Social Resilience to Flooding: The Implications of Scale

by

Samantha Hao Yiu Chu

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Science
in
Geography

Waterloo, Ontario, Canada, 2021

Author’s Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be electronically available to the public.

Abstract

Resilience to environmental hazards refers to the capacities and abilities to resist, adapt and recover from the impacts of a potential hazard, such as flooding. Building resilience is increasingly recognized as a strategy to prevent exposure to hazards, reduce vulnerability to environmental risks and climate change impacts, and increase preparedness for response and recovery. Previous studies have assessed resilience to environmental hazards based on socioeconomic characteristics derived from census data, such as income, family structure, and dwelling conditions. These indicators can be combined into an index to compare geographic areas or populations to understand what makes a population resilient against flood impacts and where these resilient characteristics and populations are located. However, due to confidentiality reasons, census data are aggregated into different census units of varying scale to serve as proxies of individual characteristics. Spatial analysis of the same data using different spatial scales manifests in the modifiable areal unit problem (MAUP), where varying spatial scales can produce different, and at times, contradictory results. With the use of census data to infer population characteristics, the implications of its conjoined spatial component are often overlooked. As a result of the MAUP, the effects of scale from the use of census data may be further propagated and ultimately affect the information that is imparted from these analyses of social resilience.

This research applies a mixed methods approach for investigating the implications of spatial scale when using a social flood resilience index to inform disaster risk management and climate change adaptation efforts. The methods include applying a geographic information system (GIS) and statistical analysis of the scale effects related to the MAUP, and conducting a resident survey and interviews with experts through a case study in the City of Vancouver. The Social Resilience Index (SoRI), which is derived from census data, was used to empirically identify scale effects across census programs in three cities: Vancouver, Canada; Los Angeles, USA; and Edinburgh, UK.

Mapping the SoRI using different census scales and different index construction methods yielded contrasting patterns of social resilience to flooding, which has implications in both statistical and spatial contexts. Larger census units were more suitable for representing the statistical results, whereas smaller census units were more suitable for representing the spatial distribution of the SoRI. When constructing the SoRI, the stakeholder-driven multi-criteria analysis (MCA) method indicated less sensitivity to scale effects. The perspectives of residents and experts in the City of Vancouver suggest that the scale of flood resilience analysis (i.e., census scales) does not necessarily align with the scale that flood resilience is developed or built (i.e., community and individual scale). The issue of scale in assessments of flood resilience are linked to types of information that can be obtained at different scales. Quantitative metrics such as the SoRI are used to understand the differences in individual- and household-level capacities, but they do not fully capture the actions that are undertaken to develop flood resilience – nor the individual-level perceptions and needs to build resilience.

The survey and interview responses revealed that building resilience in Vancouver could be directed at improving access to resources that residents require to respond to a flood, increasing awareness towards the available flood protection measures, and improving neighbourhood connections. The contrasting perspectives of flood resilience between residents and experts indicate that theoretical knowledge may not necessarily align with the perceptions of individuals in reality. This study demonstrates that assessments of flood resilience to inform planning and policy can address underlying social factors that determine the actions taken to build resilience, and not only quantify resilience based on aggregate census data.

Keywords: environmental hazards, social resilience, flood preparedness, modifiable areal unit problem (MAUP), GIS, spatial analysis, Vancouver

Acknowledgements

First and foremost, I would like to express my sincerest gratitude to my thesis supervisor, Dr. Su-Yin Tan, for your unconditional support, smiles and dedication to get me across two finish lines. Thank you for seeing the potential in me that I never imagined myself to have. I am also grateful to my co-supervisor and committee member, Ms. Linda Mortsch, for your encouragement, expertise and insights, which have been invaluable throughout this journey. It has been an honour to have worked alongside the both of you.

I would like to express sincere appreciation to members of the Suzuki Elders in Vancouver and CityStudio Vancouver for their insights and support with recruitment for survey participants. My appreciation and gratitude are extended to the survey and interview participants for providing their input and expertise which have been instrumental to this research.

I would like to thank my friends and family who have put up with my endless complaints and have anticipated my graduation as their own. My deepest gratitude goes to my parents for their love and support as I pursued my graduate studies, and to my late grandparents who were the source of my strength to persevere through these years.

A special thanks to Mr. M. Garritsen, Ms. N. Minaj, Ms. T. Y. Kim, Ms. H. J. Ho, for all their inspiration and support at times when it truly mattered the most.

Table of Contents

List of Tables

List of Figures

1.0 Introduction

1.1 Background

Resilience has been increasingly adopted as the paradigm for disaster risk management and climate change adaptation strategies ranging from the global scale, such as the Sendai Framework for Disaster Risk Reduction (UNDRR, 2015) and the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (Mimura et al., 2014), the national scale, such as the Emergency Management Strategy for Canada (PSC, 2019), to the municipal scale, such as the Resilient Vancouver Strategy (City of Vancouver, 2019). As defined by the Sendai Framework for Disaster Risk Reduction, resilience refers to "*The ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions*." (UNDRR, 2015, p.9). There is an increasing recognition to build resilience by enhancing the capacities of people, communities and societies to prevent exposure to hazards, reduce vulnerability to environmental risks and climate change impacts, and increase adaptive and transformational capacities for response and recovery (City of Vancouver, 2019; Joakim et al., 2015; PSC, 2019; UNDRR, 2015).

The increasing focus on building resilience has led to efforts to develop indicators of resilience (Cutter et al., 2008; Cutter et al., 2014; Cutter, 2016; Jones & Tanner, 2017; Feldmeyer et al., 2019; Morrow, 2008) and metrics to quantify resilience (Cutter et al., 2010; Damude et al., 2015; Joakim et al., 2016). These studies assess resilience by postulating how socioeconomic characteristics, such as housing tenure, family structure and household income, may translate to different levels of resilience against environmental hazards. Understanding the relative levels of resilience between populations can be used to identify priority areas to inform disaster risk management and climate change policy efforts (100RC, 2019; Cutter et al., 2008; Cutter et al., 2014; Spielman et al., 2020). Implicit in these efforts to measure resilience is that socioeconomic characteristics represent the differences among people and households that may influence their capacity and ability to build resilience. These socioeconomic characteristics are often represented through quantitative indicators such as census data, to investigate the distribution of social and financial resources that may be available in the event of a disaster (Buckle et al., 2000; Cutter et al., 2003; Cutter et al., 2008; Oulahen et al., 2015; Prouse et al., 2014; Schuurman et al., 2007; Tapsell et al., 2002).

Census data report socioeconomic characteristics of populations over geographic areas. It is a form of spatial data, which possesses the unique property of containing both attribute and geographic information – that is, information about *which* socioeconomic characteristics and *where* such characteristics are located (Carrington et al., 2018; Dorling, 1993; Mendelson, 2001). These data are commonly used in the social sciences to make inferences about various population characteristics, to inform policy and the allocation of resources, examine social trends, and test social theory (Carrington et al., 2018; Dorling, 1993; Flowerdew, 2011). For privacy reasons, individual census responses at the household-level are not made publicly available, but rather compiled into aggregation units that serve as proxies to represent individual socioeconomic characteristics (Mendelson, 2001; Prouse et al., 2014). The process of aggregation into different census units manifests in the modifiable areal unit problem (MAUP). The MAUP is a phenomenon that occurs when spatial analysis of the same data produces varying results based on the definition of the areal units (Fotheringham & Wong, 1991; Openshaw, 1984). Variations in the size and the boundaries of areal units correspond to the scale and zoning effects, respectively, of the MAUP (Openshaw, 1984). The scale effect is a result of the size and the number of areal units defined, or the level of spatial resolution whereas the zoning effect arises from the number of possible configurations of areal units over a given area (Jelinski & Wu, 1996; Openshaw, 1984). The differences in areal units used to make inferences can lead to different, and at times, contradictory results (Carrington et al., 2018; Fotheringham & Wong, 1991; Gehlke & Biehl, 1934; Openshaw, 1984). There are countless ways in which a geographic area can be divided into areal units, but the data and analytical results are often only presented for one set of areal units – or only one of the *possible* analytical results (Openshaw, 1984).

The effects of scale on resilience assessments are not only manifested through aggregate indicators, but also the type of information that can be obtained at different spatial scales. While aggregate indicators can be used to represent social and financial capital that influence household capacities, they do not explain the individual-level decisions, beliefs and behaviours that lead to the awareness, the actions taken or the outcomes of resilience (Cutter et al., 2014; Jones & Tanner, 2017; Jones et al., 2018). Resilience frameworks have emphasized the need to capture and incorporate local contexts (100RC, 2019; PSC, 2019; UNDRR, 2015) and understand the perspectives of residents and the communities that they are part of, in order to develop effective strategies to build resilience (City of Los Angeles, 2018; City of Vancouver, 2018; City of Vancouver, 2019). In the absence of a geographic standard for spatial analysis and assessments of resilience, there is a gap in understanding the impacts of scale and its implications for informing policy and decision making.

1.2 Overview of Research Design & Research Questions

Common assessments of resilience are either quantitative, which relies on information from aggregate indicators (Cutter et al., 2008; Cutter, 2016; Damude et al., 2015; Morrow, 2008), or qualitative, which relies on information that is derived from personal perceptions and experiences (Jones & Tanner, 2017; Jones et al., 2018; Quinlan et al., 2016). Quantitative assessments often involve mapping socioeconomic characteristics as indicators of resilience using one spatial scale, often the smallest scale available, to inform and target disaster risk management and climate change adaptation efforts. However, there is lack of empirical research on the implications of using different spatial scales for these mapping exercises and the information that is imparted at different spatial scales. While there is existing research on the effects of scale for *individual* socioeconomic characteristics (Amrhein, 1995; Flowerdew, 2011; Gehlke & Biehl, 1934; Openshaw, 1984; Seguin et al., 2012), there is far less research on the effects of scale for *composites* of socioeconomic characteristics, such as an index. Despite the emphasis on incorporating local contexts and qualitative aspects in the assessment of resilience, there has been limited attention on investigating resilience based on the individual perceptions and self-evaluation of household capacities.

In order to contribute to these gaps in the literature, this research uses a mixed methods approach. First, a quantitative approach is used to investigate the effects of spatial scale on the Social Resilience Index (SoRI) by Damude et al. (2015). Second, qualitative methods involving surveys and interviews are used to assess resident and expert perspectives of resilience to flood hazards through a case study in the City of Vancouver. This research sets out to understand the implications of scale in social flood resilience assessments by addressing the following research questions in each of the manuscripts:

1. ***What are the effects of spatial scale on the SoRI derived from census data? What are the effects of spatial scale on the individual variables comprising the SoRI?***

The first manuscript (Chapter 2) investigates this research question by mapping the SoRI using hierarchical census scales across three study areas. The cities of Vancouver (Canada), Los Angeles (USA) and Edinburgh (Scotland), are used to offer insights on different census programs and census geographies. The varying census geographies can help identify the sensitivity of different census scales (i.e., is the smallest unit always "better"?), identify potential trends and support more robust conclusions. Mapping of a composite index measure allows visualization with two objectives: 1) to identify the spatial patterns of social resilience, and 2) to identify the scale effects of the MAUP when using different census scales.

2. ***Is the method of constructing the SoRI sensitive to scale effects? What other options of index construction can be considered to inform policy efforts?***

The second manuscript (Chapter 4) investigates these research questions by conducting an assessment of data-driven and stakeholder-driven approaches in constructung the SoRI. The objectives are to identify the sensitivity to scale effects of the methodology used to construct the index and how this sensitivity manifests at different census scales.

3. ***How do residents' perceptions of flood resilience compare with quantitative assessments of flood resilience, such as the SoRI? What are some important aspects for building household flood resilience as identified by residents and experts' insights?***

The third manuscript (Chapter 6) aims to uncover the perspectives of flood resilience at the individual-level from residents and experts through a case study in the City of Vancouver. Survey questionnaires were used to capture resident perspectives towards flood resilience, such as what residents were doing to increase their resilience towards flood hazards. Interviews with experts in academia and non-government organizations (NGOs) were used to uncover the local contexts and to identify what residents *could* be doing to build their flood resilience. The use of qualitative methods allows an alternate approach to assess flood resilience at the individual scale, and can provide insights for experts and practitioners involved in disaster risk management and climate change adaptation to better inform policy and planning efforts.

1.3 Conceptual Framework

This research aims to contribute to the current literature on the social aspects of hazards, disasters and climate change. Inherent and pre-existing social conditions may contribute to how populations perceive risk and what they choose to do about these risks, which ultimately determines their ability and capacity to resist, recover and adapt to potential impacts of environmental hazards (Cutter, 2016; Hewitt, 1983). The following section proposes a conceptual framework of the relationships between the physical and social aspects of resilience to environmental hazards.

In this framework, the role of resilience is conceptualized as an opportunity in the social environment to prepare for and protect from the environmental hazards that emerge from the physical environment. The social environment includes the inherent socioeconomic conditions and risk perception and preparedness that influence adaptation capacity and serve as indicators of resilience.

The conceptual framework is adapted from the "Pressure and Release (PAR) Model" by Blaikie et al. (1994) and Wisner et al. (2004), as illustrated in Figure 1.

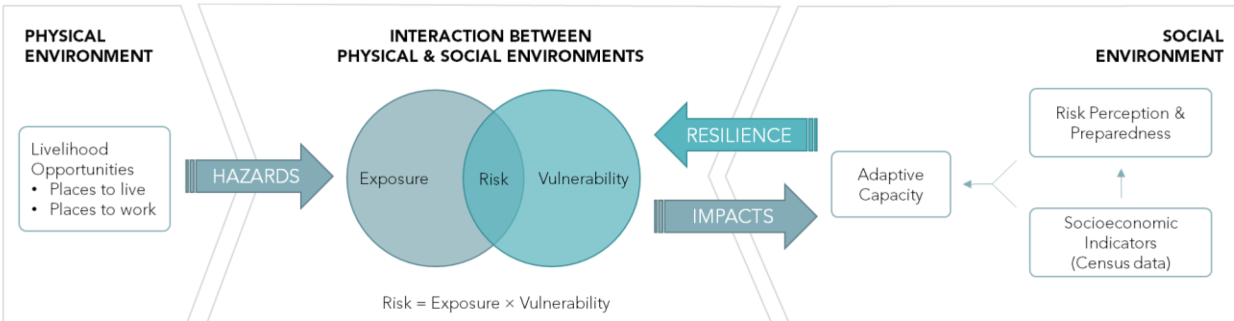


Figure 1. Conceptual framework of the relationships between physical and social factors on resilience to environmental hazards

This conceptual framework distinguishes between the physical and social environments to isolate the physical hazard from the social conditions which create the potential for harm (Blaikie & Brookfield, 1987; Blaikie et al., 1994; White, 1942; Wisner et al., 2004; UNDP, 2017). The framework aligns with previous work from Wisner et al. (2004), which warned against separating "*'natural' disasters from the social frameworks that influence how hazards affect people, thereby putting too much emphasis on the natural hazards themselves, and not nearly enough on the surrounding social environment*" (Wisner et al., 2004, p.4). In this framework, the main distinction between the physical and social environments is the degree of human influence. The physical environment involves components that humans have little control over, such as the occurrence of natural settings such as where mountains, oceans, and floodplain zones occur. The physical environment refers to locations on Earth offering livelihood opportunities, such as places to live and work (Oliver-Smith, 1998; Wisner et al., 2004). The social environment involves aspects of the human society, defined by dimensions of social, economic, institutional and political characteristics (ISDR, 2002).

A hazard is defined as a threat with the *potential* to cause damage (UNDRR, 2004; Birkmann, 2013) and its occurrence is something that humans have little control over (Marre, 2013). The potential for a hazard to become a disaster thus arises from the interaction of two opposing forces: the processes that generate vulnerability arising from the social environment, and the natural hazard arising from the physical environment (Blaikie & Brookfield, 1987; Oliver-Smith, 1998; Wisner et al., 2004). This interaction is contingent on the concept of risk, which is the probability that susceptible units (i.e., people and households) will suffer damage or injury as a result of the hazard (Birkmann, 2013; Cutter, 1996; Lemmen et al., 2016; UNDRR, 2004). Risk is defined as a function of exposure and vulnerability (Blaikie et al., 1994; Wisner et al., 2004), which is expressed as:

$$risk = exposure \times vulnerability \tag{1}$$

Where exposure refers to the coincidence of the physical hazard and the susceptible units in both space and time (Birkmann, 2013; Chambers, 1989; Cutter et al., 2008;) and vulnerability is the degree of susceptibility to damage or injury as a result of the hazard (Birkmann, 2013; UNDRR, 2004).

While the hazard is the event that arises from the physical environment to the social environment, resilience is the counterbalance that links the social environment to the physical environment. Resilience is conceptualized as a condition or state that determines how the impacts of the hazard will be experienced by the susceptible units. Furthermore, the processes that create vulnerability are counteracted by resilience, and are similarly represented as opposing entities in the conceptual framework (Joakim et al., 2015; Wisner et al., 2004).

In the context of hazards, impacts are defined as the effects on natural and human systems as the result of some climatic or environmental event (IPCC, 2014a). The magnitude and type of impacts that are experienced by susceptible units are dependent upon the conditions of the social environment, which determines the capacity to adapt. Adaptive capacity is defined as the ability to adjust to or cope with potential impacts and consequences and take advantage of opportunities based on the pre-existing social conditions (IPCC, 2014b). These social conditions are often represented by indicators such as census data, which are quantifiable measures of socioeconomic characteristics of a population. In addition to adaptive capacity, these social conditions may also play a role in risk perception of and preparedness towards the hazard. Risk perception refers to the subjective judgement about the characteristics and severity of a risk or the potential for consequences (Bronfman et al., 2008; IPCC, 2014b; Lemmen et al., 2016; Slovic, 1992). It is important to note that the influence of socioeconomic indicators is uni-directional, such that they may influence risk perception and preparedness, but not the other way around. For example, characteristics such as household income and employment status may influence whether a household has flood insurance but purchasing flood insurance does not affect the household income or employment status.

The distinction between the physical and social environments in the conceptual framework also aligns with the definitions of shocks and stresses in municipal resilience strategies. As defined by the municipal resilience strategies for the City of Vancouver, Canada and the City of Los Angeles, USA, shocks are sudden or acute events that cause immediate impacts, such as earthquakes, floods and extreme weather events (City of Los Angeles, 2018; City of Vancouver, 2018). Shocks refer to external events that humans have little control over and aligns with the physical environment (indicated on the left side of the framework). Stresses are chronic challenges that weaken the social environment on a gradual basis, such as housing affordability, social inequalities, and racism (City of Los Angeles, 2018; City of Vancouver, 2018). Therefore, stresses are events that humans have direct influence over and involve the inherent social conditions of everyday life.

1.4 Study Areas & Data

This study uses an exploratory approach to investigate the implications of scale when using census data in three cities: The City of Vancouver, Canada; The City of Los Angeles, USA; and The City of Edinburgh, Scotland. The three cities are not used for a comparative analysis but were chosen because of their regularly occurring census programs that feature significant differences in their census geographies. Furthermore, each of these coastal cities are characterized by unique and diverse socioeconomic demographics, which may be valuable for understanding how spatial scale may affect policy efforts to build resilience against flood hazards.

1.4.1 City of Vancouver, British Columbia, Canada

For the City of Vancouver and across Canada, Statistics Canada is responsible for conducting and disseminating the census program. The census is conducted once every five years, with the most recent censuses conducted in 2016 and 2011. *Census tracts* (CTs) are small, relatively stable geographic units that generally have a population between 2,500 to 8,000 people (Statistics Canada, 2012). *Dissemination areas* (DAs) are the smallest standard census geography units comprising of populations between 400 to 700 people (Statistics Canada, 2012). DAs are contained within CTs, such that their boundaries must respect those of the bounding CT unit (Statistics Canada, 2012), as illustrated in Figure 2.

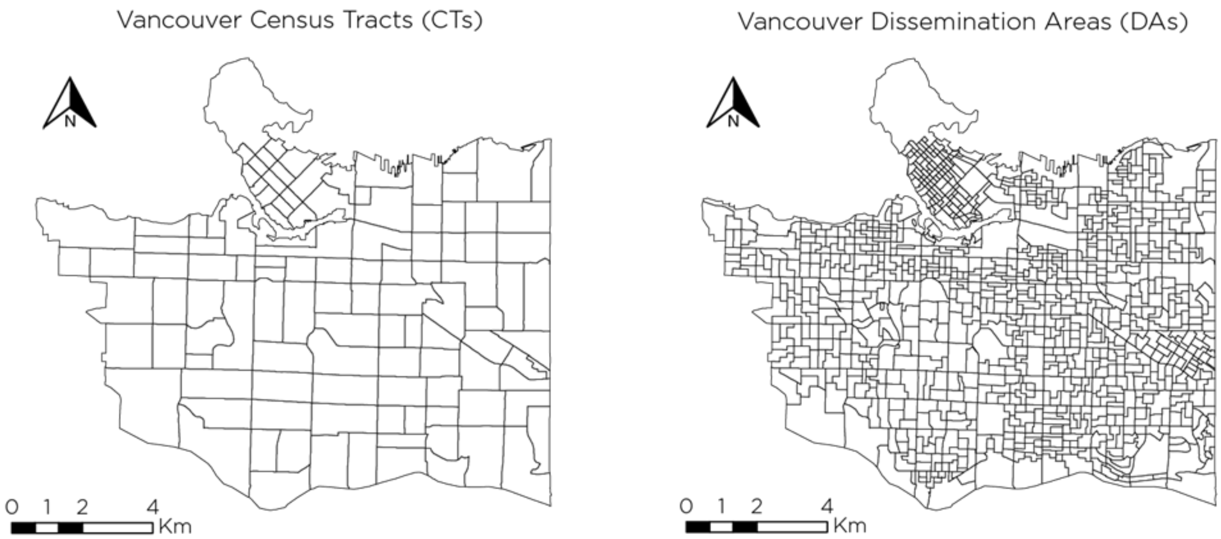


Figure 2. 2011 Census tracts (CTs) and dissemination areas (DAs) for the City of Vancouver, Canada

1.4.2 City of Los Angeles, California, United States of America (USA)

For the City of Los Angeles and across USA, the United States Census Bureau is responsible for conducting and disseminating the census program. The census is conducted once every 10 years, with the most recent census conducted in 2010. *Census tracts* (CTs) are small, relatively permanent geographic units containing 2,500 to 8,000 people that are as homogenous as possible with respect to population characteristics, economic status, and living conditions (U.S. Department of Commerce, 1994a). *Block groups* (BGs) are subdivisions of a census tract (Figure 3), with units containing 250 to 550 households (target of 400 households). It is the smallest geographic entity for which the census tabulates and publishes sample data (U.S. Department of Commerce, 1994b).

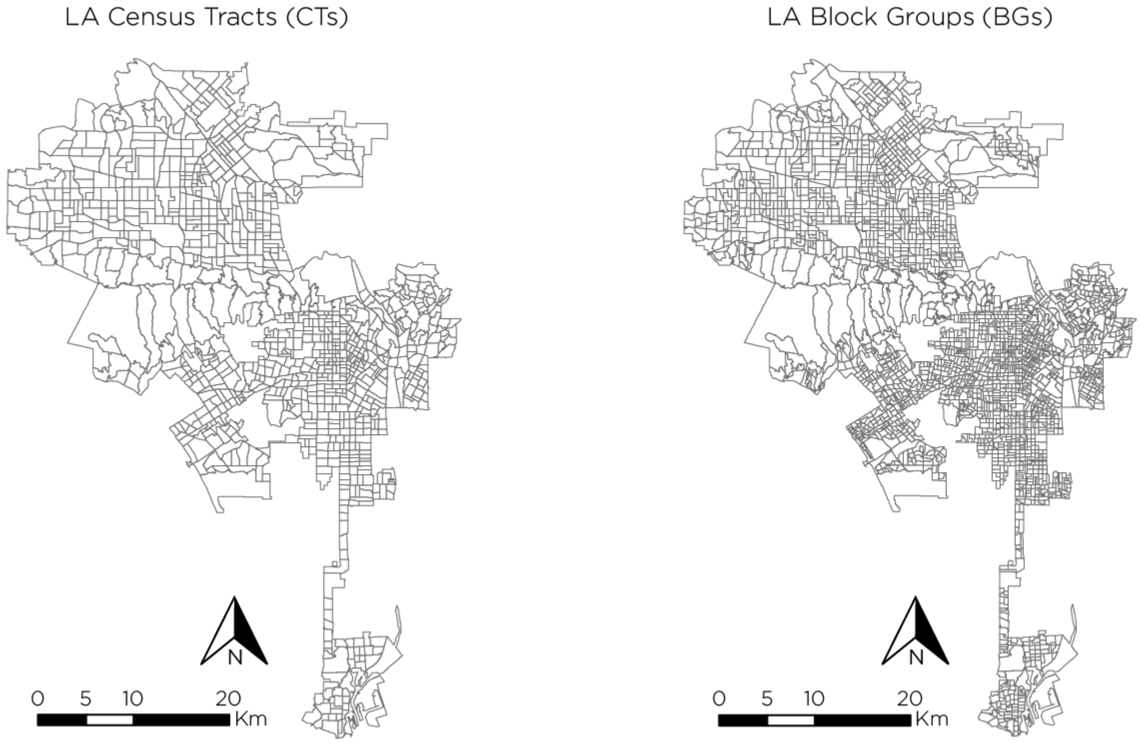


Figure 3. 2010 Census tracts (CTs) and block groups (BGs) for the City of Los Angeles, USA

1.4.3 City of Edinburgh, Scotland, United Kingdom (UK)

For the City of Edinburgh and across Scotland, the National Records of Scotland is responsible for conducting and disseminating the census program. The census is conducted once every 10 years, with the most recent census conducted in 2011. *Data zones* (DZs) are census units that have a population of approximately 500 to 1,000 people (NRS, 2018a). *Output areas* (OAs) are the smallest unit in which census results are produced, and all census outputs are formed by the aggregation of OAs (NRS, 2018b), as illustrated in Figure 4. They are delineated to contain a minimum of 50 people and 20 households, and generally have a maximum of approximately 78 households (NRS, 2015).

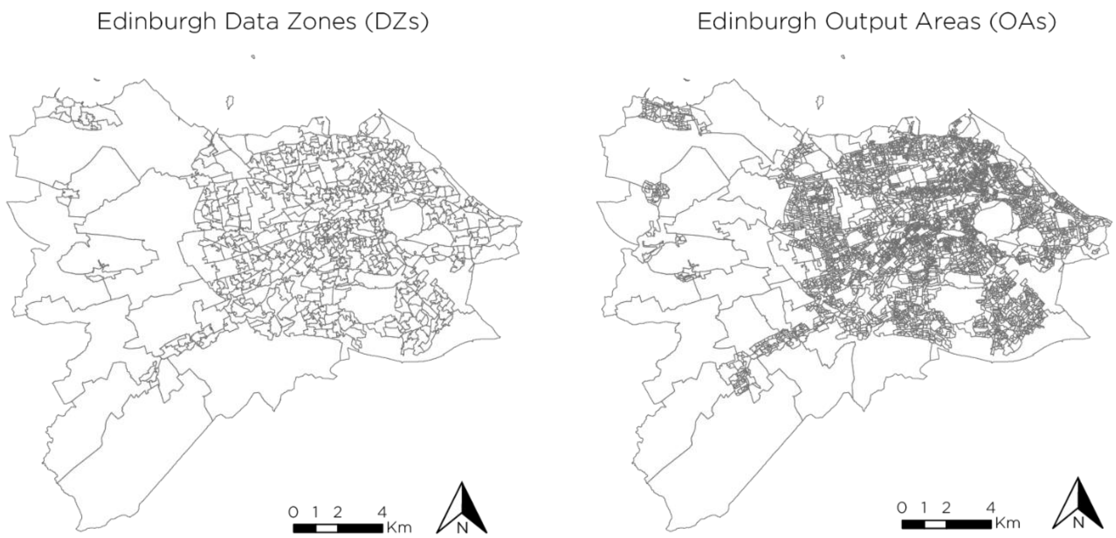


Figure 4. 2011 Data zones (DZs) and output areas (OAs) for the City of Edinburgh, Scotland

1.5 The Social Resilience Index (SoRI)

The Social Resilience Index (SoRI) by Damude et al. (2015) was developed for the Metro Vancouver area to demonstrate the relationship between available census data and population resilience to flooding. The SoRI is particularly suited for investigation of the MAUP because of its dependence on socioeconomic census data, which is only made available at an aggregated level in order to maintain confidentiality. The census variables comprising of the SoRI are intended to explain how different socioeconomic characteristics (i.e., differences in people) may translate to differences in resilience. The SoRI is comprised of fourteen (14) variables from the Canadian census that are further categorized by a directional component to either: increase resilience (+) or decrease resilience (-) as detailed in Table 1 below.

Table 1. Social Resilience Index (SoRI) variables

Indicator	Variable Name	Rationale	+/-[1]
Housing and Families	*Dwellings Major Repair*	Housing that is older and in a poorer state is more likely to receive greater damage from floods (Chakraborty et al., 2005; Cutter et al., 2000; Hebb & Mortsch, 2007; Morrow, 2008). Moveable dwellings or relocation can cause stresses both personally and financially (Damude et al., 2015).	-
	Mobile Dwellings		-
	Dwellings 1960		-
	Rental Dwellings	Populations that rent are less likely to have homeowners' insurance and lack control over construction quality or repairs (Hebb & Mortsch, 2007; Wu et al., 2002;). Recovery may also be delayed as it must go through the landlord (Damude et al., 2015; Morrow, 2008;).	-
	Lone Parent	Single-parent families are more likely to rely on social resources (Cutter et al., 2003) and have less available assets, which reduces the ability to recover from flooding events (Flax et al., 2002; Hebb & Mortsch, 2007; Rygel et al., 2006). Dependents may also create stress under evacuation conditions (Damude et al., 2015; Thrush et al., 2005).	-
Income and Assets	*Avg Household Income*	Having readily available financial assets enhances the ability to pay for protection measures prior to the flood (i.e., flood insurance, installing sump pumps, etc.) and for repairs and other expenses required to recover after the flood event (Cutter et al., 2000; Morrow, 2008; Wu et al., 2002).	+
	Avg Dwelling Value		+
	Low Income	A low-income and/or unemployment status have less financial assets to pay for protection measures prior to the flood and the expenses of recovery after the flood (Flax et al., 2002; Rygel et al., 2006; Tapsell et al., 2002). Populations that receive government transfers are restricted from recovery due to reliance on government aids before, during and after flooding events (Cutter et al., 2003; Morrow, 2008).	-
	Government Transfers		-
	Unemployment		-
Isolated Population	*Living Alone (age 65+)*	These populations are identified as 'isolated' due to limited mobility for evacuation or being dependent on social networks during evacuation (Cutter et al., 2000; Flax et al., 2002; Rygel et al., 2006; Morrow, 2008).	-
	Immigration	Recent immigrants and populations that do not speak the official languages are more likely to be unfamiliar with the region (Penning-Rowsell et al.,1986), and face challenges with information transfer and emergency preparedness (Cutter et al., 2014; Flax et al., 2002; Rygel et al., 2006; Tapsell et al., 2005).	-
	Knowledge of Official Languages		-
	Canadian Citizen	Populations with Canadian citizenship are likely to have stronger social networks, such as opportunities for alternate accommodations or information transfer (Penning-Rowsell et al., 1986). Access to government aid is guaranteed for citizens both during and after flood events (Damude et al., 2015).	+

[1] Positive (+) relationship increases resilience; negative (-) relationship decreases resilience.

The census variables used to derive the SoRI were retrieved from the corresponding census program for each study area (Appendix A). Since the SoRI was developed based on variables available from the Statistics Canada census program, the same variables may not be available for the Los Angeles and Edinburgh study areas. In order to maintain a consistent analysis within each study area, only the variables that were available were included in the computation of the SoRI for that study area. This ensured that the same variables and the same number of variables were being compared between census scales in each study area (Table 2).

Table 2. Social Resilience Index (SoRI) variables for each study area

Variable Name	**City of Vancouver, Canada[1]**	**City of Los Angeles, USA[1]**	**City of Edinburgh, Scotland[1]**
Dwellings Major Repair	✓	--	--
Mobile Dwellings	✓	✓	✓
Dwellings 1960	✓	✓	--
Rental Dwellings	✓	✓	✓
Lone Parent	✓	✓	✓
Avg Household Income	✓	✓	--
Avg Dwelling Value	✓	✓	✓
Low Income	✓	✓	--
Government Transfers	✓	✓	✓
Unemployment	✓	✓	✓
Living Alone (age 65+)	✓	✓	✓
Immigration	✓	✓	✓
Knowledge of Official Languages	✓	✓	✓
Citizenship	✓	✓	✓
Census Year	**2011**	**2010**	**2011**

[1] "✓" indicates variables used in the SoRI index; "--" indicates variables that were not included in the construction of the SoRI

In accordance with Damude et al. (2015), the retrieved data were expressed as percentages according to Table 1 and then transformed into z-scores (i.e., mean of 0 and standard deviation of 1) to standardize the raw census data before constructing the index (Appendix A).

1.6 Census Data: Social & Spatial Indicators

Census data involves conjoined social and spatial components that allow investigation of both the underlying population characteristics as well as its geographic distribution and patterns. As noted by Dorling (1993), census data is particularly valuable for "… *the great spatial detail that is provided – showing how each neighbourhood, each block of streets, each hamlet, differs socially from its neighbours (for every place in the* *country simultaneously)*" (Dorling, 1993, p.167). Relationships between social attributes are therefore not only characterized by the attribute itself, but also by its physical location, particularly the tendency for groups with similar characteristics to occupy similar areas (Anselin, 2017). As an area-based indicator, the use of census data has become increasingly prevalent across a number of disciplines, such as natural hazards (Briguglio, 2003; Cutter et al., 2003; Felsenstein & Lichter, 2014; Oulahen et al., 2015; Rickless et al., 2019), health (Denny & Davidson, 2012; Pampalon et al., 2009; Schuurman et al., 2007), crime (Fabio et al., 2011; Kawachi et al., 1999), and poverty (Prouse et al., 2014; Seguin et al., 2011).

As a social indicator, census data is the most common large-scale source of information about populations and its characteristics (Martin, 1998). As a spatial indicator, census data allows investigation of how these characteristics are distributed across space (Dorling, 1993). Spatial analysis is often concerned with spatial patterns - that is, the 'non-random' of phenomena over space, rather than the random (O'Sullivan & Unwin, 2010). This is because completely random and uniform geographical surfaces in the real world are rare and would also be of little interest if every single location on Earth was the same (O'Sullivan & Unwin, 2010).

1.7 The Modifiable Areal Unit Problem (MAUP)

The use of social indices is reliant on census data, which are only made available as aggregated units at different census scales. Due to privacy reasons, individual-level census data is disseminated as areal units of varying shape and size for both statistical and administrative purposes (Dorling, 1993; Mendelson, 2001; Openshaw, 1984; Prouse et al., 2014). The same set of individual-level data can therefore be analyzed at different census scales and different zonal boundaries (Openshaw, 1984; Flowerdew, 2011). There is no standard unit for analysis of census data, as it involves "*the arrangement of continuous space into defined regions for purposes of data reporting*" (Amrhein, 1995, p.107) and thus any continuous study area can be defined in countless ways (Carrington et al., 2018). This discordance in the nature of spatial data is the source of the modifiable areal unit problem (MAUP).

The MAUP is a phenomenon where the spatial analysis of a dataset can produce varying results based on the definition of areal units (Fotheringham & Wong, 1991; Openshaw, 1984). In other words, results of statistical analyses using spatial data are sensitive to the modifiable and arbitrary geographic boundaries in which they are defined (Carrington et al., 2018; Flowerdew, 2011; Fotheringham & Wong, 1991; Gehlke & Biehl, 1934; Openshaw, 1984). The differences in the areal units used to make inferences can lead to different, and at times contradictory, results (Carrington et al., 2018). Areal units can be defined by their size and shape, which correspond to the scale and zoning effects, respectively, of the MAUP (Fotheringham & Wong, 1991; Openshaw & Taylor, 1979; Openshaw, 1984). The scale effect arises from variations in the size and the number of areal units defined, or the level of spatial resolution (Openshaw, 1984). For example, an analysis using data aggregated by dissemination areas (DAs) will differ from that aggregated by its bounding counterpart, census tracts (CTs). The zoning effect arises from the number of possible configurations of boundaries over a geographic region (Jelinski & Wu, 1996; Openshaw, 1984). For example, an analysis of data aggregated into 1-kilometre grid cells will differ from that aggregated into 1-kilometre circles. There is no standard unit for spatial analysis, and thus any continuous study area can be delineated in a very large number of ways (Carrington et al., 2018; Openshaw, 1984).

As a result of the MAUP, the socioeconomic characteristics captured by the census are defined by the areal units in which they are contained. These areal units that inferences are drawn from have little to no connection to the underlying processes that are represented by the data and simply serve as operational requirements for the census and government administration (Brunsdon, 2009; Flowerdew, 2011; Openshaw, 1984). It is therefore a type of statistical bias that assumes the administrative boundaries of an area aligns with the variation of the underlying attribute being represented. For privacy reasons, census data is aggregated into areal units that serve as proxies to represent individual-level socioeconomic characteristics (Carrington et al., 2018; Denny & Davidson, 2012; Prouse et al., 2014; Taylor et al., 2003). This presents a case of ecological fallacy – a special case of the MAUP, when aggregated census data is used to inform characteristics and address problems at the individual-level (Openshaw, 1984; Robinson, 1950). The process of aggregation manifests the MAUP by creating generalizations and masking disparities within individual areal units (Openshaw, 1984; Prouse et al., 2014) (*see also* Clark & Avery, 1976; Fotheringham & Wong, 1991; Jelinski & Wu, 1996; Openshaw, 1984; Prouse et al., 2014; Schuurman et al., 2007; Seguin et al., 2011; Steel & Holt, 1996).

With the use of census data to infer population resilience, the implications of its conjoined spatial component are often overlooked. This research aims to better understand the use of census data in social indices to identify priority areas for disaster risk management and climate change adaptation efforts. Bridging the gap between the scientific efforts to *quantify* resilience and the policy efforts to *build* resilience can contribute to more targeted solutions to enhance resilience against environmental hazards, such as flooding.

1.8 Structure of Thesis

This thesis is written following the manuscript option, where each of the chapters 2, 4 and 6 is a separate manuscript that has been prepared for submission to academic journals. The manuscripts are meant to stand alone, but together answer the broader research questions. This thesis aims to contribute to the understanding of the implications of scale when using social flood resilience assessments to inform policy and planning efforts. Chapters 2 and 4 investigate the implications of scale for the SoRI when using aggregate census data at different scales. Chapter 6 explores the qualitative perspectives of flood resilience at the individual-level through a survey with residents in Vancouver and interviews with experts. Chapters 3 and 5 provide linkages to connect the three manuscripts. The thesis concludes with chapter 7, which summarizes the contributions of the overall thesis and recommendations for future study directions.

2.0 Mapping Social Resilience to Flooding: Understanding the Modifiable Areal Unit Problem (MAUP)

2.1 Introduction

Socioeconomic attributes are commonly used to characterize vulnerability and resilience to environmental hazards as an approach to inform and prioritize disaster risk management and climate change adaptation (Cannon, 1994; Cutter, 1996; Buckle et al., 2000; Cutter et al., 2000; Oulahen et al., 2015; Rickless et al., 2019; Tapsell et al., 2002). Not only are the impacts of a hazard unequally distributed geographically, but also the pre-existing and inherent socioeconomic characteristics of the underlying population (Cannon, 1994; Cutter, 1996; Cutter et al., 2003; Felsenstein & Lichter, 2014; Sevoyan et al., 2013). The purpose of investigating socioeconomic characteristics is recognizing that certain populations possess inherent attributes, such as greater access to resources, that increases their resilience compared to populations that are deprived of these same attributes (Cannon, 1994; Cutter, 1996; Cutter et al., 2003; Frerks et al., 2011; Sayers et al., 2017; Sevoyan et al., 2013; Tapsell et al, 2002; Wisner et al., 2004).

One of the most common and easily accessible forms of socioeconomic data is census data. Due to privacy reasons, individual-level census data are not made publicly available but aggregated into units at varying census scales (Dorling, 1993; Flowerdew, 2011; Openshaw, 1984; Prouse et al., 2014). The process of aggregation into different types of census units, manifests in the Modifiable Areal Unit Problem (MAUP). The MAUP is a phenomenon where the analysis of a dataset can produce varying results based on the definition of areal units (Fotheringham & Wong, 1991; Openshaw, 1984). This is a problem because the results of analyses using spatial data are sensitive to the modifiable and arbitrary geographic boundaries in which the data are defined (Carrington et al., 2018; Flowerdew, 2011; Fotheringham & Wong, 1991; Openshaw, 1984). The differences in the areal units used to make inferences can lead to different, and at times, contradictory results (Carrington et al., 2018; Gehlke & Biehl, 1934; Openshaw, 1984). The use of socioeconomic census data to infer social vulnerability and resilience may also be subject to the effects of the MAUP.

2.1.1 Quantifying Social Resilience

The focus on resilience has become increasingly prominent in social policy to aid disaster risk reduction and management (100RC, 2019; City of Los Angeles, 2018; City of Vancouver, 2019; Scottish Government, 2019; The Heinz Center, 2009; The Royal Society, 2014; The World Bank, 2015). Resilience can be defined as "*the capacity of a system, community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain an acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organizing itself to increase its capacity for learning from past disasters for better future protection and to improve risk reduction measures*" (UNDRR, 2004, p.6). When exposed to environmental hazards, certain populations may possess socioeconomic characteristics and resources that can be used to accommodate the negative impacts or exploit potential benefits arising from the hazard (Cannon, 1994; Cutter, 1996; Cutter et al., 2000; Felsenstein & Lichter, 2014; MacCallum et al., 2014; Sevoyan et al., 2013; Rickless et al., 2019; Wisner et al., 2004). Household income, gender, age, race or minority status, education and language can affect the ability of different populations to prepare for, cope with, and recover from, environmental hazards (Berke et al., 2015; Blaikie & Brookfield, 1987; Cannon, 1994; Cutter, 1996; Felsenstein & Lichter, 2014; Hebb & Mortsch, 2007; Sevoyan et al., 2013; Susman et al., 1983; Rickless et al., 2019; Wisner et al., 2004). Inequalities in these pre-existing socioeconomic conditions, ultimately creates inequalities in the level of impacts that different people may face, particularly those that are already socially, economically and politically marginalized (Douglas et al., 2012; Gotham & Greenberg, 2014; MacCallum et al., 2014; Wisner et al., 2004). The extent to which a hazard becomes a disaster are therefore not explained solely by the behaviour of the physical hazard itself, but rather the ongoing social order and everyday conditions (Hewitt, 1983; Blaikie & Brookfield, 1987; Cutter, 1996).

A common method to investigate the role of socioeconomic characteristics and the distribution of disaster risk is through the use of indices (Cutter et al., 2000; Cutter et al., 2010; Cutter et al., 2014; Cutter, 2016; Felsenstein & Lichter, 2014; Oulahen et al., 2015; Rickless et al., 2019; Sayers et al., 2017; Tapsell et all., 2002). The purpose of an index is to condense the complexity of multiple quantifiable characteristics into a single numeric value to allow comparison between geographic areas or population subgroups (Briguglio, 2003; Cutter et al., 2003; Cutter, 2016; Oulahen et al., 2015; Rickless et al., 2019). The general process of operationalizing social indices is illustrated in Figure 5.

Figure 5. Schematic process of operationalizing social indices

The use of social indices are constrained by data availability and accessibility, which often results in the use of census data as the data source (Briguglio, 2003; Buckle et al., 2000; Cutter et al., 2000; Cutter et al., 2003; Felsenstein & Lichter, 2014; Oulahen et al., 2015; Prouse et al., 2014; Tapsell et al., 2002; Willis & Fitton, 2016). These census variables serve as indicators to postulate the correlation between the measured socioeconomic characteristic and its relevance to social resilience (Birkmann, 2003; Cutter, 2016; Willis & Fitton, 2016). The quantification of social resilience is a relative measure of socioeconomic characteristics between geographic areas. Understanding these relative differences between population subgroups can aid disaster risk management and adaptation planning (Cutter et al., 2000; Cutter et al., 2010; Cutter et al., 2014; Felsenstein & Lichter, 2014; Oulahen et al., 2015; Rickless et al., 2019; Sayers et al., 2017).

2.1.2 The Modifiable Areal Unit Problem (MAUP)

Quantifying social resilience using indices is often reliant on census data, which are only disseminated as aggregated units at different census scales. These aggregated units are delineated from the same set of individual-level data, and therefore, the same set of data can be analyzed at different census scales (Carrington et al., 2018; Flowerdew, 2011; Openshaw, 1984). This manifests in the MAUP, where the analysis of the same data can produce different results based on the definition of the areal units (Fotheringham & Wong, 1991; Openshaw, 1984;). While some research has been conducted involving developing and analyzing indices to explore social vulnerability and resilience in the fields of disaster risk management and climate change, there lies a gap in understanding the implications of spatial scale on these indices. For example, numerous metrics have been developed using available census data, such as the Social Flood Vulnerability Index (SFVI) (Tapsell et al., 2002); the Social Vulnerability Index (SoVI) (Cutter et al., 2003; Cutter et al., 2000); the Disaster Resilience of Place (DROP) (Cutter et al., 2008); the Baseline Resilience Indicators for Communities (BRIC) index (Cutter et al., 2014; Cutter et al., 2010); the Social Resilience Index (SoRI) (Damude et al., 2015); and the Neighbourhood Flood Vulnerability Index (NFVI) (Sayers et al., 2017). The SFVI was operationalized at the enumeration district (ED) scale for England and Wales (Tapsell et al., 2002); the SoVI at the United States county scale (Cutter et al., 2003); the SoRI at the Canadian dissemination area (DA) scale (Damude et al., 2015); and the NFVI at the lower layer super output area (LSOA) scale in England, the data zone (DZ) scale in Scotland and the super output area (SOA) scale in Northern Ireland (Sayers et al., 2017). These data and analytical results are presented for one set of areal units, and as a result of the MAUP, represent only one *possible* set of the analytical results (Openshaw, 1984).

Consequences of the MAUP have been identified in bivariate and multivariate analyses (Clark & Avery, 1976; Fotheringham & Wong, 1991; Gehlke & Biehl, 1934; Openshaw & Taylor, 1979; Steel and Holt, 1996). Variations in correlation coefficients over the entire range from -1 to 1 can be achieved by using different boundary configurations (Openshaw & Taylor, 1979). Multivariate statistical results were found to be unreliable and "*essentially unpredictable*" (Fotheringham & Wong, 1991, p.1025) when different spatial scales and zoning systems were used (Fotheringham & Wong, 1991). Wong (1997) demonstrated that measures of segregation could vary significantly at different geographic scales, if the observations were not strongly positively spatially autocorrelated (i.e., if neighbouring observations were not similar to each other). They found that previous conclusions of the MAUP were only partially applicable in the study of segregation and concluded that different types of analysis and data will react to the MAUP differently. Schuurman et al. (2007) investigated the effects of scale on deprivation indices using multiple census scales and demonstrated a homogenizing effect with increasing aggregation (i.e., combining smaller areal units to form a larger unit). They concluded that MAUP effects towards measures of deprivation were best addressed by using the smallest unit of analysis possible. Seguin et al. (2011) had similar conclusions in their analysis of poverty in Montreal across three geographic scales where they found that poverty occurred in small pockets in the city and were only uncovered using the finest spatial scale. These varying results present a special case of the MAUP, called ecological fallacy, when aggregate census data are used as the basis for decision making that addresses problems at the individual level (Openshaw, 1984; Robinson, 1950).

2.2 Methodology

In the absence of a standard geographic scale that is best suited for spatial analysis, it is important to understand the effects of spatial scale when multiple census scales exist. This study aims to answer the following research question:

What are the effects of spatial scale on the SoRI derived from census data? What are the effects of spatial scale on the individual variables comprising of the SoRI?

This study addresses this research question, using the SoRI by Damude et al. (2015) as a case study between hierarchical census scales for:

(1) The City of Vancouver, British Columbia, Canada at the census tract (CT) and dissemination area (DA) scales;

(2) The City of Los Angeles, California, USA at the census tract (CT) and block group (BG) scales; and

(3) The City of Edinburgh, Scotland, UK at the data zone (DZ) and output area (OA) scales.

The three study areas were used to gather insights across the different census programs and census geographies, and to support more robust conclusions on the effects of spatial scale. This study adopts an exploratory analysis approach involving five main steps for investigating the scale effect of the MAUP: 1) a principal components analysis (PCA) to compute a composite SoRI value; 2) mapping of the SoRI; 3) a Moran's I test to identify potential spatial patterns of social resilience; and 4) a variable sensitivity analysis.

2.2.1 Principal Component Analysis & SoRI Values

Following the methodology in Damude et al. (2015), which was adapted from the original methodology in Cutter et al. (2003), the SoRI value is computed using principal components analysis (PCA). A PCA is a multivariate statistical method that condenses the input variables by identifying the dimensions, or principal components (PCs), in which the overall dynamics of the dataset occur (Cutter et al., 2003). A separate PCA was conducted at the census scales for each study area using the IBM Statistical Package for the Social Sciences (SPSS) software.

Since the PCA is a statistical method to identify correlations, the directional components may not be representative of the variable relationships in reality. Following the original method by Cutter et al. (2003), if the majority of variables correlated to a PC had a negative relationship (i.e., decreases resilience) then the sign for that PC was also adjusted to be negative. On the contrary, if most variables correlated to the PC has a positive relationship (i.e., increases resilience) then the sign was adjusted to be positive. If variables with different signs were correlated to the same PC, then the absolute value was used. Although the absolute value is theoretically assigning a positive relationship, the SoRI resulted in 11 variables with a negative relationship, compared to only three variables identified with a positive relationship. The resulting SoRI values are a sum of the resulting principal component correlation values, which were used to map social resilience.

2.2.2 Social Resilience Mapping

In order to isolate and investigate the scale effect of the MAUP, the SoRI was mapped using the Esri ArcGIS desktop software for each census scale in the three study areas. Since the SoRI is a relative measure, the maps are symbolized based on quintiles of standard deviation (SD): high (>1.5 SD), medium-high (0.5-1.5 SD), medium (-0.5-0.5 SD), medium-low (-1.5 – (-0.5) SD) and low (<-1.5 SD). The sign of the SD values indicates the direction of social resilience, where negative values indicate low resilience (i.e., red areas) below the city average, and positive values indicate high resilience (i.e., blue areas) above the city average.

2.2.3 Moran's I Test for Spatial Autocorrelation

Following social resilience mapping which identifies *where* populations have attributes of high and low resilience, an investigation of spatial patterns was conducted to understand *how* such populations are distributed over space. Spatial autocorrelation refers to spatial patterns measured by the extent of similarity or dissimilarity between neighbouring features (Anselin, 2016; Fortin & Dale, 2009). The global Moran's I statistic is a common measure of spatial autocorrelation that is used to identify the type of spatial pattern present based on both the spatial location and spatial value (Anselin, 2016; Fortin & Dale, 2009). In the absence of a spatial pattern (i.e., the null hypothesis) the occurrence of a SoRI value at one location is equally likely at any other location (Anselin, 2016). The presence of a spatial pattern is described as the tendency of the SoRI to be clustered (i.e., positive spatial autocorrelation) or dispersed (i.e., negative spatial autocorrelation). While there is the common understanding that certain SoRI variables tend to cluster spatially, such as household income and average dwelling value, other variables such as knowledge of official languages and the population aged 65+ living alone, may not necessarily follow the same spatial clustering. The global Moran's I will test for spatial patterns of the SoRI, which may differ from the spatial patterns of the variables comprising it.

2.2.4 Sensitivity Analysis of SoRI Variables

This analysis aims to investigate the sensitivity of the individual variables comprising the SoRI to scale effects ***before*** variables are combined to construct an index. Due to privacy reasons, individual-level census data is aggregated into areal units at multiple census scales and are therefore subject to scale effects before any analysis occurs. In order to evaluate the scale effects of the SoRI, this analysis uses the mean scale difference (MSD) and a Fisher's Z transformation to evaluate differences between census scales.

Mean Scale Difference (MSD)

The mean scale difference (MSD) measure provides a cumulative measure of the MAUP on each of the possible relationships that each variable has with the others (Flowerdew, 2011). If the correlation between a pair of variables varies at different census scales, it would be indicative of a higher sensitivity to scale effects. The MSD for each variable was calculated using (2) below from Flowerdew (2011):

$$MSD_{var} = \frac{max\ difference\ in\ correlation\ value\ between\ scales\ for\ variable}{total\ number\ of\ possible\ pairwise\ correlations\ for\ variable} \tag{2}$$

Pearson's bivariate correlations (i.e., *r*-value) are used to compare all possible pairwise combinations of variables between the two census scales. The numerator is calculated using matrix subtraction of correlation values (i.e., *r*-values), and the total number of possible pairwise relationships for the variable is the denominator. The higher the MSD_{var} value is, the higher the sensitivity of the variable to scale effects of the MAUP.

Fisher's Z Transformation

The Fisher's Z transformation is used to determine whether changes between census scales are statistically significant (Flowerdew, 2011). The first step involves standardizing the correlation coefficients (i.e., *r*-values) for the pairwise correlations at the respective census scales using (3) below from Flowerdew (2011):

$$\mathrm{z_{ijk}} = 0.5\ \times \ln \left[\frac{(1-\mathrm{r_{ijk}})}{(1+\mathrm{r_{ijk}})}\right] \tag{3}$$

Where $\mathrm{r_{ijk}}$ is the correlation of variables *i* and *j* at scale *k,* and the z-score $\mathrm{z_{ijk}}$ is calculated for every pairwise correlation at each scale. Once the correlation coefficients have been standardized, they can be compared to determine the statistical significance. Using (4) below from Flowerdew (2011), the difference between the pairwise correlations at a scale *k* and the second scale *h*, are statistically significant (i.e., $p<0.05$) if:

$$z_{ijk} - z_{ij\mathrm{h}}\ \geq 1.96\ \times \sqrt{\frac{1}{(m_k-3)}+\frac{1}{(m_k+3)}} \tag{4}$$

Where there are m_k areal units at scale *k*, and m_h areal units at scale *h*. If the inequality is satisfied (i.e., the left side is larger than the right side), then the differences in the correlation coefficients between the two scales *is* statistiscally significant, and the MAUP affects the interpretation of the results (Flowerdew, 2011).

2.3 Results & Findings

2.3.1 SoRI Values and Principal Components Analysis

In the first step of computing the SoRI values, the PCA indicated varying results when different census scales were applied in each study area. Differences were observed in the percentage of variance captured and the factor loadings between the census scales across all three study areas. Factor loadings are correlation values between the census variable and the PCs and represents how much each census variable contributes to the overall SoRI value. The results of the PCA are explained for each study area in the following sections, and the SPSS procedure for the PCA are provided in Appendix B.

2.3.1.1 City of Vancouver

For the City of Vancouver, the PCA factor loadings for the 2011 census data (Table 3) indicate that the CT scale (i.e., larger unit) captures a higher percentage of variance than the DA scale (i.e., smaller unit). This is supported by the total percentage of variance captured at each scale, and also by the percentage of variance captured by principal component 1 (PC1), which captures the highest amount of variance possible in the dataset. At the CT scale, PC1 captures 29.946% of variance and at the DA scale, PC1 captures 19.881% of variance. This suggests that the data structure for the SoRI is better captured at the larger census unit than at the smaller census unit.

The PCA factor loadings (Table 3) also indicate differences in the variables between census scales which are indicative of scale effects. In comparing the variables related to dwelling characteristics, namely *dwellings major repair*, *mobile dwellings* and *dwellings 1960*, the factor loadings are significant (i.e., > 0.5, whether positive or negative) for the SoRI at the CT scale but not at the DA scale (i.e., < 0.5, which appear as "--" in the table). This essentially suggests that the significance of certain dwelling characteristics will vary depending on the census scale that is chosen for the SoRI in Vancouver. The SoRI value will also depend on different census variables based on the census scale that is used. The correlations for the *low income*, *government transfers*, and *lone parent* variables were relatively consistent between census scales, which indicates that these variables may be less sensitive to scale effects of the MAUP.

Table 3. Summary of PCA results for the City of Vancouver

SoRI Census Variable	Principal Component (PCs) Factor Loadings: Census Tracts (CTs)				Dissemination Areas (DAs)			
	1	2	3	4	1	2	3	4
Dwellings Major Repair	--	--	0.687	--	--	--	--	--
Mobile Dwellings	--	--	--	0.603	--	--	--	--
Dwellings 1960	-0.509	--	--	--	--	--	--	--
Rental Dwellings	0.608	-0.691	--	--	--	0.770	--	--
Lone Parent	0.555	0.606	--	--	0.606	--	--	--
Avg Household Income	-0.833	--	--	--	--	--	--	-0.739
Avg Dwelling Value	-0.708	--	--	--	--	--	--	-0.621
Low Income	0.781	--	--	--	0.590	--	--	--
Government Transfers	0.755	0.523	--	--	0.777	--	--	--
Unemployment*	0.727	--	--	--	0.699	--	--	--
Living Alone (age 65+)	--	-0.869	--	--	--	0.864	--	--
Immigration	--	--	-0.826	--	--	--	-0.853	--
Knowledge of Official Languages	--	0.841	--	--	0.593	-0.587	--	--
Citizenship	--	--	0.912	--	--	--	0.853	--
% Variance	29.946	21.965	16.461	8.584	19.881	16.844	13.860	10.038
Total % Variance	76.956				60.623			
Sign Adjustment[1]	| |	-	| |	-	-	-	| |	+

" * " indicates variables that were not available at the smaller census unit and values were taken to be equal to the value of the larger unit in which it was contained within and were omitted from the discussion of MAUP effects.
"--" indicates factor loadings that are less than 0.5 (i.e., not a significant correlation) and have been supressed
[1] "-" indicates negative relationship; "+" indicates positive relationship; "| |" indicates absolute value

A discrepancy in the directionality of the variables towards the SoRI is also observed in the factor loadings (Table 3). First, the factor loadings indicate that a single variable can simultaneously contribute both positively (i.e., increase resilience) and negatively (i.e., decrease resilience) to the SoRI. For example, this can be observed for the *rental dwellings* variable at the CT scale, where PC1 has a positive factor loading of 0.608, but PC2 has a negative factor loading of -0.691. This also contradicts the initial rationale for the contribution of each variable in the SoRI. The *rental dwellings* variable was assigned a negative directionality, as it was a characteristic that decreased resilience. However, by using a PCA to compute the index value, the *rental dwellings* variable could contribute positively to the overall SoRI value. Second, this discrepancy in variable directionality is also observed between census scales. For example, the *living alone (age 65+)* variable has a negative factor loading value of -0.869 at the CT scale, yet simultaneously has a positive factor loading value of 0.864 at the DA scale. This occurs because the PCA identifies the directionality of the variable towards the PC and not the directionality towards the SoRI. While the sign adjustment procedure from Cutter et al. (2003) was intended to address this discrepancy, it does not fully address the problem because it applies a sign adjustment to the entire PC and not to individual variables. For example, for the *Unemployment* variable at the CT scale, PC1 has a positive value of 0.727 and the sign adjustment applies an absolute value (i.e., positive) which ultimately increases resilience to the SoRI.

2.3.1.2 City of Los Angeles

For the City of Los Angeles, the PCA results for the 2010 census data (Table 4) indicate that the CT scale (i.e., larger unit) captured a higher total percentage of variance than the BG scale (i.e., smaller unit). However, it is important to note that PC1 at the CT scale captured 34.4% of variance, which is less than PC1 at the BG scale, which captured 36.7% of variance. This could be caused by very diverse socioeconomic characteristics that occur at a finer level in Los Angeles, which could cause the higher variance captured for PC1 using the smaller BG units. Although this was not further addressed in this study, it could be further explored in future research.

Table 4. Summary of PCA results for the City of Los Angeles

SoRI Census Variable	Principal Component (PCs) Factor Loadings							
	Census Tracts (CTs)				Block Groups (BGs)			
	1	2	3	4	1	2	3	4
Mobile Dwellings	--	--	--	0.809	--	-0.536	--	0.668
Dwellings 1960	--	0.915	--	--	--	--	0.757	--
Rental Dwellings	0.781	--	0.543	--	0.693	--	--	--
Lone Parent		--	--	--	0.643	--	--	--
Avg Household Income	0.780	--	0.544	--	-0.840	--	--	--
Avg Dwelling Value	--	--	0.626	--	-0.628	--	--	--
Low Income	--	--	--	--	0.824	--	--	--
Government Transfers*	0.789	--	--	--	0.822	--	--	--
Unemployment	--	--	--	0.519	--	--	--	--
Living Alone (age 65+)	--	--	0.550	--	-0.611	--	--	--
Immigration	--	0.908	--	--	--	0.696	--	0.594
Knowledge of Official Languages	0.762	--	--	--	0.631	--	--	--
Citizenship*	-0.587	0.668	--	--	-0.636	--	--	--
% Variance	34.446	16.623	11.298	9.188	36.688	9.613	8.878	8.661
Total % Variance	71.555				63.840			
Sign Adjustment*	| |	| |	| |	-	| |	-	-	-

" * " indicates variables that were not available at the smaller census unit and values were taken to be equal to the value of the larger unit in which it was contained within and were omitted from the discussion of MAUP effects.
"--" indicates factor loadings that are less than 0.5 (i.e., not a significant correlation) and have been supressed
[1] "-" indicates negative relationship; "+" indicates positive relationship; "| |" indicates absolute value

The results in Table 4 indicate scale effects where different variables are more significant for computing the SoRI depending on the scale of analysis. The results indicate that *unemployment* is a significant variable (i.e., > 0.5, whether positive or negative) for the SoRI at the CT scale but not the BG scale (i.e., < 0.5, which appear as "--" in the table). Conversely, *lone parent* and *low income* are significant for the SoRI at the BG scale but not the CT scale. The relatively consistent correlations at both scales for the *rental dwellings*, *avg household income* and *knowledge of official languages* variables suggest that these variables may be less sensitive to scale effects of the MAUP.

Discrepancies in the directionality of the variables for constructing the SoRI were also observed in the factor loadings (Table 4). For example, at the CT scale, the *living alone (65+)* variable has a positive factor loading (0.550) for PC3 yet simultaneously has a negative factor loading (-0.611) for PC1 at the BG scale. This was also observed between scales for the *mobile dwellings* variable. Furthermore, at the CT scale, the *living alone (65+)* variable has a positive factor loading of 0.550, which contradicts the initial rationale that this variable contributes negatively (i.e., elders who live alone are generally less resilient) to the SoRI. These results again indicate that a single variable can simultaneously contribute negatively (i.e., decrease resilience) and positively (i.e., increase resilience). This change in directionality is suspected to be caused by MAUP effects in the original data before it was input into the PCA, where differences in the initial census data between census scales were propagated through the PCA. In this case, the sign adjustment for the *living alone (65+)* variable assigned an absolute value, which did not address the discrepancy in the variable directionality and again contradicts the initial theoretical rationale of the SoRI variables.

2.3.1.3 SoRI for the City of Edinburgh

For the City of Edinburgh, the PCA results for the 2011 census data (Table 5) indicate that the DZ scale (i.e., larger unit) captured a higher percentage of variance than the OA scale (i.e., smaller unit). This is supported by the total percentage of variance captured at each scale, 76.7% at the DZ scale and 62.2% at the OA scale. This is further supported by PC1, which captures the highest portion of variance in the dataset, 42.7% at the DZ scale and 32.8% at the OA scale. This is consistent with the findings of the other study areas in this study, where data variance for the SoRI is better captured at the larger census unit than at the smaller census unit.

The PCA factor loadings in Table 5 are indicative of scale effects, where a variable can have a significant factor loading (i.e., > 0.5, whether positive or negative) at one scale, but also have an insignificant factor loading (i.e., < 0.5, whether positive or negative) at the other scale. For example, the *mobile dwellings* variable is significant for the SoRI at the DZ scale but not at the OA scale, whereas *knowledge of official languages* is significant at the OA scale but not the DZ scale. Again, these results suggest that the variables comprising of the SoRI can vary based on the census scale chosen for analysis. The relatively consistent correlations observed for the *rental dwellings*, *lone parent* and *citizenship* variables may suggest that these variables are less sensitive to the scale effects of the MAUP.

Table 5. Summary of PCA results for the City of Edinburgh

<table>
<tr><th rowspan="3">SoRI Census Variable</th><th colspan="6">Principal Component (PCs) Factor Loadings</th></tr>
<tr><th colspan="3">Data Zones (DZs)</th><th colspan="3">Output Areas (OAs)</th></tr>
<tr><th>1</th><th>2</th><th>3</th><th>1</th><th>2</th><th>3</th></tr>
<tr><td>Mobile Dwellings</td><td>--</td><td>--</td><td>0.865</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Rental Dwellings</td><td>0.879</td><td>--</td><td>--</td><td>0.831</td><td>--</td><td>--</td></tr>
<tr><td>Lone Parent</td><td>0.743</td><td>--</td><td>--</td><td>0.695</td><td>--</td><td>--</td></tr>
<tr><td>Avg Dwelling Value*</td><td>-0.746</td><td>--</td><td>--</td><td>-0.726</td><td>--</td><td>--</td></tr>
<tr><td>Government Transfers*</td><td>0.844</td><td>--</td><td>--</td><td>0.795</td><td>--</td><td>--</td></tr>
<tr><td>Unemployment</td><td>0.845</td><td>--</td><td>--</td><td>0.698</td><td>--</td><td>--</td></tr>
<tr><td>Living Alone (age 65+)</td><td>--</td><td>0.537</td><td>--</td><td>--</td><td>0.503</td><td>0.712</td></tr>
<tr><td>Immigration</td><td>0.512</td><td>-0.822</td><td>--</td><td>--</td><td>-0.758</td><td>--</td></tr>
<tr><td>Knowledge of Official Languages</td><td>0.673</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Citizenship</td><td>--</td><td>0.854</td><td>--</td><td>--</td><td>0.796</td><td>--</td></tr>
<tr><td>% Variance</td><td>42.685</td><td>23.548</td><td>10.505</td><td>32.818</td><td>18.314</td><td>11.032</td></tr>
<tr><td>Total % Variance</td><td colspan="3">76.738</td><td colspan="3">62.164</td></tr>
<tr><td>Sign Adjustment*</td><td>| |</td><td>| |</td><td>-</td><td>| |</td><td>| |</td><td>-</td></tr>
</table>

" * " indicates variables that were not available at the smaller census unit and values were taken to be equal to the value of the larger unit in which it was contained within and were omitted from the discussion of MAUP effects.
"--" indicates factor loadings that are less than 0.5 (i.e., not a significant correlation) and have been supressed
[1] "-" indicates negative relationship; "+" indicates positive relationship; "| |" indicates absolute value

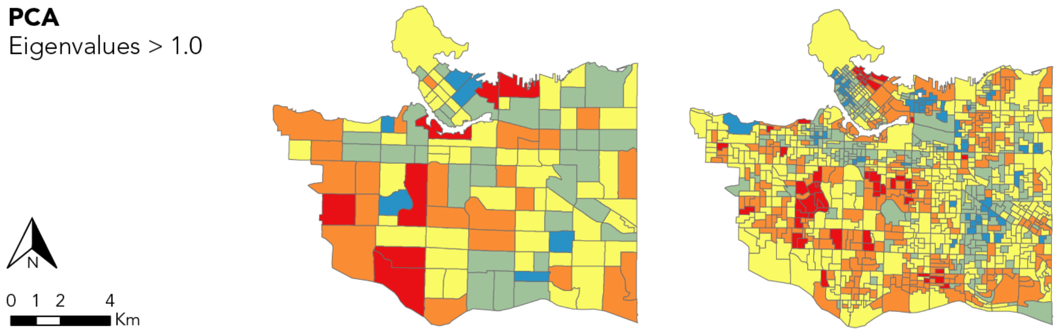
The factor loadings in Table 5 indicate discrepancies in the directionality of the variables only between PCs and not between census scales, a finding which was observed in Vancouver and Los Angeles. For the SoRI in Edinburgh, only the *immigration* variable at the CT scale indicates a positive factor loading of 0.512 for PC1 and a negative factor loading of -0.822 for PC2. These results again indicate that a single variable can simultaneously contribute positively (i.e., increases resilience) and negatively (i.e., decreases resilience) to the SoRI. While the sign adjustment procedure was intended to correct this discrepancy, it can be observed that the absolute value applied to PC1 and PC2 at the CT scale ultimately results in the *immigration* variable contributing positively (i.e., increases resilience) to the SoRI, which contradicts the initial rationale of the variable.

2.3.2 Spatial Patterns of Social Resilience Across Three Cities

Following the PCA which generated composite index values, the SoRI was mapped at the corresponding census scales for each study area. The SoRI maps for all three study areas illustrate the scale effects of the MAUP, where the differences between census scales can be significant. Disparities were observed between census scales – where areas of the highest resilience (i.e., blue areas) at one scale can be identified as an area of the lowest resilience (i.e., red areas) at the other scale. The spatial distribution of the SoRI are described for each study area in the following sections.

2.3.2.1 City of Vancouver

For the City of Vancouver, the discrepancies between census scales are most easily observed in the central-western portion of the city and along the northern shoreline (Figure 6). An area having the highest social resilience (i.e., blue areas) at the CT scale, can simultaneously be identified to have the lowest social resilience (i.e. red areas) at the DA scale. This discrepancy in the mapped SoRI is consistent with the results from the PCA factor loadings, where the results will vary when different census scales are applied. Spatially, the identification of priority areas (i.e., areas of low resilience) will also vary depending on the scale of analysis that is used.



Social Resilience Index (SoRI)		2011 Census Tracts (CTs)	2011 Dissemination Areas (DAs)
	Lower than average (lower social resilience)	< -1.5 Std. Dev. (7)	< -1.5 Std. Dev. (94)
		-1.5 - -0.5 Std. Dev. (20)	-1.5 - -0.5 Std. Dev. (196)
	Average	-0.5 - 0.5 Std. Dev. (48)	-0.5 - 0.5 Std. Dev. (363)
		0.5 - 1.5 Std. Dev. (31)	0.5 - 1.5 Std. Dev. (248)
	Higher than average (higher social resilience)	> 1.5 Std. Dev. (10)	> 1.5 Std. Dev. (90)

SoRI Statistics	Percentage of Units per SoRI Quintile (%)					
	Scale	< -1.5 Std. Dev.	-1.5 - -0.5 Std. Dev.	-0.5 - 0.5 Std. Dev.	0.5 - 1.5 Std. Dev.	> 1.5 Std. Dev.
	CT	8.62	26.72	41.38	17.24	6.03
	DA	9.08	25.03	36.63	19.78	9.49

Figure 6. The Social Resilience Index (SoRI) for City of Vancouver based on 2011 census data

The discrepancies between census scales are also observed in the spatial patterns of the SoRI. At the CT scale, areas of high resilience are adjacent to areas of the lowest resilience – a pattern that is not reflected at the DA scale. This observation is further supported by the results of the Global Moran's I test for potential spatial patterns (Table 6). While the consistently positive Moran's I index values suggest that social resilience based on the SoRI is spatially clustered, the corresponding p-values suggest that the SoRI was randomly distributed at the CT scale (i.e., null hypothesis should not be rejected, but was clustered at the DA scale (i.e., null hypothesis rejected) in Vancouver. These contrasting results between census scales indicate that measures of spatial patterns may also be sensitive to the scale effects of the MAUP.

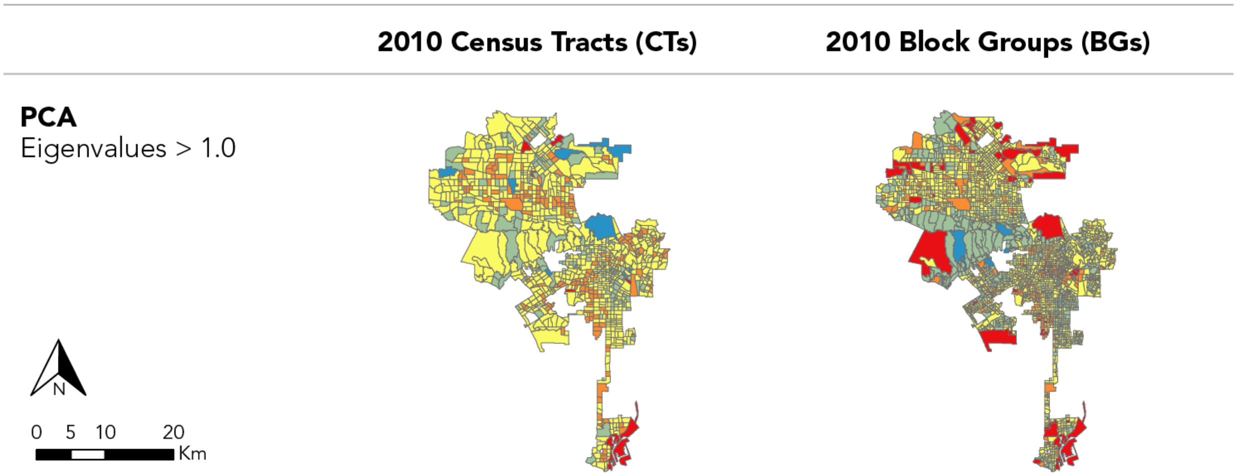
Table 6. Global Moran's I test for spatial autocorrelation for Vancouver

City	Scale	Moran's I	p-value
Vancouver	CT	+ 0.0896	0.0557
	DA	+ 0.4518	0.0000

When comparing the two census scales, it can be observed that the DA scale (i.e., smaller census units) is able to better capture extreme values (i.e., red and blue areas) than the CT scale. This is also supported from the SoRI statistics (Figure 6), where the DA scale captured a higher percentage of units in the highest resilience category (i.e., > 1.5 Std. Dev.) and lowest resilience category (i.e., < -1.5 Std. Dev.) than at the CT scale. While these mapped results indicate that the DA scale is able to better capture extremes, this is inconsistent with previous results from the PCA, which found that the CT scale captured a higher percentage of variance. These results suggest an unexpected implication of scale effects – that the CT scale is more suitable for representing statistical results, whereas the DA scale is more suitable for representing the spatial distribution of results.

2.3.2.2 City of Los Angeles

For the City of Los Angeles, the discrepancies in the SoRI between census scales are most prevalent along the central and northern edges of the city boundaries (Figure 7). At the BG scale, several areas having the lowest social resilience (i.e., red areas) can simultaneously have the highest social resilience (i.e., blue areas) at the CT scale. This discrepancy in the mapped SoRI is supportive of the previous results from the PCA factor loadings, where the SoRI will vary when different census scales are used.



Social Resilience Index (SoRI)	Lower than average (lower social resilience)	< -1.5 Std. Dev. (7)	< -1.5 Std. Dev. (65)
		-1.5 - -0.5 Std. Dev. (178)	-1.5 - -0.5 Std. Dev. (336)
	Average	-0.5 - 0.5 Std. Dev. (656)	-0.5 - 0.5 Std. Dev. (1567)
		0.5 - 1.5 Std. Dev. (152)	0.5 - 1.5 Std. Dev. (532)
	Higher than average (higher social resilience)	> 1.5 Std. Dev. (8)	> 1.5 Std. Dev. (5)

	Percentage of Units per SoRI Quintile (%)					
SoRI Statistics	**Scale**	< -1.5 Std. Dev.	-1.5 - -0.5 Std. Dev.	-0.5 - 0.5 Std. Dev.	0.5 - 1.5 Std. Dev.	> 1.5 Std. Dev.
	CT	0.80	15.18	65.53	17.78	0.70
	BG	0.20	21.24	62.55	13.41	2.59

Figure 7. The Social Resilience Index (SoRI) for City of Los Angeles based on 2010 census data

The discrepancies between census scales can also be observed in the spatial patterns of the SoRI (Figure 7). At the CT scale, more high resilience areas (i.e., blue areas) are captured, whereas the DA scale captures more low resilience areas (i.e., red areas). These areas of high resilience and low resilience also largely occur as clusters within the city of Los Angeles. This is supported by the Global Moran's I test for potential spatial patterns (Table 7). The consistently positive Moran's I index values and very small p-values (i.e., $p < 0.001$) indicates that social resilience based on the SoRI is spatially clustered in Los Angeles.

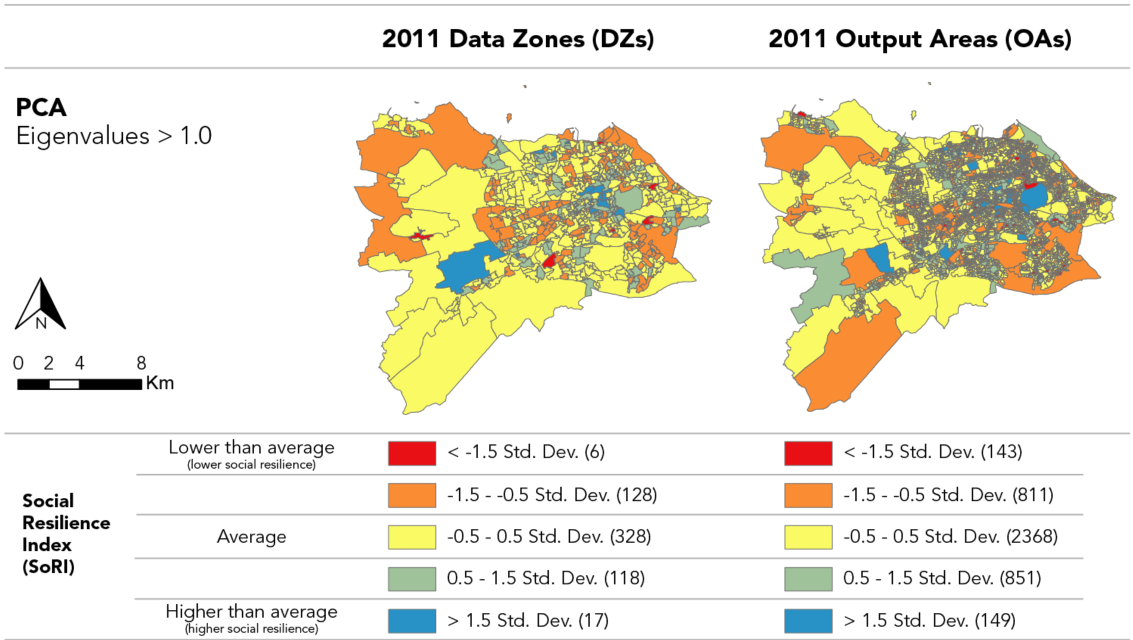
Table 7. Global Moran's I test for spatial autocorrelation for Los Angeles

City	Scale	Moran's I	p-value
Los Angeles	CT	+ 0.1089	0.0000
	BG	+ 0.1334	0.0000

When comparing the two census scales, it is can be observed that the CT scale (i.e., larger unit) captures more high resilience areas (i.e., blue areas), whereas the BG scale (i.e., smaller unit) captures more low resilience areas (i.e., red areas). This may suggest that diverse socioeconomic characteristics occur at a finer level in Los Angeles, but it is not possible to verify whether the CT scale is overestimating the SoRI or the BG scale is underestimating the SoRI. In the absence of individual-level data or local contexts, it cannot be verified which census scale is representing the SoRI more accurately. The previous results of the PCA indicated that the CT scale captures a higher percentage of variance, which suggests that the CT scale is better suited for representing statistical results of the SoRI.

2.3.2.3 City of Edinburgh

For the City of Edinburgh, the inconsistencies between census scales occurs in parts of the city centre (Figure 8). An area having the highest social resilience (i.e., blue areas) at the DZ scale can simultaneously have the lowest social resilience (i.e., red areas) at the OA scale. This discrepancy is supportive of the results from the PCA factor loadings, where the results can vary when different census scales are used.



		Percentage of Units per SoRI Quintile (%)				
	Scale	< -1.5 Std. Dev.	-1.5 - -0.5 Std. Dev.	-0.5 - 0.5 Std. Dev.	0.5 - 1.5 Std. Dev.	> 1.5 Std. Dev.
SoRI Statistics	DZ	1.01	21.44	54.94	19.77	2.85
	OA	3.31	18.76	54.79	19.69	3.45

Figure 8. The Social Resilience Index (SoRI) for the City of Edinburgh based on 2011 census data

The discrepancies between census scales can also be observed in the spatial patterns and spatial statistics of the SoRI (Figure 8). At the OA scale, more low resilience areas (i.e., red areas) and high resilience areas (i.e., blue areas) are captured than at the DZ scale. The differences observed between census scales are relatively lower than the other study areas. In the absence of individual-level data, it cannot be verified whether the DZ scale is underestimating the SoRI or the OA scale is overestimating the SoRI. The previous results of the PCA indicated that the larger DZ units capture more variance, which suggests that the DZ scale is better suited for representing statistical results. Furthermore, the results of the Global Moran's I test for potential spatial patterns (Table 8) indicate that these areas of high resilience and low resilience occur as clusters within the city of Edinburgh. This is supported by the positive Moran's I index value and very small p-values (i.e., $p < 0.0001$).

Table 8. Global Moran's I test for spatial autocorrelation for Edinburgh

City	Scale	Moran's I	p-value
Edinburgh	DZ	+ 0.1635	0.0000
	OA	+ 0.1800	0.0000

When comparing the two census scales, it can be observed that the DZ scale (i.e., larger unit) captures more low resilience areas (i.e., red areas), whereas the OA scale (i.e., smaller unit) captures more high resilience (i.e., blue areas).

2.3.3 Scale Effects on the SoRI

The scale effects of the MAUP on the SoRI was demonstrated in the statistical results of the PCA and the spatial results of the SoRI maps and the Moran's I test for spatial autocorrelation. Across all study areas, the results of the PCA consistently indicate that the larger census unit (i.e., CTs in Vancouver and Los Angeles, and DZs in Edinburgh) captures a higher percentage of variance than the smaller census unit. This was an unexpected result, because it is commonly presumed in the literature that smaller areal units (i.e., DAs in Vancouver, BGs in Los Angeles and OAs in Edinburgh) show a greater level of detail and variation than larger areal units (Clark & Avery, 1976; Fotheringham & Wong, 1991; Prouse et al., 2014; Schuurman et al., 2007; Seguin et al., 2011; Steel & Holt, 1996). Larger areal units are subject to more generalizations and masking of extremes within the unit, and thus variation tends to decrease (Fotheringham & Wong, 1991; Openshaw & Taylor, 1979; Prouse et al., 2014; Wong et al., 1999). This is commonly why smaller units are presumed to be "better", as they can represent values that would otherwise be masked with increasing aggregation. The results of this study demonstrate that scale effects cannot always be mitigated by using the smallest areal unit.

In an effort to synthesize the scale effects of the MAUP from the mapped results, a summary of the number of units belonging to each SoRI quintile (i.e., each colour on the map) in each study area is summarized in Table 9. The smaller census units consistently capture more areas of high resilience (i.e., >1.5 quintile) than the corresponding larger census scale. This same trend, however, is not observed for capturing areas of low resilience (i.e., <-1.5 quintile). It is commonly anticipated that the smaller census scale is able to better capture extreme values that would otherwise be masked at the larger census scale. However, based on the SoRI statistics (Table 9), the smaller census unit does not consistently have greater minimum and maximum values (*min* and *max*). Furthermore, the SoRI maps indicate that the number and magnitude of differences observed between census scales are largely unpredictable. More importantly, it is difficult to attribute these observed relationships solely to the scale effects of the MAUP, because without the individual-level disaggregate data, it cannot be verified whether the larger scale is underestimating the SoRI or the smaller scale is overestimating the SoRI, or vice versa.

Table 9. Summary of SoRI by study area and census scale

City	Scale	Percentage of Units per SoRI Quintile (%)					SoRI Statistics		
		> 1.5	0.5 – 1.5	-0.5 – 0.5	-1.5 - -0.5	< -1.5	Min	Avg	Max
		Highest Resilience	----------------			*Lowest Resilience*			
Vancouver	CT	6.03	17.24	41.38	26.72	8.62	-4.33	0.16	3.00
	DA	9.49	19.78	36.63	25.03	9.08	-6.33	0.02	4.55
LA	CT	0.70	17.78	65.53	15.18	0.80	-16.41	1.31	29.11
	BG	2.59	13.41	62.55	21.24	0.20	-52.09	-0.83	1.91
Edinburgh	DZ	2.85	19.77	54.94	21.44	1.01	-17.78	1.20	4.33
	OA	3.45	19.69	54.79	18.76	3.31	-7.86	0.87	21.68

2.3.4 Variable Sensitivity Analysis

The results of the PCA factor loadings (see Tables 3, 4, 5) demonstrated the sensitivity of individual SoRI variables to scale effects. It was observed that variables could have a significant correlation (i.e., factor loadings > 0.5) at one census scale but not the other (i.e., insignificant correlations are represented by "--" in the tables). These findings suggest that different variables will contribute to the SoRI depending on the census scale that is adopted for analysis, which was a manifestation of scale effects of the MAUP. While some variables had contradictory factor loadings between scales, other variables were also observed to have relatively consistent factor loadings (i.e., > 0.5) between census scales which indicated less sensitivity to scale effects (Table 10). Note that the variables that were not available at the smaller unit and were assigned the value at the larger unit (i.e., the variables marked with " * " in Tables 3, 4, 5) were omitted from the analyses in this section. This ensures that the results being presented are representative of scale effects between the two census scales for each study area.

Table 10. Sensitivity of census variables to the scale effect of the MAUP

City	Social Resilience Index (SoRI) Variables	
	Manifestation of Scale Effects	Less Sensitive to Scale Effects
Vancouver	• *Dwellings major repair* • *Mobile dwellings* • *Dwellings 1960*	• *Low income* • *Government transfers* • *Lone parent*
LA	• *Unemployment* • *Lone parent* • *Low income*	• *Rental dwellings* • *Avg household income* • *Knowledge of official languages*
Edinburgh	• *Mobile dwellings* • *Knowledge of official languages*	• *Rental dwellings* • *Lone parent* • *Citizenship*

The MSD and Fisher's z transformation were used to further investigate the sensitivity of the individual SoRI variables to scale effects. The results of these analyses are summarized in Table 11 below, where variables with the highest values (i.e., max values) indicate the highest sensitivity to scale effects, and the variables with the lowest values (i.e., min values) indicate the lowest sensitivity to scale effects.

Table 11. Summary of variable sensitivity analysis

City		Mean Scale Difference (MSD)		Fisher's z Transformation	
		Min *(Least scale effects)*	**Max** *(Most scale effects)*	**Min** *(Least scale effects)*	**Max** *(Most scale effects)*
Vancouver	Value	0.0144	0.0591	1	8
	Variable	Mobile dwellings	Rental dwellings; Avg household income	Mobile dwellings	Avg household income
LA	Value	0.0125	0.1274	1	5
	Variable	Mobile dwellings	Rental dwellings; Avg household income	Rental dwellings	Avg dwelling value
Edinburgh	Value	0.0110	0.0446	3	9
	Variable	Mobile dwellings	Rental dwellings Immigration	Mobile dwellings	Immigration

The results of the MSD indicate that the *rental dwelling* variable is the most sensitive to scale effects, which consistently had the highest value (i.e., max) across all three study areas. Additionally, the *avg household income* variable for Vancouver and LA, and the *immigration* variable for Edinburgh also had the highest MSD values, indicating the highest sensitivity to scale effects. On the contrary, the *mobile dwellings* variable consistently had the lowest value (i.e., min) across all study areas, indicating the lowest sensitivity to scale effects. It is important to note that the occurrence of mobile homes is rare, and all study areas will commonly have a value of "0" for the *mobile dwellings* variable at both census scales, which is likely to have led to the lowest sensitivity to scale effects.

The results of Fisher's z transformation also indicated similar findings, where the *average household income* for Vancouver, the *average dwelling value* for LA, and the *immigration* variable for Edinburgh had the highest number (i.e., max) of pairwise correlations with statistically significant differences between census scales. This suggests that interpreting correlations involving these variables may also be affected by scale effects. On the contrary, the *mobile dwellings* variable for Vancouver and Edinburgh, and the *rental dwellings* variable for LA had the lowest number (i.e., min) of pairwise correlations with statistically significant differences between census scales.

2.4 Discussion

Scale effects of the MAUP were observed between the census scales for each study area in both the statistical and the spatial results. Between the census scales for each study area, the variables comprising of the SoRI can differ, a given variable can both increase and decrease resilience between census scales, and a census unit that is identified to have high resilience at one scale can simultaneously have low resilience at the other scale.

The PCA method used to construct the SoRI indicated scale effects between census scales in each study area which contradicted theoretical understanding. Firstly, a given variable can be significant for the SoRI at one scale, but insignificant at the other census scale. This suggests that the SoRI value will be based on different variables depending on the census scale that is used. In evaluating scale effects, the intent of this study was to ensure that the same variables and the same number of variables would be used in the derivation of the SoRI at both census scales for each study area. Recall that census data are non-modifiable entities – the individual disaggregate data comprising of the aggregate census units does not change. Therefore, the variables that are significant for the derivation of the SoRI (i.e., the variables that are correlated to the PCs) were expected to be the same at both census scales for each study area. This presents an important implication of using census data, where the MAUP is prevalent before any spatial analysis is conducted. Secondly, a variable that theoretically decreases resilience (i.e., negative), can ultimately increase resilience (i.e., positive) when constructed using the PCA. For example, the *unemployment*, *lone parent* and *government transfers* variables are theoretically postulated to decrease resilience, however the positive factor loadings across all three study areas indicated that it ultimately increased resilience when they are represented using the SoRI. This finding suggests that the PCA method used to construct the SoRI may not be suitable for representing the theoretical understandings of social resilience.

A spatial unit with high social resilience at one census scale can have low social resilience at the other scale. For the City of Vancouver, the inconsistent and contradictory results of the SoRI showing spatial clustering at one scale (i.e., the smaller units, DAs) while behaving simultaneously as a random process at another scale (i.e., the larger units, CTs) were not expected as a manifestation of MAUP effects. Since aggregate census data is comprised of the same underlying individual-level data, it was not expected that spatial patterns of social resilience would differ based on the census scale chosen. However, this result was not consistently observed for any of the study areas, which may suggest that the larger units are masking a spatial pattern that occurs at a finer scale in Vancouver. Furthermore, the number and magnitude of differences observed between census scales are largely unpredictable and do not follow any consistent or definitive trends. These inconsistencies significantly impact the purpose and conclusions drawn from the SoRI in identifying disadvantaged populations and priority areas for attention. A further consequence of MAUP is that there is no way of confirming which scale is representing the original disaggregate values more accurately, since the original disaggregate values are not available in order to maintain confidentiality.

The sensitivity of the PCA method to scale effects was also identified through the contrasting results with the sensitivity analysis of the individual SoRI variables (i.e., MSD and Fisher's Z measures). The sensitivity analysis may indicate that a given variable has the highest sensitivity to scale effects, yet the PCA results can indicate that the same variable has the lowest sensitivity to scale effects. For example, the PCA results indicated that the *mobile dwellings* variable manifested in scale effects for Vancouver and Edinburgh, but the MSD and Fisher's Z results indicated that it had the lowest sensitivity to scale effects. This is likely due to *mobile dwellings* having similar values between census scales (i.e., most values were "0" between census scales), which suggests that variables that are localized spatially and tend to have similar values, may be less sensitive to scale effects (Wong, 1997).

However, this scale effect should also be interpreted in the context of a social resilience index. While the variable may be less sensitive to scale effects because it has similar values, it also suggests that it may not be a significant nor a representative characteristic that is influential towards the SoRI.

The SoRI for the three study areas were comprised of different numbers of variables – 14 variables for Vancouver, 13 variables for Los Angeles and 10 variables for Edinburgh, due to the unavailability of certain variables from the different census programs. This constraint suggests that scale effects of the MAUP prevails in multivariate analyses, regardless of the varying number of input variables. This also suggests that the number of variables in a multivariate analysis may not be an indicator of sensitivity to scale effects. Similar variables across all three study areas accounted for the most variance in the PCA, which suggests their significance in the SoRI. The *rental dwellings*, *average dwelling value*, *government transfers*, *living alone (age 65+)*, *immigration* and *citizenship* variables were significant for the derivation of the SoRI at both census scales across all three study areas. This suggests that variables related to household wealth and isolated populations (i.e., elders living alone, recently immigrated, and non-citizens) are important indicators for the SoRI across different geographic contexts.

The results indicate that the smaller census units provide a more stable representation of spatial structure. This is supported by a consistent and very low significance (i.e., p-value) of the Global Moran's I statistic that was consistently observed for all study areas. The results for Vancouver further suggest that the smaller census unit is more suitable for representing the extremes or the spatial distribution of the SoRI, but this finding was not consistently observed for any of the other study areas. In contrast, the larger census unit consistently captured a higher percentage of variance in the PCA, which suggests that it offers a better spatial structure for capturing the overall dynamics of the SoRI variables, even though it is a larger and more aggregated areal unit. These findings, however, are inconsistent with previous findings that variance decreases with an increase in aggregation (Clark & Avery, 1976; Fotheringham & Wong, 1991; Openshaw, 1984; Prouse et al., 2014; Schuurman et al., 2007; Seguin et al., 2011; Steel & Holt, 1996). Openshaw (1984) explains that with increasing aggregation, the resemblance to the original disaggregate values decreases. This inconsistency could be due to the PCA method used to construct the SoRI values. Since a PCA extracts PCs based on variance in the dataset, it relies solely on existing data structure rather than theory.

The inconsistencies observed in the statistical and spatial results between census scales are consistent with previous warnings of the MAUP - that analytical results are dependent upon the units in which the data is contained (Fotheringham & Wong, 1991; Openshaw, 1984). When compounded with the inconsistencies observed from the results of the PCA, these findings of this study forewarn that mapping exercises of socioeconomic indices to inform disaster risk management and climate change adaptation efforts should be interpreted with caution.

2.5 Limitations & Future Research Directions

Due to data constraints of the census programs, certain SoRI variables were only made available at the larger areal unit (i.e., CTs for Vancouver and LA, and DZs for Edinburgh) for each study area. To ensure that the SoRI was comprised of the same census variables at both census scales, the value for these SoRI variables at the smaller areal unit (i.e., DAs for Vancouver, BGs for LA, and OAs for Edinburgh) were taken to be equal to the value of the larger (hierarchical) areal unit that it is contained within. This limitation could cause misleading results, where these variables appear to be less sensitive to scale effects, but in actuality, is due to the variable having the same value at both census scales. All variables that were subject to this limitation were not discussed in this study as a manifestation of scale effects. A detailed breakdown of the SoRI census variables and their availability for analysis at each census scale are provided in Appendix A. This limitation emphasizes the inevitable constraint of data availability when using census data at different census scales. Future studies of the MAUP could investigate potential solutions when data are only made available at specific census scales (i.e., is assigning the value for the smaller areal unit from the larger areal unit the best compromise?).

Further research is required to better understand and to differentiate whether these inconsistencies between the census scales is a result of the MAUP, the statistical methods (i.e., PCA), the selection of SoRI variables, the delineation of census units, or a combination of these. In addition to scale effects, further research of socioeconomic indices could also consider multi-collinearity tests and land use factors for a more representative metric. An alternate avenue of research could consider using ground-truth data, such as qualitative survey data with local communities to validate statistical results.

2.6 References

100RC (100 Resilient Cities), 2019. *Resilient Cities, Resilient Lives – Learning from the 100RC Network*. New York, London, Mexico City, Singapore: 100 Resilient Cities. [online] Available at: <http://100resilientcities.org/wp-content/uploads/2019/07/100RC-Report-Capstone-PDF.pdf> [Accessed 2 June 2020].

Anselin, L., 2016. *Spatial Data, Spatial Analysis and Spatial Data Science*. Chicago: The Center for Spatial Data Science (University of Chicago).

Berke, P., Newman, G., Lee, J., Combs, T., Kolosna, C., & Salvesen, D., 2015. Evaluation of Networks of Plans and Vulnerability to Hazards and Climate Change: A Resilience Scorecard. *Journal of the American Planning Association*, 81(4), pp. 287-302.

Blaikie, P., and Brookfield, H., 1987. *Land Degradation and Society*. London: Methuen & Co. Ltd.

Briguglio, L., 2003. *The Vulnerability Index and Small Island Developing States - A Review of Conceptual and Methodological Issues*. Malta: University of Malta.

Brunsdon, C., 2009. Statistical Inference for Geographical Processes. In: A. S. Fotheringham & P. A. Rogerson, eds. *The SAGE Handbook of Spatial Analysis*. London: SAGE Publications Ltd., pp. 207-224.

Buckle, P., Mars, G. & Smale, R. S., 2000. New approaches to assessing vulnerability and resilience. *Australian Journal of Emergency Management*, 15(2), pp. 8-15.

Cannon, T., 1994. Vulnerability Analysis and the Explanation of 'Natural' Disasters. In: A. Varley, ed. *Disasters, Development and Environment*. Chichester: John Wiley & Sons Ltd., pp. 13-30.

Carrington, A., Rahman, N. & Ralphs, M., 2018. *The Modifiable Areal Unit Problem: Research Planning*. (NSMAC 11, 11th Meeting of the National Statistics Methodology Advisory Committee). South Wales: Office for National Statistics. Available at: https://www.ons.gov.uk/ons/guide-method/method-quality/advisory-committee/2005-2007/eleventh-meeting/the-modifiable-areal-unit-problem--research-planning.pdf [Accessed 15 September 2019].

City of Vancouver, 2019. *Resilient Vancouver Strategy*. Vancouver: City of Vancouver. [online] Available at: <https://vancouver.ca/files/cov/resilient-vancouver-strategy.pdf> [Accessed 15 January 2020].

Clark, W.A.V. & Avery, K.L., 1976. The effects of data aggregation in statistical analysis. *Geographical Analysis*, 8, pp. 428-438.

Cutter, S. L., 1996. Vulnerability to environmental hazards. Progress in Human Geography, 20(4), pp. 529-539.

Cutter, S. L., Mitchell, J. T., & Scott, M. S., 2000. Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. *Annals of the Association of American Geographers*, 90(4), pp. 713-737.

Cutter, S. L., Boruff, B. J. & Shirley, W. L., 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly*, 84(2), pp. 242-261.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E. & Webb, J., 2008. A place-based model for understanding community resilience to natural disasters. *Global Environmental Change*, 18, pp. 598-606.

Cutter, S. L., Burton, C. G. & Emrich, C. T., 2010. Disaster Resilience Indicators for Benchmarking Baseline Conditions. *Journal of Homeland Security and Emergency Management*, 7(1), article 51.

Cutter, S. L., Ash, K. D. & Emrich, C. T., 2014. The geographies of community disaster resilience. *Global Environmental Change*, 29, pp. 65-77.

Cutter, S. L., 2016. The landscape of disaster resilience indicators in the USA. *Natural Hazards*, 80, pp. 741-758.

Damude, K., Mortsch, L. & Joakim, E., 2015. *Draft Report: Methods for Quantifying Social Resilience in Metro Vancouver, Canada*. Ontario: Coastal Cities at Risk (CCaR) Project.

Dorling, D., 1993. Map design for census mapping. *The Cartographic Journal*, 30, pp. 167-183.

Douglas, E. M., Kirshen, P. H., Paolisso, M., Watson, C., Wiggin, J., Enrici, A., & Ruth, M., 2012. Coastal flooding, climate change and environmental justice: identifying obstacles and incentives for adaptation in two metropolitan Boston Massachusetts communities. *Mitigation and Adaptation Strategies for Global Change*, 17(5), pp. 537-562.

Felsenstein, D. & Lichter, M., 2014. Social and economic vulnerability of coastal communities to sea-level rise and extreme flooding. *Natural Hazards*, 71, pp. 463-491.

Flowerdew, R., 2011. How serious is the Modifiable Areal Unit Problem for analysis of English census data?. *Population Trends*, 145, pp. 106-118.

Fortin, M. & Dale, M., 2009. Spatial Autocorrelation. In: A. Fotheringham & P. Rogerson, eds. *The SAGE Handbook of Spatial Analysis*. London: SAGE Publishing Ltd., pp. 89-103.

Fotheringham, A. S. & Wong, D. W. S., 1991. The modifiable areal unit problem in multivariate statistical analysis. *Environmental and Planning A*, Volume 23, pp. 1025-1044.

Frerks, G., Warner, J. & Weijs, B., 2011. The Politics of Vulnerability and Resilience. *Ambiente & Sociedade*, 14(2), pp. 105-122.

Gehlke, C.E. & Biehl, K., 1934. Certain effects of the grouping upon the size of the correlation coefficient in census tract material. *Journal of the American Statistical Association*, Supplement 29, pp. 169-170.

Gotham, K. F., & Greenberg, M., 2014. *Crisis Cities: Disaster and Redevelopment in New York and New Orleans*. Oxford: Oxford University Press.

Hebb, A. & Mortsch, L., 2007. *Floods: Mapping Vulnerability in the Upper Thames Watershed under a Changing Climate*. CFCAS Report: Assessment of Water Resources Risk and Vulnerability to Changing Climate Conditions. Project Report XI.

Jelinski, D. E. & Wu, J., 1996. The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology*, 11(3), pp. 129-140.

Lerch, D., 2015. *Six Foundations for Building Community Resilience*. California: Post Carbon Institute. [online] Available at: <https://www.scribd.com/document/290100841/Six-Foundations-for-Building-Community-Resilience-2015#fullscreen&from_embed> [Accessed 6 February 2020].

MacCallum, D., Byrne, J., & Steele, W., 2014. Whither justice? An analysis of local climate change responses from South East Queensland, Australia. *Environment and Planning C: Government and Policy*, 32(1), pp. 70-92.

Openshaw, S., 1984. The Modifiable Areal Unit Problem. *Concepts and Techniques in Modern Geography No. 38 ed.* Norwich: GeoBooks.

Openshaw, S. & Taylor, P., 1979. A million or so correlation coefficients: three experiments on the modifiable areal unit problem. In: Wrigley N. ed. 1979. *Statistical applications in the spatial sciences*. London: Pion.

Oulahen, G., Mortsch, L., Tang, K. & Harford, D., 2015. Unequal Vulnerability to Flood Hazards: "Ground Truthing" a Social Vulnerability Index of Five Municipalities in Metro Vancouver, Canada. *Annals of the Association of American Geographers*, 105(3), pp. 473-495.

Prouse, V., Ramos, H., Grant, J. L. & Radice, M., 2014. How and when scale matters: the modifiable areal unit problem and income inequality in Halifax. *Canadian Journal of Urban Research*, 23(1), pp. 61-82.

Rickless, D. S., Yao, X. A., Orland, B. & Welch-Devine, M., 2019. Assessing Social Vulnerability through a Local Lens: An Integrated Geovisual Approach. *Annals of the American Association of Geographers*, 0(0), pp. 1-20.

Robinson, W.R., 1950. Ecological Correlation and the Behaviour of Individuals. *American Sociological Review*, 15, pp. 351-357.

Sayers, P.B., Horritt, M., Penning Rowsell, E. and Fieth, J., 2017. *Present and future flood vulnerability, risk and disadvantage: A UK scale assessment. A report for the Joseph Rowntree Foundation.* Watlington: Sayers and Partners LLP. [online] Available at: <http://www.sayersandpartners.co.uk/uploads/6/2/0/9/6209349/sayers_2017_-_present_and_future_flood_vulnerability_risk_and_disadvantage_-_final_report_-_uploaded_05june2017_printed_-_high_quality.pdf> [Accessed 26 February 2020].

Schuurman, N., Bell, N., Dunn, J. & Oliver, L., 2007. Deprivation Indices, Population Health and Geography: An Evaluation of Indices at Multiple Scales. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, 84(4), pp. 591-503.

Scottish Government, 2019. *Preparing Scotland – Scottish Guidance on Resilience – Philosophy, Principles, Structures and Regulatory Duties*. Edinburgh: Ready Scotland. [online] Available at: < https://www.readyscotland.org/media/1496/preparing-scotland-hub-updated-published-version-may-2019-new-h-s-diagram.pdf> [Accessed 2 June 2020].

Seguin, A., Apparicio, P. & Riva, M., 2011. The Impact of Geographical Scale in Identifying Areas as Possible Sites for Area-Based Interventions to Tackle Poverty: The Case of Montreal. *Applications of Spatial Statistics*, 5, pp. 231-251.

Sevoyan, A., Hugo, G., Feist, H., Tan, G., McDougall, K., Tan, Y. and Spoehr, J., 2013. *Impact of Climate Change on* Disadvantaged *Groups: Issues and Interventions*. Adelaide: National Climate Change Adaptation Research Facility.

Steel, D. & Holt, D., 1996. Analysing and Adjusting Aggregation Effects: The Ecological Fallacy Revisited. *International Statistical Review*, 64(1), pp. 39-60.

Susman, P., O'Keefe, P & Wisner, B., 1983. Global disasters, a radical interpretation. In: K. Hewitt, ed. 1983. *Interpretations of Calamity from the viewpoint of human ecology*. London: Allen & Unwin Inc. Ch.14.

Tapsell, S. M., Penning-Rowsell, E. C., Tunstall, S. M. & Wilson, T. L., 2002. Vulnerability to flooding: health and social dimensions. *Philosophical Transactions of the Royal Society A*, 360, pp. 1511-1525.

The Heinz Centre, 2009. *Resilient Coasts: A Blueprint for Action*. Washington: The H. John Heinz III Center for Science, Economics and the Environment. [online] Available at: < https://www.travelers.com/iw-documents/travelers-institute/ResilientCoastsBlueprint.pdf> [Accessed 2 June 2020].

The Royal Society, 2014. *Resilience to extreme weather*. London: The Royal Society. [online] Available at: < https://royalsociety.org/-/media/policy/projects/resilience-climate-change/resilience-full-report.pdf> [Accessed 2 June 2020].

The World Bank, 2015. *Investing in Urban Resilience - Protecting and Promoting Development in a Changing World*. Washington: Office of the Publisher, The World Bank. Available at: <https://openknowledge.worldbank.org/bitstream/handle/10986/25219/109431-WP-P158937-PUBLIC-ABSTRACT-SENT-INVESTINGINURBANRESILIENCEProtectingandPromotingDevelopmentinaChangingWorld.pdf?sequence=1&isAllowed=y> [Accessed 16 January 2020].

UNDRR (United Nations International Strategy for Disaster Reduction), 2004. *Living with Risk: A Global Review of Disaster Reduction Initiatives - Volume II Annexes*. Geneva: UN Publications. [online] Available at: <https://www.preventionweb.net/files/657_lwr21.pdf> [Accessed 6 February 2020].

Willis, I. & Fitton, J., 2016. A review of multivariate social vulnerability methodologies: a case study of the River Parrett catchment, UK. *Natural Hazards and Earth System Sciences*, 16, pp. 1387-1399.

Wisner, B., Blaikie, P., Cannon, T. and Davis, I., 2004. *At risk: natural hazards, people's vulnerability and disasters*. Reprint 2004. New York: Routledge.

Wolstenhome, R., Barrett, F., Baxter, H., Carmen, E., Currie, M., Fazey, I., Irving, D., Mabon, L., Revell, P., Yates, G., 2018. *Community resilience and climate justice – key messages for policy and practice*. Edinburgh: Sniffer. Available at: <https://www.sniffer.org.uk/Handlers/Download.ashx?IDMF=e61f5751-d754-4453-b801-858327483ccf> [Accessed 16 January 2020].

Wong, D.W.S., 1997. Spatial dependency of segregation indices. *The Canadian Geographer*, 5, pp. 128-136.

Wong, D. W. S., Lasus, H. & Falk, R. F., 1999. Exploring the Variability of Segregation Index *D* with Scale and Zonal Systems: An Analysis of Thirty U.S. Cities. *Environment and Planning A*, 31, pp. 507-522.

3.0 Connecting Manuscript 1 and Manuscript 2

Manuscript 1 (i.e., Chapter 2) identified scale effects which were manifested through contrasting results when the Social Resilience Index (SoRI) was constructed at different census scales. The results suggest that the sensitivity of the SoRI to scale effects may be related to the method of index construction. The following manuscript 2 (i.e., Chapter 4) investigates scale effects of the method used to construct the SoRI, and evaluates its reliability against an alternate method of index construction that is based on stakeholder input. While manuscript 1 investigated scale effects for the data source (i.e., census data at different census scales), manuscript 2 investigates scale effects that may arise from the method used to construct the SoRI. Since the effects of scale can lead to contrasting results in the SoRI, further investigation can contribute to understanding the implications of scale when using quantitative social flood resilience assessments for informing planning and policy efforts.

4.0 Evaluating the Effects of Scale on Indices: A Case Study of the Social Resilience Index (SoRI)

4.1 Introduction

Socioeconomic factors are often integrated into disaster risk management and climate change adaptation planning quantitatively via indices. Such indices involve the aggregation of several social and economic characteristics into a single value to allow comparison between different populations and areas (Cutter et al., 2003; Cutter et al., 2014; Felsenstein & Lichter, 2014). These inherent socioeconomic characteristics serve as indicators of how different populations may experience, respond to, and are affected by hazards (City of Los Angeles, 2018; City of Vancouver, 2019; Cutter et al., 2008; Gotham & Greenberg, 2014; Oulahen et al., 2015; Sevoyan et al., 2013; Wisner et al., 2004). Indices are often used to provide policy-relevant information to enhance climate change adaptation, inform policymakers, and build disaster resilience (Cutter et al., 2008; Oulahen et al., 2015; Sevoyan et al., 2013; Spielman et al., 2020).

Due to data availability and accessibility, indices based on socioeconomic characteristics are often reliant on census data, which are only made available as aggregated units. To protect the confidentiality at the individual-level, census data are aggregated into units of varying size and shape to form different census scales for dissemination (Dorling, 1993; Flowerdew, 2011; Openshaw, 1984). This process of aggregation manifests in the modifiable areal unit problem (MAUP), where the same set of census data can be analyzed at different spatial scales and different geographic boundaries (Openshaw, 1984). The results of analyses using spatial data are thus sensitive to the geographic boundaries in which the data are defined (Fotheringham & Wong, 1991; Openshaw, 1984). The differences in spatial scale can lead to different, and at times, contradictory, analytical results (Carrington et al., 2018; Fotheringham & Wong, 1991; Gehlke & Biehl, 1934; Spielman et al., 2020). As a result of the MAUP, the use of socioeconomic census data and the methods of index construction may also be subject to the effects of spatial scale.

In order to contribute to the academic debates on the implications of using quantitative indices, this study investigates the effects of scale when using different methods of index construction. It compares an objective, data-driven method compared to a subjective, stakeholder-driven method to construct the Social Resilience Index (SoRI) by Damude et al. (2015). The sensitivity to scale effects will serve as an indicator of the reliability and stability of the index construction methods (i.e., whether a certain method may be less sensitive to scale effects). The aim is to contribute to the understanding of methodological considerations when using indices, while also offering insight to the end users of indices, such as policymakers and practitioners.

4.1.1 Social Vulnerability & Resilience Indices: Creating a Composite Index Value

Quantitative indices are commonly used as a proxy to investigate the distribution of disaster risk and to identify priority areas where people may have lower capacities to respond to environmental hazards. These indices are constructed using various numerical methods to combine indicators for computing composite index values. Specific to social vulnerability and resilience indices in the literature, these methods generally fall under the categories of objective approaches which are statistical and data-driven, or subjective, stakeholder-driven approaches which are based on local knowledge, opinions, experience and stakeholder needs (Oulahen et al., 2015; Reckien, 2018; Willis & Fitton, 2016). These approaches are described in the following subsections.

4.1.1.1 A Data-driven Approach: Principal Components Analysis (PCA)

A principal component analysis (PCA) is a common data-driven method that combines a set of input variables by representing them as a smaller set of hypothetical variables, or principal components (PCs). The PCs are extracted such that they capture the majority of variance in the dataset (Coleman, 2012; Oulahen et al., 2015). Each extracted PC is ordered, such that PC1 captures the most variance possible and subsequent PCs capture as much of the remaining variance as possible (Coleman, 2012). A PCA reduces the number of variables in a dataset by capturing the variables that are interrelated and have a similar data structure, by representing them as PCs (Coleman, 2012). A PCA is therefore a strictly statistical, data-driven method that relies on capturing existing data structure of variables in a dataset (Coleman, 2012).

The use of a PCA for computing index values was made prominent by Cutter et al. (2003) for assessing social vulnerability and subsequently used for a number of indices, such as the Social Vulnerability Index by Oulahen et al. (2015) and the Social Resilience Index by Damude et al. (2015) and others (Cutter et al., 2008; Fekete 2009; Fekete 2012; Schmidtlein et al., 2011; Tate et al., 2010). PCA allows a consistent method to assess temporal changes in vulnerability and it "*facilitates replication of the variables at other spatial scales, thus making data compilation more efficient*" (Cutter et al., 2003, p.251). In the methodology by Cutter et al. (2003), PCs were extracted using the Kaiser stopping criterion, where eigenvalues > 1.0 were considered significant in capturing variance in the data (*see also* Cutter & Finch, 2008). Eigenvalues represent the total amount of variance in the dataset that is captured by each principal component (Coleman, 2012; Oulahen et al., 2015). The Kaiser criterion is commonly used because below this threshold, the PCs that are extracted will capture less variance than any of the original input variables, and thus the PCs would not be representative of the dataset (Coleman, 2012). A PCA can be conducted by either specifying an eigenvalue threshold or a specific number of PCs to be extracted. A scree plot is often used to determine the specific number of PCs to extract. The scree plot is a plot of the eigenvalue (i.e., the amount of variance) that is captured by each PC (Coleman, 2012; Oulahen, et al., 2015). The scree plot provides a visual representation of the inflection point, which is the point where there is a steep decline in the amount of variance that is represented by the PCs, and allows determination of the number of PCs to extract (Coleman, 2012). Using these extraction parameters, factor scores are computed, which are a measure of the correlation between the original variables to each principal component (Coleman, 2012). These factor scores are summed to produce the final composite index values (Cutter et al., 2003). The contribution of each variable towards determining the SoRI is based on the amount of variance, or the existing structure in the dataset.

4.1.1.2 A Stakeholder-Driven Approach: Multi-Criteria Analysis (MCA)

Multi-criteria analysis (MCA), also referred to as multi-criteria decision analysis (MCDA), is a method used to evaluate the suitability or favourability of a range of inputs (Eakin & Bojorquez-Tapia, 2008; Huang et al., 2011; Tate 2012). These inputs are often multidisciplinary and incorporate user-defined knowledge into a quantitative decision-making process (O'Sullivan & Unwin, 2010; Huang et al., 2011). In the context of geographical analysis, an MCA is used to combine information from different spatial datasets to identify areas where particular variables or characteristics spatially intersect (O'Sullivan & Unwin, 2010). This method is used to identify priority areas and populations to inform the allocation of resources and policy in disaster risk management and climate change adaptation (Cutter, 1996; Cutter et al., 2003; Cutter et al., 2014; Eakin & Bojorquez-Tapia, 2008; Felsenstein & Lichter, 2014; Oulahen et al., 2015; Rickless et al., 2019; Tate, 2012).

To combine information from different datasets, the MCA method is used to construct an index through summation, where each of the variables are assumed to contribute to the underlying theme being measured. Each of the input variables are rescaled into a common scale so that it can be represented as a single metric. The equation below from O'Sullivan & Unwin (2010) represents the MCA method as a function of favourability or suitability.

$$F = \sum_m w_m X_m \tag{5}$$

X_m = rescaled value each of the input variables
w_m = weight of each of the input criteria
F = ordinal favourability score that ranges from 0 (unfavourable) to n (most favourable)

In the absence of a theoretical basis, the inputs, or the constituents of an index, are often weighted equally (i.e., w_m = 1), with the implicit assumption that all variables comprising it are equally important (Cutter et al., 2003; Cutter & Finch, 2008; Eakin & Bojorquez-Tapia, 2008; Fekete, 2012; Oulahen et al., 2015). This is often due to uncertainty in the relative importance between indicators for an objective index (Fekete, 2012; Oulahen et al., 2015; Tate, 2012). In the MCA approach, the intent is to incorporate expert knowledge to assess - *what* is favourable (i.e., the value of X_m) and *how* favourable it is (i.e., the value of w_m). The contribution of each variable towards the composite index value is therefore based on knowledge and assessment from experts, stakeholders and end-users of the index (Fekete, 2012; Oulahen et al., 2015; Tate, 2012).

4.1.2 Methodological Issues in Social Vulnerability & Resilience Indices

While there have been many research efforts to develop methods of quantifying social resilience, there is still much debate on methodological issues for the use of such indices (Reckien, 2018; Schmidtlein et al., 2008; Tate, 2012; Willis & Fitton, 2016). Empirical studies on social vulnerability indices have found that decisions about data source, variable selection, variable weighting and methods of index construction can lead to large differences in the classification and understanding of priority areas for disaster risk management efforts (Reckien, 2018; Schmidtlein et al., 2008; Spielman et al., 2020; Willis & Fitton, 2016).

When using census data as the source for quantitative indices, the analytical results may be sensitive to the method of index construction as well as the scale effects of the MAUP. Schmidtlein et al. (2008) conducted a sensitivity analysis of the Social Vulnerability Index (SoVI) to changes in scale and changes in the method of construction. They demonstrated that scale effects (i.e., different levels of aggregation) had a minimal impact on the index, but rather the method of construction (i.e., PCA) had a significant impact on the spatial patterns of vulnerability. Furthermore, they found that running the PCA using the Kaiser criterion, which is the original methodology for constructing the SoVI from Cutter et al. (2003), resulted in substantially different results from all other modes of selection criteria.

Willis & Fitton (2016) found that different statistical methods led to very different interpretations of social vulnerability for the same population group. They emphasize that there are numerous, yet "*equally plausible*" methods that can be used to construct an index (Willis & Fitton, 2016, p.1397). Reckien (2018) further demonstrated that using different methods to construct an index can yield "remarkably different" results. They explain that the PCA is a reductionist model of index construction that is based on statistical, rather than correlational or theoretical reasoning. They demonstrate that using more input variables in the PCA model does not necessarily lead to a larger explained variance.

In a more recent study, Spielman et al. (2020) found that by changing the scale of analysis, they demonstrated that SoVI for the same location can yield significantly different results. In the most extreme cases, variables that were the most influential at one scale could be the least influential at another. Additionally, they found that the SoVI results often misaligned with theory, where variables that theoretically increase vulnerability were found to decrease vulnerability when measured by the PCA. Spielman et al. (2020) concluded that these differences are attributed to the PCA method used to construct the index, where a change in a single variable can cascade throughout the index. They warn that while indices reduce complexity, it is often "*at the expense of interpretability and alignment with theory*" and caution against the use of the SoVI in policy and disaster risk reduction efforts (Spielman et al., 2020, p. 419). In addition to the implications of spatial scale when using census data as inputs for such indices, these additional findings in the literature warrant a further investigation of the methods that are used to construct the indices.

4.2 Research Objectives

This study aims to evaluate the effects of scale when using different methods to construct the Social Resilience Index (SoRI) by Damude et al. (2015) by answering the two-part research questions:

- ***Is the PCA method of constructing the SoRI sensitive to scale effects? Through a more detailed analysis of the PCA method, do different extraction parameters reduce scale effects?***
- ***If the PCA method is sensitive to scale effects, what other options of index construction can be considered to inform policy efforts?***

This study addresses these research questions using the SoRI as a case study between hierarchical census scales for:

(1) The City of Vancouver, British Columbia, Canada at the census tract (CT) and dissemination area (DA) scales;
(2) The City of Los Angeles, California, USA at the census tract (CT) and block group (BG) scales; and
(3) The City of Edinburgh, Scotland, UK at the data zone (DZ) and output area (OA) scales.

The three study areas were used in an exploratory approach to whether a certain method of index construction may be less sensitive to scale effects and whether the findings may be applicable across the different census programs.

4.3 Methodology

This study investigates the research questions in two parts. First, the data-driven PCA method is assessed by comparing the sensitivity to scale effects when different PC extraction parameters are used. Second, the stability and sensitivity of the stakeholder-driven MCA method to scale effects is assessed as an alternate approach for constructing the SoRI. Each method of index construction involved three main steps: 1) constructing the composite SoRI value; 2) mapping the SoRI; and 3) using a Moran's I test to identify potential spatial patterns of social resilience.

4.3.1 Comparing PC Extraction Approaches for SoRI Construction

4.3.1.1 Constructing the SoRI Value

The SoRI was first constructed using the data-driven PCA method to test the two different parameters that can be used to extract PCs. The first parameter follows the original method from Cutter et al. (2003), which extracts PCs with eigenvalues > 1.0 to construct the index. The second approach is exploratory in nature and extracts a specific number of PCs based on the inflection point on the scree plot. Based on the scree plots (Figure 9), a different number of PCs were extracted for each study area – 5 PCs for Vancouver, 2 PCs for Los Angeles and 3 PCs for Edinburgh.

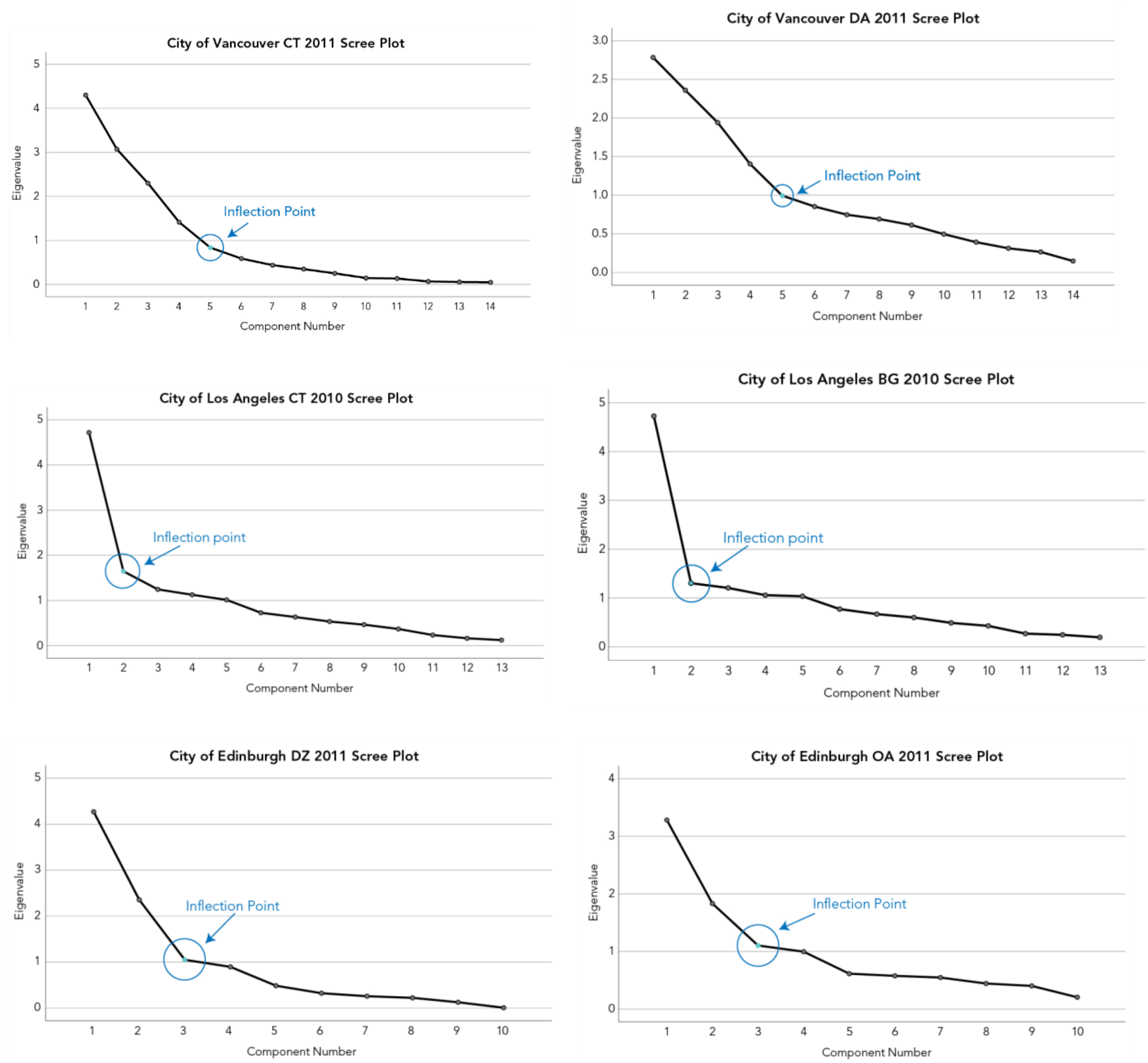


Figure 9. PCA scree plots for each study area and census scale

A summary of each of the PCA tests and a description of their rationale are detailed in Table 12 below. The PCA was conducted using the IBM Statistics Package for the Social Sciences (SPSS) software. The detailed procedure and parameter settings are provided in Appendix B.

Table 12. Summary of tests for constructing the SoRI

Name of Test	Rationale	Description
PCAoriginal	This is the original PCA method to construct the SoRI from Damude et al. (2015), which is based on the commonly used methodology to construct the SoVI from Cutter et al. (2003).	This PCA is conducted using the Kaiser criterion, where PCs with eigenvalues > 1.0 are extracted to construct the SoRI.
PCAscree	This iteration of the PCA is exploratory and tests whether using the inflection point as a threshold to extract PCs may be less sensitive to scale effects.	This PCA extracts the number of PCs based on the inflection point of the scree plot (Figure 9): Vancouver = 5 PCs Los Angeles = 2 PCs Edinburgh = 3 PCs

4.3.1.1 Social Resilience Mapping

The results of the SoRI were mapped using the Esri ArcGIS desktop software for each census scale in the three study areas. The maps are represented by quintiles of standard deviation (SD): high (>1.5 SD), medium-high (0.5-1.5 SD), medium (-0.5-0.5 SD), medium-low (-1.5 – (-0.5) SD) and low (<-1.5 SD). Directionality of the standard deviations represents the direction of the mean, where a negative sign indicates a SoRI score below the mean (i.e., low resilience) and a positive standard deviation indicates a SoRI value above the mean (i.e., high resilience). This allows a *relative* measure between geographic areas in comparison to the city as a whole.

4.3.1.2 Moran's I Test for Spatial Patterns

The Global Moran's I statistic was used to identify spatial patterns, or spatial dependency, of the SoRI. It is a measure of how similar (i.e., clustered) or dissimilar (i.e., dispersed) neighbouring features are (Anselin, 2016; Fortin & Dale, 2009). A positive Moran's I statistic would indicate that similar SoRI values tend to cluster – that is areas of high resilience tend to be near other areas of high resilience, and low resilience areas tend to cluster around other low resilience areas. A negative Moran's I statistic would indicate that the SoRI values are spatially dispersed, where areas of high resilience tend to be near areas of low resilience, and vice versa. Since it is not expected that spatial patterns would differ between census scales (i.e., the census data itself does not change) the differences in the statistic between census scales for each method of construction, may be suggestive of the relative stability of the index construction method.

4.3.2 Assessing the MCA Approach for SoRI Construction

The stakeholder-driven MCA method was then assessed as an alternate approach to constructing the SoRI. The SoRI was constructed using the MCA method as an unweighted index, such that each input variable contributed equally to the composite SoRI value. Since the SoRI did not provide details for variable weighting (Damude et al., 2015), an unweighted index was used as an exploratory analysis to identify scale effects using a straightforward summation method.

In accordance with Damude et al. (2015), the census data were first expressed as percentages (Appendix A) and then transformed into z-scores (i.e., mean of 0 and standard deviation of 1) to standardize the variables. To apply the MCA method, the resulting z-scores were re-scaled to positive integers between 1 to 5, to allow summation of the variables that contribute to both increasing and decreasing resilience (Table 13). Using a scale of 1 to 5, a higher value represents higher social resilience and a lower value represents lower social resilience.

Table 13. Summary of directionality and re-scaling of SoRI variables

Positive Variables (+) ***Increase Resilience***		Negative Variables (-) ***Decrease Resilience***	
Variable z-score	*Re-scale Value*	*Variable z-score*	*Re-scale Value*
< - 1.5	1	< -1.5	5
-1.5 - -0.5	2	-1.5 - -0.5	4
-0.5 - 0.5	3	-0.5 - 0.5	3
0.5 - 1.5	4	0.5 - 1.5	2
> 1.5	5	> 1.5	1

SoRI variables with positive directionality (+) contributes positively to the SoRI (i.e., variables that represent higher resilience). A higher z-score (i.e., > 1.5) therefore indicates higher social resilience and is rescaled to a higher value. For example, the areas with a higher percentage of citizenship are likely to have stronger social networks, which can increase resilience. The SoRI variables with negative directionality (-) contributes negatively to the SoRI (i.e., variables that represent lower resilience). A higher z-score (i.e., > 1.5) therefore indicates lower social resilience and is rescaled to a lower value.

For example, the areas with a higher percentage of unemployment are expected to have reduced assets, which can decrease resilience. The final SoRI score is calculated as a sum of these rescaled variables to represent a composite of the 14 census variables.

4.4 Results & Findings

4.4.1 Construction of the SoRI using the Data-driven PCA Methods

In the first step of computing the SoRI values, the results indicate that a wide range of SoRI values can be obtained when different PCA threshold settings are used. The results suggest that using different PCA extraction parameters to construct the SoRI will quantify the SoRI values very differently and are subject to different levels of scale effects (Table 14). For example, using the *PCAoriginal* test, the difference between scales in the average SoRI values is 0.134 for Vancouver, 2.150 for Los Angeles and 0.324 for Edinburgh. Using the *PCAscree* test, the difference in the average SoRI values was 0.008 for Vancouver, 0.701 for Los Angeles and 1.821 for Edinburgh (Table 14). While the *PCAoriginal* test yielded the smallest differences in the SoRI between scales for Vancouver and Edinburgh, it simultaneously yielded the largest differences for Los Angeles. While one method appears to be less sensitive to scale effects for one study area, the same method can simultaneously be the most sensitive to scale effects for another study area.

Table 14. Summary of descriptive statistics of the SoRI values for each method for PC extraction

Name of Test		Vancouver		Los Angeles		Edinburgh	
		CT	DA	CT	BG	DZ	OA
PCAoriginal	Min	-4.33	-6.33	-16.41	-52.09	-17.78	-7.87
	Max	3.00	4.55	29.11	1.91	4.33	21.68
	Avg	0.16	0.02	1.32	-0.83	1.20	0.87
	SD	1.12	1.17	1.38	1.68	1.11	1.71
PCAscree	Min	-10.79	-22.24	-32.07	-3.02	-23.33	-13.65
	Max	1.27	2.20	-0.02	26.34	-0.47	12.63
	Avg	-1.83	-1.82	-1.03	-0.33	-2.06	-0.24
	SD	1.57	1.67	1.17	0.97	1.18	1.44

**Min = minimum SoRI value; max = maximum SoRI value; Avg = average SoRI value; SD = standard deviation of SoRI values*

From previous MAUP literature, it was found that larger areal units had the tendency to mask extremities that occurred at a finer level (Fotheringham & Wong, 1991; Prouse et al., 2014; Schuurman et al., 2007; Seguin et al., 2011). The results from Table 14 are consistent with these previous findings, where the smaller census unit consistently had a higher SD (with the exception of Los Angeles for the *PCAscree* test), indicating that SoRI values are spread out further from the mean and more extreme values are captured using the smaller census unit. Based on this understanding from MAUP literature, the results of the two PCA tests (Table 14) indicate contrasting masking effects. From the *PCAoriginal* test, the larger census unit (i.e., CT in Vancouver and Los Angeles, and DZ in Edinburgh) consistently had a higher average SoRI value. This would suggest that the larger units may be masking small pockets of ***low*** resilience areas (i.e., areas with low SoRI values). However, when using the same dataset for the *PCAscree* test, the smaller census unit (i.e., DA in Vancouver, BG in Los Angeles, and OA in Edinburgh) consistently had a higher average SoRI value. This would suggest that the larger units are masking small pockets of ***high*** resilience areas (i.e., areas with high SoRI values), which is opposite from the *PCAoriginal* test. In other words, the use of different PCA parameters can result in contrasting understandings of the SoRI. In the absence of individual level data, it cannot be verified whether the *PCAoriginal* test is overestimating the SoRI (i.e., consistently higher average SoRI values) or if the *PCAscree* test is underestimating the SoRI (i.e., consistently lower average SoRI values). In a rather unpredictable nature, each of the PCA tests captured different interpretations of social resilience and varying levels of scale effects.

4.4.1.1 Spatial Patterns of the SoRI

Following the construction of the SoRI using the different PCA thresholds, the results were mapped for each census scale of the study areas. In addition to identifying scale effects, the maps aim to also illustrate the spatial patterns of social resilience. The SoRI maps are represented by quintiles of standard deviation (SD): high (>1.5 SD), medium-high (0.5-1.5 SD), medium (-0.5-0.5 SD), medium-low (-1.5- (-0.5) SD) and low (<-1.5 SD). The sign of the SD values indicates the direction of social resilience, where negative values indicate low resilience (i.e., red areas) below the city average, and positive values indicate high resilience (i.e., blue areas) above the city average. The SoRI maps for Vancouver (Figure 10), Los Angeles (Figure 11) and Edinburgh (Figure 12) are illustrated below.

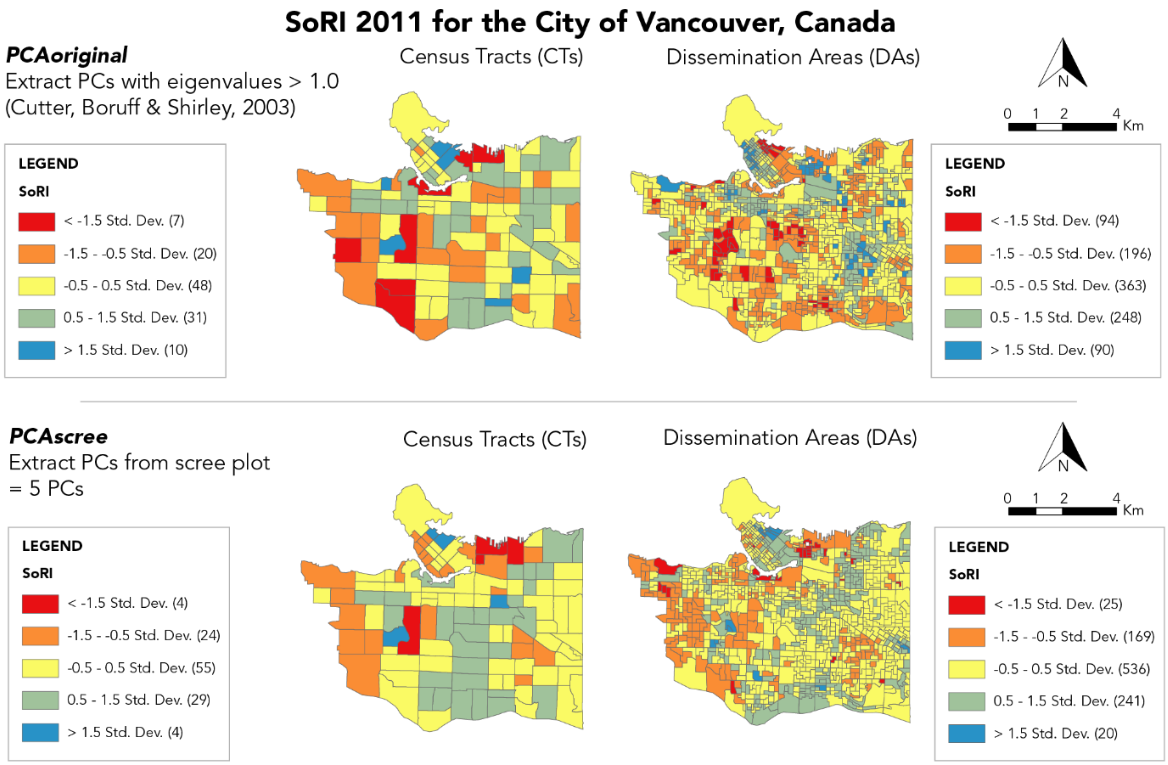


Figure 10. SoRI maps for the City of Vancouver for each PCA threshold test

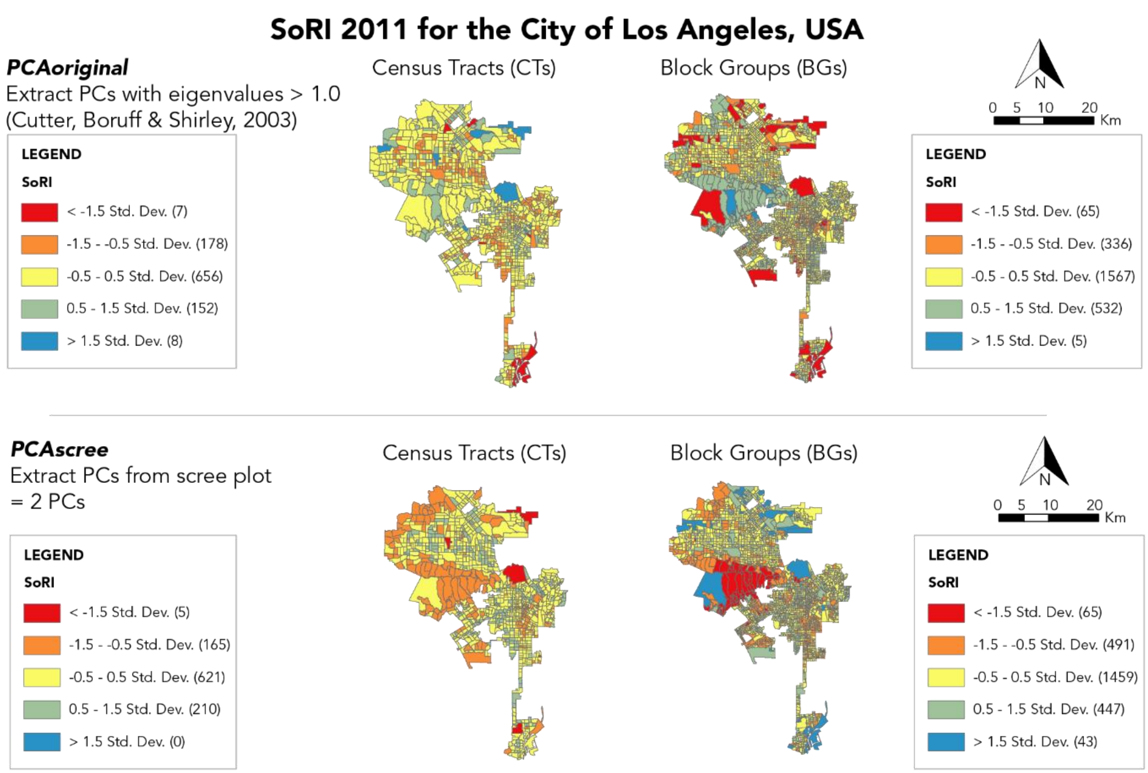


Figure 11. SoRI maps for the City of Los Angeles for each PCA threshold test

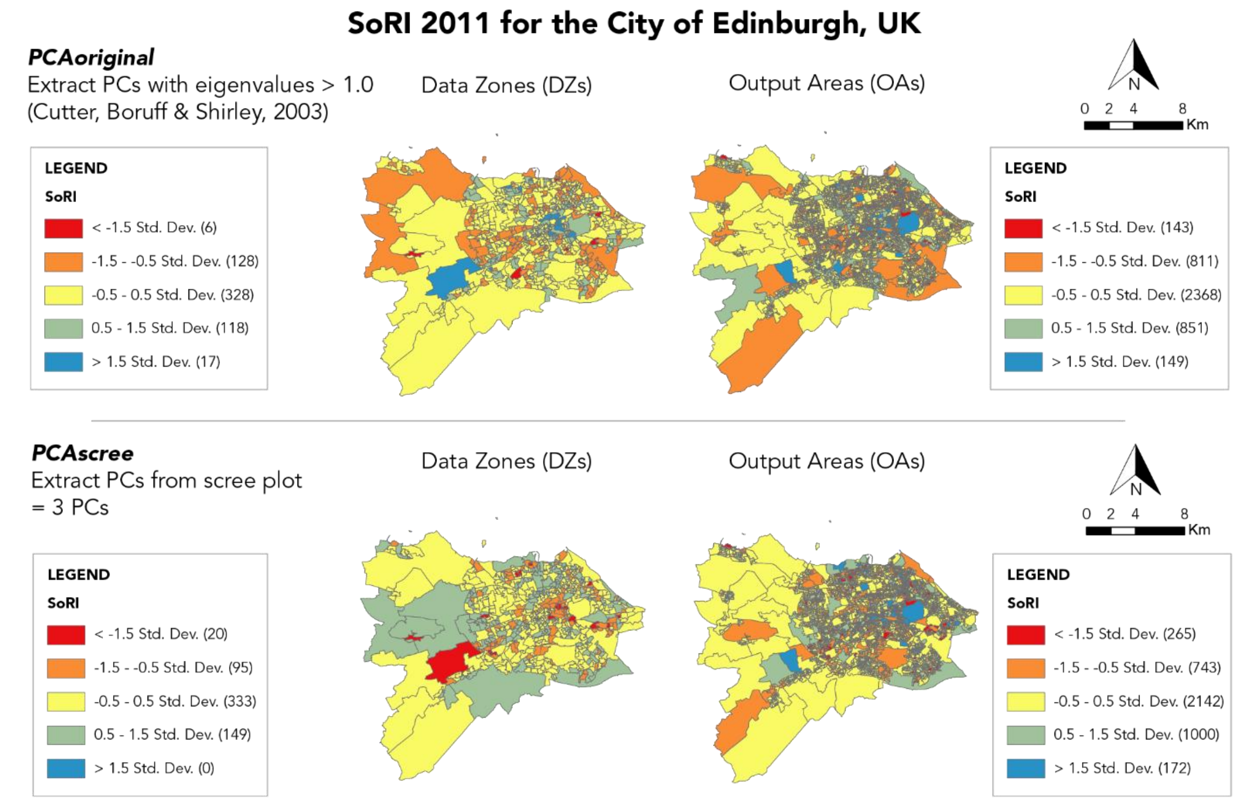


Figure 12. SoRI maps for the City of Edinburgh for each PCA threshold test

The maps indicate that there are significantly different spatial patterns of social resilience when different PCA extraction parameters are used to construct the SoRI. This ultimately suggests that different priority areas will be identified depending on the parameters chosen for the PCA. The most critical concern is that areas with the lowest resilience (i.e., red areas) can simultaneously be an area with the highest resilience (i.e., blue) when a different PCA threshold setting is used. This is the most easily observed in the City of Los Angeles along the north-eastern shoreline (Figure 11), and in the City of Edinburgh in the central-western portion of the city at the DZ scale (Figure 12).

In addition to the differences in spatial patterns between the different PCA threshold settings, there are also differences observed in the spatial patterns between census scales. Again, areas with the lowest resilience (i.e., red areas) can simultaneously be identified as an area with the highest resilience (i.e., blue) when different census scales are used. This is the most easily observed between scales for the City of Vancouver in the Arbutus Ridge (central-western area) and the Downtown and West End neighbourhoods, along the northern shoreline (Figure 10). For the City of Los Angeles, in the Hollywood Hills neighbourhood (along the north-eastern shoreline) between CTs and BGs (Figure 11). The Arbutus Ridge (Vancouver) and Hollywood Hills (Los Angeles) neighbourhoods are locally known to be affluent areas, where the cost of housing and average cost of living is higher than the rest of the city. The Vancouver Downtown and West End areas are locally known for its cultural diversity and affordability. Although this was not explored in this study, this may suggest that the neighbourhoods containing the "extremes" (i.e., the most affluent or the impoverished) are the most sensitive to scale effects. To further evaluate scale effects of each PCA test, the absolute differences in the percentage of spatial units per SoRI quintile (i.e., the difference in the percentage of units for each colour on the maps) were calculated and summarized in Table 15.

Table 15. Summary of SoRI quintiles for each PCA threshold test by study area

Method	SoRI Quintile	Difference in percentage of units per SoRI quintile (%)			
		Vancouver CT - DA	Los Angeles CT - DA	Edinburgh DZ - OA	Sum of differences by method
PCAoriginal	< -1.5	3.45	1.90	2.30	34.61
	-1.5 - -0.5	2.54	4.37	2.68	
	-0.5 – 0.5	4.75	2.98	0.15	
	0.5 – 1.5	1.70	6.05	0.08	
	> 1.5	0.46	0.60	0.60	
	Sum of differences by study area	12.90	15.90	5.81	
PCAscree	< -1.5	0.93	2.10	2.78	43.29
	-1.5 - -0.5	3.64	3.12	1.28	
	-0.5 – 0.5	6.67	3.79	6.22	
	0.5 – 1.5	0.68	3.13	1.82	
	> 1.5	1.43	1.72	3.98	
	Sum of differences by study area	13.35	13.86	16.08	

The cumulative differences in the SoRI between census scales indicate that magnitude of scale effects differs between study areas. This suggests that the sensitivity to scale effects may be caused by specific combination of the input variables and a specific index construction method. These scale effects represent differences in the number of spatial units measured by the SoRI between census scales, but does not explain the differences that are observed in the SoRI maps, where an area having high resilience (i.e., blue-coloured) at one scale could simultaneously have low resilience (i.e., red-coloured) at the other scale.

The Moran's I statistic was used to determine the spatial patterns of the SoRI and to identify whether scale effects manifested in the statistic itself, or in the method of index construction (Table

16). The consistently positive Moran's I index values indicate that social resilience based on the SoRI is spatially clustered for all three study areas. This clustering pattern is stable for the different methods and study areas, as supported by the largely consistent and very small p-values (i.e., $p < 0.05$). However, the corresponding p-values for Vancouver using the *PCAoriginal* test suggests that the SoRI was randomly distributed at the CT scale, but was clustered at the DA scale. Recall that census data for a given year does not change, and thus it would not be expected that SoRI be spatially clustered at one census scale and simultaneously be spatially dispersed at the other census scale.

Table 16. Moran's I statistic for each PCA test by study area

PCA test		Vancouver		Los Angeles		Edinburgh	
		CT	DA	CT	BG	DZ	OA
PCAoriginal	Moran's I	+ 0.09	+ 0.45	+ 0.11	+ 0.13	+ 0.16	+ 0.18
	Sig	0.06	0.00	0.00	0.00	0.00	0.00
PCAscree	Moran's I	+ 0.25	+ 0.30	+ 0.10	+ 0.23	+ 0.14	+ 0.27
	Sig	0.00	0.00	0.00	0.00	0.00	0.00

These results altogether indicate that the *PCAscree* test was less sensitive to the effects of scale than the *PCAoriginal* test. When using the data-driven PCA method to construct an index, extracting PCs based on the inflection point on the scree plot may offer a more stable representation of the SoRI than the conventional eigenvalue threshold. Although both methods yielded varying spatial patterns of social resilience, the *PCAscree* method did not result in contrasting results in the Moran's I statistic between census scales. In other words, extracting PCs using the inflection point did not yield counter-intuitive results between census scales, which suggests that it offers a more stable method for constructing the SoRI.

4.4.2 Assessing an Alternative Stakeholder-driven MCA Approach

An alternate approach to constructing the SoRI is to use the stakeholder-driven MCA method (Table 17). The sensitivity to scale effects is used to compare the reliability and stability of the stakeholder-driven MCA method with the data-driven PCA (i.e., *PCAscree*) method. Scale effects are identified as the differences that are observed between census scales in each study area (i.e., differences between CTs and DAs for Vancouver, between CTs and BGs for Los Angeles, and between DZs and OAs for Edinburgh). Recall that data comprising of the census scales are the same, and therefore it is not expected that the SoRI statistics vary largely between census scales.

Table 17. Summary of descriptive statistics of the SoRI values for the MCA method of index construction

Method		Vancouver		Los Angeles		Edinburgh	
		CT	DA	CT	BG	DZ	OA
MCA	Min	25	25	28	24	17	16
	Max	56	52	49	55	41	40
	Avg	42.026	42.458	39.043	39.030	30.654	30.338
	SD	5.228	4.236	4.450	5.889	5.537	4.652
PCAscree	Min	-10.782	-22.238	-32.066	-3.018	-23.326	-13.650
	Max	1.269	2.197	-0.022	26.338	-0.466	12.626
	Avg	-1.828	-1.820	-1.031	-0.330	-2.061	-0.240
	SD	1.568	1.671	1.169	0.968	1.177	1.442

**Min = minimum SoRI value; max = maximum SoRI value; Avg = average SoRI value; SD = standard deviation of SoRI values*

The results (Table 17) further indicate that the sensitivity to scale effects may be dependent on both the combination of input variables and the method of index construction. Recall that each study area was comprised of a different number of input variables due to data constraints from the respective census programs. For example, using the *PCAscree* method, the difference between census scales for the average SoRI values is 0.008 for Vancouver, 0.701 for Los Angeles and 1.821 for Edinburgh (Table 17). When using the *MCA* method, the difference in the average SoRI values is 0.432 for Vancouver, 0.013 for Los Angeles and 0.316 for Edinburgh. While the *PCAscree* method was the least sensitive to scale effects in Vancouver, the *MCA* method was the most sensitive to scale effects in Vancouver. These results align with the findings of the PCA tests from section 4.4.1 above, where one method would be the least sensitive to scale effects for one study area, yet could simultaneously be the most sensitive to scale effects for another study area. Therefore, the sensitivity to scale effects appear to be dependent on both the combination of input variables and the method of index construction.

4.4.2.1 Spatial Patterns of the SoRI

The results of the SoRI using the PCA and MCA methods of index construction were mapped according to section 4.3.1.1 above. The units in red represent areas of low resilience and the units in blue represent areas of high resilience as measured by the SoRI. The number of units belonging to each SoRI quintile is provided in brackets in the SoRI maps for Vancouver (Figure 13), Los Angeles (Figure 14) and Edinburgh (Figure 15) below.

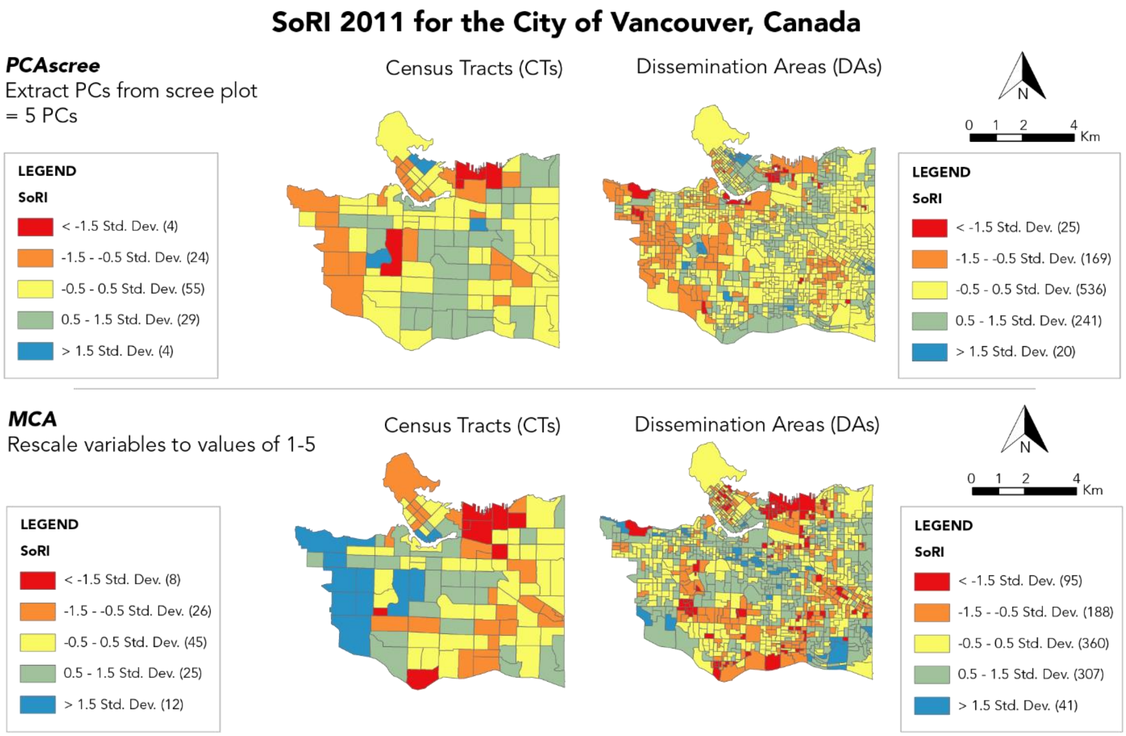


Figure 13. SoRI maps for the City of Vancouver for the data-driven PCA and stakeholder-driven MCA methods

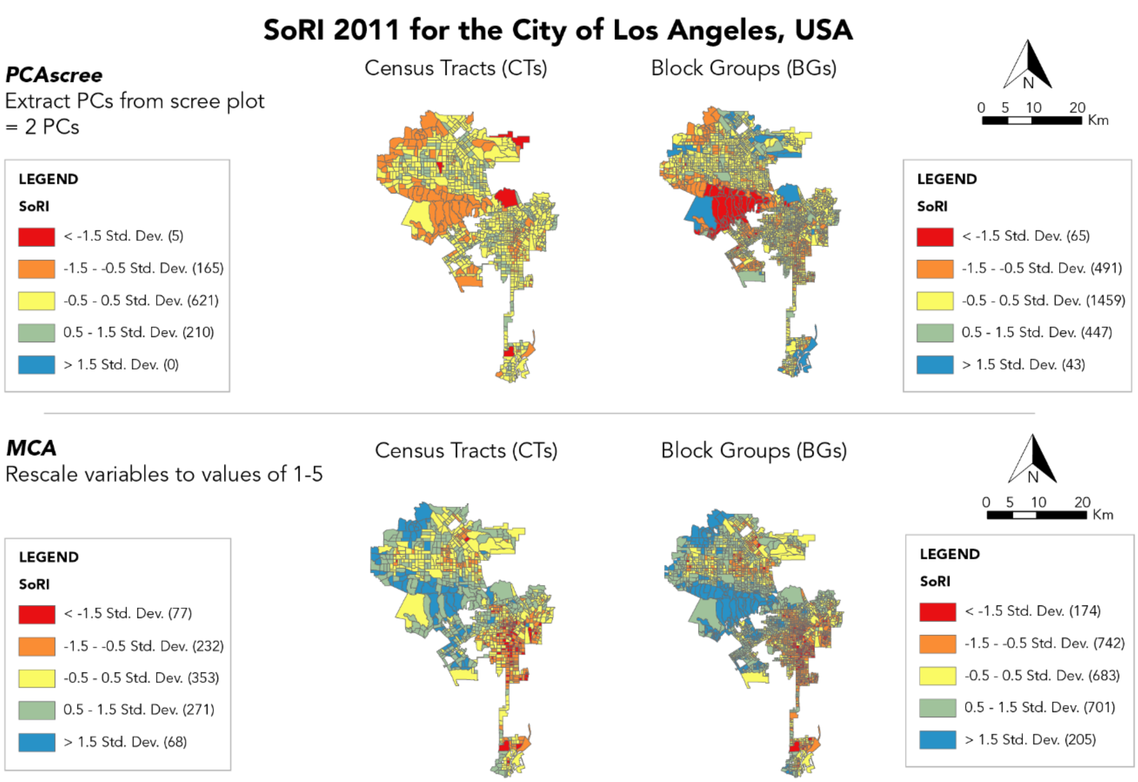


Figure 14. SoRI maps for the City of Los Angeles for the data-driven PCA and stakeholder-driven MCA methods

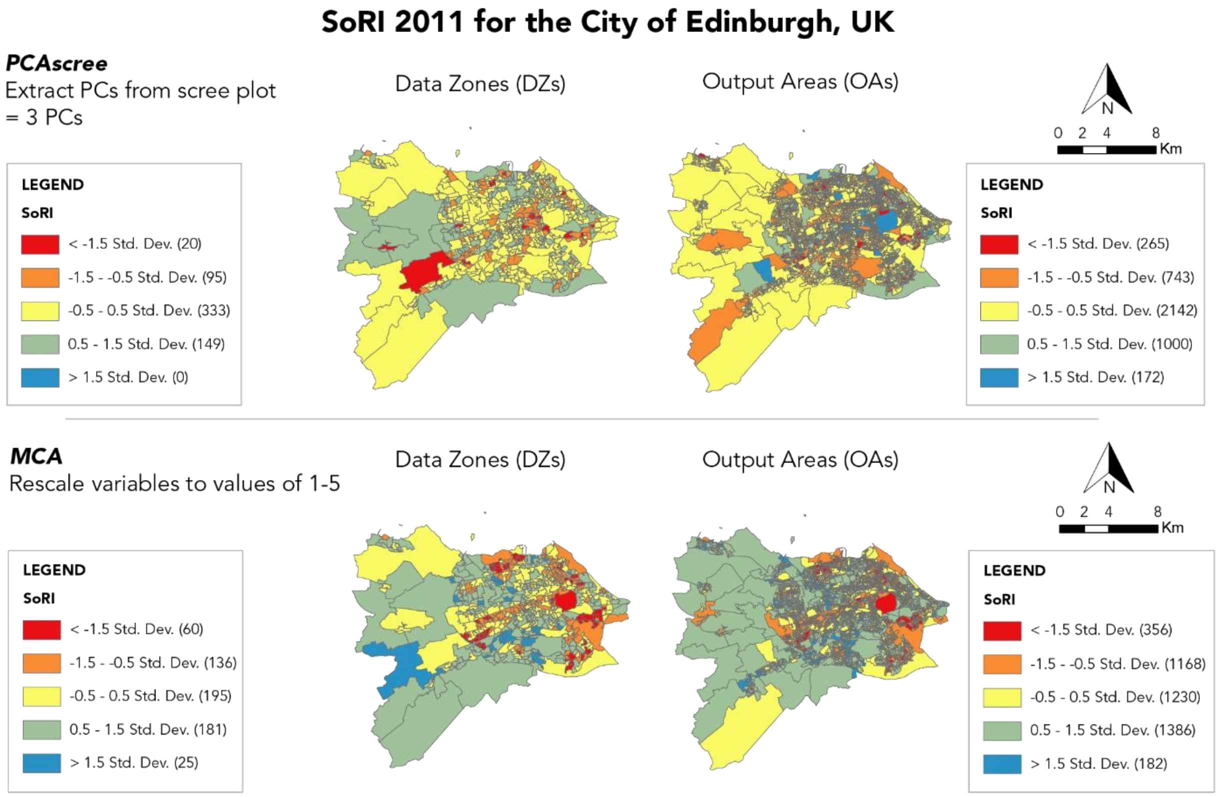


Figure 15. SoRI maps for the City of Edinburgh for the data-driven PCA and stakeholder-driven MCA methods

In identifying scale effects of the SoRI between census scales, the most important concern is that spatial units that appear blue (i.e., have the highest resilience) at one scale can simultaneously appear red (i.e., have the lowest resilience) at the other scale. The theory-driven MCA method illustrates a relatively lower number of such contrasting differences between census scales. Furthermore, the number of spatial units that appear blue (i.e., the highest resilience) and red (i.e., the lowest resilience) should not vary largely between census scales. To further evaluate scale effects of each index construction method, the absolute differences between census scales (i.e., the difference in the number of units of each colour on the map between census scales) were calculated and summarized in Table 18 below. Again, in quantifying scale effects, the interest lies in identifying large differences that may occur between census scales when using different methods of index construction.

Table 18. Summary of differences in SoRI quintiles between census scales for the PCA and MCA methods by study area

Method	SoRI Quintile	Difference in percentage of units per SoRI quintile (%)			
		Vancouver CT - DA	Los Angeles CT - DA	Edinburgh DZ - OA	Sum of differences by method
PCAscree	< -1.5	0.93	2.10	2.78	43.29
	-1.5 - -0.5	3.64	3.12	1.28	
	-0.5 – 0.5	6.67	3.79	6.22	
	0.5 – 1.5	0.68	3.13	1.82	
	> 1.5	1.43	1.72	3.98	
	Sum of differences by study area	13.35	13.86	16.08	
MCA	< -1.5	2.69	0.75	1.81	53.75
	-1.5 - -0.5	3.44	6.44	4.24	
	-0.5 – 0.5	2.47	8.00	4.20	
	0.5 – 1.5	9.43	0.91	1.75	
	> 1.5	6.21	1.39	0.02	
	Sum of differences by study area	24.24	17.49	12.02	

In evaluating the cumulative differences in the SoRI between census scales, the *PCAscree* method appears to be the least sensitive (i.e., sum of differences = 43.29) to scale effects. However, the magnitude of scale effects differs between study areas, indicating that the sensitivity to scale effects may be caused the specific combination of input variables in each study area compounded with the method of index construction. It is important to recognize that this is an elementary method to quantify scale effects without consideration of the spatial inconsistencies between census scales. In other words, these results do not explain the observed differences in the SoRI maps, where an area having high resilience (i.e., blue-coloured) at one scale could simultaneously have low resilience (i.e., red-coloured) at the other scale.

The Moran's I statistic was used to further describe the spatial patterns of the SoRI and to identify potential scale effects when the different methods of index construction are used (Table 19). The consistently positive Moran's I index values indicate that social resilience based on the SoRI is spatially clustered for all three study areas. The very small p-values (i.e., $p < 0.05$) indicate that the clustering pattern is consistently observed for both the data-driven *PCAscree* (i.e., a PCA that extracts PCs from the scree plot) and the stakeholder-driven MCA methods of index construction. The results of the

Moran's I statistics in Table 16 and Table 19 altogether indicate that the sensitivity to scale effects is attributed to the method of index construction (i.e, *PCAoriginal*) and not the spatial statistic itself.

The consistently positive Moran's I index values indicate that social resilience based on the SoRI is spatially clustered for all three study areas. The very small p-values (i.e., $p < 0.05$) indicate that the clustering pattern is consistently observed for both the data-driven *PCAscree* (i.e., a PCA that extracts PCs from the scree plot) and the stakeholder-driven MCA methods of index construction. The results of the Moran's I statistics in Table 16 and Table 19 altogether indicate that the sensitivity to scale effects is attributed to the method of index construction (i.e, *PCAoriginal*) and not the spatial statistic itself.

Table 19. Moran's I statistic by methodology and study area

Method		**Vancouver**		**Los Angeles**		**Edinburgh**	
		CT	***DA***	***CT***	***BG***	***DZ***	***OA***
PCAscree	Moran's I	+ 0.2549	+ 0.2961	+ 0.0993	+ 0.2270	+ 0.1415	+ 0.2695
	Sig	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MCA	Moran's I	+ 0.4011	+ 0.4689	+ 0.6781	+ 0.7807	+ 0.5499	+ 0.6857
	Sig	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4.5 Discussion

This study investigated the sensitivity to scale effects when using different methods to construct the SoRI. The sensitivity to scale effects were identified as significant differences that occurred between the census scales for each study area. Since the individual-level data comprising of the census scales does not change, it was not expected that significant differences would occur between the census scales. The results of this study indicated different, and at times contradictory, results of the SoRI between census scales when different methods of index construction were used for each study area. Recall that the SoRI was comprised of a different number of input variables for each study area due to data constraints across the different census programs. While one method appeared to be less sensitive to scale effects for one study area, the same method could simultaneously be the most sensitive to scale effects for another study area. Furthermore, while one method was the least sensitive to scale effects for one study area, the other method could be the most sensitive to scale effects for the same study area. In a rather unpredictable nature, the sensitivity to scale effects were observed to be dependent on both the combination of input variables and the method of index construction. This is consistent with the previous findings from Fotheringham & Wong (1991), where the nature of scale effects of the MAUP are largely unpredictable in multivariate analyses.

The results from this study further indicated that the data-driven PCA, and stakeholder-driven MCA methods of index construction quantifies the SoRI values very differently and yield very different spatial patterns of social resilience. This presents an important implication particularly when quantitative indices and socioeconomic mapping are intended to inform policy. Different priority areas (i.e., spatial differences) and a different number of priority areas (i.e., statistical differences) can be identified depending on the extraction parameters for the PCA, as well as the chosen method of index construction. However, the results of this study suggest that using different PCA extraction parameters can be less sensitive to scale effects. The results of the Moran's I statistics (Table 16 and Table 19) identified that the sensitivity to scale effects were attributed to the PCA extraction parameters (i.e., the *PCAoriginal* test) rather than the statistic itself. Counter-intuitive results of the Moran's I were also only observed for Vancouver (i.e., spatially clustered at the DA scale but spatially random at the CT scale) when using the *PCAoriginal* test, and not for any of the other study areas or index construction methods. The results of this study suggest that the *PCAscree* test offers a more stable and intuitive representation of the SoRI, which is less sensitive to scale effects than the conventional threshold (i.e., eigenvalues > 1.0) from the *PCAoriginal* test. Recall that the *PCAscree* test extracts PCs based on the inflection point where there is a significant drop in the variance of the dataset. Since a PCA is data-driven method based on existing structure in the dataset, then the threshold should intuitively also be based on the variance in the dataset itself rather than a conventional threshold. Furthermore, the use of a conventional threshold is also at risk of omitting key dynamics of the dataset if it is marginally close to the threshold value (e.g., an eigenvalue of 0.98).

Since individual-level, disaggregate census data is not made publicly available, decisions regarding the choice of index construction methods should reflect on the initial purpose of the exercise. Data-driven methods such as a PCA captures existing data structure and can be considered when there is uncertainty in the input variables. The results of this study indicate that when using the PCA method of index construction, extracting PCs based on the inflection point of the scree plot (i.e., *PCAscree*) offers a more stable threshold parameter than the conventional threshold based on eigenvalues (i.e., eigenvalues > 1.0). Alternatively, the stakeholder-driven MCA approach can be considered when there is some level of agreement in the input variables from incorporating user knowledge, experience and opinions. The results of this study indicated that as an unweighted method of summation, the MCA method also offered a stable method of index construction. This was supported by the consistent Moran's I values, which did not indicate contrasting spatial patterns between census scales. While scale effects of the MAUP persists in spatial analysis, the results from this study indicate that its effects can be mitigated and serve as a useful tool to support disaster risk management, climate change adaptation efforts and to build disaster resilience.

4.6 Limitations & Future Research Directions

This study investigated the PCA and MCA methods of index construction as they are commonly favoured for their replicability and used by policymakers. Future studies could further explore the stability of other index construction methods by evaluating its sensitivity to scale effects. Future research could also investigate the sensitivity to scale effects when different weights are applied to the stakeholder-driven MCA method of index construction and evaluate how it compares to an unweighted index.

Due to data constraints of the census programs, certain SoRI variables were only available for the larger areal unit (i.e., CTs for Vancouver and LA, and DZs for Edinburgh) for each study area. To ensure that the SoRI was constructed using the same census variables at both scales for each study area, the value for these SoRI variables at the smaller areal unit (i.e., DAs for Vancouver, BGs for LA, and OAs for Edinburgh) were taken to be equal to the value of the larger, hierarchical areal unit that it is contained within (Appendix A). This limitation highlights the inevitable implication of data availability when using census data at different census scales, and the implication of using indices that rely solely on census data. Future studies could consider exploring alternate sources of data to construct indices, such as qualitative data through survey questionnaires, to capture information that is not available at the aggregate level.

Each of the study areas presented a "variation" of the SoRI due to the different number of input variables used to construct the index – 14 variables for Vancouver; 13 variables for Los Angeles; and 10 variables for Edinburgh. This emphasizes the subjective nature of the selection of variables used in an index, as each of these variations arguably still serve as an indicator of social resilience. Future research could investigate whether the number of input variables improves the quantification of social resilience. For example, whether including more input predictor variables would produce a more accurate reflection of the social resilience characteristics of communities in reality.

4.7 References

Anselin, L., 2016. *Spatial Data, Spatial Analysis and Spatial Data Science.* Chicago: The Center for Spatial Data Science (University of Chicago).

Carrington, A., Rahman, N. & Ralphs, M., 2018. *The Modifiable Areal Unit Problem: Research Planning.* (NSMAC 11, 11th Meeting of the National Statistics Methodology Advisory Committee). South Wales: Office for National Statistics. Available at: <https://www.ons.gov.uk/ons/guide-method/method-quality/advisory-committee/2005-2007/eleventh-meeting/the-modifiable-areal-unit-problem--research-planning.pdf> [Accessed 15 September 2019].

City of Los Angeles, 2018. *Resilient Los Angeles*. Los Angeles: Mayor's Office of Resilience. [online] Available at: <https://www.lamayor.org/sites/g/files/wph446/f/page/file/Resilient%20Los%20Angeles.pdf> [Accessed 6 February 2020].

City of Vancouver, 2019. *Resilient Vancouver Strategy*. Vancouver: City of Vancouver. [online] Available at: <https://vancouver.ca/files/cov/resilient-vancouver-strategy.pdf> [Accessed 15 January 2020].

Coleman, J. S. M., 2012. Principal Components Analysis. In: Salkind, N. J. ed. *The Encyclopedia of Research Design*. Thousand Oaks: SAGE Publications Inc., pp. 1098-1102.

Cutter, S. L., 1996. Vulnerability to environmental hazards. *Progress in Human Geography*, 20(4), pp. 529-539.

Cutter, S. L., Boruff, B. J. & Shirley, W. L., 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly*, 84(2), pp. 242-261.

Cutter, S. L. & Finch, C., 2008. Temporal and spatial changes in social vulnerability to natural hazards. *Proceedings of the National Academy of Sciences of the United States of America*, 105(7), pp. 2301-2306.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E. & Webb, J., 2008. A place-based model for understanding community resilience to natural disasters. *Global Environmental Change*, 18, pp. 598-606.

Cutter, S. L., Ash, K. D. & Emrich, C. T., 2014. The geographies of community disaster resilience. *Global Environmental Change*, 29, pp. 65-77.

Damude, K., Mortsch, L. & Joakim, E., 2015. *Draft Report: Methods for Quantifying Social Resilience in Metro Vancouver, Canada*. Ontario: Coastal Cities at Risk (CCaR) Project.

Dorling, D., 1993. Map design for census mapping. *The Cartographic Journal*, 30, pp. 167-183.

Eakin, H. & Bojorquez-Tapia, 2008. Insights into the composition of household vulnerability from multicriteria decision analysis. *Global Environmental Change*, 18, pp. 112-127.

Fekete, A., 2009. Validation of a social vulnerability index in context to river-floods in Germany. *Nat. Hazards Earth Syst. Sci.,* 9, pp. 393-403.

Fekete, A., 2012. Spatial disaster vulnerability and risk assessments: challenges in their quality and acceptance. *Natural Hazards*, 61, pp. 1161-1178.

Felsenstein, D. & Lichter, M., 2014. Social and economic vulnerability of coastal communities to sea-level rise and extreme flooding. *Natural Hazards*, 71, pp. 463-491.

Flowerdew, R., 2011. How serious is the Modifiable Areal Unit Problem for analysis of English census data?. *Population Trends*, 145, pp. 106-118.

Fortin, M. & Dale, M., 2009. Spatial Autocorrelation. In: A. Fotheringham & P. Rogerson, eds. *The SAGE Handbook of Spatial Analysis*. London: SAGE Publishing Ltd., pp. 89-103.

Fotheringham, A. S. & Wong, D. W. S., 1991. The modifiable areal unit problem in multivariate statistical analysis. *Environmental and Planning A*, Volume 23, pp. 1025-1044.

Gehlke, C.E. & Biehl, K., 1934. Certain effects of the grouping upon the size of the correlation coefficient in census tract material. *Journal of the American Statistical Association*, Supplement 29, pp. 169-170.

Gotham, K. F., & Greenberg, M., 2014. *Crisis Cities: Disaster and Redevelopment in New York and New Orleans*. Oxford: Oxford University Press.

Huang, I. B., Kiesler, J. & Linkov, I., 2011. Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends. *Science of the Total Environment*, 409, pp. 3578-3594.

Openshaw, S., 1984. The Modifiable Areal Unit Problem. *Concepts and Techniques in Modern Geography No. 38 ed*. Norwich: GeoBooks.

O'Sullivan, D. & Unwin, D. J., 2010. *Geographic Information Analysis*. Hoboken: John Wiley & Sons, Inc.

Oulahen, G., Mortsch, L., Tang, K. & Harford, D., 2015. Unequal Vulnerability to Flood Hazards: "Ground Truthing" a Social Vulnerability Index of Five Municipalities in Metro Vancouver, Canada. *Annals of the Association of American Geographers*, 105(3), pp. 473-495.

Prouse, V., Ramos, H., Grant, J. L. & Radice, M., 2014. How and when scale matters: the modifiable areal unit problem and income inequality in Halifax. *Canadian Journal of Urban Research*, 23(1), pp. 61-82.

Reckien, D., 2018. What is an index? Construction method, data metric, and weighting scheme determine the outcome of composite social vulnerability indices in New York City. *Regional Environmental Change*, 18, pp. 1439-1451.

Rickless, D. S., Yao, X. A., Orland, B. & Welch-Devine, M., 2019. Assessing Social Vulnerability through a Local Lens: An Integrated Geovisual Approach. *Annals of the American Association of Geographers*, 0(0), pp. 1-20.

Schmidtlein, M. C., Deutsch, R. C., Piegorsch, W. W. & Cutter, S. L., 2008. A Sensitivity Analysis of the Social Vulnerability Index. *Risk Analysis,* 28(4), pp. 1099-1114.

Schmidtlein M. C., Shafer, J. M., Berry, M. & Cutter, S. L., 2011. Modeled earthquake losses and social vulnerability in Charleston, South Carolina. *Applied Geography,* 31(1), pp. 269-281.

Schuurman, N., Bell, N., Dunn, J. & Oliver, L., 2007. Deprivation Indices, Population Health and Geography: An Evaluation of Indices at Multiple Scales. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, 84(4), pp. 591-503.

Seguin, A., Apparicio, P. & Riva, M., 2011. The Impact of Geographical Scale in Identifying Areas as Possible Sites for Area-Based Interventions to Tackle Poverty: The Case of Montreal. *Applications of Spatial Statistics*, 5, pp. 231-251.

Sevoyan, A., Hugo, G., Feist, H., Tan, G., McDougall, K., Tan, Y. and Spoehr, J., 2013. *Impact of Climate Change on* Disadvantaged *Groups: Issues and Interventions*. Adelaide: National Climate Change Adaptation Research Facility.

Spielman, S. E., Tucillo, J., Folch, D. C., Schweikert, A., Davies, R., Wood, N. & Tate, E., 2020. Evaluating social vulnerability indicators: criteria and their application to the Social Vulnerability Index. *Natural Hazards*, 100, pp. 417-436.

Tate, E., Cutter, S. L. & Berry, M., 2010. Integrated multihazard mapping. *Environment and Planning B: Planning and Design*, 37, pp. 646-663.

Tate, E., 2012. Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. *Natural Hazards*, 63, pp. 325-347.

Willis, I. & Fitton, J., 2016. A review of multivariate social vulnerability methodologies: a case study of the River Parrett catchment, UK. *Natural Hazards and Earth System Sciences*, 16, pp. 1387-1399.

Wisner, B., Blaikie, P., Cannon, T. and Davis, I., 2004. *At risk: natural hazards, people's vulnerability and disasters*. Reprint 2004. New York: Routledge.

5.0 Connecting Manuscript 2 to Manuscript 3

The previous manuscripts (Chapter 2 and Chapter 4) have focused on the implications of spatial scale on efforts to quantify resilience, but these efforts do not necessarily address the policy needs to build resilience. These quantitative assessments capture and measure the status of resilience with the intent of informing policy and directing efforts to build resilience. Furthermore, the issue of scale in these resilience assessments is not only a result of the MAUP, but also the type of information that is available at different spatial scales. There are many characteristics that can affect flood resilience, but they do not occur and are not represented at aggregate scales. For example, individual-level perceptions, household-level flood protection measures and community-level initiatives are aspects of flood resilience that are not represented through aggregate census data. Understanding these aspects of resilience often requires the use of qualitative approaches to uncover.

The following manuscript 3 (i.e., chapter 6) investigates flood resilience perspectives through the use of surveys and interviews to assess flood resilience at the individual-level, based on qualitative perspectives from residents in Vancouver and experts. Exploring qualitative perspectives aims to improve the insights that are used to inform policy efforts to build flood resilience.

6.0 Flood Resilience Perspectives in the City of Vancouver

6.1 Introduction

The focus on resilience has become increasingly prominent in social policy to aid disaster risk management to prevent exposure to hazards, reduce vulnerability to environmental risks and climate change impacts, and increase preparedness for response and recovery to environmental hazards, such as floods (Joakim et al., 2015; PSC, 2019; UNDRR, 2015). Resilience in the context of environmental hazards refers to the capacity of individuals, communities and social systems to resist, withstand, cope with, recover and from potential threats and risks (Cutter, 2016; Joakim et al., 2015). In contrast to vulnerability, which refers to the characteristics that *create* the potential for harm, resilience refers to the characteristics to *cope* with the potential for harm. A focus on resilience thus emphasizes the "strengths", capacities and abilities of a population – what they can do for themselves and how to enhance their capacities, rather than the "sensitivities" (Lerch, 2015; Twigg, 2009). A number of studies have developed quantitative metrics to distinguish levels of resilience amongst populations based on socioeconomic indicators, called social resilience (Cutter et al., 2008; Damude et al., 2015; Morrow, 2008). These indicators are used to represent financial and social capital that can affect resilience in the event of a flood (Cutter et al., 2008; Damude et al., 2015; Joakim et al., 2015; Jones & Tanner, 2017; Morrow, 2008). These socioeconomic indicators are often retrieved through census data, which represents individual-level characteristics as aggregate census units (Mendelson, 2001; Prouse et al., 2014). However, this presents an issue of scale, called ecological fallacy, when aggregate indicators are used to draw conclusions about the capacities at the individual-level (Openshaw, 1984; Robinson, 1950). Therefore, policy and planning that is based solely on quantitative analyses at the aggregate level may not fully address the underlying issues affecting resilience at the individual level (Jones & Tanner, 2017; Jones et al., 2018). While a number of efforts have developed quantitative metrics to measure and model resilience using aggregate indicators, there is a gap in understanding how flood resilience is perceived and implemented at the individual-level. At the individual-level, the "subjective" assessments of how people perceive their own capacities and the types of actions that they might take against flood hazards may be critical for building resilience, particularly through policy and planning initiatives.

This study explores a qualitative approach to understanding flood resilience at the individual-level from the perspectives of residents and experts through a case study in the City of Vancouver. These perspectives were captured using a survey and interviews to: 1) identify how people perceive their capacities towards flood hazards; 2) identify what people are doing to personally address flood hazards at the household-level; and 3) compare the perspectives between residents and experts on the factors that can affect flood resilience. The use of qualitative information may present alternate patterns of flood resilience, which may differ from the information from quantitative metrics. Understanding these qualitative aspects can provide a more holistic understanding of flood resilience and contribute to the development of more targeted approaches for building flood resilience.

6.1.1 The Concept of Resilience to Environmental Hazards

Resilience to environmental hazards refers to the capacity of a system, community or society to prepare and plan for, respond, absorb and adapt to, and recover and learn from actual and potential threats to maintain an acceptable level of functioning (Cutter, 2016; PSC, 2019; UNDRR, 2004). This can also be understood as the capacities prior to the event (i.e., planning and preparedness), during the event (i.e., responding, coping and adapting) and after the event (i.e., recovery and adaptive transformation) (Bruneau et al., 2003; Cutter, 2016; Joakim et al., 2015). While it is recognized that there are numerous definitions of resilience across disaster risk management and climate change literature (Blaikie & Brookfield, 1987; IPCC, 2014; Joakim et al., 2015; Keck & Sakdapolrak, 2013; Lerch, 2015; Mercer Clarke et al., 2016; PSC, 2019), the commonality across these definitions is the emphasis on the abilities and capacities of people and societies in the face of environmental hazards. These abilities and capacities are determined by the inherent socioeconomic conditions and "everyday life" that allow people to prepare for, resist, cope and respond to and recover from potential threats (Blaikie & Brookfield, 1987; Cannon, 1994; Cutter et al., 2008; Hewitt, 1983; Susman et al., 1983; PSC, 2019). As a result, resilience frameworks often place an emphasis on the societal system and local contexts, rather than the physical hazard itself (Cutter, 1996; Cutter et al., 2008; City of Vancouver, 2019a; Hewitt, 1983). Policy and planning efforts to build resilience therefore involves creating or strengthening these capacities of the human societal system (Lerch, 2015; PSC, 2019).

6.1.2 Quantifying Social Resilience

The increasing focus on resilience has led to a number of quantitative assessments to measure the status of resilience between different populations and geographic areas using aggregate indicators, such as census data (Cutter et al., 2008; Cutter, 2016; Damude et al., 2015; Morrow, 2008). These aggregate indicators are derived from household-level dynamics as a proxy to measure the assumed capacity towards flood hazards (Jones & Tanner, 2017). Implicit in these quantitative assessments is that socioeconomic characteristics represent the differences among people and households that may influence their capacity and ability to develop resilience. Previous studies have modelled and quantified social resilience to environmental hazards based on social and economic characteristics from census data, such as the Disaster Resilience of Place (DROP) model (Cutter et al., 2008); the Baseline Resilience Indicators for Communities (BRIC) (Cutter et al., 2014); and the Social Resilience Index (SoRI) (Damude et al., 2015). These metrics are often used to inform disaster risk management and climate change adaptation planning to build resilience against the impacts of environmental hazards (Cannon, 1994; Cutter, 1996; Cutter et al., 2003; Frerks et al., 2011; Oulahen et al., 2015; Rickless et al., 2019).

These quantitative metrics are used to postulate how socioeconomic conditions may influence how people receive, perceive and interpret risks, but they do not explain how people perceive risks and whether they will act to reduce such risks (Phillips et al., 2006; Bronfman et al., 2008). This was emphasized in Cutter, Ash & Emrich (2016), "*We know little about whether such indexes are meaningful and whether they, in fact, capture the outcomes or processes of resilience*" (p.1238). While quantitative assessments provide a measure of assumed resilience, qualitative assessments provide a measure of perceived resilience that is based on subjective elements and perspectives (Jones & Tanner, 2017; Jones et al., 2018). These subjective elements involve the individual-level perceptions, decisions and behaviours that may be critical for building resilience (Jones & Tanner, 2017; Jones et al., 2018). These elements are related to a number of issues including risk perception, social cohesion and exclusion, social status and power, and beliefs and culture (Saunders, Naidoo & Griffith, 2007; Bronfman et al., 2008; Hogarth et al., 2014; Jones & Tanner, 2017; Jones et al., 2018; Rickless et al., 2019). Implicit in these subjective elements of resilience is that people have a direct and genuine understanding of their own capacities, abilities and willingness to act (Jones & Tanner, 2017; Jones et al., 2018). While there are a number of studies focused on quantitative assessment resilience, there has been limited research on qualitative assessments of resilience, which are important for understanding the underlying factors for building resilience through policy and planning (Hogarth et al., 2014; Jones & Tanner, 2017; Jones et al., 2018).

6.1.3 Scale of Analysis

The abilities, capacities and assets that are required to prepare for, respond to, cope with and recover and learn from environmental hazards are largely defined by household-level dynamics (Cutter et al., 2008; Hebb & Mortsch, 2007; Jones & Tanner, 2017; Morrow, 2008). At the household-level and the community that it is part of, the "everyday life" conditions and social interactions are the richest, which often have the greatest impact on the ability to develop resilience (City of Vancouver, 2018; Cutter et al., 2008; Morrow, 2008; Lerch, 2015). Every individual in a household is a stakeholder in the community and has an invested effort and responsibility (Lerch, 2015). Efforts to build resilience need to understand the capacities of individuals and households, which are determined by aspects of peoples' everyday life (City of Vancouver, 2018; City of Vancouver, 2019a; Jones & Tanner, 2017; Lerch, 2015; Twigg, 2009).

Since many of the aspects that are critical for achieving and building resilience are related to household-level dynamics, the efforts to quantify resilience at the aggregate level may not be representative of the capacities, needs and outcomes of resilience at the individual household-level. Outcomes of flood resilience refer to the actions that are undertaken to build or achieve resilience, such as installing flood protection measures. Qualitative assessments of household resilience suggest that the capacities perceived by individuals may be significantly different from the capacities that are assumed from aggregate census data (Bronfman et al., 2008; Hogarth et al., 2014; Jones & Tanner, 2017; Jones et al., 2018; Rickless et al., 2019). As noted in Bronfman et al. (2008), "*So, results from aggregated data analyses can not be used reliably to predict individual behaviours*" (p. 736). This may have implications for policy and planning if the scale at which resilience is quantified does not align with the initiatives that policy and planning are intended to address (i.e., to build resilience). There is a gap in understanding whether efforts to quantify resilience using socioeconomic characteristics and integrating them into an index are representative of the outcomes, or the personal actions that are taken to build resilience against flood hazards.

6.1 Study Area – City of Vancouver

In recent years, the City of Vancouver has developed resilience strategies that are aimed to address both acute shocks and chronic stresses that the city experiences (City of Vancouver, 2018). Acute shocks are defined as sudden events, such as earthquakes, floods and severe weather events, whereas chronic stresses refer to ongoing issues, such as poverty and reduced social cohesion (City of Vancouver, 2018). The 2019 Resilient Vancouver Strategy defines resilience as "… *the capacity of individuals, communities, institutions, businesses and systems within a city to survive, adapt and thrive, no matter what kinds of chronic stresses and acute shocks they experience*." (City of Vancouver, 2019a, p.12). The strategy identifies human capacity, neighbourhood connections and lived experiences, as the aspects that matter the most when it comes to coping and recovering from environmental shocks (City of Vancouver, 2019b). Understanding these aspects about residents and communities are critical for developing effective solutions to build resilience in Vancouver (City of Vancouver, 2019a).

The SoRI was developed for the Metro Vancouver area to demonstrate how socioeconomic indicators from census data may translate into different levels of social flood resilience between different areas and populations (Damude et al., 2015) (Figure 16). The SoRI is an example of a quantitative assessment that represents flood resilience at the aggregate level (i.e., using census data). It was used to identify issues of scale when compared to the qualitative assessment in this study, which explored flood resilience at the individual level.

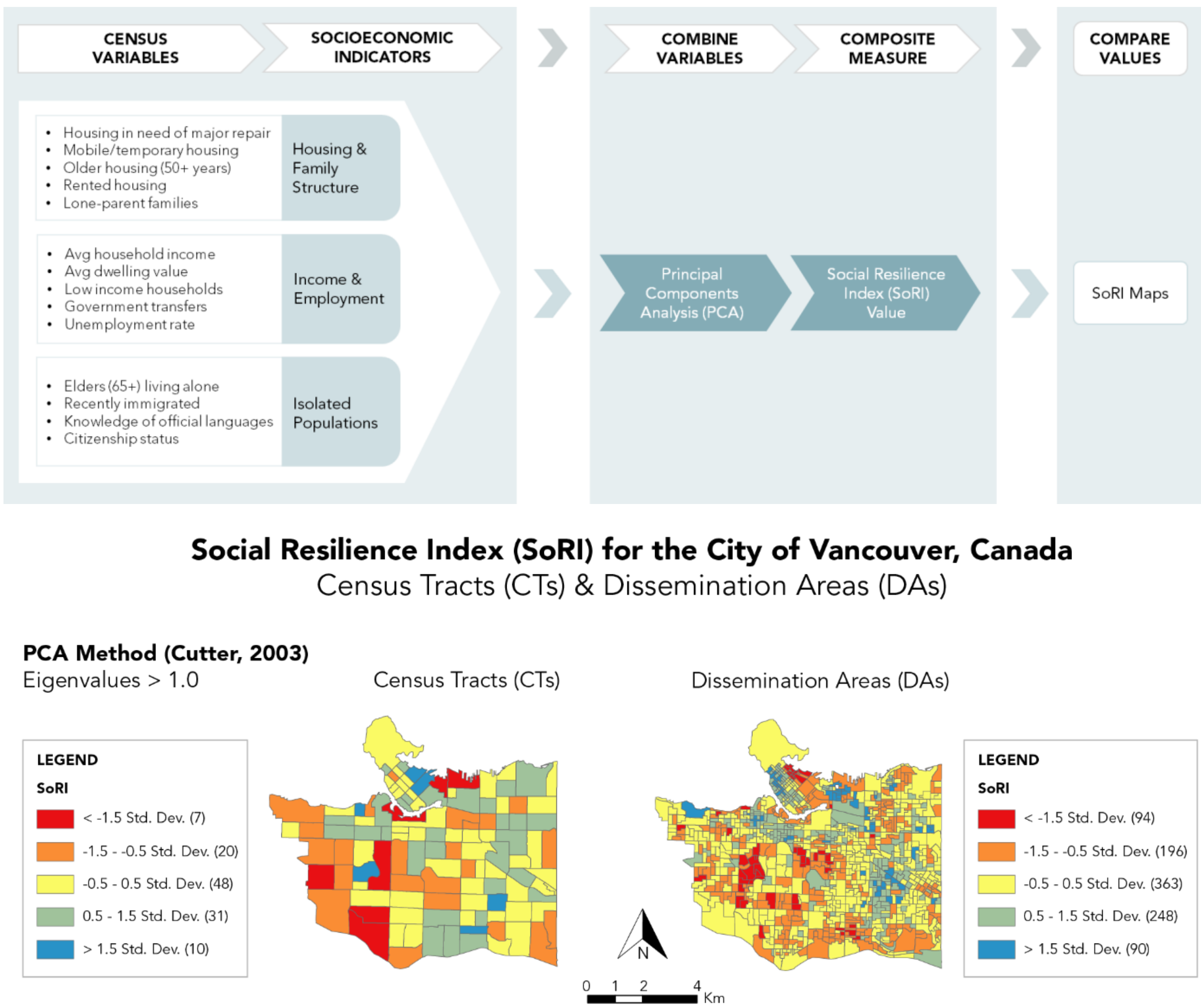


Figure 16. Quantifying social resilience: The Social Resilience Index (SoRI) based on 2011 census data

The purpose of this study was to explore the issues of scale that may occur between quantitative and qualitative assessments of flood resilience in Vancouver. While the SoRI represents flood resilience that is measured at the aggregate-level, this study collected qualitative perspectives and aspects of household flood resilience at the individual-level. The study set out to answer the following research questions:

- ***How do residents' perceptions of flood resilience compare with quantitative assessments flood resilience, such as the SoRI?***
- ***What are important aspects for building household flood resilience as identified by residents and experts' insights?***

6.2 Methodology

The use of qualitative methods provides an alternate approach to understanding flood resilience that is based on personal perceptions, knowledge and experiences (Baxter & Eyles, 1997; Bird & Dominey-Howes, 2008; Hogarth et al., 2014; Jones & Tanner, 2017; Jones et al., 2018; Rickless et al., 2019). A combination of online surveys and interview tools were used to elicit the perspectives of two distinct groups: 1) residents in Vancouver and 2) experts involved in social vulnerability, resilience, adaptation and community initiatives (Bird & Dominey-Howes, 2008; Bird, 2009; Sandink, 2011). The survey tool was used to identify residents' perceptions, actions and knowledge of their resilience towards flood hazards, which are used to represent the actions that are undertaken to achieve resilience, or the outcomes of flood resilience. Semi-structured interviews with experts were used to understand what residents *could* be doing to build resilience to a flood hazard. A follow-up survey was sent to experts to compare the perspectives between residents and experts. Due to restrictions for in-person activities as a result of the COVID-19 pandemic, all surveys and interviews were conducted virtually, where the surveys were conducted online via Google Forms and interviews were conducted by telephone.

6.2.1 Resident Survey

Primary data collection of resident's perspectives was conducted using an online survey. The survey consisted of 22 questions which were developed by the author and informed by previous social vulnerability and hazards studies (City of Vancouver, 2019b; Jones & Tanner, 2017; Oulahen, 2015; Sandink, 2011; Sevoyan et al., 2013). The survey was comprised of open-ended, 5-point Likert scale, nominal-type questions (Bird, 2009). The survey was used to investigate two key themes: "*Flood Impacts & Preparedness*" and "*Protecting Your Home*" (Table 20).

Table 20. Themes and research objectives of the resident survey

Theme	Purpose of Questions and Research Objectives
Flood Impacts and Preparedness	The purpose of this theme was to identify perceptions and preparedness towards flood risks, including the necessary resources, the household conditions and reliance on social networks in the event of a flood (City of Vancouver, 2019a). This theme aimed to address the following research objectives: • How do residents perceive their own capacities to respond to a flood? • What are the resources that residents require to respond to a flood? • What are the household conditions that would affect flood resilience?
Protecting Your Home	The purpose of this theme was to identify the types of actions that residents have undertaken to protect against flood impacts, such as purchasing flood insurance (Thistlethwaite, 2017; IBC, 2019). This theme aimed to address the following research objectives: • What are the types of actions that residents undertake to address flood hazards at the household-level? • What are the considerations for undertaking flood protection measures?

6.2.1.1 Data Collection

A survey of community residents was conducted online via Google Forms during May to July 2020. Potential participants were recruited via an email script and consent materials that were sent to a total of 8 organizations, including community centres (also known as neighbourhood houses in British Columbia) and NGOs in the City of Vancouver (see Appendix C). Recruitment via community organizations was focused on the Arbutus-Ridge, Dunbar-Southlands, Kitsilano, Mount Pleasant and Collingwood neighbourhoods as they corresponded to, or were in proximity to, areas of low resilience identified in the SoRI maps (Figure 16).

The link to the online residents' survey was shared via the social media platforms and contact lists of CityStudio Vancouver, the Suzuki Elders Resilience Group and forwarded via anonymous community members in the City of Vancouver. CityStudio Vancouver is an innovation hub that connects students with city staff to work on urban challenges in the city. The Suzuki Elders Resilience Group engages with the communities to build resilience to the social impacts of climate disruption.

Since the contact lists of the organizations were not provided to the researcher, it was not possible to determine how many people were contacted and a response rate could not be determined.

6.2.1.2 Data Analysis

A total of 116 survey responses were received and used for the analysis in this study. The analysis involved a synthesis of the survey results and mapping using geographic information systems (GIS). The survey included a question that asked respondents to indicate the City of Vancouver neighbourhood that they resided in, which allowed a spatial component to be attached to the survey responses. Note that survey respondents could skip questions, so the number of responses received for each question varied.

6.2.2 Expert Interviews & Survey

Interviews with experts from academia and NGOs were intended to capture how social resilience to floods was implemented in practice, such as through planning and community initiatives. The initial list of potential interviewees was developed from an internet search for those who were professionally involved with community outreach initiatives, social vulnerability and resilience, climate change adaptation and disaster risk management. Eighteen experts were contacted by email, which introduced the researcher and the study, outlined the expertise of the potential interviewee that could contribute to the research and provided the consent letter, as an invitation to participate in this study (Appendix C). The initial intent of the interviews was to engage with practitioners, such as the City of Vancouver municipal staff, but they were unable to participate in the study due to conflicting priorities with coordinating the COVID-19 response. As a result, experts from NGOs in Vancouver and academia were interviewed during May to July 2020, which involved semi-structured phone interviews (n=4) and an online survey (n=6). Note that 2 experts answered the online survey but were unavailable for a phone interview, resulting in response rates of 22.2% for the phone interviews and 33.3% for the online survey.

The semi-structured interviews with experts lasted from 30 – 60 minutes and were comprised of a mix of key interview questions and additional topics that emerged from the conversation (see Appendix C). The key questions for the interviews included:

- What do you think is important for building social resilience to flooding at the household level?
- What are the challenges to building flood resilience at the household level?

In addition to open-ended interviews, the experts were also asked to complete an online survey. The survey consisted of 11 questions which were developed by the author and was informed, in part, by previous social vulnerability and hazards studies (Cutter et al., 2008; Sevoyan et al., 2013; Oulahen, 2015) to explore perspectives towards social resilience. The survey was used to investigate the indicators that are influential for identifying social resilience, as well as to compare with some of the results from the resident survey. The survey was used to investigate two key themes: "*Household Social Resilience*" and "*Flood Risks and Impacts*" (Table 21).

Table 21. Themes and research objectives of the expert survey

Theme	Purpose and Rationale for Questions
Household Flood Resilience	The purpose of this theme was to identify the socioeconomic indicators that are influential for household resilience to flood hazards (Cutter et al, 2008; Cutter, 2016; Morrow et al., 2008). This theme aimed to answer the following research objectives: • What are important indicators of household flood resilience?
Flood Risks and Impacts	The purpose of this theme was to identify the household characteristics that may influence household resilience to flood hazards. One question is replicated from the resident survey to compare the perspectives between experts and residents. This theme aimed to answer the following research objectives: • What are the household conditions that may influence household resilience to floods? • How do these responses compare with the residents'?

6.2.2.1 Data Analysis

The experts' responses to interview questions were taken as notes by the researcher during the phone interview. Since the interviews were not recorded, the key messages from the interview were verbally confirmed with the experts at the end of the interview. The commentaries were interpreted and summarized by the researcher to articulate what interviewees expressed were important for determining and enhancing social resilience in Vancouver (Baxter & Eyles, 1997). To maintain anonymity, a notation protocol according to the experts' organization was followed by assigning a unique number to reference their survey responses and insights from the interview throughout the results and discussion sections. Academic respondents were denoted by "AI", such that "AI 1" refers to respondent #1 and non-governmental organization interviewees were denoted by "NGOI", such that "NGOI 1" refers to respondent #1. Due to logistical constraints from COVID-19 that resulted in the small number of interviews (n=4), this study focuses on the qualitative perspectives of experts as an exploratory analysis (Baxter & Eyles, 1997).

6.3 Results & Findings

6.3.1 Resident Perceptions and Preparedness towards Flood Hazards

The online resident survey was used to identify residents' perceptions and the understanding of their own capacities to respond to flood risks. The questions addressed two issues – how residents perceived their preparedness for responding to a flood event, and their capacity and access to resources to prepare for a flood event. Only 1% of residents strongly agreed that they had the resources and knowledge to respond to a flood. The majority of respondents did not feel prepared for (39%) and did not have the resources (44%) to respond to a flood (Figure 17).

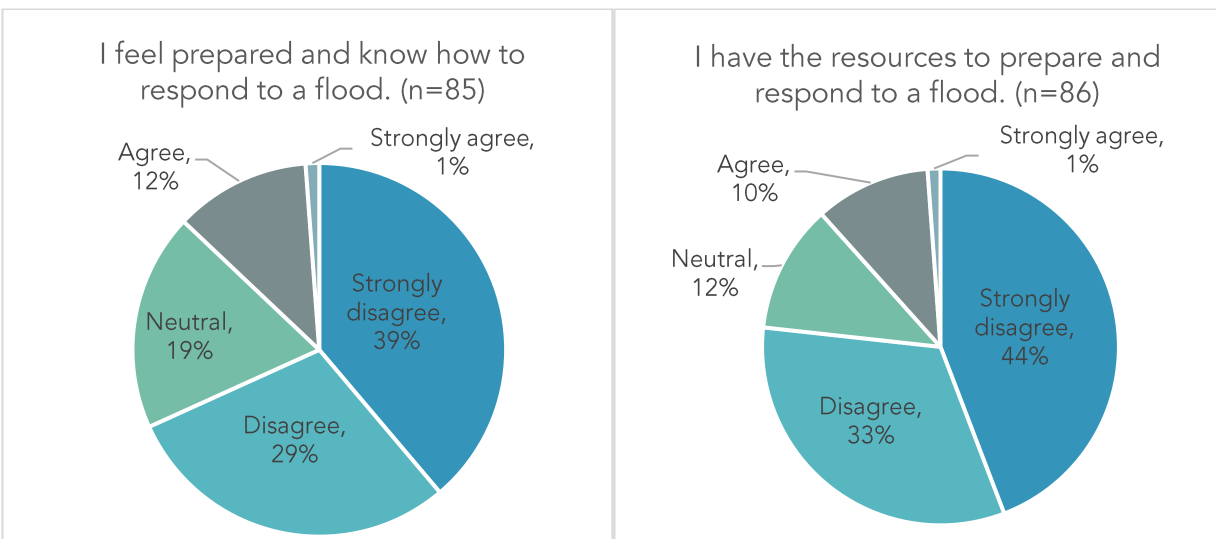


Figure 17. Resident survey results – perspectives on flood preparedness

The respondents were asked to elaborate on the resources that they required in order to prepare and respond to a flood. A total of 72 short-answer responses were received, with numerous responses indicating similar items that fell under three broad categories: daily necessities, physical flood protection and supplies, and emergency procedures and communication (Table 22). Note that respondents mentioned several resources, and therefore the breakdown of responses exceeds the total number of short-answer responses received.

Table 22. Resident survey results - the resources required to prepare and respond to a flood

Category of the resources required	Examples of short-answer responses	Number of responses received
Daily necessities	Food, water, medication, first aid supplies and clothing	49
Physical flood protection and supplies	Sandbags, flood protection barriers, flashlights, batteries and flotation devices	21
Emergency procedures and communication	Evacuation plans, neighbourhood contacts and access to bulletin boards and websites	13

While the majority of responses identified physical items, emergency procedures and communication needs were also identified. This suggests that the knowledge of emergency procedures and access to information are also important indicators of social resilience. This aligns with expert respondents, which similarly identified the following considerations to enhance resilience:

- "*Homelessness and food security*" (AI 3)
- "*Detailed awareness about flooding risks and procedures to follow in the event of flooding.*" (NGOI 2)
- "*Access to information, e.g., internet, phone; support/info/resource networks; transportation*" (AI 2)

The short-answer responses from the residents' survey indicate that 57% of all survey respondents have some level of understanding of their requirements to be prepared for flood hazards. These results altogether appear contradictory, while the majority of residents do not feel prepared or have the resources to respond to a flood (Figure 17), they simultaneously had some level of knowledge of the resources that would help them to respond to a flood. Planning and risk management therefore could be directed at improving access to resources that can help residents respond to a flood event.

6.3.2 Outcomes of Flood Resilience: Flood Protection & Flood Insurance

Measures that can increase household flood resilience are often promoted by insurance companies and include actions such as installing physical flood protection measures, such as sump pumps and backwater valves, and purchasing flood insurance (IBC, 2019). The survey asked residents about the flood protection measures that they have undertaken for their home. The results (Figure 18) indicate that the majority of respondents (i.e., 66%) have not undertaken any flood protection measures on their home. This reveals a gap in the residents' use of flood protection measures and an opportunity for planning and risk management to encourage the use of such measures to enhance household resilience to floods.

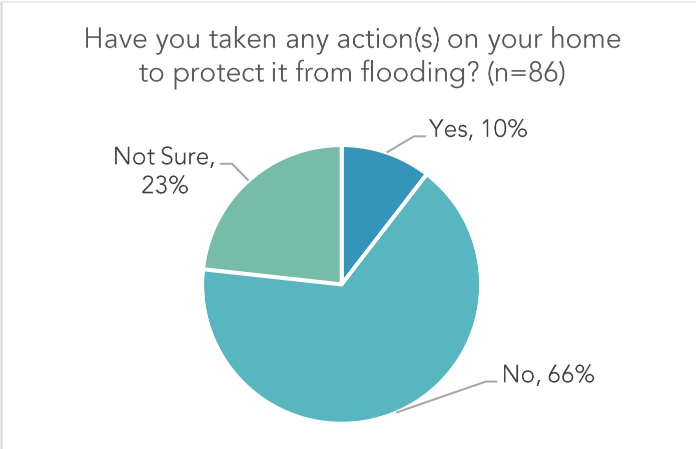


Figure 18. Resident survey results – flood protection measures

Respondents were asked to elaborate on the types of actions that they have undertaken to protect their homes. Responses (n=12) included: installing sump pumps and backwater valves, applying sealants around egresses and installing floor drains. Residents who live in apartment buildings perceive and are subject to a different level of flood risk, which will not only influence the types of actions that they may take, but also influences their decision to take action or the inaction towards flood risks (Slovic, 1992; Bronfman et al., 2008; Morrow, 2008). Three of the responses supported that housing tenure and housing type can be influential in the decisions and actions taken to protect against flood risks:

- *"We live on a Third floor so we are not at risk but we did think about it tho!"*
- *"I rent so not sure if the owners took any of these actions."*
- *"we live on the 12th flood of a highrise in Vancouver, and our building is way up from English Bay, and is well maintained, with sump pump etc. So we are not as vulnerable as many. Mainly flooding from within the building, leaks, etc. which we've experienced."*

Purchasing flood insurance is another action that can be taken against flood hazards as an outcome of resilience. Flood insurance offers coverage that can help reduce the financial losses from flooding, which can enhance resilience by increasing the ability recover from flood impacts (IBC, 2019). In Canada, there are two types of optional flood insurance that can be added to a home insurance policy – water- or sewer-backup insurance, and overland flood insurance (IBC, 2019). Overland flood insurance was first made available in Canada in 2015 (Thistlethwaite, 2017). The survey asked residents to indicate whether or not they had purchased supplementary flood insurance, and to indicate the reason(s) that influenced their decision for this additional coverage. The majority of respondents were unsure of whether or not they had this additional flood coverage - 41% for water/sewer backup insurance (Figure 19) and 55% for overland insurance (Figure 20). The predominant reason for not purchasing this optional coverage was that they were unaware of this option - 33% of responses for water/sewer backup insurance (Figure 19) and 35% of responses for overland insurance (Figure 20).

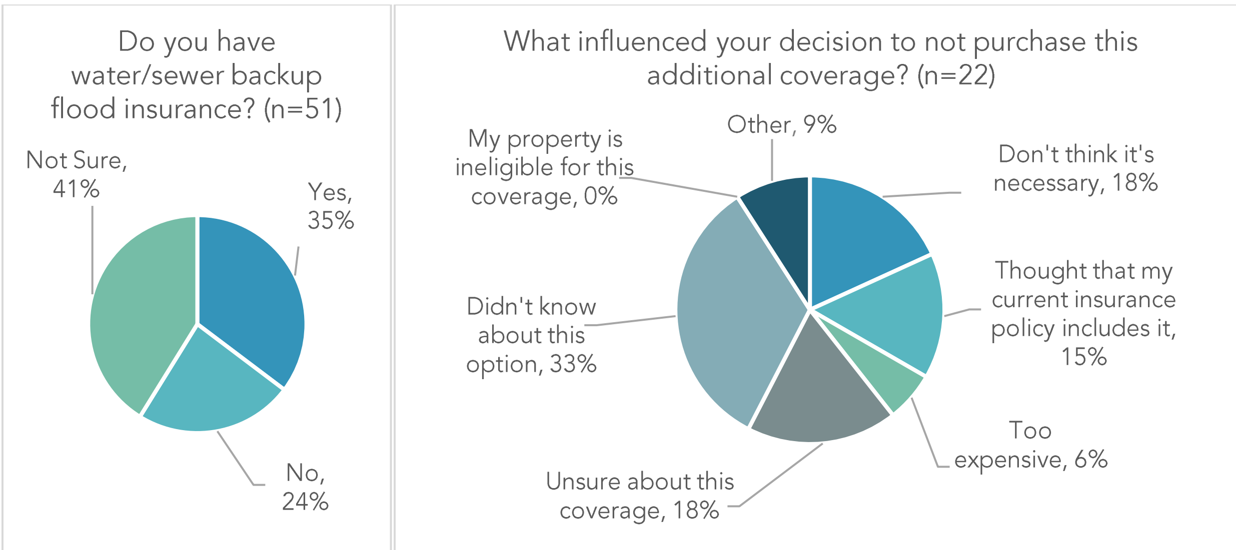


Figure 19. Resident survey results – uptake and considerations for purchasing water backup insurance

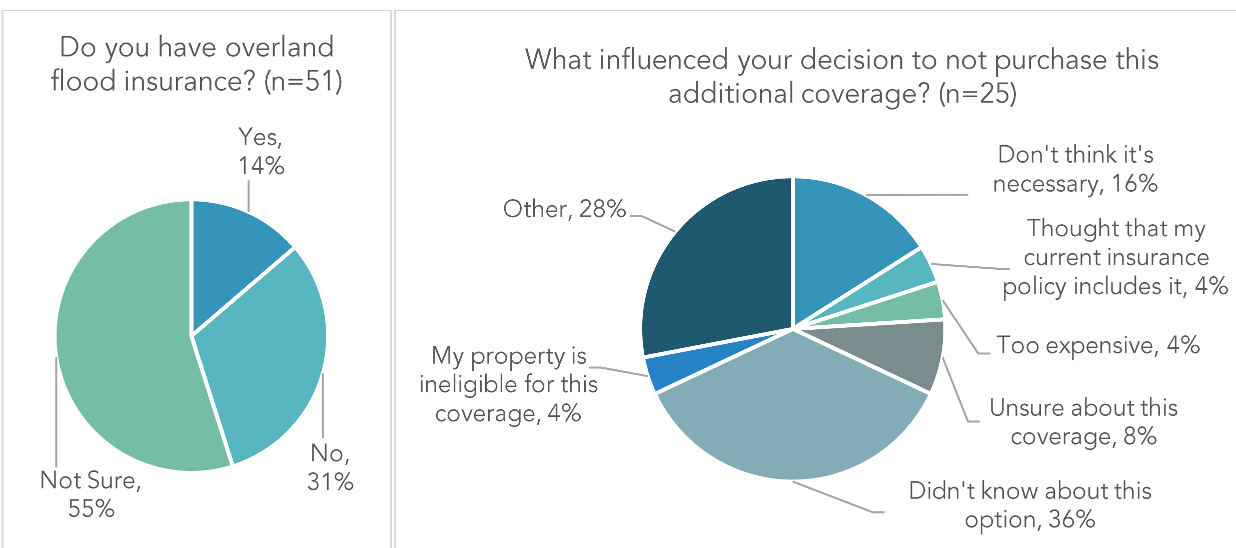


Figure 20. Resident survey results – uptake and considerations for purchasing overland flood insurance

Since flood insurance offers an option to protect against flood hazards, increasing its uptake could be a potential option for increasing flood resilience in Vancouver. These results suggest that improving knowledge of the available options for flood insurance could help enhance flood preparedness among residents in Vancouver.

6.3.3 A Comparison of Flood Resilience Perspectives between Residents and Experts

The everyday household conditions may not only affect the ability to prepare for a flood, but also the ability to recover from a flood (City of Vancouver, 2018; City of Vancouver, 2019a). The resident and expert surveys asked respondents to identify the household conditions that would affect their ability to prepare for and recover from the impacts of flooding. Respondents were provided a list of 10 common household conditions based, in part, by Sevoyan et al. (2013), and asked to check all that applied. An option "*Other*" allowed respondents to add additional household conditions. Residents identified physical housing condition, housing costs (e.g., costs to relocate, costs for flood repairs, etc.) and housing availability as the most important conditions affecting flood resilience (Figure 21).

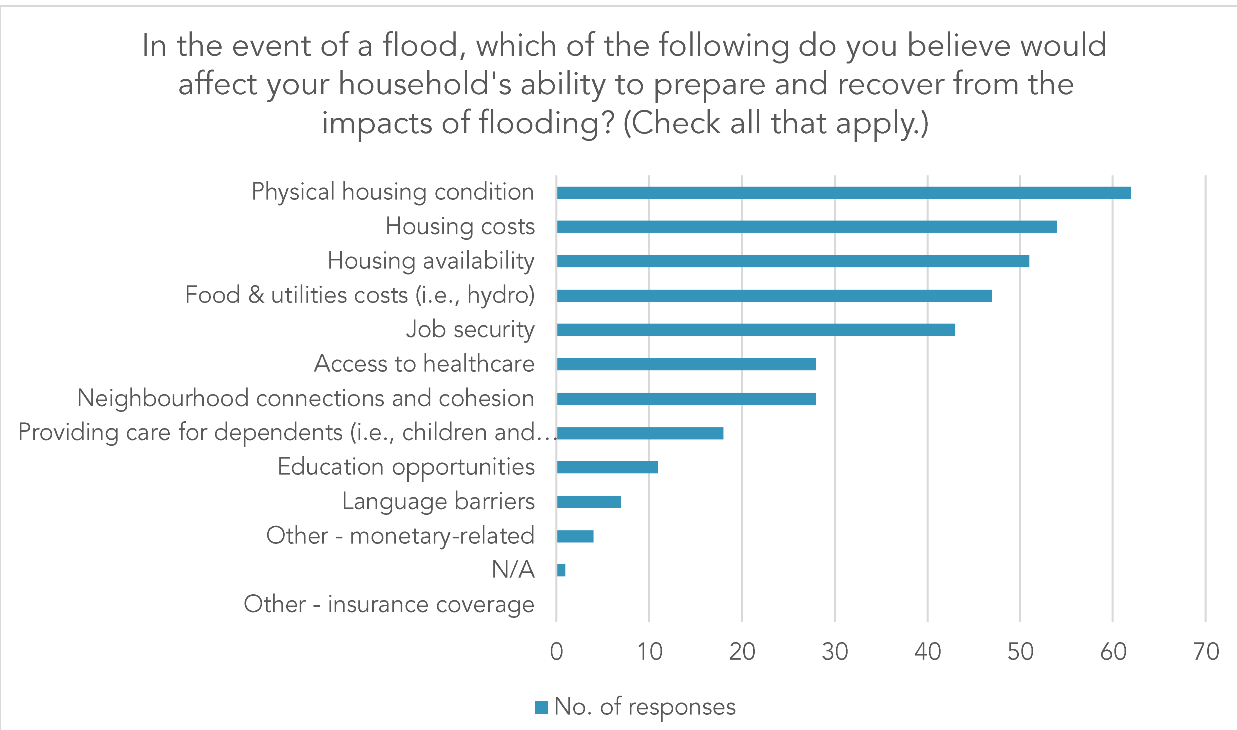


Figure 21. Resident responses – household barriers to flood preparedness and recovery

In comparison, experts perceive job security, physical housing condition, housing costs and neighbourhood connections as the most important household conditions that affect flood preparedness and recovery.

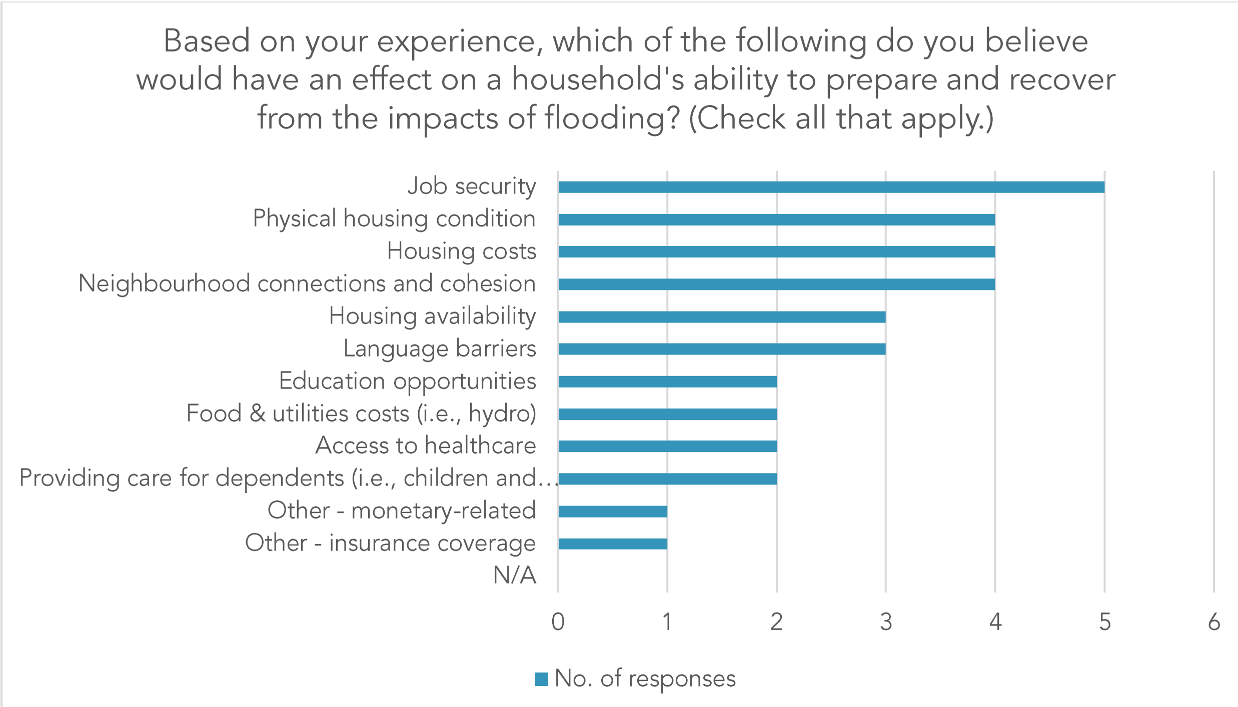


Figure 22. Expert responses – household barriers to flood preparedness and recovery

Since a different number of responses were received between the expert (n=5) and resident (n=86) surveys, the results are intended to highlight the contrast that can occur between academic perspectives (i.e., from experts) and the underlying challenges that policy aims to address (i.e., perspectives from residents). While there was largely agreement between residents and experts on the majority of the household conditions that were listed, there is a noteworthy difference in perceptions towards food and utilities costs, neighbourhood connections and cohesion and language barriers. Experts identified language barriers and neighbourhood connections as important household conditions that affect flood preparedness and recovery. For example, "[Community cohesion] *is even more important than financial assets yet it's that big houses don't have community cohesion*"(AI 2). Wealthy households and neighbourhoods are often secluded, and neighbours are physically distant from one another, which may lessen social cohesion and could lessen the reliance on or "fallback" to neighbours, who would be the most readily available in the event of a flood (AI 2, NGOI 2). In contrast, residents identified personal concerns related to the cost of food and utilities, and housing availability. These results highlight the importance of capturing local contexts, as theoretical knowledge may not necessarily align with the lived experiences and perceptions of the individuals in a community. If the goal is to build resilience by overcoming the household and individual-level barriers, then the policy and planning efforts should also target concerns that residents are most concerned about.

6.3.3.1 Reliance on Networks

Social networks that are shaped by personal relationships between friends, family, neighbours and members of a community can become important resources to cope with disturbances in the event of a flood (Damude et al., 2015; Morrow, 2008). These relationships facilitate co-ordination and co-operation between community members and allows the unique situation of different communities to be addressed in the event of a flood (City of Vancouver, 2019a; Lerch, 2015). The Resilient Vancouver Strategy identifies neighbourhood preparedness and connections as key priorities to build resilience against environmental shocks. It emphasized the need to "*empower communities to support each other during crises and recover after disasters*" (City of Vancouver, 2019a, p.53).

The residents' survey explored reliance on different networks in the event of a flood, to identify the reliance on personal networks versus public authorities (i.e., government). The majority of residents would rely on the government and family and friends, rather than their neighbours (Figure 23). There was a divide in residents' reliance on neighbours, with 41% of respondents (n=35) indicating reliance on their neighbours, while 33% of respondents would not. Out of the three networks, the reliance on neighbours also received the fewest "strongly agree" responses (n=7) and the most "strongly disagree" (n=11) responses, which suggests that residents may not necessarily perceive their neighbours as a resource in the event of a flood.

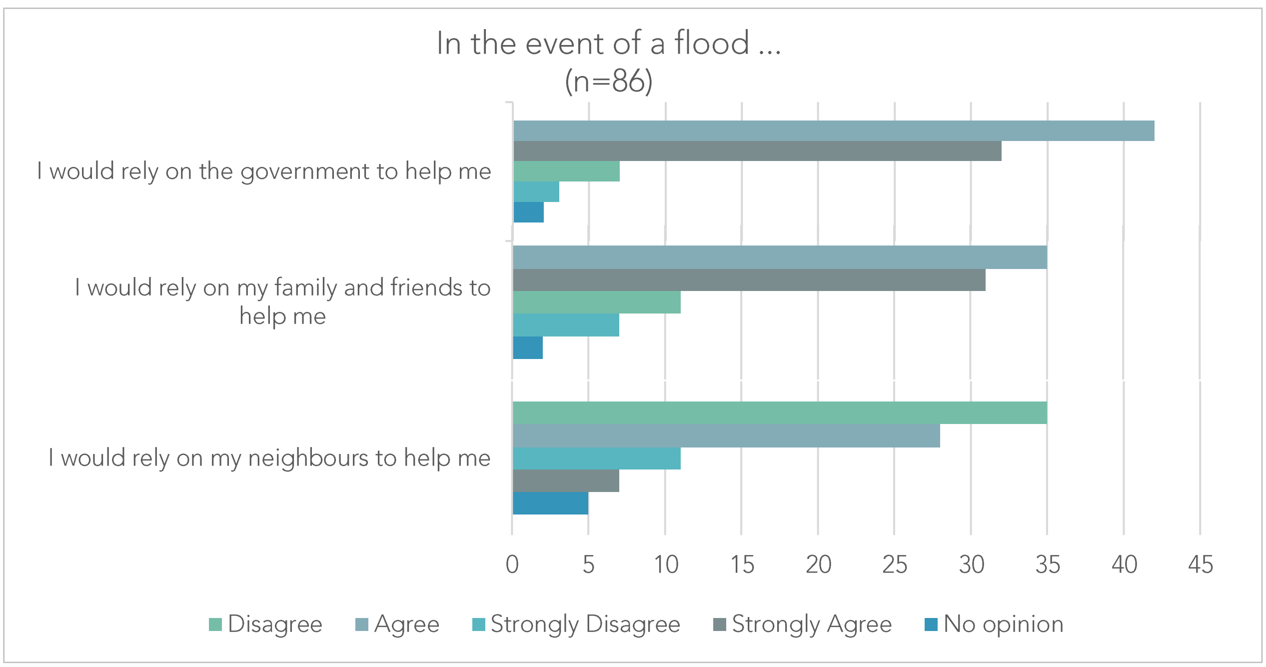


Figure 23. Resident survey results – reliance on networks

Experts emphasized the importance of neighbourhood connections during a crisis, which can often address the unique challenges that different people and households face (AI 2, NGOI 1, NGOI 2). There can be very different conditions between households even though they are situated next to one another, such as family structure, economic status, and even race, which will affect the capacities and needs between households (AI 1, AI 2, NGOI 2):

> "*My situation is so different from the situation of my neighbours even though we live directly next to each other. A single-parent family will face a very different set of challenges than their neighbours who are an elderly retired couple*" (AI 2).

Building community and neighbourhood relationships is not only important for understanding the capacities of individuals, but also for understanding the synergies that can be crucial in a time of crisis (AI 2, NGOI 1, NGOI 1).

> "*Building resilience should absolutely be addressed at the community level. You need to build a community of people who care for each other and think about people at the grassroots."* (NGOI 1)

These results indicate that neighbourhood connections are an important outcome of flood resilience that may require strategies to improve among residents in the City of Vancouver. This aligns with the priority in the Resilient Vancouver Strategy, which identified the need to improve neighbourhood preparedness and connections for more effective outcomes of resilience towards environmental shocks (City of Vancouver, 2019a).

6.3.4 Assessing Qualitative Perspectives and the SoRI

The SoRI is a quantitative assessment of flood resilience at the aggregate level (i.e., census data) that was used to measure the assumed capacities and abilities in Vancouver (Damude et al., 2015) (Figure 16). Through the semi-structured interviews, experts indicated agreement that social resilience to flooding was often understood based on social inequities that occur between different people and communities (AI 1, AI 2, NGOI 2). In the event of a flood, existing inequities would be magnified and disproportionately impact particular groups of people, such as people without insurance, elders who live alone and people who cannot speak English (AI 1, AI 2, NGOI 2). Local experts also voiced concerns over the disproportionate effects on vulnerable populations, such as those with health concerns:

> "*People would lose their valuables and be deeply inconvenienced, but people with serious health conditions would face a different type of crisis, as it could be terminally dangerous for them."* (AI 2)

Furthermore, they emphasized that the level of mental and psychological distress, such as why people with serious anxiety, would also be differentially impacted (AI 2, NGOI 1):

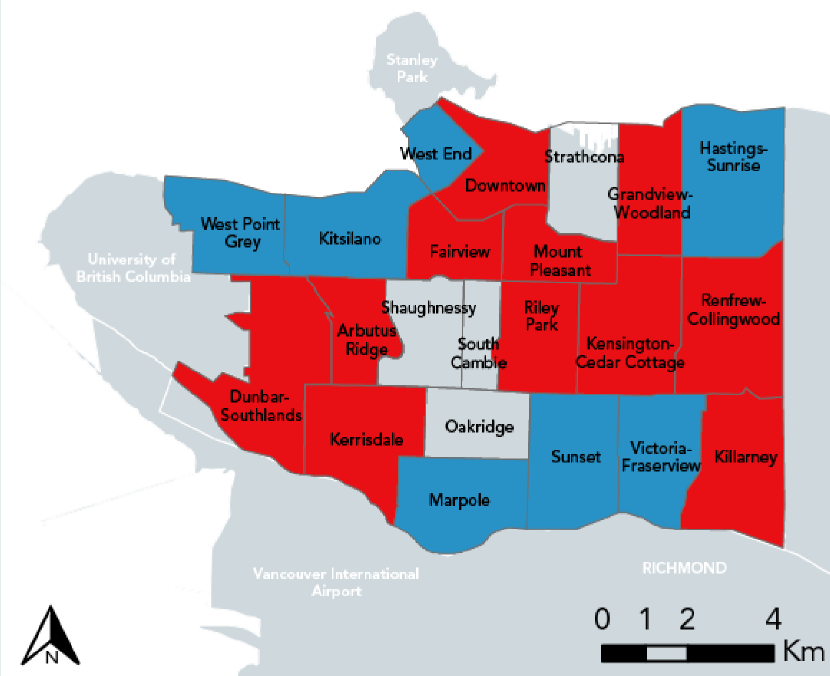
> "… *no attention is being given to take care of the people who are feeling emotional stress of knowing what's going on with climate change and the dangers of flooding."* (NGOI 1)

The experts emphasized that uneven access to resources, including access to services and information, creates differences in individual capacities and leads to disparities in flood resilience across the city (AI 1, AI 2).

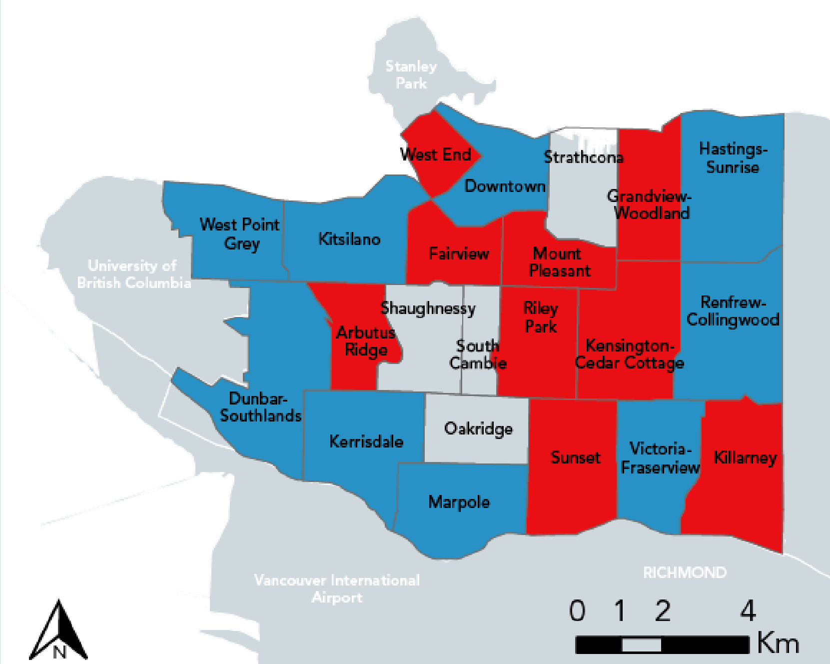
The residents' survey in this study was an exploratory qualitative assessment of flood resilience at the individual level to investigate the perceived capacity and abilities as identified by the residents themselves. The residents' survey identified the types of actions that were undertaken to protect against flood impacts, such as installing physical flood protection measures (Figure 18) and purchasing flood insurance (Figure 19 and Figure 20), to represent outcomes of social resilience. Respondents were asked to indicate the neighbourhood that they live in, which allowed a City of Vancouver neighbourhood to be attached to the responses (n=85 out of 116 responses). These neighbourhoods are an official spatial unit for the city, which are also known as local areas or local planning areas (City of Vancouver, 2019c).

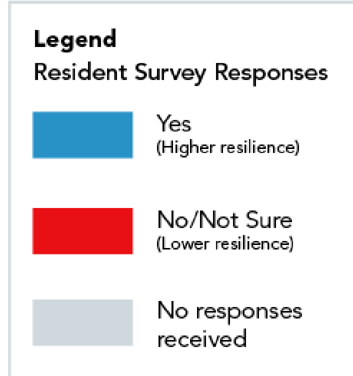
The mapping of residents' perspectives by neighbourhood (Figure 24) suggests that areas that have low resilience as measured by the SoRI (Figure 16) can be an area that has resilience by undertaking flood protection measures, and vice versa. For example, the Downtown and West End neighbourhoods are locally known to be more affordable (i.e., have lower income) and more culturally diverse, which results in lower resilience as measured by the SoRI. However, the resident responses in these neighbourhoods indicate that they can have resilience by implementing flood protection measures. The socioeconomic indicators used in the SoRI may influence how people receive, perceive and interpret risks, but they do not necessarily explain the willingness to take action to reduce such risks (Bronfman et al., 2008; Cutter & Morath, 2013; Phillips et al., 2006). While socioeconomic indicators of social resilience are quantifiable at various census scales, the risk perceptions and actions taken to address flood hazards do not occur and are not represented at these same scales. Consistent with findings from previous studies, the individual-level risk perceptions and household-level flood protection measures are aspects of social resilience that are not represented by aggregate census data (Hogarth et al., 2014; Sevoyan et al., 2013; Rickless et al., 2019). In other words, the quantitative metrics used to measure resilience do not necessarily represent the actual outcomes of resilience that are enacted in practice. It is important to note that small number of responses received per neighbourhood (i.e., between 1 to 10 responses) does not necessarily represent the outcomes of flood resilience of the entire neighbourhood. These results are intended to demonstrate the differences that can occur between quantitative assessments at the aggregate-level versus qualitative assessments at the individual-level, which affects the type of information that is imparted for informing planning and policy.

Have you taken any action(s) on your home or property to protect it from flooding?



Do you have flood insurance (water/sewer backup or overland flood insurance)?





Number of Responses per Vancouver Neighbourhood

Neighbourhood	No. of responses (n)
Arbutus Ridge	1
Downtown	10
Dunbar-Southlands	4
Fairview	2
Grandview-Woodland	5
Hastings-Sunrise	3
Kensington-Cedar Cottage	8
Kerrisdale	2
Killarney	5
Kitsilano	9
Marpole	7
Mount Pleasant	7
Oakridge	0
Renfrew-Collingwood	4
Riley Park	5
Shaughnessy	0
South Cambie	0
Strathcona	0
Sunset	3
Victoria-Fraserview	5
West End	4
West Point Grey	1

Figure 24. Outcomes of social resilience from resident survey by neighbourhood

6.4 Discussion

The qualitative assessment of flood resilience at the individual household-level revealed perceptions and perspectives of residents that can have implications for inform planning and policy initiatives in Vancouver. Most residents indicated that they do not feel prepared and do not think that they have the resources to respond to a flood. Yet, over half of the respondents were able to indicate some type of resource to prepare and respond to a flood, including daily necessities, physical flood protection supplies, and emergency procedures and communication (Table 22). This suggests that residents are aware of potential flood risks but they lack the resources they require to respond to a flood. Planning and risk management efforts to build flood resilience in Vancouver could be directed at improving public knowledge towards flood response and improving access to the resources that residents require to respond to a flood. Another priority area for building resilience in Vancouver is to improve neighbourhood connections and cohesion among residents. The efforts to quantify social resilience should also include indicators of knowledge and awareness, which may be just as important as economic indicators that represent the financial capital and assets that may be available to respond to a flood.

Experts expressed that social resilience is attributed to social inequities and unequal access to resources, which leads to differences in individual capacities to prepare for, cope with and recover from, flood impacts. This aligns with the use of metrics and indices that were developed to quantify resilience based on individual- and household-level differences, which can be influenced by differential access to resources (Cutter et al., 2008; Damude et al., 2015; Oulahen et al., 2015; Rickless et al., 2019). The factors that experts believed were most important for developing social resilience, did not necessarily align with the perceptions of residents. While experts emphasized neighbourhood connections for developing flood resilience, there was less agreement found among residents (Figure 23). This demonstrates that theoretical knowledge may not necessarily align with the residents' perceptions of their capacities and understandings of flood resilience. Experts aim to enhance resilience in practice such as through planning and policy whereas residents undertake the actions to achieve resilience in reality. Comparing the perspectives between these two distinct groups can support the development of more targeted strategies for building resilience, such as improving neighbourhood cohesion and reliance in Vancouver.

The issue of scale in understanding flood resilience is attributed to the different types of information that can be collected at the aggregate-level versus at the individual-level. Quantitative analyses at the aggregate-level can be useful for measuring and identifying relative levels of resilience between geographic areas and populations. This information can be used to inform planning and policy for *where* to direct efforts to enhance resilience. Qualitative analyses at the individual household-level can be useful for identifying the perceptions and needs of the residents and community members. This information can be used to inform *what* planning and policy efforts can address to build resilience. Qualitative perspectives may not only provide more detailed insights to inform policy efforts but may also offer a complementary approach to quantitative assessments of flood resilience. The implications of scale should be interpreted in the context of the initial problem itself, that assessments of resilience should not only be focused on measuring resilience, but also understanding the underlying factors to build resilience.

6.5 Limitations & Future Research Directions

Due to logistical constraints with participant recruitment due to COVID-19, the small sample of expert interviews (n=4) were used as an exploratory analysis to demonstrate the use of qualitative methods to uncover insights that can contribute to the understanding of flood resilience. Future studies could compare and contrast the perspectives of practitioners, such as municipal staff, with the perspectives of residents to further uncover how planning and policy efforts can enhance resilience to flooding, as well as resilience towards other environmental hazards.

Due to the low response rate per neighbourhood for the residents' survey, the results in Figure 24 were not intended for identifying priority areas, but were intended to demonstrate a proof-of-concept. The information illustrated in Figure 24 is aggregated from the individual-level survey responses into the Vancouver neighbourhood units. In the survey, respondents were asked to indicate their neighbourhood of residence, so that a spatial component could be attached to their responses while ensuring confidentiality. This highlights a limitation but also an implication of analyses at the individual-level, that the results will always be subject to some degree of generalization or aggregation in order to maintain confidentiality. Similarly, census data is also aggregated from individual household-level responses into aggregate units at varying census scales. Since this is a constraint of areal data sources, future studies perhaps should not be focused on finding the "perfect" scale, but rather to understand the various types of information that can be retrieved at different scales.

It is important to recognize that both quantitative and qualitative assessments of flood resilience provide a static "snapshot" at a specific time of something that may be a dynamic process. The SoRI was constructed based on 2011 census data, which is not comparable with the survey and interview responses that took place from May to July 2020. The results in this study were intended to explore the types of information that is available at different scales, and not to evaluate which assessment is more accurate for representing flood resilience. This is a limitation but also a consequence of any analysis that measures a "state", such as the state of flood resilience. Furthermore, the measurement or quantification of resilience is still largely debated in the literature. Future studies could explore the temporal aspect of social resilience to flooding and investigate its implications for informing planning and policy. For example, should social resilience to environmental hazards be measured every 5 years (i.e., to align with the census)? Another avenue of research could investigate the capacities before a flood (i.e., planning and preparedness), during a flood (i.e., responding, coping and adapting) and after the event (i.e., recovery and adaptive transformation), and how these temporal aspects may relate to the spatial analyses of social flood resilience.

Future research could also consider investigating the role of risk perception compared to the role of preparedness towards flood resilience. This study assumed that the perception of flood risk led to some degree of preparedness, such as taking action to protect their homes against flooding. However, there may be factors that may distinctly affect only one or the other. For instance, an individual may have experienced a previous flood event and perceive it as a risk (i.e., role of risk perception) but choose not to take action (i.e., role of preparedness). These perceptions may be related to socioeconomic characteristics, which are also influential towards flood resilience. Future studies could also delineate the role of socioeconomic indicators versus risk perceptions and preparedness towards flood resilience and determine whether both elements contribute equally to understanding flood resilience (i.e., is one more important or more representative of resilience than the other?).

6.6 References

Baxter, J. & Eyles, J., 1997. Evaluating Qualitative Research in Social Geography: Establishing 'Rigour' in Interview Analysis. *Transactions of the Institute of British Geographers,* 22(4), pp. 505-525.

Bird, D. & Dominey-Howes, D., 2008. Testing the use of a 'questionnaire survey instrument' to investigate public perceptions of tsunami hazard and risk in Sydney, Australia. *Nat Hazards*, 45, pp. 99-122.

Bird, D. K., 2009. The use of questionnaires for acquiring information on public perception of natural hazards and risk mitigation – a review of current knowledge and practice. *Nat. Hazards Earth Syst. Sci.*, 9, pp. 1307-1325.

Blaikie, P., and Brookfield, H., 1987. *Land Degradation and Society*. London: Methuen & Co. Ltd.

Bronfman, N. C., Cifuentes, L. A., & Gutiérrez, 2008. Participant-focused analysis: explanatory power of the classic psychometric paradigm in risk perception. *Journal of Risk Research,* 11(6), pp. 735-753.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A. & von Winterfeldt, D., 2003. A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, 19(4), pp. 733-752.

Cannon, T., 1994. Vulnerability Analysis and the Explanation of 'Natural' Disasters. In: A. Varley, ed. 1994. *Disasters, Development and Environment*. London: John Wiley & Sons Ltd., pp. 8-15.

City of Vancouver, 2018. *Preliminary Resilience Assessment*. Vancouver: City of Vancouver. [online]. Available at: <https://vancouver.ca/files/cov/resilient-vancouver-2018-preliminary-resilience-assessment.pdf> [Accessed 11 June 2020].

City of Vancouver, 2019a. *Resilient Vancouver Strategy*. Vancouver: City of Vancouver. [online] Available at: <https://vancouver.ca/files/cov/resilient-vancouver-strategy.pdf> [Accessed 15 January 2020].

City of Vancouver, 2019b. *Emergency Preparedness Survey 2019 Summary Report.* Vancouver: City of Vancouver. [online] Available at: < https://www.talkvancouver.com/MediaServer/126/documents/EmergencyPreparedness2019_SurveySummaryReport_5June2019.pdf> [Accessed 28 July 2020].

City of Vancouver, 2019c. *Local area boundary.* Vancouver: City of Vancouver. [online] Available at: <https://opendata.vancouver.ca/explore/dataset/local-area-boundary/information/> [Accessed 6 Nov 2020].

Cutter, S. L., 1996. Vulnerability to environmental hazards. *Progress in Human Geography*, 20(4), pp. 529-539.

Cutter, S. L., Mitchell, J. T. & Scott, M. S., 2000. Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. *Annals of the Association of American Geographers*, 90(4), pp. 713-737.

Cutter, S. L., Boruff, B. J. & Shirley, W. L., 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly*, 84(2), pp. 242-261.

Cutter, S., L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E. & Webb, J., 2008. A place-based model for understanding community resilience to natural disasters. *Global Environmental Change*, 18, pp. 598-606.

Cutter, S. L., Burton, C. G. & Emrich, C. T., 2010. Disaster Resilience Indicators for Benchmarking Baseline Conditions. *Journal of Homeland Security and Emergency Management, 7(1), Article 51*.

Cutter, S.L. & Morath, D.P., 2013. The evolution of the Social Vulnerability Index (SoVI). In: J. Birkmann, ed. 2013. *Measuring Vulnerability to Natural Hazards*. Tokyo, New York, Paris: United Nations University Press. Ch. 12.

Cutter, S. L., Ash, K. D. & Emrich, C. T., 2014. The geographies of community disaster resilience. *Global Environmental Change*, 29, pp. 65-77.

Cutter, S. L., Ash, K. D. & Emrich, T., 2016. Urban-Rural Differences in Disaster Resilience. *Annals of the American Association of Geographers,* 106(6), pp. 1236-1252.

Cutter, S. L., 2016. The landscape of disaster resilience indicators in the USA. *Natural Hazards*, 80, pp. 741-758.

Damude, K., Mortsch, L. & Joakim, E., 2015. *Draft Report: Methods for Quantifying Social Resilience in Metro Vancouver, Canada*. Ontario: Coastal Cities at Risk (CCaR) Project.

Frerks, G., Warner, J. & Weijs, B., 2011. The Politics of Vulnerability and Resilience. *Ambiente & Sociedade*, 14(2), pp. 105-122.

Hebb, A. & Mortsch, L., 2007. *Floods: Mapping Vulnerability in the Upper Thames Watershed under a Changing Climate*. CFCAS Report: Assessment of Water Resources Risk and Vulnerability to Changing Climate Conditions. Project Report XI.

Hewitt, K., 1983. *Interpretations of calamity from the viewpoint of human ecology*. London: Allen & Unwin Inc.

Hogarth, J. R., Campbell, D. & Wandel, J., 2014. Assessing Human Vulnerability to Climate Change from an Evolutionary Perspective. In: Z. Zommers & A. Singh, eds. *Reducing Disaster: Early Warning Signs*. Dordrecht: Springer, pp. 63-87.

IBC (Insurance Bureau of Canada), 2019. *A Primer on Severe Weather and Overland Flood Insurance in Canada*. Toronto: Insurance Bureau of Canada. [online] Available at: < http://assets.ibc.ca/Documents/Resources/A-Primer-on-Severe-Weather-in-Canada.pdf> [Accessed 27 Sep 2020].

IPCC (Intergovernmental Panel on Climate Change), 2014. Annex II Glossary. In: V. Barros, et al. eds. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects*. United Kingdom, New York: Cambridge University Press, pp. 1757 – 1776.

Joakim, E. P., Mortsch, L. & Oulahen, G., 2015. Using vulnerability and resilience concepts to advance climate change adaptation. *Environmental Hazards*, 14(2), pp.137-155.

Joakim, E. P., Mortsch, L., Oulahen, G., Harford, D., Klein, Y., Damude, K. & Tang, K., 2016. Using system dynamics to model social vulnerability and resilience to coastal hazards. *International Journal of Emergency Management*, 12(4), pp. 366-391.

Jones, L. & Tanner, T., 2017. 'Subjective resilience': using perceptions to quantify household resilience to climate extremes and disasters. *Regional Environmental Change*, 17, pp. 229-243.

Jones, L., Samman, E. & Vinck, P., 2018. Subjective measures of household resilience to climate variability and change: insights from a nationally representative survey of Tanzania. *Ecology and Society*, 23(1):9.

Keck, M. & Sakdapolrak, P., 2013. What is social resilience? Lessons learned and ways forward. *Erkunde*, 67(1), pp. 5-19.

Lerch, D., 2015. *Six Foundations for Building Community Resilience*. California: Post Carbon Institute. [online] Available at: <https://www.scribd.com/document/290100841/Six-Foundations-for-Building-Community-Resilience-2015#fullscreen&from_embed> [Accessed 6 February 2020].

Mendelson, R., 2001. *Geographic Structure As Census Variables: Using Geography to Analyse Social and Economic Processes*. Statistics Canada Geography Working Paper Series Catalogue no. 92F0138MIE. Ottawa: Statistics Canada. [online] Available at: <https://www150.statcan.gc.ca/n1/en/pub/92f0138m/92f0138m2001001-eng.pdf?st=Hpe_u6Jb> [Accessed 19 April 2019].

Mercer Clarke, C., Manuel, P. & Warren, F., 2016. The Coastal Challenge. In: C. Mercer Clarke, P. Manuel & F. Warren, eds. *Canada's Marine Coasts in a Changing Climate*. Ottawa: Government of Canada, pp. 69-98.

Morrow, B. H., 2008. *Community Resilience: A Social Justice Perspective*. Oak Ridge: Community and Regional Resilience Initiative (CARRI). [online] Available at: < https://www.researchgate.net/publication/280611548_Community_resilience_A_social_justice_perspective> [Accessed 6 July 2020].

Openshaw, S., 1984. The Modifiable Areal Unit Problem. *Concepts and Techniques in Modern Geography No. 38 ed*. Norwich: GeoBooks.

Oulahen, G., Mortsch, L., Tang, K. & Harford, D., 2015. Unequal Vulnerability to Flood Hazards: "Ground Truthing" a Social Vulnerability Index of Five Municipalities in Metro Vancouver, Canada. *Annals of the Association of American Geographers*, 105(3), pp. 473-495.

Phillips, B., Metz, W. & Nieves, 2006. Disaster threat: preparedness and potential response of the lowest income quartile. *Environmental Hazards*, 6, pp. 123-133.

Prouse, V., Ramos, H., Grant, J. L. & Radice, M., 2014. How and when scale matters: the modifiable areal unit problem and income inequality in Halifax. *Canadian Journal of Urban Research*, 23(1), pp. 61-82.

PSC (Public Safety Canada), 2019. *Emergency Management Strategy for Canada – Toward a Resilient 2030*. Ottawa: Government of Canada. [online] Available at: <https://www.publicsafety.gc.ca/cnt/rsrcs/pblctns/mrgncy-mngmnt-strtgy/mrgncy-mngmnt-strtgy-en.pdf> [Accessed 10 October 2020].

Rickless, D. S., Yao, X. A., Orland, B. & Welch-Devine, M., 2019. Assessing Social Vulnerability through a Local Lens: An Integrated Geovisual Approach. *Annals of the American Association of Geographers*, 0(0), pp. 1-20.

Robinson, W.R., 1950. Ecological Correlation and the Behaviour of Individuals. *American Sociological Review*, 15, pp. 351-357.

Sandink, D., 2011. *Involving Homeowners in Urban Flood Risk Reduction. A Case Study of the Sherwood Forest Neighbourhood, London, Ontario*. Toronto: Institute for Catastrophic Loss Reduction.

Sayers, P.B., Horritt, M., Penning Rowsell, E. and Fieth, J., 2017. *Present and future flood vulnerability, risk and disadvantage: A UK scale assessment. A report for the Joseph Rowntree Foundation.* Watlington: Sayers and Partners LLP. [online] Available at: <http://www.sayersandpartners.co.uk/uploads/6/2/0/9/6209349/sayers_2017_-_present_and_future_flood_vulnerability_risk_and_disadvantage_-_final_report_-_uploaded_05june2017_printed_-_high_quality.pdf> [Accessed 26 February 2020].

Saunders, P., Naidoo, Y. & Griffiths, M., 2007. *Towards New Indicators of Disadvantage: Deprivation and Social Exclusion in Australia*. Sydney: Social Policy Research Centre. [online]. Available at: <

https://www.researchgate.net/publication/215441466_Towards_New_Indicators_of_Disadvantage_Deprivation_and_Social_Exclusion_in_Australia> [Accessed 11 June 2020].

Schmidtlein, M. C., Deutsch, R. C., Piegorsch, W. W. & Cutter, S. L., 2008. A Sensitivity Analysis of the Social Vulnerability Index. *Risk Analysis,* 28(4), pp. 1099-1114.

Sevoyan, A., Hugo, G., Feist, H., Tan, G., McDougall, K., Tan, Y. and Spoehr, J., 2013. *Impact of Climate Change on Disadvantaged Groups: Issues and Interventions*. Adelaide: National Climate Change Adaptation Research Facility.

Slovic, P., 1992. Perceptions of Risk: Reflections on the Psychometric Paradigm. In: D. Golding & S. Krimsky, eds. *Theories of Risk*. New York: Praeger, pp. 117-152.

Spielman, S. E., Tucillo, J., Folch, D. C., Schweikert, A., Davies, R., Wood, N. & Tate, E., 2020. Evaluating social vulnerability indicators: criteria and their application to the Social Vulnerability Index. *Natural Hazards*, 100, pp. 417-436.

Susman, P., O'Keefe, P & Wisner, B., 1983. Global disasters, a radical interpretation. In: K. Hewitt, ed. 1983. *Interpretations of Calamity from the viewpoint of human ecology*. London: Allen & Unwin Inc. Ch.14.

Thistlethwaite, J., 2017. The Emergence of Flood Insurance in Canada: Navigating Institutional Uncertainty. *Risk Analysis*, 37(4), pp. 774-755.

Twigg, J., 2009. *Characteristics of a Disaster-Resilient Community*. London: University College London Hazard Centre. [online] Available at: < https://discovery.ucl.ac.uk/id/eprint/1346086/1/1346086.pdf> [Accessed 2 June 2020].

UNDRR (United Nations Office for Disaster Reduction), 2004. *Living with Risk: A Global Review of Disaster Reduction Initiatives - Volume II Annexes*. Geneva: UN Publications. [online] Available at: <https://www.preventionweb.net/files/657_lwr21.pdf> [Accessed 6 February 2020].

UNDRR (United Nations Office for Disaster Reduction), 2015. *Sendai Framework for Disaster Risk Reduction 2015 – 2030*. Sendai: UN Publications. [online] Available at: <https://www.preventionweb.net/files/43291_sendaiframeworkfordrren.pdf> [Accessed 1 October 2020].

White, G.F., 1942. Human Adjustment to Floods: A Geographical Approach to the Flood Problem in the United States. In: W. Calef, ed. 1945. *The University of Chicago: Department of Geography Research Papers*. Chicago: The University of Chicago.

Wisner, B., Blaikie, P., Cannon, T. and Davis, I., 2004. *At risk: natural hazards, people's vulnerability and disasters*. Reprint 2004. New York: Routledge.

7.0 Conclusions

This research investigated the implications of scale when using quantitative and qualitative assessments of flood resilience for informing disaster risk management and climate change adaptation. The first manuscript (chapter 2) investigated the implications of scale on the Social Resilience Index (SoRI) by Damude et al. (2015) which is a quantitative measure of flood resilience based on aggregate census data. The second manuscript (chapter 4) investigated the effects of spatial scale and the methods used to construct the SoRI. The third manuscript (chapter 6) explored a qualitative assessment of flood resilience at the individual-level based on resident perceptions and expert insights in the City of Vancouver. This chapter summarizes the findings and overall contributions of this research.

7.1.1 The Modifiable Areal Unit Problem (MAUP)

When constructing the SoRI, this study identified that the larger census unit was more suitable for representing statistical results, whereas the smaller census unit scale may be more suitable for representing the spatial distribution of the SoRI. In the absence of a standard geographic unit for conducting socioeconomic research, Openshaw (1984) and Fotheringham & Wong (1991) noted that the modifiable areal unit problem (MAUP) was often readily assumed to be negligible with no significant impact on the analytical results. However, this study has demonstrated that mapping the SoRI using different census scales can yield significantly different patterns of social resilience. The same dataset, when analyzed using different methods of index construction can identify different priority areas – both in the number of priority areas and the physical location of these priority areas (i.e., areas having low resilience). Differences between the SoRI were not expected to be contradictory, where an area having high resilience at one scale could simultaneously have the lowest resilience at the other scale, and vice versa. This indicates a serious implication to decisionmakers when using quantitative indices to inform policy and allocate resources to enhance resilience. The inconsistencies observed for the SoRI forewarn that mapping exercises of other indices based on census data may also be subject to scale effects of the MAUP and may require further investigation before it is used to inform planning and policy. The MAUP is therefore not always a negligible phenomenon and can have a significant impact on small area statistical results and conclusions.

7.1.2 The Effects of Scale and Methods on Construction of the SoRI

Construction of the SoRI using the data-driven principal components analysis (PCA) method (i.e., *PCAoriginal*) indicated contrasting results between census scales which manifested scale effects. A SoRI variable that contributes positively to the SoRI at one scale, could simultaneously contribute negatively to the SoRI at another scale. The directionality of variables also contradicted their postulated relationships, where variables that contribute positively (i.e., increase resilience), would ultimately contribute negatively (i.e., decrease resilience) when the SoRI was constructed by the PCA method. Different variables could also contribute to the SoRI depending on the census scale that was chosen. When using the PCA method of index construction, extracting principal components (PCs) from the scree plot offers a more stable and intuitive representation of the SoRI. The results from this study suggest that scale effects are further propagated through the PCA method of index construction (Reckien, 2018; Spielman et al., 2020).

When using the PCA method of index construction, the results were found to contradict previous findings from MAUP literature. Across all study areas, the results of the PCA tests consistently indicated that the larger census unit (i.e., CTs in Vancouver and Los Angeles and DZs in Edinburgh) captured a higher percentage of variance than the corresponding smaller census unit (see section *2.3.3 Scale Effects on the SoRI*). This is contradictory to MAUP literature, which found that larger areal units were subject to more generalizations and thus lower variances (Fotheringham & Wong, 1991; Openshaw & Taylor, 1979; Openshaw, 1984; Prouse et al., 2014; Wong et al., 1999). The sensitivity to scale effects of the MAUP therefore appears to be dependent on the specific combination of input variables (i.e., 14 variables for Vancouver) along with specific index construction methods (i.e., *PCAoriginal*). Each study area had a different number of input variables to construct the SoRI due to data constraints from their respective census programs. This is consistent with previous findings, where the effects of the MAUP in multivariate analyses were largely unpredictable (Fotheringham & Wong, 1991).

In the absence of individual-level data, the stakeholder-driven multi-criteria analysis (MCA) method is an alternate method of constructing the SoRI that is less sensitive to scale effects of the MAUP. Construction of the SoRI using the stakeholder-driven MCA method resulted in less contrasting results between census scales, including a more consistent interpretation of the Moran's I statistic between census scales. From a theoretical perspective, the use of an index inherently assumes that each input variable explains a different element of resilience in the overall index. Therefore, a summation of the input variables in the MCA method is an attempt to combine the different factors that all inherently contribute to the same theme (i.e., resilience) being measured (Reckien, 2018). The stakeholder-driven MCA method of constructing the SoRI offers a more stable and reliable method for identifying priority areas (i.e., areas of low resilience) to inform planning and policy efforts.

7.1.3 Flood Resilience Perspectives and Insights in the City of Vancouver

This study explored the use of qualitative methods, including surveys and interviews, to collect flood resilience perspectives at the individual-level, from experts and Vancouver residents. The qualitative perspectives of residents revealed their perceived capacity or the levels of flood resilience that were based on their own perceptions, which can be important for building and achieving resilience in reality. The results indicate that efforts to build flood resilience in Vancouver should consider improving residents' access to resources that they required to respond to a flood, improving public knowledge and awareness on the available flood protection options, and enhancing neighbourhood connections and cohesion. While experts emphasized the importance of neighbourhood connections and cohesion as a barrier to flood preparedness and recovery, there was a large divide among the residents' reliance on their neighbours in the event of a flood. This raises an important implication that theoretical knowledge (i.e., expert insights) may not necessarily align with the perceptions of individuals in actuality (i.e., resident perceptions).

The perceived capacity of Vancouver residents did not necessarily align with the assumed resilience that quantitative metrics, such as the SoRI, were intended to measure. An area that has low resilience as measured by the SoRI, could have resilience by undertaking flood protection measures, and vice versa. These results support the findings from previous literature, that aggregate socioeconomic data, no matter how fine the spatial scale, do not explain the local dimensions nor the differences in perceptions that can affect resilience (Bronfman et al., 2008; Hogarth et al., 2014; Rickless et al., 2019). The implications of the scale of analysis was supported through two main findings in this study: 1) the resident survey results suggest that outcomes of resilience, such as the actions taken to protect against flood hazards, are not necessarily represented by quantitative metrics such as the SoRI; and 2) the results from the expert interviews and international and national disaster risk management strategies and official city documents suggest that building resilience against environmental hazards also occur at the local level. If building resilience occurs through local policy and locality-specific initiatives, then the efforts to quantify resilience should intuitively also occur at the same scale. This study demonstrated a proof-of-concept that incorporating local, nonexpert knowledge can not only reveal alternate patterns of resilience, but also uncover the underlying factors that can inform resilience efforts, such as improving neighbourhood connections and cohesion among residents in Vancouver.

7.2 Contributions of the Study

This research demonstrated that quantitative mapping exercises of the SoRI are subject to scale effects of the MAUP which led to variations in the information imparted at different census scales, and ultimately impeded meaningful interpretation of the results. However, the findings in this study also indicated that scale effects can be mitigated by selecting a specific method to extract PCs in a PCA and by using an alternate method of index construction that is based on stakeholder input (i.e., MCA). This indicates an implication of spatial analysis, that scale effects may require additional investigation, but it should not be considered an insoluble problem. As quoted by Jelinski and Wu (1996), "*…the MAUP is not really a 'problem', per se; rather it may reflect the 'nature' of the real systems that are hierarchically structured*" (Jelinski & Wu, 1996, p. 138). Openshaw (1984) concludes that the MAUP should be used as a tool for analyzing the structure of areal datasets and for understanding the implications of the spatial component in numerical analyses. Future studies perhaps should not be fixated on discovering the single "solve-all" solution to resolve the MAUP, but rather to further understand and quantify its implications in spatial analysis.

The MAUP will persist in studies and analyses based on aggregate data because the process of aggregation and generalization is a method of maintaining confidentiality. Since the use of disaggregate, individual-level census data is not a viable solution for social resilience indices, future analyses could report the analytical results at different spatial scales (i.e., census scales) and incorporate the use of local contexts for the areas that appear contradictory between scales. In the context of social flood resilience, disaster risk management and climate change adaptation also do not occur at the individual-level, but rather at aggregate units, such as communities and neighbourhoods. Using qualitative approaches to understand the local contexts, such as using surveys and interviews, can be supplementary to quantitative analyses to inform planning and policy efforts to enhance social flood resilience.

The implications of scale in assessments of flood resilience are manifested in the types of data that are available at different scales. Quantitative assessments, such as the SoRI, are derived from census data which represents flood resilience at the aggregate level. These assessments are useful for identifying priority areas (i.e., areas having low resilience), to inform *where* planning and policy efforts can be directed. Qualitative assessments, such as surveys and interviews, are derived from individual perspectives and responses, which represents flood resilience at the individual-level. These assessments are useful for identifying *what* planning and policy efforts should address to build resilience. These analyses should not be an alternative to one another, but rather supplementary, to better inform planning and policy initiatives that can measure and ultimately build resilience to flood hazards.

The issue of scale in social flood resilience assessments is further linked to an uncertainty between the spatial units that inferences are drawn from (i.e., census units) and the behavioural units that represent the true and unknown spatial extents of the underlying processes (Brunsdon, 2009; Kwan, 2012). The delineation of census units does not affect the spatial entities contained within them and simply serve as operational requirements for the census and government administration (Openshaw, 1984). This spatial uncertainty, called the uncertain geographic context problem (UGCoP), is caused by making individual-level inferences based on spatial contexts that occur and are measured at the aggregate-level. The spatial and temporal contexts of social flood resilience are dynamic and are not captured or represented by the units in which they are measured (Kwan, 2012). While this was not explicitly investigated in this study, the UGCoP may have implications in the use of aggregate census data to infer social flood resilience. However, this study has also demonstrated that incorporating the use of local contexts using qualitative assessments (Chapter 6.0) may be a solution to mitigate these uncertainties. As noted in Kwan (2012), understanding the geographic contexts and dynamics across space and time can contribute to mitigating both the UGCoP and the MAUP, which can further improve assessments of social flood resilience.

7.3 Future Study Directions

The effects of the MAUP and index construction methods can be further explored by conducting similar analyses with more recent datasets. For example, starting from the 2016 census, Statistics Canada introduced a rule that delineates CTs to be as homogeneous as possible in terms of socioeconomic characteristics (Statistics Canada, 2016). This rule could have implications for the PCA since it requires the initial dataset be free of outliers, this new rule would further reduce potential outliers in census data. Another data-driven research approach may be to use multi-level modelling of hierarchical census scales across different census programs to investigate the MAUP.

It is important to recognize that the definition and measurement of resilience as some quantifiable outcome or characteristic, is largely debated in the literature. There is no single definition, index, or methodology that is agreed upon. The concept of resilience to environmental hazards is fraught with complexity, as it is multidimensional, multidisciplinary and context specific. It is a common critique when defining the concept of resilience – resilience *of what* (e.g., households, communities, cities, etc.) *to what* (e.g., floods, earthquakes, landslides) and at what *scale* (e.g., local, provincial, national). The tools and methods used to measure resilience are largely subjective (*see also* Spielman et al., 2020). From the definition of resilience (*see* Bruneau et al., 2003; Joakim et al., 2015), to selection of indicator variables (*see* Cutter 2008; Feldmeyer et al., 2019; Morrow, 2008), to the relative importance of each variable (*see* Oulahen et al., 2015) to how each of these variables are represented (e.g., percentage of population or people/km^2) (*see* Reckien, 2018) are all subject to numerous debates. In this research, "social" resilience was a broad term encompassing the inherent, non-physical characteristics of different populations. However, many of the references cited in this paper have different conceptualizations of these characteristics. For instance, this study considered household income as a component of social resilience since it is derived from census data, which is a social survey, but several others (i.e., Bruneau et al., 2003; Cutter et al., 2014) have considered income to be an economic dimension that is distinct from the social dimension. The SoRI also did not contain variables that previous literature has identified as important indicators for resilience, such as those relating to education, populations with disabilities, and mobility. While the scope of this study was not to test whether these are "correct" measures of resilience, it highlighted the importance of uncovering whether or not these measurements of resilience actually translate into societal outcomes. Future studies can investigate the local contexts in different study areas to validate the robustness of the survey results from this study. Another avenue of research could be to further explore qualitative perspectives and local contexts from experts and practitioners to verify the input variables in identifying resilience and the final mapped results.

8.0 References

100RC (100 Resilient Cities), 2019. *Resilient Cities, Resilient Lives – Learning from the 100RC Network*. New York, London, Mexico City, Singapore: 100 Resilient Cities. [online] Available at: <http://100resilientcities.org/wp-content/uploads/2019/07/100RC-Report-Capstone-PDF.pdf> [Accessed 2 June 2020].

Anselin, L., 2017. Spatial Regression – Introduction & Review (SOCI 40217). Chicago: The Center for Spatial Data Science (University of Chicago).

Amrhein, C.G., 1995. Searching for the elusive aggregation effect: evidence from statistical simulations. *Environment and Planning A*, 27, pp. 105-119.

Birkmann, J., 2013. *Measuring Vulnerability to Natural Hazards*. Tokyo, New York, Paris: United Nations University Press.

Blaikie, P., and Brookfield, H., 1987. *Land Degradation and Society*. London: Methuen & Co. Ltd.

Blaikie, P., Cannon, T., Davis, I., Wisner, B., 1994. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. 1st ed. London: Routledge.

Briguglio, L., 2003. *The Vulnerability Index and Small Island Developing States - A Review of Conceptual and Methodological Issues.* Malta: University of Malta.

Bronfman, N. C., Cifuentes, L. A., & Gutiérrez, 2008. Participant-focused analysis: explanatory power of the classic psychometric paradigm in risk perception. *Journal of Risk Research,* 11(6), pp. 735-753.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A. & von Winterfeldt, D., 2003. A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, 19(4), pp. 733-752.

Brunsdon, C., 2009. Statistical Inference for Geographical Processes. In: A.S. Fotheringham & P. A. Rogerson, eds. 2009. *The SAGE Handbook of Spatial Analysis*. London: SAGE Publications Ltd., pp. 207-224.

Buckle, P., Mars, G. & Smale, S., 2000. New Approaches to Assessing Vulnerability and Resilience. *Australian Journal of Emergency Management*, 15(2), pp. 8-14.

Cannon, T., 1994. Vulnerability Analysis and the Explanation of 'Natural' Disasters. In: A. Varley, ed. 1994. *Disasters, Development and Environment*. London: John Wiley & Sons Ltd., pp. 8-15.

Carrington, A., Rahman, N. & Ralphs, M., 2018. *The Modifiable Areal Unit Problem: Research Planning.* (NSMAC 11, 11th Meeting of the National Statistics Methodology Advisory Committee). South Wales: Office for National Statistics. Available at: https://www.ons.gov.uk/ons/guide-method/method-quality/advisory-committee/2005-2007/eleventh-meeting/the-modifiable-areal-unit-problem--research-planning.pdf [Accessed 15 September 2019].

Chakraborty, J., Tobin, G. & Montz, B., 2005. Population evacuation: assessing spatial variability in geophysical risk and social vulnerability to natural hazards. *Natural Hazards Review* 6(1): 23-33.

Chambers, R., 1989. Editorial Introduction: Vulnerability, Coping and Policy. IDS Bulletin, 20(2), pp. 1-7.

City of Los Angeles, 2018. *Resilient Los Angeles*. Los Angeles: Mayor's Office of Resilience. [online] Available at: <https://www.lamayor.org/sites/g/files/wph446/f/page/file/Resilient%20Los%20Angeles.pdf> [Accessed 6 February 2020].

City of Vancouver, 2018. *Preliminary Resilience Assessment*. Vancouver: City of Vancouver. [online]. Available at: <https://vancouver.ca/files/cov/resilient-vancouver-2018-preliminary-resilience-assessment.pdf> [Accessed 11 June 2020].

City of Vancouver, 2019. *Resilient Vancouver Strategy*. Vancouver: City of Vancouver. [online] Available at: <https://vancouver.ca/files/cov/resilient-vancouver-strategy.pdf> [Accessed 15 January 2020].

Clark, W.A.V. & Avery, K.L., 1976. The effects of data aggregation in statistical analysis. *Geographical Analysis*, 8, pp. 428-438.

Cutter, S. L., 1996. Vulnerability to environmental hazards. *Progress in Human Geography*, 20(4), pp. 529-539.

Cutter, S., Mitchell, J. & Scott, M., 2000. Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. *Annals of the Association of American Geographers*, 90(4), pp. 713-737.

Cutter, S. L., Boruff, B. J., & Shirley, W. L., 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly*, 84(2), pp. 242-261.

Cutter, S., L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E. & Webb, J., 2008. A place-based model for understanding community resilience to natural disasters. *Global Environmental Change*, 18, pp. 598-606.

Cutter, S. L., Burton, C. G. & Emrich, C. T., 2010. Disaster Resilience Indicators for Benchmarking Baseline Conditions. *Journal of Homeland Security and Emergency Management*, 7(1), Article 51.

Cutter, S. L., Ash, K. D. & Emrich, C. T., 2014. The geographies of community disaster resilience. *Global Environmental Change*, 29, pp. 65-77.

Cutter, S. L., 2016. The landscape of disaster resilience indicators in the USA. *Natural Hazards*, 80, pp.741-758.

Damude, K., Mortsch, L. & Joakim, E., 2015. *Draft Report: Methods for Quantifying Social Resilience in Metro Vancouver, Canada*. Ontario: Coastal Cities at Risk (CCaR) Project.

Denny, K. & Davidson, M.J., 2012. Area-based Socio-economic Measures as Tools for Health Disparities Research, Policy and Planning. *Canadian Journal of Public Health*, 103(2), pp. S4-S6.

Dorling, D., 1993. Map design for census mapping. *The Cartographic Journal*, 30, pp. 167-183.

Douglas, E. M., Kirshen, P. H., Paolisso, M., Watson, C., Wiggin, J., Enrici, A., & Ruth, M., 2012. Coastal flooding, climate change and environmental justice: identifying obstacles and incentives for adaptation in two metropolitan Boston Massachusetts communities. *Mitigation and Adaptation Strategies for Global Change*, 17(5), pp. 537-562.

Fabio, A., Tu, L.-C., Loeber, R. & Cohen, J., 2011. Neighbourhood Socioeconomic Disadvantage and Shape of the Age-Crime Curve. *American Journal of Public Health*, 101(S1), pp. S325-S332.

Feldmeyer, D., Wilden, D., Kind, C., Kaiser, T., Goldschmidt, R., Diller, C. & Birkmann, J., 2019. Indicators for Monitoring Urban Climate Change Resilience and Adaptation. *Sustainability*, 11, 2931.

Felsenstein, D. & Lichter, M., 2014. Social and economic vulnerability of coastal communities to sea-level rise and extreme flooding. *Natural Hazards*, 71, pp. 463-491.

Flax, L., Jackson, R. & Stein, D., 2002. Community vulnerability assessment tool methodology. *Natural Hazards Review* 3(4), pp. 163-176.

Flowerdew, R., 2011. How serious is the Modifiable Areal Unit Problem for analysis of English census data?. *Population Trends*, 145, pp. 106-118.

Fotheringham, A. S. & Wong, D. W. S., 1991. The modifiable areal unit problem in multivariate statistical analysis. *Environmental and Planning A*, Volume 23, pp. 1025-1044.

Frerks, G., Warner, J. & Weijs, B., 2011. The Politics of Vulnerability and Resilience. *Ambiente & Sociedade*, 14(2), pp. 105-122.

Gehlke, C.E. & Biehl, K., 1934. Certain effects of the grouping upon the size of the correlation coefficient in census tract material. *Journal of the American Statistical Association*, Supplement 29, pp. 169-170.

Hebb, A. & Mortsch, L., 2007. *Floods: Mapping Vulnerability in the Upper Thames Watershed under a Changing Climate*. CFCAS Report: Assessment of Water Resources Risk and Vulnerability to Changing Climate Conditions. Project Report XI.

Hewitt, K., 1983. *Interpretations of calamity from the viewpoint of human ecology*. London: Allen & Unwin Inc.

Hogarth, J. R., Campbell, D., Wandel, J., 2014. Assessing Human Vulnerability to Climate Change from an Evolutionary Perspective. In: Z. Zommers and A. Singh, eds. 2014. *Reducing Disaster: Early Warning Systems for Climate Change*. Dordrecht: Springer. Ch. 4.

IPCC (Intergovernmental Panel on Climate Change), 2014a. Summary for Policymakers. In: C. Field, et al. eds. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects*. Cambridge (UK) and New York (USA): Cambridge University Press, pp. 1-32.

IPCC (Intergovernmental Panel on Climate Change), 2014b. Annex II Glossary. In: V. Barros, et al. eds. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects*. United Kingdom, New York: Cambridge University Press, pp. 1757 - 1776.

ISDR (International Strategy for Disaster Reduction), 2002. Background document for the World Summit on Sustainable Development (WSSD). *Disaster Risk and Sustainable Development: Understanding the Links between Development, Environment and Natural Hazards Leading to Disasters*. Geneva: ISDR.

Jelinski, D. E. & Wu, J., 1996. The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology*, 11(3), pp. 129-140.

Joakim, E. P., Mortsch, L. & Oulahen, G., 2015. Using vulnerability and resilience concepts to advance climate change adaptation. *Environmental Hazards*, 14(2), pp.137-155.

Joakim, E. P., Mortsch, L., Oulahen, G., Harford, D., Klein, Y., Damude, K., & Tang, K., 2016. Using system dynamics to model social vulnerability and resilience to coastal hazards. *International Journal of Emergency Management*, 12(4), pp. 366-391.

Jones, L. & Tanner, T., 2017. 'Subjective resilience': using perceptions to quantify household resilience to climate extremes and disasters. *Regional Environmental Change*, 17, pp. 229-243.

Jones, L., Samman, E. & Vinck, P., 2018. Subjective measures of household resilience to climate variability and change: insights from a nationally representative survey of Tanzania. *Ecology and Society*, 23(1):9.

Kawachi, I., Kennedy, B.P. & Wilkinson, R.G., 1999. Crime: social disorganization and relative deprivation. *Social Science & Medicine*, 48, pp. 719-731.

Kelly, P. M. & Adger, W. N., 2000. Theory and Practice in Assessing Vulnerability to Climate Change and Facilitating Adaptation. *Climatic Change*, 47, pp. 325-352.

Lemmen, D., Warren, F. & Mercer Clarke, C., 2016. Introduction. In: D. Lemmen, F. Warren, T. James & C. Mercer Clarke, eds. *Canada's Marine Coasts in a Changing Climate*. Ottawa: Government of Canada, pp. 17-26.

MacCallum, D., Byrne, J., & Steele, W., 2014. Whither justice? An analysis of local climate change responses from South East Queensland, Australia. *Environment and Planning C: Government and Policy*, 32(1), pp. 70-92.

Marre, K., 2013. Components of risk: A comparative glossary. In: J. Birkmann ed. *Measuring Vulnerability to Natural Hazards*. Tokyo, New York, Paris: United Nations University Press, Ch. 23.

Martin, D. 1998. Optimizing census geography: the separation of collection and output geographies. *International Journal of Geographical Information Science*, 12(7), pp. 673-685.

Mendelson, R., 2001. *Geographic Structure As Census Variables: Using Geography to Analyse Social and Economic Processes*. Statistics Canada Geography Working Paper Series Catalogue no. 92F0138MIE. Ottawa: Statistics Canada. [online] Available at: <https://www150.statcan.gc.ca/n1/en/pub/92f0138m/92f0138m2001001-eng.pdf?st=Hpe_u6Jb> [Accessed 19 April 2019].

Mimura, N., Pulwarty, R.S., Duc, D.M., Elshinnawy, I., Redsteer, M.H., Huang, H.Q., Nkem, J.N. & Sanchez Rodriguez, R.A., 2014. Adaptation planning and implementation. In: C.B. Field, V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea & L.L. White, eds. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, New York: Cambridge University Press, pp. 869-898.

Morrow, B. H., 2008. *Community Resilience: A Social Justice Perspective*. Oak Ridge: Community and Regional Resilience Initiative (CARRI). [online] Available at: < https://www.researchgate.net/publication/280611548_Community_resilience_A_social_justice_perspective> [Accessed 6 July 2020].

NRS (National Records of Scotland), 2015. *Geography – Background Information Comparison of Thresholds.* [online] Available at: < https://www.nrscotland.gov.uk/files//geography/2011-census/geography-bckground-info-comparison-of-thresholds.pdf> [Accessed 2 April 2020].

NRS (National Records of Scotland), 2018a. *SNS Data Zone 2011*. [online] Available at: < https://www.scotlandscensus.gov.uk/variables-classification/sns-data-zone-2011> [Accessed 2 April 2020].

NRS (National Records of Scotland), 2018b. *Output Area 2011*. [online] Available at: < https://www.scotlandscensus.gov.uk/variables-classification/output-area-2011> [Accessed 2 April 2020].

O'Dowd, L., 2003. Ecological Fallacy. In: R. L. Miller & J. Brewer eds. *The A-Z of Social Research*. London: SAGE Publications, Ltd, pp. 84-85.

Oliver-Smith, A., 1998. Global Changes and the Definition of a Disaster. In: E. L. Quarantelli ed., *What is a Disaster?*. London and New York: Routledge, pp. 177-194.

Openshaw, S., 1984. The Modifiable Areal Unit Problem. *Concepts and Techniques in Modern Geography No. 38 ed*. Norwich: GeoBooks.

Openshaw, S. & Taylor, P., 1979. A million or so correlation coefficients: three experiments on the modifiable areal unit problem. In: Wrigley N. ed. 1979. *Statistical applications in the spatial sciences*. London: Pion.

O'Sullivan, D. & Unwin, D. J., 2010. *Geographic Information Analysis*. Hoboken: John Wiley & Sons, Inc.

Oulahen, G., Mortsch, L., Tang, K. & Harford, D., 2015. Unequal Vulnerability to Flood Hazards: "Ground Truthing" a Social Vulnerability Index of Five Municipalities in Metro Vancouver, Canada. *Annals of the Association of American Geographers*, 105(3), pp. 473-495.

Pampalon, R., Hamel, D. & Gamache, P., 2009. *A comparison of individual and area-based socio-economic data for monitoring social inequalities in health*. Component of Statistics Canada Catalogue no. 82-003-XPE, 20(3), pp.85-93.

Penning-Rowsell, E. C., Parker, D. J. & Harding, D. M., 1986. *Floods and Drainage*. London: Allen & Unwin.

PSC (Public Safety Canada), 2019. *Emergency Management Strategy for Canada – Toward a Resilient 2030*. Ottawa: Government of Canada. [online] Available at: <https://www.publicsafety.gc.ca/cnt/rsrcs/pblctns/mrgncy-mngmnt-strtgy/mrgncy-mngmnt-strtgy-en.pdf> [Accessed 10 October 2020].

Prouse, V., Ramos, H., Grant, J. L. & Radice, M., 2014. How and when scale matters: the modifiable areal unit problem and income inequality in Halifax. *Canadian Journal of Urban Research*, 23(1), pp. 61-82.

Quinlan, A. E., Berbés-Blázquez, M., Haider, L. J. & Peterson, G. D., 2016. Measuring and assessing resilience: broadening understanding through multiple disciplinary perspectives. *Journal of Applied Ecology*, 53, pp. 677-687.

Reckien, D., 2018. What is an index? Construction method, data metric, and weighting scheme determine the outcome of composite social vulnerability indices in New York City. *Regional Environmental Change*, 18, pp. 1439-1451.

Rickless, D. S., Yao, X. A., Orland, B. & Welch-Devine, M., 2019. Assessing Social Vulnerability through a Local Lens: An Integrated Geovisual Approach. *Annals of the American Association of Geographers*, 0(0), pp. 1-20.

Robinson, W.R., 1950. Ecological Correlation and the Behaviour of Individuals. *American Sociological Review*, 15, pp. 351-357.

Rygel, L., O'Sullivan, D. & Yarnal, B., 2006. A method for constructing a social vulnerability index: an application to hurricane storm surges in a developed country. *Mitigation and Adaptation Strategies for Global Change*, 11(3), pp.741-764.

Schuurman, N., Bell, N., Dunn, J. & Oliver, L., 2007. Deprivation Indices, Population Health and Geography: An Evaluation of Indices at Multiple Scales. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, 84(4), pp. 591-503.

Seguin, A., Apparicio, P. & Riva, M., 2011. The Impact of Geographical Scale in Identifying Areas as Possible Sites for Area-Based Interventions to Tackle Poverty: The Case of Montreal. *Applications of Spatial Statistics*, 5, pp. 231-251.

Sevoyan, A., Hugo, G., Feist, H., Tan, G., McDougall, K., Tan, Y. and Spoehr, J., 2013. *Impact of Climate Change on Disadvantaged Groups: Issues and Interventions*. Adelaide: National Climate Change Adaptation Research Facility.

Slovic, P., 1992. Perceptions of Risk: Reflections on the Psychometric Paradigm. In: D. Golding & S. Krimsky, eds. *Theories of Risk*. New York: Praeger, pp. 117-152.

Spielman, S. E., Tucillo, J., Folch, D. C., Schweikert, A., Davies, R., Wood, N. & Tate, E., 2020. Evaluating social vulnerability indicators: criteria and their application to the Social Vulnerability Index. *Natural Hazards*, 100, pp. 417-436.

Statistics Canada, 2012. *Geography Catalogue, 2011 Census*. Ottawa: Statistics Canada. [online] Available at: <https://www150.statcan.gc.ca/n1/en/pub/92-196-x/92-196-x2011001-eng.pdf?st=jmBPtww6> [Accessed 2 June 2020].

Statistics Canada, 2016. *Dictionary, Census of Population, 2016. Census tract (CT).* Ottawa: Statistics Canada. [online] Available at: <https://www12.statcan.gc.ca/census-recensement/2016/ref/dict/geo013-eng.cfm> [Accessed 3 June 2020].

Steel, D. & Holt, D., 1996. Analysing and Adjusting Aggregation Effects: The Ecological Fallacy Revisited. *International Statistical Review*, 64(1), pp. 39-60.

Tapsell, S. M., Penning-Rowsell, E. C., Tunstall, S. M. & Wilson, T. L., 2002. Vulnerability to flooding: health and social dimensions. *Philosophical Transactions of the Royal Society A*, 360, pp. 1511-1525.

Taylor, C., Gorard, S. & Fitz, J., 2003. The modifiable areal unit problem: Segregation between schools and levels of analysis. *International Journal of Social Research Methodology*, 6(1), pp. 41-60.

Thrush, D., Burningham, K. & Fielding, J., 2005. *Flood warning for vulnerable groups: A qualitative study*. Bristol: Environment Agency. [online] Available at: < https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/290692/scho0505bjbu-e-e.pdf> [Accessed 30 June 2020].

Twigg, J., 2009. *Characteristics of a Disaster-Resilient Community*. London: University College London Hazard Centre. [online] Available at: < https://discovery.ucl.ac.uk/id/eprint/1346086/1/1346086.pdf> [Accessed 2 June 2020].

UNDRR (United Nations Office for Disaster Reduction), 2004. *Living with Risk: A Global Review of Disaster Reduction Initiatives - Volume II Annexes*. Geneva: UN Publications. [online] Available at: <https://www.preventionweb.net/files/657_lwr21.pdf> [Accessed 6 February 2020].

UNDRR (United Nations Office for Disaster Reduction), 2015. *Sendai Framework for Disaster Risk Reduction 2015 – 2030*. Sendai: UN Publications. [online] Available at: <https://www.preventionweb.net/files/43291_sendaiframeworkfordrren.pdf> [Accessed 1 October 2020].

UNDP (United Nations Development Programme), 2017. *Natural disasters don't exist but natural hazards do*. [online] Available at: http://www.undp.org/content/undp/en/home/blog/2017/5/18/Natural-disasters-don-t-exist-but-natural-hazards-do.html [Accessed 12 Nov 2018].

U.S. Census Bureau, 2019. *U.S. Census Bureau QuickFacts*. [online] Available at: <https://www.census.gov/quickfacts/fact/table/losangelescitycalifornia,US/PST045219> [Accessed 6 January 2020].

U.S. Department of Commerce, 1994a. Chapter 10 – Census Tracts and Block Numbering Areas. In: R. A. LaMaccachia, R. W. Marx & J. Sobel, eds. *Geographic Areas Reference Manual*. [online] Available at: <https://www2.census.gov/geo/pdfs/reference/GARM/Ch10GARM.pdf>

U.S. Department of Commerce, 1994b. Chapter 11 – Census Blocks and Block Groups. In: R. A. LaMaccachia, R. W. Marx & J. Sobel, eds. *Geographic Areas Reference Manual*. [online] Available at: <https://www2.census.gov/geo/pdfs/reference/GARM/Ch11GARM.pdf>

White, G.F., 1942. Human Adjustment to Floods: A Geographical Approach to the Flood Problem in the United States. In: W. Calef, ed. 1945. *The University of Chicago: Department of Geography Research Papers*. Chicago: The University of Chicago.

Wisner, B., Blaikie, P., Cannon, T. and Davis, I., 2004. *At risk: natural hazards, people's vulnerability and disasters*. Reprint 2004. New York: Routledge.

Wong, D. W. S., Lasus, H. & Falk, R. F., 1999. Exploring the Variability of Segregation Index *D* with Scale and Zonal Systems: An Analysis of Thirty U.S. Cities. *Environment and Planning A*, 31, pp. 507-522.

Wu, S.-Y., Yarnal, B. & Fisher, A., 2002. Vulnerability of coastal communities to sea-level rise: a case study of Cape May County, New Jersey, USA. *Climate Research,* 22, pp. 255-270.

Appendix A – Data Dictionary by Study Area

Data Dictionary – 2011 Canadian Census Data

Social Resilience Index (SoRI) Variables by Dissemination Areas (DA) and Census Tracts (CT) for the City of Vancouver, British Columbia, Canada

Summary of Final SoRI Census Variables for Mapping

	SoRI Variable	Census Tract (CT)	Dissemination Area (DA)
VAR001	Total Population – Canadian Citizenship	✓	--
VAR002	Total number of occupied private dwelling – construction period up to 1960	✓	✓
VAR003	Average value of private dwellings	✓	✓
VAR004	Total number of occupied private dwelling – need of major repair	✓	✓
VAR005	Total number of occupied private dwelling – moveable dwelling	✓	✓
VAR006	Total number of occupied private dwellings – rental	✓	✓
VAR007	Income percentage – payments from government transfers	✓	✓
VAR008	Average household income – private households	✓	✓
VAR009	Total immigrant population – census period of immigration	✓	--
VAR010	Total population age 15 and over – unemployed	✓	--
VAR011	Total population age 65 and over – living alone	✓	✓
VAR012	Total number of families – lone parent	✓	✓
VAR013	Population percentage in private household – low income	✓	✓
VAR014	Total population – no official languages knowledge	✓	✓
	Total Number of Variables	14	11

Where variables were available for CTs but not DAs, the value of DAs was taken to be equal to the value of the CT it is contained within

Calculation of SoRI Census Variables for Mapping

VAR001: Total Population – Canadian Citizenship

DA: *Citizenship_DA*

- Column Headings: DAUID, CTUID, VAR001, zVAR001
  - DAUID → 2011 Census, dissemination area geography code
  - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
  - VAR001 → total percentage of population with Canadian citizenship for DA equal to the value of the CT that it is contained within
  - zVAR001 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR001} = \boldsymbol{value\ from\ CT\ contained\ in}$	Mean = 0.865443 Standard deviation = 0.051047

CT: *Citizenship_CT*

- Column Headings: CTUID, TOTAL_POP, Citizen, VAR001, zVAR001
  - CTUID → 2011 Census, census tract geography code
  - TOTAL_POP → total population in private households
  - VAR001 → total percentage of population with Canadian citizenship
  - zVAR001 → normalized z-score of variable

Calculation	Z-scores
$VAR001 = \frac{Citizen}{Total\_POP}$	Mean = 0.86125 Standard deviation = 0.053625

VAR002: Total Number of Occupied Private Dwelling – Construction Period Up to 1960

DA: *Construc1960_DA*

- Column Headings: DAUID, CTUID, HOUSEHOLDS, Construc1960, VAR002, zVAR002
    - DAUID → 2011 Census, dissemination area geography code
    - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
    - HOUSEHOLDS → total number of households in DA unit
    - Construc1960 → total number of households with period of construction in 1960 or before
    - VAR002 → total percentage of households constructed in 1960 or earlier
    - zVAR002 → normalized z-score of variable

Calculation	Z-scores
$VAR002 = \frac{Construc1960}{HOUSEHOLDS}$	Mean = 0.321345 Standard deviation = 0.218646

CT: *Construc1960_CT*

- Column Headings: CTUID, HOUSEHOLDS, Construc1960, VAR002, zVAR002
    - CTUID → 2011 Census, census tract geography code
    - HOUSEHOLDS → total number of households in CT unit
    - Construc1960 → total number of households with period of construction in 1960 or before
    - VAR002 → total percentage of households constructed in 1960 or earlier
    - zVAR002 → normalized z-score of variable

Calculation	Z-scores
$VAR002 = \frac{Construc1960}{HOUSEHOLDS}$	Mean = 0.30079 Standard deviation = 0.162641

VAR003: Average Value of Private Dwellings

DA: *AvgHousePrice_DA*

- Column Headings: DAUID, CTUID, AVERAGE_VA, VAR003, zVAR003
    - DAUID → 2011 Census, dissemination area geography code
    - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
    - AVERAGE_VA → average value of dwelling in $100,000 (missing values replaced with variable mean)
    - VAR003 → average value of dwelling in Canadian dollars ($)
    - zVAR003 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 536619.6 Standard deviation = 287784.2

CT: *AvgHousePrice_CT*

- Column Headings: CTUID, VAR003, zVAR003
    - CTUID → 2011 Census, census tract geography code
    - VAR003→ average value of dwelling in Canadian dollars ($)
    - zVAR002 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 897851.9 Standard deviation = 463956.3

VAR004: Total Number of Occupied Private Dwelling – Need of Major Repair

DA: *MajorRepair_DA*

- Column Headings: DAUID, CTUID, HOUSEHOLDS, Construc1960, VAR002, zVAR002
    - DAUID → 2011 Census, dissemination area geography code
    - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
    - HOUSEHOLDS → total number of households in DA unit
    - MajorRepair → total number of households in need of major repairs (missing values replaced with variable mean)
    - VAR004 → total percentage of households in need of major repairs
    - zVAR002 → normalized z-score of variable

Calculation	Z-scores
$VAR004 = \frac{MajorRepair}{HOUSEHOLDS}$	Mean = 0.060345 Standard deviation = 0.083852

CT: *MajorRepair_CT*

- Column Headings: CTUID, HOUSEHOLDS, MajorRepair, VAR004, zVAR004
    - CTUID → 2011 Census, census tract geography code
    - HOUSEHOLDS → total number of households in CT unit
    - MajorRepair → total number of households in need of major repairs (missing values replaced with variable mean)
    - VAR004 → total percentage of households in need of major repairs
    - zVAR004 → normalized z-score of variable

Calculation	Z-scores
$VAR004 = \frac{MajorRepair}{HOUSEHOLDS}$	Mean = 0.081434 Standard deviation = 0.0356

VAR005: Total Number of Occupied Private Dwelling – Moveable Dwelling

DA: *Mobile_DA*

- Column Headings: DAUID, CTUID, HOUSEHOLDS, Moveable_Dw, VAR005, zVAR005
    - DAUID → 2011 Census, dissemination area geography code
    - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
    - HOUSEHOLDS → total number of households in DA unit
    - Mobile → total number of moveable dwellings (missing values replaced with variable mean)
    - VAR005 → total percentage of moveable dwellings
    - zVAR005 → normalized z-score of variable

Calculation	Z-scores
$VAR005 = \frac{Movable\_Dw}{HOUSEHOLDS}$	Mean = 0.000271 Standard deviation = 0.003336

CT: *Mobile_CT*

- Column Headings: CTUID, HOUSEHOLDS, Moveable_Dw, VAR005, zVAR005

- CTUID → 2011 Census, census tract geography code
- HOUSEHOLDS → total number of households in CT unit
- Mobile → total number of moveable dwellings (missing values replaced with variable mean)
- VAR005 → total percentage of households in need of major repairs
- zVAR005 → normalized z-score of variable

Calculation	Z-scores
$VAR005 = \frac{Movable\_Dw}{HOUSEHOLDS}$	Mean = 0.008916 Standard deviation = 0.092431

VAR006: Total Number of Occupied Private Dwellings – Rental

DA: *Rental_DA*

- Column Headings: DAUID, CTUID, HOUSEHOLDS, Rental, VAR006, zVAR006
  - DAUID → 2011 Census, dissemination area geography code
  - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
  - HOUSEHOLDS → total number of households in DA unit
  - Rental → total number of rented dwellings (missing values replaced with variable mean)
  - VAR006 → total percentage of rental-type housing tenure
  - zVAR006 → normalized z-score of variable

Calculation	Z-scores
$VAR006 = \frac{Rental}{HOUSEHOLDS}$	Mean = 0.45415 Standard deviation = 0.258921

CT: *Rental_CT*

- Column Headings: CTUID, HOUSEHOLDS, Rental, VAR006, zVAR006
  - CTUID → 2011 Census, census tract geography code
  - HOUSEHOLDS → total number of households in CT unit
  - Rental → total number of rented dwellings (missing values replaced with variable mean)
  - VAR006 → total percentage of rental-type housing tenure
  - zVAR006 → normalized z-score of variable

Calculation	Z-scores
$VAR006 = \frac{Rental}{HOUSEHOLDS}$	Mean = 0.479804 Standard deviation = 0.195959

VAR007: Income Percentage – Payments from Government Transfers

DA: *GovTransfers_DA*

- Column Headings: DAUID, CTUID, Transfers, VAR007, zVAR007
  - DAUID → 2011 Census, dissemination area geography code
  - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
  - VAR007 → government transfer payments, as percentage of total income (missing values replaced with variable mean)
  - zVAR007 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 10.66347 Standard deviation = 7.653683

CT: *GovTransfers_CT*

- Column Headings: CTUID, Transfers, VAR007, zVAR007
  - CTUID → 2011 Census, census tract geography code
  - VAR007 → government transfer payments, as percentage of total income (missing values replaced with variable mean)
  - zVAR007 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 10.31897 Standard deviation = 5.858076

VAR008: Average Household Income – Private Households

DA: *HhIncome_DA*

- Column Headings: DAUID, CTUID, Transfers, VAR007, zVAR007
  - DAUID → 2011 Census, dissemination area geography code
  - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
  - VAR008 → average household income in Canadian dollars ($) (missing values replaced with variable mean)
  - zVAR008 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 54015.9 Standard deviation = 31440.2

CT: *HhIncome_CT*

- Column Headings: CTUID, VAR008, zVAR008
  - CTUID → 2011 Census, census tract geography code
  - VAR008 → average household income in Canadian dollars ($) (missing values replaced with variable mean)
  - zVAR008 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 83750.32 Standard deviation = 40125.54

VAR009: Total Immigrant Population – Census Period of Immigration

DA: *Immigrant_DA*

- Column Headings: DAUID, CTUID, VAR009, zVAR009
  - DAUID → 2011 Census ,dissemination area geography code
  - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
  - VAR009 → total percentage of immigrant population during census period of 2006 to 2011, value of DA equal to value of CT it is contained within
  - zVAR009 → normalized z-score of variable

Calculation	Z-scores
$VAR009 =$ $value\ from\ CT\ contained\ in$	Mean = 0.070017 Standard deviation = 0.031118

CT: *Immigrant_CT*

- Column Headings: CTUID, TOTAL_POP, Immigrants, VAR009, zVAR009
    - CTUID → 2011 Census, census tract geography code
    - TOTAL_POP → total population in private households
    - Immigrants → total number of immigrants during 2006 to 2011 period (missing values replaced with variable mean)
    - VAR009 → total percentage of immigrant population during census period of 2006 to 2011
    - zVAR009 → normalized z-score of variable

Calculation	Z-scores
$VAR009 = \frac{Immigrants}{Total\_POP}$	Mean = 0.071617 Standard deviation = 0.031817

VAR010: Total Population Age 15 and Over – Unemployed

DA: *Unemploy_DA*

- Column Headings: DAUID, CTUID, Lab_Force, Unemployed, VAR010, zVAR010
    - DAUID → 2011 Census, dissemination area geography code
    - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
    - VAR010 → percentage of unemployed persons in the labour force, value of DA equal to value of CT it is contained within
    - zVAR010 → normalized z-score of variable

Calculation	Z-scores
$VAR010 =$ $value\ from\ CT\ contained\ in$	Mean = 0.072246 Standard deviation = 0.022265

CT: *Unemploy_CT*

- Column Headings: CTUID, TOTAL_POP, Unemployed, VAR010, zVAR010
    - CTUID → 2011 Census, census tract geography code
    - Lab_Force → total population in the labour force
    - Unemployed → number of unemployed persons age 15 and over
    - VAR010 → percentage of unemployed persons in the labour force
    - zVAR010 → normalized z-score of variable

Calculation	Z-scores
$VAR010 = \frac{Unemployed}{Lab\_Force}$	Mean = 0.07204 Standard deviation = 0.02346

VAR011: Total Population Age 65 and Over – Living Alone

DA: *LiveAlone_DA*

- Column Headings: DAUID, CTUID, TOTAL_NUM, Living_Al, VAR011, zVAR011
    - DAUID → 2011 Census, dissemination area geography code
    - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
    - TOTAL_NUM → total number of persons aged 65 years and over in private households (missing values replaced with variable mean)
    - Living_Al → total number of persons living alone
    - VAR011 → total percentage of population age 65 and over living alone
    - zVAR011 → normalized z-score of variable

Calculation	Z-scores
$VAR011 = \frac{Living\_Al}{TOTAL\_NUM}$	Mean = 0.287375 Standard deviation = 0.210967

CT: *LiveAlone_CT*

- Column Headings: CTUID, TOTAL_NUM, Living_Al, VAR011, zVAR011
  - CTUID → 2011 Census, census tract geography code
  - TOTAL_NUM → total number of persons aged 65 years and over in private households (missing values replaced with variable mean)
  - Living_Al → total number of persons living alone
  - VAR011 → total percentage of population age 65 and over living alone
  - zVAR011 → normalized z-score of variable

Calculation	Z-scores
$VAR011 = \frac{Living\_Al}{TOTAL\_NUM}$	Mean = 0.30568 Standard deviation = 0.178571

VAR012: Total Number of Families – Lone Parent

DA: *LoneParent_DA*

- Column Headings: DAUID, CTUID, TOTAL_NUM, LoneParent, VAR012, zVAR012
  - DAUID → 2011 Census, dissemination area geography code
  - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
  - TOTAL_NUM → total number census families in private households (missing values replaced with variable mean)
  - LoneParent → total number of lone-parent families (missing values replaced with variable mean)
  - VAR012 → percentage of lone parent families
  - zVAR012 → normalized z-score of variable

Calculation	Z-scores
$VAR012 = \frac{LoneParent}{TOTAL\_NUM}$	Mean = 0.162821 Standard deviation = 0.073492

CT: *LoneParent_CT*

- Column Headings: CTUID, TOTAL_NUM, LoneParent, VAR012, zVAR012
  - CTUID → 2011 Census, census tract geography code
  - TOTAL_NUM → total number census families in private households (missing values replaced with variable mean)
  - LoneParent → total number of lone-parent families (missing values replaced with variable mean)
  - VAR012 → percentage of lone parent families
  - zVAR012 → normalized z-score of variable

Calculation	Z-scores
$VAR012 = \frac{LoneParent}{TOTAL\_NUM}$	Mean = 0.161329 Standard deviation = 0.0467

VAR013: Population Percentage in Private Household - Prevalence of Low Income

DA: *LowIncome_DA*

- Column Headings: DAUID, CTUID, VAR013, zVAR013
  - DAUID → 2011 Census, dissemination area geography code

- CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
- VAR013 → percentage of low-income population in private households based on 2010 after-tax low-income measure (missing values replaced with variable mean)
- zVAR013 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 21.06638 Standard deviation = 8.422087

CT: *LowIncome_CT*

- Column Headings: CTUID, VAR013, zVAR013
    - CTUID → 2011 Census, census tract geography code
    - VAR013 → percentage of low-income population in private households based on 2010 after-tax low-income measure (missing values replaced with variable mean)
    - zVAR013 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 21.06638 Standard deviation = 8.422087

VAR014: Total Population – No Official Languages Knowledge

DA: *Language_DA*

- Column Headings: DAUID, CTUID, TOTAL_POP, NeitherLang, VAR014, zVAR014
    - DAUID → 2011 Census, dissemination area geography code
    - CTUID → 2011 Census, census tract geography code (CT unit that DA is contained within)
    - TOTAL_POP → total population in private households
    - NeitherLang → total number of persons with no knowledge of English nor French
    - VAR014 → total percentage of population with no official languages knowledge
    - zVAR014 → normalized z-score of variable

Calculation	Z-scores
$VAR014 = \frac{NeitherLang}{TOTAL\_POP}$	Mean = 0.077897 Standard deviation = 0.06944

CT: *Language_CT*

- Column Headings: CTUID, TOTAL_POP, NeitherLang, VAR014, zVAR014
    - CTUID → 2011 Census, census tract geography code
    - TOTAL_POP → total population in private households
    - NeitherLang → total number of persons with no knowledge of English nor French
    - VAR014 → total percentage of population with no official languages knowledge
    - zVAR014 → normalized z-score of variable

Calculation	Z-scores
$VAR014 = \frac{NeitherLang}{TOTAL\_POP}$	Mean = 0.076996 Standard deviation = 0.061516

Data Dictionary – 2010 US Census Data & Official Statistics

Social Resilience Index (SoRI) Variables by Block Group (BG) and Census Tract (CT) for the City of Los Angeles, California, United States

Summary of Final SoRI Census Variables for Mapping

	SoRI Variable	Census Tract (CT)	Block Group (BG)
VAR001	Total Population – Citizenship	✓	--
VAR002	Total number of occupied private dwelling – construction period up to 1970	✓	✓
VAR003	Average value of private dwellings	✓	✓
VAR004	Total number of occupied private dwelling – need of major repair	--	--
VAR005	Total number of occupied private dwelling – moveable dwelling	✓	✓
VAR006	Total number of occupied private dwellings – rental	✓	✓
VAR007	Income percentage – payments from government transfers	✓	--
VAR008	Average household income – private households	✓	✓
VAR009	Total immigrant population – census period of immigration	✓	--
VAR010	Total population age 15 and over – unemployed	✓	--
VAR011	Total population age 65 and over – living alone	✓	--
VAR012	Total number of families – lone parent	✓	✓
VAR013	Population percentage in private household – low income	✓	--
VAR014	Total population – no official languages knowledge	✓	✓
	Total Number of Variables	13	7

Where variables were available for CTs but not BGs, the value of BGs was taken to be equal to the value of the CT it is contained within

Calculation of SoRI Census Variables for Mapping

VAR001: Total Population – US Citizenship

BG: *VAR001*

- Column headings: BGID10, CTID10, VAR001, zVAR001
  - BGID10 → 2010 Census, block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - VAR001 → value of population with US citizenship for BG equal to the value of the CT that it is contained within
  - zVAR001 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR001 = value\ from\ CT\ contained\ in}$	Mean = 0.773262 Standard deviation = 0.195356

CT: *VAR001*

- Column headings: CTID10, Population, Citizenship, VAR001, zVAR001
  - CTID10 → 2010 Census, census tract geography code
  - Population → total number of people in CT unit
  - Citizenship → total number of US citizens (estimated by ACS)
  - VAR001 → total proportion (decimal) of population with US citizenship

- zVAR001 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR001} = \frac{\boldsymbol{Citizenship}}{\boldsymbol{Population}}$	Mean = 0.758683 Standard deviation = 0.247995

VAR002: Dwelling Construction Period Up to 1970

BG: *VAR002*

- Column headings: BGID10, CTID10, Occupied Dwellings, Construc1970, VAR002, zVAR002
  - BGID10 → 2010 Census, block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - Occupied Dwellings → total number of occupied dwellings in CT unit
  - Construc1970 → total number of occupied dwellings constructed up to 1970
  - VAR002 → total proportion (decimal) of dwellings constructed up to 1970
  - zVAR002 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR002} = \frac{\boldsymbol{Construc1980}}{\boldsymbol{Occupied\ Dwellings}}$	Mean = 0.799264 Standard deviation = 0.261945

CT: *VAR002*

- Column headings: CTID10, Occupied Dwellings, Construc1970, VAR002, zVAR002
  - CTID10 → 2010 Census, census tract geography code
  - Occupied Dwellings → total number of occupied dwellings in CT unit
  - Construc1970 → total number of occupied dwellings constructed up to 1970
  - VAR002 → total proportion (decimal) of dwellings constructed up to 1970
  - zVAR002 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR002} = \frac{\boldsymbol{Construc1980}}{\boldsymbol{Occupied\ Dwellings}}$	Mean = 0.763556 Standard deviation = 0.213182

VAR003: Average Value of Private Dwellings

BG: *VAR003*

- Column headings: BGID10, CTID10, VAR003, zVAR003
  - BGID10 → 2010 Census, block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - VAR003 → average value of private dwelling
  - zVAR003 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{N/A}$	Mean = 582231.5 Standard deviation = 241079

CT: *VAR003*

- Column headings: CTID10, VAR003, zVAR003

- CTID10 → 2010 Census, census tract geography code
- VAR003 → average value of private dwelling
- zVAR003 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 568219 Standard deviation = 221831.9

VAR005: Total Number of Occupied Dwellings – Moveable Dwellings

BG: *VAR005*

- Column headings: BGID10, CTID10, Occupied Dwellings, Mobile Dwellings, VAR005, zVAR005
  - BGID10 → 2010 Census, block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - Occupied Dwellings → total number of occupied dwellings in BG unit
  - Mobile Dwellings → total number of mobile homes and all other types of temporary housing units
  - VAR005 → total proportion (decimal) of households that are moveable dwellings
  - zVAR005 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR005} = \frac{\textbf{Mobile Dwellings}}{\textbf{Households}}$	Mean = 0.005263 Standard deviation = 0.025956

CT: *VAR005*

- Column headings: CTID10, Occupied Dwellings, Mobile Dwellings, VAR005, zVAR005
  - CTID10 → 2010 Census, census tract geography code
  - Occupied Dwellings → total number of occupied dwellings in CT unit
  - Mobile Dwellings → total number of mobile homes and all other types of units
  - VAR005 → total proportion (decimal) of households that are mobile homes
  - zVAR005 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR005} = \frac{\textbf{Mobile Dwellings}}{\textbf{Occupied Dwellings}}$	Mean = 0.006165 Standard deviation = 0.025051

VAR006: Total Number of Occupied Private Dwellings – Rental

BG: *VAR006*

- Column headings: BGID10, CTID10, Occupied Dwellings, Rental Dwellings, VAR006, zVAR006
  - BGID10 → 2010 Census, block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - Occupied Dwellings → total number of occupied dwellings in BG unit
  - Rental Dwellings → total number of renter-occupied dwellings
  - VAR006 → total proportion (decimal) of dwellings that are renter-occupied
  - zVAR006 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR006} = \frac{\textbf{Rental Dwellings}}{\textbf{Households}}$	Mean = 0.645809 Standard deviation = 0.253776

CT: *VAR006*

- Column headings: CTID10, Occupied Dwellings, Mobile Dwellings, VAR006, zVAR006
    - CTID10 → 2010 Census, census tract geography code
    - Occupied Dwellings → total number of occupied dwellings in CT unit
    - Rental → total number of renter-occupied dwelling units
    - VAR006 → total proportion (decimal) of households that are rental dwellings
    - zVAR006 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR006 = \frac{Rental}{Occupied\ Dwellings}}$	Mean = 0.684353 Standard deviation = 0.230898

VAR007: Income Percentage – Payments from Government Transfers

BG: *VAR007*

- Column headings: BGID10, CTID10, VAR007, zVAR007
    - BGID10 → 2010 Census, block group area geography code
    - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
    - VAR007 → value of percentage income from government transfers (social security income, supplemental security income, public assistance income) in BG equal to the value of the CT that it is contained within
    - zVAR007 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR007 =}$ $\boldsymbol{value\ from\ CT\ contained\ in}$	Mean = 0.165396 Standard deviation = 0.067549

CT: *VAR007*

- Column headings: CTID10, VAR007, zVAR007
    - CTID10 → 2010 Census, census tract geography code
    - VAR007 → percentage of income from government transfers (social security income, supplemental security income, public assistance income)
    - zVAR007 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{N/A}$	Mean = 0.17022 Standard deviation = 0.069408

VAR008: Average Household Income – Private Households

BG: *VAR008*

- Column headings: BGID10, CTID10, VAR008, zVAR008
    - BGID10 → 2010 Census, block group area geography code
    - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
    - VAR008 → average (mean) household income; estimated from ACS
    - zVAR008 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{N/A}$	Mean = 73681.13 Standard deviation = 54497.66

CT: *VAR008*

- Column headings: CTID10, VAR008, zVAR008
    - CTID10 → 2010 Census, census tract geography code
    - VAR008 → average (mean) household income; estimated from ACS
    - zVAR008 → normalized z-score of variable

Calculation	Z-scores
N/A	Mean = 70729.04 Standard deviation = 53788.36

VAR009: Total Immigrant Population – Census Period of Immigration

BG: *VAR009*

- Column headings: BGID10, CTID10, VAR009, zVAR009
    - BGID10 → 2010 Census, census block group area geography code
    - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
    - VAR009 → value of immigrant population in BG equal to the value of the CT that it is contained within
    - zVAR009 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR009 =}$ $\boldsymbol{value\ from\ CT\ contained\ in}$	Mean = 0.0879 Standard deviation = 0.157049

CT: *VAR009*

- Column headings: CTID10, Population, Immigration, VAR009, zVAR009
    - CTID10 → 2010 Census, census tract geography code
    - Population → total number of people in CT unit
    - Immigration → total number of non-U.S. citizens that entered the US during 2000 to 2010
    - VAR009 → total proportion (decimal) of immigrant population
    - zVAR009 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR009 = \frac{Immigration}{Population}}$	Mean = 0.102837 Standard deviation = 0.240077

VAR010: Total Population Age 16 and Over – Unemployed

BG: *VAR010*

- Column headings: BGID10, CTID10, VAR010, zVAR010
    - BGID10 → 2010 Census, block group area geography code
    - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
    - VAR009 → value of unemployment in BG equal to the value of the CT that it is contained within
    - zVAR009 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR010 =}$ $\boldsymbol{value\ from\ CT\ contained\ in}$	Mean = 0.097383 Standard deviation = 0.046952

CT: *VAR010*

- Column headings: CTID10, Labour Force, Unemployment, VAR010, zVAR010

- CTID10 → 2010 Census, census geography code
- Labour Force → total population 16 and over in the labour force
- Unemployment → number of unemployed persons 16 and over
- VAR010 → total proportion (decimal) of unemployed population
- zVAR010 → normalized z-score of variable

Calculation	Z-scores
$VAR010 = \frac{Unemployment}{Labour\ Force}$	Mean = 0.097277 Standard deviation = 0.049204

VAR011: Total Population Age 65 and Over – Living Alone

BG: *VAR011*

- Column headings: BGID10, CTID10, VAR010, zVAR010
  - BGID10 → 2010 Census, census block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - VAR009 → value of unemployment in BG equal to the value of the CT that it is contained within
  - zVAR009 → normalized z-score of variable

Calculation	Z-scores
$VAR011 =$ $value\ from\ CT\ contained\ in$	Mean = 0.031462 Standard deviation = 0.022684

CT: *VAR011*

- Column headings: CTID10, Population, Living Alone, VAR011, zVAR011
  - CTID10 → 2010 Census, census tract geography code
  - Population → total number of people in CT unit
  - Living Alone → total number of people age 65 and over living alone
  - VAR0011 → total proportion (decimal) of population age 65 and over living alone
  - zVAR011 → normalized z-score of variable

Calculation	Z-scores
$VAR011 = \frac{Living\ Alone}{Population}$	Mean = 0.030971 Standard deviation = 0.025067

VAR012: Total Number of Families – Lone Parent

BG: *VAR012*

- Column headings: BGID10, CTID10, Families, Lone Parent, VAR012, zVAR012
  - BGID10 → 2010 Census, block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - Families → total number of families in BG unit
  - Lone Parent → total number of lone parent families
  - VAR012 → total proportion (decimal) of lone parent families
  - zVAR012 → normalized z-score of variable

Calculation	Z-scores
$VAR012 = \frac{Lone\ Parent}{Families}$	Mean = 0.056759 Standard deviation = 0.056592

CT: *VAR012*

- Column headings: CTID10, Families, Lone Parent, VAR012, zVAR012
  - CTID10 → 2010 Census, census tract geography code
  - Families → total number of families in CT unit
  - Lone Parent → total number of lone-parent families
  - VAR0012 → total proportion (decimal) of lone parent families
  - zVAR012 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR012} = \frac{\boldsymbol{Lone\ Parent}}{\boldsymbol{Families}}$	Mean = 0.230403 Standard deviation = 0.132492

VAR013: Percentage of Families in Poverty - Prevalence of Low Income

BG: *VAR013*

- Column headings: BGID10, CTID10, VAR013, zVAR013
  - BGID10 → 2010 Census, block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - VAR013 → percentage of families below poverty level (estimated by ACS) in BG equal to the value of the CT that it is contained within
  - zVAR013 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR013} =$ $\boldsymbol{value\ from\ CT\ contained\ in}$	Mean = 17.91859 Standard deviation = 13.86984

CT: *VAR013*

- Column headings: CTID10, VAR013, zVAR013
  - CTID10 → 2010 Census, census tract geography code
  - VAR013 → percentage of families below poverty level (estimated by ACS)
  - zVAR013 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{N/A}$	Mean = 19.08846 Standard deviation = 14.81721

VAR014: Total Population – No Official Languages Knowledge

BG: *VAR014*

- Column headings: BGID10, CTID10, Population, Official Language, VAR014, zVAR014
  - BGID10 → 2010 Census, block group area geography code
  - CTID10 → corresponding 2010 Census, census tract geography code that block group (BG) is within
  - Population → total number of people in BG unit
  - Official Language → total number of people that do not speak English at all
  - VAR014 → total proportion (decimal) of population with no knowledge of official language
  - zVAR014 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR014} = \frac{\boldsymbol{Official\ Language}}{\boldsymbol{Population}}$	Mean = 0.060709 Standard deviation = 0.071622

CT: *VAR014*

- Column headings: CTID10, Population, Official Language, VAR014, zVAR014
    - CTID10 → 2010 Census, census tract geography code
    - Population → total number of people in CT unit
    - Official Language → total number of people that do not speak English at all
    - VAR014 → total proportion (decimal) of population with no knowledge of official language
    - zVAR014 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR014} = \frac{\boldsymbol{Official\ Language}}{\boldsymbol{Population}}$	Mean = 0.066898 Standard deviation = 0.065757

Data Dictionary – 2011 UK Census Data & Official Statistics

Social Resilience Index (SoRI) Variables by Output Area (OA) and Data Zones (DZ) for the City of Edinburgh, Scotland, United Kingdom

Summary of Final SoRI Census Variables for Mapping

	SoRI Variable	Data Zones (DZ)	Output Area (OA)
VAR001	Total Population – Canadian/UK Citizenship	✓	✓
VAR002	Total number of occupied private dwelling – construction period up to 1970	--	--
VAR003	Average value of private dwellings	✓	--
VAR004	Total number of occupied private dwelling – need of major repair	--	--
VAR005	Total number of occupied private dwelling – moveable dwelling	✓	✓
VAR006	Total number of occupied private dwellings – rental	✓	✓
VAR007	Income percentage – payments from government transfers	✓	--
VAR008	Average household income – private households	--	--
VAR009	Total immigrant population – census period of immigration	✓	✓
VAR010	Total population age 15 and over – unemployed	✓	✓
VAR011	Total population age 65 and over – living alone	✓	✓
VAR012	Total number of families – lone parent	✓	✓
VAR013	Population percentage in private household – low income	--	--
VAR014	Total population – no official languages knowledge	✓	✓
	Total Number of Variables	10	8

A "--"symbol indicates that the variable was not included in the social resilience score for the study area.

Calculation of SoRI Census Variables for Mapping

VAR001: Total Population – UK Nationality (Citizenship)

OA: *VAR001*

- Column headings: OA2011, Residents, National Identity, VAR001, zVAR001
  - OA2011 → 2011 Census, output area geography code
  - Residents → total number of usual residents (i.e., population) in each OA unit
  - National Identity → total number of people who identify with UK affiliations
  - VAR001 → total proportion (decimal) of population with self-determined UK affiliations
  - zVAR001 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR001} = \frac{\boldsymbol{National\ Identity}}{\boldsymbol{Residents}}$	Mean = 0.886837 Standard deviation = 0.101081

DZ: *VAR001*

- Column headings: DZ2011, Residents, National Identity, VAR001, zVAR001
  - DZ2011 → 2011 Census, data zone geography code
  - Residents → total number of usual residents (i.e., population) in each DZ unit
  - National Identity → total number of people who identify with UK affiliations
  - VAR001 → total proportion (decimal) of population with self-determined UK affiliations
  - zVAR001 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR001} = \frac{\boldsymbol{National\ Identity}}{\boldsymbol{Residents}}$	Mean = 0.890172 Standard deviation = 0.081286

VAR003: Average Price of Private Dwellings

OA: *VAR003*

- Column headings: OA2011, DZ2011, VAR003, zVAR003
  - OA2011 → 2011 Census, output area geography code
  - DZ2011 → 2011 Census, data zone geography code (DZ unit that OA is contained within)
  - VAR003 → average value of private dwelling for OA equal to the value of the DZ that it is contained within
  - zVAR003 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR003} =$ $\boldsymbol{value\ from\ DZ\ contained\ in}$	Mean = 200474.6 Standard deviation = 98459.03

DZ: *VAR003*

- Column headings: DZ2011, VAR003, zVAR003
  - DZ2011 → 2011 Census, data zone geography code
  - VAR003 → average value of private dwelling
  - zVAR003 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{N/A}$	Mean = 202360.8 Standard deviation = 101568.9

VAR005: Total Number of Occupied Private Dwellings – Moveable Dwellings

OA: *VAR005*

- Column headings: OA2011, Households, Mobile, VAR005, zVAR005
  - OA2011 → 2011 Census, output area geography code
  - Households → total number of households in OA unit
  - Mobile → total number of caravan or other mobile or temporary structures
  - VAR005 → total proportion (decimal) of households that are moveable dwellings
  - zVAR005 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR005} = \frac{\boldsymbol{Mobile}}{\boldsymbol{Households}}$	Mean = 0.000335 Standard deviation = 0.007772

DZ: *VAR005*

- Column headings: DZ2011, Households, Mobile, VAR005, zVAR005
  - DZ2011 → 2011 Census, data zone geography code
  - Households → total number of households in DZ unit
  - Mobile → total number of caravan or other mobile or temporary structures
  - VAR005 → total proportion (decimal) of households that are moveable dwellings
  - zVAR005 → normalized z-score of variable

Calculation	Z-scores
$VAR005 = \frac{Mobile}{Households}$	Mean = 0.000359 Standard deviation = 0.004313

VAR006: Total Number of Occupied Private Dwellings – Rental

OA: *VAR006*

- Column headings: OA2011, Households, Rental, VAR006, zVAR006
  - OA2011 → 2011 Census, output area geography code
  - Households → total number of households in OA unit
  - Rental → total number of rented households
  - VAR006 → proportion of households (decimal) that are rented
  - zVAR006 → normalized z-score of variable

Calculation	Z-scores
$VAR006 = \frac{Rental}{Households}$	Mean = 0.384242 Standard deviation = 0.26769

DZ: *VAR006*

- Column headings: DZ2011, Households, Rental, VAR006, zVAR006
  - DZ2011 → 2011 Census, data zone geography code
  - Households → total number of households in DZ unit
  - Rental → total number of rented households
  - VAR006 → proportion of households (decimal) that are rented
  - zVAR006 → normalized z-score of variable

Calculation	Z-scores
$VAR006 = \frac{Rental}{Households}$	Mean = 0.37377 Standard deviation = 0.235005

VAR007: Payments from Government Transfers

OA: *VAR007*

- Column headings: OA2011, DZ2011, VAR007, zVAR007
  - OA2011 → 2011 Census, output area geography code
  - DZ2011 → 2011 Census, data zone geography code (DZ unit that OA is contained within)
  - VAR007 → proportion of people (decimal) claiming government transfers in OA equal to the value of the DZ that it is contained within
  - zVAR007 → normalized z-score of variable

Calculation	Z-scores
$VAR007 =$ $value\ from\ DZ\ contained\ in$	Mean = 0.306154 Standard deviation = 0.302776

DZ: *VAR007*

- Column headings: DZ2011, VAR007, zVAR007
  - DZ2011 → 2011 Census, data zone geography code

- Residents → total number of usual residents (i.e., population) in each DZ unit
- GovTransfers → total number of people claiming Income Support, Jobseeker's Allowance, and Employment and Support Allowance
- VAR007 → proportion of people (decimal) claiming government transfers
- zVAR007 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR007 = \frac{GovTransfers}{Residents}}$	Mean = 0.311448 Standard deviation = 0.324183

VAR009: Total Immigrant Population – Census Period of Immigration

OA: *VAR009*

- Column headings: OA2011, Persons, Immigration, VAR009, zVAR009
  - OA2011 → 2011 Census, output area geography code
  - Residents → total number of usual residents (i.e., population) in each OA unit
  - Immigration → total number of people arrived in the UK during 2001- 2011 census period
  - VAR009 → proportion of population (decimal) immigrated during 2001 – 2011 census period
  - zVAR009 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR009 = \frac{Immigration}{Residents}}$	Mean = 0.2367 Standard deviation = 0.379604

DZ: *VAR009*

- Column headings: DZ2011, Residents, Immigration, VAR009, zVAR009
  - DZ2011 → 2011 Census, data zone geography code
  - Residents → total number of usual residents (i.e., population) in each DZ unit
  - Immigration → total number of people arrived in the UK during 2001- 2011 census period
  - VAR009 → proportion of population (decimal) immigrated during 2001 – 2011 census period
  - zVAR009 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR009 = \frac{Immigration}{Residents}}$	Mean = 0.108085 Standard deviation = 0.085434

VAR010: Total Population Age 15 and Over – Unemployed

OA: *VAR010*

- Column headings: OA2011, Workforce, Unemployed, VAR010, zVAR010
  - OA2011 → 2011 Census, output area geography code
  - Workforce → total number of people aged 16 to 74 in each OA unit
  - Unemployed → number of people in workforce (i.e., economically active) that are unemployed
  - VAR010 → proportion of population (decimal) that is unemployed
  - zVAR010 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR010 = \frac{Unemployed}{Workforce}}$	Mean = 0.041011 Standard deviation = 0.037126

DZ: *VAR010*

- Column headings: DZ2011, Workforce, Unemployed, VAR009, zVAR009
  - DZ2011 → 2011 Census, data zone geography code
  - Workforce → total number of people aged 16 to 74 in each DZ unit
  - Unemployed → number of people in workforce (i.e., economically active) that are unemployed
  - VAR010 → proportion of population (decimal) that is unemployed
  - zVAR010 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR010} = \frac{\boldsymbol{Unemployed}}{\boldsymbol{Workforce}}$	Mean = 0.03981 Standard deviation = 0.025285

VAR011: Total Population Age 65 and Over – Living Alone

OA: *VAR011*

- Column Headings: OA2011, Ppl in Households, Living Alone, VAR011, zVAR011
  - OA2011 → 2011 Census, output area geography code
  - Ppl in Households → total number of people in households in OA unit
  - Living Alone → total number of one-person households with person aged 65 and over
  - VAR011 → proportion of population (decimal) age 65 and over, living alone
  - zVAR011 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR011} = \frac{\boldsymbol{Living\ Alone}}{\boldsymbol{Ppl\ in\ Households}}$	Mean = 0.061879 Standard deviation = 0.072197

DZ: *VAR011*

- Column Headings: DZ2011, Ppl in Households, Living Alone, VAR011, zVAR011
  - DZ2011 → 2011 Census, data zone geography code
  - Ppl in Households → total number of people in households in DZ unit
  - Living Alone → total number of one-person households with person aged 65 and over
  - VAR011 → proportion of population (decimal) age 65 and over, living alone
  - zVAR011 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR011} = \frac{\boldsymbol{Living\ Alone}}{\boldsymbol{Ppl\ in\ Households}}$	Mean = 0.057333 Standard deviation = 0.032794

VAR012: Total Number of Families – Lone Parent

OA: *VAR012*

- Column Headings: OA2011, Families, Lone Parent, VAR012, zVAR012
  - OA2011 → 2011 Census, output area geography code
  - Families → total number of families in OA unit
  - Lone Parent → total number of households with lone parent families
  - VAR012 → proportion of families (decimal) with lone parent families in OA
  - zVAR012 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR012} = \frac{\textbf{Lone Parent}}{\textbf{Families}}$	Mean = 0.115814 Standard deviation = 0.122996

DZ: *VAR012*

- Column Headings: DZ2011, Families, Lone Parent, VAR012, zVAR012
  - DZ2011 → 2011 Census, data zone geography code
  - Families → total number of families in DZ unit
  - Lone Parent → total number of households with lone parent families
  - VAR012 → proportion of households (decimal) with lone parent families in DZ
  - zVAR012 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR012} = \frac{\textbf{Lone Parent}}{\textbf{Families}}$	Mean = 0.07683 Standard deviation = 0.062885

VAR014: Total Population – No Official Languages Knowledge

OA: *VAR014*

- Column headings: OA2011, People Age 3+, Language, VAR014, zVAR014
  - OA2011 → 2011 Census, output area geography code
  - People Age 3+ → total number of people age 3 and over in each OA unit
  - Language → total number of people age 3 and over who understands but does not speak, read or write English/Scots; and have no skills in English/Scots
  - VAR014 → proportion of population (decimal) with no knowledge of official languages
  - zVAR014 → normalized z-score of variable

Calculation	Z-scores
$\boldsymbol{VAR014} = \frac{\textbf{Language}}{\textbf{People Age 3+}}$	Mean = 0.018933 Standard deviation = 0.021695

DZ: *VAR014*

- Column headings: DZ2011, People Age 3+, Language, VAR014, zVAR014
  - DZ2011 → 2011 Census, data zone geography code
  - People Age 3+ → total number of people age 3 and over in each DZ unit
  - Language → total number of people age 3 and over who understands but does not speak, read or write English/Scots; and have no skills in English/Scots
  - VAR014 → proportion of population (decimal) with no knowledge of official languages
  - zVAR014 → normalized z-score of variable

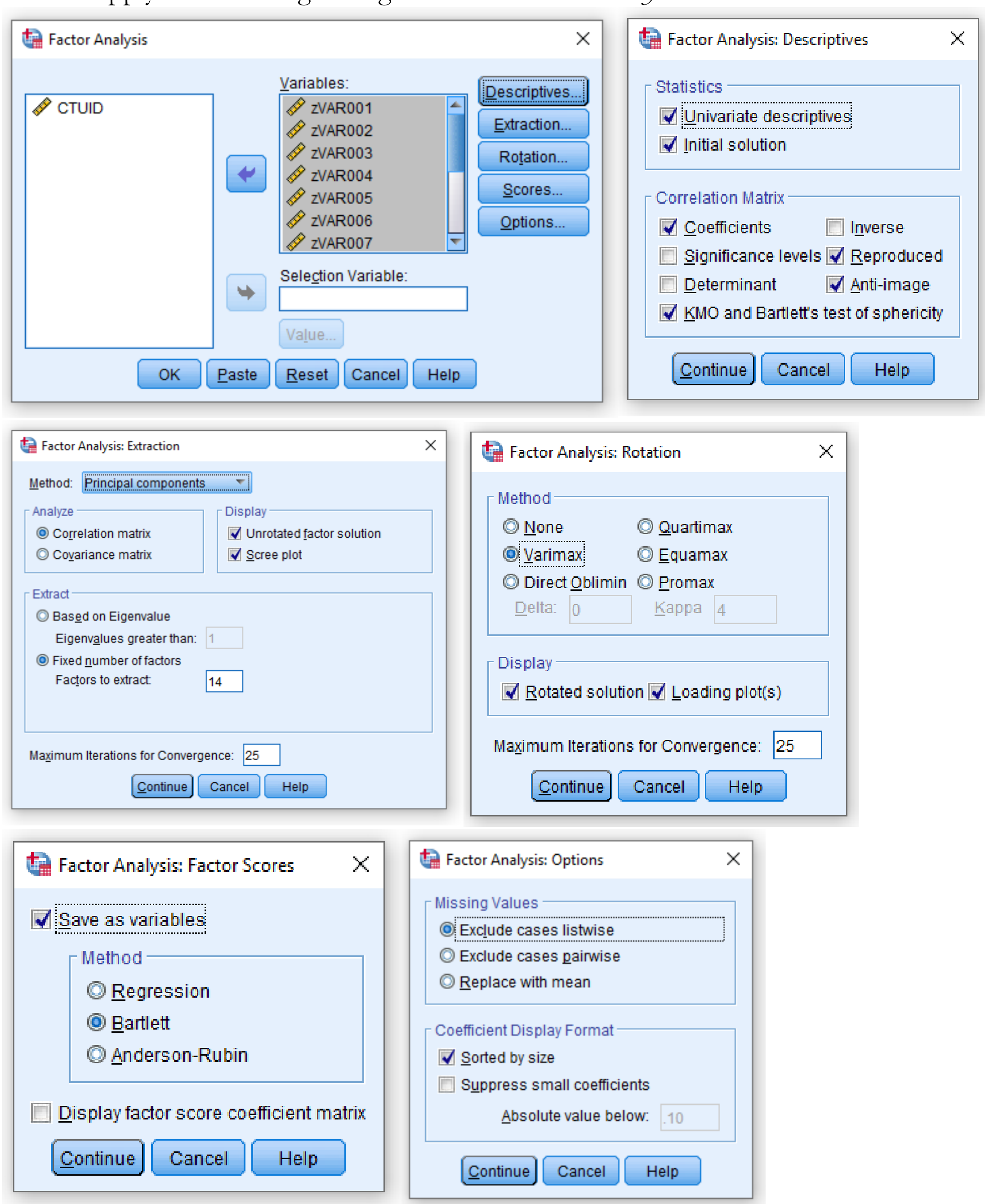
Calculation	Z-scores
$\boldsymbol{VAR014} = \frac{\textbf{Language}}{\textbf{People Age 3+}}$	Mean = 0.018305 Standard deviation = 0.012171

Appendix B - Principal Components Analysis (PCA) Procedure

The principal components analyses (PCA) were conducted using the IBM Statistics Package for the Social Sciences (SPSS) Version 26 software. The procedure and settings for running the PCA is detailed below.

1. Run SPSS Factor Analysis Tool
   Toolbar: Analyze > Dimension Reduction > Factor…

2. Apply the following settings from the *"Factor Analysis"* window:



From the "*Extraction*" settings window, under the "*Fixed number of factors*" button, the "*Factors to extract:*" option was adjusted for each iteration of the PCA according to the table below.

Name of PCA Test	**Description of Method**	**Rationale**
PCA	PCA which extracts principal components based on eigenvalues > 1.0.	Method for constructing the SoRI from Damude et al. (2015), based on the original methodology from Cutter et al. (2003).
PCA2a	PCA which extracts the same number of principal components as the number of input variables (i.e., number of principal components = number of input variables for each study area). *no. of PCs = no. of input variables* Vancouver = 14 PCs Los Angeles = 13 PCs Edinburgh = 10 PCs	First "baseline" iteration of PCA to extract the same number of principal components as the number of input variables (i.e., number of principal components = number of input variables for each study area). This iteration of the PCA is required to detect data structure and produce a scree plot for the subsequent experiment.
PCA2b	PCA to extract the number of principal components based on the inflection point of the scree plot. *no. of PCs = point of inflection on scree plot* Vancouver = 5 PCs Los Angeles = 2 PCs Edinburgh = 3 PCs	The intent of this experiment is to capture the sensitivity of the PCA extraction parameters. The inflection point on the scree plot is an indication of where there is a significant drop in the eigenvalues, and the principal components are no longer able to capture significant variance in the dataset, and there is a significant drop in (Coleman, 2012).

Suitability of PCA

The Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity are diagnostic measures used to evaluate the suitability of a PCA for a dataset. The KMO test measures the proportion of variance in the variables that may be caused by underlying factors; strength of relationships among variables; indication of whether PCA will yield distinct and reliable components (Coleman, 2012; Oulahen et al., 2015). The KMO measure ranges from 0 to 1, with higher values (i.e., closer to 1), indicating a higher suitability of a PCA for the dataset. 0.6 is a suggested minimum (Coleman, 2012).

Bartlett's test of sphericity is a statistic that measures whether the variables in the dataset are related such that the PCA would be suitable for structure detection (Coleman, 2012; Oulahen et al., 2015). The null hypothesis is that the correlation matrix is an identity matrix – each variable is not correlated to any other variable except for itself. A highly significant test statistic ($p < 0.001$) that rejects the null hypothesis indicates that the PCA is an appropriate procedure for the dataset. The results of the KMO test and Bartlett's test for each census scale and study area are summarized below.

City	Scale	KMO Test	Bartlett's Test
Vancouver	Census Tracts (CT)	0.669	0.000
	Dissemination Areas (DA)	0.646	0.000
LA	Census Tracts (CT)	0.762	0.000
	Block Groups (BG)	0.821	0.000
Edinburgh	Data Zones (DZ)	0.804	0.000
	Output Areas (OA)	0.727	0.000

The results from both statistics indicate that the PCA is an appropriate procedure for computing the SoRI with the available census data.

Sign Adjustment

Since the PCA is a statistical method to identify correlations, the directional components may not be representative of the variable relationships in reality. Sign adjustments were applied based on the contribution of the correlation coefficients from the positive variables that increase resilience and the negative variables that decrease resilience. For each principal component:

- Sum correlation coefficients for all positive (+) variables (i.e., increases resilience)
- Sum correlation coefficients for all negative (-) variables (i.e., decreases resilience)

If the positive (+) variables (i.e., increases resilience) had a greater sum, then the sign for that principal component was adjusted to be positive. On the contrary, if the negative (-) variables (i.e., decreases resilience) had a greater sum, then the sign for that principal component was adjusted to be negative.

Note that this is different from the the original method by Cutter, Boruff & Shirley (2003)[2]. In their methodology, if the majority of variables correlated to a PC has a negative relationship, then the sign for that PC was also adjusted to be negative. On the contrary, if most variables correlated to the PC has a positive relationship (i.e., increases resilience), then the sign was adjusted to be positive. If variables with different signs were correlated to the same PC, then the absolute value was used.

Thresholds for PCA2b, based on PCA2a Scree Plots

City	Scale	No. of Variables (Factors to extract)	No. of Components (Scree Plot inflection point)
Vancouver	Census Tracts (CT)	14	5
	Dissemination Areas (DA)	14	5
LA	Census Tracts (CT)	13	2
	Block Groups (BG)	13	2
Edinburgh	Data Zones (DZ)	10	3
	Output Areas (OA)	10	3

References

Coleman, J. S. M., 2012. Principal Components Analysis. In: Salkind, N. J. ed. The Encyclopedia of Research Design. Thousand Oaks: SAGE Publications Inc., pp. 1098-1102.

Cutter, S.L., Boruff, B.J., Shirley, W.L., 2003. Social Vulnerability to Environmental Hazards. Social Science Quarterly, 84(2), pp. 242-261.

Damude, K., Mortsch, L. & Joakim, E., 2015. Draft Report: Methods for Quantifying Social Resilience in Metro Vancouver, Canada. Ontario: Coastal Cities at Risk (CCaR) Project.

Oulahen, G., Mortsch, L., Tang, K. & Harford, D., 2015. Unequal Vulnerability to Flood Hazards: "Ground Truthing" a Social Vulnerability Index of Five Municipalities in Metro Vancouver, Canada. *Annals of the Association of American Geographers*, 105(3), pp. 473-495.

Appendix C - Survey Instruments, Ethics Materials & Interview Prompt

Title of the Study: The Inequalities of Resilience: A Case Study of Flood Risk Perceptions & Preparedness in Vancouver

Summary of Proposed Research

Flooding is the costliest climate issue in Canada, impacting both social systems and the built environment. As the largest city in British Columbia and the third-largest metropolitan area in Canada, Vancouver is a coastal seaport city and is therefore exposed to considerable risk to the impacts of flooding. In addition to environmental exposure, the socioeconomic characteristics of a population, such as social status and income, can further affect their resilience to such impacts. This study investigates the implications of using census data to identify spatial patterns in social inequalities and how these inequalities can translate into social resilience towards flood hazards. Indicators of social resilience are not limited to just census variables, and include the elements of risk perception and household preparedness. In order to capture these risk perceptions and the actions taken towards flood hazards, surveys will be conducted with local practitioners and residents in the City of Vancouver.

The intent of conducting both a practitioner survey and a local resident survey is to gather different perspectives to identify potential gaps and common themes of concern between residents and decision-makers. The surveys will gather perspectives about the awareness of flood risks, the influence of socioeconomic characteristics, and the elements of building resilience. While socioeconomic characteristics are quantitative and quantifiable such as census data, other elements of resilience cannot be captured by census data. For example, individual-level risk perceptions, household-level protection measures, and community-level initiatives. As identified by the City of Vancouver's Climate Change Adaptation Strategy[1] and Resilient Vancouver Strategy[2], a key priority area is building connected and prepared communities.

Through the integration of quantitative census data and qualitative data from the local resident and practitioner surveys, the objectives of this research are to investigate:

1) The implications of using census data as socioeconomic indicators to identify the spatial distribution of social inequalities.
2) The influence of these socioeconomic indicators towards risk perception and the actions taken towards flood hazards at the household level.
3) The suitability of using census data as socioeconomic indicators for the spatial analysis of social inequalities and social resilience.

The specific research questions that the surveys aim to address are the following:

- How do socioeconomic characteristics influence the actions taken towards flood hazards – if they choose to take action (i.e., risk perception), what types of actions, and whether they are able to implement such actions (i.e., adaptive capacity)
- Do inequalities in socioeconomic characteristics influence risk perception and the actions taken towards flood hazards between different neighbourhoods (i.e., spatial patterns)?
- What is the role of community cohesion and community preparedness towards building resilience in the City of Vancouver?

---

[1] City of Vancouver, 2019. *Climate Change Adaptation Strategy – 2018 Update and Action Plan*. Vancouver: City of Vancouver. Available at: <https://vancouver.ca/files/cov/climate-change-adaptation-strategy.pdf>

[2] City of Vancouver, 2019. *Resilient Vancouver Strategy*. Vancouver: City of Vancouver. Available at: <https://vancouver.ca/files/cov/resilient-vancouver-strategy.pdf>

Expert Interview Document

Title of the Study: The Inequalities of Resilience: A Case Study of Flood Risk Perceptions & Preparedness in Vancouver

Practitioner Interviews

Preamble – Summary of Research

Thank you for taking the time to meet with me today and for contributing to my research. Before we get started, I would like to confirm with you again, if you are okay with our interview today being recorded? (*Don't ask this if they have already said 'no' to recording in the consent form*.) I would like to reassure you that whether or not this is recorded, your identity will not be linked to any of your responses and your identity will remain anonymous in my thesis.

- I'd like to start by asking a bit more about your organization – what do you do or what is your involvement in the City Vancouver?
  - *In the final thesis, this is intended to categorize the type work that the practitioner is involved in – for example, urban planning or community engagement or a non-profit organization.*
- To get some more context, could you provide some examples of projects that your organization has completed or is currently working on?
  - *In the final thesis, this is intended to categorize the type work that the practitioner is involved in – for example, urban planning or community engagement or a non-profit organization.*
  - Names of projects?
- What is your role in the organization?
  - *The final thesis will not include specific job titles/organization roles. This is intended for use by the researchers to better understand the type of work that the practitioner is involved in.*

Thank them for the introduction – move onto introducing research:

My research investigates how inequalities in social and economic characteristics, such as housing type and income, can affect resilience towards flood hazards. These characteristics may also influence people's choice to take action and what types of actions they take towards flood hazards. While socioeconomic characteristics are quantitative and quantifiable such as census data, we would like to explore other elements of resilience cannot be captured by census data. For example, individual-level risk perceptions, household-level protection measures, and community-level initiatives. As identified by the City of Vancouver's Climate Change Adaptation Strategy[3] and Resilient Vancouver Strategy[4], a key priority area is building connected and prepared communities. This is another key theme of social resilience that cannot be identified through census data, and that I hope to capture through our discussion today.

Survey

I would like to start off by asking you to complete a written survey that I've prepared. If there are any questions that you don't feel comfortable answering, you can skip them; and if at any point you feel that you no longer want to participate in this research, please let me know and I will destroy all materials that I have up until this point. If there are any questions that you are unclear about, you are welcome to ask.

[3] City of Vancouver, 2019. *Climate Change Adaptation Strategy – 2018 Update and Action Plan*. Vancouver: City of Vancouver. Available at: <https://vancouver.ca/files/cov/climate-change-adaptation-strategy.pdf>

[4] City of Vancouver, 2019. *Resilient Vancouver Strategy*. Vancouver: City of Vancouver. Available at: <https://vancouver.ca/files/cov/resilient-vancouver-strategy.pdf>

Discussion

Thank you very much for completing the survey. Before moving onto the discussion, did you have any questions about the survey that you just answered?

- If the entire city was flooded, do you think that the impacts will affect the neighbourhoods of Vancouver evenly? Why or why not?
- Do you think that these causes of social inequalities are evenly dispersed around the city? Why or why not?
    - Based on your experience, what do you think are some causes of social inequalities in Vancouver?
- Top challenges to building household resilience
- Top challenges to building community resilience
- Needed improvements to build resilience for the city
- Do you think that floods that among the top environmental hazards for Vancouver?
    - Are there other environmental hazards that you think Vancouver would face a greater risk?

Closing Statements

Thank you again very much for your time and contribution today. That's all the questions that I have for you today. Do you have any other questions or feedback about our interview, the survey or the research study?

All of your responses that I've collected today, including the audio recording and your written survey will be securely retained at the University of Waterloo for at least 1 year. Only the research group will have access to the study data, which will not contain any identifying information. My final thesis containing the results of this study will be uploaded to the University of Waterloo repository, which is publicly available. Would you like to be notified when the final thesis is available?

If you have anything you'd like to add or have any further questions, comments or concerns about this study, please feel free to contact me via email at any time.

Organization Email Recruitment

Dear *name*:

I am writing to you as a Master’s student from the Department of Geography and Environmental Management at the University of Waterloo, Ontario to request for ***[name of organization]***’s assistance with a study that I am conducting as part of my Master's degree. The title of my research study is “*The Inequalities of Resilience: A Case Study of Flood Risk Perceptions & Preparedness in Vancouver*”. I would like to provide you with more information about this project that explores the influence of social inequalities towards flood risk perception and preparedness in the City of Vancouver.

The purpose of this study is to find out how different individual and household socioeconomic characteristics may affect the perceptions and the actions taken towards flood hazards. I hope to invite community members who are engaged in the programs of the ***[name of organization]*** to participate in this study. I believe that the community members of your program have local knowledge and investment relating to household flood resilience. During this study, I will be gathering information through an online survey.

To respect the privacy and rights of the ***[name of organization]*** and its participants, I will not be contacting community members directly. I have attached an email recruitment script to be distributed at the discretion of ***[name of organization*]**. If an individual is interested in participating, they will be invited to click the link to the online survey, which will direct them to the introduction page detailing their rights as a participant and information about the study. Individuals will be able to provide their consent to participate in the study before the survey commences.

Participation of any community member is completely voluntary. Each individual will make their own independent decision as to whether or not they would like to be involved. All participants will be informed and reminded of their rights to participate or withdraw at any time in the study.

Participants will not be asked for any identifying information, with the exception to enter their email into a separate link to enter a draw for 1 of 5 $25 UberEats digital gift cards. Participants will not be identifiable, and only described as community member/individual/participant.

If the ***[name of organization]*** wishes the identity of the organization to remain confidential, a pseudonym will be given to the organization. All data collected will be maintained on a password-protected computer database in a restricted access area of the university. Further, the data will be electronically archived after completion of the study and maintained for a minimum of 1 year on a university-owned network drive with no personal identifiers. Finally, only myself and my advisor, Dr. Su-Yin Tan in the Department of Geography & Environmental Management at the University of Waterloo will have access to these materials. There are no known or anticipated risks to participants in this study.

I would like to assure you that this study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee. However, the final decision about participation belongs to the ***[name of organization],*** and the community members.

If you have any questions regarding this study or would like additional information to assist you in reaching a decision about participation, please contact me at hschu@uwaterloo.ca. You may also contact my supervisor, Dr. Su-Yin Tan at 1-519-888-4567 ext. 38772 or by email at su-yin.tan@uwaterloo.ca.

I hope that the results of my study will be beneficial to the ***[name of organization]***, to community members, and to the practitioners involved in planning, flood risk management, and emergency preparedness as well as the broader research community. I very much look forward to speaking with you and thank you in advance for your assistance with this study.

Yours sincerely,

Samantha Hao-Yiu Chu
MSc Candidate
Department of Geography & Environmental Management
University of Waterloo

Su-Yin Tan, PhD
Director, Applied Geomatics Research Laboratory
Department of Geography & Environmental Management
University of Waterloo

Email Recruitment Script
Sent on Behalf of the Researcher

Sample Email Subject Line: University of Waterloo Study on Flood Risk Perceptions & Preparedness

Dear members of the community/program participants,

Samantha Chu, a student at the University of Waterloo, has contacted **[name of organization]** asking us to tell our community members about a study she is doing about flood risk perceptions and preparedness in Vancouver. This research is part of her Master of Science program in Geography at the University of Waterloo. The following is a brief description of her study.

If you are interested in getting more information about Samantha's study, please read the description below and/or **CONTACT SAMANTHA DIRECTLY** at her UWaterloo email (hschu@uwaterloo.ca). The researcher will not be able to identify any participants nor their affiliation with **[name of organization]** in the survey. Taking part or not taking part in this study will not affect your status or any activities that you are involved in here at **[name of organization].**

You are invited to participate in a research study conducted by Samantha Chu, under the supervision of Dr. Su-Yin Tan from the Department of Geography and Environmental Management of the University of Waterloo, Canada. The purpose of the study is to find out how different individual and household characteristics may affect the perceptions and the actions taken towards flood hazards.

If you decide to volunteer, you will be asked to complete a 20-minute online survey that is completed anonymously. Participation in this study is voluntary. You may decline to answer any questions that you do not wish to answer, and you can withdraw your participation at any time by not submitting your responses. You will not be asked for any identifying information during the survey, with the exception of providing your email in a separate link if you wish to be entered in a draw for 1 of 5 $25 UberEats digital gift cards. Samantha has asked us to attach a copy of her information letter to this email, which provides full details about her study (Attachment: *Information Consent Letter – Resident_online*).

The study website below, will direct you to the introduction page detailing your rights as a participant and you will be able to provide your consent to participate in the study before the survey commences.
If you wish to participate, please visit the study website at: https://forms.gle/PnBET7yCDhnBaQyMA

This study has been reviewed and received ethics clearance through the University of Waterloo Research Ethics Committee (ORE# 41881).

Sincerely,
[*Holder of Participants' Contact Information]*