SOCIAL VULNERABILITY ASSESSMENT IN MADEIRA ISLAND

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Declaration of originality

I declare that the content of this document is my own and not from somebody else. All assistance received from other people is acknowledged and all sources (published or not published) are referenced.

This work has not been previously submitted for evaluation at NOVA Information Management School or any other institution.

Lisbon, February the 26th of 2018

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ABSTRACT

Social Vulnerability is an area of growing interest among researchers and decision makers. As disaster losses mount, it emerged the understanding that disasters are not just a product of Hazards characteristics and Exposure, but also a Social construct that creates differentiate levels of ability to cope with, resist to and recover from extreme events.

The assessment of a multidimensional and intangible phenomenon like Social Vulnerability is extremely complex and over the years a number of indexes have emerged as an attempt to reduce the phenomenon to a simple metric, temporal and spatially comparable.

Social Vulnerability Index (SOVI) is a particularly robust and widely used index. A recent version of this algorithm, the Social Vulnerability to Natural and Technological Hazards Index (SOVI_NTH) addressed the caveat of having in the same SOVI Components variables regarding the socioeconomic attributes that make people vulnerable and the support structures and facilities that help them to resist and recover. Both indexes were implemented using the Hazards-of-Place model, that combines Social Vulnerability and Hazards Susceptibility to pinpoint areas where both have high scores.

In this research we compared the results and the statistical performance of both indexes to determine their consistency. Additionally, we analysed the sensitivity to data aggregation in order to determine whether it is possible to use very small spatial statistical units to highlight asymmetries and niches of particularly high Social Vulnerability.

KEYWORDS

Social Vulnerability

Social Vulnerability Index

Social Vulnerability to Natural and Technological Hazards Index

Index sensitivity

Data aggregation

Geographical Information Systems

LIST OF ABBREVIATIONS AND ACRONYMS

GDP – Gross Domestic Product

INE – National Institute of Statistics

PCA – Principal Components Analysis

SOVI – Social Vulnerability Index

SOVI_NTH – Social Vulnerability to Natural and Technological Hazards Index

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1. INTRODUCTION

1.1. Introduction

Risk has become a growing concern as societies are faced with disasters that escape their ability to control or prevent them (Beck, 1992). Risk, often represented as a product of Hazards and Vulnerability, refers to the probability of harmful consequences or losses due to natural or human-induced Hazards and vulnerable conditions or, in other words, the likelihood of occurrence of a hazardous phenomenon and the potential consequences and losses associated with it (Tate, 2011; UNISDR, 2004; Varnes, 1984).

In Risk and Disaster research there has historically been a predominance of studies focusing on Hazards (i.e. probability, intensity, distribution and triggering factors) and, thus, most initiatives implemented aim to control, or at least curb, the processes that induce Hazards (i.e. protective infrastructures, warning systems) having undervalued its social dimensions (Jorn Birkmann, 2007; Cutter, Emrich, Morath, & Dunning, 2013; Lewis, 1999).

As the number of disasters affecting people increase, Vulnerability studies are growingly seen as vital for Risk reduction (Balica, Douben, & Wright, 2009; Jorn Birkmann, 2006a; United Nations, 2005). There is a variety of methodological and conceptual approaches that show the growing vitality of this research topic, including the Social aspects of Vulnerability (Jorn Birkmann, 2006b; Cutter, Boruff, & Shirley, 2003; Cutter, Emrich, Webb, & Morath, 2009; Lundgren & Jonsson, 2012; Moret, 2014; Willis & Fitton, 2016; Wisner, Blaikie, Cannon, & Davis, 2004).

Vulnerability is a complex concept that generally refers to the potential of loss caused by a Hazard, but it has different meanings for different scientific areas – even within the context of Risk and Disaster research (Jorn Birkmann, 2006a; Guillard-Gonçalves, 2016; Moret, 2014). Social Vulnerability, in particular, considers the characteristics of individuals and communities that influence their frailty in the face of Hazards, their (in)ability to cope with, resist to, and recover from the impacts of Hazards, and why people exposed to the same event are affected differently (Cutter et al., 2003, 2013; Cutter & Finch, 2008).

Cutter et al. (1996, 2000, 2003), proposed an approach that combines both Exposition and Social Vulnerability to Hazards to produce the composite Vulnerability of a given place (Place Vulnerability) – the Hazards-of-Place model, highlighting those that are simultaneously more socially vulnerable and exposed to Hazards.

Assessing Hazards' probability and spatial Susceptibility is a complex task. Assessing Social Vulnerability may be even harder, given that it is a less tangible concept, not directly observable, multidimensional, harder to define and that can only be expressed by proxy measures (Cutter et al., 2003; Tate, 2011, 2013). Consequently, its assessment is also difficult to validate, and although some simple proxy indicators are often used (i.e. number of dead or injured) they can hardly account for all types of potential losses (Tate, 2011).

The difficulty in measuring Vulnerability begins in the concept itself. Different interpretations and perspectives of Vulnerability expand the field of research to a wide range of useful approaches, but complicates a common understanding of how to define and measure it (Jorn Birkmann & Wisner, 2006). Some aspects may even be '*beyond quantification*' which does not mean they cannot be measured, or at least assessed and systematized, but that they're not easily quantifiable objectively (Jorn Birkmann & Wisner, 2006).

The most disseminated approach is to use quantitative methods. Indexes, in particular, are a valued tool, simplifying the multidimensional nature of Social Vulnerability into a single metric that facilitates the comparation between places, creates new information and facilitates its communication (Jorn Birkmann, 2006a; Gall, 2007; Rygel, O'sullivan, & Yarnal, 2006; Tate, 2011, 2013). Despite the growing interest for such indexes, they face questions about their accuracy and ability to represent such a complex and multidimensional phenomenon (Gall, 2007; Rygel et al., 2006; Tate, 2011).

Social Vulnerability Index (SOVI) in particular, is a robust, widely used and tested index that has been used in different regional and scale contexts (Borden, Schmidtlein, Emrich, Piegorsch, & Cutter, 2007; Boruff, Emrich, & Cutter, 2005; Burton & Cutter, 2008; Cutter et al., 2006). It uses a large set of variables representing different dimensions of Social Vulnerability that are reduced using a Principal Component Analysis (PCA) to obtain a small number of Components and a relative value of Social Vulnerability within the studied area (Cutter et al., 2003).

Mendes et al. (2009), reflecting on some conceptual caveats of SOVI, proposed a Social Vulnerability Index to Natural and Technological Hazards (SOVI_NTH) where Criticality and Support Capacity are analysed separately, resulting in two sub-indexes, that are only then combined into an overall Social Vulnerability score.

When assessing Social Vulnerability, aspects like scale of analysis, data resolution and data availability should be aligned with the objectives of the research. These aspects also affect the statistical performance of the PCA (Garson, 2009; O'Rourke & Hatcher, 2013; Schmidtlein, Deutsch, Piegorsch, & Cutter, 2008). Social Vulnerability, especially when framed by the Hazards-of-Place model, is a place specific phenomenon and should be analysed in a specific geographic context (Cutter, 1996; Cutter, Mitchell, & Scott, 2000).The analysis based on the Hazards-of-Place model may be done considering one type of Hazard or a combination of several Hazards (Cutter, 2003; Cutter et al., 2000).

Small island territories are particularly sensitive to disasters because of their small size, location, dependency on a small set of economic activities and less resources and capacities to respond to disasters (Lewis, 1999; Rodrigues, 2005).

In Madeira island, the combination of natural features (i.e. steep slopes; geology; dimension and shape of river basins; vegetation; clime) and anthropic characteristics (i.e. urbanization of susceptible areas; land use and soil impermeabilization; hydraulic structures) in a small insular territory, with limited availability of urbanization areas, creates conditions propitious for a high probability of occurrence of severe disasters affecting exposed and vulnerable population (Municipia, 2014; Oliveira et al., 2010; Policarpo, 2012; Quintal, 1999; Rodrigues, 2005; Sepúlveda, 2011).

Recurrent extreme natural events have through the years caused property damage, life loss and disruption of the socioeconomic fabric (Municipia, 2014; Quintal, 1999; Rodrigues, 2005; F. Silva & Menezes, 1978). Some of these disasters are listed on Appendix I. The need to balance the challenges posed by a territory prone to natural Hazards and the human occupation of an exiguous insular territory makes Madeira a singular case study.

In this dissertation we apply the Social Vulnerability Index (SOVI) and the Social Vulnerability Index to Natural and Technological Hazards(SOVI_NTH) and reflect about the methodological challenges including index implementation, data aggregation and data availability. We adopt the framework Hazards-of-Place model (Cutter, 1996; Cutter et al., 2000; Cutter & Solecki, 1989) to explore Social Vulnerability in Madeira Island.

We will test the performance of SOVI and SOVI_NTH, in the context of Madeira, and compare their statistical performance and information provided to determine whether SOVI_NTH can be a viable, if not preferable, option. Additionally, we will test their sensitivity to data aggregation, the way it affects statistical performance, the interest of the information provided. We want to determine whether an analysis using a resolution finer than those commonly used, with very small statistical units, is possible within the acceptable statistical performance parameters.

We aim to produce information that can inform future discussions about adequate policies, strategies and priorities to prevent and mitigate disaster impact, exploring the potential of Geographic Information Science and Systems, not only to process and analyse data, but also to communicate information to the public, experts or policy makers, in a visual and easily understandable way (i.e. Cartography).

1.2. Objectives

The objectives of this research include:

a) Contribute to the discussion about disaster prevention and mitigation strategies in Madeira Island by assessing Social Vulnerability, within the Hazards-of-Place model.
b) Test and compare the performance and applicability of both the SOVI and SOVI_NTH indexes in the context of Madeira.
c) Test the indexes sensitivity to scale and data aggregation and determine the applicability to very small statistical units.

1.3. Hypotheses

The hypothesis used as start point for this research include:

a) SOVI can be used to effectively assess Social Vulnerability in Madeira.
b) SOVI_NTH offers a valid alternative, with a conceptual edge and with an extra layer of information.
c) Hazards-of-Place model provides an adequate framework to integrate Hazards Susceptibility and Social Vulnerability and create information and cartography relevant to the discussion about Risk and Disasters.
d) Social Vulnerability's assessment should include different types of data aggregation, including fine and very fine resolution, in order to offer a better understanding and illustration of existing patterns and asymmetries.

1.4. General Methodology

In each Chapter we will detail the methodology and the data used at every step. We present here the general methodology of this dissertation.

We started this work by researching and reviewing existing literature about the main concepts regarding Disaster, Risk, Hazard, Vulnerability and Social Vulnerability. We selected the Hazards-of-Place model and the Social Vulnerability Index proposed by (Cutter, 1996;

Cutter et al., 2003, 2000) due to its robustness and suitability to the research objectives. Additionally, we implemented an adjusted version of the SOVI, the SOVI_NTH proposed by Mendes *et al*. (2009), to test its performance and the information produced, particularly by its two sub-indexes (Criticality and Support Capacity).

We systematized the steps of both the SOVI and SOVI_NTH algorithms, and identified the data, statistical and analytical requirements, as well as performance parameters for a successful application. Because one of the objectives was to explore the sensitivity to scale and data aggregation, we implemented the algorithms using different statistical units to, first, test the performance and viability of the analysis and, second, to assess the usefulness of the obtained information for Risk and Disaster management. We considered issues such as data availability, variables selection, data aggregation, statistical requirements and quality parameters of the resulting model. We compared the performance of these indexes, the quality of the PCA model, the resulting components, retained variables, the information provided and the resulting Social Vulnerability spatial patterns.

To evaluate the effect of using more disaggregated data, we used PCA performance and quality parameters. We also determined the percentage of statistical units that have a SOVI level (i.e. in a scale of 1 to 5) at a smaller statistical unit, different than the one that they would have if the value calculated for a more aggregated unit would be assigned to all the smaller units that compose it.

In order to apply SOVI and SOVI_NTH we collected and prepared statistical information. Some variables were calculated or obtained by performing spatial analysis using ArcGis. The indexes were calculated using SPSS and the results were then imported to ArcGis and combined with other geographic information.

To implement the Hazards-of-Place model, Social Vulnerability was combined with Hazards Susceptibility maps, using spatial analysis and raster calculation in ArcGis. We used both Hazard and Multi-Hazard analysis. In the latter case, we first combined different Hazards' spatial Susceptibility into one single Multi-Hazards map and only then combined it with Social Vulnerability.

The combination of Hazards Susceptibility and Social Vulnerability in one single map allows to characterize Social Vulnerability and Hazards patterns, highlighting areas where high Hazard Susceptibility and high Social Vulnerability coincide (Cutter, 1996; Cutter et al., 2003, 2000).

Asymmetries in overall Social Vulnerability and the distribution of the different components that contribute to that overall Social Vulnerability were analysed.
Social Vulnerability was calculated and analysed for the entire island, but because we were not allowed to use all the existing regional Hazard's cartography, the combination with some Hazards was only possible regarding Funchal.
Finally, we reflect about the lessons learned, the new information and knowledge produced and reflect on how it can be useful for disaster prevention and mitigation strategies.

1.5. Structure

The dissertation is organized in 6 chapters:

I. **Introduction**: In this chapter we frame this study by presenting its objectives, hypotheses, general methodology and the dissertation structure.

II. **Conceptual framework**: In this chapter we present the main theories and conceptual framework supporting this research.

III. **Social Vulnerability in Madeira Island**: In this chapter we describe the methodological approach to assess Social Vulnerability and present the results.

IV. **Hazards-of-Place**: In this chapter we implement the Model Hazards-of-Place by combining Social Vulnerability whit spatial Susceptibility to Hazards.

V. **Discussion:** In this chapter we discuss the results of both the application of Social Vulnerability indexes to Madeira, as well as the sensitivity analysis of the indexes and data aggregation units.

VI. **Conclusion**: In the final chapter we summarize the main conclusions of this research.

2. CONCEPTUAL FRAMEWORK

2.1. Introduction

In this Chapter we review significant literature regarding Risk, Disaster, Vulnerability, Social Vulnerability assessment methods and frameworks, and the challenges posed by scale of analysis and data aggregation. The purpose is to contextualize this research within the existing conceptual models.

We started with a broad perspective, reviewing different theories and conceptual frameworks in order to identify those that better would serve the purpose of our research. After the selection of the Hazards-of-Place model and the assessment indexes, additional literature was analysed to provide conceptual and methodological information.

2.2. Risk and Disasters

We live in a society of Risk, where there is a growing concern about disasters that often escape our grasp and our ability to control and prevent them (Beck, 1992). In the mid-twentieth century there might have been the hope that technology would eventually allow us to control natural phenomena, and we would be able to prevent nefarious consequences (Bateira, 2001), but societies are now more aware about the challenges of preventing, controlling, or even fully understanding these Hazards (Beck, 1992).

Risk refers to the combination of the probability of an hazardous event and its negative consequences (UNISDR, 2009), or in other words, the interaction between Hazards of natural or human induced origin and the Vulnerability of those exposed to potential harmful consequences or losses (Julião, Nery, Ribeiro, Branco, & Zêzere, 2009; Randolph, 2004; Rebelo, 2003; UNISDR, 2009; Wisner et al., 2004). It is usually represented by the conceptual formula '*Risk = Hazard x Vulnerability*', meaning the product of a Hazard (likelihood of a damaging phenomenon) and Vulnerability (potential loss due to that phenomenon) (Jorn Birkmann, 2006a; Varnes, 1984; Zêzere, Pereira, & Morgado, 2006). Some consider the concept of Total Risk as the product of Hazards, Vulnerability and Exposed Elements (i.e. people, property): '*Risk = Hazard x Vulnerability x Exposed Elements*' (Randolph, 2004; Tavares & Cunha, 2008; Varnes, 1984; Zêzere et al., 2006)

The concept of Hazards refers to a phenomenon, occurring independently, in a sequence or combination of different types, at different times, with a given degree of intensity and severity, that can cause variable losses (i.e. fatality, injury, property damage, socioeconomic disruption, environmental degradation) and can be originated by natural or human processes, sometimes acting in combination (UNISDR, 2004, 2009; Wisner et al., 2004).

They can be seen as the probability of occurrence of a phenomenon within a specified period of time and within a given area. Its potential negative consequences may have varying degrees of severity, depending not only on the intensity of the phenomena itself but also people and systems' ability to deal with them (Ayala Carcedo & Olcina Cantos, 2002; Varnes, 1984; Zêzere et al., 2006). Hazards can be characterized by their location, intensity, duration, spatial extent, frequency and probability (UNISDR, 2004, 2009). The propensity of a given area to be affected by Hazards, due to its location and characteristics, is called Susceptibility (Ayala Carcedo & Olcina Cantos, 2002; Julião et al., 2009).

There are different types of Hazards. Natural Hazards are phenomena or processes of natural origin (i.e. floods, landslides, earthquake) and Technological Hazards are those where the source of danger is human activity (i.e. dam failures, technological accidents, urban fires) (Julião et al., 2009; UNISDR, 2004, 2009). When the event arises from natural processes whose intensity or frequency is amplified by human activity, they can be called Socio-Natural Hazards (i.e. forest fire, desertification) (UNISDR, 2009).

Vulnerability refers to conditions determined by physical, social, economic, and environmental factors that affect the potential impact of Hazards (UNISDR, 2009). It represents a potential or degree of lost endured by an element exposed to a hazardous phenomenon of a given intensity (Varnes, 1984; Zêzere et al., 2006). Exposed Elements include people, property and human or natural systems in areas susceptible to Hazards and subject to potential losses (Balica et al., 2009; Randolph, 2004; UNISDR, 2009; Zêzere et al., 2006). This potential of loss is paramount to the concept of Risk because it is this exposure of people and property to Hazard induced losses that completes the Risk equation (Lourenço, 2003). We only have Risk if due to a hazardous event someone or something is actually *at risk* (Castro, Peixoto, & Rio, 2005; Rebelo, 2003).

The ability of a system, community or society to (re)organize itself, adapt and learn with past events in order to withstand the impact of a Hazard, maintain or quickly recover its basic systems and structures and increase its ability to withstand future Hazardous events is called Resilience (Adger, Arnell, & Tompkins, 2005; Balica et al., 2009; Moret, 2014; UNISDR, 2004, 2009). There is some discussion whether it refers (mostly) to the capacity to absorb the impact of Hazards and resist to them, or the ability of a social system to learn and adapt from incremental or sudden changes and restore its major functions (Jorn Birkmann, 2006c).

To increase resilience and protect from Hazards, prevention and mitigation strategies should be applied. The first aims at (*completely*) avoiding negative impacts from Hazards by taking actions in advance, and the second, because more often than not it is impossible to completely avoid losses, refers to reducing the potential consequences as much as possible by using existing capacities, through structural (i.e. protective structures or systems) and non-structural (i.e. legal framework, public awareness, education, research, public participation) measures (UNISDR, 2004, 2009).

When extreme events occur, Response and Recovery measures should be put in place, respectively, to protect those exposed and care for basic immediate subsistence needs during and immediately after the impact of a Hazard, restore or improve living conditions and reduce future disaster Risk (UNISDR, 2004, 2009).

Even when adequate prevention strategies are put in place, the complete eradication of negative consequences from Hazards is hardly achieved, leading to Crises or even Disasters. A crises represents a situation where a threatening condition causes disruption to the normal functioning of existing systems and requires urgent action to prevent it from escalating into a more serious situation (UNISDR, 2009). When an event causes extensive losses and its impact exceeds the capacity of the affected community to cope using only its own resources, the situation represents a Disaster (Wisner et al., 2004).

Crises and disasters are not a function of only the intensity of the hazardous phenomenon but also the attributes of the exposed communities, and a same event can represent a crisis or disaster in one context, and not in another, due to local conditions (UNISDR, 2004, 2009; Wisner et al., 2004). Managing disasters requires an integrated approach to both Hazard and Vulnerability, covering: Risk assessment and analysis (i.e. susceptibility map), the implementation of strategies to Risk reduction and control (i.e. mitigation measures in Hazard susceptible areas), and transfer of the cost associated with Risk from individuals or communities (i.e. tax benefits for protective measures) (UNISDR, 2009).

Because disasters are spatial phenomena resulting from interactions between people and places, their analysis requires a spatial approach and ability to combine different layers of information, which makes disaster management adequate for the application of Geographic Information Systems (GIS) (Tomaszewski, 2014).

Disaster Risk Management, through the implementation of prevention, preparedness and mitigation strategies (i.e. institutional, legal, organizational, operational), should develop coping capacity, reduce the potential impact of extreme events and create safer societies

(UNISDR, 2004, 2009). Strategies should include promoting Risk awareness, Risk education and research, legislation, spatial planning, protection of critical facilities, weather forecasting and early warning systems (UNISDR, 2009).

2.3. Vulnerability and Social Vulnerability

Vulnerability is an elusive concept with different definitions, even within the context of Risk and Disasters, depending on the researchers' focus, conceptual frameworks and background (Balica et al., 2009; Jorn Birkmann, 2006a; Cutter, 1996, 2001; Cutter et al., 2003; Guillard-Gonçalves, 2016; Moret, 2014). Geography, bridging between biophysical and human perspectives, allied with the use of Geographic Information Systems, is a driving force behind Vulnerability research (Cutter et al., 2003).

Vulnerability is broadly associated with the potential losses that an element can suffer from a hazardous event, of a given intensity, as well as the ability to resist and recover (Jorn Birkmann, 2006c; Cunha, Mendes, Tavares, & Freiria, 2011; Cutter, 1996; Cutter et al., 2003; Schmidtlein et al., 2008; Wisner et al., 2004). It considers the physical, social, economic and environmental characteristics or processes of an element or system, that make it susceptible to the impact of a Hazard (UNISDR, 2004, 2009), representing a predisposition to suffer losses (i.e. Injury, death, destruction, ecosystem disturbance), influenced by the systems characteristics (Cutter, 1996) and its ability to adapt (Adger, 2006; Balica et al., 2009).

Vulnerability to Hazards manifest differently to different groups because the access to resources and the ability to resist is differentiated. Its study is widely accepted as important to the development of prevention and mitigation strategies (Cutter, 2001; Cutter et al., 2003). Some authors focus more on exposure to the Hazard itself, others on the characteristics of those exposed (Balica et al., 2009). Vulnerability to Hazards is a multidimensional construct that encompasses several dimensions that affect the ability to deal with Hazards (i.e. social, economic, demographic, institutional) (Cutter, 1996).

Vulnerability is sometimes divided into two perspectives: Biophysical Vulnerability, referring to Hazards, the biophysical context and its interaction with society that influence the likelihood of losses and the ability to recover and adapt; Social Vulnerability that considers the frailty of individuals or groups to potential losses from Hazards based on attributes (i.e. age, income, gender) that influence losses and a differentiated impact of a same event in different individuals (Jorn Birkmann, 2006c; Cutter, 1996; Schmidtlein et al., 2008; WBGU, 2005)

The concept of Vulnerability has changed over the past decades (Balica et al., 2009) and encompassed several thematic areas, i.e. economic, environmental and institutional vulnerability (Jorn Birkmann, 2007). Initial studies focused mainly in the biophysical dimension, Hazards, the triggering factors, the people exposed and how to prevent or protect from hazardous events (Balica et al., 2009; Jorn Birkmann, 2006c, 2007; Cutter, 1996), providing the basis for the definition of prevention and mitigation strategies that aimed at control, or at least curb, Hazards (i.e. protective infrastructures, warning systems), while the Vulnerability dimension was often undervalued (Jorn Birkmann, 2006a; Cutter et al., 2013; Lewis, 1999).

Researchers have long acknowledged that human decisions influence the outcome of Hazards but the explicit focus on Vulnerability as a Social construct is more recent (Schmidtlein et al., 2008; Wisner et al., 2004). Thus, Vulnerability assessment and quantification is less advanced (Jorn Birkmann, 2007; Cunha et al., 2011). In recent years, a growing number of studies addressed Vulnerability assessment (Jorn Birkmann, 2007) with methodologies determined by the conceptual framework, including the specific definition of Vulnerability itself, and the objectives of the assessment (Moret, 2014).

In this dissertation we focus on Social Vulnerability, that refers to characteristics of individuals and communities that influence their sensitivity to Hazards, their (in)ability to cope with, resist to, and recover from their impact (Cutter et al., 2003, 2013; Cutter & Finch, 2008). It refers to '*the Susceptibility of Social groups to potential losses from Hazard events or society's resistance and resilience to Hazards*' (Cutter et al., 2000).

Although an area may be affected by a given natural phenomenon (almost) regardless of the Social context, the impact of that phenomenon is affected by the social conditions of those exposed. People affected by the same Hazard, may experience its impact differently, suffering varying degrees of loss, and it is this differentiated Vulnerability that Social Vulnerability addresses (Cutter, 1996; Cutter et al., 2003; Hummell, Cutter, & Emrich, 2016). People's characteristics influence the capacity to anticipate, cope with, resist to, and recover from the impact of Hazards (Wisner et al., 2004). Therefore, identifying those more prone to suffer losses or that would find more difficult to recover is vital to Risk and Disaster management (Chen, Cutter, Emrich, & Shi, 2013; Cutter et al., 2013; Fuchs, 2009).

Despite being called 'Social' Vulnerability, it is a construct of different dimensions that amplify or reduce Vulnerability to Hazards, including social (i.e. poverty, racial discrimination), demographic (i.e. age, gender), economic (i.e. employment) and build environment (i.e. medical facilities) aspects, and Social Vulnerability assessment should include those dimensions (Jorn Birkmann, 2006a, 2006c; Chen et al., 2013; Cutter et al., 2003; Hewitt, 1997; Wisner et al., 2004). The factors that influence how Hazards impact individuals and communities and are, therefore, most often used in Social Vulnerability assessment include: age, race, gender, income, education attainment, professional activity and income levels, unemployment, population growth, family structure, special needs population (i.e. physical or mental impairments), behaviour and Risk perceptions, social or family support networks, house property, lack of access to resources (i.e. information, technology, political representation), social dependency, immigrants, homeless, prevalent economic sector, rural or urban area, buildings' quality, infrastructure and lifelines (i.e. medical, police, transportation) (Birkmann, 2006; Cutter, 2001; Cutter, Boruff, & Shirley, 2003; Cutter et al., 2000; Hewitt, 1997; Schmidtlein, Deutsch, Piegorsch, & Cutter, 2008; Tierney, Lindell, & Perry, 2001; Wisner, Blaikie, Cannon, & Davis, 2004).

According to Cutter et al. (2003), there are three main Vulnerability research perspectives. The first, Exposure model, assumes Vulnerability as a pre-existing condition and focuses on the spatial distribution of Hazards and people and assumes that exposure and proximity to Hazards is determinant when considering Vulnerability and that those living in Hazard susceptible areas are inherently more vulnerable (Anderson, 1995; Cutter, 1996; Cutter et al., 2003, 2000). The priority is to reduce exposure and promote coping and recovery capacity by predicting Hazards and building protective infrastructures (Anderson, 1995; Cutter, 1996; Cutter et al., 2003). This model does not account for the fact that disasters impact differently people living in areas with the same level of exposure and, thus, socioeconomic context must also be considered (Anderson, 1995; Cutter et al., 2000; Hummell et al., 2016)

The second model views Vulnerability as a social response to Hazards (Cutter, 1996; Cutter et al., 2000). The nature of the Hazard event itself is usually taken as a given, and the focus is the social construction of Vulnerability rooted in the underlying historical, cultural, social and economic context, as well as people's perceptions, behaviour and decisions, that create an unsafe context and greatly influence the individual or society's ability to deal with Hazards (Anderson, 1995; Cutter, 1996; Cutter et al., 2003; Wisner et al., 2004).

The third approach, Hazards-of-Place, integrates the previous two models and considers that both Exposure and Social response are relevant. Both Susceptibility to Hazards and Vulnerability are space specific, manifesting themselves geographically and can, therefore, be integrated to reveal the Place Vulnerability (Cutter, 1996; Cutter et al., 2003). Different combinations of different levels of Susceptibility and Exposure to Hazards and different degrees of Social Vulnerability result in a Place Vulnerability pattern that allows to prioritize areas of intervention (Cutter, 1996; Cutter et al., 2003). This is the same rationale of the concept of Risk, product of Hazards and Vulnerability, but in this dissertation we will refer to the result as Place Vulnerability, instead of Risk, as that is the nomenclature defined in the Hazards-of-Place model.

Social Vulnerability is a multidimensional construct, complex to measure (Cutter et al., 2003), not easily captured with a single variable nor easily quantifiable (Cutter & Finch, 2008). Being a relatively recent field of research, is still in the process of developing and consolidating methodologies to assess and compare different places with a comprehensive, robust, scale and context adjustable metric (Cutter et al., 2003; Rygel et al., 2006).

Vulnerability Science uses Qualitative and Quantitative methods to describe and operationalize Vulnerability (i.e. analytical approaches, contextual and statistical analyses, GIS and mapping techniques) (Jorn Birkmann, 2006b, 2007; Jorn Birkmann & Wisner, 2006; Cutter, 1996; Cutter et al., 2003; Cutter & Corendea, 2013; León, 2006; Lundgren & Jonsson, 2012; Moret, 2014). Qualitative methods are usually applied at local level but have been fundamental to identify and understand the influence of key Vulnerability drivers and better understand the process of Social Vulnerability construction (Jorn Birkmann, 2006a; Tate, 2011).

Quantitative methods have used the insight collected from qualitative studies to develop indexes of Vulnerability (Tate, 2011). Social Vulnerability assessment should include the context characterization, identification of drivers and implementation of a quantitative model (Polsky, Neff, & Yarnal, 2007).

An often used approach is simplifying the complexity of Social Vulnerability into a simple metric using indicators or indexes (Tate, 2011). Indicators may use one variable or a combination of variables, measuring the variable of interest directly or another that serves as a substitute, adjusted for statistical purposes (i.e. percentage), and aims to represent a characteristic of a system (Gall, 2007; Tate, 2011). Indexes are composite indicators, combining two or more indicators into one single score that represents an abstract theoretical construct (Gall, 2007; Tate, 2011). Social indicators have been used for several decades, but more complex Vulnerability indexes are more recent, with different variable and scale selection. Subnational Social Vulnerability indexes are less prevalent (Tate, 2011).

Vulnerability indexes attract growing interest as a tool to understand, measure and monitor Social Vulnerability, compare it over time and space, present a complex reality in simple terms, creating new information not easily perceptible otherwise and facilitating its communication (Gall, 2007; Rygel et al., 2006; Tate, 2013).

An index representing Social Vulnerability in a single metric, comparable across time and space and widely accepted, would be extremely valuable but also extremely difficult to obtain due to the difficulty of developing and validating indexes (Rygel et al., 2006; Tate, 2011). There are many practical and methodological challenges: subjectivity in variable selection and weighting; scale and data aggregation; data accuracy, aggregation and availability at different scales; difficulties validating the results because Social Vulnerability cannot be measured directly; simplify, without becoming over simplistic; not being so complex as to mask the underlaying structure and causes (Jorn Birkmann, 2007; Cutter et al., 2003; Eakin & Luers, 2006; Gall, 2007; Rygel et al., 2006; Tate, 2011).

Despite these issues, indicators and indexes have been developed to different scales, contexts and objectives, offering a way of reducing the complexity of Social Vulnerability, allowing to compare, map and communicate it (Jorn Birkmann, 2007; Fekete, Damm, & Birkmann, 2010; Gall, 2007; Tate, 2011).

The accuracy of Social Vulnerability indexes is paramount but the validation of such indexes is not a consolidated area (Rygel et al., 2006; Tate, 2011). While environmental models are often validated with an independent data set, with Social Vulnerability this is much more difficult because Social Vulnerability is not tangible or directly observable, and because there is no device to measure it, the use of proxy measures is required (Tate, 2011). Indicators often used for validating Vulnerability include mortality, injured, damage to buildings, economic losses, forced migration (Tate, 2011). These and other indicators do not account for all types of losses (i.e. trauma, impairing anxiety, loss of possessions with affective value, a child growing without its parents). In any case, those measures use the consequences of post-event as a validation of implicit Social Vulnerability, but indexes generally represent pre-event conditions (Tate, 2011).

Alternative approaches perform internal validation of indexes by examining how changes in the algorithm affect results (i.e. sensitivity analysis), analysing indexes' inherent uncertainty, and comparing indexes (Beccari, 2016; Gall, 2007; Schmidtlein et al., 2008; Tate, 2011).

SOVI should be seen as an algorithm for quantifying Social Vulnerability and is a particularly reliable, recognized and widely used index and the ability to replicate it using different scales and data unit aggregations, variables and regional contexts with similar performance, suggests it is a fairly robust algorithm (Armaș & Gavriș, 2013; Borden et al., 2007; Boruff et al., 2005; Burton & Cutter, 2008; Chen et al., 2013; Cutter et al., 2006; Cutter & Finch, 2008; Guillard-Gonçalves, Cutter, Emrich, & Zêzere, 2015; Hummell et al., 2016; Mendes, 2009; Schmidtlein et al., 2008). SOVI uses a Principal Components Analysis with variables representing different dimensions of Social Vulnerability, chosen based on empirical and theoretical studies and that should be adjusted to context specificities (Burton & Cutter, 2008; Chen et al., 2013; Cutter et al., 2003). It has evolved over the years benefiting from the use of the algorithm and growing understanding about the driver variables affecting Social Vulnerability (Chen et al., 2013; Mendes, Tavares, Freiria, & Cunha, 2009).

Social Vulnerability encompasses both the sensitivity of a population to Hazard and its ability to respond to and recover from its impact. These are two complementary but not equal dimensions. Some authors consider that it may not be adequate to join in the same Component individual (i.e. age, income, gender) and structural characteristics (i.e. lifelines like medical or police facilities) that influence Social Vulnerability (Eakin & Luers, 2006; Mendes et al., 2009; Prescott-Allen, 2001). In fact, SOVI algorithm's result may aggregate in the same Component variables about both people's sensitivity and proneness to suffer losses and characteristics that helps them to resist and recover. To address that, Mendes *et al*. (2009) created the Social Vulnerability Index to Natural and Technological Hazards (SOVI_NTH), replicating the rationale of SOVI but with a two stage process that allows to assess these two dimensions separately, Criticality (i.e. characteristics or behaviour that contribute to the disruption of the system) and Support Capacity (i.e. social resources that help to react, resist and recover) as well as a final overall Social Vulnerability score, thus also providing extra information for Risk governance (Cunha et al., 2011; Mendes, Tavares, Cunha, & Freiria, 2011; Mendes et al., 2009).

2.4. Hazards-of-Place

The model Hazards-of-Place was first proposed by Cutter and Solecki (1989) to examine the distribution of Hazards and processes that give rise to them. They questioned whether certain places are more at Risk only due to their geographic location (Cutter & Solecki, 1989). 'Hazardousness' was perceived as a function of both Risk factors (i.e. incident-specific and contextual variables that increase the likelihood of losses) and mitigation factors (i.e. that lessen the Hazard potential) (Cutter & Solecki, 1989). Additionally, they intended to explore Multi-Hazards analysis and intersect it with vulnerable populations (Vulnerability), which was not, at the time, a common approach (Cutter et al., 2000).

This approach build upon previous research, including Kasperson et al. (1988) that suggested that Risks interact with cultural, social, and institutional processes that reduce or amplify their impact and limit or heighten public response (Cutter et al., 2000; Kasperson et al., 1988). The results from practical applications showed that areas more biophysically susceptible to Hazards don't always coincide with the more vulnerable populations (Cutter et al., 2000). Areas with higher Risk but significant mitigation capacity may be less hazardous than areas with lower Risk but no mitigation efforts (Cutter & Solecki, 1989). Areas of greater economic affluence may in the case of a disaster represent greater amount of economic losses, but that population may, simultaneously, have greater resources to absorb and recover (Cutter et al., 2000). Conversely, a moderate intensity Hazard may have devastating consequence if it affects an area of economically and socially deprived population (Cutter et al., 2000).

As the model was subsequently developed (Figure 1), it proposed that Risk (i.e. likelihood of a Hazard event occurring, the consequences of the Risk itself, and an estimate of its frequency of occurrence) interacts with Mitigation (i.e. actions to reduce Risks or lessen their impacts such as planning or structural improvements in buildings) creating Hazard Potential, which can be reduced or amplificated by the Geographic Context (i.e. biophysical characteristics that affect phenomenon frequency and intensity) and the Social Fabric (i.e. contextual variables that affect the impacts of the phenomenon, including economic, demographic, and housing characteristics) (Cutter, 1996; Cutter et al., 2003, 2000).

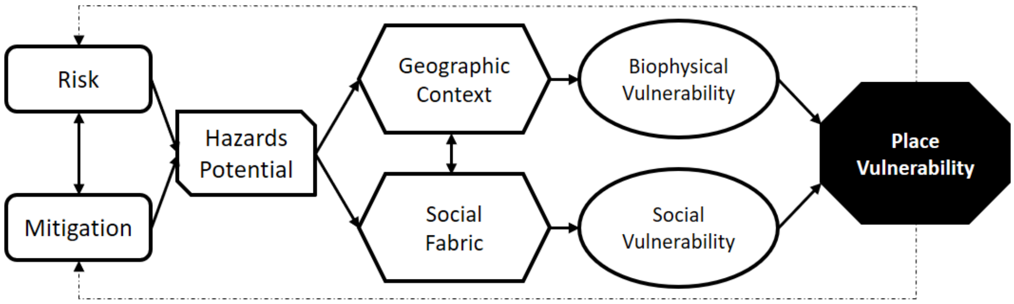


Figure 1: Hazards-of-Place Model. Adapt. Cutter, et al. (2003)

The Geographic Context and Social Fabric interact with the Hazard Potential resulting respectively in Biophysical Vulnerability (i.e. underlying biophysical elements that contribute to Vulnerability) and Social Vulnerability (i.e. underlying Social elements that contribute to Vulnerability). These, in turn, combine in an overall Vulnerability of a specific place and the people who live there (Cutter et al., 2003, 2000).

Hazards-of-Place offers a method for assessing Place Vulnerability in spatial terms using both biophysical and social underlying elements, assess their interaction and intersection and how they affect places, highlighting those simultaneously socially vulnerable and exposed to Hazards (Cutter, 1996; Cutter et al., 2003, 2000)

Risk is seen as the product of the probability of an event (Hazards) and its potential negative consequences (Vulnerability) (UNISDR, 2004, 2009) and Risk analysis should, therefore, include the combination of information (i.e. data analysis, map overlaying) about Hazards, Exposed Elements and Vulnerability (Randolph, 2004). The Hazards-of-Place model offers a conceptual framework to this approach and is the one we adopt in this research.

To operationalize this model we calculated Social Vulnerability and used existing Hazards Susceptibility maps to combine into the overall Place Vulnerability (Cutter et al., 2000). This combination of Hazard and Vulnerability follows the rationale of the Risk equation, but we will refer to this combination using the terminology of this model – Place Vulnerability. The model can be applied to one Hazard or multi-Hazard to address several Hazards concurrently (Cutter et al., 2000).

2.5. Importance of Scale

The word scale is used with different meanings, to some extent contradictory (Longley, Goodchild, Maguire, & Rhind, 2005). There are different types of scales (i.e. spatial, temporal) and researchers also refer to scale of the phenomenon and scale of observation. The first refers to the scale or extent at which the phenomenon or process manifests itself. The scale of observation refers to the way we measure or observe it and includes the extent (i.e. small or large area of observation) and spatial resolution (i.e. density or data aggregation) (Fekete et al., 2010). Spatial resolution includes finer scales (i.e. more detailed, small statistical units) and coarser scales (i.e. more aggregated data) (Longley et al., 2005).

The scale of a map refers to the ratio of distance on the map and the real distance. Large scale maps represent a small area but with many details (i.e. city block) and small scale maps illustrate a larger area but with little detail (i.e. continents) (Longley et al., 2005). In this research, the extension of the analysis is the island of Madeira and resolution includes three different data aggregation units, from the finer data aggregated by sub-block and block, to coarser aggregation by parish. We refer to each statistical spatial entity as data aggregation units.

Scale and data aggregation can potentially create some problems like the Modifiable Areal Unit Problem (MAUP) and the Ecological Fallacy. The MAUP happens when data measures of spatial phenomena are aggregated using artificial boundaries and the resulting patterns are influenced by the shape and size of the aggregation units. The same individual may be differently represented by the aggregated values depending on the shape and size of the aggregation unit (Fekete et al., 2010; Jenerette & Wu, 2000; Longley et al., 2005).

The Ecological Fallacy is a logical fallacy in the interpretation of statistical data that may occur when generalizing from observations made on one level to another. This happens when a statistical value that has been calculated for a group is assigned to a member of that group. Because when considering a statistical unit and a value that was assigned to it we cannot be sure that a given individual inside that unit has the same value, there is always some degree of uncertainty – the Ecological Fallacy (Fekete et al., 2010; Longley et al., 2005).

Parish is the smallest administrative level in Portugal. Block and sub-block are created by the National Institute of Statistics (INE) as smaller, homogeneous units representing agglomerates of residencies within a community. This, however, does not exclude the possibility of the results being affected by MAUP and Ecological Fallacy.

For Disaster Management and Social Vulnerability assessments scale is important because it affects both the level of detail of represented elements and the accuracy of data and should be adequate to the objectives (Fekete et al., 2010; Tomaszewski, 2014). Because systems operate at different scales, and systems at different scales interact, multi-scale analysis of

Social Vulnerability provides a more holistic approach and a way of simplifying the integration of scales is to analyse each scale separately (Fekete et al., 2010).

Different scales allow different levels of policy and decision making (Cunha et al., 2011; Eakin & Luers, 2006). A more coarse Social Vulnerability analysis and cartography (i.e. data aggregated by regions) informs decision makers' strategic and structural decisions but the broader patterns obtained may sacrifice local patterns and asymmetries (Cunha et al., 2011; Gall, 2007; Mendes et al., 2009). A finer approach will show local patterns and asymmetries that can be used for more operational specific interventions (Cunha et al., 2011; Fekete et al., 2010; Gall, 2007).

An assessment model performing consistently at different scales and data aggregations, will allow to compare how Social Vulnerability expresses differently at each scale and use it to create specific Risk and disasters prevention and mitigation policies (Mendes et al., 2009).

Retained components and variables may vary slightly at different scales because drivers of Social Vulnerability and their relevance at different scales also differs (Mendes et al., 2009), but if the same set of variables is used, the identification of Social Vulnerability drivers will not be greatly affected by the scale of data aggregation (Schmidtlein et al., 2008). Analysis at different scales can be used to compare and validate their performance and patterns (Fekete et al., 2010). SOVI was created for counties but SOVI analysis can be performed using data with other resolution, including smaller aggregation units (Cutter et al., 2000).

In Madeira, particularly in the case of floods, debris-flows and, in less degree, landslides, the affected areas have such a limited spatial expression, although the impacts can be great, that using a small size of unit analysis is necessary.

3. SOCIAL VULNERABILITY IN MADEIRA

3.1 Introduction

Social Vulnerability science emphasizes that disasters are not just a product of the intensity of the extreme event but also the underlying Social Vulnerability, resulting from different demographic, socioeconomic and build environment factors that influence the capacity to cope with, resist to and recover from Hazards (Chen et al., 2013; Cutter et al., 2003; Hewitt, 1997; Wisner et al., 2004). Methodologies to assess Social Vulnerability should include the characterization of the study area, identification of the Vulnerability drivers and the implementation of a quantitative model (Polsky et al., 2007).

In this chapter we illustrate the implementation of two Social Vulnerability indexes that provide a relative measure to compare between different areas and facilitate the identification of priority areas of intervention (Frazier, 2012; Mendes et al., 2009).

SOVI is a particularly reliable, recognized and widely used index that can be replicated with different scales, indicators and regional contexts with similar performance, having a proven track of successful application to different areas, which suggests it is a fairly robust algorithm (Armaș & Gavriș, 2013; Borden et al., 2007; Boruff et al., 2005; Burton & Cutter, 2008; Chen et al., 2013; Cutter et al., 2006; Cutter & Finch, 2008; Guillard-Gonçalves et al., 2015; Hummell et al., 2016; Mendes, 2009; Schmidtlein et al., 2008).

Some authors argue that SOVI may join in the same Components variables regarding people's characteristics that make them vulnerable and the structural context that helps them to cope and resist, and that this is not the best approach (Eakin & Luers, 2006; Mendes et al., 2009; Prescott-Allen, 2001). SOVI_NTH addresses that issue with a two stage process that allows to assess these two dimensions separately: Criticality (i.e. characteristics or behaviour that contribute to the frailty and disruption of the system) and Support Capacity (i.e. social resources that help to react and resist), as well as a final overall Social Vulnerability score (Cunha et al., 2011; Mendes et al., 2011, 2009).

Different data aggregation when analysing Social Vulnerability produces different spatial patterns and using smaller units reveals spatial asymmetries that are not shown when using a coarser resolution. The indexes algorithms are sensitive to the number and size of data statistical units, thus creating some challenges regarding the algorithm's performance (Schmidtlein et al., 2008). Testing index performance in the context of Madeira, as well as its sensitivity to scale and data aggregation, is an important step to validate and create acceptance for the subsequent results of the analysis of Social Vulnerability. Comparing the performance of SOVI and SOVI_NTH will allow to validate the applicability, if not even preferability, of using the SOVI_NTH version.

The analysis of performance and results of both indexes, with each unit of data aggregation, will use a set of performance and statistical parameters. To compare both indexes we will use not only statistical performance parameters but also more conceptual aspects. If the analysis determines the indexes perform well and the resulting Social Vulnerability patterns are credible in this specific context, they can be a useful spatial planning tool for those responsible for managing disasters (Chen et al., 2013; Cutter & Finch, 2008; Mendes et al., 2009).

Mapping Social Vulnerability using a simple comparative map may be an important communication tool to illustrate the patterns, distributions, asymmetries, drivers as well as the interaction with Hazards Susceptibility (Chen et al., 2013).

In this chapter we assess Social Vulnerability in Madeira island using SOVI and SOVI_NTH and three different data aggregation units. The objective is not just to illustrate Social Vulnerability patterns in Madeira but also to compare the indexes' performance and results, analyse the sensitivity to changes in scale and data aggregation and test the applicability in very small statistical units.

3.2 Study Area

The Archipelago of Madeira (Figure 2) is located between the 30º01'N and 33º08'N parallels and the 15º51'W and 17º16'W meridians, in the North Atlantic. It includes the Islands of Madeira, Porto Santo, Desertas' islands and Selvagens' islands. The archipelago is located to the Southwest of the Iberian Peninsula, North of the Canaries and the Southwest of Continental Portugal - 950 km Southwest of Lisbon (M. Ribeiro & Ramalho, 2007).

Madeira is the largest island of the archipelago with around 740 km^2, an elongated, almost rectangular form, with a length of about 58 km in the E-W direction and a width of 23Km in the N-S direction, with 10 municipalities that account for over 92% of the archipelago area and over 98% of its population (Brum da Silveira, Madeira, Ramalho, Fonseca, & Prada, 2010; M. Ribeiro & Ramalho, 2007; O. Ribeiro, 1985).

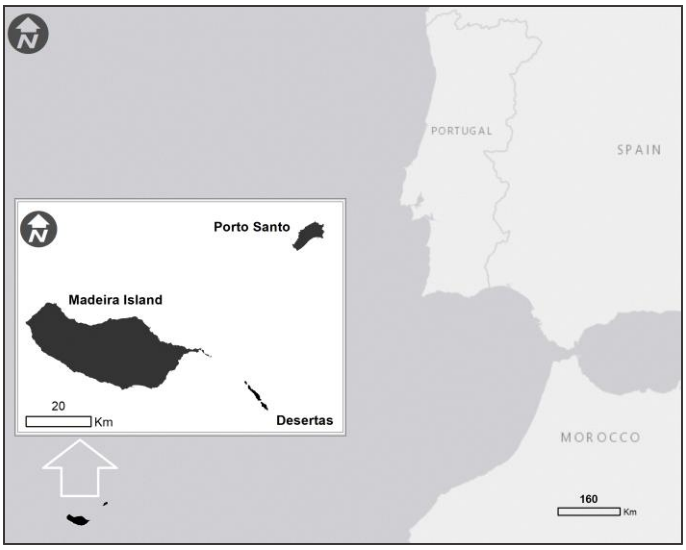


Figure 2: Location of Madeira

The island is constituted mainly by volcanic rocks, with some sedimentary formations of limited importance associated to the erosion of igneous rocks (A. Almeida et al., 2003; M. Ribeiro & Ramalho, 2007).

The erosion and drainage characteristics of the basaltic rocks, the layers of basalt intercalated with pyroclastic materials, fractured basalt, existence of deposits of mass movements and alluvial fans, declivity of the landforms, slope instability and the frequent events of extreme precipitation, creates a combination of factors that favors the occurrence of rockfalls, topples, major landslides and debris-flows (Brum da Silveira et al., 2010; Quintal, 1999; Rodrigues, 2005). The island is distant from the Atlantic Rift (1600km to the East) and the Azores-Gibraltar Fault (500km to the South) and has no significative Risk of volcanic or seismic events, but seismicity, even if low intensity, can trigger landslides, particularly if occurring during or immediately after intense precipitation (Brum da Silveira et al., 2010). Although very unlikely, the volcanic and seismic events are not completely ruled out (Brum da Silveira et al., 2010; Prada, 2000).

Madeira's landscape is marked by high peaks and deep and eroded valleys (Ribeiro, 1985). The average altitude is 646 m, about 95% of the territory is above 500 meters and about a quarter has an altitude above 1000m, being the percentage of area below 100 m of altitude only residual (A. Almeida et al., 2003; M. Ribeiro & Ramalho, 2007; P. Silva, 2007).

The average slope of the island is 56% and about two-thirds of its area has a slope higher than 25%. The morphology of the island, particularly the irregular relief, was influenced by the volcanic structures, the youth of its relief and the nature of its rocks, the presence of alternations, in varying thickness, of materials with very different characteristics - very strong basalts and extremely friable pyroclastic materials. Sea level variations, rainfall and time of exposure to erosion agents were also determinant in the creation of landforms (A. Almeida et al., 2003; Brum da Silveira et al., 2010; Carvalho & Brandão, 1991; M. Ribeiro & Ramalho, 2007; P. Silva, 2007).

Precipitation events create superficial drainage and rivers of torrential regime, that erode depressions, particularly in soft permeable pyroclastic materials, leaving abrupt slopes that often collapse due to gravity and slope instability (Carvalho & Brandão, 1991). Pyroclastic rocks, when in contact with the atmospheric agents, disintegrate rapidly, thus allowing their rapid transport by rainwater and rivers (M. Ribeiro & Ramalho, 2007). These characteristics contribute to the frequency of landslides, rockfalls and debris-flows, known locally as '*Aluviões'*.

On the coast, erosion produced high cliffs, interspersed by coves where small shingle beaches are formed and with vestiges of major topples and rockfalls, especially on the North coast of the island**.** The retreat of the coast depends on the energy of the sea and the resistance of the rocks. Rockfalls and topples are natural Hazards that occur frequently (Nascimento, 1990; Prada, 2000; M. Ribeiro & Ramalho, 2007). There are also records of major landslides in coastal cliffs causing tsunamis, including one in 1930 that killed 29 people (Rodrigues, 2005).

The climate of Madeira is strongly influenced by the Azores Anticyclone, Latitude, atmospheric circulation, exposure and relief (Brum da Silveira et al., 2010). The great local variability in the distribution of precipitation and temperature values in the island is due to the irregular relief, differences in altitude, shape and orientation of the island approximately perpendicular to the direction of the prevailing North-easterly winds (A. Almeida et al., 2003; Prada, 2000). The East-West orientation of the central mountain range and plateaus, with altitudes above 1200m, almost perpendicular to the prevailing North-easterly winds, determines a protected and sunny South slope, and a more exposed and rainy North slope.

Madeira's climate has similarities with Mediterranean climate (Ribeiro, 1985), though smoother, predominantly temperate with oceanic influence (A. Almeida et al., 2003; Machado, 1970). The Northern slope of the island, due to its exposure and prevailing winds, has more precipitation and lower temperatures than the Southern slope. The average annual air temperature varies between 9º C and 19º C and temperatures below 0ºc are rare and limited to high altitude areas (A. Almeida et al., 2003). The weighted average annual precipitation in Madeira is 1689 mm, with values between 600mm and 2900mm, concentrated mainly between October and April (A. Almeida et al., 2003). Northern and Northeasterly winds are prevailing, and the average maximum speed stays under 30 km/h.

In Winter, the depression systems that cross the Atlantic, influenced by the anticyclone of Western Europe or the Polar Front, sometimes affect Madeira causing abundant precipitation in a short time, triggering flash floods and debris-flows as well as landslides and rockfalls (A. Almeida et al., 2003). Occasionally, East winds from the Sahara accompanied by masses of hot dry air cause high temperatures and low Relative Humidity periods, favorable to severe forest fires (A. Almeida et al., 2003).

The rivers of Madeira Island present characteristics typical of mountain rivers, running in generally deep and narrow valleys flanked by enormous cliffs and diverge from the central peaks of the island flowing roughly perpendicular to the coastline (A. Almeida et al., 2003; M. Ribeiro & Ramalho, 2007). Almost all major streams have slopes greater than 1200m and extensions that rarely reach 20 Km (A. Almeida et al., 2003). The rivers of Madeira Island have torrential regime during the winter and dry in the summer, reflecting the relief of the islands and the precipitation regime (A. Almeida et al., 2003; M. Ribeiro & Ramalho, 2007).

Rivers with major longitudinal slopes and narrower valleys occur in areas of mostly non-altered basaltic mantles. Where there is a predominance of pyroclastic levels or deeply altered mantles, wider valleys occur. Extremely concentrated precipitation and very fast flow of water in steep narrow valleys, combined with basins with a small time of concentration and the abundance of eroded solid material in instable slopes, creates the conditions for the occurrence of very destructive floods, debris-flows and landslides that are among the most destructive Hazards in the island (Policarpo, 2012; Rodrigues, 2005; Sepúlveda, 2011).

The island of Madeira has a diverse vegetation, from xerophyte vegetation on the coast, followed by transition forest and by Laurissilva forest, located between 600 and 1300m in altitude, to Urzal vegetation at higher altitude areas (Quintal, 1996). Large areas, about 2/3 of the island, are protected areas, including Laurissilva forest. Vegetation plays a very important role in the defense against erosion on the steep slopes of the Island and is a key aspect of managing geomorphological and hydrological Risks (i.e. erosion, landslides, floods, debris-flows) (Pimenta de França, 2003; Quintal, 1996; SRA, 2003). Forest area occupies a large part of the island, mainly Laurissilva forest. According to the Corine Land Cover 2012, forests occupy 44% of the island, urbanized areas 15%, agricultural areas 15% and natural pastures and moors 18%.

Madeira Island, with its ten municipalities (Figure 3), has a population of 262302 (47% are men), which is 98% of the archipelago population. The daily floating population, mainly due to tourism, is around 20000 people. Funchal is the most populated municipality with 111892 inhabitants (43%). The Southeast municipalities, Santa Cruz (43005), Câmara de Lobos (35666), Machico (21828) and Funchal concentrate 81% of the island’s population which is evidence of territorial asymmetries. The less populated municipalities are in the North: São Vicente (5723), Porto Moniz (2711), and Santana (7719) (INE, 2012).

Figure 3: Municipalities in Madeira

Population density varies greatly between municipalities like Funchal (1470 per km^2) or Câmara de Lobos (684 per km^2) and the Northern municipalities of Porto Moniz (33 per km^2), São Vicente (73 per km^2) and Santana (81 per km^2) (INE, 2012). Madeira has a dominantly adult population with 16% of young people under 15 years old and 15% over 64 years old. Here the spatial asymmetries are also significant with the five North-western municipalities (Ponta do Sol, Calheta) and the Northern municipalities (Porto Moniz, São Vicente and Santana) having higher percentages of older population and, conversely, lower percentage of younger population. Porto Moniz, for example, has more than two times the number of people over 64 when compared with people under 15 (INE, 2012). The ratio of population over 75 years old is also significant in the Northern municipalities. Considering the ratio of young adults (20-29) and older adults (55-64), the differences between the North and South of the island are also evident, a tendency that accentuated over the inter Census period (INE, 2012).

About 16% of the population over four years old has some disability or impairment (i.e. sigh, audition, walking, memory, cognition), being mobility the main impairment. Among people over 64 years old the percentage of people with disability or impairment grows to over 50%. This trend reflects naturally on a major prevalence of these population in the more aged municipalities in the North of Madeira (INE, 2012).

Analphabetic population (over nine years old) represents 7% of the population, with strong asymmetries between the South-eastern municipalities and the North of the island where that percentage doubles. The same spatial pattern can be seen when analysing the percentage of population over 14 years old with no formal degree, that is far greater in the Northern municipalities and also Ribeira Brava in the South (INE, 2012). Almost half the population finished at least the Third Cycle of Education (9th grade), and almost 30% the Secondary Education, with higher values in South-eastern municipalities and much lower in the North and also Câmara de Lobos. Higher education was only achieved by 13% of the population and they concentrate in the more urban, young and dynamic municipalities of Funchal and Santa Cruz, where it reaches 17% of the population, while in the Northern municipalities and Câmara de Lobos it is little more than a third of that (INE, 2012).

Active population represents 57% of the population over 14 years old, with a difference of almost 10 percental points between genders in favour of men (INE, 2012). Active population percentage is lower in the three more aged municipalities in the North. The unemployment rate was high in 2011 (14%), in the middle of an economic crisis, and was bigger for men (16%) than women (12%), a reflect of the crisis that hit the economic sector of construction. Unemployment is prevalent among younger population exceeding 50% of those between 15 and 19 years old and almost a third of those between 20 and 24 years old. Unemployment is higher among men with only First or Second Cycle of Education and women with only Third Cycle and Secondary Education (INE, 2012).

The employed population in the RAM is mainly concentrated in the tertiary sector (80%) and the primary sector is residual (3%). Nevertheless, the regional economy and the employment market depend essentially on trade, services and activities linked to tourism (INE, 2012). In Madeira the importance of tourism is evident, as it represents a direct contribution to the GDP of more than 20% and a total contribution that is expected to approach a third of the GDP (IDR, 2013). The more economically dynamic municipality is Funchal, followed by the surrounding municipalities. The North of the island has a much less developed economy.

The more populated municipalities mentioned before concentrate the majority of the island's 88238 buildings and 124683 family residences, particularly Funchal that alone holds 33% of buildings and 42% of family residences (INE, 2012). The percentage of very degraded building was under 2% but the percentage of those needing repairing exceed 30%. The spatial pattern is less regular than in other indicator mentioned before but is noticeable that Funchal has 36% of building needing repairs which is significant because it has one third of the total number of building in Madeira (INE, 2012).

3.3 Methods and Data

In this chapter we test the application of Social Vulnerability Index (SOVI) proposed by Cutter et al. (2003) and an alternative version developed by Mendes et al. (2009).

Both indexes use Principal Component Analysis (PCA). PCA is a technique of variable reduction used when we have a large number of variables, allowing to reduce them into a smaller set of independent variables, linear combinations of the original variables, called Principal Components (O'Rourke & Hatcher, 2013). These account for most of the Variance of the original variables and can be used in subsequent analyses, with the advantage of being easier to analyse and interpret (Chen et al., 2013; Marôco, 2014; O'Rourke & Hatcher, 2013). Each Component explains a part of the total Variance of the data, and the more Variance a Component can explain, the more information it contains (Chen et al., 2013). The first Component accounts for a maximal amount of total Variance of the observed variables and the second and subsequent Components account for a maximal amount of the Variance not captured by the previous ones (O'Rourke & Hatcher, 2013). Components measure different dimensions of the data and are uncorrelated in order of their importance, only describing data variation (Burton & Cutter, 2008).

Social Vulnerability is a multidimensional construct not representable by one single variable (Cutter & Finch, 2008) demanding the analysis of different facets (Cutter et al., 2003). SOVI algorithm simplifies the analysis of a large number of input variables by reducing them to a robust and consistent small number of Components that broadly reflect the main dimensions of Social Vulnerability and account for most of the data variability (Burton & Cutter, 2008; Chen et al., 2013; Cutter et al., 2003; Cutter & Finch, 2008; Schmidtlein et al., 2008). Because the results are highly dependent on the input variables it is important to carefully select them, as well as determining their effect on Social Vulnerability (i.e. Cardinality) (Burton & Cutter, 2008). PCA is sensitive to missing data and when a variable has missing data it should be excluded or substituted by some alternative (i.e. average) (Chen et al., 2013; Cutter et al., 2003; O'Rourke & Hatcher, 2013). Areas with no population or buildings should not be considered because they do not have Social Vulnerability indicators.

A Varimax Rotation should be used to obtain the best combination of variables, simplifying the structure of underlying dimensions and produce more robust set of independent Components (Cutter et al., 2003; Cutter & Finch, 2008; Hummell et al., 2016).The purpose of this rotation is to obtain a factorial Component structure in which each variable is only strongly associated with one Component, and each Component is defined by only a small number of variables, maximizing the Variance explained by a small number of Components and simplifying their interpretation (Abdi, 2003; Chen et al., 2013; Cutter et al., 2003; Guillard-Gonçalves et al., 2015; HVRI, 2010; Kaiser, 1958; Schmidtlein et al., 2008).

The number of Components is defined using the Kaiser Criterium – only Components with eigenvalues (i.e. amount of Variance captured by a Component) higher than 1 are retained (Cutter et al., 2003; HVRI, 2010; O'Rourke & Hatcher, 2013; Schmidtlein et al., 2008). This can result in an inadequate number of Components (i.e. if eigenvalue is 0.99) and results can be improved by combining this criterium with others: Scree Test, desired percentage of explained Variance retained by selected Components and interpretation of Components (Marôco, 2014; O'Rourke & Hatcher, 2013).

To validate weather the factorial model explains well the correlations existent in the original variables, several parameters are used, including minimum Communalities, Kaiser–Meyer–Olkin (KMO) and Components explained Variance (Marôco, 2014). Communality is the part of Variance in an observed variable that is accounted for by the retained Components. High Communality means that it loads heavily on at least one of the Components and that variables are adequately correlated for a factor analysis. A value of 0.6 means at least 60% of the variables' Variance is explained by the resulting Components (Marôco, 2014; O'Rourke & Hatcher, 2013; Tavares et al., 2015). With high Communalities, a good performance can be reached almost regardless of sample size (Maccallum, Widaman, Preacher, & Hong, 2001). Thus, using samples smaller than traditionally recommended is accepted if Communalities are high (Mendes, 2009; O'Rourke & Hatcher, 2013).

KMO is a measure of sampling adequacy that compares the simple correlations with partial correlations between some variables. It varies between 0 and 1 and higher values indicate that the extracted Components are reliable (Marôco, 2014). Values greater than 0.5 are acceptable (Kaiser & Rice, 1974), but a value of more than 0.7 is a common threshold for good performance (Hair, Black, Babin, & Anderson, 2010; Kaiser & Rice, 1974). Bartlett's Test of Sphericity is also used and should be significant (below 0.05), meaning the variables considered in the analysis are correlated but Components are independent between them (Marôco, 2014).

Frequently used SOVI parameters include minimum Communalities of 0.6, KMO above 0.7, and explained Variance above 70% (Burton & Cutter, 2008; Chen et al., 2013; Cutter et al., 2003; Cutter & Finch, 2008; Guillard-Gonçalves et al., 2015; Hummell et al., 2016; Mendes, 2009; Mendes et al., 2011; Schmidtlein et al., 2008; Tavares et al., 2015).

Additionally, the model quality may be signaled by low percentage of residuals above 0.05 (i.e. SPSS Reproduced Correlations Matrix), and variables with Measure of Sampling Adequacy (MSA) in the Anti-Image Matrix above 0.5, meaning they are well adjusted within the resulting factorial model and should be kept (Marôco, 2014).

PCA performance is affected by the number of cases and the level of data aggregation. A minimum number of cases is needed to PCA, and although there is no absolute rule about exactly how many those cases should be, a common reference is a minimum number of cases above 100 or a number of cases above five times the number of variables being analysed (Garson, 2009; O'Rourke & Hatcher, 2013). A smaller number of cases can be used but, in that case, it is important to ensure good KMO and Communalities values (Maccallum et al., 2001; Mendes, 2009). Using small statistical units creates a high number of cases, but it may result in a more elevated number of Components and a smaller percentage of explained Variance (Schmidtlein et al., 2008).

In this dissertation, because we wanted to test data aggregation sensitivity and compare two indexes, it was important to use variables available for both indexes and data aggregation units, which affected the choice of variables. For example, it is possible to use the ratio Health Centre/inhabitants to compare parishes. However, this would not be ideal to compare blocks or sub-blocks. If all blocks are assigned the value of the parish, all blocks within that parish would have the same value and the comparative usefulness would be limited. If the number of Health Centre in each parish (one) was divided by the number of people per block it would also not be ideal because two blocks with different populations would get very different ratios, although served by the same and only Health Centre of the parish.

Alternatively, distance to each facility was used because it can be calculated for each statistical unit (i.e. parish, block or sub-block) and in the case of disasters the distance to critical facilities is, in fact, relevant. On the other hand, there were cases where to cover a given dimension of Social Vulnerability only variables per parish were available, but given the inexistence of valid alternatives, it was judged pertinent to use them.

The dynamic nature of the algorithm's steps, when calculating both indexes and each index at different scales may create small differences in the final set of variables and composition of each component. Previous sensitivity analysis showed that if the same basic dimensions of Social Vulnerability are represented the results are valid regardless of changes in scale and small differences in components constitution (Schmidtlein et al., 2008).

Statistical data used derived mainly from Census 2011. Most variables were provided by the National Institute of Statistics (INE), including both the statistical units' delimitation (.*shapefile*) and the different variables (.*csv* file), at parish, block and sub-block level.

The selection of variables was done having in mind both the dimensions of Social Vulnerability and the regional context. The more dimensions are represented in the input, the more complete and holistic will the resulting analysis be (Cutter et al., 2003; Schmidtlein et al., 2008; Tavares et al., 2015). Some variables available only at the parish level were used to represented otherwise neglected dimensions of Social Vulnerability (i.e. qualified employment, people with physical impairments, doctors and nurses per 1000 inhabitants).

In a previous study where variables of a more aggregated unit where generalized to all the smaller units that constitute it, some were retained, meaning they preserve some explicative capability and add value to the represented dimensions of Vulnerability (Tavares et al., 2015). If we consider the variables at parish level, there is really not that much distortion in applying, for example, the value of doctor per 1000 habitants in a parish to all the blocks of that same parish because each parish in Madeira has its own Health Care Centre, and parishes are relatively small.

Additionally to the statistical data, Social Vulnerability assessment also requires data regarding build environment, infrastructure and lifelines (Cutter, 1996; Cutter et al., 2008, 2003; Schmidtlein et al., 2008; Tavares et al., 2015). This data was obtained in shapefile format from public institutions (i.e. Regional Office of Environment and Natural Resources, City Councils, Regional Service of Civil Protection). This data includes the location of critical facilities (i.e. medical facilities, fire departments, police, public services) as well as other contextual information. Some of the necessary variables were obtained by spatial analysis of the provided elements using ArcMap. The use of variables regarding distance to critical facilities had the advantage of minimizing the impact of applying parish level variables to smaller statistical units, because distances could be calculated for every spatial unit. Distances to a given type of infrastructure were calculated to the closest element, thus eliminating the limitation of administrative borders.

Madeira Island has 10 municipalities and 53 parishes. Smaller statistical units are used to report the data from Census. Blocks correspond to a homogeneous area inside a parish, comprising, on average, around 300 residencies. Sub-block is the smallest statistical unit, representing a continuous homogeneous area inside a block that corresponds broadly to a city block limited by roads, on urban areas, or a small residential nucleus in more rural areas.

Considering the minimum number of cases required for PCA, it would be inadequate to use municipalities because as units, because it would amount to only 10 cases. We used the 53 parishes to calculate the indexes, having in mind the performance metrics mentioned before for smaller samples, including high KMO and high Communalities values (Maccallum et al., 2001; Mendes, 2009). There are 380 blocks which is a sufficient number. The number of statistical sub-blocks is very high – over 4500. Although this number respects the minimum number of cases, it raises the issue of desegregation increase leading to a higher number of Components and a smaller percentage of Variance explained, which should be monitored (Cunha et al., 2011; Mendes et al., 2011; Schmidtlein et al., 2008).

Some sub-blocks may not be adequate. Some are residual and correspond to areas with no human occupation and should not be considered. Others have no resident population. Social Vulnerability is a 'human' phenomenon and should be calculated where there are people potentially exposed to disasters. Buildings, infrastructures or tourists in hotels are obviously exposed elements. However, most of the available variables, particularly from Census, refer to resident population and do not exist where there are no residents. Thus, we used only sub-blocks with residents.

Risk governance and the definition of prevention and mitigation strategies can benefit from a multi-scale analysis because the spatial pattern resulting from the relative measure of Social Vulnerability at coarser scales may be used for strategical and structural polices' definition, and analysis using finer units like blocks is useful to define more local, specific and differentiated interventions (Eakin & Luers, 2006; Mendes et al., 2011). Although changing scale and data unit aggregation affects the performance of PCA, it does not have a great impact in terms of variables and the resulting Components (Schmidtlein et al., 2008) and it should, therefore, be possible to use different data aggregation, with a similar set of variables, to compare the resulting information and spatial patterns (Fekete et al., 2010).

We analysed how the changes to SOVI introduced by SOVI_NTH affect their performance and results. The indexes' sensitivity to different data aggregation was assessed in terms of statistical performance (i.e. KMO, Variance explained, Communalities, MSA, etc.) and resulting outputs (i.e. Variables retained, number of Components, spatial patterns).

To quantify the effect of using more desegregated units in terms of describing with more detail the Social Vulnerability patterns we adopted a simple approach, by calculating the percentage of statistical units that have a different Social Vulnerability level (i.e. in a scale of

1 to 5) at a smaller statistical unit (i.e. block), than the one that it would have if the value of a more aggregated unit (i.e. parish) was assigned to all the smaller units that compose it.

Because these indexes are sensitive to changes in the algorithm (Schmidtlein et al., 2008), some differences in the resulting relative levels of Social Vulnerability are expected. To compare SOVI and SOVI_NTH and examine whether the application of SOVI_NTH in Madeira constitutes, not just a valid alternative, but eventually a preferable option, we calculated both indexes with the same set of initial variables, with the adjustments required by the algorithms, and compared their performance using statistical measures (i.e. KMO, MSA, Communalities, Variance explained) as well as the retained variables and Components.

When analysing sensitivity to different data aggregation and differences in the algorithms, we ensured the analysis respected the data requirements and statistical performance, but we do not make any assumption on whether different results using a smaller statistical unit or using SOVI_NTH instead of SOVI, mean more correct results.

Extrapolating from those differences to interpretation about the 'best' analysis would require that the validity of each model was objectively assessed and quantified. As mentioned on chapter 2.3, validity assessment of Social Vulnerability indexes is still a very recent and contentious subject. Different types of Vulnerability result in different Vulnerability indexes and, consequently, different ways to validate them.

As an example, Vulnerability to floods has been validated with a data set with number of people displaced and that needed emergency shelter (Fekete, 2009); Vulnerability to Natural Disaster validated using linear regression with property losses, fatalities and disaster declarations (Bakkensen, Fox-Lent, Read, & Linkov, 2016); validation using the Desinventar Database with records of losses and damage per district (Cabral, Augusto, Akande, Costa, & Amade, 2017); or validate heat Vulnerability with the health outcomes (Bao, Li, & Yu, 2015). Validating Social Vulnerability, if approached as a more multidimensional phenomenon, is more difficult (Tate, 2011) and the potential losses go beyond loss of life and destruction of buildings. Indicators often used to validate Vulnerability indexes (i.e. fatalities, houses destroyed, displaced people, economic losses) are not available at parish or block level. Even if they were, they could hardly account for the complexity of what is a loss within the concept of Social Vulnerability (i.e. loss of affective values, emotional suffering, life changing impairments, loss of job) or what is encapsulated in the ability to resist or recover from a disaster (i.e. long-life trauma, quality of life).

A more holistic post-event assessment methodology would have to be developed and implemented in the context of disasters in Madeira, with pre and post-event information collected, including over a period of time after the event, with information regarding different dimensions of loss and recovery. Only then can someone go beyond conceptual or statistical performance analysis of indexes and determine which index or data aggregation level better illustrates the ‘real’ level of Social Vulnerability in Madeira.

3.3.1 Social Vulnerability Index

The steps of the SOVI algorithm are summarized next (Armaș & Gavriș, 2013; Burton & Cutter, 2008; Chen et al., 2013; Cutter et al., 2003; Cutter & Finch, 2008; Guillard-Gonçalves et al., 2015; Hummell et al., 2016; HVRI, 2008, 2010, 2011; Mendes, 2009; O’Rourke & Hatcher, 2013; Schmidtlein et al., 2008; Tavares et al., 2015):

A) Input variables are selected to represent different dimensions of Social Vulnerability, including demographic and socioeconomic attributes, build environment and lifelines. Normalized variables should be used (i.e. percentages) to reduce data amplitude.

B) To reduce the number of variables and exclude redundant ones, a Pearson Correlation is used. When two variables are highly correlated (i.e. 0.7), they are analysed to determine if they represent similar dimensions of Vulnerability and one should be eliminated. If they represent different attributes, both are kept.

C) Variables are normalized to reduce the amplitude of values (i.e. z*scores,* with Mean 0 and Standard Deviation 1). PCA is performed using a Varimax Rotation, extraction of Components with Eigenvalue >1, validated or adjusted with other methods. Different combinations are tested to obtain the desired performance.

D) The Cardinality of each Component is assigned according to their effect on Social Vulnerability (i.e. Increase or decrease), by analyzing the variables loading above 0.6. Those that theoretically increase Social Vulnerability receive a positive sign (+) and those that decrease it receive a negative sign (-). If the effect is ambiguous or have conflicting signs, an absolute value is used. If a Component has both variables that increase and decrease Social Vulnerability and they have the ‘correct’ loadings (+ or -) then the Cardinality is maintained. If a Component’s variables tend to decrease Social Vulnerability but have a positive loading (or vice-versa), the Component´s Cardinality is adjusted by multiplying by -1.

E) Each Component is named based on the variables with significant factor loadings (higher than 0.6 or lower than -0.6).

F) All Components are added, considering their Cardinality, with no weightings, to generate the overall SOVI score. No *a priori* assumption is made about differentiate importance of each Component. The resulting scores are not absolute values and should be seen essentially as relative measures to compare between the statistical units analysed.

G) The resulting SOVI values are illustrated using five classes according to the Standard Deviation (SD) from the Mean, which allows to highlight the extremes: Very High (above 1.5 SD); High (between 0.5 and 1.5 SD); Moderate (between -0.5 and 0.5 SD); Low (between −1.5 and −0.5 SD); Very Low (under −1.5 SD).

3.3.2 Social Vulnerability to Natural and Technological Hazards Index

The steps of the SOVI algorithm version (Cunha et al., 2011; Mendes et al., 2011, 2009) are summarized next:

A) Input variables are selected to represent different dimensions of Social Vulnerability. Because Criticality and Support Capacity are calculated separately, the step is performed twice, choosing a set of normalized variables for each of the sub-indexes.

B) A Pearson Correlation is used to reduce the number of variables and exclude redundant variables (above 0.7). Because Criticality and Support Capacity are calculated separately, the step is performed twice.

C) The PCA is performed with a Varimax Rotation. It is an iterative process in order to obtain a robust and valid combination of data using performance parameters. Because Criticality and Support Capacity are calculated separately, the step is performed twice.

D) The resulting Components are interpreted to determine Cardinality, both of Criticality and Support Capacity.

E) Each Component of both Criticality and Support Capacity is named based on the variables with significant factor loadings (i.e. higher than 0.6 or lower than -0.6).

F) All Components are added, considering their Cardinality, with no weightings, to generate both the Criticality and Support Capacity sub-indexes.

G) The results from the PCA, Criticality and Support Capacity sub-indexes, are subject to a Quadratic Linear Transformation to obtain values with equal amplitude, between 0 and

1. Having results normalized allows the appropriate calculation of the overall score of Social Vulnerability by having Criticality and Support Capacity with values with same amplitude.

H) The final Social Vulnerability score is obtained by the following formula: 'SV=Criticality x (1 - Support Capacity)'. Support capacity is subtracted from 1 because it has the inverse effect of Criticality as it reduces Social Vulnerability.

I) To represent Social Vulnerability, and each of its two sub-indexes, the methodology follows the one proposed to SOVI by using standard-deviation to create the same five classes.

3.4 Results

Before presenting the results, we should note that variables from the 2011 Census were used and, therefore, these representations of Social Vulnerability are a snapchat from that year. In fact, although using more recent data would be preferable, the need to use a large number of variables and data referring to blocks and sub-blocks, imposes the choice of Census data. Because Census are decennial, it was not possible to use data from 2017.

SOVI is a place specific metric and the results presented are specific to this implementation in the context of Madeira island. Additionally, the Social Vulnerability scores presented here result from the options during the iterative PCA procedure. Different options could result in slightly different results.

The results include nine sets of outputs, regarding SOVI, SOVI_NTH Criticality and SOVI_NTH Support Capacity, and cover three statistical units (i.e. parish, block, sub-block). The detailed statistical results can be found on Appendix IV.

The initial data set included 140 variables that were reduced, based on existing literature, to 57 variables that cover the main dimensions of Social Vulnerability. These were used as input to the Pearson Correlation analysis. In the case of SOVI_NTH, due to the existence of two sub-indexes, 46 were used for Criticality and 15 for Support Capacity. The more correlated pairings of variables were analysed, and several were removed. In some cases, despite the existence of significative correlations, both were kept, if representing different aspects. The number of retained variables was very similar across aggregation level, as visible in Table 1.

The list of variables selected for the PCA procedure, as well as their theoretical effect on Social Vulnerability, Criticality and Support Capacity are presented on Appendix III.

	SOVI			SOVI_NTH Criticality			SOVI_NTH Support Capacity		
	Parish	Block	sub-block	Parish	Block	sub-block	Parish	Block	sub-block
Initial variables	140	140	140	140	140	140	15	15	15
Pearson input	57	57	57	46	46	46	13	13	13
PCA input	46	46	46	35	35	35	13	13	13
Retained by PCA	23	20	20	18	14	15	9	10	9

Table 1: Variables used in SOVI and SOVI_NTH.

The PCA was performed for SOVI and SOVI_NTH (i.e. Criticality and Support Capacity). It was possible to obtain valid results, according to the defined parameters, for the three aggregation levels (i.e. parish, block, sub-block), with similar levels of performance, as illustrated on Table 2.

	SOVI			SOVI_NTH Criticality			SOVI_NTH Support Capacity		
	Parish	Block	Sub-block	Parish	Block	Sub-block	Parish	Block	Sub-block
Number of Components	6	6	9	4	4	7	3	4	4
Explained Variance	83.32	80.10	79.03	81.52	86.00	77.94	79.97	90.12	83.58
Variance explained by first Component	25.79	23.94	17.24	31.20	30.67	22.10	31.24	22.20	22.68
KMO	.722	.805	.721	.706	.785	.711	.747	.743	.665
Communalities above 0.6	✓	✓	✓	✓	✓	✓	✓	✓	✓
Less than 50% Residuals >0.05	✓	✓	✓	✓	✓	✓	✓	✓	✓
High MSA	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2: Performance parameters for SOVI and SOVI_NTH, with different data aggregation units.

The results were obtained with all variables' Communalities above 0.6, less than 50% of residuals higher than 0.05 and using the Measure of Sample Adequacy in the Anti-Image Matrix to assess variables' contribute to the model. Regarding the KMO criterium, also a measure of sample quality, all have good values, above 0.700. The only exception was the result for Support Capacity in sub-blocks, were the selected result had a KMO of 0.665. Although other options during the PCA procedure resulted in higher KMO values, above 0.7, this was the one that provided the best interpretability of the retained variables and resulting Components. In any case, as mentioned before, 0.6 is also the minimum value of KMO used in many SOVI applications and with an explained Variance of 83.6%, minimum Communalities of 0.715 and only 16% of residuals >0.05, we considered this performance acceptable.

Overall, the best performing unit was the block, which is in line with the expected effect of small number of units (parishes) or small size of units (sub-blocks), but performance results for parish and sub-block were also good.

The analysis showed that using less than 100 cases, in this case 53 parishes, can result in a valid model provided the values of KMO and Communalities are high (Maccallum et al., 2001; Mendes, 2009). When comparing the performance of statistical units, the results coincide with previous sensitivity analysis findings: smaller statistical units, tend to result in more Components and lower values of KMO and explained Variance (i.e. total and first Component) (Table 2) (Schmidtlein et al., 2008). In any case, this did not obstruct valid results for the sub-blocks, given that the obtained values for these three parameters were good.

Both indexes had similar performance. At the same aggregation level, the performance parameters, are similar. Given the two-step nature of SOVI_NTH, each of its two sub-indexes individually had a smaller number of components than SOVI, higher if combined. Regardless, the values of KMO and explained Variance of SOVI and SOVI_NTH Criticality and even SOVI_NTH Support Capacity are similar (i.e. differences around 5%). The biggest difference is for SOVI_NTH Support Capacity at block level, with explained Variance of 90%.

The total explained Variance has a similar performance across indexes. At block level, however, the performance of the two SOVI_NTH sub-indexes was quite better than SOVI. Regarding the Variance explained by the first Component, the two SOVI_NTH sub-indexes also tend to have a better performance than SOVI.

Some variables available only at municipality and parish level were considered as input because they represent dimensions otherwise neglected or less represented at block and sub-block level (Appendix II). After the PCA analysis most were not retained. The exceptions were those referring to qualified or unqualified work and people with at least one impairment, at parish level. These variables contribute to the representation of Social Vulnerability, including at block and sub-block level, about the socioeconomic context.

The results of each PCA, including the resulting Components interpretation, are detailed on Appendix IV. We present here a brief summary.

The SOVI calculation for parishes (Table 3) had a KMO of 0.722, 83% of total explained Variance, and resulted in six Components and 23 variables retained. The Components cover dimensions like education & economy, frail groups, distance to critical facilities, unemployment and housing conditions. Most have the appropriate loading sign (- or +), the Components increase Social Vulnerability and have the appropriate positive Cardinality. One Component, buildings built after 2001, had its Cardinality corrected by multiplying by -1.

SOVI Parish					
Comp. 1 (+)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (+)	Comp. 5 (+)	Comp. 6 (x -1)
Education and Economy	Frail Groups	Critical Facilities	Housing Conditions	Unemployment	Buildings
res_ens_sup	res_+64_fem	dist_farmacia	aloj_1_2_div	res_desemp	edif_pos2001
emp_quali1e2_freg	res_+64	dist_bom	aloj_50m		
res_sect_3	res_pens_ref	dist_police	aloj_fam_banho		
med_priv_conc	res_-14_+64	dist_csaude			
res_analfabeto	res_femin				
emp_n_quali9freg	pop+5_1dif_freg				
dens_pop					
res_1_ciclo					

Table 3: PCA results for SOVI in parishes

The SOVI calculation for blocks (Table 4) had a KMO of 0.805, 80% of total explained Variance, and resulted in six Components and 20 variables retained. The Components cover dimensions like education & economy, frail groups, distance to critical facilities, unemployment and housing conditions. All variables have the appropriate loading sign (- or +), the Components increase Social Vulnerability and have a positive Cardinality.

SOVI Block					
Comp. 1 (+)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (+)	Comp. 5 (+)	Comp. 6 (+)
Education and Economy	Frail Groups	Critical Facilities	Unemployment	Housing Conditions	Housing Conditions II
emp_quali1e2_freg	res_+64	dist_farmacia	fam_+1_desemp	aloj_1_2_div	aloj_fam_n_class
emp_n_quali9freg	res_+64_fem	dist_csaude	res_desemp	aloj_50m	
med_priv_conc	res_pens_ref	dist_police			
res_sect_3	res_-14_+64	dist_bom			
res_ens_sup					
res_analfabeto					
res_1_ciclo					

Table 4: PCA results for SOVI in blocks

The SOVI calculation for sub-blocks (Table 5) had a KMO of 0.721, 79% of total explained Variance, and resulted in nine Components and 20 variables retained. The Components cover dimensions like frail groups, distance to critical facilities, unqualified employment and dominant economic sectors, unemployment, housing conditions, gender and education. All variables have the appropriate loading sign (- or +), and the Components increase Social Vulnerability and have a positive Cardinality.

SOVI Sub-Block								
Comp. 1 (+)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (+)	Comp. 5 (+)	Comp. 6 (+)	Comp. 7 (+)	Comp. 8 (+)	Comp. 9 (+)
Frail Groups	Critical Facilities	Unqualified Employment	Critical Facilities II	Unemployment	Housing Conditions	Activity Sector	Gender	Primary Education
res_+64	dist_juntas	emp_n_quali9freg	dist_bom	fam_+1_desemp	aloj_1_2_div	res_emp_sect1	res_idoso_fem	res_1_ciclo
res_pens_ref	dist_csaude	emp_quali1e2_freg	dist_police	res_desemp	aloj_50m	res_sect_3 (-)	res_femin	
res_+64_fem	dist_farmacia							
res_-14_+64								

Table 5: PCA results for SOVI in sub-blocks

The SOVI_NTH Criticality (Table 6) calculation for parishes had a KMO of 0.706, 82% of total explained Variance, and resulted in four Components and 18 variables retained. The Components cover dimensions like education and economy, frail groups, unemployment and housing conditions. All variables have the appropriate loading sign (- or +), the Components increase Criticality and have a positive Cardinality.

Criticality Parish			
Comp. 1 (+)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (+)
Education and Economy	Frail Groups	Housing Conditions	Unemployment
res_ens_sup (-)	res_+64_fem	aloj_50m	res_desemp
emp_quali1e2_freg (-)	res_+64	aloj_1_2_div	fam_+1_desemp
res_sect_3 (-)	res_-14_+64	aloj_fam_banho	
res_1_ciclo	pop+5_1dif_freg		
dens_pop (-)	res_femin		
res_analfabeto			
emp_n_quali9freg			
res_ens_sup			

Table 6: PCA results for Criticality in parishes

The SOVI_NTH Criticality calculation for blocks (Table 7) had a KMO of 0.785, 86% of total explained Variance, and resulted in four Components and 14 variables retained. The Components cover dimensions like education and economy, frail groups, unemployment and housing conditions. All variables have the appropriate loading sign (- or +), the Components increase Criticality and have a positive Cardinality.

Criticality Block			
Comp. 1 (+)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (+)
Education and Economy	Frail Groups	Unemployment	Housing Conditions
emp_quali1e2_freg (-)	res_+64	res_desemp	aloj_1_2_div
emp_n_quali9freg	res_+64_fem	fam_+1_desemp	aloj_50m
res_sect_3 (-)	res_pens_ref		
res_ens_sup (-)	res_-14_+64		
res_analfabeto			
res_1_ciclo			

Table 7: PCA results for Criticality in blocks

The SOVI_NTH Criticality calculation for sub-blocks (Table 8) had a KMO of 0.711, 78% of total explained Variance, and resulted in seven Components and 15 variables retained. The Components cover dimensions like frail groups, unqualified employment, unemployment, housing conditions, gender and education. Most variables have the appropriate loading sign (- or +), the Components increase Criticality and have a positive Cardinality. One Component, Unqualified employment, had its Cardinality corrected by multiplying by -1.

Criticality Sub-Block						
Comp. 1 (+)	Comp. 2 (x-1)	Comp. 3 (+)	Comp. 4 (+)	Comp. 5 (+)	Comp. 6 (+)	Comp. 7 (+)
Frail Groups	Unqualified Employment	Unemployment	Housing Conditions	Activity Sector	Gender	Primary Education
res_+64	emp_n_quali9freg (-)	fam_+1_desemp	aloj_1_2_div	res_emp_sect1	res_idoso_fem	res_1_ciclo
res_pens_ref	emp_quali1e2_freg	res_desemp	aloj_50m	res_sect_3	res_femin	
res_-14_+64						
res_+64_fem						

Table 8: PCA results for Criticality in sub-blocks

The SOVI_NTH Support Capacity (Table 9) calculation for parishes had a KMO of 0.747, 80% of total explained Variance, and resulted in three Components and nine variables retained. The Components cover dimensions like Urban/Rural, support personnel and distance to critical facilities. Most variables have the appropriate loading sign (- or +), the Components increase Support Capacity and have a positive Cardinality. One Component, distance to Critical Facilities, because it reduces Support Capacity, had its Cardinality corrected by multiplying by -1.

Support Capacity Parish		
Comp. 1 (+)	Comp. 2 (x-1)	Comp. 3 (+)
Urban areas	Critical Facilities	Support Personnel
dens_pop	dist_csaude	bombeiro_conc
dens_edif	dist_farmacia	enf_csaude_conc
med_priv_conc	dist_police	
	dist_bom	

Table 9: PCA results for Support Capacity in parishes

The SOVI_NTH Support Capacity (Table 10) calculation for blocks had a KMO of 0.743, 90% of total explained Variance, and resulted in four Components and 10 variables retained. The Components cover dimensions like Urban/Rural, support personnel and distance to critical facilities. Components regarding the distance to Critical Facilities, because it reduces Support Capacity but had positive loadings, had its Cardinality corrected by multiplying by -1.

Support Capacity Block			
Comp. 1 (x-1)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (x-1)
Critical Facilities	Support Personnel	Urban areas	Critical Facilities II
dist_juntas	bombeiro_conc	dens_pop	dist_bom
dist_csaude	enf_csaude_conc	dens_edif	dist_police
dist_farmacia		med_priv_conc	

Table 10: PCA results for Support Capacity in blocks

The SOVI_NTH Support Capacity calculation for sub-blocks (Table 11) had a KMO of 0.665, 84% of total explained Variance, and resulted in four Components and nine variables retained. The Components cover dimensions like urban/rural areas, support personnel and distance to critical facilities. Components regarding the distance to Critical Facilities, because it reduces Support Capacity but had positive loadings, had their Cardinality corrected by multiplying by -1.

Support Capacity Sub-Block			
Comp. 1 (x-1)	Comp. 2 (x1)	Comp. 3 (+)	Comp. 4 (+)
Critical Facilities	Critical Facilities II	Support personnel	Urban areas
dist_juntas	dist_bom	bombeiro_conc	dens_pop
dist_csaude	dist_police	enf_csaude_conc	dens_edif
dist_farmacia			

Table 11: PCA results for Support Capacity in sub-blocks

As stated before, the statistical performance of the algorithm for SOVI and SOVI_NTH had the expected sensitivity to the changes in the algorithm itself (i.e. changes introduced by SOVI_NTH) as well as the data aggregation level.

The resulting Components, or at least the Social Vulnerability dimensions they represent, are similar when comparing across indexes and data aggregation levels. Nonetheless, the conceptual interpretation of the resulting Components and Social Vulnerability dimensions also shown some signs of the up mentioned sensitivity, although some may be due not just to the algorithm's sensitivity, but also the choices of the researcher during the PCA.

Table 12 illustrates how if we compare SOVI at each of the aggregation units (i.e. parish, blocks and sub-blocks), a very similar set of dimensions is present, although not exactly with the same retained variables or percentage of Variance explained by each of them. Even in the case of sub-blocks, the represented dimensions are very similar, regardless of being divided into more Components (i.e. level of job qualification, type of dominant economic sector and educational attainment dimensions are represented by only one Component at parish level and divided by three different Components at sub-block level). The same can be said regarding the SOVI_NTH sub-indexes, as the dimensions represented in Criticality and

Support Capacity, respectively are essentially the same even if not exactly with the same Component's structure, at all three data aggregation levels.

SOVI		
Parish	**Block**	**Sub-block**
Education & Economy	Education & Economy	Education
Frail Groups	Frail Groups	Frail Groups
Distance to Critical Facilities	Distance to Critical Facilities	Distance to Critical Facilities
Housing Conditions	Housing Conditions	Housing Conditions
Unemployment	Unemployment	Unemployment
Buildings		Unqualified employments
		Activity Sector
SOVI_NTH Criticality		
Parish	**Block**	**Sub-block**
Education & Economy	Education & Economy	Education
Frail Groups	Frail Groups	Frail Groups
Housing Conditions	Housing Conditions	Housing Conditions
Unemployment	Unemployment	Unemployment
		Unqualified employment
		Activity Sector
SOVI_NTH Support Capacity		
Parish	**Block**	**Sub-block**
Urban/Rural	Urban/Rural	Urban/Rural
Distance to Critical Facilities	Distance to Critical Facilities	Distance to Critical Facilities
Support Personnel	Support Personnel	Support Personnel

Table 12: Dimensions of Social Vulnerability retained in SOVI and SOVI_NTH

One of the objectives of this research was to analyse Social Vulnerability's patterns and asymmetries, testing whether small statistical units allow the identification of scores otherwise masked. The resulting SOVI and SOVI_NTH scores, as well as Criticality and Support Capacity, were illustrated using ArcMap. Social Vulnerability cartography, potentiated by GIS tools, is extremely important for communicating Social Vulnerability and integrating it in Risk governance at different scales (Cunha et al., 2011). Some Components explain more Variance than others, but all are added with no weighting, and give an equal contribute to the final score (Cutter et al., 2003). It is, however, possible to analyse Components' loadings in a given statistical unit and identify those that contribute the most to that specific score.

The SOVI at parish level is illustrated on Figure 4. There are clear asymmetries not only between parishes but also between municipalities, with some having several of their parishes with High or Very High scores of SOVI (i.e. Santana, Ribeira Brava and Porto Moniz). Most lower scores are concentrated in the Southeast coastal parishes between Funchal and Machico. Ribeira Brava, Porto Moniz and Santana on the contrary, concentrate several parishes with High or Very High scores. The parishes with Very Low scores are São Martinho (Funchal), Caniço and Gaula (Santa Cruz). The highest scores are found in Tabua (Ribeira Brava), Faial and São Roque do Faial (Santana).

These scores result from different combinations of Components. In Tabua the Components with higher positive loadings are Housing Conditions, Buildings and Frail Groups, while in Faial are distance to Critical Facilities, Buildings and Unemployment. These examples illustrate how SOVI allows not only to detect Social Vulnerability patterns, but also analyse how those overall scores result from different combinations of Components' loadings.

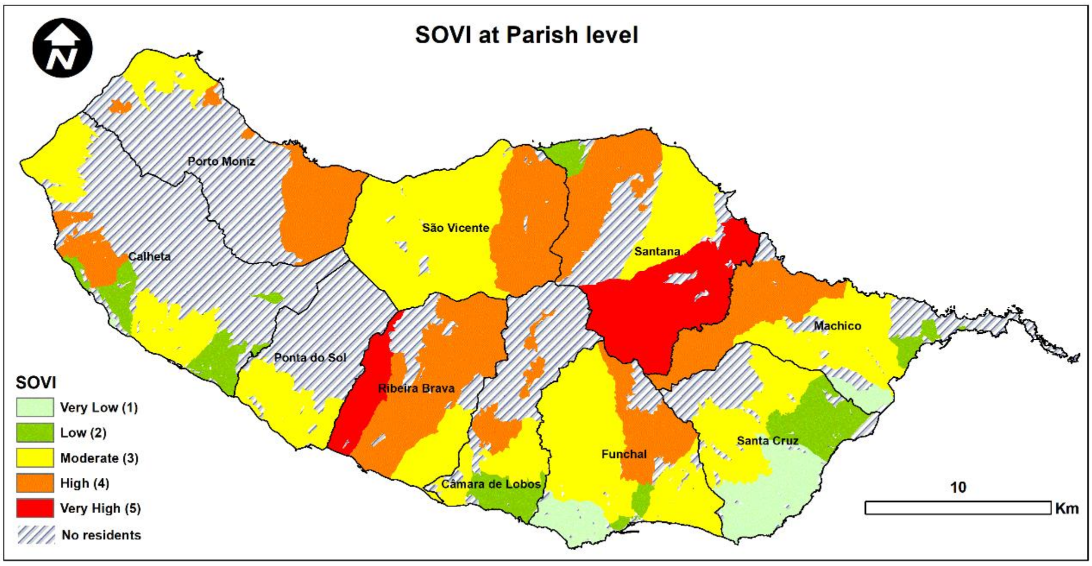


Figure 4: SOVI at Parish level

SOVI, however, may at times join in the same Component individual characteristics that make people vulnerable (i.e. age, income, gender) and structural characteristics that help them to cope and resist (i.e. critical facilities, medical resources, available capacities) that influence Social Vulnerability (Eakin & Luers, 2006; Mendes et al., 2009; Prescott-Allen, 2001). That happens in this output, to some extent. There are Components that relate mostly with people's attributes (Component 2 "Frail Groups") and others that focus on structural factors (Component 3 "Critical Facilities"). Component 1, however, includes variables regarding both dimensions. SOVI_NTH is intended to prevent this situation and, as we will see, in this application it was in fact successful in that regard.

It is noteworthy that many of the parishes with higher SOVI scores are peripheric and have the distance to critical facilities as an important contributor to its scores. SOVI_NTH Criticality may present a different pattern because it does not include this aspect as it is represented in Support Capacity.

The results using data aggregated by block are illustrated in Figure 5. The general pattern is, inevitably, similar to the one described before, as these blocks compose the parishes. However, with this more desegregated data, a more complex and diverse pattern emerges. Parishes like São Martinho (Funchal) with Very Low SOVI scores include blocks with High and even Very High scores. These blocks with Very High Vulnerability within São Martinho, locate in the West of the parish and are poor areas, with many housing problems and unemployment. In the same parish, blocks in the area of Ajuda are some of the more affluent in Madeira, with more educated and qualified population and less unemployment and Very Low SOVI scores. Parishes with Low scores like Câmara de Lobos (Câmara de Lobos) or Sé (Funchal) also contain blocks with High or Very High scores. Conversely, Ribeira Brava (Ribeira Brava) has High SOVI but contains blocks with Low SOVI score.

In fact, the general pattern of SOVI at parish level masks significative asymmetries inside those parishes that a block analysis highlights. The main clusters of Very Low and Low, or Very High and High scores occupy the same general areas of the island with both aggregations units – parish and blocks. Using blocks does however bring a clear advantage of pinpointing areas of diverse scores within each parish.

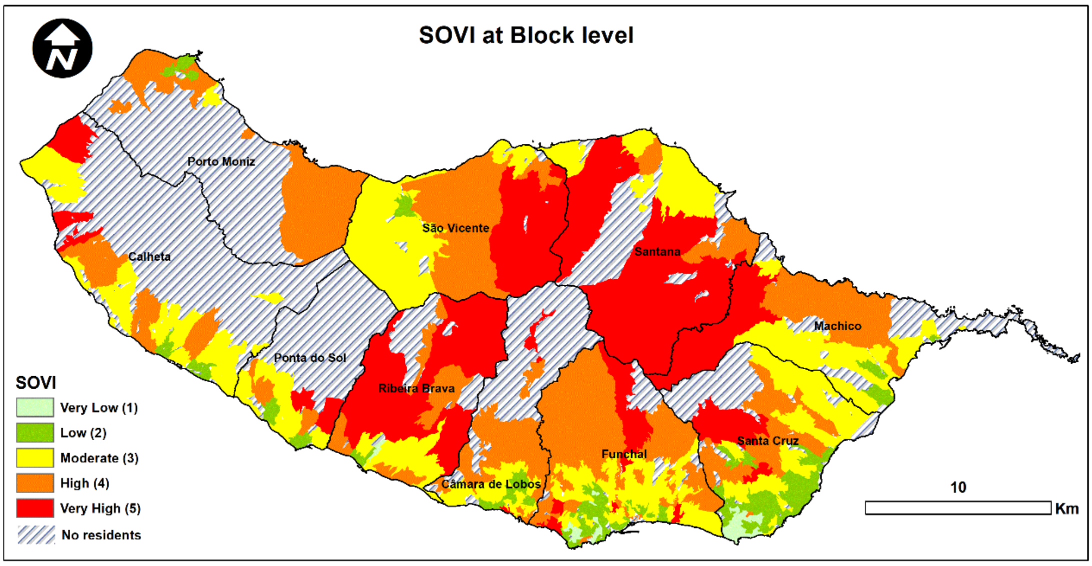


Figure 5: SOVI at Block level

Additionally, the analysis of how different Components combine in different SOVI scores is even more detailed when using blocks. In Funchal, the largest parish, Santo António, is an elongated area that extends from close to the city centre in the South to the less consolidated areas at higher altitudes towards North. Areas in the Northern fringes of Funchal are known as less affluent and more deprived. In Santo António, Southern blocks have Very Low and Low SOVI scores, benefitting from a population with less unemployed, older or retired residents, while North blocks show higher scores as the loading regarding unemployment and especially poor housing conditions and distance to critical facilities increases.

In Camacha parish, a different set of Components determines the existing asymmetries. Although the parish has a Moderate SOVI score, it encapsulates blocks with Low scores, but also with Very High scores in the three blocks. One of these blocks with Very High score corresponds broadly to Bairro da Nogueira which is an area of social housing projects. The Components regarding Unemployment, Housing Conditions and Education & Economy, have high loadings and, as expected in such area, contribute to the Very High SOVI score, despite performing well regarding population age and proximity to critical facilities. On the other hand, two other blocks in more rural on the North of the parish, have Very High SOVI scores but in these cases Components regarding Unemployment and Housing Conditions aren't as bad, but the one regarding peoples' education and job qualification are worse.

Finally, the SOVI calculated for sub-blocks provides an even more detailed picture of the Social Vulnerability pattern (Figure 6). As before, the general pattern and clusters of Very High and High or Very Low and Low scores at sub-block level are generally identical to the ones at parish and block level. It does however allow the identification of very local contrasts, inside parishes but also inside blocks.

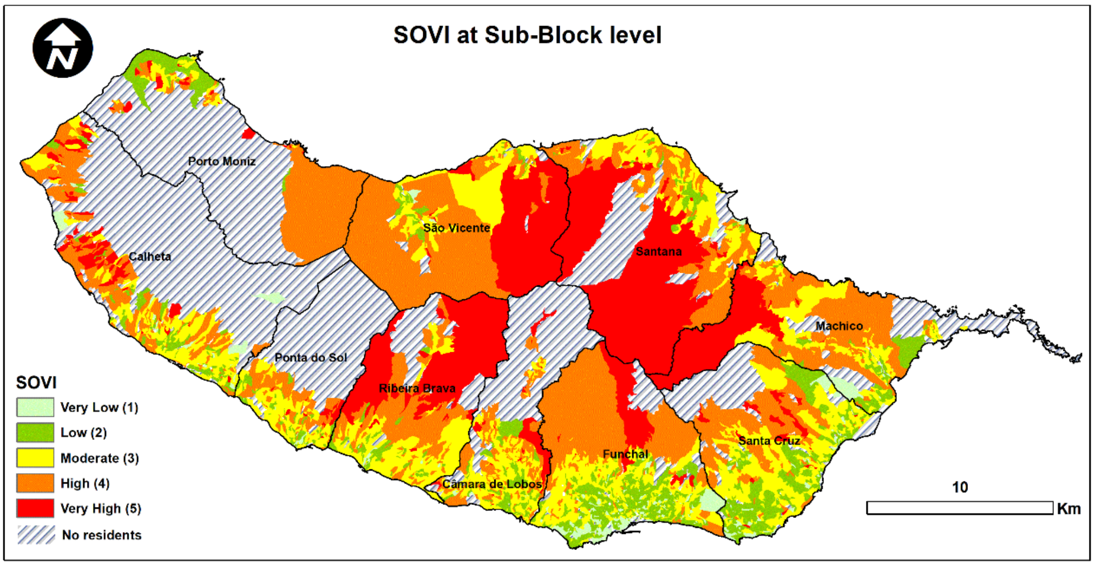


Figure 6: SOVI at Sub-Block level

Overall, when comparing the results at block and sub-block, the extension of units (sub-blocks) with High and Very High score seem to be smaller and only a portion of larger units (blocks), particularly in coastal areas in Câmara de Lobos, Funchal and Santa Cruz. Ribeira Brava and Santana also show this trend but to less extent and the blocks in more interior areas of those municipalities retain their Very High and High score. In Calheta, the largest municipality in Madeira, the aggregation by sub-block results in a much more complex pattern. In the more isolated and deprived parishes of Ponta do Pargo, Fajã da Ovelha and Prazeres the sub-blocks with Very High and High scores are prevalent. The same can be said of the areas farther from the coast in Santana, Ribeira Brava, Câmara de Lobos and Funchal.

As mentioned before, PCA performance at sub-block wasn't as good, and the Components structure is less close to the one at block or parish level. This inevitably affects the ability to compare the results between these different aggregation levels and caution should be exerted when reaching and using conclusions.

Sub-block agreggation does offer a very detailed information but it also poses some challenges, methodological and practical. First, with blocks with 10 or 15 houses and 40 or 50 people, a few outlyer values can easily result in Very High or Very Low SOVI scores. Additionally, the practical implications of individually analysing over 4700 sub-blocks in Madeira or even the over 1200 sub-blocks in Funchal are quite clear.

It's interesting to notice that in terms of information useful for regional of local authorities, not only the comparative SOVI score, but particularly the analysis of the cartography of each Component seems to be particularly useful to compare areas with similar overall SOVI score but with different causes, allowing to identify specific dimensions of Social Vulnerability requiring intervention (Figure 8).

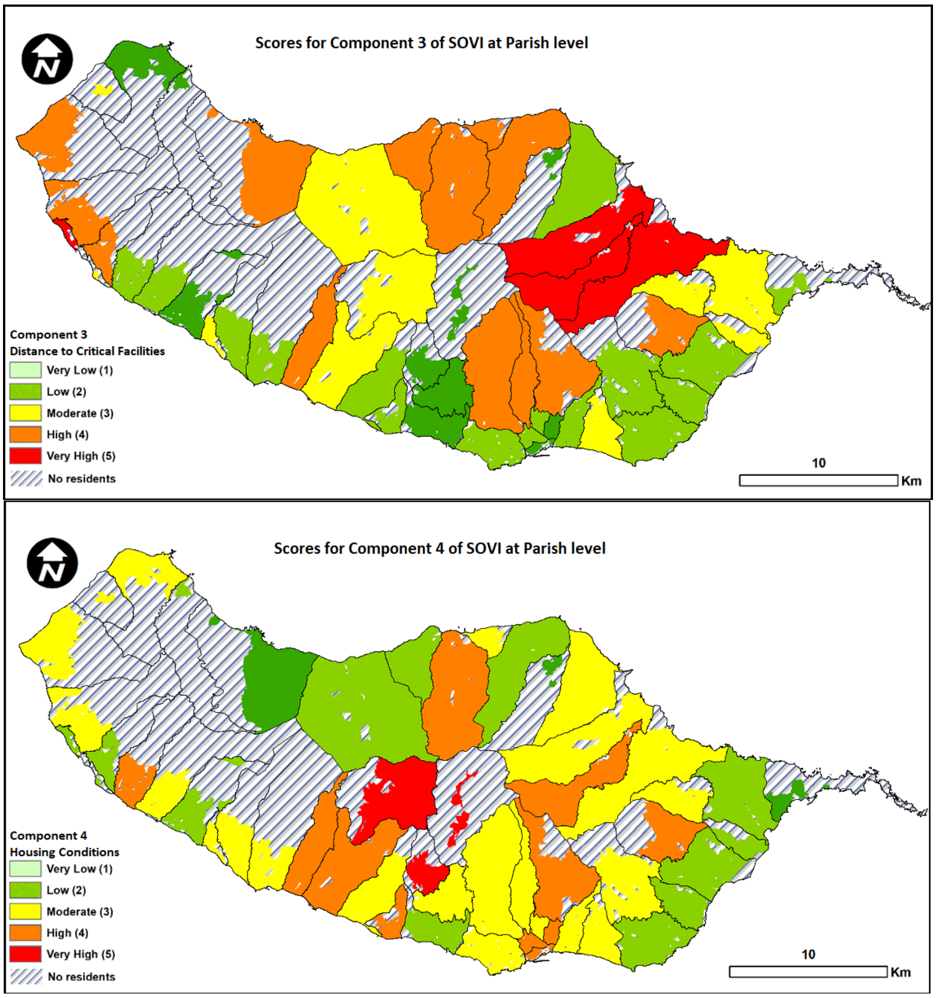


Figure 7: Example of 2 distinct Components patterns regarding the SOVI at Parish level

Figure 8, illustrates how how with smaller aggregation units the same general pattern is obtained but with much more detail and identifying local specificities.

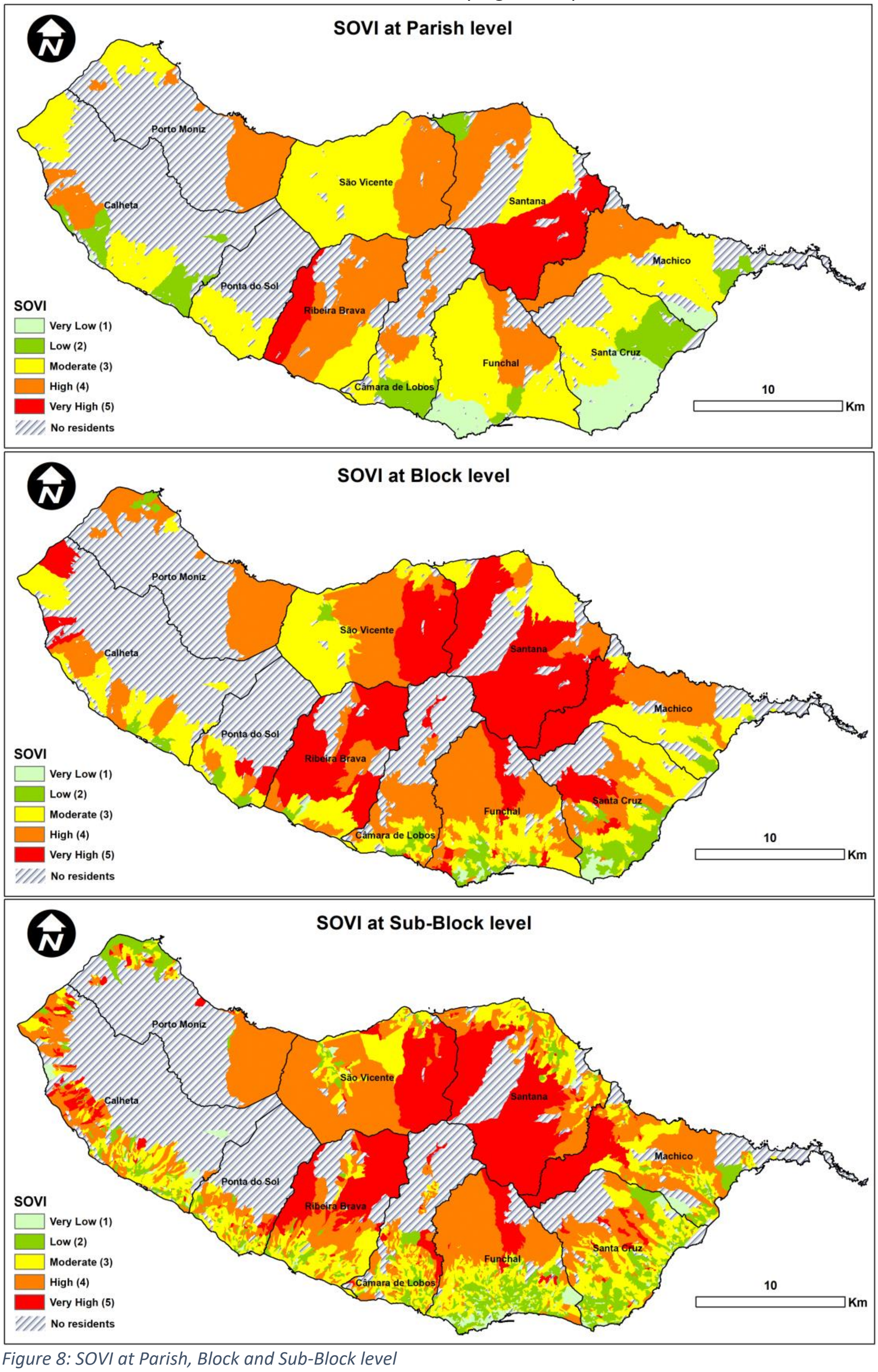


Figure 8: SOVI at Parish, Block and Sub-Block level

Regarding SOVI_NTH, Criticality and Support Capacity were fist analysed them separately and only then combined them in the overall SOVI_NTH. At the parish level, the spatial pattern of Criticality (Figure 9) is very similar to the one of SOVI, which is expected considering it retains many of the same variables, except those analysed separately in the Support Capacity.

Lower scores of Criticality are also found in parishes in Funchal and Santa Cruz and higher scores in Ribeira Brava and Santana. In Funchal and Santana there is a trend for lower scores, while some more isolated parishes like Seixal (Porto Moniz), Serra de Água (Ribeira Brava) and Curral das Freiras have higher scores. As with SOVI, Criticality Components have different impact on the final score of a parish. Seixal, Curral das Freiras and Serra de Água are small, rural parishes with Very High Criticality. In Seixal, the Components loading higher are Unemployment and Frail Groups (i.e. women, older people, people with impairments) with Housing Conditions loading negatively (i.e. decreasing Criticality). Oppositely, in Serra de Água and Curral das Freiras, the Housing Conditions are precisely the Component with higher positive loading (i.e. increase Criticality) and Unemployment has a little impact.

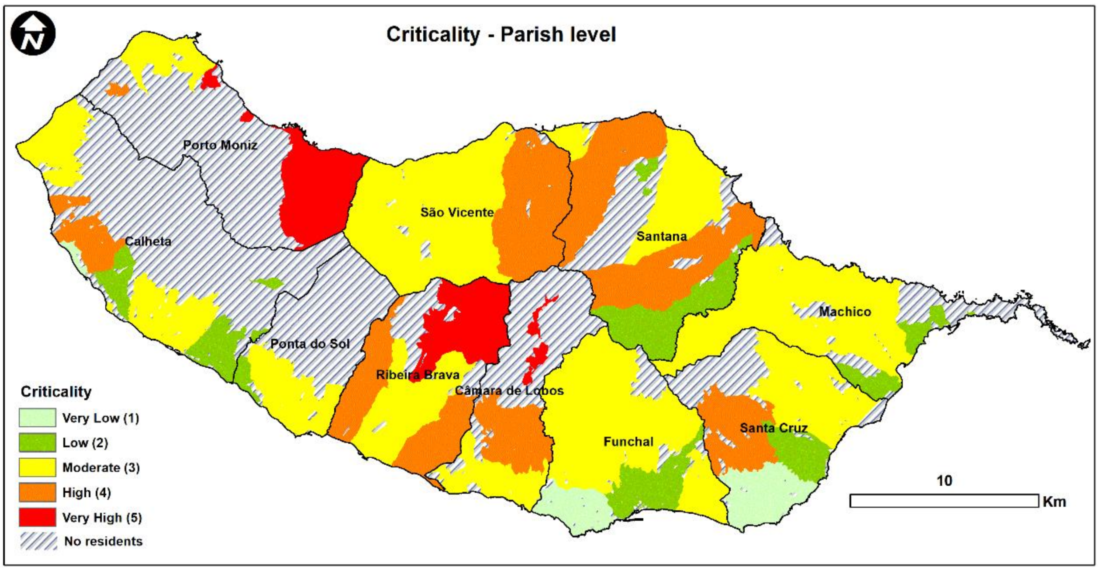


Figure 9: Criticality at Parish level

Criticality spatial pattern using blocks' data (Figure 10) is evocative of the one using parish data but with some important differences and details. In Funchal, where all the parishes have Moderate or lower scores of Criticality, a few blocks with High and even Very High scores are found – due to high Unemployment scores in some cases, Housing Conditions in others. In Ponta do Sol a similar situation occurs due to niches with high scores in Components regarding Housing Conditions or Education & Economy. Although the general distribution of Very High or Very Low Criticality scores remains essentially the same, the block aggregation results in a more complex pattern and allows the identification of niches inside parishes.

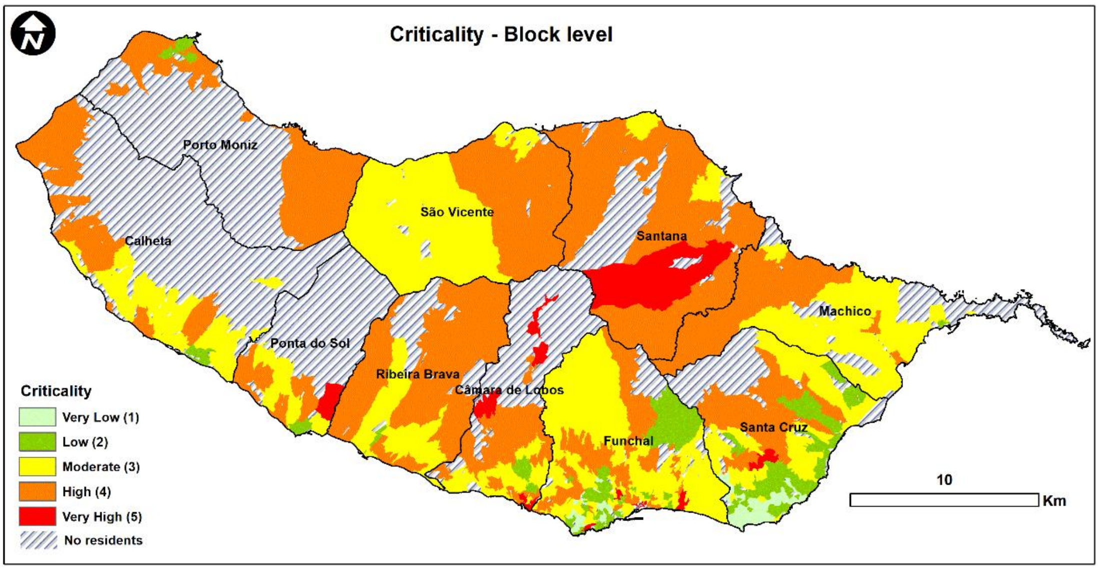


Figure 10: Criticality at Block level

Finally, the Criticality results regarding sub-blocks (Figure 11) provide a more detailed portrait of Criticality pattern. The general pattern and clusters of higher and lower scores at sub-block level are generally identical to the ones at block level. It does, however, allow the identification of local contrasts, particularly inside bigger blocks in more rural parishes. There seems to be a tendency of many blocks with High scores to include several sub-blocks with lower scores which transmits a visual perception of less Criticality in some areas, particularly where blocks are larger. Funchal and Santa Cruz that have many smaller blocks shows a pattern with more Low and Very Low score sub-blocks. On the contrary, in Ribeira Brava the visual pattern shows a trend of more Criticality with some sub-blocks scoring Very High.

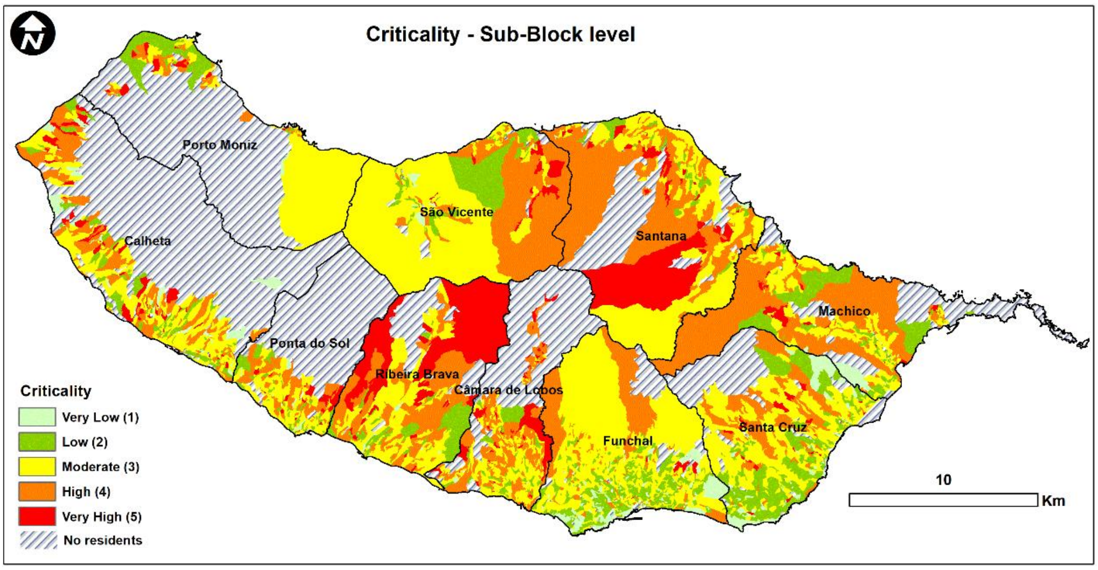


Figure 11: Criticality at Sub-Block level

SOVI_NTH Support Capacity sub-index calculation relied mainly on the distance to certain critical facilities (i.e. Fire Department, Health Centre), the emergency and health staff (i.e. firefighters, nurses) and attributes of urban areas where support network is better. The Components and retained variables are very similar between the different aggregation levels. Because critical facilities, as well as emergency and health personnel, are usually located in central areas of the municipalities and parishes, the Support Capacity patterns are to great extent a function of the proximity to such facilities. Urbanity (i.e. population density and additional private medical services) is a retained Component in the three PCA and does offer some nuances to the Support Capacity patterns.

Analysing the results for parishes (Figure 12), it is clear that those that are the capitals of the respective municipality tend to have higher Support Capacity scores, and parishes farther from them have lower scores. This is in line with the effect of the loading of the variables regarding distance to critical facilities. That effect is reinforced by the fact that at parish level, those that are the capital of the municipality also tend to have higher population density and additional services (i.e. private doctors).

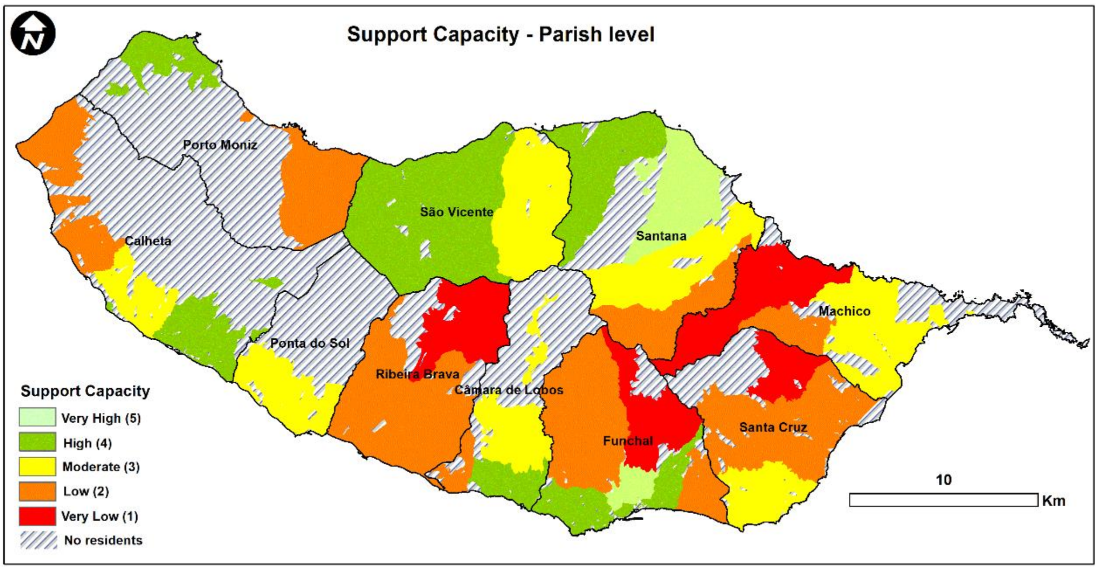


Figure 12: Support Capacity at Parish level

When we downscale the analysis to blocks (Figure 13), some asymmetries arise in parishes, resulting from different Components effect. In many cases the reason for that is that the blocks closest to the centre (i.e. where facilities and resources are) will have higher score of Support Capacity. In other cases, more central blocks do not have higher scores, and the asymmetries are due to other specific aspects. That happens because blocks in the edge of a parish may actually be relatively close to, for example, a medical facility, fire department or pharmacy in another parish or even municipality. In disaster situations, these support facilities and services do not exclude victims based on administrative borders. It also happens because inside parishes, even the more central, there are some areas that have population density much higher than others (i.e. there are more people close that can help in an emergency and have therefore higher Support Capacity).

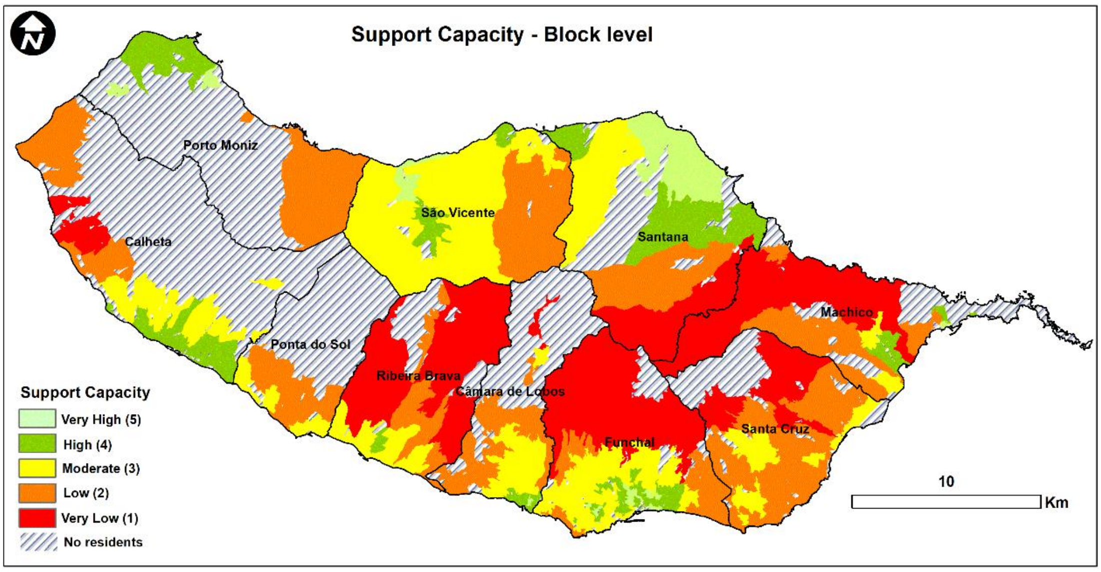


Figure 13: Support Capacity at Block level

The results by sub-block (Figure 14) follow the same trend described before with obviously a more detailed and complex pattern due to the small spatial extent of some sub-blocks.

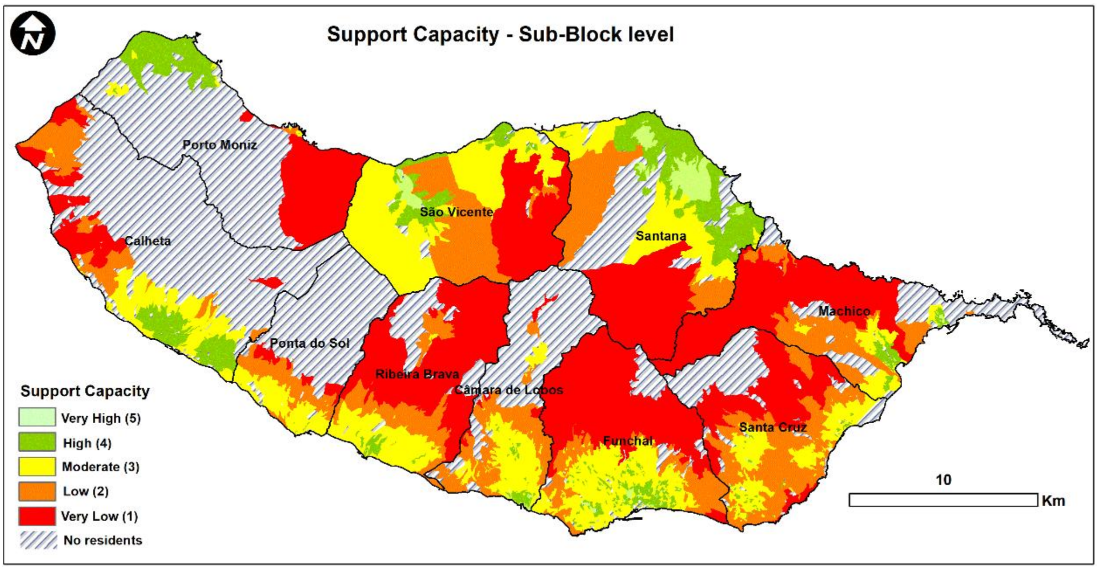


Figure 14: Support Capacity at Sub-Block level

By combining Criticality and Support Capacity we obtain SOVI_NTH. At parish level (Figure 15) we obtained a spatial pattern that is quite similar the one of SOVI although with some differences particularly regarding Santana. Lower scores of SOVI_NTH are found in parishes of Funchal, Câmara de Lobos, Santa Cruz as well as Santana. Very High scores are found in

Tabua and Serra de Água (Ribeira Brava), Curral das Freiras (Câmara de Lobos), Porto da Cruz (Machico) and Fajã da Ovelha (Calheta).

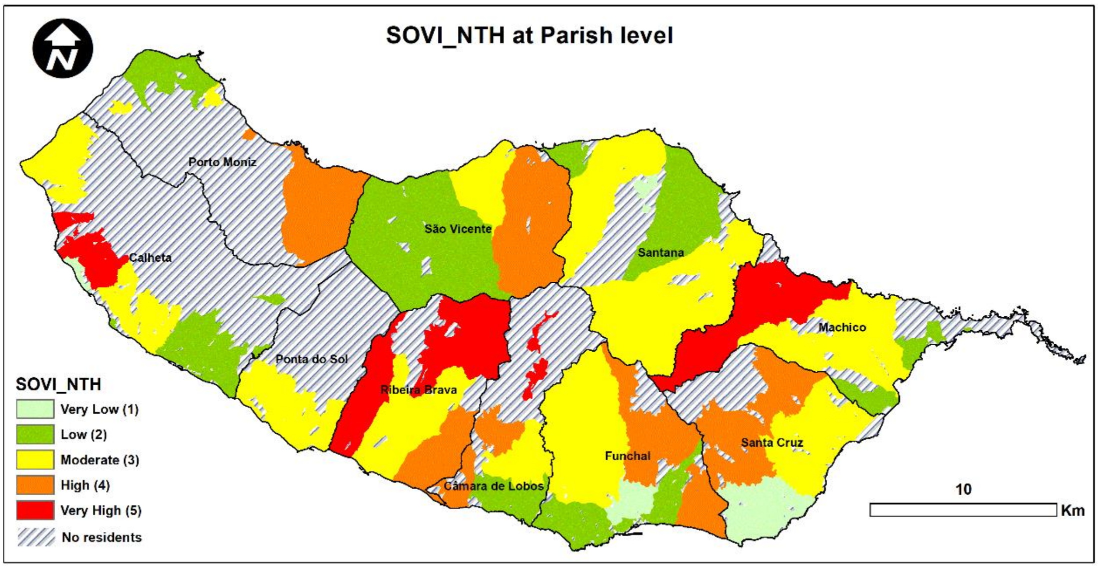


Figure 15: SOVI_NTH at Parish level

The overall Social Vulnerability in the SOVI_NTH model is a result of the balance between Criticality (ideally with low scores) and Support Capacity (ideally with high scores) and similar SOVI_NTH scores may result from different combinations. For example, if we compare Porto da Cruz (Machico), and Curral das Freiras (Câmara de Lobos) they have a similar SOVI_NTH score but if in the first case it is the result of Moderate Criticality and Very Low Support Capacity, in the second case it is the result of a Very High Criticality compensated by Moderate Support Capacity.

This example illustrates how SOVI_NTH, by having the two Sub-indexes, allows a relatively simple interpretation and illustration on whether a place with a high SOVI_NTH score demands intervention regarding its Criticality factors, the Support Capacity factors, or both. This seems, at least in the context of our implementation, to accomplish the purpose that led to the creation of SOVI_NTH. The analysis of the several components of SOVI may also prove useful as described before, but involves 6 or 7 components and the same component may include variables regarding both Criticality factors and Support Capacity factors.

SOVI_NTH results at block (Figure 16) level give a more complex and detailed pattern and the first visual impression is an increase in the portion of units with Very High scores compared with parishes, that was not evident in the previous analysis (i.e. SOVI or Criticality). This is mainly an issue of spatial extent because the percentage of units with Very High scores in parishes and blocks is similar but blocks with higher scores are larger. These blocks are mainly in the same municipalities that have more parishes with Very High scores, Calheta, Ribeira Brava, Câmara de Lobos and Machico, as well as, in this case, Santana.

The main clusters of highest or lowest score of SOVI_NTH maintain the same general pattern as in parishes but in some cases, it is possible to pinpoint dissonant values. Santo António and São Roque (Funchal), Estreito de Câmara de Lobos (Câmara de Lobos), Ribeira Brava (Ribeira Brava) and Ponta do Sol (Ponta do Sol) are all parishes with Moderate SOVI_NTH scores that include blocks with Very High scores. This happens because portions of these parishes have, for example, a lower Support Capacity (i.e. farther from emergency facilities and personnel) and therefore higher SOVI_NTH than the surrounding blocks of the same parish. Parishes in Funchal and Calheta with Low or Very Low SOVI_NTH scores at that level, when analysed at block level also present some with High scores.

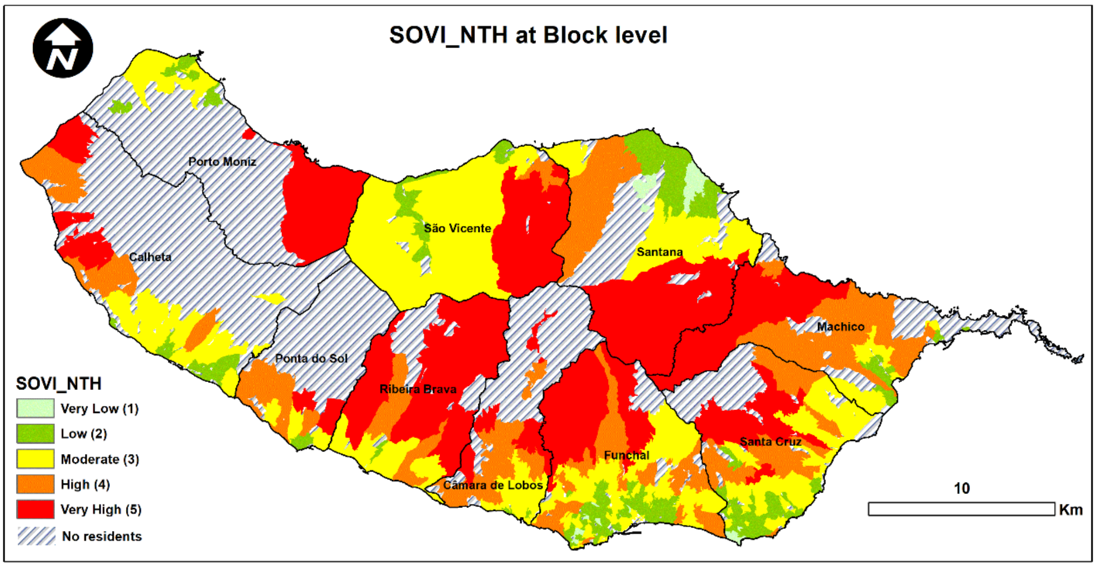


Figure 16: SOVI_NTH at Block level

At block level, the asymmetries inside parishes are determined by different reasons. In some blocks a given level of Criticality is mirrored by an equivalent level of Support Capacity and both dimensions have a similar importance. In others, Criticality is relatively high, or low, and Support Capacity relatively low, or high, balancing each other to reduced levels of SOVI_NTH but given rise to different concerns, because in some cases the interventions should prioritize reducing the high Criticality, and in other increasing the Support Capacity. This illustrates how Criticality and Support Capacity combine in different ways.

The results of SOVI_NTH using sub-blocks (Figure 17), as with SOVI, follow the general pattern and clusters of higher and lower scores obtained at block level, although with greater details and complexity. This complexity is naturally higher where the blocks divide in more sub-blocks, in more urban coastal areas. With the division of blocks into sub-blocks there is an overall trend to descrease in SOVI_NTH scores in the more coastal urban areas as oposite to the ones in more interior areas.

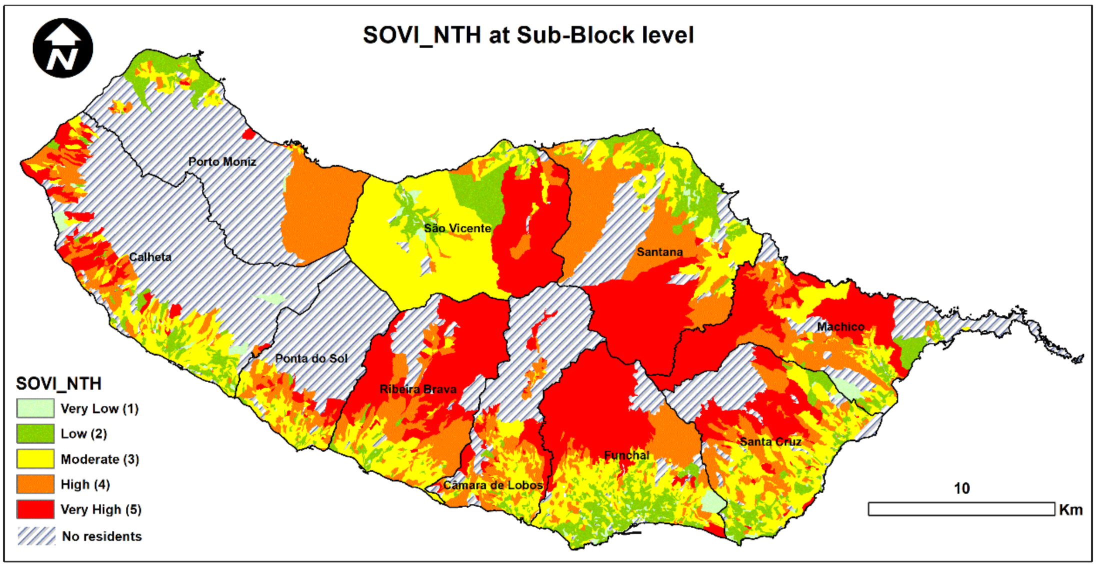


Figure 17: SOVI_NTH at Sub-Block level

As in SOVI, the praticality of analysing this amount of sub-blocks in order to produce information for Risk and Disaster governance is arguable. Yet, when performing a more local analysis, inside a municipality, it does highlight areas demanding special attention.

Figure 18 illustrates the results at the three aggregation levels, showing once more a consistency in terms of the general patterns but with an increased detail at block and sub-block level that allows to identify asymmetries, at times significant, inside parishes. Figure 18 illustrates the results of both indexes at the same aggregation level.

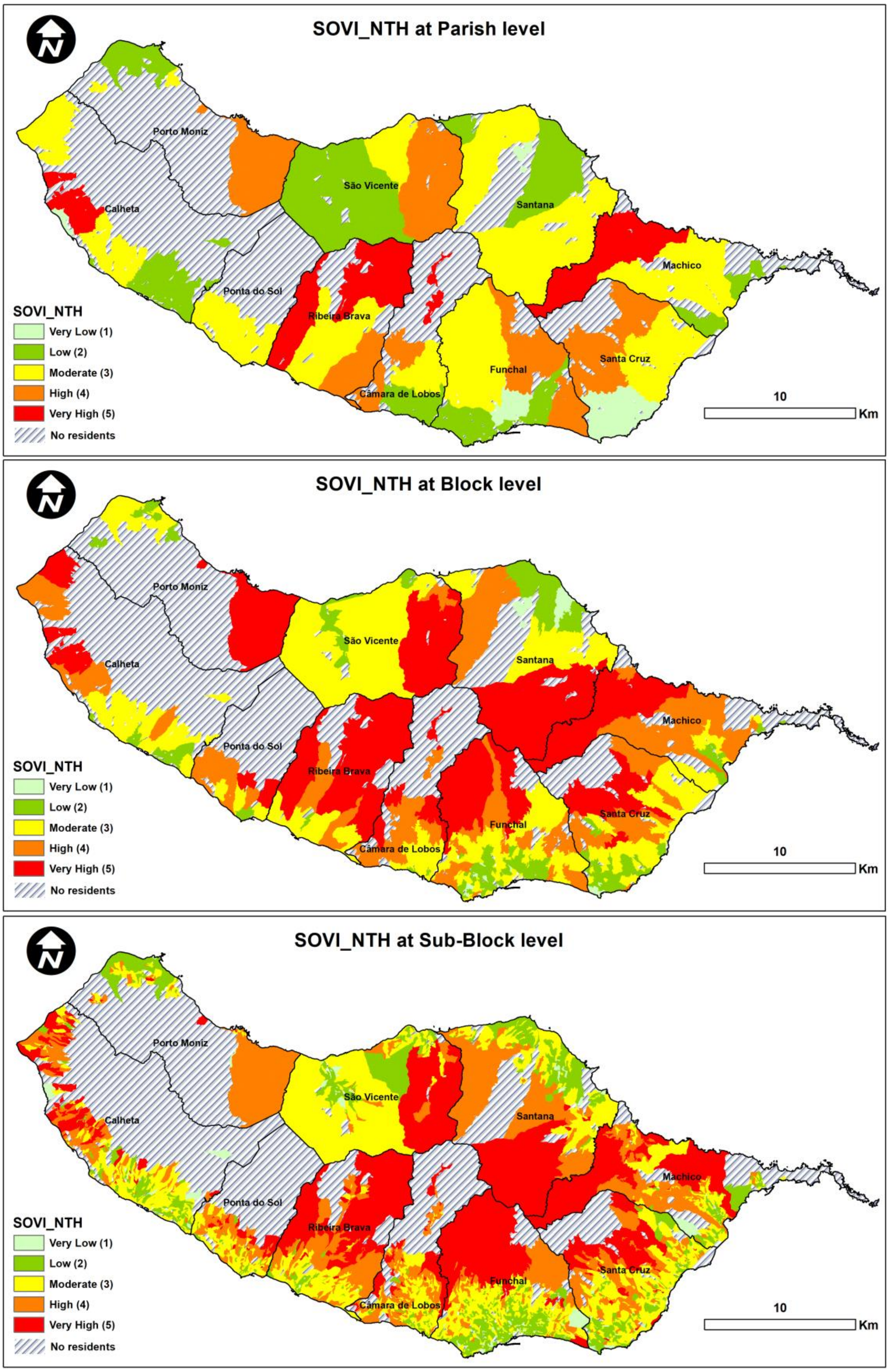


Figure 18: SOVI_NTH at Parish, Block and Sub-Block level

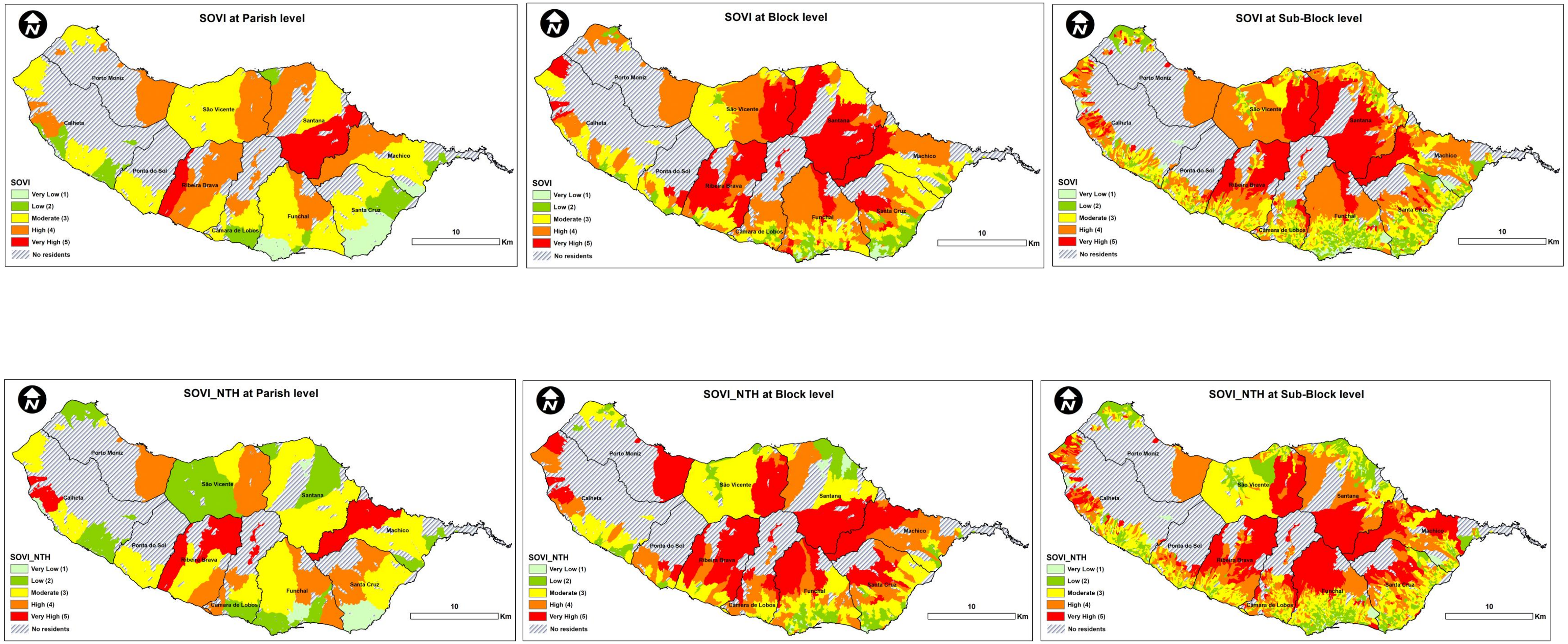


Figure 19: Social Vulnerability patterns across indexes and data aggregation units

We compared the results of SOVI and SOVI-NTH (Figure 18) because indexes are sensitive to changes in the algorithm (Schmidtlein et al., 2008) and some differences in the relative levels of Social Vulnerability are expected. Overall, the results between indexes at the same aggregation level are very similar. Because visual interpretation is somewhat complex, particularly at block and sub-block level, we used ArcMap to compare the level of Social Vulnerability in each aggregation unit with both indexes.

The results using data aggregated per parish are very similar (Figure 20). The major differences are found in Santana where SOVI_NTH resulted in two less parishes with Very High scores. In Ribeira Brava, Câmara de Lobos, Calheta and Machico there are parishes that have SOVI scores of High and Very High in SOVI_NTH. There are other differences in parishes' scores, but mostly with small amplitude, meaning differences on just one level (i.e. in a scale of 1 to 5). Over 41% of parishes have the same relative level with both indexes, 47% a difference of just one level, and only 9% a difference of two levels. Only one parish has a difference of three levels, in Santana.

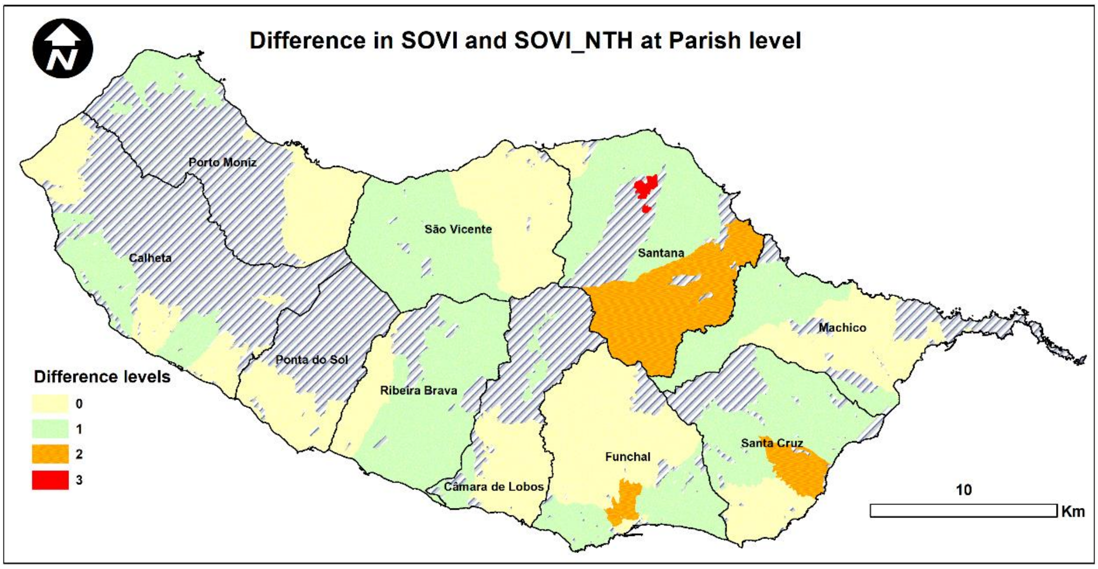


Figure 20: Difference in results between SOVI and SOVI_NTH at Parish level

Ilha parish in Santana has a High SOVI score and only Low SOVI_NTH because although it's a rural, aged parish, it has a good support network and is close to critical facilities, showing how the combination of Criticality and Support Capacity shows a dinamic masked by SOVI. Faial and São Roque do Faial, also in Santana, have a difference similar to the one in Ilha.

In the case of Gaula parish in Santa Cruz the oposite happens. Although not being so deprived and not having big Criticality, it has less Support Capacity due to support personnel and distance to critical facilities, an has therefore a higher sore with SOVI_NTH than with SOVI.

São Pedro and Imaculado are aged areas of Funchal with moderate Criticality, but because they are so close to medical and emergency facilities they have a lower score with SOVI_NTH than with SOVI.

The results of SOVI and SOVI_NTH at block level (Figure 21) are even more similar, with 55% of blocks having the same level of Social Vulnerability, and only less than 3% have a difference of two or three levels. The differences are located mostly in Santana.

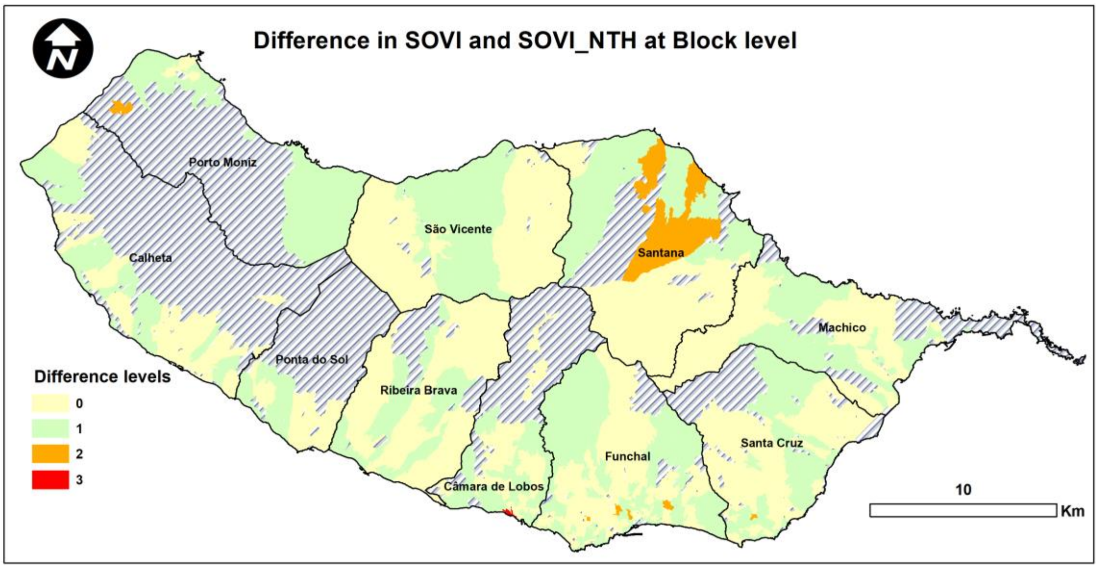


Figure 21: Difference in results between SOVI and SOVI_NTH at Block level

Similar reasons explain the variations at block level. In Achadas da Cruz, a rural, aged and deprived area of Porto Moniz, has a High SOVI but because it is close to support facilities and structures it has a Low SOVI_NTH, because Support Capacity is analysed independently and subtracted to Criticality.

A similar situation, even more significate, happens in the centre of Câmara de Lobos, a socioeconomic deprived area with Very High SOVI but so close to all the support stractures and facilities that it has a Low SOVI_NTH score because Criticality is balanced by the higher Support Capacity. The same happens in several blocks in Santana.

These examples show how the two sub-indexes of SOVI_NTH can be useful to identify distint situations and quickly determine whether the major concern in a given area is due to its intrinsic socioeconomic attributes or the (in)existence of support resources.

At sub-block (Figure 22) the similarities between indexes are even more striking, with over 66% of sub-blocks having the same relative level with both indexes, and only 0.7% having a difference of more than 1 level. The level of detail of so small statistical units is apparently less affected by the difference in the algorithms.

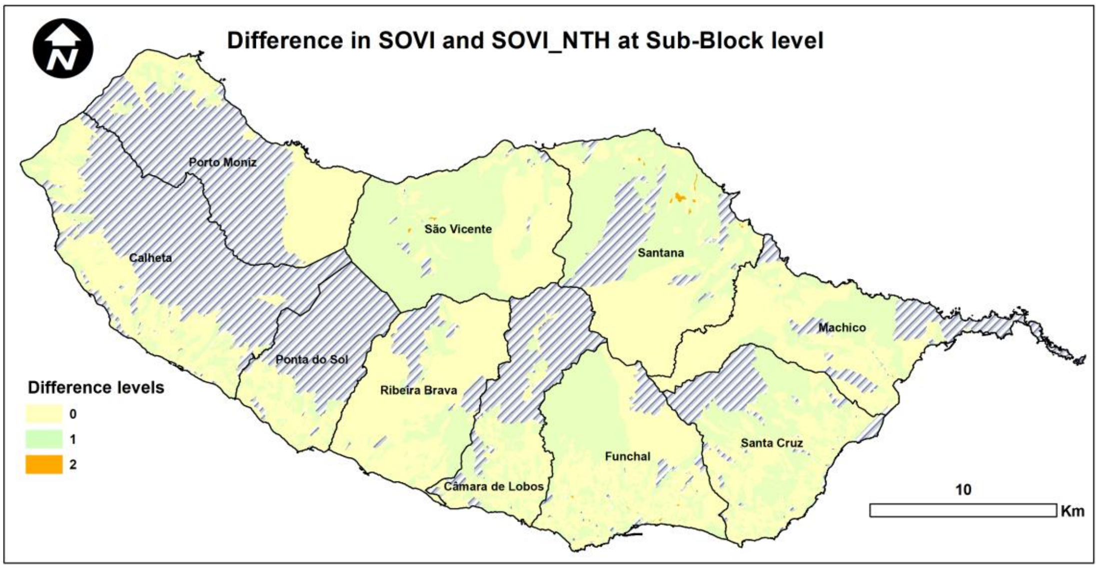


Figure 22: Difference in results between SOVI and SOVI_NTH at Sub-Block level

The previous examples of difference between SOVI and SOVI_NTH show how the two sub-indexes of SOVI_NTH can be useful to quickly identify distint situations and determine whether the major concern in a given area is due to its intrinsic socioeconomic attributes or the (in)existence of support structures and facilities. This is less evident with SOVI and the 6 or 7 Components retained. More significative, SOVI often retains in the same components variables regarding both the socioeconomic attributes and support structures and facilities, like it happens in this research with the SOVI PCA output for parishes and blocks.

Finally, we compared the effect of changing data aggregation level by determining the percentage of statistical units that have a different SOVI level (i.e. In a scale of 1 to 5) at a smaller statistical unit different than the one that it would have if the value calculated for a more aggregated unit would be assigned to all the smaller units that constitute it.

Most sections have a level of SOVI that is the same, or similar, to the one they would have if the parish value was assigned – 41% have the same level, 47% one level of difference and only 12% a difference of two or more levels (Figure 22). Because the classes are defined using Standard Deviation to highlight the extreme values, a difference up to one level does not have a big impact and it corresponds to 88% of blocks in Madeira. Likewise, if we consider the difference of Social Vulnerability in sub-blocks calculated at sub-block level or assigning the block score, the results are also very similar – 43% have the same level, 47% have a difference of one level, and only 10% a difference of two or more levels (Figure 24).

The comparation regarding SOVI_NTH showed a very similar performance. Only 14% of blocks have a difference of two or more levels comparing to the one corresponding to the parishes where they are located, 38% have the same level and 49% one level of difference.

The similarity is even bigger considering sub-block scores and the level calculated for the blocks where they are located – 50% have the same level, 42% have a difference of one level and only 8% two or more levels of difference.

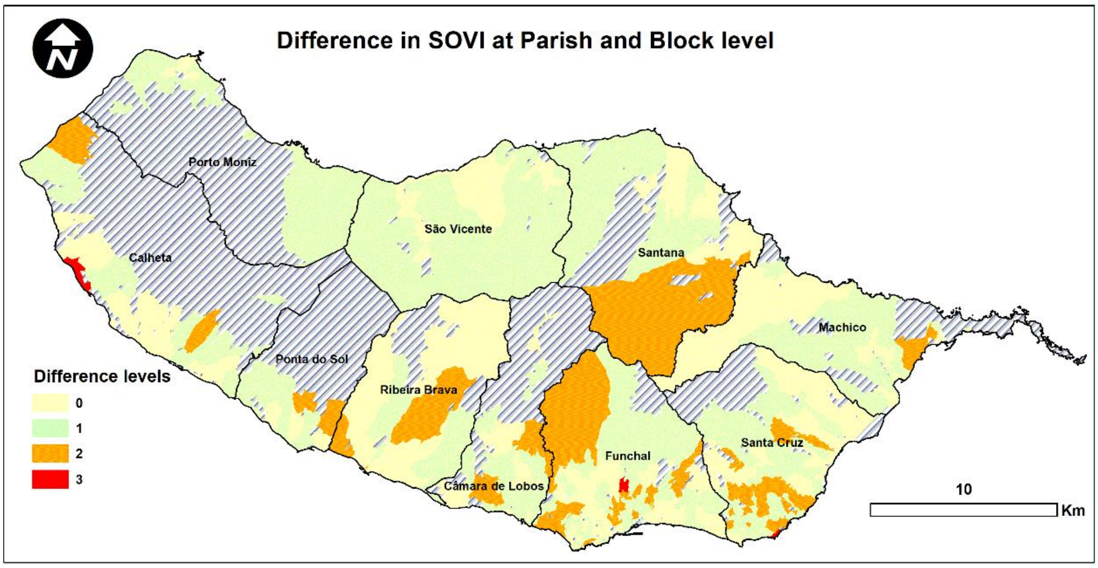


Figure 23: Difference in SOVI result at Parish and Block level

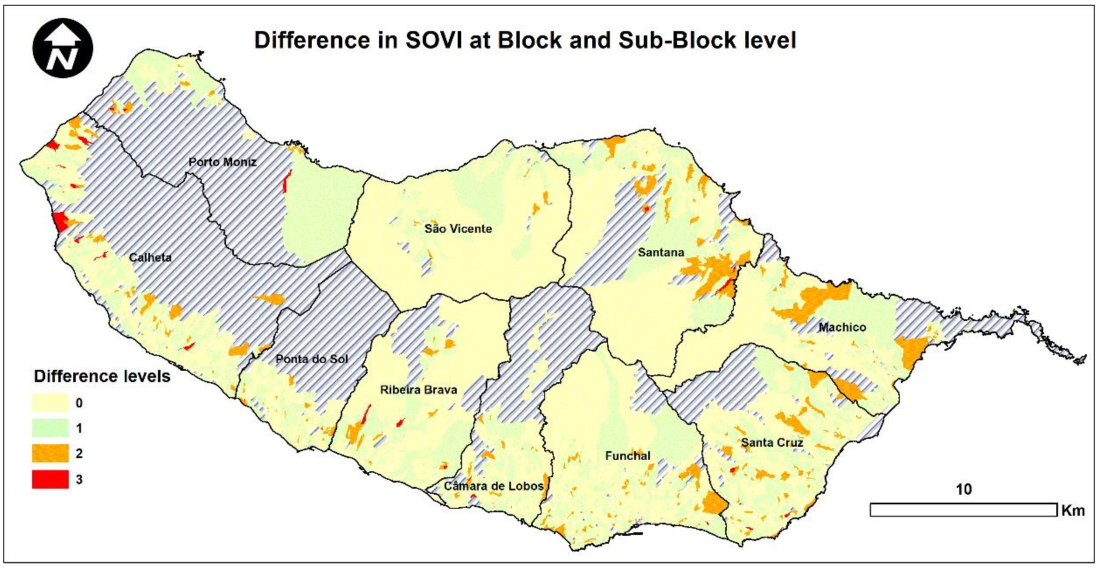


Figure 24: Difference in SOVI result at Block and Sub-Block level

Although, as we see on Figure 19, areas with High and Very High Social Vulnerability with both SOVI and SOVI_NTH, particularly at block and sub-block level, occupy a significative portion of the territory, that does not translate to the amount of people living in such areas. In fact, as we can see on Table 13, most population lives in areas of Moderate or Low Social Vulnerability and the percentages of population living in areas with Very High scores is under 8%. Regardless, it is possible to identify areas with cluster of population with Very High Social Vulnerability. With both SOVI and SOVI_NTH, the percentage of residents in areas with High or Very High Social Vulnerability is higher at block level. Figure 25 illustrates that most residents live in areas of Moderate or Low Social Vulnerability.

Madeira Island	SOVI			SOVI_NTH		
	Parish	Block	Sub-block	Parish	Block	Sub-block
Residents - Very High score	1%	6%	2%	3%	8%	4%
Residents - High score	10%	23%	18%	13%	20%	16%
Residents – Moderate score	50%	44%	43%	36%	39%	41%
Residents – Low score	16%	20%	33%	31%	30%	36%
Residents – Very Low score	22%	6%	5%	17%	3%	4%

Table 13: Residents in Madeira per SOVI and SOVI_NTH score at parish, block and sub-block level

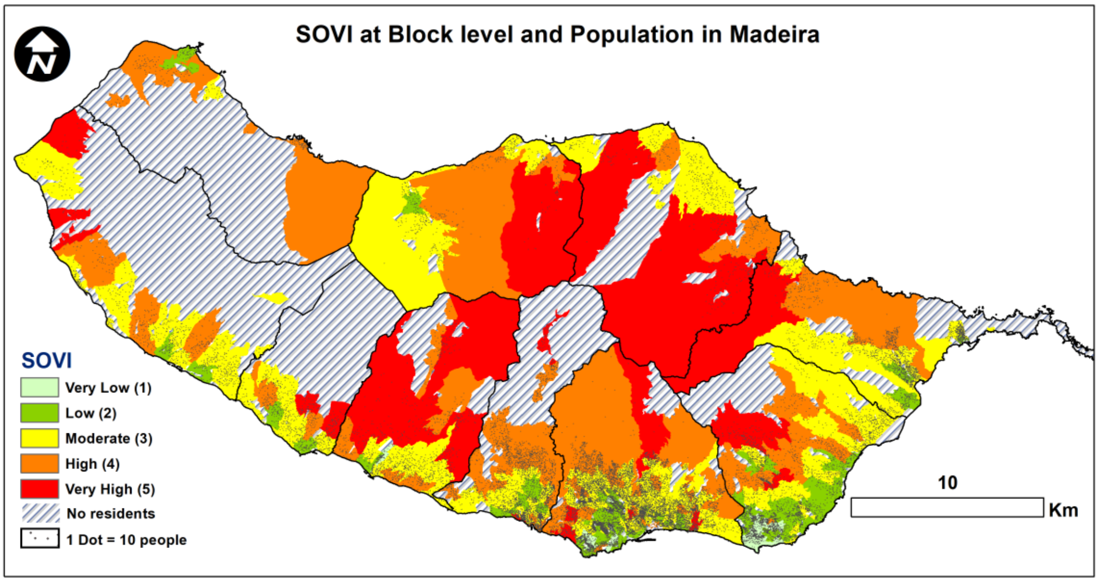


Figure 25: SOVI at Block level and Population in Madeira

We have also analysed how certain groups distribute among the five classes of Social Vulnerability scores to determine whether some are over represented, compared to the percentage for total residents (Table 14).

Madeira	SOVI											
	Parish				Block				Sub-block			
scores	**Res**	**>64**	**Fem**	**1ºC**	**Res**	**>64**	**Fem**	**1ºC**	**Res**	**>64**	**Fem**	**1ºC**
Very High	**1%**	2%	1%	2%	**6%**	8%	6%	9%	**2%**	3%	2%	3,5%
High	**10%**	14%	11%	14%	**23%**	25%	23%	30%	**18%**	21%	18%	26%
	SOVI_NTH											
	Parish				Block				Sub-block			
scores	**Res**	**>64**	**Fem**	**1ºC**	**Res**	**>64**	**Fem**	**1ºC**	**Res**	**>64**	**Fem**	**1ºC**
Very High	**3%**	4%	3%	5%	**8%**	9%	8%	8%	**4%**	5%	4%	7%
High	**13%**	14%	13%	16%	**20%**	21%	20%	30%	**16%**	18%	16%	22%

Res – Residents
>64 – Residents with more than 64 years old
Fem – Female residents
1ºC – Residents with only the 1st Cycle of Education or less

Table 14: Groups in Madeira per SOVI and SOVI_NTH score at parish, block and sub-block level

In some cases, there is no significative trend (i.e. female residents, residents with 14 or less years). In other cases, as expected, there is an over representation of groups that are known to be particularly vulnerable in the face of disasters (i.e. residents over 64 years old, residents with lower school attainment, women above 64 years old). This is not just a concretization of the theoretical dimensions of Social Vulnerability, but also a result of the statistical procedure of PCA.

If we zoom to Funchal, most population also lives in areas of Low to Moderate Social Vulnerability, considering both indexes and across data aggregation units. Although areas of High or Very High Social Vulnerability have a big spatial expression (i.e. bigger parishes, blocks and sub-blocks), the amount of population living in areas classified with High or Very High scores of Social Vulnerability is relatively small according to both SOVI and SOVI_NTH, although with significative differences across data aggregation units (Table 15). With both indexes, the results at block level show higher percentage of people with High (i.e. 4% and 3% respectively) and Very High (i.e. 20% and 15% respectively) scores of Social Vulnerability.

Funchal	**SOVI**			**SOVI_NTH**		
	Parish	**Block**	**Sub-block**	**Parish**	**Block**	**Sub-block**
Residents - Very High score	0%	4%	0,1%	0%	3%	1%
Residents - High score	6%	20%	7%	12%	15%	8%
Residents – Moderate score	63%	50%	41%	33%	38%	38%
Residents – Low score	8%	20%	42%	38%	38%	46%
Residents – Very Low score	24%	6%	9%	17%	5%	7%

Table 15: Residents in Madeira per SOVI and SOVI_NTH score at parish, block and sub-block level

SOVI_NTH resulted in a higher number of units (parishes, blocks or sub-blocks) with Very High scores, though mainly in less populated areas. In the more populated urban areas most people live in areas with Very Low and Low scores, particularly with data aggregated at parish and sub-block level, with both indexes (Figure 26). However, in certain areas in the urban perimeter of Santo António, West areas of São Gonçalo and several areas along the riverbanks, there is a significative number of people living in High and Very High level of Social Vulnerability and these areas should deserve particular attention from the local and regional authorities.

In Funchal the same over representation of some groups in areas of higher Social Vulnerability, including older residents, older women and residents with lower education attainment.

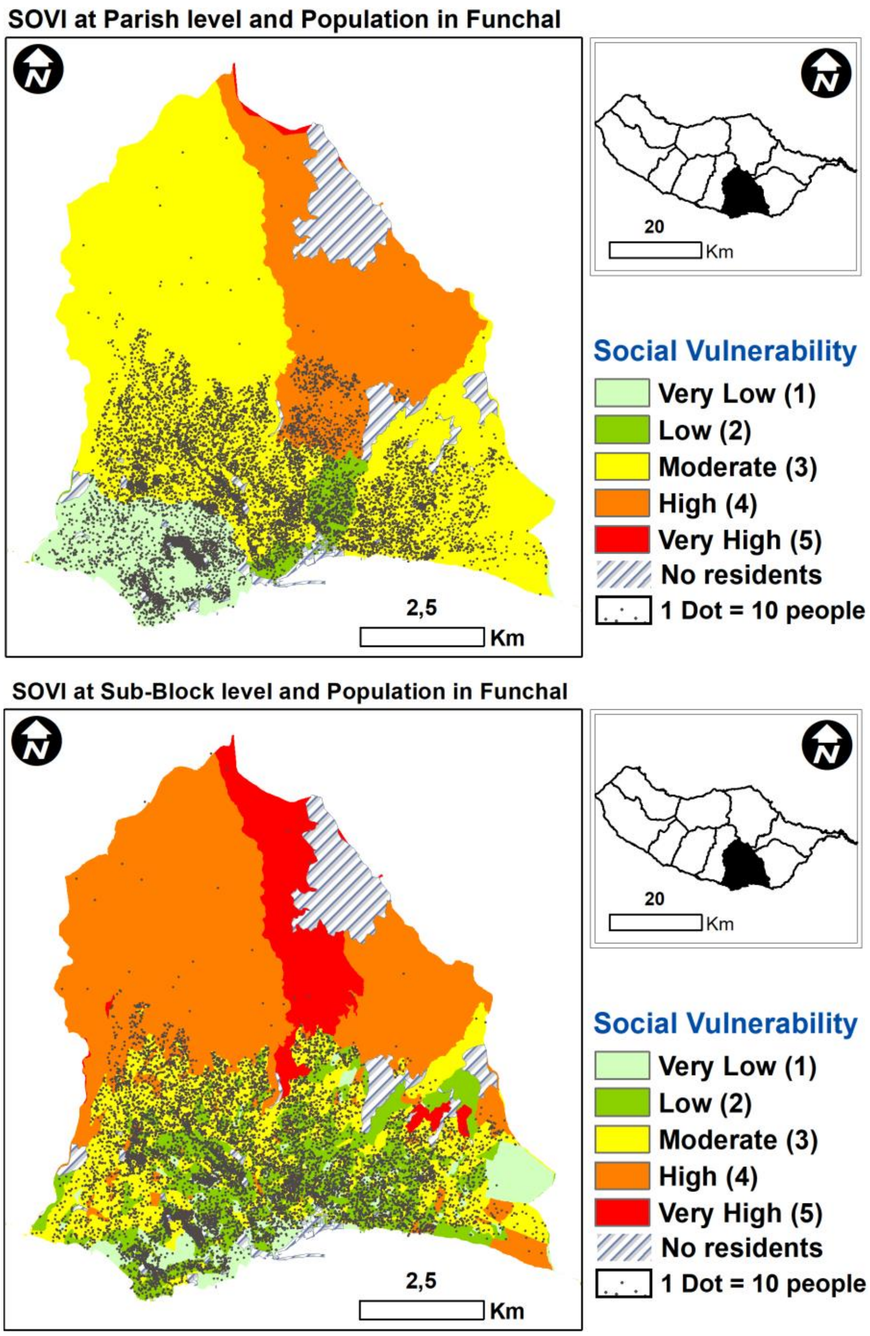


Figure 26: SOVI and SOVI_NTH patterns at Sub-Block level

4. HAZARDS-OF-PLACE

4.1. Introduction

The Hazards-of-Place model combines the Susceptibility to Hazards with Social Vulnerability to produce the overall composite Place Vulnerability pattern, allowing to highlight those areas simultaneously highly socially vulnerable and susceptible to Hazards.

In this Chapter we broadly characterize Susceptibility to Hazards in Madeira, and in Funchal, and complete the Hazards-of-Place model by combining Social Vulnerability with Hazards Susceptibility to obtain the Place Vulnerability.

4.2. Hazards in Madeira

In Madeira recurrent extreme natural events, concentrated in its small area, have through the years caused property damage, life loss and disruption of the socioeconomic fabric. The combination of natural features (i.e. steep slopes; geology; dimension and shape of river basins; vegetation; clime) and anthropic characteristics (i.e. urbanization of susceptible areas; land use and soil impermeabilization; hydraulic structures) in a small insular territory creates conditions propitious for both severe and frequent disasters affecting. Thus, the historical record is full of extreme events like floods, debris flows, landslides, rockfall and forest fires. These happen particularly in moments of extreme weather conditions, and the succession of such events has over the years had a severe impact in terms of life and property losses (Abreu, Tavares, & Rodrigues, 2008; B. Almeida, Oliveira, França, Rodrigues, & Silva, 2010; Municipia, 2014; Municipia & FCT, 2016; Oliveira et al., 2011; Peixoto, 2013; Policarpo, 2012; Quintal, 1999; Rodrigues, 2005; Sepúlveda, 2011; F. Silva & Menezes, 1978).

Madeira is a small island, where two thirds of its area is protected and cannot be urbanized resulting in limited construction areas. The intense urbanization in the last decades led to the occupation of many inadequate areas (i.e. close to rivers or instable slopes) increasing people's exposure to severe consequences, even if the frequency or intensity of such events remains the same (B. Almeida et al., 2010; Municipia, 2014; Sousa, 2013).

The frequent occurrence of extreme events and the losses they have induced are well documented, especially regarding the events occurred in the last decades (Appendix II) and the increasing attention devoted to Hazards has led to a high number of academic studies and technical reports, focusing mainly on the analysis of the biophysical conditions, the phenomenology and triggering factors of Hazards and the study of specific events (Abreu et al., 2008; B. Almeida et al., 2010; Andrade, 2014; Caetano, 2014; Municipia, 2014; Municipia & FCT, 2016; Oliveira et al., 2011; Peixoto, 2013; Policarpo, 2012; Quintal, 1999; Rodrigues, 2005; Sepúlveda, 2011; F. Silva & Menezes, 1978).

In the last 100 years, the more severe events involved a combination of multiple Hazardous events' typology occurring simultaneously and in a short period of time, triggered by extreme precipitation (i.e. flash-floods, debris-flows, landslides). Floods and debris-flows in moments of extreme precipitation are particularly serious due to its frequency and severity of events. Smaller magnitude events occur more frequently but with less impact per event (i.e. rockfall, topple). In the last decades some forest fires have also affected Madeira with a severity that left extensive areas of forest burnt and several houses destroyed and in 2016 three lives were lost (B. Almeida et al., 2010; Caetano, 2014; Municipia, 2014; Municipia & FCT, 2016; Oliveira et al., 2011; Quintal, 1999; Rodrigues, 2005; Sepúlveda, 2011; F. Silva & Menezes, 1978).

Other Hazards like snow, heat waves, cold snaps or earthquakes are neither frequent nor cause significative impacts. Tsunamis, although not frequent do occur. In 1930 a tsunami caused by a coastal landslide killed 29 people in Câmara de Lobos (Municipia, 2014).

Major storms in Madeira happen virtually every year, particularly between October and April, with strong winds and extreme rainfall that results in major floods, debris-flows and landslides, often simultaneously. Gale winds happen mostly in areas above 1000m of altitude, and in those cases have a limited impact. Extreme precipitation storms affect the island regularly and although the highest precipitation values are registered in high altitude areas, superficial drainage and rivers extend its impact to most river basins (Municipia, 2014).

Because of Madeira's steep slopes and small basins in narrow valleys, when severe precipitation hits high altitude areas, rainfall is concentrated and drained at high speeds through the affected river basins. Additionally, due to slopes instability, the existence of a large amount of solid materials and the speed of drainage, floods are often associated with landslides and varying amounts of solid material in the water flow.

Floods and debris-flows although affecting the island as a whole, are clearly more prevalent in some areas. Funchal is the more susceptible area and accounts for over half the events. Ribeira Brava, Câmara de Lobos, Santa Cruz and Machico are the other very susceptible areas. Though less frequent, there are also records of severe events in Ponta do Sol (i.e. Madalena), Calheta, Porto Moniz (i.e. Ribeira da Janela) and São Vicente (i.e. Rosário).

Mass movements are other major Hazard in Madeira, including landslides, rockfall and topples. Some landslides are significative with several tonnes of material. Smaller and more located events, rockfall and topples, affect small areas but are very frequent and end up adding up to large losses over the years. High and Moderate Susceptibility cover 70% of the island so the Susceptibility to this Hazard is considerable, particularly where slopes are above 20 degrees (Municipia, 2014). They affect particularly the central area of Câmara de Lobos (i.e. Curral das Freiras), Ribeira Brava (i.e. Serra de Água) and Ponta do Sol (i.e. Ponta do Sol) where slopes are more accentuated (Municipia, 2014). Other susceptible areas include coastal portions of Calheta (Ponta do Pargo), Porto Moniz (Achada da Cruz) Santana and Machico. Rock fall close to roads happens particularly between São Vicente and Porto Moniz and between Ponta do Sol (Lugar de Baixo) and Calheta (Paul do Mar) (Municipia, 2014).

For the municipality of Funchal (Figure 27), it was possible to access the Susceptibility maps regarding the more relevant Hazards (Figure 28). In Funchal storms are frequent, mainly between October and April. They are characterized by both heavy rainfall and strong winds, and its consequences are felt in the urbanized area below (Municipia & MedFirst, 2013).

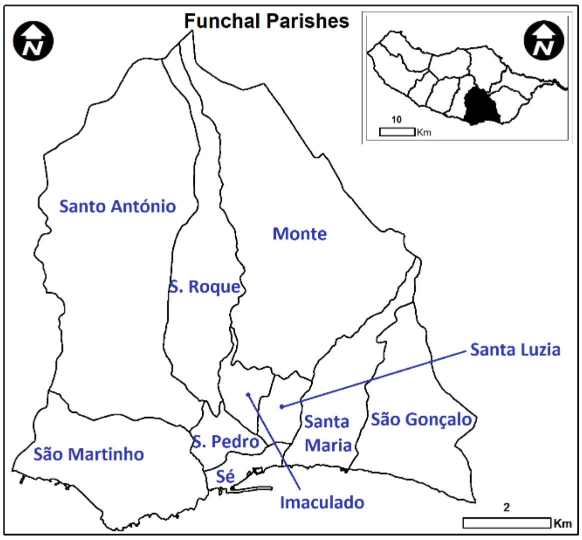


Figure 27: Funchal Parishes

Extreme precipitation events are not rare, particularly in Autumn and early Spring, causing major floods and other concomitant Hazard typologies, including hyper concentrated flows, debris-flows and landslides (Municipia & MedFirst, 2013). The more susceptible areas are the banks of the three main water courses, Ribeira de João Gomes, Ribeira de Santa Luzia and Ribeira de São João, particularly the river mouths under 70 metres of altitude. In their course, parallel to each other and perpendicular to the sea, they have steep slopes that reach 77 degrees in the upper portions. This results in high speed flows with a large capacity to transport sediments (Municipia & MedFirst, 2013).

Mass movements are also frequent, particularly landslides, rockfall and topples. They affect mostly areas with steep slopes. Rockfall and topples are more common in volcanic material areas in mid and low altitudes of the municipality and in higher altitude areas. In narrow valleys with pyroclastic materials landslides are more frequent, often contributing to solid content of floods when precipitation is very high (Municipia & MedFirst, 2013). In general, the Northern part of Funchal, closer to the mountain peaks, is more susceptible. Very High and High Susceptibility corresponds to 40% of the municipality area. Santo António and Monte parishes , with 62% and 59% respectively, are the ones with more percentage of their area with Very High and High Susceptibility (Municipia & MedFirst, 2013).

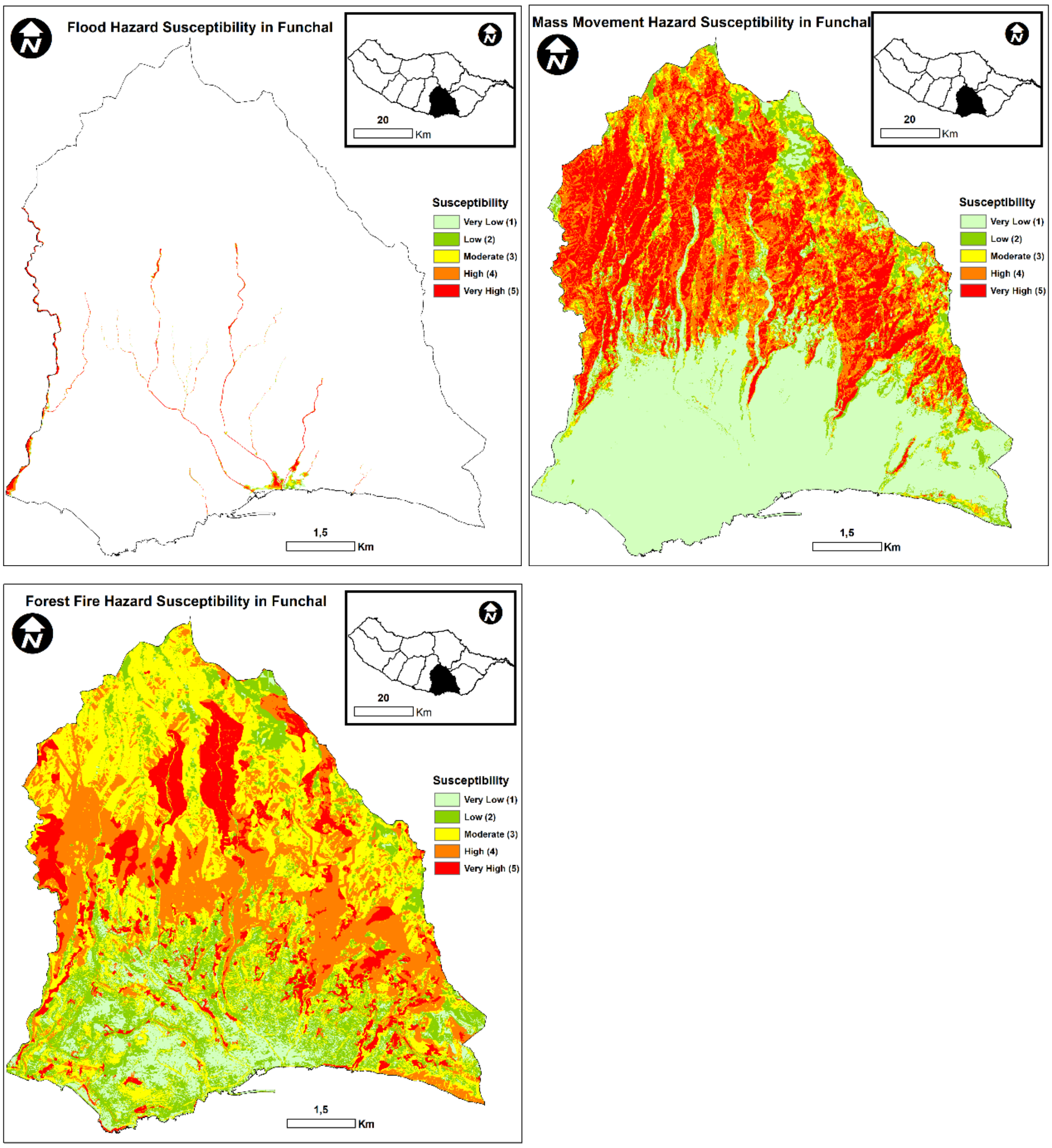


Figure 28: Illustration of Floods, Mass Movements and Forest Fires

Northern areas of Funchal have a significative forest fire susceptibility. In 2016 an unusually severe forest fire actually entered the urban area causing three deaths and several houses destroyed. São Roque (44%), Monte (41%) and Santo António (33%) are the parishes with more percentage of their territory with Very High or High Susceptibility to forest fires (Municipia & MedFirst, 2013). Other areas of concern include some portions of the valleys of Ribeira de Santo António, Ribeira de Santa Luzia and between Ribeira do Curral das Freiras and Ribeira da Lapa, as well as a strip of land North of the urban perimeter of Santo António, São Roque, Monte, Santa Maria and São Gonçalo (Municipia & MedFirst, 2013).

4.3. Methodology

To implement the Hazards-of-Place model, we combined Social Vulnerability and Hazards Susceptibility (i.e. both Hazard and Multi-Hazard analysis), using spatial analysis and raster calculation in ArcGis by using Raster Calculator to add both maps, divided in five classes and adjusting the results, again, to five classes.

Flood Hazard Susceptibility maps was available for the entire island. For the remaining relevant Hazard, only the municipality of Funchal provided Susceptibility maps for the more significant Hazards typologies. For this municipality it was possible to combine several Hazard types (i.e. mass movements, forest fires, floods) to obtain a Multi-Hazards map. This was done by combining the raster maps in ArcGis. This combination can be done with an additive model, averaging the scores, or using the maximum score per raster cell. Averaging in each cell the score of the three maps does not seem to be an appropriate approach because it masks extreme values. Some areas in downtown Funchal have a Very High (5) Susceptibility to floods but the Susceptibility to forest fires or mass movements is Very Low (1) which would result in an average of Low. This would not be appropriate because the record of the last 200 years shows this is a priority area. A better approach is to use an additive model, adding the scores of each Hazard score, which can result in values between 3 and 15 (i.e. because we are using three Hazards' maps). However, summing the scores mentioned in the last example would result in a score of 7, a moderate value despite this area being periodically affected with destructive consequences. The purpose of SOVI classification is to identify extreme values. The same approach is adopted here, and to determine to each cell the highest Hazard level (i.e. among the three Hazards used, chosen for being those that have an history of frequent and severe events) and to do that, we used the maximum value of Hazard in each cell, using raster calculation in ArcGis.

The floods Hazard maps for Madeira and the Multi-Hazards for Funchal, as well as each Hazard independently, were combined with Social Vulnerability indexes (i.e. SOVI and SOVI_NTH) calculated to different data aggregation units (i.e. parish, block, sub-blocks) to obtain the Place Vulnerability.

ArcMap 10.3.1 was used to analyse and process the geographic information. All layers used were normalized for Projected Coordinate System ITRF93_UTM_Zone28N, Projection Transverse Mercator, and Datum D_ITRF_1993. Raster files were produced using cells of 5x5m.

4.4. Results

We overlaid the Social Vulnerability maps (i.e. SOVI and SOVI_NTH) regarding different data aggregation units (i.e. parish, block and sub-block) with the flood Hazard Susceptibility map for Madeira island and, in the case of Funchal, with floods, mass movements, forest fires and Multi-Hazards (i.e. combination of the three Hazard maps).

The results regarding Madeira Flood Hazard's Susceptibility show a very specific pattern since major floods, despite sometimes having tremendous severity, do not affect a very extended area, due to the narrow valleys. Even in the more affected areas, the flood usually does not extend to more than a few dozen meters to each side of the river bank. Thus, the area of flood Susceptibility that overlays the Social Vulnerability map producing different scores is limited to the river banks (Figure 29).

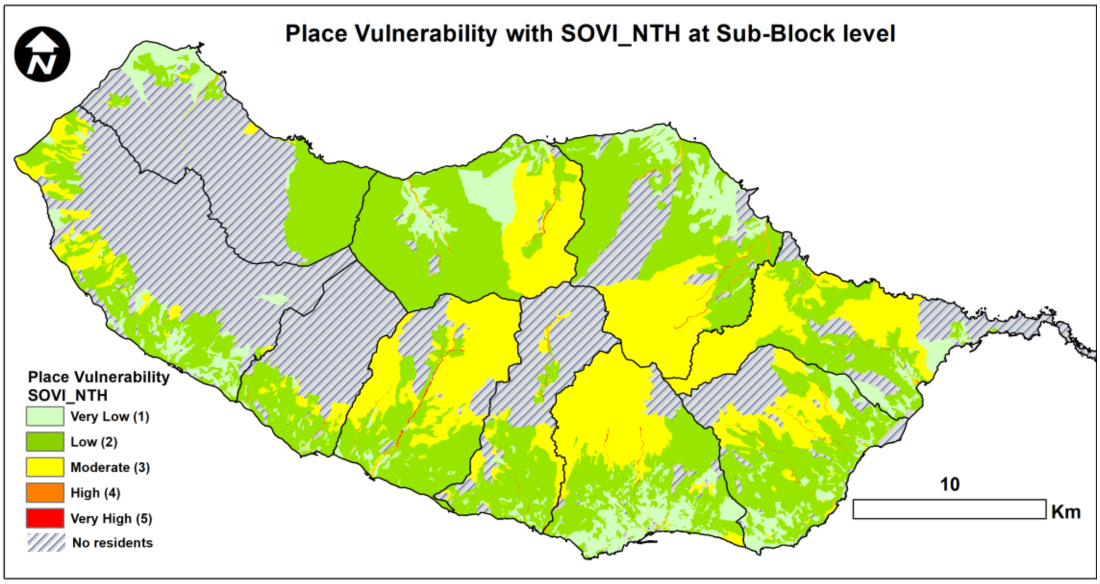


Figure 29: Place Vulnerability with SOVI_NTH at Sub-Block level

However, when we zoom to a particular area, it is noticeable that similar levels of Social Vulnerability coincide with different levels of Susceptibility and, likewise, similar levels of Susceptibility overlay with different degrees of Social Vulnerability. More significantly, some areas were highlighted as having Very High scores, meaning they have both Very High levels of Susceptibility and Social Vulnerability and should therefore be seen as areas of priority intervention. The areas with higher Place Vulnerability are extensions of the susceptible areas where Social Vulnerability is also higher.

Ribeira Brava (Figure 30) and Santana have parishes (i.e. Ribeira Brava, Faial, São Roque do Faial) with High or Very High Social Vulnerability that coincide with Very High Susceptibility to floods, and the Place Vulnerability is High and Very High along most of the river banks that cross those parishes. When analysed at block and sub-block level, because those parishes have areas with low Social Vulnerability, in those areas the resulting Place Vulnerability is not as high. In some areas of Funchal and São Vicente the opposite happens, and when using sub-block Social Vulnerability data instead of parish, blocks or sub-blocks with higher Social Vulnerability than the surrounding blocks or sub-blocks in the same parish, niches of Very High Place Vulnerability are highlighted.

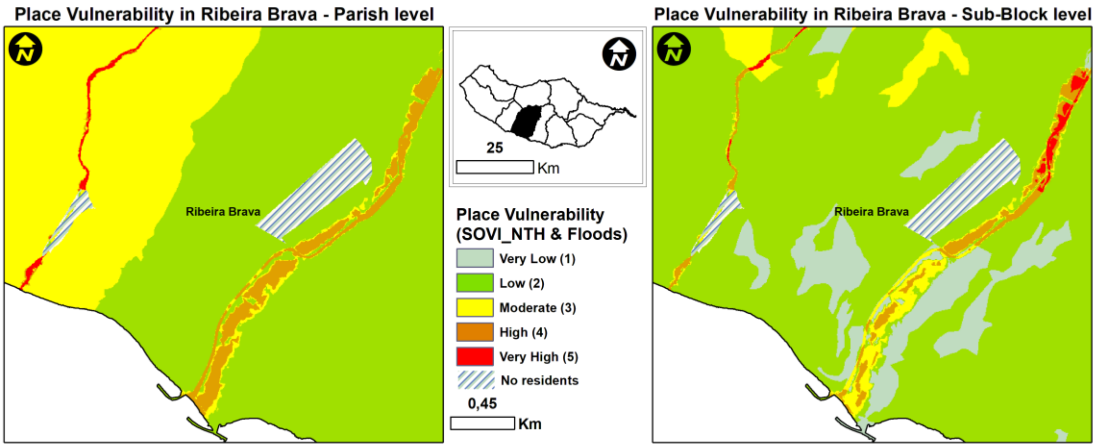


Figure 30: Detail of Place Vulnerability in Ribeira Brava at Parish and Sub-Block level

When we consider the different data aggregation units, it is clear that applying the model Hazards-of-Place with smaller statistical data units provides a more detailed analysis and facilitates the identification of niches with both Very High Social Vulnerability and Susceptibility that are not noticeable if SOVI or SOVI_NTH are calculated for parishes.

In the maps below (Figure 31), we can see how due to overall low level of Social Vulnerability in central parishes of Funchal there are no areas with Very High Place Vulnerability when overlaying with Susceptibility to floods. When using the Social Vulnerability maps per sub-block, some Very High Social Vulnerability niches appear inside several parishes and in some cases coincide with Very High Susceptibility resulting in Very High Place Vulnerability, including in São Pedro (a), Monte, Imaculado Coração (b).

On the other hand, in Santa Maria, an area often inundated, the analysis using sub-block Social Vulnerability allows to limit the extend of the area classified with high Place Vulnerability (c).

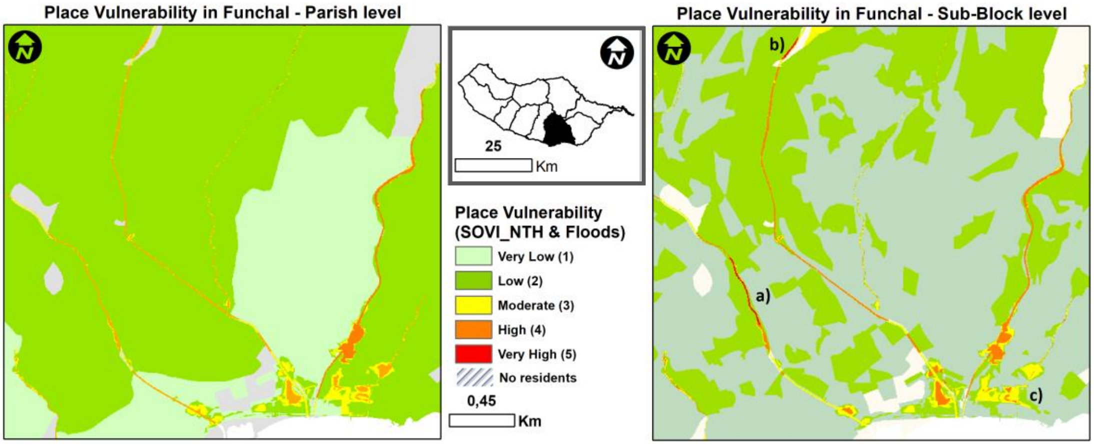


Figure 31: Detail of Place Vulnerability in Funchal at Parish and Sub-Block level

The analysis of the Place Vulnerability in Funchal, according to the model Hazards-of-Place was done with both the SOVI and SOVI_NTH maps and the Susceptibility to individual Hazards (i.e. floods, mass movements and forest fires) and Multi-Hazards.

Regarding mass movement Hazard, at parish level the highest scores of Place Vulnerability are observed in the Northern parts of the parishes of Santo António, São Roque and Monte as well as São Gonçalo (Figure 32). The lowest levels are registered in the Southern parishes. The results using block and sub-block show a more complex pattern. In the Southern parishes, particularly São Martinho and São Gonçalo, several areas with Place Vulnerability higher or smaller than the one of the rest of the parish emerge.

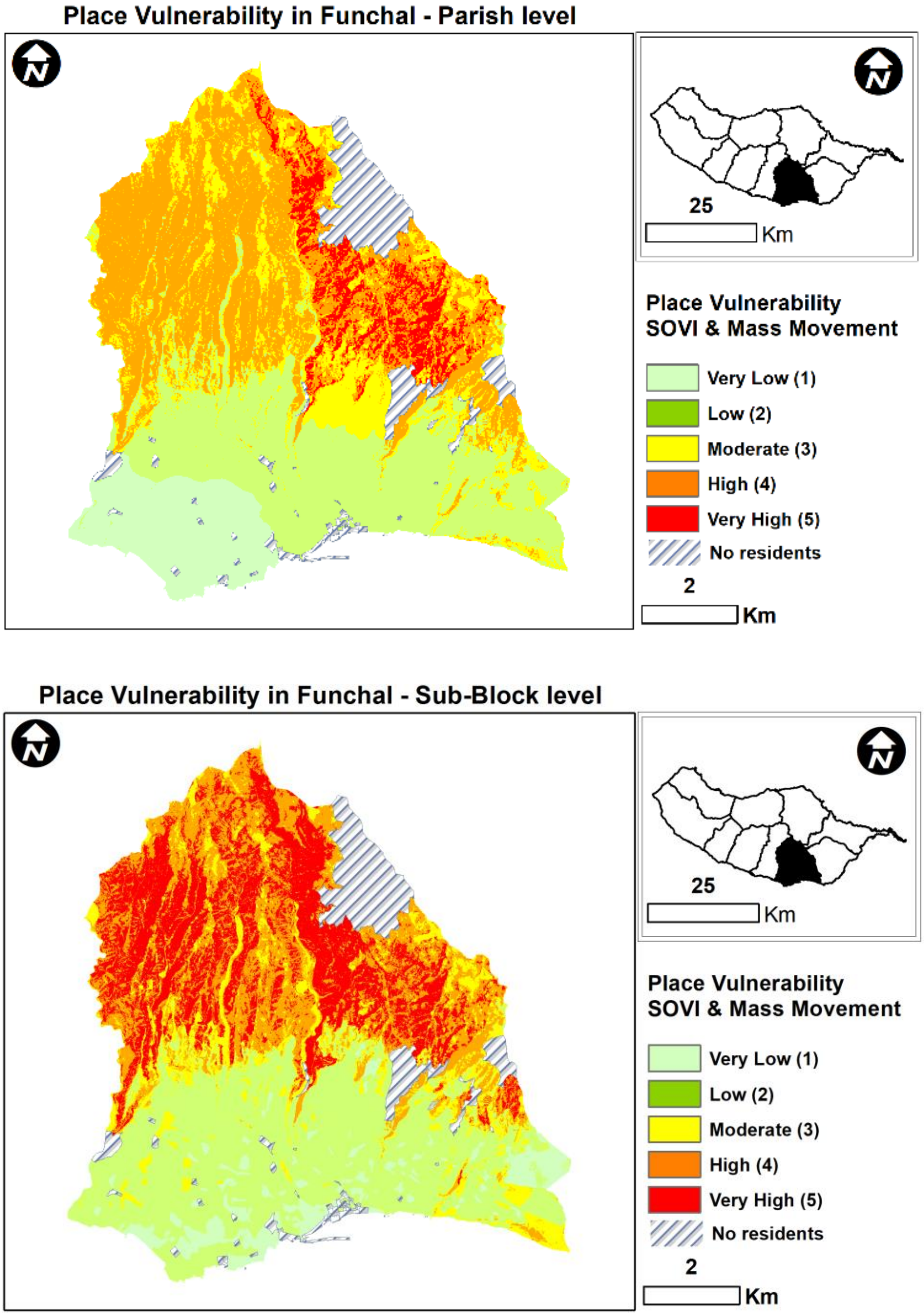


Figure 32: Place Vulnerability regarding Mass Movements and SOVI at Parish and Sub-Block level

The biggest difference on the spatial pattern when block and sub-block level Social Vulnerability are used is registered in the Northern area of Funchal. Santo António and São Roque are very large parishes that extend from close to the city centre to more deprived peri-urban areas at higher altitudes. The Social Vulnerability scores for the parishes, precisely because of their area and socioeconomic asymmetries, hide a big diversity of situations and when analysed at block and sub-block level present a much more complex pattern with blocks or sub-blocks in the fringe areas having much greater levels of Social Vulnerability. As a result, areas in the North of Funchal have a greater SOVI and SOVI_NTH score than those down South. Those areas at greater altitude and steep slopes are also areas of High and Very High mass movement Hazard Susceptibility.

When combining Social Vulnerability at parish level with mass movements Hazards Susceptibility, those areas in the North reveal a Moderate to High level of Place Vulnerability benefitting from the overall Social Vulnerability of the parish. However, when analysing with block or sub-block Social Vulnerability (Figure 33), the blocks and sub-blocks inside those parishes go from Low to Moderate scores in the Southern part of the parish to High and Very High in the Northern area. The result in terms of Hazards-of-Place model is that in the Northern areas the Very High Susceptibility to mass movements is combined with High and Very High Social Vulnerability obtaining higher levels of Place Vulnerability. In the Southern blocks or sub-blocks, the lower scores of both Susceptibility and Social Vulnerability are combined and result in low to moderate Place Vulnerability. The asymmetries and details highlighted at block or sub-block level show the benefit of using more desegregated Social Vulnerability data.

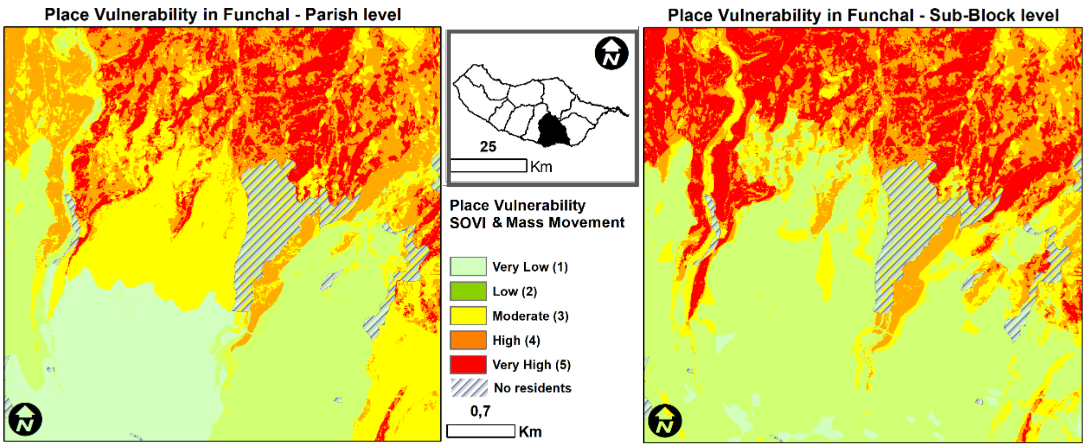


Figure 33: Detail of Place Vulnerability regarding Mass Movements and SOVI at Parish and Sub-Block level

The Place Vulnerability regarding forest fires Hazard and Social Vulnerability at parish level has a spatial pattern similar to the one regarding mass movements, with higher levels in areas at higher altitude and steeper slopes corresponding mainly to the Northern part of the parishes of São Roque, Santo António and Monte, as well as São Gonçalo in the Southeast of Funchal (Figure 34).

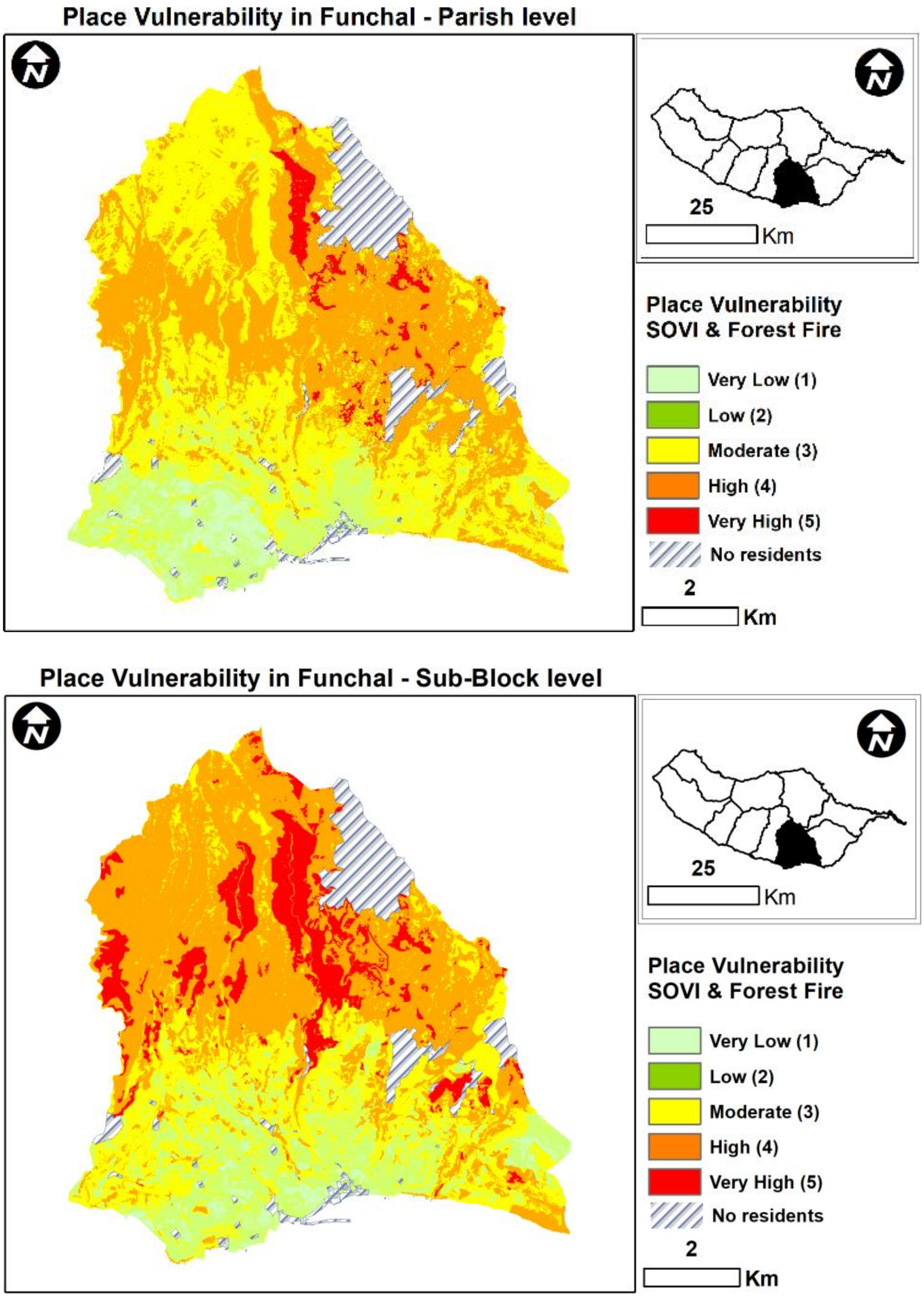


Figure 34: Place Vulnerability regarding Forest Fire and SOVI at Parish and Sub-Block level

A similar effect of using Social Vulnerability at block or sub-block level is also visible, with the Northern portions of Funchal getting higher levels of Place Vulnerability, due to asymmetries in Social Vulnerability between the overall value for parishes and the more detailed pattern for blocks and sub-blocks that increases from South to North. São Martinho and São Gonçalo also reveal a more complex pattern when using Social Vulnerability finer resolution.

The Place Vulnerability resulting from combining Social Vulnerability and floods Susceptibility has a pattern that is different from the described to the other two Hazard types because of the limited extent of the area susceptible to floods. Using Social Vulnerability at parish level most areas have Low or Very Low levels. Because Social Vulnerability has Very Low to Moderate scores in most parishes, the variability in the Place Vulnerability in the areas subject to floods is mainly the result of the Susceptibility scores (Figure 35).

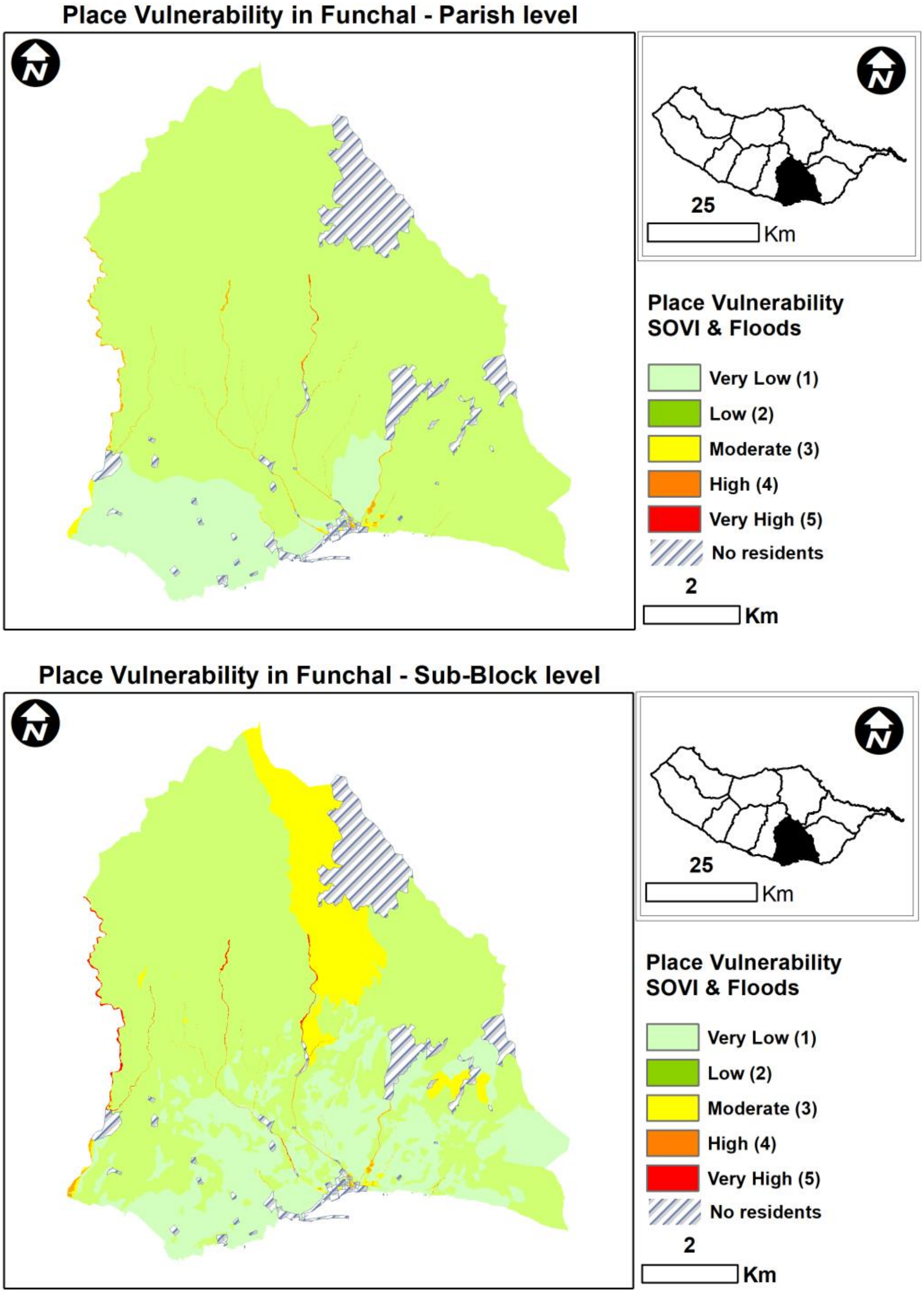


Figure 35: Place Vulnerability regarding Floods and SOVI at Parish and Sub-Block level

When using Social Vulnerability at block and particularly sub-block (Figure 36) level a much more complex and asymmetric pattern emerges as the influence of variability in Social

Vulnerability reflects itself in the variability of the Place Vulnerability. It allows a much more detailed analysis and detect areas where intervention is particularly necessary.

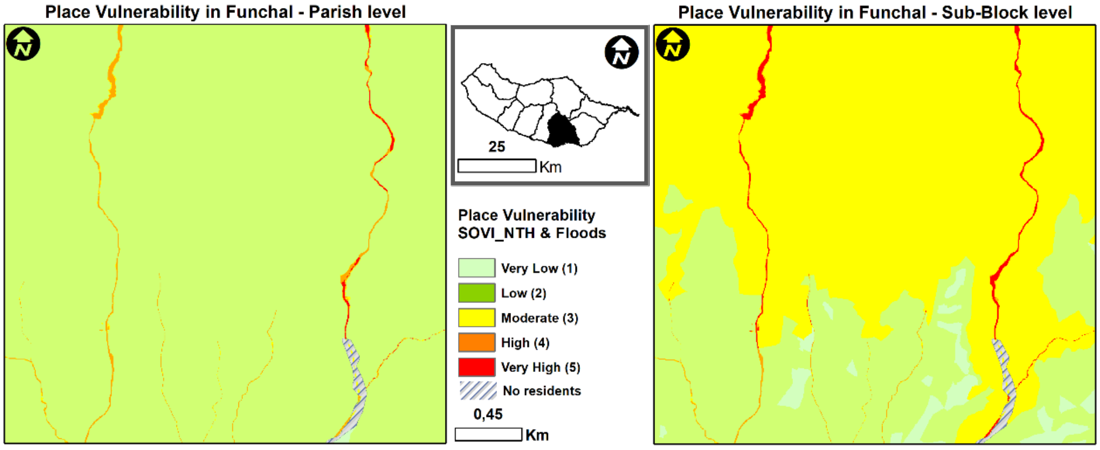


Figure 36: Detail of Place Vulnerability regarding Floods and SOVI at Parish and Sub-Block level

In several areas, especially in the Northern extent of the rivers Ribeira Santa Luzia, Ribeira São João and Ribeira João Gomes, the use of block and sub-block Social Vulnerability allows to isolate areas with Very High Social Vulnerability inside parishes with lower scores that combined with Very High Susceptibility highlights areas of Very High Place Vulnerability.

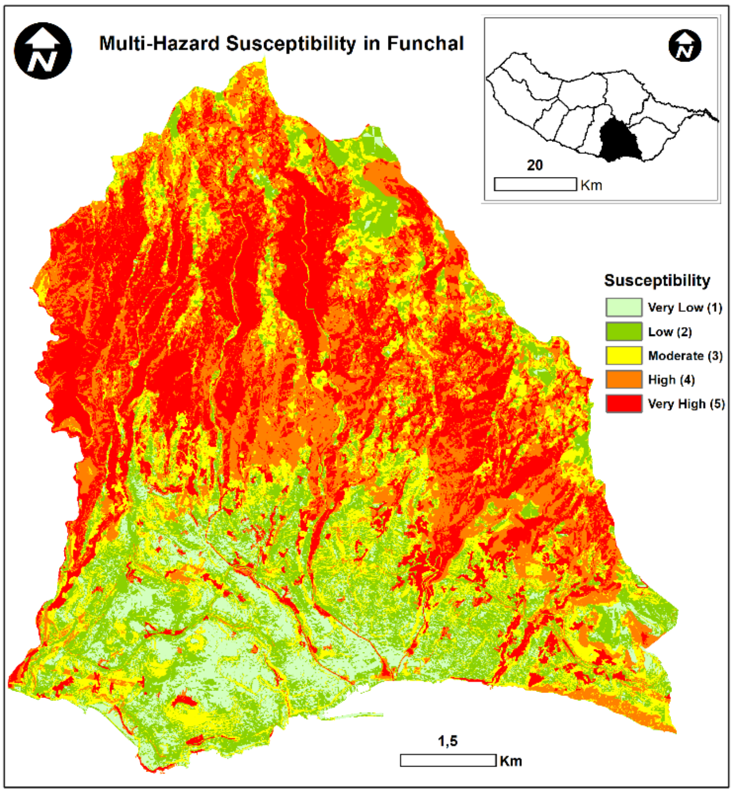
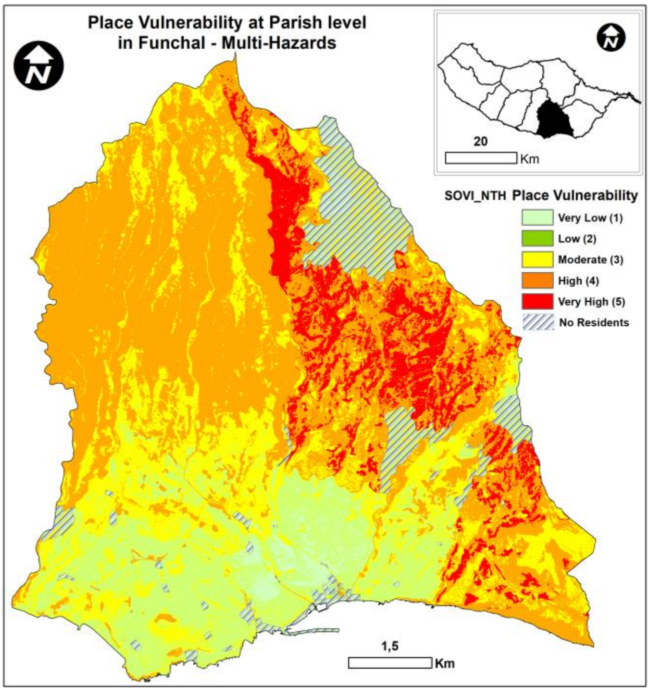


Figure 37: Multi-Hazards Susceptibility in Funchal

Finally, the Place Vulnerability was analysed using the Multi-Hazards map. We used the maximum score of Susceptibility in each cell, considering the three types of Hazards that have over the years had a greater impact in terms of disasters. The spatial pattern of Susceptibility shows High and Very High levels of Susceptibility in the Northern areas of Santo António, São Roque, Monte, São Gonçalo in the Southeast (i.e. forest fire and mass movements) and along the river banks (i.e. floods). The lowest Susceptibility levels are found in some areas (i.e. farther from rivers and steep slopes) of the parishes of São Martinho, Sé, São Pedro, Santa Luzia and Imaculado, as well as the Southern portions of Santo António, São Roque, Monte and Santa Maria (Figure 37).

Place Vulnerability levels are lower in the centre of Funchal, were both Hazards Susceptibility (except close to rivers) and Social Vulnerability are mostly Low or Very Low. As the distance to that centre increases, so does the level of Place Vulnerability (Figure 38).



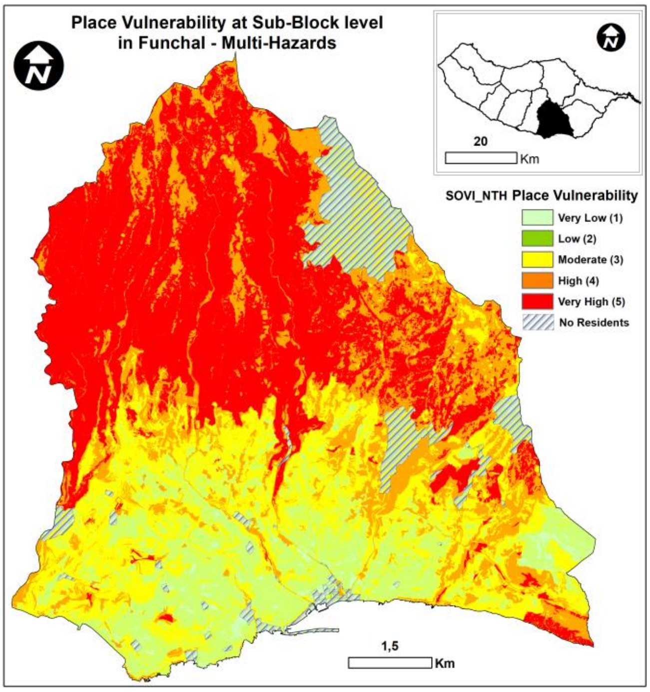


Figure 38: Place Vulnerability regarding Multi-Hazard and SOVI_NTH at Parish and Sub-Block level

Using Social Vulnerability at parish level, there are larger homogeneous areas. When using Social Vulnerability at block or sub-block level the results has more niches of diverse levels of Place Vulnerability. The difference pattern of Place Vulnerability between parish and sub-block analysis described before, regarding mass movement and forest fires Hazards, is also visible with Multi-Hazards Susceptibility.

Conversely, it is also possible to identify small areas, blocks or sub-blocks, where the detailed Social Vulnerability score combined with very High Susceptibility highlights situations of Very High Place Vulnerability, not revealed at parish level (Figure 39).

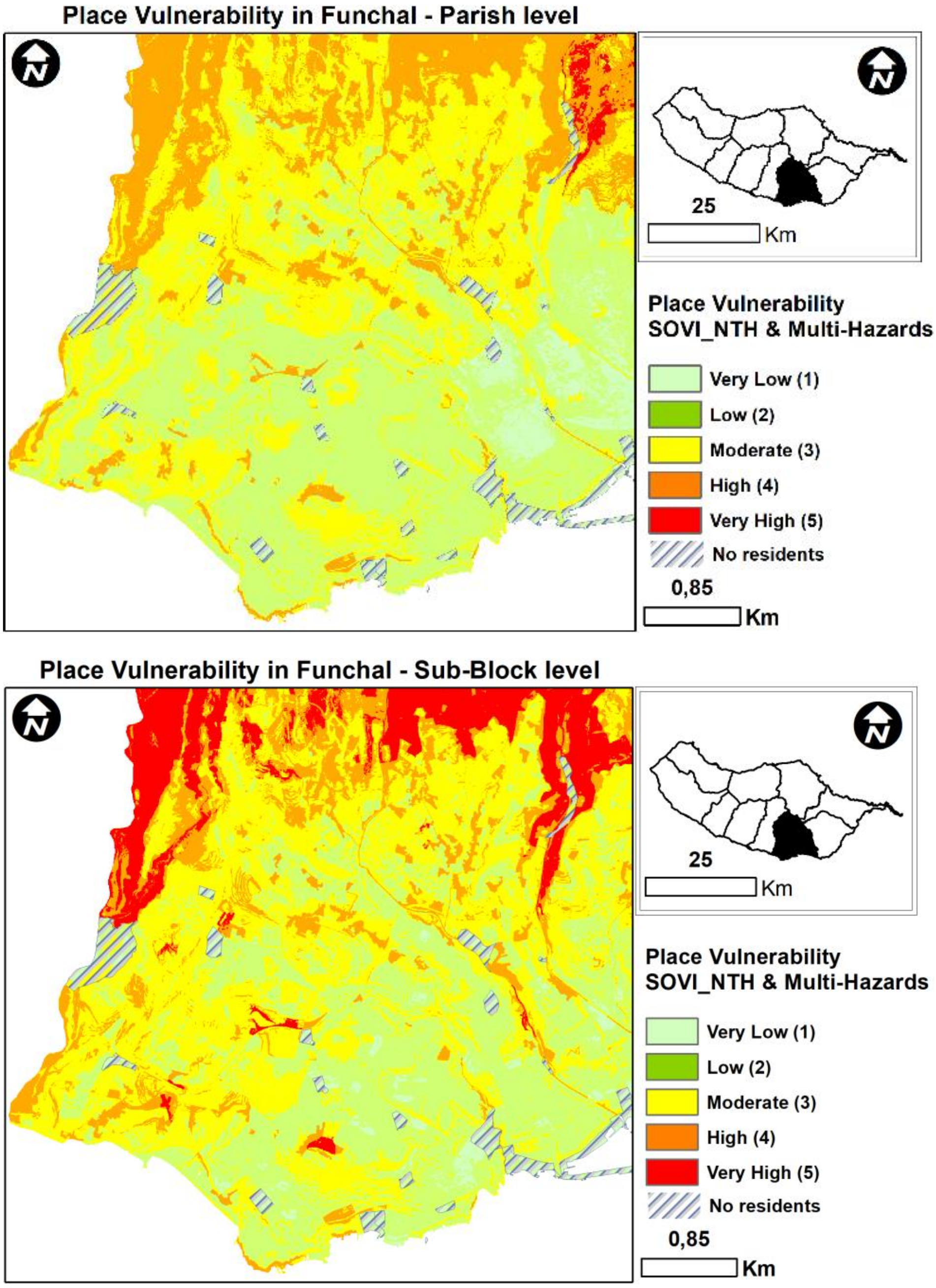


Figure 39: Detail of Place Vulnerability regarding Multi-Hazard and SOVI_NTH at Parish and Sub-Block level

In Funchal, as in Madeira, most people live in areas of Low or Very Low Hazard level. However, there is also a worrying amount of people that live in areas of High or Very High Susceptibility, particularly close to the three main rivers, in areas of steep slopes susceptible to mass movements in Santo António, São Roque, Monte and São Gonçalo, and also areas susceptible to forest fires all along the limits of the urban perimeter of Funchal and even areas closer of the centre, in Santa Maria, São Pedro and Imaculado (Figure 40).

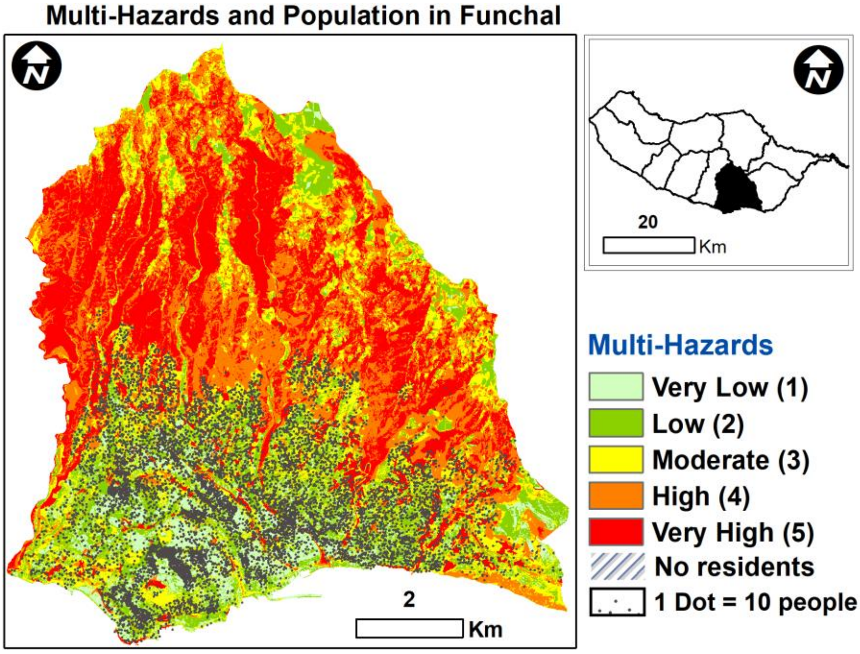


Figure 40: Multi-Hazards and Population in Funchal

Most population in Funchal lives in areas of Very Low to Moderate Place Vulnerability, particularly in the South of the Funchal amphitheatre (Figure 41). However, there are clusters of population living in areas of High or Very High Place Vulnerability particularly in central areas of Santo António and São Roque, some areas of Monte and in S. Gonçalo

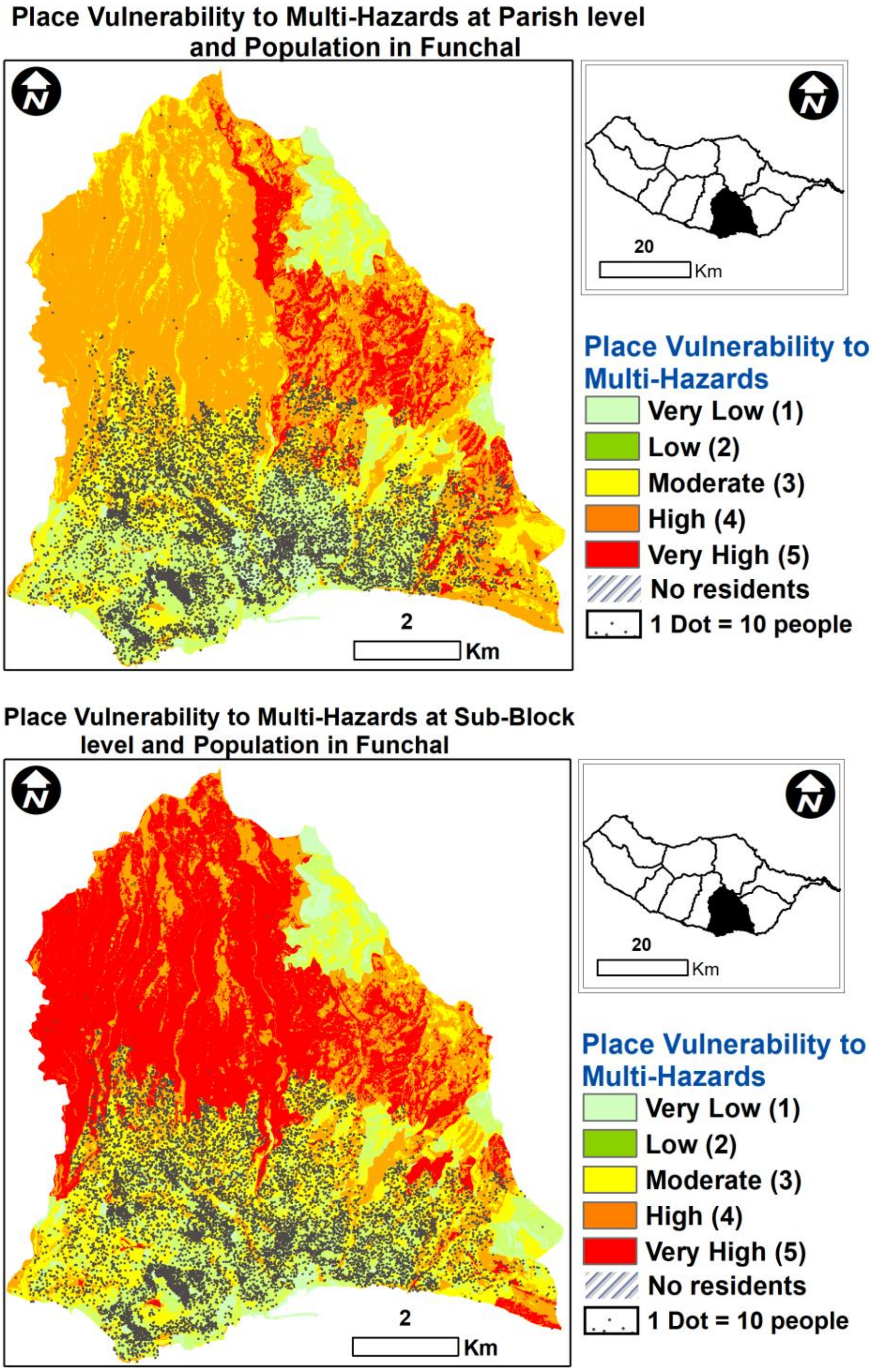


Figure 41: Place Vulnerability to Multi-Hazards in Funchal at Parish and Sub-Block Level

5. DISCUSSION

The fundamental objectives of this research were to assess Social Vulnerability in Madeira, within the model Hazards-of-Place, addressing an existing information gap. At the same time, we wanted to compare the performance and results of SOVI and SOVI_NTH and test the sensitivity of these indexes to different data aggregation, particularly very small statistical units. The original premises were that SOVI_NTH index may offer some conceptual, methodological and informational upper-hand when compared with SOVI, and that it is possible to use statistical units smaller than is usually done in such studies. In both cases a minimum set of statistical performance parameters had to be met.

In terms of statistical performance and modelling quality of the PCA, both indexes (i.e. SOVI and SOVI_NTH) and the three statistical units (i.e. parish, block, sub-block) had a good and very similar performance. The results were in line with the expected sensitivity to the changes in SOVI algorithm introduced by SOVI_NTH and to the size and number of statistical units. This however did not compromise the statistical validity of the PCA which indicates that these indexes are robust and that changes in data aggregation units are possible.

Regarding the resulting Components, dimensions of Social Vulnerability represented and the retained variables, the results were very similar across indexes and data aggregation levels, which is also in line with previous analysis that showed that if the same set of input variables is used, a consistent set of results can be obtained despite changes in the data aggregation.

SOVI_NTH was created to address the caveat of SOVI's Components sometimes combining variables regarding people's attributes that make them frailer in the face of disasters (Criticality) and structural factors that help people to resist and recover from a disaster (Support Capacity). Our results showed that to a certain extent SOVI does create such results, if the complete set of variables is used. SOVI_NTH presents these two dimensions separately, one closer to Vulnerability, the second closer to Resilience.

This conceptual upper-hand can only be useful if the PCA model has quality. Using SOVI as a reference, the statistical performance was equally good, and the variables and dimensions represented (i.e. in the case of SOVI_NTH distributed by the two sub-indexes) very similar, across aggregation units.

Accepting the premise that it is advantageous to represent separately Criticality and Support Capacity, SOVI_NTH did in fact showed quality in the information provided with a similar, at times better, statistical performance. It is easier to interpret the results using the two sub-indexes, rather than 6 or 7 Components, to determine whether in an area with high Social

Vulnerability the main concern are the intrinsic socioeconomic attributes that affect frailty towards Hazards or the (in)existence of support structures and facilities. Additionally, using SOVI, those Component may integrate variables about both these dimensions.

It should however be noted that in terms of information useful for regional of local authorities, the analysis of each of the PCA components (as well as Criticality and Support Capacity or the Components that constitute Criticality) actually seems to be a particularly important and useful in order to pinpoint exactly which dimensions of Social Vulnerability need more attention or to compare areas with similar SOVI/SOVI_NTH score but with different causes, allowing to identify different types of needs specific of each area and the type of required intervention.

This can be useful for Risk governance, allowing to analyse those issues separately, because the type of intervention they require is different. Some areas may require mainly interventions to reduce Criticality because they already have good Support Capacity, in others the Criticality may even not be that high, but the lack of Support Capacity may be a priority concern. In some areas with High SOVI the score may be mainly due to a Component related to aged population with mobility issues or may be due to a population with a elevated number of children but with high unemployment and poor housing conditions.

The resulting spatial patterns of overall Social Vulnerability are very similar, with a very low percentage of significative difference between both indexes, but SOVI_NTH offers an additional layer of information (i.e. not just Components and Social Vulnerability scores, but additionally the two sub-indexes of Criticality and Support Capacity).

SOVI analysis are usually done at county level, sometimes at municipality or parish level. More recently, statistical blocks were also used as source of data aggregation. Very small statistical units, like statistical sub-blocks, are not commonly used. However, in a territory like Madeira island, smaller than some of the counties to which SOVI has been applied, the use of smaller statistical units is necessary, not only due to the need of having a minimum number of statistical units to serve as PCA input, but also to facilitate the spatial analysis and identification of asymmetries.

Using finer units, we get a more complex and detailed image of Social Vulnerability patterns than the one provided by coarser units. Even small units like parishes and blocks have inside them niches of much lower or higher scores of Social Vulnerability than the surrounding units. Using very small aggregation units allows to identify not only asymmetries in SOVI or SOVI_NTH scores but also in the Components, Criticality or Support Capacity.

In Madeira, the more destructive Hazards (i.e. floods and debris-flows) affect an extension of only a few dozen meters to each side of the river banks. The same can be said about the small extension of some areas with high susceptibility to mass movements. In order to apply the model Hazards-of-Place in such area a very detailed analysis of Social Vulnerability would be adequate.

We aimed to contribute to an initial exploration of this approach by testing the applicability of both SOVI and SOVI_NTH to the smallest statistical unit, the sub-block. The results showed a very similar set of dimensions represented, although not exactly with the same retained variables, and also a similar statistical performance, within the defined parameters in SOVI literature. The premise that using more desegregated data would make evident patterns, details and asymmetries otherwise masked seems to be correct.

The consistent statistical performance at parish, block and sub-block level indicates that the implementation can be done with some flexibility in terms of amount and size of statistical data units and that the changes introduced by SOVI_NTH do not pose a statistical obstacle to a successful application. The small variation in the results may not be due only to the index sensitivity, but also to the choices of the researcher during the PCA.

The effect of data aggregation in the resulting pattern of Social Vulnerability is, in both indexes, to highlight inside coarser units the existence of smaller units that correspond to niches of higher or smaller Social Vulnerability. This does not seem to be arbitrary because the broader patterns stay stable and consistent. By comparing the difference between the Social Vulnerability level at coarser statistical units the one calculated for the finer statistical units that constitute it, we've determined that the general pattern is similar (i.e. 88% of blocks with the same level of SOVI or up to one level difference from the one calculated for parishes and 90% when comparing blocks and sub-blocks; 86% and 92%, respectively, in the case of SOVI_NTH).

Yet, more significative differences that may require a more detailed analysis are also identified (12% of blocks and 10% of sub-blocks in the case of SOVI; 14% and 8% in the case of SOVI_NTH).

The refinement of overall Social Vulnerability scores when using smaller statistical units allows to identify specific dimensions (i.e. in Components, Criticality, Support Capacity) in that unit that make it have a different level of Social Vulnerability than the one calculated for the coarser unit.

On the other hand, it also became apparent that the use of very small units creates other challenges. If analysing 380 blocks is demanding but possible, the analysis of thousands of sub-blocks is hardly practical. Even using only sub-blocks with resident population they amount to 4781. Sub-blocks of Funchal, the more populated municipality, amount to 1200. The analysis of Social Vulnerability in such small statistical units, that may only include as little as 10 houses or a couple dozen residents, should be done carefully and prudently.

This seems to point to the need of developing ways of perfecting the selection and aggregation of some sub-blocks. This could be achieved with a sensitivity analysis, similar to the one developed in this dissertation, but testing and identifying practical and valid criteriums to group sub-blocks (i.e. only using sub-block when blocks and area or population above a given threshold; grouping sub-blocks to ensure the smaller ones have a minimum number of people; using a given variable or combination of variables to define a minimum value for sub-blocks to remain ungrouped).

Although our research revealed good performance of the indexes, at different scales of data aggregation, determined by statistical parameters, it is not assumed that this an absolute measure of the indexes' validity. That would have to be determined in a different analysis by validating Social Vulnerability scores with 'real' Social Vulnerability – i.e. using proxy measures and post-event research. The validation of Social Vulnerability indexes is a contentious subject.

Proxy measures of Vulnerability like fatalities, houses destroyed, displaced people or cost of rebuilding infrastructures are often use. They are collected after a disaster, but usually are not available at sub-national or sub-regional level and could hardly be used to analyse blocks or even parishes. Even if such variables were available with the desired aggregation, they would hardly account for all the types of losses that Social Vulnerability encompasses (i.e. loss of affective values, emotional suffering, loss of job, trauma, quality of life). Additionally, they would not account for the capacity to recover from disasters. That would require other variables, collected at one or more points in time, after the disaster.

The development of conceptually appropriate methods to validate Social Vulnerability is not the only challenge. Even if such model is developed, the collection of information after disasters, with the extension and resolution necessary, in more than one point in time, raises issues of practicality, cost, confidentiality, and time lapse between observations, immediately after disaster (resist) and months or years later (recover).

Cartography allows to represent the patterns, asymmetries and effects of data aggregation and indexes' algorithms of Social Vulnerability and provide a good tool to illustrate, analyse and communicate it. It should therefore be a tool to inform discussions about Social Vulnerability and, more broadly, Risks and Disasters governance.

When Social Vulnerability is combined with Hazards Susceptibility cartography it facilitates the analysis of Risk, Place Vulnerability in the context of the Hazards-of-Place model. In Madeira most people live in areas of Low or Moderate Place Vulnerability, considering the analysis with both indexes and the three aggregation units. The analysis with Multi-hazards was only possible to Funchal, but the same conclusion probably applies to the rest of the island: even in areas with High and Very High Vulnerability occupy a significative part of the territory, these constitute mainly areas of small population density and the percentage of residents in such areas is small. There are however several clusters of Very High Place Vulnerability with significative population and these should be areas of priority intervention. This model offers a great potential of highlighting where more vulnerable people live in areas of higher susceptibility and are therefore particularly at risk. The results also showed that when identifying these priority areas, the use of very small aggregation units like blocks and particularly sub-blocks offers a level of detail and resolution not seen in the coarser aggregation units usually used in this type of analysis. The asymmetries and details highlighted at block or sub-block level show the benefit of using more desegregated Social Vulnerability data. Combined with the good statistical performance of the indexes at such statistical units, this is at least an indicator that such approaches should be more explored.

This research revealed Social Vulnerability patterns in Madeira, using the Hazards-of-Place framework to highlight areas where particularly high Social Vulnerability and Hazards Susceptibility coincide and identify clusters of more vulnerable people. This was inexistent in the context of Madeira island and can inform the prevention and mitigation planning.

Both indexes had a very similar statistical performance. In this context, SOVI_NTH had the advantage of providing an extra layer of information through the two intermediate sub-indexes (i.e. Criticality and Support Capacity).

The results were consistent with both indexes across the three aggregation units, although with the expected sensitivity to scale, size and number of statistical units. This points to the validity of exploring very small statistical units to identify patterns of Social Vulnerability otherwise masked in coarser analysis, particularly within the Hazards-of-Place model.

The major challenges of this approach were the availability of data, the selection of the smallest aggregation units and the validation of Social Vulnerability. These indexes are data driven and the success of application is affected by data availability. Several challenges regarding data availability: unavailability of variables, inexistence of data for small statistical units (i.e. GDP), underrepresentation of variables regarding some dimensions of Social Vulnerability; the more desegregated and abundant data comes from Census, that are only collected every ten years. This does not prevent the application of SOVI or SOVI_NTH and some strategies can be employed (i.e. calculating variables with spatial analysis, like distance or density of critical facilities), but it does affect it.

The issues of MAUP and Ecological Fallacy that apply to block sub-block aggregation data also exist at parish, municipality or even county aggregation, with the advantage that blocks and sub-blocks have a rationale of community homogeneity when they are created.

Validation of Social Vulnerability is another important challenge. Results are analysed based on parameters of statistical and modelling performance, standards from previous applications and interpretation of the resulting dimensions of Social Vulnerability represented. This does not however confront the SOVI and SOVI_NTH scores with the 'real' Social Vulnerability.

This research successfully contributed to the understanding of Social Vulnerability in Madeira, a gap in the discussion about Risk and Disasters in the island. Additionally, it showed that SOVI_NTH offer not only a valid alternative to SOVI, with a similar performance, but also with an extra layer of information. The research also demonstrated that there is room to explore the use of statistical units smaller than the ones usually used, to obtain very detailed patterns of Social Vulnerability and combine with Hazards.

6. CONCLUSION

Madeira has over the years been affected by disasters that have taken a high toll of destruction and lives lost. In the last two decades there has been a growing concern with Risk management and several initiatives were implemented, mainly regarding Hazards study, prevention and control.

Because disasters are not a product of just the Hazard's characteristics but also a social construct that determines that among those exposed some are more vulnerable than others and, thus, Social Vulnerability should be used to inform the discussions about Risk and Disaster management. There is an overall understudy of Social Vulnerability and that also happens in Madeira, a gap that needs to be addressed.

In this dissertation we contribute to that discussion by applying SOVI and SOVI_NTH to calculate and cartograph to obtain spatial patterns of Social Vulnerability and identifying areas where it is particularly high. Additionally, by applying the Hazards-of-Place model, combining Social Vulnerability and Hazards, it was possible to demonstrate how this approach can highlight areas where Very High Social Vulnerability coincide with Very High Hazard Susceptibility and should therefore be areas of priority attention.

SOVI_NTH offers a conceptual upper-hand and additional layer of information, when compared with the original SOVI, and because it does have a very similar statistical performance and overall Social Vulnerability pattern, it's used should be more explored.

When analysing the way human systems interact with Hazards, general patterns and tendencies are important. Having the overall picture allows to define strategic priorities. However, detail is also important to define local interventions and that requires the use of small statistical units. This research showed that the indexes are stable and consistent across aggregation scale and that the detail of information provided by block and sub-block can pinpoint asymmetries and high-Risk niches, which is particularly useful in a small territory like Madeira island. Although it is not current practise to use statistical units as small in Social Vulnerability quantitative assessment, our results point to the fact that such practice is not only possible but also useful in terms of information produced.

Social Vulnerability is a recent science and more research is necessary regarding the way to select and aggregate statistical data as well as how to validate the Social Vulnerability indexes. Additionally, the (un)availability of variables to all aggregation scales and the need for extensive and recent data sets is also something that will benefit from further studies.

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APPENDIX

Appendix I

1724	Floods and debris-flows in Machico	26 fatalities, 80 houses destroyed
1803	Floods and debris-flows in Funchal, Santa Cruz and Machico	Between 800 and 1000 fatalities, dozens of buildings destroyed
1895	Floods and debris-flows in Calheta, Ribeira Brava and S. Vicente	Several fatalities and houses and roads destroyed
1920	Floods and debris-flows in Funchal, Ribeira Brava and Camacha	5 fatalities and 500 people displaced
1929	Floods and debris-flows in Machico and S. Vicente	32 fatalities, over 100 buildings destroyed
1930	Tsunami in Câmara de Lobos	29 fatalities
1939	Floods and debris-flows in Madalena do Mar	4 fatalities
1956	Floods and debris-flows in Machico and Santa Cruz	6 fatalities
1963	Floods and debris-flows in Ribeira Brava	5 fatalities
1970	Ribeira Brava	4 fatalities
1977	Câmara de Lobos	4 fatalities and 45 people displaced
1979	Floods and debris-flows in Machico Calheta and Ponta do Sol	14 fatalities
1993	Floods and debris-flows in Funchal	8 fatalities, 306 displaced, 27 injured
2001	Floods and debris-flows in Curral das Freiras and S. Vicente	5 fatalities and 120 displaced people
2010	Floods and debris-flows in Fuchal, Ribeira Brava, Câmara de Lobos and Santa Cruz	48 fatalities, 120 injured, 900 people displaced, around 1000 million euros in damages
2013	Floods and debris-flows in Machico	1 fatality and damages to several buildings and roads
2016	Forest Fire	3 fatalities, several houses destroyed, and many hectares of forest destroyed.

Source: Abreu, Tavares, & Rodrigues, 2008; B. Almeida, Oliveira, França, Rodrigues, & Silva, 2010; Municipia, 2014; Municipia & FCT, 2016; Oliveira et al., 2011; Peixoto, 2013; Policarpo, 2012; Quintal, 1999; Rodrigues, 2005; Sepúlveda, 2011; F. Silva & Menezes, 1978

Appendix II

VARIABLES	EFFECT
Personal wealth, employment status, job qualification, activity sector, residential property	These variables are associated with more economic resources. Higher socio-economic status and higher levels of personal wealth are linked to higher abilities to prepare and recover from disasters due to greater economic power and accessibility to necessary resources. Unemployed people, unqualified and primary sector workers and renters tend to have less resources and increased Social Vulnerability.
Age	Children and the elderly due to mobility and autonomy issues are potentially more vulnerable to disasters. Children and elderly require additional care, help, resources and supervision before, during and after the disaster due to limitations in movement, cognitive ability or medical requirements.
Retired, Pensioners	People that are retired tend to be, simultaneously, older and with lower income and are therefore potentially more socially vulnerable. They usually have fewer financial resources, so the full recovery from disasters takes longer.
Social Benefits	Those who receive Social Security have less resources and often have also concomitant difficulties and have more Social Vulnerability.
Density of the Built Environment, Density of Population	Areas with higher density in population, buildings and economic activities tend to provide better support networks and are associated with less Social Vulnerability.
Single-Sector Economic Dependence	Areas that rely strongly in one economic activity, like tourism, may be more severely affected by disasters.
Race and ethnicity	Race and ethnicity have been shown to play a role in Vulnerability too due to cultural differences, and unfavorable socio-economic position of minority racial and ethnic groups. In Madeira there are no significative minority communities.
Infrastructure and Lifelines	The existence of critical facilities and lifelines helps to protect the population and reduce Social Vulnerability. Additionally, the existence of rescue, emergency and health personnel support people in case of disaster and facilitate their resistance and recovery.
Gender	Women can be considered as more vulnerable, as they often have lower wages and family responsibilities that make recovery from a disaster more difficult.
Family Structure	Families with more dependents and single-parent families have a harder time recovering from disasters due to having to balance work and family responsibilities.
Education	Education affects Vulnerability in two ways – lower education levels are linked to lower socio-economic status and difficulties in understanding warning and recovery information.

Medical Service and Access	Availability of health care providers affects both the immediate relief, but also long-term recovery from a disaster, and higher availability of services decreases Social Vulnerability.
Special needs population	Institutionalized individuals, homeless, ill or transient populations usually have less resources and often have less access to recovery programs after disasters, which makes them more vulnerable.

Source: Adger, 2006; Armaș & Gavriș, 2013; Balica et al., 2009; Birkmann, 2006a, 2006b, 2006c; Blaikie et al., 1994; Borden et al., 2007; Boruff et al., 2005; Burton & Cutter, 2008; Chen et al., 2013; Cutter, 2001; Cutter et al., 2006, 2003, 2009, 2000; Cutter & Finch, 2008; Guillard-Gonçalves et al., 2015; Hewitt, 1997; Hummell et al., 2016; HVRI, 2008, 2010, 2011; Lundgren & Jonsson, 2012; Mendes, 2009; Moret, 2014; O'Rourke & Hatcher, 2013; Schmidtlein et al., 2008; Tavares et al., 2015; Tierney et al., 2001; Willis & Fitton, 2016; Wisner et al., 2004

Appendix III

Social Vulnerability Index – Variables selected for analysis

SOVI			
Variable	**Description**	**Effect on Social Vulnerability**	**Pearson**
res_+64	Residents over 64	Increase	✓
res_+64_fem	Resident women above 64	Increase	✓
resid_-14	*Residents under 14*	*Increase*	×
res_-5	Residents under 5	Increase	✓
res_-14_+64	Residents under 14 or over 64	Increase	✓
res_femin	Percentage of women	Increase	✓
res_idoso_fem	Women among residents over 64	Increase	✓
fam_class_+64	*Families with members over 64*	*Increase*	×
fam_class_-14	*Families with members under 14*	*Increase*	×
res_desemp	Residents unemployed	Increase	✓
fam_1_desemp	*Families with 1 unemployed member*	*Increase*	×
fam_+1_desemp	Families with 2 or more unemployed members	Increase	✓
fam_com_des	*Families with unemployed members*	*Increase*	×
res_pens_ref	Pensioners	Increase	✓
n_fam_inst	Institutional families	Increase	✓
res_analfabeto	Residents that can´t read and write	Increase	✓
res_1_ciclo	Residents with 1st cycle of education	Increase	✓
res_3_ciclo	*Residents with 3rd cycle of education*	*Decrease*	×
res_ens_sec	*Residents with secondary education*	*Decrease*	×
res_ens_sup	Residents with higher degrees	Decrease	✓
res_emp_sect1	Worker in primary sector	Increase	✓
res_sect_3	Worker in tertiary sector	Decrease	✓
dens_pop	Population density	Decrease	✓
edif_class_1919	Buildings built before 1919	Increase	✓
edif_class_1946	*Buildings built before 1946*	*Increase*	×
edif_class_1980	Buildings built before 1980	Increase	✓
edif_class_pos2001	Buildings built after 2001	Decrease	✓
aloj_fam_nao_class	Non-classic homes	Increase	✓
aloj_fam_arrend	Rented homes	Increase	✓
aloj_fam_agua	Homes without water	Increase	✓
aloj_fam_banho	Homes without bath	Increase	✓
aloj_fam_esgot	*Homes without sewage*	*Increase*	×
edif_betao	Concrete buildings	Decrease	✓
edif_adobe_pedra	Stone buildings	Increase	✓
aloj_2+estac	Homes with 2 or more parking spaces	Decrease	✓
aloj_0_estac	*Homes with no parking space*	*Increase*	×
aloj_1_2_div	Homes with 2 or less rooms	Increase	✓
aloj_-4_div	Homes with 4 or less rooms	Increase	✓
aloj_50m	Homes under 50 m2	Increase	✓
aloj_100m	*Homes under 100 m1*	*Increase*	×
aloj_+200m	Homes with over 200 m2	Decrease	✓

bombeiro_conc	Fire Department personnel per 10000 residents (municipality)	Decrease	✓
cent_saude_freg	Health centre per 10000 residents (municipality)	Decrease	✓
med_priv_conc	Private Doctors per 10000 residents (municipality)	Decrease	✓
med_csaude_conc	Doctors in health centre per 10000 residents (municipality)	Decrease	✓
enf_csaude_conc	Nurses in health centre per 10000 residents (municipality)	Decrease	✓
farm_1000_freg	Pharmacy per 10000 residents (parish)	Decrease	✓
pop+5_1dif_freg	People over 5 with at least one impairment	Increase	✓
rend_soci_rsi_freg	People over 15 living on social benefits	Increase	✓
emp_n_quali(9)freg	Unqualified Employment (parish)	Increase	✓
emp_quali(1e2)freg	Qualified Employment (parish)	Decrease	✓
fam_monopar_freg	Mono parental families (parish)	Increase	✓
dist_bom	Distance to Fire Department	Increase	✓
dist_csaude	Distance to health centre	Increase	✓
dist_police	Distance to Police	Increase	✓
dist_farmacia	Distance to Pharmacy	Increase	✓
dist_juntas	Distance to parish headquarter	Increase	✓

✓ - Retained after Pearson Correlation Analysis

× - Discard after Pearson Correlation Analysis

Social Vulnerability to Natural and Technological Hazards Index – Variables selected for analysis

CRITICALITY			
Variable	**Description**	**Effect on Social Vulnerability**	**Pearson**
res_+64	Residents over 64	Increase	✓
res_+64_fem	Resident women above 64	Increase	✓
resid_-14	*Residents under 14*	*Increase*	×
res_-5	Residents under 5	Increase	✓
res_-14_+64	Residents under 14 or over 64	Increase	✓
res_femin	Percentage of women	Increase	✓
res_idoso_fem	Women among residents over 64	Increase	✓
fam_class_+64	*Families with members over 64*	*Increase*	×
fam_class_-14	*Families with members under 14*	*Increase*	×
res_desemp	Residents unemployed	Increase	✓
fam_1_desemp	*Families with 1 unemployed member*	*Increase*	×
fam_+1_desemp	Families with 2 or more unemployed members	Increase	✓
fam_com_des	*Families with unemployed members*	*Increase*	×
res_pens_ref	Pensioners	Increase	✓
n_fam_inst	Institutional families	Increase	✓
res_analfabeto	Residents that can´t read and write	Increase	✓
res_1_ciclo	Residents with 1st cycle of education	Increase	✓
res_3_ciclo	*Residents with 3rd cycle of education*	*Decrease*	×
res_ens_sec	*Residents with secondary education*	*Decrease*	×
res_ens_sup	Residents with higher degrees	Decrease	✓
res_emp_sect1	Worker in primary sector	Increase	✓
res_sect_3	Worker in tertiary sector	Decrease	✓

dens_pop	Population density	Decrease	✓
edif_class_1919	Buildings built before 1919	Increase	✓
edif_class_1946	*Buildings built before 1946*	*Increase*	×
edif_class_1980	Buildings built before 1980	Increase	✓
edif_class_pos2001	Buildings built after 2001	Decrease	✓
aloj_fam_nao_class	Non-classic homes	Increase	✓
aloj_fam_arrend	Rented homes	Increase	✓
aloj_fam_agua	Homes without water	Increase	✓
aloj_fam_banho	Homes without bath	Increase	✓
aloj_fam_esgot	*Homes without sewage*	*Increase*	×
edif_betao	Concrete buildings	Decrease	✓
edif_adobe_pedra	Stone buildings	Increase	✓
aloj_2+estac	Homes with 2 or more parking spaces	Decrease	✓
aloj_0_estac	*Homes with no parking space*	*Increase*	×
aloj_1_2_div	Homes with 2 or less rooms	Increase	✓
aloj_-4_div	Homes with 4 or less rooms	Increase	✓
aloj_50m	Homes under 50 m2	Increase	✓
aloj_100m	*Homes under 100 m1*	*Increase*	×
aloj_+200m	Homes with over 200 m2	Decrease	✓
pop+5_1dif_freg	People over 5 with at least one impairment	Increase	✓
rend_soci_rsi_freg	People over 15 living on social benefits	Increase	✓
emp_n_quali(9)freg	Unqualified Employment (parish)	Increase	✓
emp_quali(1e2)freg	Qualified Employment (parish)	Decrease	✓
fam_monopar_freg	Mono parental families (parish)	Increase	✓

SUPPORT CAPACITY			
Variable	**Description**	**Effect on Social Vulnerability**	**Pearson**
bombeiro_conc	Fire Department personnel per 10000 residents (municipality)	Decrease	✓
cent_saude_freg	Health centre per 10000 residents (municipality)	Decrease	✓
med_priv_conc	Private Doctors per 10000 residents (municipality)	Decrease	✓
med_csaude_conc	Doctors in health centre per 10000 residents (municipality)	Decrease	✓
enf_csaude_conc	Nurses in health centre per 10000 residents (municipality)	Decrease	✓
farm_1000_freg	Pharmacy per 10000 residents (parish)	Decrease	✓
dens_pop	Population density	Decrease	✓
dens_edif	Buildings density	Decrease	✓
dist_bom	Distance to Fire Department	Increase	✓
dist_csaude	Distance to health centre	Increase	✓
dist_police	Distance to Police	Increase	✓
dist_farmacia	Distance to Pharmacy	Increase	✓
dist_juntas	Distance to parish headquarter	Increase	✓

✓ - Retained after Pearson Correlation Analysis

× - Discard after Pearson Correlation Analysis

Appendix IV

SOVI – Parish

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,722
Bartlett Sphericity Test	Aprox. Chi-square	1563,503
	gl	300
	Sig.	,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	9,077	36,309	36,309	6,448	25,793	25,793
2	4,379	17,517	53,827	5,673	22,692	48,485
3	2,567	10,266	64,093	2,903	11,611	60,096
4	2,124	8,495	72,588	2,527	10,107	70,203
5	1,505	6,022	78,609	1,790	7,160	77,363
6	1,178	4,712	83,322	1,490	5,959	83,322

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
res_+64	,958
res_+64_fem	,970
res_-14_+64	,851
res_desemp	,718
res_pens_ref	,930
res_analfabeto	,902
res_1_ciclo	,819
res_ens_sup	,946
res_emp_sect1	,849
res_sect_3	,875
dens_pop	,746
edif_pos2001	,887
aloj_fam_banho	,825
aloj_1_2_div	,868
aloj_50m	,766
med_priv_conc	,760
enf_csaude_conc	,701
pop+5_1dif_freg	,785
emp_n_quali9freg	,781
emp_quali1e2_freg	,883
dist_bom	,797
dist_csaude	,876
dist_police	,767
dist_farmacia	,822
res_femin	,750

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component					
	1	2	3	4	5	6
res_ens_sup	-,952					
emp_quali1e2_freg	-,927					
res_sect_3	-,811					
med_priv_conc	-,792					
res_analfabeto	,781					
emp_n_quali9freg	,733					
dens_pop	-,714					
res_1_ciclo	,705					
res_+64_fem		,961				
res_+64		,946				
res_pens_ref		,932				
res_-14_+64		,891				
res_femin		,799				
pop+5_1dif_freg		,639				
enf_csaude_conc						
dist_farmacia			,820			
dist_bom			,760			
dist_police			,724			
dist_csaude			,684			
aloj_1_2_div				,859		
aloj_50m				,819		
aloj_fam_banho				,657		
res_desemp					,662	
res_emp_sect1						
edif_pos2001						,900

SOVI Parish					
Comp. 1 (+)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (+)	Comp. 5 (+)	Comp. 6 (x -1)
Education and Economy	Frail Groups	Critical Facilities	Housing Conditions	Unemployment	Buildings
res_ens_sup	res_+64_fem	dist_farmacia	aloj_1_2_div	res_desemp	edif_pos2001
emp_quali1e2_freg	res_+64	dist_bom	aloj_50m		
res_sect_3	res_pens_ref	dist_police	aloj_fam_banho		
med_priv_conc	res_-14_+64	dist_csaude			
res_analfabeto	res_femin				
emp_n_quali9freg	pop+5_1dif_freg				
dens_pop					
res_1_ciclo					

Component 1 – Education & Economy: explains 25.8% of the variance and includes 8 variables, mainly regarding education attainment and type of employment. It has variables that theoretically increase Social Vulnerability and others that decrease it, but all with the appropriate loading (+ or -), so the Cardinality is positive. Lower levels of education and literacy and less qualified jobs increase Social Vulnerability and higher educational attainment, more qualified or tertiary jobs and more population density decrease Social Vulnerability. Higher scores, as expected, are found mainly in the more rural parishes of Calheta, Ribeira Brava and Câmara de Lobos as well as in the Northern municipalities. Parishes in the more urban municipality of Funchal, as well as Caniço in Santa Cruz, show lower scores. Curral das Freiras and Achadas da Cruz have particularly high scores.

Component 2 – **Frail Groups**: explains 25.8% of the variance and includes 6 variables regarding factors like age, gender, and health. Older residents, women, older women, children and people with physical impairments tend to be more vulnerable. All variables load positively, because they increase Social Vulnerability, and the Component has a positive Cardinality. The lowest scores are found in the parishes around Funchal, between Câmara de Lobos and Machico. Noticeably, the more aged parishes in Funchal downtown have higher scores. The highest scores are found in the parishes of the Northern municipalities as well as Calheta, Ponta do Sol and Ribeira Brava.

Component 3 – **Critical Facilities**: explains 11.6% of the variance and includes 4 variables regarding the distance to critical facilities (i.e. Fire Department, Health Centres, Police and Pharmacies). Longer distances increase Social Vulnerability. All these variables load positively and the Component has a positive Cardinality. As expected, parishes in more urban Funchal, Câmara de Lobos and Santa Cruz, and the parishes that serve as capital of the municipality have the lowest scores, and as the distance to that centre increases, so do the scores. This is due mostly to the effect of the location of Fire Department, Police and Pharmacies. In the case of Health Centres, each parish has its own.

Component 4 – **Housing Conditions**: explains 10.1% of the variance and includes 3 variables regarding poor housing conditions. All variables load positively and the Component has a positive Cardinality. Where the percentage of poor housing conditions is higher, that is probably a consequence of economic shortcomings that increase Social Vulnerability. Higher scores are found in Ribeira Brava and Northern parishes of Câmara de Lobos as well as some of the parishes in older parts of Funchal.

Component 5 – **Unemployment**: explains 7.2% of the variance and includes 2 variables regarding unemployment. This is a proxy indicator of lower income that is usually associated with increased Social Vulnerability. The variables load positively and the Component has a positive Cardinality. The spatial distribution shows higher scores in Seixal and parishes from Ribeira Brava, Funchal, Santa Cruz, Machico and Santana.

Component 6 – **Buildings**: explains 5.96% of the variance and includes only one variable regarding recent constructed buildings, which is usually a sign of socioeconomic vitality that decreases Social Vulnerability. Because the variable loads positively, it was necessary to invert its Cardinality by multiplying by -1. The consolidated urban parishes of Funchal, Câmara de Lobos as well as the parishes of Faial and São Roque do Faial have the highest scores.

SOVI – Statistical Block

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,805
Bartlett Sphericity Test	Aprox. Chi-square	8657,700
	gl	231
	Sig.	0,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	7,443	33,834	33,834	5,268	23,944	23,944
2	3,798	17,266	51,100	4,384	19,927	43,872
3	2,316	10,528	61,628	2,932	13,326	57,198
4	1,769	8,041	69,669	2,178	9,900	67,098
5	1,279	5,812	75,481	1,781	8,095	75,193
6	1,016	4,618	80,099	1,080	4,907	80,099

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
res_+64	,979
res_+64_fem	,968
res_-14_+64	,840
res_desemp	,880
fam_+1_desemp	,867
res_pens_ref	,964
res_analfabeto	,793
res_1_ciclo	,797
res_ens_sup	,792
res_emp_sect1	,616
res_sect_3	,802
aloj_fam_banho	,645
aloj_1_2_div	,786
aloj_50m	,831
med_priv_conc	,750
emp_n_quali9freg	,783
emp_quali1e2_freg	,826
dist_bom	,629
dist_csaude	,700
dist_police	,684
dist_farmacia	,784
aloj_fam_n_class	,905

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component					
	1	2	3	4	5	6
emp_quali1e2_freg	-,891					
emp_n_quali9freg	,848					
med_priv_conc	-,824					
res_sect_3	-,815					
res_ens_sup	-,735					
res_analfabeto	,681					
res_1_ciclo	,624					
res_emp_sect1						
aloj_fam_banho						
res_+64		,977				
res_+64_fem		,971				
res_pens_ref		,969				
res_-14_+64		,868				
dist_farmacia			,836			
dist_csaude			,806			
dist_police			,744			
dist_bom			,692			
fam_+1_desemp				,901		
res_desemp				,900		
aloj_1_2_div					,860	
aloj_50m					,806	
aloj_fam_n_class						,948

SOVI Block					
Comp. 1 (+)	**Comp. 2 (+)**	**Comp. 3 (+)**	**Comp. 4 (+)**	**Comp. 5 (+)**	**Comp. 6 (+)**
Education and Economy	**Frail Groups**	**Critical Facilities**	**Unemployment**	**Housing Conditions**	**Housing Conditions II**
emp_quali1e2_freg	res_+64	dist_farmacia	fam_+1_desemp	aloj_1_2_div	aloj_fam_n_class
emp_n_quali9freg	res_+64_fem	dist_csaude	res_desemp	aloj_50m	
med_priv_conc	res_pens_ref	dist_police			
res_sect_3	res_-14_+64	dist_bom			
res_ens_sup					
res_analfabeto					
res_1_ciclo					

Component 1 – Education & Economy: explains 23.9% of the variance and includes seven variables, mainly regarding education attainment and type of employment. It has variables that theoretically increase Social Vulnerability and other that decrease it, but all with the appropriate loading (+ or -) so the Cardinality is positive. Lower levels of education and literacy and less qualified jobs increase Social Vulnerability and higher educational attainment, more qualified or tertiary jobs decrease Social Vulnerability. Higher scores are found in Câmara de lobos, Calheta, Porto Moniz, São Vicente and Santana. Câmara de Lobos has the highest prevalence of Blocks with very high scores, and Funchal has the lowest.

Component 2 – **Frail Groups**: explains 19.9% of the variance and includes 4 variables regarding age and gender factors. Older residents, women, older women, children tend to be more vulnerable. All variables load positively and the Component has a positive Cardinality. Most blocks with very high scores are found in Calheta, Ponta do Sol, São Vicente and Santana, as well as downtown Funchal. Câmara de Lobos and Santa Cruz have most of the Blocks with low scores.

Component 3 – **Critical Facilities**: explains 13.3% of the variance and includes 4 variables regarding the distance to critical facilities (i.e. Fire Department, Health Centres, Police and Pharmacies). Longer distances increase Social Vulnerability. All these variables load positively and the Component has a positive Cardinality. Blocks in Funchal, Câmara de Lobos and Santa Cruz, as well as Blocks closer to the capital of municipalities have the lowest scores, and as the distance to that centre increases, so do the scores.

Component 4 – **Unemployment**: explains 9.9% of the variance and includes 2 variables regarding unemployment. This is a proxy indicator of lower income that is usually associated with increased Social Vulnerability. The variables load positively and the Component has a positive Cardinality. The spatial distribution shows higher scores in Seixal and parishes from Ribeira Brava, Funchal, Santa Cruz and Santana.

Component 5 – **Housing Conditions**: explains 8.1% of the variance and includes 2 variables regarding poor housing conditions, usually a proxy of limited economic resources associated with increased Social Vulnerability. All variables load positively, because they increase Social Vulnerability, and the Component has a positive Cardinality. The spatial distribution shows higher scores are found in Ribeira Brava and Northern blocks of Câmara de Lobos, Boaventura in S. Vicente, as well as some of the blocks in older parts of Funchal.

Component 6 – **Housing Conditions II**: explains 4.9% of the variance and includes only 1 variable regarding poor housing conditions, usually a proxy of limited economic resources associated with increased Social Vulnerability. All variables load positively, because they increase Social Vulnerability, and the Component has a positive Cardinality. Higher scores are found in Ribeira Brava and Northern blocks of Câmara de Lobos, Boaventura in S. Vicente, as well as some of the blocks in older parts of Funchal and Santa Cruz.

SOVI – Sub-Block

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,721
Bartlett Sphericity Test	Aprox. Chi-square	55229,533
	gl	231
	Sig.	0,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	4,723	21,468	21,468	3,792	17,237	17,237
2	3,089	14,041	35,509	2,114	9,609	26,846
3	2,006	9,119	44,629	2,099	9,542	36,388
4	1,763	8,012	52,641	2,007	9,125	45,513
5	1,408	6,401	59,042	1,623	7,378	52,891
6	1,205	5,479	64,520	1,560	7,090	59,981
7	1,159	5,266	69,787	1,510	6,862	66,843
8	1,030	4,681	74,468	1,392	6,326	73,169
9	1,003	4,557	79,025	1,288	5,856	79,025

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
res_pens_ref	,864
res_+64	,950
res_+64_fem	,917
res_-14_+64	,769
res_desemp	,788
fam_+1_desemp	,802
res_analfabeto	,671
res_1_ciclo	,882
res_ens_sup	,635
res_emp_sect1	,824
res_sect_3	,683
aloj_1_2_div	,778
aloj_50m	,755
emp_n_quali9freg	,857
emp_quali1e2_freg	,872
dist_bom	,863
dist_csaude	,794
dist_police	,837
dist_farmacia	,705
dist_juntas	,822
res_femin	,603
res_idoso_fem	,717

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component								
	1	2	3	4	5	6	7	8	9
res_+64	,954								
res_pens_ref	,908								
res_+64_fem	,869								
res_-14_+64	,867								
res_analfabeto									
dist_juntas		,902							
dist_csaude		,880							
dist_farmacia		,618							
emp_n_quali9freg			,915						
emp_quali1e2_freg			-,884						
dist_bom				,904					
dist_police				,884					
fam_+1_desemp					,893				
res_desemp					,870				
aloj_1_2_div						,874			
aloj_50m						,838			
res_emp_sect1							,890		
res_sect_3							-,712		
res_idoso_fem								,824	
res_femin								,714	
res_1_ciclo									,906
res_ens_sup									

SOVI Sub-Block								
Comp. 1 (+)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (+)	Comp. 5 (+)	Comp. 6 (+)	Comp. 7 (+)	Comp. 8 (+)	Comp. 9 (+)
Frail Groups	Critical Facilities	Unqualified Employment	Critical Facilities II	Unemployment	Housing Conditions	Activity Sector	Gender	Primary Education
res_+64	dist_juntas	emp_n_quali9freg	dist_bom	fam_+1_desemp	aloj_1_2_div	res_emp_sect1	res_idoso_fem	res_1_ciclo
res_pens_ref	dist_csaude	emp_quali1e2_freg	dist_police	res_desemp	aloj_50m	res_sect_3 (-)	res_femin	
res_+64_fem	dist_farmacia							
res_-14_+64								

Component 1 – Frail Groups: explains 17.2% of the variance and includes 4 variables regarding factors of age and gender. Older residents, women, older women or children tend to be more vulnerable. All variables load positively, because they increase Social Vulnerability, and the Component has a positive Cardinality. The highest scores are found in sub-blocks all around the island but particularly in Ribeira Brava, Ponta do Sol, Calheta, São Vicente and Santana.

Component 2 – Critical Facilities: explains 9.6% of the variance and includes 3 variables regarding the distance to critical facilities. Longer distances increase Social Vulnerability. All these variables load positively and the Component has a positive Cardinality. As expected, parishes in more urban Funchal, Câmara de Lobos and Santa Cruz, and the parishes that serve as capital of the municipality are closer to facilities and have lower scores.

Component 3 – **Unqualified Employment**: explains 9.5% of the variance and includes 2 variables regarding the type of employment. More qualified workers tend to have a better socioeconomic status and less qualified workers tend to have less economic resources and be more vulnerable. The variables have the correct loadings and the Component has a positive Cardinality. The highest scores are found in more peripheric and interior areas, particularly in Câmara de Lobos, Santana and Machico.

Component 4 – **Critical Facilities**: explains 9.1% of the variance and includes 2 variables regarding the distance to critical facilities. Longer distances increase Social Vulnerability. All these variables load positively and the Component has a positive Cardinality. Areas closer to parishes that serve as capital of the municipality are closer to facilities and have lower scores.

Component 5 – **Unemployment**: explains 7.4% of the variance and includes 2 variables regarding unemployment. This is a proxy indicator of lower income that is usually associated with increased Social Vulnerability. The variables load positively and the Component has a positive Cardinality. The spatial distribution shows a very diverse pattern with sub-blocks scoring high all over the island.

Component 6 – **Housing Conditions**: explains 7.1% of the variance and includes 2 variables regarding poor housing conditions. All variables load positively and the Component has a positive Cardinality. Where the percentage of poor housing conditions is higher, that is probably a consequence of economic shortcomings that increase Social Vulnerability. Higher scores are found in Ribeira Brava and Northern blocks of Câmara de Lobos, Boaventura in S. Vicente, as well as some of the blocks in older parts of Funchal and Santa Cruz.

Component 7 – **Activity Sector**: explains 6.9% of the variance and includes 2 variables regarding the activity sector of workers. Workers from the primary sector are associated with more deprived contexts and higher Social Vulnerability. The variables have the appropriate loading and the Component has a positive Cardinality. The higher scores are found in the more rural areas, away from Funchal, Between Ponta do Sol and Calheta and also the Northern municipalities.

Component 8 – **Gender**: explains 6.3% of the variance and includes 2 variables regarding gender and older women, both associated with greater Social Vulnerability. The variables load positively and the Component has a positive Cardinality. The higher scores are found in Ribeira Brava, Ponta do Sol Calheta and the Northern municipalities.

Component 9 – **Primary Education**: explains 5.9% of the variance and includes 1 variables regarding low school attainment, usually associated with lower socioeconomic status and higher Social Vulnerability. The variable loads positively and the Component has a positive Cardinality. The higher scores are found in sub-blocks in Ponta do Sol, Calheta, Porto Moniz, São Vicente and Santana.

SOVI_NTH – Criticality – Parish

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,706
Bartlett Sphericity Test	Aprox. Chi-square	1077,469
	gl	153
	Sig.	,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	6,813	37,850	37,850	5,615	31,197	31,197
2	3,971	22,059	59,909	4,190	23,278	54,475
3	2,398	13,324	73,233	2,592	14,399	68,873
4	1,492	8,290	81,523	2,277	12,650	81,523

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
res_+64	,923
res_+64_fem	,946
res_-14_+64	,851
res_femin	,628
res_desemp	,867
fam_+1_desemp	,791
res_analfabeto	,880
res_1_ciclo	,799
res_ens_sup	,951
res_emp_sect1	,772
res_sect_3	,850
dens_pop	,653
aloj_fam_banho	,775
aloj_1_2_div	,824
aloj_50m	,731
pop+5_1dif_freg	,787
emp_n_quali9freg	,756
emp_quali1e2_freg	,890

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component 1	Component 2	Component 3	Component 4
res_ens_sup	-,970			
emp_quali1e2_freg	-,923			
res_sect_3	-,847			
res_1_ciclo	,803			
dens_pop	-,772			
res_analfabeto	,745			
emp_n_quali9freg	,647			
res_emp_sect1				
res_+64_fem		,913		
res_+64		,891		
res_-14_+64		,868		
pop+5_1dif_freg		,760		
res_femin		,748		
aloj_50m			,838	
aloj_1_2_div			,803	
aloj_fam_banho			,673	
res_desemp				,865
fam_+1_desemp				,767

Criticality Parish			
Comp. 1 (+)	**Comp. 2 (+)**	**Comp. 3 (+)**	**Comp. 4 (+)**
Education and Economy	**Frail Groups**	**Housing Conditions**	**Unemployment**
res_ens_sup (-)	res_+64_fem	aloj_50m	res_desemp
emp_quali1e2_freg (-)	res_+64	aloj_1_2_div	fam_+1_desemp
res_sect_3 (-)	res_-14_+64	aloj_fam_banho	
res_1_ciclo	pop+5_1dif_freg		
dens_pop (-)	res_femin		
res_analfabeto			
emp_n_quali9freg			
res_ens_sup			

Component 1 – Education & Economy: explains 31.2% of the variance and includes 8 variables, mainly regarding education attainment and type of employment. It has variables that theoretically increase Criticality and others that decrease it, but all with the appropriate loading (+ or -), so the Cardinality is positive. Lower levels of education and literacy and less qualified jobs increase Social Vulnerability and higher educational attainment, more qualified or tertiary jobs and more population density decrease Social Vulnerability. Parishes in the more urban municipality of Funchal, as well as Caniço in Santa Cruz, show lower scores. Higher scores are found mainly in the more rural parishes of Calheta, Ribeira Brava and Câmara de Lobos as well as in the Northern municipalities. Curral das Freiras and Achadas da Cruz have particularly high scores.

Component 2 – Frail Groups: explains 23.3% of the variance and includes 5 variables regarding factors like age, gender, and health. Older residents, women, older women, children and people with physical impairments tend to be more vulnerable. All variables load positively, because they increase Social Vulnerability, and the Component has a positive Cardinality. The highest scores are found in sub-blocks all around the island but particularly in Ribeira Brava, Ponta do Sol, Calheta, São Vicente and Santana.

Component 3 – **Housing Conditions**: explains 14.4% of the variance and includes 3 variables regarding poor housing conditions. All variables load positively and the Component has a positive Cardinality. Where the percentage of poor housing conditions is higher, that is probably a consequence of economic shortcomings that increase Criticality. Higher scores are found in Ribeira Brava and Northern blocks of Câmara de Lobos, Boaventura in S. Vicente, as well as some of the blocks in older parts of Funchal and Santa Cruz.

Component 4 – **Unemployment**: explains 12.7% of the variance and includes 2 variables regarding unemployment. This is a proxy indicator of lower income that is usually associated with increased Criticality. The variables load positively and the Component has a positive Cardinality. The spatial distribution shows higher scores in areas from Porto Moniz, Ribeira Brava, Funchal, Santa Cruz, Machico and Santana.

SOVI_NTH – Criticality – Statistical Block

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,785
Bartlett Sphericity Test	Aprox. Chi-square	6424,474
	gl	91
	Sig.	0,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	5,554	39,674	39,674	4,292	30,660	30,660
2	3,604	25,746	65,420	4,149	29,633	60,293
3	1,659	11,849	77,269	2,024	14,457	74,751
4	1,223	8,738	86,007	1,576	11,256	86,007

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
res_+64	,979
res_+64_fem	,969
res_-14_+64	,841
res_desemp	,916
fam_+1_desemp	,893
res_pens_ref	,964
res_analfabeto	,789
res_1_ciclo	,807
res_ens_sup	,806
res_sect_3	,744
aloj_1_2_div	,885
aloj_50m	,845
emp_n_quali9freg	,769
emp_quali1e2_freg	,836

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component			
	1	2	3	4
emp_quali1e2_freg	-,907			
emp_n_quali9freg	,862			
res_sect_3	-,835			
res_ens_sup	-,822			
res_analfabeto	,765			
res_1_ciclo	,712			
res_+64		,975		
res_+64_fem		,969		
res_pens_ref		,966		
res_-14_+64		,871		
res_desemp			,923	
fam_+1_desemp			,914	
aloj_1_2_div				,923
aloj_50m				,802

Criticality Block			
Comp. 1 (+)	Comp. 2 (+)	Comp. 3 (+)	Comp. 4 (+)
Education and Economy	Frail Groups	Unemployment	Housing Conditions
emp_quali1e2_freg (-)	res_+64	res_desemp	aloj_1_2_div
emp_n_quali9freg	res_+64_fem	fam_+1_desemp	aloj_50m
res_sect_3 (-)	res_pens_ref		
res_ens_sup (-)	res_-14_+64		
res_analfabeto			
res_1_ciclo			

Component 1 – Education & Economy: explains 30.7% of the variance and includes 6 variables, mainly regarding education attainment and type of employment. It has variables that theoretically increase Criticality and others that decrease it, but all with the appropriate loading (+ or -), so the Cardinality is positive. Lower levels of education and literacy and less qualified jobs increase Social Vulnerability and higher educational attainment, more qualified or tertiary jobs and more population density decrease Social Vulnerability. Areas in the more urban municipality of Funchal, as well as Caniço in Santa Cruz, show lower scores. Higher scores are found mainly in the more rural parishes of Calheta, Ribeira Brava and Câmara de Lobos as well as in the Northern municipalities.

Component 2 – Frail Groups: explains 29.6% of the variance and includes 4 variables regarding factors like age and gender. Older residents, women, older women and children tend to be more vulnerable. All variables load positively, because they increase Social Vulnerability, and the Component has a positive Cardinality. The highest scores are found mostly in Ribeira Brava, Ponta do Sol, Calheta, São Vicente and Santana.

Component 3 – Unemployment: explains 14.5% of the variance and includes 2 variables regarding unemployment. This is a proxy indicator of lower income that is usually associated with increased Criticality. The variables load positively and the Component has a positive Cardinality. The spatial distribution shows a very diverse pattern with sub-blocks scoring high particularly in Porto Moniz, Ribeira Brava, Funchal, Santa Cruz, Machico and Santana.

Component 4 – Housing Conditions: explains 11.3% of the variance and includes 2 variables regarding poor housing conditions. All variables load positively and the Component has a positive Cardinality. Where the percentage of poor housing conditions is higher, that is probably a consequence of economic shortcomings that increase Criticality. Higher scores are found in Ribeira Brava and Northern blocks of Câmara de Lobos, Boaventura, as well as some of the blocks in older parts of Funchal and Santa Cruz.

SOVI_NTH – Criticality – Statistical Sub-Block

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,711
Bartlett Sphericity Test	Aprox. Chi-square	42830,309
	gl	136
	Sig.	0,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	4,472	26,305	26,305	3,751	22,062	22,062
2	2,509	14,760	41,065	2,085	12,266	34,328
3	1,615	9,501	50,566	1,629	9,581	43,909
4	1,398	8,225	58,791	1,573	9,255	53,164
5	1,219	7,172	65,963	1,526	8,976	62,140
6	1,030	6,059	72,022	1,407	8,274	70,414
7	1,007	5,924	77,946	1,280	7,532	77,946

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
res_+64	,949
res_+64_fem	,917
res_-14_+64	,770
res_desemp	,784
fam_+1_desemp	,799
res_analfabeto	,650
res_1_ciclo	,885
res_ens_sup	,585
res_emp_sect1	,800
res_sect_3	,691
emp_n_quali9freg	,857
emp_quali1e2_freg	,868
aloj_1_2_div	,756
aloj_50m	,756
res_pens_ref	,864
res_femin	,602
res_idoso_fem	,719

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component 1	2	3	4	5	6	7
res_+64	,954						
res_pens_ref	,909						
res_-14_+64	,867						
res_+64_fem	,866						
res_analfabeto							
emp_n_quali9freg		-,920					
emp_quali1e2_freg		,912					
fam_+1_desemp			,891				
res_desemp			,869				
aloj_1_2_div				,862			
aloj_50m				,845			
res_emp_sect1					,885		
res_sect_3					-,739		
res_idoso_fem						,828	
res_femin						,717	
res_1_ciclo							,912
res_ens_sup							

Criticality Sub-Block						
Comp. 1 (+)	Comp. 2 (x-1)	Comp. 3 (+)	Comp. 4 (+)	Comp. 5 (+)	Comp. 6 (+)	Comp. 7 (+)
Frail Groups	Unqualified Employment	Unemployment	Housing Conditions	Activity Sector	Gender	Primary Education
res_+64	emp_n_quali9freg (-)	fam_+1_desemp	aloj_1_2_div	res_emp_sect1	res_idoso_fem	res_1_ciclo
res_pens_ref	emp_quali1e2_freg	res_desemp	aloj_50m	res_sect_3	res_femin	
res_-14_+64						
res_+64_fem						

Component 1 – Frail Groups: explains 22% of the variance and includes 4 variables regarding factors like age and gender. Older residents, women, older women and children tend to be more vulnerable. All variables load positively, because they increase Social Vulnerability, and the Component has a positive Cardinality. The highest scores are found in sub-blocks all around the island but particularly in Ribeira Brava, Ponta do Sol, Calheta, São Vicente and Santana.

Component 2 – Unqualified Employment: explains 12.3% of the variance and includes 2 variables regarding the type of employment. More qualified workers tend to have a better socioeconomic status and less qualified workers tend to have less economic resources and be more vulnerable. The variables have the opposite loadings and the Component had its Cardinality by multiplying by -1. The highest scores are found in more peripheric and interior areas, particularly in Câmara de Lobos, Santana and Machico.

Component 3 – Unemployment: explains 9.6% of the variance and includes 2 variables regarding unemployment. This is a proxy indicator of lower income that is usually associated with increased Criticality. The variables load positively and the Component has a positive Cardinality. The spatial distribution shows a very diverse pattern with sub-blocks scoring high all over the island, particularly in Porto Moniz, Ribeira Brava, Funchal, Santa Cruz, Machico and Santana.

Component 4 – **Housing Conditions**: explains 9.3% of the variance and includes 2 variables regarding poor housing conditions. All variables load positively and the Component has a positive Cardinality. Where the percentage of poor housing conditions is higher, that is probably a consequence of economic shortcomings that increase Criticality. Higher scores are found in Ribeira Brava and Northern blocks of Câmara de Lobos, Boaventura in S. Vicente, as well as some of the blocks in older parts of Funchal and Santa Cruz.

Component 5 – **Activity Sector**: explains 8.98% of the variance and includes 2 variables regarding the activity sector of workers. Workers from the primary sector are associated with more deprived contexts and higher Criticality. The variables have the appropriate loading and the Component has a positive Cardinality. The higher scores are found in the more rural areas, away from Funchal, between Ponta do Sol and Calheta and also the Northern municipalities.

Component 6 – **Gender**: explains 8.3% of the variance and includes 2 variables regarding gender and older women, both associated with greater Criticality. The variables load positively and the Component has a positive Cardinality. The higher scores are found in Ribeira Brava, Ponta do Sol Calheta and the Northern municipalities.

Component 9 – **Primary Education**: explains 7.5% of the variance and includes 1 variables regarding low school attainment, usually associated with lower socioeconomic status and higher Criticality. The variable loads positively and the Component has a positive Cardinality. The higher scores are found in sub-blocks in Ponta do Sol, Calheta, Porto Moniz, São Vicente and Santana.

SOVI_NTH – Support Capacity – Parish

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,747
Bartlett Sphericity Test	Aprox. Chi-square	362,143
	gl	36
	Sig.	,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	4,580	50,889	50,889	2,812	31,241	31,241
2	1,550	17,218	68,107	2,230	24,782	56,023
3	1,068	11,867	79,974	2,156	23,951	79,974

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
dens_pop	,908
dens_edif	,843
bombeiro_conc	,934
med_priv_conc	,812
enf_csaude_conc	,941
dist_bom	,618
dist_police	,648
dist_farmacia	,811
dist_csaude	,684

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component		
	1	2	3
dens_pop	,903		
dens_edif	,874		
med_priv_conc	,771		
dist_csaude		,815	
dist_farmacia		,784	
dist_police		,629	
dist_bom		,614	
bombeiro_conc			,930
enf_csaude_conc			,899

Support Capacity Parish		
Comp. 1 (+)	**Comp. 2 (x-1)**	**Comp. 3 (+)**
Urban areas	**Critical Facilities**	**Support Personnel**
dens_pop	dist_csaude	bombeiro_conc
dens_edif	dist_farmacia	enf_csaude_conc
med_priv_conc	dist_police	
	dist_bom	

Component 1 – Urban areas: explains 31.2% of the variance and includes 3 variables that indicate the existence of more urban areas. Urban areas are associated to the existence of more support networks in case of disaster and increased Support Capacity. All variables load positively and the Component has a positive Cardinality. The higher scores are found in and around Funchal.

Component 2 – **Critical Facilities**: explains 24.8% of the variance and includes 4 variables regarding the distance to critical facilities. Bigger distance to these facilities increases the time of response and therefore decrease the Support Capacity. Because variables decrease Support Capacity but they load positively, the Cardinality was corrected by multiplying by -1. The higher scores, more Support Capacity, are found in the urban areas in and around parishes that serve as municipal capital where most facilities are located.

Component 3 – **Support Personnel**: explains 23.96% of the variance and includes 2 variables regarding medical and emergency personnel. The higher the number of resources available, the higher the Support Capacity. The variables have positive loadings and Cardinality. The higher in more rural areas, with less population, have a more beneficial ratio of personnel per population and therefore higher scores of Support Capacity.

SOVI_NTH – Support Capacity – Statistical Block

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,743
Bartlett Sphericity Test	Aprox. Chi-square	2780,257
	gl	55
	Sig.	0,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	4,828	43,892	43,892	2,441	22,194	22,194
2	1,876	17,053	60,945	2,281	20,736	42,930
3	1,096	9,961	70,906	2,050	18,632	61,562
4	1,014	9,216	80,122	2,042	18,560	80,122

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
dens_pop	,695
dens_edif	,732
bombeiro_conc	,898
cent_saude_freg	,643
med_priv_conc	,715
enf_csaude_conc	,922
dist_bom	,814
dist_csaude	,855
dist_police	,840
dist_farmacia	,827
dist_juntas	,872

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component			
	1	2	3	4
dist_juntas	,909			
dist_csaude	,907			
dist_farmacia	,709			
bombeiro_conc		,922		
enf_csaude_conc		,885		
cent_saude_freg				
dens_pop			,791	
dens_edif			,770	
med_priv_conc			,731	
dist_bom				,848
dist_police				,841

Support Capacity Block			
Comp. 1 (x-1)	**Comp. 2 (+)**	**Comp. 3 (+)**	**Comp. 4 (x-1)**
Critical Facilities	**Support Personnel**	**Urban areas**	**Critical Facilities II**
dist_juntas	bombeiro_conc	dens_pop	dist_bom
dist_csaude	enf_csaude_conc	dens_edif	dist_police
dist_farmacia		med_priv_conc	

Component 1 – **Critical Facilities**: explains 22.2% of the variance and includes 3 variables regarding the distance to critical facilities. Bigger distance to these facilities increases the time of response and therefore decrease the Support Capacity. Because variables decrease Support Capacity but they load positively, the Cardinality was corrected by multiplying by -1. The higher scores, more Support Capacity, are found in the urban areas in and around parishes that serve as municipal capital where most facilities are located.

Component 2 – **Support Personnel**: explains 20.8% of the variance and includes 2 variables regarding medical and emergency personnel. The higher the number of resources available, the higher the Support Capacity. The variables have positive loadings and Cardinality. The higher in more rural areas, with less population, have a more beneficial ratio of personnel per population and therefore higher scores of Support Capacity.

Component 3 – Urban areas: explains 18.6% of the variance and includes 3 variables that indicate the existence of more urban areas. Urban areas are associated to the existence of more support networks in case of disaster and increased Support Capacity. All variables load positively and the Component has a positive Cardinality. The higher scores are found in and around Funchal.

Component 4 – **Critical Facilities II**: explains 18.6% of the variance and includes 2 variables regarding the distance to critical facilities. Bigger distance to these facilities increases the time of response and therefore decrease the Support Capacity. Because variables decrease Support Capacity but they load positively, the Cardinality was corrected by multiplying by -1. The higher scores, more Support Capacity, are found in the urban areas in and around parishes that serve as municipal capital where most facilities are located.

SOVI_NTH – Support Capacity – Statistical Sub-Block

KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,665
Bartlett Sphericity Test	Aprox. Chi-square	22305,629
	gl	36
	Sig.	0,000

Total Explained Variance

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1	3,377	37,527	37,527	2,041	22,681	22,681
2	1,883	20,922	58,449	1,961	21,791	44,471
3	1,209	13,433	71,882	1,943	21,592	66,063
4	1,052	11,693	83,575	1,576	17,512	83,575

Extraction Method: Principal Components Analysis

Cummunalities

	Extraction
dens_edif	,779
dens_pop	,781
bombeiro_conc	,944
enf_csaude_conc	,947
dist_bom	,878
dist_csaude	,802
dist_police	,842
dist_farmacia	,715
dist_juntas	,835

Extraction Method: Principal Components Analysis

Rotated Matrix

	Component			
	1	2	3	4
dist_juntas	,906			
dist_csaude	,880			
dist_farmacia	,636			
dist_bom		,917		
dist_police		,884		
bombeiro_conc			,953	
enf_csaude_conc			,938	
dens_pop				,861
dens_edif				,858

Support Capacity Sub-Block			
Comp. 1 (x-1)	**Comp. 2 (x1)**	**Comp. 3 (+)**	**Comp. 4 (+)**
Critical Facilities	**Critical Facilities II**	**Support personnel**	**Urban areas**
dist_juntas	dist_bom	bombeiro_conc	dens_pop
dist_csaude	dist_police	enf_csaude_conc	dens_edif
dist_farmacia			

Component 1 – **Critical Facilities**: explains 22.7% of the variance and includes 3 variables regarding the distance to critical facilities. Bigger distance to these facilities increases the time of response and therefore decrease the Support Capacity. Because variables decrease Support Capacity but they load positively, the Cardinality was corrected by multiplying by -1. The higher scores, more Support Capacity, are found in the urban areas in and around parishes that serve as municipal capital where most facilities are located.

Component 2 – **Critical Facilities II**: explains 21.8% of the variance and includes 2 variables regarding the distance to critical facilities. Bigger distance to these facilities increases the time of response and therefore decrease the Support Capacity. Because variables decrease Support Capacity but they load positively, the Cardinality was corrected by multiplying by -1. The higher scores, more Support Capacity, are found in the urban areas in and around parishes that serve as municipal capital where most facilities are located.

Component 3 – **Support Personnel**: explains 21.6% of the variance and includes 2 variables regarding medical and emergency personnel. The higher the number of resources available, the higher the Support Capacity. The variables have positive loadings and Cardinality. The higher in more rural areas, with less population, have a more beneficial ratio of personnel per population and therefore higher scores of Support Capacity.

Component 4 – Urban areas: explains 17.5% of the variance and includes 2 variables that indicate the existence of more urban areas. Urban areas are associated to the existence of more support networks in case of disaster and increased Support Capacity. All variables load positively and the Component has a positive Cardinality. The higher scores are found in and around Funchal.