnerability analysis takes an important role within risk management. Since, the vulnerability of a system can be reduced with policy and adaptation measures. In contrary to hazards and exposure, which are usually beyond the control of the decision makers (Hiete et al. 2012).

When applying the above disaster risk reduction concepts, the most often used method to assess risk for field application, is the INFORM model (section: 2.5). This model is a composite indicator that identifies countries at risk of humanitarian crises and disaster that would overwhelm national response capacity. The INFORM model considers vulnerability as social vulnerability solely and captures the physical, economic and environmental dimension with the use of hazard and lack of coping capacity indicators (European Commission, Joint Research Centre 2017). The equation that is used to calculate risk is depicted below.

$$Risk = Hazard\&Exposure^{\frac{1}{3}} X Vulnerability^{\frac{1}{3}} X Lackofcopingcapacity^{\frac{1}{3}} \tag{2.2}$$

2.2 SCIENTIFIC APPROACH TO VULNERABILITY

Vulnerability can be defined in quantitative terms, as the extent of harm or damage that results from an event. Meaning that in engineering science the concept is often linked to physical objects such as houses, vehicles, etc. However, the concept of vulnerability can also be used in a social aspect (Cutter et al. 2003), where it is defined as the degree at which life and livelihood are affected by a disturbance. The social vulnerability thus calls on the susceptibility of and impact on social groups, on contrary to physical vulnerability that calls on the susceptibility and impact for structural elements (Birkmann 2006; 2007; Guillard-Gonçalves and Zêzere 2018). However, it is important to use a balanced approach between social and physical vulnerability indicators since the two are not inseparable. Often, physical vulnerability is an expression of social vulnerability, for example women with lack of access to safe shelters. Therefore Birkmann (2006) and Guillard-Gonçalves and Zêzere (2018) argue that it is important to combine both in vulnerability assessments.

In addition, Fernandez et al. (2016) shows that there are usually four dimensions that need to be considered in vulnerability assessment: i) the physical dimension that represents the potential of physical impact on the built environment: ii) the economic dimension that accounts for the potential impacts of hazards on economic assets: iii) the social dimension that is related to the presence of human beings, individuals or communities, and their capacity to cope, resist and recover from hazard impacts; and iv) the environmental dimension that refers to potential impacts on the natural environment and the ability of ecosystems to cope and recover from hazard impacts" (Fernandez et al. 2016).

Furthermore, it is important to note, that vulnerability might vary according to different spatial and temporal perspectives. Due to small changes in spatial or temporal status, an area might become highly vulnerable (Chen and Lin 2021). There is increasing attention to understanding the effects of spatial variance, and changing vulnerability over time (Chang and Chen 2016; Yang et al. 2018b;a). Understanding the change of vulnerability over spatial and temporal components, might provide better understanding of disasters to improve disaster risk reduction (Chen and Lin 2021). To explore the spatial patterns of vulnerability, previous research has used univariate spatial autocorrelation techniques. In addition to this, bivariate spatial autocorrelation can be used to assess the patterns in vulnerability over space and time (Chen and Lin 2021). In chapter 4 the definition of vulnerability for this research is discussed.

Disaster risk management is required for mitigating potential damages that are identified by disaster risk analysis on hazards and vulnerability. As discussed, there is an increasing consensus that risk is not solely driven by hazards, but depends for a large part on the interaction between the hazard, exposure and vulnerability. It is thus important to understand how vulnerability is quantified. In this context both, physical as well as social vulnerability are used. The needs to understand vulnerability are emphasized by the Sendai Framework (SENDAI 2015). In response, numerous studies were undertaken. Nevertheless, both terminology and methodology used in assessments are still a subject of discussion. To be more precise, some studies consider vulnerability as a function of exposure and susceptibility, while others separate these concepts (Moreira et al. 2021b). This research follows the work developed by Cutter (Cutter et al. 2003) and considers solely social susceptibility for floods. Since this is the most used framework in scientific literature. The framework is well documented and thus suitable for repetitive work. However in this research, it will be elaborated with the conflict dimension that affects social vulnerability.

2.3 CONSTRUCTING AN INDEX

The most common used methods for assessing vulnerability against floods are (1) stage damage functions, (2) damage matrices, and (3) vulnerability indices. Since the first two methods only assess physical vulnerability, and there exists a clear urge to combine both physical and social vulnerability, hence it is decided to use vulnerability indices in this research. In addition, SVi require less data in contrast to other methods. Which is a good response to the data scarcity in BFA. Indices serve as a summary of complex and multidimensional issues to assist decision-makers. With the use of SVi, the vulnerability degree can be mapped throughout the aggregation of both physical and social indicators. However, due to the decision to follow the vulnerability index developed by Cutter (2003), only social vulnerability is considered. Nonetheless, in future research, the index developed in this thesis can be scaled up with physical vulnerability. The index is constructed through the unitless aggregation of multiple quantified indicators (Abson et al. 2012; Reckien 2018). These indicators are measurable variables that each indicate a characteristic of the index (Cutter and Finch 2008). In this approach, data for each of the indicators is collected at a certain spatial level, for example administrative units. The indicators are standardized, weighted, aggregated and then mapped. The resulting maps can help identify areas and communities that are most vulnerable. This aids in developing targeted policy measures and interventions that mitigate current challenges and future risks(Abson et al. 2012).

An extensive review article on vulnerability analysis by Moreira et al. (2021b) focuses mainly on research conducted with regard to vulnerability for flooding, and considers vulnerability also with respect to the social components. Moreira et al. (2021a) shows that an increasing number of studies considered SVi in recent years, about 80% is published since 2015, coinciding with the year the Sendai Framework was published. Analyzing the location of where these studies were executed provides interesting insights. There where fewer studies in East and West Africa, de-

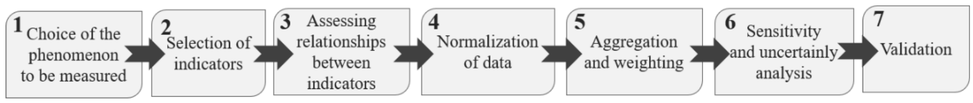


Figure 2.2: Overview of the different steps involved in constructing an index (Moreira et al. 2021b; Tate 2012)

spite the frequent occurrence of floods and the high mortality they cause in these regions (Moreira et al. 2021b). Furthermore, indicators relating to the populations coping and adaptive capacity were rarely used. The focus in previous research is placed on the social indicators that increase vulnerability. The preference for these indicators is often given by data scarcity. However, the capacity of people to anticipate and respond to disasters is very important in understanding vulnerability when considering the semantic definition. Acquiring data on these topics, often requires local research that captures the behavioral dynamics over time (Kuhlicke et al. 2011). Setting up an active quest for these data, contributes to the inclusion of local and traditional knowledge that is gathered in grey literature (Bonato 2018).

In most papers, a new vulnerability index is developed. This is due to the variety in indicator selection, that depends for large parts on the data availability and context of the location. A general overview of the different steps of constructing an index is depicted in figure 2.2. For all steps, different methods can be used, these are presented in table 2.1 , 2.2 and 2.3, but will be discussed more elaborately in section 3.

The aggregation of all indicators, leads to a vulnerability index. In general, this constructions exists of seven steps as presented in figures 2.2. During the first stage, the phenomenon to be measured is defined. This will lead to the development of a clear framework of the phenomena. This is important, since what is badly defined will likely be badly measured (Nardo, Saisana M., Saltelli A., and Tarantola S 2008). Hereafter, the indicators that are used will be selected, this is an important step, since a composite indicator is nothing more than the sum of its parts. It is thus important to be aware of the strengths and weaknesses of the selected indicators. In this stage, the missing data also needs to be treated. Data can be missing in a random or non-random fashion (Nardo, Saisana M., Saltelli A., and Tarantola S 2008). There are three methods for dealing with the missing data, (i) case detection, (ii) single imputation and (iii) multiple imputation (Nardo, Saisana M., Saltelli A., and Tarantola S 2008). The uncertainty in the imputed data needs to be reflected by a variance analysis. So that the effect of the imputation can be considered in the analysis. Thirdly, it is important that the relationship between the indicators is assessed. This is necessary, to group indicators with similar characteristics. Methods for this are presented in 2.1 and largely overlap with the methods for weighing the indicators.

After understanding the relations between the indicators, they need to be normalized so that they can be aggregated into one index. Several methods for normalization exist. The selection of the suitable method is not trivial and largely depends on the structral method that is used to gather and weigh the indicators (Tate 2012). Therefore it deserves special attention in order to scale adjustments (Ebert

Type	Method	Description	Reference	Use in articles
Hierarchical	Equal Weighing	All indicators receive the same weight	Hernández-Uribe et al. (2017)	24.2%
Statistically based – Inductive	Principal Component Analysis	PCA is used for factor extraction. The weights are obtained from the rotated factor matrix since the area of each factor represents the proportion of the total unit of the variance in the indicators that is explained by the factor.	Gu et al. (2018)	29.5%
	Entropy method	Weights are assigned based on the degree of variation in the indicator values.	Morimoto and Lianxiao (2019)	1.21%
Participatory or expert based – Deductive or Hierarchical	Expert opinion (AHP)	Experts agree on the contribution of each indicator for the studies problem.	Shah et al. (2018)	2.1%
	Public opinion	They focus on the notion of people's concern about certain problems measures by the indicators	Schuster-Wallace et al. (2018)	6.3%
	Multi criteria decision-making	It is a set of methods based on multiple criteria and objectives for structuring and evaluating alternatives	de Brito and Evers (2016)	4.2%

Table 2.1: Characteristics of the main methods for selecting and weighing the indicators. *Source: (Moreira et al. 2021b)*

and Welsch 2004). The characteristics of the most used normalization methods are presented in table 2.2.

The next step contains the weighing of the indicators. Moreira (2021b) showed that the most used method for this are statistical methods (30.5% of all research). Other less common used approaches are depicted in table 2.1. Furthermore, it is assumed that when practitioners, experts and people in the field are involved in creating the index, the likelihood that they will trust and use the results increases (Oulahen et al. 2015). When it comes to aggregating the indicators, the majority of research used primarily linear aggregation (80%) or geometric aggregation (10.5%) (Moreira et al. 2021b). The linear method is most usefull when all indicators have the same unit or when they are normalized and thus comparable. Geometric aggregation is better applicable when assessing the degree of non-compensation between the indicators.

Table 2.2: Characteristics of the main methods for normalizing the indicators. *Source: (Moreira et al. 2021b)*

Method	**Equation**	**Description**	**Reference**	**Use in articles**
Ranking	$Y_{in} = Rank(X_{in})$	Based on ordinal variables that can be turned into quantitative variables	Carlier et al. (2018)	7.4%
Z scores	$y_{in} = \frac{x_{in} - \bar{X}_{in}}{max(x_{in} - min(x_{in})}$	Converts all indicators to a common scale with a mean of 0 and a standard deviation of 1.	Gerrard (2018)	12.6%
Min-max	$y_{in} = \frac{x_{in} - min(x_{in})}{max(x_{in}) - min(x_{in})}$	Rescales values between 0 and 1. It subtracts the minimum value an divides it by the range of the maximum value subtracted by the minimum.	Jha and Gundimeda (2019)	30.5%
Distance from group leader	$y_{in} = \frac{x_{in}}{max(x_{in})}$	Rescales values between 0 and 1. It is defined as the ratio of the value of the indicator to its maximum value.	Munyai et al. (2019)	12.6%
Division by total	$y_{in} = \frac{x_{in}}{\sum(x_{in})}$	It is defined as the ratio of the value of the indicator to the total value for the indicator	Jamshed et al. (2019)	2.1%
Categorical scale	$y_{in} = \begin{cases} 0 if x_{in} < P^{1}5 \\ 20 if P^{15} \leq x_{in} < P^{25} \\ 40 if P^{25} \leq x_{in} < P^{65} \\ 60 if P^{65} \leq x_{in} < P^{85} \\ 80 if P^{85} \leq x_{in} < P^{95} \\ 100 if x_{in} \leq x^{t}_{qc} \end{cases}$	Assign a value for each numeric or qualitative indicator. Values are based on percentage	de Andrade and Szlafsztein (2018)	3.2%
Binary standard	None	It is calculated using simple boolean 0 and 1 values	Garbutt et al. (2015)	3.2%

The before last step entails the sensitivity and uncertainty analysis. Necessary, because each step in constructing the SVi contributes to uncertainty in the final result (Saisana et al. 2005). Sensitivity analysis focuses at how the uncertainty of each indicator contributes to the variance of the results. Uncertainty analysis considers how the uncertainty of a single indicator affects the outcomes of the index (Saisana and Tarantola 2002; Saisana et al. 2005). Several methods are used for uncertainty and sensitivity analysis in flood vulnerability indexes. These are shown in table 2.3. Even though uncertainty and sensitivity analysis are important to understand the applicability of a SVi only 3% of previously executed SVi research applied an uncertainty analysis and only 9% executed a sensitivity analysis (Moreira et al. 2021b).

The final stage of the SVi construction consists of validating the index results. This process is important to ensure that the index is compatible with the real world. However only 11.6% of prevously executed research validated the resutls. The methods used for validation of SVi use proxies that identify the consequences of vulnerability such as mortality rates, affected people, and destroyed houses. This can be done with the use of post-event surveys (Fekete et al. 2010), the absolute number of disasters (Debortoli et al. 2017), and emergency service requests Kontokosta and Malik (2018).

Table 2.3: Characteristics of the main methods used for uncertainty and sensitivity analysis. *Source: (Moreira et al. 2021b)*

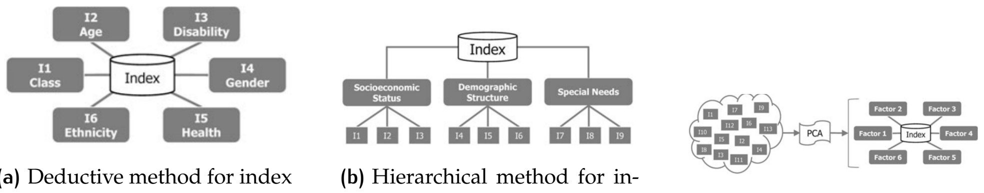
Method	Description	Reference
One-at-a-time sensitivity analysis	By changing input data parameters, it was verified how these disturbances affect the results when all other parameters remained constant.	de Brito et al. (2019)
Monte Carlo simulation	Computational algorithm which uses a probabilistic method that uses repeated random sampling	Feizizadeh and Kienberger (2017)
Statistical tools	Use of statistical tools such as regression, correlation analysis and cross validation.	Nazeer and Bork (2019); Moreira et al. (2021a)

2.3.1 Selecting a robust index design method

As presented in table 2.1 and 2.2 different methodologies are used for these approaches. These methodologies can be divided into three sub-categories: deductive, inductive and hierarchical approaches. Based on the literature, it is decided to use an inductive PCA approach the design the index.

The decision to use PCA was not taken lightly. Many different methods are available to design the index. There are three well-known methods: deductive, hierarchical and inductive. Deductive models typically contain fewer than ten indicators, which are normalized and aggregated to the index (figure 2.3a) (Montz and Evans 2001; Wu et al. 2002; Dwyer et al. 2004; Collins et al. 2009; Lein and Abel 2010). This was the most common structure applied to early social vulnerability indices. Hierarchical designs have employed roughly ten to twenty indicators, separated into groups (sub-indices) that share the same underlying dimension of vulnerability (Vincent 2004; Chakraborty et al. 2005; Hebb and Mortsch 2007; Flanagan et al. 2011; Mustafa et al. 2011). This is also what is used for the INFORM model, often employed by the NLRC. Individual indicators are aggregated into sub-indices, and the sub- indices aggregated to the index (figure 2.3b). Inductive approaches begin with a large set of twenty or more indicators, which are reduced to a smaller set of uncorrelated latent factors using principal components analysis. The factors are then aggregated to build the index (figure 2.3c). The latter method, is the most commonly used method nowadays and was employed by Clark et al. (1998); Borden et al. (2007); Burton and

Cutter (2008); Burton (2010); Myers et al. (2008); Fekete (2009); Wood et al. (2010). The most common technique used to employ an inductive approach is PCA (Jolliffe and Cadima 2016). Nowadays, the SoVI method, which is a variation of PCA, developed by Cutter and Finch (Cutter and Finch 2008) is the most used method applied to develop social vulnerability indices. A visualization of the different structures of these methods is shown in figure 2.3.



(a) Deductive method for index design

(b) Hierarchical method for index design

(c) Inductive

Figure 2.3: Three methods for structural design of the index

When choosing one of the methods for the structural design, a robust output is important. More specifically a robust output variance caused by the interaction between the different stages of the SVi construction. Tate (2012) shows that the greatest contributor of uncertainty is the indicator selection. It is thus very important to justify the selection of indicators. Furthermore Tate (2012) demonstrates that the most robust structural design of indices is the inductive method. Tate showed that using an hierarchical approach is more accurate - e.g. better comparable with reality. In contrary to an inductive approach which is more precise - e.g. different measurement moments are better to compare. Since this research focuses at comparing vulnerability scores over time, and understanding the change it is important that a precise outcome is obtained. It is thus decided to opt for the PCA method. Figure 2.4 shows the differences between precision and accuracy.

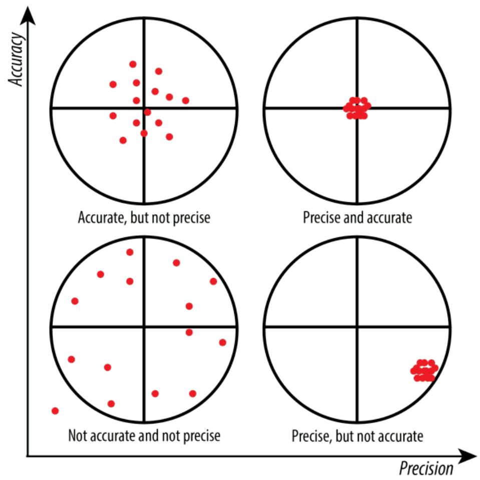


Figure 2.4: Precision vs. accuracy depicted

2.4 VULNERABILITY INDICATORS USED IN LITERATURE

The indicators that are considered are quantitative variables, that aim to represent a characteristic of the *social vulnerability*. Indicators can be employed to inform decision-making, improve the stakeholder participation, build consensus, explore underlying processes and advocacy (Parris and Kates 2003). It is important to notice, that indicators can be an index themselves, and thus the composed index that is created can exist out of other indexes. The composition of an index from multiple indicators is used to distill the complexity of *social vulnerability* into one single metric (Tate 2012).

The selection of vulnerability indicators varies a lot in different researches. In order to analyze the vulnerability indicators that are used, the following research was used: (Hagenlocher et al. 2018; Moreira et al. 2021b; European Commission, Joint Research Centre 2017). Since these sources provide an overview of vulnerability indicators in West-African countries (Hagenlocher), the most used indicators (Moreira) and the methods suggested by the EU Joint Research Centre (INFORM) which is generally used to inform national societies. An overview of the most used indicators is presented in appendix 12 in table 12.1, 12.2, 12.3. The selection of the indicators that are used, should be done carefully, as the results reflect the vulnerability which depends on the selected indicators. It is therefore important to evenly represent indicators that contribute to vulnerability and indicators that reduce vulnerability such as coping capacity and adaptive capacity. Furthermore, the spatial and temporal coverage of the indicator values are important for the inclusion.

From these tables, it is important to note, that hardly no conflict related indicators are included in the vulnerability research. However, research on the vulnerability of conflict prone areas has shown that high levels of conflict events in previous years contribute to the social vulnerability on a variety of levels (Bobojonov et al. 2014; Mason et al. 2011).

2.5 INTRODUCTION OF INFORM

The method often used by NLRC, is the hierarchical method. To be more precise, the INFORM model is often used. The method calculates risk based on three composite indicators that represent the vulnerability, hazard and exposure and lack of coping capacity of an administrative unit (European Commission, Joint Research Centre 2017). The benefits of using this method is that the work of the NLRC remains consistent and comparable.

The concept and methodology of the INFORM model is extensively described in European Commission, Joint Research Centre (2017). The aim of INFORM is to simplify the information that is related to crisis risk into one quantifiable number, that can be used as a basis for decision-making. The model is illustrated in figure 2.5. According to the INFORM model risk consists of three dimensions, which can be further subdivided into different categories and components. The three dimensions are shown below. Equation 2.3 is used to calculate the risk.

1. **The hazard and exposure:** reflects the probability of physical exposure that is associated with specific hazards.

2. **Vulnerability:** reflects the intrinsic predispositions of an exposed population to be affected or to be susceptible to the damaging effects of a hazard. Focus on social vulnerability and not on physical vulnerability.

3. **Lack of coping capacity:** reflects the ability of a administrative unit to cope with disasters in terms of formal, organised activities and the effort of a government and existing infrastructure to reduce the disaster risk.

$$Risk = Hazard\&Exposure^{\frac{1}{3}} * Vulnerability^{\frac{1}{3}} * Lack \quad of \quad Coping \quad Capacity^{\frac{1}{3}} \tag{2.3}$$

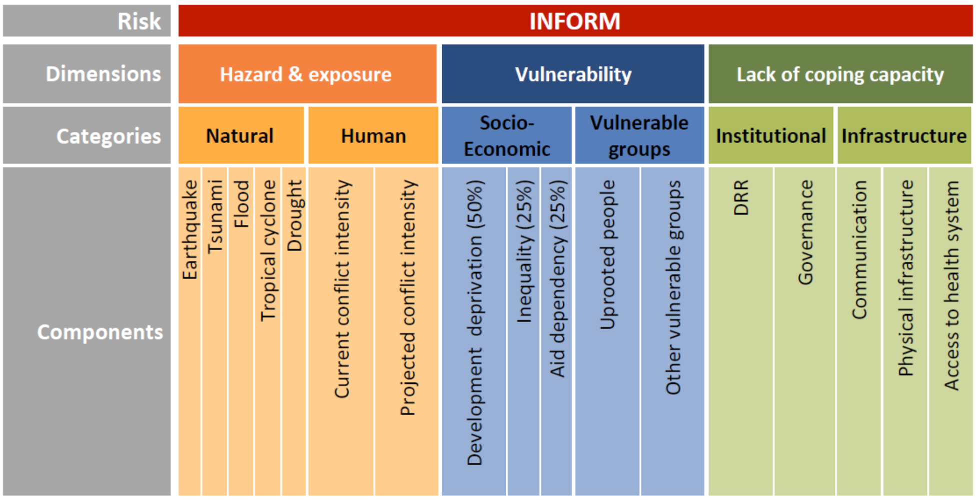


Figure 2.5: The INFORM model is a hierarchical model. This is visualised in this figure with the layered structure that is represented by components, categories, dimensions, and eventually the risk.

The methodology of the European Commission, Joint Research Centre (2017) has been used before to develop a risk index for all sub-national administrative units in the Sahel (Disaster Risk Management Knowledge Center, EC 2022). However, four limitations are present that emphasize the need for the development of a social vulnerability score based on an inductive approach. These limitations are: the lack of insight developed in the temporal dynamics, the administrative level at which the analysis are made, the conceptualization of vulnerability, and the weighting scheme that leads to a lack of insight in the dynamics of the index.

So far, no research is executed that compares the results of the vulnerability over time. This research is required to obtain insight in the temporal dynamics of social vulnerability. Secondly, the analysis are solely made on a sub-national level. Often INFORM is used to determine on which sub-national areas to prioritise DRR programs. Within these sub-national areas expert-based considerations or local data collections are used to determine on which communities to focus. This process can be improved if social vulnerability indices are developed on the community level. Thirdly, INFORM does not include previous conflict events in the vulnerability dimension. The other vulnerable groups component does include recent natural shock, but excludes the effects of conflict. Lastly, the equal weighting scheme lacks possibilities to understand the internal dynamics of the index. I.e. the weights of the indicators do not represent if an indicator becomes more or less important over time. These drawbacks are a strong call to develop better methodologies to understand the dynamics of social vulnerability over time.

2.6 KNOWLEDGE GAPS

The research discussed above provides good footing for SVi. Nevertheless, it also shows some gaps in the literature where more research is necessary. This can be divided into three subgroups (i) The spatial and temporal (dynamic) understanding of vulnerability, (ii) knowledge gaps in the construction of vulnerability indexes and (iii) the role of conflict in social vulnerability

With climate change effects intensifying, and a quick change in urban development and high human mobility – for example the IDPs in BFA, various levels of social vulnerability might occur. A better understanding of spatial and temporal changes in social vulnerability will provide better insight for disaster risk management ad climate change adaptation. This type of research has not yet been executed for BFA, where the consequences of climate change are urgent, and urbanisation of cities, increased tremendously since the conflict started (UN OCHA 2021). Moreira et al. (2021b) also emphasises that studies that capture behavioral dynamics such as migration are necessary.

Furthermore, during the construction of the SVi a variety of gaps was identified in this literature review and by Moreira et al. (2021a). First of all, it is important to identify the suitability of PCA and hierarchical approaches for data scarce areas, and for understanding the dynamic behavior over time. Furthermore, research is needed to improve the ratio of indicators that increase vulnerability and indicators that decrease - there is a temptation to include more indicators that contribute to vulnerability, in comparison with indicators that reduce vulnerability (coping capacity). On top of that, the amount of indicators can be reduced by reduction techniques so that all indicators used are uncorrelated and still a high variance is present in the data set. Lastly, it is emphasised that thorough reasoning on normalization techniques, and the execution of sensitivity and uncertainty analysis is needed.

The third research gap that can be identified, is the lack of social vulnerability analysis that includes conflict history in the indicators. This is essential since it is shown that areas that recently experience conflict are more vulnerable.

Understanding and summarizing these research needs leads to the formulation of the following research question for this thesis project:

> *"How to calculate a social vulnerability index for Burkina Faso that characterizes the spatial and temporal dynamics of social vulnerability??"*

Chapter 3 extensively discusses the sub-questions that are discussed in this research. These sub-questions are divided in three categories. The spatial dynamics of social vulnerability in Burkina Faso, the temporal dynamics of social vulnerability in Burkina Faso and lastly the comparison and sensitivity of methods.

3 METHODS

To understand the spatial and temporal dynamics of social vulnerability, a SVi is developed that captures the changes specific for BFA it social vulnerability indicators. The spatial and temporal variations are assessed over time with the use of PCA, univariate spatial autocorrelation (LISA) and regression methods. Furthermore, the suitability of PCA is assessed with a sensitivity analysis, and by means of comparing the results of this study to the results of the INFORM study.

3.1 SUB-QUESTION

Different sub-questions are developed to understand the dynamics in social vulnerability taking place in BFA. These are presented in table 3.1. The sub-questions of this study are presented in table 3.1 and divided in four categories:

1. Understanding what social vulnerability entails
2. Spatial dynamics of social vulnerability
3. Temporal dynamic of social vulnerability
4. Understanding the methods used to quantify social vulnerability

Understanding social vulnerability

This category of sub-questions focuses on the objective: *understanding what social vulnerability is*. In this section SQ1 contextualizes the working field of this research. Answering this SQ contributes to understanding the concept of social vulnerability that is applied in this research. SQ2, considers what data is necessary for the understanding of this view on social vulnerability and develops a decision approach that assesses the quality of the available data.

Spatial dynamics of social vulnerability

This category considers the spatial dynamics of social vulnerability in BFA in 2020. The analysis in this category considers social vulnerability on a commune level. It therefore is very suitable for decision making in humanitarian work. SQ3, considers the social vulnerability on a commune level (adm3) for 2020. Additionally, SQ4 considers the spatial dynamics of this social vulnerability profile in Burkina Faso. With doing so geographical patterns are identified and links with the conflict and natural hazards considered (SQ5).

Temporal dynamics of social vulnerability

Subsequently the temporal dynamics of social vulnerability are explored. In this section the social vulnerability from 2015 – 2021 in determined. These analyses consider the social vulnerability on a sub-national level (adm1). This is due to the data availability. SQ6 considers the social vulnerability on admin 1 level from 2015 – 2021. Additionally SQ7 considers the temporal dynamics of the vulnerability, with doing so the significance of the changes is assessed and linked with the conflict and natural hazards in Burkina Faso (SQ8).

Sensitivity and methodological considerations

Lastly, the sensitivity of the results for the methodological decisions will be explored. This is done in two steps. First, the methodological decisions within the principal component analysis are analysed and conclusions on the sensitivity of the results for this are presented (SQ9). Thereafter, a comparison between both PCA and an hierarchical approach is presented (SQ10). This provides insights in both the sensitivity of the results for each method, as well as which method is more suitable for what understanding of social vulnerability (SQ11).

Sub-Question	Methodology	Sources / Input	Chapter
Understanding social vulnerability			
SQ1: How should social vulnerability be defined for this research?	Literature review	Literature	4
SQ2: What spatial and temporal data is necessary and available?	Literature review and secondary data analysis	Literature and Humanitarian Data	5
Spatial dynamics of social vulnerability			
SQ3: What are the social vulnerability scores on adm3 in 2020?	PCA with varimax rotation	Results SQ 2	6
SQ4: Is there a geographical pattern visible?	LISA	Results SQ 3	6
SQ5: Are links visible between the social vulnerability score and the conflicts and natural hazards?	Visual analysis	Results SQ4 and maps Chapter 1	6
Temporal dynamics of social vulnerability			
SQ6: What are the social vulnerability scores on adm1 level from 2015 - 2021	PCA with varimax rotation	Results SQ2	7
SQ7: What are the temporal dynamics of social vulnerability?	Linear Regression	Results Disaster Risk Management Knowledge Center, EC (2022)	7
SQ8: Are links visible between the pattern and the conflicts and natural hazards?	Visual analysis	Results SQ7 and maps Chapter 1	7
Sensitivity and methodological considerations			
SQ9: What methodological decisions cause sensitivity in the results?	Three way ANOVA	Results SQ4	8
SQ10: What is the difference in results with inductive and hierarchical approaches?	Three way ANOVA	Results SQ3 and de Vries (2022)	9
SQ11: What method is more suitable for determination of social vulnerability?	Literature Review	this research	9

Table 3.1: Overview of sub-questions, methods used and relations to vulnerability index construction phases.

3.2 RESEARCH FLOW

The research methodology is composed of eight key steps, namely (i) defining social vulnerability for this research. (ii) assessing the data requirements for (a) the spatial assessment, and (b) the temporal assessment. (iii) Running the PCA for (a) the spatial assessment, and (b) the temporal assessment. (iv) assessing the spatial dynamics. (v) assessing the temporal dynamics. (vi) executing a sensitivity analysis and (vii) calculate the social vulnerability score with the use of INFORM and lastly (viii) compare the results of INFORM and PCA. Figure 3.1 visualizes the research flow of these eight steps. All of them will be explained in the section below.

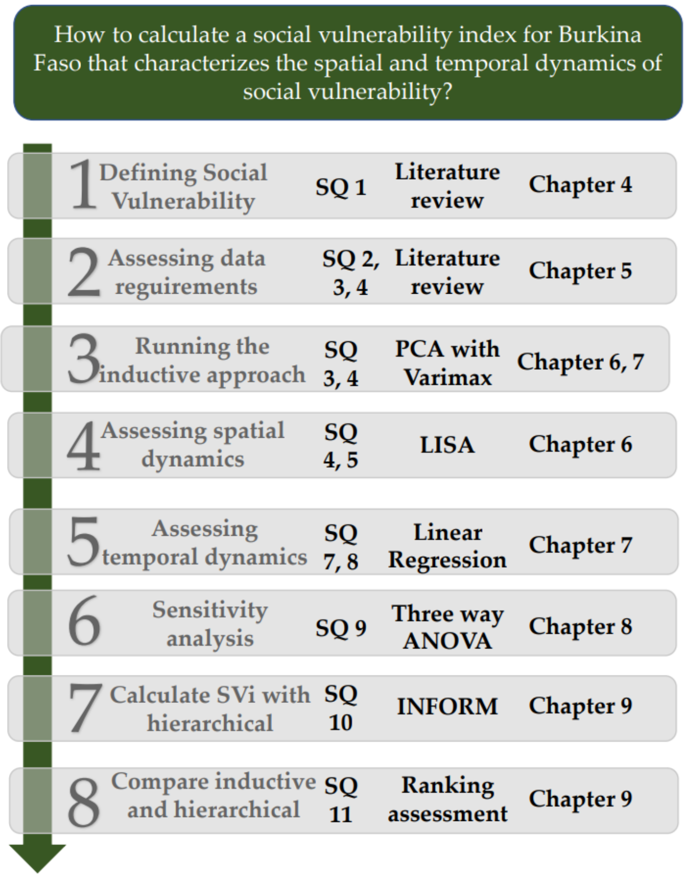


Figure 3.1: Research flow

3.2.1 Defining social vulnerability

The first key step of this research is deciding on a conceptualization of social vulnerability. The literature review showed that many different definitions of social vulnerability are present. In chapter 4 a definition of social vulnerability as how it it used in this research is presented. For this, the book written by Birkmann (2005) is used as a basis and a suitable conceptualization is derived from the multiplicity of conceptual models that are presented.

3.2.2 Assessing the data requirements

Secondly, based on the shaped definition of social vulnerability the data requirements for this research are mapped. Selecting the right indicators is the basis for useful outcome. In our data selection is it important that data has a high level of granularity and coverage since measuring the influence of social indicators on vulnerability over time, requires data at lower administrative levels.

In this section, it is first assessed which data are required. This is based on the INFORM model (European Commission, Joint Research Centre 2017) and the definition of social vulnerability as structured in chapter 4. The found set of indicators from INFORM were enhanced with indicators that are considered important to the BFRC. An overview is created of the strengths and weaknesses of each selected indicator. If needed proxy indicators are developed that support the indicators that have a too low granularity.

Before making poorly motivated concessions that consider the spatial and temporal scale of the research, it was decided to analyse the data availability extensively. For this the following method was used. First, the data for the indicators identified in the INFORM handbook were gathered. Open sources such as the humanitarian data hub and grid3 were employed to do so. The focus was on finding data available from 2010 - 2021 at community level. Thereafter the BFRC and ICRC were asked if they were able to supplement the data with data in their own possession. Furthermore, the BFRC was asked to identify the underlying processes that contribute to social vulnerability in BFA specifically. From this two extra indicators came forward that were added to the long list of already collected secondary data: the travel time to the closest city and the elderly rate.

For all found information, a systematic approach was used to analyze the secondary data availability and its quality. This systematic approach consists of an assessment of the resolution and the coverage. This is important since data can have a high resolution for only one administrative unit. In this research, country wide spatial coverage is required. Similar, data coverage is needed for all years in the temporal assessment. To find the right data, as a starting point, the humanitarian data exchange hub from UN OCHA is used. Subsequently, it is attempted to derive data points for each year on adm3 resolution.

3.2.3 Principal Component Analysis

To deal with the big set of indicators, it is useful to reduce its dimensionality. For this principal component analysis is one of the oldest and most widely used techniques (Jolliffe and Cadima 2016). After the consideration of several index design methods (2.3.1), PCA was chosen to be employed for this research. For this the SoVi approach, that is developed by Cutter and Finch (2008) is used as a basis.

The steps of running a PCA are the following. 1. Select data for the indicators that shape the social vulnerability 2. Standardize all input variables to z-scores. 3. Verify the use of PCA for the indicator set. 4. Create a correlation matrix and assess the collinearity. 5. Eliminate redundant data 6. Perform the PCA with the standardized input values. 7. Select the number of components to be further used. 8. Rotate the initial PCA solution, when this is desired. 9. Interpret the resulting components on how they might influence vulnerability. Based on this, signs are assigned to the components. The output of the loadings is the determining factor for assigning the sign. The indicator with the highest loading in the component determines the sign. If this indicator is positively correlated with the social vulnerability, a positive sign will be assigned and vice versa. 10. The component scores are combined into a univariate score based on the predetermined weighting scheme. These steps are visualized in figure 3.2. The PCA method was used with the help of python software package FactorAnalyzer (Pedregosa et al. 2011)

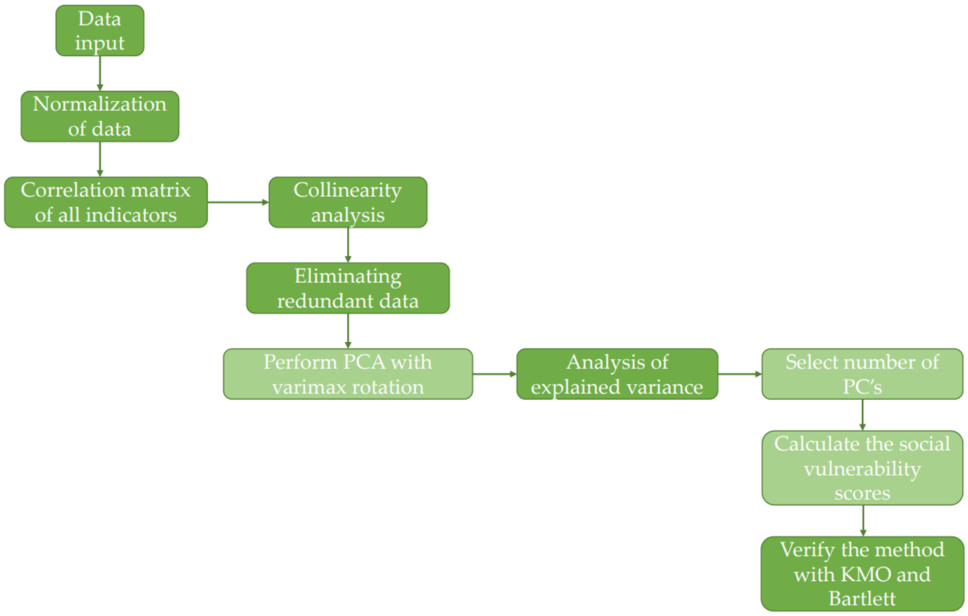


Figure 3.2: Overview of structure statistical methods necessary to execute the PCA. The lighter green steps represent the steps were methodological decisions are made.

Selecting and standardizing the indicator data

To apply PCA first all indicators were standardized. It is statistically necessary to normalize the data prior to the data aggregation, since the indicators have different measurement units and need to be comparable and all indicators should be represented on the same scale before entering the analysis. There is a variety of normalization methods possible as discussed in section 2.3. Since not all data sets have an abundance of data measurements, it is important that the normalization method is applicable to small data sets. Lastly the normalization should be non-categorical, since there is a need to rank the outcomes. Hence, the normalization that is chosen is z-score normalization. This complies with the requirements as stated below, and is in line with the recommendations made by (Cutter et al. 2003) and (Tate 2012) to use z-score normalization whenever conduction a PCA analysis.

Verifying the use of PCA for the indicator set

To verify the use of PCA on the initial data set a Bartlett Sphericity test and Kaiser-Mayer-Olkin test were applied. Bartlett's Test of Sphericity compares the obtained correlation matrix to the identity matrix. Essentially it checks if there is a redundancy between the variables that we can summarize with a fewer number of indicators and thus if the right amount of indicators were removed based on $Pearson'sR$. For this analysis the scipy package of python was used (Virtanen et al. 2020). If data are perfectly uncorrelated a PCA is not possible, so not to much data should be removed. To verify this, the KMO-test is executed, which is testing the contrary of Bartlett Sphericity. The test measures the sampling adequacy of each variable in the data set and for the complete data set. The adequacy refers to the measure of proportion of variance among variables that might be common variance. The lower the proportion, the more suitable the data set is for PCA.

Eliminating redundant data

In the third and fourth stage, the amount of indicators is reduced. It is assumed that some are correlated, or might not contribute to clustering the structure of the data set. Hence, a correlation matrix is built and the collinearity is assessed (Török

2018). For this the indicators with Pearson's R $>$ 0.7 where first removed. This helps with understanding the underlying structure and relationships between the indicators and reducing the amount of indicators. It is necessary to remove these abundant indicators since principal components will otherwise represent the same mechanisms that are presented by multiple indicators. This is called double counting and results in outcomes that over represent some mechanisms and do not evenly reflect the influence of each mechanism on the social vulnerability index.

Perform the PCA, and select no. components

The calculation of PCA is based on the construction of a correlation matrix. From this matrix eigenvalues and eigenvectors are calculated. The eigenvalues show the amount of variance that is explained by the eigenvector. The eigenvector's are the principal components (PC) that are shown as columns in figure 3.3. Geometrically speaking, principal components represent the directions of the data that explain a maximal amount of variance. Meaning the vector that captures most information on the data set. The eigenvectors are ranked in descending order based on their eigenvalues. This is were the first methodological decision is made. In the analysis it is decided to include as much as PC as is needed to obtain 90% explained variance. This is the sum of the cumulative eigenvalues. It is also possible to use the Kaiser criterion and include all eigenvectors that have an eigenvalue $>$ 1 (Braeken and Van Assen 2017).

Rotate the PCA matrix

Based on the matrix obtained from the principal components that meet the requirements for the selection of number of components, the varimax rotation is considered. It is also possible to continue with an unrotated solution. However calculating the varimax rotation contributes to the simplification of the underlying structure of the dimensions and to create a higher statistical independence between the variables. This minimizes the number of indicators that have a high loading and clarifies the interpretation of the scores (Gu et al. 2018; Zhou et al. 2014; Fekete 2009; Török 2018). The varimax rotation maximizes the sum of the variance of the squared loading. In this, loadings refer to the correlation between the indicators and the principal components. This usually results in high PC loadings for a smaller number of indicators and low PC loadings for the rest. In simple terms, the result is a small number of important indicators, which makes it easier to interpret the results.The matrix that is obtained after the varimax rotation is called the loading matrix.

Interpret the results

To calculate the score of each principal component per administrative unit, the dot product of the loading matrix and the normalized indicator values is determined. The cardinality of each PC is determined based on the effect on vulnerability of the highest contributing indicator in the component (figure 3.3).

Calculate the social vulnerability scores

Lastly, the weighted sum of the component scores is calculated to present the social vulnerability in each administrative unit. The equation used for this is given in equation 3.1. We now assign a high value to the communities, that score high on an indicator, that also has a high variance. In this way the indicators that are different in each community – and thus have potential to improve both mathematically and through a humanitarian intervention, score high. It is also possible to apply a mathematical approach as a weighting scheme. This approach solely uses the first PC to represent the social vulnerability. However, the explained variance of this PC is too low to use this approach. Furthermore, it would be possible to calculate a weighted sum of each principal component based on the explained variance. The first approach was chosen since this is the most widely used approach (Cutter and Finch 2008). KMO-values and Bartlett's test of sphericity are used to verify the use of PCA.

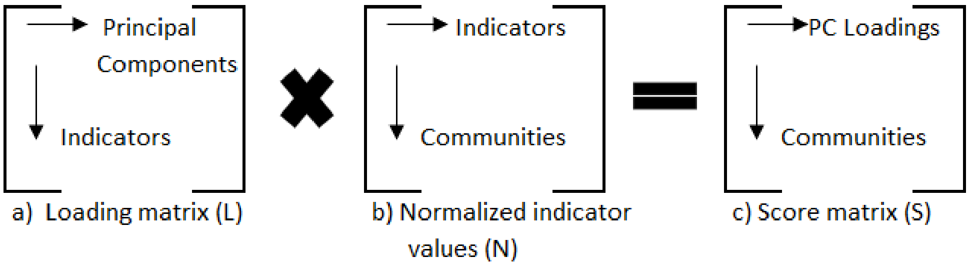


Figure 3.3: Equation to determine the score matrix. Indi. represents the indicators,

$$MatrixS = (x_{ij}) \qquad socialvulnerability_{communityj} = \sum_{j=1}^{i} x_{ij} \tag{3.1}$$

In summary, PCA is a multivariate analysis that is used to identify the key indicators of the entire indicator set. Furthermore, the determination of the weights is executed with the Varimax rotation and Kaiser normalization. The whole structure of this process is visualised in figure 3.2.

3.2.4 Assessing the spatial dynamics

According to Tobler's "First Law of Geography", spatial autocorrelation is used to explore spatial relationships based upon spatial distance (Goodchild 2009). The goal was to identify patterns with respect to the indicator values. This will contribute to answering sub-question 5. With applying spatial autocorrelation analysis, similarity and proximity between the vulnerable areas can be revealed Griffith et al. (2003). In this study Moran's I method is applied to study the global spatial autocorrelation. This method combines similarity and proximity. The attribute values are calculated in reference to the means. It is therefore very consistent with the traditional correlation coefficient of (-1, 1) (Chen and Lin 2021). Moran's I formula is:

$$I = \frac{n \sum \sum w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{W \sum (x_i - \overline{x})^2} \tag{3.2}$$

$$E_I = \frac{-1}{n-1} \tag{3.3}$$

The variables in this equation represent the following: x_i is the value of vulnerability in spatial area i, x_j is the value of vulnerability in spatial area j, W is the sum of the spatial weight matrix, n is the total number of spatial areas, w_{ij} is the proximity between area i and j. The expected value E_I shows the expected autocorrelation and is defined by equation 3.3. if $I \geq E_I$, the areas form a clustered pattern, if $I \leq E_I$, there is a dispersed pattern between the areas, and if $I = E_I$, there is no pattern between the two areas.

Next, these correlations need to be depicted on the map and understood from a local perspective. Therefore Local Indicators of Spatial Association (LISA) is used in

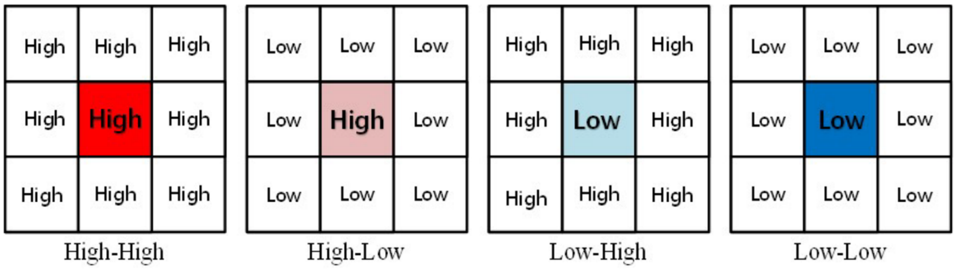


Figure 3.4: Demonstration of patterns defined by LISA. *Source Chen and Chang (2018)*

this thesis. LISA identifies spatial clusters, as high-high and low-low clusters, high-low outliers, and low-high outliers (Chen and Lin 2021). HH indicates that many spatial areas are clusterd together, LL indicates that not that many spatial areas are clustered together. The outliers indicate that spatial areas with different values are clustered. This is depicted in figure 3.4. For both Moran's I and LISA calculation the python package pySAL will be used (Rey and Anselin 2007).

3.2.5 Assessing the temporal dynamics

To assess the temporal dynamics of social vulnerability the vulnerability scores obtained by Disaster Risk Management Knowledge Center, EC (2022) are used. That is, because the method of the temporal PCA analysis was not found valid due to a too low KMO–value. Thus as input values for the temporal assessment the social vulnerability scores obtained by INFORM are used. The INFORM analysis is executed on a sub-national level. A drawback of using these values is, that the context specific indicators that are proposed by the BFRC are not included in the analysis. Since, this analysis includes both vulnerability and lack of coping capacity to shape social vulnerability, the results from the INFORM analysis are calculated into a social vulnerability score with the aid of equation 14.1.

$$Socialvulnerability = Vulnerability_{INFORM}^{1/2} * Lackofcopingcapacity_{INFORM}^{1/2} \quad (3.4)$$

To identify the change in vulnerability over time, the individual social vulnerability scores are normalized with the use of z–score normalization. By using a simple linear regression, a line of best fit is calculated for each region. The resulting R^2 assessed the strength of the relationship between the best fit and the yearly measured social vulnerability points. The slope of the line of best fit shows the direction of change over time. Meaning: a positive slope indicates an increase in vulnerability, and a negative slope indicates a decrease in vulnerability. Based on Cutter and Finch (2008) the relationship was considered significant at a 0.05 significance level. An obvious temporal change is considered if the slope was > 0.5 or < -0.5.
Next, interesting changes in indicators, and important hazard events were plotted on the temporal graphs of each interesting region to identify relations between the indicators, the hazard events and the changes in vulnerability.

3.2.6 Sensitivity analysis

Sensitivity analysis can be performed on several levels of this research. We can evaluate the outcome's sensitivity for various indicator values, using various approaches, or using a combination of the two first options. It has been agreed that the primary emphasis of this study will be the methodology's Sensitivity Analysis (SA). This decision is made, since the largest contribution of this research lies in the comparison of methods. Furthermore, it is not possible to evaluate the sensitivity for various indicator values due to time limits.

	No. Component	Rotation	Weighting scheme
1	90 % explained variance	Unrotated	Sum of PC
2	Kaiser criterion	Varimax	Mathematical approach
3			Weighted sum based on explained variance

Table 3.2: Methodological options that are available.

Literature shows that the methodological choices made during the various stages of the composite index construction involve assumptions, subjectivity, and uncertainties that should be identified, acknowledged, and communicated across the quantitative procedure (Nazeer and Bork 2019). This stage considers the sensitivity of the developed social vulnerability indicator. This contributes to the assessment of robustness of the SVi (Nardo, Saisana M., Saltelli A., and Tarantola S 2008). This is necessary to understand sources of uncertainty. Consequently, this uncertainty can be taken into account when developing policy advice for the BFRC. In recent studies it is shown that there exists divergence among experts on indicator weightings, and the differences in results from different index construction approaches (Bucherie et al. 2022; Tate 2012). This might question the use of vulnerability indexes for decision-making without undertaking validation and sensitivity analysis.

When zooming in into the methodological sensitivity, it can be seen that three methodological decisions have to be made within the set up of the PCA. These decisions of which method to executed are called the methodological decisions. This comprises the choice of the criteria that will be used to establish the number of components to be included, the type of rotation to be utilised, and the applied weighting scheme. In total, 12 combinations of methodological decisions were developed. On these twelve combinations a three-ways ANOVA analysis was executed. This section assesses the sensitivity of the index based on the methodology for sensitivity analyses developed by Schmidtlein et al. (2008). The different options available are presented in table 3.2.

In total the combination of these three sections of sensitivity lead to 12 different social vulnerability indexes. To execute a statistical comparison between these outcomes, all social vulnerability values were standardized with a z-score with mean 0 and variance 1. Positive values now indicate a high social vulnerability, whereas negative values show a lower vulnerability.

Table 3.3: Combination of PCA set-ups assessed

Name	No. Component	Rotation	Weighting scheme
Combi 1	Variance	Varimax	Sum
Combi 2	Kaiser	Varimax	Mathematical
Combi 3	Variance	Unrotated	Mathematical
Combi 4	Kaiser	Unrotated	Mathematical
Combi 5	Variance	Varimax	Mathematical
Combi 6	Kaiser	Varimax	Sum

Combi 7	Kaiser	Unrotated	Sum
Combi 8	Variance	Unrotated	Sum
Combi 9	Kaiser	Varimax	Sum weighted
Combi 10	Variance	Unrotated	Sum weighted
Combi 11	Kaiser	Unrotated	Sum weighted
Combi 12	Variance	Varimax	Sum weighted

To assess the sensitivity of all constructed methods, a three-way ANOVA is applied. The three-way ANOVA is used to determine if there is an interaction effect between three independent variables on the dependent variable. The independent variables in this case are the methodological decision that are made in the set-up of the PCA. Namely, how the number of components is determined, the rotation method that is used, and the weighting scheme applied. The dependent variable is the social vulnerability score. To apply a three-way ANOVA the data set has to meet six conditions as summarized in table 3.4. To prove the homogeneity of variance Levene's test was executed and obtained a p-value of 0.09 which is not significant and leads to the conclusion that all combinations have equal variance. To meet all the assumptions as presented in table 3.4, the outliers of the data where removed, based on the condition that the z-score should be between -1.5 and 1.5. The distribution of the obtained data set after this manipulation is shown in figure 3.5. Which also shows the lack of significant outliers. The combination of independent variables that are tested are shown in table 3.3. The analysis was executed with the use of the python package statsmodels (Seabold and Perktold 2010).

Table 3.4: Requirements that must be met in order to apply three-way factorial analysis

Assumption	**Verified**
Dependent variables are measured at a continuous level	✓
Independent variables should consist of two or more categorical and independent groups	✓
There should be an independence of observation	✓
There should be no significant outliers	✓
The dependent variable should be approximately normally distributed for each combination of the independent variables	✓
There should be homogeneity of variance for each combination of the independent variables	✓

It would have been insightful, to also assess the sensitivity with global SA methods, that compare the results obtained in the current analysis with results that use different indicator values. This was previously done by Nazeer and Bork (2019); Rogelis et al. (2016). This would have assessed the uncertainty of the data selection process. Furthermore, in this section, special attention could have been given to the sensitivity for indicators that are related to the conflict and migration structures that are visible in BFA. This will contribute to a better understanding of the role of conflict and migration in flood vulnerability. However these are recommendations for future research due to time constraints.

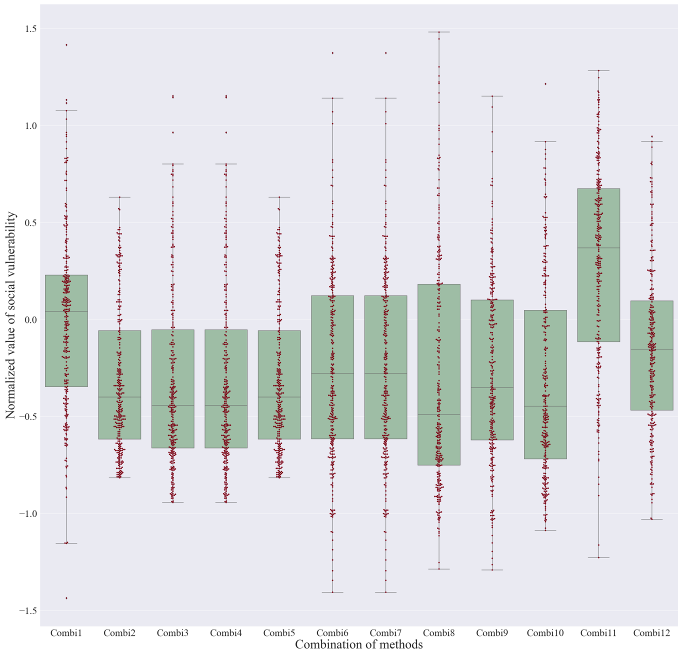


Figure 3.5: Distribution of data points that emphasizes the lack of significant outliers, and normal distribution of the dependent variable.

3.2.7 Calculation of SVi with INFORM

Previous social vulnerability studies and risk assessments executed by the NLRC have always been executed with the use of a hierarchical structural design. In this thesis the usefulness of an inductive structural design for social vulnerability studies in the humanitarian field was assessed. Even tough the method works, it is useful to balance the pros and cons of both methods before concluding which method is most suitable. The PCA approach is part of statistically based inductive methods, whereas the hierarchical processes, also called AHP is part of participatory or expert-based methods. To develop a comparison between both approaches the social vulnerability scores for Burkina Faso are calculated with the INFORM method.

The INFORM method is an hierarchical approach that conducts equal weighting. The indicators selected are the same as selected for the spatial assessment of social vulnerability in 2020. The hierarchical structure that was set up is shown in figure 9.1. After pre-processing the indicators, the INFORM model applies the min-max rescaling technique to standardize the indicators. This technique decomposes each variable into an identical range between zero and ten (equation 3.5.

$$Y_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} * 10 \qquad (3.5)$$

Where Y_i is the standardized value for the indicator value (X_i). and X_{min} and X_{max} represent the minimum and maximum value. To reduce outliers, in this study the minimum and maximum value are chosen based on Disaster Risk Management Knowledge Center, EC (2022). For the indicators not used in the INFORM model for the Sahel, the 25^{th} percentile was used for the X_{min} and the 75^{th} percentile was used for the X_{max}. Subsequently. the standardized indicator values are aggregated by calculating the mean of each sub-layer in the hierarchical lay-out of social vulnerability (figure 9.1).

3.2.8 Comparison of INFORM and PCA

Lastly, the results of the PCA approach are compared to the results of the more tradition hierarchical approach to constructing the SVi. The results are compared and discussed and pros and cons of both methods are discussed.

To do so, the distribution of social vulnerability scores is visualized and discussed. Additionally, the differences in social vulnerability ranking of the communities is calculated (equation 3.6).

$$ranking = |Rank_{PCA} - Rank_{INFORM}| \tag{3.6}$$

Part B Results

4 CONCEPTUALIZING VULNERABILITY

This chapter assesses which definition is best to use for social vulnerability in this research. In the early years, disaster risk reduction mainly focused on reducing the hazards. This is considered the hazard approach. Over the years, the vulnerability approach has developed as a concept, this approach focuses on the susceptibility of a geographic area for hazards. In this approach many different definitions are used that describe vulnerability (Birkmann 2006). In this chapter the best suitable definition for this research is presented.

> The following Sub Questions are answered in this chapter:
>
> SQ1: : How should vulnerability be defined for this research?

Vulnerability has evolved as a concept in response to the hazard oriented approach of disaster risk reduction (Kelman 2018; Birkmann 2005). The hazard oriented approach is challenged by the vulnerability approach since the 1980's. Today the UNDRR is embracing this new approach and calls for better understanding of vulnerability. Which entails the susceptibility of people and communities exposed with their social, economic and cultural abilities to cope with the consequences of disaster events (Hilhorst and Bankoff 2013). Their is a distinction between social vulnerability and (bio)physical vulnerability. The social vulnerability thus calls on the susceptibility of and impact on social groups, on contrary to physical vulnerability that calls on the susceptibility of and impact on structural elements (Birkmann 2005; 2007; Guillard-Gonçalves and Zêzere 2018). Vogel and O'Brien (2004) state that it is important to acknowledge the following aspects of vulnerability. It is multi-dimensional and differential, meaning that it differs over space and among different social groups. Furthermore, it is scale dependent, and thus results of different scales cannot be compared with each other. Lastly, vulnerability is dynamic and hence changes over time, that is because the characteristics and driving forces change over time. Furthermore Cannon et al. (2003) acknowledge that vulnerability is only partly defined by the type of hazard and mainly driven by the social circumstances in which a community experiences and responses to the impacts of hazardous events. Which suggests that the same value for social vulnerability can be used for different disaster risk assessments.

Different schools of social vulnerability agree that vulnerability should not be limited to the direct impacts of hazard events. In contrary, it should encompass the wider environment in which hazards happen, so that it reflects the coping mechanisms. This underlines the fact that vulnerability should also consider coping capacity of an affected community. Considering all different scales at which vulnerability is considered in

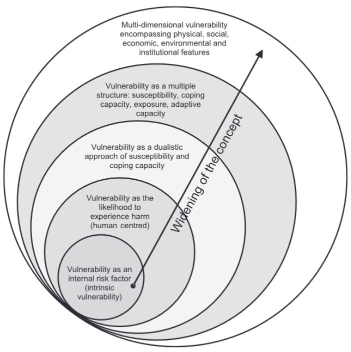


Figure 4.1: Key spheres of the concept of vulnerability.
Source: Birkmann 2005

literature Birkmann developed spheres of vulnerability as presented in figure 4.1.

In this thesis, vulnerability is considered with a dualistic approach of susceptibility and coping capacity. This underlines that vulnerability is shaped by both negative indicators that shape the likelihood of severe impact. And, on the contrary, it is reduced by the ability of a community to cope and recover from impacts (Wisner et al. 2012). Writing this in a mathematical expression would look as the following:

$$vulnerability = susceptibility - copingcapacity \tag{4.1}$$

This is contrary to with the original school of the disaster risk community. They define coping capacity and vulnerability as separate features of the disaster risk equation (see: 2.2). Nevertheless, since both coping capacity and vulnerability say something on the proneness of a community for hazard events, and the sum of both says something about the need of additional disaster risk reduction strategies, it is decided that in this research it is best to follow the first proposed concept.

SQ1: : How should vulnerability be defined for the Burkina Faso Research?

In this thesis, vulnerability is considered with a dualistic approach of susceptibility and coping capacity. This underlines that vulnerability is shaped by both negative indicators that shape the likelihood of severe impact. And on the contrary, it is reduced by the ability of a community to cope and recover from impacts (Wisner et al. 2012). Writing this in a mathematical expression would look as the following:

$$vulnerability = susceptibility - copingcapacity \tag{4.2}$$

Since both coping capacity and vulnerability say something on the proneness of a community for hazard events, and the sum of both says something about the need of additional disaster risk reduction strategies, it is necessary to include both susceptibility and coping capacity in the definition of vulnerability in this research.

5 DATA AVAILABILITY

The goal of this research, is to understand which methods are most suitable for understanding social vulnerability over space and time. This requires a high resolution on both temporal and spatial level in order to understand the dynamics that are taking place. In contrary to the regular construction of vulnerability indexes it is thus important to be aware that proxy indicators from other time spans, or different spatial resolutions can make the results invalid. Therefore, a thorough analysis on the secondary data availability was set-up. As a starting point, the humanitarian data exchange hub from UN OCHA was used to gather information. Where after *snowballing* led us to data sources with a higher resolution. Eventually, the open Source data that were gathered, were augmented with private data from the BFRC. This chapter is structured in the following manner section 5.1 shows why data availability is an important topic to discuss. Section 5.2 explains the indicators that are included, section 5.3 shows the decision process that is developed for the spatial analysis, and section 5.4 does the same for the temporal analysis.

The following Sub Questions are answered in this chapter:

SQ2: What spatial and temporal data is necessary and available?

5.1 UNDERSTANDING THE PROBLEMS OF DATA AVAILABILITY

Vulnerability indices typically use demographic data to populate indicators describing the effect of social, economic, political, and institutional factors on the spatial distribution of human susceptibility to hazard impacts (Tate 2012). The selection of this data is the first stage where selection is done by the modeller, and thus inherently ambiguous and sensitive for subjectivity. Changes in these input data, can have a significant effect on the outcomes. It is therefore decided to extensively report on the data selection process.

It is generally known that there is a high data scarcity in West-African countries. It is thus important to analyze the data availability before a start is made with the construction of the index. The data requirements for this research are demanding. A high resolution is required to analyze the effects of internal migration and conflict on the vulnerability scores over time. This is important since statistical relationships between social indicators often vary across scales, meaning that the same index produced at different scales may yield distinct patterns of vulnerability (Tate 2012).

While gathering the data the biggest challenge proved to be, finding the data on a high resolution in history. E.g. all indicators are available at country scale for at least 20 years past. However, data on community level have to be derived from OpenStreetmaps, or research that did not analyse time dynamically but solely at a single time perspective. It is thus complicated to gather information on a small aggregation scale, back in time.

To deal with this complication, it is decided to first analyse the vulnerability on a high resolution, while using indicator data from the past five years. Thereafter, the social vulnerability from 2015 - 2021 is analyzed on admin 1 level. The following part of this section is structured as follows. First section 5.2 describes the indicators and the reason for inclusion. Thereafter section 5.3 and 5.4 presents the decision process used for the indicators inclusion in the spatial and the temporal analysis. Lastly, a conclusion on sub-question 2 is presented.

5.2 DESCRIPTION OF INCLUDED INDICATORS

In this section, an overview of all considered indicators is presented. It provides an overview of all indicators, the temporal and spatial scale they are available on, the minimum and maximum value, the unit and the data source. In this appendix the description, relevance and reason for inclusion of all used indicators will be discussed. Below, each category will be highlighted and a flowchart on the inclusion criteria with regard to spatial and temporal availability is presented.

5.2.1 Socio-economic vulnerability indicators

The indicators belonging to this section all have a relation to the economic state of the regions. Embedded governance of the economic system is required to set-up pre-disaster and post disaster measures to reduce the impact of a disaster. Therefore, the level of economic development has a significant impact on a social system's resilience to flooding (Khazai et al. 2013). The indicators in this category belong to three sub categories, Development and Deprivation, Inequality and Aid Dependency. The category development and deprivation presents the level of development of the country. This category is deemed important for social vulnerability because it is assumed that, the more developed a country is, the better people are able to respond to humanitarian needs. Additionally, the inequality category introduces the dispersion of the development amongst the people. Lastly, the aid dependency points out which countries lack sustainable development growth, due to either economic instability or humanitarian crises. The indicators that are chosen to present the economic state of the social system are in line with the European Commission, Joint Research Centre (2017) and Cutter et al. (2003).

Development and Deprivation

The **Human Development Index** (HDI) is an index that measures the development of a country by combining several indicators of life expectancy, education level and income. The spatial resolution of this data is partly sub-national, and the temporal resolution of this data is from 2000 - 2019. Unfortunately, for 2020 and 2021 the data from 2019 have to be used. It is expected that in better developed countries, people will respond more adequate to humanitarian crises with the aid of their own individual or national resources. A good example is the timely and suitable response to the riverine floods in the south of the Netherlands (HDI = 0.944) in July 2021 (Expertise netwerk water en veiligheid 2021). Where emergency aid started already before the floods occurred. Figure 5.1 shows the structure of the HDI. In table 5.2 the facts on the HDI are presented. Since the data are indexes it is assumed that disaggregation can take place by using the same value for admin 1 level to admin 3 level.

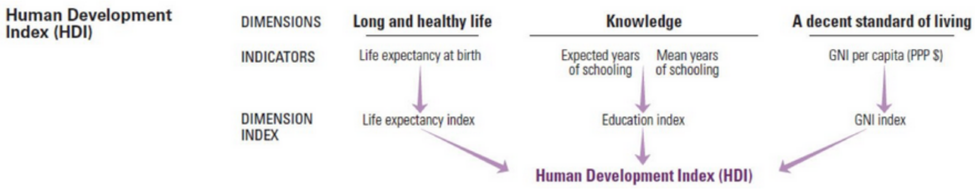


Figure 5.1: Structure of HDI

Table 5.1: Metadata HDI

Spatial availb.	Temporal availb.	Min-Max	Source	Equation
Region	2010 - 2019	0.29 - 0.25	UNDP (2020)	$HDI = (I_{health} + I_{Education} + I_{income})^{1/3}$

The **Multidimensional Poverty index** (MDPI) uses the same dimensions as the HDI, living standards, education and health. However it shows the average poor people and deprivations with which poor households contend. The MDPI is published on a yearly bases by the Oxford Poverty & Human Development Initiative (OPHI) and the United Nations Development Programme (UNDP). The additional value of the MDPI in combination with the HDI lies in the fact that the HDI focuses on the average achievements of a country, whereas the MDPI assess the section of the population below the basic human development threshold (Oxford Poverty and Human Development Initiative 2018). These data are available on a national level from 2010 - 2014, and on a sub-national level from 2015 - 2020. Since the data are indexes it is assumed that disaggregation can take place by using the same value for admin 1 level to admin 3 level.

Table 5.2: Metadata MPI

Spatial availb.	Temporal availb.	Min-Max	Source	Equation
Region	2010 - 2020	0.19 - 0.69	UNDP (2020)	$MPI = \sum_{j=1}^{10} c_j h_j$ c = weights of indicators h = value of indicators

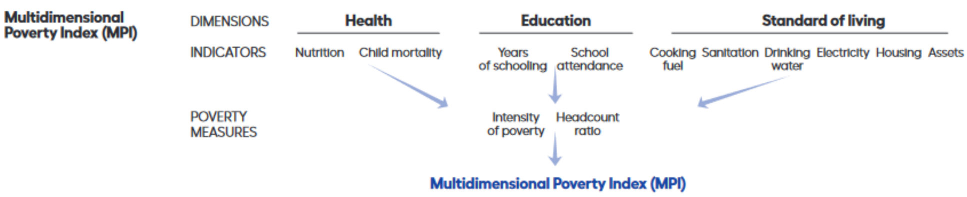


Figure 5.2: Structure of MPI

Inequality

The **Gender Inequality Index** represents gender based drawbacks for three indicators: reproductive health, empowerment and the labour market. The higher the score, the more inequality is present in a country that disadvantages the women. The index shows the dispersion of the conditions that are shown with the HDI and MDPI between men and women. Income inequalities reinforce other inequalities such as education and health access (UNDP 2011). Even though the MDPI, HDI and GII are strongly related, including both is important because it shows how the average persons is doing does not mean the whole is doing the same.

The GII index is calculated each year on a national level. Since the data are indices it is assumed that disaggregation can take place by using the same value for admin 1 level to admin 3 level. However, because the vulnerability index is a pseudo-equation that shows how the vulnerability of one region compares to other regions, including indicators with the same value for each spatial region does not make sense. But since we also want to compare the vulnerability over time, before it is possible to exclude GII from the index, the statistical significance over time is assessed.

For this an Augmented Dickey-Fuller (ADF) test is executed. This test verifies the stationarity of a time series (Cheung and Lai 1995). It tests the below hypothesis: the null hypothesis (H0) is: the time series is not stationary. The alternative hypothesis (H1) is: The time series is stationary. A p-value of 0.013 was found, so it can be concluded that the GII is a stationary variable and can be excluded from the analysis.

Spatial availb.	**Temporal availb.**	**Min-Max**	**Source**	**Equation**
Country	2010 - 2019	0.59 - 0.62	UNDP (2020) $HARM(G_f, G_m)$ = $G_{F,M}$ =	$GII = 1 - \frac{HARM(G_f, G_m)}{G_{F,M}}$ harmonic mean females and males geometric mean of arithmetic means of all indicators

Table 5.3: Metadata GII

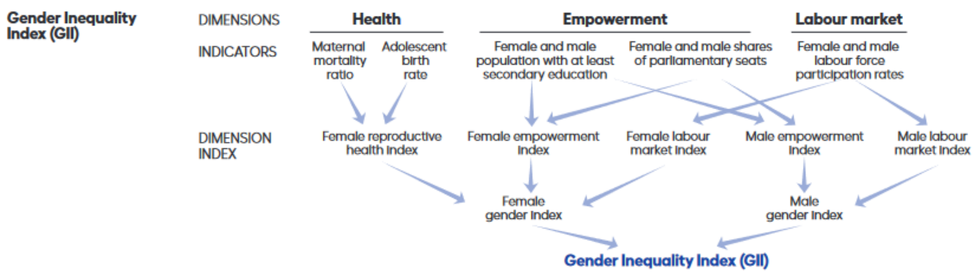


Figure 5.3: Structure of GII

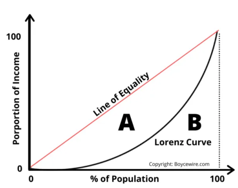


Figure 5.4: Structure of GINI

The **GINI-Index** is an additional index to measure if the income division in a country is equal. However instead of considering solely gender, the GINI-index considers the distribution of income over households. The values of the GINI deviate from 0 - 100, in which 0 represents 100% equality and 1, 100% inequality. Just as the Gender Inequality Index, this indicator shows how the development & deprivation components are dispersed in a country. The GINI-coefficient is calculated each year by the World Bank and is available on a sub-national level from 2017 - 2021 and on a national level for 2015 and 2016.

Table 5.4: Metadata GINI

Spatial availb.	Temporal availb.	Min-Max	Source	Equation
Country	2010 - 2019	0.1 - 0.47	Lerman and Yitzhaki (1984)	$GINII = \frac{A}{(A+B)}$ A = area above Lorentz B = area below Lorents

Aid dependency

The **Official Development Assistance (ODA)** received is the total amount of government aid that "promotes and specifically targets the economic development and welfare of developing countries. The Development Assistance Committee (DAC) adopted ODA as the "gold standard" of foreign aid in 1969 and it remains the main source of financing for development aid. ODA data is collected, verified and made publicly available by the Organisation for Economic Co-operation and Development (OECD)." (OECD 2021). The aid dependency shows which regions lack the individual sustainability in development growth. This can be due to economic instability and humanitarian crises.

The Total ODA is given in US dollar. On top of this indicator, also the **global humanitarian funding per capita (in US dollar)** and the **netto ODA received in % of the GNI** are considered in the analysis. By including these indicators, not only governmental aid is included but also the disbursements of loans made on concessional terms and grans by official agencies of the members of the DAC, multilateral institutions and non-DAC countries. For these variables, data are available on a country scale. To obtain values at commune level, the data are dis-aggregated. This was done with regard to the amount of people in need (permanent residents + IDPs + refugees) in a community in March 2022.

This is a suitable disaggregation method for the vulnerability assessment of 2020. However, since no data is available on the total number of persons in need for years before, it is not possible to dis-aggregate the data in historic perspective. When verifying the stationarity of the data set with the ADF method, a p-value of 0.948 was found for the total ODA, the data is thus not stationary. Because no suitable aggregation method can be found for this variable the indicator is excluded form the index. The same counts for the global humanitarian funding (p-value = 0.536). Lastly, the net ODA of GNI can be excluded without any problems, since this is a stationary variable (p-value = 0.00014).

Table 5.5: Metadata International funding

Spatial availb.	Temporal availb.	Min-Max	Source	Equation	Unit
Total ODA Country	2011 - 2019	892 - 1730	Lerman and Yitzhaki (1984) OECD (2020)	$\sum_{n=1}^{n} n$ n = DAC countries' investment	Million US dollar
Global Hum. Fund, Country	2012 - 2021	45655328 - 383724102	UN OCHA, Financial Tracking Service (2020)	$\sum allfunding$	US dollar
Net ODA of GNI, Country	2010 - 2019	6.5 - 11.6		$\frac{ODA}{GNI} * 100$	%

5.2.2 Vulnerable groups

People have different living conditions, this makes their response and recover mechanisms to a flood different (Cutter and Finch 2008). Communities with more resilient demographic groups will be less affected and can better sustain losses and recover faster from similar floods (Zhang et al. 2018). The vulnerable groups are divided into six sub-categories. Namely, the uprooted people, the health conditions, the children, the elderly, the food insecurity and recent shocks. The uprooted people are included because refugees, and internally displaced persons and returnees are among the most vulnerable groups in a humanitarian crisis. The health conditions include indicators that decrease the ability of people to cope with humanitarian crisis. Those are also specifically highlighted for children, because children do not yet have individual coping capacities and are thus dependent on other persons. Furthermore, the elderly will become less mobile and are designated by the BFRC to be extremely vulnerable. Food security is a large topic in Burkina Faso, many people suffer from malnutrition, and is thus included in the analysis. The sub-category recent shocks is extended in this research with both natural hazards and conflict. This indicator identifies the regions that are recovering from previous humanitarian crisis situations. The indicators chosen to represent the demographics are derived from the European Commission, Joint Research Centre (2017) and previous flood experiences from the BFRC.

Absolute and Relative persons in need, this includes all refugees, asylum-seekers, returnees, stateless persons and groups of IDPs but excludes permanent residents that are in need of assistance. In Burkina Faso, the latter takes the biggest part of this group. For the years 2020 and 2021, data is available on commune level, both in absolute and relative number of persons in need. Before those years, the people were registered per region, thus data is available on regional levels. The inclusion of the persons in need, is relevant since those are among the most vulnerable people in a humanitarian crisis (EC, European Civil Protection and Humanitarian Aid

Operations 2020).

Table 5.6: Metadata Persons in Need

Spatial availb.	Temporal availb.	Min-Max	Source	Equation	Unit
Persons in need, Region	2010 - 2020	0 - 494107	UN OCHA (2022)	count by CONASUR	persons
Persons in need, commune	2020 - 2021	0 - 262637	UN OCHA (2022)	count by CONASUR	persons
Persons in need, Region	2010 - 2020	0 - 20	UN OCHA (2022)	count by CONASUR	%
Persons in need, Commune	2020 - 2021	0 - 90	UN OCHA (2022)	count by CONASUR	%

Health conditions

The **Prevalence of HIV and AIDS above 15 years** is shown as the estimated number of adults aged 15 - 49 years old with an HIV infection. The indicator is expressed as the percent of the total population in that age group. However only available on a country level for the years 2010 - 2020, and on admin 1 level for 2017 - 2021. This indicator is one of the indicators pointing out the health condition of the population. Apart from HIV also **tuberculosis, malaria** are included. All of these are only available on a country scale. These diseases are considered as pandemics of low- and middle-income countries. These infectious disease outbreaks such as waterborne, rodent-borne, and vector-borne diseases have been associated with flooding before (Brown and Murray 2013; Okaka and Odhiambo 2018). Since the goal is to present also some vulnerable groups in the index, but all data on the inform indicators is only available on the country level, it is decided to used the **disables persons in need** on adm3 scale for the analysis of vulnerability in 2020. These data are not available for the historic years. Therefore stationary assessment was executed for the period from 2010 - 2020. This showed that all three indicators are stationary, and can thus be neglected for the comparison of vulnerability from 2010 - 2020. The metadata for the health conditions are presented in table **??**.

Table 5.7: Metadata Health conditions

Spatial availb.	Temporal availb.	Min-Max	Source	Unit
Prevalence HIV - Country	2010 – 2016	1.1 – 1.1	Bank (2022c)	%

Prevalence HIV - Adm1	2017 – 2021	0.08 – 4.02	Disaster Risk Management Knowledge Center, EC (2022)	%
Tuberculosis Prevalence - Country	2010 – 2020	0.045 – 0.058	Bank (2022b)	people per 100.000
Malaria mortality rate - Country	2010 – 2020	0.095 – 0.224	Organisation (2022)	%
Disabilities - Adm3	2020	0 – 5611	World Health Organisation (2020)	%

Children

Children are extra vulnerable for humanitarian crisis due to their dependence on others. Especially children that live in unsure health circumstances can get affected by these events. Therefore, **Children $<$ 5, the child mortality and the underweight in children** are also considered as indicators. The children $<$ 5 is available on a high enough resolution both for the for the spatial analysis but not for the temporal analysis. The child mortality is not available for the spatial analysis and no proxy could be found thus is not included. However was available for the temporal analysis and thus included there. Lastly, the underweight in children was available for both and thus included.

Table 5.8: Metadata information on Child vulnerability

Spatial availb.	**Temporal availb.**	**Min-Max**	**Source**	**Unit**
Children $<$ 5 – Community	2022	12.15 – 30.53	GRID3 (2022a)	%
Child mortality – Regional	2015 - 2021	95 – 250	UNICEF (2022)	Deaths per 1.000 births
Underweight – Community	2021	12.5 – 43.1	OCHA (2021)	%
Underweight – Regional	2015 – 2021	5 –31 %	Disaster Risk Management Knowledge Center, EC (2022)	%

Elderly

In the sub-category **elderly** only the percentage of elderly of the total population was considered. Unfortunately, this data is not available on the temporal scale. Therefore is only included in the spatial assessment.

Table 5.9: Metadata information on Elderly

Spatial availb.	Temporal availb.	Min-Max	Source	Unit
Elderly > 60 – Community	2022	1.84 – 7.4	GRID3 (2022a)	%

Food insecurity

The food insecurity reflects the lack of food available for all people in the communities. For this, different information is considered in the spatial and temporal analysis. The spatial analysis takes **Percentage of population category 3 – 5 and malnutrition levels** into account. Whereas the temporal analysis focuses on **Prevalence of GAM (WHZ) in children 6-59 months of age Prevalence of low body mass index (BMI) in Women and the percentage of population in category 3 – 5 of malnutrition**. This is due to the data availability for the temporal analysis.

Table 5.10: Metadata information on Food insecurity

Spatial availb.	Temporal availb.	Min-Max	Source	Unit
Category 3 – 5: Community	2021	9761 – 52649	FNSGW (2021)	%
Category 3 –5:Regional	2015 – 2021	6900 - 767413	FNSGW (2021)	Absolute number
Prevalence of GAM in children – Regional	2015– 2021	5.5 – 11.9	UNICEF (2020)	%
Prevalence of low BMI in women – Regional	2015 – 2021	7.7 – 31.1	UNICEF (2020)	%
Malnutrition – Community	2021	7.1 – 53.8	OCHA (2021)	%

People affected by recent shocks

Furthermore, people that are previously affected by natural hazard or conflict will me more vulnerable for a new hazardous event. Therefore, the number of affected people in the previous three years are also identified. Both for natural hazard and for conflict. The latter is an addition to the INFORM framework that does not include the people affected by conflict. However, because BFA is suffering a lot from conflict, it is decided to include this indicator as well. The establishment of the people affected by conflict is though. Thus it is decided to use the proxy variable of the amount of people that died from conflict. This data was derived from Raleigh et al. (2010). The metadata for these indicators are presented in table 5.11. For the analysis of vulnerability in 2020, the natural disaster data were scaled to adm3 level with regard to the local population.

Table 5.11: Metadata previously affected people

Spatial availb.	Temporal availb.	Min-Max	Source	Unit
Affected by natural disaster - Region	2015 - 2020	0 - 2656	EM-DAT, CRED / UCLouvain (2022)	absolute number
Conflict events - Community	2010 - 2022	0 - 408	Raleigh et al. (2010)	absolute number
Deaths by conflict – Community	2010 - 2022	0 - 408	Raleigh et al. (2010)	absolute number
Conflict events - Regional	2010 - 2022	0 - 408	Raleigh et al. (2010)	absolute number
Deaths by conflict – Regional	2010 - 2022	0 - 408	Raleigh et al. (2010)	absolute number
Affected by natural disaster - Community	2020	0 - 2656	EM-DAT, CRED / UCLouvain (2022)	absolute number

5.2.3 Lack of coping capacity – institutional

The next set of indicators focuses on the *disaster culture* in Burkina Faso. It represents the capability of the institutions to respond to disasters (Zhang et al. 2018). Past experience in disaster response contributes to the development of better response strategies. This reduces the potential negative impacts of a flooding events. The institutional indicators, can be divided into two sub-categories, the disaster risk reduction and governance category. The DRR indicators quantify the level of implementation of DRR activity. The governance indicators capture the ability of the public services to effectively build resilience across all sectors of the society. The inclusion of indicators in this category is based on the INFORM framework (European Commission, Joint Research Centre 2017).

Disaster risk reduction

The **Hyogo framework for action (HFA)** indicator, is an indicator developed by the UNDRR. It presents the activity in a country to reduce the disaster risk. However, it must be noted that the values for the HFA are based on self-assessment. Which has the tendency to perceive a process biased and grade higher. The data is only available on a country level. Thus it stationarity was assessed. The p-value found with the ADF-test was 0.001, therefore the variable is stationary and can be excluded from the analysis.

Governance

Furthermore, the **government effectiveness** is included. This variable shows the perceptions of the quality of public and civil services and the degree of independence from political pressure (Disaster Risk Management Knowledge Center, EC 2022; Kaufmann et al. 2011). The Corruption Perception Index ranks countries on how corrupt the public sector is perceived to be, based on surveys and assessments on corruption. It is additional value with regard to the HFA and government effectiveness is that it captures the misuse of political power for private benefit (Disaster Risk Management Knowledge Center, EC 2022; Transparency International 2022). Both the CPI and government effectiveness are only available on a country level, however are non-stationary values (p-value: 0.57 and p-value: 0.056). Therefore they have to be excluded from the analysis. Unfortunately no suitable proxy indicator was found. The metadata of the institutional indicators are presented in table 5.15.

Table 5.12: Metadata Institutional category

Spatial availb.	Temporal availb.	Min-Max	Source	Equation	Unit
HFA - Country	2015 - 2021	3.72 – 3.67	Disaster Risk Management Knowledge Center, EC (2022)		Index
Government effectiveness (GE) Country	2010 - 2020	-0.49 – -0.75	Kaufmann et al. (2011)	$y_{jk} = a_k + b_k(g_j + e_{jk})$ y = a_k and b_k = g = the normally distributed random	index GE Unobserved governance variable with mean 0 and variance 1
CPI - Country	2012 – 2020	38 – 42	Transparency International (2022)	Combination of at least 3 data sources drawn from 13 different corruption surveys and assessments	Index

5.2.4 Lack of coping capacity - infrastructural

The infrastructural indicators that represent the lack of coping capacity, can be considered as social security indicators. These indicators influence the potential losses, injuries, and fatalities due to flood disasters (Cutter et al. 2003). If a society is strong with regard to these indicators, its coping mechanisms are strong and it can help minimize the effects of floods. The indicators included in this section are derived from the European Commission, Joint Research Centre (2017) and local knowledge of the BFRC.

Communication

The communication component aims to measure the efficiency of dissemination of early warnings through the communication network of the country. Furthermore, it assesses the coordination of preparedness and emergency activities. The **access to electricity** represents the percentage of the population that has access to electricity. The resolution of the data is on national scale. Thus it's stationarity was verified and a p-value of 0.46 was found. Thus proxies had to be found, nevertheless those are not available. The **radio and television access** is available on adm2 scale for the 2020 analysis. For the temporal analysis only country wide data were found that are not stationary. Therefore these indicators are removed from the analysis. Furthermore the **adult literacy rate** is available on regional scale from 2017 - 2019 and on a country level from 2020 - 2021. No data is available for the previous years. The metadata of the institutional indicators are presented in table 5.13.

Table 5.13: Metadata Infrastructural Communication

Spatial availb.	**Temporal availb.**	**Min-Max**	**Source**	**Unit**
Electricity - Country	2010 – 2020	13.1 - 18.96	Bank (2022a)	%
Internet users - Country	2010 - 2020	2.4 - 22	The World Bank, World Development Indicators (2021a)	%
Mobile phone use - Country	2010 - 2020	60.2 - 105.8	The World Bank, World Development Indicators (2021c)	%
Radio access - Adm2	2020	0.5 - 77	GRID3 (2022b)	%
TV access - Adm2	2020	0.96 - 71.7	GRID3 (2022b)	%
Literacy rate - Adm1	2017 - 2021	6.2 - 65.2	The World Bank, World Development Indicators (2021b)	%

Physical connectivity

The physical connectivity indicators try to assess the accessibility as well as the redundancy of the physical connectivity. Both are crucial characteristics in a humanitarian crisis situation. When considering the **road density**, only data from 2022 are available on an adm3 level, and no data is available for the temporal analysis. This also holds up for the **the travel time to the closest city**. All metadata are presented in table 5.14.

Table 5.14: Metadata Infrastructure - Physical connectivity

Spatial availb.	Temporal availb.	Min-Max	Source	Unit
Roads density - Adm3	2022	0.06 – 6.38	Humanitarian OpenStreetMapTeam (2020)	%
Physicians - Adm3	2022	0–146	(2020)	absolute number
Travel time to city - Adm3	2022	30 – 895	Forest Resources and Carbon Emissions (IFORCE) (2015)	minutes

Health care

The last sub-category considers the health care development in the country. Among which the **health care facilities in the neighborhood**. These are sources of relief during and after disasters. A lack of health services, increases the time for relief and long-term recovery (Zhang et al. 2018). Preparing the health workforce to work towards the attainment of a country's health objectives represents one of the most important challenges for its health system. This data is only available for the spatial analysis, because no data is available on the historic years. Next, the **health expenditure per capita** is available on a country level for all years between 2015 – 2020. The Augmented Dickey Fuller test (ADF) analysis found this is a stationary data, thus it was excluded from the analysis. The **measles immunization rate** and **DTC immunization rates** are assessed among children under one year of age who have received at leas one doses. This calls on the health care infrastructure component of the coping capacity and is important since the component assesses both the accessibility as well as the redundancy of the system because both are crucial characteristics in a crisis situation. Both data are only available on a country level, with the use of ADF the stationarity is assessed and based on this both data were removed. Data on **improved sanitation, and water sources** are available on a regional level from 2017 - 2021.

Table 5.15: Metadata Infrastructure - Health care

Spatial availb.	Temporal availb.	Min-Max	Source	Unit
Improved water source - Adm1	2017 – 2021	13.99 – 98.4	The World Bank, World Development Indicators (2021d)	%
Improved sanitation - Adm1	2017 – 2021	6.7 – 63.9	The World Bank, World Development Indicators (2021e)	%
Health expenditure – Adm1	2015 – 2021	0 – 88	Organisation (2022)	Purchasing Power Parities (PPP)
Measles immunization – Country	2015 – 2020	88 – 95	Organisation (2022)	%
Immunization rate DTC – Country	2015 – 2020	88 – 95	Organisation (2022)	%

5.3 DECISION PROCESS FOR INCLUSION OF INDICATORS – SPATIAL ANALYSIS

Due to the scarcity of data in Burkina Faso, the data availability on all selected indicators had to be verified. For the analysis of the vulnerability in 2020, the decisions process presented in figure 5.5 is developed.

The indicator assessed is first verified on its aggregation level. If the data is available at community level (adm3), district sanitair (DS) or province level (adm2) and available for any of the years after 2017, the most suitable year is selected, and the data for the indicator is included in the data set. In the case that the data is only available at a regional level, the data is disaggregated with a suitable method and thereafter included. Whenever all theses steps did not succeed, country level data are considered. If there is any data available from a year after 2017, it was attempted to disaggregate the data to higher aggregation levels. However, if this was not possible, it was decided to exclude the data set from the analysis. This decision is made because this research considers the index as a pseudo equation. A pseudo-equation can be used to visualize and compare the differences in vulnerability but is not quantitatively interpretable (Kelman 2018). In this research we aim to observe differences in vulnerability between communities, using the same value for an indicator in all communities will not contribute to understanding the variability of the vulnerability.

The results of the decision process are shown in table 5.16. This shows, that originally 43 indicators were put into the decision process. From these, only 31 were included into the principal component analysis.

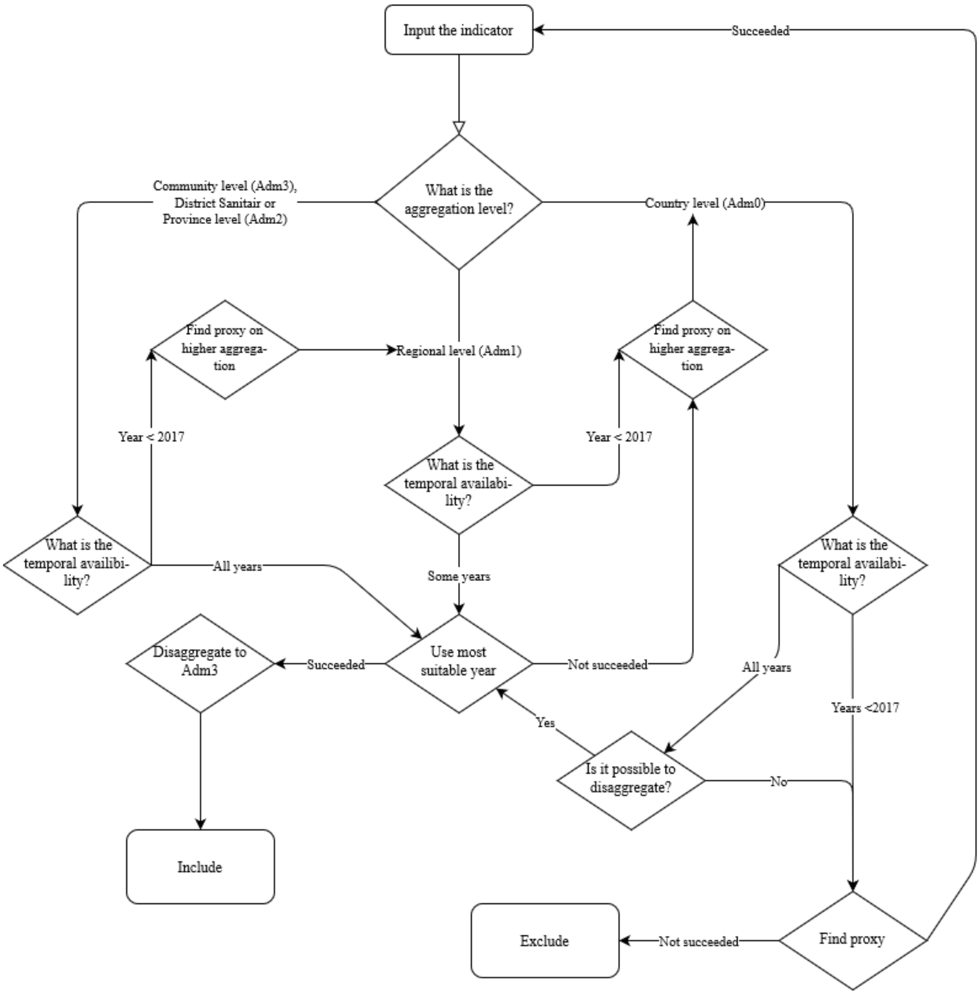


Figure 5.5: Decision Process indicator inclusion vulnerability 2020.

Table 5.16: Indicators with their influence on vulnerability, original scale and disaggregation method

Indicator	Influence	Original scale	Disaggregation method	Number unique values
Percentage Children < 5	–	Adm 3		351
Percentage Elderly > 60	–	Adm 3		351
Number of IDPs	–	Adm 3		250
Number of People in Need	–	Adm 3		172
Number of Disabled in Need	–	Adm 3		135
Percentage of people in Phase 3 – 5 food security	–	Adm 3		45
Travel Time to city in minutes	–	Raster	Average of community	226
People affected by conflict in last three years	–	Point	Sum of events	107
Number of health sites	+	Point	in community	13
Road density	+	Raster	Density calculation	351
Global Humanitarian Funding	+	Country		172
Total ODA	+	Country	Division by people	172
Public Aid	+	Country	in need on Adm 3	172
Gross National Income	+	Country	Division by population	351
Percentage of malnutrition	–	DS	Percentages applied to	67
Percentage radio access	+	DS	all communes in DS	69
Percentage of television access	+	DS		69
HDI	+	Adm 1	Index applied to	13
MDPI	–	Adm 1	all communes in Adm1	13
GINI	+	Adm 1		13
Percentage of HIV 15 - 49 year	–	Adm 1		13
Percentage of underweight	–	Adm 1		13
Percentage with access to electricity	+	Adm 1		13

Percentage improved access to sanitation	+	Adm 1	Percentage applied to	13
Percentage improved access to water source	+	Adm 1	all communes in Adm 1	13
Measles immunisation	+	Adm 1		13
Percentage affect by hazard last three years	−	Adm 1		13
ODA of GNI	+	Adm1		172
GII	−	Country		1
Governmental effectiveness	+	Country		1
Percentage of Tuberculosis	−	Country		1
Percentage of malaria mortality	−	Country		1
Mortality rate children	−	Country	Excluded	1
HFA	+	Country		1
CPI	−	Country		1
Percentage phone subscriptions	+	Country		1
Percentage internet users	+	Country		1
Literacy rate adults	+	Country		1
Tuberculosis effected	−	Coutnry		1
Mortality rate	−	Country		1
CPI	−	Country		1
Access to electricity absolute	+	Adm 1		
Health expenses	−	Country		1

5.4 DECISION PROCESS FOR INCLUSION OF INDICATORS – TEMPORAL ANALYSIS

Due to the scarcity of data in Burkina Faso, the data availability on all selected indicators had to be verified. For the analysis of the temporal vulnerability from 2015 – 2021, the decisions process presented in figure 5.6 is developed.

The indicator assessed is first verified on its aggregation level. If the data is available at community level (adm3), district sanitair (DS) or province level (adm2) and available on all years, the data is aggregated to admin 1 level and thereafter included. If the data is not available on all years, data on regional level are searched. When these are available on regional level for all years, the data set is included. If the data is available only one some years, attempts are made to scale the available data to other years, if this is possible, the data is included. If not, data on a country level are searched. If the temporal available is sufficient, it is attempted to disaggregate the data to regional levels. If this is not possible the stationarity of the data is assessed. If the data is stationary, it was excluded from the analysis. If the data is not stationary, a quest for proxies was set up. The values for the stationarity tests on the indicators are presented in section **??**.

The results of the decision process are shown in table 5.17 and 5.18. This shows that originally 33 indicators were included in the decision process. From these, only 19 were included into the principal component analysis.

Table 5.17: 19 Indicators with their influence on vulnerability, original scale and disaggregation method and number of unique values based on analysis of 2020.

Indicator	**Influence**	**Original scale**	**Aggregation method**	**Number unique values**
Conflict count	+	Adm3	Count conflicts in region	13
Development AID	–	Country	Division by people in need	11
GNI	–	Country	Division by population	13
Net ODA received (% of GNI)	–	Country	Aggregated by GNI and ODA	13
Mortality rate < 5	+	Regional		13
Prevalence of Underweight	+	Regional		8
One-year-old immunized against measles	–	Regional		13
One-year-old immunized against DTC	–	Regional		13

HIV prevalence	+	Regional		11
Clinically confirmed measles cases	+	Regional		10
Affected by Natural Hazards	+	Regional		13
Cadre Harmonisé	+	Regional		13
Number of IDPs	+	Regional		13
Refugees by country of asylum	+	Regional		5
Prevalence of GAM	+	Regional		10
Prevalence of low BMI	+	Regional		13
Improved sanitation	−	Regional		13
Improved water sources	−	Regional		13
Multidimensional Poverty Index	−	Regional		13
Physician density	+	Regional		2

Table 5.18: 15 Indicators that were not included in the analysis due to too low data resolution

Indicator	**Influence**	**Original scale**	**Reason for exclusion**
HDI	–	Country	Stationary
Physician Density	–	Country	Not available
Immunization rate DTC	–	Country	Stationary
Tuberculosis prevalence	+	Country	Stationary
Cholera reported cases	+	Country	Not available
Health expenditure	–	Country	Stationary
Malaria death rate	+	Country	Stationary
Gender Inequality Index	–	Country	Not stationary, but no proxy available
HFA scores	–	Country	Stationary
Government effectiveness	–	Country	Not stationary, but no proxy available
Corruption Perception Index	+	Country	Not stationary, but no proxy available
Access to electricity	+	Country	Not stationary, but no proxy available
Adult literacy rate	+	Country	Not stationary, but no proxy available
Internet Users	+	Country	Not stationary, but no proxy available
Mobile cellular subscriptions	+	Country	Not stationary, but no proxy available

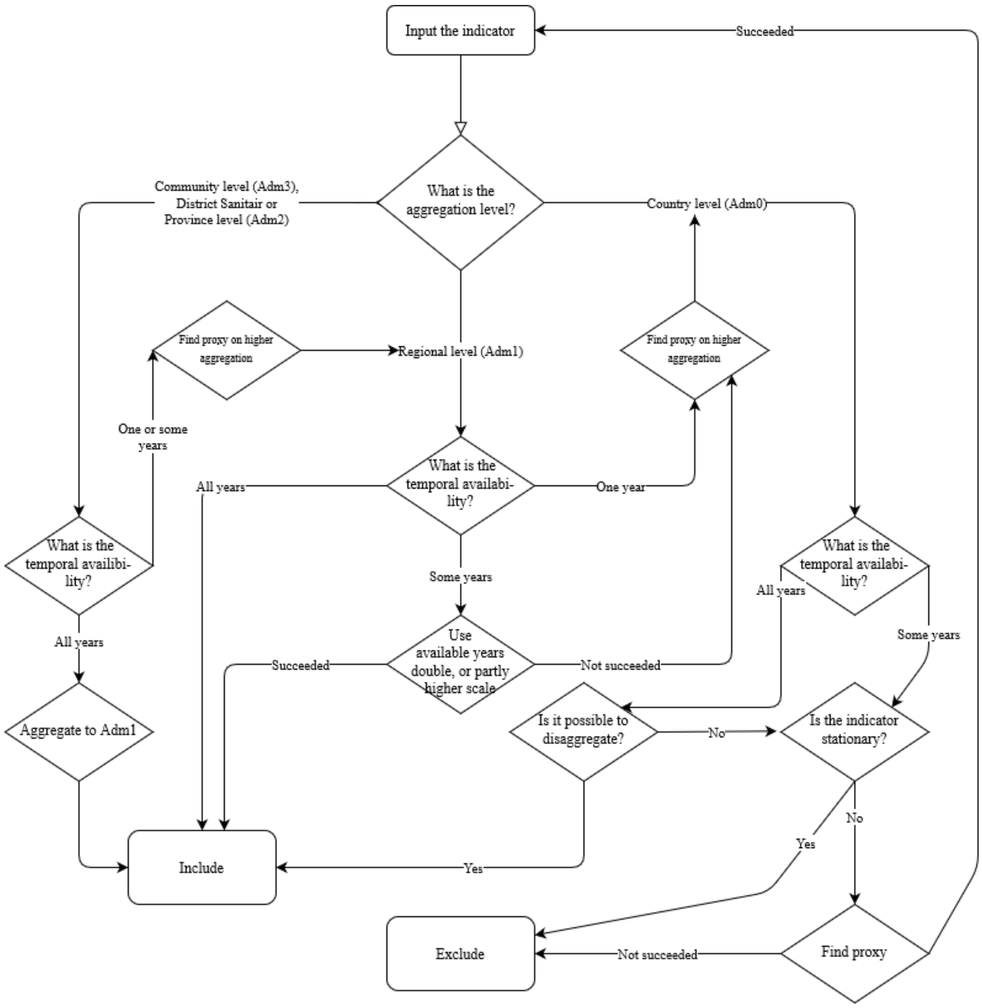


Figure 5.6: Decision Process indicator inclusion vulnerability for the temporal analysis.

SQ2: What spatial and temporal data is necessary and available?

To represent social vulnerability in a way that it matches with the way social vulnerability is defined in chapter 4 we need indicators from the following categories: socio–economic vulnerability indicators, vulnerable groups, institutional lack of coping capacity and infrastructural lack of coping capacity.

Diving more into detail on the data availability, it becomes clear that all indicators are available at country scale for at least the past 20 years. However, data on community level has to be derived from OpenStreetmaps, or from researches that did not analyse the indicators dynamically over time, but solely at a single time perspective in the recent past (2015 – 2022). The same counts for data on province level, it is thus not useful to make a differentiation between analysis on admin 2 or admin 3 level. Hence, it is not possible to analyse to social vulnerability over time, since not enough data with the right resolution is available to analyse the historic developments. However, it is possible to develop a community based social vulnerability index for 2020, that is based on data between 2018 – 2022. Additionally, a temporal social vulnerability analysis can be developed on admin 1 level from 2015 – 2021. Based on these results the importance of community level data gathering must be emphasized. The analysis can provide insight in to the spatial dynamics of social vulnerability that are not assessed in regular social vulnerability indexes such as INFORM.

When the temporal analysis is considered, it can be noted that a lot of data is available, and large part of the preprocessing work was executed by INFORM. INFORM analyzed the risk for Burkina Faso from 2015 until 2021 on admin 1 level. The data from INFORM is open access and can thus be reused to develop a social vulnerability index. Additionally to this data, previous conflict events are included in the social vulnerability component. Furthermore, contrary to what INFORM did, this research will assess the temporal change in social vulnerability and use a more precise method to set-up the index.

Additionally, it is noted that in the case of Burkina Faso, data availability and coverage is lacking in the following groups of social vulnerability: socio-economic indicators are rarely available on a higher resolution than the country level. Additionally, some health indicators are available on a highly dis-aggregated level, but meanwhile indicators such as malaria, mortality and tuberculosis are only available on a country level. Lastly, many indicators that refer to the communication possibilities are only available on a country level.

SQ2: What spatial and temporal data is necessary and available?

Policy recommendations
A strong call of action is given by the SENDAI (2015) on better understanding the dynamics of social vulnerability to develop better risk-reducing strategies. Quantitative research is necessary to identify on which regions to focus with qualitative research. With the current available open source data, the data resolution is not high enough to identify this for the temporal dynamics of social vulnerability.

As noted earlier by Bonato (2018) setting up an active quest for these data, contributes to the inclusion of local and traditional knowledge, and better understanding of vulnerability in the regions. It is thus much needed to develop a better data gathering mechanism. The well gathered data can then be used by research institutes, universities, and aid organisation to map and understand the temporal dynamics of vulnerability.

This data quest should mainly focus on the historical coverage of indicators, especially with regard to socio-economic indicators on a high resolution, health indicators on a high resolution and indicators that refer to the communication possibilities.

The data gaps in this research can be a results of several factors. There might be legal, commercial, financial or technical barriers. However, to find out what the specific barriers are in BFA it is recommended to discuss these topics more specified with experts in BFA.

The insight into the data availability provides a clear call for action for the humanitarian data field, and the Census office in Burkina Faso. The need to better understand dynamics of vulnerability, should develop hand in hand with the accessibility of data resources. Currently, this availability is lacking. Hence, the international organisation on humanitarian aid such as the UNDRR, ICRC, International Federation of the Red Cross and Red Crescent Movement (IFRC) and other The United Nations (UN)-departments, should stimulate development of Census offices that provide open source and high resolution data.

Future research
The development of SVi is an iterative processes that can be continuously improved through the means of better data input. The results of this analysis also show that development of input data, will improve the results. Furthermore, current published research provides little consideration to the data inclusion criteria, and sensitivity for the included data. Improving this, will contribute to data awareness and understanding the internal dynamics of each SVi.

Additionally, this section showed that it is is difficult to develop suitable dis-aggregation methods in data scarce areas. To resolve this challenge, better qualitative understanding of the data and the area can contribute to the development of more suitable dis-aggregation methods. It is thus recommended to apply further research into these mechanisms.

6 SPATIAL DYNAMICS OF SOCIAL VULNERABILITY

As this research focuses on understanding the dynamic behavior of social vulnerability, it is decided that is important to understand the differences in vulnerability on a as small as possible spatial scale. So that, the differences in communities, can be understood with local changes in indicators. Furthermore, this contributes to identifying which communities are in need of humanitarian aid. This chapter focuses on the results of the spatial analysis. Which identified the social vulnerability in Burkina Faso on commune level (admin3). The chapter is structured as follows. First, the correlation matrix and the set-up and results of the PCA are presented (section: 6.1.1). Thereafter, the SVi is mapped on the geographical areas. Second, the spatial pattern is identified with the use of LISA (section 6.2). Lastly, the identified spatial pattern is related to the conflict and hazard situation in BFA (section: 6.3).

The following Sub Questions are answered in this chapter:

SQ3: What are the social vulnerability scores on commune level in 2020?
SQ4: Is there a geographical pattern visible?
SQ5: Are links visible between the social vulnerability score and the conflicts and natural hazards?

6.1 RESULTS

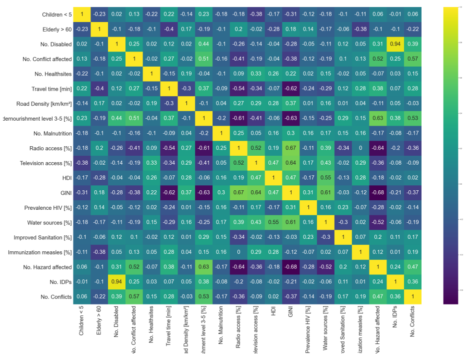
6.1.1 Set-Up Principal Component Analysis

Table 5.16 shows all included indicators in the spatial analysis together with the original scale, the direction of correlation with vulnerability, the disaggregation method that was used when necessary, and finally the number of unique values in the data set.

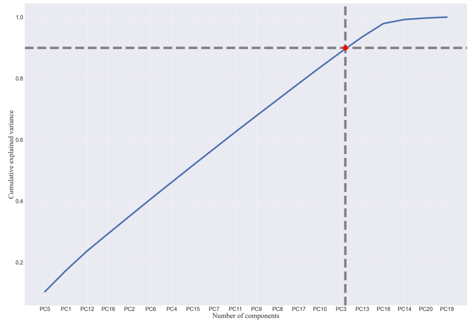
After the multicollinearity assessment, from the 31 indicators that passed the decision process 20 indicators were selected that fulfilled the correlation requirements. Those indicators are presented in the correlation matrix in figure 6.1a. Furthermore, it is important to note that from 11 indicators, only 13 unique values are present. This reflects that the disaggregation method did not make any distinction in values for these indicator, that go beyond admin 1 level. This is not in line with the expectations of the differences. For example for improved water sources, it can be assumed that more than 13 different numbers for improved water sources are present in the country, since it is not logical to assume the water sources are equally distributed over the admin 1 levels.

With all identified indicators a PCA analysis with Varimax rotation was employed to derive the principal components of this data set. The number of included components, is determined based on the argument that at least 90% of the variance should be explained by the included components in the index (figure 6.1b).

To verify the use of PCA on the initial data set a Bartlett Sphericity test and Kaiser-Mayer-Olkin test were applied. Bartlett's Test of Sphericity compares the obtained correlation matrix to the identity matrix. Essentially it checks if there is a redundancy between the variables that we can summarize with a few number of factors and thus if the right amount of indicators were removed based on $Pearson'sR$. If data are perfectly uncorrelated a PCA is not possible, so not too much data should be removed. For this analysis the scipy package of python was used (Virtanen et al. 2020). A p-value of 0.0001 was found, thus based on Bartlett Sphericity the data set is suitable for PCA. Additionaly, the KMO-test is executed, which is testing the contrary of Bartlett Sphericity. The test measures the sampling adequacy of each variable in the data set and for the complete data set. The adequacy refers to the measure of proportion of variance among variables that might be common variance. The lower the proportion, the more suitable the data set is for PCA. A KMO-value of 0.62 was found, which indicates the data set is suitable for PCA (Dziuban and Shirkey 1974).



(a) Correlation between indicators after removing indicators based on multicollinearity.



(b) The cumulative explained variance needed is 90%. For this 15 PCs are needed.

Figure 6.1: Information on indicator and component selection

The explained variance plotted in figure 6.1b shows that 15 principal components are necessary to explain 90% of variance. The results of the PCA analysis are shown in table 6.1. In this table the components that explain 90% of the explained variance are shown. Additionally the amount of variance explained by each component is shown. The direction is determined by the indicators in that component that has the highest loading.

Table 6.1: Vulnerability components summary of 2020

Component	Variance	+ or –	Dominant Variables	Loadings
PC5 – People in Need	12.37%	+	Disability IDPs	0.96 0.97
PC1 – Hazards	9.42%	+	Hazard affected	0.85
PC12 – Distance to city	6.34%	–	Travel time	0.91
PC16 – Television access	5.85%	–	Television access	0.84
PC2 – HDI	5.85%	–	HDI	0.90
PC6 – HIV prevalence	5.80 %	+	Prevalence of HIV	0.97
PC4 – Sanitation	5.73%	–	Improved sanitation	0.96
PC15 – Affected by conflict	5.45%	+	No. affect by conflict	0.92
PC7 – Road density	5.39%	–	Road density $[km/km^2]$	0.97
PC11 – Malnutrition	5.4%	+	Prevalence of malnutrition	0.97
PC17 – Water sources	5.34%	–	Improved water sources	0.86
PC9 – Measles	5.32 %	–	Measle immunization	0.95
PC8 – Children	5.32 %	+	Children < 5	0.96
PC10 – Health access	5.32 %	–	Health sites	0.97
PC3 – Elderly	5.32 %	+	Elderly > 60	0.92

6.1.2 Vulnerability Profile 2020

Based on the sum of the scores derived from the component loadings and initial values for each variable in each community the vulnerability score per commune is obtained. Results are presented in figure 6.2a. Table 6.1 shows the mathematical representation of how the social vulnerability score of each community is built up. The direction of the component is based on the influence of the dominant variables on social vulnerability. If the dominant variables are positively correlated to social vulnerability the direction will be positive, however when negative related, the direction is chosen to be negative. The decision on the correlation is based on expert knowledge within the NLRC.

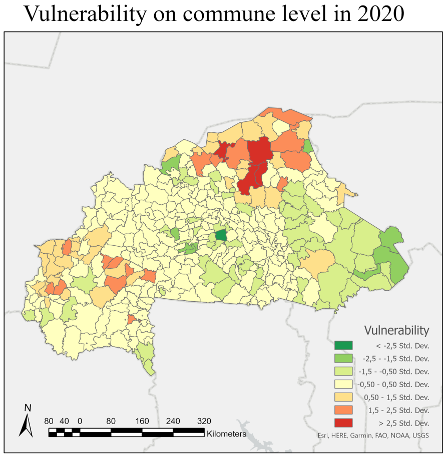
From this mathematical approach, two different visual analysis can be made. A comparison of the social vulnerability score with the hazards, conflicts and IDPs in each commune (figure 6.2), and an analysis of the composition of social vulnerability in the ten most vulnerable communes (figure 6.4a). The former shows a high

Commune	Social–Vulnerability Score
Djibo (Sahel)	33.2
Pensa (Centre–Nord)	15.96
Barsalogho (Centre–Nord)	13.52
Arbinda (Sahel)	13.49
Kaya (Centre–Nord)	12.62
Kaïn (Nord)	9.95
Fada–Ngourma (Est)	8.5
Tongomayel (Sahel)	8.17
Pissila (Centre–Nord)	8
Bourzanga (Centre–Nord)	7.04

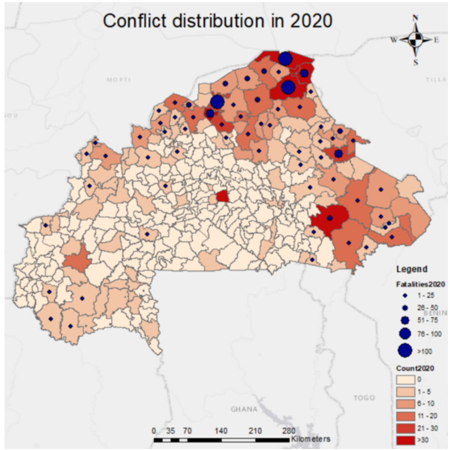
Table 6.2: Top 10 most vulnerable communes

social vulnerability in the conflict and IDPs prone areas in the North of the country. The results show that communes in the Sahel and Centre–Nord and Haute–Bassins regions have the highest social vulnerability. Table 6.2 shows the top ten communes of Burkina Faso that have the highest social vulnerability. In contrary, it can be seen that the regions in the centre and east of the country have the lowest social vulnerability. Especially around Ouagadougou, and in the admin 1 areas Boucle du Mouhoun, Centre–Ouest, Centre–Sud, Centre-Est and Est and Plateau Central communes have a relative low social vulnerability. When comparing these results to the visual interpretation of the natural hazards, conflicts and location of IDPs, it can be seen that social vulnerability is high in conflict–prone areas. Three out of the 10 most vulnerable communes are also in the top 10 of communes most prone to conflict. However, when considering the broader perspective, all communes in the top 10 are part of the 30 communes most affected by conflict. Additionally, when zooming into the IDPs it can be seen that six out of the 10 most vulnerable communes are in the top 10 of communes that host the most IDPs. This could indicate that conflict, IDPs and their impact contribute to the social vulnerability in an area, that the social vulnerability contributes to conflict, or that these to aggravate each other.

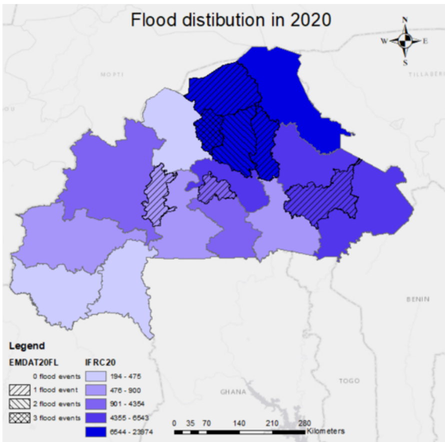
However, it should also be noted that this is not always the case. Especially in the Haute–Bassins region, it can be noted that some communes with a relative high social vulnerability are found, but not many conflict incidents and IDPs are present in this region. Furthermore, regions in the East with high conflict scores such as Pama and Matakoali have a relative low social vulnerability. It is also interesting to see that the communes in the Centre surrounding Ouagadougou are all part of the top 10 least vulnerable communes. However, these regions have been subjected to conflict and floods in 2020. The relation suggested based on the top 10 most vulnerable communes does thus not seem to hold up for the ten lowest vulnerable communes.



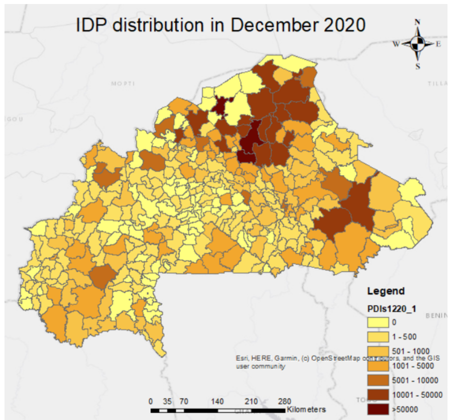
(a) **Vulnerability in 2020**



(b) **2020**



(c) **2020**

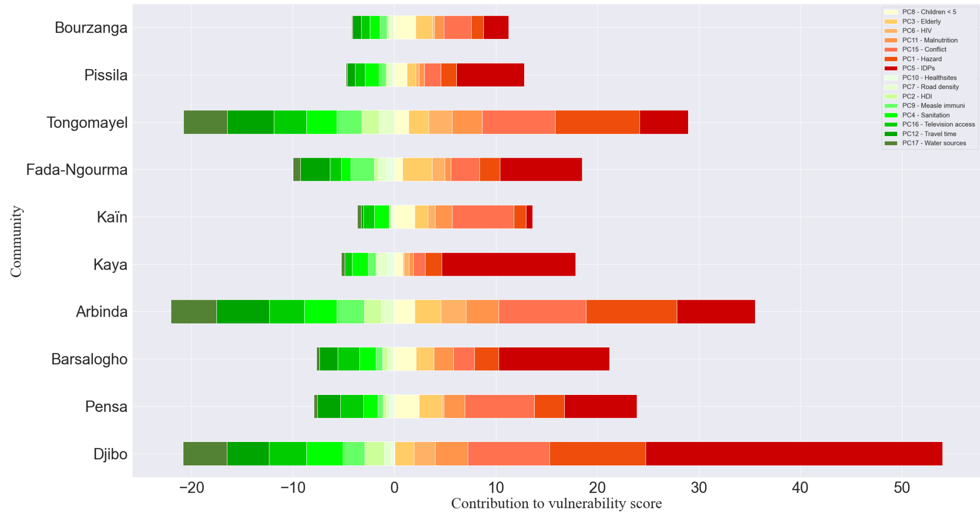


(d) **IDPs in December 2020**

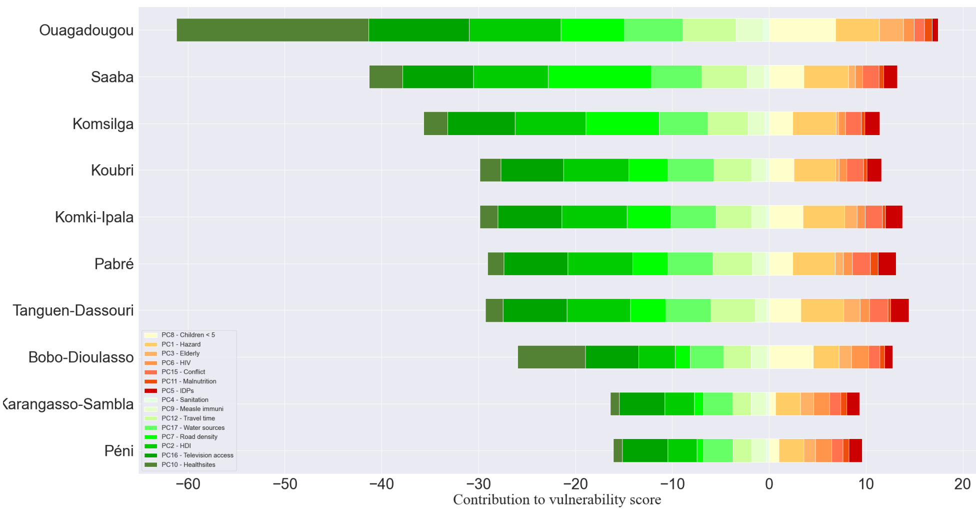
Figure 6.2: Social vulnerability in Burkina Faso compared to the natural hazards, conflicts and IDPs.

In figure 6.3 the contribution of each principal component to the vulnerability score of the ten most and least vulnerable communes is shown. Showing that, PC5, PC1, PC15 and PC11 contribute a lot to the social vulnerability in many of these communes. In these components the highest contribution is delivered by the number of IDPs, the people affected by hazards, conflict and Undernourishment. On the other side, the vulnerability is mainly decreased by PC17, PC12 and PC16, which are mainly representing the improved water sources, the travel time, and the access to television. Additionally, figure 6.4b zooms into the composition of the social vulnerability in the ten least vulnerable communes. From these communes seven out of the ten are located in the Centre region. It can be seen that especially in Ouagadougou the presence of health sites contributes a lot to the reduction of social vulnerability. Furthermore, the road density and access to communication (television access) are important factors that reduce the social vulnerability in these communes.

When considering the correlation between the found social vulnerability score and the original value of the indicators, no correlations with a $Pearson'sR$ value > 0.7 are found. This indicators that the cause for social vulnerability is differing a lot for each commune. An overview of all quantitative vulnerability scores and their composition is given in appendix 13.



(a) The contribution of each principal component to the ten most vulnerable communities.



(b) The contribution of each principal component to the ten least vulnerable communities.

Figure 6.3: Composition of top 10 most and least vulnerable communes

SQ4a: What are the vulnerability scores on commune level in 2020?

High vulnerable areas can be identified in the Sahel and Centre-Nord. Where they are clustered around conflict- and IDPs–prone areas. The composition of the vulnerability index shows that vulnerability in these areas is mainly caused by undernourishment, people with disabilities and conflict. In contrary to the high vulnerable areas in the Haute-Bassin where high vulnerability is a result of the prevalence of HIV, malnutrition and gender inequality. In all ten high vulnerable areas, vulnerability is mainly reduced by the access to improved sanitation systems.

The ten least vulnerable areas are mostly surrounding the capital city of Burkina Faso, Ouagadougou in the Centre. It can be seen that especially in Ouagadougou the presence of health sites contributes a lot to the reduction of social vulnerability. Furthermore, the road density and access to communication (television access) are important factors that reduce the social vulnerability in these communes.

Policy recommendations
The admin 3 level approach of this research gives good insight in the differences between neighboring communities. An important motivation for considering social vulnerability on such a level is the goal to support high-risk communities with more capacities and information. Analyzing the risk and vulnerability on commune level provides the possibility to decision-makers to derive priority settings for risk-reduction strategies on a community level. Based on the insight in the vulnerability composition, adequate risk-reduction strategies can be developed for the situation belonging to a specific community.

The derived results are useful for humanitarian decision makers. Due to the PCA indicators are clustered in principal components. Developing policy measures that address the principal components will affect all the indicators that have a high loading in that principal component due to their correlation. Furthermore, the additional insight into the composition of the social vulnerability (figure 6.3, shows which principal components are accounting for the highest part of the vulnerability. Based on this, focused decisions can be made that deliver aid on the principal components that are contributing the most to social vulnerability.

Future research
This research develops insight in a quantitative approach of social vulnerability. Additional value can be obtained by looking into the qualitative developments in the highly vulnerable areas. It is thus recommended, to develop focused field research into the red areas depicted on figure 6.2a.

6.2 SPATIAL ASSESSMENT OF VULNERABILITY

According to Tobler's "First Law of Geography", spatial autocorrelation analysis is used to explore spatial relationships based on spatial distance (Goodchild 2009; Tobler 1970; Chen and Lin 2021). The purpose of applying these spatial autocorrelation tests is to identify clusters or dispersed geographical patterns in the results. The aim is to reveal the proximity and similarity between vulnerable areas. Both a global and a local spatial autocorrelation tests was run.

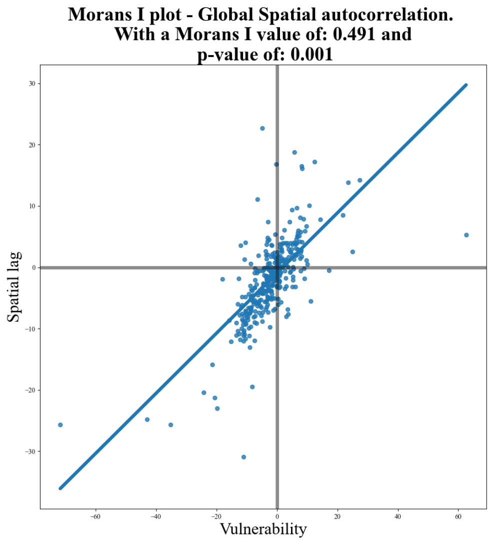
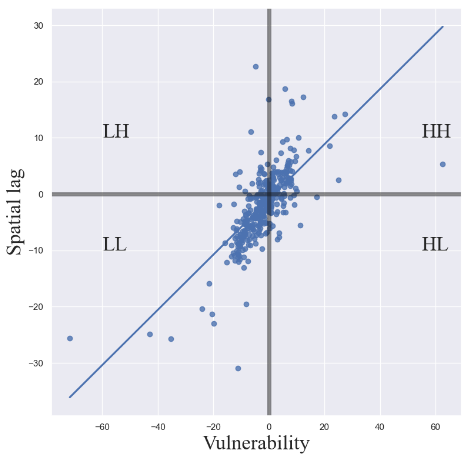


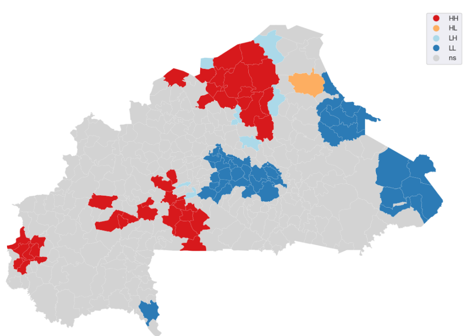
Figure 6.5: The figure above displays the relationship between the standardized vulnerability and its spatial lag which can be interpreted as the average vulnerability in the surrounding areas of a given commune. In order to guide the interpretation of the plot, a linear fit is also included in the graph. This line represents the best linear fit to the scatter plot.

The global autocorrelation is assessed with the use of Moran's I algorithm, of which the results are presented in figure 6.5. The plot displays a positive relationship between both variables. This is associated with the presence of positive spatial autocorrelation: similar values tend to be located close to each other. This means that the overall trend is for high vulnerability to be close to other high vulnerability areas, and for low vulnerability to be surrounded by other low vulnerability areas.

This however does not mean that this is the only situation in Burkina Faso: there can of course be particular cases where high vulnerability is surrounded by low vulnerability and vice versa. But it means that, if we had to summarize the main pattern of the data in terms of how clustered similar vulnerability profiles are, the best way would be to say they are positively correlated and, hence, clustered over space.



(a) Illustration of where each of quadrant falls into the Moran Plot can be seen in figure



(b) Mapping of high and low correlated clusters in Burkina Faso.

Figure 6.6: Results LISA analysis social vulnerability 2020 on commune level

According to the results of the global Moran's I, there is a form of positive correlation between vulnerability over space. Through the means of Moran's I, the data set is summarized into a single value that captures the degree of clustering. However, it is not yet identified which areas are specifically clustered with each other. For that purpose local measures of spatial autocorrelation are applied. This method considers each single commune in a data set and operates on them, as opposed to on the overall data set. For this LISA is used (Anselin 1995). At the core of this method is a classification of the observations in a data set into four groups derived from the Moran Plot: high values surrounded by high values (HH), low values nearby other low values (LL), high values among low values (HL), and vice versa (LH). Each of these groups are typically called "quadrants". An illustration of where each of these groups fall into the Moran Plot can be seen in figure 6.6a.

Additionally, figure 6.6b shows which communes belong to which type of social vulnerability cluster. The results of the univariate spatial autocorrelation analysis show that with regard to the global spatial autocorrelation there is positive spatial autocorrelation between the neighboring communes. Meaning, that highly vulnerable areas are surrounded with other highly vulnerable communes. If this is analyzed on a more specific scale, three high vulnerable clusters are identified:

- The Sahel and Centre-Nord cluster
- The Western Haute Bassins cluster
- The East Haute Bassins and Centre-Ouest cluster

Furthermore, three low vulnerability clusters are identified:

- The East cluster
- The Capital (Centre) cluster
- The Sahel South-Est cluster

However more important, for policy implication might be the addition information that can be derived from this analysis in comparison to the vulnerability map. The outliers in spatial autocorrelation can be either low vulnerable areas that are surrounded with high vulnerable areas, or high vulnerable areas that are surrounded with low vulnerable areas. The differences in neighboring communities are not well visible in the regular vulnerable plot, and require your attention in this map. The communities are:

- High vulnerable areas in low vulnerable clusters:
  - Dori in Séno in the Sahel South-Est cluster
- Low vulnerable areas in high vulnerable cluster:
  - Diguel in Soum in the Sahel and Centre-Nord cluster
  - Déou in Oudalan in the Sahel and Centre-Nord cluster
  - Bouroum in the Centre-Nord in the Sahel and Centre-Nord cluster
  - Boussouma in Sanmatenga in the Sahel and Centre-Nord cluster
  - Namissiguima in Sanmatenga in the Sahel and Centre-Nord cluster

SQ4: Can geographical patterns be identified?

The results of the univariate spatial autocorrelation analysis show that with regard to the global spatial autocorrelation there is positive spatial autocorrelation between the neighboring communities. Meaning, that high vulnerable areas are surrounded with other high vulnerable communities. If this is analyzed on a more specific scale, three high vulnerable clusters are identified:

- The Sahel and Centre-Nord cluster
- The Western Haute Bassins cluster
- The East Haute Bassins and Centre-Ouest cluster

Furthermore, three low vulnerability clusters are identified:

- The East cluster
- The Capital (Centre) cluster
- The Sahel South-Est cluster

However more important, for policy implication might be the additional information that can be derived from this analysis in comparison to the vulnerability map. The outliers in spatial autocorrelation can be either low vulnerable areas that are surrounded with high vulnerable areas, or high vulnerable areas that are surrounded with low vulnerable areas. The differences in neighboring communities are not well visible in the regular vulnerable plot, and require your attention in this map. The communities are:

- High vulnerable areas in low vulnerable clusters:
  - Dori in Séno in the Sahel South-Est cluster
- Low vulnerable areas in high vulnerable cluster:
  - Diguel in Soum in the Sahel and Centre-Nord cluster
  - Déou in Oudalan in the Sahel and Centre-Nord cluster
  - Bouroum in the Centre-Nord in the Sahel and Centre-Nord cluster
  - Boussouma in Sanmatenga in the Sahel and Centre-Nord cluster
  - Namissiguima in Sanmatenga in the Sahel and Centre-Nord cluster

Policy recommendations
The outlier communities identified with the spatial autocorrelation deserve special attention in risk–reduction strategies and further research. Since there is a high human mobility in these areas that is caused by the movement of IDPs (de Vries 2022), two things are interesting in these areas that deserve better understanding. The HL areas, might need less external help with the risk reduction strategies, because the surrounding communities are relatively strong and can assist the community with high vulnerability in gaining more resilience. On the contrary the LH communities might face more IDPs in the short future. Since the circumstances in these communities are relatively good, they might be attractive to move to when displacement occurs in the high vulnerable surrounding communities.

6.3 INTERPLAY BETWEEN SOCIAL VULNERABILITY, CONFLICT, HAZARDS, AND IDPS

An important aspect of this study is the understanding of the interplay between conflict, IDPs, natural hazard ans social vulnerability. Figure 6.2 shows the distribution of all three in one figure and figure 6.7 shows the interplay between the four. The latter suggests an interaction between the social vulnerability score and the presence of natural hazards, conflict and IDPs. The most vulnerable communities all score high on those three indicators. However, when considering figure 6.7 where all data points are plotted, no strong relation can be derived between any of the combinations.

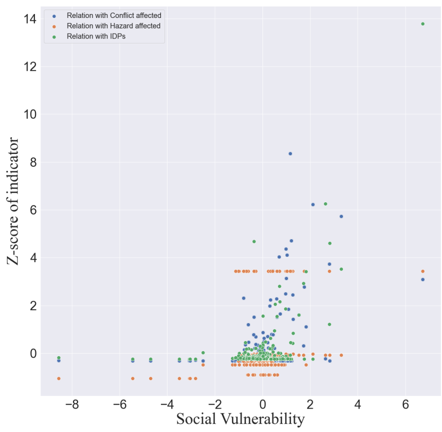


Figure 6.7: The relation between social vulnerability and number of people affected by conflict, natural hazards and the number of IDPs.

Nevertheless, it can be seen that there are several communes in the Sahel, Centre–Nord and Est regions, which host a high number of IDPs, and are classified to experience many conflict events and have a high social vulnerability. These communes are areas with large urban areas (e.g. regional and provincial capitals) and their neighboring communes. These are also the regions that shows clusters with communes with a high social vulnerability (figure 6.6b). Figure 6.7 also shows that for natural hazards no pattern is visible, similar z–scores for natural hazards show no relation with the social vulnerability score.

SQ5: Are links visible between the social vulnerability score and the conflicts and natural hazards?

It is complicated to derive clear patterns between the social vulnerability score and the indicators, number of people affected by conflict, natural hazards and the number of IDPs in a commune. This chapter showed that the top ten vulnerable communes score high on these indicators. Which suggests an interaction between the social vulnerability score and the presence of hazards, conflict and **idps!**. However, when comparing the results for all communes, no patterns can be identified. In many communes, different principal components that are not related with these three shape the social vulnerability.

Policy recommendations
It is recommended to focus humanitarian aid on all communes that have a high social vulnerability. These are also the communes that often suffer from conflict, hazards and host a lot of IDPs. It is likely that these communes benefit the most from humanitarian aid. However, before making funding decisions qualitative analysis is recommend to thoroughly understand the needs of the communes.

Future research
Future research would be beneficial in understanding the interplay between social vulnerability, conflict, natural hazards and IDPs. In contrast to this research, qualitative research would be beneficial. This will contribute to a better understanding of the qualitative processes taking place in the country. Additionally, this will reduce the risks of circular argumentation (e.g. the output of the analysis is caused by the input but double counted for).

7 TEMPORAL DYNAMICS OF SOCIAL VULNERABILITY

With the use of PCA a vulnerability index was developed for each region in Burkina Faso for all years between 2015 - 2021. For this the same method was used as for the spatial analysis. However, a different indicator inclusion decision process is followed. More insight could have been derived from this part of the analysis if data were available on a higher resolution. Unfortunately this is not the case, thus the decision was made to analyse the vulnerability over the years on regional scale (admin 1). It is important to note, that the results provide insight in the entire region, and not on specific communes within the region. This chapter is structured as follows:Section 7.1 shows the results of the temporal analysis. Next, section 7.2 discusses the temporal dynamics that are visible. Finally, section 7.3 discusses the interplay between the important indicators and the social vulnerability.

> The following Sub Questions are answered in this chapter:
>
> SQ6: What are the social vulnerability scores on admin 1 level from 2015 – 2021?
> SQ7: What are the temporal dynamics of social vulnerability?
> SQ8: Are links visible between the pattern and the conflicts and natural hazards?

7.1 RESULTS

7.1.1 Set-Up Principal Component Analysis

Table 5.17 shows all included indicators in the temporal analysis together with the (dis–)aggregation method that was used if necessary and the number of unique value, and the number of unique values for that indicator in the data set. Table 5.18 shows for which indicators no suitable data set was found. In total 34 indicators were assessed in the decision process. From these 19 were considered suitable to include in the analysis. After the multicollinearity assessment, from these 19 indicators, the correlated indicators with a $Pearson'sR$ of 0.7 or greater were excluded. The exact number of removed indicator is different in each year and presented in table 7.1. It is important to remove these too correlated variables. That is because principal components will otherwise represent the same mechanisms that is represented in multiple variables. This is called double counting and results in outcomes that do not evenly reflect the influence of each mechanisms on the social vulnerability index. The final obtained correlation matrix is presented for each year in appendix 15.1

With these identified indicators a PCA analysis with Varimax rotation was employed to derive the principal components of each data set. The number of included components, is determined based on the argument that at least 90% of the variance should be explained by the included components in the index. All analyses capture the original data set with 90% of the variance when 7 principal components are

Year	Removed indic.	No. PC	Bartlett p-value	KMO p-value
2015	8	7	0.010	0.24
2016	8	7	0.0058	0.22
2017	5	7	0.001	0.19
2018	5	7	0.001	0.18
2019	5	7	0.001	0.13
2020	7	7	0.001	0.375
2021	6	7	0.001	0.18

Table 7.1: Amount of indicators included in the analysis. P-values that are < than 0.001 are presented with 0.001.

included. This is shown in appendix 15.2.

Adequate p-values were found for each year (table 7.1), thus based on Bartlett Sphericity the data set is suitable for PCA. If data are perfectly uncorrelated a PCA is not possible, so not to much data should be removed. The data sets for all year showed a too low KMO-value that is < 0.5. Meaning that the results of this analysis should be challenged since it is ambiguous if an adequate sampling is presented in the data sets for each year. It is thus decided not to use PCA for the analysis of the temporal dynamics of social vulnerability. For this, higher resolution indicators are required, since other wise the objectivity of the data can not be guaranteed.

Therefore, it was decided that the PCA results are not trustworthy to identify temporal patterns in social vulnerability (the results are shown and discussed in appendix 14). Thus the analysis for the temporal pattern identification is executed on the Social Vulnerability scores obtained by INFORM. Unfortunately, INFORM does not consider the elderly, and past conflict as an indicator. Which are important indicators for the social vulnerability specific in Burkina Faso. To obtain the social vulnerability from the INFORM data sets, the following equation is used:

$$Socialvulnerability = Vulnerability_{INFORM}^{1/2} * Lackofcopingcapacity_{INFORM}^{1/2} \quad (7.1)$$

Hence, in future research, it would be better to either obtain more measurement points to develop the PCA, but for this better data availability is necessary. Or develop the social vulnerability score with the use of hierarchical methods, but this will deliver less precise results for a temporal comparison and will make it more difficult to understand the contribution of indicators to the social vulnerability since this is determined by the modeller.

7.1.2 Vulnerability profile 2015 – 2021

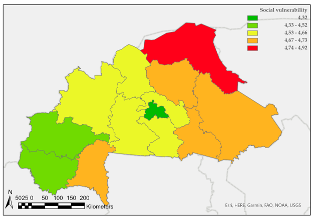
Table 7.2 shows the social vulnerability scores that are obtained with the INFORM model for each region from 2015 – 2021. Additionally, figure 7.1 presents the social vulnerability profile of Burkina Faso for the year 2015 – 2021. This shows that high social vulnerability scores are visible in the Sahel and Eastern regions. Furthermore, an initial look at these maps, shows that high social vulnerability is often present in areas with many conflict events. However, not all areas with high conflict events, have a high social vulnerability. For example, after the conflict intensified (2017), the Sahel was the most vulnerable region 80 % of the time, and also has the highest number of conflict events. However, the Sud–Ouest and Boucle du Mouhoun region, also score high on social vulnerability during 2018, 2019 and 2020, nevertheless the number of conflict events, IDPs and hazards is not high in these regions.

A high social vulnerability score is thus not solely caused by conflict. Additionally, the results show a low social vulnerability in the Centre region where the capital is located.

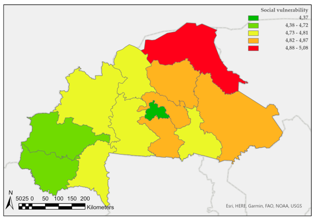
	2015	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Boucle	4.66	4.79	4.81	5.69	4.89	5.04	4.99
Cascades	4.52	4.72	4.59	5.28	4.62	4.73	4.87
Centre	4.32	4.37	4.30	4.34	4.25	4.32	4.19
Centre-Est	4.71	4.81	4.68	5.49	4.70	4.88	4.79
Centre-Nord	4.71	4.83	4.63	5.46	4.96	5.19	5.33
Centre-Ouest	4.62	4.79	4.66	5.63	4.68	4.77	4.82
Centre-Sud	4.66	4.83	4.65	5.44	4.68	4.71	4.85
Est	4.73	4.87	4.76	5.66	4.77	5.06	5.22
Hauts Bassin	4.52	4.72	4.74	5.54	4.59	4.77	4.79
Nord	4.66	4.81	4.78	5.97	4.68	5.19	5.25
Plateau Central	4.64	4.83	4.61	5.53	4.71	4.77	4.93
Sahel	4.92	4.72	5.08	6.45	5.15	5.19	5.11
Sud-Ouest	4.68	4.74	4.76	5.72	4.79	4.86	4.97

Table 7.2: Social vulnerability per region per year

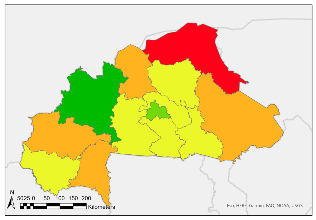
When taking a closer look into the composition of the social vulnerability index a drawback of the hierarchical approach such as INFORM becomes visible. Since all indicators are grouped, and consists of different levels which were equally weighted it is more complicated to derive insight in the composition of the social vulnerability index. Additionally, the inductive approach (PCA) showed the relation between the indicators very well through the correlation assessment and the loading on the principal components. This relation is now not visible, and therefore it becomes complicated to derive effective and focused policy measures for the indicators that cause most of the social vulnerability. With the hierarchical approach, we can thus not present figures for interpretation as in chapter 6, since too many indicators will be included an their relation is unclear. However, when the numbers that are available are assessed it can be concluded that in the Sahel, Centre–Nord, Nord and Est, the indicator components *Uprooted people, Malnutrition and Food security* show relatively high compared to the other regions and *Infrastructure and access to health care* score relatively low.



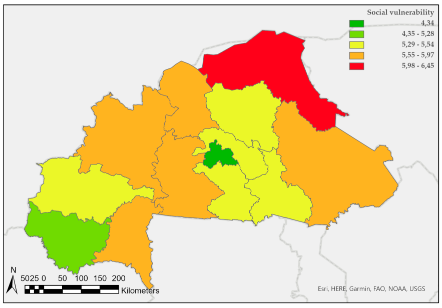
(a) 2015



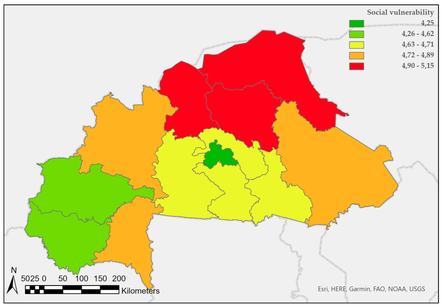
(b) 2016



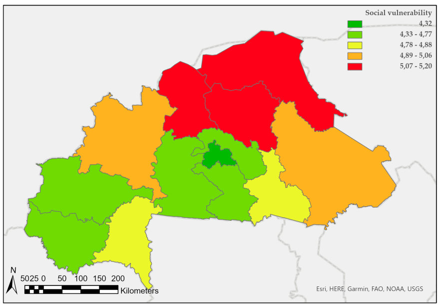
(c) 2017



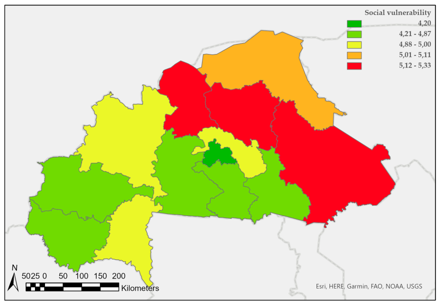
(d) 2018



(e) 2019



(f) 2020



(g) 2021

Figure 7.1: Social Vulnerability profile of Burkina Faso per admin 1 region, plotted from 2015 – 2021.

SQ6: What are the social vulnerability scores on admin 1 level from 2015 – 2021?

According to the study, using PCA on an admin 1 scale to construct social vulnerability indicators is unfeasible. This is because such data sets have a small number of data points. This has the effect of producing too low KMO-values, which show that it is possible that the variance in the original indicator set is caused by common variance. Thus, the INFORM technique is used to conduct an analysis of societal vulnerability at the regional level from 2015 to 2021.

The Sahel and Eastern regions exhibit high social vulnerability scores. The maps demonstrate that places with frequent conflict incidents also have high levels of social vulnerability. Not all locations with a lot of conflict incidents have a high social vulnerability. So conflict is not the only factor that contributes to a high social vulnerability score. Additionally, the findings indicate that the Centre region, where the capital is situated, has the lowest social vulnerability in all years.

A flaw in the hierarchical approach is revealed when the social vulnerability index's composition is examined in further detail. It is more difficult to gain insight into the makeup of the social vulnerability index because all indicators are grouped and comprise distinct levels that were equally weighted. Through the correlation analysis and the loading on the principle components, the inductive technique demonstrated the relationship between the indicators extremely effectively. Since this connection is no longer apparent, it is harder to develop effective and targeted policy actions focused on the indicators that contribute most to social vulnerability. However, after analysing the data, it can be said that in the Sahel, Centre—Nord, Nord, and Est, the indicator components *Uprooted people, and Food security* show relatively high compared to the other regions.

Policy recommendations
According to the discovered social vulnerability profiles, social vulnerability patterns change throughout time. The Sahel and the East exhibit high vulnerability profiles, which would necessitate humanitarian intervention in these areas. The profiles, however, are only offered on a regional level, which lacks information for applying local humanitarian relief. This is contrary to the PCA method that offers insight into the vulnerability's structure and how the composition changes over time because of the statistical approach. Unlike hierarchical techniques, this shift is not the result of the choices made by the experts during the weighing stage. Deriving these results on a community level, will provide useful insight for humanitarian aid decision making. For this better granularity of indicator data is necessary.

Future research
This analysis has shown that the PCA model cannot always be utilised to determine the social vulnerability index. The initial indicator set becomes invalid for PCA if the data set has too few measurement points, which is the situation if SVi is taken into account at the regional level. In this situation, various models, such as the hierarchical INFORM approach, can be used to carry out the study. These models don't provide ground truth data about social vulnerability. Future study is required to fully grasp the differences between the methodologies because they take a distinct conceptualization and mathematical approach to social vulnerability.

Furthermore, the understanding of the relationship between the indicators is a weakness of the hierarchical approach. Future studies should devise strategies to comprehend how the indicators relate to one another while employing the hierarchical approach. This is significant because it explains the patterns that are apparent and offers justification on how to create effective policy actions to lessen social vulnerability.

7.2 ASSESSING THE TEMPORAL RELATION OF SOCIAL VULNERABILITY

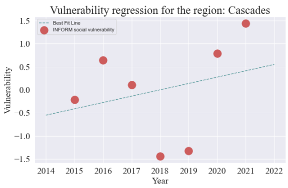
The results of the temporal assessement of social vulnerability in each admin 1 region are shown in figure 15.4. Analyzing the results of the regression algorithm, shows two interesting insights. First, the results between the PCA and INFORM method are very different. This is due to the inconsistency in the set-up for the PCA method applied on a regional analysis. Due to data scarcity, the method does not prove suitable for an analysis on regional level. Thus the temporal analysis is executed with the INFORM method, which shows that in almost all regions of Burkina Faso, the social vulnerability seems to have increased from 2015 – 2021. This can be explained by the large increase in the conflict, hazard and undernourishment components. However, if the conditions developed by Cutter 2008 are followed, the slope of the best fit line, should be at least 0.5 to consider the change inevitable and the corresponding p-value should be > 0.05. No slope > 0.5 was found.

Since the analysis is made on a period of only seven years it is complicated to indicate a long term trend. However, it can be seen that there is a short term trend that increases vulnerability, especially in the Boucle du Mouhoun, the Centre-Nord and Nord. It is striking, that there is no significant change in the social vulnerability in the Sahel. This can be attributed to the low amount of data that are considered, and the high changes in social vulnerability that are visible in the INFORM model (figure: **??**). The large differentiation in social vulnerability in the final 3 years, makes it complicated to derive a statistical significant result from these developments.

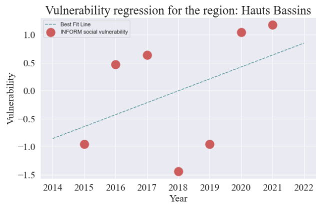
To understand the areas that do show a statistical significant result better, the correlation between the indicators and the social vulnerability score was assessed. This showed that, in Boucle du Mouhoun, the increase can be derived from the increase in child mortality, and the decrease in health care and water availability. A strong correlation between the social vulnerability and the amount of conflict, HDI, GNI, Physicians Density, Cadre Harmonisé, IDPs, GAM and Adult literacty rate was found, with $Pearson'sR$ values of respectively, 0.85, 0.86, 0.77, 0.88, 0.92, 0.92, 0.72, 0.77. Negative correlations were found for the MDPI and immunization rate, with $Pearson'sR$ values of respectively -0.88 and -0.94.

In the Centre-Nord a steady increase in social vulnerability can be seen, apart from the years 2017 and 2018, where an increase in children's health decreased the social vulnerability for two years. The overall increase in social vulnerability is caused by an increase in conflict and presence of IDPs. A strong correlation between the social vulnerability and the amount of conflict, physicians density, Cadre Harmonisé, the amount of IDP's and the adult literacy rate, was found, with $Pearson'sR$ values of respectively, 0.91, 0.86, 0.82, 0.91, 0.89. A negative correlation was found with the immunization rate and the government effectiveness with $Pearson'sR$ values of respectively: -0.77, -0.89, -0.72.

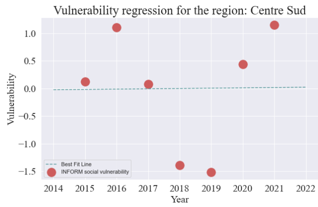
In the Nord, also a steady increase can be derived from the regression analysis. Apart from the years 2018 and 2019, where a drop in social vulnerability is caused by an increase in water availability. The steady increase is just as for the Centre-Nord, mainly caused by conflict and child malnutrition. A strong correlation between the social vulnerability and the amount of conflict, Cadre Harmonisé, the amount of IDPS, the adult literacy rate was found with a $Pearson'sR$ value of respectively: 0.91, 0.89, 0.82, 8.91, 0.89. Negative correlations were found with the MDPI, Immunization rate, and government effectiveness with $Pearson'sR$ values of respectively: -.89, -0.77, -0.72.



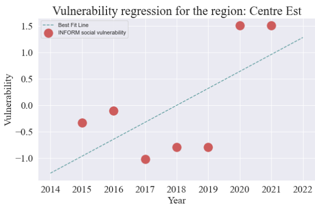
(a) Slope = 0.13, p = 0.551



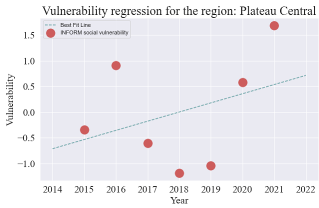
(b) Slope = 0.21, p = 0.34



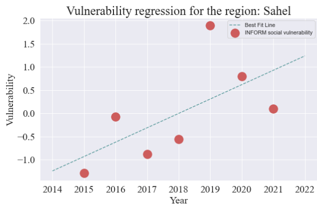
(c) Slope = 0.006, p = 0.98



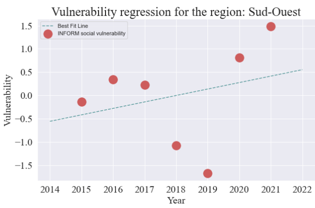
(d) Slope = 0.32, p = 0.12



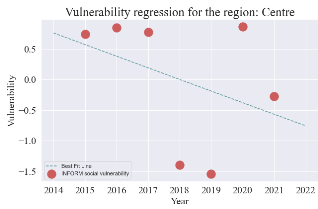
(e) Slope = 0.18, p = 0.43



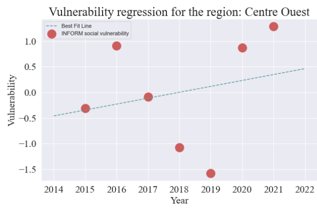
(f) Slope = 0.3, p = 0.137



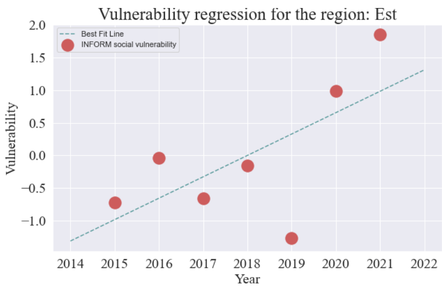
(g) Slope = 0.14, p = 0.55



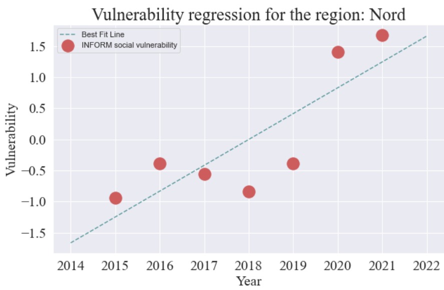
(h) Slope = -0.19, p = 0.40



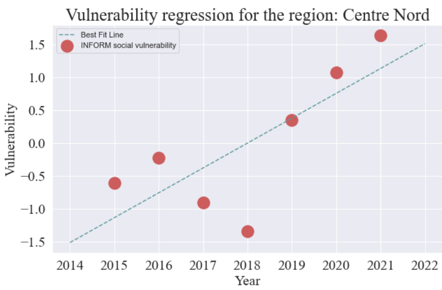
(i) Slope = 0.12, p = 0.62



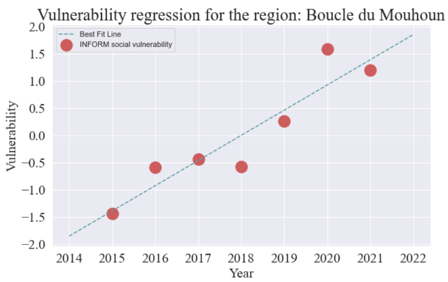
(j) Slope = 0.33, p = 0.111



(k) Slope = 0.42, p = 0.021



(l) Slope = 0.38, p = 0.049



(m) Slope = 0.46, p = 0.003

Figure 7.2: Simple linear regression over time with INFORM

The Centre–Sud and Centre show a decrease or constant behavior of social vulnerability over time. Despite the found regression is not significant, it remains interesting because these areas also score relatively low on the social vulnerability that is presented in section 7.1. This could be linked to the development and humanitarian interventions that have taken place over the years. To verify this, additional research is necessary and could provide interesting results that emphasize the effectiveness of humanitarian aid.

Table 7.3: Regression of social vulnerability INFORM. *The p-value shows the chance that the results are random and the slope is a coincidence. The R-sqaured value shows the percentage of variation in the slope that is explained by the social vulnerability scores. If the p-value < 0.05, the results are significant. However, in order to conclude that the change is inevitable, the slope also needs to be > 0.5 or< -0.5. Non significant results are shown with: Not Significant (N.S.)*

Region	**P-value**	**R-squared**	**Slope**	**Temporal dynamic**
Boucle du Mouhoun	0.003	86.2%	0.46	Increase, with slope < 0.5
Cascades	0.551	7.5%	0.13	N.S.
Centre	0.40	14.3%	-0.19	N.S.
Centre-Est	0.12	41.2%	0.32	N.S.
Centre-Nord	0.049	57.2%	0.38	Increase, with slope < 0.5
Centre-Ouest	0.62	5.3%	0.12	N.S.
Centre-Sud	0.98	0%	0.006	N.S.
Est	0.111	42.8%	0.33	N.S.
Hauts-Bassins	0.34	18.1%	0.21	N.S.
Nord	0.021	69.0%	0.42	Increase, with slope < 0.5
Plateau-Central	0.43	12.7%	0.18	N.S.
Sahel	0.137	38.5%	0.31	N.S.
Sud-Ouest	0.55	7.7%	0.14	N.S.

SQ7: What are the temporal dynamics of social vulnerability?

After verification of the social vulnerability results computed with PCA on a regional level, it became clear that these results are not trustworthy to use for the temporal analysis. Hence, the temporal changes are assessed based on the results from the INFORM analysis. It is important to note, that this social vulnerability index, does not consider the elderly, and past conflict as an indicator. They are important indicators for the social vulnerability specific in Burkina Faso.

In most regions, no significant changes were found over time. Apart from Boucle du Mouhoun, the Centre-Nord and the Nord, where the vulnerability increased from 2015 – 2021 with a slope of respectively, 0.46, 0.38 and 0.42. According to Cutter 2008, this is not an obvious temporal change, however it does reveal a pattern in the development of social vulnerability. In Boucle du Mouhoun, this increase can be derived from the increase in child mortality, and the decrease in health care and water availability. A strong correlation between the social vulnerability and the amount of conflict HDI, GNI, Physicians Density, Cadre Harmonisé, IDPs, GAM and Adult literacy rate was found.

In the Centre-Nord a steady increase in social vulnerability can be seen, apart from the years 2017 and 2018, where an increase in children's health decreased the social vulnerability for two years. The overall increase of social vulnerability is caused by an increase in conflict and presence of IDPs. A strong correlation between the social vulnerability and the amount of conflict, physicians density, Cadre Harmonisé, the amount of IDP's and the adult literacy rate, was found.A negative correlation was found with the immunization rate, the multidimensional poverty index and the government effectiveness.

In the Nord, also a steady increase can be derived from the regression analysis. Apart from the years 2018 and 2019, where a drop in social vulnerability is caused by an increase in water availability. The steady increase is just as for the Centre-Nord, mainly caused by conflict and child malnutrition. A strong correlation between the social vulnerability and the amount of conflict, Cadre Harmonisé, the amount of IDPS, the adult literacy rate was found. Negative correlations were found with the Immunization rate, and government effectiveness and .

Policy recommendations
The temporal analysis is executed on a regional level. Of which the statistical evidence of the temporal analysis is calculated based on the INFORM social vulnerability, that does not incorporate the important indicators for the case specific situation of Burkina Faso; namely conflict and the elderly. For suitable policy recommendations that are applicable for the humanitarian field, it is necessary to obtain insight on a community level. Because the aid is delivered on this specific level.

However, the insight in the composition of the social vulnerability, compared with the statistical results of the temporal dynamics are promising for insight to base humanitarian decisions upon. Hence, it is important that researchers from academic institutions or humanitarian organisation obtain data on a higher resolution.

SQ7: What are the temporal dynamics of social vulnerability?

Policy recommendations
Furthermore, despite the fact that the research did not find many statistically significant temporal patterns in the social vulnerability, figure 15.4 shows that the social vulnerability is highly dynamic over time. This has important implication for the practice and policy making. The chancing dynamics would suggest different decision making each year. In practice, this is not possible because the processes to develop humanitarian aid programs is likely to take longer than one year. Therefore, it would be wise for policy makers to develop programs guided by different scenarios so that decision on social vulnerability can be adjusted to the temporal dynamics of the social vulnerability.

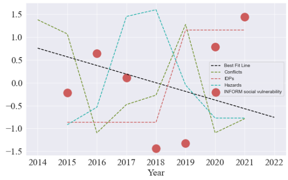
Future research
More research is necessary to understand the relationships between social vulnerability indicator changes over time and the temporal pattern of the social vulnerability. For this high resolution data is necessary to set-up a validated PCA analyses. Furthermore, a hierarchical analysis on regional level could already contribute to the understanding of social vulnerability and its relation to conflict.

The Centre–Sud and Centre show a decrease or constant behavior of social vulnerability over time. Despite the found regression is not significant, it remains interesting because these areas also score relatively low on the social vulnerability that is presented in section 7.1. This could be linked to the development and humanitarian interventions that have taken place over the years. To verify this, additional research is necessary and could provide interesting results that emphasize the effectiveness of humanitarian aid.
Better verification of the PCA analyses will make it possible to execute the same simple linear regression also with results from the PCA social vulnerability score. In this way, the correlation between the principal components and the increase or decrease in social vulnerability can also be assessed. Furthermore, since the results of the PCA are more precise, this will also yield better results in a simple linear regression.

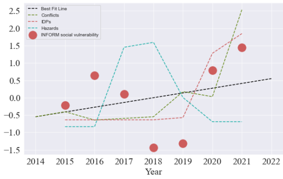
As identified in the previous section, there is a high need for scenario analysis in humanitarian policy making. However, not many research has been executed on this yet. Therefore it is recommended to develop scenario models for humanitarian policy making. These can assess both the uncertainty of the input indicators and as such address a historical analysis. Meanwhile this is also useful the develop a better understanding of future perspectives of humanitarian needs, so that decision making will be supported and decisions can better address the temporal dynamics.

7.3 INTERPLAY

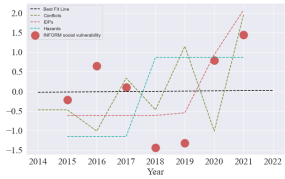
An important aspect of this study is the understanding of the interplay between conflict, IDPs, natural hazards and social vulnerability. In chapter 1 conflict, natural hazards and the location of IDPs are already plotted for all years that we have assessed. This showed an increase in all communities and regions in conflict and IDPs from 2015 – 2021. Sub–question 7 assessed the temporal dynamics of social vulnerability. This showed us that apart from the Centre and Centre–Sud all admin 1 areas showed an increase in social vulnerability over time. However, not all of these increases proved to be significant according to a simple linear regression. To understand the relation between the increase in social vulnerability and the increase in conflict events, IDPs presence and natural hazards, the trend of the four of them are plotted for each admin 1 area (figures: 7.3).



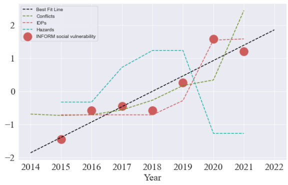
(a) Trends in Centre



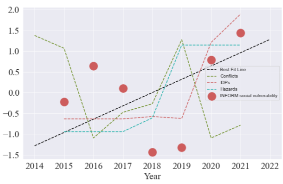
(b) Trends in Cascades



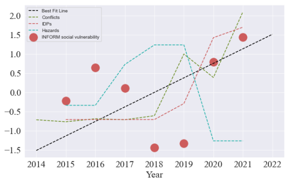
(c) Trends in Centre–Sud



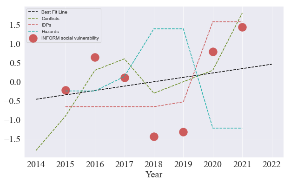
(d) Trends in Boucleau du Mouhoun



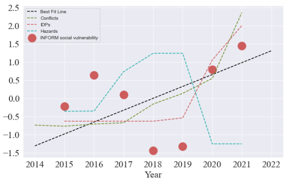
(e) Trends in Centre – Est



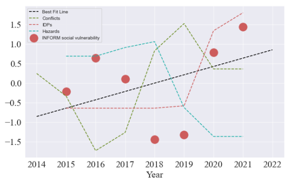
(f) Trends in Centre–Nord



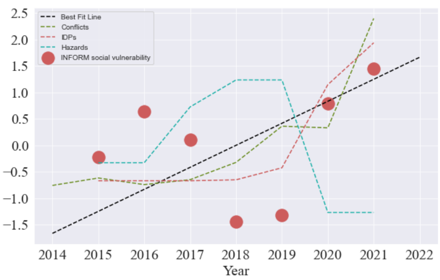
(g) Trends in Centre–Ouest



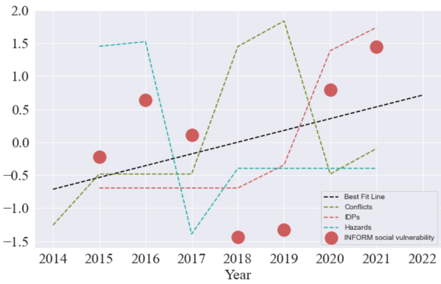
(h) Trends in Est



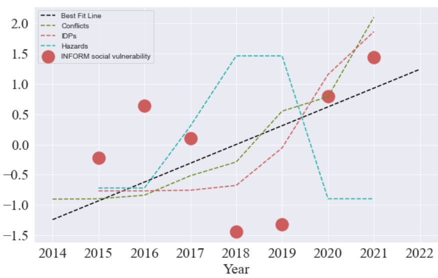
(i) Trends in Hautes Bassin



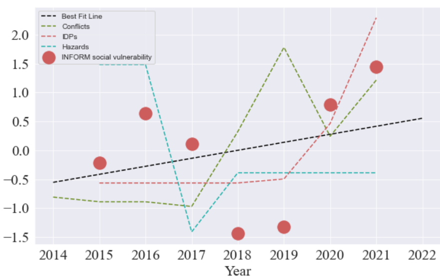
(j) Trends in Nord



(k) Trends in Plateau Central



(l) Trends in Sahel



(m) Trends in Sud–Ouest

Figure 7.3: Interplay between natural hazards, conflict, IDPs and social vulnerability

A visual inspection of these trends suggests no strong correlation between natural hazards and the social vulnerability. If we look at figure 7.4b, 7.4d, 7.4f, 7.4g, 7.4h, 7.4i, 7.4j, 7.4k, 7.4l, 7.4m the best fit line suggest an increase in social vulnerability, while the hazard line moves down over the time. Additionally, 7.4e and 7.4h, 7.4l, 7.4f, 7.4a and 7.4b even show a strong decrease of social vulnerability in 2017 and

2018 in the found INFORM value, while the hazard impact is registered the highest in these months. It is important to note, that this could be due to the fact that hazards are not a continuous process, and therefore the absolute number of affected people that is used, might not be a correct representation of the impact of hazards on the society.

However, a clearer role is denoted for conflict events. In figure 7.4d, 7.4e, 7.4f, 7.4g, 7.4h, 7.4i, 7.4j and 7.4l a clear increase in conflict events moves hand in hand with an increase of the best fit line of social vulnerability. If we compare the measured points of social vulnerability with the trend line of conflict, especially in the Boucleau du Mouhoun and Centre–Ouest similar patterns can be seen.

Lastly, the interplay between IDPs and social vulnerability is assessed. The visual analysis shows 2 important insights. First, the Centre, is the only region where the trend of the IDPs moves contrary to the best fit line. This suggests that the IDPs are increasing in all other admin 1 areas in the same manner as the best fit line. Additionally is can be seen, that the IDPs and conflict counts are strongly related. This emphasizes the suggestion made by Internal Displacement Monitoring Centre (2021) that most IDPs in Burkina Faso were driven by conflict to move.

SQ8: Are links visible between the pattern and the conflicts and natural hazards?

The visual inspection of the trends that are visible when considering the social vulnerability, natural hazards, conflict and IDPs suggests no correlation between natural hazards and social vulnerability. The best fit line often suggests an increase in social vulnerability while hazard decreases over time. It is important to note, that this could be due to the fact that hazards are not a continuous process, and therefore the absolute number of affected people that is used, might not be a correct representation of the impact of hazards on the society.

A clear role is visible for both IDPs and conflicts. Which both show a similar increase over time as does the best fit line of social vulnerability. It can be seen, that the conflict and IDPs are strongly related. This emphasizes the suggestions made by Internal Displacement Monitoring Centre (2021) that most IDPs in Burkina Faso were driven by conflict to move.

Policy recommendations
Based on these outcomes an initial idea of the interplay between conflict, natural hazard, IDPs and social vulnerability is developed. This suggests that the social vulnerability is driven by the presence of conflict and IDPs, and not as much by previous natural hazard events. When the aim of policy interventions is to reduce the social vulnerability of people in Burkina Faso, these results suggest that it is more important to focus on areas with a lot of conflict event compared to areas with many natural hazard events.

It is however important to note, that the risk is shaped by a combination of hazard exposure times (social) vulnerability. Thus, neglecting the hazard locations since this does not increase social vulnerability, does not suggest to neglect the hazard exposure component of the risk equation.

Additionally, this section solely focuses on the interplay between three of the indicators that shape the social vulnerability. And therefore should be merely considered as an explanation of the effect of conflict and natural hazards on social vulnerability and not as the cause for a high social vulnerability. That is because a high social vulnerability score can additionally be explained by other indicators. It would thus not be wise to only focus on conflict reduction to reduce social vulnerability, since this decision would neglect the composition of social vulnerability as presented in section 6.1.1.

Future research
The interplay between social vulnerability, conflict, natural hazards and IDPs is interesting to further understand. The contribution of these indicators seem important, and largely shape the discussion around humanitarian aid. To guide these discussion additional research is necessary. So far, only visual analysis were executed to understand the relation between the four over time. Insights from statistical approaches such as simple and multiple linear regression analysis, with improved sample sizes will improve the insights that are developed which can guide the humanitarian decision making.

8 SENSITIVITY IN PCA

In recent studies it is shown that there exists divergence among experts on indicator weightings, and the differences in results from different index construction approaches (Bucherie et al. 2022; Tate 2012). This might question the use of vulnerability indexes for decision-making without undertaking validation and sensitivity analysis. However, only 11% of social vulnerability construction articles have executed this part of the research (Moreira et al. 2021b). Over time the SoVI approach developed by Cutter et al. (2003), that was used for his research, has developed into an algorithm for quantifying social vulnerability rather than a simple index. In this research, the algorithm has been expanded with the impact of previous conflict, and was adjusted to the Burkina Faso case study. The method has illustrated its value, however not many sensitivity analyses were executed apart from the research developed by Schmidtlein et al. (2008). This chapter assesses the sensitivity of the index that is constructed in this research based on the method for sensitivity analysis developed by Schimdtlein et al. 2008. The chapter focuses on the construction of the social vulnerability for a community analysis, since the PCA method for regional analysis has shown uncertainty. The chapter is structured as follows: section 8.1 shows an overview of the pca algorithm, section 8.2 discussess the sensitivity of the indicator input. Lastly section 8.3 discusses the sensitivity of the methodological decisions that are made.

> The following Sub Questions are answered in this chapter:
>
> SQ9: What methodological decisions cause sensitivity in the results??

8.1 OVERVIEW PCA ALGORITHM

To develop the social vulnerability score for Burkina Faso, the SoVI method developed by Cutter 2003 was used. However this method was extended with the imputation of conflict related indicators. Our method consists of 10 sequential steps where both objective and subjective decisions are made to derive the social vulnerability score. The steps that are undertaken are presented below:

1. Select data for the indicators that shape the social vulnerability
2. Standardize all input variables to z-scores.
3. Verify the use of PCA for the indicator set.
4. Create a correlation matrix and assess the collinearity.
5. Eliminate redundant data
6. Perform the PCA with the standardized input values.
7. Select the number of components to be further used.
8. Rotate the initial PCA solution, when this is desired.

9. Interpret the resulting components on how they might influence vulnerability. Based on this, signs are assigned to the components. The output of the loadings is the determining factor for assigning the sign. The indicator with the highest loading in the component determines the sign. If this indicator is positively correlated with the social vulnerability, a positive sign will be assigned and vice versa.

10. The component scores are combined into a univariate score based on the predetermined weighting scheme

This sensitivity analysis focuses on the four sections of the algorithm that are subjective to sensitivity: (i) the selection of the indicator data, (ii) the number of components selected, (iii) the type of rotation that is used and (iv) the weighting scheme that was applied. The four of them are derived into two groups, of which the first contains the indicator selection and largely focuses on the uncertainty that is present in the selected data sets. The second group contains the other aspects of sensitivity, and focuses on the sensitivity that is caused by the decision made in the construction of the algorithm, which is referred to as *methodological decisions*.

8.2 SENSITIVITY IN INDICATOR SELECTION

It is a common understanding in the modelling field that incorrect or poor quality input will always produce faulty output. It is thus important to consider the variability that is created by the indicator's data that are poorly dis-aggregated or of bad quality. For this all input data should be assessed. Nevertheless, it quickly becomes clear that an extensive local and global sensitivity analysis is necessary to analyse the outcomes, since many of the data found are prone to high levels of uncertainty. In this research, no time was available to set-up an extensive sensitivity analysis on the input data.

Currently the code is set-up as hard code, and not as a function. Hence, it is recommended to restructure the code that is developed into a code that can be called with the use of one function. In this way, sensitivity can be assessed with existing tools such as SALib, Monte Carlo or the EMA-Workbench. SALib is a python package that introduces commonly used methods to develop a global sensitivity analysis. It is a useful simulation package to evaluate the influence of model inputs or exogenous factors on the output. This can be executed with the SALib algorithm (Iwanaga et al. 2022). Furthermore, the Monte-Carlo techniques can also be used to assess the global sensitivity of the model. Monte-Carlo provides probabilistic results, hence shows what can happen and the likelihood of each outcome. In Monte-Carlo, it is easy to see which inputs significantly affect the overall results. Lastly, the EMA-Workbench entails different sensitivity and uncertainty methods such as SALib and Monte-Carlo that are based on the assessment of an abundance of scenarios to reveal the impact of possible future scenarios on the outcome of the model. Applying this method will provide insight into social vulnerability scenario's. Hence it provides insight and tools for policy-makers to take the uncertainty of the indicator selection to a higher level and create insight into it to develop policies for disaster risk reduction (Kwakkel 2017).

8.3 SENSITIVITY IN THE INDEX CONSTRUCTION

Secondly, the sensitivity of the methodological decisions during the set-up of the algorithm are assessed. Three aspects are analysed in this section. Namely, the selection criterion that is used to determine the amount of components that is considered. Second, the method used for the rotation of the matrix, and lastly the weighting scheme that is applied when calculating the final social vulnerability score.

8.3.1 Sensitivity in the selection of number of components

The selection of the number of components is one of the methodological decisions that are made during the construction of the index. In this research, the percentage of explained variance is used to determine the amount of indicators. As many components as needed to obtain 90% of the variance are retained. However, the Kaiser criterion (Kaiser 1960) is also a commonly used method. This method includes all components who's eigenvalues are larger than 1, which are usually less components than necessary to obtain 90% variance. Furthermore, Horn's parallel analysis can be used. Which is similar to the Kaiser criterion, but it does not use a fixed eigenvalue threshold and requires the eigenvalue to be greater than the expected eigenvalue of the component. However, this requires high computation times, which is not possible in this time of the research, and is therefore excluded. Lastly, expert opinion can be used to choose the number of components that is considered. This approach subjectively identifies a set of components that is meaningful for the case. Since no experts were available to execute this selection, this option is removed from the sensitivity analysis.

8.3.2 Sensitivity in the type of PCA rotation

Furthermore, the type of PCA rotation is topic of debate in constructing the social vulnerability index. In this sensitivity analysis two commonly used PCA rotation methods are considered. The one applied in this research, which is a Varimax rotation that loads each indicator highly in one component. This leads to an easier interpretation of the components. Second, the unrotated solution is considered, this explains the components with the greatest percentage of the original variation best. More rotation methods are possible, but are not considered in this research since these two are the most commonly used methods when using PCA for the construction of social vulnerability indexes (Nardo, Saisana M., Saltelli A., and Tarantola S 2008).

8.3.3 Sensitivity in the weighting of components

The last step of the construction of an index considers the weighting of the obtained components. In this research, an equal weighting was applied that sums the component scores. It assumes that each PC absorbs one of the aspects of social vulnerability and is thus equally important. There is also a mathematical approach that considers only the component with the highest variance in the original data. Mathematically speaking, this component will provide the optimal value to summarize all input indicators. Lastly, one could consider the weighted sum, based on the explained variance. This is a compromise of the first two methods. Based on the mathematical importance, each component is summed.

8.3.4 Results

The three way ANOVA analysis was set-up to assess the null hypothesis: "all combinations of method set-ups yield to comparable results in the z-score of social-vulnerability." The alternative hypothesis that is tested is "Some combinations of method set-ups do not yield to comparable results in the z-score of social vulnerability". An alpha value of 0.05 is used to be not too lenient, nor to strict. If the obtained p-value is $<$ the alpha value the null hypothesis can be rejected, if the p-value is $>$ the alpha value, the null hypothesis can not be rejected. The results are presented in table 8.1.

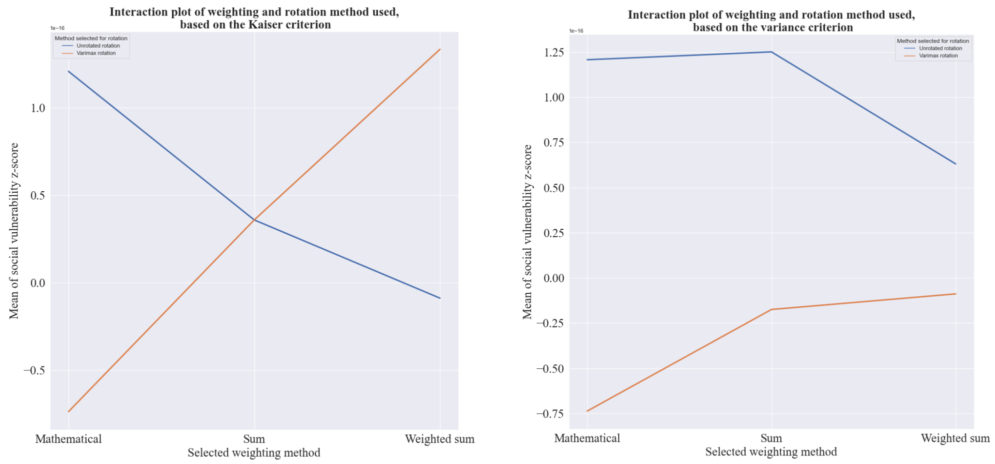
In the analysis, a partial ("Type III") sum of squares is employed to assess the importance of each subjective option. The associated p-values were treated as measures of the that influence each subjective option has on the final social vulnerability z-score. Based on the proposed null hypothesis, small p-values suggest that changes in the choice of that subjective option have a large impact on the final social vulnerability z-score, whereas large p-values suggest that choices within that subjective option do not substantially impact the final value.

Table 8.1: Results of three-way ANOVA test. *All p-values < 0.001 are presented as < 0.001*

	Squared Sum	**df**	**F**	**PR(> F)**
Intercept	128.65	1	489.06	< 0.001
Selection of components	0.51	1.0	1.95	0.161
Weighting scheme	23.24	2.0	44.16	< 0.001
Rotation method	1.59	1.0	6.03	0.0141
Components * Weighting	21.51	2.0	40.88	< 0.001
Components * Rotation	1.78	1.0	6.78	0.0092
Weighting * Rotation	11.02	2.0	20.94	< 0.001
Components * Weighting * Rotation	11.03	2.0	20.96	< 0.001
Residual	1010.43	3841	0	0

The results show, that the selection of components method does not have a significant impact on the social vulnerability score (p-value = 0.16). This is contrary to the weighting scheme and the rotation method, which do both have a significant impact on the results (table: 8.1). Thus, meaning that the method used for the selection of components does not have an influence on the outcome when it is considered independently. However, the p-values in the last four rows of table 8.1 indicate that there is also interaction between all three methodological decision. Figure 8.1 and table 8.2 visualize what interaction presents. Figure 8.1a shows the different mean values of social vulnerability for all possible combination of methodological decisions, while keeping the selection of number of components on the Kaiser criterion. Figure 8.1b shows the different mean values of social vulnerability for all possible combination of methodological decisions, while keeping the selection of number of components on the 90% of explained variance criterion. The different lines, show that the influence of the weighting scheme, depends on the rotation method that is considered. Since the graphs are different in Figure 8.1a and 8.1b, it can be concluded that the social-vulnerability is also affected by the interaction between all three methodological decisions and thus also by the selection criterion for the number of components.

It can thus be concluded that when considering the methodological decisions separately the selection of components does not have a significant impact on the results. However, when the interaction between the methodological decisions is considered, there is a significant difference in outcomes. The interaction of the three has a sta-



(a) Interaction between weighting method and rotation when using Kaiser.

(b) Interaction between weighting method and rotation when using explained variance.

Figure 8.1: Interaction between the weighting scheme that is selected and the rotation method that is used. Plotted both for the component selection based on Kaiser criterion and 90% explained variance.

	Kaiser Criterion				90% Explained Variance			
	Math.	Sum	Weight Sum	Mean	Math.	Sum	Weight Sum	Mean
Varimax	$-7.36e^{5}$	3.58	$1.33e^{-1}$	3.18	−7.37	−1.74	$-8.86e^{1}$	−3.33
Unrotated	$1.21e^{-1}$	3.58	$-8.85e^{1}$	4.92	$1.21e^{-1}$	$1.25e^{-1}$	6.31	$1.03e^{-1}$
Mean	2.35	3.58	6.23		2.35	5.38	2.71	

Table 8.2: Mean values of social-vulnerability to visualize the interaction between the variables. All values must be multiplied with $e^{-}17$.

tistically significant impact on the social-vulnerability score F(2, 20.96) = $8.83e^{-10}$.

This proves that when considering the statistics of the social vulnerability construction, it's values are sensitive for the methodological decisions that are made. This analysis is a quantitative approach. However, it has been stated before, that the constructed value does not have any quantitative meaning. It is therefore important to understand what the qualitative impact of the different methodological decisions is.

To do so, the ranking of the communities with the different methods is considered. When all outcomes are significantly lower for the combination with 90% explained variance, the varimax rotation and the sum weighting scheme, this does not have to be a problem. Because the values of social vulnerability have a relative meaning towards each other. Hence, it is important, what mathematical consequences occur within the construction process when making other methodological decisions in the set-up. Therefore, the change in ranking of each commune is considered. For this, the ranking of each community was determined under all methodological decisions. Based on these values, the standard deviation of the ranking of each community is determined.

Figure 8.2 shows that the differences are big, which implies that different disaster risk reduction strategies will be applied when different methodological decisions are made. Implying that the choice of methods matters in the final outputs and

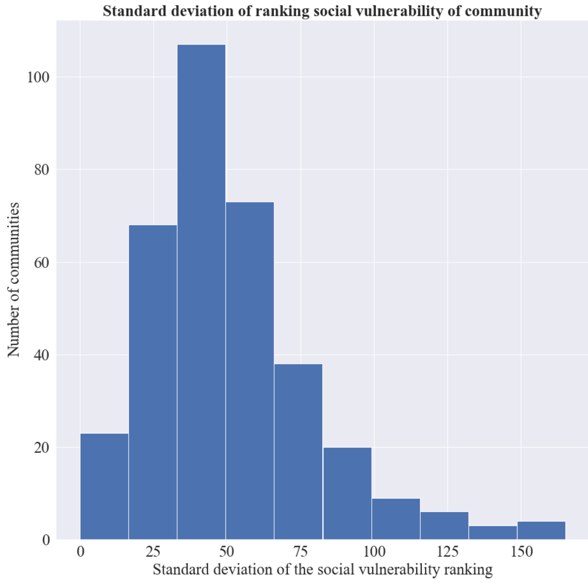


Figure 8.2: Histogram of the standard deviation of the ranking of each commune under different methodological decisions

can considerably influence local disaster management decisions. This emphasizes the need, to thoroughly understand the qualitative impact of the methodological decision that are made.

SQ7:For which methodological decisions is the social vulnerability index sensitive?

The sensitivity analysis is split in two sections. First the input values of the model should be assessed. For this a global sensitivity analysis is needed to assess all uncertainties in the input. Since the code currently does not have the right structure to execute global sensitivity tests, this section is not assessed and recommendations are made for further research. A global sensitivity analysis will lead to insight into the indicator's sensitivity and which ones should be improved.

Secondly, the sensitivity caused by methodological decisions that are made in the construction of the PCA algorithm were assessed. With the use of a tree-way ANOVA, it is found that there is interaction between the different variables of the ANOVA assessment. This shows that the results of the social vulnerability score are highly dependent on the methodological decisions that are made during the construction of the algorithm. Hence, the sensitivity of the results for different combinations of PCA composition is high. Since social vulnerability is considered relative towards social vulnerability scores of other communities, the change in ranking of the communities is important. It is shown that different methodological decisions, lead to different rankings in social vulnerability, the standard deviation of these ranking is high. Implying that the choice of methods matters in the final outputs and can considerably influence local disaster management decisions.

Policy recommendations

To better understand the meaning of the input indicators in models used for decision making in the humanitarian field, it is recommended to set-up extensive Decision Making under Deep Uncertainty (DMDU) models (Kwakkel 2017). With doing so, the uncertainty in the input of historical models can be assessed. Additionally, predictive decisions can be made based on a more robust analysis on what the future will look like.

Additionally, it is recommend that policy makers thoroughly discuss with each other how to understand social vulnerability and what type of number they need to base decisions for disaster management on. This is important since currently all available methods derive different results. Therefore a better semantic definition of social vulnerability will guide which method best presents the social vulnerability and can thus be used as a guidance.

The outcome is deliberately referred to as *a guidance*, since it is important to note that no calculation of social vulnerability will present a ground truth number of the concept. It remains a composite indicator that represent interaction between indicators, but is not interpretative as an absolute value in it self.

SQ9: What methodological decisions cause sensitivity in the results?

Future research
To make SVi better applicable to decision making, the sensitivity of the model should be properly understood. Until today, most articles that develop these indexes do not provide solid sensitivity processes. In future research, these steps are very important, and could be executed with SALib or Monte-Carlo analysis. With doing so insight will be derived into the influence of uncertainty in the indicator selection. The next step, entails incorporating this uncertainty into the decision-making. For this methods present in the EMA-Workbench can be used. This will not only contribute to understanding historic social vulnerability, but will also develop scenario's for future social vulnerability, that can be used to better develop disaster risk reduction strategies. Doing so acknowledges the dynamic facets of the social vulnerability profile that are highlighted in chapter 7.

The sensitivity analysis clearly showed that the results are dependent on the decisions that are made during the building of the algorithm. This is a quantitative identification of the result. To understand the relevance of the found sensitivity, better understanding should be developed of the semantic meaning of the methodological decisions that are made for the qualitative representation of social vulnerability.

It would have been insightful, to also assess the sensitivity with global SA methods, that compare the results obtained in the current analysis with results that use different indicator values. This was previously done by Nazeer and Bork (2019); Rogelis et al. (2016). This would have assessed the uncertainty of the data selection process. Furthermore, in this section, special attention could have been given to the sensitivity for indicators that are related to the conflict and migration structures that are visible in BFA. This will contribute to a better understanding of the role of conflict and migration in social vulnerability. However these are recommendations for future research due to time constraints.

9 METHODOLOGICAL CONSIDERATION

Previous social vulnerability studies and risk assessments executed by the NLRC have always been executed with the use of a hierarchical structural design. In this thesis the usefulness of an inductive structural design for social vulnerability studies in the humanitarian field was assessed. Even though the method works, it is useful to balance the pros and cons of both methods before concluding which method is most suitable. The PCA approach is part of statistically based inductive methods, whereas the hierarchical processes, also called AHP is part of participatory or expert-based methods. In this chapter first the differences in social vulnerability scores for each commune in Burkina Faso will be assessed by using both an AHP and a PCA approach (section 9.1. Thereafter, (mathematical) benefits and drawbacks of both methods are discussed (section 9.2.

The following Sub Questions are answered in this chapter:

SQ10: What is the difference in results with inductive and hierarchical approaches?
SQ11: What method is more suitable for determination of social vulnerability?

9.1 DIFFERENCES IN SOCIAL VULNERABILITY FOR BURKINA FASO

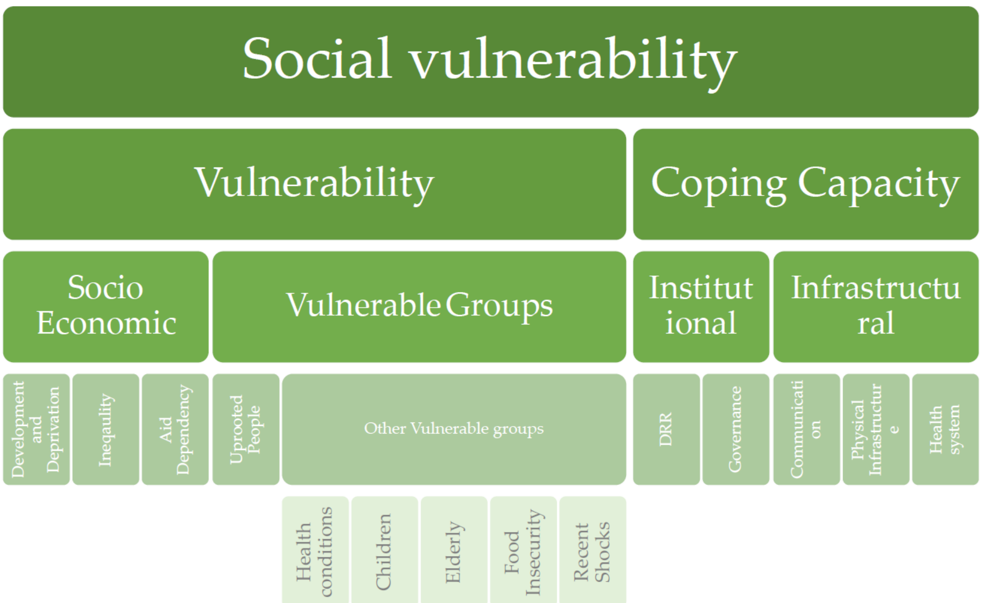
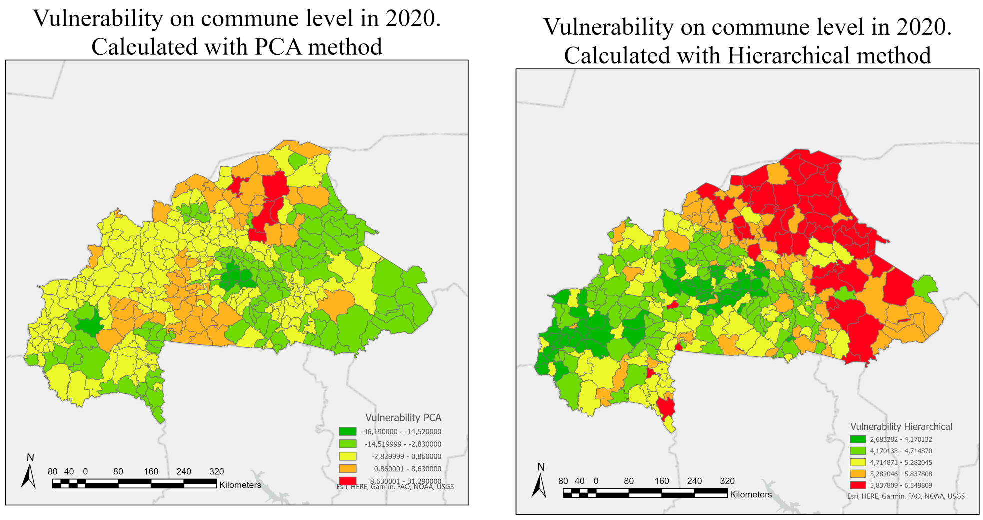


Figure 9.1: The structure of the hierarchical lay-out. Each level's components are weighted equally and form input for the higher level.

Results of an hierarchical analysis are available on the Sub-National scale for 2015 – 2021 for Mali, Niger and Burkina Faso. However, to compare the effectiveness of PCA and AHP an hierarchical method is also developed at the community level. The hierarchical structure is visualized in figure 9.1. Calculation of the social vulnerability starts at the lowest level, where each component in that level obtains the same weight and the value for that level is determined. For example, the value for *Other vulnerable groups* is the average of *health conditions, children, elderly, food insecurity and recent shocks*. The final equation that is used to calculate the social vulnerability is equation 14.1.

9.1.1 Results

The social vulnerability that is obtained with this method is plotted in figure 9.2 together with the social vulnerability obtained with the PCA method. There are several points standing out from these results. First considering the scale of the results. The results from the PCA method differ from -14 – 32, whereas the results from the AHP method vary from 3 - 7. Furthermore, with the AHP method it can be seen that the spread of the results is wider and more communities have a social vulnerability score that is $>$ 2.5 times the standard deviation of the results. This is visualized in figure 9.3. When considering the mean squared error between the two methods, an error of 54.77 is found..



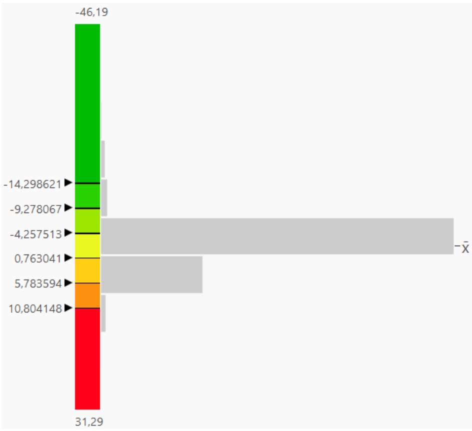
(a) Social vulnerability calculated with PCA method

(b) Social vulnerability calculated with hierarchical method

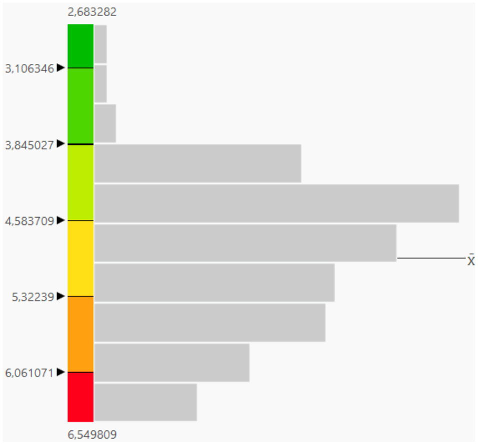
Figure 9.2: Results PCA and Hierarchical approach

It stands out, that the differences in the results with both methods are large. However, when applying the method for decision making, often the most vulnerable communities will receive aid. It was already mentioned before that the value of social vulnerability it self does not have a qualitative meaning. And thus it is important, that when comparing the results between analyses methods, we are aware of how policy makers treat the results. Therefore, the differences in ranking of the communities is compared.

The top 10 most vulnerable communities identified with each method is shown in table 9.4. The top 10 shows completely different communities to focus aid on. Thus, it is decided to zoom more into detail with a mathematical approach. The difference between the ranking of method 1 and method 2 is calculated, and plotted in figure 9.4c. This histogram, shows that 40 communities differ between 0 - 15 position in the ranking, 18 differ between 15 and 30, and so on. From this figure it can be derived that at least 50 % of the communities differ more than 50 position in the ranking. Hence, there is a big difference in results between the PCA or AHP approach. Which method to chose is a qualitative decision, that should be based on the system that one is willing to present, but also on the semantic meaning of the approach. The first will be discussed in the section below. The latter requires more qualitative research and debates between social vulnerability practitioners and researchers and requires an answer to the question: "What does a social vulnerability index represent and for what is it used?".



(a) Distribution of social vulnerability calculated with PCA



(b) Distribution of social vulnerability calculated with INFORM

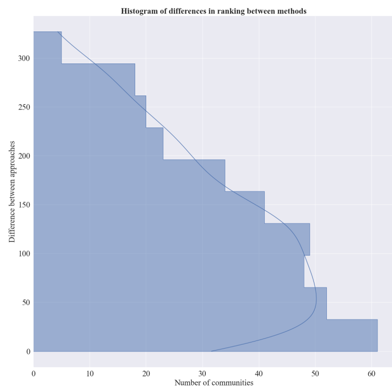
Figure 9.3: Distribution of social vulnerability scores based on the standard deviation.

Tougouri
Gorgadji
Sebba
Gayéri
Déou
Oursi
Gorom-Gorom
Pama
Markoye
Tin-Akoff

(a) Top 10 most vulnerable with AHP approach

Djibo
Pensa
Barsalogho
Arbina
Kaya
Fada - Ngourma
Tongomayel
Pissila
Bourzanga
Titao

(b) Top 10 most vulnerable with PCA approach



(c) Histogram that captures the differences in ranking

Figure 9.4: Differences between AHP and PCA

SQ10: What is the difference in results with inductive and hierarchical approaches?

The derive an answer on this question, the results from a PCA approach which is inductive and the INFORM method which is hierarchical are compared. It showed important differences that can not be neglected. Initial results showed large differences in social vulnerability in absolute number. Furthermore, the distribution of the scores has a higher standard deviation when applying the PCA method. The top 10 most vulnerable communes are completely different when using PCA or INFORM, and this can be extend to the overall results, since a completely different ranking of the communes is obtained with both methods.

Policy recommendations
It is difficult to develop disaster risk reduction strategies if two methods are contradicting each other. It is thus recommended not to develop policy measures based on solely the quantitative analysis. I valuable next step would be to assess the social vulnerability in a qualitative matter through the means of field work, both in the communes that score high on social vulnerability in the PCA approach as well as in the INFORM approach. This can also provide insights for the semantic discussion that is needed to understand which method will be more suitable.

9.2 DRAWBACKS AND BENEFITS OF BOTH METHODS

The two distinct methods are both, often used for the construction of social vulnerability indexes. Table 9.1 presents the benefits and drawbacks of all methods as presented by Gan et al. (2017). Based on these insights and the four specific challenges that were encountered for the development of an index for Burkina Faso this chapter provides a trade-off between both methods when applied in geographical locations that are (partly) depending on humanitarian aid.

9.2.1 Insight in dynamic behavior

Over the last years, the UNDRR has been calling for a better understanding of the dynamic behavior of (social) vulnerability. To do so, it is necessary to develop insight into social vulnerability scores over time, over space (e.g. the external dynamics) and into the composition of social vulnerability, which I will call internal dynamics. Comparing the results over times to understand the dynamic behaviour, implies that it is less important to obtain an accurate result that is in line with reality, and more important to obtain precise results that show results that are well comparable over time (see figure 2.4). Thus, to understand the changes over time, a model is needed that approaches the vulnerability in a precise matter. For this Tate (2012) showed the added value of an inductive approach. Tate (2012) argues that inductive methods are more precise, and less accurate in comparison to the hierarchical approaches. However, considering the goal of understanding dynamic behaviour a more precise method is preferable.

Helpful, but challenging aspects of the PCA approach, when considering the external dynamic behaviour of social vulnerability over time, is that the dimensions and weights may differ from year to year. It can be the case, that with the data set from one year 8 components are needed to explain 90% of variance, whereas one year later these are only 7 components. At first sight, this seems to suggest that scores can become much higher or lower over the years. However, normalization will

Method name	**Method Type**	**Formulas**	**Benefits**	**Drawbacks**
Equal weigh-ting	Hierar chical	$\omega_i = \omega$ i = 1, ...m Where ω_i is the weight of thei^{th} indicator and ω a constant that is used as the weights for all indicators.	Simple, replic able, and straightforward	No insights into relationships between indicators, risk of double counting.
AHP	Hierar chical	$A\omega = \lambda\omega$ Where A is the comparison matrix, $\lambda$the largest eigenvalue of A, and ω the weight vector as well as the eigenvector corresponding to λ.	Has a hierar chical structure that is in line with the structure of vulnerability frameworks. Simple and Flexible	Requirement of a high number of pairwise comparisons. Inconsistency and cognitive stress may exist if there are too many indicators in each cluster.
PCA	Inductive	$\omega_i = r_j(l_{ij}^2/E_j)$ $i = 1, ...m$ Where r_j is the proportion of explained variance by component j, l_{ij} is the component loading of the i^{th} indicator on component j, and E_j the variance explained by j.	Reduces the risk of double counting, classifies ungrouped indicators.	Dimensions of vulnerability are unpredictable, and weights may differ from reality.

Table 9.1: Benefits and Drawbacks of construction methods. *Source:* Gan et al. (2017)

counter this challenge. The interpretation of the components remains complicated. Since different indicators might have the highest loading in a principal component when comparing years with one an other. This emphasizes the need to thoroughly understand these statistical relations which will provide more insight in the development of the contribution of each indicator to social vulnerability over time.

Furthermore, understanding the dynamics requires understanding the internal dynamics of social vulnerability. In both hierarchical approaches, the composition of social vulnerability is determined by equal weighting or by expert judgement. Expert judgements are often considered to be a weak deductive argument, which should only be used for indicator selection (Bucherie et al. 2022). Using this approach for weighting, and thereafter considering the contribution of each indicator to the social vulnerability, is a way of biased self confirmation. The weight determined by the subjective insight of experts determines the composition of the social vulnerability. With this method, it is thus not possible to evaluate the composition of the constructed index, since it is something created by the modeller. This is a disadvantage compared to PCA, that obtains a more objective approach in the weighting of indicators, and is thus more suitable to compare the composition of the social vulnerability index over time.

PCA aims at understanding the data relationships. It assumes that all indicators that shape social vulnerability are equally valued as part of social vulnerability. The statistical approach determines the contribution of each variable based on the variance it explains. This provides better insights into the composition of the social vulnerability index since it explains the data relationship, and generates the social vulnerability index of what is qualitatively expected to represent social vulnerability (Bucherie et al. 2022). Hence, a PCA approach is more suitable to understand the internal dynamics of social vulnerability.

9.2.2 Data Availability

A key difference between PCA and hierarchical methods is the amount of data that is necessary to set-up the computation. PCA is a statistical method to derive social vulnerability. Hence, many data points are necessary to obtain statistical significant results. In the case of Burkina Faso, chapter 5 showed, that data availability creates an enormous challenge in executing social vulnerability research. Furthermore, chapter 7 showed that it is not possible to obtain statistically significant results for a regional analysis in Burkina Faso, since only 13 measurement points were considered, it can not be excluded that the variance is created by common variance.

The poor data resolution in areas that are largely dependent on humanitarian aid, might be an explanation why the use of PCA for social vulnerability index construction hardly occurs in these regions. As a consequence of the low data resolution, the analyses that are executed, are analyses executed at sub-national level with hierarchical methods. This results in a lack of insight in where to deliver humanitarian aid, because sub-national levels are not adequate levels to base local decision making on. Secondly, it keeps researchers away from the possibility to assess the internal dynamics of the social vulnerability, since this is better visible in inductive PCA approaches.

The PCA method is thus limited by the data availability. An AHP approach can be applied on lower granularity of data. However, this might not lead to the insights that are required to develop robust information for decision–making.

9.2.3 Validation

While there are no completely good or bad methods to generate composite vulnerability indices (Tate 2012; Bucherie et al. 2022; Gan et al. 2017; Chakraborty et al. 2005), the results show that the choice of methods matters in the final outputs and can considerably influence local disaster management decisions. The simple and straightforward aspect of AHP methods, has caused controversies that focus on the validity and transparency of indexes (Gan et al. 2017). Since there is no insight into the relationships of the indicators, a high risk of double counting is created. The lack of sensitivity and validation research in the field of social vulnerability index construction contributes to the lack of transparency and insight in the construction of the index. The need to thoroughly understand the sensitivity of both methods is emphasized in this study but requires further research.

9.2.4 Feasibility

The feasibility of the research is important to ensure research can be executed, replicated, and understood by it's users. de Brito and Evers (2016) attribute the preference for AHP in many studies towards the fact that it is a straightforward and flexible method. AHP is a method that requires the involvement of practitioners and experts. This participation is believed to be a key component to foster effective disaster risk reduction strategies with the use of these models (Fekete et al. 2021).

The risk of PCA methods, is that they can quickly become a *blackbox*. Due to the high dimension of the statistical approach, understanding what happens within the reduction and rotation process can become challenging. This might lead to results that are only used but not entirely understood by the field, and as stated by Oulahen et al. it is thus more likely that end-users will not trust its results.

SQ8: What method is more suitable for determination of social vulnerability hierarchical or PCA?

There is no completely good or bad method for the generation of composite vulnerability indicators. This chapter shows that both methods have benefits and drawbacks, and that the differences in the results are big. However, the call for the understanding of the dynamic behavior of social vulnerability is large. For this, PCA provides better insight in the composition of vulnerability, the change in composition of the social vulnerability and in how the variance of the social vulnerability changes over time. Furthermore, the social vulnerability calculated with PCA provides more precise results to compare with different measurement moments with each other. However, executing the PCA is a challenging assignment due to high data resolution requirement in contrast to the low data resolution availability in areas that are in need of humanitarian aid. It is thus necessary to develop better data gathering and sharing mechanisms. So that, disaster risk reduction strategies can be improved.

Policy recommendations
The use of PCA proves promising for the understanding of the dynamic behaviour of social vulnerability. Despite the effort it will take to entirely understand the statistical behavior of the separate steps in the construction of the index, and the qualitative research that has to be applied to find out which methodological decisions lead to an index that describes the vulnerability best, PCA will deliver the best understanding of social vulnerability dynamics. This is of great importance to improve disaster risk reduction strategies. Based on this research, it is recommended for humanitarian policy makers to invest in data gathering mechanisms, so that PCA can be applied in all areas that are (partly) dependent on humanitarian aid.

Future research
The lack of sensitivity and validity research in the field of social vulnerability index construction contributes to the minimal of transparency and insight in the construction of the index. This research shows clear differentiation between a PCA and an AHP approach. It is important to understand what the approach represents, and thus which approach complements the quantitative needs of the humanitarian field best. For this I recommend the development of qualitative research on the meaning of social vulnerability with both approaches and debates between researches and practitioners to develop a common understanding. When developing this understanding, it might be needed to differentiate SVi per sector. E.g. for health interventions different **svi!** (svi!) might be required then for a livelihood intervention.

Part C

Discussion
Conclusion
Future Work

10 DISCUSSION

The primary contribution of this study lies in the identification of the social vulnerability profile for the communes in Burkina Faso in 2020. Furthermore, the analysis of the temporal dynamics of social vulnerability on admin 1 level, showed the influence of conflict, natural hazards and IDPs on social vulnerability. The interplay between conflict and IDPs and social vulnerability was demonstrated by combining this understanding with the internal dynamics of social vulnerability that were made visible by the use of PCA in the spatial analysis; however, no direct correlation was discovered with natural hazards. Additionally, the application of principal component analysis for social vulnerability index creation in the humanitarian field delivered insight into the usefullness of PCA in comparison to the more traditional INFORM models. This shows that PCA provides a deeper understanding in the dynamics of social vulnerability over time, and in the internal dynamics of social vulnerability that reveals which indicators contribute most.

Based on this technique, this thesis provides a scientific insight for understanding the Burkinabé social and demographic conditions that make some geographic communes more vulnerable than others. The results of this study are useful for planners and policymakers, and could be used to inform risk-based hazard management strategies and improve disaster resilience for the areas that are very vulnerable. Furthermore, this research can be understood as an encouragement to further develop the understanding of social vulnerability indexes that are developed with the use of PCA. PCA will provide more insight in the composition of the social vulnerability, and makes it possible to compare the internal dynamics of social vulnerability of time. For which an urgent need exists in the humanitarian sector.

Nevertheless, it must be acknowledged that several data, and methodological limitations are present in this research. These are structured in five categories: firs, a discusiion on the value of the methos is presented in section 10.1, second, the limitations in the indicator selection (section 10.2), third the limitations in the spatial analysis (section 10.3), fourth limitation in the temporal analysis (section 10.4, and lastly limitation in the sensitivity analysis (section 10.5).

10.1 THE VALUE OF THE METHOD

When calculating social vulnerability using several methodologies, this study revealed differing results. This is the most important outcome of this study. It shows that even tough a social vulnerability index does never represent a ground truth of social vulnerability it is important to thoroughly consider which method to use. That is because decision on disaster risk management are made based on the ranking of social vulnerability indices. The study showed these rankings are very different when using different methods. At this moment, literature does not show a firm consensus methodology about the methods to be used. There is a high need to search for this consensus between both humanitarian aid workers and analysts who calculate the indices.

This can be organised through the means of expert meetings. Humanitarian aid workers must explain why and how they use the indices, e.g. what they think it represents and what it is required to represent to be useful in the field. Subsequently, such a semantic discussion will provide argumentation for analysts that will guide the methodological decisions that are made. Having this discussion will deliver an outcome that is better applicable for policy makers and guarantees the right method is chosen. With doing so, the uncertainty created by the methodological decisions can be reduced.

10.2 LIMITATIONS IN INDICATOR SELECTION

Several points of discussion came forward during the selection of indicators. First, for the selection of context-specific variables, there is no firm consensus on which methodology to use. Often, indicator selection is a random process based on the indicators included in other published papers, and indicators that are easily available. Additional steps would include a thorough verification with local experts, who are aware of the factors that contribute to social vulnerability in that area. Admittedly, this will lead to indicators explaining social vulnerability in one geographical region, that may not be transferable to other regions (Chakraborty et al. 2005).

Furthermore, for both the spatial as well as the temporal analysis, problems with data availability and coverage were encountered during the indicator selection process. Many indicators had to be removed for the simple reason that the data are only available on a country level (spatial analysis), or were not available for enough years (temporal analysis). This is a big limitation of this research, since the obtained social vulnerability score does not present the entire concept of social vulnerability but solely a part of it. In consequence, the data inclusion decision-tree as presented in chapter 5 was developed.

10.3 LIMITATIONS IN SPATIAL ANALYSIS

Spatial considerations are key for social vulnerability assessments. It is recognized that, as the concept of non-stationarity shows, what makes people vulnerable differs spatially. Therefore, composite social vulnerability indices could be generated at different spatial units, leading for instance to different indicator contributions and outputs for each sub-region. Furthermore, what spatial unit to consider for the social vulnerability assessment matters. In this research, it was decided to analyse the social vulnerability at a commune level, because this is the level of scale on which the BFRC makes policy decisions. Nonetheless, it is important to acknowledge that the values considered for the communes represent average values and do not capture the heterogeneity of social vulnerability that is present within the communes in reality.

In this analysis, higher level data from regional and country scales were dis-aggregated to community level. Within this disaggregation assumptions were made that can be challenged. Several times, the average of the region was applied to all communes within this region for a number of indicators. This offers the same limitation that was previously discussed, but on a higher scale. For many indicators the average of the region was applied to all communes within this regions (table 5.16). This provides the same limitation as discussed before, but on one scale higher. The variability within a region is not represented by the average for that region. The arguments considered for the disaggregation can be improved, leading to more heterogeneity in the community level data.

To conclude, for 10 indicators it was not possible to provide acceptable dis-aggregation methods. These were entirely removed from the analysis, and are thus not presented in the obtained social vulnerability score.

10.4 LIMITATIONS IN TEMPORAL ANALYSIS

The temporal analysis executed with a PCA approach, provided challenges. The KMO-values found were to small to prove that the variance in the data sets was not solely caused by common variance. Making the results less reliable for use in further research or application for decision-making. The low KMO-values are due to the low amount of measurements. Since Burkina Faso consists of 13 regions, only 13 are available for each indicator. Hence, it can not be concluded that the variance is not caused by common variance.

Consequently, the results obtained by the official INFORM analysis are used to further assess the temporal relations (Disaster Risk Management Knowledge Center, EC 2022). While in fact, the INFORM analysis has skipped on some important social vulnerability indicators for Burkina Faso: the people recently affected by conflict, and the amount of elderly. Furthermore, INFORM considers social vulnerability and coping capacity as two separate components of vulnerability. Therefore, the assumption was made, that equation 14.1 presents social vulnerability in a similar way as the PCA.

The results found for the social vulnerability over time with the use of INFORM are used to determine if a significant trend is visible. A simple linear regression analysis was executed with only seven data points for each region. This is generally too little to identify significant patterns. Which explains why hardly any of the identified patterns proved significant. Additionally, the best fit lines obtained are compared with the trend of conflict, IDPs and natural hazards. From this visual analysis conclusions on the interplay of the four were drawn. This conclusions can be enhanced with a statistical multi linear regression.

10.5 LIMITATION IN SENSITIVITY ANALYSIS

The sensitivity analysis is assessed without accounting for the location of the measurements. It should be better to also account for continuity of each location, by viewing the community within each study area as a blocking factor, that is, an explanatory variable where the community represents a known source of variability. This helps to reduce residual variation and improve precision in the three way ANOVA. Because the computed index values do not represent a truly random sample drawn from some broader population (Schmidtlein et al. 2008).
Furthermore, during the sensitivity analysis outliers were removed to make the data set applicable for three-way ANOVA. All measurements, with a z-score for vulnerability $<$ -1.5 or $>$ 1.5 were removed. This was an educated guess, based on the 75th percentile of the data set. It would be better to substantiate the value for outlier removing in literature or analyse the amount of outliers considered as a fourth variable and compute a four-way ANOVA analysis.

Fourth, the study is unable to "ground-truth" social vulnerability due to unavailability of both pre-event and post-event data and limited local information related to exposure, sensitivity, and adaptive capacity that are often collected through specific site visits and qualitative survey methods (Schmidtlein et al. 2008).

It would have been insightful, to also assess the sensitivity with global SA methods, that compare the results obtained in the current analysis with results that use different indicator values. This was previously done by Nazeer and Bork (2019); Rogelis et al. (2016). This would have assessed the uncertainty of the data selection process. Furthermore, in this section, special attention could have been given to the sensitivity for indicators that are related to the conflict and migration structures that are visible in BFA. This will contribute to a better understanding of the role of conflict and migration in flood vulnerability. However these are recommendations for future research due to time constraints.
Nevertheless, despite these potential limitations, this research is the first to present a social vulnerability index for Burkina Faso on a commune level. Furthermore, it developed good insights in the sensitivity of the method, and the benefits of PCA when analyzing the dynamic behavior of social vulnerability.

11 CONCLUSION

This chapter presents the conclusions and recommendations, based on the findings in this study. First, the research questions are answered. Section 11.1 answers the main research question. Section 11.2 presents the answers to the sub questions. Thereafter, sections 11.4 and 11.3 reflect on the scientific and societal contribution of this research. This is followed by the relevance of this research through the lens of the EPA masters program in section 11.5. The chapter is concluded with suggestions for further research in section 11.6.

11.1 ANSWERING THE MAIN RESEARCH QUESTION

This research was developed to answer the following research question:

> How to calculate a social vulnerability index for Burkina Faso that characterizes the spatial and temporal dynamics of social vulnerability?

Currently, the living circumstances in Burkina Faso are deteriorating. Increasing conflict numbers in the Sahel, East, Nord and Centre-Nord lead to rapidly rising numbers of internally displaced persons. Who live in shelters that are repeatedly affected by the flood events that are happening with a higher frequency due to climate change. Burkina Faso is facing a variety of complex problems, that challenges the humanitarian needs of its inhabitants. This has led humanitarian organisation to conclude that Burkina Faso is facing 'by far the largest protection crisis in the Central Sahel.'

Therefore, this research was draft with three purposes. First of all, to develop an understanding of social vulnerability for the people in Burkina Faso. Having an idea on the social vulnerability in Burkina Faso will contribute to better decisions made by the BFRC and ICRC when assisting the local population and IDPs affected by conflict and floods. In the second place, the temporal aspect of this research question addresses the call for action that is draft by the UNDRR to better understand the dynamics of social vulnerability. To conclude more insight was required in the different methodologies that are used for construction of SVi.

11.1.1 Method

An extensive methodology was developed and is presented in chapter 3. It focuses on applying the PCA to the Burkina Faso case. Where after results are compared to the more traditional hierarchical approach (section: 9), and the sensitivity of the different methodological decisions within the PCA method is verified, with the use of a three way ANOVA analysis.

11.1.2 Result

The primary contribution of this study lies in the identification of the social vulnerability profile for the communes in Burkina Faso in 2020. Furthermore, the analysis of the temporal dynamics of social vulnerability on admin 1 level, showed the influence of conflict, natural hazards and IDPs on social vulnerability. The interplay between conflict and IDPs and social vulnerability was demonstrated by combining this understanding with the internal dynamics of social vulnerability that were made visible by the use of PCA in the spatial analysis; however, no direct correlation was discovered with natural hazards. Additionally, the application of principal component analysis for social vulnerability index creation in the humanitarian field delivered insight into the usefullness of PCA in comparison to the more traditional INFORM models. This shows that PCA provides a deeper understanding in the dynamics of social vulnerability over time, and in the internal dynamics of social vulnerability that reveals which indicators contribute most.

11.1.3 Policy recommendations

To apply this work in the humanitarian field. A second call for action should be developed by the UNDRR that asks for better data gathering mechanism that are set-up by national Census offices. Furthermore, it is recommended to develop commune level social vulnerability assessments, for the simple reason that this is also the level on which decisions for humanitarian aid are made. If SVi are created on a community level, it is recommended to apply PCA. Because this will deliver better insights in the (internal) dynamics of the social vulnerability. However, when the index will be developed on a sob-national level of higher, applying PCA does not provide statistical trustworthy results and more traditional methods such as AHP are recommended.

Additionally, the study showed the social vulnerability rankings are very different when using different methods. At this moment, literature does not show a firm consensus methodology about the methods to be used. There is a high need to search for this consensus between both humanitarian aid workers and analysts who calculate the indices. This can be organised through the means of expert meetings. Humanitarian aid workers must explain why and how they use the indices, e.g. what they think it represents and what it is required to represent to be useful in the field. Subsequently, such a semantic discussion will provide argumentation for analysts that will guide the methodological decisions that are made. Having this discussion will deliver an outcome that is better applicable for policy makers and guarantees the right method is chosen. With doing so, the uncertainty created by the methodological decisions can be reduced.

11.2 ANSWERING THE SUB—RESEARCH QUESTIONS

To answer the research question as presented before, several sub-questions were answered. In this section, the answer on each sub-question will be discussed, together with a short description of the used method and the policy recommendations that follow from the answer.

SQ1: How should social vulnerability be defined for this research?

Result

In this thesis, social vulnerability is considered with a dualistic approach of susceptibility and coping capacity. This underlines that social vulnerability is shaped by both negative indicators that shape the likelihood of severe impact. On the contrary, positive indicators reduce the social vulnerability by the ability of a community to cope and recover from impacts. Writing this in a mathematical expression would look as the following:

$$vulnerability = susceptibility - copingcapacity \tag{11.1}$$

Method

To derive these results, well known literature on social vulnerability was reviewed that showed different framworks to social vulnerability conceptualization. Based on this the most suitable framework is applied in this research.

SQ2: What spatial and temporal data is necessary and?

Results

It is decided to include indicators from four different groups, socio-economi vulnerability indicators, indicators that identify vulnerable groups, indicators that show the coping capacity on an institutional level, and indicators that show the coping capacity on an infrastructural level.

A secondary data analysis was used to identify the useful data sources for this research. It quickly becomes clear that all indicators are available on a country scale for at least 20 years past. However, data on community level have to be derived from OpenStreetMaps, or local research that is executed stationary and not over time. Therefor, data on with a high data resolution, is not available over time. Leading to the decision to analyse social vulnerability and its spatial dynamics for 2020 on a community level. And social vulnerability and it temporal dynamics from 2015 - 2021 on a regional level. The lacking data are mostly considering the socio–economic indicators on a high resolution, health indicators on a high resolution and indicators that refer the the communication possibilities. The data gaps in this research can be the result of several factors. There might be legal, commercial, financial or technical barriers. However it is recommended to discuss this in more detail with experts in BFA.

To justify and clearly report on the inclusion of indicators, two decisions processes on indicator inclusion for both methods are developed. With the use of this process for the spatial analysis 43 indicators were assessed of which 31 are included in the set up of the social vulnerability index. For the temporal analysis, thus number is 31 against 19.

Policy recommendations

The insight into the data availability provides a clear call for action towards the humanitarian data field, and the Census office in Burkina Faso. The need to better understand dynamics of vulnerability, should develop hand in hand with the accessibility of data resources. Currently, this availability is lacking. Hence, the international organisation on humanitarian aid such as the ICRC, IFRC and UN-departments, should stimulate development of Census offices that provide open source and high resolution data.

The decision process that is developed in SQ2, was used as a first step for the inclusion of indicators for both analysis. Thereafter, a correlation assessment was used to assess the relation between the indicators. If the $Pearson'sR$ was found to be greater than 0.7 one of the indicators was removed.

SQ3: What are the social vulnerability scores on Adm3 level for 2020?

The social vulnerability scores for the spatial assessment in 2020, were derived with the use of a PCA where 90% explained variance was used as a rule of thumb for the amount of components considered, a varimax rotation took place, and the components were equally weighted.

Results

High vulnerable areas can be identified in the Sahel and Centre-Nord. Where they are clustered around conflict prone areas. The composition of the SVi shows that social vulnerability in these areas is mainly caused by undernourishment, people with disabilities and conflict. In contrary to the high vulnerable areas in the Haute-Bassin were high social vulnerability is a result of the prevalence of HIV, malnutrition and gender inequality. In all areas, vulnerability is mainly reduced by the access to improved sanitation systems. The ten least vulnerable areas are mostly surrounding the capital city of Burkina Faso, Ouagadougou in the Centre. It can be seen that especially in Ouagadougou the presence of health sites contributes a lot to the reduction of social vulnerability. Furthermore, the road density and access to communication (television access) are important factors that reduce the social vulnerability in these communes.

Policy recommendations

The admin 3 level approach of this research gives good insight in the differences between neighboring communities. An important motivation for social vulnerability assessments on the community level, is the goal to support high risk communities with more capacities and information. Analyzing the risk and vulnerability on commune level provides the possibility to decision-makers to derive priority settings for risk-reduction strategies on a community level. Based on the insight in the vulnerability composition, adequate risk-reduction strategies can be developed for the situation belonging to a specific community.

The derived results are useful for humanitarian decision makers. Due to the PCA indicators are clustered in principal components. Developing policy measures that address the principal components will affect all the indicators that have a high loading in that principal component due to their correlation. Furthermore, the additional insight into the composition of the social vulnerability (figure 6.3, shows which principal components are accounting for the highest part of the vulnerability. Based on this, focused decisions can be made that deliver aid on the principal components that are contributing the most to social vulnerability.

SQ4: Can geographical patterns be identified?

For the assessment of the geographical patterns in social vulnerability, all social vulnerability scores were normalized and assessed with Moran's I and LISA.

Results

The results show that there is a positive global spatial auto correlations. Meaning that high vulnerable communities are surrounded with other high vulnerable communities. Considering this on a local scale, three high social vulnerability clusters were identified: the Sahel and Centre-Nord cluster, The Western Haute Bassins cluster and the Eats Haute Bassins and Centre-Ouest cluster. Additionally, three low social vulnerability clusters are identified: the east cluster, the capital cluster and the Sahel South-Easth cluster. Furthermore, six outliers were identified, that are either high vulnerable areas in low vulnerable clusters or vice versa. The high vulnerable area surrounded by low social vulnerable areas is Dori in the Sahel South-East cluster. Low vulnerable areas in high vulnerable clusters are, Diguel, Déou, Bouroum, Boussouma and Namissiguima.

Policy recommendations

The outlier communities identified with the spatial autocorrelation deserve special attention in risk-reduction strategies and further research. Since there is high human mobility in these areas, two things are interesting in these areas that deserve better understanding. The HL areas, might need less external help with the risk reduction strategies, because the surrounding communities are relatively strong and can assist the community with high vulnerability in gaining more resilience. On the contrary the LH communities might face more IDPs in the short feature. Since the circumstances in these communities are relatively good, they might be attractive to move to when displacement occurs in the high vulnerable surrounding communities

SQ5: Are links visible between the social vulnerability score and the conflicts and natural hazards?

Results

It is complicated to derive clear patterns between the social vulnerability score and the indicators, number of people affected by conflict, natural hazards and the number of IDPs in a commune. This chapter showed that the top ten vulnerable communes score high on these indicators. Which suggests an interaction between the social vulnerability score and the presence of hazards, conflict and **idps!**. However, when comparing the results for all communes, no patterns can be identified. In many communes, different principal components that are not related with these three shape the social vulnerability.

Policy recommendations

It is recommended to focus humanitarian aid on all communes that have a high social vulnerability. These are also the communes that often suffer from conflict, hazards and host a lot of IDPs. It is likely that these communes benefit the most from humanitarian aid. However, before making funding decisions qualitative analysis is recommend to thoroughly understand the needs of the communes.

SQ6: What are the social vulnerability scores on admin 1 level for 2015 – 2021?

Since PCA proofed unfeasible for the temporal assessment, the social vulnerability scores for the temporal assessment from 2015 – 2021 were derived with the use of the INFORM framework.

Results

Over the years a clear increase in vulnerability can be see within the entire country. It can be seen that the social vulnerability in the high vulnerable regions is mainly composed of a high contribution of conflict, hazards, food scarcity, and child and female health. Furthermore, an initial look at these maps, shows that high social vulnerability is often present in areas with many conflict events. However, not all areas with high conflict events, have a high social vulnerability. There are also regions, where well working coping mechanisms reduce the vulnerability, these are high water availability and immunization rates.

The Sahel and Eastern regions exhibit high social vulnerability scores. The maps demonstrate that places with frequent conflict incidents also have high levels of social vulnerability. Not all locations with a lot of conflict incidents have a high social vulnerability. So conflict is not the only factor that contributes to a high social vulnerability score. Additionally, the findings indicate that the Centre region, where the capital is situated, has the lowest social vulnerability in all years.

A flaw in the hierarchical approach is revealed when the social vulnerability index's composition is examined in further detail. It is more difficult to gain insight into the makeup of the social vulnerability index because all indicators are grouped and comprise distinct levels that were equally weighted. Through the correlation analysis and the loading on the principle components, the inductive technique demonstrated the relationship between the indicators extremely effectively. Since this connection is no longer apparent, it is harder to develop effective and targeted policy actions focused on the indicators that contribute most to social vulnerability. However, after analysing the data, it can be said that in the Sahel, Centre—Nord, Nord, and Est, the indicator components *Uprooted people, and Food security* show relatively high compared to the other regions.

explains why PCA is often used on community level assessments and not in regional assessments

Policy recommendations

According to the discovered social vulnerability profiles, social vulnerability patterns change throughout time. The Sahel and the East exhibit high vulnerability profiles, which would necessitate humanitarian intervention in these areas. The profiles, however, are only offered on a regional level, which lacks information for applying local humanitarian relief. This is contrary to the PCA method that offers insight into the vulnerability's structure and how the composition changes over time because of the statistical approach. Unlike hierarchical techniques, this shift is not the result of the choices made by the experts during the weighing stage. Deriving these results on a community level, will provide useful insight for humanitarian aid decision making. For this better granularity of indicator data is necessary.

SQ6: Are there significant temporal changes from 2015 – 2021?

The identification of the temporal dynamics is tested on the results of the subnational INFORM analysis due to the low reliability of the PCA results. For this a simple linear regression was executed for all regions.

Results

In most regions, no significant changes were found over time. Apart from Boucle du Mouhoun, the Centre-Nord and the Nord, were the vulnerability increased from 2015 – 2021 with a slope of respectively, 0.46, 0.38 and 0.42. According to Cutter 2008, this is not an obvious temporal change, however it does reveal a pattern in the development of social vulnerability. In Boucle du Mouhoun, this increase can be derived from the increase in child mortality, and the decrease in health care and water availability. A strong correlation between the social vulnerability and The amount of conflict HDI, GNI, Physicians Density, Cadre Harmonisé, IDPs, GAM and Adult literacy rate was found.

In the Centre-Nord a steady increase in social vulnerability can be seen, apart from the years 2017 and 2018, where an increase in children's health decreased the social vulnerability for two years. The overall increase of social vulnerability is caused by an increase in conflict and presence of IDPs. A strong correlation between the social vulnerability and the amount of conflict, physicians density, Cadre Harmonisé, the amount of IDP's and the adult literacy rate, was found.A negative correlation was found with the immunization rate, the multidimensional poverty index and the government effectiveness.

In the Nord, also a steady increase can be derived from the regression analysis. Apart from the years 2018 and 2019, where a drop in social vulnerability is caused by an increase in water availability. The steady increase is just as for the Centre-Nord, mainly caused by conflict and child malnutrition. A strong correlation between the social vulnerability and the amoung of conflict, physician density, Cadre Harmonisé, the amount of IDPS, the adult literacy rate was found. Negative correlations were found with the MDPI, Immunization rate, and government effectiveness.

Policy recommendations

Ddespite the fact that the research did not find many statistically significant temporal patterns in the social vulnerability, figure 15.4 shows that the social vulnerability is highly dynamic over time. This has important implication for the practice and policy making. The chancing dynamics would suggest different decision making each year. In practice, this is not possible because the processes to develop humanitarian aid programs is likely to take longer than one year. Therefore, it would be wise for policy makers to develop programs guided by different scenarios so that decision on social vulnerability can be adjusted to the temporal dynamics of the social vulnerability.

SQ8: Are links visible between the pattern an natural hazards?

Results

The visual inspection of the trends that are visible when considering the social vulnerability, natural hazards, conflict and IDPs suggests no correlation between natural hazards and social vulnerability. The best fit line often suggests an increase in social vulnerability while hazard decreases over time. It is important to note, that this could be due to the fact that hazards are not a continuous process, and therefore the absolute number of affected people that is used, might not be a correct representation of the impact of hazards on the society.

A clear role is visible for both IDPs and conflicts. Which both show a similar increase over time as does the best fit line of social vulnerability. It can be seen, that the conflict and IDPs are strongly related. This emphasizes the suggestions made by Internal Displacement Monitoring Centre (2021) that most IDPs in Burkina Faso were driven by conflict to move.

Policy recommendations

Based on these outcomes an initial idea of the interplay between conflict, natural hazard, IDPs and social vulnerability is developed. Since the aim of policy interventions is to reduce the social vulnerability of people in Burkina Faso, these results suggest that it is more important to focus on areas with a lot of conflict event compared to areas with many natural hazard events. It is however important to note, that the risk is shaped by a combination of hazard exposure times (social) vulnerability. Thus, neglecting the hazard locations since this does not increase social vulnerability, does not suggest to neglect the hazard exposure component of the risk equation.

Additionally, this section solely focuses on the interplay between three of the indicators that shape the social vulnerability. And therefore should be merely considered as an explanation of the effect of conflict and natural hazards on social vulnerability and not as the cause for a high social vulnerability. That is because a high social vulnerability score can additionally be explained by other indicators. It would thus not be wise to only focus on conflict reduction to reduce social vulnerability, since this decision would neglect the composition of social vulnerability as presented in section 6.1.1.

SQ9: What methodological decisions cause sensitivity in the results?

To assess the sensitivity of the PCA 12 different ways to set-up the PCA analysis were assessed. There are three places were different decisions can be made: the number of components that is included, the type of rotation that is used and the weighting scheme. Of which the first two have two options, and the last has three options. Thus a three-way ANOVA test was applied to identify if significant results in the outcome can be attributed to (a combination) of methodological decisions. Apart from assessing the change in absolute output, also the change in ranking was assessed by determining the standard deviation of the ranking of each community.

Results

It is found that there is interaction between the different variables of the ANOVA assessment. This shows that the results of the social vulnerability score are highly dependent on the decisions made in the construction of the algorithm. Hence, the sensitivity of the results for different combinations of PCA composition is high. Since social vulnerability is considered relative towards social vulnerability scores of other communities, the change in ranking of the communities is important. It is shown that different methodological decisions, lead to different rankings in social vulnerability, the standard deviation of these ranking is high. Which emphasizes the importance of choosing the right method to create a social vulnerability index.

Policy Recommendations

To better understand the meaning of the input indicators in models used for decision making in the humanitarian field, it is recommended to set-up extensive DMDU models (Kwakkel 2017). With doing so, the uncertainty in the input of historical models can be assessed. Additionally, predictive decisions can be made based on a more robust analysis on what the future will look like.
Additionally, it is recommend that policy makers thoroughly discuss with each other how to understand social vulnerability and what type of number they need to base decisions for disaster management on. This is important since currently all available methods derive different results. Therefore a better semantic definition of social vulnerability will guide which method best presents the social vulnerability and can thus be used as a guidance.

The outcome is deliberately referred to as *a guidance*, since it is important to note that no calculation of social vulnerability will present a ground truth number of the concept. It remains a composite indicator that represent interaction between indicators, but is not interpretative as an absolute value in it self.

SQ10: What is the difference in results with inductive and hierarchical approaches?

Results

The derive an answer on this question, the results from a PCA approach which is inductive and the INFORM method which is hierarchical are compared. It showed important differences that can not be neglected. Initial results showed large differences in social vulnerability in absolute number. Furthermore, the distribution of the scores has a higher standard deviation when applying the PCA method. The top 10 most vulnerable communes are completely different when using PCA or INFORM, and this can be extend to the overall results, since a completely different ranking of the communes is obtained with both methods.

Policy recommendations

It is difficult to develop disaster risk reduction strategies if two methods are contradicting each other. It is thus recommended not to develop policy measures based on solely the quantitative analysis. I valuable next step would be to assess the social vulnerability in a qualitative matter through the means of field work, both in the communes that score high on social vulnerability in the PCA approach as well as in the INFORM approach. This can also provide insights for the semantic discussion that is needed to understand which method will be more suitable.

SQ11: What method is more suitable for determination of the SVi, hierarchical of PCA

To determine which method is more suitable for the determination of the SVi, first the results of chapter 6 were compared with results for the SVi when using an hierarchical approach. There after, the benefits and drawbacks of both methods were discussed based on literature and insights derived from the execution of this research.

Results

There is no complete good or bad method for the generation of composite vulnerability indicators. Both methods have benefits and drawbacks, and that the differences in the results are big. However, the call for the understanding of the dynamic behavior of social vulnerability is large. For this, PCA provides better insight in the composition of vulnerability, the change in composition of the social vulnerability, provides interesting insights in how the variance of the social vulnerability changes over time. Furthermore, the social vulnerability calculated with PCA provides more precise results to compare with different measurement moments with each other. However, executing the PCA is a challenging assignment due to the low data resolution in areas that are in need of humanitarian aid. It is thus necessary to develop better data gathering mechanisms. So that, disaster risk reduction strategies can be improved.

Policy recommendations

The use of PCA proves promising for the understanding of the dynamic behaviour of social vulnerability. Despite the effort it will take to entirely understand the statistical behavior of the separate steps of the construction of the index, and the qualitative research that has to be applied to find out which methodological decisions lead to an index that describe the vulnerability best, PCA will deliver the best understanding of social vulnerability dynamics. This is of great importance to improve disaster risk reduction strategies. Based on this research, it is recommended for humanitarian policy makers to invest in data gathering mechanisms, so that PCA can be applied in all areas that are (partly) dependent on humanitarian aid.

11.3 SOCIETAL CONTRIBUTION

The first section of this research focused on developing applied value for society based on scientific models. The social vulnerability index developed on community level can be used by the ICRC and BFRC to identify which areas are the most vulnerable. The results can be used as a guidance in decision-making. Knowing which *indicators* contribute most the the high vulnerable areas will assist in deciding what type of humanitarian aid is necessary to improve the resilience of the inhabitants.

Furthermore, the methods developed in this research provide guidance for humanitarians that can be used to derive insight in (internal) dynamics of social vulnerable in other geographic areas than Burkina Faso.

Lastly, this research emphasizes the need for better data gathering mechanism. If the goal of the UNDRR is to eventually understand the dynamics behind social vulnerability. It much needed that more research will take place that maps social vulnerability on a high resolution. However, currently national Census offices do not gather enough data, to provide the input for these type of models. Apart from contributing to the decision-making process, the research is thus also a call for action.

11.4 SCIENTIFIC CONTRIBUTION

Secondly, this thesis focused on methodological consideration with regard to the development of social vulnerability indices. This thesis started by addressing the gap in existing literature regarding the understanding of spatial and temporal dynamics in social vulnerability, regarding the construction of the vulnerability indexes and lastly the role of conflict in social vulnerability. As shown in chapter 2, much research has been done in building social vulnerability indices. How ever not often was the methodology thoroughly assessed.

This research assessed the social vulnerability at a community level with the aid of PCA. This spatial assessment provided insight in the spatial autocorrelation of the social vulnerability in Burkina Faso. However, based on this set-up, it also became possible to assess the methodological decisions in the construction of the PCA. This showed important new insights that emphasize how sensitive the results are for these decisions.

However, it must be emphasized, that this research did not manage to provide an answer to which method is best. When doubting between hierarchical approached and PCA, it becomes clear that PCA will always provide more insight into the dynamics of social vulnerability. Nevertheless, when research is executed in data scare environments, it will be better to apply a hierarchical method.

Additionally, the comparison between the hierarchical approach and the PCA showed that it is very useful to invest in better data gathering. Since this paves a path for applying PCA more often. Hence, better insight will be developed into the internal dynamics of social vulnerability. Because biased modeller assumptions are removed. This is a call for action for the scientific field to acknowledge the added value of PCA and apply this method more often.

11.5 RELEVANCE THROUGH THE EYE OF THE EPA MASTERS PROGRAM

This master thesis is conducted in partial fulfillment of the requirements for the degree Master of Science in Engineering and Policy Analysis. In the program a lot of attention is given to grand societal challenges. The challenges that are addressed have both a technical and a social component and thus require a systematical view. In this research the technical challenges are visible in the climate change challenges but also in the construction of the index. The societal component is evidently visible in the context of the Burkina Faso, that is surrounded by conflict and IDPs. But also in the understanding of the indicators that are used to create the index. In this research both components and the systematical approach of the challenges are used to develop policy recommendations for the BFRC and ICRC.

11.6 FUTURE WORK

The fact that PCA has proven to be a suitable method to understand the internal dynamics for social vulnerability opens the path for more research using this approach. Diving into the other facets that shape risk, but also understanding the link between the methodological decisions and qualitative meaning of vulnerability more in depth. Some suggestions for further research are given below.

Firstly, it is important to develop a qualitative understanding of the different methodological decisions that are made in construction the PCA algorithm, and how they relate to the qualitative meaning of social vulnerability. This is important since all different methodologies derive different rankings between communities, and thus have an enormous influence on the policy-decisions that are made.

Secondly, a large part of sensitivity and uncertainty is gathered in the input of the model: the selected indicators. Often, the process of selection indicators is a random process, that gathers data points from several years around the moment that is considered for the research. This should be improved with the further development of the decision process on the inclusion of indicators. This decision process should also verify the quality of the input data.

Thirdly, when the quality of the input data is known, elaborate sensitivity analysis can be executed. I suggest to test the uncertainty and sensitivity in the input with the use of the EMA-workbench. With doing to, an abundance of scenario's is tested, and very robust policy recommendations can be developed.

Fourthly, when ranking the social vulnerability outcome is not necessary for policy interpretations, it could be interesting to use a K-means algorithm that clusters all geographical areas based on the indicators. Clustering will remove the biased weighting by modellers in hierarchical models, and the blackbox that is present in PCA. Meanwhile, it will very well show the internal dynamics of social vulnerability.

Fifthly, it would be interesting to assess a simple correlation between the input indicators and historical impact data. With doing so, a better understanding of the relative importance of each indicator can be developed. This could also be used to guide the weighting scheme. This could also be combined into a PCA and Impact driven weighting approach. However often low quality of impact data is available which will make this challenging.

Lastly, the interpretation of chapter 6 and 7 would benefit from a qualitative field work that attempts to understand the differences in vulnerability between the communities.

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12 VULNERABILITY INDICATORS USED IN LITERATURE

Indicator	Hagenlocher	Moreira	INFORM	CRA
Female headed households	X	X		
Travel time to closest city	X			X
People with disabilities	X	X		
People malnourished	X	X		X
People with chronic illness	X			
People illiterate	X	X		X
People below national poverty	X	X	X	X
Dependency ratio	X	X		
GINI index	X		X	X
Dependent on agri	X			
Access to irrigation				
Access to sanitation	X	X		X
Access to clean watter	X	X		X
Access to electricity	X	X	X	X
People living in infor.settl	X			
People living in poorly cons. houses	X	X		X
Population affected by hazard	X	X	X	X
Number of IDPs		X		
Population density		X		X
Unemployment rate		X		
Female Rate		X		
Elderly rate		X		X
Male rate		X		
Children rate		X	X	X
Aged < 5		X	X	
Food insecurity		X		X

Table 12.1: Overview of Susceptibility indicators

Indicator	Hagenlocher	Moreira	INFORM	CRA
Areas protected by structural measures	X			
Population who cannot swim	X			
Households with access to information	X		X	X
Existence of early warning	X	X		
Households previously received EW	X			
Households attended disaster prep training	X			
Access to shelter places	X			
Access to water treatment	X	X	X	X
Access to rural markets	X			
Number of health facilities	X	X	X	
Distance to facilities		X	X	
Access to electricity	X	X	X	X
Density of transportation network	X			
Education facilities per 1000		X	X	X
Individual means of transportation	X	X		
Poor governance	X			
Availability of food reserves	X			
Volume of water storage	X			
Hospital beds per 1000	X	X	X	X
Public Health Expenditure	X		X	X
Social capital	X			
Households with gross savings	X			
Households with access to bank / micro credit	X			
Househoulds receiving remittance	X			
Households without any insurance	X			

Table 12.2: Overview of Coping capacity indicators

Indicator	Hagenlocher	Moreira	INFORM	CRA
Population that has adapted before	X	X		
Population that has experienced hazard in last 10 years 7 X	X			
Existence of hazard maps	X			
Existence of adaptation policies	X			
Foreign Direct Investment	X			
Donor aid for adaptation	X			
Percentage of GDP spent on adaptation and innovation	X			
Percentage of households with adjusted farming practice	X			
Percentage of farmers with different crops	X			
Number of out-migrants per 1000	X			
Income generating activities per household	X			

Table 12.3: Overview of Adaptive capacity indicators

13 VULNERABILITY OVERVIEW OF ALL COMMUNES IN 2020

Commune	PC2	PC1	PC19	PC8	PC13	PC3	PC11	PC9	PC12	PC10	PC6	PC7	PC5	SVi
Djibo	34.25	-7.11	10.3	8.38	-3.13	-3.63	4.65	2.29	2.91	-2.09	-0.34	0.42	-0.01	46.89
Pensa	7.18	-0.72	4.27	6.6	-1.13	-1.57	0.03	0.04	1.65	-0.44	-0.73	1.93	-0.22	16.89
Barsalogho	12.05	-0.24	3.68	1.2	-1.42	-1.5	0.44	0.45	1.29	-1.16	-0.11	1.65	-0.2	16.13
Arbinda	5.56	-6.35	6.93	6.58	-3.78	-2.57	4.29	2.15	2.35	-1.82	-0.57	1.4	-0.39	13.78
Pobé-Mengao	1.77	-5.88	6.41	6.42	-2.44	-2.31	4.31	1.86	2.38	-1.33	-0.68	1.52	-0.11	11.92
Dori	9.56	-6.19	5.56	3.14	-4.13	-2.68	4.17	1.75	1.35	-1.7	-0.3	0.2	-0.05	10.68
Bouroum-Bouroum	9.75	-1.89	0.39	0.46	-1.13	-0.21	1.68	0.72	1.33	-0.28	-0.42	0.4	-0.67	10.13
Gorom-Gorom	8.46	-6.7	5.51	4.59	-4.91	-2.71	4.4	1.68	1.62	-1.74	-0.77	1.47	-0.82	10.08
Kayan	7.9	-3.48	1.35	0.69	-1.32	-0.28	2.42	1.62	2.98	-1.12	-0.82	1.55	-1.5	9.99
Titao	6.04	-0.8	2	2.04	-0.32	-0.97	0.66	1.09	0.08	-0.03	-0.17	0.14	-0.15	9.61
Boni	1.48	-3.58	1.93	1.22	-0.66	-0.23	2.6	1.79	3.83	-1.14	-0.15	2.25	-0.06	9.28
Orodara	1.57	-4.04	2.2	1.41	-1.95	-0.1	2.76	1.92	3.39	-0.98	-0.57	4.09	-0.43	9.27
Tongomayel	2.91	-6.02	6.3	5.39	-3.33	-2.41	4.17	1.99	2.26	-1.67	-0.58	0.88	-0.68	9.21
Tin-Akoff	2.69	-7.29	6.12	10.5	-5.64	-2.76	4.57	1.91	1.82	-2.09	-0.78	1.18	-1.14	9.09
Koumbia	1.44	-3.69	1.94	1.24	-1.01	-0.2	2.63	1.79	3.81	-1.08	-0.26	1.83	-0.05	8.39
Koti	1.07	-3.56	1.89	1.2	-0.68	-0.22	2.56	1.79	3.78	-1.1	-0.09	1.92	-0.19	8.37
Yalgo	2.82	-0.16	2.01	0.45	-1.13	-1.06	0.3	0.16	0.29	-0.91	-0.79	7.2	-0.89	8.29
Kourinion	1.54	-3.84	2.06	1.35	-1.65	-0.06	2.63	1.83	3.28	-0.88	-0.2	2.2	-0.01	8.25
Békui	1.17	-3.8	1.98	1.29	-1.38	-0.17	2.62	1.88	3.81	-0.99	-0.17	2.13	-0.14	8.23
Béréba	1.11	-3.9	2.03	1.31	-1.64	-0.17	2.68	1.9	3.84	-0.99	-0.24	2.48	-0.19	8.22
Djigouèra	1.47	-3.71	2	1.25	-1.11	-0.11	2.66	1.71	3.31	-1.07	-0.22	2	-0.17	8.01
Nassoumbou	2.54	-6.09	6.33	5.71	-3.55	-2.44	4.19	1.97	2.27	-1.74	-0.54	0.12	-0.8	7.97
Kelbo	1.69	-5.8	6.22	4.96	-2.93	-2.38	4.2	1.89	2.18	-1.5	-0.03	0.37	-1.01	7.86
Koutougou	1.98	-6.67	6.77	7.34	-5.11	-2.57	4.32	2.29	2.32	-2.14	-0.61	0.91	-1.01	7.82
Dablo	1.84	-0.23	2.92	2.52	-0.9	-1.24	0.23	0.24	1.3	-0.8	-0.22	2.45	-0.42	7.69

Gorgadji	2.55	-6.22	5.51	4.99	-3.99	-2.45	4.29	1.77	1.54	-1.44	-0.53	2.05	-0.67
Kaïn	0.26	-0.87	0.56	5.59	-0.37	-1.5	0.61	0.98	1.56	-0.04	-0.14	1.02	-0.45
Banzon	0.51	-3.83	1.99	1.24	-1.47	-0.12	2.67	1.78	3.31	-1.06	-0.32	2.65	-0.19
Founzan	1.39	-3.43	1.75	1.13	-0.42	-0.17	2.5	1.62	3.72	-1.07	-0.11	0.49	-0.3
Ndôrôla	0.99	-3.71	1.96	1.2	-1.24	-0.09	2.64	1.71	3.15	-1.04	-0.23	1.89	-0.14
Karangasso-Vigué	1.27	-3.69	1.81	1.21	-0.91	-0.21	2.56	1.76	4.36	-1.03	-0.09	0.12	-0.15
Tougouri	5.55	-0.31	2.03	0.51	-0.55	-1.33	0.43	0.54	0.45	-0.84	-0.23	0.85	-0.53
Samôgôgouan	1.6	-3.7	1.94	1.37	-1.57	-0.02	2.38	1.86	3.14	-0.59	-0.09	0.65	-0.53
Samôgôyiri	1.43	-3.6	1.85	1.22	-1.1	-0.02	2.52	1.63	3.18	-0.89	-0.06	0.5	-0.23

Commune	PC2	PC1	PC19	PC8	PC13	PC3	PC11	PC9	PC12	PC10	PC6	PC7	PC5	SVi
Fada-Ngourma	7.53	-3.02	2.46	2.31	-2.31	-0.73	0.91	1.23	0.63	-2	-0.54	0.57	-0.62	6.42
Kangala	1.53	-3.65	1.89	1.3	-1.41	-0.02	2.43	1.76	3.13	-0.68	-0.13	0.24	-0.04	6.35
Sindo	1.16	-3.53	1.86	1.28	-0.99	-0.03	2.31	1.81	3.15	-0.72	-0.07	0.97	-0.87	6.33
Déou	5.15	-6.76	5.31	5.03	-5.28	-2.67	4.37	1.72	1.55	-1.81	-0.78	1.25	-0.84	6.24
Toussiana	1.55	-3.42	1.96	1.29	-1.91	-0.15	2.44	1.79	0.79	-0.48	-0.36	2.82	-0.09	6.23
Markoye	3.88	-6.78	5.36	6.01	-5.13	-2.65	4.41	1.69	1.58	-1.78	-0.77	1	-0.64	6.18
Baraboulé	1.7	-5.54	5.69	2.86	-2.46	-2.27	4.02	1.77	2.12	-1.33	-0.59	0.77	-0.59	6.15
Morlaba	1.41	-3.52	1.85	1.17	-0.46	-0.11	2.53	1.54	3.23	-1.19	-0.23	1.08	-1.36	5.94
Houndé	0.41	-3.57	1.75	1.16	-0.98	-0.16	2.47	1.78	3.68	-0.92	-0.06	0.41	-0.04	5.93
Kourouma	1.4	-3.83	1.97	1.26	-1.31	-0.07	2.66	1.64	3.28	-1.11	-0.36	1.49	-1.53	5.49
Kaya	4.49	-0.55	3.13	0.72	-0.51	-1.5	0.52	0.6	0.09	-1.03	-0.87	0.66	-0.33	5.42
Faramana	1.41	-3.03	1.66	0.98	-0.44	0	2.32	1.58	1.64	-0.78	-0.02	0.41	-0.38	5.35
Diguel	1.93	-5.77	5.82	3.36	-3.11	-2.34	4.1	1.8	2.16	-1.47	-0.6	0.07	-0.84	5.11
Solenzo	1.18	-0.21	1.15	0.64	-0.18	-2.46	0.77	2.19	1.46	-0.59	-0.16	1.25	-0.28	4.76
Sollé	0.02	-0.91	1.77	4.31	-0.12	-1.09	0.72	0.96	0.1	-0.22	-0.19	0.01	-0.61	4.75
Padéma	1.35	-3.26	1.71	1.11	-1.11	-0.06	2.43	1.57	1.65	-0.71	-0.05	0.46	-0.41	4.68
Fo	1.32	-3.28	1.71	1.1	-1.02	-0.04	2.45	1.54	1.71	-0.8	-0.14	0.2	-0.09	4.66
Koundougou	1.4	-3.32	1.76	1.16	-1.29	-0.06	2.43	1.64	1.66	-0.66	-0.08	0.11	-0.31	4.44
Namissiguima	3.68	-0.07	0.23	0.49	-0.66	-1.69	0.82	0.97	0.75	-0.06	-0.03	0.75	-0.94	4.24
Pissila	2.66	-0.41	2.81	1	-0.11	-1.34	0.34	0.6	0.04	-1.08	-0.18	0.32	-0.46	4.19
Boundoré	3.01	-6.41	5.16	4.18	-4.6	-2.54	4.23	1.7	1.59	-1.69	-0.74	1.21	-0.98	4.12
Zimtanga	1.51	-0.51	1.18	1.78	-0.08	-0.92	0.46	0.46	0.43	-0.94	-0.19	1.48	-0.54	4.12
Wolonkoto	1.49	-1.86	1.71	1.12	-1.05	-0.24	1.4	0.71	0.11	-1.54	-0.25	2.48	-0.01	4.07
Bourzanga	0.77	-0.49	1.32	1.75	-0.05	-0.95	0.5	0.42	0.39	-1	-0.18	1.88	-0.49	3.87
Kombissiri	1.29	-1.58	1.35	0.95	-0.91	-1.11	0.77	1.27	1.6	-1.58	-0.13	1.95	-0.07	3.8
Tankougounadié	2.15	-6.74	5.36	4.88	-5.39	-2.57	4.51	1.69	1.65	-1.64	-0.62	0.81	-0.36	3.73
Oursi	5.6	-6.63	4.96	3.42	-5.45	-2.64	4.34	1.62	1.47	-1.82	-0.73	0.32	-0.73	3.73
Dandé	0.7	-3.49	1.79	1.16	-1.68	-0.05	2.48	1.67	1.71	-0.69	-0.23	0.68	-0.34	3.71
Lèna	0.57	-3.27	1.72	1.09	-1.59	-0.06	2.44	1.68	1.02	-0.62	-0.26	1.06	-0.14	3.64
Bahn	1.08	-0.56	1.28	1.07	-0.25	-1.19	0.79	1.08	0.04	-0.05	-0.26	0.68	-0.1	3.61
Léo	1.36	-1.99	1.56	0.97	-0.54	-0.5	0.12	0.77	1.38	-0.5	-0.04	1.13	-0.13	3.59
Tchériba	0.06	-0.07	1.03	0.56	-0.62	-2.46	0.76	2.22	0.91	-0.66	-0.06	1.74	-0.06	3.35

Satiri	1.37	-3.28	1.72	1.14	-1.54	-0.09	2.41	1.64	1.05	-0.58	-0.35	0.41	-0.57
Toma	1.26	0	1.23	0.72	-0.72	-2.39	0.81	1.99	0.61	-0.7	-0.06	0.7	-0.12
Fara	0.81	-0.47	0.49	0.3	-0.13	-2.26	0.68	2.2	1.18	-0.57	-0.14	1.37	-0.14
Bama	1.36	-3.49	1.79	1.19	-1.64	-0.08	2.46	1.64	1.71	-0.65	-0.41	0.12	-0.68
Bana	0.78	-0.48	0.6	0.44	-0.15	-2.32	0.63	2.14	1.18	-0.74	-0.24	1.55	-0.13
Boura	1.08	-1.84	1.5	0.96	-0.27	-0.5	0.01	0.75	1.32	-0.44	-0.2	0.95	-0.1
Gassan	1.37	-0.18	1.2	0.75	-0.45	-2.39	0.64	1.89	0.7	-0.87	-0.22	1.05	-0.29
Douna	1.06	-2.15	1.82	1.17	-1.63	-0.25	1.53	0.78	0.01	-1.61	-0.51	3.79	-0.83
Kiembara	2.29	-0.28	0.35	0.28	-0.74	-2.21	0.66	2.06	0.9	-0.65	-0.12	0.92	-0.28
Kankalaba	1.42	-1.93	1.71	1.1	-1.18	-0.23	1.49	0.64	0.08	-1.61	-0.29	2.01	-0.11
Bondokui	1.21	-0.24	1.11	0.63	-0.15	-2.43	0.72	2.15	0.9	-0.68	-0.21	0.6	-0.51
Kôlôkô	1.57	-3.85	1.91	1.37	-1.62	-0.02	2.36	1.77	3.31	-0.71	-0.23	0.41	-3.17

Commune	**PC2**	**PC1**	**PC19**	**PC8**	**PC13**	**PC3**	**PC11**	**PC9**	**PC12**	**PC10**	**PC6**	**PC7**	**PC5**
Moussodougou	1.46	-1.86	1.3	1.09	-1.56	-0.33	1.31	0.89	0.11	-1.29	-0.1	2.07	-0.03
Kona	1.19	-0.36	1.06	0.59	-0.2	-2.42	0.69	2.21	0.91	-0.62	-0.25	0.84	-0.63
Péni	1.33	-3.26	1.76	1.12	-1.42	-0.17	2.45	1.51	0.75	-0.63	-0.21	0.11	-0.34
Sanaba	0.52	-0.38	1.03	0.47	-0.36	-2.42	0.79	2.33	1.46	-0.39	-0.03	0.72	-0.78
Imasgho	1.35	-2.43	1.73	1.06	-1.63	-0.48	0.42	0.69	1.58	-0.57	-0.46	1.9	-0.26
Yé	1.18	-0.13	1.12	0.64	-0.45	-2.41	0.78	2.11	0.66	-0.69	-0.21	0.89	-0.59
Bané	0.61	-0.31	0.73	0.44	-0.01	-0.82	0.55	0.92	0.54	-1.27	-0.08	2.29	-0.74
Garango	1.2	-0.26	1.05	0.73	-0.92	-0.56	0.54	0.93	0.2	-1.5	-0.06	1.78	-0.32
Tougo	1.12	-0.02	0.8	0.61	-1.07	-1.89	0.94	1.07	1.27	-0.52	0	0.94	-0.44
Kouka	1.21	-0.08	1.16	0.69	-0.76	-2.55	0.77	2.17	1.52	-0.79	-0.08	0.04	-0.5
Sourgou	1.43	-2.68	1.75	1.18	-1.82	-0.5	0.33	0.62	2.98	-0.44	-0.21	0.47	-0.34
Kombori	0.6	-1.08	0.17	3.61	-1.16	-2.06	0.33	2.24	0.67	-0.32	-0.01	0.04	-0.27
Gossina	1.51	-0.15	1.01	0.52	-0.59	-2.33	0.75	2.06	0.67	-0.64	-0.1	0.14	-0.12
Yaho	1.07	-0.36	0.71	0.5	-0.41	-2.3	0.73	2.09	1.12	-0.71	-0.12	0.64	-0.26
Po	3.63	-0.18	0.05	0.05	-0.31	-1.63	0.29	1.39	0.76	-1.75	0	0.93	-0.53
Boussé	3.35	-0.25	0.44	0.31	-0.84	-0.99	1.33	0.09	0	-0.63	-0.22	0.13	-0.03
Bérégadougou	0.71	-2.11	1.39	1.03	-1.77	-0.42	1.58	0.83	0.31	-1.68	-0.52	3.74	-0.46
Godyr	1.24	-2.05	1.01	0.86	-1.11	-0.35	0.16	0.71	2.05	-0.42	-0.27	1.07	-0.3
Dolo	1.09	-1.52	0.21	0.39	-0.43	-0.36	1.38	0.87	0.64	-0.2	-0.42	1.33	-0.43
Ouarkoye	0.74	-0.33	1.05	0.57	-0.1	-2.41	0.69	2.18	0.93	-0.63	-0.12	0.6	-0.64

Commune	PC2	PC1	PC19	PC8	PC13	PC3	PC11	PC9	PC12	PC10	PC6	PC7	PC5	Vulnerabil
Pâ	1.08	-0.49	0.66	0.47	-0.13	-2.3	0.66	2.1	1.18	-0.74	-0.23	0.88	-0.64	2.5
Boussou	1.08	-0.13	0.76	0.52	-0.68	-1.85	0.94	1.01	1.22	-0.4	-0.18	0.67	-0.47	2.49
Zawara	1.21	-2.04	1.02	0.84	-0.98	-0.35	0.18	0.75	1.98	-0.49	-0.22	0.82	-0.25	2.47
Gaô	0.77	-2.01	1.51	0.9	-0.22	-0.52	0.16	0.97	1.68	-0.69	-0.18	0.36	-0.27	2.46
Malba	1.11	-1.63	0.42	0.41	-0.55	-0.4	1.41	0.89	0.92	-0.26	-0.44	1.01	-0.44	2.45
Rambo	0.99	-0.07	0.74	0.52	-0.24	-1.77	1.02	0.93	0.69	-0.12	-0.09	0.11	-0.28	2.43
Goursi	1.14	-0.02	0.85	0.62	-1.15	-1.87	0.95	1.14	1.22	-0.52	-0.01	0.21	-0.14	2.42
Doulougou	1.44	-1.63	1.37	1.08	-1.45	-1.01	0.58	1.44	1.46	-1.99	-0.03	1.4	-0.26	2.4
To	1.44	-2.03	1.57	1.03	-0.85	-0.56	0.08	0.75	1.33	-0.34	-0.19	0.23	-0.06	2.4
Sami	1.24	-0.52	0.97	0.56	-0.69	-2.47	0.55	2.3	1.59	-0.62	-0.48	0.13	-0.22	2.34
Ouindigui	0.58	-0.51	1.16	0.9	-0.35	-1.22	0.78	1.16	0.03	-0.12	-0.15	0.15	-0.08	2.33
Kougny	1.27	-0.23	1.13	0.67	-0.23	-2.39	0.68	2.03	0.68	-0.75	-0.23	0.08	-0.39	2.32
Toéni	0.07	-0.62	0.03	2	-0.21	-2.15	0.59	2.15	1.04	-0.53	-0.28	0.66	-0.44	2.31
Yaba	1.25	-0.08	1.19	0.71	-0.62	-2.4	0.76	2	0.66	-0.76	-0.16	0.15	-0.44	2.26
Zonsé	0.96	-0.49	0.47	0.41	-0.36	-0.71	0.8	0.93	0.95	-1.73	-0.1	1.45	-0.33	2.25
Kalsaka	0.23	-0.06	0.68	0.5	-0.78	-1.85	1.01	0.91	0.77	-0.24	-0.19	1.47	-0.23	2.22
Lanfièra	0.61	-0.4	0.48	0.43	-0.23	-2.24	0.64	2.08	0.87	-0.69	-0.14	0.95	-0.19	2.17
Bagaré	0.97	-0.06	0.22	0.43	-0.58	-1.66	0.96	0.99	0.43	-0.23	-0.23	1.03	-0.11	2.16
Gaongo	1.39	-1.03	1.12	0.87	-0.24	-1.09	0.38	1.23	1.4	-1.78	-0.42	0.55	-0.24	2.14
Nébiélianayou	1.39	-2.09	1.56	1	-0.93	-0.56	0.16	0.8	1.34	-0.41	-0.05	0.12	-0.2	2.13
Bani	2.43	-5.88	4.71	2.56	-3.86	-2.36	4.06	1.65	1.31	-1.51	-0.73	0.74	-1.01	2.11
Niabouri	0.7	-1.85	1.41	0.93	-0.54	-0.57	0.05	0.8	1.22	-0.3	-0.37	0.84	-0.25	2.07
Boromo	1.04	-0.52	0.66	0.39	-0.01	-2.25	0.66	2.06	1.17	-0.68	-0.04	0.2	-0.66	2.02
Douroula	0.82	-0.14	1.14	0.65	-0.38	-2.43	0.72	2.09	0.95	-0.71	-0.4	0.02	-0.34	1.99
Kokologo	1.4	-2.26	1.58	1.08	-1.8	-0.62	0.15	0.66	1.34	-0.12	-0.25	0.99	-0.2	1.95
Zôrgho	1.05	-0.07	0.41	0.51	-0.8	-1.08	1.33	0.33	0.14	-0.85	-0.18	1.22	-0.06	1.95
Safané	0.61	-0.21	1.1	0.65	-0.4	-2.45	0.66	2.07	0.95	-0.8	-0.25	0.43	-0.44	1.92
Kordié	1.41	-2.21	1.16	1.02	-1.62	-0.37	0.09	0.46	2.07	-0.21	-0.19	0.83	-0.53	1.91
Mansila	1.92	-6.31	5	3.78	-4.38	-2.52	4.17	1.6	1.53	-1.58	-0.7	0.43	-1.06	1.88
Diébougou	0.85	-1.38	0.18	0.31	-0.22	-0.36	1.22	0.75	0.58	-0.05	-0.2	0.63	-0.44	1.87
Bassi	1.17	-0.13	0.89	0.67	-1.38	-1.89	0.98	1.16	1.24	-0.55	-0.46	0.16	0	1.86
Ténado	1.27	-2.16	1.09	0.91	-1.34	-0.36	0.2	0.67	2	-0.42	-0.15	0.18	-0.04	1.85

Nouna	0.9	-0.42	0.67	0.47	-0.42	-2.16	0.67	2.07	0.28	-0.47	-0.01	0.58	-0.32
Zecco	1.22	-0.68	0.64	0.71	-0.93	-1.47	0.35	1.84	0.89	-2.21	-0.22	1.67	-0.02
Nagbingou	2	-0.52	1.46	0.08	-0.37	-1.11	0.3	0.76	0.42	-1.06	-0.35	0.25	-0.07
Zamo	1.29	-2.1	1.08	0.91	-1.25	-0.37	0.16	0.65	1.96	-0.38	-0.22	0.25	-0.2
Ziga	0.92	-0.52	2.15	0.21	-0.2	-1.11	0.45	0.55	0.41	-1.08	-0.22	0.8	-0.59
Balavé	0.85	-0.55	0.97	0.5	-0.69	-2.44	0.65	2.34	1.54	-0.51	-0.15	0.02	-0.77
Siby	0.84	-0.34	0.55	0.43	-0.82	-2.32	0.59	2	1.33	-0.94	-0.4	1.15	-0.31
Dédougou	0.33	-0.07	1.14	0.6	-0.29	-2.36	0.83	2.12	0.96	-0.54	-1.56	0.86	-0.27
Senguènèga	0.9	-0.11	0.79	0.56	-1.01	-1.82	1.01	1.1	0.75	-0.37	-0.12	0.49	-0.42
Bagassi	0.62	-0.47	0.66	0.46	-0.17	-2.28	0.66	2.07	1.17	-0.71	-0.16	0.34	-0.45
Legmoin	0.61	-1.66	0.17	0.28	-0.96	-0.28	1.38	0.81	0.55	0	-0.36	1.44	-0.25
Kirsi	1.02	-0.19	0.22	0.43	-0.35	-1.65	0.88	1.05	0.43	-0.27	-0.27	0.54	-0.11
Bouroum	0.78	-0.34	1.78	0.74	-0.84	-1.24	0.47	0.53	0.54	-0.84	-0.24	0.84	-0.46
Poa	0.9	-2.37	1.67	1.1	-1.93	-0.55	0.23	0.57	1.42	-0.25	-0.1	1.12	-0.1
Toécé	1.41	-1.55	1.32	1.06	-1.36	-0.99	0.53	1.42	1.41	-2.05	-0.2	0.73	-0.06
Gbondjigui	1.08	-1.42	0.2	0.42	-0.03	-0.44	1.4	0.89	0.7	-0.37	-0.53	0.24	-0.49
Loumana	1.31	-1.85	1.61	1.01	-0.88	-0.23	1.5	0.49	0.07	-1.73	-0.25	0.71	-0.11
Tansila	0.56	-0.53	0.96	0.5	-0.59	-2.45	0.61	2.31	1.57	-0.55	-0.17	0.04	-0.63
Pibaoré	0.11	-0.6	2.11	0.14	-0.08	-1.16	0.49	0.57	0.15	-1.01	-0.12	1.07	-0.07
Guéguéré	0.95	-1.61	0.13	0.3	-0.35	-0.35	1.36	0.81	0.95	-0.21	-0.28	0.12	-0.23
Tangaye	1.13	-0.04	0.75	0.44	-0.93	-1.78	0.97	1.13	0.6	-0.39	-0.17	0.03	-0.17
Ouri	0.69	-0.33	0.75	0.54	-0.61	-2.3	0.68	1.96	1.16	-0.81	-0.12	0.35	-0.41
Karangasso-Sambla	0.33	-3.2	1.65	1.01	-1.4	-0.14	2.41	1.5	0.69	-0.66	-0.19	0.01	-0.47
Tenkodogo	1.15	-0.03	0.86	0.64	-0.66	-0.63	0.65	0.95	0.14	-1.58	-0.11	0.53	-0.37
Mégué	1.06	-0.14	0.3	0.45	-0.26	-1.09	1.45	0.26	0.18	-0.85	-0.3	0.59	-0.13
Dakôrô	0.93	-1.79	1.58	0.97	-0.71	-0.26	1.48	0.5	0.1	-1.75	-0.23	1.04	-0.35
Didyr	0.78	-2.03	1.03	0.85	-1.06	-0.32	0.09	0.61	2.05	-0.39	-0.22	0.22	-0.18
Kassoum	0.6	-0.47	0.45	0.34	-0.19	-2.19	0.59	1.99	0.9	-0.7	-0.06	0.26	-0.12
Ouéléni	0.88	-1.8	1.57	0.98	-0.77	-0.24	1.46	0.5	0.11	-1.73	-0.22	0.83	-0.23
Lèba	0.38	-0.07	0.79	0.59	-1.26	-1.88	0.94	1.1	1.22	-0.49	-0.11	0.35	-0.25
Mangodara	0.9	-1.53	0.92	0.63	-0.03	-0.65	1.44	0.61	1.35	-1.95	-0.03	0.19	-0.55
Bourasso	1.15	-0.52	0.67	0.48	-0.49	-2.22	0.61	2.09	0.38	-0.59	-0.32	0.52	-0.46
Bieha	0.15	-1.81	1.35	0.82	-0.23	-0.49	0.02	0.88	1.28	-0.53	-0.23	0.3	-0.22

Dokui	1.08	-0.58	0.62	0.39	-0.79	-2.19	0.65	2.19	0.35	-0.45	-0.3	0.89	-0.58	1.28
La-Toden	1.05	0	0.35	0.5	-0.89	-1.65	1.01	1.14	0.41	-0.3	-0.16	0.42	-0.6	1.28
Niaogho	1.18	-0.38	1.05	0.75	-1.36	-0.5	0.52	0.93	0.21	-1.61	-0.1	0.88	-0.3	1.27
Pouni	0.9	-2.15	1.07	0.89	-1.33	-0.36	0.18	0.66	1.99	-0.42	-0.15	0.07	-0.09	1.26

Commune	**PC2**	**PC1**	**PC19**	**PC8**	**PC13**	**PC3**	**PC11**	**PC9**	**PC12**	**PC10**	**PC6**	**PC7**	**PC5**	**SVi**
Iôlôniôrô	0.98	-1.44	0.14	0.32	-0.25	-0.4	1.36	0.77	0.62	-0.19	-0.43	0	-0.23	1.25
Kossouka	0.31	-0.08	0.68	0.54	-0.98	-1.85	0.9	1.07	0.88	-0.42	-0.22	0.51	-0.09	1.25
Sindou	0.81	-1.69	1.52	1.02	-0.84	-0.18	1.26	0.61	0.26	-1.43	-0.03	0.27	-0.34	1.24
Nagréongo	0.92	-0.15	0.49	0.47	-0.72	-0.98	1.24	0.08	0.04	-0.74	-0.28	1.2	-0.34	1.23
Koumbri	0.01	-0.3	0.39	0.01	-0.88	-1.74	0.83	1.09	1.32	-0.48	-0.2	1.38	-0.23	1.2
Kayao	1.3	-1.81	1.46	1.02	-1.3	-0.91	0.8	1.07	1	-1.58	-0.22	1.71	-1.34	1.2
Dourtenga	0.28	-0.54	0.39	0.4	-0.37	-0.83	0.86	1.16	0.94	-1.75	-0.2	1.32	-0.49	1.17
Dissihn	0.52	-1.75	0.07	0.26	-0.68	-0.32	1.46	0.83	0.99	-0.21	-0.33	0.45	-0.13	1.16
Komtoèga	1.17	-0.02	0.88	0.64	-0.35	-0.53	0.7	0.81	0.31	-1.56	-0.33	0.16	-0.72	1.16
Poura	0.47	-0.28	0.74	0.54	-0.8	-2.3	0.69	1.94	1.17	-0.85	-0.11	0.36	-0.42	1.15
Pompoï	0.53	-0.39	0.7	0.5	-0.46	-2.3	0.64	1.99	1.18	-0.81	-0.16	0.01	-0.28	1.15
Nandiala	0.74	-2.21	1.54	0.97	-1.36	-0.53	0.23	0.75	1.43	-0.43	-0.07	0.12	-0.04	1.14
Niou	1.13	-0.34	0.75	0.64	-0.87	-0.91	1.27	0.17	0.12	-0.8	-0.24	0.29	-0.07	1.14
Zam	0.95	-0.05	0.27	0.42	-0.47	-1.06	1.35	0.16	0.17	-0.79	-0.3	0.58	-0.12	1.11
Madouba	1.11	-0.58	0.65	0.45	-0.77	-2.19	0.62	2.14	0.35	-0.48	-0.28	0.4	-0.33	1.09
Samba	1.01	-0.01	0.3	0.45	-0.85	-1.67	1	1.08	0.41	-0.29	-0.19	0.34	-0.49	1.09
Arbollé	1	-0.12	0.24	0.43	-0.36	-1.63	0.93	1.05	0.5	-0.24	-0.79	0.15	-0.09	1.07
Silly	0.21	-2.08	1.47	0.86	-0.72	-0.5	0.25	0.94	1.39	-0.66	-0.31	0.25	-0.03	1.07
Solhan	0.71	-6.05	4.65	2.35	-3.9	-2.4	4.18	1.47	1.43	-1.29	-0.75	0.75	-0.09	1.06
Di	0.4	-0.44	0.41	0.23	-0.04	-2.15	0.73	2.14	0.86	-0.45	-0.5	0.12	-0.25	1.06
Kampti	0.97	-1.71	0.2	0.16	-1.2	-0.46	1.42	0.49	1.27	-0.03	-0.31	0.68	-0.42	1.06
Namissiguima	0.47	-0.49	2.31	0.88	-0.67	-1.16	0.41	0.64	1	-1.14	-0.15	0.61	-1.68	1.03
Sebba	1.33	-6.23	4.9	2.99	-4.38	-2.51	4.12	1.61	1.44	-1.54	-0.69	0.71	-0.73	1.02
Bousséra	1.03	-1.8	0.27	0.32	-0.9	-0.43	1.48	0.74	1	-0.27	-0.64	0.99	-0.77	1.02
Guiba	0.94	-0.63	0.39	0.5	-0.33	-1.18	0.44	1.09	0.02	-1.91	-0.34	2.65	-0.64	1
Bougnounou	1.59	-2.55	1.8	1.25	-1.75	-0.63	0.11	0.59	1.76	-0.24	-0.35	1.6	-2.19	0.99
Gomponsom	1.06	-0.06	0.32	0.49	-0.77	-1.66	0.96	1.14	0.43	-0.33	-0.21	0.22	-0.6	0.99
Ziniaré	1.07	-0.31	0.63	0.58	-1.14	-0.98	1.24	0.26	0.02	-0.85	-0.06	0.57	-0.05	0.98

Môgtédo	0.88	-0.16	0.23	0.35	-0.03	-1.12	1.33	0.08	0.13	-0.63	-0.25	0.38	-0.21
Soa	1.18	-1.71	1.33	0.8	-1	-0.43	0.22	0.77	0.24	-0.42	-0.14	0.4	-0.27
Sidéradougou	0.86	-1.3	0.72	0.52	-0.48	-0.68	1.25	0.56	1.25	-1.98	-0.09	0.4	-0.07
Korsimoro	1.24	-0.75	2.09	0.17	-0.66	-1.13	0.55	0.59	0.28	-1.02	-0.02	0.11	-0.5
Doumbala	0.64	-0.52	0.64	0.4	-0.74	-2.16	0.68	2.18	0.3	-0.36	-0.18	0.19	-0.13
Lankoué	1.13	-0.1	0.66	0.59	-1.11	-2.28	0.74	1.91	0.89	-0.88	-0.66	0.09	-0.04
Tiankoura	0.7	-1.54	0.14	0.33	-0.46	-0.38	1.4	0.81	0.68	-0.2	-0.49	0.46	-0.53
Barga	0.66	-0.19	0.38	0.19	-1.15	-1.71	0.87	1.13	1.29	-0.42	-0.06	0.57	-0.64
Zabré	0.94	-0.46	0.52	0.42	-0.41	-0.75	0.77	1	0.9	-1.7	-0.24	0.36	-0.45
Kassou	1.31	-2.77	1.83	1.18	-2.48	-0.66	0.45	0.73	1.76	-0.36	-0.04	0.05	-0.1
Pouytenga	0.76	-0.62	0.73	0.66	-1.22	-0.62	0.39	0.78	0.63	-1.25	-0.07	1.41	-0.68
Thiou	0.17	-0.29	0.42	0.4	-0.69	-1.69	0.87	1.11	1.22	-0.41	-0.08	0.51	-0.67
Koupèla	0.93	-0.24	0.59	0.6	-1.04	-0.58	0.57	0.83	0.39	-1.53	-0.35	0.81	-0.11
Ziou	1.13	-0.58	0.55	0.62	-0.53	-1.49	0.38	1.69	0.9	-2.06	-0.25	0.72	-0.22
Yako	0.98	-0.11	0.34	0.5	-0.89	-1.63	1.02	1.14	0.5	-0.27	-1.48	0.75	0
Nako	0.95	-1.72	0.3	0.28	-0.91	-0.4	1.35	0.67	0.91	-0.08	-0.48	0.7	-0.73
Zitenga	1.04	-0.25	0.57	0.56	-1.04	-0.96	1.28	0.2	0.06	-0.87	-0.15	0.44	-0.05

Commune	**PC2**	**PC1**	**PC19**	**PC8**	**PC13**	**PC3**	**PC11**	**PC9**	**PC12**	**PC10**	**PC6**	**PC7**	**PC5**
Andemtenga	0.33	-0.14	0.5	0.53	-0.33	-0.57	0.67	0.67	0.36	-1.4	-0.43	1.2	-0.57
Mané	1.09	-0.69	2.12	0.17	-0.51	-1.19	0.52	0.67	0.14	-1.06	-0.15	0.02	-0.32
Niangoloko	1.15	-1.51	1.06	0.71	-0.15	-0.45	1.42	0.47	0.18	-1.87	-0.26	0.61	-0.56
Zambo	0.96	-1.71	0.11	0.27	-0.6	-0.33	1.37	0.8	0.96	-0.17	-0.43	0.15	-0.59
Loropéni	0.92	-1.75	0.27	0.2	-1.04	-0.38	1.35	0.64	0.93	-0.04	-0.26	0.77	-0.83
Gaoua	0.7	-1.74	0.21	0.2	-1.03	-0.38	1.3	0.56	0.89	-0.03	-0.47	1.45	-0.88
Sourgoubila	1.05	-0.4	0.72	0.6	-1.11	-0.86	1.2	0.09	0.08	-0.81	-0.32	1.13	-0.59
Toèguen	1.1	-0.39	0.75	0.62	-0.97	-0.9	1.22	0.13	0.13	-0.77	-0.24	0.18	-0.09
Bagré	0.18	-0.05	0.7	0.48	-0.36	-0.64	0.62	0.76	0.13	-1.4	-0.24	0.93	-0.36
Yargo	1.03	-0.04	0.49	0.56	-0.5	-0.56	0.74	0.79	0.47	-1.6	-0.33	0.16	-0.5
Baskouré	1.09	-0.1	0.56	0.62	-0.9	-0.53	0.71	0.85	0.44	-1.67	-0.28	0.09	-0.18
Tiébélé	0.69	-0.48	0.5	0.6	-0.41	-1.49	0.26	1.74	0.85	-2.15	-0.32	0.91	-0.02
Périgban	1.02	-1.54	0.41	0.26	-1.06	-0.49	1.37	0.54	1.1	-0.05	-0.38	0.35	-0.85
Boken	1.01	-0.02	0.29	0.48	-0.78	-1.66	0.98	1.09	0.5	-0.3	-0.82	0.14	-0.24
Pella	1.28	-1.69	1.27	0.87	-1.23	-0.52	0.01	0.68	0.13	-0.1	-0.04	0.65	-0.66

Commune	PC2	PC1	PC19	PC8	PC13	PC3	PC11	PC9	PC12	PC10	PC6	PC7	PC5	SVi
Bingo	0.99	-2.31	1.58	1.09	-1.89	-0.61	0.1	0.6	1.33	-0.1	-0.03	0.29	-0.4	0.64
Gomboro	1.08	-0.3	0.54	0.16	-0.84	-2.27	0.66	1.94	0.91	-0.88	-0.22	0.37	-0.51	0.64
Bomborokui	0.85	-0.47	0.6	0.42	-0.69	-2.15	0.66	2.18	0.25	-0.37	0	0.15	-0.8	0.63
Seytenga	2.33	-6.1	4.77	2.42	-4.69	-2.43	4.14	1.71	1.27	-1.65	-0.73	0.35	-0.76	0.63
Tensobentenga	1.09	-0.13	0.56	0.6	-0.96	-0.52	0.67	0.81	0.46	-1.65	-0.18	0.38	-0.51	0.62
Titabè	1.98	-6.27	4.79	2.45	-4.57	-2.48	4.17	1.59	1.49	-1.52	-0.79	0.88	-1.1	0.62
Yargatenga	0.95	-0.67	0.31	0.34	-0.14	-0.84	0.82	0.97	0.92	-1.6	-0.03	0.06	-0.51	0.58
Kogho	0	-0.19	0.14	0.25	-0.02	-1.11	1.33	0	0.18	-0.59	-0.31	1.4	-0.51	0.57
Bitou	0.02	-0.41	0.49	0.35	-0.13	-0.71	0.72	0.79	0.71	-1.51	-0.28	1.22	-0.7	0.56
Roukô	0.71	-0.77	0.7	0.16	-0.28	-0.82	0.53	0.61	0.33	-1.17	-0.23	1.29	-0.5	0.56
Gbomblora	1.9	-2.02	0.01	0.04	-1.73	-0.29	1.41	0.46	0.96	-0.22	-0.5	1.45	-0.91	0.56
Pilimpikou	0.36	-0.03	0.2	0.34	-0.77	-1.62	1.06	0.99	0.41	-0.13	-0.14	0.61	-0.72	0.56
Saaba	1.19	-6.68	2.73	1.71	-2.9	-0.66	3.66	1.18	0.34	-0.46	-0.69	1.15	-0.01	0.56
Komin-Yanga	0.92	-0.08	0.47	0.52	-1.66	-0.7	0.68	1.11	0.86	-1.9	-0.02	0.74	-0.39	0.55
Zoaga	0.96	-0.68	0.39	0.19	-0.07	-0.78	0.92	1.05	1	-1.75	-0.32	0.2	-0.58	0.53
Barani	0.38	-0.66	0.43	0.49	-0.86	-2.13	0.59	2.19	0.41	-0.36	-0.01	0.25	-0.19	0.53
Dapeolgo	0.56	-0.08	0.49	0.5	-0.65	-0.99	1.37	0.2	0.1	-0.85	-0.33	0.3	-0.13	0.49
Ouéssa	0.04	-1.74	0.06	0.18	-0.77	-0.28	1.36	0.78	0.95	-0.03	-0.34	0.82	-0.56	0.47
Ambsouya	0.56	-0.12	0.49	0.49	-0.73	-0.98	1.32	0.17	0.09	-0.82	-0.31	0.59	-0.28	0.47
Kando	1.05	-0.33	0.66	0.62	-0.67	-0.58	0.52	0.71	0.45	-1.34	-0.26	0.26	-0.64	0.45
Djigouè	0.84	-1.84	0.24	0.17	-1.7	-0.49	1.33	0.29	1.16	-0.19	-0.55	2.31	-1.13	0.44
Ouô	0.21	-1.43	0.88	0.68	-0.29	-0.66	1.37	0.56	1.32	-2	-0.03	0.2	-0.38	0.43
Bissiga	0.6	-0.37	0.61	0.41	-0.49	-0.67	0.73	0.68	0.2	-1.35	-0.41	1.41	-0.93	0.42
Koper	0.93	-1.79	0.08	0.23	-0.9	-0.3	1.37	0.75	0.95	-0.08	-0.41	0.26	-0.67	0.42
Dalô	1.19	-2.45	1.7	1.15	-1.43	-0.61	0.12	0.71	1.78	-0.38	-0.12	0.94	-2.19	0.41
Ouargaye	0.09	-0.61	0.3	0.31	-0.1	-0.86	0.81	1.03	0.92	-1.6	-0.07	0.69	-0.55	0.36
Gounguen	0.85	-0.16	0.46	0.51	-0.67	-0.57	0.61	0.63	0.33	-1.39	-0.22	0.82	-0.89	0.31
Tougan	0.47	-0.31	0.43	0.22	-0.43	-2.15	0.72	1.99	0.97	-0.65	-1.51	0.79	-0.24	0.3
Kongoussi	2.65	-1.26	0.72	0.18	-1.89	-0.87	0.76	0.81	0.24	-1.3	-0.11	0.56	-0.21	0.28
Koudougou	1.4	-2.66	1.78	1.15	-2.14	-0.51	0.4	0.62	1.59	-0.47	-1.24	2.18	-1.82	0.28
Soudougui	0.91	-0.85	0.25	0.19	-0.75	-0.9	0.87	0.92	0.88	-1.46	-0.1	0.58	-0.33	0.21

Ourgou-Manéga	0.61	-0.12	0.51	0.48	-0.61	-1.01	1.29	0.15	0.05	-0.74	-0.25	0.13	-0.28
Sampelga	0.73	-5.77	4.45	2.18	-4	-2.4	3.93	1.58	1.13	-1.64	-0.5	1.22	-0.71
Boulsa	0.6	-0.58	1.26	0.07	-0.07	-1.09	0.53	0.77	0	-1.12	-0.13	0.37	-0.42
Dargo	0.15	-0.49	1.4	0.04	-0.13	-1.08	0.5	0.65	0.06	-1.07	-0.24	1	-0.61
Sônô	0.04	-0.42	0.54	0.27	-0.04	-2.2	0.65	2.06	0.45	-0.56	-0.25	0.33	-0.69
Zéguédéguen	0.14	-0.41	1.43	0.08	-0.4	-1.1	0.49	0.6	0.05	-0.99	-0.24	1.13	-0.62
Zoungou	0.97	-0.29	0.23	0.35	-0.25	-1.13	1.41	0.13	0.18	-0.68	-0.32	0.09	-0.53
Ipelsé	1.32	-1.67	1.37	1.02	-1.5	-0.8	0.67	1.1	0.73	-1.93	-0.22	0.54	-0.49
Saponé	1.35	-1.73	1.4	1.05	-1.68	-0.79	0.67	1.14	0.75	-1.97	-0.19	0.28	-0.19
Guibaré	0.88	-1.01	0.43	0.38	-0.86	-0.8	0.57	0.85	0.21	-1.33	-0.04	1.09	-0.28
Dialgaye	0.51	-0.05	0.5	0.54	-0.75	-0.55	0.69	0.78	0.46	-1.58	-0.29	0.35	-0.53
Midebdo	0.87	-1.85	0	0.19	-1.34	-0.33	1.43	0.61	0.64	-0.01	-0.61	1.3	-0.84
Banfora	1.22	-1.94	1.16	0.92	-1.7	-0.28	1.4	0.66	0.07	-1.39	-0.49	0.52	-0.1
Gayéri	0.72	-3.08	3.44	1.35	-2.14	-0.86	1.02	0.99	0.56	-1.77	-0.34	0.36	-0.21
Boussouma	0.45	-0.73	2.07	0.14	-0.65	-1.1	0.52	0.6	0.28	-1.1	-0.04	0.15	-0.58
Lalgaye	0.43	-0.69	0.25	0.25	-0.36	-0.87	0.78	0.87	0.88	-1.43	-0.05	0.25	-0.31
Laye	0.77	-0.46	0.77	0.67	-1.3	-0.87	1.29	0.24	0.08	-0.92	-0.27	0.14	-0.16
Saolgo	0.35	-0.03	0.28	0.38	-0.5	-1.09	1.33	0.18	0.16	-0.73	-0.23	0.06	-0.2
Djibasso	0.2	-0.63	0.54	0.37	-0.8	-2.15	0.54	2.1	0.39	-0.52	-0.18	0.09	-0.03
Boudri	0.12	-0.23	0.16	0.28	-0.04	-1.13	1.39	0.09	0.2	-0.65	-0.31	0.44	-0.41
Gogo	1.12	-0.64	0.56	0.63	-0.37	-1.25	0.37	1.38	0.01	-2	-0.2	0.77	-0.49
Oronkua	0.83	-1.95	0.04	0.12	-1.41	-0.29	1.38	0.58	0.96	-0.06	-0.49	0.99	-0.85
Dano	0.27	-1.81	0.01	0.14	-1.1	-0.26	1.34	0.67	0.93	-0.07	-0.12	0.22	-0.41
Boala	0.29	-0.44	1.41	0.06	-0.35	-1.12	0.49	0.66	0.07	-1.01	-0.03	0.36	-0.61
Siglé	0.35	-1.69	1.25	0.78	-1.32	-0.47	0.02	0.6	0.06	-0.16	-0.02	0.58	-0.26
Pabré	1.83	-6.91	2.8	1.83	-3.27	-0.69	3.67	1.27	0.92	-0.44	-0.79	1.25	-1.78
Zogoré	0.65	-0.18	0.77	0.64	-1.19	-1.81	0.92	1.16	0.53	-0.43	-0.08	0.08	-1.39
Béguédo	0.69	-0.43	1	0.73	-1.6	-0.47	0.53	0.91	0.25	-1.66	-0.15	0.04	-0.22
Diapangou	0.71	-2.36	1.22	0.28	-1.23	-0.28	0.78	0.97	0.47	-1.56	-0.45	1.71	-0.66
Kyon	1.27	-2.36	1.12	0.96	-1.69	-0.39	0.2	0.66	2.08	-0.41	-0.32	0.18	-1.72
Yamba	0.44	-2.49	1.22	0.28	-1.71	-0.27	0.79	1.08	0.48	-1.61	-0.33	2.64	-0.97
Oula	0.02	-0.21	0.76	0.62	-1.53	-1.82	0.93	1.24	0.62	-0.53	-0.14	0.2	-0.61
Nanoro	1.3	-1.76	1.32	0.9	-1.33	-0.51	0.02	0.65	0.18	-0.13	-0.13	0.04	-1.03

Tiéfora	0.34	-1.79	1.1	0.86	-1.15	-0.37	1.42	0.59	0.16	-1.63	-0.15	0.17	-0.08	-0.53
Koala	0.55	-1.67	1.04	0.03	-0.73	-0.28	0.61	0.55	0.2	-1.15	-0.39	0.87	-0.28	-0.65
Kpuéré	0.9	-1.88	0.02	0.17	-1.54	-0.3	1.4	0.59	0.6	-0.08	-0.55	0.8	-0.79	-0.66
Diabo	0.51	-2.1	1.03	0.11	-0.39	-0.24	0.77	0.73	0.5	-1.31	-0.05	0.29	-0.52	-0.67
Ramongo	0.05	-2.37	1.53	1.04	-2.08	-0.61	0.13	0.61	1.24	-0.1	-0.58	0.59	-0.12	-0.67
Guiaro	0.86	-0.16	0.23	0.16	-0.61	-1.57	0.31	1.41	0.84	-1.77	-0.36	0.65	-0.73	-0.74
Loumbila	1.07	-0.53	0.68	0.65	-1.49	-0.98	1.2	0.27	0.15	-0.79	-0.06	1.04	-1.96	-0.75
Komki-Ipala	1.14	-6.43	2.48	1.48	-2.43	-0.72	3.56	1.06	0.11	-0.56	-0.73	0.43	-0.2	-0.81

Commune	PC2	PC1	PC19	PC8	PC13	PC3	PC11	PC9	PC12	PC10	PC6	PC7	PC5	SVi
Foutouri	0.35	-3.52	3.7	3.1	-3.39	-0.97	1.04	1.25	0.6	-2.27	-0.31	0.44	-0.86	-0.84
Rollo	0.63	-1.03	0.51	0.27	-0.86	-0.83	0.6	0.8	0.19	-1.27	-0.12	0.9	-0.64	-0.85
Tikaré	0.44	-0.84	0.62	0.25	-0.51	-0.84	0.53	0.75	0.3	-1.26	-0.15	0.2	-0.35	-0.86
Tibga	0.56	-2.37	1.2	0.24	-1.2	-0.27	0.82	0.91	0.5	-1.48	-0.38	1.39	-0.78	-0.86
Nasséré	0.19	-0.8	0.64	0.04	-0.32	-0.83	0.48	0.72	0.3	-1.23	-0.04	0.13	-0.19	-0.91
Sangha	0.34	-0.75	0.18	0.1	-0.37	-0.88	0.8	0.87	0.92	-1.42	-0.22	0.33	-0.82	-0.92
Nobéré	1.17	-0.85	0.64	0.71	-1.06	-1.19	0.43	1.44	0	-2.14	-0.18	0.49	-0.41	-0.95
Komsilga	0.91	-6.65	2.63	1.61	-2.8	-0.65	3.72	0.99	0.24	-0.58	-0.7	0.34	-0.02	-0.96
Yondé	0.93	-0.89	0.24	0.27	-0.75	-0.88	0.88	0.91	0.92	-1.52	-0.31	0.04	-0.85	-1.01
Kindi	0.39	-1.84	1.29	0.82	-1.59	-0.5	0.12	0.68	0.06	-0.16	-0.66	0.44	-0.11	-1.06
Bobo-Dioulasso	1.17	-4.05	2.03	1.21	-2.31	-0.05	2.9	1.58	0.49	-0.96	-6.36	3.87	-0.66	-1.14
Bakata	0.13	-2.35	1.56	1	-1.03	-0.56	0.13	0.84	1.75	-0.57	-0.36	0.38	-2.09	-1.17
Niankôrôdougou	0.22	-2	1.56	0.99	-1	-0.22	1.54	0.36	0.06	-1.85	-0.39	0.13	-1.62	-1.22
Bilanga	1.38	-2.5	1.45	0.42	-1.65	-0.44	0.8	0.96	0.04	-1.69	-0.48	1.34	-0.89	-1.26
Béré	0.65	-0.51	0.45	0.52	-0.04	-1.27	0.37	1.25	0	-1.87	-0.23	0	-0.61	-1.29
Boussouma	0.99	-0.32	0.89	0.66	-0.96	-0.52	0.64	0.79	0.1	-1.5	-0.02	0.03	-2.11	-1.33
Boussou-Koula	0.85	-1.91	0.01	0.02	-1.7	-0.27	1.37	0.55	0.58	-0.18	-0.5	0.62	-0.82	-1.38
Ouahigouya	4.69	-0.55	0.24	0.22	-2.07	-1.56	1.07	1.07	0.23	-0.1	-0.97	1.83	-5.53	-1.43
Dassa	0.34	-2.26	0.96	0.85	-1.34	-0.35	0.1	0.73	2.22	-0.51	-0.01	0.66	-2.87	-1.48
Batié	0.13	-1.81	0	0.14	-1.37	-0.26	1.39	0.64	0.58	-0.12	-0.44	0.07	-0.44	-1.49
Bindé	0.69	-0.86	0.59	0.69	-1.16	-1.17	0.37	1.47	0.05	-2.21	-0.11	0.29	-0.17	-1.53
Bartiébougou	0.38	-3.32	3.41	1.44	-3.06	-0.85	1.03	1.2	0.59	-2.03	-0.46	0.94	-0.82	-1.55

Gomboussougou	0.61	-0.88	0.56	0.61	-0.96	-1.21	0.5	1.32	0.02	-1.97	-0.11	0.15	-0.2
Partiaga	1.3	-3.47	1.8	0.95	-3.58	-0.62	1.07	1.1	0.9	-1.9	-0.41	1.82	-0.7
Thion	0.5	-2.45	1.33	0.26	-1.65	-0.43	0.8	0.88	0.25	-1.62	-0.55	1.51	-0.74
Niégo	0.85	-2.15	0.07	0.06	-2.12	-0.21	1.42	0.56	0.93	-0.22	-0.44	0.03	-0.92
Koubri	1.27	-6.92	2.77	1.76	-3.22	-0.67	3.72	1.15	0.5	-0.55	-1.28	1.47	-2.19
Manga	1.21	-1.17	0.73	0.81	-1.51	-1.2	0.44	1.49	0.25	-2.06	-0.19	1.87	-2.87
Sabsé	0.73	-0.97	0.56	0.31	-0.42	-0.83	0.57	0.65	0.14	-1.13	-0.36	0.04	-1.58
Sapouy	0.63	-2.47	1.56	1.06	-1.09	-0.52	0.04	0.77	2	-0.58	-0.43	1.96	-5.28
Mani	0.46	-2.54	1.37	0.41	-1.94	-0.46	0.79	0.92	0.26	-1.72	-0.52	1.24	-0.88
Matiakoali	0.14	-3.08	1.6	1.46	-3.28	-0.44	0.98	1.24	0.51	-1.95	-0.56	1.74	-0.98
Tanguen-Dassouri	0.64	-6.86	2.68	1.64	-3.38	-0.62	3.78	1.05	0.27	-0.52	-0.9	0.14	-0.56
Bogandé	0.46	-2.41	1.29	0.28	-1.6	-0.41	0.75	0.91	0.04	-1.68	-0.42	0.76	-0.72
Soubakaniédougou	0.42	-1.91	1.08	0.92	-1.35	-0.32	1.31	0.6	0.21	-1.55	-0.31	0.26	-2.15
Piéla	0.35	-2.51	1.35	0.29	-1.73	-0.41	0.87	0.86	0.05	-1.6	-0.4	0.66	-0.63
Liptougou	0.47	-2.6	1.37	0.46	-2.12	-0.43	0.8	0.99	0	-1.76	-0.5	1.16	-0.95
Kompienga	0.49	-2.6	1.43	0.28	-1.45	-0.63	0.92	0.54	0.03	-1.52	-0.13	1.58	-2.09
Madjoari	0.11	-3.4	1.97	1.59	-3.25	-0.71	1.09	0.92	0.33	-1.82	-0.58	1.29	-0.72

Commune	PC2	PC1	PC19	PC8	PC13	PC3	PC11	PC9	PC12	PC10	PC6	PC7	PC5	SVi
Tansarga	0.62	-3.15	1.42	0.37	-2.83	-0.57	1.11	0.73	0.76	-1.59	-0.34	1.17	-0.89	-3.19
Kantchari	0.33	-3.18	1.51	0.77	-2.89	-0.62	0.93	0.87	0.77	-1.8	-0.29	0.75	-0.57	-3.42
Lôgbou	1.02	-4	1.97	0.93	-5.16	-0.69	1.26	1.27	0.96	-2.06	-0.63	2.47	-1.12	-3.78
Namouno	0.5	-3.48	1.69	0.61	-3.39	-0.58	1.22	0.86	0.97	-1.57	-0.64	0.66	-0.8	-3.95
Pama	2.04	-4.34	2.52	2.17	-6.05	-0.97	1.34	1.29	0.38	-2.39	-0.69	1.37	-1.05	-4.38
Tambaga	0.46	-3.61	1.67	0.62	-4.08	-0.62	1.2	0.99	0.87	-1.78	-0.59	0.69	-0.34	-4.52
Botou	0.43	-3.28	1.52	0.52	-3.22	-0.6	0.96	0.95	0.8	-1.81	-0.42	0.36	-0.96	-4.75
Thiou	0.82	-2.85	1.47	1.04	-1.71	-0.41	0.16	0.74	3.24	-0.68	-0.69	0.13	-6.16	-4.9
Diapaga	1	-3.75	1.85	1.18	-4.53	-0.73	1.13	1.11	0.9	-2.09	-0.26	0.24	-1.02	-4.97
Réo	1.34	-2.69	1.16	1.09	-2.28	-0.41	0.1	0.57	2.42	-0.35	-0.5	0.48	-5.97	-5.04
Falagountou	0.91	-5.78	4.69	2.33	-4.83	-2.44	4.11	1.89	0.83	-1.98	-0.14	0.12	-4.87	-5.16
Sabou	1.42	-3.46	1.89	1.33	-2.54	-0.44	0.42	0.67	3.59	-0.85	-1.81	2.28	-9.06	-6.56
Ouagadougou	1.44	-8.58	3.08	1.76	-4.69	-0.97	4.74	1.03	0.47	-1.37	-18.56	5.73	-4.74	-20.66

14 DISCUSSION OF RESULTS TEMPORAL ANALYSIS WITH PCA

Table 14.1: Vulnerability components summary of 2015

Component	Variance	+ or –	Dominant Variables	Loadings
PC3 – Conflicts	20.37%	+	GNI Conflicts	0.72 0.97
PC2 – Underweight	17.49%	+	Prevalence GAM Prevalence Underweight	0.94 0.73
PC5 – Chronic Malnutrition	13.87%	+	Chronic malnutrition	0.97
PC9 – Immunization rates	12.25%	–	Immunization DTP	0.94
PC6 – Measle cases	12.25%	+	Measle cases	0.99
PC4 – Cadre Harmonisé	11.32%	+	Cadre Harmonisé	0.97
PC1 – Natural Disaster	10.88%	+	Affected Natural disaster	0 87

Table 14.2: Vulnerability components summary of 2016

Component	Variance	+ or –	Dominant Variables	Loadings
PC1 – Underweight	14.96%	+	Underweight	0.89
PC4 – Measle cases	12.94%	+	Measle cases	0.96
PC7 – Female malnutrition	12.91%	+	Chronic malnutrition in woman	0.94
PC5 – GAM in children	12.49%	+	GAM in children	0.91
PC8 – Cadre Harmonisé	12.36%%	+	Cadre Harmonisé	0.91
PC3 – Immunization rate	12.13%	–	Immunizatrion DTP	0.93
PC2 – Conflict	11.03%	+	No. Conflict	-0.82

Table 14.3: Vulnerability components summary of 2017

Component	Variance	+ or –	Dominant Variables	Loadings
PC2 – Immunization and Disaster	16.56%	+	Immunization rate DTP	0.92
			No. affected by natural disaster	0.84
PC1 – Conflict and malnutrition	15.96%	+	ACLED	0.71
			Low BMI women	0.87
PC7 – Migration	12.39%	+	No. IDPs	0.96
PC4 – Measles	11.04%	+	Confirmed measles cases	0.95
PC5 – Child malnutrition	10.48%	+	GAM in children	0.96
PC3 – Water availability	10.07%	–	Improved water sources	0.98
PC8 – Child mortality	9.59%	+	Mortality rate	0.67

Table 14.4: Vulnerability components summary of 2018

Component	Variance	+ or –	Dominant Variables	Loadings
PC1 – Disaster and literacy rate	16.56%	+	Literacy rate	0.91
			No. affected by natural disaster	0.93
PC2 – Conflict	15.96%	+	Conflict	0.0.89
			IDPs	0.91
PC4 – Children's health	12.39%	–+	Mortality rate	0.71
			Fully immunized children	0.91
PC7 – Undernourishment	11.04%	+	Cadre Harmonisé	0.90
PC3 – Measles	10.48%	+	Confirmed measles cases	0.98
PC5 – Water availability	10.07%	–	Improved water sources	0.99
PC6 – HIV	9.59%	+	Adults living with HIV	0.94

Table 14.5: Vulnerability components summary of 2019

Component	Variance	+ or –	Dominant Variables	Loadings
PC1 – Conflict	18.84%	+	ACLED	0.92
			IDPs	0.96
PC2 – Immunization	17.26%	–	Immunization rate DTC	0.79
			Immunization against measles	0.96
PC6 – Natural Disaster	13.15%	+	Affected by disaster	0.82
			Adult literacy rate	0.78
PC4 – Measles	11.15%	+	Confirmed measles cases	0.96
PC8 –Female health	9.89%	+	Low BMI women	0.89
PC3 – Health care availability	9.70%	–	Physician density	0.98
PC5 – Water availability	9.50%	–	Improved water sources	0.97

Table 14.6: Vulnerability components summary of 2020

Component	Variance	+ or –	Dominant Variables	Loadings
PC1 – Conflict	20.98%	+	ACLED	0.72
			IDPs	0.98
PC2 – Disaster	17.64%	+	Affected by disaster	0.91
			GNI	0.83
PC4 – Measles	12.82%	+	Confirmed measles cases	0.96
PC3 – Mortality	12.34%	+	Mortality rate under 5	0.82
PC6 – Immunization	10.61%	+	Immunization against measles	0.94
PC7 –Female health	10.51%	+	Low BMI women	0.85
PC5 – Water availability	9.50%	–	Improved water sources	0.99

Table 14.7: Vulnerability components summary of 2021

Component	Variance	+ or −	Dominant Variables	Loadings
PC2 – Disaster	17.19%	–	GNI Affected by disaster	0.86 0.87
PC1 - Immunization Measles	13.57%	–	Measle immunization	0.89
PC8 – Water availability	13.02%	–	Improved water sources	0.88
PC7 – Female health	10.94%	+	Low BMI women	0.88
PC4 – Conflict	10.91%	+	Conflict barometer	0.95
PC6 – IDPs	10.20%	+	IDPs	0.91
PC3 – Measles	10.19%	+	Confirmed measles cases	0.92

14.0.1 Results vulnerability in temporal analysis

Table 14.1 until table 14.7 show how the vulnerability score of each region is built up. It shows that due to the low amount of input variables, many components where needed to present 90% of the variance from the original data set. This was also shown by the low KMO-value. Due to the low amount of measurement points, the algorithm can not find the perfect sampling adequacy and the proportion of variance among the results might be due to common variance. When zooming back into the tables, it is important to note that the direction of the component is based on the influence of the dominant variables on social vulnerability. If the dominant variables are positively correlated to social vulnerability the direction will be positive, however when negative related, the direction is chosen to be negative. The decision on the correlation is based on expert knowledge within the NLRC. It is important to note, that in some cases, one dominant variable can be positively related, whereas the other is negatively related. Such is the case with PC3 in table 14.1. In these cases, the dominant variable with the highest loading was considered normative.

The social vulnerability scores are mapped in figure 14.1a until figure 14.7a, and shown in table 14.8. This shows that high social vulnerability scores are visible in the Sahel - and Eastern regions, the capital region. Furthermore, an initial look at these maps, shows that high social vulnerability is often present in areas with many conflict events. However, not all areas with high conflict events, have a high social vulnerability. For example, after the conflict intensified (2017), the Sahel was the most vulnerable region 80 % of the time, and also has the highest number of conflict events. However, the Centre-Nord, and Nord also have a high number of conflict events, but do not have high vulnerability scores.

When taking a closer look into the composition of the social vulnerability it can be seen, that the reasoning behind the social vulnerability is different in each region. In some cases the vulnerability is drastically decreased due to decreasing vulnerability indicators, such as in the Centre in 2017. Over the years, high values for social vulnerability are constantly visible in the Sahel, the East, the Centre and Centre-East. Mainly caused by the high contribution of conflict, hazards, food scarcity, and child

	2015	2016	2017	2018	2019	2020	2021
Boucle	3.57	2.98	-0.21	0.48	-1.49	0.35	3.29
Cascades	8.25	13.69	1.67	4.72	0.04	4.6	4.62
Centre	8.51	6.15	3.45	14.17	7.42	9.77	2.71
Centre-Est	5.06	4.89	4. 22	3.88	1.81	3.65	4.65
Centre-Nord	8.16	5.30	3.23	2.4	0.61	1.99	4.63
Centre-Ouest	2.07	2.20	1.81	3.55	1.61	2.32	0.60
Centre-Sud	4.64	0.38	2.78	1.73	-1.42	1.13	2.66
Est	5.68	16.13	16.62	9.09	6.22	9.75	8.10
Hauts Bassin	7.99	7.41	2.88	10.13	4.02	5.01	1.18
Nord	2.35	5.57	0.52	1.19	-1.02	-0.31	0.85
Plateau Central	3.35	3.18	2.66	2.39	0.58	3.56	8.81
Sahel	2.99	5.64	15.49	14.47	8.46	16.62	1.73
Sud-Ouest	4.61	2.06	3.76	2	-1.81	5.07	1.54

Table 14.8: Social vulnerability per region per year

and female health. If these results are to be used for policy implication, it is thus important to consider the composition of social vulnerability in each region separately.

14.0.2 Validation of results

To identify patterns in social vulnerability, it is important that the obtained results are trust worthy. Results of the KMO-score, already showed that the data set has a too low amount of data points to blindly trust the results. Verification of the social vulnerability values is thus extra important due to the low scores of the KMO-tests.

While it is practically impossible to prove the complete correctness of the PCA model that was developed, systematic verification can greatly reduce the number of errors. To guarantee this, continuous integration and testing took place while setting up the model. This led to the decision to always use 7 principal components, even if 6 would have been enough to present 90% of variance. This is necessary because, the sum of component scores is taken to determine the social vulnerability, a different amount of components between the years would lead to too great a disparity in the results. Furthermore, extreme value testing was used. Which has led to the insight that indicators with constant values over regions are not competitive with PCA, because they do not contribute to variance and are thus removed. Furthermore, a *smell test* was executed with employees of 510 which verified sensible results. Finally, the vulnerability profiles obtained with the PCA method, are compared to the result of the well-known sub-national INFORM model that is devel-

Region	Mean Squared Error
Boucleau du Mouhoun	2.46
Cascades	1.27
Centre	2.74
Centre-Est	1.55
Centre-Nord	2.29
Centre-Ouest	2.84
Centre-Sud	1.28
Est	2.02
Hauts-Bassins	3.38
Nord	2.60
Plateau-Central	0.35
Sahel	1.94
Sud-Ouest	0.91

Table 14.9: Difference between social vulnerability calculated with PCA and INFORM.

oped for the entire Sahel region (Disaster Risk Management Knowledge Center, EC 2022). However, this shows very different results when comparing the relative difference in social vulnerability between the regions and over time. The mean-squared error between the two is presented for each region in table 14.9. The differences between both vulnerability scores is mapped in appendix 15.3.

Therefore, it was decided that the PCA results are not trustworthy to identify temporal patterns in social vulnerability. Thus the analysis for the temporal pattern identification is executed on the Social Vulnerability scores obtained by INFORM. Unfortunately, INFORM does not consider the elderly, and past conflict as an indicator. Which are important indicators for the social vulnerability specific in Burkina Faso. To obtain the social vulnerability from the INFORM data sets, the following equation is used:

$$Socialvulnerability = Vulnerability^{1/2}_{INFORM} * Lackofcopingcapacity^{1/2}_{INFORM} \tag{14.1}$$

Hence, in future research, it would be better to either obtain more measurement point to develop the PCA, but for this better data availability is necessary. Or develop the social vulnerability score with the use of hierarchical methods, but this will deliver less precise results for a temporal comparison and will make it more difficult to understand the contribution of indicators to the social vulnerability since this is determined by the modeller.

SQ: What are the vulnerability scores on regional level from 2015 – 2021 when calculated with PCA?

Over the years a clear increase in vulnerability can be see within the entire country. It can be seen that the social vulnerability in the high vulnerable regions is mainly composed of a high contribution of conflict, hazards, food scarcity, and child and female health. Furthermore, an initial look at these maps, shows that high social vulnerability is often present in areas with many conflict events. However, not all areas with high conflict events, have a high social vulnerability. There are also regions, where well working coping mechanisms reduce the vulnerability, these are high water availability and immunization rates. The results differ tremendously per region. Hence, if these results are to be used for policy implication, it is important to consider the composition of social vulnerability in each region separately.

Nevertheless, these results need to be challenged due to the low KMO-value that was found in the validation of the method. All years obtained a sufficient score for Barlett Sphericity test. Indicating that there was enough variance in the data set to execute a PCA analysis. However, the KMO-test showed that the sampling adequacy of the data set is not sufficient, meaning that the variance might be caused by common variance, and results are unreliable. Larger data sets are needed to obtain sufficient KMO-values. This explains why PCA is often used on community level assessments and not in regional assessments.

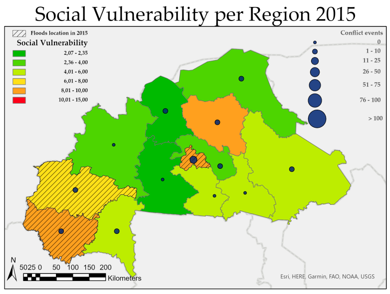
Policy recommendations

The found social vulnerability profiles show a varying social vulnerability pattern over time. High vulnerable profiles are visible in the Sahel and East, which would call for humanitarian action in these regions. Nevertheless, the profiles are only available on a regional level, which lacks insight for local applied humanitarian aid. Due to the statistical approach the PCA method provides an insight in the composition of vulnerability, and the change of composition over time. In contrary to hierarchical methods, this change is not caused by the decisions experts make during the weighing stage. Deriving these results on a community level, will provide useful insight for humanitarian aid decision making. For this better granularity of indicator data is necessary. In this section it is important to note, that the reliability of these results is questionable due to the low KMO-values.

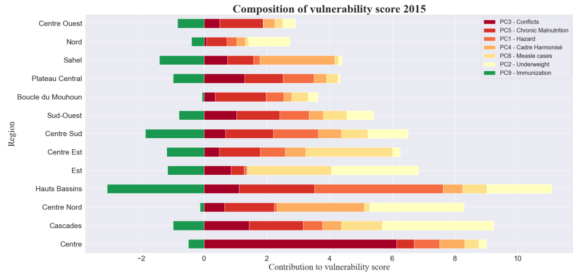
Future research

In future research, it would be better to either obtain more measurement points to develop the PCA on community levels so that the KMO-value will be sufficient and results will be more useful to make decisions in humanitarian aid work. Or develop the social vulnerability score with the use of hierarchical methods. However, this will not provide a non-biased insight in the composition of the social vulnerability score. Which will deliver better insights in the temporal change in vulnerability, since it can be derived how the social vulnerability components are build up.

The shown comparison could be improved by calculating an hierarchical value for the social vulnerability with that includes past conflict events and the number of elderly.

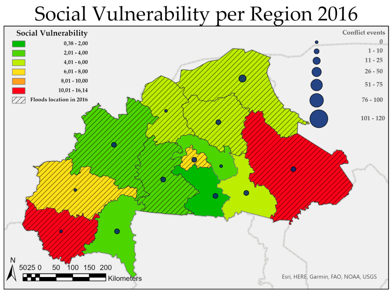


(a) Vulnerability profile of 2015, plotted together with the conflict and hazard events.

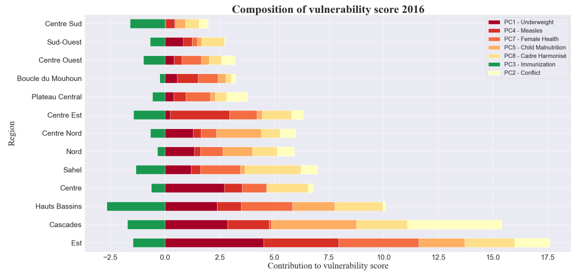


(b) Composition of social vulnerability per region.

Figure 14.1: Social vulnerability 2015

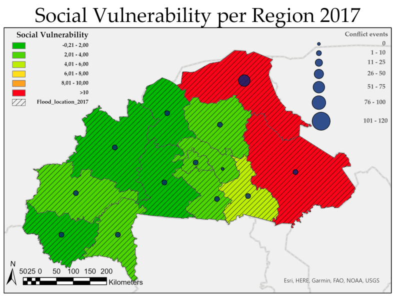


(a) Vulnerability profile of 2016, plotted together with the conflict and hazard events.

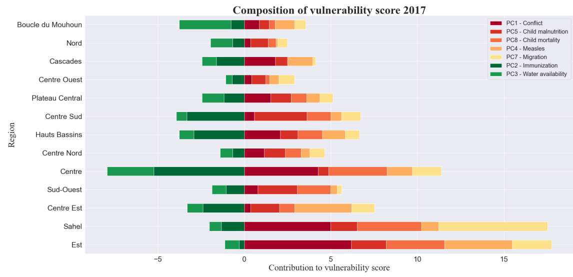


(b) Composition of social vulnerability per region.

Figure 14.2: Social vulnerability 2016

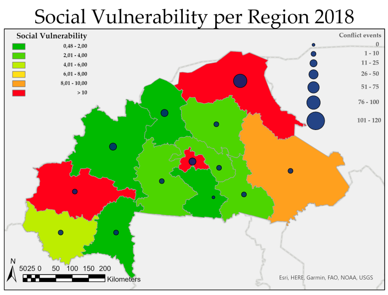


(a) Vulnerability profile of 2017, plotted together with the conflict and hazard events.

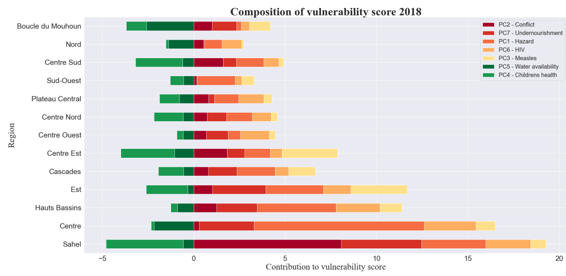


(b) Composition of social vulnerability per region.

Figure 14.3: Social vulnerability 2017

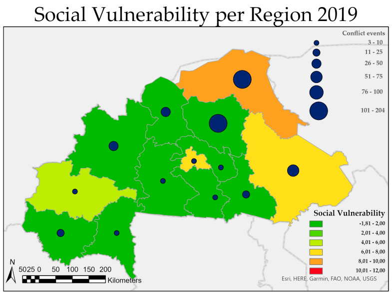


(a) Vulnerability profile of 2018, plotted together with the conflict and hazard events.

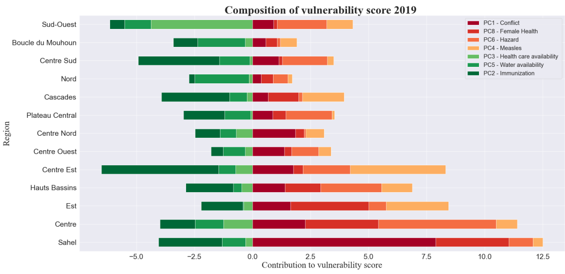


(b) Composition of social vulnerability per region.

Figure 14.4: Social vulnerability 2018

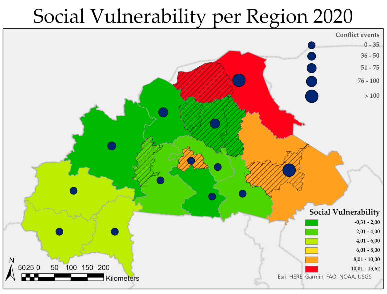


(a) Vulnerability profile of 2019, plotted together with the conflict and hazard events.

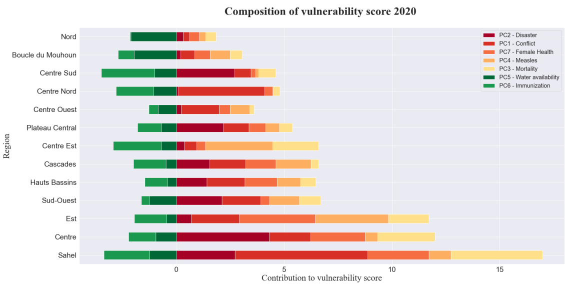


(b) Composition of social vulnerability per region.

Figure 14.5: Social vulnerability 2019

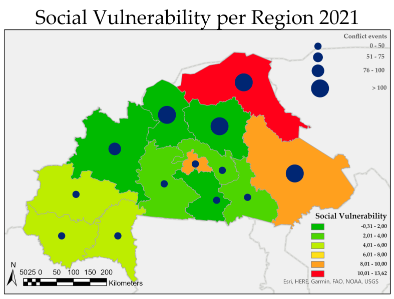


(a) Vulnerability profile of 2020, plotted together with the conflict and hazard events.

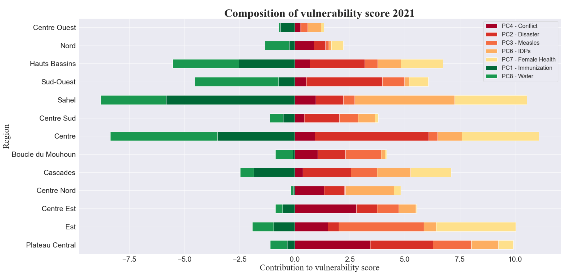


(b) Composition of social vulnerability per region.

Figure 14.6: Social vulnerability 2020



(a) Vulnerability profile of 2021, plotted together with the conflict and hazard events.



(b) Composition of social vulnerability per region.

Figure 14.7: Social vulnerability 2021

15 TEMPORAL DYNAMICS OF SOCIAL VULNERABILITY

15.1 CORRELATION MATRICES

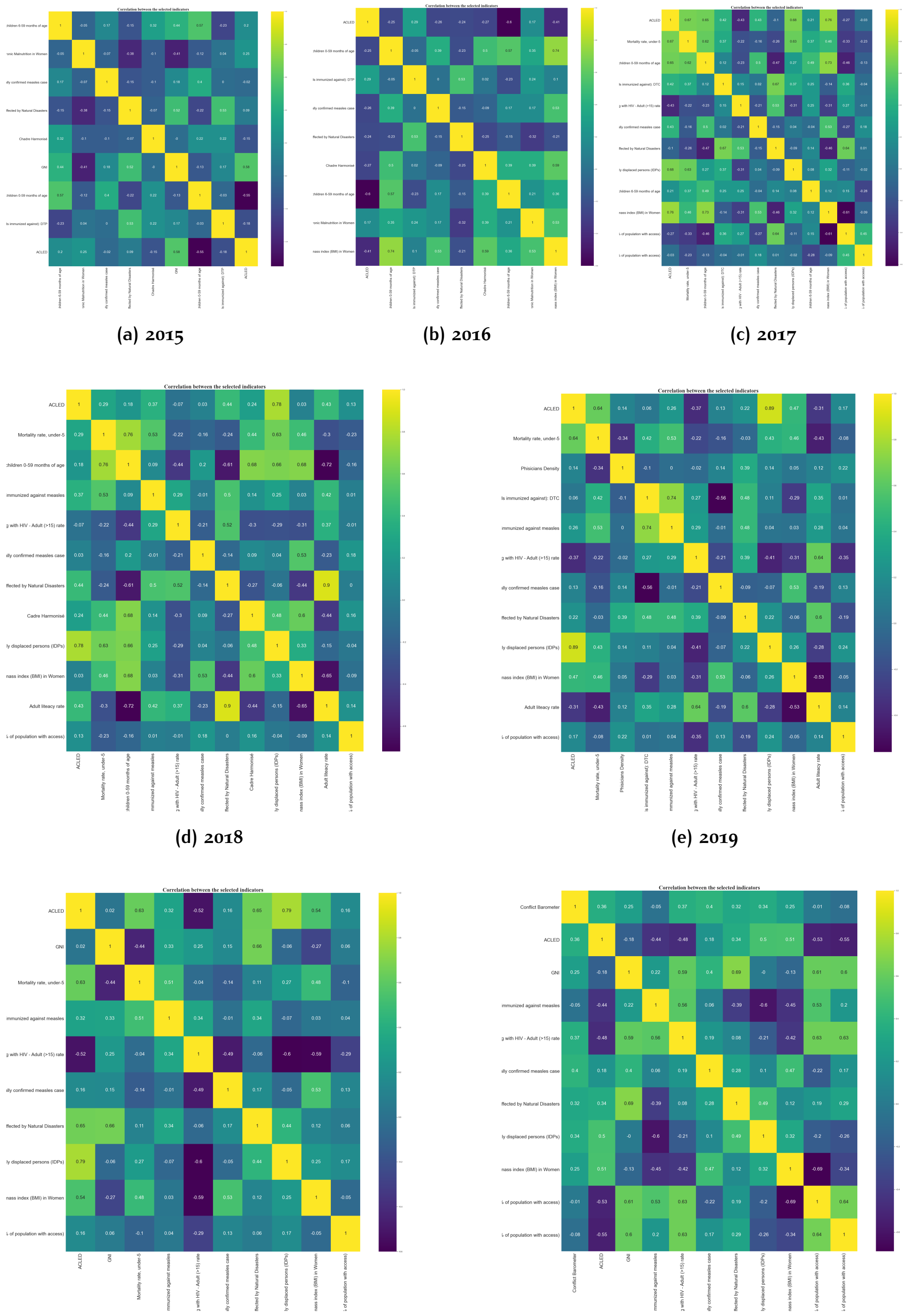
The figures in this section present the correlation between the included indicators in the research.

15.2 NUMBER OF COMPONENTS INCLUDED

This section shows the plots that show the amount of explained variance for each component. The cumulative explained variance should be 90%.

15.3 DIFFERENCE IN VULNERABILITY SCORES

The graphs below plot in green the value for social vulnerability calculated with PCA, in red the value of social vulnerability given by INFORM (Disaster Risk Management Knowledge Center, EC 2022). The blue dotted line, shows the best fit line for the prediction of social vulnerability based on the pca analysis.

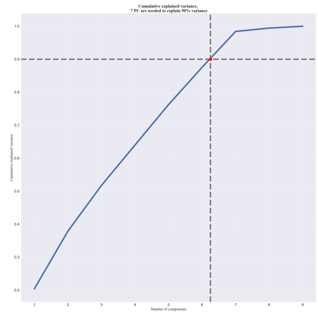


(a) 2015 (b) 2016 (c) 2017

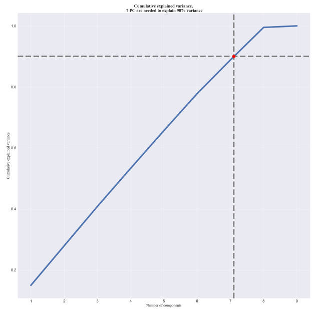
(d) 2018 (e) 2019

(f) 2020 (g) 2021

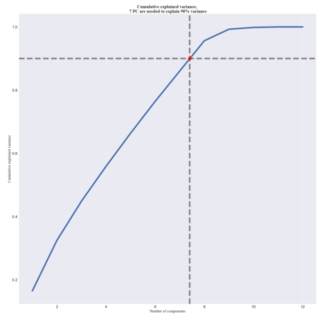
Figure 15.1: Correlation between the included indicators.



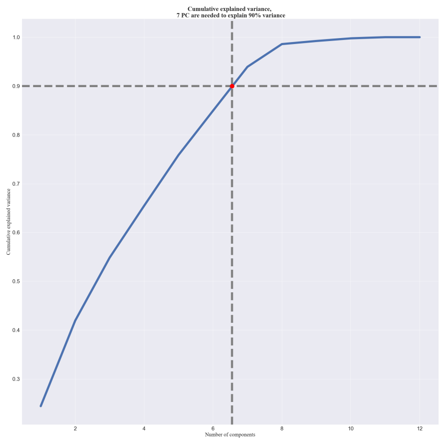
(a) 2015



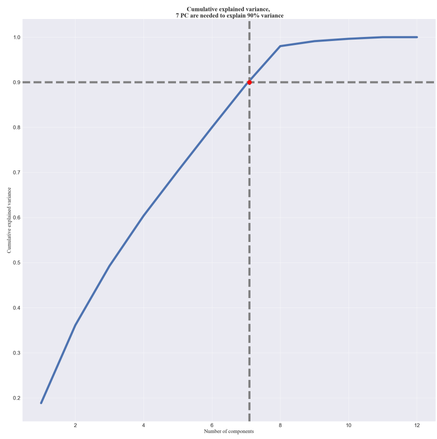
(b) 2016



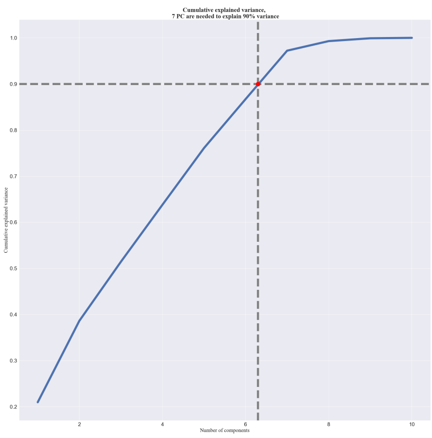
(c) 2017



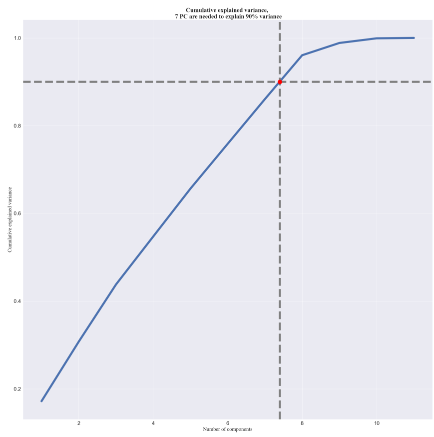
(d) 2018



(e) 2019

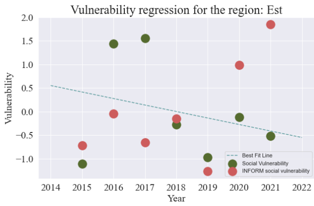


(f) 2020

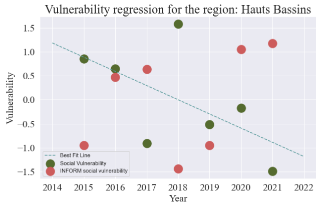


(g) 2021

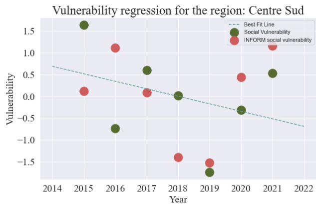
Figure 15.2: 90 % of variance is given by 7 principal components for all years.



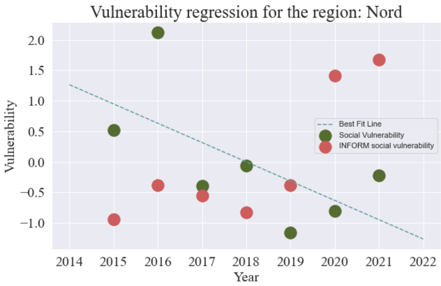
(a) **Vulnerability score per year in Est**



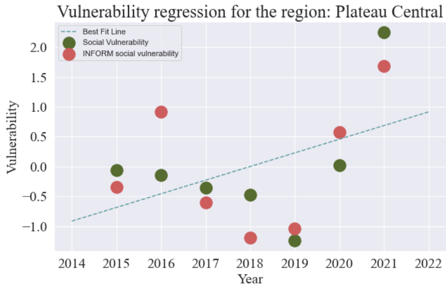
(b) **Vulnerability score per year in Hauts Bassins**



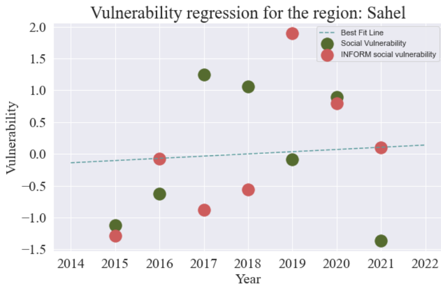
(c) **Vulnerability score per year in Centre Sud**



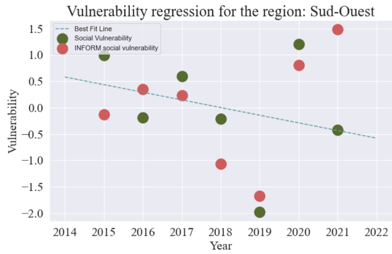
(d) **Vulnerability score per year in Nord**



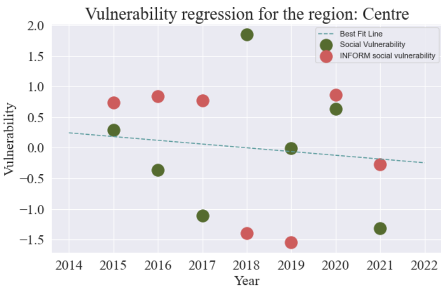
(e) **Vulnerability score per year in Plateau Central**



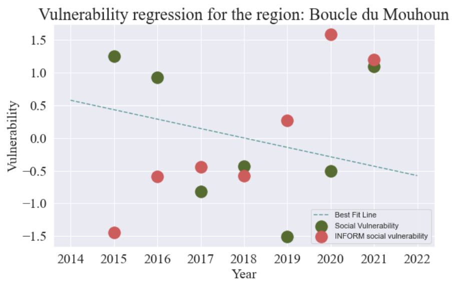
(f) **Vulnerability score per year in Sahel**



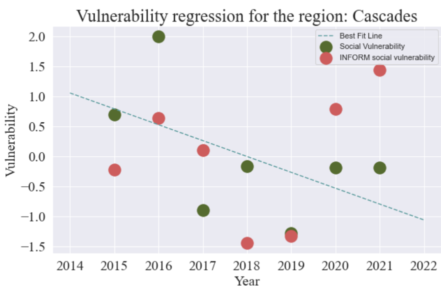
(g) **Vulnerability score per year in Sud-Ouest**



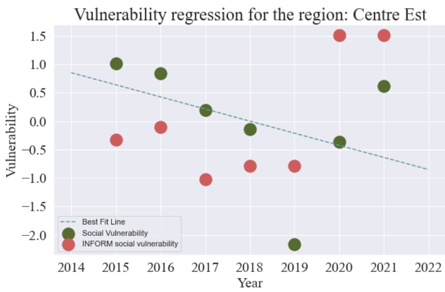
(h) **Vulnerability score per year in Centre**



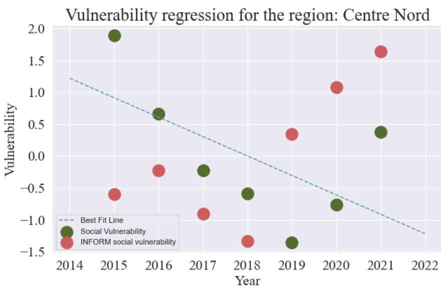
(i) **Vulnerability score per year in Boucle du Mouhoun**



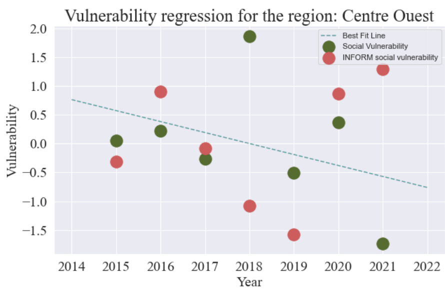
(j) **Vulnerability score per year in Cascades**



(k) **Vulnerability score per year in Sud-Ouest**

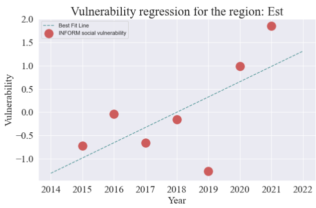


(l) **Vulnerability score per year in Centre**

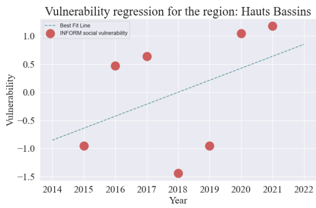


(m) **Vulnerability score per year in Centre**

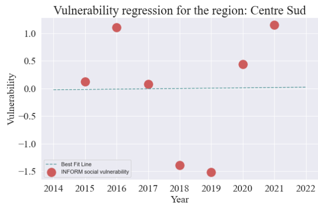
15.4 SIMPLE LINEAR REGRESSION OVER TIME — INFORM



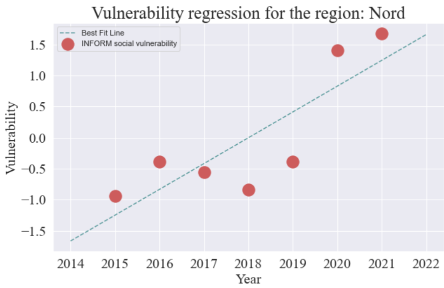
(a) **Vulnerability score per year in Est**



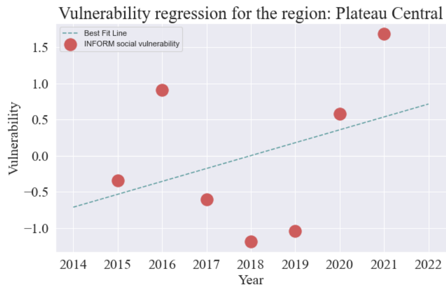
(b) **Vulnerability score per year in Hauts Bassins**



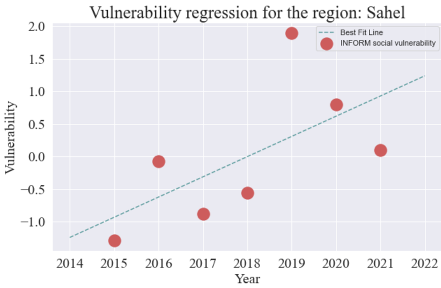
(c) **Vulnerability score per year in Centre Sud**



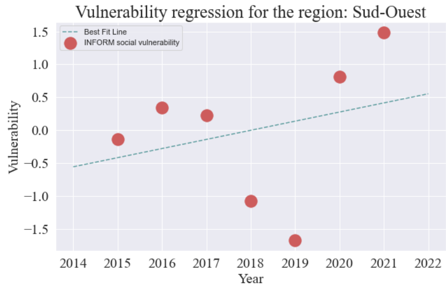
(d) **Vulnerability score per year in Nord**



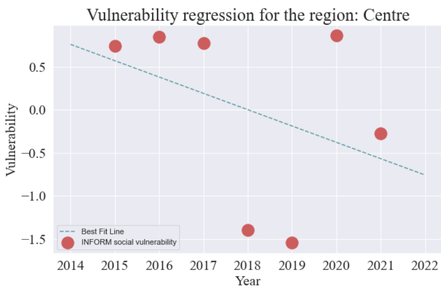
(e) **Vulnerability score per year in Plateau Central**



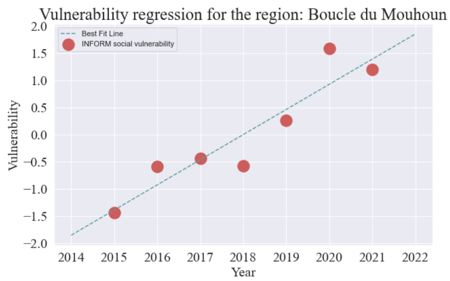
(f) **Vulnerability score per year in Sahel**



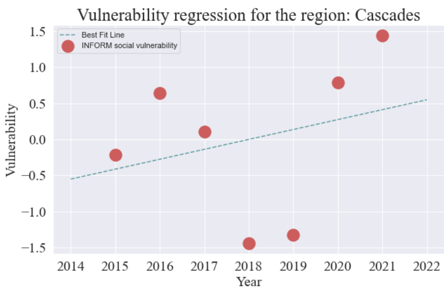
(g) **Vulnerability score per year in Sud-Ouest**



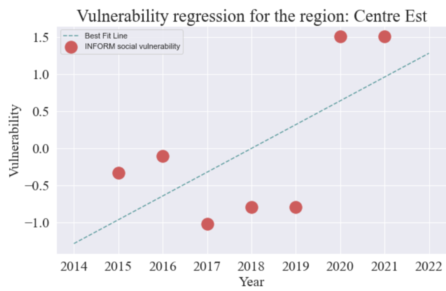
(h) **Vulnerability score per year in Centre**



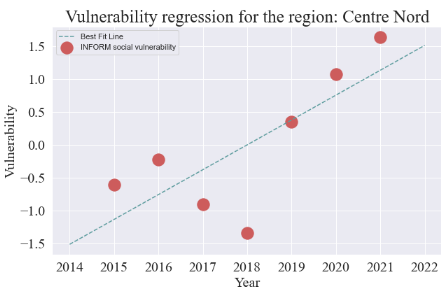
(i) **Vulnerability score per year in Boucle du Mouhoun**



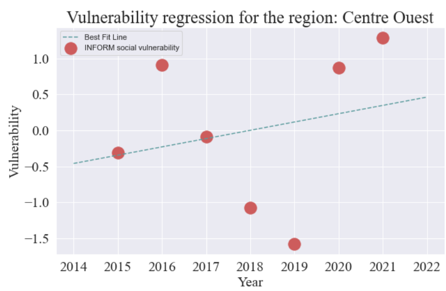
(j) **Vulnerability score per year in Cascades**



(k) **Vulnerability score per year in Sud-Ouest**



(l) **Vulnerability score per year in Centre**



(m) **Vulnerability score per year in Centre**

COLOPHON

This document was typeset using LaTeX. The document layout was generated using the arsclassica package by Lorenzo Pantieri, which is an adaption of the original classicthesis package from André Miede.

TU Delft