Social vulnerability to tropical cyclones: A case study in Muscat Governorate, Oman

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Abstract

Social vulnerability (SV) assessment reveals the hidden weaknesses in the human system that make populations susceptible to loss following exposure to external stress. In this study, SV to natural hazards, such as tropical cyclones, are studied and assessed at the local level for coastal cities in Oman. Vulnerability is determined using the underlying social characteristics specific to people in Oman that put them at risk from cyclones.

Oman is a developing country exposed to frequent tropical cyclones that create devastating impacts on its coastal cities, yet disaster risk reduction is undeveloped, with limited understanding of the spatial and temporal distribution of risk and vulnerability, and limited investment in resources and skills in this field. In particular, Oman lacks a natural hazard risk assessment system, hence the response to cyclone events is still reactive and not scientifically based. Some unpublished biophysical vulnerability studies exist that focus mainly on the coastal vulnerability to tsunami in Oman, but there have been no prior studies of SV to natural hazards. In this research, an SV model is adopted and applied at the local level (smallest administration boundary) for four coastal cities in the Muscat capital region.

Drawing on a conceptual framework of social vulnerability, based on the work of Susan Cutter, the study identified appropriate SV variables reported by the 2010 census. From a preliminary list of 38 potential variables, 24 variables in 9 social dimensions were selected following exclusion of variables due to multicollinearity and singularity. These variables were then used in a principal component analysis (PCA) to further reduce the number of factors to a few meaningful components/factors/indicators. This process produced three indicators, each consisting of a cluster of variables that make up a construct representative of a vulnerable social group. The subsequent aggregation of these variables created a social vulnerability index (SVI) used in GIS to map the spatial distribution of SV to cyclones across Muscat region. This analysis was then repeated for the 1993 and 2003 censuses, which along with the 2010 analysis, allowed an exploration of the temporal variation of SV over two decades.

The results show that for Muscat's coastal cities, in addition to their exposure to physical hazards, there are clusters of municipal blocks with high SV to cyclones, and others with very low social vulnerability. The level of SV also increases over time. In 1993 there were only three municipal blocks with high SV to cyclones, but by 2010 there were 20 high SV municipal blocks, and a decline in low vulnerability areas. This increase in SV is attributed mainly to an increase in population (particularly rural to urban migration for employment), and an increase in the number of non-Omanis arriving for work, especially those in low wage categories. The study thus demonstrates the need to consider the dynamic nature of SV in natural hazard risk assessment and management.

The results can be useful in practice, with the spatial SV maps supporting decision makers in planning and resource allocation before and during an emergency event. The Muscat case study can also be replicated elsewhere in Oman, based on the common nationally available small area data.

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Abbreviations

ADCIRC	ADvanced CIRCulation
BGS	British Geological Survey
CRED	Centre for Research on the Epidemiology of Disaster
DEM	Digital Elevation Model
DFID	Department for International Development
DGMAN	Director General Meteorology and Air Navigation
DGM	Directorate General for Meteorology
EFA	Expletory Factor Analysis
EM-DAT	EMergency events DATabase
FA	Factor Analysis
FEMA	Federal Emergency Management Agency
GIS	Geographical Information System
HWM	Hurricane Wave Model
IDNDR	International Decade for Natural Disaster Reduction
IMA	Indian Meteorological Agency

IPCC	Intergovernmental Panel on Climate Change
IRGC	International Risk Governance Council
ISDR	International Strategy for Disaster Reduction
JTWC	Joint Typhoon Warning Centre
KMO	Kaiser-Meyer-Olkin measure of sampling adequacy
LISA	Local Indicators of Spatial Association
MDL	Meteorological Development Laboratory
MRMWR	Ministry of Regional Municipalities and Water Resources
MSZ	Makran Subduction Zone
NCSI	National Center for Statistics and Information
NCCD	National Committee of Civil Defence
NCEP	National Centres for Environmental Prediction
NGO	Non-Governmental Organisations
NHC	National Hurricane Centre
NSA	National Survey Authority
NSC	National Security Council
OCO	Oman Charitable Organization
PAR	Pressure and Release
PCA	Principal Component Analysis
SAC	Spatial AutoCorrelation
SPSS	Statistical Package for the Social Sciences
SLOSH	Sea, Lake and Overland Surges from Hurricanes
SMC	Squared Multiple Correlation
SMC	Squared Multiple Correlation
SV	Social Vulnerability
SVI	Social Vulnerability Index

SoVI	Social Vulnerability Index, Cutter's model 2003
SWAN	Simulating WAves Nearshore
UNFCCC	United Nations Framework Convention on Climate Change
UNISDR	United Nations International Strategy for Disaster Reduction
WCDR	World Conference on Disaster Reduction
WMO	World Meteorological Organization
WMS	Watershed Modelling System

1 Introduction

This introductory chapter contains several sections that discuss the background to, and motivation behind, this study, including the overarching aim and the reason for choosing the case study area. The aim and objectives are outlined in the following section, which elaborates on the main research question, and the sub questions posed to help answer this. A research matrix is provided to illustrate the sequence of questions, the scope of the study, the source of the data, and the type of analyses used. Following this, the scientific and practical significance of this study is justified. Finally, a summary section presents the sequence of the remaining chapters, providing a brief description of the contents of each.

1.1 Background and Motivation

1.1.1 Overarching theory

Disasters related to natural hazards such as hurricanes, tropical cyclones, and floods are expected to happen more frequently as a result of climate change (Knutson et al., 2010; Coumou and Rahmstorf, 2012; Lesk et al., 2016). These natural phenomena can cause significant harm and damage, resulting in loss of life and economic costs (EM-DAT, 2015). Recently it has been shown that the impact of these extreme events can be alleviated, and avoided on some occasions, by making society more resilient to such phenomena. The field of vulnerability science embraces the idea that it is possible to mitigate the impact through planning (Coppola, 2011). These plans will be clearly influenced by social characteristics, such as population growth; for example, it is likely that the more densely populated an area, the higher the level of Social Vulnerability SV. On the other hand, the higher the income, the less socially vulnerable the population is due to their capacity to respond and implement a fast recovery. Effective planning of mitigation measures and responses to natural disasters depends on the level of understanding of the nature of risk and its complexities. Risk assessment involves determining the vulnerability of areas and the physical assets, so called biophysical vulnerability, as well as the vulnerability of affected people, which is social vulnerability. Together, these vulnerabilities represent the overall vulnerability of a place (Cutter, 1996; Ferrier and Haque, 2003; Cutter et al., 2003). In order to develop appropriate mitigation and resilience measures it is important to develop risk assessment sensitive to local context. This includes all attributes relevant to disaster risk, including uncertainty related to hazards, likelihood of occurrence and magnitude, and also the vulnerability of society to those hazards, and the consequent losses (Karimi and Hüllermeier, 2007).

The presence of a scientifically based risk assessment system is important, particularly in developing countries, as they are the most affected by natural disasters according to the United Nations Office for Disaster Risk Reduction (UNISDR) (UNISDR, 2013). This is due to their geographical locations and exposure to natural hazards, and/or poor development processes with limited resources and lack of attention to risk assessment and its management. Consistent with this perspective, in Article 4.4, the United Nations Framework Convention on Climate Change (UNFCCC) promoted help to meet adaptation costs for developing countries that are considered more vulnerable to the impact of climate change (UNFCCC, 1992).

SV is a significant concept in natural hazard risk assessment processes, as indicated by many researchers in the field (Cutter, 2003; Adger, 2006; Füssel, 2007; Birkmann, 2007; Blaikie et al., 2014). The analysis of SV involves an exploration of the underlying physical, social, economic, and environmental factors contributing to risk. These factors explain how people respond to, cope with, and recover from natural hazards, and analysis of them involves exploring both biophysical and human systems in the same space and time. However, despite recognition of its importance, SV's status and conditions are hard to assess because of the difficulty of finding appropriate metrics to quantify these.

Selecting the right metric system or indicators to capture the complex underlying processes from the local social characteristics or demographic data is an important part of SV analysis. Such indicators vary due to the nature of the vulnerability addressed, the hazards considered, the geographical area, and the population's socio-economic status (Vincent, 2004). Therefore, there is a need to develop local indicators of SV for any system in order to measure the risk associated with a given hazard and how it changes. National level indicators are directed towards resource distribution from global organisations such as the UNFCCC, as help from this organisation will be given only if based on agreed transparent and strong criteria (Adger et al., 2004).

Communities across the world vary in their social and structural characteristics. This variation is observed in socio-economic status, ethnicity, occupation status, education level, household structure, housing units, age structure, health status and level of social dependency, and mobility, etc. The combinations of such characteristics give rise to the geographical profile that is often unique for each community (Van Zandt et al., 2012). Local vulnerability indicators must be developed to address this variability, which differs by scale (community, households, and individuals), both within and between these scales, and over time (Vincent, 2004; Cutter and Finch, 2008; Aubrecht et al., 2012; Zhou et al., 2014). Knowledge of local level vulnerability is very important to develop an adequate picture of subnational and national vulnerabilities. However, measuring SV is hard because of the number of determinants contributing to it at different scales, yet having the right indicators capture the complex interactions in underlying processes is important (Vincent, 2004).

Several models for SV to natural hazards are available in the literature (Ferrier and Haque, 2003; Cutter et al., 2003; Turner et al., 2003; Karimi and Hüllermeier, 2007; Blaikie et al., 2014). Some of these models are theoretical and cannot be operationalised or applied in the real life; a few can be empirically applied, such as that of Cutter et al. (2003). Applying these models to local communities with different social characteristics generates different outcomes depending on characteristics of hazards, the exposed system, and specific conditions of people in the population affected. In this study, the Social Vulnerability Index SoVI model of Cutter et al. (2003) is chosen, a model which uses a factor analysis statistical approach to develop the SVI. This SV model is selected in this study because it is empirically applicable, can be spatially represented using a Geographical Information System (GIS), and it can be performed using available census data. The result from this model can be further used to create a comparison between different time periods using the same variables/indicators to explore the trend of SV. It can also be combined with biophysical vulnerability to form the overall vulnerability of a place. Cutter's SoVI model is used in this study for the construction and spatial representation of SVI to tropical cyclones for four coastal cities in Oman in three census years, 1993, 2003, and 2010, making this the first study of its kind to be conducted in the country.

1.1.2 Why Oman is a good example to apply in this study

Oman is a developing country in a location that experiences both climatic and seismic hazards. Studies of Oman's history of natural disasters are scarce, although existing studies have provided evidence that Oman's coastal areas are frequently hit by tropical cyclones (Al-Shaqsi, 2009; Krishna and Rao, 2009;Fritz et al., 2010; Al-Shaqsi, 2011; Wang et al., 2012; Mashhadi et al., 2013; Al-Hatrushi, 2013). Table 1 shows the major extreme climatic events that have hit the country since 1890, documented by the international disaster database (EM-DAT, 2015). A study of the mega cyclone of 2007, named Gonu, the event that reshaped the perception of natural disasters for the whole country, revealed that Oman is prone to natural disasters, particularly cyclones, tsunamis, storm surges, floods, and seismological hazards. In history and before Gonu, Oman was hit by mega-cyclones in 865 and 1890 (Fritz et al., 2010).

Table 1 Tropical cyclones that have made landfall in Oman since 1890. Sources AL Minji S, (2018)

DATE	Disaster	No. killed	Damage	Cost (US $)
June 5, 1890	Tropical cyclone	727	Palm trees, boats, and houses collapsed	9 million at that time.
May 24, 1959	Tropical cyclone	141	Two ships coming from Zanzibar sank in the Arabian Sea	Not available
May 26, 1963	Tropical cyclone, Cat 3	Not available	Not available	Not available
June 13, 1977	Tropical cyclone	105	Buildings damaged on Masirah island, including the military base.	Not available
Aug 10, 1983	Tropical storm (Aurora)	Not available	Not available	Not available
May 10, 2002	Tropical storm	7	Hundreds of cattle drowned, and several cars were swept away	25 million
June 6, 2007	Super cyclone (Gonu)	50	Damaged 25,419 houses and over 13,000 vehicles	4 billion
June 3, 2010	Tropical cyclone (Phet)	16	Roads and power lines damaged.	780 million
Nov 2, 2011	Tropical storm (Kyla)	14	Flash flooding caused damage to roads and buildings.	80 million
Oct 31, 2014	Cyclone (Nilofar)	4	Flash flooding caused damage to vehicles, roads, and buildings	Not available
June 12, 2015	Cyclonic Storm (Ashobaa)	Not available	Flash flooding caused damage to vehicles, roads, and buildings	Not available

May 26' 2018	Tropical cyclone (Mekunu) Cat 3.	30	Extreme wind, flash flood that caused large scale destruction to buildings, houses, and roads	Not available

Applying this study to a new area in a new region is important; Oman has its own unique conditions, culture, and demographic structure. Oman's culture and specific conditions along with its high exposure create a complex system to which to apply a SV study and construct the SVI that addresses its own special characteristics. The study will create knowledge about SV spatial distribution in a new area with a new population and geographical profile. When developing the SVI in Oman the study will create a link between the scientific field and policy in the field of disasters management by producing knowledge about the nature of risk in the study area. This will help decision makers in planning for and responding to any disasters.

In Oman, most decisions and actions taken in the disaster management process are still reactive in nature (Al-Shaqsi, 2011), and the impact of the outcome is short term, for instance, repairing roads after an event without introducing preventative measures allows for damage to happen again in the next event. Therefore, this study is important in encouraging more proactive planning for disaster. This will be applied in a new environment (physical, cultural, and institutional) with different driving factors than those affecting other areas in the world. These indicators will help us to understand human system sensitivity, and the SVI will be useful for comparing changes in SV over time, and across geographical areas in countries sharing the same social characteristics. To date, no local level index of SV to tropical cyclones has been constructed in any Omani risk appraisal (Wang and Zhao, 2008; Al-Shaqsi, 2010,;Fritz et al., 2010; Alhinai, 2011; Wang et al., 2012). The absence of an SV index that is scientifically based, considering local cultures and conditions, is a significant constraint on effective disaster risk management (Al-Shaqsi, 2011). Therefore, this thesis develops a comparable set of local SV indicators using 2010 census data with 24 relevant variables. The resulting SV index (SVI) is used to show the spatial distribution of the current SV in the study area. Using the Cutter et al. (2003) framework better reveals the current nature of risk through understanding its social components at the local level. It will also help to explore the temporal variation of SVI in the study area across the three census years, 1993, 2003, and 2010.

1.2 Aims and Objectives

"The aim of the research is to identify the risk of social and economic impacts from tropical cyclones in the study area, by revealing the SV of four coastal cities in Muscat governorate in Oman"

The following are the two sub-questions used to address the research goal:

1. How does SV to natural hazards (tropical cyclones) vary spatially across Muscat governorate's coastal cities?
2. How does the spatial pattern of SV change temporally across the last three censuses (1993, 2003, and 2010)?

In table 2 a research matrix links the research aims and objectives to the research design, and the methods used, throughout the chapters. In this research matrix, the main question and sub questions are stated along with clear objectives. The scope of answering each sub-question is made clear through a sequence that will be followed throughout the thesis, and data sources and analysis methods are described in each case.

Table 2 Research matrix showing research sub-questions and type of analysis used. (Author, 2018)

Sub-questions	Scope	Data
1. How does SV to natural hazards (tropical cyclone) vary spatially across Muscat governorate's coastal cities?	1) Review literature for SV, generic variables for tropical cyclones, selecting the relevant variables, constructing SV index, mapping SVI.	1. Literature review
	2) Previous local studies, historical events reports.	2. Census data from the National Center for Statistics and Information NCSI of Oman.
	3) Adopt a suitable method for SVI from literature review	3. Literature review.
	4) Acquire the relevant variables, from local context through NCSI census 2013 data.	4. Data collection from census data for the year 2010 for 38 variables.

	5) Apply a suitable statistical analysis method to develop the required indicators	5. Statistical analysis of data using SPSS/MINITAB
	6) Identify the composite SVI using the factors produced.	6. Additive model developed using weighted indicators
	7) Map the SVI zones in the study area	7. GIS to map the SVI
2. How does the spatial pattern of SV change across the last three census period (1993, 2003, and 2010)?	1. Use the same variables and method as in chapter 5 to construct the SVI for two more census years - 1993 and 2003 - and explore the changes.	1. NCSI census data for 1993 and 2003.
	2. Add the time dimension by comparing the three different data sets to represent temporal change in the SVI.	2. Use SPSS to carry out another factor analysis for the older census data using the same variables.
		3. Use GIS to map the two new SVI. And apply cluster analysis to study the change in SV.

1.3 Contribution

The original contributions to knowledge anticipated from this thesis will derive from the research presented in chapters five and six, which is conducted as follows:

In chapter five the study applies risk assessment to natural hazards, using the SV approach (SoVI) of Cutter et al. (2003), to a new social and geographical context. The knowledge added comes from selecting relevant variables for constructing the SV index for a new area and exploring the spatial distribution of SV in the study area. This will help researchers and decision makers to differentiate high vulnerability areas from low vulnerability areas that need more attention in planning and emergency responses. It will also explain why these areas are highly vulnerable by describing the driving social characteristics that influence SV during extreme events.

In chapter six temporal variation in SV is studied through its evolution over the last three censuses, using the same method and set of variables as in chapter five. With this knowledge, decision makers, specialists and researchers will be able follow the trend of SV at a local level in each municipal block. The knowledge about SV produced in both chapters will be a foundation for any future studies and replication in any adjacent areas with the same social characteristics.

1.4 Thesis summary

The thesis consists of eight main chapters (Figure 1). Chapter one is an introductory chapter that includes the background and motivation to the study, its aim and objectives, and a thesis summary. Chapter two reviews literature on the key topics related to natural disasters, natural hazards, risk, and social vulnerability. Chapter three introduces the case study, describing Oman and the reason for selecting this country as a case study, the natural hazards in Oman, and the risk assessment and management process in Oman. Chapter four describes the research design, giving the methodological background, a review of and rationale for the modelling approach adopted, and the methods used in developing the SV indicators. Chapter five, the first research chapter of the thesis, constructs the SV index for tropical cyclones in the Omani context and gives a spatial representation of SV in the study region. Chapter six assesses temporal variation in the SVI to identify how SV to natural hazards in Oman changed from 1993-2010 (addressing all censuses conducted by the government), in response to demographic change and societal development. Chapter seven discusses the findings of the analytical chapters, whilst chapter eight draws conclusions and presents recommendations for further research and for work to be carried out by policy makers in practice.

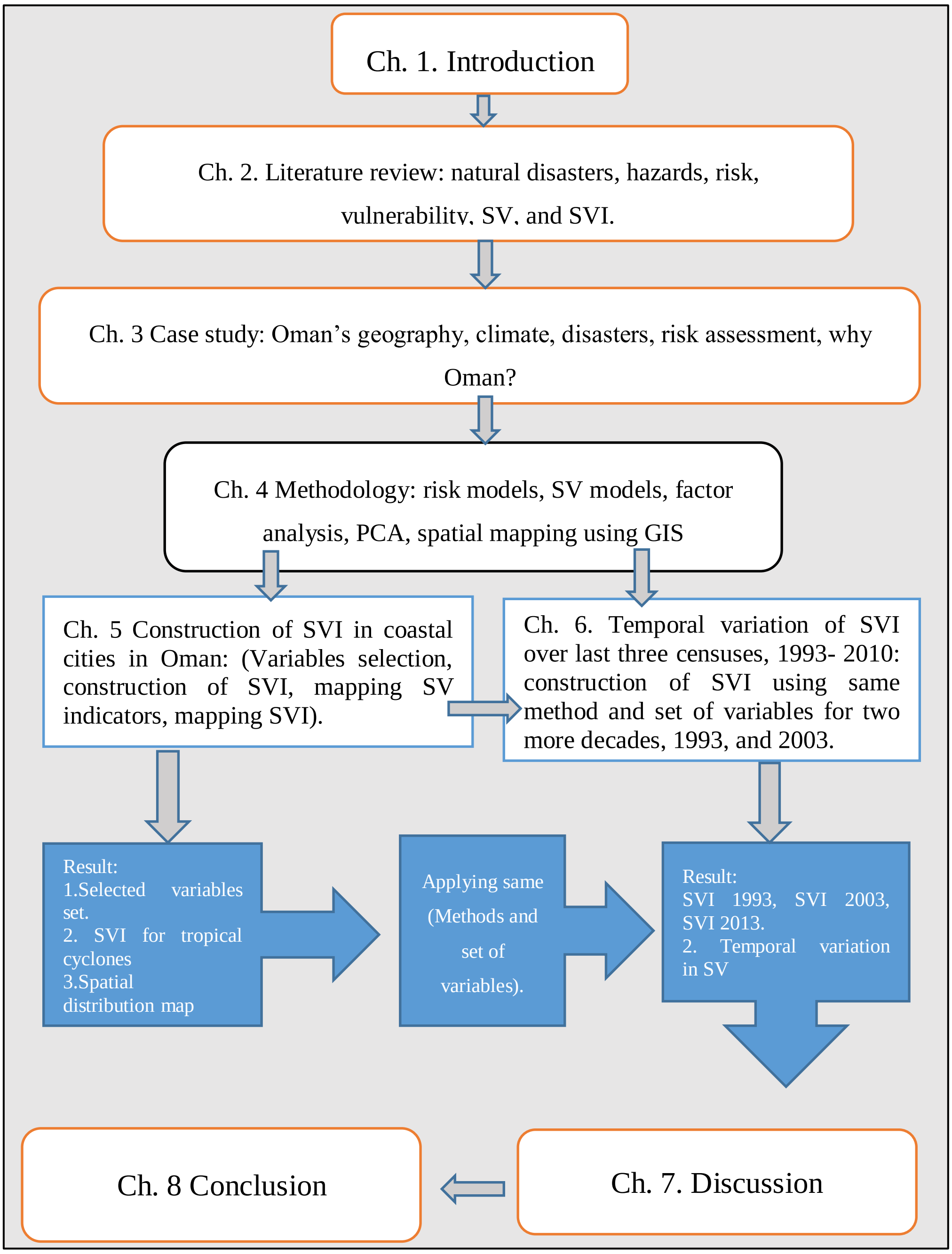

Figure 1 Flow chart of structure of thesis chapters. (Author, 2018)

1.5 Terms used in the study and their definitions

In this thesis, various terms will be used that normally have various meanings. Therefore, it is crucial to state the exact definition and context of each term.

Disaster "is a serious disruption of functioning of a society, causing widespread human, materials, and environmental losses, which exceed the ability of the affected society to cope using only its own resources" (UNISDR, 2015:9).

Hazard is “a dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage” (UNISDR, 2015:17).

Risk is “the combination of the probability of an event and its negative consequences”. Risk results from natural events interacting with vulnerable conditions (UNISDR, 2015: 25). It has three main elements:

- Source of risk;
- Impact of risk (high, medium, low); and
- Frequency of occurrence.

Vulnerability “is the likelihood that an individual or group will be exposed to and adversely affected by a hazard. It is the interaction of the hazards of place (risk and mitigation) with the social profile of communities” (Cutter, 1996:532).

SV is “the susceptibility of a given population, system, or place to harm from exposure to the hazard and directly affects the ability to prepare for, respond to, and recover from hazards and disasters” (Cutter et al., 2009: 2).

Resilience is “The ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions” (UNISDR, 2009. 24).

Disaster risk reduction is “The concept and practice of reducing disaster risk through systematic efforts to analyse and manage the causal factors of disasters, including through reduced exposure to hazards, lessened vulnerability of people and property, wise management of land and environment, and improved preparedness for adverse events” (UNISDR, 2009. 10).

Adaptation is “The adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities” (UNISDR, 2009. 04)

2 Literature review

2.1 Introduction

The climate is changing, and the environment is changing with it, for example, sea levels are forecast to rise by 2 m or more within this century (Hardy and Hauer, 2018). The impact of climate change is measurable through many other natural phenomena, including the increased number and intensity of natural hazards. The cost of increase in frequency of these events is high and is affecting international organisations and countries by either increasing their resilience through experience from past events or exhausting their resources and therefore reducing their capacity. The consequences, according to many studies, occur in a pattern and depend on the local factors of the impacted place, such as socioeconomic attributes of the population exposed to these hazards (O'Keefe et al., 1976; Cutter et al., 2000; Cutter et al., 2003; Willis et al., 2014). In developing countries, such events are more overwhelming, due to limited resources and poor development. It is difficult for developing countries to cope and recover quickly. Policy makers should be urged to develop effective disaster risk management and adaptation to protect vulnerable populations (Lesk et al., 2016). Identifying the vulnerable social groups is essential to determine how to reduce risk from natural disasters and is made possible by identifying vulnerability factors, and how they combine to influence the vulnerability of populations and places.

This chapter reviews the literature about risk from natural hazards and the theoretical approach in the field of social vulnerability. It begins by discussing natural disasters, natural hazards, and climatic hazards. It then discusses risk from natural hazards, the risk assessment process along with risk management, before concluding with a discussion of vulnerability and social vulnerability, addressing in detail the components of the SVI including indicators, statistical analysis related to SVI construction, and finally the spatial representation of the SV index.

2.2 Natural Disasters

Hazards originate from natural phenomena that occur all over the world, with highest impact in countries such as the United States, India, Bangladesh, China, the Philippines, and Indonesia (EM-DAT, 2015). Asia and Latin America are the main two regions that have experienced the most floods and hurricane events during the last century (EM-DAT, 2015). The impact of natural hazards is higher in certain countries despite the same magnitude of hazard. Statistics from the international disaster database and other official disaster organisations clearly show that greater adverse consequences occur in developing countries (Alexander, 1993; EM-DAT, 2015).

The number of natural disasters recorded in annual disaster statistics on the EM-DAT website for the year 2013 was 330 events. There is a decline in trend compared to the average annual number of disasters recorded from 2003 to 2012, which was 388. Similarly, the same report shows a decline in the average annual number of people lost in more than a decade of disaster history. Deaths for this period totalled 21,610, but that number is far below the annual average for the previous decade, when it was around 106,654 (EM-DAT, 2015). This reduction is to the credit of the global organisations working in the field of risk assessment and disaster management and of course because these countries are getting wealthier, and more educated.

The decrease in the number of natural disasters in 2013 is mostly due to the smaller numbers of climatological and hydrological disasters around the globe, with a total of 159 and 106 events, respectively. During the last decade, five countries have experienced the major share of disaster occurrences: The United States, China, India, the Philippines, and Indonesia. China was the most highly affected country, experiencing 17 floods, 15 storms, 7 earthquakes, one mass movement, one drought and one extreme temperature event, in 2013 (EM-DAT, 2015). The annual global estimate of economic loss due to natural disasters is around $300 billion. This figure is expected to grow more in the built environment due to accelerated development (Desai et al., 2015).

There were considerable changes in the nature of floods, droughts, and extreme temperature events in many regions around the world in the twentieth century, in terms of the frequency and intensity (Lesk et al., 2016). The World Meteorological Organization issued a statement on 11 August 2010 confirming that the world is currently threatened by widespread and severe weather events that are related to global warming (WMO, 2010). During the past decade, the Earth has seen exceptionally extreme weather. In 2011, the United States, for example, experienced around 14 events that caused losses of about US $14 billion (Coumou and Rahmstorf, 2012).

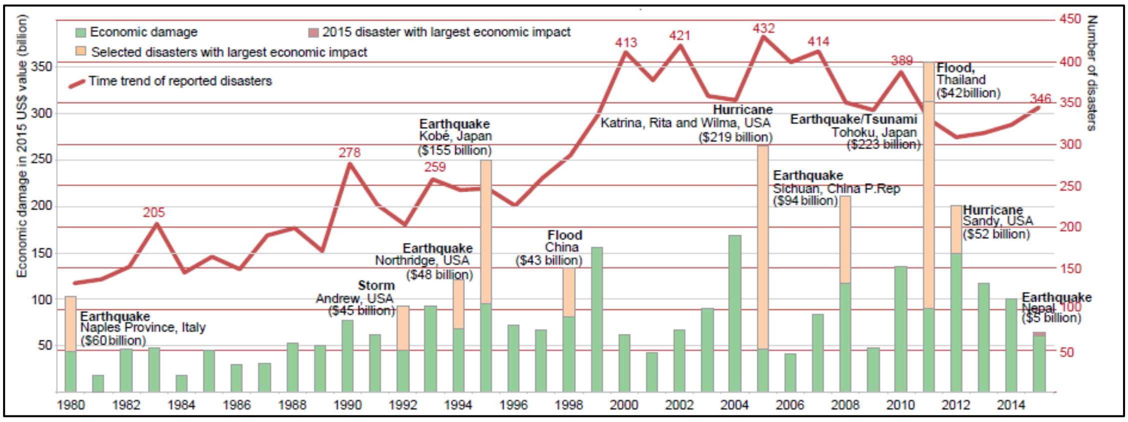

Figure 2 Annual reported economic damages from disasters 1980- 2015 Source: EM-DAT, 2015).

Among the top ten countries with the highest rates of disaster deaths in 2013, five have low to middle range incomes according to the World Bank's international country classification. These countries accounted for 88% of global disaster mortality that year, with the Philippines and India at the top of the list (EM-DAT, 2015). This leads us to ask why this distribution occurs. According to Smith (2006), natural disaster is a term that does not exist among environmental geographers as disasters are simply a *social* calculus. It is about how well society is prepared for the event and how resilient it is to it.

Natural disasters are divided into five groups: biological, geophysical, hydrological, meteorological, and climatological, each of which contains threats with their own characteristics (table 3). The last three groups can be aggregated to one family called hydro-meteorological disasters. Biological disasters are caused by exposure to germs and toxic substances, geophysical disasters originate from solid earth, hydrological disasters are caused by deviations in the normal water cycle caused by wind, meteorological disasters are caused by small to mesoscale atmospheric processes, and climatological disasters are caused by macro-scale processes (EM-DAT, 2015).

Table 3 Natural disasters general classification (EM-DAT, 2015).

Natural Disasters			
Biological	Geophysical	Hydrological	Metrological

➢ Epidemic • Viral infectious disease • Bacterial infectious disease • Parasitic infectious disease • Fungal infectious disease • Prion infectious disease ➢ Insect infection ➢ Animal stampede	➢ Earthquake ➢ Volcano ➢ Mass movement (dry) • Rockfall • Landslide • Avalanche • Subsidence	➢ Flood • General flood • Flash flood • Storm surge/ coastal • Flood • Mass movement (wet) • Rockfall • Landslide • Avalanche • Subsidence	• Storm • Tropical • Extra-tropical cyclone • Local storm
			Climatological
			➢ Extreme temperatures • Heat wave • Cold wave • Extreme winter condition ➢ Drought ➢ Wildfire • Forest fire • Land fire

Hydrological disasters related to floods were the most common disaster type in 2013 (48% of all natural disasters). Overall, they accounted for 33.2% of victims and 46.5% of total deaths. Meteorological disasters such as storms represented 31.1% of the total disasters in 2013 with 106 events reported, and these had a high human impact. Climatological disasters such as extreme temperature events happened at a 10% occurrence rate, slightly less than the average for the last decade, when it was 15.5%. Geophysical disasters represented 9.7% of total occurrences in this field, which is not far off the annual average of the decade. The number of deaths resulting from this type of disasters is low, around 1,166, or 5.4% of total mortality (EM-DAT, 2015).

During 2016, 342 disasters were triggered by natural hazards. This figure is lower than the year before, when it was around 395 events. The number of deaths due to these natural hazards was 8733 (figure 3). This was the second lowest number during the last ten years, but in contrast the number of people affected increased to 564.4 million, the highest since

2006. Natural disasters during that year cost the affected nations around US $154 billion, the fifth costliest damages since 2006 (CRED, 2016).

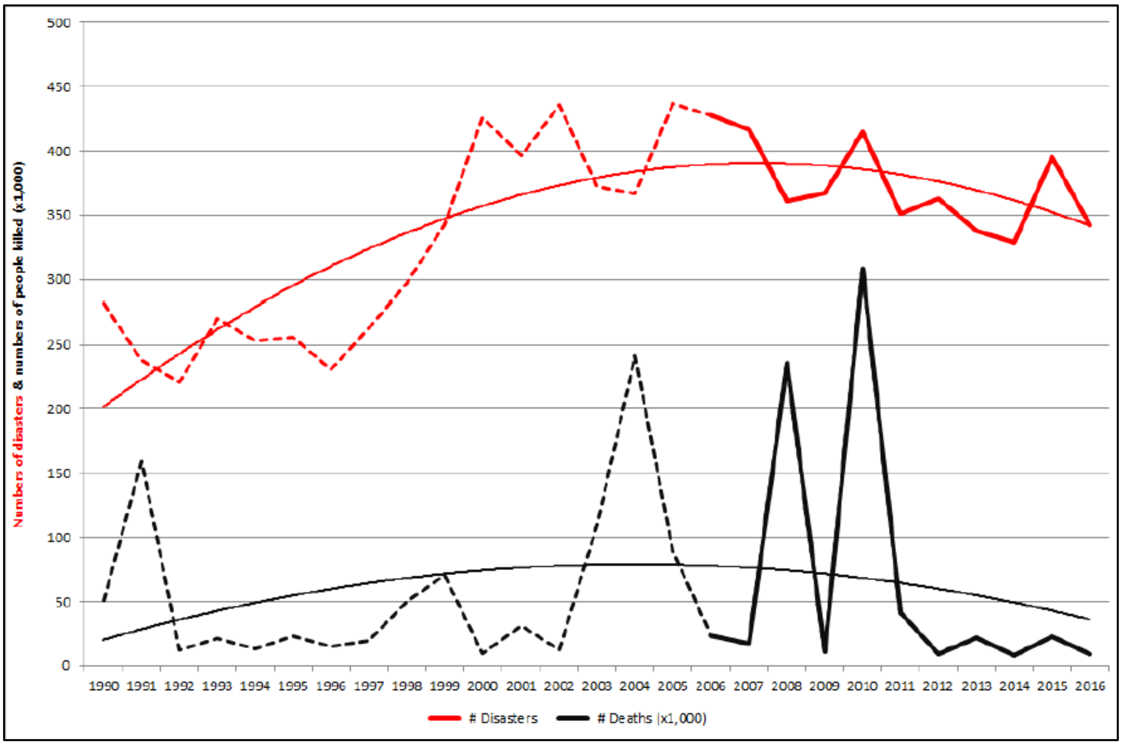

Figure 3 Number of disasters and deaths/1000 in period 1990-2016 (CRED, 2016).

Hydrological and meteorological disasters have accounted for the largest share of natural disasters since 2006, at 51.8% and 28.1%, respectively. During this period, the United States, China, India, Indonesia, and the Philippines have remained the top five countries most impacted by natural disasters (CRED, 2016).

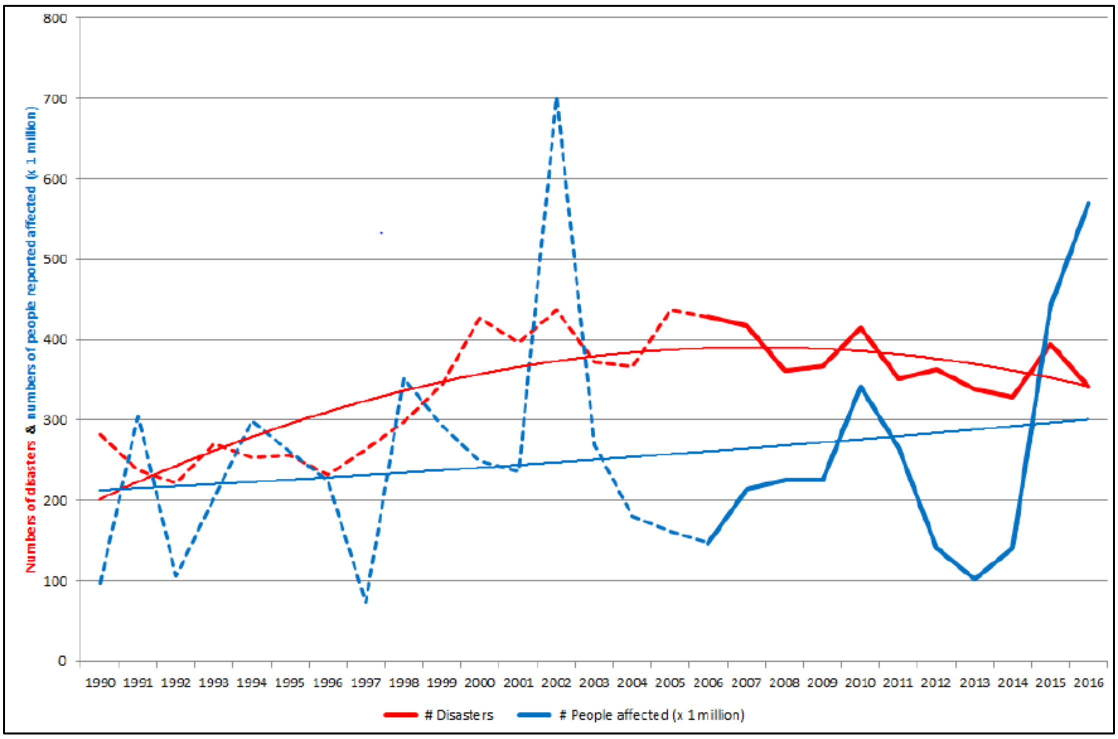

Figure 4 Number of disasters and total number affected in millions in the period 1990-2016 (CRED, 2016).

The number of disasters is continuously fluctuating, whereas since 2013 the number of affected people has been increasing (Figure 4). The year 2014 shows a decrease in the number of disasters, but the affected population is still large. In most natural disasters, the local social system interacts with the hazard, making the population vulnerable to greater risk (Van Zandt et al., 2012). For instance, poverty reduces access to resources compared to higher income people, but in contrast the wealthy population more often own properties that are close to the seashore or in river flood plains, making them more vulnerable (Alcántara-Ayala, 2002). The increasing impact of climate change, expansion in urban areas, and rapid social and economic growth all increase the chances of natural hazard events becoming a disaster. Addressing these factors within planning and development can reduce risk (UNISDR, 2015).

Disasters will be always a question of whether a population is vulnerable to a specific type of natural hazard and this supports the notion that there is no such thing as a 'natural disaster', but that a disaster occurs when SV overlaps with extreme natural processes (Smith, 2006). Disaster happens when a hazard hits vulnerable communities, whose capacity is not sufficient to protect against, cope with and easily recover from its damaging effects. It is not the natural environment or the natural hazards that determine whether a natural process can turn into a natural disaster. It mainly depends on human beings' behaviours and characteristics in that area (Raschky, 2008). Thus, disasters occur in different countries in various ways that depend on the local context (Frigerio et al., 2016). There are several definitions used across the research community for the term disasters, as shown in table 4.

Table 4 Disaster definitions across the literature (Author, 2018)

Disaster definition	Defined/cited by	General theme
During the 1960s the term disaster was recognised as "an uncontrollable event resulting in a danger state for the society, and disrupting all or some of the essential services and functions of the society"	Fritz, (1961:655).	Extreme event + resulting disruption of functions
Disaster is "the interaction between extreme physical or natural disruption and destruction, loss of life and livelihood, and injury"	O'Keefe et al., (1976:566).	Physical disruption + harmful to life
Natural disasters are "rapid, instantaneous or profound impact of the natural environment upon the socio-economic system. Or a sudden disequilibrium of balance between natural forces and counteracting forces of the social system"	Alexander, (1993.4).	Disequilibrium (natural forces & social system)
Disaster is "an event that has big impact on society, disrupts the working of society and may or may not lead to death and has severe economic impacts"	Tobin, (1997:6).	Major consequences for society's functioning
Disaster is "a serious disruption of functioning of a society, causing widespread human, material, or environmental losses, which exceed the ability of the affected society to cope using only its own resources"	UNISDR, (2009: 9).	Extreme force = function disruption + losses, that exceed society's coping capacity.

Most disaster research has focused on disaster exposure risk and assessment of biophysical vulnerability (Turner et al., 2003; Cutter et al., 2008; Lee, 2014).

2.3 Climate Change

The whole world is being influenced by climate change, and all countries are experiencing the impact through frequent natural phenomena, global warming (figure 5), and sea level rises (figure 6) (WMO, 2010; CRED, 2016). According to the Intergovernmental Panel on Climate Change's (IPCC) fourth assessment report, sea surface temperatures in areas where tropical cyclones originate increased during the past few decades due to the impact of greenhouse gas emissions (IPCC, 2014).

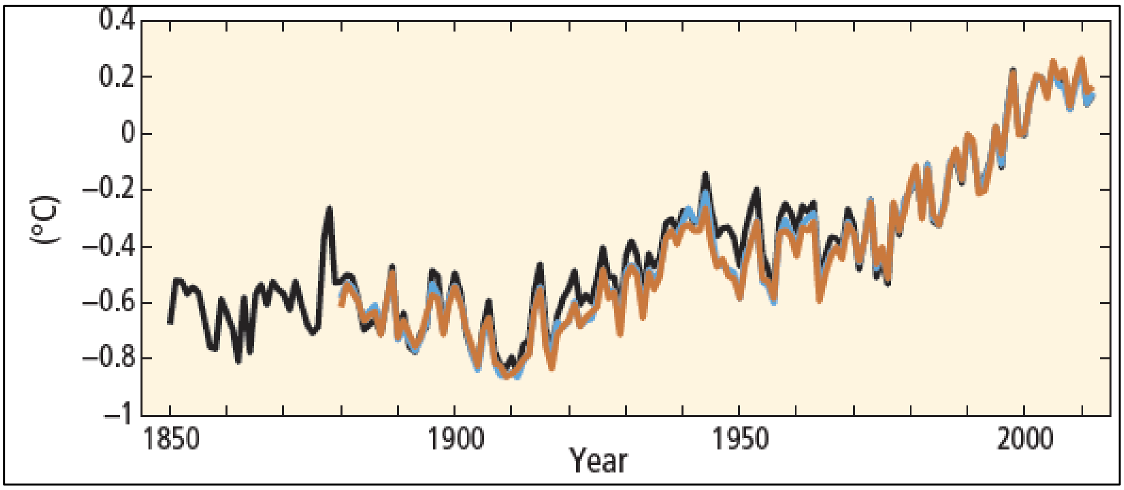

Figure 5. Average global combined land and ocean surface temperature anomalies from the year 1850 to 2000 (IPCC, 2014).

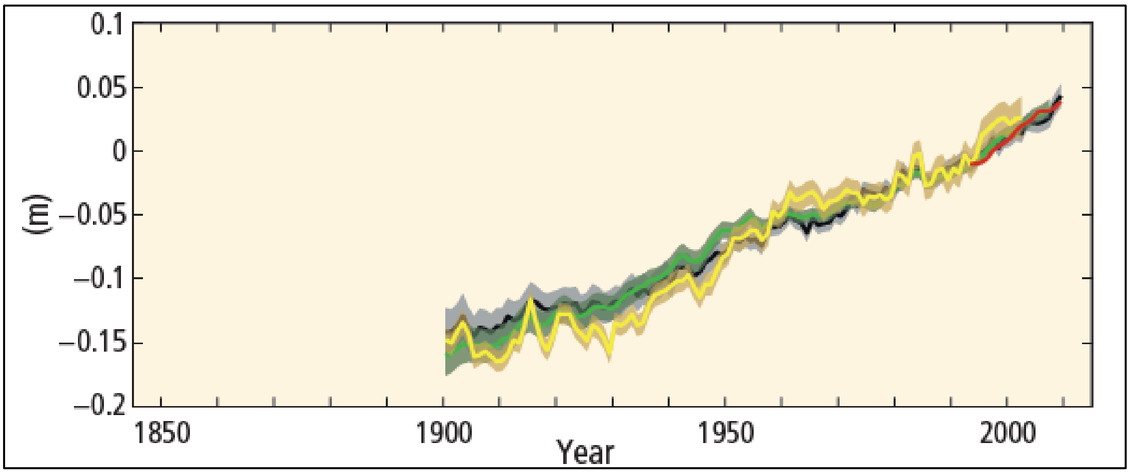

Figure 6. Average global sea level rise from the year 1850 to 2000 (IPCC, 2014).

According to Knutson et al. (2010), climate change is one factor, amongst others, affecting the evolution of cyclones. Human influence on the climate system is clear, and recent anthropogenic emissions of greenhouse gases are the highest in history. Recent climate changes have had widespread impacts for the human system in the natural environment (figure 7) (IPCC, 2014).

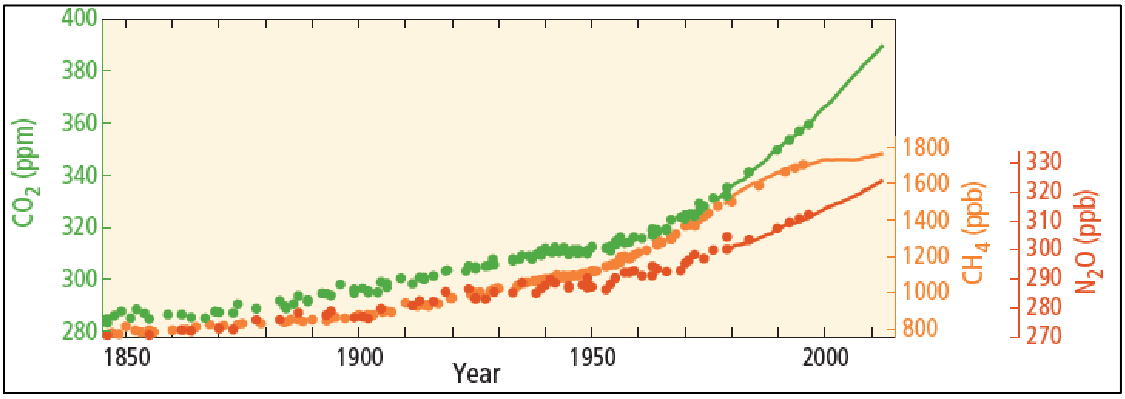

Figure 7. Global anthropogenic CO2 emissions from the year 1850 to 2000 (IPCC, 2014).

Figures 5, 6, and 7 all show clear rises in temperature, sea level and greenhouse gas emissions, the trend in the above graphs suggesting that the number of occurrences of climate extreme events and their intensity are going to continue to grow. As an example, Raschky (2008) indicated that a few scientific sources suggest that climate change intensifies the frequency of extreme weather events in some regions. In an experimental study, Sugi (2010) made a detailed projection for future climate change that simulated tropical cyclones. It shows that the global number of tropical cyclones is going to decrease, but their intensity will increase due to global warming. In addition, Dibajnia et al. (2010) conducted a study using 30 years of data on the northern Indian Ocean, including 2007, the year Cyclone Gonu occurred. They suggest more than 8.8 m maximum wave heights for offshore design of coastal structures along the Iranian coastline. In contrast, and based on the occurrence of Cyclone Gonu, Dibajnia et al. (2010) suggested that this might be part of a long-term cycle of about 100 years and not due to global warming. From these three studies, we can see that scientists are still not sure whether the increase of frequency and intensity of storms is related to global warming or to other causes such as long-term cycles.

Nevertheless, climate change through global warming gives rise to large interactions between the natural system and the human system, both spatially and temporally. This complex process raises uncertainty in any model used, although it is remains clear that policy makers need to understand relationships between people, the environment, and physical infrastructures at the local level (Corfee-Morlot et al., 2011).

2.4 Natural hazards

People often misuse multiple key terms associated with hazards and risk, changing the meaning by using the same word for several contexts or deploying several words to represent one meaning. This is common in the field of disasters where some terms are used interchangeably in studies, such as the two popular terms ‘risk’ and ‘vulnerability’, which creates confusion. Researchers, experts, and organisations need to recognise the need for common definitions in the field (Pine, 2014). Table 5 lists some of the hazard definitions in the literature reviewed.

Table 5 Hazard definitions in the reviewed literature. (Author, 2018)

Hazard definition	Defined / cited by	General themes
Hazards are “events or physical conditions that have the potential to cause fatalities, injuries, property damage, infrastructure damage, agricultural losses damage to the environment, adverse impact on economic or other types of harm or loss”	FEMA, (1997: xxi).	Extreme events create harm
Hazard (Environmental): “the threat potential posed to man or nature by events originating in, or transmitted by, the natural or built environment”	(Kates 1978, 14).	Natural processes cause life loss and destruction
Hazard (Natural): “A natural hazard represents the potential interaction between humans and an extreme natural event. It represents the potential or likelihood of an event (it is not the event itself)”	(Tobin & Montz 1997, 5).	Potential for harm

Hazards fall into three main categories: natural (storms, floods, hurricanes, earthquakes, wildfires), technological (power outages, nuclear accidents, hazardous materials spills) and combined, which result from a combination of the first two types (e.g. a dam failure that results in flooding) (Wisner et al., 2004). When any severe extreme event meets vulnerable and exposed human and natural systems, then it results in a disaster (Lesk et al., 2016). The impact of natural hazards on human beings is not of concern when no human system exists or is exposed; such cases are merely more of a threat to the biological and environmental system. The interaction of the human system with the hazard begins because the human system keeps evolving and changing its different components to become more exposed to hazards. In other words, when both natural and human vulnerabilities exist in the same geographical location and time, then natural disasters occur. The magnitude of any hazard can be also a function of time; the longer it stays, the greater its impact and magnitude (Pine, 2014).

Natural disasters happen in many countries, but their impact varies from one country to another, with developing countries the most affected (Pine, 2014). Natural hazards in general have different levels of effects, ranging from harmless to total destruction. It is possible for people to avoid some hazardous events. Modern science and knowledge can prepare people with necessary tools and measures against some hazards. However, it is not possible for geophysical phenomena to be precisely predicted (Burton and Kates, 1963).

It is very difficult to determine precisely the occurrence of some natural phenomena in time and space. Estimates can be made by considering relative frequency or studying the underlying descriptive frequency of distribution. So, identifying any natural events will depend on the knowledge of the magnitude and the occurrence in time and space. This can be visualised in patterns using a spatial distribution of hazards. For example, earthquake belts are distributed in a pattern, whilst volcanic eruptions also occur in certain places on tectonic plates (Burton and Kates, 1963).

Researchers from many disciplines highlight the increase in frequency of hydrological and meteorological hazards, and that their impact is increasing. According to Knutson et al. (2010), the past few decades have seen increases in economic disruption and damage due to tropical cyclones, mainly because of increased interactions with humans and development, i.e. increase in exposure of coastal populations and the overall rise of infrastructure values in these coastal areas. There is recent evidence of increasing extreme rainfall intensity globally (CRED, 2016). Research indicates that there is an increase in short duration storms that is leading to increases in both the frequency and magnitude of flash floods (Westra et al, 2014). Table 6 lists definitions of the various threats of natural hazards.

Table 6 Hazard glossary established by Integrated Research on Disaster Risk IRDR disaster loss data group. (IRDR, 2014).

Hazard/threat	**Definition**
Floods	A general term for the overflow of water from a stream channel onto normally dry land in the floodplain (riverine flooding), higher than normal levels along the coast and in lakes or reservoirs (coastal flooding) as well as ponding of water at or near the point where the rain fell (flash floods).
Flash flood	Heavy or excessive rainfall in a short period of time that produces immediate runoff, creating flooding conditions within minutes or a few hours during or after the rainfall.
Tropical cyclone	A tropical cyclone originates over tropical or subtropical water. It is characterised by a warm-core, non-frontal synoptic-scale cyclone with a low-pressure centre, spiral rain bands and strong winds. Depending on their location, tropical cyclones are referred to as hurricanes (Atlantic, northeast Pacific), typhoons (northwest Pacific), or cyclones (south Pacific and Indian Ocean)
Tsunami	A series of waves (with long wavelengths when travelling across the deep ocean) that are generated by a displacement of massive amounts of water through underwater earthquakes, volcanic eruptions, or landslides. Tsunami waves travel at very high speed across the ocean but as they begin to reach shallow water they slow down, and the wave grows steeper.
Storm surge	An abnormal rise in sea level generated by a tropical cyclone or other intense storms.
Wind	Difference in air pressure resulting in the horizontal motion of air. The greater the difference in pressure, the stronger the wind. Wind moves from higher pressure toward low pressure.

2.5 Vulnerability

In any disaster management process, the actual size and extent of the consequences to any events should be mapped, and vulnerability must be assessed effectively for resources to be deployed effectively. This is a key step in risk assessment, and it must be carried out accurately with a very good quality of data (IPCC, 2014). Whilst vulnerability is a popular term in the science of disasters, the field is fragmented and affected by conflicting theory and terminology (Vincent, 2004). Having several disciplines within the climate change field itself has resulted in several definitions of vulnerability. In spite of that ambiguity, there is good collaboration among these disciplines. For this collaboration to be fruitful, several authors have promoted the idea of having a common term for vulnerability that is related to a particular context (Füssel, 2007). Thus, in general, vulnerability is viewed as one of two types: 1) amount of damages caused by a specific climate event (Jones and Boer, 2003), or 2) an existing state of system before impact or an inherent property (Kelly and Adger, 2000; Allen, 2003, Cutter et al., 2003).

Füssel and Klein (2006b) assumed that there is no single conceptual framework for vulnerability that would fit the assessment of several contexts because the application is to different systems and different hazards. Consequently, answering any question related to vulnerability needs a clear description of the context and purpose of the vulnerability assessment. No single universal model or theory has defined or measured or understood vulnerability to date (Adger et al., 2004). Adger (2006) reviewed several vulnerability methods and epistemologies, and stated that while there is an obvious lack of convergence in the current research of vulnerability, that is a sign of strength and great vitality, not a weakness. Alwang et al. (2001) reviewed selective vulnerability literature and found that most disciplines focus either on the risks or the underlying conditions. Some literature, including the environmental literature and disaster management literature, considers risk assessment to be the same as vulnerability assessment.

Vulnerability plays an important role in the risk context because identifying and reducing the vulnerability of various exposed elements is a key factor in reducing risk of disasters (Greiving et al., 2006). The probability that a natural disaster might have more impact on one area than another depends on the local vulnerability of each area (Cutter et al., 2003).

Despite the differences in the various studies of vulnerability assessment, there are a few common themes among most of them: a social-ecological perspective (the main domain), place-based studies, dealing with vulnerability as an equity issue, and using vulnerability to facilitate mitigation measures (Cutter et al., 2000; o'Brien et al., 2004). Researchers from different disciplines and fields use various concepts and meanings of vulnerability, which has led to diverse ways of measuring it. Each discipline views vulnerability in different ways and uses the outcomes as the main focus that is concerned with various forms of risk. For example, disaster literature sees vulnerability as risk related to natural disasters (Alwang et al., 2001). Vulnerability is, however, defined in a variety of ways, with natural disasters studies working on different versions of its relationship with disasters (Table 7).

Table 7 Vulnerability definitions in the reviewed literature (Author, 2018)

Vulnerability definition	Defined / cited by	General theme
"Vulnerability is defined as the characteristics of a person or group in terms of their capacity to anticipate, cope, resist and recover from the impact of natural hazards"	Wisner et al., (2004:7)	Characteristics of human system
"The characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard"	UNISDR, 2009. 30)	Conditions influence level of impact
"Human condition or process resulting from physical, social, economic, and environmental factors, which determine the likelihood and scale of damage from the impact of a given hazard"	(UNDP, 2004:11)	Human condition process
"Vulnerability is the state of susceptibility to harm from exposure to stresses associated with environmental and social changes and from the absence of capacity to adapt".	Adger, (2006:268)	Susceptibility to harm and level of capacity
"Vulnerability is the susceptibility of an object, human, or ecological system to damage from any hazard. It has four main dimensions: physical, social, economic, and environmental".	Coppola, (2011a: 33)	Susceptibility to damage
"Vulnerability is the degree to which a system is susceptible to and is unable to cope with adverse effects of climate change".	IPCC, (2014).	Susceptibility and coping level

Despite the various applications of the term in the literature, definitions of vulnerability will always have in common the characteristics of people (Wisner et al., 2004). Füssel and Klein (2006a) describe climate-related vulnerability assessments based on the characteristics of the vulnerable system, the type and number of hazards, their source of origin, their effects on the system, and the time perspective of the assessment. Although it has numerous definitions, vulnerability has several clear characteristics: it is a) scale dependent, b) multi-dimensional, and c) is dynamic, changing spatially and/or temporally. With respect to the local context there are five dimensions that need investigation: physical, economic, social, environmental, and political or institutional (Ciurean et al., 2013). Few attempts have been made to study these characteristics simultaneously for the same geographical area (Cutter et al., 2000). Vulnerability is considered multi-faceted, with a wide range of fields and dimensions, and dynamic in that it varies in time and space (Cutter et al., 2008; Cutter and Finch, 2008; Lee, 2014a).

Vulnerability in natural disasters focuses on the relationship between the disaster and human vulnerability. The degree of vulnerability is measured by social factors, and in natural disaster research, all areas are vulnerable, but some subgroup areas are more vulnerable due to their locations and social characteristics (Alwang et al., 2001). In the field of risk management, vulnerability relates to consequence analysis and depends on four main dimensions: physical, social, environmental, and economic. These factors interact within the same space and time to form the consequences; for example, poor design and inadequate protection of assets cause vulnerability. The two main general perspectives on vulnerability assessment are the damage caused to a system by a specific hazard and the system's state that exists before it faces a hazard (Ciurean et al., 2013). Many governmental bodies use vulnerability assessment in different fields; however, the application of vulnerability assessment in a holistic way (physical, social, environmental, and economic) to the field of disasters is still lagging behind. Many decision makers prefer to measure the physical vulnerability to a hazard and do not include other components such as socio-economic impacts (Cutter et al., 1997).

In her studies of the term vulnerability, Cutter (Cutter, 1996; Cutter et al., 2003) treats vulnerability as exposure in her first study and in the second study as social conditions, which were then integrated into one model focusing on the vulnerability of place. SV is measured on many levels: individual, household (Morrow, 1999), community (Abramovitz and Albrecht, 2013; Allen, 2003), municipality (Posey, 2009), county (Cutter et al., 2000; Cutter et al., 2003), region (Boruff et al., 2005), and nation (O'Brien et al., 2004).

SV is a multidimensional characteristic produced by a blend of mainly socioeconomic factors that results in a different degree of impact from any hazard (Ferrier and Haque, 2003). Several recent studies have adopted an integrated approach to vulnerability assessment, suggesting using both social and biophysical vulnerabilities in the assessment process, such as a hazard of place model of vulnerability (Cutter et al., 2000; Adger et al., 2004).

Vulnerability can be lowered or increased through certain measures or practices. For instance, it can be lowered in a flood-prone area by introducing structural measures such as flood defences. According to the United Kingdom Department for International Development (DFID), the conceptual idea of vulnerability is based on the equation below (White et al. 2005):

$$\text{Vulnerability} = \text{Exposure X Susceptibility/Coping Capacity} \quad \text{Eq. 2.1}$$

Hazard and vulnerability are two independent terms. Hazards are natural phenomena and cannot be changed, but vulnerability can be altered. Risk and vulnerability are two different concepts and cannot be interchangeably used. It is very important when estimating the risk of a system from any hazard to identify the actual threat exerted by the hazard (Cardona, 2004). The vulnerability of a population does not depend on the nature of the hazards and the proximity to the source of the hazards alone; additionally, people's social characteristics are a key determinant of how vulnerable they are (Cutter et al., 2000). Vulnerability assessment is used to predict the consequences of a system's exposure to hazards. Moreover, it is very difficult for decision makers to take the right decision from a large set of alternatives in a disaster without vulnerability and risk assessment (Downing et al., 2005). The literature includes several techniques, frameworks, and conceptual models for SV assessment to advance theoretical and practical applications of vulnerability in natural disasters (Cutter et al., 2003; Wisner et al., 2004; Adger, 2006; Füssel, 2007).

2.5.1 Social Vulnerability

The social components of vulnerability are associated with the properties of the affected group that influence the amplification or reduction of the damage resulting from the first order hazard's impact (Adger et al., 2004). It is a function of certain characteristics of the system, depending on the nature of hazards to which the system is exposed. The impact of a natural hazard event upon any population varies according to the socio-economic attributes of that population (O'Keefe et al., 1976; Willis et al., 2014). SV is studied by the scientific community for two main reasons: 1) to estimate the size of the impact to take suitable action, and 2) to prepare remedial action that limits the impacts (Adger and Kelly, 1999; Adger et al., 2004).

According to Cutter et al. (2003), the research arena mainly focuses on biophysical and built environment vulnerabilities because these are simpler to calculate and quantify.

They argue that it is important to include SV in spite of the difficulty in quantifying it. They were among the first to conduct SV assessments across the United States, comparing the SV of all US counties using a statistical analysis of 42 variables (Kumpulainen, 2006).

Studies in the field of SV over the last few years have used many approaches to measure SV to natural hazards. These studies have examined the nature of SV in several parts of the world including Italy (Frigerio and De Amicis, 2016; Frigerio et al., 2016), the United Kingdom (Tapsell et al., 2002), and the United States (Adger and Kelly, 1999; Cutter et al., 2003; Adger, 2006). In research conducted during the last few decades, an increasing number of studies have considered disasters to be more of a social construct (Cutter, 1996; Cutter et al., 2003; Adger et al., 2004; Smith, 2006). Many studies and researchers embrace this approach (Cutter et al., 2003; Adger et al., 2004; Lee, 2014; Guillard-Gonçalves et al. 2015; Frigerio and De Amicis, 2016).

Lee (2014) emphasises the uses of the SV as a planning tool to enhance social sustainability, especially to cope with climate change. In his study applying the SV approach to planning, through a developed framework at the township level in Taiwan, Lee (2014) stated that applying SV for this purpose is important to achieve sustainability in response to extreme climate events. In Cutter’s and other studies, SV is derived from the social context of the place, and it is characterised through spatial distribution of the various social groups and their various levels of entitlement and endowment and the capacities of government institutions to reduce risk (Collins et al., 2009).

Cutter et al. (2003) express SV as two factors: identification of people's characteristics that influence the social impact from risk and how these characteristics affect the distribution of risk and losses. An example is the elderly and children who will be affected by mobility. Because they need special care during events, they are more susceptible to harm than other social groups. According to this study, vulnerability assessment can be carried out at the sub-county level by using census data as the best resolution. SV can also be measured over time provided the data are available for consistent variables and geographies. Cutter et al. (2000) argue that SVI could be used for other cultural contexts, countries, poor data environments and homogenous populations. This model integrates SV and systems exposure, but it fails to account for the causes of inherited social vulnerability in the larger contexts.

Impact from natural hazards cannot be wholly avoided but can be alleviated by reducing the SV of exposed populations (Coppola, 2011; Zakour and Gillespie, 2013). It is therefore desirable to consider quantifying and mapping SV of people in unsafe conditions to give decision makers a good visual representation to support risk planning and mitigation (Cutter et al., 2003; Rygel et al., 2006).

In the field of disaster research, SV is mostly defined as specific social inequalities in the context of a disaster (O'Keefe et al., 1976). This translates to the characteristics of individuals or groups in terms of social diversity and cultural and economic factors that have shaped their capacity to cope with extreme events. There is general consensus about some of the major dimensions and variables that influence SV in the social science community (Cutter et al., 2003; Wisner et al., 2004; Blaikie et al., 2014). Studies on disasters have identified common indicators of SV as ethnicity/race, income, poverty, gender, age, education, religion, social isolation, and housing (Van Zandt et al., 2012). These common characteristics often result in disparities in response during disasters (figure 8). For instance, temporary occupants who rent their homes tend to evacuate faster than locals because they do not have other relatives or as many assets to care about. It is often assumed that people in the same area and having the same resources and information will react in the same way in a disaster situation. However, lower income and minority households tend to be more vulnerable, perhaps due to the quality of their houses, as lower socio-economic status can contribute to reduced hazard awareness, or reduced capacity to cope and recover due to financial limitations (Van Zandt et al., 2012).

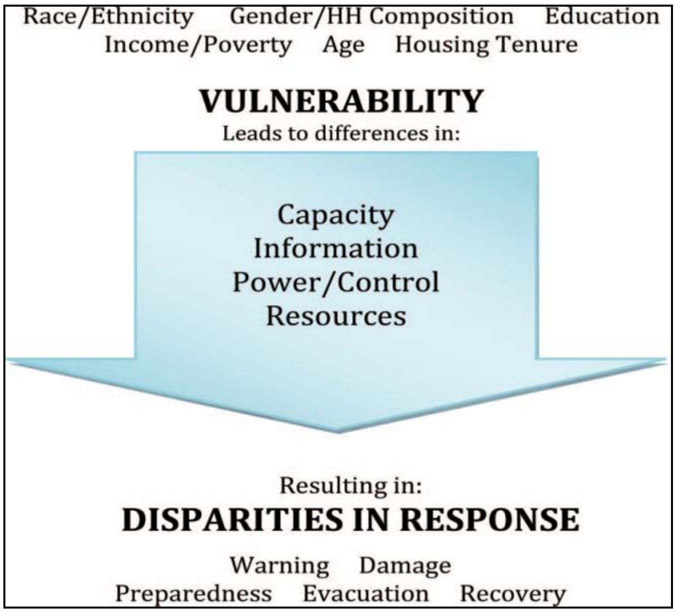

Figure 8. How vulnerabilities lead to disparities in disaster response (Source: Van Zandt et al., 2012).

Cutter and other scholars are among the few to undertake scientific approaches to map SV (Cutter et al., 2000). They analysed extensive literature and drew up a set of 85 indicators to measure SV in the United States in 1990. Van Zandt et al. (2012) emphasise that mapping social and physical vulnerabilities with the right indicators in conjunction with hazard maps can facilitate community planning for disasters (Van Zandt et al., 2012). Partial mapping of single indicators in SV at the local level will help identify the impact on a particular vulnerable group of a specific hazard. Many researchers have attempted to put this into practice and measure SV by operationalising the concept with indicators and indices (Tapsell et al., 2002; Cutter et al., 2003; Penning-Rowsell et al., 2005). They hypothesise the existence of a strong positive correlation between high vulnerability and low socio-economic status of the people exposed.

2.6 Resilience

Resilience is often misunderstood as a concept, in some studies seen as the inverse of vulnerability, while in others as an independent concept, and especially in disaster risk reduction policy at community level, confusion may appear (Cannon, 2008). Socially the notion of resilience is basically the move from highlighting vulnerability or viewing passivity and suffering to showing the causes and how it can be reduced (Cannon, 2008). Disaster resilience is a new shift in hazards studies that has moved disasters agencies in the US away from disaster vulnerability, with resilience being a proactive approach that represents community engagement towards disaster reduction (Cutter et al., 2008). According to Cutter et al. (2008), the main challenge in assessing disaster resilience is the identification of the right metrics. During Hyogo World Conference in Kobe, Japan, held in 2005, the importance of building resilient communities was emphasised using the following ways: 1) integrating disaster measures in sustainable development policies; 2) increasing local capacity; 3) incorporating risk reduction factors in the design process in the affected communities (ISDR, 2005). Both vulnerability and resilience are dynamic processes, which are viewed as static phenomena when measured. Holling (1973) was the first to use the term resilience to measure systems' ability to absorb changes and disturbance. In this study resilience was defined as the capacity to absorb and re-organise into a functioning system and develop to an advanced state through learning and adaptation (Adger et al., 2004, Cutter et al., 2008). The context in which the term resilience is used might change but the concept is always related to capability and the ability to return to a stable state after disruption, with the term being applicable to both individual and organisational responses (Bhamra et al., 2011).

Figure 9 illustrates Gallopín's (2006) conceptual linkages between vulnerability, adaptive capacity, and resilience. In this case resilience is viewed as a component of a system's capacity or response, which is related to that system's ability to adjust, moderate the effects, and cope with the consequences of system transformations (Bhamra et al., 2011). This conceptual framework refers to vulnerability as the capacity to preserve the structure of the system, while resilience is the capacity to recover (Turner et al., 2003, Bhamra et al., 2011). Four characteristics are identified by Fiksel (2003) as contributing to resilience: 1) Diversity in forms and behaviours, 2) efficiency in resources, 3) flexibility to changes, 4) cohesion between the system's elements and variables. Resilience can be enhanced and therefore improved through learning from past experiences of frequent disasters. Resilience is dynamic and can fluctuate over time due to changes in the characteristics of each geographical area (Zhou et al., 2010)

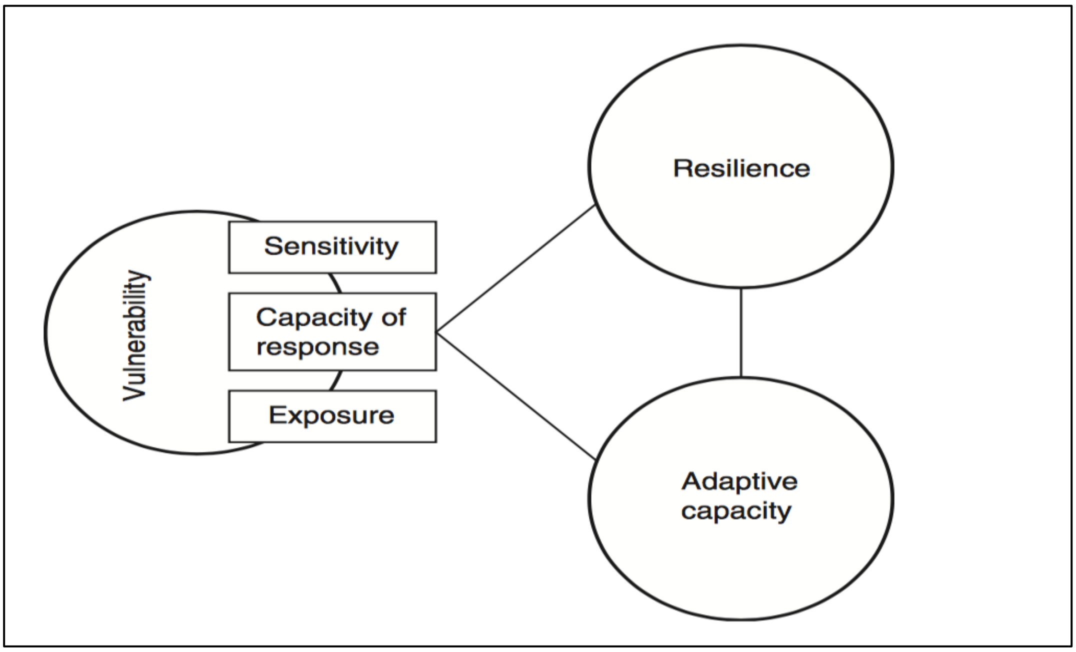

Figure 9 The concept of vulnerability: source Gallopin (2006).

Demographic, economic, and institutional variables are used to examine resilience in social systems (Zhou et al., 2010); for example, distribution of income among populations, migration and mobility are important indicators for resilience (Kelly and Adger, 2000). Meanwhile, dependency is another social resilience indicator as an individual depending on a single resource is less resilient than another with many resources. Similar to vulnerability, resilience can be predicted through the characteristics of the exposed group to a particular hazard. The disaster resilience of the place DROP model developed by Cutter et al. (2008) addressed the relationship between resilience and vulnerability, in a model that can be applied to real problems. Vulnerability and resilience can be viewed as the two ends of a spectrum, the higher the level of vulnerability in the system the lower the level of its resilience and vice versa. So, by reducing the vulnerability of any community we are basically increasing the resilience of that community (Cannon, 2008). Although studying resilience is not within the scope of the current study, the result of this study could guide towards resilience by showing the causes of vulnerability and hence suggesting recommendations for adaptation to overcome the root causes of social vulnerability.

2.7 Risk in natural hazards

“Risk is a product of the vulnerability of a community, or of subgroups within that community, to the effects from a given event and the potential for the occurrence of that event" (Ferrier and Haque, 2003). Risk of any disaster can only happen through the intersection of hazards and vulnerability, and in the absence of one, there is no disaster. According to the United Nations Office for Disaster Risk Reduction UNISDR (2009), risk is the combination of the probability of an event and the magnitude of its negative consequences.

The risk concept was introduced in management of natural hazards in the 1980s and 1990s to quantify the degree of hazard (Bründl et al., 2009). Figure 10 displays Brundl's concept of risk that is used in risk management. It has three phases: risk analysis, risk evaluation and finally planning an evaluation of mitigation measures (i.e. risk management). The International Decade for Natural Disaster Reduction (IDNDR) promoted increased awareness of the term 'risk' in natural hazards and emphasised it as key to deal with natural hazards (Bründl et al., 2009). According to statistics from the last century, the level of mortality associated with exposure to natural hazards has declined globally, whereas a significant increase in economic asset exposure has been attributed to rapid urbanisation, which has increased economic losses (IPCC, 2014).

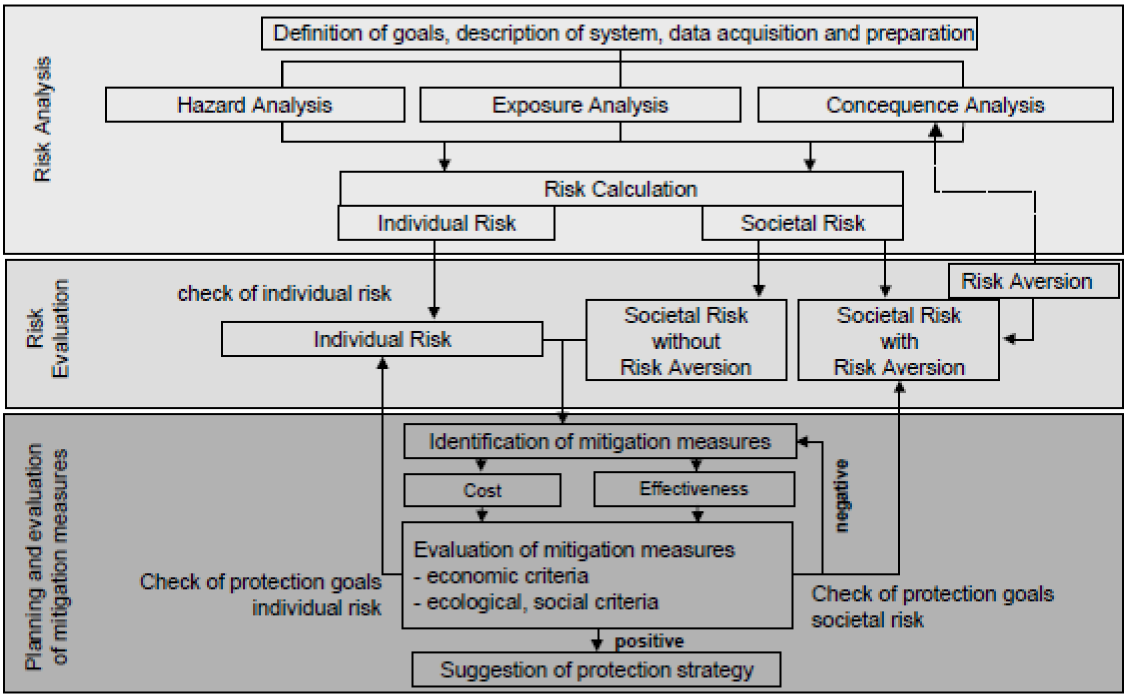

Figure 10 Risk concept: source (Bründl et al., 2009).

Risk reduction is a very important process and cannot be skipped in disaster management, which aims to minimise the losses from any known hazard. Achieving the optimum safety for any system involves judgements and contributions by all stakeholders to involve different perceptions in risk analysis, to maximise the amount of knowledge and skills during risk management (Smith and Petley, 2009). The risk quantification process will always be associated with some uncertainty; this has to be made clear to stakeholders. The term risk involves balancing between profit and loss, and it is associated with almost all aspects of life. It is associated with uncertainty; if there is no uncertainty, there is no risk. Risk assessment reduces any adverse consequences; it involves evaluating the significance of a particular threat by either quantitative or qualitative means. Quantitative assessment is generally based on estimating the probability of an event together with the magnitude of its known adverse consequences. It is expressed in the following equation:

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \quad \text{(Blaikie et al., 2014)} \qquad \text{Eq. 2.2}$$

Risk (R) is the product of the combination of people's exposure to a hazard (H) and the differential SV(V) (Blaikie et al., 2014).

The size of losses due to natural disasters around the world during the last few decades has forced emergency managers and policy makers to shift from reaction after disasters to being more proactive and focused in preparedness and mitigation (Cutter et al., 2000). During the 1990s, the International Decade for Natural Disaster Reduction (IDNDR) was the first international effort to build a framework for disaster risk reduction. Four years later, in Japan, at the first UN world conference focusing on disaster risk reduction, the SV aspect of risk became the dominant focus of disaster risk assessment, superseding the earlier focus on the biophysical side of disasters (Cutter et al., 2008).

The main goal of risk management in terms of disaster reduction is to lessen the known threats from natural, technological, man-made or combined sources while maximising any related benefits. In risk management, it is always good to have both a sound objective approach when using a scientifically based approach, and a sound subjective choice of reaction during disasters, based on experience and knowledge. The approach depends on choice, which is conditioned on the beliefs of individuals and on circumstances, such as financial constraints and societal attitudes, that the history of all types of disasters shows have impacted local and regional development in many ways and dimensions. Finding the best way to identify the overall risk should be the priority of any system (Greiving et al., 2006)

A study carried out by Ferrier and Haque (2003) resulted in a standardised framework that emergency managers could use for carrying out SV assessment regardless of their level of education, making the process possible for any level. Understanding people's risk perceptions is a very important element in the risk management process, as risk assessment based on perception is valued more than objective risk analysis (Smith, 2013).

2.8 Risk perception

Decision and policy makers need to understand how lay people perceive risk in relation to any type of hazard. This will provide the foundation for planning and mitigation efforts because it will help provide an understanding of public responses to hazards. The understanding of how people value risk will improve communication of risk information among decision makers, technical experts, and lay people. i.e. it requires expertise to understand what people mean when they use the word 'risky' about a hazardous event and to investigate the factors that caused their perceptions (Slovic, 1987). Social amplification of risk is a confusing problem in risk analysis, i.e. why some minor risk events provoke strong public concerns that lead to greater impact on society and economy (Kasperson et al., 1988).

People consider the current level of risk to be very high, covering a broader area of life compared to any time in the past (Smith, 2013). Early geographical studies considered risk only in reference to human behaviour against natural hazards, but later on, technological hazards were included as a main source of hazards. According to Smith (2013), sociological and anthropological studies have shown that risk perception is rooted in social and cultural factors. It has also been argued that the perception of and response to hazards are influenced by social environments, including such as friends, family, fellow workers, and officials. When evidence of risk or risk characteristics is very clear, it does not mean that lay people, decision makers, and experts should not debate the interpretation of risk with respect to any hazard. Risk characteristic interpretation helps change people's perspectives about risk. Across the hazard field, there is very little relationship between perceptions of the current risks from some hazards and their benefits, such as nuclear power. Public contributions in the risk assessment process involve both wisdom and error, depending on people's knowledge about hazards, so all stakeholders need to communicate during risk assessment (Slovic, 1987).

Risk perception will vary among people and age groups, but studies have shown that risk perception is measurable and predictable. Each person, group, and organisation have a unique risk perception and attitude, so the meaning of risk will be different for each; for instance, experts estimate risk technically based on annual fatalities (Smith, 2013). Both risk assessment and risk management are influenced by personal perceptions and the conditions of any system, which is why one should employ a scientific approach in risk assessment. Personal perceptions can depend on either objective or perceived risk. Risk perception varies across all lifestyles and across time as well; for instance, the risk of terrorism is important for some nations, but less important to other nations compared to other more common risks.

Because of their belief in personal control, individuals tend to tolerate more risk related to voluntary behaviour (Smith, 2013). According to Starr (1969), people are willing to accept voluntary risk 1,000 times more than involuntary risk. He also showed that the acceptable risk from any technology is approximately equal to the third power of the benefits from that technology.

2.9 Managing risk from natural hazards

Disaster risk management is a 'systematic process of using administrative decisions, organizations, operational skills, and capacities to implement policies, strategies, and coping capacities of the communities to lessen the impacts of natural hazards and related environmental and technological disasters' (UNISDR, 2002: 27). During the last couple of decades, the field of disaster management has shifted from controlling and reacting to disasters through clean-up and recovery to focusing more on loss reduction through mitigation, preparedness, and good responses (Cutter et al., 2000). According to the third United Nations World Conference and the 2015 Sendai Framework for Disaster Risk Reduction, disaster management should achieve four outcomes at all administration levels:

- disaster risk understanding: this will lead to better policies and practices in disaster management
- strengthening disaster risk governance
- disaster risk reduction must invest in resilience
- enhancing preparedness for better response, recovery, and reconstruction

The International Risk Governance Council's (IRGC) risk management escalator and stakeholder involvement outlined four classifications of stakeholder involvement in risk management according to knowledge level: 1) simple risk involving agency staff; 2) complex risk requiring external experts and agency staff; 3) uncertain risk requiring expert actors such as external experts, agency staff, and limited stakeholders; and 4) ambiguous risk requiring full participation, including all the aforementioned actors in addition to lay people or the public (Renn and Walker, 2008).

2.9.1 Disaster risk reduction

When disaster risk reduction was first addressed in Japan during the first UN world conference, the importance of SV was highlighted (Cutter et al., 2008). The Hyogo framework that emerged from the 2005 conference emphasised integration of disaster risk reduction elements into sustainable development in all fields. (ISDR, 2005). Reducing the vulnerability of a location was to be achieved by building community resilience, through planning and reconstruction of physical and socio-economic structures, and drawing on lessons learnt in all phases of the disaster as a window of opportunity to do it in the best way.

Among the many factors that affect the resilience of communities, social vulnerability deriving from socioeconomic and demographic factors plays a major role in adversely affecting people in exposed areas (Flanagan et al., 2011). Social vulnerability indexes therefore have a very important part to play in informing various aspects of the emergency management process. The identification of socially vulnerable communities to provide them with the necessary support over the course of a disaster is a vital element of disaster risk reduction. In many countries, especially developing nations, the local authorities are underfunded or understaffed and their resources will be seriously stretched by an emergency situation. In such situations the indigenous knowledge of local and tribal officials can be of great assistance. The Hyogo framework endorsed the need to adopt a comprehensive approach to disaster risk reduction in order to achieve substantial reduction in disaster losses (UNISDR, 2009).

Disaster risk and vulnerability are highly correlated, therefore vulnerability must be addressed in order for disaster risk to be reduced (Kelman, 2015).According to the disaster risk reduction definition stated in section 1.5, the aim is to lessen the vulnerability of people and property, so one of the first steps to be taken in this field is to identify vulnerable groups of population via a risk assessment process. It is clear that risk assessments that focus on physical hazards, legislation, institutional and technical capacities are insufficient without addressing social vulnerability (Weichselgartner and Pigeon, 2015). Hence, this study is focusing on identifying a form of social vulnerability assessment that will be useful for future risk reduction application.

2.9.1.1 Indigenous knowledge

Although the importance of local knowledge in relation to hazards and disasters has been recognised since the 1970s, it has only been seen in practical application within developing countries (Mercer et al., 2010). Sometimes this knowledge challenges the scientific thinking that for the most part underestimates this knowledge. However, there is now more interest among non-governmental organisations that have worked with affected populations and have seen how indigenous knowledge can contribute in disaster risk reduction (Mercer et al., 2007). Over the years indigenous populations have used the knowledge gained from disasters to gradually adapt their ways of life, which means that it is necessary to take their valuable knowledge into account alongside physical hazard risk (Blaikie et al., 2004). The benefits of incorporating local knowledge has been illustrated in the literature in many fields, such as natural resources management, land management, health, climate, fisheries, and agriculture (Mercer et al., 2010).

If it is to be utilised effectively, indigenous knowledge needs to be incorporated into a conceptual framework, such as that developed by Dekens (2007) for data collection and analysis in the field of disaster preparedness. Other similar frameworks could be developed to form a bridge between the indigenous and scientific fields and use the strengths of each in a complementary way. In Oman this area of knowledge has not been fully utilised , as this is a new field and there is a lack of awareness of the enormous contribution that this knowledge could make.

While indigenous knowledge has been applied in a few fields in Oman, such as water resources, agriculture (Choudri et al., 2018), and fisheries, no studies could be found in the natural disaster field. Despite the importance of this knowledge in many related fields, especially that of disaster management, it is beyond the scope of this study of development of a social vulnerability index.

2.9.1.2 Risk assessment in natural hazards

Natural hazard risk assessment is a topic that is receiving global attention, but local level application is limited due to other priorities in the development process, limited resources, or lack of awareness of natural hazards, and specifically of disaster risk reduction. All these factors have resulted in there being little assessment of risk of natural hazards in many developing countries, in particular. At the regional level, attention has been devoted to individual factors of vulnerability with little or no comprehensive view. Vulnerability assessment should cover all sectors of development and all dimensions in order for countries to plan coherent national strategy.

Risk is always associated with complexity, which explains the difficulty in identifying and quantifying the links between risk and its causes. If the cause and effect between the chains of events follow a linear relationship, simple models can be applied to determine the probability of harm, but this is not always the case. Risk always presents with high uncertainty. Its complexity can be a result of several factors: continuous interaction between actors, delay periods between cause and effect in some hazards, and intervening variables of inter-individual variation (Klinke and Renn, 2012). Risk assessment is the overall process of risk identification, risk analysis, and risk evaluation (EU, 2010). Risk assessment is basically an analysis that combines exposure, hazard, and vulnerability using spatial representation (Randolph, 2004).

The main goal of assessing risk is to be able to manage it and reduce it. It is about the quantitative and qualitative evaluation of a threat with respect to the associated uncertainty in a way that must be well communicated to the public (Smith, 2013). A report by the European Commission titled 'Risk Assessment and Mapping guidelines for Disaster Management' affirmed the importance of the role of risk assessment within disaster management. It is the central component for a more general process that helps nations identify resources and capacities needed to reduce risk (EU, 2010). Risk management and risk assessment constitute two essential ingredients in policies and planning. Future risk is determined by future exposure (Füssel, 2007). Most literature studies in this field have adopted a discipline-based perspective rather than an inclusive approach.

Every system has strengths and weaknesses that should be assessed. Knowing the system's weaknesses can help confront potential consequences and overcome and reduce weaknesses. Assessing risk from natural disasters will protect social, economic, and biophysical systems and provide a hazard mitigation plan that can be integrated into any current and future development plans (Smith, 2013). Thus, one of the main targets in conducting vulnerability or risk assessment is to incorporate the outcome into development plans. According to Kates and Kasperson (1983), risk assessment has three main steps:

- identification of a hazard
- estimation of the likelihood of the hazard
- evaluation of the social consequences of the hazard

The nature of the impact depends on both the event and the environment in which it occurs, as well as on the vulnerability of the community's physical and social components. Kasperson and Archer (2005) suggest that risk interacts with social, cultural, and institutional processes of the community and disrupts public response or intensifies it. Understanding the hazard's characteristics is very important but is not sufficient to measure the risk from a particular threat. Understanding of environmental effects and societal conditions is required in the risk management process; for example, an earthquake that happens on a mountain will not have the same impact as one in a submarine fault, which might generate a tsunami. Vulnerability will evolve over time as a reflection of the constantly changing structure and characteristics of the population and community.

To measure risk, characteristics and parameters must first be identified (Ferrier and Haque, 2003). The risk assessment process has three main elements, the first being hazard assessment. The hazard's basic characteristics can be obtained from several sources, such as satellite images, aerial photographs, topographic and geological maps, and historical records. This assessment is presented as an intensity map. Second, exposure analysis is about identifying the number and types of people and assets exposed to risk and determining the probability of exposure. Consequences analysis, the third element, concerns the overall expected loss considering all scenarios when combining the hazard and exposure (Bründl et al., 2009). Risk assessment is a key process that requires the right level of consideration at local and national levels in each country. Much risk information has been produced to date and is increasing with time as more data are becoming available. On the other hand, scientific and technical capacities are increasing also, so it is very necessary to transform these data into risk information to help decision makers and emergency managers (Desai et al., 2015).

2.9.1.2.1 Hazard assessment

Natural hazards can be measured for magnitude and frequency by area delineation. There is an inverse relationship between frequency and magnitude (figure 11). Despite the uncertainty level in the probability approach to extreme events, this method can help engineers design many key structures in hazard-prone areas. The frequency of reoccurrence influences the design as well as the nature of the hazard and the vulnerability level of the element at risk (Smith, 2013).

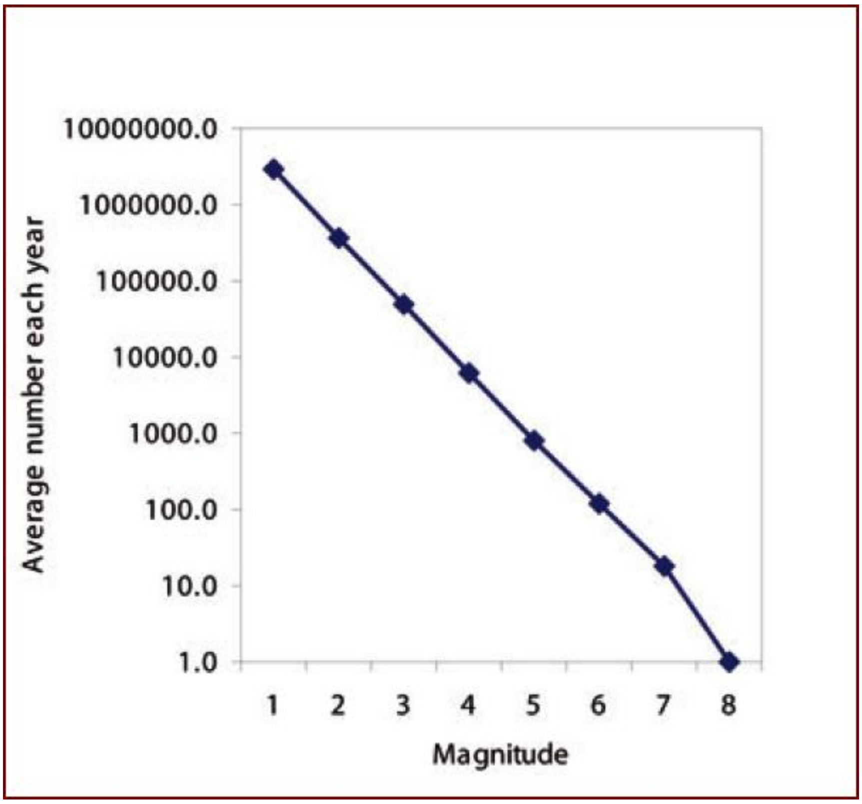

Figure 11. Relationship between the annual average number of global earthquakes and their magnitude (Source: BGS UK, 2015).

The distribution of the annual maximum and minimum values of the most extreme events helps in analysis of these events, such as large floods and windstorms, in any area. Having reliable data is very important in this type of probability approach, and the quality should be verified (Smith, 2013).

Natural hazards relevant to climate change show dynamic characteristics over time, so using past data to predict future conditions might not yield effects on the environmental system. In statistical terms, these changes in the frequency of events can be expressed by changes in the mean and standard deviation of the data set; for example, changes in the environmental temperature cause changes to the temperature mean and variability. A change of only one standard deviation can cause a 20-year event to become five times more frequent (Smith, 2013).

Analysis of extreme events focuses on the statistical spread of the maximum or minimum value in a given area. When the available data set is too short to represent a certain period, it is possible to extrapolate, bearing in mind the risk of error. This is often applied to high-magnitude events such as tsunamis for which data are scarce; in such cases, experts will rely on geological data to create modelling scenarios for these events. In general, the reliability of the probability approach will depend completely on the quality of the data set (Smith, 2013). Many studies have investigated multiple hazards using a hazard of place vulnerability model (Guillard-Gonçalves et al., 2015).

2.9.1.2.2 Social vulnerability assessment

Many cities are prone to disasters because of high density of population in a limited geographical area. Assessment of the population's SV helps us to understand the types of vulnerable groups (Wood et al., 2010; Guillard-Gonçalves et al., 2015). Nevertheless, since many social characteristics can play major roles in social vulnerability, it has not been clear to decision makers how this can be put into practice. It was only at the beginning of this century that researchers began to work on systemic application and development of measurements for SV and its spatial representation (Morrow, 1999; Cutter et al., 2003; Adger et al., 2004; Van Zandt et al., 2012).

Diversity in the uses of SV terminology in the field of climate change and natural disasters has led to diversity in methodologies for assessing vulnerability (Hinkel, 2011). Using the expression 'measuring vulnerability' is inappropriate because vulnerability is a theoretical concept. It is therefore more accurate to use the term 'operationalising vulnerability'. Operationalising vulnerability is accomplished by providing a method to map it to an observable concept. Several variables are required to make a concept operational (Hinkel, 2011).

Developing a tool for operationalising vulnerability is an important step in disaster risk reduction, which in turn can be used in the decision-making process. To achieve this goal, it is important to know the objective of the assessment, the targeted group, and system characteristics. It is also important to define the component of vulnerability assessment that is used in each case to communicate from the same perspective. The overall outcome of the risk/vulnerability assessment will be affected by both the quality of data and amount of subjectivity (Ciurean et al., 2013). It is crucial to address the vulnerability of a system to build ability for disaster risk reduction. This involves the ability to identify and understand the various vulnerabilities involved in determining the risk of any hazard.

Setting indicators helps in estimating vulnerability, but many studies in the field of disaster management have struggled to come up with suitable metrics for vulnerability because it is a dynamic phenomenon of continuous change of both social and biophysical processes, so it is not easy to produce a single metric (Adger, 2006), and vulnerability indicators chosen or developed for one context might not be appropriate for other contexts (Alwang et al., 2001). The definition of an indicator here denotes “a measurable metric that provides information of broader significance than the normal limits about a trend or process that might not be noticeable”, i.e. capturing the complex reality in a single concept (Hammond and Institute, 1995: 1). Another definition is 'vulnerability indicator to natural hazards', defined as ‘an operational representation of a characteristic or quality of a system able to provide information regarding the susceptibility, coping capacity and resilience of a system to an impact of an albeit ill-defined event linked with a natural hazard ' (Birkmann , 2006).

Indicators are useful to decision makers at all levels, allowing them to monitor system changes over time. They can be used individually or aggregated to form an index, leading to better and more comprehensive understanding of reality (Vincent, 2004). They are tools for measuring vulnerability and coping capacity (Birkmann, 2006).

Many researchers have attempted to measure vulnerability indicators (Gallopin, 1997; Cutter et al., 2003; Adger et al., 2004; Eriksen and Kelly’ 2007; Klein, 2009). Several studies have focused on vulnerability indicators in natural hazards, aiming to develop effective measures for disaster relief. Most of these studies have focused on the nature of the impact and mainly for developing countries at the local level. According to Hinkel (2011), measuring vulnerability indicators creates issues between policy makers who always demand such indicators and researchers who criticise these indicators. This is because of confusion about what vulnerability indicators are and the reasons and context for building them, and, on the other hand, what problems policy makers need these indicators to solve. When he was asked whether vulnerability indicators are the right way to identify vulnerable populations, Hinkel (2011) answered that it is feasible at the local scale where they can be defined by a few variables, but not at larger scale because collapsing the complex systems at this level to one indicator is not possible. According to Alwang et al. (2001), translations of this complex set of parameters into a quantifiable metric scale do not reveal its actual complexity and therefore might underestimate the vulnerability.

In developing vulnerability indicators for any system, three main factors need to be addressed particularly carefully because of their influence on the process: scale, dynamism, and complexity (Adger et al., 2004). Indicators should capture the causes of vulnerability, and their relationship should be understood and illustrated in the process of identifying them to explore their interaction. Kuhlicke et al. (2011) studied risk of flooding and found that identifying a common set of social indicators to explain vulnerability throughout the disaster phases is not possible. They argue that vulnerability is a product of specific socioeconomic-demographic, spatial, institutional, and cultural contexts. The assumptions of vulnerability indicators selection should be very clear throughout the study, and the findings should be more specific and comparable with other studies' outcomes for the same area (Adger et al., 2004).

Vulnerability indicators are meant to work on six issues in the impacted community: 1) identification of vulnerable people or communities, 2) identification of mitigation measures, 3) adaptation funds allocations, 4) monitoring adaptation, 5) raising awareness, and 6) using scientific research. It is very obvious that the main problem addressed by the indicators is the identification of vulnerable populations at the local scale (Hinkel, 2011). According to Kumpulainen (2006), vulnerability indicators selection should consider the following criteria: 1) they should cover the two sides of vulnerability, which are damage potential and coping capacity, 2) they should cover the three ranges of vulnerability dimensions (social, economic, and ecological). Damage potential indicators are about damage to any physical object, and this has scale and can be measured, whereas coping capacity indicators are those that can measure the response capability of a community. Lee (2014) identified two main characteristics of SV factors. First, they are general, i.e. SV factors tend to be more general than specific. Second, they are objective or focused on objective dimensions such as population density and infrastructures.

Furthermore, a vulnerability assessment process can be performed only with the help of indicators that will allow comparison between current and future vulnerabilities. This was stressed by the international community in the final documents of the 2005 World Conference on Disaster Reduction (WCDR) in Kobe, Japan. The Hyogo Framework for Action 2005-2015 also addressed the importance of such indicators: "Developing disaster risk and vulnerability indicators at national and sub-national scales, will enable decision makers to assess the impact of disasters on social, economic and environmental components and disseminate the results to the public and populations at risk" (ISDR, 2005: 7). Adger et al. (2004) found that comparing both people and places' vulnerabilities is possible across time and space at different scales, whereas the aggregation of vulnerability across various scales is less meaningful because the causes of vulnerability are different at each scale.

A few world organisations have developed a set of social and environmental indicators, such as the United Nations Development Program and the Human Development Index. The World Bank has produced a similar set of indicators to link environmental conditions and human welfare. Each indicator estimates the value of a certain characteristic of a system that arises from its relationship to the natural phenomena that are used to interpret it. Any developed or used vulnerability indicators should be comparable spatially and temporally to make them more tractable. It is very important to use a reliable conceptual framework that provides reliable outcome of the vulnerability assessment (Alwang et al., 2001).

The strength and weakness of the indicators depend on the quality of the of underlying variables, which should be sound, measurable, and relevant to the measured phenomenon (Freudenberg, 2003). Lack of the relevant data is one of the main problems of using this method, either due to difficulty of measuring the behaviour or because no one has ever measured it. The amount of subjectivity involved in variables selection means that there is no single set of indicators for any given behaviour Freudenberg, 2003). Appropriate choice of SV indicators is critical and depends on the quality and relevance of the selected variables and the bias involved in their selection (Nardo et al., 2005).

Vulnerability indicators can be validated by using other independent variables of a different data set and running a regression model (Fekete, 2012). Vulnerability changes with time. Places that were less vulnerable last year might show high vulnerability this year because exposure is continuously increasing. Vulnerability indicators are the bridge between academia and politics. They help synthesise complex variables into a single or a few numbers that can easily be used by policy makers. The indicators that influence the vulnerability of individuals and communities are numerous, but there is consensus about the main indicators that can best represent the socially vulnerable (Cutter et al., 2003; Van Zandt et al., 2012; Lee, 2014)

2.9.1.2.2.1 SV indicators

As alluded to earlier, there is consensus on a number of generic SV indicators for climatic hazards. For example, Peduzzi et al. (2009) argue that poor populations are more vulnerable to tropical cyclones. Cutter et al. (2003) suggest that key social indicators during natural disasters are age, ethnicity, gender, disability, and income and housing units. Table 8 shows the social indicators/variables that researchers have identified as influencing vulnerability to natural disasters.

Table 8 Generic variables used in natural disaster vulnerability studies (Author, 2018)

Dimensions	Variable	Cited by
Gender	Female-headed family	Blaikie et al, (1994); Fothergill, (1996); Enarson and Morrow, (1998); Morrow and Philips, (1999); Peacock, Morrow and Gladwin, (1997).
Age	<18 (children presence)	Morrow, (1999); Cutter, (2003); Martin et al., (2006); Madrid et al., (2006).
	>65 (elderly presence)	Cutter, (2003). Eidson et al., (1990); Schmidlin and King, (1995); Morrow, (1999); Peek-Asa et al., (2003); White et al., (2006); McGuire et al., (2007); Rosenkoetter et al., (2007).
Socioeconomic status	Low income family	Blaiki et al., (1994); Clark et al., (1998); Morrow, (1999); Fothergill and Peek, (2004)

	Limited economic entitlement	Burton et al., (1993); Hewitt, (1997); Morrow, Peacock and Gladwin, (1997); Platt, (1999); Cutter, Mitchell, and Scott, (2000).
	Essential needs (food, water, power, telecommunication)	(Cutter et al., 2003)
Special needs	Disability	Morrow, (1999).
Ethnicity	Race	Bianchi and Spain, (1996); Peacock and Girard, (1997); Gladwin and Peacock, (1997); Yelvington, (1997); Clark et al., (1998); Fothergill, (1999).
		Morrow, (1999); Cutter et al., (2003).
		Bolin, (1993); Marrow and Gladwin, (1997); Bolin and Stanford, (1998); Pulido, (2000).

2.10 GIS in risk assessment of natural hazards

GIS is a fundamental spatial tool for decision makers and emergency managers. Local government offices usually store large amounts of information that can be integrated with dynamic layers of information on evolving floods or storms extracted from satellite data (Smith, 2013). There is increasing use of GIS in emergency management to plan the response and estimate losses and levels of devastation after an event (Marcello, 1995), and it has proven to be a powerful tool (Palm and Hodgson, 1992). GIS-related studies contribute greatly to the field of hazard identification (Wadge, 1994; Jones, 1995; Carrara et al., 1996). GIS has been used most successfully in the monitoring and forecasting of meteorological and flood hazards and has provided profound support for advance warning and evacuation systems (Dymon, 1999).

Furthermore, GIS can enhance emergency responses by identifying the areas to be evacuated based on delineation of threat areas, which can support implementation of effective risk reduction measures. Other data on social community characteristics can also be visualised better with this tool (Morrow, 1999; Kaiser et al., 2003). A few researchers have used GIS to understand both biophysical and SV (Cutter, 2003; Rygel et al., 2006; Frigerio et al., 2016). Emmi and Horton (1993) investigated vulnerability to extreme storm events and sea-level rise, whereas Cutter et al. (2000) applied this tool to social and biophysical vulnerability mapping of multiple hazards of a place. Thus, we can conclude that GIS is an important tool that supports geographical inquiry and decision-making, including within the disaster risk reduction field.

2.11 Literature review summary

Climate change is a fact and global warming is increasing; statistics show that some climate related natural hazard events are decreasing in frequency, but their intensity is increasing. The developing countries are among the most impacted by these natural hazards due to their poor development or system characteristics and their geographical location. The most frequently occurring natural hazards are of hydrological and meteorological origins, and these are considered the most devastating natural disasters. The impact of some types of disasters can be alleviated by reducing the factors that influence the vulnerability of the exposed population. This is done by carrying out risk assessment through vulnerability assessment that is fundamentally about understanding the social characteristics that influence the impact of natural hazards. SV varies in time and space, a characteristic that gives rise to the need to study SV in local areas using place-relevant social and demographic data to reveal the nature of social vulnerability, by constructing and mapping a SV index. Using the same index through a fixed period of time can help to understand the SV trend in any area.

2.12 Research needs/gaps

Country-specific conditions, culture and exposure are key determining factors of a society's response to natural hazards and therefore its vulnerability level. Assessing these characteristics across a place helps to identify the most affected social groups (Albala-Bertrand, 1993; Raschky, 2008). The literature reviewed in relation to natural disasters, risk assessment, and vulnerability assessment very clearly shows that efforts are still scattered and superficial, lacking foundation steps to advance risk assessment in Oman (Al-Shaqsi, 2009; Al-Shaqsi, 2011; DGMAN, 2013). However, there is an obvious gap in understanding the nature of risk from tropical cyclone natural hazards in Oman's coastal cities. This study will seek to fill this gap by exploring the spatial patterns of SV via developing a suitable metric that will further examine the temporal variation of SVI by studying the historical data for three successive censuses. This will reveal the nature of SV across time and identify whether it increases or decreases in the study area. This will be achieved using statistical analysis and a GIS tool to map a spatial representation of social vulnerabilities in the same geographical area using the same set of variables.

The study also aims to develop a suitable local SV index. To this end the study adopted a well-tested and widely referenced approach, the SoVI developed by Susan Cutter in 2003. To make possible application of this approach to the Omani context, many adaptations were made, such as selection of variables according to data availability in Oman and their relevance to the local culture and how they influence SV to tropical cyclones. This required obtaining information on past events experience and interaction with local authorities involved in emergency management.

The study anticipated that the following challenges would be encountered along the way:

- data available but scattered
- lengthy process for acquiring data due to undefined responsibility and lack of awareness of data sharing policy
- most organisations work alone, hence there is no data sharing procedure and no central database
- exploration and analysis of data would be more difficult due to the undeveloped nature of the emergency management system

The main motivation to overcome these challenges, specifically the data issue, was the strong emphasis from the Supreme Council of Planning in Oman on the need to facilitate the work of researchers on sustainable development in general and disaster management in particular. This presented an opportunity to develop knowledge on SV to natural hazards in Oman.

3 Oman case study

3.1 Introduction

This chapter builds on the preceding literature review by describing how the Oman case study was deployed in the larger context of risk assessment of natural disasters. The chapter describes the geography of Oman that is relevant in the context of disasters, Oman’s cultures, its specific conditions, and exposure to natural disasters. This is followed by description of the country's history of natural disasters, the main associated threats, and Oman's natural hazard risk assessment system. The concluding section describes the geographical area within Oman selected for the case study and explains the rationale for the choice of this study area.

3.2 Oman's geography

The Sultanate of Oman is located in the south-eastern corner of the Arabian Peninsula in the Middle East. Oman’s coastline extends more than 2000 km from the north at the Strait of Hormuz to the borders of the Republic of Yemen at the southernmost tip of the country. Oman is surrounded by three bodies of water: the Arabian Gulf (also called the Persian Gulf on some maps), Oman Gulf, and the Arabian Sea Figure 12.

Figure 12. Location of Oman within the Arabian Peninsula (NCSI, 2013).

Oman is a developing Middle Eastern country occupying an area of 309,500 km² on the Arabian Peninsula. The country's long coastline overlooks the Indian Ocean across the Arabian Sea to the east (Fisher, 1994; Al-Awadhi, 2010). Oman is surrounded by four countries: the Islamic Republic of Iran to the north across the Gulf of Oman; to the northwest, United Arab Emirates; to the west, the Kingdom of Saudi Arabia; and to the south, the Republic of Yemen. The country is divided into eleven administrative regions called governorates (states or provinces) (NCSI, 2013): Ad Dakhiliyah, Ad Dhahirah, Al Batinah North, Al Batinah South, Al Buraimi, Al Wusta, Ash Sharqiyah North, Ash Sharqiyah South, Dhofar, Muscat (the capital), and Musandam (Figure 13). Each governorate has sub-divisions called wilayat (city). The total number of wilayats in Oman is 60 (NCSI, 2013).

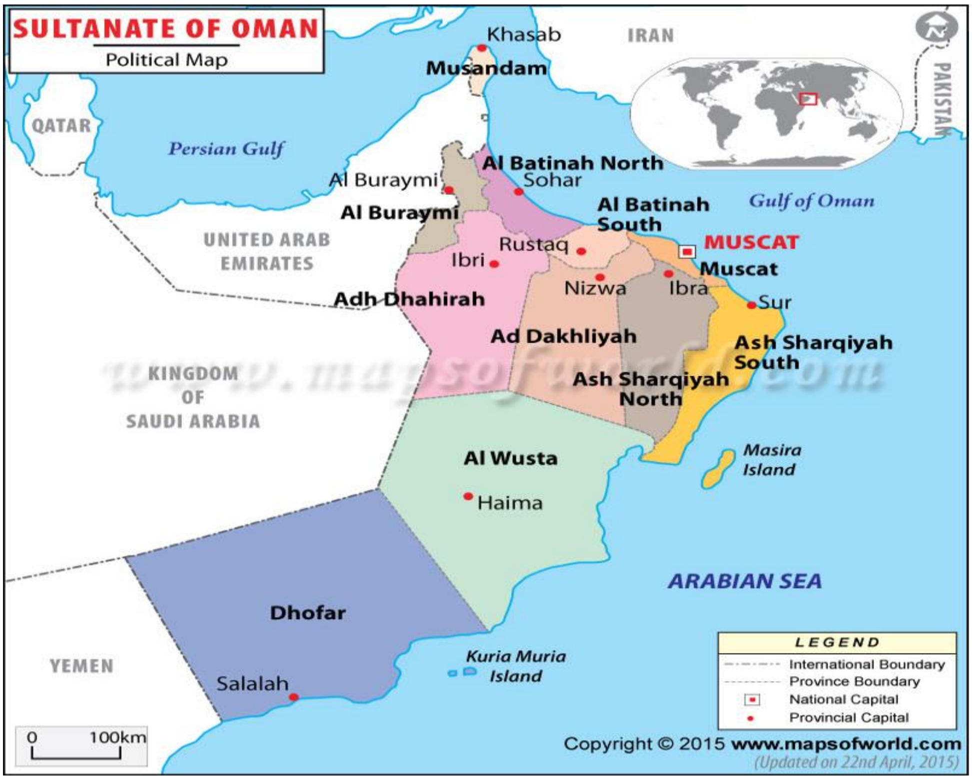

Figure 13. Oman's regions and governorate administration boundaries (source: www.mapsofworld.com).

Geographically, Oman can be divided into four areas: the coastal plain, the Batinah Plain, the Ash Sharqiah region on the eastern coast, and the Salalah Plain along the southern coast. Land elevations in Oman range from a few meters in the coastal areas to 500m further inland. In all, 15% of the country is mountainous. The highest mountain peak is the Jebel Al Akhdar (the green mountain) in the north, with a height of 3000m. Between the coastal plain and the mountains to the north and south lies the internal area, which covers 82% of the country, with elevation not exceeding 500 metres and consisting mainly of desert, sand, and gravel plains (NCSI, 2013; Al-Hatrushi, 2013). The Strait of Hormuz to the north of Oman has strategic importance as part of the main marine trading and oil route in the region. The strait connects the Indian Ocean to the Arabian Gulf and is a key route to other Gulf countries.

In 2015, Oman's population was about 4,250,000 according to the National Census for Statistics and Information, with Omanis representing 55.6% of the total population and the remaining 44.4% made up of non-Omanis, predominantly migrant workers from India, Pakistan and Bangladesh who contribute to infrastructure development and other economic growth activities for which domestic labour is in short supply. This situation is in sharp contrast to the population figures for 1977, when 91% of the 901,000 population were Omanis (NCSI, 2013). The majority of the Oman population are young, and around half of Omani residents live in Muscat and the Al Batinah coastal plain, the main hub for jobs in governmental institutions and private sector firms (NCSI, 2013). Omani communities are mainly tribal and consist of three main identities or groups: Omanis (mainly Arabs), a small segment of Omani citizens from Baluchi and African-rooted minorities, and finally non-Omanis (ethnic Indians, Pakistanis, and Bangladeshis and other foreign minorities). According to the Oman Census, four main languages besides Arabic are spoken in Oman: English, Baluchi, Urdu and various Indian dialects. Oman's main and official language is Arabic, and English is becoming widely spoken, especially in business (NCSI, 2013).

3.3 Oman's climate and the impact of climate change

Oman, like many other developing countries, only started documenting data recently due to low literacy levels, low economic levels, and non-existence of technology before the last five decades. Oman's climate is mainly hyper-arid with less than 100 mm of rainfall annually and ranging to semi-arid in some areas with 250-500 mm. Water resources in general are scarce in Oman; when it rains, the surface runoff in water channels does not last long due to high evaporation rates and dry aquifers. The annual average rainfall is 117.4 mm, ranging from as low as 76.9 mm in the interior dry deserts to as high as 181.9 mm in the southern part of Oman (Kwarteng et al., 2009). There are slight variations in climate between areas in Oman due to the size of the country and its various topographies.

There are two main rainy periods: in winter from November to April and in summer from June to September (Frenken, 2009).

The average annual temperature in Oman fluctuates from 10 to 30º C (Figure 14). The average maximum temperatures range from 23 to 42º C, whereas the average annual minimum temperatures can be from -3 to 20º C (Charabi and Al-Hatrushi, 2010).

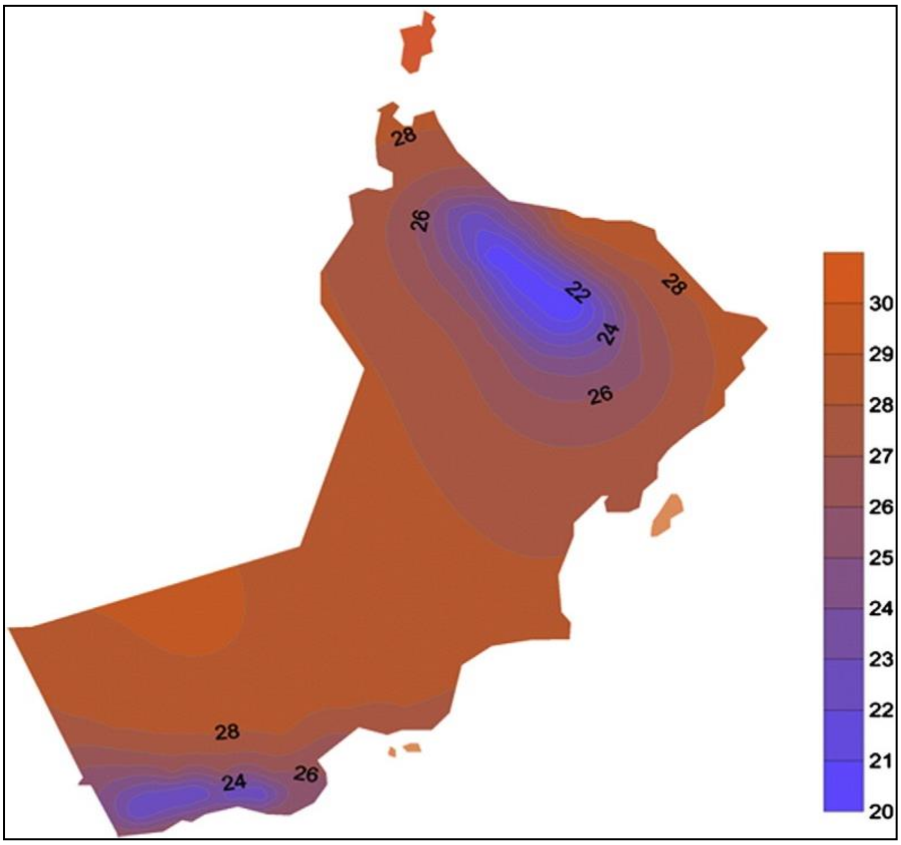

Figure 14. Annual average temperatures in Oman in ºC, 1984-2007 (Source: Charabi and al Hatrushi, 2010).

Evaporation varies from 1660 mm/year on the Salalah plain in the south to 3000 mm/year in the very dry interior, and 2200 mm/year at the Al Batinah coast. During the monsoon season rainfall occurs in the south (Dhofar region), causing temperature drops compared to other regions (Fao.org, 2009). AlSarmi and Washington (2011) examined trends in temperature and precipitation for the Arabian Peninsula for the last decade. Eight of the monitoring stations used during the study were in Oman, where a statistically significant warming trend was observed. Another study, analysing 27 years of rainfall in Oman (1977-2003), suggested that extreme rainfall events with more than 50 mm per day are very rare and represent only 2.9% of rainy days (Kwarteng et al., 2009).

A more recent study, conducted by Gunawardhana and AL-Rawas (2014), found evidence of changes in precipitation and temperature in Oman, from analysis of daily precipitation and temperature records in Oman's capital city of Muscat that focused on extremes. The results indicate that long term wetting is obvious in total precipitation which might be due to increases in extreme precipitation in recent few decades. Other relevant studies have been conducted recently for or by the Oman meteorological department to meet specific national operational demands. Many of these studies show evidence of climate change impact, some of which will be described in the relevant sections below (Fisher, 1994; Zhang et al., 2005; Kwarteng et al., 2009; Charabi and Al-Hatrushi, 2010; AlSarmi and Washington, 2011; Al-Hatrushi, 2013; Al-Yahyai et al., 2013; Al-Rawas et al., 2013; Charabi and Al-yahyai, 2013; AlSarmi and Washington, 2014).

Rainfall

Rainfall occurs in the region as a result of four meteorological conditions that originate from various geographical regions including central Asia, the Indian Ocean, tropical Africa, and the Mediterranean (Al-Hatrushi, 2013). According to Kwarteng et al. (2009), rainfall in Oman is caused by convection rainstorms that develop locally, mostly in summer, from cold frontal troughs (November to April) coming from the Mediterranean Sea, summer monsoon currents (June and September) covering the southern part of Oman, and tropical storms and cyclones over the Arabian Sea in the pre-monsoonal (May to June) and post-monsoonal periods (October to November).

Few studies have been conducted of rainfall variability in Oman despite its importance for assessment of water resources and the runoff process. However, such studies have become possible using the country's network of rain gauges in the last few decades (Fisher, 1994, Gunawardhana and AL-Rawas, 2014). Oman has limited freshwater resources and its extremely hot summer and high evaporation rate exacerbate water stress issues created by high water demand from a rapidly increasing population and urbanisation (MRMWR, 2013). However, rainfall tends to occur seasonally in Oman and can constitute a natural hazard, particularly when associated with major storm events. Westra et al. (2014) note that floods due to heavy rainfall are often costly and devastating natural hazards, stating that in 2011, floods caused an estimated $70 billion in damages globally and more than

6000 fatalities. During the year 2007, when Cyclone Gonu struck Oman, the cost of the damage was estimated to be around $ 4billion (Al-Shaqsi, 2009).

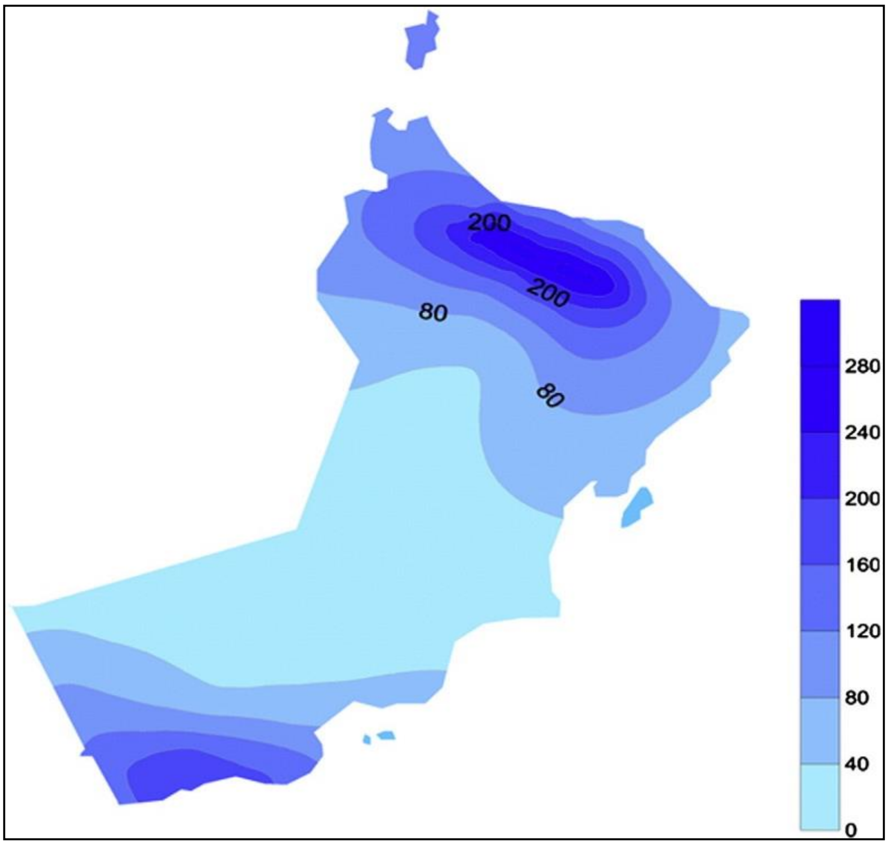

Figure 15. Annual average rainfall (mm) 1984-2007. Source: (Charabi and Al-Hatrushi, 2010).

Tropical cyclones

Tropical cyclones (TC) originate in tropical and subtropical waters, according to their location. Higher categories (see Table 11 for classification) of TC are associated with high speed winds, storm surges, and floods. Around 7% to 13% of global tropical cyclones happen in the northern part of the Indian Ocean. During the last 120 years, 18 tropical storms and 10 tropical cyclones have affected Oman's coastal areas (table 1 section 1.1.2) (Al Najar and Salvekar, 2010). Gonu was the strongest recorded TC in the last 60 years although two other mega cyclones have been recorded, in 1890 and 1895. The 1890 cyclone was the most devastating and deadliest natural disaster in Oman’s history, with 727 fatalities reported (Bailey, 1988; Fritz et al., 2010). Gonu was the worst disaster in Oman's recent history (see section 3.4.1 below) and the extent of destruction suggested that the country was not prepared for this kind of hazard event (Piontkovski and Al-Azri, 2010; Alamri, 2017).

Sarker and Sleigh (2015) modelled maximum significant wave heights based on data from Oman's meteorological office and from the WMO. Table 9 shows the modelled wave heights during Cyclone Gonu; despite differences in the estimated wave heights, there is good agreement on the general magnitude and patterns of waves in the coastal areas and, in the absence of observed data, this study reveals the likely hazard posed to coastal areas by such cyclones in the Oman region.

Table 9 Comparison of maximum wave heights of the main two mega cyclones in Oman (Sarker and Sleigh, 2015).

1) Comparison of wave height results for Cyclone Gonu (2007)			
	Maximum significant wave heights (m)		
Location	World Meteorological Organization (WMO)	Oman Met Office	Study of Sarker and Sleigh (2015)
Chabahar, Iran at 30 m depth (Point AW2)	4.2	-	4.5
Gulf of Oman	8	-	9
Arabian Sea	11	6-12	Up to 15
2) Comparison of wave height results for Cyclone Phet (2010)			
	Maximum significant wave heights (m)		
Location		Oman Met Office	Study of Sarker and Sleigh (2015)
Gulf of Oman		4	4
Arabian Sea		7 to 8	13

Storm surge

The world's greatest natural disasters are triggered by tropical cyclones whose impacts are caused by storm surges that result from the cyclone (Needham et al., 2015). Oman has coastal areas facing the northern Indian Ocean that are threatened by storm surges caused by severe cyclones. There is evidence of serious destruction along the coasts of

Oman that is attributed to storm surges; Cyclone Gonu, the most recent example, caused total damage estimated at $4 billion (Dube et al., 2009). Oman's coastal bathymetry around the Muscat area is steep, which helps decrease the impact of storm surges but also increases the effect of waves. In a worst-case scenario, storm surges can reach up to 10m if the cyclone makes landfall perpendicular to the shoreline of Oman (Blount et al., 2010; Fritz et al., 2008).

A study using water marks (buoys) for field observations across a 270 km stretch of coast from Ras al Hadd south of Muscat to Abu Abali village 90 km north of Muscat found that the maximum water height caused by storm surges was 5m (above mean sea level) and the maximum in Muscat was up to 3m (figure 16) (Fritz et al., 2010). In a collaborative effort by various scientists, an operational numerical storm surge prediction model was introduced and applied in the Arabian Sea and Bay of Bengal; the model is intended to enhance preparation and development of evacuation plans (Dube et al., 2009).

Wadi flooding

Flash floods are different from any other threats because they often occur without warning and can cause huge devastation and loss of life (Montz and Gruntfest, 2002; Saleh and Al-Hatrushi, 2009). Flash floods are caused by heavy rainfall in elevated areas that produces a torrent of floodwater moving toward lowlands and coastal areas. Oman’s wadis are common cases of this type of phenomenon, for example, the Hail al Ghaf Wadi produces a flow of water 5m deep in a 1 km wide channel; this is one of the large-scale examples of this type of threat in Oman (Fritz et al., 2010; Fritz et al., 2010).

Assessment of risk from such flash floods requires a different approach than other associated threats, from the initial rain event to the downstream environment. A holistic approach should include the rain detection system, land use, soil characteristics, warning systems, and evacuation plans (Montz and Gruntfest, 2002). Poor planning is one factor, along with rapid urbanisation and the reduction of permeable surfaces, that increase the impact of flooding in general and flash flooding in particular in Oman (Al-Rawas, 2013). Al-Rawas (2009) suggests that the increase in the frequency of flash floods is due to increased surface runoff. Reversing losses from these threats has yet to be achieved through improving forecasting, warnings, and real-time observations (Saleh and Al-Hatrushi, 2009). [1]

Figure 16. The impact of flash flooding on one of the roads during Cyclone Gonu. NCSI, (2015)

Wind

The damage and fatalities from Cyclone Gonu were caused by flooding, storm surges and winds (Fritz et al., 2010). Therefore, wind is an important factor that needs to be addressed (and is the key criterion by which cyclones are categorised - table 10).

Table 10 Saffir-Simpson Hurricane Wind Scale. (EM-DAT, 2015)

Category	Sustained Winds	Types of Damage Due to Hurricane Winds
1	74-95 mph	Very dangerous winds will produce some damage: Well-constructed frame homes could have damage to roof, shingles, vinyl siding and gutters. Large branches of trees will snap, and shallowly rooted trees may be toppled. Extensive damage to power lines and poles likely will result in power outages that could last from a few hours to several days.
	64-82 knot	
	119-153 km/h	

[1] Wadi is a noun (plural Wadis) defined (in certain Arabic-speaking countries) as a valley, ravine, or channel that is dry except in the rainy season. Oxford dictionary

2	96-110 mph	Extremely dangerous winds will cause extensive damage: well-constructed frame homes could sustain major roof and siding damage. Many shallowly rooted trees will be snapped or uprooted and block numerous roads. Near-total power loss is expected with outages that could last from several days to weeks.
	83-95 knot	
	154-177 km/h	
3	111-129 mph	Devastating damage will occur: well-built framed homes may incur major damage or removal of roof decking and gable ends. Many trees will be snapped or uprooted, blocking numerous roads. Electricity and water will be unavailable for several days to weeks after the storm passes.
(major)	96-112 knot	
	178-208 km/h	
4	130-156 mph	Catastrophic damage will occur: well-built framed homes can sustain severe damage with loss of most of the roof structure and/or some exterior walls. Most trees will be snapped or uprooted, and power poles downed. Fallen trees and power poles will isolate residential areas. Power outages will last weeks to possibly months. Most of the area will be uninhabitable for weeks or months.
(major)	113-136 knot	
	209-251 km/h	
5	157 mph or higher	Catastrophic damage will occur: a high percentage of framed homes will be destroyed, with total roof failure and wall collapse. Fallen trees and power poles will isolate residential areas. Power outages will last for weeks to possibly months. Most of the area will be uninhabitable for weeks or months.
(major)	137 knots or higher	
	252 km/h or higher	

Oman has been impacted by a few mega cyclones of category 3 and 4 with wind exceeding 96 knots. Most recently cyclone Mekunu landed (category 3) with wind in excess of 110 knots. Like Mekunu, and Gonu in 2007, many of the cyclones that hit Oman in the past had strong winds that caused significant damage to buildings, especially temporary structures or those with unstable materials. Flying debris represents the main threat to life, with many casualties recorded.

3.4 Natural disasters in Oman

From the above sections it is clear how climate in Oman is influenced by global warming through an increase in the intensity of extreme weather; this is evident from Oman's hazards history which shows that cyclones have during the last decade become almost an annual event (see table 9, section 3.3). With this level of hazard, and the resultant exposure of the country's coastal cities and the acceleration of urbanisation, the risk of natural disasters has become greater. The country is exposed to natural hazards, principally as tropical cyclones, but also to earthquakes, and tsunamis (Al-Shaqsi, 2010; Azaz, 2010; Fritz et al., 2010; Wang et al., 2012; Hoffmann et al., 2013). Due to Oman's location facing the Indian Ocean, extreme weather events such as tropical cyclones are frequent (Al-Awadhi, 2010).

Literature related to the history of disasters in Oman is sparse because these events were relatively uncommon and documented in an ad hoc way (Blount et al., 2010; Fritz et al., 2010; Hoffmann et al., 2014; Hoffmann et al., 2013). The international disaster database in the Centre for Research on the Epidemiology of Disaster (CRED), National Hurricane Centre (NHC), Joint Typhoon Warning Centre (JTWC), and Indian Meteorological Agency (IMA) are the best available public sources of statistics about disasters in Oman. Despite the scant documentation, there is long history of natural hazards in Oman. During the last 1200 years, three tropical mega cyclones have been recorded, in 865, 1890 and, in 2007, Cyclone Gonu (Blount et al., 2010). Now the policy makers have noticed that cyclones have become more frequent events.

Oman is a fast-developing country, and urbanisation is increasing, mainly in the coastal areas. According to the National Centre for Statistics and Information (NCSI), the population of Muscat Governorate (the capital region) rose from about 775,000 in the 2003 census to 1,155,000 in the 2010 population census. This population growth is attributed to continuous movement toward the capital, Oman's main employment and industrial hub (NCSI, 2013). This development has resulted in increased surface runoff and hence flash floods in the urban areas of Oman are more common (Al-Rawas, 2013). There is as yet no planning/regulation in place to prevent development in wadi (water channels) mouths and floodplains, therefore flood risk is increasing.

Oman's long coastline has many coastal cities facing the Indian Ocean that are prone to natural hazards (Wang and Zhao, 2008; Dube et al., 2009; Blount et al., 2010; Dibajnia et al., 2010; Sarker and Sleigh, 2015). The following sections will briefly summarise each type of threat to which Oman is exposed.

Tsunamis

Oman is exposed to tsunamis because of a main seismic zone under the Gulf of Oman, named the Makran subduction zone (MSZ), around 500 km from Oman. Makran is a region in Iran that falls on a shallow tectonic plate subduction zone where crustal subsidence can give rise to tsunamis moving towards both Oman and Iran. Several studies have found evidence of tsunamis' impact in countries overlooking the Makran subduction zone in the Arabian Sea. Geological evidence found in Oman’s mountains indicates to a past tsunami connected with an earthquake in the Makran subduction zone (MSZ) in 1945 (Hoffmann et al., 2013). This type of hazard is outside of our study’s scope and is not covered in detail, although building resilience to cyclone risk should also raise resilience to tsunami. According to earth scientists, the region is overdue for a tsunami based on the geological record (Shah-hosseini et al., 2011; Heidarzadeh et al., 2008; Hoffmann et al., 2013).

Cyclones

A tropical cyclone is a natural phenomenon limited in space and time, but whose impact can be large enough to disrupt community activities on a large scale for a long time (Patwardhan and Sharma, 2005). Oman is affected by many tropical cyclone events that develop in the Arabian Sea and northern Indian Ocean (Figures 17 & 18) (Fritz et al., 2010; Krishna and Rao, 2009; Al-Shaqsi, 2010). Figure 18 shows the best tracks for most of the cyclones/storms that occurred from 1945 to 2007 according to the Joint Typhoon Warning Centre (JTWC). These events are most often generated in the northern part of the Indian Ocean during two seasons (Al-Shaqsi, 2009; Al-Shaqsi, 2010; Fritz et al., 2010). All the mega cyclones have been formed in the same season, in May to June, which is the season of the monsoon t flows from the northern Indian Ocean (Blount et al., 2010).

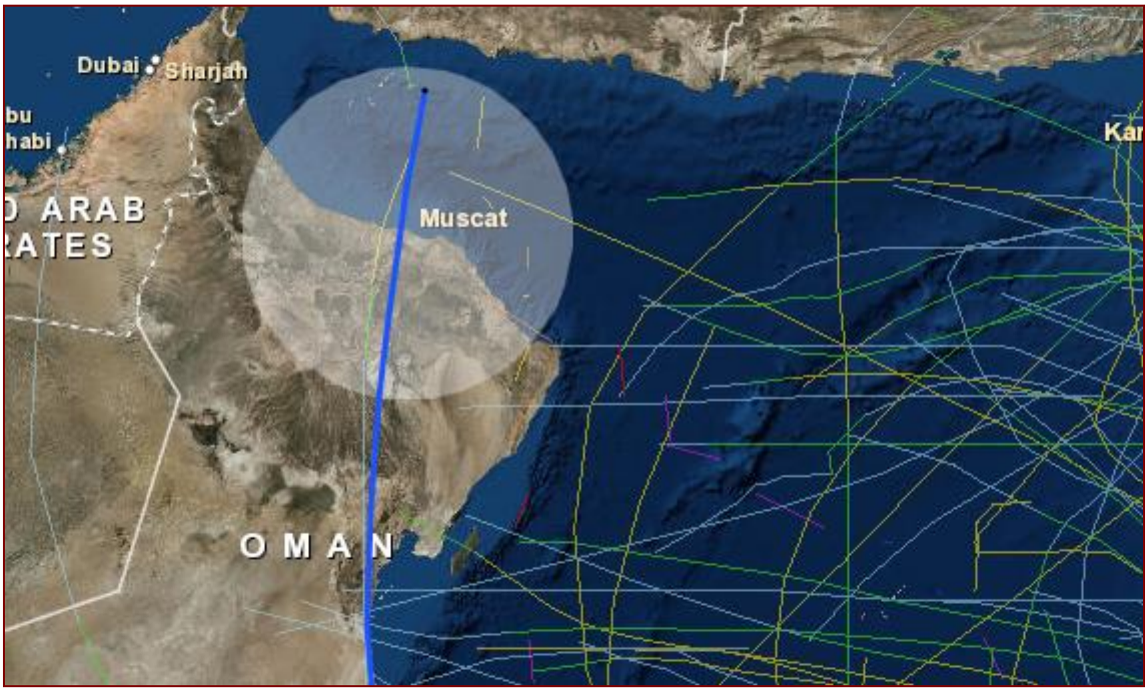

Figure 17. The historical best track of tropical cyclones in the northern part of Oman and the historical storms in the Arabian Sea, 1990-2014, source: CRED (2016).

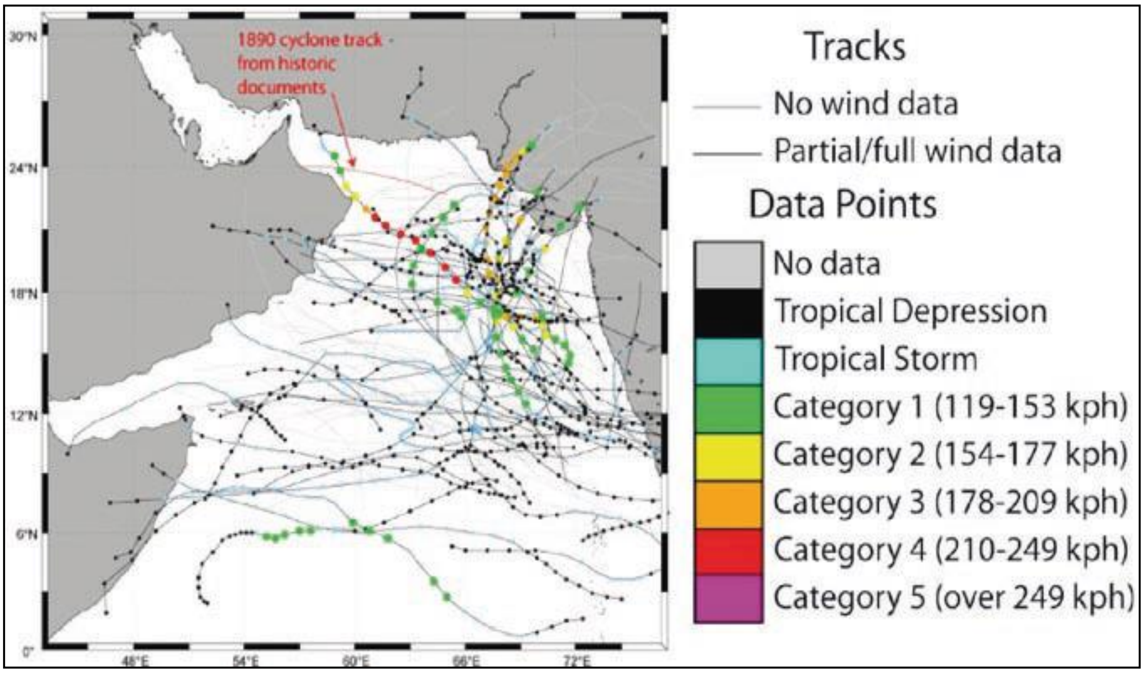

Figure 18. Tropical cyclone best track data in the Arabian Sea, 1945-2007. Source: JTWC (2015).

In Oman's history, several cyclones were recorded, of which the most significant to affect Oman were:

– Muscat Cyclone on June 5, 1890. More than 285 mm of rainfall were recorded in 24 hours (Al-Awadhi, 2010), for what is considered the most devastating natural disaster in Oman's history, affecting the coastal stretch from Sur to A'Suwaiq, a distance of around 300 km. Intense rainfall was associated with strong winds. The main impact was felt in Mattrah city in the capital Muscat. The number of deaths was 727, and around 100,000 date trees, the main source of local income at the time, were destroyed.

– Mega cyclone Gonu on June 5, 2007. The storm lasted for three days, during which precipitation reached 610 mm/day and wind speed reached 100 km/h. Gonu is the worst recent (last few decades) natural disaster to have affected the country. Deaths totalled 49, with damage to infrastructure estimated at $4 billion (Coumou and Rahmstorf, 2012; EM-DAT, 2015).

The frequency of cyclones appears to be increasing, with many other cyclones also occurring after Gonu, including tropical cyclones Phet (2010), Kyla (2011), Nilofa (2014), Ashobaa (2015) and Mekunu (2018). Many of these cyclones were high category, and two made landfall (Phet and Mekunu), causing significant economic damage.

Flash flooding

Flash flooding is a severe threat to Oman's urban and rural areas. Rainfall and watershed characteristics and lengths of rainstorms are some of the main elements of this natural phenomenon (Al-Rawas, 2009). Flash flooding can be forecast with the help of integration of data from several sources, such as rainfall data, remote sensing, and satellite data. Many methods are available to help in flash flood forecasting, such as the rainfall comparison method, the flow comparison method, and the flash flood susceptibility assessment method (Hapuarachchi et al., 2011).

It is however very difficult to improve flash flood forecasting to include a good lead time, due to the uncertainties associated with rainfall forecasts (Al-Rawas, 2009; Al-Rawas et al., 2013). Many studies have investigated flood risk in Oman (Scholz, 1980; Wayne and David, 1986; Saleh and Alhatrushi, 2009; Alkalbani, 2010; Alrawas and Voleo, 2010). A flash flood can be generated by upstream rainfall several miles away, whilst its level of impact depends on asset proximity to water channels (wadis). The built area can help reduce surface permeability and increase surface runoff (figure 19), so highly populated urban areas can be at further risk of flash flooding because of their densely built areas such as highways and parking lots. It is important to introduce mitigation to protect urban areas from flash floods in flood-prone areas (Al-Rawas et al., 2013).

Figure 19. Flash floods and damages during Cyclone Mekunu 2018 (Alwatan, 2018)

Al Rawas (2013) investigated the impact of urbanisation on the runoff process, which decreases infiltration and increases the rate and volume of water transported to the river. He suggested that the conversion of large areas of Oman's agricultural lands to commercial and residential areas has contributed to surface impermeability. In addition, wadi /water channel capacities have been reduced due to urban expansion.

3.4.1 Tropical Cyclone Gonu

Cyclone Gonu was a landmark event in Oman, as it was the most significant natural hazard event in generations, whose size and impacts led to the development of natural hazard management in the country:

> "Oman, 5^{h} June 2007, even with the weaker wind speeds, Gonu, which means a bag made of palm leaves in the language of the Maldives, is believed to be the strongest cyclone to threaten the Arabian Peninsula since record-keeping started in 1945" (Harmeling, 2008: 6).

Gonu developed in the eastern part of the Arabian Sea (figure 20). On June 2, it was classified as a cyclone one day after its formation, when it was 710 km from the nearest coast of Oman. On June 3, the cyclone reached category 5, with a maximum wind speed of 270 km/hour. On June 4, the cyclone was 285 km southeast of Masirah Island, the nearest point it reached to Oman’s coast before diverting towards Iran. Gonu started to weaken when approaching Oman due to cooler water temperatures and dry air coming from the mainland. The cyclone reached its nearest point to the eastern-most tip of Oman (Ras-alhad) with a wind speed of 164 km/h on June 5. Then, fortunately for Oman, it moved away to the north-northwest, but towards the Makran coast of Iran on June 7, where it finally made landfall with subsequent loss of life and major structural damage (Fritz et al., 2010; EM-DAT, 2015).

The maximum high-water mark measured after the cyclone was 5.1 m in the village of Ras Alhad, and an inland inundation of 200 meters was observed there. In Muscat, the top water mark was at 2-3 m, with massive coastal erosion and beach road destruction. The continuous rain in the mountainous and hilly coastal areas in Muscat and other cities sent torrents of floodwater towards the coastal cities. The cyclone fatalities and damages were caused mainly by the flash floods of wadis and the storm surge (Fritz et al., 2010).

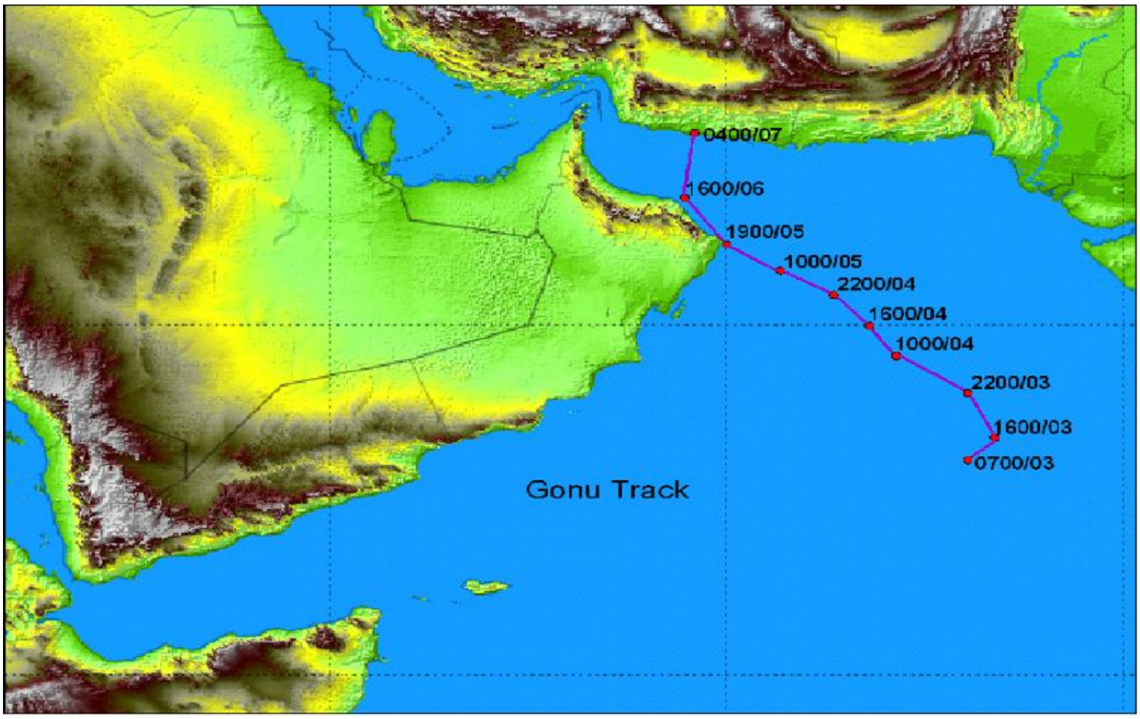

Figure 20. Cyclone Gonu's best track (EM-DAT, 2015)

As Cyclone Gonu passed close to the coast of Oman, the coastal area was exposed to a large amount of rainfall. The Altaeeyen Dam rain station recorded more than 900 mm of rainfall per day (Al-Awadhi, 2010). The cyclone resulted in an enormous amount of rainfall that led to huge levels of destruction never seen before (Figure 21).

Figure 21. Examples of destruction in Oman caused by the super cyclone Gonu, June 2007. (Local newspaper, 2007)

The destruction was so extensive that people were heavily dependent upon support from the government and also non-governmental organisations such as the Oman Charitable Organization (OCO). There was also extraordinary support from local people and individual businessmen, which shows the strength of social bonds in the country. For the government to help, the first step was to immediately survey the destruction and identify the number of built areas that had been damaged. Table 11 shows the result of the damage assessment. Flooding destroyed bridges and houses, uprooted trees, and washed away roads. The government started reviewing the total damages over the country immediately after the event. A survey of more than 60,000 building units stated that 50% of these units were badly damaged. Among the surveyed units 85% were in Muscat city, of which 77%

were declared damaged. More than 13,000 cars were declared damaged, of which around 88% had no comprehensive insurance (Al-Awadhi, 2010).

Table 11 Cyclone Gonu damage assessment carried out by Oman government. Source: Al-Awadhi (2010).

Wilayat (city)	Houses surveyed (No)	Houses accounted (No)	Houses damaged (No)	Furniture (No)	House equipment (No)	Personal belongs (No)	Transportation vehicles (No)
Mutrah	4273	1135	888	718	730	542	428
Bosher	7179	3894	2776	2680	2721	2310	4065
A ‘Seeb	30498	12239	9035	7614	7888	6311	5676
Al-Amerat	5968	3468	3089	2013	2044	1419	397
Muscat	607	500	470	387	359	369	144
Qurayat	3512	3115	2891	2470	2478	2436	944

Table 11 shows the results of the damage survey carried out by the authorities in the coastal areas of the Muscat capital region . It is clear that the amount of destruction and losses varied across different cities. A’Seeb, for example, had the highest figures in all categories, which can be explained by it having the largest population in the Muscat capital region with representation of most social groups, very low land, and some of the bigest water channels and flood plains. Meanwhile, the lowest impact was in Muscat city itself, because of the small population due to many of its houses being old and abandoned .

3.5 Social vulnerability in Oman

As indicated earlier, Oman lags behind in assessment of risk and vulnerability to natural hazards. Barely any studies have discussed SV to natural hazards at all, let alone in the context of tropical cyclones. A few studies have noted reasons why the population in the impacted area were vulnerable, but their analysis was purely a qualitative appraisal of past events (Al-Shaqsi, 2010; Al-Rawas et al., 2013). From the nature of impacts during the last few events, it is obvious that there are drivers of vulnerability of populations to tropical cyclones, but it is also obvious that vulnerability from tropical cyclones in Oman comes from more than one dimension (Al-Shaqsi, 2009; Al-Shaqsi, 2011).

Al-Shaqsi (2011) identified several of these dimensions: living in an industrial area with low standard houses whose occupancy exceeded the designed capacity, in an exposed area, was one of the main causes of death during Cyclone Gonu in 2007. Low community awareness of risk is another factor that played a big role also in the same event. Gonu was the first cyclone many people had experienced and so they were not ready and had no clue how to react and where to evacuate to. In Gonu the main death toll was among low-income expatriates, due to their working and living in industrial areas with low living standards and no coping capacity. There were many other types of devastation related to exposure and proximity to the hazard source: destroyed roads, interrupted utilities, water pollution, health hazards, and destroyed infrastructure (Azaz, 2010).

As indicated by Al-Rawas et al. (2013), during their study of the relationships between watershed characteristics and mean Wadi flood peaks in arid regions, the main driver of vulnerability in the flooded area was the increase in urbanisation that caused increases in the impermeable areas. There has been a very large and rapid increase in population in Oman in general and in the Muscat capital region’s coastal cities specifically. This urbanisation has led to many associated changes such as expansion in planning areas, and development of infrastructure, roads, farms, industrial areas, commercial areas, and private houses. All of these have contributed heavily to surface sealing and reduction of surface water infiltration.

Increases in urban area, with changing land use from agriculture to residential, commercial, and industrial uses, increases flood-peak discharges (Saleh and Al-Hatrushi, 2009). These expansions and developments have neglected to consider design and implementation of a suitable surface water management system to address increases in peak flow (Al-Awadhi, 2010). According to Al-Shaqsi (2010), underestimation of the power of flash floods caused by cyclones is another major cause of loss of life during cyclones. As an example, during Cyclone Phet, seven people were killed while trying to cross flooded water channels caused by flash flooding. Language barriers amongst expatriates (e.g. incomprehension of emergency instructions given only in Arabic) also contributed to loss of life, along with their poor living conditions, often on construction sites. Among the main factors increasing vulnerability in Oman are geographical location, urbanisation (bad planning specifically), and low wages of non-Omani workers, especially in the field of construction as due to their low wages these workers tend to live in poor and unstable temporary wooden houses.

Table 12 shows some of the local drivers of vulnerability during tropical cyclones in Oman, drawn from available reports of past cyclone events incurring loss of life and property. No systematic assessment of vulnerability to tropical cyclones in Oman has been conducted to date. Completing this step is crucial because tropical cyclones are the main destructive natural hazards in Oman and whilst super cyclones like Gonu are rare, cyclones are frequent. Since Gonu, smaller cyclones such as Ashoba, Phet and Mekunu have impacted significantly on Oman.

Table 12 Literature based vulnerability drivers from Oman history (Author, 2018)

Dimensions	Factor	Cited by
Social	Underestimation of the power of flash floods by crossing water channels	Al-Shaqsi (2010)
Social	Language barriers for expatriates	Al-Shaqsi (2010)
Social	Living conditions of non-Omanis	Al-Shaqsi (2010)
	Low income non-Omani workers	
Social	Living in industrial areas	Al-Shaqsi (2011)
Social	Low standard housing	Al-Shaqsi (2011)
Social	House occupancy exceeding capacity	Al-Shaqsi (2011)
Social	Low community awareness	Al-Shaqsi (2011)
Social	Urbanisation	Al-Rawas et al., (2013)
Environmental	Land use (farming)	Al-Rawas et al., (2013)
	Workers in construction jobs with low wages	Al-Shaqsi, (2015)

	Land use change	Saleh and Al-Hatrushi, (2009). Al-Rawas et al., (2013)
	Suitable discharge design for rain water	Al-Awadhi, (2010)
	Warning system	(Al-Shaqsi, 2010)
	Flood measures	(Al-Shaqsi, 2010)

3.6 Risk Management in Oman

The history of Oman indicates that it is a disaster-prone country (Hoffmann et al., 2013; EM-DAT, 2015). The country is developing at a good pace, but in terms of dealing with disasters and emergencies, it is still lagging behind. Al-Shaqsi (2010) said that there is a need for more responsibility to be given to local authorities, better communications between various organisations and better awareness within emergency organisations. However, some years after Gonu, when cyclone Phet hit in 2010, it was evident that Oman’s disasters experts were still reacting to disasters rather than planning for them.

Oman's risk assessment system and decision support system are still based on lessons learned from past experience and not yet scientifically based. Skills and emergency management resources that can deal with such disasters also do not exist (Al-Shaqsi, 2011). Since the emergency management system in Oman has evolved because of lessons learned, changes and modifications depend on need. After the most recent extreme events, and specifically after Cyclone Phet in 2010, the National Committee of Civil Defence (NCCD), the principal organisation concerned with emergencies and disasters, started holding frequent meetings with members from several government organisations (Al-Shaqsi, 2010). The first emergency management system was established in 1988 at the national level, and in that same year, the National Committee of Natural Disasters was formed. Four main governmental bodies took part in this committee: The Ministry of Interior, the Royal Oman Police, Ministry of Social Affairs, and the Ministry of Health.

In 1999, the committee’s name was changed to the National Committee of Civil Defence (NCCD) and it was assigned to the control of the Royal Oman Police (Figure 22). The committee was subsequently detached from the Royal Oman Police and continued as an independent body consisting of eight subcommittees. In 2007, the NCCD was given full authority for restructuring and appointment of new members, which was completed in 2008. In 2010, this committee was ordered to establish a national crisis management committee (Al-Shaqsi, 2011).

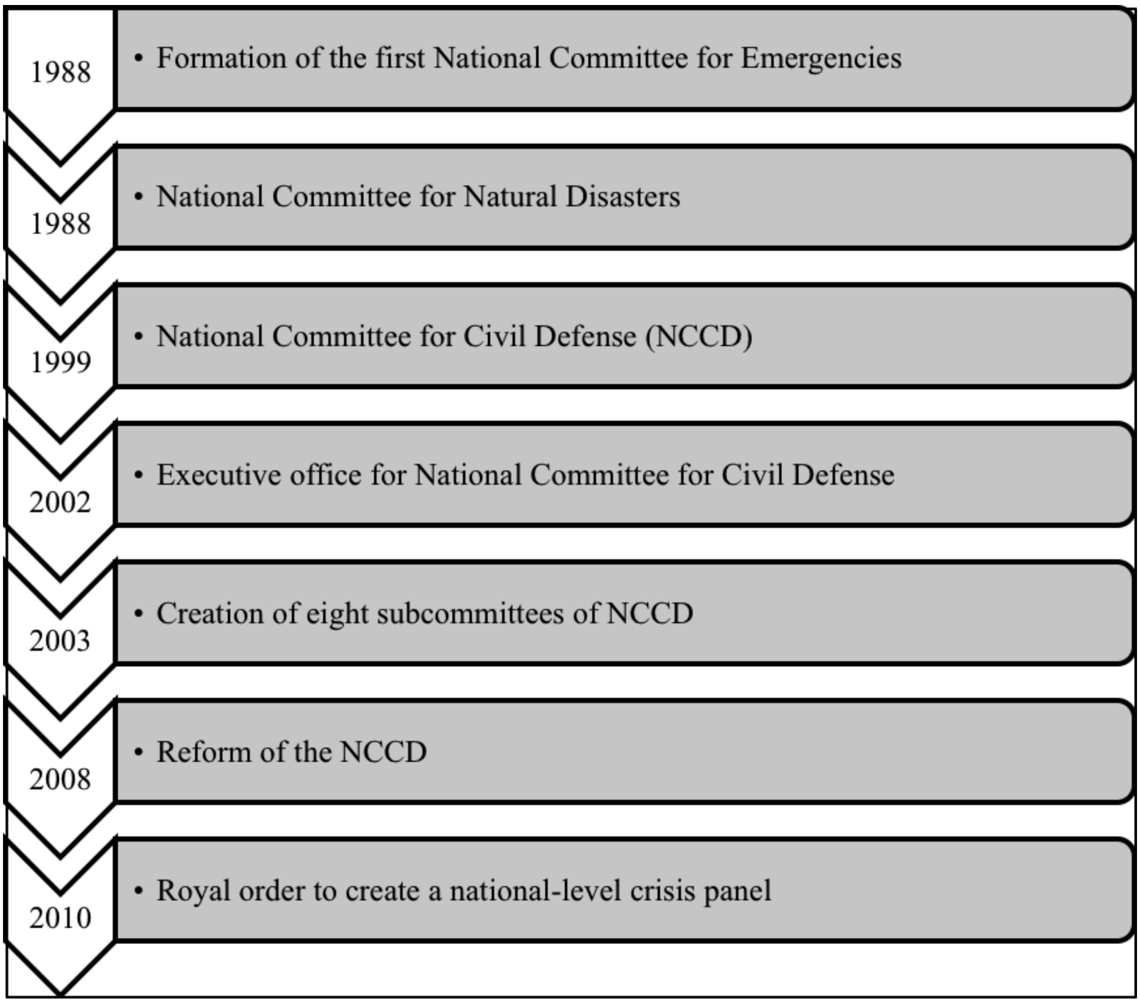

Figure 22. Emergency management institution evolution (Source: Al-Shaqsi ,2012).

In April 2008, the cabinet issued an order that the committee should comprise a chairman, deputy chairman and 21 members from most of the governmental agencies concerned with ensuring improvement of responses to emergencies and crises (NCCD, 2010). Today, the NCCD consists of 16 members from various government sectors that represent different fields; the inspector chairs the committee general of the Royal Oman Police. The current NCCD does not have any non-governmental organisation (NGO) representatives or any participation by the private sector to date.

The notion of risk assessment from natural hazards is receiving global attention, but at the local level its application is limited in Oman. Competing priorities in the development process, limited resources, and a low level of awareness in this field have resulted in the absence of risk assessment for natural hazards.

Today the NCCD, with its permanent members, plays a major role in preparation, evacuation, and operations during emergencies. It is very obvious that the relations among the members and their presence in the field before, during and after the event have improved dramatically. Their efforts have become much more efficient due to the experience the country has gained from frequent tropical cyclone events. All these efforts are focused on preparation for confronting these events in ways that will reduce losses and damages and how to rescue people in cases of emergency with the proper logistics, shelter, and relief. The role of NGOs has become outstanding and more organised as it is controlled centrally through the main NCCD committee. So, the NCCD is operating in a more effective way but its work is still not scientifically based.

From the semi-structured interviews conducted with eight members including the NCCD executive office representatives it was evident that improvements are still needed on the following points: 1) there is still a lack of available documentation on experience gained and lessons learnt from past events; 2) there are still no clear response plans available for the members or the executive office; 3) there is no proper handover procedure between members in the various sectors, which has created gaps in knowledge and experience; 4) their plans continue to be reactive to events, in spite of more training being conducted in this field by the committee or individual members.

With regards to laws and policy, Oman has two laws that address emergency and disaster management: civil defence law and the state of emergency law, the former issued by royal decree 76 in 1991 and the latter by royal decree 75 in 2008:

Civil Defense Law Royal Decree 76/1991. This law involves civil defence recognition and related terms such as state of emergency. Section two of this law outlines the measures to be taken by the civil defence. Section three defines command and authorities during the state of emergency. The NCCD appoints the chairman, who has the right to override normal national laws during emergencies or as required (NCCD, 2010; Al-Shaqsi, 2011).

State of Emergency Law Royal Decree 75/2008. This law defines the process of declaring a state of emergency by His Majesty the Sultan and the extent of the declaration. This law outlines the power of the National Security Council (NSC) during emergencies and states that the operational side of the emergency state is controlled by the Royal Oman Police (NCCD, 2010; Al-Shaqsi, 2011).

The NCCD remains the focal body in any emergency management operation against natural disasters or any other type of disasters under the command of the Royal Oman

Police. It is activated to respond to any national-level disasters. During such disasters, the main NCCD will be supported by the armed forces and other civil organisations. The NCCD is also the focal body in Oman for the newly established regional crisis centre of the Gulf Cooperation Council (GCC). The main task of this regional centre is to improve disaster risk management through all phases of natural and human-made disasters in the region (NCCD, 2010).

Vulnerability studies can be conducted holistically or dimension-wise. Since this study is focused on social vulnerability, the institutional dimension does not come within the study scope even though this has a direct influence on the overall vulnerability to tropical hazards in Oman.

3.7 Case study area

Oman as a country lacks understanding of its vulnerability to natural hazards, a research gap that this thesis seeks to address (see aim and objectives, Chapter One). In order to advance this understanding a case study area was required where a suitable investigation could be conducted. The case study area needed to be an area where vulnerability assessment and natural hazard risk assessment knowledge is largely absent (which is true for Oman as a whole), and a well-defined coastal area prone to multiple hazards, but particularly flooding, as the most prominent hazard. The chosen area needed to be capable of delivering general tools and lessons that can be applied to other coastal cities in Oman, thus besides being prone to substantial natural hazards it needed to include a range of social characteristics representative of SV more generally. Thus, the case study area needed to act as a model of the wider national coastal context in order for the developed approach to be applied for other locations in future studies. The area selected is the four coastal cities of the Muscat capital region, which meets all these requirements. This area also has the highest level of urban development and important infrastructure, so it is of high priority to the government.

The case study area chosen for the operationalisation of the selected framework in Oman comprises the following four coastal cities of the Muscat Governorate capital region: A' Seeb, Muscat, Bauscher and Muttrah. These cities are very important in terms of location and population size compared to other cities in the country. This region lies between longitudes 58° 02' E and 58° 20' E and latitudes 23° 28' N and 23° 42' N (Figure 23) and is bounded to the west by Barka city (Al Batinah South Governorate), to the east by

Qurayat city, to the south by Bidbid city (A, Dakhiliyah Governorate) and to the north by the Sea of Oman (Information, 2013).

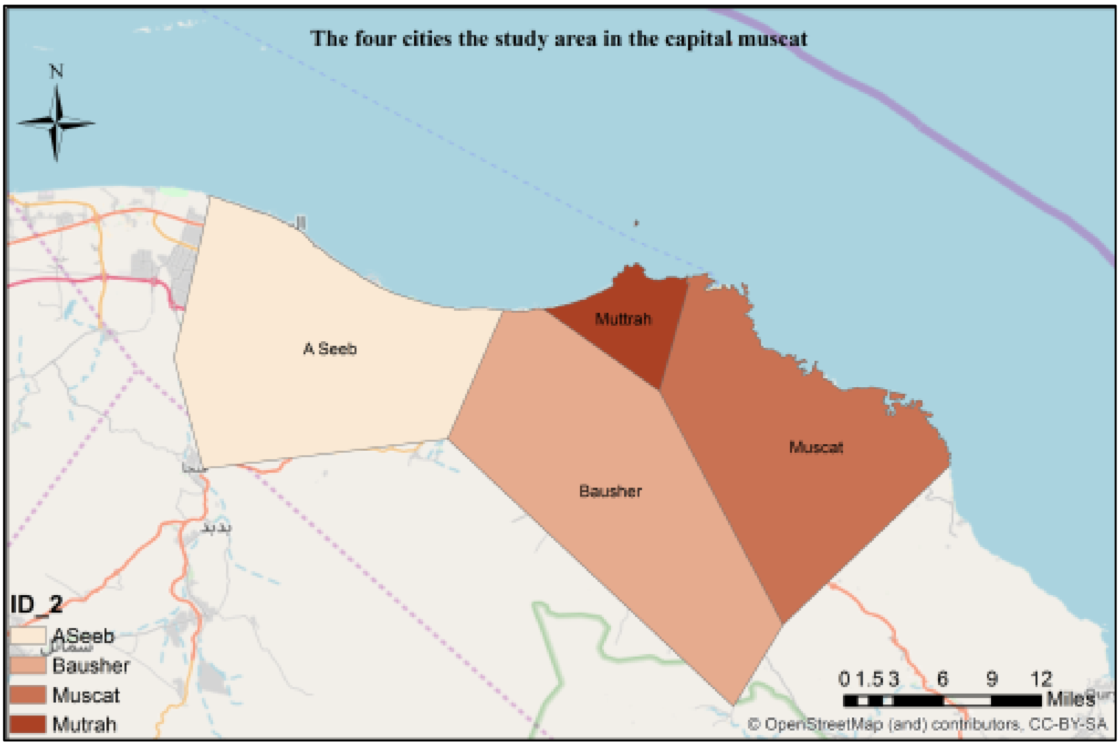

Figure 23. Study area used to apply the adopted model (Author, 2018)

The study area has a population of 643,226 (NCSI, 2013), and a very diverse social structure. It includes areas below sea level, wadi areas, farms, residential sections, and other types of land cover. It has important infrastructure such as the international airport of Muscat, many bridges, shopping malls, dams, and the headquarters for many government and private sector organisations, so it is important commercially and politically.

Rainfall records analysed by Kwarteng et al. (2009) indicate that the capital Muscat and the surrounding areas are susceptible to tropical cyclones with catastrophic rainfall greater than 100 mm/day almost every 50 years. Historically, this coastal area has been affected by one landfall of a tropical cyclone, whilst other events have impacted the area without making direct landfall. During the study and hazard assessment, the extent of the exposure of the study area to tropical cyclones and flooding due to extreme events will be further detailed.

Thus, the following characteristics of the Muscat Governorate region make it a suitable case study area:

- the area is prone to all the natural hazards occurring in the country
- there is a lack of knowledge on vulnerability and natural hazard risk
- there is a sizeable population that is growing as people are attracted by employment opportunities
- there is a concentration of at-risk capital assets and infrastructure
- there are large populations of citizens and non-citizens who represent the widest range of socioeconomic characteristics

Additional practical reasons for selecting this area include:

- it is in the capital area and results generated for this region are likely to be of particular interest to risk management authorities in Oman
- as the capital, it has the longest and best data records available in most fields for Oman; all maps and aerial images are available in good resolution and scales suitable for the study's purposes
- it offers the best available socio-demographic data, covering a wide range of social characteristics (citizens of all categories, expatriates of many nationalities, various languages spoken, different income levels, etc.)
- data is available on damage from prior hazard events; for example, in Wilayat A'Seeb more than 50% of built units were surveyed and around 39% of these units were declared damaged during Cyclone Gonu
- the study area has three of the largest wadis in Muscat (Wadi Addai, Wadi Al-Koudh and Wadi Al-Jifinian) which are areas thought to be particularly vulnerable to flooding

4 Methodology

4.1 Introduction

This research aims to study SV to natural hazards in Oman using local data to construct a SVI and explore its spatial distribution, knowledge which currently does not exist. The applied model will reveal the current vulnerability to tropical cyclones and explore how risk has changed across time and space. To achieve this goal a suitable conceptual framework is needed that can be applied to a new context that has its own specific characteristics and conditions. This will allow development of new knowledge about the type of SV to natural hazards in Oman and how this is changing. Research methods are reviewed in this chapter to help select a conceptual framework that can be empirically applied to assess SV to tropical cyclones.

This chapter reviews the research methodologies developed, applied, tested, and adopted by other researchers in this field. Then the approach selected for this study and its methods and data sources used to develop the model are described in detail. The position of the researcher in this field is also explained. The last section explains the chosen research methods using a schematic diagram that illustrates the process pursued in the following research chapters and how the methods have been applied empirically to achieve the final goal.

4.2 Review of methodologies in risk assessment for natural hazards

Natural disasters occur due to the interaction between extreme events (exposure) and the human system (vulnerabilities). It is essential to determine the extent of a society's vulnerability in order to reduce future risk and plan for mitigation and resource distribution. Many models in this field attempt to estimate risk and measure vulnerability of the human system to natural hazards (Cutter, 1996; Ferrier and Haque, 2003; Cutter et al., 2003; Turner et al., 2003; Greiving et al., 2006; Adger, 2006; Karimi and Hüllermeier, 2007; Blaikie et al., 2014).

Rather than estimating risk using a quantitative approach alone, incorporating qualitative methods would enable the study to select and label the right indicators and variables, to arrive at the most comprehensive picture about risk that would determine precisely the root causes of vulnerability by revealing its drivers and could be used to increase resilience (Birkmann, 2007).

4.2.1 Risk assessment in the literature

The use of a formal methodology to understand the nature of social vulnerability is necessary in all countries and particularly the developing countries, where this presents a challenge to existing practices and decision makers due to lack of knowledge, skills and resources. This is because each country differs in terms of the conditions and characteristics that shape its development processes. Furthermore, the scientific arena is unable to provide a common conceptual framework for both risk assessment and vulnerability assessment. Risk assessment cannot be separated from value judgements and choices that are primarily conditioned by individual beliefs and circumstances (Ferrier and Haque, 2003). A few researchers have undertaken extensive and comprehensive analysis of risk to natural hazards (Kates and Kasperson, 1983; Cutter et al., 2000; O'Brien, 2000; Ferrier and Haque, 2003; Smith, 2004; Blaikie et al., 2014). Despite their contributions, the work on risk assessment methodology is still narrow and limited.

In their study, Cutter et al. (2000) view risk as having two components: biophysical vulnerability and SV, which when combined together in the same geographical space produce the overall vulnerability of a place. Greiving et al. (2006) produced a methodology for an integrated risk assessment that identifies the overall risk for highly sensitive areas such as mega cities. Their approach combined many hazards in one map and all vulnerabilities in another, producing an integrated risk map unlike other methodologies that focus on limited disciplines and serve a specific purpose. They suggested that it is risk that should be measured and not vulnerability only.

4.2.2 Vulnerability assessment in the literature

There are two main approaches in conceptualising vulnerability. The first treats vulnerability as potential exposure to physical hazards, while the second takes exposure as given and focuses on searching for patterns of differential losses among the affected population (Wu et al., 2002). Based on these two approaches Cutter (1996) and Cutter et al. (2000) developed a third approach, the vulnerability of place, in which vulnerability is a combination of both biophysical (hazard) and social responses in the same geographical area. Additionally, Clark et al. (1998: 59) defined vulnerability as "people's differential incapacity to deal with hazards, based on the position of the groups and individuals with both the physical and social worlds".

Developing a common measurement method for vulnerability assessment in all disciplines is difficult due to the uncertainty deriving from the dynamic and changing nature of both the scale and characteristics associated with vulnerability (Cutter et al., 2009). Vulnerability changes in space due to variation in natural environments and social structures of different geographical areas. It also varies in time because people's conditions change across time through mobility and changes in life style (Uitto, 1998). It is very important to separate short-term and long-term vulnerabilities, especially in the disaster recovery stage (Mitchell, 1996). Cutter also suggested that place vulnerability can change over time due to changing risk mitigation measures (Cutter et al., 2000). One of the important issues highlighted in vulnerability studies by Kelly and Adger (2000) is the starting point and the end point views of vulnerability; the starting point concerns pre-existing conditions, whereas the end point means residual vulnerability following adaptation.

Several techniques, frameworks, and conceptual models are available to advance the theoretical and practical application of SV concepts in natural disasters (Cutter et al., 2000; Adger, 2006; Füssel, 2007; McLaughlin and Dietz, 2008). Many methods for vulnerability assessment have been developed, applied, and tested, but the majority are hazard-specific (Ciurean et al., 2013). Many researchers also consider vulnerability as having more than one dimension, so they include hazard exposure and the social response (Cutter et al., 2000; Clark et al., 1998; Chakraborty et al., 2005)

4.2.2.1 Vulnerability of place model

Cutter (1996) developed the hazards of place model of vulnerability (figure 24). Cutter (1996) focuses on the hazards of particular places, using the interaction between the biophysical system and the social system along with where the hazard takes place. This model created a paradigm shift in risk and hazard studies. Cutter's model is basically a spatial representation using a conceptual understanding of how unsafe conditions interact with hazards to reflect a place's vulnerability at the local scale (Cutter et al., 2003). The model combines as many disciplines as possible into the same geography to create a visualisation that makes the outcome more useful.

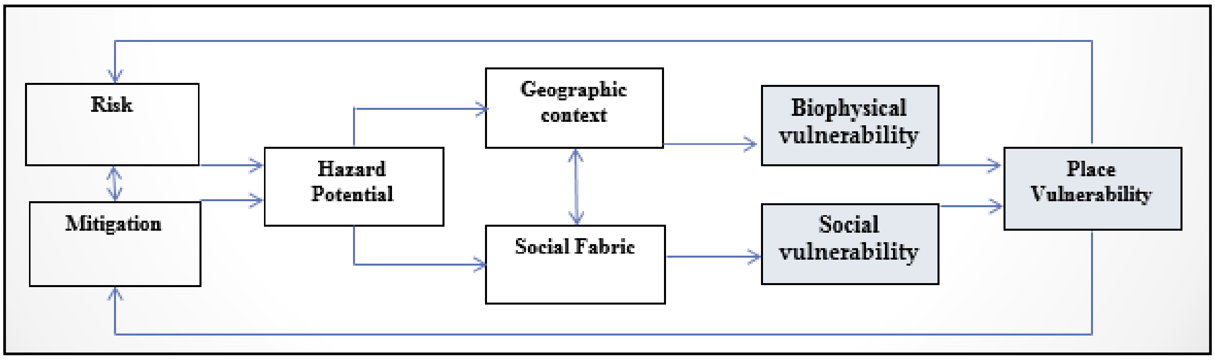

Figure 24. Hazards of place: The vulnerability model (Cutter, 1996).

Many researchers have used Cutter's hazard of place model (Tapsell et al., 2002; Rygel et al., 2006; Reid et al., 2009; Kuhlicke et al., 2011; Holand and Lujala, 2013; Willis et al., 2014; Frigerio et al., 2016). Cutter et al. (2000) suggest that when applying this model the most biophysically vulnerable places do not always intersect with the most socially vulnerable areas. Vulnerability of place estimation thus involves the intersection of composite layers of both hazard and SV in the same geographical area using GIS, the first through frequency and delineation of the area and the second by identifying and quantifying the socio-demographic characteristics that influence the vulnerability of people through the produced SVI. Cutter et al.'s (2000) approach was to overlay all hazard (threat) maps and vulnerability maps in one composite layer of polygon intersection using GIS software. This approach can also be used to study the risks posed by multi-threat hazards in the same geographical context.

Cutter's framework covers most aspects of disasters holistically (the hazard, its impact on society, and infrastructure and environmental exposure). The model focuses on three elements: biophysical, social, and place vulnerability. It can be applied at the local, sub-county and state level (Greiving et al., 2006) and the international level (Cutter et al., 2003). The main advantage of Cutter's hazard of place model lies in its ease of practical application as it can be applied empirically and can be represented spatially using GIS (Cutter et al., 2009).

There are however some limitations to the hazard of place model of vulnerability. Greiving et al. (2006) state that it requires intensive data work, including searching, collecting, and processing, whilst the results from the model are inherently difficult to interpret. Weighting factors, a modelling step, is difficult too. The calculation of hazard scores depends solely on occurrence and neglects hazard intensity. Furthermore, the weighting of all factors is assumed to be equal, which should not be the case (Greiving et al., 2006).

4.2.3 Social vulnerability conceptual frameworks in the literature

The term 'social vulnerability' means the susceptibility of social groups to possible losses due to hazard events (Blaikie et al., 2014). It is the social fabric which consists of characteristics that influence the community's experience of previous events and its ability to respond, cope and recover from events. SV is about the influence of socioeconomic and demographic characteristics to increase or decrease a hazards' impact on populations (Cutter et al., 2009). It is a composite attribute shaped by many factors originating mostly from social characteristics that cause hazards to have different levels of impact (Ferrier and Haque, 2003).

Uitto (1998) aimed to develop a reliable model of SV in Tokyo. He indicated that special attention should be given to social dimensions to improve disaster management. Using an SV approach to develop a general framework of SV in planning at the township level in Taiwan, Lee (2014) concluded that considering the social dimension is important to achieve sustainability. Disaster impact varies from one place to another depending on local vulnerability. Therefore, assessing local SV is crucial. Frigerio et al. (2016) and Polsky et al. (2007) both suggested that there is little consensus in the literature about best practice in SV assessment and that producing comparable findings is one aspect that lacks scientific guidance.

To examine local social vulnerability, both socioeconomic and demographic data are required, mainly via census data in the smallest census unit (Cutter et al., 2003). According to White et al. (1975), several main factors contribute to social vulnerability, including changes in population, migration to urban areas, increasing mobility, and economic industries. SVI construction methods place emphasis on three main design decisions: 1) specific scale, 2) clear variables, and 3) aggregation method (Adger et al., 2004, Cutter et al., 2009).

In the literature several theories have been proposed that formalise SV in a framework:

1. In their book *At Risk*, Blaikie et al. (1994, 2014) present a vulnerability model called the pressure and release (PAR) model. They suggest that the underlying factors rooted in day-to-day activities bounce back as a dynamic pressure that leads to unsafe conditions during disasters, when they coincide with hazards, time, and geography. This pressure from being at risk can be released when the degree of vulnerability is changed through mitigation and building resilience.

   (PAR model) Disaster risk = exposure to hazard event + inherited vulnerability

   $$R= H \times V \text{ (Blaikie et al., 2014) Eq. 4.2}$$

   The key limitation of this model is that it fails to address the role of proximity to the source of the hazard and the interaction between the natural system and the social system. The model is useful for descriptive analysis rather than as an empirically tested model (Cutter et al., 2009).

2. Clark et al. (1998) propose a model that integrates social, environmental, and social factors leading to different abilities of people to respond to hazards with the classic causal model of hazards, to understand the composite (social and physical) vulnerability for the city of Revere in USA.
3. Ferrier and Haque (2003) propose a standardised framework of risk assessment by emergency managers regardless of their level of education. The framework uses a simple numerical ranking of hazard frequency times the numerical ranking of hazard magnitude under the worst-case scenario. The result is multiplied by the social consequences and assessed by comparing the community's exposure level to various events.
4. Cutter et al. (2003) presented the (SoVI), which is based on both the Pressure and Release PAR model (Blaikie et al., 2014 second edition of the 1994 book) and the hazards of place model (Cutter, 1996). The model was applied empirically using a factor analysis approach with 42 socioeconomic variables at US county level. Cutter was able to explain 76.4% of the total variances in vulnerability among US counties using 11 indicators (Kumpulainen, 2006). Many researchers have since adopted Cutter’s SoVI model (Rygel et al., 2006; Lee, 2014; Frigerio et al., 2016; Koks et al., 2015; Myers et al., 2008). Cutter suggested expanding the scope of the model by adding hazards and economic loss data into the model. Rygel et al. (2006) applied Cutter’s SoVI model in another context and suggested adding a

weight for the aggregation according to ranking of indicators, unlike Cutter's original model, in which the weight of the indictors is considered equal in terms of their contribution.

5. Karimi and Hüllermeier (2007) present a model for assessing risk to natural disasters during high uncertainty conditions when almost no physical knowledge or statistical data are available, by using probabilistic risk analysis and fuzzy probability. This model uses an additional dimension of uncertainty to complement the probability theory and focuses more on hazard characteristics and less on social vulnerability.
6. Turner (2003) propose a model that locates the local vulnerabilities within larger contexts that influence the process at higher scales. However, the model fails to differentiate between exposure and SV and does not give a clear view where vulnerability starts or ends (Cutter et al., 2009).

The above are some of the commonly cited conceptual frameworks for SV to hazards, of which few have been empirically applied (most remain theoretical). For any model that is empirically applied, a system is required that provides a method of assessing changes in social vulnerability, in space and time, as measured using a relevant set of indicators, combined in an appropriate way.

4.2.4 Indicators

Indicators are very important metric representations that have been used widely, and their usefulness has been proven in many fields over the past few decades. There has clearly been more emphasis on indicators in environmental sustainability along with vulnerability since the 1990s (Cutter et al., 2009). Often, indicators are biased due to variability of data availability and the cost of obtaining the information (Gallopin, 1997).

The definition of indicators and the uses of this term are confusing (Bakkes et al., 1994). One approach followed in the assessment of climate change variability is the dynamic international vulnerability assessment (DIVA), which was used in Italy to assess climate change vulnerability to sea level rise in a coastal area of Venetia (Cutter et al., 2009). Frigerio et al. (2016) indicated in their assessment of social vulnerably to seismic hazard that there are no guidelines on the procedure, or the type of variables used in construction of the index because of differences in social and cultural characteristics between countries or areas. Thus, it is necessary to improve our understanding of the root causes of vulnerability to develop robust, effective vulnerability indicators to manage risk from natural hazards. Three areas need serious consideration to select suitable indicators: 1) clear differentiation of vulnerability level, scale, and phase, 2) transparency in assumptions, and 3) verification of findings (Eriksen and Kelly, 2007).

The level of vulnerability is influenced by factors such as socio-economic status, wealth, ethnicity, gender, disability, and age (Uitto, 1998). The most commonly used variables are children less than 5 and elderly over 65 (Morrow, 1999; Boruff et al., 2005; Cutter et al., 2008), education, employment, population growth, and ethnicity (Cutter et al., 2003). Table 13 shows the vulnerable sub-groups within a community that should be identified to enhance disaster planning according to Ferrier and Haque (2003).

Table 13 Social groups that could be at risk from natural hazards (source: Ferrier and Haque, 2003).

Elderly	Large families
Children	Single parent families
Disabled (mental and physical)	Workers at risk from machinery
People in poverty	Limited psychosocial coping
Non-English (majority language) speakers	People with limited financial resources
Indigenous peoples	People with inadequate accommodation
Socially isolated	People on holiday
Physically isolated	Foreign tourists
Seriously ill	People living close to areas of hazard
People dependent upon technology-based life support systems	People already affected by an earlier hazard

Vincent (2004) created an SVI to assess levels of SV to climate change induced variations in water availability, with an aggregated index constructed using a weighted average of five indicators. Rygel et al. (2006) argued that in constructing a SVI it is possible to construct the index without weighting the individual indicators. This is the same approach as used in Cutter's SoVI index, where the calculation of SVI was conducted using an additive model without assigning weights to factors (Cutter, 2003; Holand and Lujala, 2013).

Wood et al. (2010) also indicated that in Cutter's model all components were given equal weight when applying the additive model, but noted that it is very important to represent the relative influence of each factor on social vulnerability. Thus Rygel et al. (2006) applied weighting based on the percentage of total variance explained by each factor, whilst Frigerio et al. (2016) applied the same weighting method to derive the composite SVI. The weighting of each factor was created by multiplying the factor score by the percentage of variance determined for that factor, with the higher variance being more influential on vulnerability. Willies et al. (2010) took a similar approach in summing variables but did not use additional extraction of the coefficient scores. Rygel et al. (2006), on the other hand, used no input census variables, instead using only the vulnerability extraction scores to provide a summary of the output area. They recommend applying Pareto ranking to the extraction scores, which involves placing observation into discrete blocks or ranges depending on how many components are inputted (Reid et al., 2009).

4.2.4.1 Variables selection

Selection of variables was a very important step in this study and involved identifying the right variables from census data by considering the influence on tropical cyclones. The decisions on selecting the variables were supported by three methods. The majority of these decisions were supported theoretically by the literature review as discussed in detail in section 5.2.1. In addition, two main qualitative methods were used in a very informal way to support the use of the remaining variables, namely semi-structured interviews with eight NCCD members and analysis of a local newspaper before and during the Gonu mega event in 2007. The way in which these quantitative and qualitative methods were used to explore the research field is illustrated in figure 29 in chapter five.

During the interview process there were high expectations regarding the amount of information that would be obtained from the NCCD members. But in reality, very little information was delivered and most of it concerned physical vulnerability, especially of the built environment. There was very little valuable information about the social dimension. The main variables highlighted by this process are: gender, house quality, proximity, population aged 18-35, ethnicity, poverty. The newspaper was examined for the period from 3 to 18 of June, from 3 days before to almost 10 days after the event. This process was very informative regarding such as the physical, institutional, and economic dimensions but produced little on the social dimension.

The problem that emerged during these two processes was that only a limited amount of information could be obtained due to a tendency to maintain confidentiality during the event, deriving from reasons such as the need to avoid creating panic among the population during the event. The interviews raised some issues that hindered the quality of information obtained and which can be summarised as follows: change of representatives without proper handover, absence of SOPs and emergency response plan, and absence of any documentation (reports and lessons learnt) from the past events.

4.2.5 GIS in spatial analysis

In the disaster management field significant effort has been devoted to developing vulnerability mapping techniques. Vulnerability maps help to evaluate overall risk of natural hazards, assess the probability of different natural hazards in a region, and identify the degree of vulnerability of communities located in high risk areas. They can also be used to map poverty and thereby highlight needs and target assistance in the aftermath of a disaster (Regalia et al., 2000; Alwang et al., 2001). One of the strongest and most popular tools for combining and integrating analysis of physical, social, and other dimensions of vulnerabilities is the geographical information system (GIS) (Uitto, 1998). GIS is useful for mapping exposure of physical structures and displaying endangered populations (Uitto, 1998). It can be effectively employed for mapping damage after disasters (Al-Rawas, 2009). GIS allows for mapping of several hazards in the same area with good presentation of the spatial extent and is an easy tool for emergency managers to use.

SVI are very meaningful when they are visualised. For the purpose of locating and comparing sensitive populations, the use of spatial representations of social vulnerability is vital. During all phases of disasters, the deployment of vulnerability maps helps estimate community need for support (Morrow, 1999). Visualising SV provides a good foundation to understand the spatial pattern and variation in social vulnerability (Frigerio et al., 2016). Many studies involving SV assessments have employed mapping techniques to represent SV spatially (Cutter et al., 2000; Cardona, 2006; Cutter et al., 2008; Fekete, 2009; Lee, 2014). Using GIS allows editing, analysis, transporting, visualising, and storing of the data. There are also many useful statistical analysis and spatial analysis tools in GIS to handle big data and produce the best spatial intelligence. Among these are the spatial auto correlation tools.

4.2.5.1 Spatial autocorrelation tools in GIS

Spatial autocorrelation is a term used to define the relationship between nearby spatial units and is a commonly used feature in GIS mapping (Fischer and Getis, 2009). Spatial autocorrelation measures the correlation of a variable with itself through space. Positive spatial autocorrelation occurs when similar values occur near one another, whilst negative spatial autocorrelation occurs when dissimilar values occur near one another. The idea originates from the principle of nearness and how much stronger an effect nearby features have on each other than those that are further apart; in other words, near things are more related than distant ones (Tobler, 1970). The phenomenon is important to SV mapping as observations made at different locations may not be independent of each other (e.g. different indicators used to construct an SVI may be dependent, hence bias is introduced to the index).

Garrison first cited the term spatial autocorrelation around 1960 and it was later developed as a statistical framework by Cliff and Ord (1969). Spatial autocorrelation in older social science and statistics literature is referred to as ‘spatial association’, ‘spatial dependence’, and ‘spatial interaction’. Spatial autocorrelation testing to measure the extent of the potential problem is defined by the scale and scope of the analysis and is usually separated into global and local categories. Global tests, using such as Moran’s I (Global Moran’s I), involve taking all elements together in the assessment and including all associations of spatial units as one value. In local tests, such as the Local Indicators Spatial Analysis (LISA) measure, the focus is on one particular spatial unit (Fischer and Getis, 2009).

A few studies have applied this test to SV assessment of natural hazards to better locate high and low vulnerability areas (Cutter and Finch, 2008; Yoon, 2012; Zhou et al., 2014; Koks et al., 2015). Cutter and Finch (2008) demonstrated in their study of temporal variation in SV the use of global spatial statistics to measure spatial dependence from many locations in order to find whether a pattern exists or not, whilst the local indicator LISA was applied to capture local variation and to identify the location of similar clusters (high and low social vulnerability). Spatial autocorrelation offers various means to measure the degree of spatial associations, including: a) identifying spatial clusters; and

b) identifying outliers. Moran's I is a leading statistic that both measures and tests for spatial autocorrelation at global and local levels, whilst the Local Indicators of Spatial Analysis (LISA) is a widely used spatial autocorrelation method at local level, also known as Anselin's Local Moran's I test. LISA is used to identify the significant (P-value < 0.05) concentration of high values and concentration of low values and spatial outliers, and helps to locate auto correlated clusters, but does not indicate why they occur (Anselin, 1995).

4.2.6 Developing an SVI using multivariate statistical analysis

In the process of developing an SVI, large numbers of proxies or variables are collected and statistically analysed to generate a smaller set of components that explain the same social construct. This number has to be reduced to a smaller number that keeps the main characteristics, and at the same time is easier to use for further analysis than dealing with a large number of variables. Statistical analysis is used here to identify which variables cluster together and for exploring the influencing factors. This form of statistical analysis dates back to the 1900s, when Charles Spearman developed the two-factor theory and factor analysis. Factor analysis is used in many fields such as social sciences, geography, economics, and medicine and is made possible by various technological software advancements (Yong and Pearce, 2013).

Applying multivariate statistical analyses such as principal component analysis (PCA) and factor analysis (FA) as reductionist techniques helps to extract the latent dimensions of social vulnerability. These are popular in vulnerability studies and help to produce a smaller set of independent factors to account for a majority of the total variance within the data set (Cutter et al., 2003; Rygel et al., 2006; Fekete, 2009; Frigerio et al., 2016). Multivariate statistical analysis is the most common method for reducing the number of variables in a data set (Frigerio and De Amicis, 2016).. The differences between the two techniques relate to communality estimation and variables' correlation with each other. Factor analysis methods work by using a mathematical model to generate factors, while principal component analysis decomposes the original data set into linear variates (Dunteman, 1989). In a study comparing the difference in results of the two techniques, Stevens (2012) concluded that if there are more than 30 variables having communality greater than 0.7, there would not be any differences in the solution compared to the case of less variables with communality of less than 0.4.

Labelling any factor produced by this process requires a minimum of three variables loading on the matrix of that factor (Tabachnick and Fidell, 2006). The ratio of observation to variables should be at least 10:1, and exploratory factor analysis (EFA) works better with larger data sets (Yong and Pearce, 2013). However, as Guadagnoli and Velicer (1988) stated, if the data set has many high loading factors of >0.80, then a data set of n>150 should be sufficient. According to Hatcher (1994, cited by Guillard-Gonçalves et al., 2015 and Garson, 2008), a minimum number of cases greater than 100 is required, or more than five times the number of variables that should be used in factor analysis. It is also recommended that the correlation coefficient r between variables must be 0.3 or greater because values less than that suggest very weak relationships between variables. Also, if the data set has any missing values, deleting those observations is recommended to avoid overestimation (Tabachnick and Fidell, 2006).

Cutter et al. (2008) highlighted that factor analysis depends highly on the variables and how good the subjective research judgement is. Factor analysis has three main uses: to reduce the number of variables in a data set, to understand the structure of a latent factor, and to understand the structure of the clustered variables (Field, 2009).

4.2.6.1 Factor analysis

Factor analysis is a statistical method applicable to various disciplines. For example, psychologists use it to measure the dimensions of personality, and economists to reduce several variables such as productivity of the workforce and profits to one dimension such as company growth (Stevens, 2012). Clark et al. (1998) applied factor analysis to reduce a data set of 34 variables to five factors that explained most of the variance in their study of SV (Yong and Pearce, 2013).

One of the main steps in factor analysis is measuring inter-correlation, produced as an R-matrix, which shows correlation between variables. Using this matrix to observe any strong correlation between clusters of variables could explain that they might measure the same underlying construct, known as a factor (or component) (Field, 2009). Factor analysis is used to reduce the predictor variables to a small set of uncorrelated factors, or components in the case of principal component analysis.

4.2.6.2 Principal component analysis

Principal component analysis (PCA) is another statistical method used to reveal the underlying dimensions of a large data set and transform them mathematically into a smaller set of components (factors) based on the inter-correlation between the original variables (Yoon, 2012), and is considered the best multivariate statistical analysis technique when data sets are highly correlated (Frigerio and De Amicis, 2016). Many researchers have adopted PCA as the multi-variate analysis method in their construction of an SVI (Rygel et al., 2006; Lee, 2014; Frigerio and De Amicis, 2016; Kolli et al., 2016; Cutter et al., 2003; Boruff et al., 2005; Cutter and Finch, 2008; Cutter et al., 2007). PCA is a non-parametric procedure and is therefore exempt from any data probability distribution assumptions (Abdi et al., 2014). Reid et al. (2009), in their study about community determinants of heat vulnerability, revealed that decisions made on the basis of PCA lead to reasonable results about vulnerable populations. Figure 25 illustrates the PCA model and how multiple variables can contribute to the formation of fewer underlying factors.

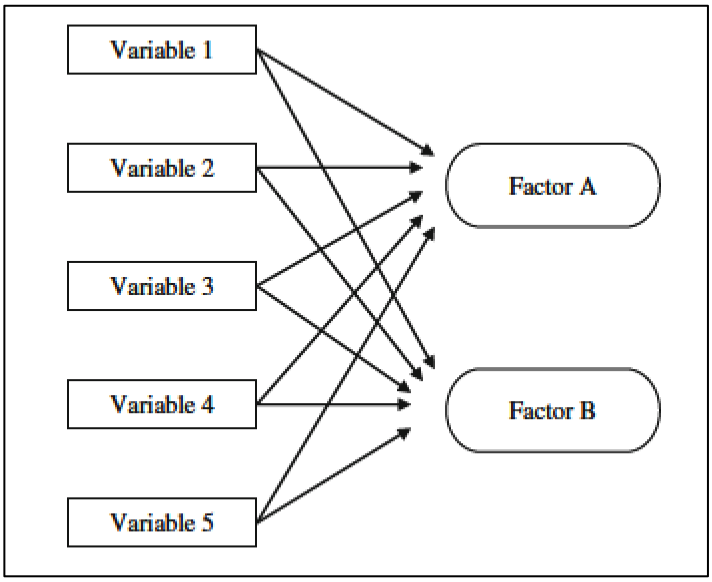

Figure 25. The model for principal component analysis technique (source: Yoon, 2012)

4.2.6.3 Data screening

Exploring the data set is very important to select the right statistical analysis. As Field (2009) suggested, data should be checked for multicollinearity and singularity between variables. If they are either too high or too low, the researcher may need to remove these variables from the analysis. Browsing values in the correlation matrix is instrumental to these decisions (Field, 2009). However, in most cases, applying PCA anticipates that the variables will correlate because they are measuring the same construct. Mild multicollinearity is not a problem for factor analysis, but extreme multicollinearity is not acceptable. Factor analysis will overcome mild multicollinearity when creating the factors; the problem should vanish because those variables are now combined into a smaller number of factors. In factor analysis, to overcome this problem practically, we selected the Anderson-Rubin method to generate scores.

4.2.6.4 Data transformation

Since variables are often measured in different units, standardisation is important to eliminate different units by transforming the data set to a small and specified scale. There are many rescaling techniques widely used in the literature; Z score, log 10, square root, and maximum value are all options (Yoon, 2012), which must be applied before any reduction technique, such as factor analysis or PCA. Zahran et al. (2008) developed a three variables SVI, with variable observations transformed using z scores, before summing in the composite index. Other studies in SV apply the maximum value transformation or the ratio of value before applying statistical analysis (Cutter et al., 2000; Wu et al., 2002).

4.3 The adopted methods of the study

From the literature review and considering the context of our study and local conditions, such as the non-existence of a proper risk assessment process in general or a method to quantify risk in particular, it is clear that assessing vulnerability is the first step to be taken. From the several models available in this field, Cutter's SoVI model (Cutter et al., 2003) has been selected for this study. The approach involves selecting variables backed up theoretically by the literature and then applying PCA to reduce the number of variables to a smaller number of factors. The factors are weighted using percentages of total variance (Rygel et al., 2006), and then the final composite index is calculated and mapped spatially for the whole study area (Cutter et al., 2003), as chapter five will explain. In chapter six, three census years' data sets for the same variables will be compared to explore the nature of spatio-temporal changes in the SVI in the study area.

Why select Cutter's SoVI model?

- It focuses on SV that increases or decreases hazards' impact on populations

- It can be applied to many scales and levels
- It can be empirically applied in new contexts
- It is comparable and transferable
- It deploys spatial representation to translate the result into a simple visual representation of the index
- It uses a common set of variables that allow for comparison over space and time
- It is widely used and applicable to various contexts
- It can be integrated with the physical dimension of vulnerability to form vulnerability of place

4.4 Geographical scale

Scale is an important factor in any spatial data model. GIS is a good tool for representing the world, but when the scale is poorly selected, GIS can be misleading. A larger scale of up to 1:5000 offers a good source of details in the current study area, whereas the smaller scale of 1:15000 is a good start for exploring the vulnerability of a place.

For the Muscat governorate study area, the required data are available at 1:5000, 1:10000, and 1:15000. A Digital Elevation Model (DEM) also is available at these scales. In this study, a scale of 1: 15000 is adopted for representing the overall impact of hazards in the study area and showing interaction among risk elements. Most Oman government organisations have parcel maps at the 1:15000 scale, a scale at which other required data from the National Centre of Statistics and Information (NCSI) are available.

For more detailed mapping, and particularly studying the spatial pattern of risk by social group, and for assessing exposure of infrastructures, a larger 1:5000 scale will be used. This gives a higher resolution for those features considered of particular importance in the vulnerability analysis. Data used in the vulnerability analysis drawn from the population census is available at block level, the smallest administration level in the country.

4.5 Data collection

This is a very important task because the study outcome depends on data quality. This task proved challenging due to the scattered nature of data in Oman, which still does not have a central database serving fields like disaster management, requiring data to be collected from various sources in each organisation. The data required as per the methods and techniques applied here are however mainly socio-economic and demographic data from the National Center for Statistics and Information in Oman. Data was obtained in count format for 38 variables for the three census years (1993, 2003, and 2010), the only censuses conducted in Oman to date. The data set of the 2010 census is used in chapter five to obtain the most recent SVI status and to map SV across the study area. The two older data sets are used in chapter six, along with the 2010 analysis, to map the SVIs over time (and conduct a spatial-temporal autocorrelation analysis) to reveal the nature of the historical trend in SV. This provides insight into potential future SV.

From reviewing the literature on social vulnerability, with consideration of the local characteristics of the Omani populations, a data set of 38 potentially relevant variables was obtained from Oman (largely via the NCSI). These variables are grouped into nine key vulnerability-based dimensions (Table 14): population, age, family structure, gender, unemployment, employment, education, housing unit and attitude to risk. Table 14 presents a preliminary list of potential vulnerability variables which were subjected to multicollinearity and singularity tests that reduced the number of variables to the 24 used throughout the remainder of the study.

Table 14 Preliminary list of variables obtained from NCSI. (Author, 2018)

Dimensions	Variable label	Description
Population	#population	Total number of populations in each block
	#Omani male	Omani male population in each block
	#Omani female	Omani female population in each block
	#Omani	Total Omani population in each block
	#non-Omanis	Non-Omani population in each block
	#non-Omani male	Non-Omani male population
	#non-Omani female	Non-Omani female population
Age	population < 5 yrs.	Population of children aged less than 5 years
	population < 14 yrs.	Population of children aged less than 14 years
	Omani < 14 yrs.	Population of Omani children aged less than 14 years

	Omani > 15 yrs.	Population of Omani children aged greater than 14 years
	Omani 15-64 yrs.	Population of Omanis aged between 15 to 64 years
	non-Omani. 15-64 yrs.	Number of non-Omanis aged between 15 and 64 years.
	Omani > 65 yrs.	Number of Omanis aged greater than 65 years.
	non-Omani.> 65 yrs.	Number of non-Omanis aged greater than 65 years.
Family structure	total family	Number of families in each block
	Omani family	Number of Omani families in each block
	non-Omani family	Number of non-Omani families in each block
	family size 5 or less	Number of families with 5 or less members in each block
	family size 6-9	Number of families with 6 to 9 members
	family size 10 or more	Number of families with greater than 10 members
Gender	fem. 18 - 64 yrs.	Female population aged 18 to 64 years
	female headed families	Families headed by female
	# widows	Number of widows in each block
Unemployment	# Job seekers pop.	Number of job seekers in each block
	Omani job seekers	Number of Omani job seekers
	non-Omani job seekers	Number of non-Omani job seekers
Employment	working Omani >15	Number of working Omanis aged greater than 15 years
	working Expat. > 15 yrs.	Number of working non-Omani aged greater than 15 years
Education	illiterate Omani > 15 yrs.	Number of illiterate Omani aged greater than 15 years.
	illiterate Expat. > 15 yrs.	Illiterate non-Omani aged greater than 15 years
	Omani pop. > 15≥ high school	Omanis aged greater than 15 years with education level of high school or greater
	non-Omanis.> 15 ≥ high school	Non-Omanis aged greater than 15 years with education level of high school or greater

Housing units	total number of houses	Number of houses in each block
	occupied houses	Number of occupied houses
	unoccupied houses	Number of unoccupied houses
	old (Arabic) houses	Number of old Arabic houses
	rural houses	Number of rural houses
	houses connected water network	Number of houses connected with public water network
	houses with no water connection	Number of houses getting water through other means, such as bowsers.
Attitude to risk	# pop. 18-35 yrs.	Population aged 18 to 35 years

These social characteristics data were used at municipal block level, with 217 municipal blocks covering the four coastal cities (Muscat, Mutrah, Bawsher and A'Seeb) in Muscat governorate (figure 26).

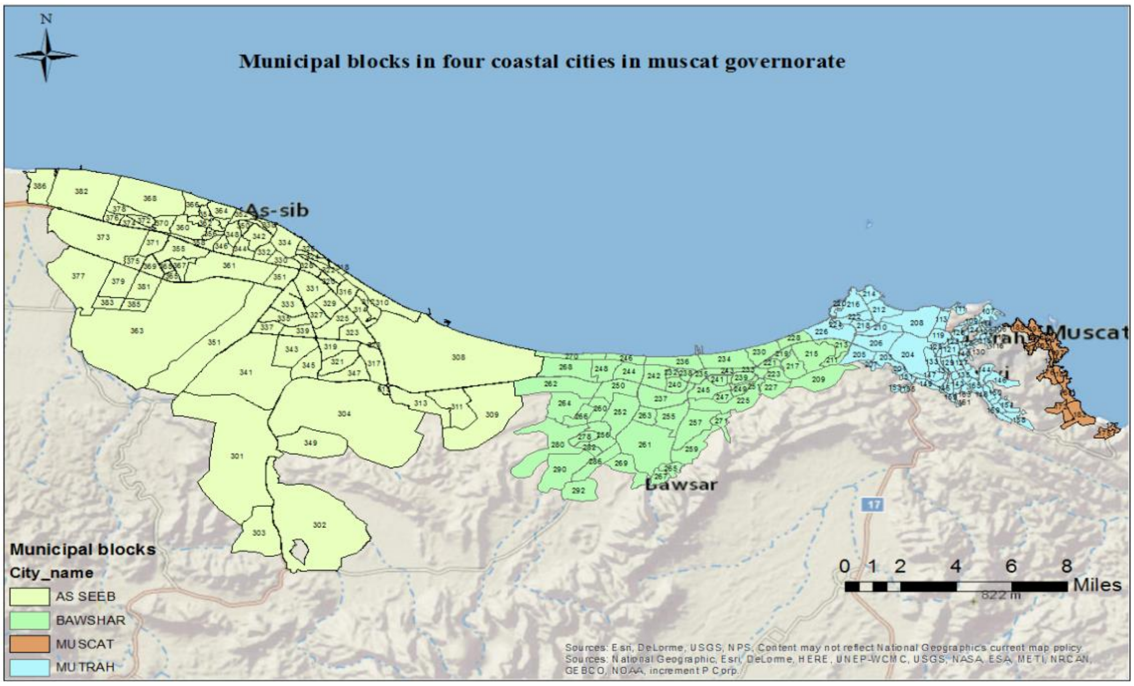

Figure 26. The four coastal cities and municipal blocks used for this study. (Author, 2018)

Municipal blocks are given numbers by the local authority and these are used in official communications. Table 15 lists the municipal blocks by each city. Municipal block spatial and label attributes were obtained as a shape file against which the corresponding vulnerability indicator was mapped.

Table 15 Municipal blocks in each city (Author, 2018)

City	Municipal blocks
Bawsher	209,211,213,215,217,219,221,223,225,227,228,230,232,233,234,235,236,237,238,239,240,241,242,243,244,245,246,247,248,249,250,251,252,255,256,257,259,260,261,262,263,264,265,266,267,268,269,270,271,278,280,282,286,290,292.
Muscat	178,180,182,184,186,188,189,191,193,195,197,172,176,183,185,187,175,177
Mutrah	146,148,150,152,154,158,165,203,205,206,207,121,123,127,129,131,135,142,144,119,125,204,133,137,139,141,143,145,147,149,159,161,163,169,220,224,226,106,107,108,109,110,111,112,113,114,116,118,120,122,124,126,128,130,132,140,208,210,212,214,216,218,222,151,153,155,201
A' Seeb	301,302,304,311,313,315,349,303,323,325,327,329,331,312,314,316,318,320,322,326,328,334,333,335,337,339,351,361,363,386,382,330,332,338,340,342,344,346,348,350,352,358,364,356,360,362,368,370,309,355,365,367,369,371,373,375,377,379,381,383,385,374,376,317,319,321,341,343,245,247,354,366,372,378,308,310,324

Census data were obtained for these municipal blocks for 1993, 2003 and 2010. As is the case with many other fields in Oman, data for the natural disasters management field are available from the many local organisations that have responsibility for maintaining data on emergency management and hazards. In the same context, other international organisations, some of which are official organisations and others non-governmental organisations, also maintain the same records and data in various forms and these are accessible by the public. The following describes the two main types of data sources used in the thesis.

4.5.1 Local sources of data

- Ministry of Water Resources: Flood risk maps (100-year, 20-year and five-year)
- The National Committee for Civil Defence (NCCD): information about their role and the role of each member of the committee
- National Center for Statistics and Information (NCSI): All socio-economic statistics of the population in the study area. Also, all parcel maps for lifelines and base maps

- Muscat Municipality: All services and infrastructures in the study area

4.5.2 International databases and sources

Since Oman is a developing country, data quality and availability are still thorny issues for researchers. However, international databases can provide additional reliable historical data to support studies. Table 16 lists the global organisation databases sourced in the current study, the types of data accessed, and their usage.

Table 16 Global disaster databases: Free access sources that provide data about Oman (Author, 2018)

Hazard	Database	Provider	Type of data	Usage
Tropical cyclone	National Oceanic and Atmospheric Administration	National Hurricanes Center (NHC)	Historical tropical cyclones' best tracks, locations, wind, pressure	Study of cyclones' historical tracks and associated data
	Indian Meteorological Agency	India Met. Department (IMD)	Historical tropical cyclones' best	Study of cyclones' historical tracks
	Joint Typhoon Warning Center (JTWC)	US government website	Cyclone tracks, speed, rainfall	Cyclone data set
Hazard statistics	EM-DAT	GRED 2009 Belgium	Historical data and statistics of hazards	Historical event statistics

4.6 Methodology process flow chart

The Figure 27 flow chart below summarises the research framework and methodology developed and implemented in the study.

Research problem

What is the nature of SV to tropical cyclones and how does it change spatially and temporally in a country like Oman?

Research limitation and focus

Revealing the nature of risk from natural hazards (cyclones) using an adopted SV model (SoVI) (Cutter, 2003), this thesis focuses on developing SVI using the latest census data (2010) and explores the nature of SV through spatial representation using GIS. Also, it explores the temporal trend of SV to tropical cyclone by carrying out comparisons of SV using the same variables from census data for the years 1993, 2003, and 2010.

Case study area

The country of study is Oman, and the area is the Muscat capital region, specifically four coastal cities: A'Seeb, Bawsher, Mutrah and Muscat city. All are highly populated and have almost all types of social groups. Throughout history, these cities have experienced several cyclone events that adversely impacted them.

Key concepts: Disasters, risk assessment, climate change, natural hazards, disasters, vulnerability, resilience, social vulnerability.

Research Area: Natural disasters, climate change, tropical cyclone, risk assessment, social vulnerability, factor analysis, principal components.

Research sub-questions

The research question will be answered through the following sub-questions.

1. How does SV to natural hazards (tropical cyclone) vary spatially across Muscat governorate coastal cities?

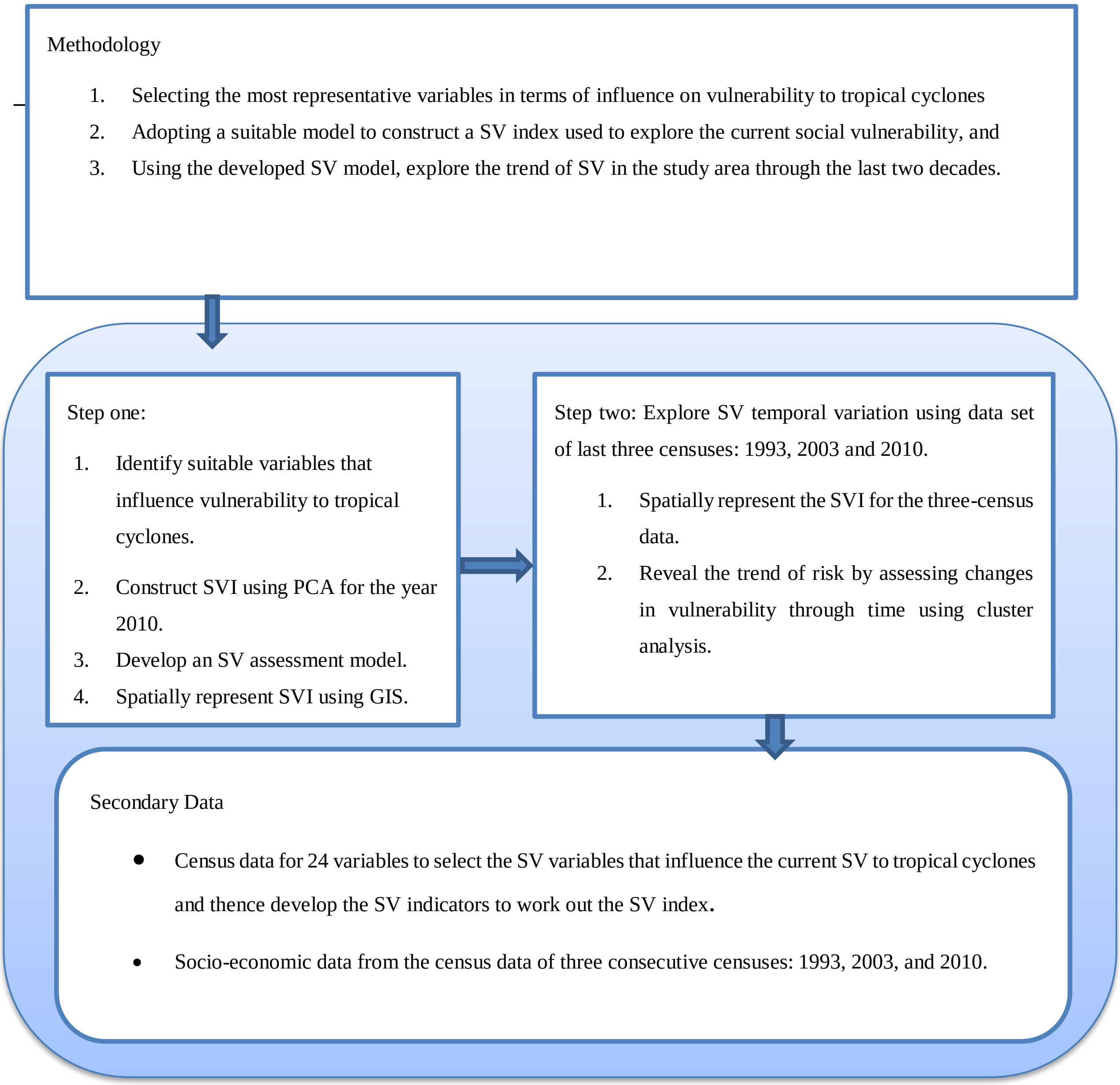

Figure27. Analytical process adopted in the study (Author, 2018)

4.7 Conclusion

In this chapter, we have reviewed methodologies relevant to risk and vulnerability assessment. No consensus was found on risk and vulnerability terms, conceptual frameworks, or common indicators. Five conceptual models of SV found in the literature were reviewed in this study, and it is evident that few have been empirically operationalised. It is difficult to have one general representation of vulnerability that can be used in the disasters field due to the dynamic nature vulnerability and complexity of the drivers in each environment and the particular geography. The model selected to address our main overarching questions is Cutter's SV (SoVI) model (Cutter et al., 2003), amended by adding the weighting method proposed by Rygel et al. (2006). Our study area has its own local conditions shaped by culture and geography, hence locally specific variables have been added to the wider list of generic variables suggested by the literature review, so as to develop a geographical context specific model. The next two chapters will supply further detail of the SV model's application.

5 Construction of an SVI for tropical cyclones – The case of Oman

5.1 Introduction

Natural disasters occur when natural hazards overlap with human systems: the more fragile and weaker the human system, the greater the disaster's impact. Many of the consequences of disasters can be avoided through preparation, mitigation, and resilience building. But avoidance also requires knowledge about risk, vulnerable groups, and places; thus, the importance of risk assessment. Recent studies of the risk assessment process have highlighted the importance of SV assessment (Uitto, 1998; Cutter et al., 2003; Turner et al., 2003; Polsky et al., 2007; Blaikie et al., 2014; Lee, 2014). SV is a function of hazard type and the characteristics of the exposed people and place, and so it varies both spatially and temporally as these changes. Cutter et al. (2003) emphasise the importance of assessment of local vulnerability to natural hazards (reviewed in chapter two).

The impact of natural hazards is higher in certain countries than others due to different levels of development: cultural, social, political, and economic factors contribute to the level of impact in any society (Alcántara-Ayala, 2002). Societies in different areas of the world have diverse compositions of social characteristics that differ in intensity and structure across various levels, which makes the impact of natural hazards variable (Van Zandt et al, 2012). The pre-disaster socio-economic status of households has a significant influence on their ability to respond to and cope with disasters (Masozera et al., 2007; Highfield et al., 2014)

SV is considered a determinant of biophysical vulnerability (Brooks, 2003) and interests scientists in this field for two main reasons: 1) to estimate the size of the impact in order to take suitable action (mitigation), and 2) to prepare for remedial action that will limit the impacts (adaptation) (Adger and Kelly, 1999; Adger et al., 2004). Nevertheless, SV is often overlooked because it is difficult to measure. Rufat et al. (2015) conducted a meta-analysis of flood disasters from 1997 to 2013 and suggested that the demographic characteristics of health and socioeconomic status are the drivers of SV to floods. Conversely, in another flood risk study, Kuhlicke et al. (2011) concluded that identifying a common set of social indicators to explain vulnerability throughout all disaster phases is not possible. They argue that vulnerability is a product of specific socioeconomic-demographic, spatial, institutional, and cultural contexts. From their study, Adger et al. (2004) concluded that comparing vulnerabilities of people and places is possible across time and space at different scales, but that aggregation of vulnerability measured at different scales is less meaningful because the causes of vulnerability vary by scale.

Vulnerability indicators are crucial tools for measuring vulnerability and coping capacity (Birkmann, 2006). In developing vulnerability indicators, three main factors need to be carefully addressed as they influence the process of developing indicators: scale, dynamism, and complexity (Adger et al., 2004). A considerable number of studies focus on vulnerability indicators relevant to natural and other types of hazards with the aim of developing effective disaster management and relief. The strength and weakness of indicators depend on having effective variables to quantify the indicator topic. The variables should be sound, measurable, and relevant to the measured phenomenon (Freudenberg, 2003). Indicators are still the most effective tool used to monitor progress in communities, but they need to be consistent when the target is to compare the changes, therefore it helps to construct indicators within an appropriate methodological framework (Mitchell et al., 1995). No universally agreed set of indicators for any given phenomenon exists, because there is subjectivity in variable selection (Freudenberg, 2003). For example, vulnerability indicators constructed for one context might not be appropriate for other contexts (Alwang et al., 2001). Indicators also vary due to the nature of the vulnerability addressed, the hazards considered, the geographical area, and socio-economic status.

During planning for emergencies and disaster response or recovery, authorities must identify the vulnerable population to increase support for those most in need during a disaster (Flanagan et al., 2011). According to the United Nations Office for Disaster Risk Reduction (UNISDR) a scientifically based SV assessment system is particularly important in developing countries, as they are the most affected by natural disasters (UNISDR, 2013). The United Nations Framework Convention on Climate Change (UNFCCC), Article 4.4, advocates help for developing countries vulnerable to the impact of climate change in meeting the costs of adaptation. There is a strong need to develop local indicators of SV to determine the level of impact of a certain hazard and to understand the underlying processes. Knowledge of local level vulnerability is important for understanding national and subnational levels of vulnerability.

From the discussion above, it becomes obvious that there is an essential need to develop a local level SVI for tropical cyclones because this has yet to be addressed for Oman (Wang and Zhao, 2008; Al-Shaqsi, 2010; Fritz et al., 2010; Alhinai, 2011, Wang et al., 2012). Developing countries exposed to natural hazards must carry out this assessment to help in planning and effective use of limited resources. Oman has its own particular context and needs a tailored SV assessment to support its disaster risk reduction efforts.

5.2 Methods

This study seeks to reveal local level SV to natural hazards in Oman. The analysis involves the construction of an SVI using a suitable applied conceptual framework in the field of disaster risk reduction. The focus is on developing the best comparable set of local SV indicators for tropical cyclones, which are context-sensitive, and use representative variables from the latest (2010) census. The produced indicators will be used later in this chapter to: 1) calculate the SVI, 2) map the SVI across the study area. The SVI is calculated using a summation of weighted factors (Siagian et al., 2014; Frigerio and De Amicis, 2016).

The study is conducted in Muscat governorate, an area exposed to the impact of several tropical cyclones that includes a long coastal stretch that often faces this type of hazard. The reasons for selecting this area were explained in detail in the case study discussion in Chapter Three. The analysis is based on the smallest administration unit, a municipal block (figure 26), for which data were obtained for sufficient variables addressing common generic dimensions identified in the literature review (section 2.6.3.2.1) along with proxies for local Omani social characteristics' influence on vulnerability during natural disasters obtained using two qualitative methods: semi-structured interviews, and analysis of information from a local newspaper about mega cyclone Gonu, 2007. The output from this part is used later in this chapter to carry out further spatial analysis by mapping SV indices exploring the nature of risk in the study area.

Consensus exists as to some generic SV variables to represent risk from natural hazards. Cutter et al. (2003) suggest that social indicators that influence vulnerability of a population during natural disasters should include age, ethnicity, gender, disability, income, and housing units (other social indicators mentioned earlier were examined further in Chapter Two, Literature Review). Peduzzi et al. (2009) argue that poor populations are more vulnerable to tropical cyclones. Hence, whilst some of the selected variables are theoretically supported by prior studies, others reflect the specifics of the place.

As discussed in Chapter Four, the SoVI conceptual model is adopted in this study (Cutter et al., 2003). The application of this model requires its adaptation to the Omani context by including variables that contribute to local SV during a tropical cyclone event (data availability must be considered too). These variables which reflect the specific Oman context include, for example, gender, total job seekers, non-Omani job seekers, old Arabic houses, rural houses, housing with no connected water supply, and the most risk-taking population (aged 18-35). These features are thought to raise vulnerability; for example, the younger population group aged 18-35 is selected as it reflects a stubborn attitude during disasters, where people do not listen to instructions and are slow to evacuate (the main cause of death from Phet cyclone in 2011, according to interviews with staff from the Executive Office of the NCCD).

Figure 29 shows the process of constructing an SVI for cyclones in Oman and reflects the structure of the remainder of the chapter. This includes the integration of quantitative methods (using statistical analysis as a reductionist method to minimise the number of selected variables) with qualitative methods (using semi-structured interviews and newspaper analysis).

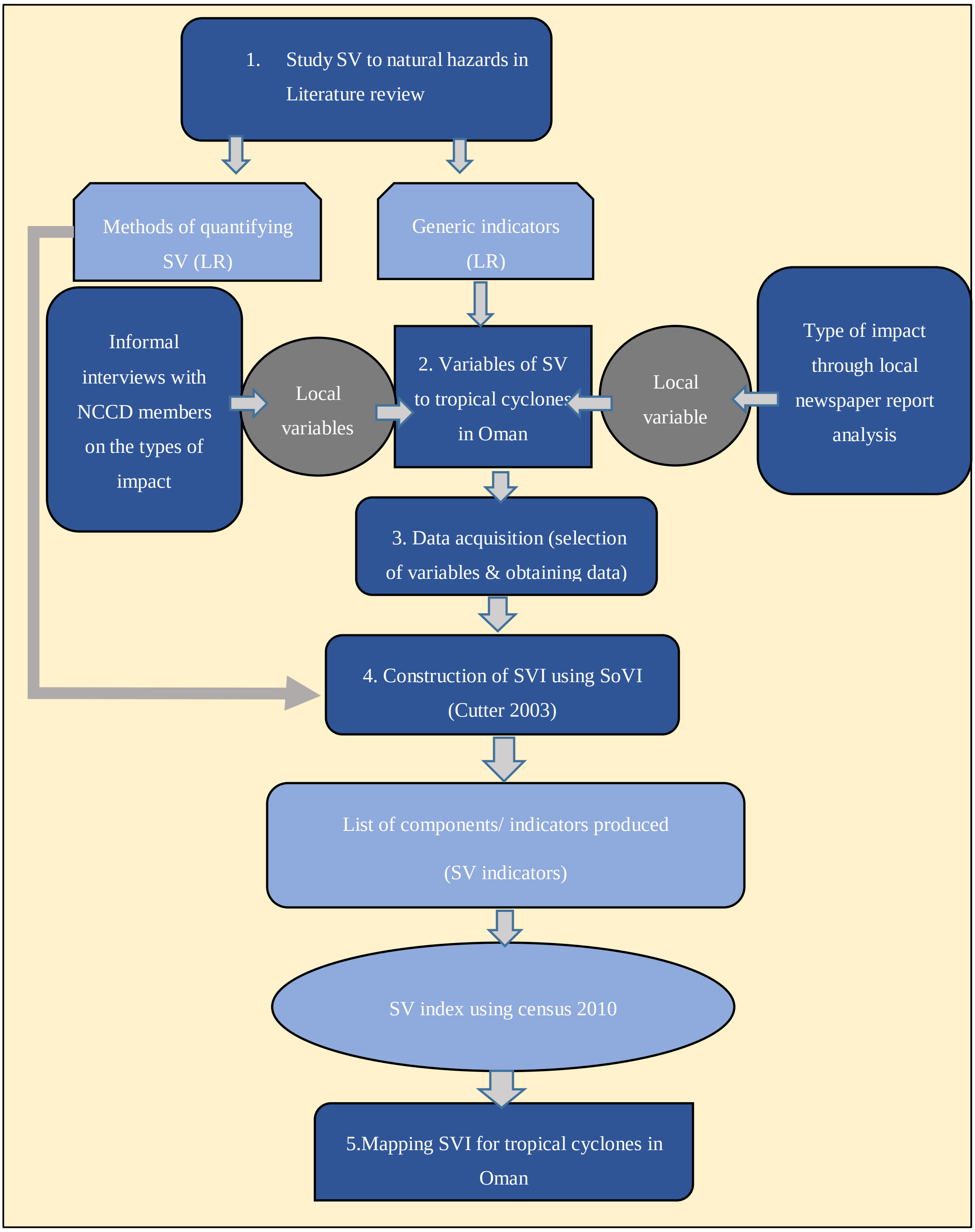

Figure 29. SV index construction process (Author, 2018). (Dark blue represents the main steps, light blue shows the output of each step),SV, social vulnerability; LR , literature review , SoVI Cutter's model;

The first step was to review the literature on SV to natural hazards, its conceptual frameworks, and explore common generic variables that influence vulnerability to natural hazards, specifically tropical cyclones. The second was to select SV variables from both the literature review and a specific consideration of the Omani context, achieved by review of local media and interviews with NCCD members. Once the main dimensions and variables were identified, data availability was determined, and geographically referenced data collected (third step) (from the National Centre for Statistics and information in Oman). The fourth step was to apply the method adopted to construct the SVI, and extract indicators using statistical analysis. Then the composite SV index was calculated and mapped for the study area to reveal the local social vulnerability. So, in other words SVI construction follows six main steps: 1) reviewing the literature for methods of constructing SV and generic variables; 2) variables selection according to criteria mentioned in the literature review; 3) data collection for all cases from each variable against each geographical entity; 4) data screening and transformation; 5) performing PCA and SVI calculation; 6) mapping the SVI.

5.2.1 Social variables selection

The local population characteristics are used here as sources of variables in SV assessment (Cutter et al., 2003, Rufat et al., 2015). Therefore, a detailed exploration of census data was conducted to determine the possible variables that could influence social impact during an extreme climatic event in Oman. The selection of variables is based on the variables' relevance to SV from tropical cyclones. The 2010 census was the main source for variables in this chapter. The final social data obtained and used in the study covers nine dimensions, with 24 variables retained to construct the SVI. The following are overviews of the dimensions and the included variables, with further detail including justification and direction of effect (increases or decrease vulnerability) given in Table 18.

Population

Population is an important dimension for indicating population distribution and growth. It is useful to include a variety of demographic variables from this dimension as these influence community vulnerability from a range of perspectives. Five variables were chosen to represent this dimension of total population: Omani population, non-Omani population, Omani female population, and non-Omani female population. Having the total Omani population as a separate variable allows measurement of the weight and the impact of this social group because it represents the main component of the society. The non-Omanis are also important due to their special social characteristics and economical status, especially those who were impacted highly during the last few mega events.

Age

Extremes in age affect movement away from a dangerous situation. Parents expend time and money caring for children, so this dimension is one of the most important indicators of social dependency and slow response to hazard. Local authorities are not well prepared to deliver specific support and help to this category (Morrow 1999; Madrid et al. 2006). Similarly, the elderly is more dependent and likely to require support in a hazard event situation. The two variables selected in this dimension are Omanis aged less than 14 years of age and Omani elderly greater than 65 years of age.

Gender

This dimension is important, especially in a developing country like Oman, where cultural factors influence some behaviours, and is represented here by three variables: females 18-64 years, female headed families, and widows. They share common characteristics, such as reduced capacity with respect to hazards, due to reduced access to resources, often due to cultural constraints (particularly on interaction with men who mostly are gatekeepers to key resources), and also due to the nature of their daily tasks and care giving roles in this region especially and middle eastern countries in general. This variable is among those supported theoretically in the academic field and is also addressed locally by NCCD members in the social affairs sector.

Family structure

Family structure is another important dimension, especially in Oman, where the family structure is quite different from that of Western countries. Omani families are often large with multiple nuclear families per household because the extended family shares the same house as part of a culture of social connectivity, and due to the weakness in institutional capacity to care for the elderly. In this dimension, the obtained variables influence the level of impact from tropical cyclones and people's reactions to similar major events. The three variables selected here are Omani families, non-Omani families, and family size of five or less. This variable is supported theoretically in the academic field as well as being addressed by NCCD members in the social affairs sector.

Unemployment

The unemployment level is a dimension that can reflect socio-economic status, which influences a population's ability to respond and recover from natural hazards. Two variables were selected from the available data: total job seekers and non-Omani job seekers.

Employment

Employment rate is an important proxy which reflects the socio-economic status of workers. Employment indicates a prosperous life and hence an ability to respond to and recover from natural hazards, whilst low, unskilled, and low-income general labourer jobs reflect more limited access to resources. Two variables were selected to represent this dimension: the total number of workers and working Omanis older than 15 years.

Housing units

The housing unit is another aspect of socio-economic status. It is important as it demonstrates income, and wealth. Occupied houses, old Arabic houses, rural houses, and houses without a connected water supply are the four variables obtained for this dimension. This variable is among those supported theoretically in the academic field as well as being addressed by NCCD members of the social affairs sector through the interviews and by newspaper reports.

Education

This dimension denotes further aspects of socio-economic status, which help to build the economic story of communities where obtaining direct income data is not possible. This is especially the case for information considered confidential due to cultural predisposition, as is the case in Oman. The two variables selected here are: illiterate Omanis greater than 15 years of age, and non-Omani greater than 15 years of age with education above high school level.

Attitude

This dimension represents local people's behaviour during a hazard event and is dominated by the age group that most often takes the risk of crossing water channels in flooded areas. This variable therefore represents the population aged 18 to 35, who are not fully mature in terms of cyclone experience and tend to take excessive risks. This has caused a lot of deaths in prior Oman cyclones, often as vehicles full of family members attempted to cross flooded channels, or individuals attempted to cross these channels on foot. These people are less likely to listen to authority instructions and warnings during the disaster. This happens not only during cyclones, but also with heavy rain flooding. This variable is addressed by newspaper reporting on the 7th of June and is also considered the main cause of death during Phet cyclone, 2010.

Table 17 shows the dimensions, selected variables (for which data is available), further justification of variable selection, and indication of the direction of relationships with social vulnerability. Variable units are mainly counts, with some variables normalised (e.g. percentage). The raw variable data set addresses 217 municipal blocks.

Table 17 Dimensions and variables influencing SV in Oman (Author, (2018)

Dimension	Variables	Description	Relation to vulnerability
Population Downing et al, (2001); Adger et al, (2004);IPCC, (2012); Holand, (2011,2013); Martins (2012); Armas, (2013); Nan (2013),Gu et al, (2015);Cutter, (2016).	Total population	Countries experiencing rapid growth, lack of quality housing and the social services networks with insufficient time to adjust to natural phenomena.	Positive (+)
	Omani population	They are the main occupants of the area, so this is a significant variable.	Positive (+)
	Non-Omani population	Migrants may not speak the language and not be familiar with formalities for obtaining relief or recovery information, all of which increase vulnerability (Cutter et al., 2000; Morrow, 1999).	Positive (+)
	Omani female population	Reflects social dependency in our culture so far.	Positive (+)
	Non-Omani female population	Weak females with less access to resources and social connections.	Positive (+)
Age	Omani<14 yrs.	Highly dependent group that cannot protect themselves in emergency and disaster events.	Positive (+)

Age indicator is very important, since the elderly and the young tend to be more vulnerable to environmental risk (O'Brien and Mileti, 1992). These two groups are the most vulnerable in disasters (Cutter et al., 2003). In the case of Oman, the country is not prepared to provide specific services for these groups.	Omani >65 yrs.	Elderly may have mobility constraints, when day care facilities are affected by disasters this increases the load of care. This group often have special needs, such as for medicine or assistance from others (Cutter et al., 2000; Morrow, 1999)	Positive (+)
Gender Gender influences level of vulnerability (Enarson and Morrow, 1997). Women have a more difficult time during disasters than men, due to their specific role and family care responsibilities. (Blaikie et al., 1994; Enarson and Morrow, 1998; Enarson and Scanlon, 1999; Morrow and Phillips, 1999; Fothergill, 1996; Peacock, Morrow, and Gladwin, 1997, 2000; Hewitt, 1997; Cutter, 1996).	Female. 18 - 64 yrs.	Women in a country like Oman have a reduced capacity relative to men due to their more limited social connections, due to cultural influence. The men are the main active agents when it comes to any responsibility outside the house, which limits their exposure and skills.	Positive (+)
	Female headed family	More responsibility as the male responsibility is added to their established role.	Positive (+)
	Widows	Widows more vulnerable, there is no male in the family, they do all external work along with care giving.	Positive (+)
Family structure Families with large numbers of dependents often have limited resources and extra responsibility (Blaikie et al., 1994; Morrow, 1999; Heinz Center for Science,	Omani families	Represent the main occupants of any settlement and tend to settle together in the same area reflecting the same socio-economic status.	Positive (+)
	Non-Omani families	Represent the working population and mainly from low wages category.	Positive (+)

Economics, and the Environment, 2000); Puente, 1999; Cutter, 2016) (Interview with social affairs member of NCCD).	Family size 5 or less	This reflects educated and higher status Omanis and almost all non-Omani groups.	Negative (-)
Unemployment This variable reflects the economic status of the society. (Cutter, 2003); Cutter, 2016)	Total job seekers population.	People on the same income tend to occupy the same areas.	Positive (+)
	Non-Omani job seekers	This group tend to settle in the same area according to their financial status, this will make them more vulnerable as they tend to lack language skills and knowledge about the area.	Positive (+)
Education Low level of education is related to poverty and minority status, so the least educated are the lower skilled in this way it is linked with vulnerability, (Tierney, 2006;Morrow, 1999).	Illiterate Omanis > 15 yrs.	These variables are directly related to income level most of the time.	Positive (+)
	Non-Omanis > 15 & > high school	This reflects low literacy and high level of income in most cases.	Negative (-)
Employment People on the same wages tend to occupy the same residential area and have similar living standards. (Cutter, 2003; Cutter, 2016)	# workers	This is an important variable because it represents education level, income, and awareness gained from exposure to the working environment.	Negative (-)
	Working Omanis >15	This variable gives an idea about the economic status of the family and their awareness in general of the importance of education, which therefore characterises the community they live in.	Negative (-)
Housing units	Occupied houses	More occupied houses mean more vulnerable people.	Positive (+)

(Cutter et al., 2003; Rygel et al., 2006; Wood, 2010; Wood, 2010; Chen, 2013; Li, 2010; Schmidtlein, 2008; Holand, 2013; Armas, 2013; Cutter, 2016) (addressed by NCCD members of social affairs and Muscat municipality sectors).	Old Arabic houses	More of this type of dwelling means more vulnerable population.	Positive (+)
	Rural houses	More of this type of dwelling means more vulnerable population.	Positive (+)
	Houses without connected water supply	More of this type of dwelling means more vulnerable population due to service disturbance during disasters.	Positive (+)
Attitude (newspaper report on the 7th of June, the main cause of death during Phet cyclone 2010).	Population age 18-35 years	1. People too stubborn to obey warning and underestimate the size of the risk 2. Delay in right time evacuation.	Positive (+)

5.2.2 Data

The above indicators were selected on the basis of significant consensus in the literature with respect to cyclone hazard, plus additional local analysis (of newspaper reports and interviews with NCCD members) and were the focus of data collection work in Oman. During the study informal interviews with around 8 members of the NCCD committee were used to obtain the general picture of the emergency management system in Oman and more importantly to identify the factors that have driven SV during the last few mega events. Also, due to a shortage of documentation and reports about the nature of impacts during the last few extreme events the study had to depend on reports in Al Watan local daily newspaper from the dates 3rd to 18th of June 2007 for information on the main local possible variables that influenced population during those events. During the fieldwork and data collection visits, Oman's National Center for Statistics, and Information (NCSI) was approached to acquire the necessary social and demographic data. Initially, 38 potentially suitable variables (see Table 15 in section 4.5 in methodology) were obtained for the year 2010 census (the last census). This list was reduced to the above (Table 18) set of variables following the data screening process (see below) to reduce issues of multicollinearity and singularity amongst the 38 variables.

5.2.2.1 Data pre-screening

The data were tested for normality to ensure that the right statistical analysis was applied. The necessary tests to check for normality include plotting each variable in a histogram, scatterplots, and checking for the p value using the Anderson-Darling normality test where when the P-value is < 0.05 the data is not normally distributed, but data is normally distributed when the P-value > = 0.05. From the examination of all variables, I observed the following:

- All variables show positive skewness

After normality checks there was a careful examination of the correlation matrix of all 38 variables to determine the level of correlation and to exclude the variables that showed maximum multicollinearity and singularity. As a result of this examination the following results emerged:

- There is significant positive relation between most of the variables as is clear from the correlation matrix of each dimension, which is expected as they contribute to the same construct
- Twenty-four variables were retained to be used in the statistical analysis

More variables (e.g. on income or house value) could potentially have strengthened the SVI but it was not possible to obtain the required data due to availability and confidentiality issues. Examination of the correlation matrix (Appendix A) and a careful review of the final list of variables led to one of each of the strongly correlated variables being dropped and rerunning of the statistical analysis to check for sample adequacy. The following lists the variables removed from the original data set with the justification for this action:

Employment dimension

Omani job seeker was removed because it is highly correlated with the total number of job seekers and to non-Omani job seekers and thus less important in that it is less representative of a vulnerable group.

Working non-Omani >15 years. This variable was removed because it showed a very high correlation with the total number of non-Omanis in the area and both represent the same group as most non-Omanis are from the working group, as they came to the country for employment.

Family structure dimension

Total family, family size 6-9, and family size >10 are other variables that were removed as they show very high correlation with other important variables from the same dimension and show a close percentage with other variables, see Table 18.

Table 18 Family structure dimension correlation matrix (Author, 2018)

	Total Family	Omani. Family	Non-Omani Family	Family size 5 or less	Family size 6-9	Family size 10 or more
Total Family	1					
Omani Family	0.749	1				
Non-Omani Family	0.825	0.244	1			
Family size 5 or less	0.927	0.453	0.969	1		
Family size 6-9	0.812	0.977	0.355	0.541	1	
Family size 10 or more	0.684	0.940	0.198	0.378	0.912	1

Age dimension

Aged less than 5 was removed because the age group of less than 14 could be used instead, as this represents the same vulnerable group that is socially dependent during extreme events.

Aged 15-64 was not required for Omanis or expatriates as this does not represent a vulnerable group during cyclones.

Population dimension

Non-Omani male shows a very high correlation with non-Omani population (Table 19), and they are almost identical because most non-Omanis are males who came for work. Hence, this was removed.

Two variables were removed: **Omani male** population and **non-Omani male** population, as they are highly correlated with the total populations and other variables Table 19.

Table 19 Population dimension correlation matrix (Author, 2018)

	Total pop.	Omani male pop.	Omani female pop.	Omani pop.	Non-Omani pop.	Non-Omani Male	Non-Omani female
Total population	1						
Omani male population	0.752	1					
Omani female population	0.737	0.988	1				
Omani population	0.747	0.997	0.997	1			
Non- Omani Population	0.766	0.155	0.135	0.146	1		
Non- Omani Male	0.677	0.049	0.0319	0.0408	0.969	1	
Non- Omani female	0.657	0.429	0.407	0.420	0.573	0.35	1

Education dimension

In the education dimension, **illiterate non-Omani > 15** was removed as these people represent a close percentage to illiterate Omani > 15 years. Also removed was **Omani population > 15> high school** education, whilst non-Omani > 15 with > high school education was retained (table 20).

Table 20 Education dimension correlation matrix (Author, 2018)

	Illiterate Omani > 15 yrs.	Illiterate non-Omani. > 15 yrs.	Omani pop. > 15≥ high school	Non-Omani.> 15 ≥ high school
Illiterate Omani > 15 yrs.	1			
Illiterate Non-Omani. > 15 yrs.	0.289	1		
Omani pop. > 15≥ high school	0.689	0.388	1	
Non-Omani.> 15 ≥ high school	-0.037	0.551	0.242	1

Housing unit dimension

In the housing unit dimension, **total number of houses** was removed as it is highly correlated with occupied houses and houses connected with a water network which almost represent the same groups table 21. Also, in the same dimension, **houses connected with public water network** was removed because it is less representative of a vulnerable group and tells the same story as houses with other forms of water supply.

Table 21 Housing unit dimension correlation matrix. Author, (2018)

	Total number of houses	Occupied houses	Old Arabic houses	Rural houses	Houses connected water network	Houses using other form of water supply
Total number of houses	1					
Occupied houses	0.987	1				
Old (Arabic) houses	0.088	0.133	1			
Rural houses	0.152	0.170	0.195	1		
Houses connected with water network	0.911	0.936	0.168	0.149	1	
Houses using other forms of water supply	0.337	0.315	0.0198	-0.010	0.138	1

5.2.2.2 Data transformation

The above process recounts how the preliminary 38 variables were reduced to a final list of 24 variables considered to collectively reflect SV without undue overlap. These data must be normally distributed for subsequent factor analysis, the next step in SC index construction. Where data is not normal, data transformation can be done using an appropriate mathematical operation. In this study, the square root transformation method was applied to variables to counter evident skewness in the data, using SPSS software, which resulted in all variables being normally distributed.

5.2.3 Principal Component Analysis

Spatial data is attribute information that can be represented geographically. However, when many variables are mapped it is difficult to understand the underlying pattern (in our case, of social vulnerability). Nonetheless, there may be underlying patterns in the data that can be represented by variables grouped into a smaller number of meaningful factors that still address the same construct (Demšar et al., 2013). Such techniques attempt to capture the maximum information from the original data while minimising the error between the original and the reduced data set. Principal Component Analysis (PCA), reviewed in Chapter Two Literature Review and further discussed in Chapter Four Methodology, is used for this purpose.

The main assumption in PCA is the presence of relationships between variables which refer to an underlying structure represented by moderate to high coefficients in the variable correlation matrix. The basic concept of this technique is that multiple variables may have similar patterns of responses due to the association with a latent factor. PCA is a linear method, meaning that transformation onto a new, lower dimension is by linear projection. To aid understanding of the PCA process, it is useful to define key PCA terms:

Kaiser-Meyer-Olkin (KMO) test is a measure of data suitability for factor analysis, it measures sampling adequacy for each variable for a complete model. Essentially it is a measure of the proportion of variance among variables that have common variance.

Sphericity test: Statistical test for the overall significance of all correlations within a correlation matrix.

Common variance: Variance shared with other variables in the factor analysis.

Communality: Total amount of variance an original variable shares with all other variables included in the analysis.

Eigenvalue: The eigenvalue for a given factor measures the variance in all the variables which is accounted for by that factor. The ratio of eigenvalues is the ratio of explanatory importance of the factors with respect to the variables. If a factor has a low eigenvalue, then it is contributing little to the explanation of variances in the variables and may be ignored as being redundant relative to more important factors.

Factor: Linear combination (variate) of the original variables. Factors also represent the underlying dimensions (constructs) that summarise or account for the original set of observed variables.

Factor loadings (factor or component coefficients): The factor loadings, also called component loadings in PCA, are the correlation coefficients between the variables (rows) and factors (columns). Analogous to Pearson's r.

Factor matrix: Table displaying the factor loadings of all variables on each factor.

Factor score: Composite measure created for each observation on each factor extracted in the factor analysis. The factor weights are used in conjunction with the original variable values to calculate each observation's score. The factor scores are standardised to reflect a z-score.

PC scores: Also called component scores in PCA, these are the scores of each case (row) on each factor (column). To compute the factor, score for a given case for a given factor, one takes the case's standardised score on each variable, multiplies by the corresponding factor loading of the variable for the given factor, and sums these products.

The principal components statistical analysis was performed using SPSS software for the 24 variables for all 217 municipal blocks in the Muscat governorate. The remainder of this sub-section illustrates the process and exemplifies the PCA outputs:

The first step is generation of the variable *Correlation matrix*: the correlation matrix for the 24 variables is lengthy, hence it is presented at the end of the thesis (appendix 1).

Next, the total variance table 22, was produced by the factor analysis method and shows total variance for all variables. However, due to the high significance of the first four factors and the least significance of the remaining variables or factors, only four factors, those explaining most of the variance, are shown. The first factor explains 42.6% of the total variance and the remaining three factors explain 28.1%, 12.01%, and 6.4% of the total variance. The last two factors do not explain much of the variance, and the decision on whether to retain them is made when examining other outputs, such as the scree plot and the rotated components matrix (see below) to consider the number of variables loaded in each factor.

Table 22 Variance explained by the four extracted factors and their corresponding Eigenvalues. (Author, 2018)

Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.784	61.598	61.598	10.223	42.595	42.595
2	4.053	16.888	78.486	6.744	28.100	70.694
3	1.325	5.520	84.006	2.883	12.012	82.706
4	1.231	5.130	89.136	1.543	6.429	89.136

Next is *factor extraction:* there are three common methods that can be used to determine the number of factors to retain: Eigenvalue, scree plot, and parallel analysis. First is the Eigenvalue; this method considers all factors showing Eigenvalues greater than one, as suggested by Kaiser (1960). Second is Cattell’s (1966) scree plot method which plots all components against the corresponding Eigenvalues and then the point of inflexion is noted; components’ factors above this point of inflexion are considered and the rest are discarded (figure 30). The third method is parallel analysis, which compares the Eigenvalue from the data set before rotation with Eigenvalues generated from a matrix of random values of the same dimensionality (the same p variables and n samples). In this method all factors with Eigenvalues produced by PCA greater than Eigenvalues from parallel analysis from the corresponding random data can be retained, the rest will be discarded (Franklin, 1995). The third method is used to evaluate the first two by generating random data based on a specific number of factors. The Kaiser criterion sometimes retains many factors, while scree plot tests tend to retain few factors, however both works well when there are few factors and many cases (Hill et al., 2006).

All three factor extraction methods were used to determine the threshold for significant factors to be retained. In this study, the first two techniques were favoured because they showed agreement on the number of factors to be extracted in this study, and because these two methods are mainly applied by researchers in this field.

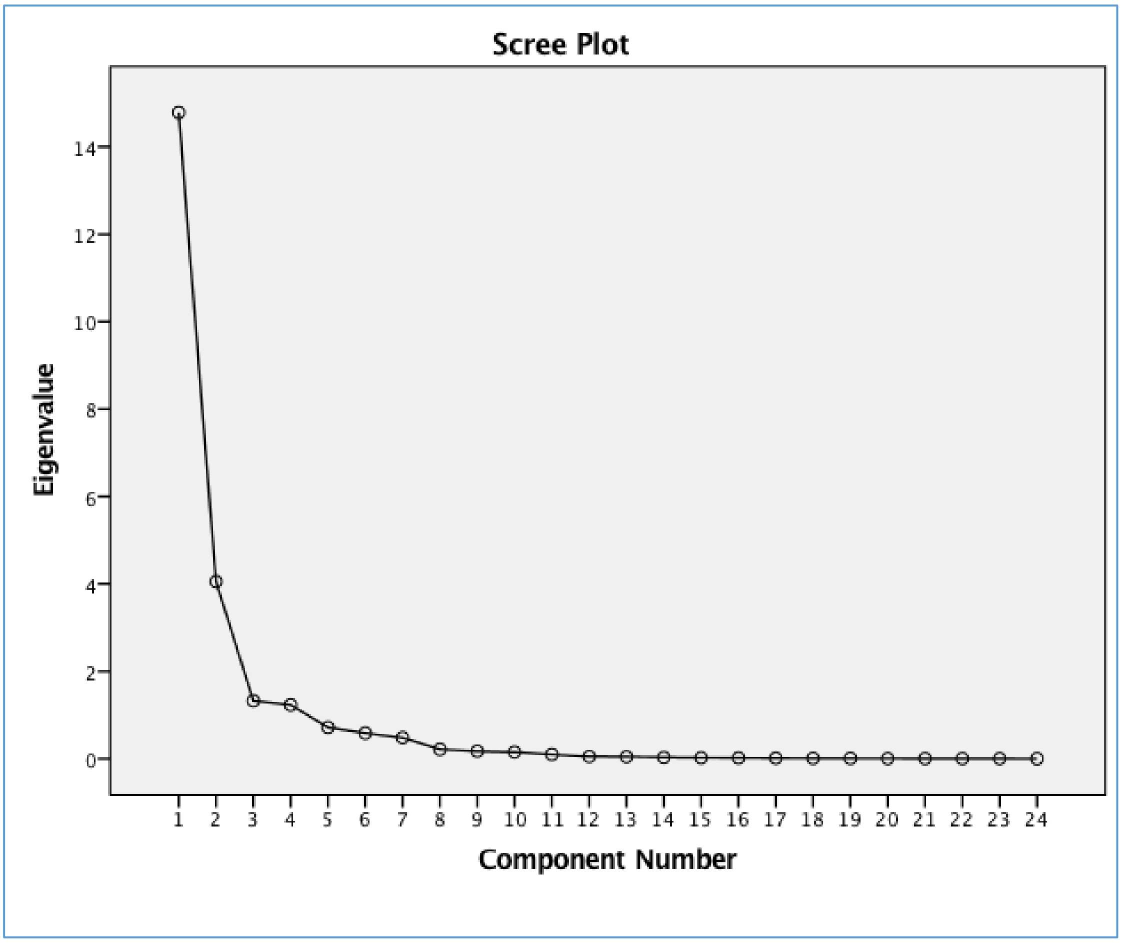

Figure 30. Scree plot showing component extracted and corresponding Eigenvalues (Author, 2018)

The rotated component matrix was produced as a by-product of the factor analysis method using the varimax rotation technique. The aim of rotation is to increase the difference between strong loading and small loading by maximising the strong loadings for an easier interpretation and to minimise the smaller loadings to be excluded from the matrix if they fall below the threshold. Table 23 shows the produced matrix with the significant loading for interpretation. According to Stevens (2002), for a sample size of around 200 observations the loadings should be greater than 0.364 to be considered significant, and therefore recommended to be used in subsequent PCA interpretation and labelling steps (Yong and Pearce, 2013).

Table 23 Rotated component matrix with variables loadings (Author, 2018)

Variables	Components			
	Socio-economic indicator	Non-Omani	Low income Working forces	To be removed due to small number of variables
#Omani female	0.959			
#Omanis	0.955			
Omani worker >15	0.935			
Omani Family	0.930			
# job seekers	0.921			
#widows	0.889			
Omani <14 yrs.	0.884			
Illiterate Omani > 15 yrs.	0.876			
Omani > 65 yrs.	0.834			
Fem. 18 - 64 yrs.	0.801	0.555		
Female headed families	0.717	0.591		
Non-Omani Family		0.943		

non-Omani female		0.909		
Family size 5 or less		0.893		
non-Omani >15 ≥ high school		0.872	0.444	
Occupied houses	0.574	0.756		
#non-Omanis		0.724	0.675	
Non-Omani job seekers		0.713		
# worker		0.525	0.782	
#pop. 18-35 yrs.	0.468	0.457	0.730	
Total population 2010	0.555	0.528	0.625	
Houses using other form of water supply	0.515		0.544	
Old (Arabic) houses				0.806
Rural houses				0.782

5.2.4 Factor loading interpretations

Table 23 shows the rotated component matrix with the variable loading in each factor. The loaded variables are examined to identify a dominant theme (i.e. higher loading ones) and permit labelling of each factor. This step occurs after excluding insignificant variables from those loaded in more than one factor or loaded with a small and insignificant value. Thus, variables with moderate to high loading are retained in this step and represent underlying components for use in the SVI. The following are the qualitative descriptions of the resulting factors derived from the PCA analysis, with their corresponding label.

- Factor one explained the highest share (42.6%) of total variance and has the maximum variables, with the majority loaded strongly. In this factor, 15 variables loaded moderately to strongly. The main theme of this factor related to the Omani population development aspect or their socio-economic conditions. This factor represents and is now named as *Omani socio-economic*.

- The second factor has 12 variables loading. Seven of the variables loaded strongly at more than 0.7. Almost all the strong loading variables represent the non-Omani population, family size, their female group, and education level and job status.

Therefore, the general theme here is non-Omani social characteristics. This factor was labelled *non-Omani socio-economic*.

- The third factor has six variables loaded, two of which loaded strongly: the number of the population 18-35 years of age, non-Omanis, the number of workers, houses without water connections. The next, lower loadings include the total population in those blocks or size of population occupying those areas in general. These variables were labelled as *low wage work force* and according to knowledge of these areas they are the main industrial areas occupied by low waged workers. This indicator will have a positive relation with vulnerability.

According to the rotated component matrix and total variance, the fourth factor was dropped as it only explained 6.4% of the total variance and had less than the minimum required variables loadings. Only two variables loaded, whilst a minimum of three variables are needed to include it as a specific factor. Thus, the final number of factors retained was three, collectively representing SV in Oman.

5.2.5 Factor scores

The factor score is a composite variable which provides information about each block's placement on the factor. The scores for each factor are produced as by-products; the software uses factor coefficients through a mathematical formula to produce the factor scores using regression method. This is conducted by multiplying the factor-loading coefficient with the observation in each municipal block to calculate the factor score. Factor scores are calculated by multiplying the component score coefficient values with each factor into the normalised variable values.

$$F = X B \quad \text{Eq. 5.1}$$

Where: F is the factor score

X is the normalised observation, and

B is the factor score coefficient value on each factor.

The factor scores are the target of our study and represent each SV indicator in each municipal block. Factor scores produced in SPSS were calculated for the three indicators (Appendix 2). Once all scores are generated the final composite SVI (SVI) can be calculated as:

$$\text{SVI} = \sum \left(\frac{42.6*Factor1}{89.13}\right) + \left(\frac{28.1*Factor2}{89.13}\right) + \left(\frac{12.01*Factor3}{89.13}\right) \quad \text{Eq. 5.2}$$

The weight (numerator) in the above equation is the percentage of variance for each retained factor produced by factor analysis, whilst the denominator is the total variance explained. The factor scores' values against each observation can then be used to map SV in the study area. Mapping uses standard deviation classes that provide a relative representation of which blocks deviate more from social vulnerability means (Borden et al. 2007) and so do not provide an absolute representation of vulnerability (where we could determine that block X is twice as vulnerable as block Y).

5.3 Result and discussion

According to the adopted approach of SV assessment, three factors were produced. Each factor is explained in more detail in the following sections.

5.3.1 Factor 1 (*Omani socio-economic*)

This factor is the first indicator and explains most of the variance (42.6%), but with an Eigenvalue of 10.2. There were 22 variables loaded in this factor before rotation, five below the value of 0.7, the recommended cut-off value for variables to be considered as a determinant of the factor. After rotation, 15 variables loaded, four below 0.7, while the other eleven variables loaded strongly according to the rotated components matrix in table 24.

Table 24 Factor one and the variables loadings (Author, 2018)

Variables	Components: Socio-economic indicator
#Omani female	0.959
#Omanis	0.955
Omani worker >15	0.935
Omani. Family	0.930

# job seekers	0.921
#widows	0.889
Omani <14 yrs.	0.884
Illiterate Omani > 15 yrs.	0.876
Omani > 65 yrs.	0.834
Fem. 18 - 64 yrs.	0.801
Female headed families	0.717
Non-Omani Family	
non-Omani female	
Family size 5 or less	
non-Omani >15 ≥ high school	
Occupied houses	0.574
#non-Omanis	
Non-Omani job seekers	
# worker	
#pop. 18-35 yrs.	0.468
Total population 2010	0.555
Houses with no water connection	0.515
Old (Arabic) houses	
Rural houses	

The remaining four variables loaded moderately, and looking at the strong loading variables, almost all variables share the theme of Omani population socio-economic characteristics (Omani dependent age groups, family size, education level, working status, and number of Omani females). There are other variables that contribute with a small loading which might support and encompass another angle of development, such as housing units, and so forth.

Figure 31 shows the spatial distribution of the socio-economic status of the Omani population in the study area. The quite high vulnerability zone of this indicator (Red, Orange) is located in the most Omani populated areas in two different clusters: the first cluster in blocks 319, 321, 325, 333, 335, 337, and 345; and the second cluster in blocks 357, 369, 371, 375, 379, and 381 (both in A'seeb). The remaining high vulnerability zones are surrounding the very high zones, with one more cluster in blocks 237, 242, 244, 248, 236, 241, 247, 249, and 239 (in Bawsher). So, these clusters represent the three highly vulnerable areas in the Omani socio-economic status dimension. Some of the very low vulnerability areas in this factor (represented by the blue and pale green shading) are less populated and some are occupied by non-Omanis. There are other municipal blocks with high population, some reaching 20 blocks, but they do not show very high or high vulnerability because other variables contributing to this indicator are either insignificant or have zero cases.

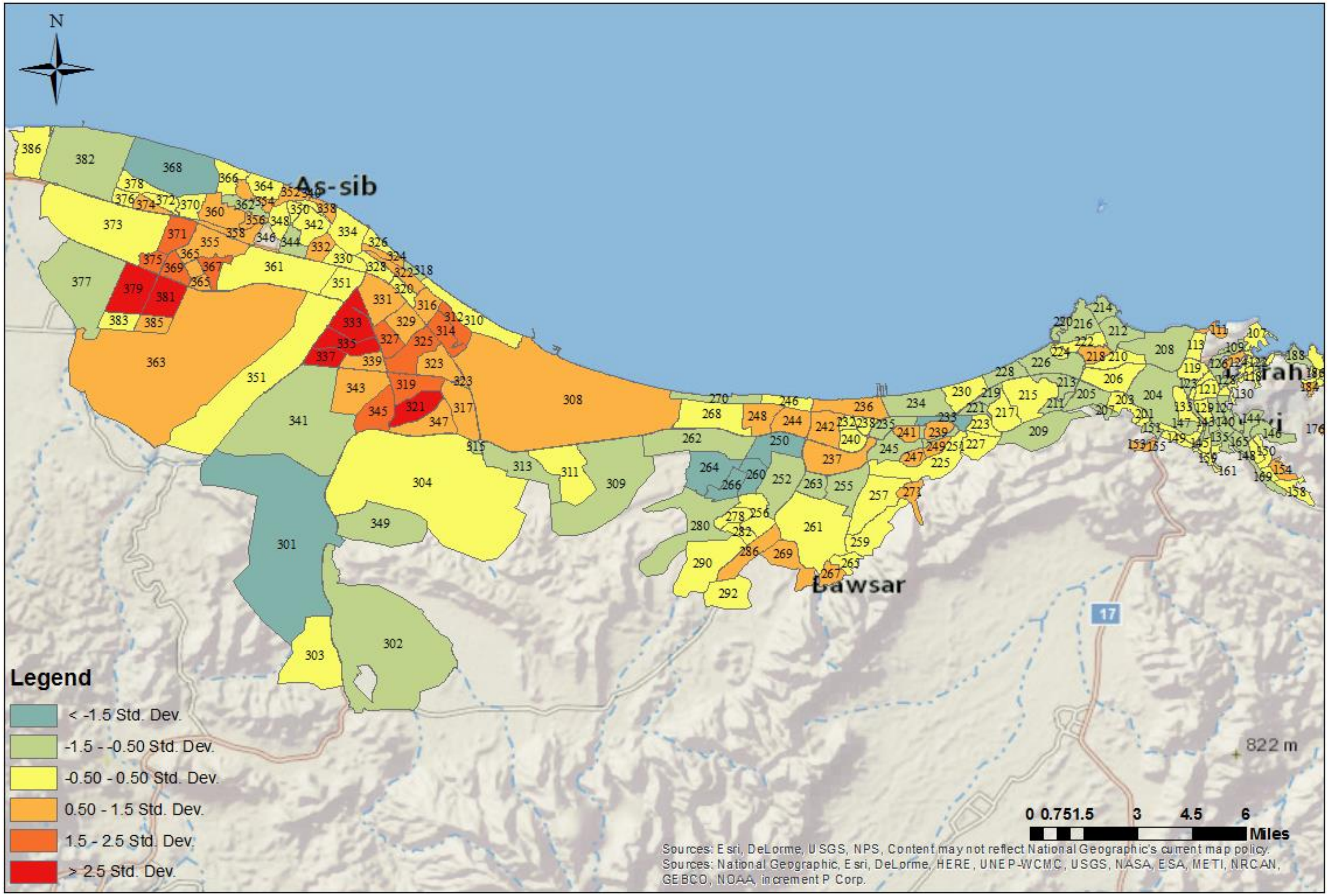

Figure 31. The *Omani socio-economic* component (Factor 1) (Author, 2018). (Green (< -0.50 Std) is low vulnerability, red (> 2.5 Std) is high vulnerability).

5.3.2 Factor 2 (Non-Omani socio-economic)

The second factor is the second highest in variance and explains 28.1% of the total variance with an Eigenvalue of 6.7. In the un-rotated component matrix 10 variables showed weak to medium loading, and half loaded negatively, which means a negative direction in relation to the other variables within the factor. Considering the same criteria, neglecting all weak loadings with less than absolute 0.7, two variables remain. After rotation, 12 variables loaded from weak to strong loading. Excluding all loadings below 0.7, seven variables were used for labelling in table 25. The retained seven variables, those that collaborate on the construct of this indicator, are all focused around the non-Omani characteristics.

Table 25 Factor two and variables loaded in this factor (Author, 2018)

Variables	Component: Non-Omani
#Omani female	
#Omanis	
Omani worker >15	
Omani. Family	
# job seekers	
#widows	
Omani <14 yrs.	
Illiterate Omani > 15 yrs.	
Omani > 65 yrs.	
Fem. 18 - 64 yrs.	0.555
Female headed families	0.591
Non-Omani Family	0.943
non-Omani female	0.909
Family size 5 or less	0.893
non-Omani >15 ≥ high school	0.872
occupied houses	0.756
#non-Omanis	0.724

Non-Omani job seekers	0.713
# worker	0.525
#pop. 18-35 yrs.	0.457
Total population 2010	0.528
Houses with no water connection	
Old (Arabic) houses	
Rural houses	

From Figure 32 and considering that the variables loaded in this factor all concern non-Omanis, the Muscat area has the maximum density of non-Omanis, which is due to this area being the country's main employment hub. Therefore, we can see the high vulnerability municipal blocks are all concentrated in areas more densely populated by non-Omanis. These municipal blocks are more densely occupied by non-Omani households or workers as some of these areas are sites of companies and factories or storage yards. There are two main areas where vulnerability is very high: one is the cluster in the Bawsher area including municipal blocks 239, 235, 237, 240, and 242 and surrounded by high vulnerability blocks; the second is in Mutrah city block number 119 and surrounded by a few blocks with high vulnerability.

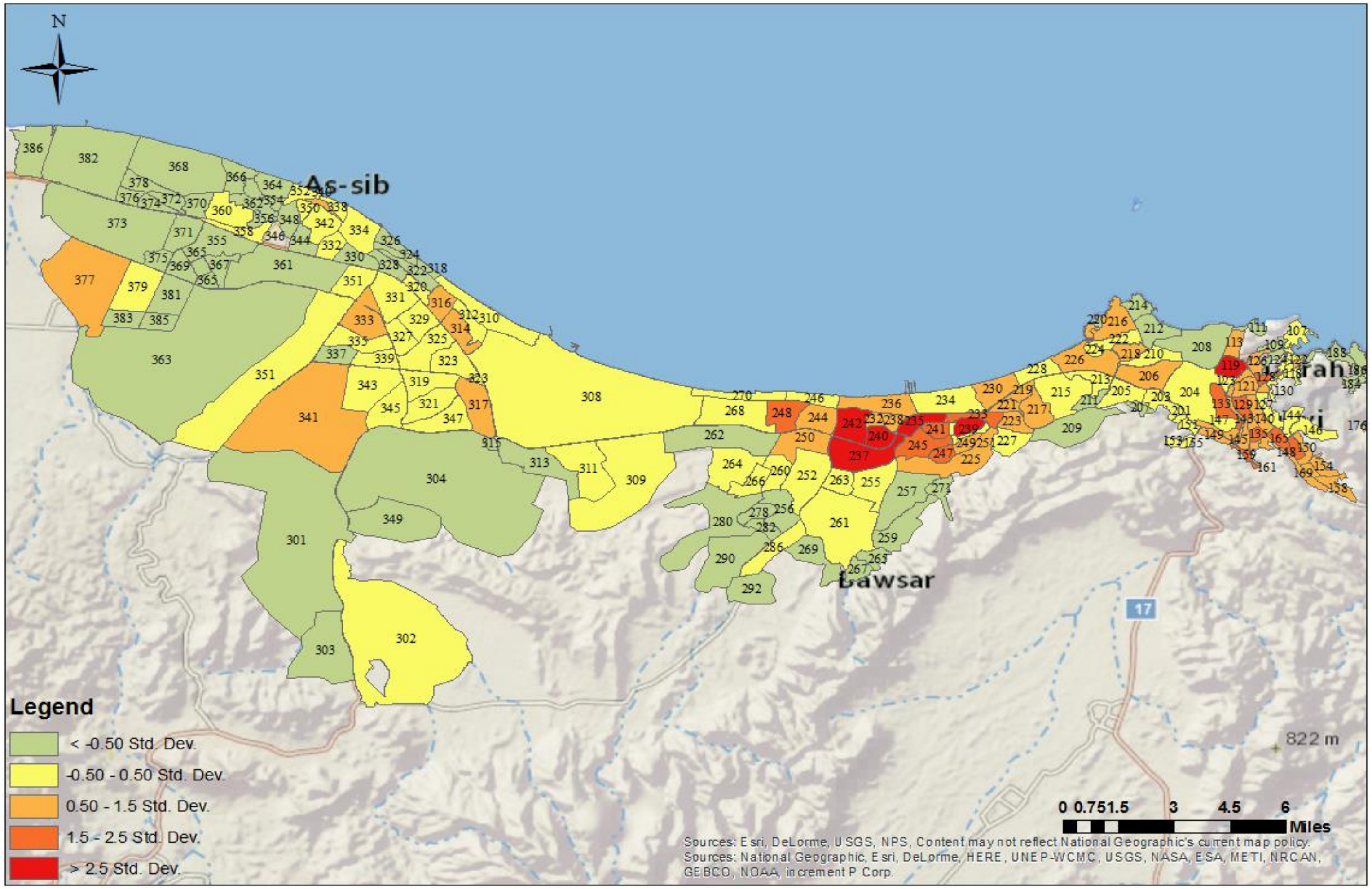

Figure 32. The *non-Omani* component of SV(Factor 2) (Author, 2018). (Green (< -0.50 Std) is low vulnerability, red (> 2.5 Std) is high vulnerability).

5.3.3 Factor 3 (low wage work force)

This third factor has a total variance of 12.01% and an Eigenvalue of 2.8. This factor explains a good amount of variance, with two variables loaded in medium loading in the un-rotated component matrix. The rotated component matrix shows better loading, with six variables showing medium to strong loading; from those, four are below 0.7 and the remaining two above.

Table 26 shows that for factor 3, six variables loaded moderately to strongly after rotation. The variables loaded in this factor are about working groups and working conditions, such as number of workers, population 18-35 years of age, non-Omanis with higher education, and number of workers, with some of the old houses with no water connection occupied by low-wage labourers, such as construction workers and low-wage plant and factory workers. This low-wage work force factor has a positive relation with SV as the higher this factor the higher the level of vulnerability.

Table 26 Factor three and variables loaded in this factor (Author, 2018)

Variables	Component: Low income work force
#Omani female	
#Omanis	
Omani worker >15	
Omani. Family	
# job seekers	
#widows	
Omani <14 yrs.	
Illiterate Omani > 15 yrs.	
Omani > 65 yrs.	
Fem. 18 - 64 yrs.	
Female headed families	
Non-Omani Family	
Non-Omani female	
Family size 5 or less	
Non-Omani >15 ≥ high school	0.444
Occupied houses	
#non-Omanis	0.675
Non-Omani job seekers	
# worker	0.782

#pop. 18-35 yrs.	0.730
Total population 2010	0.625
Houses with no water connection	0.544
Old (Arabic) houses	
Rural houses	

Figure 33 maps low income work force vulnerability and illustrates that it is very high in the industrial and commercial areas where many in the work force work and also live, in some cases. So, block numbers 160, 264, 266, 301, and 377 show very high vulnerability and in general most of the study area shows moderate to high vulnerability because this area is where the country's government and private sectors have their main warehouses, factories, and plants.

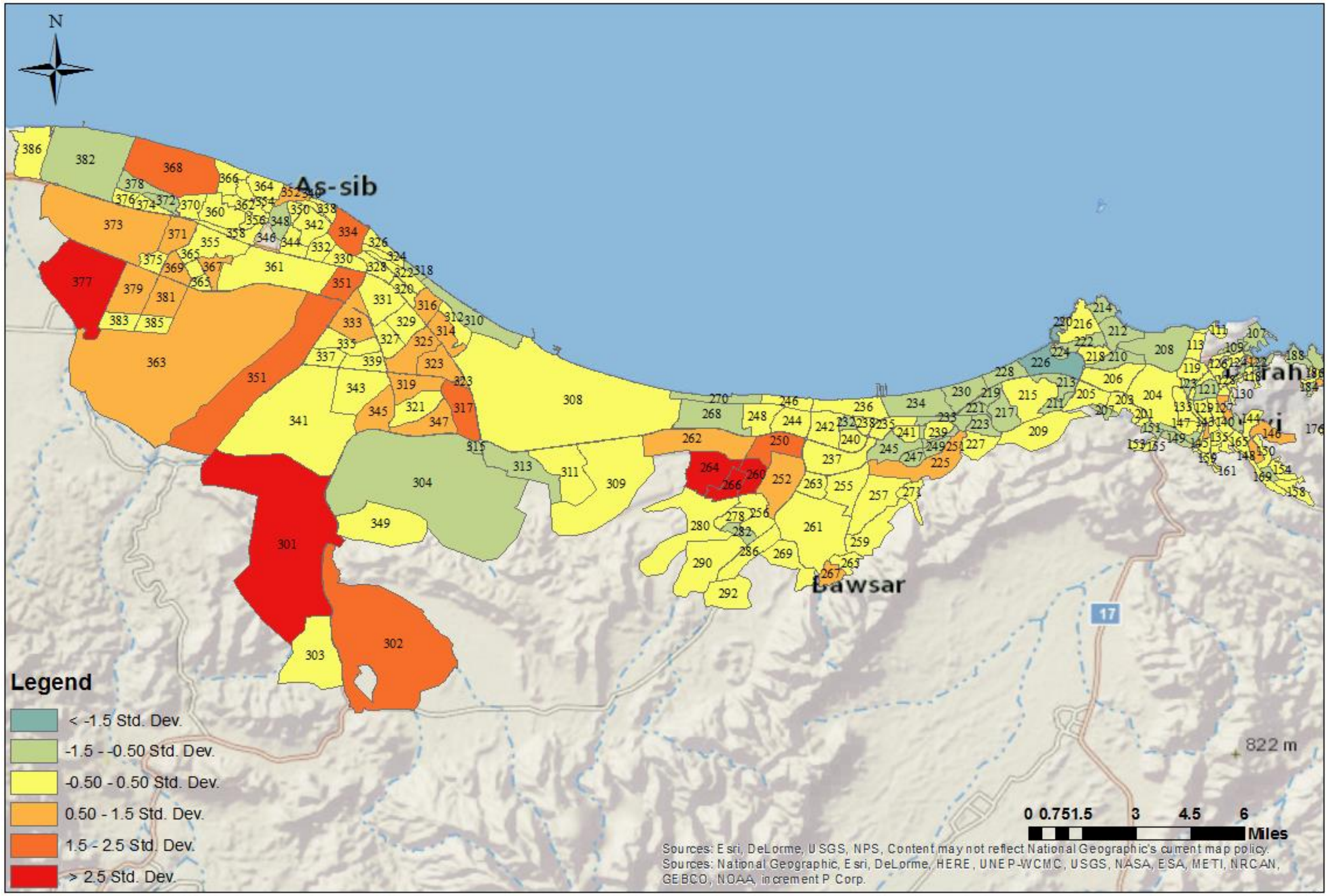

Figure 33. *Low wage work force* component of SV (factor 3) (Author, 2018). (Green (< -0.50 Std) is low vulnerability, red (> 2.5 Std) is high vulnerability).

5.3.4 Social vulnerability index SVI

Once the three indicators had been identified by PCA they were extracted as factors and labelled as indicators for use in the rest of the study, each indicator representing a socially vulnerable group: Omani socio-economic status, non-Omani economic status, and the low-wage work force group. But the aim of this study is to use these three indicators in each municipal block to produce a composite SV index. The SVI for tropical cyclones in the study area was then calculated using additive summation of all three indicators to create the cumulative index in each municipal block. This summation considers the sign of each indicator with regards to its relation to the SV (Chen et al., 2014). However, in this case study, each indicator is considered to have a different weight by applying a weighting system using its variance weight, which the original SoVI model did not consider.

Therefore, the composite SV index (now readily calculated in Excel using the above equation E.q 5.2) was produced for each municipal block. The scores were then used to map the SVI to tropical cyclones in the study area in GIS (Figure 34). From this final SVI map, it is clear that there are four high vulnerability areas characterised by high density population, high street commercial buildings, and a concentration of both work forces and non-Omani working population.

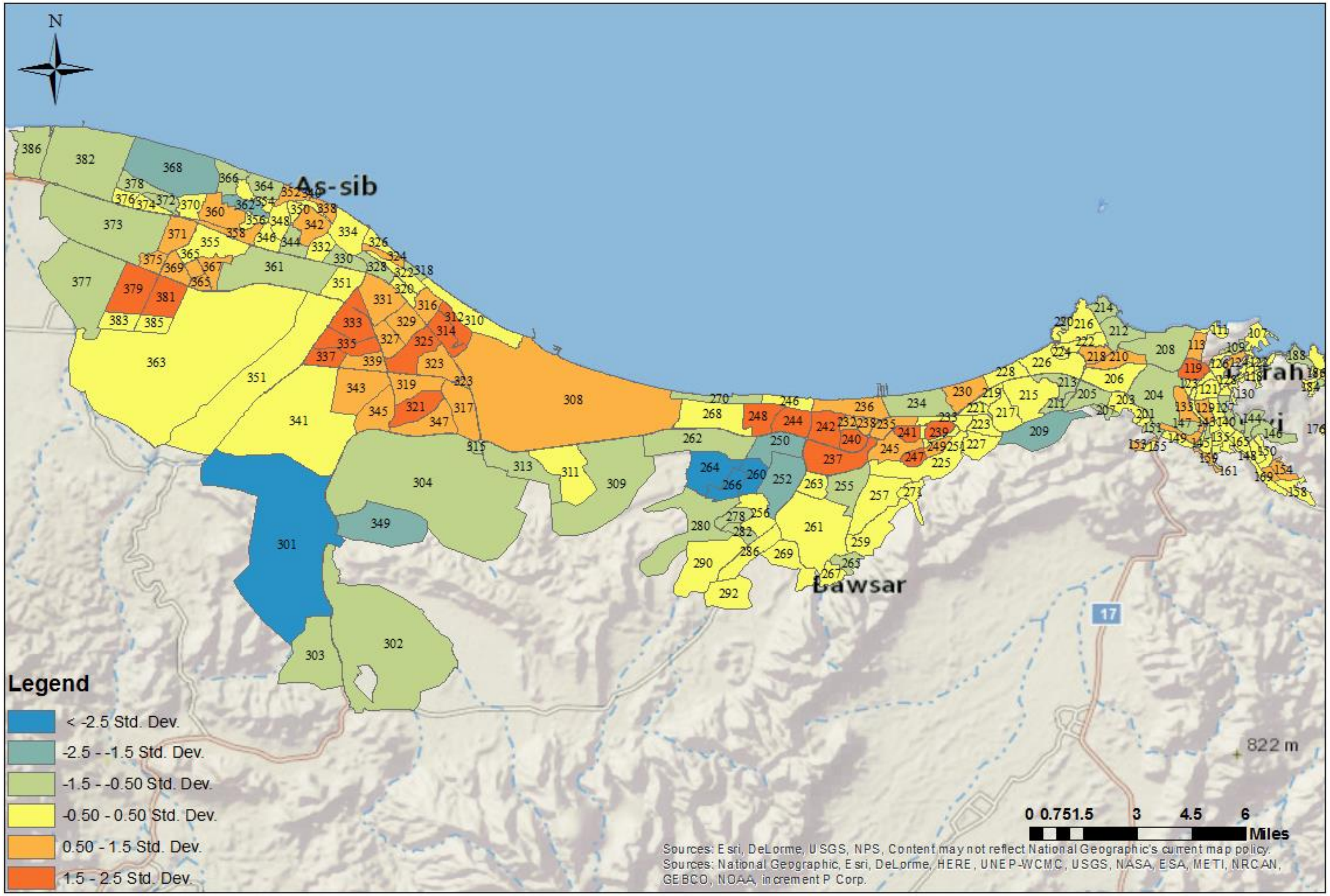

Figure 34. The current SV index (SVI) for tropical cyclones in Oman. (Author, 2018)

(Green colour (< -0.50 Std) is low vulnerability, red (> 2.5 Std) is high vulnerability).

5.4 Summary and Conclusion

The SV assessment method was applied in this case study on four coastal cities in Oman. In the analysis, 38 variables were used to represent variables of SV to tropical cyclones. Twenty-four of these variables were selected after data screening and testing for multicollinearity. The data set was normalised and a PCA process applied. Three indicators were extracted using the Kaiser Criterion that are responsible for 89.1% of the total variance. Factor loadings less than 0.4 were excluded from the component matrix and values of 0.7 and greater were only considered for interpretation and labelling of each indicator.

The composite SVI was calculated using a weighted equation. Four indicators were originally retained, but due to the fewer number and weaker loadings on the last indicator, and comparing the result with the parallel analysis, three indicators were retained: Omani socio-economic status, non-Omanis, and the low-wage work forces group. The produced factor scores or indicators represent the SV level in each geographical entity, in our case municipal blocks. Each indicator was used to map an SV group in the area. This chapter has explained the mapping of the three vulnerability indicators and the composite social vulnerably indicator as illustrated in our discussion section. The vulnerability index was mapped in GIS using standard deviations with six classes to allow for easy interpretation of the map.

The first indicator, *Omani socio-economic status*, was mapped on the 217-municipal area, and produced a very high index score on the A'Seeb area, the most populated Omanis area, in two main clusters. The other area with high vulnerability was clustered on the coastal area in Bawsher and A'Seeb. The second indicator produced two areas of very high index scores for the *non-Omani* vulnerable group located in the centre of the coastal city of Bawsher and centre of Mutrah city. This is where most of the low-wage labourers live, who are mainly of Asian origin and settled in either old Arabic houses or old commercial buildings (ageing houses that have not been replaced or renovated as the structure is weak and the building method is no longer used). The third indicator represents the *Low-wage work force* population; the map of this indicator shows very high vulnerability in the three main industrial areas in Muscat, where most of this social group work, and sometimes live. The remaining high vulnerability zones are places where most of this population stay, such as camps comprising dwellings made of unstable materials and where the population are of the same low socio-economic status.

The composite vulnerability index or SVI is an aggregation of all three indicators using a weighted summation model produced from a score corresponding to each observation. The SVI map shows very high vulnerability clustering in four areas, two of them on A'Seeb city, two km away from the coast, and the third on Bawsher city, close to the coastal area, both of which are considered high population areas. Therefore, we conclude that the most socially vulnerable populations in the study area are located in these areas (blocks numbers 240, 241, 242, 239, 237, 244, 248, 247 in Bawsher, blocks 321, 325, 312, 314, 333, 335, 337 in Al mawaleh (A'Seeb), blocks 379 and 381 in Mabeela (A'Seeb), and in Mutrah city there is one block, 119, of high vulnerability). The produced map of the SVI can help decision makers in planning during the mitigation, response, and recovery periods, as previously demonstrated by Flanagan et al. (2011). It will provide valuable information about the various vulnerable social groups in each area, which will allow the authorities to introduce the right measures, directing their resources effectively during both the response and the recovery process.

The limitations of this approach when using census data for SVI are as follows. In particular, demographic change has been very rapid in Oman due to migration and relocation, hence the vulnerability map may not reflect current conditions due to the long period from one census to the next (Flanagan et al., 2011).

SV is just one component of a risk system that also includes hazard and physical vulnerability. This study is the first attempt to construct an SV index as well as to map local SV in Oman. The study involved analysing and selecting the main dimensions and variables that might contribute to social vulnerability. The study revealed vulnerable areas that need attention from planners and formulation of preventative measures to alleviate the SV from natural hazards. The study also shows some clustering of different levels of vulnerability and clear separation of areas of low vulnerability from the highly vulnerable areas, which indicates the level of social inequality. This pattern of inequality, shown by the differences in social characteristics, highlights the differences in capacities among various communities' members during disasters.

Having selected the representative variables that influence the SV level from tropical cyclones and produced the final list of variables, the same variables can be used to conduct a new SV assessment of the previous two censuses before 2010. The justification for doing this is to explore the temporal and more dynamic nature of SV in the same geographical area, as a means to provide additional insight into how development (demographic change, urbanisation) influences the spatial pattern and intensity of social vulnerability, and to gauge the extent to which current understanding of SV is a useful guide to future patterns of vulnerability in the area. This temporal analysis is presented in the next chapter.

6 Temporal variation in SV to natural hazards in Oman

6.1 Introduction

SV is about exposure to stress as a result of social and environmental changes (Brooks, 2003). It is a relative measure of people's sensitivity to hazards and their ability to respond to, cope with and recover from hazardous events. People's capacity and ability to respond changes with time due to life cycles and other circumstances, therefore their social characteristics change over time to various degrees and hence their level of vulnerability changes. Vulnerability is time-dependent and evolves in both the long and short term due to changes in exposure to particular hazards; this will entail continuous evolution in some of the variables in dimensions such as the social, economic, and built environments. For example, vulnerability can rise as people are drawn to settle in higher hazard coastal areas, or because the demographic profiles of people in those areas change, e.g. due to population ageing. So far, this thesis has addressed SV to natural hazards in Oman from a static perspective (chapter five), but here we consider how SV has changed over time. This dynamic aspect of SV must be recognised and addressed in natural hazard emergency planning in order to respond to changing trends of SV and therefore the result should be integrated into planning for sustainable development (Aubrecht et al., 2012).

SV assessment involves identifying the social groups that are most sensitive to the impact of natural disasters both spatially and temporally and understanding the factors that underlie that vulnerability (Zhou et al., 2014). In urban areas, these population characteristics and their distribution continuously change over the short to long term due to social and economic activities and associated mobility and the normal life cycle of an individual (growing from childhood to adulthood, moving from place of birth to place of work, getting older, getting sick) (Aubrecht et al., 2012). Reducing this vulnerability is the main target of risk reduction management and requires development of strong, effective emergency management skills during disasters. To achieve this, it is important to produce and update information about the population in its various aspects in a timely manner to support decision makers during the various phases of an emergency. Mitigation measures, especially structural ones, are always designed over a long time frame. However, urban expansion and increases in population are continuing and accelerating. This, in itself, raises the necessity to review SV from time to time to accommodate this expansion. Applying structural (dams, and levees) and non-structural measures (awareness and warnings) alters vulnerability and therefore risk, so it is not possible to use the same vulnerability analysis results in any further decision-making issues after mitigations have been implemented.

Vulnerability change can occur over different time scales. The daily activities of people and daily mobility can alter people's vulnerability; for example, during the day the individual might be at work in a vulnerable area while that same person at night might be living in a low vulnerability area. Introduction of structural hazard mitigation measures, population migration, and urbanisation, in contrast, are examples of factors that can alter vulnerability over the long term. Measuring SV over time is important as it helps to understand the effects of disaster mitigation efforts in an area as well as understanding the local changes in SV caused by multiple factors at work over different spatial and temporal scales (Cutter and Emrich, 2006).

The literature review (Chapter two) revealed extensive research on common generic social characteristics that have been found to influence people's responses to natural hazards. These characteristics are applied as proxies (variables) used in statistical analysis to construct indicators that are relative measures for social vulnerability. Many of these commonly used variables are listed in chapter two along with description of indicator construction and their relation to social vulnerability. Various studies have used such measures to study SV in several countries (Uitto, 1998; Morrow, 1999; Cutter et al., 2003; Wisner et al., 2004; Boruff et al., 2005; Peduzzi et al., 2009). In this chapter the variables used in the last chapter are used again to develop a comparative analysis of SV over time.

The SV model of Cutter et al. (2003) is considered pioneering in its approach to SV and is regarded as well suited to operationalising social vulnerability. This approach's main advantage is that SV can be assessed using census data with no need to carry out additional expensive and extensive social surveys. The SoVI allows for a consistent set of variables to be used and monitored in both space *and time* to assess changes in SV. However, in practice, most SV studies focus on static mapping of social vulnerability, with only a few adding a temporal dimension to SV analysis (Cutter and Finch, 2008; Aubrecht et al., 2012; Zhou et al., 2014).These studies do, however, reveal the changing nature of SV and underline that dynamic analysis is needed.

Cutter and Finch (2008) carried out a study of temporal variation of SV in the US from 1960 to 2000 at county level. They found that SV increased over time due to rising urban density, and changes in socio-economic status, and ethnicity. SV was initially concentrated in certain areas but become more dispersed over time. There was a trend towards reduction in SV but with regional variability such that many counties exhibited an increase in vulnerability. In another study Zhou et al. (2014) investigated spatial and temporal variation in SV for 2361 counties in China, from 1980 to 2010. Many counties in eastern coastal areas of China exhibited an increase in SV, whereas in those in western and northern areas SV decreased. These temporal trends were attributed to changes in economic status, urbanisation, and rural characteristics. Given the rate of development in Oman, it is anticipated that SV will similarly not be static but reveal a spatial pattern of vulnerability that changes over time.

In chapter five, an SVI was constructed for 2010 and spatially represented for four coastal cities in Muscat governorate. Section 6.2 now reviews the research methods and data with a focus on those aspects relevant to adding the temporal dimension to the previous SV analysis to explore the trend of SV. This is followed by an account of the changes in the geographical and demographical area and a brief account of the statistical analysis which was explained in detail in chapter five. Next, the mapping of the spatial patterns of SVI and the spatial clustering classification pattern are discussed, and finally chapter conclusions are drawn.

6.2 Method

In chapter five, the SVI for the study area was constructed and the nature of the current risk, as the 2010 spatial distribution of the SVI, was revealed. This was carried out by using a set of 24 variables selected from the social characteristics in the 2010 census. In this chapter, the aim is to explore the trend in the SV index over the prior two decades, to better understand the temporal dynamic of SV in Oman, so as to bring further insight into natural hazard risk planning. The study uses past data to assess the changing nature of SV to date. This study could give an insight about future SV through following the trend, but forecasting the future would require the addition of forecasting parameters such as population increases, future planning areas, and increases in numbers of various social groups, and this is not within our scope. A more formal SV prediction would moreover raise difficulties in forecasting all the component variables. Forecasting the higher-level general variables such as population and age structure is possible but forecasting at fine spatial scale (block) is much more uncertain. Furthermore, forecasting many of the other SVI indicator variables would also be highly uncertain at the aggregate level, and the spatial resolution required to usefully forecast the SVI makes this task particularly difficult. However, tracking changes in the past SV can help us to get an idea about the general spatio-temporal trend in SV, and hence future patterns of SV.

In this chapter, the method consists of two parts: (a) replicating the statistical method carried out in chapter five for the two remaining census years (1993, and 2003) using the same set of variables; (b) statistical analysis, comprising calculation of Moran's I for each data set to find out whether spatial clustering exists in the data, and a local indicator spatial analysis (LISA) to reveal the location of any clusters. The variables used are same as those in chapter five to allow for comparison between the three census years, so there is no additional data screening required. For 2010 the study used the Moran's I analysis in chapter five and further spatial analysis is conducted in this chapter for the spatial autocorrelation process. An SVI is produced for each year using the appropriate additive model, with the signs in the additive model determined by the direction of relation of the produced component with the SV. For example, in the results of the statistical analysis for year 2010 the third indicator (low-wage work force) had a positive relation with the SV, in the same direction as the other two indicators, so this will be reflected in the model.

PCA is a reductionist method to reduce a large number of variables to smaller meaningful components that represent SV and explain a larger amount of overall variance. Extracting the right numbers of component depends on the Kaiser criterion of eigenvalues greater than one (Kaiser, 1960). The produced factor scores of each component represent the SV of each social group, and the SV index is again calculated by summing the produced components weighted using total variance represented by each component. These scores are imported into a GIS along with the geographical entities to show the social distribution patterns of each SVI. This method is applied to identify the SVI over the two older census years. The desired output is the factor scores that represent the aggregated SVI for each municipal block. Full details about this technique are provided in chapter five (section 5.2.3).

The comparison here uses the values of the factor score, a unitless measure that will be spatially represented as an index for each year. Once the mapping is complete and the

SVI pattern is shown, the spatial clustering analysis is run to see the potential for clustering. This is conducted through a process of Spatial Autocorrelation (SAC), a phenomenon that helps to analyse spatial data. Spatial autocorrelation occurs when values of variables at adjacent locations are not independent from each other (Tobler, 1970; Dormann, 2009). The term used to refer to this phenomenon is cluster. A cluster in this context means locations with significant positive local spatial autocorrelations, including the core location as well as its neighbours, and rather than individual locations it includes regions of high/low values. The spatial clustering analysis tools are used to identify the statistically significant locations including hot spots, cold spots, and outliers as a classification for the clustered areas. This analysis is useful when action is needed based on location of one or more clusters, and particularly when looking for potential causes of clustering, for instance a disease outbreak. The main function of this tool is to allow visualisation of the cluster's location and extent. This tool normally answers questions about where the clusters are, which are the denser areas, where the outliers are located, and which features are similar. Cluster analysis is used here to assess where the areas of high vulnerability population are, the extent of these areas, and whether the spatial distribution of high vulnerability areas has changed over time. These questions are also posed for low vulnerability areas.

The first step of the spatial analysis addresses whether clustering exists and is carried out by calculating the global Moran's I. Moran's I is a test to explore whether the SVI result maps any spatial pattern or not. If Moran's I show a strong value, then we move to the second step to identify the patterns of similarity in the clustering using local indicators spatial analysis (LISA). These two steps are explained in detail below:

Moran's I: There are many spatial autocorrelation statistical techniques, but Moran's I is the most common one. Moran's I is the first tool to measure spatial autocorrelation, introduced in 1950 to study stochastic phenomena in space for two or more dimensions, and is used to estimate the strength of correlation between observations using the distance separating them (Oliveau and Guilmoto, 2005). The value of this index ranges from + 1 which means a strong positive spatial autocorrelation, to 0 or a random pattern, to -1 or a strong negative spatial autocorrelation. The global spatial autocorrelation coefficient Moran's I is thus used to measure the similarity of nearby features. Its value depends on the weighting and general behaviours of the data set. It indicates the tendency towards clustering and uses Z-scores for the assessment.

The index is an effective global statistic for specification testing, and it tells us that there is a spatial clustering and not a spatially random clustering, but it does not tell us why that is the case. This index does not tell us about the location of the clusters but instead it tells us about their significance. For location determination local statistics tools are needed (see below). So, global spatial autocorrelation is about the existence and degree of clustering but does not suggest the locations of clusters. The limitation of Moran's I is its tendency to average the local variation in the strength of spatial autocorrelation, which constrains identification of cluster location. This raises the need for cluster location identification and assessment of significance, addressed in another local indicator of spatial association (Oliveau and Guilmoto, 2005).

The Local Indicators of Spatial Association (LISA) are local indicators and a form of global statistic considered a *local* equivalent of Moran's I : As an operational definition suggested by Anselin (1995), it is a statistic that satisfies the following two conditions: (a) LISA for each observation gives an indication of the extent of significant spatial clustering of similar values around that observation; (b) the Sum of LISA for all observations is proportional to global indicators of spatial association (Oliveau and Guilmoto, 2005), calculated using the following equation:

$$Li = \mathrm{f}(\mathcal{Y}i, \mathcal{Y}Ji) \quad \text{Eq. 6.1}$$

Where, f is a function, and $\mathcal{Y}ji$ are the values observed in the neighbourhood, Ji of i. The values of $\mathcal{Y}$ used might be either raw data, or a standardised version to avoid scale dependence of the local indicators, whereas in Moran's I the observations are taken as deviations from their mean. So, this test of local autocorrelation analysis helps to assess significance of local statistics at each location, and to identify the location of spatial clusters hot spots, cold spots, and spatial outliers. This test allows an assessment of autocorrelation location specific means, that is, the local spatial statistics for each location. Put another way, this is asking if the value *i* observed at this location is more similar to its immediate neighbour than would be the case randomly (positive spatial autocorrelation). Or whether the value that is observed is more dissimilar from the neighbouring one than would be the case randomly (negative spatial autocorrelation). So, this allows the location of clusters to be identified, and characterisation of the clusters as high or low values (high surrounded by low or vice versa), or outliers. This tool gives the local–global relation of the values. The global Moran's I statistic is essentially composed of the same individual elements; the global Moran's I is the average of the local Moran's I.

From the diagnostic point of view, it is a question of whether the global statistics are shaped by these particular locations or it is a kind of spreading out of values. It is a spatial analytic tool used in cases where large amounts of spatial observations are used for variation over space (Anselin, 1995). Spatial autocorrelations cluster in a LISA map (see results section Figures 42-44) and reveal two types of spatial data derived from an assessment of the autocorrelation statistic for each spatial unit (in our case municipal blocks) and the relationship of that block's autocorrelation value with the autocorrelation value for its neighbours. The types of spatial data derived in this way are thus: (a) the significant spatial clusters high-high autocorrelation (red), low–low autocorrelation (Blue)) denoted by positive autocorrelation; and (b) the spatial outliers (high-low (light red), low-high (light blue)), the individual locations that are spatially different from their neighbours (not to be confused with an interpretation of outliers in the usual sense as the tail in a distribution curve). All the above mentioned colours will be shown on the LISA analysis produced map below.

To test the significance of the local indicators in this step five scenarios are expected to appear (Anselin, 1995; Oliveau and Guilmoto, 2005):

- High-high. Also known as hot spots. Locations with high values with similar neighbours
- Low-low. Also known as cold spots. Locations with low values with similar neighbours
- High-low. Potential spatial outliers. Locations with high values with low-value neighbours
- Low-high. Potential spatial outliers. Locations with low values with high-value neighbours
- Locations with no significant local autocorrelation

Finally, an interpretation of the possible causes for any observed clustering is undertaken, considering actual life processes in these locations.

6.3 Data

The availability of good quality data is an important component in these kinds of studies. Since Oman became independent in 1970 three main population censuses have been conducted, in 1993, 2003 and 2010. The templates used in each of these censuses were different, with more variables being added over time to produce a richer and more comprehensive census. In the previous chapter, our analysis was conducted on a data set from the 2010 census, the last and best year to address SV as: a) it has the best choice of variables that can be used to represent social vulnerability, b) it produced the most recent data that is needed to understand current SV. These data sets were obtained from the National Center for Statistics and Information (NCSI, 2013). More details of data acquisition were provided in chapter four.

The statistical analysis of the same 24 social variables is first rerun for the 1993 and 2003 data sets to obtain the SVI, along with the 2010 SVI. This enables analysis of the temporal changes in each SVI across the study area through the clustering classification process described above.

The geographical entities represent municipal blocks, the smallest administration boundary in the metropolitan cities of Oman. In small cities they are called Hilla (Arabic name for settlement) (NCSI, 2013). The municipal block is the only administration boundary to remain unchanged since the first census. Some of these blocks were unplanned, and hence were unpopulated at the time of the 1993 census; therefore, in such cases, the study assumed zero observations for those blocks with no data collected during the time of the census. This does not affect the outcome of the statistical analysis as it will show in reality the absence of cases of those variables from that dependant social group.

Oman has experienced large demographic changes in recent decades. The population increased by around 93% between 1993 and 2010 table 27. This growth has been strongly driven by immigration of non-Omanis who came to Oman looking for jobs; their population increased more than threefold over the study period.

Table 27 Population changes in Oman across the three censuses, 1993-2010 (NCSI, 2015).

	1993	2003	2010
Omani	1,465,000	1,782,000	2,172,000
Non-Omani	535,000	559,000	1,683,000

Total population	2,000,000	2,341,000	3,855,000

The social characteristics of the study area in Muscat governorate (table 28) have changed significantly because Muscat is an employment hub for various sectors and as the capital this is where most development has occurred. The proportion of non-Omanis (expatriates) increased from 26% to 43% over this period, which has had a significant influence on other variables, such as occupied houses which increased by 20%. The total population has increased by more than 90% since the first census.

This is the situation for the Muscat region in general but when we assess population changes at the city level (table 28) we see that the regional pattern of population change is not uniform across the study area. For example, A'Seeb city was the fastest growing of all cities in the area, followed by Bawsher, whilst in Muscat and Mutrah population declined. A'Seeb and Bawsher are large cities in terms of area and encompass most of the areas of new or planned expansion, whilst Muscat and Mutrah cities are small in area, and old in planning terms, and surrounded by natural barriers that do not allow for expansion, encouraging people to leave for the more spacious new areas. This is an example of heterogeneity in the changing demography of the region.

Table 28 Race, household, and housing unit variables in Muscat governorate 1993–2010 (NCSI, 2015).

Dimensions	Unit	1993	2003	2010
Total population	Omani	223,443	381,612	407,006
	Expatriate (non-Omani)	233,570	250,461	368,872
Total households	Omani households	28,544	53,630	62,299
	Expatriate households	39,329	46,602	58,693
Total housing units	Occupied housing units	67,873	100,653	119,921

Table 29 Differences in total population at city level across the three years.

City	1993	2003	2010

Bawsher	102,839	148,085	18,7871
Muscat	33,179	19,796	20,272
Mutrah	171,866	86,554	150,067
A'Seeb	149,111	220,924	285,016

Figures 35-37 show changes in total population at municipal block level over time. We can see how dense some blocks were in the last census compared to 1993. During the first census some blocks were not yet planned, with zero population, but subsequently have grown significantly. For example, as part of the residence in the study area and obviously part of the population for the variable # *worker* in blocks 301 and 302 we observe a zero count in 1993, but 1632 and 1686 in 2003, and a total worker count of 9328 and 3614 by 2010.

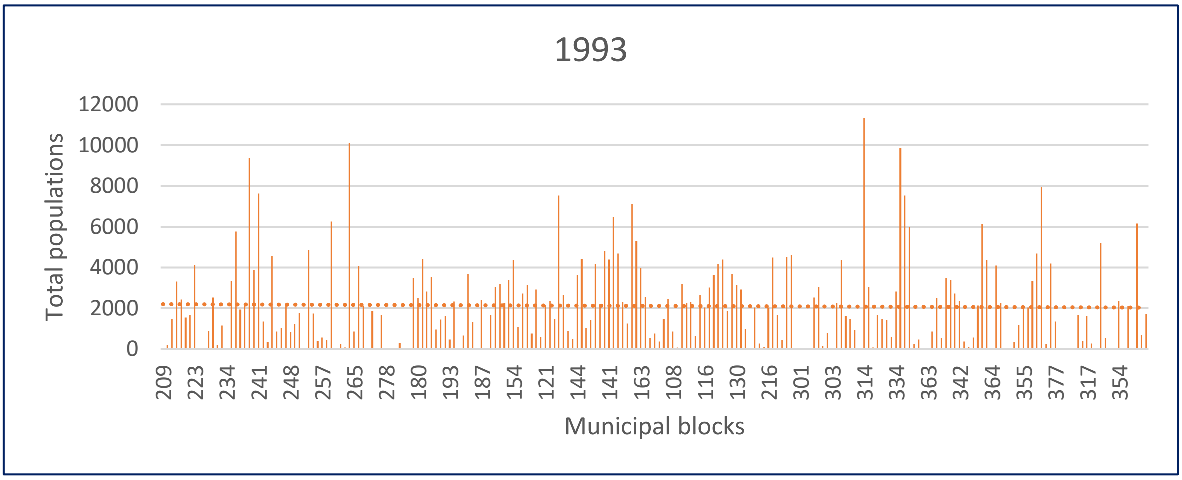

Figure 35. Frequency distribution of population in municipal blocks in the year 1993, average count. (Author, 2018)

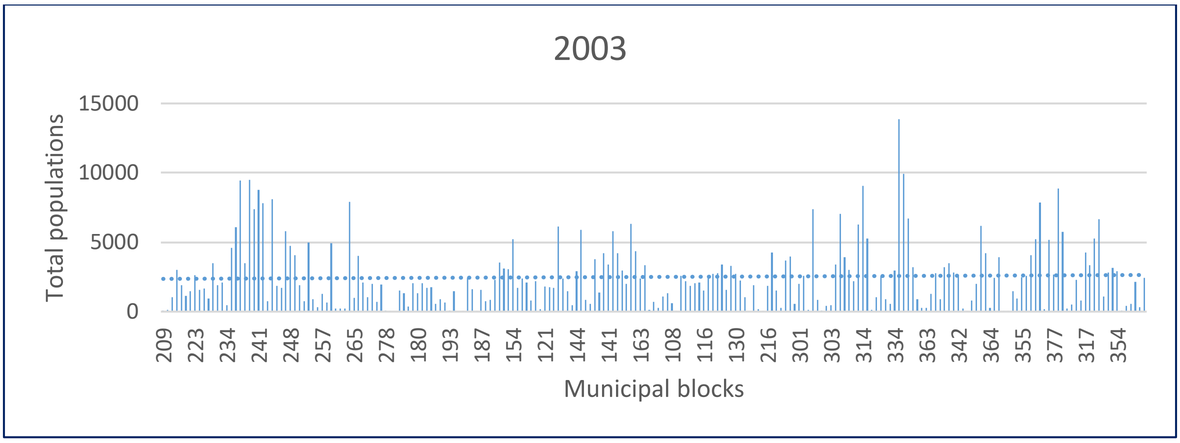

Figure 36. Frequency distribution of population in municipal blocks in 2003. (Author, 2018)

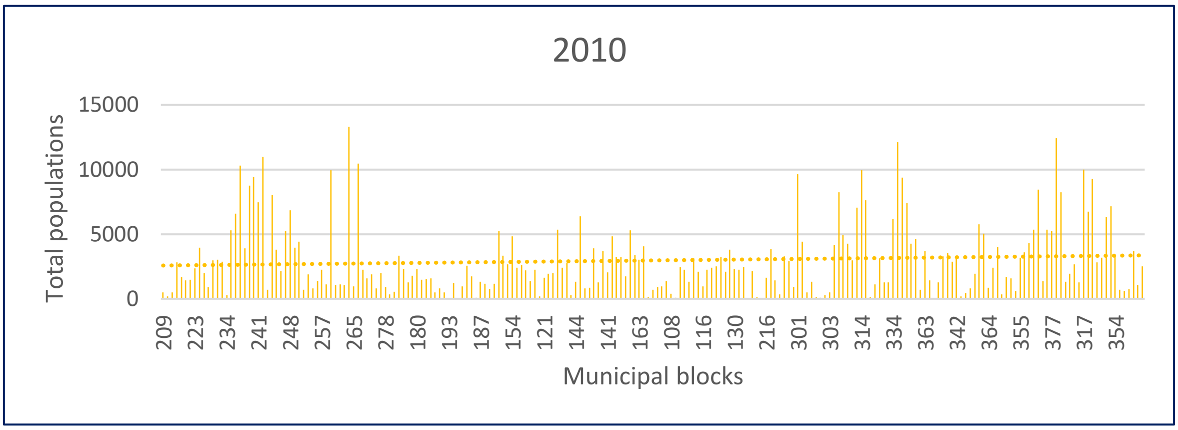

Figure 37. Frequency distribution of population in municipal blocks in 2010. (Author, 2018)

Table 31 shows the main socio-economic status variables and how they vary over time in each coastal city. For example, *# job seekers* increased by 400% in A'Seeb city and by around 330% in Bawsher city, whilst it dropped in both Muscat and Mutrah by more than 100%. Old Arabic houses is a variable of low living standards; across time these houses were mostly abandoned by the local people and taken over by low-wage workers. The number of such houses has dropped in these large cities due to new constructions, with more new developments in Muscat and Mutrah. From the same table it is clear that among the more socially dependent groups the numbers of children and elderly are decreasing dramatically in Muscat and Mutrah, which is due to more people leaving these cities, with increases in A'Seeb and Bawsher because of the new houses and new families moving there.

Table 30 Changes in the main socio-economic characteristics of Muscat Governorate cities, 1993-2010 (NCSI, 2015)

City	Census	# job seekers	Omani worker >15	Omani < 14 yrs.	Omani > 65 yrs.	Total population 2010	Illiterate Omani > 15 yrs.	Old (Arabic) houses	Houses with no water connection
Bawsher	1993	1054	9427	17670	641	102839	3940	6936	117
	2003	3806	19242	22001	1221	148085	3210	1434	54
	2010	3470	23523	22080	1716	187871	2530	908	2064
Muscat	1993	962	5941	10899	691	33197	4405	492	9
	2003	1458	3667	5179	494	19796	1982	2238	3
	2010	1060	4680	4444	530	20272	1290	1477	120
Mutrah	1993	2613	15834	24742	1332	171866	8474	4831	107
	2003	5353	16462	16368	1494	153500	5000	7104	112
	2010	3099	16744	34457	2963	150067	3190	4490	2311
A'Seeb	1993	2735	19425	47748	1751	149111	13844	8822	305
	2003	10554	33589	56477	2884	220924	11871	5307	210
	2010	11448	52550	70531	4697	285016	9385	4956	7341

From the above facts it is clear that major changes in social characteristics are happening mainly due to migration, demographic development of the resident population, and economic development.

6.4 Social variables selection

There are several factors likely to contribute to changing SV in the study area. Among these are: population increase, change in population ethnicity, growth in workers and job seekers, and rise in education level. There is agreement on the common variables that influence SV but no agreement on the selection of appropriate variables because of differences in contexts, problems of data availability, and inconsistencies in questioning techniques. Population is the variable most often viewed as contributing significantly to variation in SV (Cutter and Finch, 2008). The social variables selected in this part of our study are the same as those in chapter five: 24 variables covering the 9 dimensions of gender, employment, unemployment, family structure, population, age, education, housing units, and attitude to risk. Details about the selected variables are given in the literature review chapter (2.6.3.2.1), and chapter five (5.2.1).

6.5 Statistical analysis using principal component analysis

The factor analysis method used here is again PCA, described in chapter five (5.2.3), with the process repeated for 1993, and 2003. Once the SVIs were obtained (see appendix B & C for more details) the spatial analysis was started. The result of the PCA with a comparison of the three censuses is illustrated in table 31. The total variances produced by this analysis for the three years are very close; total variance explained by the data sets ranged from 85.8% to 89.1%; the number of components remained the same for the three years at 3. The three components that arose across the two decades are Omani socio-economic status, non-Omani characteristics, and housing units, whereas in the last decade, a new dimension – low- wage work force – appears. The workforce dimension suggests an increase of this social dimension driven by the increase in non-Omani workers populations in the capital Muscat, the main employment hub for industrial and commercial organisations.

Table 31 Comparison of PCA results for the three census years (Author, 2018)

Census year	1993	2003	2010
% of variance explained	88.7%	85.8%	89.1%
No of factors extracted	3	3	3
The factor explaining most variance	Omani socio-economic status (44.4%)	Omani socio-economics status (40.2%)	Omani socio-economic status (42.6%)
Second factor	Non-Omani characteristics (36.9%)	Non-Omani characteristics (35.3%)	Non-Omani characteristics (28.1%)
Third factor	Housing units (7.4%)	Housing units (10.3%)	Low-wage workforce (12%)

The results for the underlying variables that made up the three main components are almost the same across the three years. This is clear from the extracted rotated components matrix (the by-product of the PCA). For the first indicator, it is clear that strongly loading variables are: female headed family, female 18–64 years, number of widows, total job seekers, Omani workers >15 years, Omani family, Omani <14, Omanis >65, Omani females and number of Omanis and illiterate Omanis > 15 in high schools. These variables are used to label this component in all three decades as *Omani socio-*

economic status has almost the same number of variables loading, 11, 10, 11 respectively for the three years, with higher loading in 2010.

For indicator two, non-Omani characteristics, the number of variables loading are 9, 8 and 7 respectively across the three years. The higher loading variables used to label this component are total number of workers, non-Omani family, family size < 5, non-Omanis, non-Omani females, and non-Omani >15 yrs. > high school. These are characteristics of the *Non-Omanis*, with these variables found in all three decades to be the driving variables in this component.

The third indicator in the 1993 and 2003 comparison is *Housing unit characteristics*. This was loaded with two main variables in each decade: rural houses and housing with no water connection in 1993, and rural houses and old Arabic houses in 2003. In 2010, the third component is a new dimension labelled *low wages workforce*. This was given a medium to strong loading for 6 variables: total number of workers, population 18–35 years, non-Omanis, non-Omanis > 15yrs. > high school. The appearance of this indicator in the latter period is explained by more migration to the area by both Omani and non-Omani labour in the last two decades, especially in the low wages category where workers are more vulnerable. The development of newer industrial and commercial areas along with the expansion of existing economic areas is obvious and led to the increase of this social group.

Finally, the results of the PCA for the 2010 census data (Chapter 5) are presented as factor scores for each component against each municipal block. The calculation of the SV index (SVI) for 1993 and 2003 was similarly carried out using the same formula:

$$\text{SVI} = \sum \left(\frac{\%\ \text{variance} * Factor1}{\text{Total Variance}}\right) + \left(\frac{\%\ \text{variance} * Factor2}{\text{Total Variance}}\right) + \left(\frac{\%\ \text{variance} * Factor3}{\text{Total Variance}}\right) \quad \text{Eq. 6.2}$$

The SVI for all three years was calculated (using the 3 indicators for each census year, 1993, 2003, and 2010, see Appendix 1, and using the same component variables where applicable). The SVI was then mapped using GIS for all 217 municipal blocks, to reveal how SV has changed over two decades in the Muscat governorate.

6.6 Results

6.6.1 Mapping social vulnerability

In the last section the SVI and factor scores for the three data sets were produced using a common process, with year specific data giving rise to different SVI models (e.g. number of indicators). Using these models, the SVIs by year and municipal block were calculated are presented as GIS maps below.

Figure 38 shows the spatial distribution of the SVI for 1993. The index is classified in five classes to aid interpretation and analysis. Here, we consider that high vulnerability areas are those with > 1.5 Standard Deviation from mean SV. On the map, it can be seen that there are three main areas of very high vulnerability. One is in Bawsher city, block 239. The other two are to the west in A'Seeb city, blocks 333 and 314. The areas of high vulnerability tend to be in the centre of the oldest areas in each city, whilst the very low vulnerability areas are mainly away from the coast. This is because at the time the population in some of these blocks was very low, others had no population at all, and others were very low in other social characteristics (see population table in appendix). The moderately vulnerable blocks were scattered but, for the most part, they surrounded the high vulnerability blocks.

Figure 39 shows the spatial distribution of SVI in 2003, revealing a clustering of higher vulnerability areas still exists in the oldest occupied municipal blocks at the centre of the three cities: A'Seeb (blocks 312, 314, 325 and 333), Bawsher (blocks 236, 237, 239, 240-242 and 244); and Mutrah (city block 159). The lowest vulnerability area in this year includes most of the blocks away from the coastal areas in the south and south east and some blocks on the north eastern coast. The higher vulnerability municipal blocks show an increase in vulnerability over the previous decade.

Figure 40 shows the spatial distribution of the SVI in 2010, revealing that the high vulnerability areas are still the oldest planned areas of A'Seeb, Bawsher and Mutrah with an increase in the number of blocks in A'Seeb and Bawsher cities. Blocks 279 and 281 in A'Seeb city, and 119 in Muscat city, are new high vulnerability areas. The low vulnerability areas are shrinking slightly but they are still concentrated away from the coastal areas towards the south and south west.

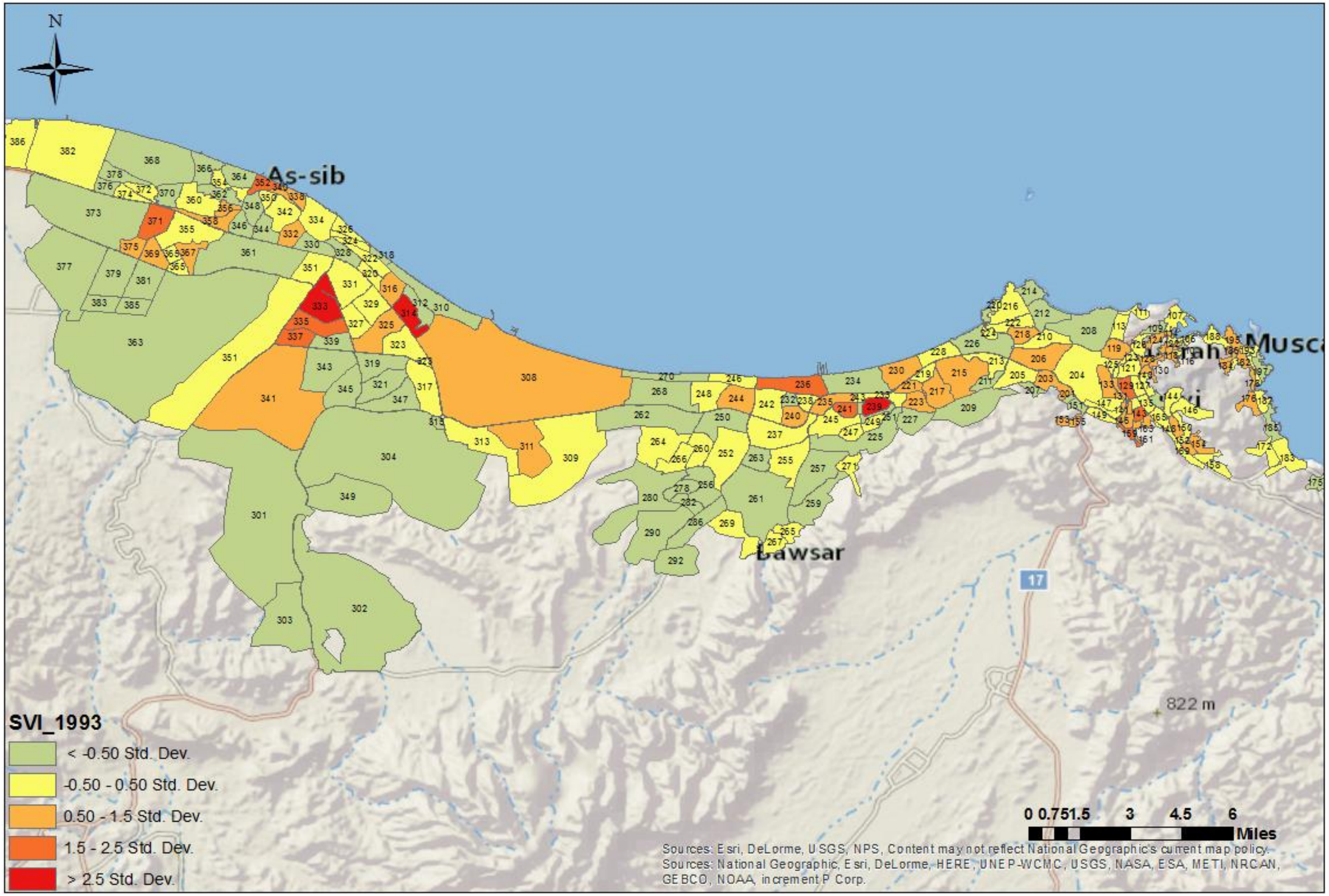

Figure 38. The spatial distribution of the SVI in 1993. (Author, 2018) (Green (< -0.50 Std) is low vulnerability, red (> 2.5 Std) is high vulnerability).

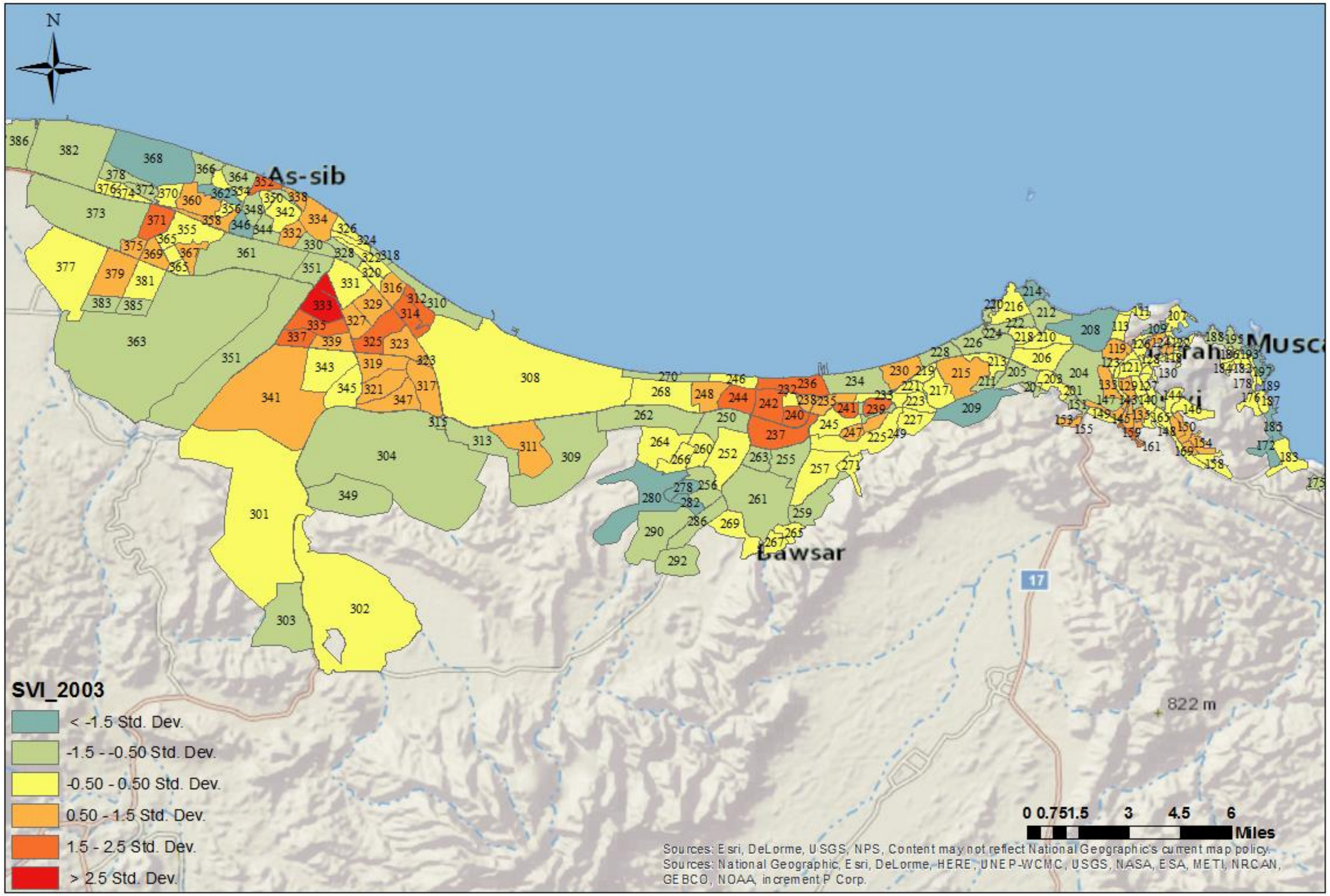

Figure 39. The spatial distribution of the SVI in 2003. (Author, 2018) (Green (< -0.50 Std) is low vulnerability, red (> 2.5 Std) is high vulnerability).

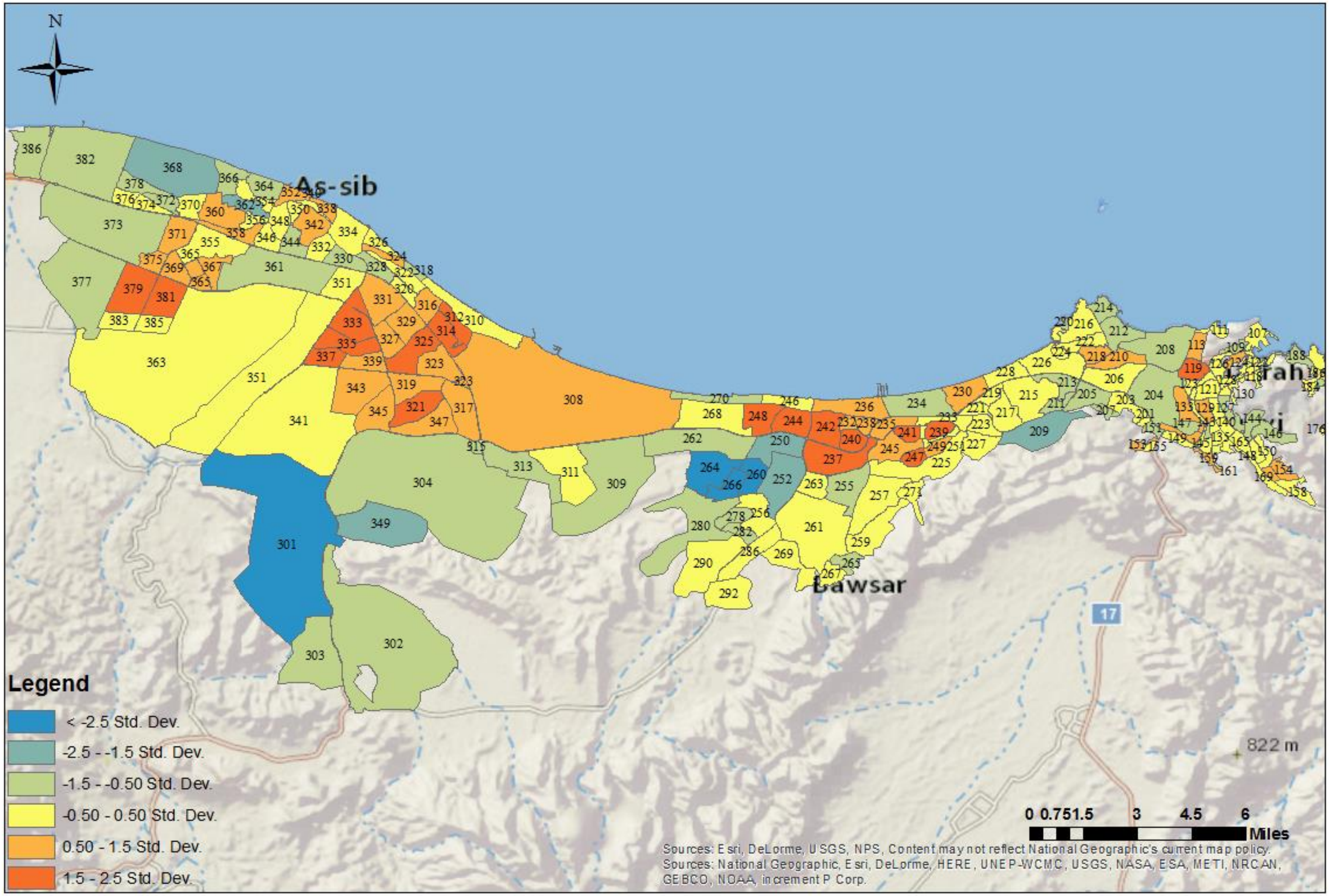

Figure 40. The spatial distribution of the SVI in 2010 (Author, 2018) (Green (< -0.50 Std) is low vulnerability, red (> 2.5 Std) is high vulnerability).

In general, it is clear that there are changes in the spatial distribution of SV over time. The areas of high and very high vulnerabilities are increasing and the level of vulnerability for many other blocks is moving from low to moderate and even to high vulnerability. As an example, blocks number 327, 329 and 331 have moved from moderate to high vulnerability in two decades. Considering just block 327 we see (comparison data in table 32) that many of the driving variables of SV increased dramatically, including female 18-64 yrs., Omani < 14 yrs., Omani > 64, whilst total population grew substantially (from 1592 to 4937). On the other hand, the number of low vulnerability blocks is declining as some of these areas have changed from low or moderate to high vulnerability. Some areas are new to high vulnerability in 2010. For example, blocks 379, 381 were in the extreme low vulnerability category in 1993 and they are now areas of extreme high vulnerability.

Table 32 Municipal block number 327 and the changes in social characteristics during three censuses. (Author, 2018)

Municipal block 327	Fem. 18 - 64 yrs.	Female headed families	#widows	Omani < 14 yrs.	Omani > 65 yrs.	# population	#non-Omanis	non-Omani female	non-Omani.> 15 ≥ high school	Houses with no water connection	N# pop. 18-35 yrs.
1993	356	10	12	487	21	1592	400	125	40	49	673
2003	1108	81	46	1265	46	3909	759	404	200	4	1540
2010	1699	104	67	1356	71	4937	1153	625	399	130	2103

From the above it is clear that the factor scores produced above are good but are not necessarily simple enough for the decision makers to understand, interpret and then make decisions, especially those who lack knowledge of analysing statistical data. This is where spatial representation comes into play to make it easier, by reflecting the factor scores for each geographical unit to visualise any geographical patterns that exist. The scores for each component were produced independently and collectively to make up the SVI for each data set and to produce a map of each data set. In this study the standard deviation classification was used because the target here is on the extremes of the SVI values. Thus, exploratory spatial data analysis was carried out to explore the variation in patterns of SV in Muscat governorate based on the developed SVI for each municipal block. In addition, the SV trends over the past three censuses years were assessed.

It is also important to improve the understanding of the clustering of similar and dissimilar areas by carrying out classification according to the type of associations using Local Indicators of Spatial Association LISA statistics.

6.7 Moran's I

Moran's I is used to examine whether the SVI index maps produce a spatial pattern among municipal blocks and to identify the patterns of similarity and dissimilarity in the clustering by classifying the pattern using Local Indicators of Cluster Association (LISA) analysis. These tools exist in ArcGIS as spatial statistics tools and are used in two steps. The first step was to use the global Moran's I statistics to find out whether clustering exists. If, as a result of this step, the Moran's I index is close to +1 or -1 then it represents a strong positive or negative spatial autocorrelation. In other words, there is high or low vulnerability, so clustering exists.

The second step was to classify the clustering, according to type of association, into four different types of spatial clusters: high-high (HH) blocks with higher SVI values surrounded by other blocks with higher values, low-low (LL) municipal blocks with low values surrounded by blocks with lower values, high-low (HL) blocks with higher values surrounded by blocks with lower values, and finally the low-high (LH) blocks with lower values surrounded by blocks with higher values. This was also carried out in GIS software using a spatial mapping tool that uses Moran's I.

6.7.1 Global Moran's I

To explore the type of spatial clustering (clustered, dispersed, random), we applied the global Moran's I statistics for SVI to each census year. Table 33 shows the progression of this index over two decades in the three data sets: 1993-2003-2010. For these years Moran's I were positive with indices 0.221, 0.317 and 0.481, and Z- scores 5.8, 4.08, and 8.78 respectively, with values above the significantly clustered threshold value of 2.54. This indicates that there is a strong spatial autocorrelation in the SVI in the study area. This test leads us to further investigate the spatial pattern using the local Moran's I.

6.7.2 Local indicators spatial association LISA (Local Moran's I)

The local indicators spatial statistics was performed using the assigned tool in GIS; the result of this analytical process is summarised in table 33, and the following maps. The number of municipal blocks in each classification and the trend of each classification throughout the three decades show an increase in the HH blocks and decrease in LL blocks.

Table 33 Moran's I and spatial clustering result for the three census years. Author, (2018)

Census year	1993		2003		2010	
Global Moran's I	0.221		0.317		0.481	
LISA cluster categories	Count	% of the total	Count	% of the total	Count	% of the total
High-High	5	2.2	12	6	20	10
Low-Low	17	8.1	15	7	14	6
Low-High	4	2	1	0.004	0	0
High-low	1	0.004	2	1	1	0.004
Non-significant	190	87.6	187	86	182	84

In table 33 the number of high-high municipal blocks increased from1993 to 2010, from 5 to 20 blocks, as can be seen in the clustering map below. The incidence of low-low decreased from 17 to 14 blocks, and the low-high blocks also decreased across the three years. The spatial cluster analysis maps using LISA are shown below (Figures 41-43).

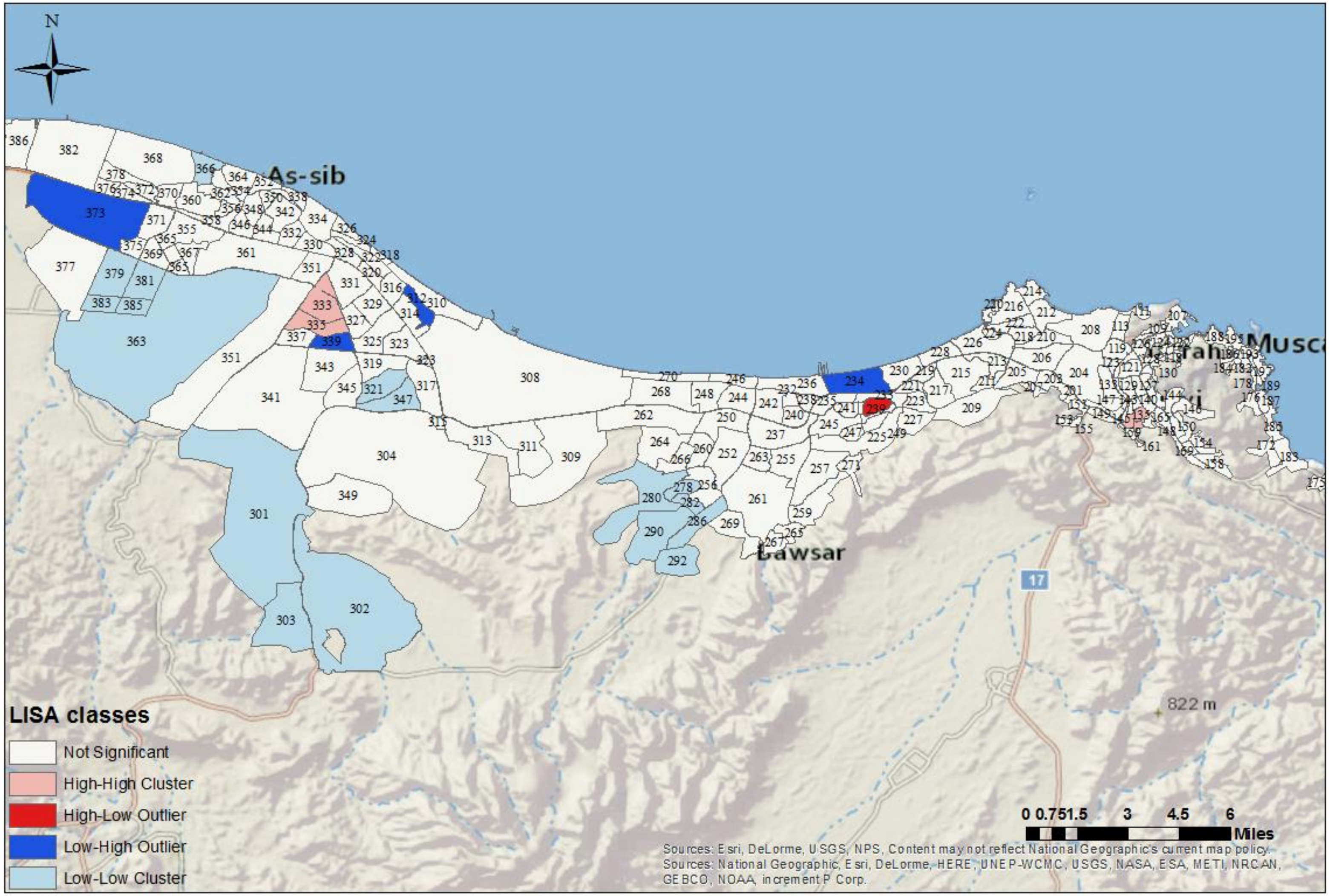

Figure 41. LISA cluster map for SV in 1993. (Author, 2018) (light blue (low-low) is low vulnerability, pink (high-high) is high vulnerability).

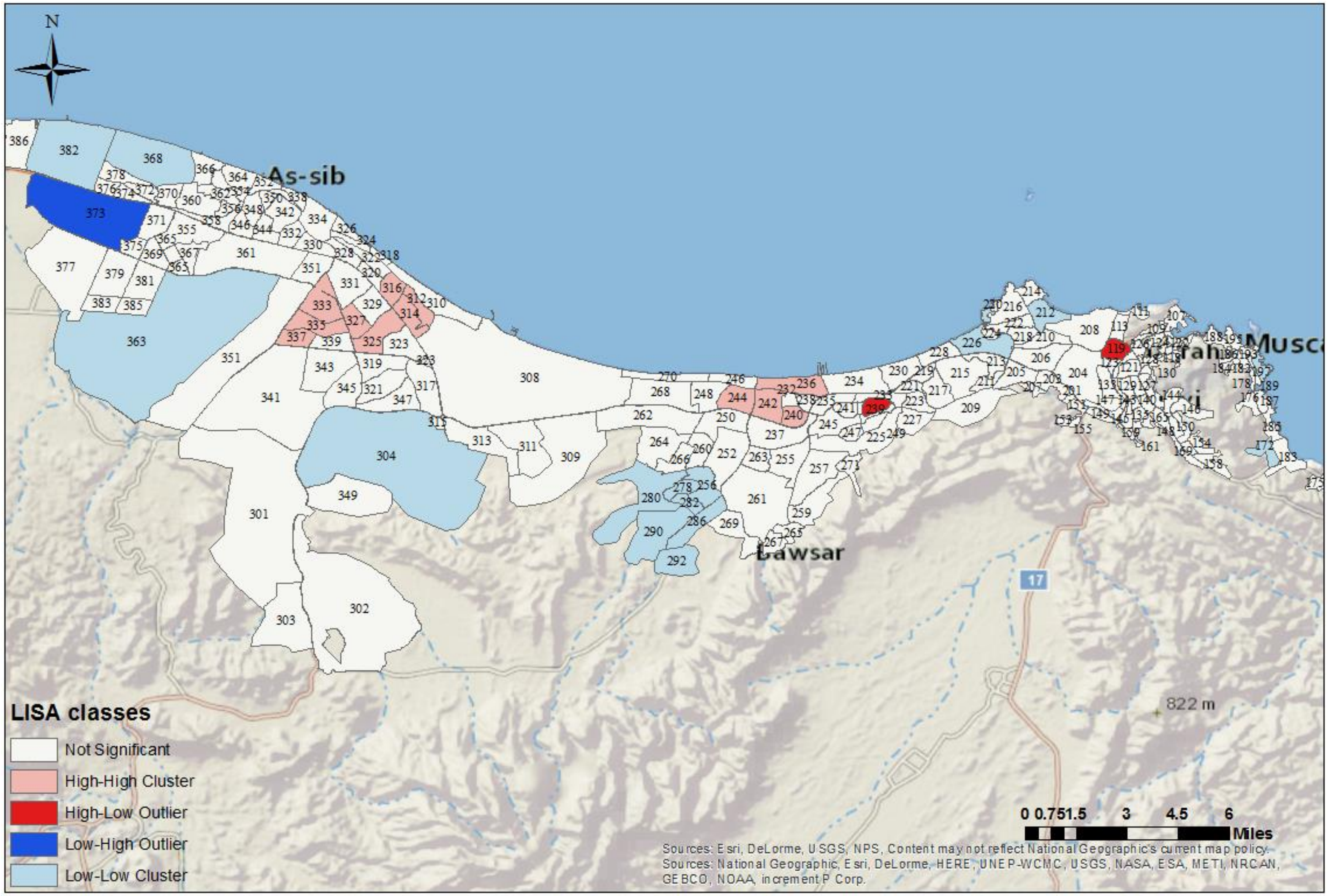

Figure 42. LISA cluster map for SV in 2003. (Author, 2018) (light blue (low-low) is low vulnerability, pink (high-high) is high vulnerability).

In figure 41 the municipal blocks with significantly higher values in 1993 were in two blocks of A'Seeb city (blocks 333 and 335 in Al khodh village, and in Mutrah city blocks 143 and 145). The low-low cluster classes were concentrated in the south and south west of the region, mainly in A'Seeb city (blocks 301-303, 363, 379, 381, 383 and 385) and in Bawsher city (blocks 278, 280, 282, 286, 290 and 292). A few outliers of the HL and the LH are clearly seen on the map, denoted by red and blue colours.

In figure 42 (2003) the high vulnerability areas in A'Seeb city expanded slightly, adding a few more blocks (312, 314, 316, 325, 327 and 337) which are in Al Hail south and Al Hail north. In the case of 312 it was not populated at all at the time of the previous census, whereas the other blocks in A'Seeb exhibit growth from smaller populations. In all but block 314 the Omani population decreased as a result of conversion of most of the buildings to commercial use (table 34).

Table 34 Social characteristics comparison in selected blocks across 1993 and 2003 censuses. (Author, 2018)

Municipal block	# worker	Omani worker >15	Omani. Family	Family size 5 or less	Omani < 14 yrs.	Omani > 65 yrs.	# population	#Omanis	#non-omanis
312 (1993)	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
312 (2003)	2192	1312	777	440	1873	116	6265	5016	1249
314 (1993)	4603	1981	1103	1692	3812	145	11329	8046	3283
314 (2003)	4221	1502	868	891	2027	123	9084	5664	3420
316 (1993)	1250	331	214	399	981	38	3028	1896	1132
316 (2003)	2222	842	501	484	1343	66	5281	3470	1811
325 (1993)	1731	734	409	652	1435	56	4344	3076	1268
325 (2003)	2661	1405	799	366	1979	100	7049	5487	1562
327 (1993)	645	273	159	246	487	21	1592	1192	400
327 (2003)	1440	809	479	218	1265	46	3909	3150	759

Another new high vulnerability area appeared in Bawsher city along the coastal blocks 236, 240, 242 and 244 as part of Al Azeebah village. In this decade, the low-low cluster class appears in A'Seeb city in four scattered blocks (304, 363, 368 and 382), and two in the south of the city, and in the other two areas along the coast these blocks are characterised by low population and absence of some of the variables. The other areas where this class is shown are in a series of blocks (256, 278, 280, 282, 286, 290 and 292) in Bawsher city, particularly Al Ansab village, new areas in Mutrah city, and in Muscat city blocks 212, 226 and 172 or Al Qurum village, the most expensive and elite area in the city.

In the final map, for 2010 (figure 43), A'Seeb area has expanded and includes five new high vulnerability blocks (317, 319, 321, 345 and 347). In the same area, block 316 moved out of this class due to decreases in some of the Omani social characteristics (table 35).

Table 35 Changes in Omanis social characteristics in block 316 across three censuses. (Author, 2018)

Census year	#widows	# total job seekers	Non-Omani job seekers	#Omani female	#Omanis	Illiterate Omani > 15 yrs.
1993	24	43	7	941	1896	303
2003	87	235	26	1652	3470	303
2010	70	177	6	167	376	231

There is also one further block in this area (block 381), in the industrial area of the city. In the same decade, in the Bawsher area two more blocks have been added to those that were there in the previous decade, block 232 and the isolated block 247. The low-low cluster area shown in this decade is in three main areas, two in A'Seeb city (blocks 301-303, 349 368 and 382), and one area in Bawsher city (blocks 250, 252, 260, 262, 266 and 280).

Figures 41-43 reveal that the number of HH or high vulnerability blocks increased from 5 blocks in 1993 to 12 in 2003, and 20 in 2010. In contrast, the number of low vulnerability areas has been shrinking. The relationships revealed show significant geographic spatial clustering and not just random distribution patterns. These changes in the location of the clusters across the three censuses are attributed to the specific social characteristics in various blocks, and how driving forces of demographic development, migration, urbanisation, and economic development have caused these block level characteristics to change over time.

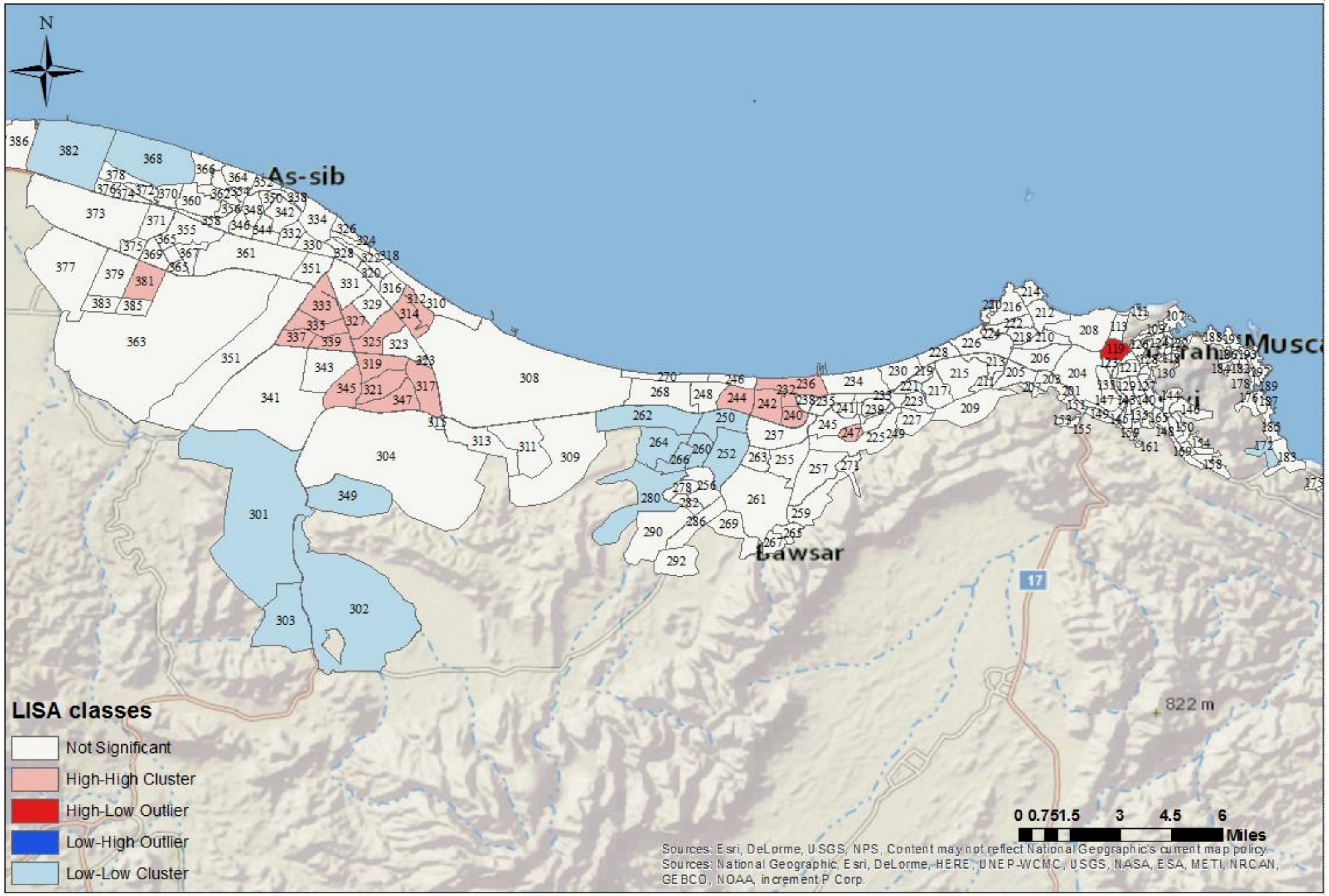

Figure 43. LISA cluster map for SV using 2010 census data. (Author, 2018) (light blue (low-low) is low vulnerability, pink (high-high) is high vulnerability).

6.8 Discussion

In this chapter three important outputs were produced; the SVI for each of three census years over two decades, SVI spatial distribution maps, and the Moran's I and clustering classification maps. It is important to show the spatial distribution of the various levels of vulnerability across the study area in the three SVI maps (Figures 41, 42 and 43). These maps support the view that SV in this metropolitan region of Oman is dynamic. This becomes evident as more blocks become higher in vulnerability from one census year to the next. This can be seen clearly in table 36 as the number of blocks falling under high to very high vulnerability increased by either expansion surrounding the old areas or formation of new areas or pockets of high vulnerability. Most of the high vulnerability areas are around the oldest inhabited municipal blocks of the cities and the industrial areas where there is a lack of modern planning, where population is high, and where low-quality dwellings are common, especially when occupied by low wage non-Omani workers. This is because the increase in population occurred mainly over the last two decades.

There is no shift in location of high vulnerability but there is expansion of the highly vulnerable areas. A shift did happen in the areas of low vulnerability, from the centre and to the south and south west. Looking at the SVI spatial maps and LISA cluster maps for each decade, we can see that there is agreement on some blocks in the high and low vulnerability levels. In 1993, only three blocks in the whole region were highlighted by both methods as highly vulnerable blocks (143, 333 and 335). In the 2003 census, this rose to ten blocks (312, 314, 325, 333, 335, 337, 236, 240, 242 and 244), and rose again to 16 blocks in 2010 (312, 314, 319, 321, 327, 345, 347, 333, 335, 337, 339, 381, 236, 340, 242 and 244).

The blocks matching in low-low values are in A'Seeb (301-303, 321, 347, 363, 379, 381, 383, 385) and Bawsher (278, 280, 282, 286, 290, 292), making a total of 16 blocks in 1993. In the next decade A'Seeb (304, 363, 368, 382), Bawsher (256, 278, 282, 286, 280, 290, 292), Mutrah (212, 226) and Muscat (172) made up a total of 14 blocks. In 2010, A'Seeb (302, 301, 303, 349, 368, 382), Bawsher (250, 252, 260, 262, 264, 266, 280) and Muscat (172) also make up a total of 14 municipal blocks. Thus, there is a modest decline in the frequency of low vulnerability blocks over the analysis period.

Table 36 Municipal blocks with extreme SV produced by both SVI and LISA cluster maps 1993-2010 (Author, 2018)

	1993		2003		2013	
	Blocks shown in SVI spatial distribution	Blocks shown with LISA.	Blocks shown in SVI spatial distribution	Blocks shown with LISA.	Blocks shown in SVI spatial distribution	Blocks shown with LISA.
High SV municipal blocks	A'Seeb (314, 333, 335, 337, 352, 371), Bawsher (235, 239, 241), Muscat (129, 143, 169)	A’Seeb (333, 335), Muscat (143, 145)	A’Seeb (312, 314, 325, 333, 335, 337, 371, 352), Bawsher (236, 237, 239, 240, 241, 242, 244), Muscat (159)	A’Seeb (312, 314, 316, 325, 327, 333, 335, 337) Bawsher (236, 240, 242, 244)	A’Seeb (308, 317, 323, 319, 321, 347, 314, 312, 316, 327, 329, 345, 343, 339, 333, 335, 337, 331, 365, 366, 367, 371, 369, 375, 379, 381) Bawsher (236, 237, 239, 240, 241, 242, 244, 235, 238, 248, 230, 215) Muscat (119, 133, 129, 124, 143, 145, 160, 154, 169,)	A’Seeb (312, 314, 325, 327, 317, 319, 321, 345, 347, 333, 335, 337, 339, 381), Bawsher (232, 236, 240, 242, 244, 247)
Low SV municipal blocks	South of A’Seeb city and Al Ansab village at Bawsher	A’Seeb (301, 302, 303, 321, 347, 363, 379, 381, 383, 385), Bawsher (278, 280, 282, 286, 290, 292)	Most of the southern and southwest blocks and north east part of study area	A’Seeb (304, 363, 368, 382) Bawsher (256, 278, 282, 286, 280, 290, 292), Mutrah (212, 226), Muscat (172)	Almost all the south and southwest blocks and north east of the study area.	A’Seeb (302, 301, 303, 349, 368, 382), Bawsher (250, 252, 260, 262, 264, 266, 280) Muscat 172

From the LISA spatial maps, and table 37 summary, we can see the number of blocks reaching a high vulnerability level is expanding, mainly in A'Seeb city where the number increased from only 2 blocks to 12, and in Bawsher where high vulnerability blocks have increased from zero to 4 since 1993. These areas have gone through large changes in the social characteristics of the local inhabitants, with many local citizens moving from the old city centres to new planned developments. These oldest settlements are now occupied by low-wage workers and some homes have been converted to commercial use. This is true of both A'Seeb and Bawsher. Most of the workers in these areas would be low income or non-Omanis. Blocks 237 in Bawsher and 379 and 381 in A'Seeb city are in industrial areas with low-quality single-storey buildings and sheds and are mainly occupied by non-Omanis who were not living there in 1993.

Table 37 The high-high LISA class and affected block numbers 1993-2010 (Author, 2018)

High-High		
1993	2003	2013
A'Seeb city	A'Seeb city	A'Seeb city
	312	312
	314	314
		319
		321
	325	
		327
335	335	335
	337	337
		339
		345
		347
		381
Bawsher city	Bawsher city	Bawsher city
		236
		240
		242
		244

Muscat city	Muscat city	Muscat city
143		

In Bawsher city, the low-low class areas moved slightly north from a less populated area or an area with fewer cases to an area of more new developments, mainly of offices and large enterprises (table 38). In A'Seeb city, there are two areas where the low-low class exists, one is in the far south where the population is lower, and there is a new area with two coastal blocks (386 and 382), surrounded by a green field area where His Majesty's palace is located.

Table 38 The low-low LISA class and blocks falling into this class 1993-2013 (Author, 2018)

Low-Low		
1993	2003	2013
A'Seeb city	A'Seeb city	A'Seeb city
301		301
302		302
303		303
	304	
321		
347		
		349
363	363	
	368	368
379		
381		
	382	382
383		
385		
Bawsher city	Bawsher city	Bawsher city
		250
		252
	256	
		260
		262
		364

		266
278	278	
280	280	280
282	282	
286	286	
290	290	
292	292	
Mutrah city	Mutrah city	Mutrah city
	212	
	226	
Muscat city	Muscat city	Muscat city
	172	172

The findings above suggest that SV in the municipal blocks in Oman is dynamic and that it changes over time and space. These changes were due to mass migration from other cities and villages to the capital region as well as an increase in non-Omani workers in all categories coming for jobs. This accounts for the population increases from decade to decade. The spatial statistics results showed that two blocks (333 and 335) in A'Seeb city remained the most vulnerable, and four blocks (301-303 and 280) were the least vulnerable of all 217 blocks over the three census years.

6.9 Conclusion

This study examined spatial and temporal patterns of SV to natural hazards in Oman over the past two decades, for 217 municipal blocks. The study was based on an underlying socioeconomic and demographic set of 24 variables representing the 9 dimensions that are suggested to influence local vulnerability to natural hazards. The outcome of this study has shown that SV in the Muscat area has increased, with a pattern of high vulnerability concentrated around some of the oldest settlements or occupied municipal blocks in each of the four cities. Two municipal blocks in A'Seeb city are among the most highly vulnerable throughout the three censuses. Areas with high SV have increased noticeably (from 3 to 20 blocks). This is less obvious from the ground observation but is clearly revealed by the SVI map. The increase in population, promoted by the various social and economic drivers in the capital region, has led to increases in key SV metrics (children, elderly, non-Omani workers, females, widows, job seekers, population 18-35, housing units and education level) that have collectively raised the level of area SV from year to year.

7 Discussion

7.1 Background:

Natural hazards are becoming common in many parts of the world, but certain countries are more exposed to specific types of hazards than others. Developing countries are among the worst affected by certain types of disasters due to their slow or poor development processes. Oman is one of these countries; it is badly impacted by tropical cyclones, which are frequent events along the coast exposed to the Indian Ocean. The impact on some countries is more devastating than on others. Such impacts can be seen in death tolls and financial losses and are demonstrated by slower recovery processes. This has been recognised as being due to certain predisposed characteristics existing in such affected systems before disaster strikes.

The consequences of natural disasters cannot be entirely avoided, in most cases, but they can be alleviated through the integration of risk assessment into the sustainable development process. Such action is highly recommended and emphasised by several international organisations as a way of lessening adverse impacts and saving lives. Certain aid organisations request this action in order to be able to release aid and support during and after a disaster.

Risk is a function of the hazard and social sensitivity, and both hazards and vulnerabilities should be known in order to assess risk to natural hazards. Hazards are measured by magnitude and frequency, and the physical exposure of a geographical area. The biophysical component of risk is common in the traditional school of risk, due to the ease of calculating and measuring it. SV, however, is newer to the field of risk assessment, having been introduced only in the last two decades, due to difficulties involved in measuring the social aspects of risk. SV is an important component of risk, although it is often omitted from the risk equation. Recently, many international organisations have begun to emphasise the need for its inclusion in risk assessments, the latest example being the Sendai Framework for Disaster Risk Reduction 2015–2030 (Sendai Framework 2005-2015). Thus, it is very important that SV assessments be integrated into sustainable development plans.

There is still no common definition of, or conceptual framework for, SV in the literature, although there are a limited number of models used by researchers to help quantify social vulnerability. There is no common, fixed SV index that can be used in natural hazard risk assessment because SV is context specific. Several studies have been conducted on SV– the application of social vulnerability, reviews of the term, and analysis of SV outcomes. Many conceptual frameworks and models have been provided concerning social vulnerability, but few can be operationalised and empirically applied (for details see sections 4.2.2 and 4.2.3). The most pioneering is the SoVI model of vulnerability (Cutter, 2003). This model is viewed as one of the best for empirical quantification of social vulnerability. It is a relative quantification, using a metric selected from the social characteristics of the local community through census data.

This model was applied in this study to reveal the nature of SV in four Omani coastal cities that consist of a total of 217 municipal blocks. During this study, an SVI was constructed using 24 variables from the 2010 census data in order to reveal the current SV to natural hazards (Chapter 5). The study was then replicated for two older censuses – 1993 and 2003 – to examine the trend of SoVI over the last two decades. To our knowledge, this is the first study that has explored an index for SV to natural hazards in Oman, as there has been very limited research in the field of natural disasters in general, and SV assessment in particular.

The aim of this research was to identify the risk to the human system from tropical cyclones in the study area, by determining the SV of four coastal cities in Muscat governorate, Oman.

The following two questions were used to address the research aim:

3. How does SV to natural hazards (tropical cyclones) vary spatially across Muscat governorate coastal cities?
4. How has the spatial pattern of SV changed across the last three censuses (1993, 2003 and 2010)?

The findings of the two-main research chapters include:

Chapter 5: A new SoVI was constructed, for Oman for the first time, using principal component statistical methods that included 24 variables from the demographic data of the local people of four coastal cities in the Muscat region. These selected variables were introduced for a new part of the world for which, up to the time of writing this study, no other studies were found that had addressed SVI development. Looking at the variables selected for the study's purposes it is clear there is too much agreement on the main indicators where the common variables are addressed. Population, age, gender, ethnicity, family structure, education, employment, and housing units are selected also in the study, with particular emphasis on gender, family structure and housing units in the area due to their greater influence in countries like Oman. A new variable that emerged and was not considered in the literature is the risk-taking attitude among the population aged 18-35, specifically to denote people who tend to take the decision to cross flash flood channels, thereby putting themselves and their families at risk. This variable reflects what is often a common characteristic in Oman and the surrounding countries.

From the resulting variables the study identified that demographic and socioeconomic characteristics are the leading drivers for SV to tropical cyclones in the country, which clearly coincides with the findings by many other literature studies (e.g. Adger et al., 2004, Rufat et al., 2015, Cutter et al., 2003). In terms of the variables selected for this study, 23 of the 24 are similar to those highlighted in other studies (Cutter et al., 2003, Rygel et al., 2006).

The conducted analysis reduced the 24 variables to three components, which showed significant loading and explained 89.1% of the total variance. These three components are *Omani socioeconomic status*, *non-Omanis,* and *low-wage work force*. The composite SVI is an aggregation of all three components using a weighted summation model, calculated using the equation 5.2 in section 5.2.5:

From this, it can be seen that the last component (*low-wage work force)* has a positive sign, which represents its positive relation to SV (i.e. a higher low-income work force measurement indicates increased vulnerability). The produced SVI represents the value of SV for each municipal block. The spatial distribution map in figure 44 shows very high vulnerability clustering in four areas, two of which are A'Seeb city (2 km from the coast) and Bawsher city (close to the coastal area); these areas contain the highest aggregation of social groups, with high populations, see figure 34 section 5.3.4.

Chapter 6: In this chapter, the objective was to explore the temporal pattern of SV from natural hazards in Oman over the past two decades, using the same methodology and set of variables. Statistical analyses were performed using data sets from the censuses of 1993, 2003 and 2010. These showed that Muscat's SV increased over the two decades, with a pattern of high SV around some of the oldest occupied municipal blocks in each city, due to changes in the social characteristics of the local population. Blocks 333 and 335 in A'Seeb city were the most vulnerable throughout the three decades. The number of blocks with high SV increased from three to 20, due to an increase in population in Muscat, it being the main hub for business and jobs for all Omani and non-Omani migrants.

Spatial clustering classification was applied, using Moran's I, after statistical calculation of the index, and the results produced for the three decades were 0.221, 0.317 and 0.481, in historical sequence. These values indicate the presence of spatial clustering of vulnerability with a positive relation. The clusters were then mapped in order to explore the relations existing between the clusters using LISA, see figures 41, 42 and 43 in section 6.7.2.

The findings of this study have answered the two research questions posed above. The steps employed in Chapter 5 produced an SVI through careful selection of relevant variables using a suitable conceptual framework and social proxies, and running statistical analyses to obtain the SVI; then the SVI was applied for each geographical area to explore the spatial patterns of SV in the study area. The produced index and map have thus answered the first question. The second question was answered in Chapter 6, by adding a time dimension and using the same variables from the two older census data sets and mapping the variation over three censuses.

Looking at the results from both chapters, and comparing these with actual knowledge of the area, it is clear that the areas with very high and high vulnerability levels are the blocks with the most cases of each dependent social group, who have characteristics that hinder their ability to react appropriately during natural disasters. For example, most of the high-values zone was concentrated in the oldest planned, occupied municipal blocks, which include very old houses, low price and overcrowding with low-wage populations (mainly non-Omanis, or low-income Omanis). Many of these blocks used to be occupied by Omani citizens who moved to better planned areas, and who have a good standard of living. Also, since the time of the first census in 1993, the population has continued to increase, and the capital, Muscat, as the main hub for jobs in the country, is still attracting migrants. This explains the increase in areas with high vulnerability across the study area, and the decrease in low-vulnerability areas.

While consistent with the literature work reviewed, these findings are new for Oman and important and informative for emergency planners and decision makers, based on the study's exploration of the actual social structure of a community. In future, having such timely information available could enhance the decision making before, during and after any event, through being able to locate and support socially vulnerable groups of people. SV can be measured relatively and quantified using the right indicators. Such indicators should be selected from local social characteristics, with variables that influence human responses to natural disaster events. Applying the same index to different geographical areas, with different social characteristics, is not recommended, as this will not reflect local vulnerabilities.

The variables selected in this study that were influential in people's vulnerability to natural hazards need to be validated in the future through understanding the ways in which impacts occurred during the last extreme events that hit the country. The finding presented in Chapter 6, that temporal variation can occur in a local SVI, confirms that the SVI is dynamic in Oman, changing with time and space. Social census data thus needs to be updated frequently in order to reflect actual social vulnerabilities, as human characteristics can change. So, in light of the findings outlined here, this study is essentially in agreement with the theory of this field, confirming the suitability of this framework to be applied to different contexts and cultures. The notion that the characteristics of SV are dynamic is also supported.

7.2 What is new in this study?

The new contributions from this study in the field of disaster risk management include: 1) the application of Cutter's (2003) SoVI to a new geographical region; 2) the selection of a suitable set of variables that can be readily used in future assessments, representing the best available variables for assessment of vulnerability to tropical cyclones from census data sets in Oman; 3) the construction of a new SVI for an important metropolitan area in Oman, in a new area and new context, where none previously existed; 4) the collection of further data and variables from two more censuses (1993, 2003); and 5) the addition of a time variable to reveal trends in the spatial distribution of SV in the study area, using three census data sets (1993, 2003, 2010).

7.3 Unexpected findings

In this study, a new dimension was introduced related to the local Omani context – attitude, or human behaviour, which is represented by an age variable. Adults aged 18–35 years have less life experience, and this leads to them taking risks such as crossing flash-flood water channels.

Also, the influence of gender was highlighted. In this part of the world, females are more vulnerable than males, as cultural norms dictate a role as primary care giver in the family, and where life experience are constrained as responsibilities outside the boundaries of the home are carried out by men. This leaves women with reduced awareness and knowledge about how to react during emergencies and disasters, due to their strong cultural isolation, limited interaction with males and public services, and limited job skills. The females in this area are generally immersed in household activities and are isolated from the media in general, and social media in particular. More variables related to this category should be added to future studies, so as to further explore the impact of social isolation of females.

7.4 Weaknesses and limitations

Whilst the study was applied to the most developed part of the country, which has experienced maximum progress in all fields, meaning data was generally good, much of the data was in practice scattered, causing the NCSI of Oman to take much time to collate and supply the required variable data. This is because this is a new field, lacking the appropriate level of attention. Some of the limitations or weaknesses of this study concern the variables and the dimensions obtained; there are likely to be other influential variables that could have been added, from different organisations, were it not for the barrier of confidentiality. These variables are related to the socioeconomic dimension, and socially independent groups, races, and ethnicities.

The study used a data set that produced 24 final variables related to SV, in nine dimensions, with a theoretical justification for their selection. This made the study worthwhile as an exploratory attempt in this field, but the addition of further direct variables concerning socioeconomic status would have been valuable. Such variables were absent due to confidentiality and cultural constraints and, instead, some indirect indicators for this theme were used, such as unemployment, work level, job seeker and education level, and house unit quality. The municipal block level was an effective unit for analysis, but the study would have been more useful for decision makers and emergency managers if the scale had been larger, with more details at household level, for example. However, a block level analysis provides a good foundation for more detailed work to identify and geo-locate the most vulnerable streets and households. Length of observation and number of cases was at a level that allowed for effective analysis and construction of the SVI, but using a greater number of areas and, therefore, observations, would be better for factor analysis purposes, which would make the results stronger.

This study attempted to construct an SVI and to map a local SVI for a new geographical area, with its own specific characteristics and conditions. This involved selecting and analysing the main dimensions and variables that might contribute to social vulnerability. The study revealed vulnerable areas that needed attention, in terms of planning and preventative measures, to alleviate SV to natural hazards. The study also showed clustering of different levels of vulnerability, and a clear separation between areas of low and high vulnerability, which indicated the socially inequality among such areas. This pattern of inequality highlights differences in capacity among various communities.

The conceptual framework used in this study was suitable and efficient in constructing the SVI and, therefore, mapping the spatial distribution of social vulnerability. It was quite flexible in allowing the use of the same variables from a secondary data set rather than a primary data set. The framework also allowed for spatial representations using GIS, which is the most important visualisation tool for decision makers and experts.

The social dimension of risk was crucial, and needed to be addressed carefully, starting with framework selection, and extending to the spatial representation of the index, as it is context specific. There is no one common index that can be applied to several contexts. A SV assessment should be integrated into development planning, and should be communicated very clearly to emergency managers, regardless of their level of qualification. SV assessments need to be updated frequently, as the population characteristics in any geographical region are constantly changing.

8 Conclusion

The impacts of natural disasters are intensifying across the world, including those from tropical cyclones that affect the coastal areas of many countries, devastating lives, places and disrupting sustainable development plans. According to scientific studies in this field, these impacts can be alleviated and even avoided, in many cases, by increasing the resilience of society to these hazards. This can be done by introducing appropriate physical and social measures to the exposed areas and populations. For planners to be able to take the right measures, it is very important to conduct SV assessments that can be integrated into the development plan. Risk from natural hazards has two components – the hazard, representing physical vulnerability, and the human system, representing social vulnerability.

Physical vulnerability is always present in risk assessments due to data being readily available and there being many methods to quantify it, whereas SV is relatively new to the field of risk assessment and is still a new application in many parts of the world. This is due to difficulties in quantifying social vulnerability. Using a scientifically-based SV assessment framework is however important, especially in developing countries, due to limited hazard-resistant skills and resources.

Different communities have different social and structural characteristics; a combination of these characteristics gives rise to a unique geographical profile for each community. Local indicators address demographic variations between areas in space and time. Knowledge of such local indicators is essential for creating a realistic representation of local and national levels of vulnerability. There are several models for the assessment of SV to natural hazards in the literature, the most commonly used in practical applications being the SoVI (Cutter, 2003). For the reasons provided in Chapter 4, Cutter’s (2003) model was adopted herein to assess SV to natural hazards in Oman.

SV assessment is a relative measure that involves the selection of suitable indicators to monitor change in spatial patterns. Choosing the appropriate indicators involves exploring the underlying local social characteristics that influence human responses to natural hazards and using them as variables in each dimension. These variables are used in statistical analysis to reduce their number to fewer, meaningful indicators, which are then aggregated, using an appropriate additive model, to provide a single SVI. The index for each geographical area is then used for the spatial representation of social vulnerability.

In this study, the aim was to examine the SV to natural hazards (tropical cyclones) in Oman, which involved two sub-questions: 1) how does SV to natural hazards (tropical cyclones) vary spatially across Muscat governorate coastal cities? and 2) how has the spatial pattern of SV changed over time, considering the last three censuses (1993, 2003 and 2010)? These questions were answered in Chapters 5 and 6.

In Chapter 5, Cutter's (2003) model was applied to the construction of the first SV index to tropical cyclones, and a set of 24 relevant variables addressing 9 dimensions were selected for statistical analysis in the developed model.

Many of these variables are commonly used to represent SV drivers in natural hazards, with others having been selected because they have been found to influence SV in the past few extreme events in the Omani context. The SV index was calculated for all 217 municipal blocks after standardisation, and the index was imported into GIS for representation of the spatial distribution of the SV pattern figure 34 section 5.3.4.

From Figure 34 it can be seen that the blocks that have the highest SV in the three clusters in the two cities of A'Seeb and Bawsher are in the oldest settlements of the oldest planned areas. Looking at the number of cases of each variable in these municipal blocks, it is clear that they are the most populated blocks, and therefore have the highest number of dependent variables, such as females, children, the elderly, non-Omanis, and people aged 18–35 years. These variables are, thus, the reason for the high level of SV. For more details about the populations of the remaining blocks, see Appendix A.

In Chapter 6, the temporal dimension was added to the current social vulnerability, using the same variables from two older census data sets. The same model was applied to two older censuses in order to calculate the historical SVI and map spatial distribution of SV in the past. These maps provide the spatial distribution of SV across the three-census time-frames along with the latest SVI constructed in Chapter 5. The results were analysed using the LISA spatial analysis clustering test to determine the locations and types of clusters for each census.

The results of this chapter suggested that SV in the study area has increased through time, and that a pattern of high SV appears to be at the centre of the oldest municipal blocks in each city. This was attributed to variations in the social characteristics of the residents. Blocks 333 and 335 (Alkhodh village) in A'Seeb city were the most vulnerable throughout the three-time frames. The number of blocks with high SV increased to 20 in 2010, from three in 1993; this is due to an increase in population and the concomitant increase in social groups such as females, children, the elderly, job-seekers, low income non-Omanis, old houses without water connection and people of 18–35 years of age.

Figure 43 in section 6.7.2 shows the current SV to natural hazards in Oman. Looking at the pattern of SV in this figure, 'high-high' clusters can be found in three main areas, two of them being in A'Seeb city, and the third in al Azeebah village in Bawsher city. From the map, it is clear that the most vulnerable areas are not necessarily those most exposed to the threat from tropical cyclones; Block 381, for example, is around 4 km from the coast. By looking at the characteristics of the people in the data set for Block 381, we can see that the majority of the population is Omani; there is a high number of females aged 18–64 years (2435), widows (115), job-seekers (555), the fourth highest number of Omani families (1014), the third highest child population (2796), and the tenth in population aged >64 years (145). This block also contains the highest number of illiterate Omanis aged >15 years (331) and houses with no water connection (227).

Looking at the remaining blocks, those that show the highest vulnerability share common characteristics, including having the highest populations, females aged 18–64 years, children (except Blocks 240 and 247, which are among the highest 60s), the elderly, widows, and houses with no water connection. It became clear during the data analysis that blocks located in A'Seeb city have dependent variables that always have higher values than those located in Bawsher city. So, in general, Omani socioeconomic characteristics are the main drivers in the SVI, with less influence from non-Omani indicators.

Recommendation for planners:

The study outlines the key social characteristics that drive SV. This result will help authorities to give more attention to these characteristics and work on improving their status and enhancing the SV informed resilience. Moreover, those who manage the reaction and response processes during emergencies will benefit from this result by being able to focus on these blocks, especially the high vulnerability ones in A'Seeb city, where the maps showed blocks with high SVI. Also, in terms of addressing individual indicators, this can be done by focusing on the blocks that contain large numbers of people of low socio-economic status (first indicator), non-Omanis (second indicator) low-wage non-Omanis (third indicator). This can be carried out in more detail by mapping each socially dependent groups (females, children, elderly and low-wage non-Omanis). The intention of this study was to highlight those groups that need to be given more attention during emergencies and disasters.

Recommendation for further research:

This study makes an important knowledge contribution about this region of the world. The study focuses on SV, considered a very significant independent element in risk assessment. At this level the study is on its own informative about the type of drivers and their influence and variation over time. This needs to be put into context in hazard studies and hazard contexts to become informative about the level of risk for each social group in each geographical entity. Hence, it is recommended that this study should be further developed through intersection of hazards with SV in the study area. This would eventually enhance knowledge of the nature of risk in the study area and therefore of the trend of risk across the three censuses. Composite hazards maps should include all threats originating from tropical cyclones (wind, floods, storm surge), and such maps should be dynamic and consider the structural measures introduced throughout the two decades of the study.

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10 Appendix A. Principal Component Analysis (PCA) output for 2010 census data analysis.

Table 39 Correlation matrix 2010 census data set.

	Fem.18 - 64 yrs	Female headed families	Number of widows	No. of job seekers pop.	Non-omani job seekers	Total number of worker	Working omani >15	Omani. Family	Expat. Family	Family size 5 or less	Omani < 14 yrs	Omani > 65 yrs	Total population	Omani female population	Omani population	Expatriate Population	Expatriate female	Illiterate omani > 15 yrs	Expat.> 15 ≥ high school	occupied houses	Old (Arabic)houses	Rural houses	Houses get water through bowser	N 1 y
Fem.18 - 64 yrs	1																							
Female headed families	0.897	1																						
Number of widows	0.781	0.634	1.000																					
No. of job seekers pop.	0.822	0.680	0.857	1.000																				
Non-omani job seekers	0.303	0.314	0.069	0.222	1.000																			
Total number of worker	0.495	0.436	0.337	0.343	0.223	1.000																		
Working omani >15	0.932	0.790	0.880	0.927	0.187	0.417	1.000																	
Omani. Family	0.935	0.794	0.887	0.902	0.180	0.419	0.992	1.000																
Expat. Family	0.531	0.557	0.092	0.141	0.440	0.451	0.233	0.244	1.000															
Family size 5 or less	0.701	0.700	0.280	0.323	0.444	0.498	0.439	0.453	0.969	1.000														
Omani < 14 yrs	0.887	0.697	0.902	0.870	0.180	0.404	0.932	0.937	0.288	0.469	1.000													
Omani > 65 yrs	0.832	0.737	0.816	0.836	0.165	0.368	0.859	0.844	0.296	0.455	0.868	1.000												
Total population	0.830	0.724	0.650	0.687	0.289	0.887	0.769	0.769	0.534	0.656	0.747	0.690	1.000											
Omani female population	0.900	0.740	0.899	0.938	0.138	0.385	0.990	0.982	0.153	0.358	0.939	0.852	0.738	1.000										
Omani population	0.905	0.752	0.898	0.945	0.148	0.393	0.993	0.986	0.171	0.376	0.937	0.859	0.748	0.997	1.000									
Expatriate Population	0.361	0.351	0.099	0.109	0.286	0.940	0.184	0.191	0.630	0.612	0.206	0.197	0.766	0.135	0.146	1.000								
Expatriate female	0.760	0.757	0.308	0.337	0.440	0.472	0.484	0.501	0.914	0.962	0.500	0.482	0.657	0.407	0.420	0.573	1.000							
Illiterate omani > 15 yrs	0.666	0.552	0.762	0.902	0.083	0.260	0.818	0.775	0.025	0.184	0.763	0.841	0.567	0.842	0.845	0.027	0.163	1.000						
Expat.> 15 ≥ high school	0.449	0.476	0.042	0.083	0.382	0.770	0.183	0.189	0.814	0.794	0.193	0.211	0.686	0.111	0.125	0.901	0.790	-0.037	1.000					
occupied houses	0.906	0.841	0.580	0.619	0.404	0.564	0.735	0.747	0.826	0.927	0.742	0.690	0.819	0.674	0.689	0.554	0.918	0.463	0.675	1.000				
Old (Arabic)houses	0.116	0.138	0.214	0.236	0.067	0.063	0.201	0.174	0.059	0.081	0.221	0.372	0.140	0.199	0.200	0.016	-0.018	0.472	-0.088	0.133	1.000			
Rural houses	0.134	0.127	0.023	0.104	0.067	0.078	0.101	0.095	0.178	0.181	0.104	0.146	0.121	0.095	0.093	0.091	0.152	0.133	0.075	0.170	0.195	1.000		
Houses get water through bowser	0.355	0.229	0.461	0.402	-0.030	0.316	0.426	0.439	0.079	0.155	0.477	0.349	0.407	0.446	0.443	0.178	0.091	0.357	0.033	0.316	0.020	-0.010	1.000	
No. pop. 18-35 yrs	0.672	0.587	0.537	0.574	0.246	0.958	0.633	0.631	0.442	0.537	0.597	0.560	0.966	0.604	0.618	0.839	0.514	0.477	0.685	0.679	0.123	0.091	0.398	

Table 40 KMO and Bartlett's sample adequacy test 2010 census.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.892
Bartlett's Test of Sphericity	Approx. Chi-Square	14106.393
	df	276
	Sig.	0.000

Table 41 Communalities matrix of 2010 census.

Communalities		
	Initial	Extraction
Fem. 18 - 64 yrs.	1.000	0.980
Female headed families	1.000	0.869
#widows	1.000	0.843
# job seekers	1.000	0.923
Non-Omani job seekers	1.000	0.582
# worker	1.000	0.973
Omani worker age >15 yrs.	1.000	0.969
Omani. Family	1.000	0.958
Non-Omani Family	1.000	0.934
Family size 5 or less	1.000	0.947
Omani < 14 yrs.	1.000	0.905
Omani < 65 yrs.	1.000	0.843
Total population 2010	1.000	0.982
#Omani female	1.000	0.975
#Omanis	1.000	0.979
#non-Omanis	1.000	0.984
non-Omani female	1.000	0.966
Illiterate Omani > 15 yrs.	1.000	0.923
Non -Omani. > 15 ≥ high school	1.000	0.961
Occupied houses	1.000	0.963
Old (Arabic) houses	1.000	0.757
Rural houses	1.000	0.645
Houses with no water connection	1.000	.565
N# pop. 18-35 yrs.	1.000	.968

Table 42 Total variance explained by each factor in 2010 data set.

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.784	61.598	61.598	14.784	61.598	61.598	10.223	42.595	42.595
2	4.053	16.888	78.486	4.053	16.888	78.486	6.744	28.100	70.694
3	1.325	5.520	84.006	1.325	5.520	84.006	2.883	12.012	82.706
4	1.231	5.130	89.136	1.231	5.130	89.136	1.543	6.429	89.136
5	0.715	2.980	92.116						
6	0.584	2.434	94.550						
7	0.479	1.996	96.546						
8	0.214	0.891	97.437						
9	0.172	0.715	98.152						
10	0.150	0.627	98.779						
11	0.097	0.405	99.183						
12	0.049	0.204	99.387						
13	0.044	0.182	99.569						
14	0.029	0.120	99.689						
15	0.021	0.087	99.776						
16	0.016	0.067	99.844						
17	0.012	0.052	99.896						
18	0.009	0.036	99.931						
19	0.006	0.026	99.957						
20	0.004	0.017	99.974						
21	0.003	0.014	99.989						
22	0.001	0.004	99.993						
23	0.001	0.004	99.997						
24	0.001	0.003	100.000						

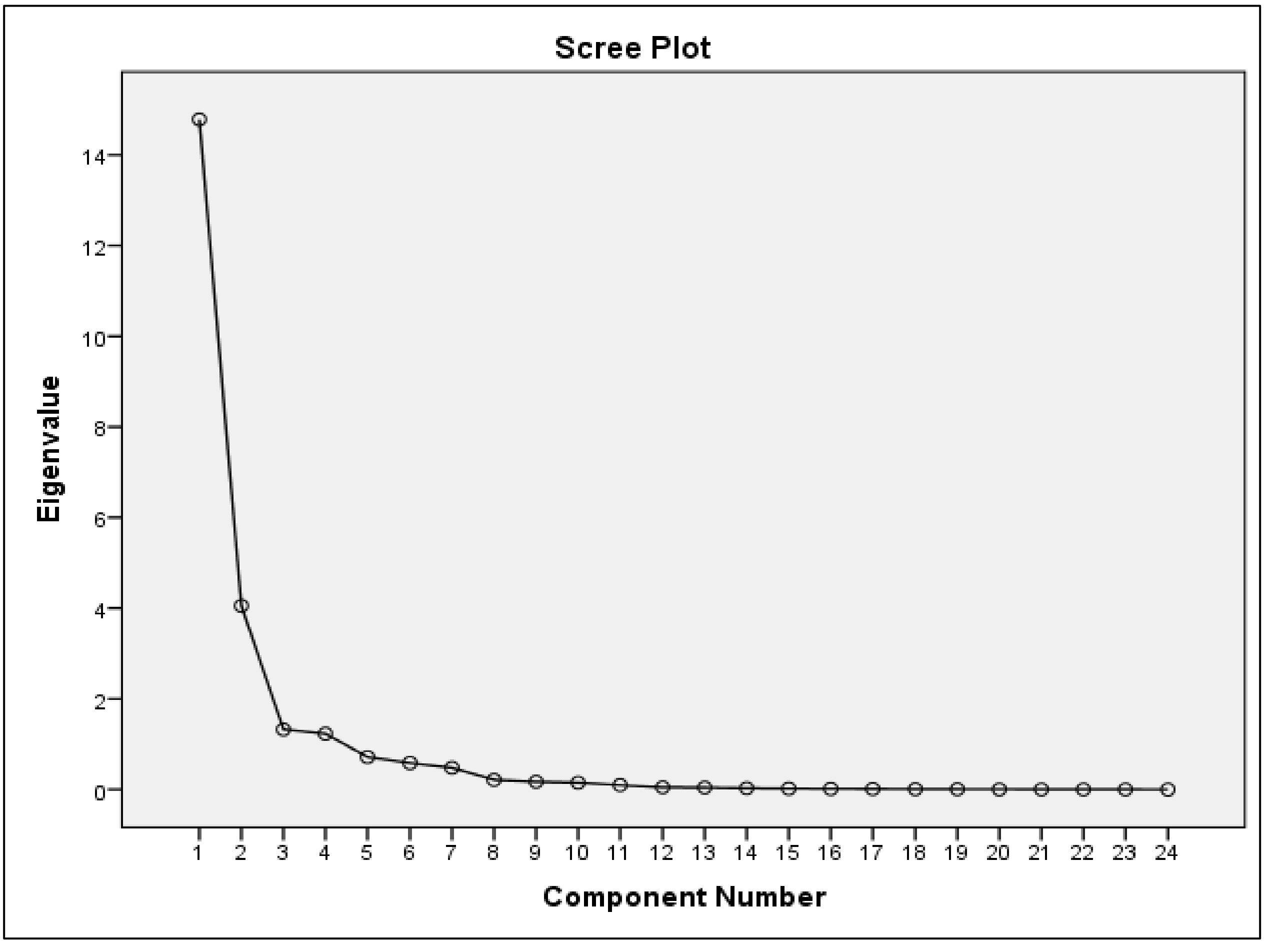

Figure 48. Scree plot graph showing 4 components extracted in 2010 census data.

Table 43 Rotated components matrix showing the loaded variables in each component.

Rotated Component Matrix				
	Component			
	1	2	3	4
# Omani female	0.959			
# Omanis	0.955			
Omani worker >15 yrs.	0.935			
Omani. Family	0.930			
# job seekers	0.921			
# widows	0.889			
Omani < 14 yrs.	0.884			
Illiterate Omani > 15 yrs.	0.876			
Omani > 65 yrs.	0.834			
fem. 18 - 64 yrs.	0.801	0.555		
female headed families	0.717	0.591		
non-Omani family		0.943		
non-Omani female		0.909		
family size 5 or less		0.893		
non-Omani > 15 ≥ high school		0.872	0.444	
occupied houses	0.574	0.756		
#non-Omanis		0.724	0.675	
Non-Omani job seekers		0.713		
# worker		0.525	0.782	
N# pop. 18-35 yrs.	0.468	0.457	0.730	
Total population 2010	0.555	0.528	0.625	
Houses with no water connection	0.515		0.544	
old (Arabic) houses				0.806
Rural houses				0.782
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. [A]				

Table 44 Coefficient matrix data set 2010 census.

	Component			
	1	2	3	4
Fem.18 - 64 yrs.	0.084	0.075	-0.088	-0.081
Female headed families	0.076	0.117	-0.171	-0.043
#widows	0.116	-0.040	-0.014	-0.050
# job seekers	0.110	-0.038	-0.023	0.017
Non-Omani job seekers	-0.009	0.186	-0.184	0.048
# worker	-0.064	-0.048	0.382	0.018
Omani worker >15	0.115	-0.023	-0.024	-0.050
Omani. Family	0.119	-0.012	-0.043	-0.073
Non-Omani Family	-0.059	0.224	-0.119	0.052
Family size 5 or less	-0.019	0.192	-0.115	0.020
Omani < 14 yrs.	0.105	0.002	-0.047	-0.037
Omani > 65 yrs.	0.088	0.016	-0.082	0.071
Total population 2010	-0.006	-0.025	0.248	-0.004
#Omani female	0.125	-0.047	-0.014	-0.053
#Omanis	0.122	-0.044	-0.010	-0.051
#non-Omanis	-0.111	0.048	0.292	0.044
non-Omani female	0.003	0.213	-0.168	-0.073
Illiterate Omani > 15 yrs.	0.088	-0.094	0.041	0.173
Non –Omani > 15 ≥ high school	-0.092	0.147	0.103	-0.029
Occupied houses	0.025	0.128	-0.067	-0.024
Old (Arabic) houses	-0.038	-0.057	0.031	0.576
Rural houses	-0.087	0.038	-0.036	0.584
Houses with no water connection	0.039	-0.166	0.330	-0.085
N# pop. 18-35 yrs.	-0.028	-0.065	0.345	0.019

Table 45 Factor scores and SVI for the 2010 census data.

Municipal blocks	Factor 1	Factor 2	Factor 3	SVI-2013
209	-1.266	-1.081	0.068	-0.955
211	-0.867	-0.711	-1.000	-0.504
213	-0.717	-0.494	-0.855	-0.383
215	-0.038	0.420	-0.315	0.157
217	-0.479	0.700	-0.850	0.106
219	-0.558	0.799	-1.019	0.122
221	-0.554	0.733	-0.916	0.090
223	-0.306	0.833	-0.540	0.189
225	-0.011	0.662	0.786	0.097
227	-0.070	0.198	-0.483	0.094
228	-0.533	0.313	-1.092	-0.009
230	0.233	0.870	-0.688	0.478
232	-0.113	1.365	-0.703	0.471
233	-1.553	2.197	-0.586	0.029
234	-1.049	-0.493	-0.710	-0.561
235	-1.302	3.104	-0.071	0.366
236	0.857	0.967	-0.315	0.757
237	0.898	2.622	0.289	1.217
238	0.285	0.805	-0.162	0.412
239	0.785	3.077	-0.471	1.409
240	0.196	3.398	0.012	1.164
241	0.523	2.362	-0.083	1.006
242	0.846	3.170	-0.327	1.448
243	-0.980	0.311	-0.906	-0.248
244	1.318	1.039	0.496	0.891
245	-0.685	2.411	-0.645	0.520
246	0.344	-0.475	-0.214	0.044
247	0.787	1.557	-0.660	0.956
248	1.105	1.659	-0.290	1.090
249	0.579	1.238	-0.791	0.774
250	-1.715	0.614	1.975	-0.892
251	-0.561	-0.036	-0.952	-0.151
252	-1.278	-0.361	1.187	-0.885
255	-1.048	-0.176	-0.312	-0.514
256	-0.046	-0.731	-0.026	-0.249
257	0.436	-0.639	0.410	-0.048
259	0.022	-0.842	-0.217	-0.226
260	-2.461	-0.053	4.790	-1.838
261	-0.447	-0.168	-0.389	-0.214
262	-1.087	-0.715	0.513	-0.814

263	-0.585	-0.170	-0.305	-0.292
264	-2.310	0.137	6.146	-1.889
265	-0.081	-1.303	-0.011	-0.448
266	-2.459	-0.250	5.081	-1.939
267	0.711	-1.463	0.601	-0.203
268	-0.237	0.280	-0.681	0.067
269	0.600	-1.183	0.049	-0.093
270	-0.633	-0.358	-0.549	-0.341
271	0.700	-1.184	0.372	-0.089
278	-0.424	-0.659	-0.263	-0.375
280	-0.913	-0.852	-0.495	-0.638
282	-0.428	-0.840	-0.609	-0.387
286	0.634	-0.375	0.413	0.129
290	0.203	-0.714	0.299	-0.168
292	0.073	-0.902	-0.104	-0.236
178	0.654	-0.871	-0.661	0.127
180	-0.257	-0.760	0.542	-0.435
182	0.443	-0.651	-0.731	0.105
184	0.530	-0.995	-0.616	0.023
186	0.256	-0.704	-0.236	-0.068
188	-0.501	-0.641	-0.712	-0.346
189	0.129	-1.071	-0.752	-0.175
191	-0.302	-1.235	-0.687	-0.441
193	-0.854	-0.947	-1.129	-0.555
195	0.143	-0.839	-0.526	-0.125
197				0.000
172	-1.556	-1.212	0.918	-1.249
176	0.860	-0.735	-0.269	0.216
183	-0.049	-0.682	0.080	-0.249
185	-1.170	-1.173	-0.635	-0.844
187	0.475	-1.064	-0.621	-0.025
175	0.241	-0.941	-0.623	-0.098
177	-0.238	-0.973	-0.660	-0.332
146	-1.230	-0.270	0.570	-0.750
148	-0.367	1.643	0.637	0.257
150	-0.043	0.914	0.373	0.218
152	0.201	0.687	-0.507	0.381
154	0.910	0.550	0.191	0.582
158	-0.189	0.802	-0.406	0.217
165	-1.194	1.588	-0.071	-0.060
203	-0.059	0.189	-0.198	0.058
205	-0.754	-0.072	0.002	-0.383

206	-0.203	0.654	-0.300	0.149
207	-1.083	-0.757	-0.670	-0.666
121	-0.465	0.917	-0.929	0.192
123	-0.351	0.742	-0.490	0.132
127	-0.887	1.302	-0.309	0.028
129	0.050	1.911	0.442	0.567
131	-0.585	1.188	-0.323	0.138
135	-0.510	1.164	0.017	0.121
142	-1.284	-0.443	-0.721	-0.656
144	-0.710	-0.058	-0.017	-0.356
119	0.273	2.577	-0.263	0.978
125	-0.605	0.057	-0.764	-0.168
204	-1.042	-0.246	-0.230	-0.545
133	-0.089	1.627	-0.305	0.512
137	-1.192	0.734	-0.422	-0.281
139	-0.796	0.640	1.172	-0.337
141	-1.018	0.699	-0.331	-0.221
143	-0.708	1.993	0.340	0.244
145	-0.377	0.683	0.233	0.003
147	-0.101	1.396	-0.569	0.469
149	-0.267	0.525	-0.756	0.140
159	-0.272	1.576	0.096	0.354
161	-0.320	0.771	0.179	0.066
163	-0.933	1.323	-0.095	-0.016
169	-0.500	1.414	0.325	0.163
220	-0.540	-0.738	-1.195	-0.330
224	-0.049	-0.360	-0.917	-0.013
226	-0.679	0.883	-1.506	0.157
106	-0.110	-0.506	-0.789	-0.105
107	-0.209	-0.047	-0.608	-0.033
108	-1.131	-0.139	-0.913	-0.461
109	-1.203	-1.011	-0.775	-0.789
110	-0.612	0.842	-0.525	0.044
111	0.691	-0.915	-0.344	0.088
112	0.157	-0.320	-0.552	0.049
113	0.031	1.162	-0.327	0.425
114	-0.409	-0.040	0.544	-0.281
116	-0.075	-0.346	-1.155	0.011
118	0.117	-0.319	-0.084	-0.033
120	0.045	0.091	-0.452	0.111
122	0.106	0.041	-0.531	0.135
124	1.310	-0.815	-0.450	0.429

126	-0.557	0.731	-0.469	0.028
128	-0.626	1.741	0.320	0.206
130	0.130	0.204	-0.179	0.150
132	-0.372	0.605	-0.131	0.031
140	-1.036	0.205	0.760	-0.533
208	-1.153	-1.267	-1.108	-0.801
210	0.192	0.464	-0.511	0.307
212	-1.113	-0.825	-0.670	-0.702
214	-1.032	-1.179	-1.005	-0.730
216	-0.562	0.507	-0.359	-0.060
218	0.673	0.643	0.150	0.504
222	-0.442	0.458	-0.569	0.010
151	-1.155	-0.109	-0.991	-0.453
153	0.958	-0.447	-0.013	0.319
155	0.515	-0.155	-0.293	0.237
201	-0.262	-0.354	-0.263	-0.201
301	-1.592	-0.833	5.140	-1.716
302	-0.620	-0.436	2.407	-0.758
304	-0.474	-0.830	-0.718	-0.391
311	-0.156	-0.369	-0.244	-0.158
313	-1.029	-1.099	-1.056	-0.696
315	-1.219	-0.903	-0.843	-0.753
349	-1.346	-0.918	-0.210	-0.904
303	-0.392	-1.358	-0.215	-0.587
323	0.695	0.246	0.507	0.341
325	1.945	0.293	0.754	0.920
327	1.535	-0.052	0.303	0.676
329	0.709	0.468	0.188	0.461
331	0.609	0.111	-0.073	0.336
312	1.863	0.371	0.152	0.987
314	1.498	1.188	1.032	0.951
316	1.090	0.819	0.874	0.662
318	-0.855	-1.048	-0.765	-0.636
320	-0.221	-0.409	-0.462	-0.172
322	1.026	-0.854	0.261	0.186
326	-0.007	-0.947	-0.274	-0.265
328	-0.240	-0.619	-0.111	-0.295
334	0.470	-0.496	1.819	-0.177
333	2.560	0.909	1.197	1.349
335	2.903	-0.100	0.433	1.297
337	2.621	-0.529	0.282	1.048
339	1.404	-0.136	-0.028	0.632

351	0.285	-0.427	2.079	-0.279
361	-0.370	-0.941	-0.268	-0.437
363	0.989	-1.174	1.495	-0.099
386	0.025	-1.142	0.130	-0.366
382	-1.153	-1.267	-1.108	-0.801
330	-0.358	-0.732	-0.043	-0.396
332	0.765	-0.317	0.030	0.262
338	0.561	0.178	-0.027	0.328
340	-0.337	0.804	-0.016	0.095
342	0.375	0.363	-0.013	0.295
344	-1.134	-1.139	-0.404	-0.846
346				0.000
348	-0.278	-0.680	-0.617	-0.264
350	0.053	0.021	-0.456	0.094
352	1.421	0.053	0.594	0.616
358	1.225	-0.213	0.357	0.470
364	-0.467	-0.834	-0.044	-0.480
356	0.568	-0.568	-0.067	0.101
360	1.313	-0.485	-0.160	0.496
362	-1.167	-1.211	0.062	-0.948
368	-1.726	-1.205	1.662	-1.429
370	-0.044	-0.649	-0.034	-0.221
309	-0.898	-0.451	-0.482	-0.507
355	0.918	-0.686	0.288	0.184
365	1.485	-1.113	0.477	0.294
367	2.035	-1.402	0.761	0.428
369	2.072	-0.933	0.816	0.586
371	2.470	-0.590	1.266	0.824
373	-0.147	-0.883	0.571	-0.426
375	2.120	-0.893	0.360	0.683
377	-0.654	0.546	2.584	-0.489
379	3.523	-0.412	0.898	1.432
381	2.843	-0.829	0.791	0.991
383	0.237	-0.975	-0.133	-0.177
385	0.645	-1.043	0.068	-0.030
374	0.914	-0.807	-0.253	0.217
376	0.165	-0.995	-0.411	-0.180
317	1.098	0.910	2.015	0.540
319	1.802	0.165	0.719	0.817
321	2.512	0.385	0.493	1.255
341	-0.587	1.269	-0.093	0.132
343	0.907	-0.191	-0.113	0.388

345	1.782	-0.191	0.714	0.695
347	1.289	0.365	1.041	0.591
354	1.241	-1.051	-0.121	0.278
366	-0.166	-1.154	-0.105	-0.429
372	-0.329	-0.922	-0.599	-0.367
378	-0.024	-1.172	-0.582	-0.303
308	0.678	0.402	0.305	0.409
310	-0.233	0.173	-0.903	0.065
324	0.936	-0.645	-0.424	0.301

11 Appendix B Principal Component Analysis (PCA) output data for census data 1993.

Table 46 Correlation matrix using data set from 1993 census.

	Female18_64	Female headed	Widows	Total job seeker	Omani job seeker	Total _WorkerSR	Omaniworker >15	Omani family	non-omani family	Family size less than 5	Omani<14yr	Omani>65	Total population	Omani female	Omanis	Non_omanis	Non_omani female	Illitrate omani>15yr	Non-omani >15> highSch	Ocupied houses	Old_arabic_houses	Rural_houses	Houses with no water connection	Pop. 18-35yres
Female18_64	1.000	0.831	0.855	0.881	0.763	0.834	0.902	0.891	0.802	0.957	0.838	0.806	0.947	0.873	0.881	0.766	0.885	0.770	0.728	0.957	0.770	0.313	0.286	0.899
Female headed	0.831	1.000	0.763	0.777	0.595	0.621	0.799	0.800	0.650	0.811	0.744	0.748	0.753	0.783	0.781	0.549	0.698	0.693	0.546	0.811	0.640	0.239	0.219	0.690
Widows	0.855	0.763	1.000	0.885	0.572	0.633	0.902	0.911	0.540	0.792	0.886	0.884	0.820	0.902	0.916	0.524	0.618	0.880	0.454	0.792	0.685	0.327	0.287	0.737
Total job seeker	0.881	0.777	0.885	1.000	0.660	0.678	0.944	0.946	0.604	0.853	0.919	0.929	0.846	0.934	0.932	0.555	0.647	0.923	0.480	0.853	0.608	0.402	0.340	0.773
Omani job seeker	0.763	0.595	0.572	0.660	1.000	0.741	0.579	0.563	0.852	0.814	0.482	0.485	0.742	0.518	0.527	0.790	0.869	0.424	0.828	0.814	0.520	0.251	0.145	0.740
Total _WorkerSR	0.834	0.621	0.633	0.678	0.741	1.000	0.676	0.635	0.836	0.858	0.567	0.561	0.943	0.591	0.614	0.967	0.856	0.554	0.799	0.858	0.561	0.335	0.287	0.970
Omaniworker >15	0.902	0.799	0.902	0.944	0.579	0.676	1.000	0.990	0.580	0.855	0.961	0.928	0.856	0.968	0.972	0.534	0.646	0.915	0.461	0.855	0.708	0.343	0.330	0.773
Omani family	0.891	0.800	0.911	0.946	0.563	0.635	0.990	1.000	0.552	0.842	0.978	0.941	0.835	0.983	0.982	0.493	0.619	0.927	0.428	0.842	0.715	0.351	0.341	0.742
non-omani family	0.802	0.650	0.540	0.604	0.852	0.836	0.580	0.552	1.000	0.908	0.455	0.475	0.805	0.499	0.514	0.898	0.946	0.402	0.904	0.908	0.531	0.224	0.202	0.819
Family size less than 5	0.957	0.811	0.792	0.853	0.814	0.858	0.855	0.842	0.908	1.000	0.772	0.759	0.938	0.802	0.813	0.823	0.909	0.718	0.785	1.000	0.692	0.303	0.299	0.903
Omani<14yr	0.838	0.744	0.886	0.919	0.482	0.567	0.961	0.978	0.455	0.772	1.000	0.918	0.790	0.990	0.985	0.408	0.524	0.944	0.330	0.772	0.680	0.364	0.370	0.688
Omani>65	0.806	0.748	0.884	0.929	0.485	0.561	0.928	0.941	0.475	0.759	0.918	1.000	0.760	0.933	0.928	0.423	0.518	0.944	0.344	0.758	0.574	0.408	0.351	0.669
Total population	0.947	0.753	0.820	0.846	0.742	0.943	0.856	0.835	0.805	0.938	0.790	0.760	1.000	0.810	0.832	0.870	0.851	0.766	0.737	0.938	0.678	0.358	0.334	0.981
Omani female	0.873	0.783	0.902	0.934	0.518	0.591	0.968	0.983	0.499	0.802	0.990	0.933	0.810	1.000	0.994	0.442	0.568	0.941	0.375	0.802	0.697	0.364	0.357	0.716
Omanis	0.881	0.781	0.916	0.932	0.527	0.614	0.972	0.982	0.514	0.813	0.985	0.928	0.832	0.994	1.000	0.468	0.584	0.945	0.392	0.813	0.705	0.356	0.354	0.745
Non_omanis	0.766	0.549	0.524	0.555	0.790	0.967	0.534	0.493	0.898	0.823	0.408	0.423	0.870	0.442	0.468	1.000	0.898	0.392	0.889	0.823	0.492	0.284	0.218	0.915
Non_omani female	0.885	0.698	0.618	0.647	0.869	0.856	0.646	0.619	0.946	0.909	0.524	0.518	0.851	0.568	0.584	0.898	1.000	0.440	0.930	0.909	0.645	0.201	0.155	0.849
Illitrate omani>15yr	0.770	0.693	0.880	0.923	0.424	0.554	0.915	0.927	0.402	0.718	0.944	0.944	0.766	0.941	0.945	0.392	0.440	1.000	0.266	0.718	0.513	0.436	0.378	0.680
Non-omani >15> highSch	0.728	0.546	0.454	0.480	0.828	0.799	0.461	0.428	0.904	0.785	0.330	0.344	0.737	0.375	0.392	0.889	0.930	0.266	1.000	0.785	0.462	0.170	0.062	0.754
Ocupied houses	0.957	0.811	0.792	0.853	0.814	0.858	0.855	0.842	0.908	1.000	0.772	0.758	0.938	0.802	0.813	0.823	0.909	0.718	0.785	1.000	0.692	0.303	0.299	0.903
Old_arabic_houses	0.770	0.640	0.685	0.608	0.520	0.561	0.708	0.715	0.531	0.692	0.680	0.574	0.678	0.697	0.705	0.492	0.645	0.513	0.462	0.692	1.000	0.130	0.246	0.616
Rural_houses	0.313	0.239	0.327	0.402	0.251	0.335	0.343	0.351	0.224	0.303	0.364	0.408	0.358	0.364	0.356	0.284	0.201	0.436	0.170	0.303	0.130	1.000	0.245	0.352
Houses with no water connection	0.286	0.219	0.287	0.340	0.145	0.287	0.330	0.341	0.202	0.299	0.370	0.351	0.334	0.357	0.354	0.218	0.155	0.378	0.062	0.299	0.246	0.245	1.000	0.321
Pop. 18-35yres	0.899	0.690	0.737	0.773	0.740	0.970	0.773	0.742	0.819	0.903	0.688	0.669	0.981	0.716	0.745	0.915	0.849	0.680	0.754	0.903	0.616	0.352	0.321	1.000

Table 47 Sample adequacy test for data set from 1993 census.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.892
Bartlett's Test of Sphericity	Approx. Chi-Square	17160.658
	df	276
	Sig.	0.000

Table 48 Communalities matrix for data from 1993 census.

Communalities		
	Initial	Extraction
Fem. 18-64	1.000	0.972
Female headed	1.000	0.745
Widows	1.000	0.874
Total job seeker	1.000	0.925
Omani job seeker	1.000	0.778
Total _Workers	1.000	0.904
Omani worker & >15	1.000	0.969
Omani family	1.000	0.984
non- Omani family	1.000	0.926
Family size less than 5	1.000	0.968
Omani&<14yr	1.000	0.971
Omani&>65	1.000	0.917
Total population	1.000	0.954
Omani female	1.000	0.983
Omanis	1.000	0.983
Non_ Omanis	1.000	0.957
Non_ Omani female	1.000	0.965
Illiterate omaniage>15yr	1.000	0.943
Non-Omani age>15age>highSch	1.000	0.914
Occupied houses	1.000	0.968
Old_ Arabic_ houses	1.000	0.620
Rural houses	1.000	0.655
Houses with no water connection	1.000	0.496
Pop. 18-35yres	1.000	0.915
Extraction Method: Principal Component Analysis.		

Table 49 Total variance explained by each factor using 1993 census data set.

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17.065	71.102	71.102	17.065	71.102	71.102	10.649	44.369	44.369
2	3.136	13.067	84.169	3.136	13.067	84.169	8.855	36.895	81.264
3	1.087	4.529	88.698	1.087	4.529	88.698	1.784	7.434	88.698
4	0.803	3.347	92.045						
5	0.477	1.988	94.033						
6	0.446	1.857	95.890						
7	0.288	1.202	97.092						
8	0.175	0.730	97.823						
9	0.140	0.584	98.406						
10	0.105	0.438	98.844						
11	0.084	0.351	99.196						
12	0.047	0.197	99.392						
13	0.043	0.177	99.570						
14	0.037	0.153	99.723						
15	0.019	0.080	99.803						
16	0.018	0.075	99.878						
17	0.012	0.048	99.926						
18	0.007	0.030	99.956						
19	0.004	0.018	99.975						
20	0.003	0.013	99.988						
21	0.001	0.006	99.994						
22	0.001	0.005	99.998						
23	0.000	0.002	100.000						
24	9.164E-08	3.818E-07	100.000						
Extraction Method: Principal Component Analysis.									

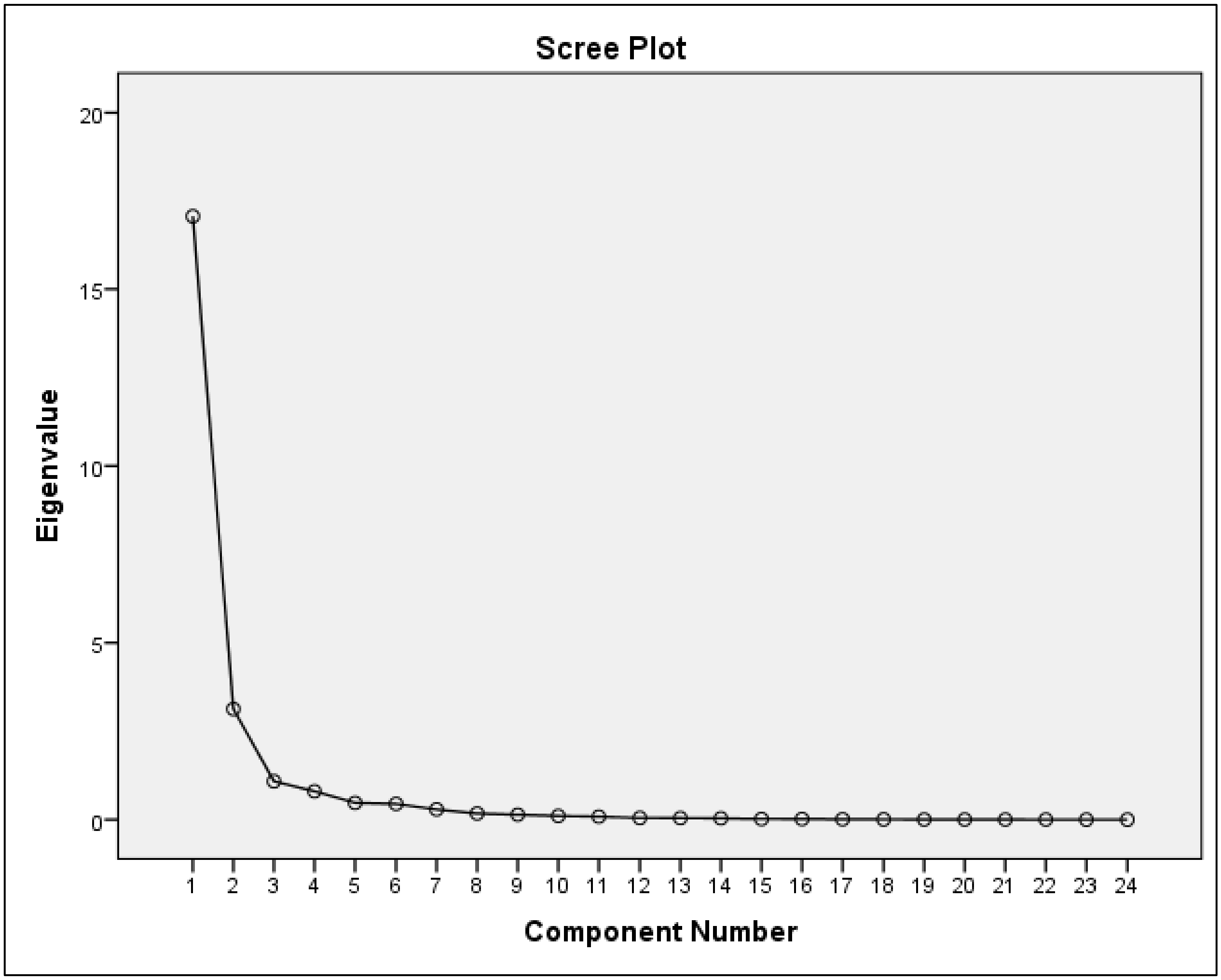

Figure 49. Scree plot showing the three factors extracted using 1993 census data.

Table 50 Rotated component matrix showing all loadings in each factor using data from 1993 census.

Rotated Component Matrix			
	Component		
	1	2	3
Female18_64	0.713	0.674	
Female headed	0.716	0.482	
Widows	0.853	0.357	
Total job seeker	0.842	0.397	
Omani job seeker	0.305	0.826	
Total _Workers	0.342	0.843	
Omani worker age>15	0.898	0.369	
Omani family	0.922	0.327	
non-Omani family		0.925	
Family size less than 5	0.617	0.756	
Omani age<14 yrs.	0.937		
Omani age>65	0.892		
Total population	0.611	0.722	
Omani female	0.936		
Omanis	0.930		
Non_ Omanis		0.941	
Non_ Omani female	0.346	0.919	
Illiterate Omani age>15 yrs.	0.895		0.341
Non-Omani age>15 >high School		0.948	
Occupied houses	0.617	0.757	
Old_ Arabic_ houses	0.645	0.436	
Rural houses			0.776
Houses with no water connection			0.662
Pop. 18-35 yrs.	0.490	0.775	
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. [A]			

Table 51 Component score coefficient matrix used for factor score calculation 1993 census.

Component Score Coefficient Matrix			
	Component		
	1	2	3
Female 18_64	0.052	0.051	-0.070
Female headed	0.098	0.013	-0.162
Widows	0.115	-0.035	-0.056
Total job seeker	0.087	-0.028	0.037
Omani job seeker	-0.046	0.136	-0.042
Total _Workers	-0.084	0.128	0.148
Omani worker age>15	0.118	-0.039	-0.041
Omani family	0.129	-0.051	-0.043
non-Omani family	-0.073	0.162	-0.016
Family size less than 5	0.016	0.080	-0.033
Omani age<14 yrs.	0.137	-0.076	-0.005
Omani age>65	0.116	-0.070	0.048
Total population	-0.004	0.070	0.073
Omani female	0.135	-0.066	-0.024
Omanis	0.131	-0.060	-0.025
Non_ Omanis	-0.122	0.173	0.123
Non_ Omani female	-0.036	0.152	-0.105
Illiterate Omani age>15 yrs.	0.109	-0.087	0.118
Non-Omani >15 yrs.>high School	-0.087	0.186	-0.068
Occupied houses	0.016	0.080	-0.033
Old_ Arabic _houses	0.108	0.015	-0.236
Rural houses	-0.126	-0.016	0.633
Houses with no water connection	-0.086	-0.033	0.527
Pop. 18-35 yrs.	-0.043	0.096	0.120
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Component Scores.			

Table 52 Factor scores and SVI using data set from 1993 census.

Municipal block	Fac1	Fac2	Fac3	SVI-1993
209	-0.835	-0.964	-0.376	-0.850
211	-0.349	-0.504	-0.987	-0.467
213	0.607	-0.603	-0.796	-0.013
215	1.137	0.491	-1.378	0.658
217	0.399	1.133	-1.291	0.563
219	-0.087	1.046	-1.600	0.258
221	0.356	0.664	-1.421	0.336
223	0.289	1.625	-0.687	0.763
225	-0.865	-1.125	-0.416	-0.936
227	-0.865	-1.125	-0.416	-0.936
228	-0.489	0.291	-1.010	-0.208
230	0.649	0.644	-1.351	0.480
232	-1.111	-0.357	-0.081	-0.711
233	-0.491	0.488	-0.824	-0.111
234	-0.973	-1.119	0.667	-0.897
235	-0.250	1.989	-1.115	0.609
236	1.430	0.444	1.628	1.036
237	0.381	0.310	-0.887	0.245
238	0.544	-0.027	-0.389	0.229
239	1.717	2.683	-1.236	1.873
240	0.885	0.665	-0.554	0.673
241	1.799	1.865	-1.218	1.575
242	-0.109	-0.208	1.100	-0.049
243	-0.489	-0.321	-0.773	-0.442
244	0.525	0.057	3.896	0.612
245	0.045	-0.062	-0.927	-0.081
246	-0.920	0.370	-0.051	-0.311
247	0.483	0.286	-1.084	0.270
248	-0.749	0.360	-0.973	-0.306
249	0.026	0.029	-0.888	-0.049
250	-1.351	0.704	0.010	-0.383
251	-0.865	-1.125	-0.416	-0.936
252	-1.237	2.190	-0.310	0.266
255	-1.367	0.369	2.562	-0.317
256	-0.391	-1.127	2.046	-0.494
257	-0.681	-0.631	1.067	-0.515

259	-0.288	-1.005	1.425	-0.443
260	-1.987	1.886	0.668	-0.154
261	-0.949	-0.848	-0.339	-0.856
262	-1.211	-0.369	0.502	-0.718
263	-0.988	-0.843	-0.269	-0.868
264	-1.989	2.538	2.013	0.228
265	-0.109	-0.876	2.137	-0.240
266	-1.298	1.281	0.569	-0.069
267	0.581	-0.769	2.310	0.164
268	-0.865	-1.125	-0.416	-0.936
269	0.495	-0.817	2.472	0.114
270	-0.865	-1.125	-0.416	-0.936
271	1.432	-1.069	-1.057	0.184
278	-0.865	-1.125	-0.416	-0.936
280	-0.865	-1.125	-0.416	-0.936
282	-0.865	-1.125	-0.416	-0.936
286	-0.496	-1.057	1.212	-0.587
290	-0.865	-1.125	-0.416	-0.936
292	-0.865	-1.125	-0.416	-0.936
178	1.910	-0.736	-0.535	0.605
180	0.562	-0.067	0.731	0.314
182	1.638	0.244	0.524	0.965
184	1.532	-0.604	0.112	0.525
186	1.007	0.378	0.662	0.717
188	0.159	-0.261	-0.141	-0.041
189	0.896	-0.851	-0.472	0.055
191	0.554	-0.221	0.430	0.222
193	-0.240	-0.294	-0.703	-0.301
195	1.249	-0.176	-0.519	0.509
197	-0.865	-1.125	-0.416	-0.936
172	0.656	-1.011	-1.333	-0.203
176	1.780	-0.540	-0.073	0.660
183	0.872	-1.076	-0.173	-0.025
185	-0.743	-1.071	-0.281	-0.841
187	1.575	-1.088	-0.495	0.294
175	-0.865	-1.125	-0.416	-0.936
177	1.258	-1.189	-0.579	0.086
146	-1.627	1.708	0.992	-0.021
148	0.065	1.314	-0.434	0.543
150	-0.417	0.842	-0.527	0.098

152	0.527	1.201	-1.134	0.669
154	1.175	0.625	0.248	0.869
158	-0.553	0.333	-0.512	-0.181
165	-1.266	1.788	-0.519	0.067
203	0.954	0.508	-1.089	0.598
205	-0.844	0.282	-0.001	-0.305
206	0.561	0.819	-0.994	0.539
207	-1.132	0.080	-0.323	-0.560
121	-0.296	1.273	-0.973	0.300
123	-0.132	1.112	-0.995	0.313
127	-1.028	1.399	-0.857	-0.004
129	0.430	3.124	-1.475	1.392
131	-0.239	1.399	-0.649	0.408
135	0.358	-0.681	-0.434	-0.140
142	-0.995	0.218	-0.327	-0.435
144	-0.954	1.548	0.452	0.204
119	0.143	1.575	0.435	0.763
125	-0.245	0.192	-0.753	-0.105
204	0.277	0.149	-0.935	0.123
133	0.121	1.991	-1.282	0.782
137	-1.087	1.587	-0.517	0.073
139	-1.170	2.063	2.376	0.471
141	-0.651	1.831	1.317	0.546
143	-0.350	2.747	0.527	1.012
145	-0.314	1.634	1.593	0.656
147	-0.030	0.903	-0.768	0.297
149	-0.077	0.121	-0.623	-0.040
159	-0.042	2.464	0.303	1.029
161	-0.026	1.981	0.123	0.821
163	-0.178	1.245	1.231	0.531
169	-0.417	0.865	-0.382	0.119
220	-0.373	-0.139	-0.790	-0.310
224	-0.037	-0.147	-0.958	-0.160
226	-0.968	-0.417	-0.383	-0.690
106	0.119	-0.068	0.584	0.080
107	0.306	0.356	0.055	0.305
108	-0.865	0.448	-0.492	-0.288
109	-0.935	-0.855	-0.248	-0.844
110	-0.242	0.805	2.484	0.421

111	1.052	-0.912	0.668	0.203
112	1.154	-0.063	-0.284	0.528
113	-0.534	-0.006	-0.503	-0.312
114	-0.194	0.693	1.196	0.291
116	0.271	-0.061	1.078	0.200
118	0.423	0.182	1.703	0.430
120	0.477	0.609	1.253	0.597
122	0.608	0.413	2.268	0.665
124	2.049	-0.240	-0.190	0.910
126	-0.038	0.436	-0.686	0.105
128	-0.918	2.349	0.000	0.518
130	0.318	0.958	0.076	0.564
132	0.064	1.254	-0.794	0.487
140	-0.472	0.421	-0.748	-0.124
208	-0.865	-1.125	-0.416	-0.936
210	0.317	0.389	-1.027	0.234
212	-1.076	-0.109	-0.630	-0.636
214	-0.931	-0.551	-0.504	-0.737
216	-0.262	1.265	-1.157	0.299
218	1.049	1.130	-0.483	0.955
222	0.021	0.937	-1.444	0.280
151	-0.779	0.210	-0.754	-0.365
153	1.463	-0.200	1.164	0.747
155	1.708	0.022	-0.100	0.856
201	-0.865	-1.125	-0.416	-0.936
301	-0.865	-1.125	-0.416	-0.936
302	-0.865	-1.125	-0.416	-0.936
304	-0.865	-1.125	-0.416	-0.936
311	0.596	0.208	-0.617	0.334
313	-0.614	0.722	-0.382	-0.039
315	-0.959	-0.421	-0.567	-0.703
349	-0.949	-0.039	-0.259	-0.513
303	-0.865	-1.125	-0.416	-0.936
323	0.368	0.196	-0.328	0.238
325	1.796	0.315	-0.962	0.950
327	0.318	-0.566	1.748	0.069
329	-0.014	-0.124	1.100	0.033
331	-0.180	-0.164	0.110	-0.149
312	-0.842	-1.122	-0.466	-0.927

314	2.883	0.910	1.668	1.961
316	0.721	0.062	0.710	0.446
318	-0.605	-1.005	-0.444	-0.758
320	0.372	-0.237	0.573	0.136
322	0.650	-0.767	0.316	0.032
326	0.555	-0.750	0.531	0.010
328	-0.258	-0.586	0.151	-0.360
334	0.901	-0.695	1.939	0.324
333	2.915	0.796	-0.333	1.763
335	2.907	0.152	-0.723	1.458
337	3.174	-0.867	-0.821	1.159
339	-0.998	-0.604	-0.199	-0.768
351	-0.200	-0.313	-0.913	-0.306
361	-0.865	-1.125	-0.416	-0.936
363	-0.865	-1.125	-0.416	-0.936
386	0.032	-0.771	0.026	-0.303
382	0.997	-0.744	-0.530	0.145
330	-0.570	-0.587	1.388	-0.414
332	1.200	-0.077	-0.028	0.566
338	0.992	0.022	0.039	0.509
340	-0.026	0.791	0.539	0.361
342	0.311	0.148	0.900	0.292
344	-1.113	-0.617	-0.042	-0.817
346	-0.903	-0.875	-0.251	-0.837
348	-0.227	-0.643	-0.041	-0.384
350	0.113	0.020	1.052	0.152
352	1.646	0.128	1.641	1.014
358	1.424	-0.413	2.325	0.735
364	-0.865	-1.125	-0.416	-0.936
356	1.181	-0.437	2.624	0.628
360	0.656	-0.519	1.460	0.234
362	-0.914	-1.011	-0.347	-0.907
368	-0.905	-1.017	-0.371	-0.907
370	-0.169	-0.880	-0.389	-0.483
309	0.258	-0.504	-0.586	-0.130
355	0.457	-0.265	1.602	0.252
365	0.907	-0.493	-0.068	0.243
367	2.177	-1.058	-0.512	0.607
369	2.711	-0.937	-0.713	0.908

371	2.872	-0.110	0.621	1.444
373	-0.537	-0.735	-0.403	-0.608
375	1.847	-0.399	0.294	0.783
377	-1.786	0.456	2.385	-0.505
379	-0.865	-1.125	-0.416	-0.936
381	-0.865	-1.125	-0.416	-0.936
383	-0.865	-1.125	-0.416	-0.936
385	-0.865	-1.125	-0.416	-0.936
374	0.722	-0.714	0.800	0.131
376	-0.087	-1.168	1.190	-0.430
317	-0.387	0.088	1.180	-0.059
319	-0.967	-0.579	0.733	-0.663
321	-0.827	-1.078	0.211	-0.845
341	-0.116	2.026	-1.543	0.656
343	0.078	-0.729	-0.795	-0.330
345	-0.865	-1.125	-0.416	-0.936
347	-0.865	-1.125	-0.416	-0.936
354	1.237	-0.975	-0.033	0.211
366	-0.865	-1.125	-0.416	-0.936
372	0.797	-0.643	0.571	0.179
378	-0.865	-1.125	-0.416	-0.936
308	-1.248	1.974	3.146	0.459
310	-0.771	-0.062	-0.595	-0.461
324	0.916	-0.706	-0.257	0.144

12 Appendix C Principal Component Analysis (PCA) output data for census data 2003.

Table 53 Correlation matrix for 2003 census.

	SR_Fem.18_64yrs	SR_Fem.head_families	SR_widows	SR_JobSeekers	SR_Non_omani_JobSeekers	SR_#workers	SR_Omani_workers	SR_Omani_families	SR_Non_Omani_families	SR_Familysize5orless	SR_Omani_lessthan14yrs	SR_Omanigt65yrs	SR_Pop2003	SR_Omanifemale	SR_#Omanis	SR_nonomanis	SR_nonomanifemale	SR_Illiterateomanigt15yrs	SR_non_omaniGt15highschool	SR_occupiedhouses	SR_OldArabichouses	SR_Ruralhouses	SR_Houseswithnowaterconnection
SR_Fem.18_64yrs	1.000	.804	.895	.782	.557	.843	.924	.917	.548	.729	.804	.779	.954	.859	.875	.645	.779	.570	.718	.903	.075	.075	.036
SR_Fem.head_families	.804	1.000	.703	.643	.549	.773	.706	.689	.561	.666	.550	.605	.804	.621	.646	.643	.699	.404	.698	.788	.188	.188	.066
SR_widows	.895	.703	1.000	.874	.349	.680	.935	.935	.283	.477	.894	.925	.857	.928	.936	.393	.499	.786	.537	.722	.250	.250	.033
SR_JobSeekers	.782	.643	.874	1.000	.420	.631	.858	.871	.223	.394	.860	.912	.812	.887	.899	.342	.358	.881	.475	.646	.406	.406	.077
SR_Non_omani_JobSeekers	.557	.549	.349	.420	1.000	.741	.360	.321	.847	.838	.155	.248	.647	.222	.249	.854	.798	.106	.669	.775	.192	.192	.175
SR_#workers	.843	.773	.680	.631	.741	1.000	.727	.682	.803	.877	.532	.554	.937	.585	.625	.903	.846	.366	.909	.954	.209	.209	.178
SR_Omani_workers	.924	.706	.935	.858	.360	.727	1.000	.987	.284	.503	.935	.881	.883	.958	.970	.414	.531	.741	.584	.746	.191	.191	.045
SR_Omani_families	.917	.689	.935	.871	.321	.682	.987	1.000	.230	.459	.955	.891	.869	.977	.987	.363	.491	.756	.547	.719	.181	.181	.026
SR_Non_Omani_families	.548	.561	.283	.223	.847	.803	.284	.230	1.000	.961	.022	.106	.642	.101	.145	.971	.903	-.067	.755	.834	.063	.063	.172
SR_Familysize5orless	.729	.666	.477	.394	.838	.877	.503	.459	.961	1.000	.250	.297	.786	.326	.370	.957	.954	.103	.803	.937	.061	.061	.154
SR_Omani_lessthan14yrs	.804	.550	.894	.860	.155	.532	.935	.955	.022	.250	1.000	.896	.756	.988	.979	.164	.278	.831	.395	.547	.222	.222	.003
SR_Omanigt65yrs	.779	.605	.925	.912	.248	.554	.881	.891	.106	.297	.896	1.000	.756	.921	.919	.225	.295	.904	.391	.570	.374	.374	.058
SR_Pop2003	.954	.804	.857	.812	.647	.937	.883	.869	.642	.786	.756	.756	1.000	.804	.837	.752	.773	.594	.819	.949	.236	.236	.122
SR_Omanifemale	.859	.621	.928	.887	.222	.585	.958	.977	.101	.326	.988	.921	.804	1.000	.993	.236	.359	.832	.445	.613	.214	.214	.004
SR_#Omanis	.875	.646	.936	.899	.249	.625	.970	.987	.145	.370	.979	.919	.837	.993	1.000	.281	.392	.828	.486	.652	.228	.228	.016
SR_nonomanis	.645	.643	.393	.342	.854	.903	.414	.363	.971	.957	.164	.225	.752	.236	.281	1.000	.920	.031	.858	.891	.101	.101	.184
SR_nonomanifemale	.779	.699	.499	.358	.798	.846	.531	.491	.903	.954	.278	.295	.773	.359	.392	.920	1.000	.031	.783	.914	-.099	-.099	.080
SR_Illiterateomanigt15yrs	.570	.404	.786	.881	.106	.366	.741	.756	-.067	.103	.831	.904	.594	.832	.828	.031	.031	1.000	.213	.375	.544	.544	.058
SR_non_omaniGt15highschool	.718	.698	.537	.475	.669	.909	.584	.547	.755	.803	.395	.391	.819	.445	.486	.858	.783	.213	1.000	.851	.117	.117	.222
SR_occupiedhouses	.903	.788	.722	.646	.775	.954	.746	.719	.834	.937	.547	.570	.949	.613	.652	.891	.914	.375	.851	1.000	.152	.152	.138
SR_OldArabichouses	.075	.188	.250	.406	.192	.209	.191	.181	.063	.061	.222	.374	.236	.214	.228	.101	-.099	.544	.117	.152	1.000	1.000	.109
SR_Ruralhouses	.075	.188	.250	.406	.192	.209	.191	.181	.063	.061	.222	.374	.236	.214	.228	.101	-.099	.544	.117	.152	1.000	1.000	.109
SR_Houseswithnowaterconnection	.036	.066	.033	.077	.175	.178	.045	.026	.172	.154	.003	.058	.122	.004	.016	.184	.080	.058	.222	.138	.109	.109	1.000
SR_#pop.1835yrs	.921	.797	.823	.799	.622	.943	.860	.847	.638	.772	.724	.727	.989	.775	.816	.754	.744	.577	.834	.933	.233	.233	.141

Table 54 Communalities values

	Initial	Extraction
Fem. 18 - 64 yrs.	1.000	0.903
Female headed families	1.000	0.758
#widows	1.000	0.884
# total job seekers	1.000	0.892
Non-Omani job seekers	1.000	0.709
# worker	1.000	0.872
Omani worker age>15	1.000	0.923
Omani. Family	1.000	0.886
Non-Omani Family	1.000	0.914
Family size 5 or less	1.000	0.873
Omani < 14 yrs.	1.000	0.945
Omani > 65 yrs.	1.000	0.902
#pop 2003.	1.000	0.902
#Omani female	1.000	0.943
#Omanis	1.000	0.888
#non-Omanis	1.000	0.959
non-Omani female	1.000	0.905
Illiterate Omani > 15 yrs.	1.000	0.913
Non- Omani.> 15 > high school	1.000	0.706
Occupied houses	1.000	0.907
Old (Arabic) houses	1.000	0.979
Rural houses	1.000	0.979
Houses with no water connection	1.000	0.158
N# pop. 18-35 yrs.	1.000	0.892
Extraction Method: Principal Component Analysis.		

Table 55 Total variance explained by significant components in 2003 census.

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squar Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumula
1	15.402	64.177	64.177	15.402	64.177	64.177	9.656	40.232	40.2
2	3.641	15.170	79.347	3.641	15.170	79.347	8.475	35.312	75.5
3	1.551	6.463	85.810	1.551	6.463	85.810	2.464	10.266	85.8
4	0.953	3.969	89.779						
5	0.781	3.256	93.035						
6	0.465	1.936	94.971						
7	0.288	1.198	96.169						
8	0.199	0.830	96.999						
9	0.153	0.638	97.636						
10	0.131	0.547	98.184						
11	0.108	0.449	98.633						
12	0.082	0.340	98.973						
13	0.053	0.222	99.195						
14	0.049	0.203	99.398						
15	0.040	0.166	99.564						
16	0.032	0.135	99.699						
17	0.027	0.110	99.809						
18	0.015	0.061	99.871						
19	0.011	0.047	99.918						
20	0.008	0.034	99.952						
21	0.007	0.029	99.981						
22	0.003	0.012	99.993						
23	0.002	0.007	100.000						
24	-2.819E-16	-1.175E-15	100.000						

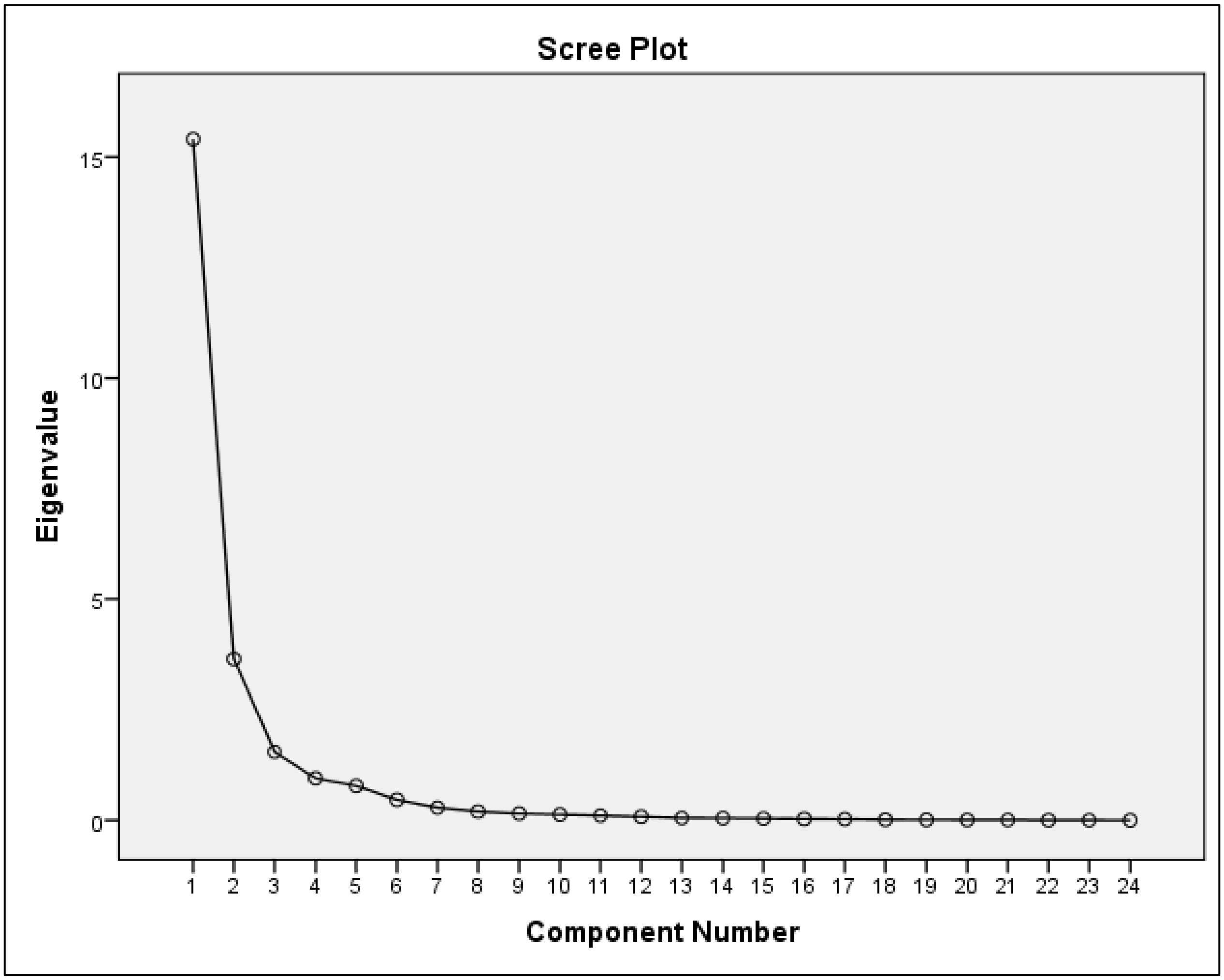

Figure 50. Scree plot showing the three components with Eigenvalues greater than one in 2003 census.

Table 56 Rotated component matrix with loadings in each factor using 2003 data set.

Rotated Component Matrix			
	Component		
	1	2	3
Fem. 18 - 64 yrs.	0.760	0.569	
Female headed families	0.616	0.598	
#widows	0.855	0.313	
# total job seekers	0.846		0.320
Non-Omani job seekers		0.780	
# worker	0.347	0.863	
Omani worker age>15	0.865	0.400	
Omani. Family	0.853	0.377	
Non-Omani Family		0.941	
Family size 5 or less	0.329	0.859	
Omani < 14 yrs.	0.949		
Omani > 65 yrs.	0.887		0.307
#pop 2003.	0.656	0.674	
#Omani female	0.934		
#Omanis	0.875	0.331	
#non-Omanis		0.971	
non-Omani female	0.336	0.890	
Illiterate Omani > 15 yrs.	0.869		0.396
Non -Omani.> 15 > high school		0.830	
Occupied houses	0.516	0.790	
Old (Arabic) houses			0.937
Rural houses			0.937
N# pop. 18-35 yrs.	0.584	0.737	
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			

Table 57 Factor scores and SVI produced using data set from 2003 census.

Municipal block	Fact_1	Fact_2	Fact_3	SVI_2003
209	-1.115	-0.916	-0.565	-0.975
211	-1.024	-0.839	0.278	-0.807
213	-0.408	-0.489	0.764	-0.314
215	0.296	0.400	0.783	0.391
217	-0.141	0.684	-0.677	0.134
219	-0.342	0.272	-0.944	-0.159
221	-0.316	0.290	-0.171	-0.055
223	0.163	0.727	-1.207	0.242
225	0.123	0.094	-1.132	-0.025
227	0.148	0.102	-0.911	0.014
228	-0.512	0.006	-0.940	-0.349
230	0.455	0.961	-1.016	0.500
232	0.266	0.209	-1.039	0.101
233	-1.105	1.228	0.251	-0.014
234	-1.084	0.044	-0.433	-0.557
235	-1.102	2.809	-0.634	0.531
236	1.760	0.271	0.441	1.014
237	1.746	2.174	-1.739	1.540
238	0.624	0.548	-0.453	0.476
239	1.328	2.620	-1.162	1.580
240	0.879	1.913	-0.484	1.149
241	1.059	2.454	0.206	1.530
242	1.475	1.668	-0.271	1.363
243	-1.070	0.388	-0.418	-0.409
244	1.807	1.293	-0.609	1.337
245	-0.235	0.641	-1.057	0.030
246	0.600	-0.477	-0.201	0.078
247	1.422	0.968	-1.745	0.894
248	1.091	0.742	-0.456	0.782
249	1.104	0.762	-1.434	0.690
250	-1.188	0.812	-1.037	-0.362
251	-0.303	-0.360	-0.856	-0.386
252	-1.214	1.781	-0.363	0.090
255	-1.139	0.201	-0.540	-0.532
256	-0.421	-0.911	-0.828	-0.663
257	0.407	-0.570	-0.897	-0.130

259	-0.085	-0.836	-0.108	-0.391
260	-1.450	1.751	-0.976	-0.104
261	-0.720	-0.636	-0.689	-0.683
262	-0.850	-0.729	-0.804	-0.796
263	-0.767	-0.657	-0.697	-0.715
264	-1.841	2.744	-0.831	0.123
265	0.157	-0.957	0.364	-0.271
266	-1.668	1.642	-0.487	-0.201
267	0.771	-0.886	1.100	0.137
268	-0.533	0.132	-0.890	-0.303
269	0.890	-1.015	0.728	0.102
270	-0.640	-0.400	-0.752	-0.555
271	1.184	-0.913	-1.251	0.071
278	-0.773	-1.277	-0.643	-0.963
280	-0.979	-1.266	-0.589	-1.053
282	-0.931	-1.256	-0.607	-1.027
286	-0.371	-1.133	-0.255	-0.666
290	-0.623	-1.248	0.816	-0.720
292	-0.890	-1.123	-0.515	-0.943
178	0.840	-0.788	1.413	0.244
180	-0.084	-0.371	1.187	-0.062
182	0.215	-0.158	1.998	0.258
184	0.735	-0.942	1.085	0.095
186	0.272	-0.452	1.666	0.131
188	-0.341	-0.703	0.649	-0.380
189	0.190	-0.975	0.433	-0.255
191	-0.201	-0.773	0.888	-0.314
193	-0.911	-1.231	-0.400	-0.984
195	0.030	-1.508	1.982	-0.380
197	-1.074	-1.273	-0.532	-1.095
172	-1.116	-1.131	-0.538	-1.059
176	1.016	-1.027	1.127	0.201
183	0.141	-0.404	0.394	-0.052
185	-1.101	-1.064	-0.559	-1.027
187	0.559	-1.040	1.034	-0.036
175	0.279	-1.244	-0.723	-0.446
177	0.027	-1.090	0.655	-0.356
146	-1.625	1.182	0.938	-0.211
148	-0.025	1.372	-0.465	0.492
150	-0.178	1.312	-0.375	0.403

152	0.299	0.768	-0.027	0.453
154	0.860	0.658	1.745	0.874
158	-0.298	0.526	-0.424	0.022
165	-1.276	1.291	-0.153	-0.116
203	0.369	0.064	-0.631	0.137
205	-0.812	0.131	-0.460	-0.392
206	0.067	0.562	-1.198	0.129
207	-1.246	-0.444	-0.494	-0.840
121	-0.522	0.827	-0.924	-0.020
123	-0.536	0.761	-0.641	-0.023
127	-1.059	1.119	-0.498	-0.117
129	0.109	2.340	-0.393	0.957
131	-0.455	1.171	-0.909	0.153
135	-0.457	0.288	1.016	0.004
142	-1.302	-0.367	0.117	-0.769
144	-1.117	1.366	0.672	0.082
119	-0.036	2.136	0.678	0.920
125	-0.518	0.051	-0.778	-0.316
204	-0.676	-0.166	-0.383	-0.438
133	-0.154	1.526	-0.593	0.477
137	-1.199	0.741	-0.335	-0.321
139	-1.144	1.905	1.938	0.424
141	-0.674	1.372	1.125	0.349
143	-1.175	2.515	1.662	0.626
145	-0.288	1.419	1.579	0.605
147	0.066	0.997	-0.267	0.406
149	-0.045	0.574	-0.461	0.160
159	-0.407	2.108	3.035	0.984
161	-0.626	1.394	2.210	0.499
163	-0.946	0.987	1.651	0.118
169	-0.512	1.398	-0.137	0.301
220	-1.038	-0.832	-0.504	-0.896
224	-0.670	-1.117	-0.240	-0.804
226	-0.890	-1.109	-0.584	-0.945
106	-0.225	-0.421	1.271	-0.142
107	-0.135	-0.314	0.941	-0.091
108	-1.284	-0.015	0.234	-0.606
109	-1.075	-1.060	-0.575	-1.015
110	-0.431	0.748	1.382	0.243

111	1.168	-1.085	0.129	0.144
112	0.062	-0.138	2.071	0.200
113	-0.014	0.542	-0.706	0.136
114	-0.801	0.728	2.053	0.128
116	0.083	-0.350	1.056	0.013
118	0.261	-0.063	1.822	0.300
120	0.018	0.487	1.537	0.373
122	0.233	0.141	1.968	0.384
124	1.354	-0.682	2.220	0.625
126	-0.417	0.209	0.142	-0.103
128	-0.968	1.722	0.472	0.276
130	-0.189	0.472	1.802	0.295
132	-0.418	0.601	1.210	0.171
140	-0.585	0.080	-0.259	-0.281
208	-1.074	-1.273	-0.532	-1.095
210	0.325	0.165	-0.890	0.128
212	-1.089	-0.604	-0.727	-0.853
214	-0.974	-1.230	-0.600	-1.037
216	-0.641	1.162	-0.807	0.071
218	-0.098	0.323	0.359	0.122
222	-0.388	-0.586	-0.759	-0.508
151	-1.143	-0.155	-0.588	-0.683
153	0.949	-0.111	2.145	0.650
155	0.730	0.143	2.395	0.674
201	-0.286	-0.340	-0.873	-0.371
301	-0.731	0.304	0.040	-0.229
302	0.093	0.361	0.508	0.247
304	-0.890	-0.497	-0.781	-0.719
311	-0.546	2.258	-0.872	0.552
313	-0.602	-0.347	-0.841	-0.525
315	-0.956	-0.960	-0.644	-0.924
349	-1.050	-0.382	-0.837	-0.756
303	-0.332	-1.148	0.173	-0.607
323	0.599	0.432	-0.031	0.463
325	2.196	0.560	-0.394	1.252
327	1.468	-0.089	-1.180	0.550
329	0.674	0.134	-0.266	0.353
331	0.584	-0.039	-0.862	0.175
312	1.927	0.308	0.739	1.143

314	1.577	1.374	1.936	1.534
316	1.067	0.590	1.152	0.883
318	-0.625	-1.124	-0.264	-0.787
320	-0.117	-0.497	0.117	-0.245
322	1.006	-0.668	0.673	0.293
326	0.076	-0.995	0.566	-0.304
328	-0.492	-0.629	0.022	-0.491
334	0.744	-0.403	1.873	0.402
333	3.045	1.510	-1.334	1.948
335	2.787	0.313	0.958	1.587
337	3.143	-0.720	-1.377	1.089
339	1.393	-0.367	-1.445	0.373
351	-0.396	-0.590	-0.219	-0.455
361	-1.088	-0.514	-0.631	-0.806
363	-0.630	-0.893	-0.672	-0.741
386	-0.788	-1.183	0.372	-0.821
382	-0.114	-1.486	-0.365	-0.696
330	-0.296	-0.529	-0.030	-0.361
332	0.900	-0.372	1.440	0.444
338	0.495	0.194	1.618	0.496
340	-0.788	-0.865	1.593	-0.560
342	-0.471	0.621	1.416	0.176
344	-0.953	-0.917	-0.455	-0.884
346	-1.099	-1.203	-0.523	-1.078
348	-0.335	-0.574	0.209	-0.372
350	-0.073	0.034	1.043	0.091
352	2.009	0.573	-1.239	1.075
358	1.416	-0.292	1.016	0.682
364	-0.587	-0.918	-0.533	-0.715
356	0.509	-0.407	1.251	0.219
360	1.184	-0.394	1.512	0.581
362	-0.975	-1.176	-0.313	-0.984
368	-0.962	-1.151	-0.596	-0.998
370	-0.184	-0.220	0.916	-0.079
309	-0.290	-0.671	0.697	-0.337
355	0.770	-0.519	0.479	0.217
365	1.414	-0.799	-1.240	0.231
367	1.961	-0.828	0.270	0.649
369	2.392	-0.450	-1.363	0.834

371	2.628	-0.100	-0.052	1.233
373	-0.789	-0.922	-0.143	-0.772
375	2.595	-0.764	-1.389	0.804
377	-1.528	1.454	-0.043	-0.160
379	2.437	-1.027	-0.041	0.766
381	1.406	-1.435	-0.280	0.074
383	-0.849	-1.275	-0.242	-0.955
385	-0.858	-1.214	-0.195	-0.930
374	0.896	-0.819	0.765	0.188
376	0.130	-0.930	-0.049	-0.318
317	1.263	0.159	-0.382	0.638
319	1.357	-0.019	-1.497	0.490
321	2.146	-0.070	-1.704	0.831
341	0.308	1.773	-1.945	0.656
343	0.195	-0.533	-1.089	-0.239
345	1.151	-0.226	-1.519	0.304
347	1.116	0.041	-1.523	0.394
354	1.172	-1.045	1.281	0.287
366	-0.905	-1.069	-0.543	-0.932
372	-0.165	-1.080	0.009	-0.516
378	0.098	-1.488	0.188	-0.534
308	0.463	-0.001	-0.677	0.151
310	-0.414	-0.768	-0.866	-0.606
324	0.888	-0.580	1.085	0.316