Social Equity Dimensions of Flood Risk Management in Canada

by

Liton Chakraborty

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner: **Dr. Greg Oulahen**
Assistant Professor
Department of Geography & Environmental Studies
Faculty of Arts, Ryerson University

Co-Supervisor(s): **Dr. Daniel Scott**
Professor & University Research Chair
Department of Geography & Environmental Management
Faculty of Environment, University of Waterloo

Dr. Jason Thistlethwaite
Associate Professor
School of Environment, Enterprise and Development
Faculty of Environment, University of Waterloo

Internal Member: **Dr. Horatiu Rus**
Associate Professor
Department of Economics and Political Science
Faculty of Arts, University of Waterloo

Internal-external Member: **Dr. Daniel Henstra**
Associate Professor
Department of Political Science
Faculty of Arts, University of Waterloo

Author's Declaration

This thesis consists of three manuscripts, all of which I authored or co-authored: see Statement of Contributions included in the 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 made electronically available to the public.

Statement of Contributions

This thesis consists in part of three manuscripts written for publication. Exceptions to sole authorship are as follows:

Chapter 2:

Chakraborty, L., Rus, H., Henstra, D., Thistlethwaite, J., & Scott, D. (2020). A place-based socioeconomic status index: Measuring social vulnerability to flood hazards in the context of environmental justice. *International Journal of Disaster Risk Reduction*, 43, 101394. https://doi.org/10.1016/j.ijdrr.2019.101394

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As a lead author of all three manuscripts, I hereby declare that I was responsible for the research conceptualization and data collection, designing methodology, writing original draft, investigation, and analysis. I was also responsible for drafting, revising, and submitting the articles for publication in the respective peer-reviewed journals and addressing reviewers' comments. The other co-authors adopted a supervisory role, provided feedback on data collection and analysis, and drafted manuscripts. My co-supervisors, Dr. Daniel Scott, and Dr. Jason Thistlethwaite, guided each step of the research, provided feedback on essential research direction.

Abstract

Disproportionate exposure to hazards among socioeconomically disadvantaged populations and racial/ethnic minority communities contributes to rising environmental injustices worldwide. Examining the link between race/ethnicity, socioeconomic status, and the location of environmental hazards provides an important foundation for understanding fundamental determinants of environmental inequities based on socioeconomic indicators and disparate impacts of hazards. To date, Canada's environmental justice (EJ) research has focused on identifying vegetation, air pollution, health, and noise-related environmental inequities, mostly in a few selected cities and metropolitan areas. This is inadequate for a national policy conversation on environmental injustices. Although flooding has emerged as the costliest and most frequently occurring natural hazard underpinning nationwide flood risk management (FRM) policy and social concerns in Canada, it is mostly unknown which population subgroups are highly vulnerable to flooding, where are the hotspots of social vulnerability to flood hazards, and whether groups of racial/ethnic minorities and socioeconomically vulnerable populations are disproportionately affected by flooding across Canada.

Assessing socioeconomic vulnerability indicators to flood hazards and identifying their disparate relations to flood exposure help policymakers understand which racial/ethnic and socioeconomic groups are inequitably exposed to flooding. This approach better assists in making evidence-informed and risk-based decisions, which will help fight racial discrimination and redress harm due to environmental injustice by developing a socially equitable flood management policy. Social equity considerations about flood management policies, programs, and legislations are consistent with the Government of Canada's commitment to implementing "Gender-based Analysis Plus (GBA+)" in decisions and developing the *National Strategy to*

Redress Environmental Racism Act that helps address differential impacts of hazards on people of all genders and diverse groups of socio-economic, ethnic, and cultural groups/communities.

This dissertation addressed several gaps in the Canadian literature on socioeconomic vulnerability to flooding and the distributive environmental justice analysis concerning differential exposure to flood hazards of people and places. It evaluated various spatial and non-spatial methodologies for assessing flood-related environmental inequity. The research has asked three sets of integrated research questions that jointly reflect the overall goal of analyzing social equity dimensions of flood risk management in Canada, including:

(1) What are the significant socioeconomic drivers of social vulnerability to flood hazards in Canada? Where are socially vulnerable neighbourhoods geographically concentrated in Canada?

(2) How exposed are residential properties to flood hazards across Canada? Do socioeconomic vulnerability and flood exposure of residential properties vary or concentrate spatially by geographic boundaries (e.g., census tracts, census metropolitan areas, and provinces/territories)? Where are the hotspots of flood risk, and which neighbourhoods are at an elevated risk of flooding and highly vulnerable to flood hazards?

(3) Are certain socially vulnerable groups, including women, the elderly, lone-parent households, people with disabilities, visible ethnic minorities, Indigenous peoples, and individuals of lower socioeconomic status, inequitably exposed to flood hazards in Canada? Are relationships between Canadians' socio-demographic characteristics and residential exposure to flood risk spatially heterogeneous? Are Canadians likely to experience environmental injustices or systemic social inequities through differential exposure to flood risk?

In answer to the first set of questions, the research developed a national-scale socioeconomic status (SES) index for Canadians to measure relative social vulnerability across census tract (CT)-level neighbourhoods. Building on the literature of social vulnerability to flood hazards and flood-related EJ research (J. Chakraborty et al., 2014; Collins et al., 2017; Susan L. Cutter et al., 2003; Grineski et al., 2015; Messer et al., 2006; Oulahen, Shrubsole, et al., 2015), a wide range of 49 social vulnerability indicators were considered from six main areas, including:

- Special needs populations and their coping ability.
- Household or family arrangement.
- Race/ethnicity status.
- Access to financial resources and social supports.
- Built environment characteristics of homes.
- Language, gender, age, education, occupation categories, and gender-based intersectional labour force characteristics.

Principal Component Analysis (PCA) on those indicators revealed 35 of the 49 census-based variables as significant representatives of social vulnerability drivers in Canada. The geographic concentration of vulnerability was delineated through geographical information system (GIS)-based choropleth mapping of SES index scores across CTs. Racial or ethnic groups were found to be among the most socially vulnerable groups in Canada, consistent with the extant environmental justice literature. Large census metropolitan areas (CMA) were substantially less socially vulnerable than their smaller counterparts. Social vulnerability was mostly concentrated in urban areas across Canada, and Atlantic Canada provinces were considerably more socioeconomically vulnerable than Western Canada and Central Canada provinces.

This dissertation provided the first nationwide and comprehensive flood risk assessment by leveraging data on flood hazards, social vulnerability, and exposure of residential properties to answer the second set of questions presented above. Flood hazard exposure analysis captured the percentage of residential properties within a CT exposed to any of pluvial (surface water), fluvial (riverine), or storm surge (coastal) flooding in a 100-year return period (with or without accounting for fluvial flood defenses). The extent of flood risk and geographic concentration of risk hotspots were identified using GIS by determining most flood vulnerable neighbourhoods, where very high social vulnerability coincided with very high flood exposure. The findings suggested that Ontario and Québec had the highest number of CTs among all provinces, revealed as "at-risk" areas of flooding (i.e., 66% of the total 5721 CTs), regardless of accounting for fluvial-flood defenses. The results indicated most of the CMAs or urban regions in Central Canada and Western Canada were geographically concentrated in flood-disadvantaged areas that were susceptible to 'high - very high' flood risk, while fluvial-flood defense was overlooked. Population subgroups and residential properties in 18 of the 5721 CTs, over nine CMAs, were detected with very high flood risk. Four CTs in Chilliwack, BC, and Windsor, ON CMAs, were nationally recognized as having the highest flood risk.

To answer the third set of questions, the dissertation investigated the environmental justice hypothesis that socioeconomically disadvantaged and visible minority population subgroups disproportionately inhabit flood zones. The dissertation also demonstrated the value of a geographically weighted regression (GWR) approach in environmental equity research to understand and examine spatial heterogeneity in exposure to flood hazards that support statistically valid analyses about the spatial relationships between flood exposure and racial, ethnic, and socio-demographic characteristics. Consistent with the environmental equity literature, the dissertation concluded that socially vulnerable residents are the predominant occupants of inland flood zones, and flood-related socioeconomic inequities are non-stationary as they vary across Canada. The research found certain vulnerable groups, such as females, lone-parent households, Indigenous peoples, South Asians, the elderly, other visible minorities, and economically insecure residents, located at a higher risk of flooding in Canadian neighbourhoods. Inland flood risk, both fluvial and pluvial, is of more significant concern for Canada as socioeconomically deprived residents disproportionately inhabit inland flood zones more than coastal flood zones.

The dissertation provided several methodological contributions to advancing scholarly knowledge in the fields of social vulnerability to environmental hazards, environmental justice (EJ), and social equity implications of flood risk, including:

1. It filled a gap of national-scale scholarly research on social vulnerability analysis by developing an SES index for Canada based on a statistically valid and empirically robust methodology of PCA for dimensionality reduction in the dataset.
2. It critically deconstructs and presents a comprehensive flood risk assessment methodology by combining social vulnerability, exposure, and flood hazards data sets at the national scale to pinpoint hotspots of flood risk across Canadian neighbourhoods.
3. It advanced the quest for the most appropriate methodological framework to analyze social and spatial inequities in exposure to flood hazards after considering spatial effects.
4. It provided a unique, nationwide, quantitative EJ study and analyzed spatial heterogeneity in flood risk exposure across Canada.

The results of this dissertation inform risk-based flood hazard management policies that are consistent with the Rawlsian distributive justice principle, that is, to help those most flood disadvantaged neighbourhoods first. The results are of interest to emergency managers who design policies that improve flood resilience to – at the very least - avoid approaches that exacerbate pre-existing environmental injustices (e.g., rendering inequitable flood relief or recovery resources to low-income households and renters). The analysis performed in the thesis is critically important to detect flood-vulnerable racial/ethnic subgroups and geographical regions in Canada, where disaster and emergency management resources are needed most for preparedness, response, and recovery. This thesis provides a solid foundation for prioritizing public investment in flood management policies and decisions that support GBA+, social justice as fairness, and vulnerability-based environmental equity principles in emergency management and disaster risk reduction. The findings should foster critical discussions involving governments at various levels, academia, regional scientists, and policymakers seeking data-driven and evidence-based solutions to disaster-related problems by addressing systemic social inequities and GBA+ in decisions.

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My academic journey for doctoral studies started with an official acceptance into the SIDA-financed Ph.D. program in Environmental and Climate Economics at the University of Gothenburg, Sweden. I owe gratitude to several professors of the Environmental Economics Unit at Gothenburg, including Dr. Håkan Eggert, Dr. Thomas Sterner, and Dr. Gunnar Köhlin, who strongly supported me to make a smooth transition from Sweden to Canada. I am indebted to professor Anindya Sen, who believed in my academic merits and endlessly supported me to continue doctoral studies at the University of Waterloo.

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Finally, I am thankful to my parents, my wife, and two lovely sons, as they are the ones who gave me the privilege and opportunity and believed in me to complete this doctoral dissertation. Thank you for always staying beside me and supporting me to follow my ambition in life.

Dedication

To the soul in peace of my beloved father, Rabindra Chakraborty.

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List of Abbreviations

AIC	Akaike Information Criteria
CA	Census Agglomeration
CMA	Census Metropolitan Area
CSD	Census Subdivisions
CT	Census Tract
DB	Dissemination Block
EFA	Exploratory Factor Analysis
EJ	Environmental Justice
FRM	Flood Risk Management
GBA+	Gender-based Analysis Plus
GIS	Geographical Information System
GWLR	Geographically Weighted Logistic Regression
GWR	Geographically Weighted Regression
IQR	Interquartile Range
NSI	Non-standardized Socioeconomic Index
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
SAR	Simultaneous Autoregressive
SE	Standard Error
SEM	Spatial Error Model
SES	Socioeconomic Status
SLM	Spatial Lag Model
SoVI	Social Vulnerability Index

Chapter 1: Introduction

1.1 Research Context

Canada has a recorded history of flooding for more than 300 years (Buttle et al., 2016; Wojtanowski, 1997). One of the earliest flooding event was recorded in New Brunswick in 1696 (Burrell & Keefe, 1989). Among Canada's climatic and meteorological hazards, floods are the most widespread, economically, and socially significant hazards (I. Burton & Kates, 1964; Jakob et al., 2013). Flooding became a major social concern for Canadians since the mid-1950s, following the Second World War, when the intensity and frequency of extreme weather events brought devastating socioeconomic impacts and longer-term social, emotional, and economic disruption on society caused by severe flooding and erosion problems. For example, 81 people lost their lives, 4000 families left homeless, 32 houses were washed away due to the Hurricane Hazel-related severe flooding event in 1954 (see https://www.hurricanehazel.ca). In response, Conservation Authorities began to be established by municipalities and the province of Ontario for protecting people and property from natural hazards, such as flooding and erosion, and for conserving natural resources for economic, social, and environmental benefits in cooperation with all levels of government, landowners, and several other organizations (Conservation Ontario, 2021).

Over the past two decades, flooding has been regarded as a significant climate change risk in Canada, causing severe damage to properties and critical infrastructures, resulting in extreme disruptions to people's well-being, socioeconomic status, and livelihoods (Feltmate & Fluder, 2018). Due to climate change, extreme weather events such as heavy rainfall, more intense storms, and changes in snowmelt timing are more likely to occur, resulting in more frequent and intense flooding and flood damages (X. Zhang et al., 2019). Flooding is Canada's costliest natural hazard (Golnaraghi et al., 2020), which accounts for about three-quarters of federal

Disaster Financial Assistance (DFAA) payments (Insurance Bureau of Canada, 2019c). Over the 25-years before 2009, the insured losses from flooding and water damages to homes averaged $400 million a year but have increased to an average of $1.4 billion per year since 2009 (Insurance Bureau of Canada, 2019a). Flood damages coupled with increased population growth and expansion of development in flood-prone areas are very likely to result in detrimental socioeconomic impacts on Canadians that are expected to worsen in the future (Burn et al., 2016; Honegger & Oehy, 2016).

Flood risk is multiplied when extreme climatic conditions interact with existing socioeconomic vulnerabilities to flood hazards that increase the chances of harmful impacts on people, property, and critical infrastructure (Agrawal et al., 2014; Susan L. Cutter et al., 2003). Flood risk management (FRM) cannot be sustainable unless FRM decision-makers consistently identify, understand, and address the socioeconomic drivers of vulnerability to flood hazards that intensify flood risk and exacerbate flood disasters (von A. Fekete, 2009; Schanze et al., 2006). Assessing and addressing social vulnerability to flood hazards and its components is an integral part of the flood risk management framework that promotes effective flood management capability and explains the flood risk (Schanze et al., 2006; Wisner et al., 2004).

In Canada, flood management is a complex arrangement of local, provincial, and federal governments, home/property owners, and some special-purpose agencies such as water conservation authorities (Sandink et al., 2010). Since the 1950s, FRM policies in Canada have evolved from engineering-based structural control measures to a risk-based flood management approach within a comprehensive Emergency Management Framework (Public Safety Canada, 2017; Shrubsole, 2014). In addition, as part of the committed efforts to national flood resiliency, Canada’s federal government announced the creation of an interdisciplinary Task

Force on Flood Insurance and Relocation Program (FIRP) on November 23, 2020, responsible for creating "a new, low-cost national flood insurance program to protect homeowners at high risk of flooding and without adequate insurance protection" (Public Safety Canada, 2020).

A national action plan is also currently in development to assist with relocating those at the highest risk of repeat flooding. As part of these national strategies, the Government of Canada, through the mandate letter to the Minister of Public Safety and Emergency Preparedness, emphasized applying GBA+, considering public policies through an intersectional lens, and addressing systemic inequities (Trudeau, 2021). Canada has also taken the first initiative to develop the *National Strategy to Redress Environmental Racism Act* (Bill C-230) for protecting Black, Indigenous, and people of colour communities facing disproportionate impacts from exposure to hazards and environmental pollutants, such as spewing from industrial plants, oil and gas wells, and toxic dumps (House of Commons of Canada, 2020; Reid & Hopton, 2021). These policy priorities require analysis to understand and then assess, address, and manage systemic inequality faced by socially vulnerable populations due to disproportionate exposure to climatic hazards, including flood hazards.

A critical barrier to addressing Canada's policy mandate is the lack of national-scale research on socioeconomic vulnerability that identifies priority locations where government interventions are essential to mitigate both physical and societal aspects of vulnerability to flooding. Scholars argue that a limited understanding of social vulnerability to flooding and geospatial distribution of socioeconomic drivers could raise concerns of social inequality in implementing FRM strategies (Tate et al., 2021). Although many Canadian studies have addressed flood vulnerability (Agrawal et al., 2014; Armenakis et al., 2017; Fox, 2008; Manuel et al., 2015; Morris-Oswald, 2007; Oulahen, 2016; Oulahen, Mortsch, et al., 2015; Oulahen, Shrubsole, et al., 2015; Stewart, 2007), these studies are largely limited in scope to a specific metropolitan area, watershed or river basin, with limited application to inform and improve national FRM policy development.

In the hazard, disaster, and emergency management literature, social vulnerability refers to the socio-demographic characteristics and socioeconomic capacities of an individual, a group, or a community that determine or influence their resiliency or susceptibility to harm from the adverse impacts of a natural hazard and/ disaster (S. L. Cutter, 1996; Flanagan et al., 2011; Wisner et al., 2004). A socioeconomic vulnerability index refers to an empirical and relative measurement of the social vulnerability of population and places, which often involves investigating various indicators of social vulnerability that can be represented on maps to allow for geographical comparisons (Susan L. Cutter et al., 2003; Oulahen, Mortsch, et al., 2015). In the human, social, and environmental geography literature, social vulnerability is a place-based relative and quantitaive measure of social capacities and social advantages/disadvantages of communities at the neighbourhood level that helps assess community's ability to cope with natural hazards and disasters (Andrey & Jones, 2008; Chang et al., 2018; S. L. Cutter, 1996; Frigerio et al., 2016). This thesis seeks to address an important gap in social vulnerability analysis by examining it at the national scale across Canadian urban neighbourhoods. Based on a statistically valid and robust methodology, the dissertation develops a comprehensive socioeconomic status (SES) index for Canada that is used to measure relative social vulnerability across Canadian neighbourhoods at the census tract level (**Chapter 2**). The composite index can help policymakers locate and understand the geographic concentration of vulnerability and the socially rooted drivers of place-based socioeconomic variability.

Social justice scholars often argue that an equitable approach to FRM policy development and funding structures should critically address geographic flood disadvantage and systemic flood disadvantage of different communities in the distribution of flood hazards (Sayers et al., 2017). Through a social justice lens, for example, it is important to identify "hotspots" of flood risk, where many socially vulnerable populations are exposed to flooding (i.e., addressing geographic flood disadvantage), and to assess the extent to which those socially vulnerable groups are inequitably affected by or exposed to flood risk (i.e., systemic flood disadvantage) (Sayers et al., 2017, p. 2). Thus, the social justice approach to FRM emphasizes analyzing social and spatial inequities in sensitivity and exposure to flood hazards (i.e., social equity) resulting from social-structural characteristics, such as socioeconomic and sociopolitical status, demographics, culture, and governance (Adger, 2006; Susan L. Cutter et al., 2003; Turner et al., 2003).

Traditionally, flood management strategies in Canada have been informed almost exclusively through geospatial mapping of hazard extents, such as flood delineation maps at 100-year or 200-year return periods only (Armenakis et al., 2017). FRM policies also focus on areas with politicized needs, with the danger of ignoring the most socially vulnerable segments of the population. This dissertation provides the first nationwide, comprehensive assessment of flood risk via addressing geographic flood disadvantage. The intersection of social vulnerability and flood hazard exposure prioritizes risk hotspots where flood management resources are needed most (**Chapter 3**).

The social or environmental equity approach to FRM often relates to three common justice principles: Egalitarianism, Rawls Difference Principle, and Utilitarianism (**Figure 1.1**). The Utilitarian maximize utility principle supports those members of society whose benefits offer the most significant gain to society. For Rawlsian, the state should target public resources to the most vulnerable, and for Egalitarian, equal opportunity to manage flood risk should be emphasized by the state. Aligned with current FRM policy and practices in England, Scotland, and Wales, this dissertation research supports Rawls Difference Principle (or the "Maximin Rule"). Such an approach maximizes the opportunities and minimizes the inequalities, differences, and disadvantages "to direct scarce public resources to the greatest benefit of the least advantaged" (Rawls, 1971, p. 302), and focuses on risk reduction policy options to be chosen to assist the most vulnerable population segments (Johnson et al., 2007; Thaler & Hartmann, 2016).

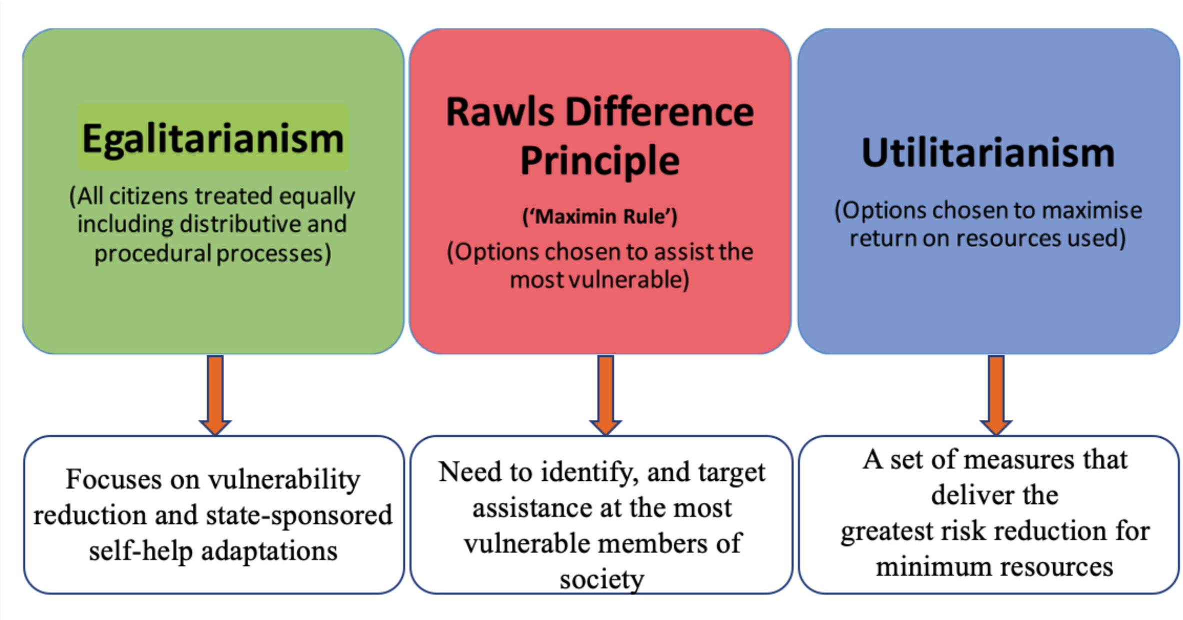


Figure 1.1 Principles to Socially Equitable FRM Approach[1]

Flood-related adverse impacts and flood exposure are unevenly distributed across affected populations, communities, and spaces (Montgomery & Chakraborty, 2015). The effects of flooding could be spatially heterogeneous as they may substantially vary by places and

[1] Contents adapted from Johnson et al. (2007); Sayers et al. (2014, 2017); Thaler & Hartmann (2016)

communities, depending on the extent of flood exposure, neighbourhood-level socioeconomic and resilience capacities, and publicly available flood recovery resources at the local level (Collins & Grineski, 2017; Grineski et al., 2015). Concerning historical, social, and environmental inequalities in exposure to flood hazards, it is critically important to determine whether specific vulnerable groups are disproportionately affected by flood hazards (i.e., addressing systemic inequities) for a better understanding of which social or demographic groups are living at the elevated risk of flooding, and what social characteristics make those groups more vulnerable to flooding than others (J. Chakraborty et al., 2019; Collins & Grineski, 2017).

Social justice scholars argue that distributive environmental justice (EJ) research highlights those socially vulnerable groups, such as racial or ethnic minorities, Indigenous peoples, and groups with a lower socioeconomic status, who are often inequitably exposed to flood risk (Collins, Grineski, Chakraborty, et al., 2019). Distributive EJ studies on flooding examine whether certain socially deprived groups, those with no or limited input regarding policy and legislation, inequitably share the burden of flood risks (Maantay & Maroko, 2009). The EJ studies on flooding are instrumental in determining who and to what extent a population subgroup is more vulnerable to flooding than others (J. Chakraborty et al., 2014; Collins et al., 2017; Grineski et al., 2015). In Canada, distributive EJ research is emerging in case of exposure to road traffic noise or environmental noise in Montreal (Carrier et al., 2016b; Dale et al., 2015), environmental hazards in Vancouver (Andrey & Jones, 2008), and air pollution in Hamilton and Montreal (Buzzelli & Jerrett, 2007; Crouse et al., 2009; Pinault et al., 2016). But, in the case of flooding, distributive EJ research has so far been largely ignored in Canada. This research gap is unfortunate as it directly hinders the development of an equitable or “fair” treatment approach in FRM policy decisions across Canada (Doorn, 2015).

For the past three decades, social vulnerability studies and vulnerability perspectives in Canada and worldwide mainly emphasized the influence of social inequalities on differential environmental risks (e.g., *process-based* inequities) through hazards and disasters lens (S. L. Cutter, 1996; Fatemi et al., 2017; Oulahen, 2016; Rufat et al., 2015; Wisner et al., 2004). However, assessing and addressing social vulnerability and its indicators with consideration to the EJ outcome leads to a critical discussion on differential vulnerabilities to environmental hazard exposure within the context of the human-environment relationship (Collins et al., 2017; Collins, Grineski, Chakraborty, et al., 2019; Collins & Grineski, 2017). This thesis attempts to connecting the perspective of social vulnerability to flood hazards with the EJ perspective on flooding to better understand the distributive dimensions of environmental injustices via the spatial correspondence between socially vulnerable groups and differential flood risks (**Chapter 4**).

Yet Canadian studies on social vulnerability to flood hazards are rare, as studies taking an EJ perspective on flood hazards. Previous research has mostly overlooked the EJ implications of flood exposure and failed to address the spatial heterogeneity in exposure to differential flood hazards across Canada. This thesis fills the gap of addressing flood-related inequalities by considering divisibility aspects of flood hazards to examine whether the types of flood hazard zones (inland vs. coastal) influence the relationships amongst flood exposure, racial/ethnic, and other socio-demographic characteristics of Canadian residents (**Chapter 4**). The research emphasizes justice implications of flood risks in Canada by leveraging national-scale flood hazards data sets (i.e., Canada Flood Maps as determined by JBA Risk Management), residential address points from DMTI Spatial Inc., and household-level microdata from the 2016 census of population.

1.2 Dissertation Objectives

This dissertation uses critical concepts from scholarship on social vulnerability, socioeconomic deprivation, distributive EJ, and geospatial distribution of flood risk and flood exposure analysis to examine the social equity dimensions of flood risk management policies and practices in Canada. The main goal of the dissertation is to analyze social and environmental inequities in flood risk exposure that are related to heterogeneous race, ethnicity, and socio-demographic characteristics of Canadian residents.

The purpose is to provide evidence of any systemic inequities in exposure to differential flood risks that can inform data-driven insights of socially equitable FRM policies for Canada, considering all aspects of GBA+ in decision-making processes. More specifically, this dissertation aims to answer three sets of interconnected research questions relevant to the overall goal:

(1) What are the significant socioeconomic drivers of social vulnerability to flood hazards in Canada? Where are socially vulnerable neighbourhoods geographically concentrated in Canada?

(2) How exposed are residential properties to flood hazards across Canada? Do socioeconomic vulnerability and flood exposure of residential properties vary or concentrate spatially by geographic boundaries (e.g., census tracts, census metropolitan areas, and provinces/territories)? Where are the hotspots of flood risk, and which neighbourhoods are at an elevated risk of flooding and highly vulnerable to flood hazards?

(3) Are certain socially vulnerable groups, including women, the elderly, lone-parent households, people with disabilities, visible ethnic minorities, Indigenous peoples, and individuals of lower socioeconomic status, inequitably exposed to flood hazards in Canada? Are relationships between Canadians' socio-demographic characteristics and

residential exposure to flood risk spatially heterogeneous? Are Canadians likely to experience environmental injustices or systemic social inequities through differential exposure to flood risk?

To answer these three sets of questions, this dissertation comprised three interconnected research projects with a broader aim to reveal insights for GBA+ in FRM policy decisions that foster community resilience in Canada's most flood vulnerable neighbourhoods. The three manuscripts used novel and 'inter/multi-disciplinary' methodology that integrated approaches from geography, environmental social science, statistics, sociology, and economics of well-being. Together they provided statistically valid and robust empirical results to advance understanding of social vulnerability and its implications for decision making in FRM, congruent with environmental justice and equity literature. The flow-chart in the following **Figure 1.2** shows a roadmap of the manuscript chapters and their corresponding methodological approaches.

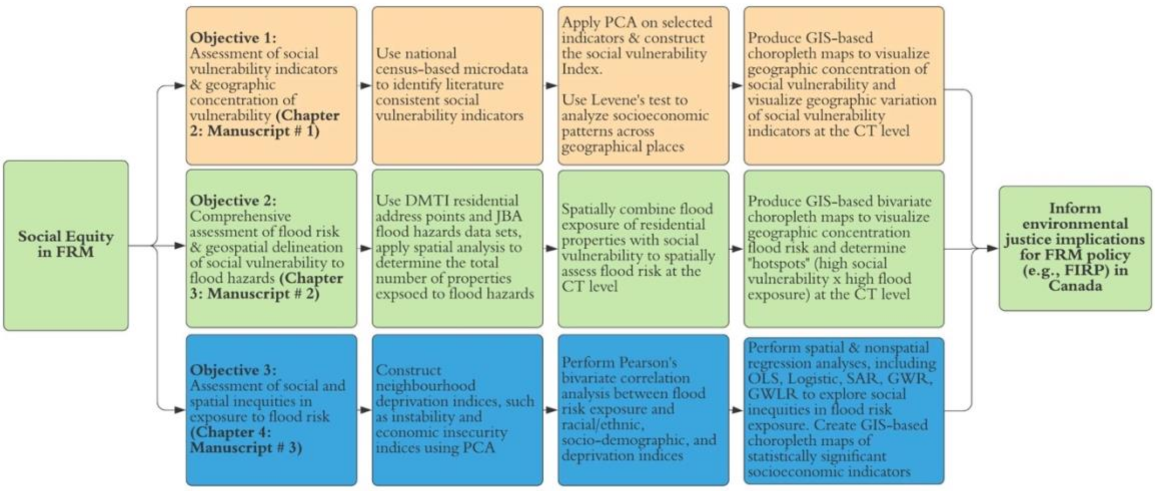


Figure 2.2 Roadmap of the Manuscript Chapters, Objectives, and Methodology

1.3 Dissertation Outline

The dissertation follows a manuscript format, and it comprises three manuscripts: the first manuscript is already published (**Chapter 2**), and the remaining two (**Chapter 3** and **Chapter 4**) are under review in peer-reviewed academic journals. Overall, the three manuscripts are interconnected and address the overarching goal of the dissertation to reveal data-driven insights of environmental injustices and socioeconomic inequalities in exposure to flood risk that inform socially equitable FRM policy.

The first chapter introduces the background, rationale, and problem context for this dissertation research. After reviewing existing scholarship on social vulnerability and environmental equity in Canada, it establishes the overall purpose of the research, specifies the objectives of the study, and outlines the structure of the dissertation. The second chapter outlines the methodological approaches to meet the specific objectives of the research presented in the three manuscripts. Each manuscript provides a more specific literature review, tailored to each specific study. Chapter three focuses the first objective of this dissertation through a paper titled, “A place-based socioeconomic status index: Measuring social vulnerability to flood hazards in the context of environmental justice,” which has been published in the *International Journal of Disaster Risk Reduction* (L. Chakraborty et al., 2020). Chapter four concentrates on objective two, through a paper titled, “Assessing social vulnerability to flood hazard exposure and delineating spatial hotspots of flood risk to inform socially just flood management policy,” which is under review in *Risk Analysis* (manuscript ID # RA-00386-2020, submitted on June 7, 2020). Chapter five addresses the third objective through the manuscript entitled, “Exploring spatial heterogeneity and environmental injustices in exposure to flood hazards using geographically weighted regression,” which is under review in *Environmental Research* (manuscript ID # ER-21-699, submitted on February 15, 2021).

Chapter six summarizes the research findings and highlights the importance of understanding social vulnerability and spatially varying relationships between flood risk exposure and racial/ethnic and socio-demographic characteristics of flood vulnerable residents at the national scale. Research implications are discussed for addressing environmental injustices and social inequities in FRM-related policy development. Finally, future research directions are proposed to reveal further evidence of flood-related environmental inequities and policy development.

Chapter 2: Manuscript #1

A Place-Based Socioeconomic Status Index: Measuring Social Vulnerability to Flood Hazards in the Context of Environmental Justice

Chakraborty, L., Rus, H., Henstra, D., Thistlethwaite, J., & Scott, D. (2020). A place-based socioeconomic status index: Measuring social vulnerability to flood hazards in the context of environmental justice. *International Journal of Disaster Risk Reduction*, 43, 101394. https://doi.org/10.1016/j.ijdrr.2019.101394

This paper proposes a national-level socioeconomic status (SES) index to measure place-based relative social vulnerability and socioeconomic inequalities across Canada. The aim is to investigate how disparities in overall socioeconomic status influence environmental justice outcomes for Canadian flood risk management planning and funding structures. A micro-dataset of the 2016 Canadian census of population was used to derive a comprehensive SES index over 5739 census tracts. The index comprises 49 theoretically significant and environmental policy-relevant indicators of vulnerability that represent diverse aspects of socioeconomic, demographic, and ethnicity status of Canadians. Bartlett's test of sphericity, Kaiser-Meyer-Olkin measure of sampling adequacy, Cronbach's alpha scale reliability, and goodness-of-fit for factor's solution were employed to assess validity, reliability, and consistency in the dataset before applying Principal Component Analysis. Our data revealed 11 statistically significant multidimensional factors, which together explained 80.86 percent of the total variation. Levene's homogeneity of variance test disclosed a considerable socioeconomic disparity across census tracts, census metropolitan areas (CMAs), and provinces/territories in Canada. Social vulnerability tends to be geographically stratified in Canada. For example, Drummondville, Saguenay, and Granby CMAs (all in Quebec) had the lowest SES scores, whereas Vancouver and Toronto CMAs had the highest SES scores. Prevalence of spatial variations in the SES has significant implications for appraising overall

social well-being and understanding the relative social vulnerability of population subgroups. The new place-based SES index has potential for assessing environmental justice outcomes in flood risk management at the census tract level.

2.1 Introduction

A combination of climate change, urbanization, population growth, and economic development have amplified flood risk in terms of augmented loss and damages (Cherqui et al., 2015). Analysts often argue that adopting sustainable flood risk management (FRM) policy requires the government to direct public resources to actions that protect the most vulnerable groups of communities and those geographical places or areas at highest risk of flooding (Sayers et al., 2017). A better understating of socially-vulnerable communities and the flood risks they face is critical in developing schemes for societal response to flood disasters[2] and recovery mechanisms (Wamsler, 2014), identifying the fundamental root causes of vulnerability (Agrawal, 2012), and addressing the social indicators of flood vulnerability (Susan L. Cutter et al., 2003).

In the context of flood hazards, indicators of social vulnerability typically relate to the social roots of people's vulnerability, which comprise their ability to cope, access to resources, race/ethnicity, household arrangements, and the built environment (Oulahen, 2016). Social vulnerability is defined as "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard" (Wisner et al., 2004, p. 11). Recognition of the places where the most socially vulnerable communities are located and their exposure to flooding (i.e., addressing geographic

[2] Flood disasters can be defined as "a social phenomenon that results when a flood hazard intersects with a vulnerable community in a way that exceeds or overwhelms the community's ability to cope and may cause serious harm to the safety, health, welfare, property or environment of people" (Public Safety Canada, 2017, p. 21)

flood disadvantage) is a prerequisite to delivering a socially-just FRM approach (Sayers et al., 2017). Such an approach emphasizes policy and planning processes that prioritize risk reduction for the most socially vulnerable communities and seeks to direct resources to those who are marginalized and socially deprived based on the Rawlsian Difference Principle or 'Maximin Rule (Rawls, 1971)' within FRM investment decisions (Johnson et al., 2007).

Identification of geographic flood-disadvantaged communities or most vulnerable neighbourhoods provides further insights for the distributional justice discourses within environmental planning and FRM decision-making processes. Distributional justice outcomes in FRM (Johnson et al., 2007; Thaler & Hartmann, 2016)—that is, addressing the spatial-temporal distribution of benefits and burdens of flood risk exposure--is a prominent concern of theoretical perspectives on environmental justice[3] in human ecology (Kaufmann et al., 2018; Mohai et al., 2009b). Environmental justice (EJ) as an equity principle refers to the governmental obligations to ensure that socially vulnerable segments of the population are not disproportionately affected by adverse environmental impacts or hazards (Jain et al., 2012). Measuring and assessing social vulnerability with consideration to the EJ outcome leads to a critical discussion on differential human vulnerability to environmental risk exposure within the context of the human-environment relationship.

An understanding of what makes people more vulnerable than others and why can advance knowledge and contribute to more equitable and sustainable risk reduction. In other words, analysis of spatio-temporal variances in human vulnerability to hazards and disasters is essential to design effective, efficient, and socially just disaster risk reduction strategies. Social

[3] The philosophies and concepts of 'social equity', 'social justice', 'intergenerational equity', and 'environmental justice' are used in the literature: these terms are contested and interpreted in many ways, with significant overlap (Ikeme, 2003).

vulnerability analysis further promotes the vulnerability-based justice principle, which maximizes opportunities and minimizes inequalities for the most benefit of least advantaged groups of communities (Werritty et al., 2007).

Previous research has documented that socioeconomic status (SES) greatly influences social vulnerability, both directly, via financial resources (e.g., income, wealth, savings) and indirectly, via nonfinancial coping resources (e.g., social support and resilient personality characteristics including education and occupation) (McLeod & Kessler, 1990). The indicators of the SES and race/ethnicity status of communities also play an important role in differential vulnerabilities, particularly to environmental hazards and disasters (Flanagan et al., 2011). Communities with a higher SES index score are less vulnerable to environmental hazards and more resilient in coping with natural disasters (Bergstrand et al., 2015; Yoon, 2012). Measuring social vulnerability with a focus on the EJ outcome requires one to reveal the differences in socioeconomic, demographic, and cultural characteristics of populations with different race, ethnicity, and class status (Messer et al., 2006). An empirical assessment of social vulnerability is critically important to monitor people's uneven capacities for disaster preparedness, response, and recovery processes related to pre-impact preparation, mitigation plans and risk assessments (Tapsell et al., 2010).

The national-level policy discourse on FRM planning and funding structures is incomplete without having a full consideration to the EJ outcome, because diverse and multicultural Canadian communities reflect a complex nature of Canadian society (e.g., demographic structure, income, education, housing, and ethnicity) (Krishnan, 2010). A national-level SES index analysis in the context of spatial and social inequalities to environmental hazards exposure is overdue for Canada. In response to growing calls for incorporating environmental justice into FRM policy discourse, this paper proposes a comprehensive design of the SES index for Canada with better consideration of the indicators of EJ outcome. The SES index reflects an operational decision support tool for risk assessment and resilience efforts while understanding the extents to which the SES varies over geographical places (e.g., census tracts[4], CMA[5], Provinces) across Canada. The paper seeks to understand how measuring the differences in SES indicators (e.g., socioeconomic structures, race/ethnicity, and coping capacities) can contribute to the EJ outcome in FRM. The proposed index can further be utilized to measure place-based relative social vulnerability and socioeconomic inequalities to environmental hazards exposure through geospatial mapping across Canada.

The paper is organized as follows. Section 2 reviews the literature on social vulnerability to flood hazards and its importance in the EJ assessment for Canadian FRM planning. Census data, relevant variables, and the steps for constructing the index are described in Section 3. Section 4 summarizes empirical results, and Section 5 concludes with cautionary remarks on the application of the index.

2.2 Assessment of Social Vulnerability to Flood Hazards

The social aspects of vulnerability are often considered to identify and understand whether some groups of people or communities are more sensitive and susceptible to the impacts of environmental hazards. This identification constructs a knowledge base that can enable more

[4] "Census tracts (CTs) are small, relatively stable geographic areas that usually have a population of less than 10,000 persons, they are located in census metropolitan areas and in census agglomerations that had a core population of 50,000 or more in the previous census" (Statistics Canada, 2019d).

[5] "A census metropolitan area (CMA) or a census agglomeration (CA) is formed by one or more adjacent municipalities centred on a population center (the core) with a total population of at least 100,000 of which 50,000 or more must live in the core based on adjusted data from the previous Census of Population Program. A CA must have a core population of at least 10,000 also based on data from the previous Census of Population Program" (Statistics Canada, 2019d).

targeted solutions and strategies for effective mitigation and increasing future social capacity and resilience (Tapsell et al., 2010). Social vulnerability emphasizes inequities in sensitivity and exposure (social equity) resulting from social-structural characteristics (Adger, 2006; Turner et al., 2003). In the literature of environmental hazards and disaster management, quantitative assessments of social vulnerability have relied heavily on the "hazards-of-place" model of vulnerability, proposed by Cutter (1996), which led to the Social Vulnerability Index (SoVI), an empirical relative measurement of the social vulnerability of places (Susan L. Cutter et al., 2003). Significant strengths of the SoVI include its conduciveness to a geospatial presentation [e.g., geographic information system (GIS)-based risk assessment maps], capacity to identify the social vulnerability of places, and ability to compare and contrast places (Susan L. Cutter & Emrich, 2017b).

The assessment of social vulnerability indicators to flood hazards is crucial because the disastrous impact of flooding may vary from physical property damage to a substantial number of fatalities, injuries, and adverse health effects (Wisner et al., 2004). Another dimension of flood vulnerability assessment from the EJ perspective is identifying whether socially vulnerable groups such as people with disabilities, ethnic minorities, Indigenous peoples[6], and individuals of lower SES are disproportionately exposed to flood risk. Distributive-type EJ studies recognize the groups of people at highest risk of floods or examine the social characteristics of the individuals living in spaces that are proximate to flood hazard zones such as along coastlines, near rivers, and close to other water bodies (J. Chakraborty et al., 2014). Considering the EJ outcome, researchers in the United States and the United Kingdom have

[6] In a separate study of comprehensive social vulnerability and flood exposure analysis for 985 on-reserve Indigenous communities versus other Canadian communities, we find that the residential property-level flood exposure at the 100- year return period is similar between non-Indigenous and Indigenous communities, but the socioeconomic vulnerability is higher on reserve lands, which confirms that the overall (socio-environmental) risk of Indigenous communities is higher (L. Chakraborty et al., 2021).

found that the most vulnerable groups to flood hazards consist of people who are poor, minorities, the elderly, children and the disabled (J. Chakraborty et al., 2014; Collins et al., 2015; Grineski et al., 2015; Mohai et al., 2009b; Montgomery & Chakraborty, 2015; Walker & Burningham, 2011).

In recent decades, the EJ implications of flooding have appeared to be complex. Some studies have yielded ambiguous findings on the relationships between the indicators of social vulnerability and flood risks (Collins & Grineski, 2017). A few US-based pre-flood EJ studies have argued that socially advantaged groups largely tend to experience the highest residential exposure to flood hazards (J. Chakraborty et al., 2014; Collins et al., 2017). These findings are anomalous from an EJ perspective (e.g., the socially powerful and elite people choose to reside in the high hazard zones particularly along the coastline due to high locational benefits including environmental amenities such as ocean views and proximity to beaches) (Bin & Kruse, 2006). Counterintuitively, UK-based research has revealed that inland flood risks are not equitably distributed, whereas coastal flood risks are disproportionately linked to the lower-class geographical areas that are susceptible to economic downturn (Jane Fielding, 2007; Walker, 2012; Walker & Burningham, 2011).

A few empirical studies have attempted to find the indicators of community and residential vulnerability to flood hazards (Hebb & Mortsch, 2007; Oulahen, Mortsch, et al., 2015; Oulahen, Shrubsole, et al., 2015; Pal, 2002). However, it is still unclear whether people with different ethnic backgrounds, visible minorities, foreign-born, newly settled immigrants, Aboriginal Peoples, and First Nations are among the most socially vulnerable groups across Canada. Canadian studies that directly relate social vulnerability to flood hazards are limited, although flooding is recognized as the most common and significant environmental hazards to major cities and urban residential neighbourhoods over the past two decades (Burn & Whitfield, 2016; Buttle et al., 2016).

Household income has appeared to be a pivotal contributor to residential vulnerability to flood hazards, and social vulnerability is found to be a substantial factor in determining overall vulnerability to flood hazards in Metro Vancouver (Oulahen, Mortsch, et al., 2015). Institutional arrangements, including property insurance and development regulations, have appeared to interact with social vulnerability to flood hazards in Metro Vancouver, and those arrangements enable a group of (affluent) people to live in hazardous places (Oulahen, Shrubsole, et al., 2015). Another study (2008) reveals that coastal communities (East and West) in Canada are vulnerable to climate change based on their location and isolation, exposure to extreme climate variability, and dependence on environmental resources for continued community health and well-being. It is also apparent that seniors (i.e., people aged 65 years and older) are the most vulnerable group of people to coastal climate change in Atlantic Canada (Manuel et al., 2015).

These empirical studies, however, are conducted in a single geographical region and at a specific CMA/municipality/county level, which limits their analytical utility for understanding flood vulnerability. These findings are inadequate for national-level FRM planning and for policy discourse considering diverse communities across Canada. There is no national-scale social vulnerability study in Canada comparable to Cutter's SoVI project for the United States (Susan L. Cutter et al., 2003), and/ a national-level SoVI analysis in the context of EJ literature is also missing for Canada. No studies have yet identified geographical places where many socially vulnerable groups of people are exposed to flooding (i.e., geographic flood disadvantage), and the degree to which the socially vulnerable communities are disproportionally affected by flooding (i.e., systemic flood disadvantage) (Sayers et al., 2017, p. 2).

Considering the EJ outcome in FRM, this paper firstly fills in the gap of Canadian literature on the social vulnerability analysis by proposing a place-based SES index construction at a national scale. Secondly, it offers an opportunity to identify geographic flood disadvantaged communities by mapping the place-based SES scores over the various flood hazard extents. Consistent with the EJ literature, the proposed design of the SES is more contextual to socially-just decision-making processes for Canadian FRM planning and policies, as the multidimensional items measuring the underlying index mainly focuses on the nature of the population (e.g., ethnicity, wealth, employment, income, Indigenous peoples, visible minority groups of people, occupations). Nevertheless, this new design of the SES index is more robust as it incorporates several analytical and methodological adjustments, including (a) assessment of the quality of index performance using a range of tests for statistical validity, reliability, and consistency of the selected socioeconomic indicators; and (ii) evaluation of goodness-of-fit for factor's solution of PCA.

2.3 Data and Methodology

2.3.1 Overview of the 2016 Census of Population

This study uses the 2016 Canadian census microdata as the census of population data are representative of all communities and are vital for planning services. The master dataset contains 8,651,677 observations and 663 variables, taken directly from Statistics Canada's dissemination database. Using Stata 14.0 software, the original microdata was aggregated and collapsed at the census tract (CT) level, which contained 5827 CTs for Canada. CTs containing less than 250 populations and 40 households (i.e., 88 CTs) were excluded to comply with the

2016 census data analysis guidelines, statistical output vetting rules (e.g., confidential homogeneity rule and dominance rule for dollar value variables), and geographical requirement.

2.3.1.1 Selection of Variables

Consistent with literature on social vulnerability and EJ, the SES index includes 49 variables that represent socioeconomic, demographic, ethnic, and cultural characteristics of the Canadian population. The selection of these variables reflects a multidimensional approach for understanding socioeconomic stratification and differentiation in resource distribution, advantages, opportunities, and capacities among subgroups of the Canadian population. The final dataset consisted of 49 variables over 5739 CTs, 50 census metropolitan areas (CMA) / census agglomeration (CA), ten provinces and three territories of current residence in the 2016 census of population. The selected 49 variables are theoretically important and policy-relevant as they represent commonly used contextual socioeconomic indicators of the social science literature, including racial/ethnic composition, household/family structure, coping capacities, access to monetary resources, built environment, occupation, and demographic characteristics of Canadian communities measured at the census tract level. **Table 2.1** describes each selected variable and its relevance to the indicators of social vulnerability. The rationales for selecting these socioeconomic indicator variables are well established and very common in the most recent review of hazards and vulnerability literature (Fatemi et al., 2017; Flanagan et al., 2011; Mavhura et al., 2017; Messer et al., 2006; Oulahen, Shrubsole, et al., 2015; Rufat et al., 2015).

Table 2.1 Social Vulnerability Indicators and Description of Variables

SoVI Component	Variable[7]	Description
Ability to cope with / Special needs population	Female	Female population
	Female labour force participation	Working-age females aged 15 or above participating in the labour force
	Age	Median age of the population
	Senior	Population aged 65 or older
	Children under 5 years of age	Population aged 0 – 4 years
	Children under 15 years of age	Population aged under 15 years
	Psychological disability	Population with activity limitations due to the emotional, psychological, or mental health conditions
	Physical disability	Population having difficulty in seeing, hearing, walking, using stairs, using hands or fingers, or doing other physical activities, learning, remembering/concentrating, emotional, psychological/mental, other health problems/long-term conditions for six months and above
	Unattached one-person household	Population living alone with separated, divorced, widowed status
	Unattached elderly	Population aged 65 or older living alone
Household / Family Structure	Lone parents	Population with lone parent family structure in census families
	More than three children in a census family	Population married and having 3 or more children in census families
	Household size	The average number of people per household
Ethnicity	Official language knowledge	Population with no knowledge of the official language in either French or English
	English/French	Population with English or French ethnic background
	First-generation status[8]	Population with the first-generation status
	Foreign-born Canadian citizens	Canadian citizens not by birth
	Aboriginal Peoples[9]	Population identified as Aboriginal Peoples ethnic background
	Indian/Inuit/Métis	Population identified as North American Indian/Inuit/Métis ethnic background
	Year of immigration	Recently immigrated between 2010 and 2016
Visible Minority[10]	White	Population identified as White
	Black	Population identified as Black
	South Asian	Population identified as South Asian
	Chinese	Population identified as Chinese
	Filipino	Population identified as Filipino
	Latin American	Population identified as Latin American
Education	No certificate / diploma	Population aged 15 or older with no certificate /diploma /degree

[7] Constructed at Census tract-level proportions of the population except for age, dwelling value, income, household size, and dwelling size. Age, dwelling value, and income were estimated using the median function, whereas household size and dwelling size were calculated using the average function.
[8] "First-generation includes persons who were born outside Canada. For the most part, these are people who are now, or once were, immigrants to Canada" (Statistics Canada, 2019d)
[9] "Aboriginal identity includes persons who are First Nations (North American Indian), Métis or Inuk (Inuit) or those who are Registered or Treaty Indians (that is, registered under the Indian Act of Canada) or those who have membership in a First Nation or Indian band. Aboriginal peoples of Canada are defined in the Constitution Act, 1982, section 35 (2) as including the Indian, Inuit and Métis peoples of Canada" (Statistics Canada, 2019d)
[10] The Employment Equity Act defines visible minorities as 'persons, other than Aboriginal peoples, who are non-Caucasian in race or non-white in colour' (Statistics Canada, 2019d)

	Post-secondary certificate	Population with college diploma/trade certificate/university certificate at bachelor level or above
Access to Financial Resources / Wealth	Shelter-cost-to-income ratio	Population with a shelter-cost-to-income ratio of over 30%
	Government transfer	Government transfers recipients within a couple
	Low income	Population with low-income status based on LICO-AT (prevalence of low income)
	Dwelling value	Median per capita home value (owner-estimated) as a proxy for per capita wealth[11]
	Income	Median per capita income of census family for all persons aged 15 or older[12]
Occupation	Management	Population with management occupations
	Business, finance & administration	Population with business, finance & administration occupations
	Health	Population with health occupations
	Education, law, social, community & govt service	Population with education, law, social, community & govt. services occupations
	Sales and service	Population with sales and service occupations
Employment Status	Unemployed	Unemployed population including experienced, inexperienced, and temporary layoff
	Not in the labour force	Male population not in the labour force
Built Environment / Accessibility	House with major repair	People living in private dwellings with a need for major repairs
	Crowded home	Household not living in suitable accommodations according to the National Occupancy Standard (NOS)
	Period of home construction	Population living in buildings or dwellings built before 1970
	Dwelling is in apartment with 5+ stories built before 1980	Population living in apartments of a building which has five or more stories constructed before 1980
	Renters	Households occupying a rental, private dwelling
	No private vehicle / Public transit	Households' primary mode of commuting /transportation in public transit as a passenger by bus, subway, LRT, Ferry
	Population density (urban/rural)	Population living in medium and large urban population centers, with a census population of 100,000 or more – percent urban population
	Mobility	Population's place of residence in the same CSD but different dwelling a year ago in 2015
	Dwelling size	The average number of rooms per dwelling

[11] Values for tenant-occupied dwelling, band housing, and farm dwelling were excluded from dwelling value variable and replaced with median (owner-estimated) home value of dwellings of all Census tracts.

[12] Negative reported income (i.e., loss of income) values were omitted and replaced with a median income of Census families of all Census tracts to normalize the dollar value variable after removing outliers

2.3.2 Construction of the Canadian SES Index

The paper adopted the Principal Component Analysis (PCA) tool to construct the SES index. In a multivariate context, PCA is a well-established data reduction technique developed by Pearson (1901) and Hotelling (1933). PCA is a preferred statistical method to transform a large number of variables from a dataset into a smaller and more coherent set of uncorrelated (orthogonal) factors - the principal components - which account for much of the variation among the set of selected variables (Jolliffe, 2002).

In 1974, PCA was first used to construct the Living Conditions Index for measuring well-being in the Netherlands, initiated by the Social and Cultural Planning Office of the Netherlands (Boelhouwer & Stoop, 1999). Since then, several researchers have employed PCA to combine multidimensional socioeconomic variables into a composite index although a lack of consensus remained in aggregation strategies to compute factor/component scores and factor weighting methods (Jones & Andrey, 2007; Messer et al., 2006; Rygel et al., 2006; Saltelli, 2007). However, in the absence of individual-level variables, PCA is a computationally-simple data reduction method, and it is useful for constructing a place-based composite index to explain the inequality of geographical places in terms of demographic and socioeconomic indicators of a population (Vyas & Kumaranayake, 2006). **Figure 2.1** depicts the detailed steps involved in the SES index construction.

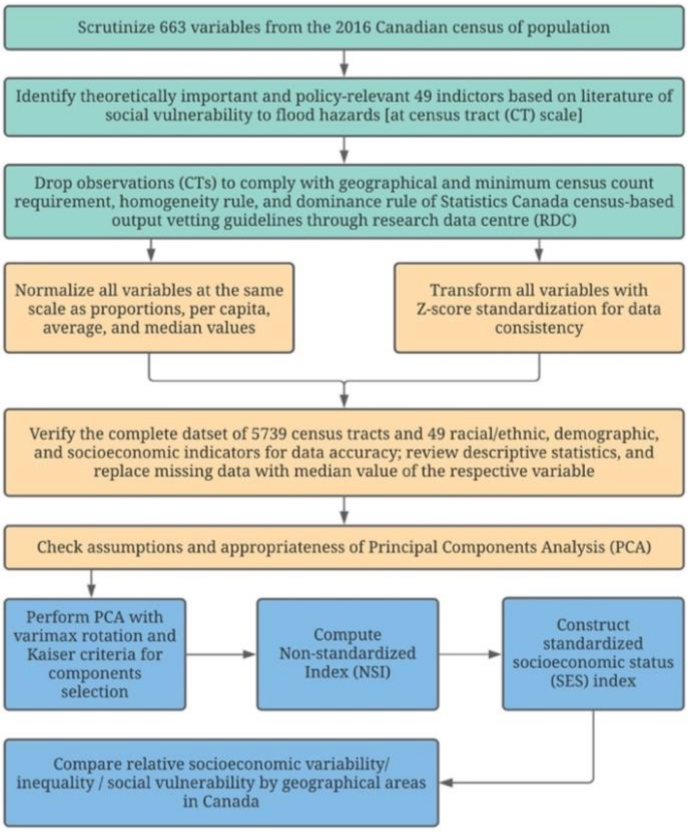


Figure 2.1 Steps of the Canadian SES Index Construction

2.4 Assessment and Interpretation of PCA Results

2.4.1 Verification of PCA Assumptions

Before developing composite indicators of socioeconomic inequality in Canada, several vital assumptions in the application of PCA were checked for conforming sample size (i.e., adequate number of cases), variable scales (e.g., interval vs. categorical level), the relevancy of sub-indicators in the correlation matrix, and multicollinearity. All variables in the study were measured at the interval-level to avoid difficulties associated with dichotomous data. The sample size also satisfied both the cases-to-variables ratio, the rule of 200, and the significance rule, as endorsed by Gorsuch (1988). Outliers were detected using the confidential Homogeneity and Dominance Rule of Statistics Canada—which obligates researchers to ensure confidentiality of census respondents—and the cases were removed from the dataset before performing PCA. All variables were normalized using proportions, median, per capita, and average functions and they were standardized at the same scale as z-score transformation with zero mean and one standard deviation.

2.4.1.1 Accuracy of the Dataset

Descriptive statistics (i.e., mean, range, and standard deviation) of the selected contextual socioeconomic and cultural variables were examined both before and after z-score transformation of the variables to check for linearity and accuracy in the dataset. Since PCA is sensitive to differences in the units of measurement of variables, it was necessary to standardize all variables at the same scale before utilizing PCA (Bolch & Huang, 1974). Missing/non-reported/negative reported data for dollar-value variables were replaced with the median value of the respective variable as outliers or extreme values can influence the mean value of a variable. This replacement did not alter the distribution of the variables in any way. Descriptive statistics also confirmed that no variables had zero standard deviation/variance to proceed with statistical analysis. Since CTs were used as the unit of analysis, any CT containing zero population counts, the unweighted population of fewer than 40 counts, and weighted population of fewer than 250 counts were omitted from the analysis to comply with Statistics Canada's output vetting requirement and guidelines. Descriptive statistics, such as skewness and kurtosis, were not used to inspect the shape of the distribution as these measures will not make a substantive difference in a large sample size situation (as in our case the sample size, N = 5739) (Tabachnick & Fidell, 2007).

2.4.1.2 Reliability, Validity, and Consistency in the Dataset

To be considered suitable for PCA, this study adopted the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy test to detect a multicollinearity problem in the dataset (Kaiser, 1974). The KMO statistic compares the magnitudes of the observed correlation coefficients to the magnitudes of the partial correlation coefficients. In other words, if the selected variables have common factors, the partial correlation coefficients should be small relative to the total correlation coefficient. The KMO overall statistic takes values from 0 and 1, with small values indicating that overall, the variables have too little in common to warrant a PCA. Historically, the KMO values are characterized and labelled as follows: a value of 0.9 is considered as ‘marvelous’, 0.80 - ‘meritorious’, 0.70 - ‘middling’, 0.60 - ‘mediocre’, 0.50 - ‘miserable’, and up to 0.49 - ‘unacceptable’. As suggested by Kaiser and Rice (1974), the KMO overall statistic should be at least 0.60 to proceed with the PCA/factor analysis, and this statistic should exceed 0.80 for the PCA results and the multi-dimensional components to be reliable (Tabachnick & Fidell, 2007). Our data revealed an overall KMO value of 0.84, indicating that the results of the PCA would be reliable as an input into the Canadian socioeconomic index.

Bartlett’s Test of Sphericity was employed to test the null hypothesis that the sub-indicators in the population correlation matrix are uncorrelated; that is, that the correlation matrix is an identity matrix (Bartlett, 1954). Bartlett’s test statistic is based on a chi-squared transformation of the determinant of the correlation matrix. For our data, the *P-value* of the chi-squared test statistic was found to be 0.000, a value that is small enough to reject the null hypothesis of identity matrix at 1% level of statistical significance. We conclude that the strength of the relationship among selected variables in this study is strong, and the correlation matrix is not an identity matrix as is required by the PCA to be valid.

We also used Cronbach’s alpha (α) coefficient, a measure of scale reliability, to check for internal consistency in the data—the extent to which all the items in a test measure the same concept or construct (Cronbach, 1951). Based on the number of test items (i.e., variables), item inter-relatedness and dimensionality, the alpha coefficient varies from 0 to 1 where a low value suggests poor interrelatedness between items or heterogeneous constructs, and a high value (> 0.90) suggests redundancies of the selected items. In practice, an acceptable value of the alpha ranges from 0.70 to 0.95, although Streiner (2003) strictly recommended a maximum alpha value of 0.90. The alpha coefficient for our 49 items is found to be 0.8865, suggesting that the items have relatively high internal consistency, and these items possibly explain the same underlying concept or construct (the SES index in our case) such that we may proceed with PCA. These three diagnostic procedures demonstrate that PCA is appropriate for our selected items/variables at the census tract level.

2.4.2 Components (Factors) Extraction Using PCA

The 49 standardized variables were entered into the PCA (using Stata 14.0 software) with varimax rotation and the eigenvalue rule for component selection. Our data identified 11 multidimensional components with eigenvalues (i.e., the variances extracted by the components) of greater than 1. Cattell's (1966) Scree plot was used as a graphical method to determine the number of factors (**Figure 2.2**). The word "Scree" refers to an appearance of large eigenvalues as the hill and small eigenvalues as the debris of loose rocks at the bottom of the hill. After examining the Scree plot, we extracted 11 factors for further analysis.

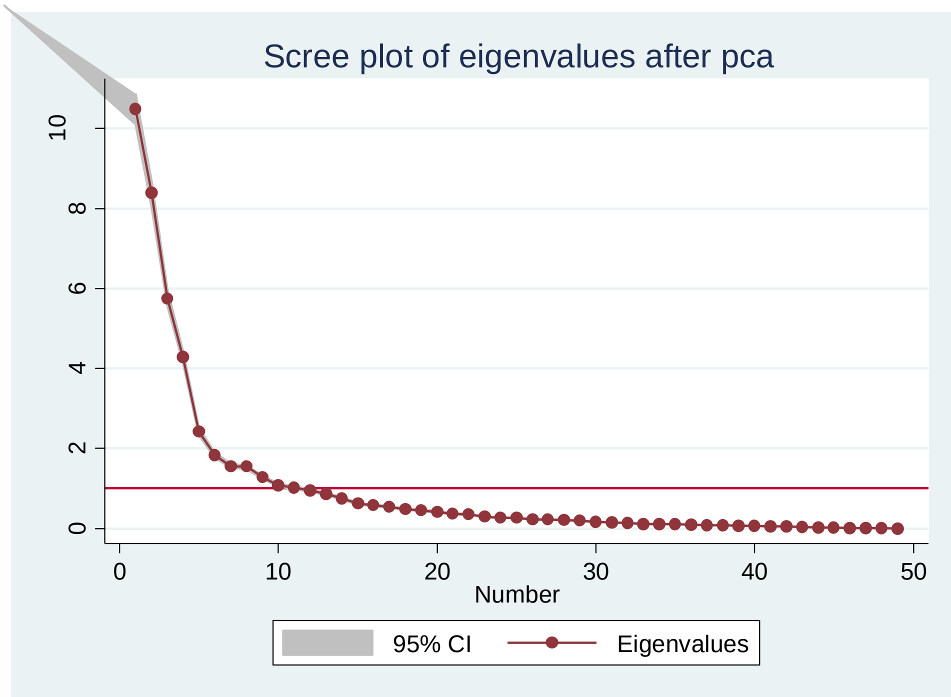


Figure 2.2 Scree Plot of Components' Eigenvalues

Factor rotations are usually helpful to facilitate the interpretation of the factors (Abdi & Williams, 2010) and to reveal the *simple structure* (making the pattern of loadings more transparent, or more pronounced) (Thurstone, 1947). The literature on exploratory factor analysis (EFA) suggests that it is useful to try at least one orthogonal rotation method (e.g., varimax) and one oblique rotation method (e.g., promax) with the factor correlation matrix of values over ±0.32 (Tabachnick & Fidell, 2007, p. 646). Our data revealed empirically consistent findings with the EFA literature that the choice of rotation (orthogonal vs oblique) may not make much difference (or very little difference) in terms of finding the pattern of factor loadings when the factors are not markedly correlated (Brown, 2009). The results of promax rotation indicated a strong pattern of loadings and a simpler structure as suggested by Thurstone (1947) in a sense that none of the variables have loadings above 0.30 on two or three factors at the same time (Brown, 2009). However, we used the results of varimax rotation to derive the index as the factor correlation matrix did not show the correlations around 0.32 and above. In other words, factor correlations are not driven by the data, and the solution remains nearly orthogonal, as suggested by Tabachnick and Fidell (2007). Component loading scores on individual variables are reported in the **Table 2.2**.

Table 2.2 Results of PCA: Component Rotation Matrix

VARIABLE	COMP1	COMP2	COMP3	COMP4	COMP5	COMP6	COMP7	COMP8	COMP9	COMP10	COMP11
ZPFEMALE					0.4661						
ZFEMLFRATE							0.3061				
ZPAG65OV			0.4420								
ZPAG15UN							-0.4600				
ZPAG5UN							-0.4786				
ZPDISABLE1						0.5385					
ZPDISABLE2						0.5383					
ZPLONEPARNT					0.4929						
ZPONEPERHH			0.3595								
ZPUNATTELDER			0.3889								
ZPNOLANG								0.4503			
ZPFIRSTGEN	0.3126										
ZPCITIZEN	0.3122										
ZPSOUTHASIAN	0.3589										
ZPCHINESE								0.6289			
ZPFILIPINO											0.4283
ZPLATINAME~A						-0.3049					
ZPABORIGIN									0.6019		
ZPINDINUTM~S									0.6168		
ZPNOHIGHEDU				-0.3962							
ZPPOSTSECOND				0.3775							
ZPGOVTRAN					-0.4857						
ZPLOWINC		0.3399									
ZPHOMEBUILT										0.3224	
ZPRENTER		-0.3648									
ZPOCCMGT				0.3385							
ZPOCCHEALTH											0.6370
ZPOCCEDUC				0.3931							
ZPOCCSALES							0.3595				
ZPMALENOLFS			0.3029								
ZPMOBILITY		0.3225									
ZMEDAGE			0.3659								
ZMEDPERCAP~C										0.5976	
ZMEDPERCAP~L										0.6199	
ZDWELSIZE		-0.3354									
TOTAL VARIANCE (80.86%)	14.12%	13.58%	10.14%	9.33%	6.10%	5.55%	5.31%	5.15%	4.73%	4.09%	2.76%

Note: A variable with a positive loading score suggests a negative association to the corresponding component (Krishnan, 2010).

The PCA with varimax rotation and the eigenvalue rule revealed 11 components, which together explained 80.86 percent of the total variation in the data. The first, second, third, ……, and eleventh components accounted for 14.12, 13.58, 10.14, ……, and 2.76 percent of the variance, respectively (**Table 2.2**). The first component accounted for 14.12 percent of the total variation in which the proportion of population with first-generation status (ZPFIRSTGEN), foreign born Canadian citizens (ZPCITIZEN), and South Asians (ZPSOUTHASIAN) showed positive loadings. This component is a measure of "race and ethnicity" - a strong indicator of socially vulnerable group of communities consistent with the conventional environmental justice literature. We did not exhaustively discuss all other loading scores as the paper's primary focus was to understand place-based socioeconomic variability across Canada by constructing a SES index using statistically sound approaches. It was more important to clearly articulate the method and robustness of the index.

2.4.3 Calculation of the SES Index

To compute a single composite index, as a first step, we estimated the component scores (factor score coefficients) using the built-in regression method in Stata (namely the post-estimation command, *predict* PC_1 PC_2 PC_3 PC_4 PC_5 PC_6 PC_7 PC_8 PC_9 PC_{10} PC_{11}, *score*). The regression method is prevalent among factor analysis users as it considers (a) the correlation between the factors and variables, (ii) the correlation between the variables, and (iii) the correlation between the factors if oblique rotation is used (DiStefano et al., 2009). Predicted factor score coefficients represent a single score for each CT in our dataset. Finally, a weighted sum of these factor scores was used to generate a non-standardized socioeconomic index for census tract *j* (NSI_j), as follows:

$$NSI_j = \sum_{i=1}^{11} W_i * PC_i \qquad (1)$$

$$\text{where, } W_i = \frac{Proportion\ of\ Variance\ for\ Factor_i}{Total\ Variance\ Explained}\ ; i = 1, 2, \dots \dots \dots, 11 \qquad (2)$$

Since the importance of the multidimensional components in quantifying and measuring overall socioeconomic condition is not the same, we used a ratio between the proportion of a component's variance (e.g., 0.1412 for Comp 1) to the total percentage of variance in the data (i.e., 0.8086) as the corresponding *weight* for a component (e.g., $W_1 = 0.1412 / 0.8086$). It is pertinent to note that there is no theoretical basis for determining the weights of a PCA-based composite index analysis (Susan L. Cutter & Emrich, 2017b)[13]. The NSI index measures the SES of one geographical place (census tract in our data) relative to the other place on a linear scale (Antony & Rao, 2007). Since the values of the NSI index can be negative or positive, making it difficult to interpret and compare the scores by places, a standardized SES index for Canada was developed for ease of comparison. The values of SES range on a scale of 0 to 100, and are calculated using the following formula for census tract *j* (Antony & Rao, 2007; Krishnan, 2010):

$$SES_{(j)} = \frac{NSI_{(j)} - NSI_{Minimum}}{(NSI_{Maximum} - NSI_{Minimum})} \times 100 \tag{3}$$

In our data, to take a random census tract, for example 705001300:

$$SES_{(705001300)} = \frac{[(3.143759) - (-1.965392)]}{[(3.974709) - (-1.965392)]} \times 100 = 86.01 \tag{4}$$

For ease of interpretation and comparison between CTs, we reversed the SES index scores; the higher the score of the index, the better the socioeconomic status of a geographical place (Krishnan, 2010). The better the socioeconomic status of a geographical place, it is more likely that the community (defined at census tracts) has been progressed in reducing the social inequalities, degenerating the vulnerability conditions, and increasing social resilience (Bergstrand et al., 2015; Buzzelli et al., 2006).

[13] We applied several options for factor weightings, such as equal weighting (Emrich & Cutter, 2011; Oulahen, 2014) and proportional weighting (Antony & Rao, 2007), before combining all factors to represent a multidimensional index. Still, there remained little or no influence of the weighting option on social vulnerability index outcome.

2.4.4 PCA Post-Estimation: Goodness-of-Fit Evaluation

The PCA-based index creation is prominent among the EFA researchers who often create a multidimensional composite index without evaluating the quality of the factor's solution. However, a standard PCA analysis is not complete unless an evaluation of the factor solution's goodness-of-fit is performed (Mooi et al., 2018). To evaluate how well the retained principal components approximate the correlation matrix, the quality of the solution (i.e., the goodness-of-fit) was assessed in the paper by checking the residuals (i.e., the differences between observed and reproduced correlations) in the fitted (reconstructed) correlation matrix (Graffelman, 2013). One way of evaluating the goodness-of-fit of the factor solution is to check whether the proportion of residuals higher than 0.05 does not exceed 50%. In practice, for a good model fit, the magnitude of the residuals should be as small as possible. We counted the number of residuals with absolute values greater than 0.05 in the residual correlation matrix. Our data revealed that 162 out of 1225 (i.e., 13.22 %) residuals are larger than the absolute value of 0.05, suggesting a good model fit, combining the selected socio-economic indicators.

In addition, PCA post-estimation tests including squared multiple correlations (SMC), KMO values and Cronbach's alpha scores for individual items (variables) were checked for robustness and sensitivity of applying PCA method within our data. The SMC measures help identify variables that cannot be explained well from the other variables. The SMC is a theoretical lower bound for commonality and thus an upper bound for the unexplained variance (Stata, 2013). In our data, none of the SMCs were found to be so small as to warrant exclusion. Item-wise Cronbach's alpha scores were also examined to observe whether the overall *Cronbach's alpha score would change if an item were deleted* from the PCA. Our data suggested that all items (variables) were well-fitted in the PCA method as the alpha score did not change/ increase significantly from 0.8865, indicating none of the items needed to be removed to make our data more reliable.

2.4.5 Socioeconomic Patterns Across Canada

The SES index scores cannot be distributed uniformly across geographical regions of Canada. For example, the index can be skewed more to the right for economically developed urban areas and skewed to the left for rural areas in Canada. Based on available microdata of the 2016 census of population, we classified 5739 CTs into the groups of 50 CMA/CA, ten provinces and three territories, where 149 CTs were not listed in CMA/CA as they belong to Canadian territories. Using the graphical method (Box Plots, see Park (2008)), we tested whether the SES index scores were normally distributed across CMAs and provinces/territories in Canada. Each dot above the boxes in **Figure 2.3** represents a higher SES index score corresponding to a CT. Numbers in the horizontal axis indicates provinces (1-10) and territories (11-13) in panel (a), whereas numbers (1-50) in the panel (b) represents CMAs across Canada. The distribution of SES index scores was found to be non-normal across Canada as the boxes appeared to be asymmetrical over different CMA and provinces/territories. Levene (1960) proposed a test statistic (W_0) to investigate the equality of variances, which was found to be robust under non-normality condition of data (Levene, 1960). Hence, we adopted Levene's robust test for equality of variances on the SES index scores to compare the socioeconomic patterns of diverse geographical places in Canada.

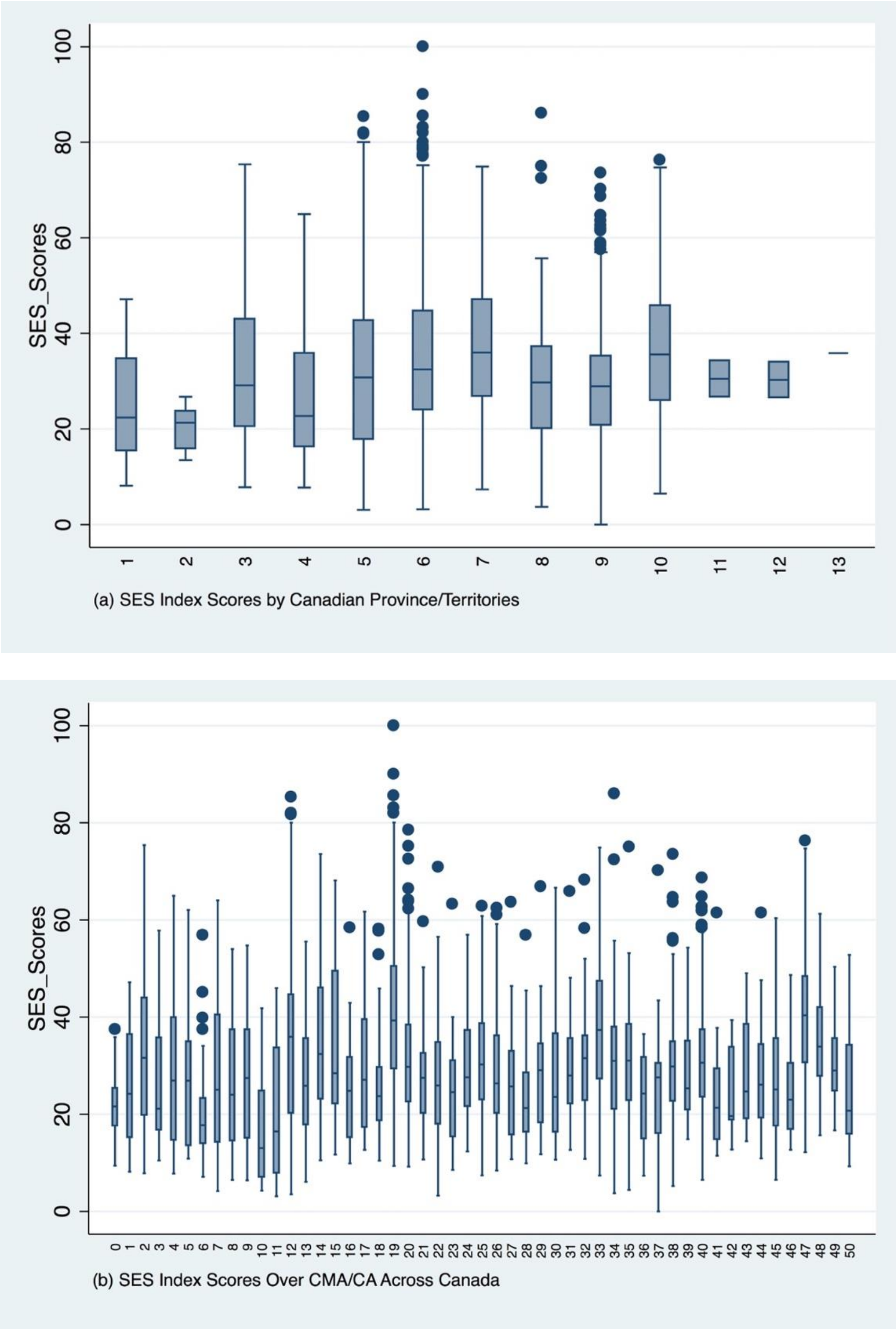
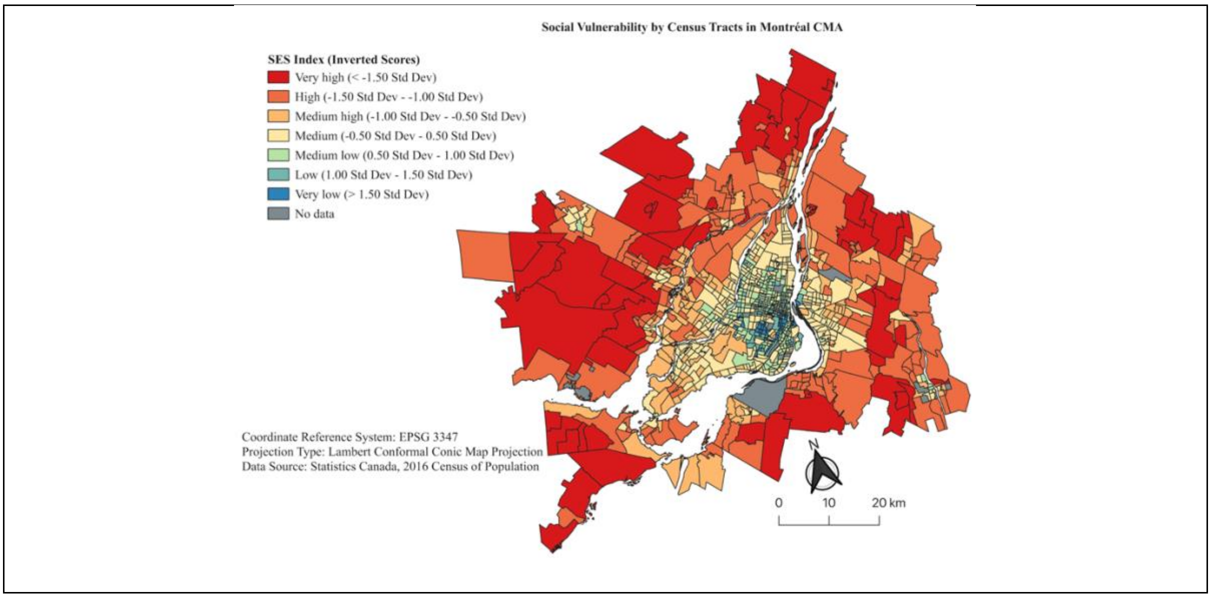


Figure 2.3 Box Plots of the SES Index Scores by CMA and Provinces/Territories

The spatial distribution of the SES index scores is also visualized at the CT level with a GIS-based choropleth mapping tool to operationalize the concept of social vulnerability as well as to improve our understanding of socioeconomic disparities in the context of Canada. Due to limited space available in the paper, we created the SES index maps for Canada’s three largest CMAs only, including Toronto, Montréal, and Vancouver, where more than one in three (35.6%) Canadians resides (Statistics Canada, 2019b). As the index was created at a national scale, it can be further utilized to create social vulnerability maps for all CMAs across Canada. The index scores were joined to the 2016 CT boundary file, and then mapped using graduated classification style along with spectral color ramp in the QGIS 3.8 software to display standard deviation (SD) of the SES index scores from the mean (**Figure 2.4**). An *inverted color ramp* on the SES scores was used to exhibit seven categories of social vulnerability: very low (> 1.50 SD), low (1.00 SD to 1.50 SD), medium low (0.50 SD to 1.00 SD), medium (-0.50 SD to 0.50 SD), medium high (-1.00 SD to -0.50 SD), high (-1.50 SD to -1.00 SD), and very high (< -1.50 SD). The maps in the **Figure 2.4** visualizes the spatial disparities of the SES scores on the three CMAs at the CT level.



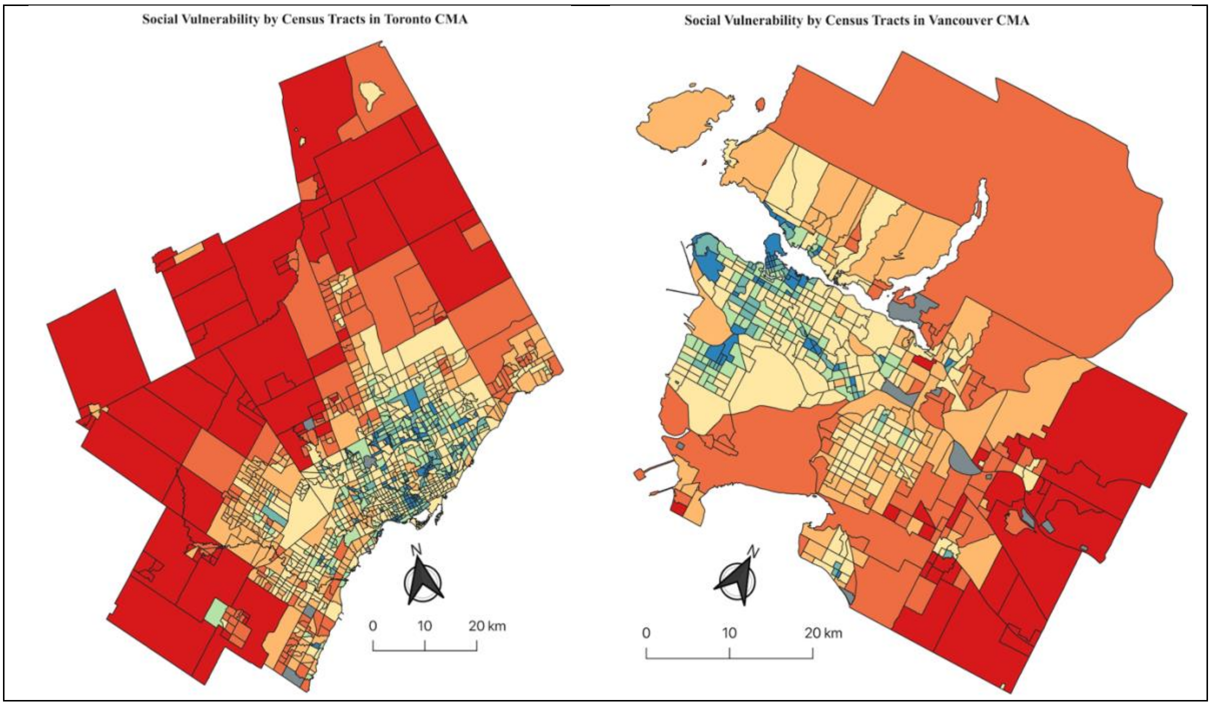


Figure 2.4 Spatial Variability of the SES Index Scores on Canada's Three Largest CMA

Table 2.3 reports a ranking of the mean SES index scores by CMAs, and **Table 2.4** discloses a ranking of the mean SES scores by province/territory, where the ranking value of "1" suggests least some social vulnerability (or, the highest SES index score) for the respective CMA/province/territory. Levene's test was used to verify the assumption that the variance of the SES index scores is the same across different CMA/CA, provinces and territories grouped by CT in Canada. If the socioeconomic index is uniformly distributed, the difference in mean SES index scores between adjacent geographical places should be even (Krishnan, 2010). We found that the difference in mean SES index scores between Oshawa and Toronto CMA as well as between Abbotsford – Mission and Vancouver CMA were higher than any other neighbouring CMA (**Table 2.3**), whereas the absolute mean difference in the SES index scores between the provinces of Prince Edward Island and Nova Scotia was more substantial than any other adjoining provinces (**Table 2.4**). The null hypothesis of the Levene's test is that the population variances are equal. One can reject the null hypothesis if Levene's robust test statistic value is higher than the upper critical value of the F distribution with k -1 and N - k

degrees of freedom at a level of significance, where the sample size, N (census tracts), can be divided into subgroups of *k* (CMA, provinces/territories).

The results of Levene's test in our analysis showed a P-value of 0.000 (**Table 2.3 & 2.4**) that is small enough to reject the null hypothesis (equal variances of the SES index score across geographical places of Canada) at 1% level of significance. Therefore, the census tracts, CMA/CA, provinces/territories in Canada demonstrate considerable socioeconomic variability. Our results on socioeconomic disparities across Canada are consistent with the previous findings in Canada (Chan et al., 2015; Krishnan, 2010). The mean SES index scores in Western Canada provinces (particularly, Manitoba and British Columbia) are tended to be significantly higher than in Atlantic Canada, and moderately higher than in Central Canada and Northern Canada provinces.

Table 2.3 Mean Standardized SES Scores by CMA/CA

CMA/CA (2016)	CMA_Code	Mean SES scores	Rank of SES Scores
Territories / Not in CMA/CA	0	21.51	48
St. John's	1	25.80	36
Halifax	2	32.45	8
Moncton	3	26.47	35
Saint John	4	28.15	23
Fredericton	5	27.97	24
Saguenay	6	20.65	50
Québec	7	27.36	30
Sherbrooke	8	25.73	37
Trois-Rivières	9	27.18	31
Drummondville	10	16.56	51
Granby	11	20.91	49
Montréal	12	33.96	6
Ottawa – Gatineau (Quebec)	13	27.02	33
Ottawa – Gatineau (ON)	14	34.89	5
Kingston	15	33.48	7
Belleville	16	25.12	40
Peterborough	17	28.67	21
Oshawa	18	25.26	39
Toronto	19	40.48	2
Hamilton	20	31.81	9
St. Catharines	21	27.54	27
Kitchener-Cambridge-Waterloo	22	27.05	32
Brantford	23	24.52	44
Guelph	24	29.14	18
London	25	30.86	12
Windsor	26	28.81	20
Sarnia	27	27.65	26
Barrie	28	23.32	45
North Bay	29	29.07	19
Greater Sudbury	30	27.54	27
Sault Ste. Marie	31	29.76	16
Thunder Bay	32	30.71	13
Winnipeg	33	37.43	3

Regina	34	31.06	10
Saskatoon	35	29.89	15
Medicine Hat	36	23.29	46
Lethbridge	37	24.61	43
Calgary	38	29.56	17
Red Deer	39	27.50	29
Edmonton	40	30.37	14
Grande Prairie	41	24.62	42
Wood Buffalo	42	22.93	47
Kelowna	43	28.54	22
Kamloops	44	27.79	25
Chilliwack	45	26.74	34
Abbotsford - Mission	46	25.50	38
Vancouver	47	40.53	1
Victoria	48	35.73	4
Nanaimo	49	31.05	11
Prince George	50	24.81	41

Table 2.4 Mean Standardized SES Scores by Province/Territories

PROVINCE/ TERRITORY OF CURRENT RESIDENCE (2016)	**Province Code**	**Mean SES Scores**	**Rank of SES Scores**
Newfoundland and Labrador	1	24.78	12
Prince Edward Island	2	20.41	13
Nova Scotia	3	31.83	5
New Brunswick	4	27.09	11
Quebec	5	31.11	6
Ontario	6	34.84	4
Manitoba	7	36.66	1
Saskatchewan	8	29.51	9
Alberta	9	28.85	10
British Columbia	10	36.31	2
Yukon	11	30.51	7
Northwest Territories	12	30.29	8
Nunavut	13	35.88	3

2.5 Findings and Conclusions

Place-based social vulnerability assessments at a small scale help identify places of high vulnerability (Khan, 2012) and aid in the planning processes of GIS-based environmental risk assessment (Oulahen, 2016). This paper proposes a geographical place-based SES index to assess the relative position of communities and neighbourhoods across Canada, that is to measure relative social inequality between small geographical places measured at the census tract level. Aligned with the theoretical discussion of social justice and environmental justice implications for disaster risk reduction, the paper contributes to the technical process for incorporating social justice principles in government policy, guidance, and practice towards flood risk management.

We find that the component and the mean socioeconomic scores are not evenly distributed across Canada. Our findings suggest that the social, economic, racial/ethnic background and built environment characteristics of a subgroup of the population make the status of the geographical places different concerning the level of socioeconomic inequality and social vulnerability. In other words, social vulnerability is geographically stratified in Canada, and some places are much more vulnerable than others. For example, Atlantic Canada provinces are considerably more socioeconomically vulnerable than Western Canada and Central Canada provinces. The populations of Vancouver and Toronto census metropolitan areas are substantially less socially vulnerable than their smaller counterparts. Drummondville, Saguenay, and Granby census metropolitan areas within Quebec have the lowest socioeconomic status index score, which could signal more considerable indicators of social vulnerability. Census tracts of Canadian territories that are not listed in the census metropolitan areas tend to be more socially vulnerable than that are included in the CMA. These findings offer a strategy of comparing overall socioeconomic conditions within and among communities for identifying socially and economically disadvantaged places (Messer et al., 2006). The proposed index also offers broad geographic generalizability in terms of socioeconomic patterns across different geographic and socio-demographic attributes of Canadian communities measured at CT level.

Based on the 2016 census of population data, we find that the socioeconomic status of Canadians is unevenly distributed within and among communities measured at the CT level, and we know that these socioeconomic differentiations affect Canadians differently. Patterns of social inequality in relation to both flood hazard exposure and social vulnerability to flooding is yet to be analyzed in Canada. The linkage between social inequality and environmental justice is often examined through the lens of race, ethnicity, socioeconomic status, gender, sexual orientation, age, immigration status, and other social factors that intersect with a disproportionate environmental burden or benefit (J. Chakraborty et al., 2016). To analyze the EJ implications to flood hazards across Canada, one must estimate various levels of flood hazard exposure (e.g., high, moderate, low) for each CT in a CMA, and then run binary logistic regression models to test the probability of a CT being located in a particular flood hazard zone, as a function of the explanatory variables describing CT-level demographic and socioeconomic characteristics, as introduced in this paper (J. Chakraborty et al., 2014).

Researchers can utilize the proposed SES index to assess environmental risks and social justice outcomes related to any other hazards (e.g., toxic, and seismic hazard) across Canada. Considering a socially just FRM policy discourse, the index can be exploited to first identify geographic flood-disadvantaged groups of communities through GIS-mapping of the index over flood hazard exposure maps, and second, to recognize systemic flood-disadvantaged groups of communities by analyzing the degree to which the socially vulnerable populations are disproportionally affected by flooding. Assessing and addressing levels of systemic flood disadvantage would require one to routinely record the flood risks faced by most vulnerable neighbourhoods and less vulnerable neighbourhoods, and to analyze comparative disadvantage faced by racial/ethnic minorities or low-income households (Sayers et al., 2017).

We are aware that flood processes occur at the spatial scale, and that the flood hazard extents data are typically stored as a “raster” data file used in GIS software to represent flood hazard exposure over a continuous surface. Meanwhile, the SES index is stored as a “vector” data file, which is used in GIS to represent the SES scores by CT. Two different file formats might create a cross-scale problem for a flood modeler seeking to combine the extents of flood hazard exposure with the SES scores by CT. To resolve the cross-scale problem, a raster data file can be transformed to a vector data file by converting grids to points. More specifically, the "Calculate Geometry" tool in ArcGIS could be used to calculate the percentage of land area exposed to flood hazards in a census tract (in square meters), following the Statistics Canada Lambert Conformal Conic projection on the raster data file. The resulting percentage of land area exposed to flooding can be stored by CT and mapped using a GIS-based bi-variate choropleth map to reveal the hotspots of flood risk (by adjoining vulnerability to flood hazards) within a Canadian CMA.

Construction of a context-specific multidimensional composite index on the socioeconomic status of people is critically important when the vulnerability is examined as a set of social, economic, and demographic factors (Susan L. Cutter et al., 2003). However, a few critiques to PCA-based composite index construction are expressed in the social science literature, including (1) there is no firm consensus about selection of context-specific variables, statistical procedures, or assumptions underlying the steps involved, and (2) there remains a lack of consensus about factor aggregation and weighting methods. A few researchers also suggested interpreting PCA-based composite index results with caution. First, the index calculated for one country may not be comparable with or transferrable to another country unless the indicators are derived by the same method for international comparison. Second, the index only provides a measure of relative social inequality between geographical places, but it cannot be utilized for understanding any absolute levels of socioeconomic and cultural attributes within a community (Krishnan, 2010). It is also noteworthy to recognize limitations to use the census of population data to construct the index as there remains a difference between census counts and actual population estimates. Population estimates differ from census counts and are usually higher, because census counts are not adjusted for undercoverage (e.g., some individuals are not enumerated) or overcoverage (e.g., some individuals are enumerated more than once) (Statistics Canada, 2019a).

Nevertheless, the current study emphasizes several operational benefits of using the SES index scores for Canada which build on Cutter's SoVI scores, including

(a) the method for SES index calculation is based on sound statistical approaches that are used to verify reliability and robustness of empirical results in the social science literature;
(b) the SES index is context-specific in a way that it focuses on the characteristics of diverse Canadian population that might influence the justice outcome in the environmental decision-making processes; and
(c) the index scores were calculated using weights of the multidimensional components (or, 11 composite factors) based on their corresponding contribution to the total variance rather than altering the signs of the factors (based on personal judgements) and using additive model to compute summary scores (Susan L. Cutter et al., 2003).

Moreover, PCA-based SES indices generate more empirically robust results than any other alternative methods of reducing dimensionality in the data, such as correspondence analysis, multivariate regression, or factor analysis (Vyas & Kumaranayake, 2006). Using PCA, a detailed and comprehensive socioeconomic status assessment across the country is both feasible and critically important, as it helps decision-makers to better understand place-based differential vulnerability and socioeconomic variability at a small scale. This understanding can further facilitate consideration and incorporation of environmental justice outcomes into all elements of the environmental policy and planning processes to implement sustainable disaster risk reduction strategies through priority programming, project development, and policy decisions.

Chapter 3: Manuscript #2

Assessing Social Vulnerability to Flood Hazard Exposure and Delineating Spatial Hotspots of Flood Risk to Inform Socially Just Flood Management Policy

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This study introduces the first nationwide spatial assessment of flood risk to identify hotspots of social vulnerability and flood hazard exposure that support policies aimed at protecting high-risk populations and geographical regions of Canada. The study used a national-scale flood hazard dataset (pluvial, fluvial, and coastal) to estimate a 1-in-100-year flood exposure of all residential properties across 5721 census tracts. Using the ArcMap10.2 geographic information systems (GIS) tool, the study integrated flood exposure data with a census-based multidimensional socioeconomic status index that included demographic, racial/ethnic and socioeconomic indicators that influence vulnerability. Bivariate choropleth mapping of relative exposure and socioeconomic status depicts geographical regions with very high flood exposure and social vulnerability. The results revealed considerable spatial variations in social vulnerability and flood exposure at the local (census tracts), regional (census metropolitan areas), and national (provinces) scales. The geographic concentration of flood risk hotspots belongs to 18 census tracts and nine census metropolitan areas (urban regions) of five provinces. The results provide a foundation for prioritizing investment and developing strategic initiatives in emergency management, flood risk reduction, and adaptation plans consistent with vulnerability-based environmental justice principles. Based on a scientific basis of resource allocation, our findings support the Rawlsian distributional justice principle to help

those geographic flood-disadvantaged neighbourhoods need most for preparedness, response, and flood recovery.

3.1 Introduction

Social vulnerability is defined as "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard" (Wisner et al., 2004, p. 11). In the context of flooding, social vulnerability relates to the variability of socioeconomic well-being of peoples and their ability to prepare for, respond to, mitigate, and recover from a flood hazard event (Susan L. Cutter, 1996). Spatial assessment of social vulnerability is fundamental for delineating and communicating flood risk at the local level (Susan L. Cutter et al., 2013; Guillard-Gonçąlves et al., 2015; Lianxiao & Morimoto, 2019; Török, 2018). Determining social vulnerability is a key endeavor for several scientific and policy communities, including those engaged in disaster risk reduction, emergency management, and climate change adaptation (Birkmann et al., 2014), because it helps decision-makers identify those socially vulnerable neighbourhoods that are at high risk of flood disadvantage (Sayers et al., 2018). Findings from social vulnerability assessment can appreciably contribute to enhancing the resiliency of both individuals and the community (Felsenstein & Lichter, 2014). For example, the use of the Social Vulnerability Index (SoVI) enables decision-makers to effectively distribute scarce resources before, during, and after disasters. Identification of place-based, relative SoVI scores provides an evidence-based approach to target and prioritize allocation of scarce disaster recovery money to those who need it most (Susan L. Cutter & Emrich, 2017a).

Social vulnerability indicators typically seek to measure a community's ability to cope, household access to resources, race/ethnicity, household arrangements, and the built environment (Susan L. Cutter, 1996; Susan L. Cutter et al., 2003, 2014). Identifying the "hotspots" where social vulnerability intersects with flood exposure (i.e., addressing geographic flood disadvantage) is a prerequisite to delivering a socially-just flood risk management (FRM) approach (Sayers et al., 2017). Such an approach prioritizes risk reduction planning for the most socially vulnerable communities and seeks to direct scarce public resources to those who are socially deprived and least advantaged (Johnson et al., 2007; Werritty et al., 2007).

In Canada, flood management strategies are informed almost exclusively by hazard exposure or identification of locations through geospatial mapping of hazard extents (Armenakis et al., 2017). Flood management policies have primarily emphasized structural mitigation measures such as building dykes, dams, and flood walls (Thistlethwaite & Henstra, 2017), while more recently (since 2018) promoting shared responsibility such as the purchase of flood insurance (Henstra et al., 2018). Such a policy prioritization often focuses on areas with politicized needs, with the danger of ignoring the most socially vulnerable segments of the population. This paper provides the first nationwide assessment combining social vulnerability and flood hazard exposure to determine areas where flood management resources are needed most and in order to inform a socially equitable approach to FRM policy and funding structures (Sayers et al., 2017) in Canada. Targeting assistance to the most flood vulnerable communities and populations is the most cost-effective, apolitical, and fiscally conscious approach to resource allocation (Susan L. Cutter & Emrich, 2017a), which aligns with the Rawlsian' distributive justice principle for FRM (Thaler & Hartmann, 2016).

It is projected that the combination of climate change and current socio-economic development trends will intensify flood risk in Canada through heavy rainfall events and sea level rise (Bush et al., 2019), which will increase flood damages and disruption (Burn et al., 2016; Davies, 2016; Honegger & Oehy, 2016). These changes in climatic conditions will interact with existing socioeconomic vulnerabilities to increase the chances of harmful impacts on people, property, critical infrastructure and emergency facilities (Agrawal et al., 2014). Hence, a national-scale assessment of flood exposure and vulnerability is important to achieve distributive justice outcomes in FRM, such that the spatial and temporal distribution of benefits and burdens among Canadian communities can be addressed effectively (Johnson et al., 2008).

Canada, like many other countries, uses an incomplete definition of risk that excludes social vulnerability in flood risk mapping. "Flood hazard" and "flood risk" are often used synonymously or interchangeably, whereas 'risk', in the hazard literature is conceptualized as a product of hazard and the social vulnerability of those exposed to the hazard (Etkin et al., 2004; Turner et al., 2003; Wisner et al., 2004). Such an understanding of flood risk is not only theoretically inconsistent but also misleading for public policy. Flood exposure mapping alone is insufficient to determine and assess flood risks to people, property, infrastructure, and services (Armenakis et al., 2017; Cho & Chang, 2017; Garbutt et al., 2015). Physical exposure[14] should be combined with hazard and vulnerability to define and practically understand the extents of flood risk at the local level (Susan L. Cutter et al., 2013; Peck et al., 2007).

This paper considers 'hazard' and exposure, along with social vulnerability, as a source of 'risk' (Byers et al., 2018; Cardona et al., 2012; Formetta & Feyen, 2019; IPCC, 2012), and develops a more complete understanding of social vulnerability of communities for risk-based

[14] Physical exposure refers to the people or assets that are likely to be affected by a hazard (UNDP, 2004, p. 136). Flood exposure is typically measured by identifying populations and communities that would be affected by a specific flood scenario, such as the 100-year flood recurrence interval (i.e., a flood the magnitude of which has a 1-in-100 (1%) chance of occurring in any given year) (Holmes & Dinicola, 2010).

flood hazard management and resilience options (von A. Fekete, 2009; Krieger, 2012). Social vulnerability is characterized in terms of communities (i.e., census-tract level population subgroups) experiencing a loss in social wellbeing (i.e., lower socioeconomic status index scores) before floods occur (Sayers et al., 2017). Flood hazard exposure analysis captures the percentage of residential properties within a census tract (CT)[15] exposed to any of pluvial (surface water), fluvial (riverine) or storm surge (coastal) flooding in a 100-year recurrence interval scenario (with or without accounting for fluvial-flood defenses). Finally, spatial 'hotspots' of flood risk are identified at the CT level to delineate location-specific (or geographic) flood disadvantages by revealing most flood vulnerable neighbourhoods, where social vulnerability coincides with flood exposure.

The paper is organized as follows. The evolution of Canadian flood hazard management policy paradigms, along with the social vulnerability perspectives, is outlined in section 2. Section 3 discusses the data and methodology, including the steps for constructing a national-scale socioeconomic status index (for additional details, see Chakraborty et al., 2020) and the spatial analysis techniques employed. Section 4 identifies hotspots of flood risk at the CT level, visualizes the geospatial risk in Canada's major and high-risk census metropolitan areas (CMA). Section 5 addresses the strengths of the study by acknowledging data limitation, and section 6 concludes with further research directions.

3.2 Social Vulnerability Perspectives in FRM Policy Paradigms

Canada has a 300 year recorded history of flooding and societal impacts (Wojtanowski, 1997). Flooding is Canada's most common and costliest natural hazard, which is also recognized as a

[15] "Census tracts (CTs) are small, relatively stable geographic areas that usually have a population of less than 10,000 persons, based on data from the previous Census of Population Program" (Statistics Canada, 2019d).

significant hydro-meteorological disaster[16] in terms of property damage (Burn et al., 2016; Public Safety Canada, 2015). Flood management is a complex arrangement of efforts by municipal, provincial, and federal governments as well as by some special purpose agencies such as water conservation authorities (Sandink et al., 2010; Shrubsole, 2000). Flood management has traditionally focused on prevention—with a reliance on structural mitigation measures such as dykes and dams—and recovery, facilitated through government-funded disaster assistance programs (Jakob et al., 2013; Shrubsole, 2007). However, this narrow approach has been criticized as ineffective over the past decade (Henstra & Thistlethwaite, 2017a, 2017b; Honegger & Oehy, 2016; Insurance Bureau of Canada, 2015), because governments face expensive maintenance and replacement costs for structural defenses and increasing disaster assistance costs for recovery. In response, Canada has embraced a risk-based flood hazard management approach by initiating the 2015 National Disaster Mitigation Program to reduce, or even negate, the effects of flood events, which fundamentally aligns with the Sendai Framework for Disaster Risk Reduction 2015-2030 (Public Safety Canada, 2016, 2018). **Figure 3.1** shows how Canada's approach to managing flooding has evolved in four phases since the early-1950s.

[16] Food is considered as a *disaster* in Canada when a flood event encompasses one or more of the following five criteria: "(i) 10 or more people are killed, (ii) 100 or more people are affected/injured/infected/evacuated or homeless, (iii) an appeal for national/international assistance, (iv) historical significance, (v) significant damage/interruption of normal processes such that the community affected by flood cannot recover on its own" (Public Safety Canada, 2019) .

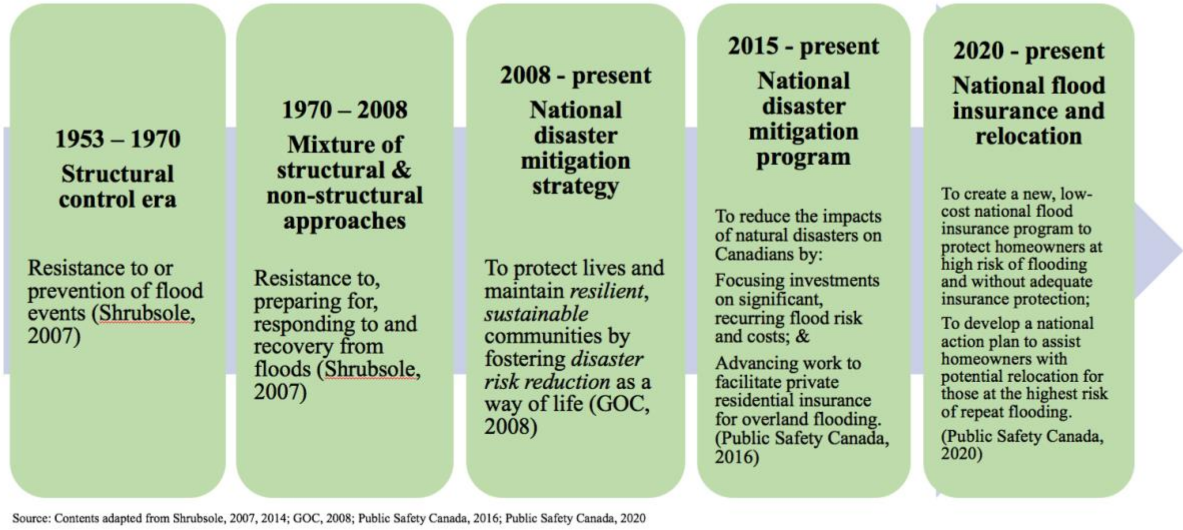


Figure 3.1 Evolution of Canadian Flood Management Policies & Programs

As **Figure 3.1** indicates, flood management has evolved from 'keeping water out of place' in the 1950s (via structural flood control or protective measures) to 'managing and reducing risk of flood hazard' beginning from the late 2000s (through risk-based all hazards management approach) (Shrubsole, 2014). This policy shift aligns with the current disaster risk management policy paradigm in the United States (Bergsma, 2019; Hardmeyer & Spencer, 2007; Shively, 2017; Tariq et al., 2014), most of the OECD-European, the Group of Eight (G8), and the Group of Twenty (G20) countries (Challies et al., 2016; Evers et al., 2016; Insurance Bureau of Canada, 2015; Krieger, 2012; OECD, 2012, 2015, 2016; Sayers et al., 2018). However, risk-based flood management is fundamentally incomplete and flawed without understanding and assessing social vulnerability of people and places and their exposure to flood hazard at the national scale (Aroca-Jimenez et al., 2017; Susan L. Cutter et al., 2013; Fernandez et al., 2016; Frigerio & De Amicis, 2016; Koks et al., 2015). Since "risk" is often conceptualized as the product of a hazard and the social vulnerability of those exposed to the hazard, the first step of flood risk management is to understand location-specific relative social vulnerability to flood hazard exposure (von A. Fekete, 2009).

Canadian studies that directly relate social vulnerability to flood hazard are very limited. Existing research focus on specific localized study areas, rather than the entire population (either provincial or national scales), potentially omitting the most vulnerable from consideration. For example, while generating spatial flood risk maps for Don River watershed (in the Province of Ontario), the 2006 census data was used to assess social vulnerability for the City of Toronto only (Armenakis et al., 2017; Armenakis & Nirupama, 2014). Based on qualitative surveys, a small number of community-based social, economic, and political indicators of flood vulnerability were investigated for the Red River Basin in the Province of Manitoba (Morris-Oswald, 2007; Morris-Oswald & Sinclair, 2005; Stewart & Rashid, 2011). A social vulnerability index deployed in a portion of the City of London, Ontario revealed that females and elderly residents were most vulnerable population subgroups in terms of ability to cope during a flooding event (Hebb & Mortsch, 2007), whereas heavy urbanization in the watershed of the Upper Thames River was found to considerably elevate risk from river flooding (Nirupama & Simonovic, 2007). Within the same basin, physical, economic, infrastructure, and social components of flood vulnerability were assessed across different Forward Sortation Areas (Peck et al., 2007).

In Canadian studies of coastal communities and metropolitan areas, including Metro Vancouver and Montréal, the groups most socially vulnerable to flooding included seniors (i.e., people aged 65 years and older), the very young, those in high density places, minority groups, low income groups, people with language barriers, and low-income households (Agrawal, 2018; Dolan & Ommer, 2008; Manuel et al., 2015; Oulahen et al., 2019; Oulahen, Shrubsole, et al., 2015). These studies are not sufficiently comprehensive for a national-level FRM policy discourse for several reasons. First, they ignore the critical analysis of race, ethnicity, and built environment and the disproportionate environmental benefits and burdens based on location (J. Chakraborty et al., 2014; J. L. Fielding, 2018; Maldonado et al., 2016). Second, studies based on a single geographical region or community have limited analytical utility for understanding and mitigating flood risk (and allocating scarce resources for recovery) at a national scale, when considering the diverse and complex sociodemographic characteristics of Canadian populations. Finally, focusing on household income as a dominant factor of social vulnerability to flood hazard is sometimes counterproductive, since socially advantaged groups can experience the highest residential exposure to flood hazard in some jurisdictions (Collins et al., 2017; Oulahen, Shrubsole, et al., 2015). Summing up the existing risk-based flood hazard management policy paradigm in Canada, there exists a clear gap of national-level flood risk analysis, where flood hazard and social vulnerability spatially intersect. This study fills this critical knowledge gap with a focus on national-scale social vulnerability assessment and its crucial role in understanding the social justice dimensions of Canadian flood risk assessment policy and practices.

3.3 Data and Methodology

3.3.1. Social Vulnerability Index Construction

This study used the most recently available 2016 Canadian census of population microdata (Statistics Canada, 2019a), taken directly from Statistics Canada's dissemination database. From the master dataset of 8,651,677 observations and 663 variables, we extracted 49 theoretically important and policy-relevant variables that represent diverse aspects of socioeconomic, demographic, ethnic, and cultural characteristics of Canadians. The original households-level census data were aggregated and collapsed at the CT level. We removed outliers for consistency in the dataset by excluding several CT-level observations (i.e., 88 CTs out of a total 5827 CTs) that did not comply with Statistics Canada's census data analysis guidelines, statistical output vetting rules (e.g., confidential homogeneity rule and dominance rule for dollar value variables), and geographical requirement (e.g., CTs containing less than 250 populations and 40 households).

To determine national-scale social vulnerability for Canada, we constructed a context-specific, multidimensional composite index on the socioeconomic status (SES) of Canadians (L. Chakraborty et al., 2020), which was informed by Cutter's social vulnerability index (SoVI) analysis (Susan L. Cutter, 1996; Susan L. Cutter et al., 2003). We used Principal Component Analysis (PCA) to construct the index with 49 constructed variables over 5739 CTs, 50 CMAs[17], ten provinces and three territories. The in-depth description of selected variables; statistical tests for verifying the accuracy, reliability, validity, and consistency in the dataset; detailed steps involved in the index construction; the empirical results of the index scores by CMAs, province/territories across Canada; and the potential of using the index for assessing environmental risks and environmental justice outcomes in FRM are documented in Chakraborty et al. (2020).

As this paper assessed national-scale flood risk and the driving social factors behind the risk, we first identify flood hazard extent, then described the PCA-based component loading scores on individual variables to reveal the social determinants of flood vulnerability, and finally the spatial delineation of flood risk through geospatial mapping.

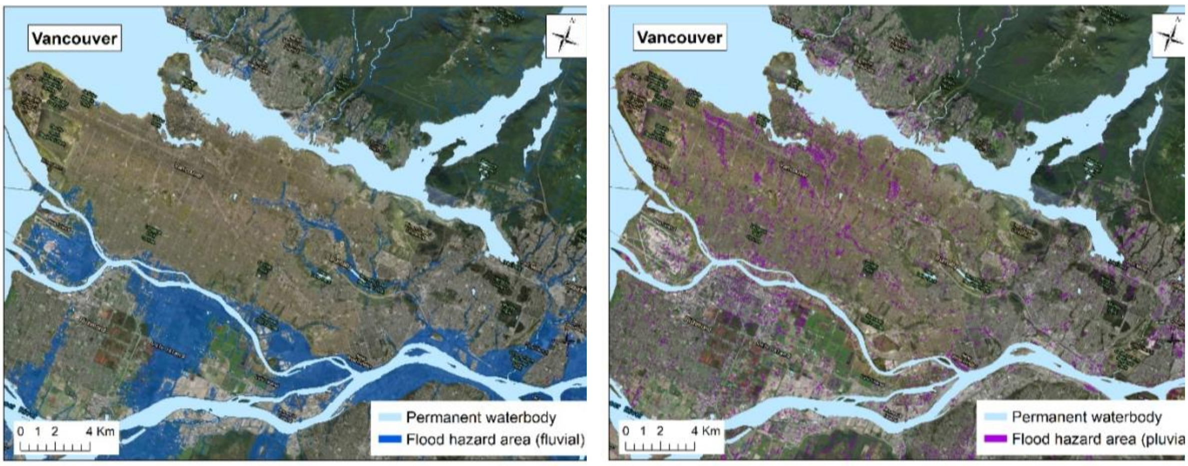
[17] "A census metropolitan area (CMA) or a census agglomeration (CA) is formed by one or more adjacent municipalities centred on a population center (known as the core). A CMA must have a total population of at least 100,000 of which 50,000 or more must live in the core based on adjusted data from the previous Census of Population Program. A CA must have a core population of at least 10,000 also based on data from the previous Census of Population Program" (Statistics Canada, 2019d).

3.3.2. *Spatial Analysis*

3.3.2.1. *Flood Hazard Identification*

This study determined fluvial (riverine), pluvial, and coastal (storm surge) flood hazard areas in Canada based on the 2018 flood hazard datasets (30-meter horizontal resolution) produced by JBA Risk Management (JBA) - a global, market-leading flood catastrophe-modelling firm. The flood hazard datasets are made available through a research partnership with the University of Waterloo. The datasets identify geographical areas in Canada exposed to fluvial, pluvial, and coastal flooding for various flood recurrence intervals such as 20, 50, 100, 200, and 500-year recurrence intervals. Flood hazard extent datasets were first imported into ArcGIS to visualize flood-prone areas as identified by JBA's flood models. For example, the maps in **Figure 3.2** show flood-prone areas around the Vancouver area in a 200-year recurrence interval - a flood event that has a 0.5% chance of occurring in any given year. The lower right **panel (d)** in the **Figure 3.2** shows spatial delineation of flood-prone areas subject to multiple types of flood hazard, including fluvial, pluvial, and coastal.

(a) Fluvial flood **(b) Pluvial flood**



(c) Storm surge (coastal) flood **(d) Three types of flood hazard**

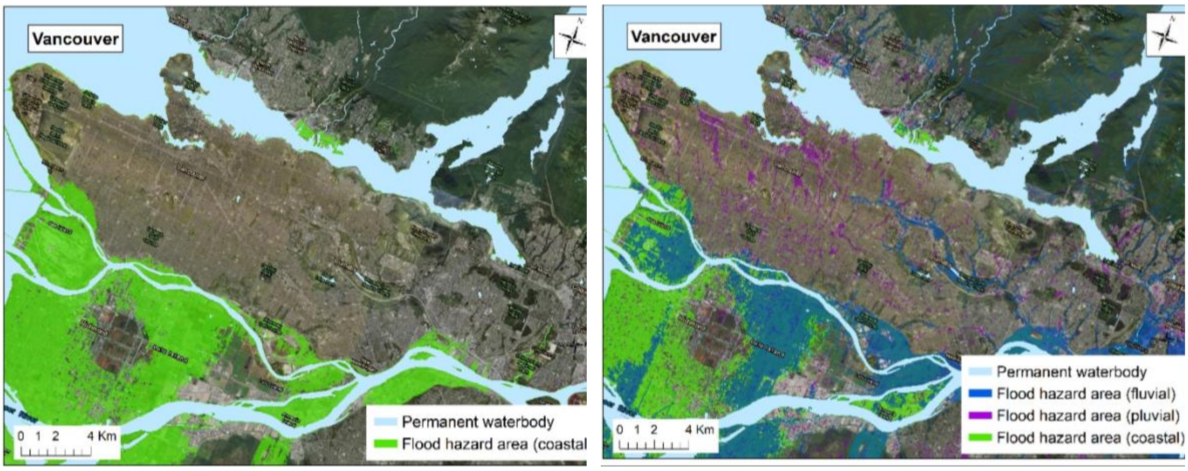


Figure 3.2 Flood-Prone Areas as Delineated by JBA Flood Hazard Modeling

This study focused on the spatial analysis of flood hazard and flood risk at the 100-year flood recurrence interval, with 1% of Annual Exceedance Probability (AEP) scenario, which is commonly used in flood hazard research and policy documents (Burn et al., 2016; C. Burton & Cutter, 2008; J. Chakraborty et al., 2014; Grineski et al., 2015; Jongman et al., 2012; Ludy & Kondolf, 2012; Maantay & Maroko, 2009). For simplicity and consistency, the remainder of the paper used the term "100-year flood hazard" to represent the magnitude of combined fluvial, pluvial, and coastal flooding, which has a 1-in-100 (1%) chance of occurring in any given year. Spatial layers of the 2016 CMA and CT-level cartographic boundaries (in polygon shapefile) were added to visualize flood hazard, social vulnerability, exposure, and flood risk at the CT level, and to finally generate flood risk maps at the CMA level.

We also used JBA's 2018 flood defense database (spatial layers in polygon shapefile) for Canada, which includes areas protected from flood impacts due to the presence of grey infrastructure (known or assumed), such as dams, dikes, and levees. The flood defense database is particularly useful to identify population subgroups, properties and assets that would be protected in the event of a 100-year flood hazard. Thus, the exposure of residential properties to 100-year flood hazard is presented with fluvial-defense and without fluvial-defense (**Figure 3.3**).

(a) Fluvial-undefended **(b) Fluvial-defended**

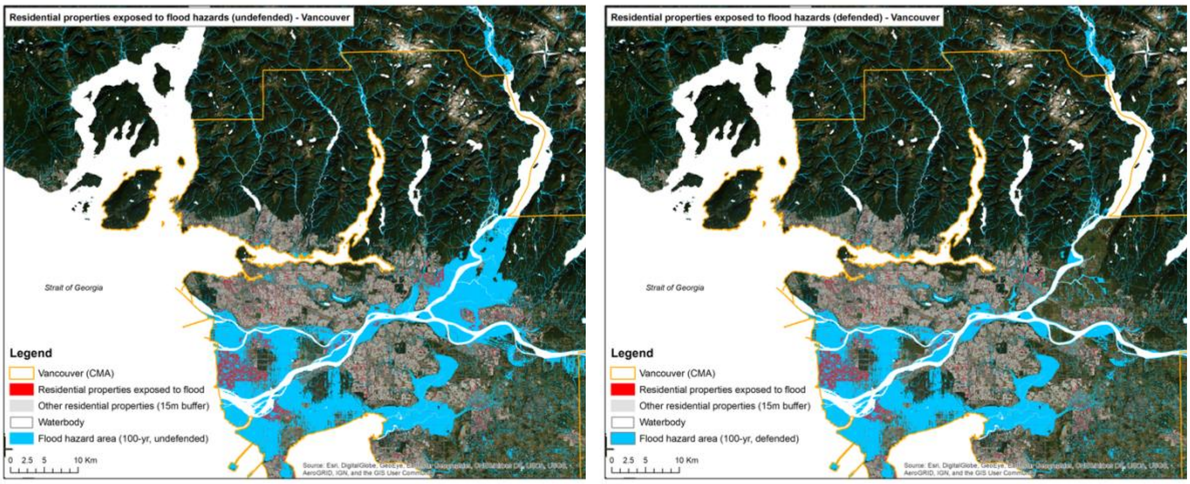


Figure 3.3 Residential Properties Exposed to 100-Year Flood Hazard Area in Vancouver

3.3.2.2. Flood Hazard Exposure of Residential Properties

The national address points dataset on "residential properties (count)" (spatial layer in point shapefile) from the DMTI Spatial (2018) was used to quantify the total number of residential properties exposed to 100-year flood hazard within each CT. The national address points dataset contains a total of 15,947,485 addresses in Canada, including industrial, commercial, and residential addresses. For all address points, data attributes of LAT (latitude), LON (longitude), and PRIM_USE (primary use) were also included in the dataset. Only address points that had primary use of "residential" were included as part of this analysis. Out of all address points in the database, 11,051,056 address points were classified as "residential" and included in the analysis.

The over 11 million residential address points were spatially joined with their respective Dissemination Block (DBs). The DBs containing a "CTUID" attribute made it possible to aggregate dissemination block data to all higher level standard geographic areas, that is the CTs. An address point represents a single unit (e.g., apartment, unit, etc.); therefore, there were cases where multiple addresses were present in the same geographic location (e.g., condo building, duplex). The CTs did not cover the entire Canadian territory, as a result, only a portion of residential properties were located inside a CT and retained for this study (8,342,118 residential properties). The majority of CTs had at least one residential property, however, 51 of the 5,721 CTs did not intersect with any residential addresses and were excluded from the analysis.

3.3.2.3. Exposure Analysis Using JBA Fluvial-Undefended Database

In the absence of building footprint data, a 15m buffer was used to estimate the extent of each residential property. Various buffer widths were tested (e.g., 30m); however, 15m appeared to fully capture the building footprints when comparing the results with satellite imagery **[Figure 3.3, panel (a)]**. Using the output buffer polygons of residential properties, a binary analysis was used to indicate if properties intersected with the 100-year flood hazard area receiving a 1 when they did, and 0 when they did not. This flood exposure analysis is consistent with the spatial methodology adopted by Qiang (2019).

3.3.2.4. Exposure Analysis Using JBA Fluvial-Defended Database

The national flood defense database supplied by JBA includes areas protected from a 100-year fluvial flood and information on the standard of protection. If the defenses (e.g., dams, dikes, and levees) are maintained and work as intended, the people and assets in these protected areas would not be impacted by a 100-year fluvial flood hazard event. To better understand the influence that defenses may have on population subgroups and assets, protected areas were masked out of the fluvial flood hazard area **[Figure 3.3, panel (b)]**. Some areas that are protected from fluvial floods can still be exposed to coastal or pluvial floods (e.g., British Columbia's Lower Mainland). For example, red-coloured areas, highlighted in **Figure 3.3 (b)**, are protected from fluvial floods but they are exposed to pluvial or coastal (lake) flood hazard. Residential properties that are only exposed to the 100-year fluvial flood hazard and are in a protected area were not counted in the exposure analysis. Results were summarized at the CT level for residential properties exposed to 100-year flood hazard (fluvial undefended and defended).

3.3.2.5. Flood Risk Analysis and Assessment Criterion

Spatial assessment of flood risk, as defined by the **Equation (1)**, was carried out by following the most commonly applied "flood risk" analysis framework (Albano et al., 2017; Armenakis et al., 2017; Frigerio et al., 2016; Ntajal et al., 2017), portrayed in **Figure 3.4**.

$$FR_{CT} = f\ (FH_{CT}, SV_{CT}, EX_{CT}) = \ FH_{CT} \cap SV_{CT} \cap EX_{CT} \tag{1}$$

where, FR_{CT} is flood risk, measured as a spatial intersection of flood hazard, social vulnerability of population and exposure of residential properties; FH_{CT} is flood hazard area (fluvial, pluvial, and storm surge merged) spatial layer, estimated at a 100-year flood recurrence interval; SV_{CT} is social vulnerability spatial layer, measured as an inverted socioeconomic status (SES)[18] index scores of populations; and EX_{CT} is physical exposure of residential properties spatial layer, at the CT level.

[18] We reversed the SES index scores for ease of interpretation and comparison of social vulnerability between CTs. For example, the higher the SES index score, the better the socioeconomic status of populations in a CT (Krishnan, 2010). The better the socioeconomic status of a CT, vulnerability conditions of the community (defined at census tracts) are likely to be degenerated through increased community resilience (Bergstrand et al., 2015; Buzzelli et al., 2006).

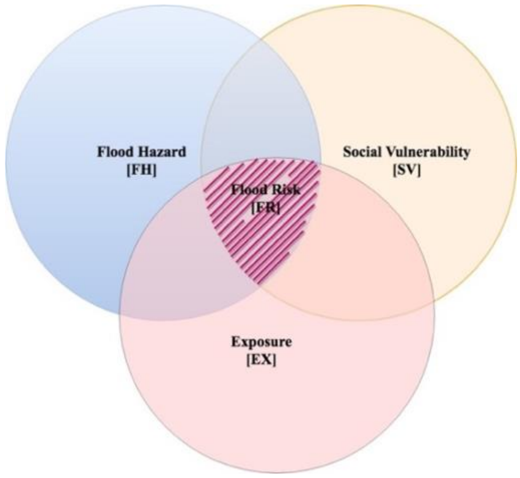


Figure 3.4 Schematic Conceptualization of Flood Risk (Red Shaded Area)

To visualize the 'hotspots' of flood risk in each CMA, we developed a *risk matrix* **(Figure 3.5)**, following a GIS-based bivariate choropleth mapping technique (Frigerio et al., 2016), which depicts the spatial relationship between social vulnerability (i.e., proportion of CT-level inverted SES index scores) and exposure of residential properties to 100-year flood hazard (i.e., percent of CT-level residential properties exposed to 100-year flood hazard).

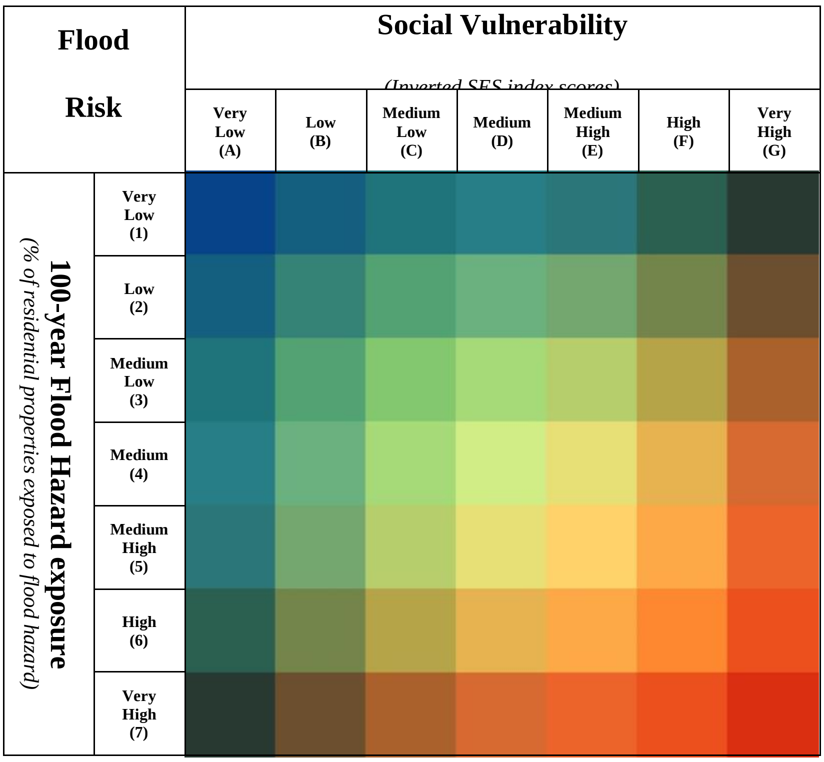


Figure 3.5 Flood Risk Assessment Matrix

The matrix combines different classes of relative social vulnerability with those of 100-year flood hazard exposure. The SES index scores were classified using 'standard deviation' classification scheme **(Figure 3.6)** and the exposure of residential properties (in percentage) were reclassified using 'equal count quantile' classification scheme, respectively, in seven categories, such as *Very Low, Low, Medium Low, Medium, Medium High, High, and Very High*. Finally, flood risk maps for Canada's three largest CMAs and five other high-risk CMAs were generated to identify the hotspot areas, that is, the CTs with high levels of social vulnerability and at the same time high levels of exposure of residential properties to 100-year flood hazard **(Figure 3.8).**

3.4 Results and Discussion

3.4.1. Social Vulnerability (SoVI) Indicators

The selected 49 standardized variables were entered into the PCA with varimax rotation. The eigenvalue rule was applied for component selection, and weighted sum of component scores was used to construct the socioeconomic status index. Our census data identified 11 multidimensional components with eigenvalues (i.e., the variances extracted by the components) of greater than 1 (L. Chakraborty et al., 2020). The 11 components together explained 80.8% of the total variation in the data. For a better understanding of the census-based social vulnerability indicators, the PCA results of varimax rotation matrix (that is, component loading scores on individual variables that are significant) were reported in the following **Table 3.1**. We found that 35 out of 49 selected variables appeared to be close representatives of socially vulnerable group membership.

Table 3.1 SoVI Indicators: PCA Results of Component Rotation Matrix

Code	Variables[19]	PCA Loading Scores	PCA Components	SoVI Indicators	Variance Explained
ZPFIRSTGEN[20]	Population with the first-generation status	0.3126	Comp 1	Race & Ethnicity	14.1%
ZPCITIZEN	Canadian citizens not by birth	0.3122			
ZPSOUTHASIAN	Population identified as South Asian	0.3589			
ZPLOWINC	Population with low-income status based on LICO-AT (prevalence of low income)	0.3399	Comp 2	Poverty & Built Environment	13.5%
ZPRENTER	Households occupying a rental, private dwelling	-0.3648			
ZPMOBILITY	Population's place of residence in the same CSD but different dwelling a year ago in 2015	0.3225			
ZDWELSIZE	The average number of rooms per dwelling	-0.3354			
ZPAG65OV	Population aged 65 or older	0.4420	Comp 3	Ability to Cope / Special Needs Population / Household Structure	10.1%
ZPONEPERHH	Population living alone with separated, divorced, widowed status	0.3595			
ZPUNATTELDER	Population aged 65 or older living alone	0.3889			
ZPMALENOLFS	Male population not in the labour force	0.3029			
ZMEDAGE	Median age of the population	0.3659			
ZPNOHIGHEDU	Population aged 15 or older with no certificate /diploma /degree	-0.3962	Comp 4	Education & Occupation	9.3%
ZPPOSTSECOND	Population with college diploma/trade certificate/university certificate at bachelor level or above	0.3775			
ZPOCCMGT	Population with management occupations	0.3385			
ZPOCCEDUC	Population with education, law, social, community & govt. services occupations	0.3931			
ZPFEMALE	Female population	0.4661	Comp 5	Ability to Cope / Special Needs Population	6.1%
ZPLONEPARNT	Population with lone parent family structure in census families	0.4929			
ZPGOVTRAN	Government transfers recipients within a couple	-0.4857			
ZPDISABLE1	Population with activity limitations due to the	0.5385	Comp 6	Ability to Cope /	5.6%

[19] Constructed at census tract-level proportions of the population except for age, dwelling value, income, household size, and dwelling size. Age, dwelling value, and income were estimated using the median function, whereas household size and dwelling size were calculated using the average function.
[20] "First-generation includes persons who were born outside Canada. For the most part, these are people who are now, or once were, immigrants to Canada" (Statistics Canada, 2019d).

	emotional, psychological, or mental health conditions			Special Needs Population & Ethnicity	
ZPDISABLE2	Population having difficulty in seeing, hearing, walking, using stairs, using hands or fingers, or doing other physical activities, learning, remembering/concentrating, emotional, psychological/mental, other health problems/long-term conditions for six months and above	0.5383			
ZPLATINAMERICA	Population identified as Latin American	-0.3049			
ZFEMLFRATE	Working-age females aged 15 or above participating in the labour force	0.3061	Comp 7	Ability to Cope / Special Needs Population / Occupation	5.3%
ZPAG5UN	Population aged 0 – 4 years	-0.4786			
ZPAG15UN	Population aged under 15 years	-0.4600			
ZPOCCSALES	Population with sales and service occupations	0.3595			
ZPNOLANG	Population with no knowledge of the official language in either French or English	0.4503	Comp 8	Ethnicity & Visible Minority	5.2%
ZPCHINESE	Population identified as Chinese	0.6289			
ZPABORIGIN [21]	Population identified as Aboriginal Peoples ethnic background	0.6019	Comp 9	Race & Ethnicity	4.7%
ZPINDINUTMETIS	Population identified as North American Indian/Inuit/Métis ethnic background	0.6168			
ZMEDPERCAPVAL	Median per capita home value (owner-estimated) as a proxy for per capita wealth[22]	0.6199	Comp 10	Access to Resources & Built Environment	4.1%
ZMEDPERCAPINC	Median per capita income of census family for all persons aged 15 or older[23]	0.5976			
ZPHOMEBUILT	Population living in buildings or dwellings built before 1970	0.3224			
ZPFILIPINO	Population identified as Filipino	0.4283	Comp 11	Occupation & Ethnicity	2.8%
ZPOCCHEALTH	Population with health occupations	0.6370			

[21] "Aboriginal identity includes persons who are First Nations (North American Indian), Métis or Inuk (Inuit) or those who are Registered or Treaty Indians (that is, registered under the Indian Act of Canada) or those who have membership in a First Nation or Indian band. Aboriginal peoples of Canada are defined in the Constitution Act, 1982, section 35 (2) as including the Indian, Inuit and Métis peoples of Canada" (Statistics Canada, 2019d).

[22] Values for tenant-occupied dwelling, band housing, and farm dwelling were excluded from dwelling value variable and replaced with median (owner-estimated) home value of dwellings of all census tracts.

[23] Negative reported income (i.e., loss of income) values were omitted and replaced with a median income of census families of all census tracts to normalize the dollar value variable after removing outliers

Note: Contents adapted from Chakraborty et al. (2020). A variable with a positive loading score suggests a negative association to the corresponding component (Krishnan, 2010).

The first component accounted for 14.1% of the total variation in the data, where the proportion of population with first-generation status (ZPFIRSTGEN), foreign born Canadian citizens (ZPCITIZEN), and South Asians (ZPSOUTHASIAN) showed positive loadings. This component, along with the variables in component 8 (Chinese, no official language knowledge in French or English) and component 9 (Aboriginal Peoples, North American Indian/Inuit/Métis), represents "race and ethnicity" characteristics of Canadians, which is a strong indicator of socially vulnerable group of populations consistent with the conventional environmental justice literature. These three components together accounted for 24% of the total variance and explain the variations in seven cultural variables. We interpreted these three components as a measure of the cultural system. The remaining eight components, including components 2,3,4,5,6,7,10, and 11 accounts for 56.9% of the total variance, and explain the variations in 28 variables that represent demographic, economic, and social characteristics of Canadians. We interpreted these components as a measure of the social system. However, the labeling or interpretation of the components 6 and 11 is less straightforward since three variables representing physical disability, mental disability, and health occupation had strong positive loading scores combined with the population subgroups such as Latin American and Filipino that are part of the visible minority populations in Canada.

To visualize national-scale socioeconomic disparities and the extents of social vulnerability across Canadian CMAs, the SES index scores were spatially joined to the 2016 census – CMA and provinces/territories boundary files, and then mapped using GIS-based choropleth mapping method. We used graduated classification style along with spectral color ramp to display standard deviation (SD) of the SES index scores from the mean (**Figure 3.6**). An inverted colour ramp on the SES index scores was used to exhibit seven categories of social vulnerability at the CT level, including very low (> 1.50 SD), low (1.00 SD to 1.50 SD), medium low (0.50 SD to 1.00 SD), medium (-0.50 SD to 0.50 SD), medium high (-1.00 SD to -0.50 SD), high (-1.50 SD to -1.00 SD), and very high (< -1.50 SD). The same geospatial mapping method and classification criteria were applied in Chakraborty et al. (2020).

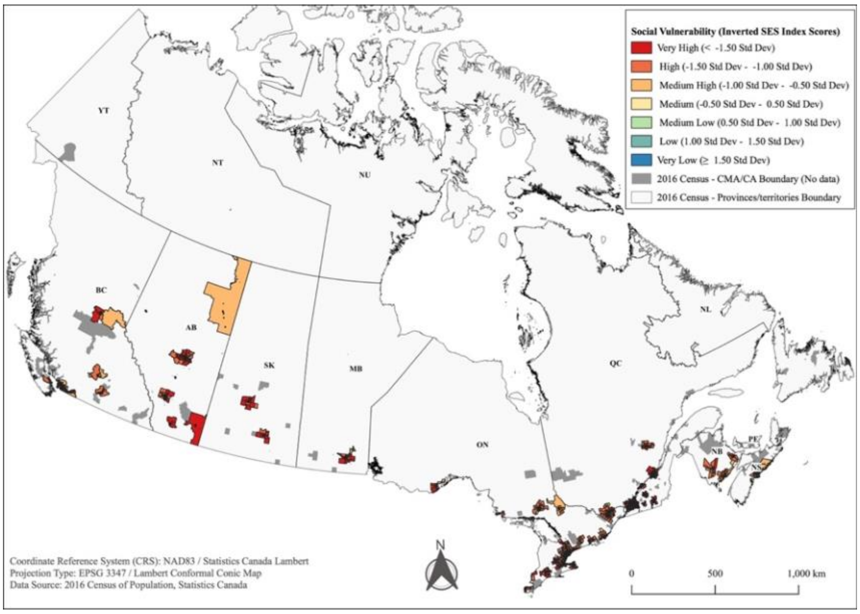


Figure 3.6 Spatial Distribution of SoVI by CMAs in Canadian Provinces

Our findings indicate that the driving forces of social vulnerability in Canada are consistent with the social and cultural factors of the environmental justice literature in the USA and UK, including race and ethnicity, income, built environment, elderly populations, education, occupation, family structure, and access to resources (J. Chakraborty et al., 2014; Collins et al., 2017; J. L. Fielding, 2012; Maldonado et al., 2016; Sayers et al., 2018; Walker, 2012). However, consistent with previous findings in Canada (Chan et al., 2015; Krishnan, 2010), we find that there remain considerable differences in the patterns of social vulnerability by CTs, CMAs, and provinces in Canada (**Figure 3.6**). For example, the social vulnerability in Western Canada provinces (particularly, Manitoba and British Columbia) tended to be significantly lower than in Atlantic Canada, and moderately lower than in Central Canada and Northern Canada provinces (L. Chakraborty et al., 2020).

3.4.2. Flood Exposure of Residential Properties

The CT-level exposure of residential properties to a 100-year flood hazard revealed that 15.9% (of the total 8,342,118) residential properties in Canada were exposed to any of fluvial, pluvial, and coastal flood hazard after accounting for fluvial-flood defenses at the CT-level. However, the flood exposure increased the number of residential properties to 20.1% of the total when fluvial-flood defense was not incorporated in the analysis. At the national level, the undefended fluvial-flood database revealed consistent results with the evidence of the Insurance Bureau of Canada that 1.7 million properties (or 19% of the population) lives in flood-prone areas of Canada (Insurance Bureau of Canada, 2019b).

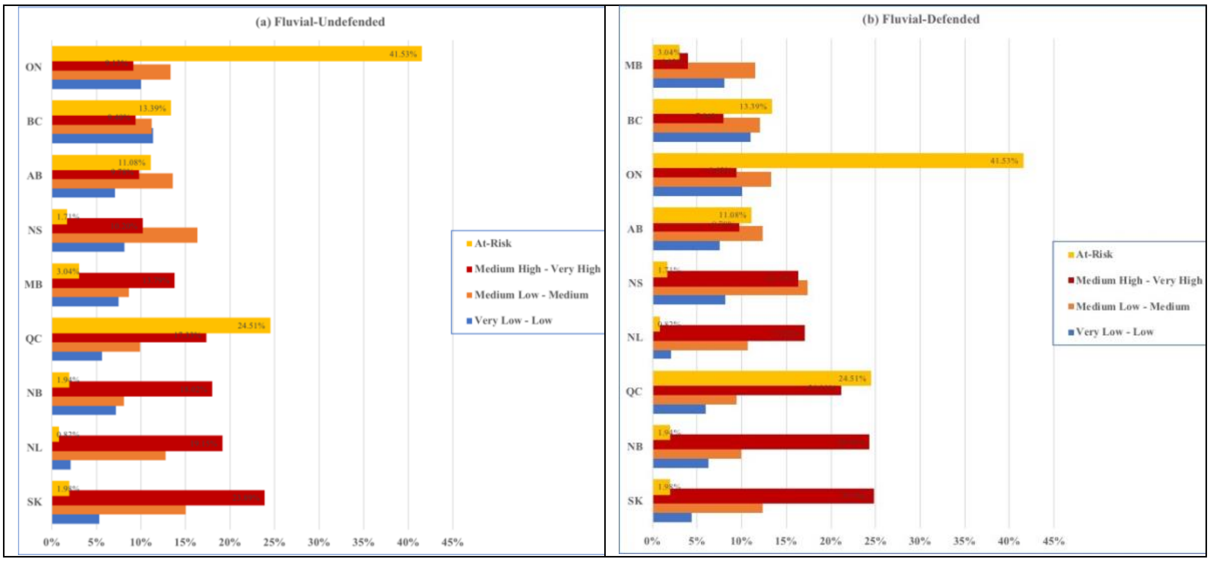


Figure 3.7 Percentage of CTs Exposed to 100-Year Flood Hazard by Provinces

For geospatial mapping of flood exposure, we classified the total number of residential properties exposed to any of fluvial, pluvial, and coastal flood hazard, using an ‘equal count quantile’ classification scheme, into seven categories such as (1) very low – less than 3.8%, (2) low – between 3.8% and 7.4%, (3) medium low - between 7.4% and 10.9%, (4) medium - between 10.9% and 14.8%, (5) medium high – between 14.8% and 20.0%, (6) high – between 20.0% and 29.6%, and (7) very high – more than 29.6% of residential properties exposed at the CT level. The same classification scheme was applied to both fluvial defended and undefended databases to reveal the difference (if there is any) in exposure of flood-prone areas. The spatial patterns of 100-year flood hazard exposure appeared to be unequally distributed across Canadian CMAs and provinces. For example, all seven categories of flood hazard exposure vary considerably by provinces, irrespective of our consideration to fluvial-flood defenses (**Figure 3.7**). In this paper, the total number of CTs intersected with all seven categories of 100-year flood hazard exposure was considered as the "at-risk" geographical areas of flooding in a province. Irrespective of considerations to fluvial-flood defenses, Ontario and Québec had the highest number of CTs found as "at-risk" areas of flooding (i.e., 66% of the total 5721 CTs) among all provinces (**Figure 3.7**). Moreover, Saskatchewan had the highest percentage of flood-prone areas (about 25% of its total CTs), detected under the categories of "medium high to very high" flood exposure of residential properties. The second largest percentage of "high-risk" (that is, medium high to very high) flood-prone areas was found in New Brunswick (with fluvial-flood defenses), and in Newfoundland and Labrador (without fluvial-flood defenses). Conversely, British Columbia and Ontario were found to have the highest number of CTs coincided with "low-risk" (that is, very low to low) categories of flood exposure. Thus, the CTs in Saskatchewan and in the Atlantic provinces of New Brunswick, and Newfoundland and Labrador had higher concentrations of "high-risk" flood-prone areas than the Central Canada province of Ontario and West Coast province of British Columbia. Within Central Canada provinces, the CTs in Québec were at more "high-risk" categories of flood exposure than Ontario.

3.4.3 GIS-Based Flood Risk Mapping and Hotspots Identification

Flood risk mapping in this study considered the 2016 CMAs or urban regions in Canada since these areas are of great importance for environmental policy and risk-based disaster management planning given their high concentrations of population and residential properties (Statistics Canada, 2020). The final flood risk maps were generated by the integration of the two spatial layers, including 100-year flood hazard exposure of residential properties and social vulnerability at the CT level (**Figure 3.8**). Similar to the GIS-based approach of Emrich and Cutter (2011), we employed a bivariate mapping technique to assess the spatial relationship between social vulnerability and exposure of 100-year flood hazard on residential properties. The spatial layers of the SES index score and 100-year flood hazard exposure were joined to the 2016 CT boundary file, and then mapped using graduated classification style, along with spectral color ramp to generate flood risk maps over 50 CMAs in Canada. Due to space limitations, only the flood risk maps for Canada's three largest CMAs are presented, including Toronto, Montréal, and Vancouver [**Figure 3.8, panel (a) – (c)**, respectively], where more than one-third of Canadians (35.7%) resided as of July 1, 2018 (Statistics Canada, 2019c). This mapping procedure permits us to assess flood risk by visualizing the relationship between social vulnerability and flood hazard exposure for each CMA. This spatial integration also allows the detection of hotspots of flood risk in Canada (**Table 3.2**) – the CTs and the CMAs with very high or elevated 100-year flood hazard exposure and very high or elevated social vulnerability – which highlights the distribution of most at high-risk CTs and CMAs. As the exposure and social vulnerability analysis was carried out at a national scale, we also created flood risk maps for five very high-risk CMAs [**Figure 3.8, panel (d)**].

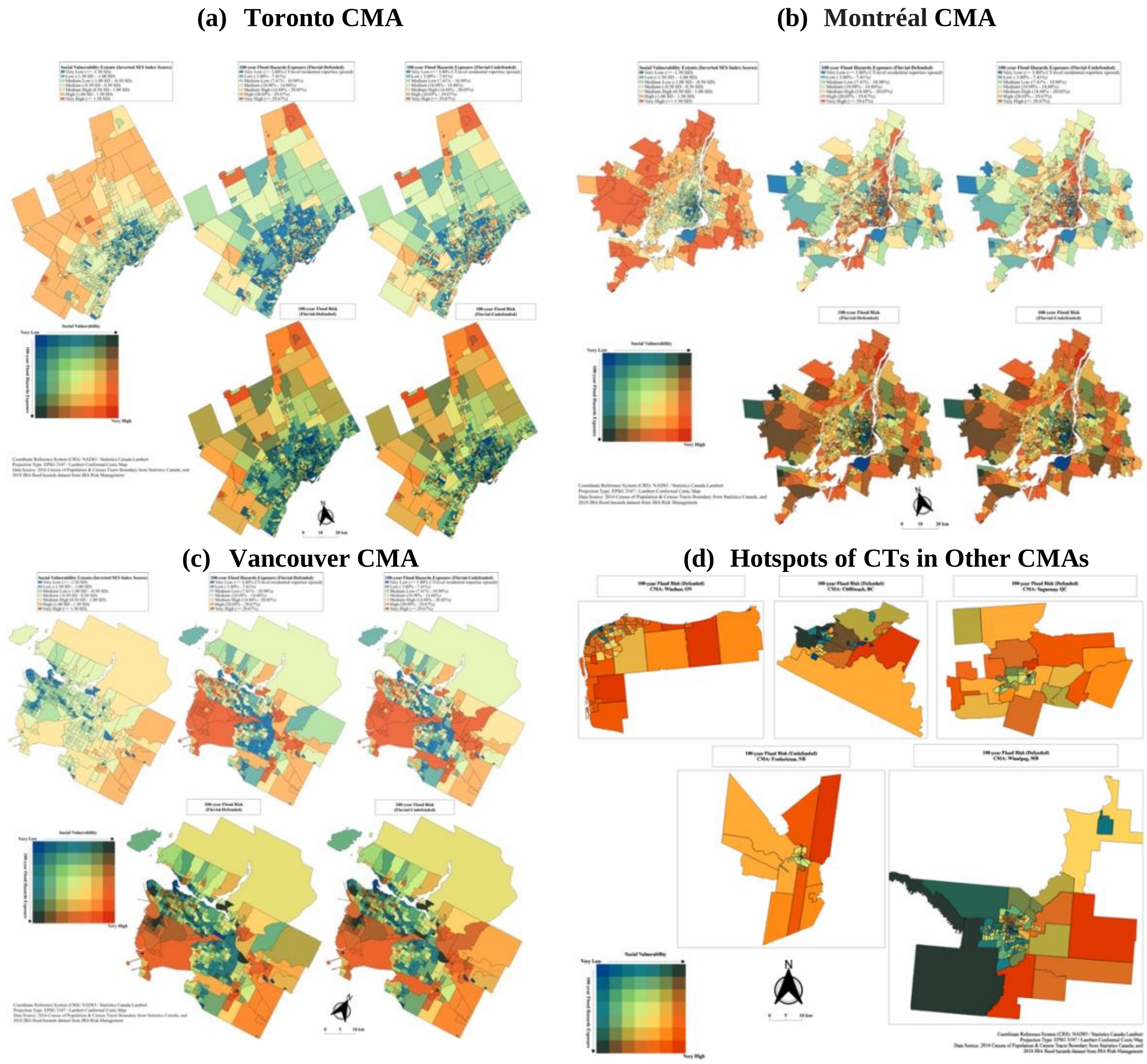


Figure 3.8 Geospatial Assessment of 100-Year Flood Risk at the CT-Level by CMAs

The maps visualize hotspots of flood risk in five CMAs, including Windsor, Chilliwack, Saguenay, Fredericton, and Winnipeg (from left to right). More specifically, population subgroups and residential properties in 18 out of the total 5721 CTs, over nine CMAs, were detected with very high flood risk, where four CTs in both Chilliwack and Windsor CMAs were found to have the highest flood risk nationally. Although flood risk and its extents appear to be distributed unequally in terms of flood hazard exposure and social vulnerability at the national scale, no hotspots of flood risk were detected in the province of Newfoundland and Labrador, Nova Scotia, and Alberta.

Most of the CMAs or urban regions in Central Canada provinces were located in high to very-high flood risk areas in Canada, which consisted of 76.5% of the total 166 CTs that were susceptible to elevated flood risk under the fluvial-undefended database [e.g., Barrie, Grand Sudbury, Hamilton, Kitchener - Cambridge – Waterloo, London, Ottawa - Gatineau (Ontario portion), Sarnia, Sault Ste. Marie, St. Catharines – Niagara, Thunder Bay, Toronto, Windsor, Drummondville, Granby, Montréal, Québec, Saguenay, Sherbrooke, and Trois-Rivières] and Western Canada (e.g., Abbotsford – Mission, Chilliwack, Kamloops, Kelowna, Prince George, and Vancouver). Our results are consistent with USA-based studies on flood hazard and vulnerability assessment in that most of the CTs and the CMAs in southern and southwestern parts of the country were located in the high to very high flood risk areas (Emrich & Cutter, 2011; Khajehei et al., 2020). The reason is also obvious as more than half of the Canadians live in cities and towns near the Great Lakes and the St. Lawrence River in southern Québec and Ontario (known as Central Canada) and the industrial and manufacturing heartland (Government of Canada, 2012).

Table 3.2 Hotspots of Flood Risk with Very High Vulnerability & Very High Exposure

Province	CMA (2016)	CT (2016)	Mean SES Score$^{\Psi}$	Exposure* Fluvial Defended (CT-level %)	Exposure* Fluvial Undefended (CT-level %)
British Columbia	Chilliwack	9300023.02	26.7	5.7%	89.7%
		9300021.00		6.7%	83.4%
		9300014.00		3.8%	76.5%
Ontario	Windsor	5590130.01	28.8	61.8%	61.8%
Manitoba	Winnipeg	6020700.00	37.4	1.9%	55.4%
Québec	Saguenay	4080120.05	20.6	55.2%	55.2%
	Montréal	4620681.00	33.9	46.7%	46.7%
New Brunswick	Fredericton	3200019.00	27.9	46.0%	46.0%
Québec	Québec	4210845.06	27.4	43.0%	43.0%
Manitoba	Winnipeg	6020600.00	37.4	40.4%	41.2%
British Columbia	Chilliwack	9300032.00	26.7	39.7%	39.7%
Ontario	Windsor	5590160.01	28.8	38.9%	38.9%
		5590170.02		35.8%	35.8%
	Barrie	5680103.01	23.3	35.6%	35.6%
Québec	Québec	4210900.00	27.4	34.1%	34.1%

Ontario	Windsor	5590100.01	28.8	32.2%	32.2%
	St. Catharines (Niagara)	5390242.01	27.5	32.0%	32.0%
Manitoba	Winnipeg	6020590.02	37.4	30.0%	30.0%

Ψ SES index scores adapted from Chakraborty et al. (2020). Higher SES index scores refer to less vulnerability (Bergstrand et al., 2015).
* Percentage of residential properties in a CT exposed to 100-year flood hazard, estimated using JBA flood hazard dataset.

3.5 Strengths and Limitations

The primary contribution of this study is its first nationwide spatial assessment of social vulnerability and exposure of residential properties to 100-year flood hazard for assessing national-scale flood risk in Canada. It provides a scientific basis for understanding the Canadian socioeconomic and demographic conditions that make a community (measured at the CT level) more vulnerable than others. The results of this study are useful for planners and policy-makers, and could be used to inform risk-based flood hazard management strategies and improve disaster resilience for the areas that are very likely to be the most flood disadvantaged areas or hotspots of flood risk (Emrich & Cutter, 2011). This analysis also provides insight for climate change adaptation plans in many communities across Canada.

We acknowledge several data and relevant analytical limitations in the paper. First, this analysis identified residential properties exposed to flood hazard exclusively based on location. If residential properties are in an area exposed to flood hazard, then these were classified as being “at-risk” of flooding. The same applies to condo units, regardless of whether they are in an upper floor of a building and may not directly be impacted by a flood (rather the main floor lobby or basement parking would be flooded). Nor does it account for other forms of impacts associated with nearby flooding (i.e., loss of power, transportation access, etc.). Second, our analysis is not an indication for the severity of flood damages that would be incurred if a property was flooded. The amount of damage produced for an individual property depends on flood water depth and velocity and duration (Romali et al., 2015). Third, the study is unable to “ground-truth” exposure and vulnerability due to unavailability of both pre-event and post-event data and limited local information related to exposure, sensitivity, and adaptive capacity that are often collected through specific site visits and qualitative survey methods (Albano et al., 2017; Schmidtlein et al., 2008). Fourth, the pluvial flood or surface water modelling that underpins the flood hazard dataset does not account for blocked sewers/drains in urban centers. In addition, JBA's Canada Flood Map hydrology data are based on historical data and do not incorporate any future climate change projections.

3.6 Conclusion

Following Cutter's (1996) hazards-of-place model and the place-based risk assessment approach (Armenakis et al., 2017; Khajehei et al., 2020), this paper introduced the first nationwide spatial assessment of flood risk through integrating flood hazard, social vulnerability, and their exposure to residential properties at the CT level in Canada. Using flood exposure analysis based on a specific flood scenario, the 100-year flood recurrence interval, this study generated flood risk maps for Canadian CMAs. Statistical and spatial analysis revealed the variations in social vulnerability and hazard exposure at the national (provinces), regional (CMAs), and local community (CTs) scales. The results show strong and considerable variations of both social vulnerability and flood exposure of residential properties across Canadian geographical regions. At the national scale, the social vulnerability index score ranges from 0 to 100 with an average of 33.4. The percentage of residential properties exposed to flood hazard in a CT ranges from 0.05% to 100% with an average of 17.3% while accounting for known fluvial-flood defenses, whereas the same exposure varies from 0.06% to 100% with an average of 21.3% when fluvial-flood defenses are not incorporated.

At the national scale, the results show that 12.8% of the 5721 CTs in Canada were located at 'medium-high' to 'very high' flood risk, even after accounting for JBA fluvial-flood defenses, whereas 18 CTs connected to nine CMAs were detected at very high flood risk areas. Among all provinces, Ontario and Québec had the highest number of CTs revealed as "at-risk" areas of flooding (i.e., 66.04% of the total 5721 CTs), regardless of accounting for fluvial-flood defenses. Our provincial-scale results are consistent with the USA-based recent studies on flood risk assessment in a way that most of the CTs and the CMAs in southern and southwestern parts of Canada were located in the high to very high flood risk areas (Khajehei et al., 2020; Qiang, 2019). The results indicate that most of the CMAs or urban regions in Central Canada and Western Canada were geographically concentrated in flood-disadvantaged areas that were susceptible from 'high to very high' flood risk, while fluvial-flood defense was overlooked. These results are useful to inform risk-based flood hazard management policies that are consistent with the distributive justice principle of Rawlsian, that is to help those geographic flood disadvantaged neighbourhoods most who in need first.

Based on the critiques of social justice scholars, risk management planning likely to be flawed, politicized and biased if the decision-making process supports the Utilitarianism and Libertarianism justice principles (Thaler & Hartmann, 2016). For example, resource allocation strategies based on the assessments of flood hazard extents or exposure only. The results provided in this paper could be useful for developing effective flood mitigation strategies with a consideration to an Egalitarian or the Rawlsian social justice approach (Sayers et al., 2018). For example, allocating scarce resources for flood recovery to the geographically flood disadvantaged areas and communities, who needed most, and were identified as flood risk hotspots in the paper. This approach provides a scientific foundation for risk analysis, promotes socially equitable and apolitical for FRM planning, and improves flood resiliency (Emrich & Cutter, 2011).

We know that the individuals and their wider communities with restricted ability to respond and lack of access to flood mitigation resources are likely to be affected adversely by flood hazard, as with other environmental hazards. Considering a socially just FRM policy discourse, the next step is to find empirical evidence on systemic flood disadvantaged areas and communities (if there is any) through analyzing the degree to which the socially vulnerable communities are disproportionally affected by flood hazard exposure (Sayers et al., 2017) in Canada. Finding such an evidence would facilitate decision-makers to improve social justice outcomes through sustainable flood risk management policy and practices.

Chapter 4: Manuscript #3

Exploring Spatial Heterogeneity and Environmental Injustices in Exposure to Flood Hazards Using Geographically Weighted Regression

Chakraborty, L., Rus, H., Henstra, D., Thistlethwaite, J., Minano, A., & Scott, D. (2021). Exploring spatial heterogeneity and environmental injustices in exposure to flood hazards using geographically weighted regression. *Environmental Research*. (Submitted on February 15, 2021, Under Review, Manuscript ID # ER-21-699).

This study deconstructs flood-related environmental injustices by investigating racial, ethnic, and socio-demographic disparities and spatial heterogeneity in the areal extent of fluvial, pluvial, and coastal flooding across Canada. The study integrates Canada's 100-year Flood Map from JBA Risk Management with the 2016 national census-based socioeconomic data to investigate whether traditionally recognized vulnerable groups and communities are exposed inequitably to inland (e.g., fluvial, and pluvial) and coastal flood hazards. Social vulnerability was represented by neighbourhood-level socioeconomic deprivation, including economic insecurity and instability indices. Statistical analyses include bivariate correlation and a series of non-spatial and spatial regression techniques, including ordinary least squares, binary logistic regression, and simultaneous autoregressive models. The study documents the quest for the most appropriate methodological framework to analyze flood-related socioeconomic inequities in Canada. Strong evidence of spatial effects has motivated the study to test for the spatial heterogeneity of covariates by employing geographically weighted regression (GWR) on continuous outcome variables (e.g., percent of residential properties in a census tract exposed to flood hazards) and geographically weighted logistic regression on dichotomous outcome variables (e.g., a census tract in or out of flood hazard zone). GWR results show that

the direction and statistical significance of relationships between inland flood exposure and all explanatory variables under consideration are spatially non-stationary. We find certain vulnerable groups, such as females, lone-parent households, Indigenous peoples, South Asians, the elderly, other visible minorities, and economically insecure residents at a higher risk of flooding in Canadian neighbourhoods. Inland flood risk is of more significant concern. Spatial and social disparities in flood exposure have critical policy implications for effective emergency management and disaster risk reduction. The study findings can be used as a foundation for a more detailed investigation of the disproportionate impacts of flood risk in Canada.

4.1 Introduction

The distributive environmental justice (EJ) literature focuses on addressing disproportionate environmental burdens and benefits associated with differential hazard exposure (J. Chakraborty et al., 2019). Over the past few decades, perspectives of distributive EJ and social justice research have been a top priority for effective risk management of physical, technological and environmental hazards (Collins & Grineski, 2017) because EJ research provides a comprehensive set of social vulnerability indicators for environmental risk assessment (Montgomery & Chakraborty, 2015). The EJ principle refers to fair treatment and equal protection of environmental laws, regulations, and policies for all people and communities irrespective of race, colour, ethnic origin, or income (Bullard, 1994; Mohai et al., 2009a). The underlying question of EJ research is whether environmental hazards are concentrated mostly in communities marked by lower socioeconomic status (SES) (Buzzelli, 2008). This question is answered by investigating the roots of socioeconomic inequalities within the empirical relationships of hazard exposure, racial or ethnic affiliation, and neighbourhood-level socioeconomic deprivation (Collins, Grineski, Chakraborty, et al., 2019).

Such an investigation helps address public policy concerns on environmental racism, defined as the excessive exposure of Black, Indigenous and people of color (BIPOC) and other racial/ethnic minority groups to environmentally hazardous areas (House of Commons of Canada, 2020; Reid & Hopton, 2021).

In the hazard, disaster, and emergency management literature, social vulnerability usually refers to the socio-demographic characteristics and socioeconomic capacities of an individual, a group or a community that determine or influence their resiliency or susceptibility to harm from the adverse impacts of a natural hazard and/ disaster (Flanagan et al., 2011; Wisner et al., 2004). The distributive EJ research identifies which racial or ethnic subgroups are most socially vulnerable to hazards and promotes an equitable or "fair" treatment approach for those groups to better cope with and recover from hazards and disasters (Doorn, 2015). Assessing spatial and socio-demographic disparities in flood hazards lays out distributive justice outcomes for effective flood management. Such an investigation provides evidence of systemic flood disadvantage in terms of racial/ethnic, demographic, and socioeconomic inequities in exposure to flood risk and its spatial distribution (Sayers et al., 2017).

Several EJ research shows cultural minorities, persons of lower socioeconomic status, and deprived socio-demographic groups or communities often experience excessive exposure to physical hazards, including noise pollution (Carrier et al., 2016b, 2016a; Casey et al., 2017; Collins, Grineski, & Nadybal, 2019) and technological hazards, including air pollution, hazardous toxic wastes, or industrial pollution through chemical spills (Andrey & Jones, 2008; Grineski et al., 2017). Nevertheless, EJ studies in the context of flooding are minimal, and they typically report ambiguous relationships between the indicators of demographic and socioeconomic status and exposure to flood hazards[24].

Some EJ studies have revealed counterintuitive results that financially affluent groups or persons with social advantage occupy flood hazard zones (Oulahen, Mortsch, et al., 2015) and face the highest residential-level flood risk exposure (Collins et al., 2017; Collins & Grineski, 2017; Maantay & Maroko, 2009). Scholars argue that a lack of consideration to *divisibility* in the patterns of exposure to an environmental hazard, such as separating potential advantages and risks correlated with a hazard, could be responsible for such inconsistency (Kates, 1971). Ignoring environmental amenities or locational benefits associated with distinctive flood risk exposure (inland vs coastal) could also be responsible (Montgomery & Chakraborty, 2015).

This paper is the first attempt to assess whether conventionally recognized socially vulnerable groups, including persons of colour (e.g., Black), females, visible minorities, Indigenous peoples, the elderly, and lone-parent households, bear a disproportionate burden of inland (such as fluvial and pluvial) and coastal flood risk in Canada. Since population census data and locations of flood exposure are often regarded as spatially-referenced data sets that strongly display effects of spatial dependence (Gibbons & Schiaffino, 2016; Wang & Wu, 2020), this study accounts for spatial heterogeneity in the distribution of flood hazards using a geographically weighted regression (GWR) approach.

The study uses empirical evidence to argue that exploring socioeconomic inequality in flood exposure is more appropriate in a spatial regression framework using the GWR approach that

[24] For ease of interpretation and consistency, "flood hazard exposure", "flood risk exposure", or "flood exposure" were used synonymously or interchangeably throughout the paper. However, 'risk' in the hazard and disaster literature is conceptualized as an intersection of hazard, exposure, and social vulnerability (Wisner et al., 2004).

highlights the existence of potentially complicated and spatially-varying relationships (Fotheringham et al., 1996). Failure to consider the heterogeneity in the spatial data modelling process may lead to model misspecification, misleading results, biased estimates, and substandard empirical predictions (L. Zhang & Shi, 2004). This paper demonstrates the value of a GWR-based analytical approach to understand and address spatial heterogeneity that supports statistically valid analyses about the relationship between flood exposure and racial, ethnic, or other socio-demographic explanatory factors. The study aims to contribute to further understanding of the spatial-heterogeneity in exposure to flood hazards, disproportionate impacts of flooding, and systemic flood disadvantages (i.e., whether and the extent to which socioeconomically disadvantaged groups, persons, or communities are inequitably exposed to flooding) (Sayers et al., 2017).

4.2 Environmental Justice in Canada

There has been very little research on EJ in Canada (Haluza-Delay, 2007). Studies on EJ perspectives of air pollution and noise exposure have been recently growing in Canada (Buzzelli & Jerrett, 2003, 2004; Carrier et al., 2016b; Pinault et al., 2016). One study by Deacon and Baxter (2012) points out procedural environmental inequity over two Eastern Canada landfills. Lesser attention to EJ research in Canada does not necessarily indicate that Canada does not possess environment-related inequity (Haluza-Delay, 2007). Some scholars argue that environmental racism or injustices in exposure to environmental hazards are not prominent in Canadian regions or rural vs urban areas (Walks & Bourne, 2006). Racial segregation and social inequalities in Canada are mainly associated with the rights to lands, management of environmental and natural resources, housing and living conditions, and the abrogation of treaties of aboriginal or Indigenous peoples in Canada (Haluza-Delay, 2007; Thompson, 2015).

Distributive EJ research on flooding is scarce in Canada (L. Chakraborty et al., 2020; Walker et al., 2006), although flooding is Canada's most common and costly climate change risk, severely disrupting people's lives and livelihoods (Burn & Whitfield, 2016; Honegger & Oehy, 2016). Some Canadian research investigates the patterns of environmental injustices in exposure to road traffic noise or environmental noise in Montreal (Carrier et al., 2016b; Dale et al., 2015), environmental hazard in Vancouver (Andrey & Jones, 2008), and air pollution in Hamilton and Montreal (Buzzelli & Jerrett, 2007; Crouse et al., 2009; Pinault et al., 2016). These studies find some statistically significant associations between hazard exposure and neighbourhood-level indicators of socioeconomic deprivation, including lone-parent households, low-income families, persons spending over 30% of their income on housing, and visible minorities such as South Asians and Latin Americans. However, the extent to which socioeconomically deprived populations are disproportionately exposed to differential flood risk across Canada is still mostly unknown.

Previous research has mostly overlooked the EJ implications of flood risk and failed to address the spatial heterogeneity in exposure to flood hazards across Canada. This research fills the gap of analyzing and addressing flood-related socioeconomic inequalities while considering divisibility aspects of flood hazards by examining whether the types of flood hazard zones (inland vs. coastal) influence the empirical relationships amongst flood exposure and racial, ethnic, and other socio-demographic characteristics of Canadian residents. This paper contributes to the emergent and quantitative EJ literature on flood-related socioeconomic disparities that emphasize addressing spatial heterogeneity in the distribution of flood hazards across flood-prone areas in Canada.

4.3 Data and Methods

The study utilizes national datasets of flood hazards, residential address points, census of population, and CT-level cartographic boundaries to determine flood-vulnerable neighbourhoods and the number of residential properties exposed to fluvial, pluvial, and coastal flooding across 4,458 census tracts (CT) in Canada. The variables influencing empirical relationships between flood risk, racial, ethnic, demographic, and socioeconomic status of households are grouped from the CT-level population characteristics to represent social vulnerability, socioeconomic and race/ethnicity status associated with the 100-year flood hazard exposure. The spatial scale of the units of analysis is the CT, representing “small, relatively stable geographic areas that usually have a population of less than 10,000 persons, they are located in census metropolitan areas and in census agglomerations that had a core population of 50,000 or more in the previous census” (Statistics Canada, 2018a, p. 84).

The 2016 national census micro-dataset contains household-level observations for 5,827 CTs in Canada. To ensure that our regression estimates are reliable and stable, we removed 1,369 CTs that did not meet Statistics Canada’s microdata-related confidential rules for vetting statistical outputs (e.g., homogeneity and dominance rules on census variables, including household income and owner estimated home values). The analysis included CTs that met minimum census count and geographical requirements only, such as CTs with at least 40 households and 250 population. The CTs with missing neighbourhood deprivation indices and racial or ethnic representation under consideration were also removed from empirical analysis, and thus we continued analyzing 4,458 CT-level observations. The sources of detailed data sets are listed in the *supplementary material*.

4.3.1 Dependent Variables

To delineate flood risks—the dependent variable in this research—we used 100-year undefended, flood-prone land areas for fluvial, pluvial, and coastal flood hazards at the 30-meter horizontal resolution, as determined by JBA Risk Management (JBA) – a global and market-leading flood modelling and analytics firm. JBA's 2018 flood hazard datasets were made available through a research partnership with the University of Waterloo. These Canada Flood Maps, the most widely used in the Canadian (re)insurance market, are national in scope, enabling flood hazard assessment at any location in Canada (Golnaraghi et al., 2020; JBA Risk Management, 2020). JBA's flood hazard extent datasets (in raster GIS file format) were first imported into ArcMap 10.7.1 to visualize flood-prone areas. Statistics Canada's spatial layers of the 2016 CT-level boundaries were added to visualize the hazard and exposure at the CT level.

For statistical analyses, flood risk was represented with three dichotomous dependent variables wherein a CT was classified according to the flood zone it intersects (Montgomery & Chakraborty, 2015). For example, the CTs that overlapped with coastal flood zones were coded "1" and categorized as at coastal flood risk and were coded "0" if they did not. Similarly, the CTs that overlapped with inland flood zones were designated as at inland flood risk.

The classification of CTs based on flood risk exposure was collectively exhaustive. Besides, a set of continuous dependent variables was constructed to capture more variation in the response variables used to represent the percentage of residential properties within a CT exposed to fluvial, pluvial, or coastal flooding at a 1-in-100-year flood return period. The 100-year flood, with 1% Annual Exceedance Probability (AEP) scenario, represents a flood that has one chance in one hundred of being equivalent or surpassed to flooding in any given year (Government of

Canada, 2013), which is commonly used in the EJ studies concerning flood hazards and FRM policy documents. A 100-year flood "can be considered a low divisibility, punctuated event with moderately rapid onset and relatively low frequency/high magnitude" (Grineski et al., 2016, p. 3). A detailed methodology of geographical information system (GIS)-based flood exposure analysis with relevant flood risk delineation maps is included in the *supplementary material*.

4.3.2 Explanatory Variables

The independent variables include race/ethnicity, two neighbourhood socioeconomic deprivation indices, and four variables on socio-demographic status, representing gender, old age, and physical disability. Based on the existing EJ literature in the context of Canada, we have chosen the racial or ethnic variables, including percentages Black, South Asian, Indigenous, and other visible minorities. These variables were chosen to test the conventional EJ hypotheses that racial, ethnic, or cultural minority groups are inequitably exposed to flood hazards and/ disproportionately affected by flood hazards.

Census populations were grouped as South Asians, including Chinese, Filipino, Southeast Asian, Korean, and Japanese origin of visible minorities, whereas 'Other visible minority'[25] subgroup represented Latin American, Arabian, and West Asian origin populations. The Indigenous population subgroup consisted of Aboriginal peoples and people with first ethnic origin identified as First Nations (North American Indian) or Inuit or Métis. Consistent with some Canadian environmental justice/equity analysis (Bocquier et al., 2013; Carrier et al., 2016b, 2016a), four socio-demographic characteristics of the population were used as

[25] Since population census count or microdata is not equally distributed across all visible minority groups, some geographical areas in Canada did not contain minimum census count or microdata to represent all racial/ethnic groups. Hence, this research considered other visible minority groups to define a heterogeneous population subgroup represented by Latin American, Arabian, and West Asian origin populations.

explanatory variables in addition to race/ethnicity and neighbourhood deprivation indices, including (1) percent female; (2) percent population with age 65 and over; (3) percent population having a disability in physical activities; and (4) percent population living alone (**Table 4.2**).

All explanatory variables were standardized and diagnosed for multicollinearity and model instability, using values of variance inflation factor (VIF) and the condition index number (i.e., difficulties identifying spatial relationship). In general, a VIF value of higher than ten (10) indicates multicollinearity and is regarded as meriting further investigation (Tabachnick & Fidell, 2007). A very high VIF value for a variable also suggests that the variable is possibly redundant. The condition index number refers to the global instability of regression coefficients. An index value of 10 or more indicates instability, and 30 or more would mean the model has difficulties identifying meaningful spatial relationships between variables (Rosenshein et al., 2011). Our data revealed a condition number of 5.43 (**Table 4.6**) and VIF values ranging from 1.27 to 6.08. Since all values of the VIF in **Table 4.2** are not above 10, our data does not exhibit substantial multicollinearity among explanatory variables, and none of the explanatory variables warrant exclusions (Huang et al., 2020).

Table 4.1 Descriptive Statistics of All Variables (N = 4,458 CTs)

	Min	Max	Mean	Std. Dev.	VIF
Dependent Dichotomous Variables					
CT in/out of 100-year fluvial flood zones	0.00	1.00	0.68	0.47	
CT in/out of 100-year pluvial flood zones	0.00	1.00	0.93	0.26	
CT in/out of 100-year coastal flood zones	0.00	1.00	0.05	0.23	
Dependent Continuous Variables					
Residential properties in fluvial flood zones	0.00	1.00	0.10	0.20	
Residential properties in pluvial flood zones	0.00	0.97	0.12	0.12	
Residential properties in coastal flood zones	0.00	1.00	0.01	0.08	
Independent Continuous Variables					
Race/Ethnicity					
Black	0.00	0.48	0.05	0.06	1.93
South Asian	0.00	0.92	0.17	0.18	2.04
Other Visible Minority	0.00	0.43	0.06	0.05	1.99
Indigenous	0.00	0.99	0.04	0.05	1.29
Instability Index	-4.25	9.54	0.00	1.95	6.08
Low-income households	0.00	0.65	0.11	0.08	4.87

Renter-occupied private dwelling	0.00	1.00	0.32	0.23	5.24
Shelter cost over 30 % of income	0.00	0.63	0.22	0.09	3.65
No private vehicle available	0.02	0.64	0.18	0.10	2.64
Not in the same house a year ago	0.03	0.50	0.14	0.06	2.66
Economic Insecurity Index	-6.05	6.41	0.00	1.65	1.80
Median household income (rescaled)	-0.00	3.63	2.38	0.40	5.71
Median home value (rescaled)	0.00	3.23	2.04	0.45	3.39
No high school diploma	0.01	0.38	0.14	0.06	2.52
Households on public assistance	0.56	0.99	0.88	0.05	1.93
Other Neighbourhood Deprivation Indicators					
Female	0.29	0.62	0.51	0.02	1.27
Age 65 and over	0.01	0.60	0.16	0.06	1.72
Disability in physical activities	0.02	0.38	0.12	0.05	2.50
Persons living alone / lone-parent household	0.00	0.64	0.13	0.09	4.98

All independent variables in **Table 4.1** except household income and owner-occupied home values represent CT-level proportions. Following Montgomery (2014), we rescaled the log of median household income and home value variables by subtracting CT-level individual values of a variable from the respective variable's maximum value. The higher the difference between the highest value and CT-level particular value of a variable, the more severe and significant the neighbourhood-level socio-economic deprivation.

4.3.3 Neighbourhood Deprivation Indices

Social vulnerability is represented through neighbourhood deprivation indices (Grineski et al., 2016). Following the methodology to construct neighbourhood deprivation indices and the literature of distributive EJ studies (Messer et al., 2006), the study applies Principal Component Analysis (PCA) with orthogonal varimax rotation on twelve standardized socioeconomic variables. The first two components extracted from PCA were neighbourhood instability and neighbourhood economic insecurity indices (Grineski et al., 2015). Component loading matrix and some PCA post-estimation results for extracted variables are included in the *supplementary material***.**

The instability index consists of poverty, housing, and transportation characteristics of populations. Five variables that represent the instability index are (1) prevalence of low income or percent populations with low-income status based on low-income cut-offs after-tax (LICO-AT) (e.g., households with no more than $30,000 as annual income); (2) population living in renter-occupied private dwellings; (3) people with shelter cost higher than 30% of income; (4) people with no private vehicle; and (5) population not living in the same house one year ago. The economic insecurity index comprises four SES variables, including (1) median household income; (2) median (owner-estimated) home values for owner-occupied homes; (3) population without a high-school diploma; and (4) population living on public or social assistance. Therefore, using these two neighbourhood deprivation indices as explanatory variables in regression specifications helps capture a more significant statistical association between neighbourhood-level deprivation and the categories of flood risk exposure.

4.3.4 Statistical Methodology and Analyses

The paper employed bivariate correlations in the first phase to identify the strength and directions of statistical associations between each explanatory variable (representing socio-demographic status) and the dependent variable (tract-level flood exposure) (**Table 5.2**). In the second phase, four sets of global models and two sets of local models were analyzed for investigating socio-cultural, demographic, and socioeconomic disparities of population subgroups in exposure to flood hazards. We first applied ordinary least squares (OLS) on the set of three continuous dependent variables, including percent of residential properties exposed to either fluvial or pluvial or coastal flood hazards at the CT level, after controlling for race/ethnicity, economic insecurity and instability indices, gender, age, and other socio-demographic status variables. Following Montgomery and Chakraborty (2015), we used the same set of independent variables to run binary logistic regression models on three dichotomous dependent variables to estimate the odds of a CT's exposure to flood hazards being a function of race, ethnicity, and social deprivation factors.

After OLS estimation, we test for spatial dependence or residual autocorrelation using *Moran's I statistic* (Chen, 2013). Spatial autocorrelation indicates "the tendency of variables to be influenced by their neighbours, a fact that will cause the errors in the regression analysis to not satisfy the independence conditions generally associated with ordinary least squares (OLS) regression" (Pastor et al., 2005, p. 134). Because significant spatial autocorrelation was detected, we ran spatial autoregressive (SAR) models, including spatial error regression and spatial lag models, following the techniques described in Grineski et al. (2015). Since the constant regression coefficients from global regressions (such as OLS, binary logistic regression, and SAR models) failed to account for the spatially-varying relationships between independent and dependent variables under consideration (Fotheringham et al., 2002), we resorted to applying GWR and GWLR methodology for modelling spatial heterogeneity to flood risk using spatially-referenced data points.

The GWR approach captures spatially-varying relationships between explanatory and response variables within a multiple regression framework (L. Zhang & Shi, 2004). The GWLR is a particular type of GWR model that focuses on the binary logistic regression model from a spatial perspective by including geographic coordinates. It is considered a valuable method for modelling spatial heterogeneity (Mayfield et al., 2018). This paper applies both GWR and GWLR approaches instead of global regression methods to identify and address spatial-nonstationarity in empirical relationships between variables (Chris Brunsdon et al., 1996; Nakaya, 2015).

To test for spatial autocorrelation and estimating SAR models, such as spatial lag model (SLM) and spatial error model (SEM), we employed the open-source software, GeoDa 1.18, following Grineski et al. (2015). SLM assumes spatial autocorrelation in the response variable, whereas SEM assumes spatial dependence in the explanatory variables (Grineski et al., 2015). A contiguity-based spatial weights matrix (with first-order *queen* criterion of contiguity) was constructed in GeoDa and used to test for spatial dependency and estimate both SAR models (Anselin, 2005).

Following Chun et al. (2017) and Atkinson et al. (2003), the paper uses the GWR4 software program to perform GWR and GWLR analyses that are considered as “local spatial analyses” (Nakaya, 2016). We selected the Gaussian-type GWR model and the 2016 census tract boundary-based latitude and longitude coordinates for projection. The adaptive bi-square kernel method was used for geographical weighting, and the golden section search criterion was applied to search for optimal distance bandwidth size (Wheeler & Páez, 2010). For GWLR models, the spherical option in a logistic (binary) model specification was selected with Gaussian adaptive kernel type using the nearest neighbour distance method (Pugh, 2016; Wu et al., 2016). Following Nakaya (2016), we selected Gaussian adaptive kernel as a safer option of geographical weighting in GWLR, where outcome distribution was assumed to be unbalanced. Like GWR, we also used the golden section search method to determine an optimum bandwidth size. This procedure was followed because the CT-based bandwidth size as the observation points across Canada consists of irregular distances. Since AICc (small sample bias-corrected Akaike Information Criteria) provides empirically better results even for logistic regression, it was selected as the most suitable method for local Gaussian regression modelling (Nakaya, 2016). Finally, all global and local regression models were compared to choose the best fit from different regression models (that is, the goodness-of-fit) using classic

AIC values, model-specific R-squared, deviance, and pseudo-R squared values (or percent deviance explained).

4.4 Results

4.4.1 Bivariate Correlations

Following the EJ analysis of Montgomery (2014) and Grineski et al. (2015), this study used Pearson's bivariate correlation coefficients to test the hypothesis that a more significant proportion of socioeconomically deprived groups of populations inhabit inland flood hazard areas. **Table 4.2** reports the results of bivariate correlation coefficients. These results are in the expected direction given the EJ hypothesis that socioeconomically deprived populations and visible minorities population subgroups disproportionately occupy inland flood zones. Our data indicate that the statistical associations between pluvial flood risk exposure and the proportion of Black, Indigenous, and other visible minorities populations are positive and significant in terms of race or ethnicity. A greater proportion of Indigenous peoples are significantly correlated with the exposure to fluvial flood risk, and a large proportion of South Asian populations are significantly associated with exposure to coastal flood risk.

Concerning socioeconomic deprivation, higher exposure to pluvial flood hazard is positively and significantly associated with instability, economic insecurity, disability, and persons living alone. Moreover, our data reveal that the relationship between economic insecurity and exposure to inland flood hazard is positive and statistically significant, indicating socioeconomic deprivation factors are strongly connected to inland flood risk zones. Interestingly, the relationships between elderly, female residents and coastal flood risk are positive and statistically significant. A negative and statistically significant relationship exists between neighbourhood economic insecurity and exposure to coastal flood risk. These results suggest that wealthy, female, and elderly populations are disproportionately occupying coastal flood hazard zones. In other words, most socially vulnerable groups, such as females, are highly susceptible to harm from exposure to coastal flood risk zones in Canada.

Since our bivariate correlation results are highly consistent with the findings of conventional EJ literature on flood hazards (J. Chakraborty et al., 2019; Collins, Grineski, & Nadybal, 2019; Collins, Grineski, Chakraborty, et al., 2019; Grineski et al., 2015; Montgomery & Chakraborty, 2015), it was a logical extension in the study to fit spatial and/non-spatial regression models to further analyze social and spatial inequalities in the exposure of three types of flood hazards.

Table 4.2 Bivariate Correlation Coefficients and Statistical Significance

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Residential properties in a fluvial flood zone	1.00												
(2) Residential properties in a pluvial flood zone	0.12***	1.00											
(3) Residential properties in a coastal flood zone	0.09***	0.02	1.00										
(4) Female	0.02	-0.05**	0.04**	1.00									
(5) Age 65 and over	0.01	-0.00	0.06***	0.42***	1.00								
(6) Disability (physical)	0.03*	0.16***	-0.05**	-0.03*	0.07***	1.00							
(7) Persons living alone	0.00	0.23***	-0.03*	0.01	0.25***	0.56***	1.00						
(8) Black	-0.07***	0.06***	-0.07***	0.06***	-0.18***	-0.13***	0.00	1.00					
(9) South Asian	-0.06***	-0.05***	0.17***	-0.02	-0.19***	-0.36***	-0.26***	0.14***	1.00				
(10) Other Visible Minority	-0.12***	0.11***	-0.04**	0.05***	-0.16***	-0.27***	0.05**	0.54***	0.28***	1.00			
(11) Indigenous	0.27***	0.11***	-0.03	-0.10***	-0.07***	0.33***	0.06***	-0.11***	-0.16***	-0.25***	1.00		
(12) Instability	-0.07***	0.23***	-0.00	-0.08***	-0.11***	0.43***	0.73***	0.28***	0.20***	0.37***	-0.00	1.00	
(13) Economic Insecurity	0.06***	0.20***	-0.05**	0.05***	0.08***	0.37***	0.26***	0.44***	-0.12***	0.18***	0.26***	0.32***	1.00

Note: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$ indicate 5%, 1%, and 0.1% significance level (two-tailed), respectively. N = 4,458 CTs with at least 260 residents. All variables except instability and insecurity indices are proportions.

4.4.2 Comparison of Estimated Regression Models

After establishing the significant bivariate association between all dependent and independent variables, we fit three OLS models for multivariate regression analysis on three types of flood exposure. **Table 4.3** shows the statistical results of two non-spatially fitted models (such as OLS and binary logistic regression) and four spatial models (such as SLM, SEM, GWR, and GWLR). *P-values* (columns 3,5,7, and 10) for estimated regression coefficients (*Coeff* columns 2,4,6, and 8) indicate whether the relationship between each dependent and corresponding independent variable is statistically significant. For example, a *P-value* close to 0.000 suggests that the respective explanatory variable is statistically significant with a confidence level of 99%.

The OLS model's multiple *R-squared* is 0.09 for inland flood risk and 0.04 for coastal flood risk. These values indicate that OLS models of inland and coastal flood risk can explain only about 9% and 4% of the total variation, respectively. Therefore, the OLS models are misspecified and provide misleading and biased parameter estimates as other variables (not taken into consideration) seem to explain the bulk of the remaining variance. GeoDa-based OLS diagnostic tests on our data suggest that all three OLS models' residuals are spatially autocorrelated. We proceeded to apply SAR models that control spatial autocorrelation (see *supplementary material*).

Table 4.3 Comparison of Spatial, Non-Spatial Regression Results & Model Performance

	Model type with global coefficient estimates (*p*-values) *									**Geographically varying (local) coefficients**			
	OLS		**SLM**		**SEM**		**Logistic**			**GWLR**		**Gaussian GWR**	
Fluvial Flood Risk Exposure	**Coeff**	***p*-values**	**Coeff**	***p*-values**	**Coeff**	***p*-values**	**Coeff**	**Odds ratio**	**Odds *p*-values**	**Min**	**Max**	**Min**	**Max**
Intercept	0.000	(1.00)	0.000	(0.98)	0.021	(0.58)	0.896	2.451	(0.00)	0.855	0.947	-4.488	4.205
Female	0.048	(0.00)	0.021	(0.04)	0.009	(0.42)	0.072	1.075	(0.09)	0.029	0.093	-0.794	0.693
Age 65 and over	-0.042	(0.03)	-0.009	(0.43)	-0.010	(0.46)	-0.135	0.873	(0.00)	-0.179	-0.101	-1.096	1.134
Disability (physical)	-0.112	(0.00)	-0.022	(0.12)	0.005	(0.83)	-0.063	0.939	(0.32)	-0.157	0.008	-1.510	1.613
Persons living alone	0.150	(0.00)	0.067	(0.00)	0.075	(0.00)	-0.086	0.918	(0.31)	-0.138	-0.022	-1.584	1.810
Black	-0.027	(0.18)	-0.012	(0.32)	-0.031	(0.07)	-0.102	0.903	(0.03)	-0.155	-0.045	-2.713	1.317
South Asian	0.032	(0.12)	0.014	(0.26)	0.014	(0.57)	-0.129	0.879	(0.01)	-0.173	-0.091	-5.871	4.982
Other Visible Minorities	-0.055	(0.01)	0.007	(0.59)	0.022	(0.23)	-0.233	0.792	(0.00)	-0.289	-0.196	-0.687	2.450
Indigenous	0.276	(0.00)	0.072	(0.00)	0.035	(0.00)	0.047	1.048	(0.63)	-0.077	0.164	-1.771	4.300
Instability	-0.134	(0.00)	-0.061	(0.00)	-0.068	(0.01)	-0.910	0.403	(0.00)	-1.076	-0.816	-1.706	1.763
Economic Insecurity	0.060	(0.00)	0.014	(0.22)	0.025	(0.22)	0.102	1.108	(0.05)	0.059	0.163	-1.097	2.024
AIC	12240		8735		8781			4634		4632		9041	
R-squared	0.09		0.66		0.66			NA		NA		0.69	
Deviance (% deviance explained)	NA		NA		NA			4612 (17.6%)		4574 (18.2%)		NA	
Pluvial Flood Risk Exposure	**Coeff**	***p*-values**	**Coeff**	***p*-values**	**Coeff**	***p*-values**	**Coeff**	**Odds ratio**	**Odds *p*-values**	**Min**	**Max**	**Min**	**Max**
Intercept	0.000	(1.00)	0.004	(0.77)	-0.007	(0.80)	2.828	16.915	(0.00)	2.820	2.839	-1.138	2.599
Female	-0.036	(0.10)	-0.022	(0.12)	-0.035	(0.03)	-0.015	0.985	(0.80)	-0.027	-0.003	-0.270	0.369
Age 65 and over	-0.009	(0.64)	-0.001	(0.96)	0.010	(0.60)	0.034	1.035	(0.70)	0.010	0.053	-0.550	0.451
Disability (physical)	-0.017	(0.53)	-0.005	(0.81)	-0.009	(0.76)	0.166	1.180	(0.10)	0.151	0.177	-0.637	0.907
Persons living alone	0.109	(0.01)	0.039	(0.16)	0.024	(0.49)	-0.303	0.739	(0.01)	-0.312	-0.288	-0.656	0.853
Black	-0.067	(0.00)	-0.054	(0.00)	-0.075	(0.00)	-0.276	0.759	(0.00)	-0.294	-0.257	-1.346	0.887
South Asian	-0.047	(0.03)	-0.025	(0.16)	-0.040	(0.13)	-0.384	0.681	(0.00)	-0.394	-0.371	-0.606	2.656
Other Visible Minorities	0.111	(0.00)	0.069	(0.00)	0.065	(0.00)	-0.036	0.965	(0.64)	-0.053	-0.018	-0.544	0.820
Indigenous	0.084	(0.01)	0.043	(0.00)	0.033	(0.05)	-0.147	0.863	(0.07)	-0.160	-0.130	-1.704	1.691
Instability	0.103	(0.01)	0.064	(0.04)	0.098	(0.01)	-0.286	0.751	(0.02)	-0.298	-0.277	-0.693	0.708
Economic Insecurity	0.128	(0.00)	0.089	(0.00)	0.114	(0.00)	0.249	1.283	(0.00)	0.233	0.264	-0.284	0.714
AIC	12236		11375		11426			2109		2108		11489	
R-squared	0.09		0.30		0.29			NA		NA		0.35	
Deviance (% deviance explained)	NA		NA		NA			2087 (7.7%)		2083 (7.9%)		NA	

Coastal Flood Risk Exposure	Coeff	*p*-values	Coeff	*p*-values	Coeff	*p*-values	Coeff	Odds ratio	Odds *p*-values	Min	Max	Min	Max
Intercept	0.000	(1.00)	-0.007	(0.32)	-0.045	(0.23)	-3.768	0.023	(0.00)	-3.968	-3.640	-3.088	9.201
Female	0.021	(0.15)	0.000	(0.98)	-0.006	(0.51)	0.055	1.057	(0.51)	0.014	0.098	-1.643	1.431
Age 65 and over	0.057	(0.00)	0.017	(0.07)	0.025	(0.03)	0.485	1.625	(0.00)	0.424	0.554	-1.336	2.907
Disability (physical)	-0.010	(0.61)	0.003	(0.76)	0.029	(0.12)	0.206	1.229	(0.08)	0.119	0.303	-5.706	6.445
Persons living alone	0.020	(0.35)	0.007	(0.67)	-0.015	(0.48)	-0.458	0.633	(0.00)	-0.666	-0.263	-1.197	5.089
Black	-0.058	(0.00)	-0.001	(0.89)	0.006	(0.66)	-1.010	0.364	(0.00)	-1.305	-0.817	-10.328	2.416
South Asian	0.207	(0.00)	0.030	(0.00)	0.053	(0.01)	0.241	1.273	(0.01)	0.188	0.296	-2.506	3.936
Other Visible Minorities	-0.068	(0.00)	-0.007	(0.52)	0.005	(0.74)	-1.090	0.336	(0.00)	-1.200	-0.992	-2.530	6.143
Indigenous	-0.016	(0.05)	-0.005	(0.55)	-0.005	(0.65)	-0.357	0.700	(0.11)	-0.677	-0.142	-15.230	1.675
Instability	-0.011	(0.73)	-0.010	(0.57)	-0.020	(0.37)	0.356	1.427	(0.04)	0.127	0.602	-4.788	0.267
Economic Insecurity	0.015	(0.34)	-0.005	(0.63)	-0.005	(0.76)	-0.190	0.827	(0.06)	-0.236	-0.142	-3.873	4.573
AIC	12470		7090		7094			1638		1635		8520	
R-squared	0.04		0.77		0.77			NA		NA		0.73	
Deviance (% deviance explained)	NA		NA		NA			1616 (14.3%)		1596 (15.4%)		NA	

* *P*-values are in parentheses represent statistical significance. A *P-value* of 0.00 means significance with a 99% confidence level.

Table 4.3 shows that the magnitude of all estimated regression coefficients from SAR models (columns 4 and 6) have decreased in absolute terms compared to the OLS model, influenced by the first order (queen) contiguity-based spatial weights matrix – clear evidence of the average influence of tract-based neighbouring observations (Shrestha, 2006). SAR model results indicate that neighbourhoods with higher percentages of Indigenous peoples are inequitably exposed to inland flooding. The percentage Black population was negatively and significantly exposed to pluvial flooding in Canada, but not significant in either fluvial or coastal flooding. SAR models also predicted a positive and significant association of persons living alone with fluvial flood exposure and the elderly population with coastal flood exposure. These findings suggest an improvement of model performance and measures-of-fit as reflected through an increase in the Log-Likelihood and a decrease in the AIC value relative to OLS models. Although the SAR model results exhibited considerable improvements over the OLS model, critical issues on spatial-nonstationarity still prevailed that cannot be explained further by global SAR models.

Some researchers argue that the binary logistic regression approach is superior to the OLS model and yields more statistically robust and valid empirical estimates when predicting an attribute’s probability (Pohlmann & Leitner, 2003). We attempt to compare our results from the common dataset by fitting non-spatial binary logistic regressions on three dichotomous response variables representing three flood risk types and the same set of independent variables. The estimated coefficients and their corresponding odds ratio are summarized in **Table 4.3**. The magnitude of all estimated regression coefficients for binary logistic regression models (columns 8) concerning fluvial and coastal flood risk has increased in absolute terms compared to both OLS and SAR models, suggesting stronger relationships between variables. The odds ratio in column 9 measures the magnitude and direction of the association between explanatory variables and the odds of flood risk exposure. They represent the odds that a CT will be exposed to either fluvial, pluvial, or coastal flood risk, given census-based population characteristics grouped by explanatory variables. A variable’s odds ratio of precisely 1, less than 1, or greater than 1 suggesting no, negative, or positive association, respectively (Pugh, 2016). For example, the odds ratio of 1.625 for age 65 and over variable suggests that the elderly population subgroup has a significantly positive relationship with the odds of coastal flood risk exposure in Canada.

Our logistic regression results suggest that Canadian neighbourhoods with higher proportions of South Asians, the elderly, and neighbourhood instability significantly exhibit increased odds of coastal flood risk exposure at the census tract level. Percent Black, other visible minorities, lone-parent families, and neighbourhood insecurity indicators are inversely associated with the odds of coastal flood risk exposure. In contrast, neighbourhood-level economic insecurity has a significantly positive relationship with the odds of exposure to inland flood risk. The relationship between neighbourhood instability and the odds of inland flood risk exposure is negative and statistically significant. A negative and significant association also exists between the odds of exposure to inland flood risk and the percentage of persons living alone, Black, South Asian, other visible minorities, and elderly populations. Our results also indicate several positive but statistically non-significant (p-value > 0.05) relationships, such as between fluvial flood risk and percent female and Indigenous peoples; between pluvial flood risk and percent disabled and the elderly; and between the odds of coastal flood risk and percent female and physically disabled populations.

The measures-of-fit for logistic regression models were substantially improved compared to both OLS and SAR models as indicated by lower AIC values. We used Hosmer–Lemeshow goodness-of-fit and Pearson chi-squared tests to detect if there remained any model misspecification (Hosmer et al., 2013). Our binary logistic regression models for both pluvial and coastal flood risk appeared to be fitted very well. In contrast, the logistic regression-based fluvial flood risk model was poorly fitted as the null hypothesis of goodness-of-fit was rejected based on a very small *p-value* of 0.000. Since our global logistic models did not account for the effects of spatial heterogeneity or nonstationarity, the estimated results could be biased (Kim & Nicholls, 2016).

To deal with spatial-nonstationarity, we applied GWR and explored the properties of GWR for logistic regression; that is, GWLR through accommodating local-spatial effects on the observations. Adding GWR and GWLR analyses enabled us to compare local models' statistical performance over their global counterpart models, such as OLS vs GWR and standard binary logistic vs GWLR (Saefuddin et al., 2012). GWR and GWLR models generated a set of local regression estimates and percent of variance explained (i.e., local r-squared values) for each CT-based location-specific model. To visualize the spatial distribution of local parameter estimates, we mapped some regression estimates in selected urban areas (**Figure 4.1-4.3**). These maps delineate spatial-nonstationarity in the relationships between each explanatory variable and flood risk exposure-related outcome variable (Matthews & Yang, 2012).

Based on the AIC goodness-of-fit statistic for model comparison, the lowest AIC value for a model represents the best model fit (Weisent et al., 2012). Our data and statistical analyses suggest that the overall best-fitting model for all three types of flood exposure is local GWLR as it produced the lowest AIC values of 4632, 2108, and 1635 for fluvial, pluvial, and coastal flood risk models, respectively. Another way of selecting a model, among all fitted models, is to compare deviance or percent deviance explained. The model with the lowest deviance or highest percent deviance explained could be selected as the best-fitted model (Teshale et al., 2020). In this study, all three GWLR models have the lowest deviance scores and higher percent deviance explained (pseudo-R-squared), providing generous support of the model comparison (Nakaya, 2016).

Nevertheless, none of our GWLR models show spatial-nonstationarity in the relationships between flood exposure-related outcome variable and the predictors (**Table 4.4**). As argued by Pugh (2016), the spatial stationarity problem could be linked to the GWR4 program and the optimum bandwidth search and selection technique applied in the program. A selection of large bandwidth size implies that GWLR models can exploit very little geographical information at the local scale. Additional research is needed to verify the spatial-nonstationarity of local GWLR models of flood risk in Canada and elsewhere. If the spatial relationships among variables do not vary significantly, there is no advantage to using the GWLR model over the standard logistic regression model or GWR over the OLS model (Shi et al., 2006). Under these circumstances, making predictions and statistical inferences on the relationships between differential exposures to flood risk and socioeconomic covariates based on binary logistic regression results would be valid and reliable. As the results of GWR analyses indicated considerable spatial variations and exhibited spatial-nonstationarity in the local coefficients of inland flood risk (**Table 4.4**), the study concerns with areas that demonstrate environmental inequities about inland flood risk and socioeconomic factors. Therefore, the paper proceeds to delineate estimated coefficients from GWR analysis using GIS-based choropleth maps for selected urban areas (**Figure 4.1-4.3**).

4.4.3 Spatial-Nonstationarity

To test for spatial-nonstationarity in the relationships among variables, the value of interquartile range (IQR) of local estimates is compared with the global mean's standard error (SE). Specifically, when the local estimate's IQR is at least twice as the global SE for a given explanatory variable, there is empirical evidence of spatial-nonstationarity, indicating a spatially varying association between the outcome and the explanatory variable under consideration (C. Brunsdon et al., 2002; Huang et al., 2020). In this study, the GWR results relating exposure to inland flood risk to racial or ethnic, demographic, and socioeconomic covariates are evidenced to be non-stationary (**Table 4.4**). However, the GWLR results for all three types of flood exposure and the GWR results for coastal flood exposure appeared to be stationary across space. Future research could address whether the evidence of spatial stationarity from GWLR models is due to the nature of binary response variables that cannot capture adequate geographical variation and spillover effects than the continuous response variables used in the GWR approach (Britt et al., 2005).

Table 4.4 Spatial-Nonstationarity Assessment

	Geographically Weighted Regression (GWR)				Geographically Weighted Logistic Regression (GWLR)			
	Global GWR	Global GWR	Local GWR	IS GWR coefficients	Global GWLR	Global GWLR	Local GWLR	IS GWLR coefficients
Fluvial Flood Hazard Exposure	SE	2XSE	IQR	Non-Stationary?	SE	2XSE	IQR	Non-Stationary?
Female	0.016	0.032	0.117	YES	0.042	0.083	0.027	NO
Age 65 and over	0.019	0.037	0.136	YES	0.048	0.097	0.025	NO
Disability (physical)	0.023	0.045	0.235	YES	0.058	0.115	0.073	NO

Persons living alone	0.032	0.064	0.320	YES	0.079	0.158	0.039	NO
Black	0.020	0.040	0.237	YES	0.047	0.094	0.058	NO
South Asian	0.020	0.041	0.275	YES	0.050	0.100	0.028	NO
Other Visible Minorities	0.020	0.040	0.184	YES	0.049	0.097	0.049	NO
Indigenous	0.016	0.032	0.378	YES	0.053	0.106	0.093	NO
Instability	0.035	0.070	0.364	YES	0.090	0.179	0.123	NO
Economic Insecurity	0.019	0.038	0.274	YES	0.049	0.098	0.043	NO
Pluvial Flood Hazard Exposure								
Female	0.016	0.032	0.152	YES	0.058	0.116	0.010	NO
Age 65 and over	0.019	0.037	0.196	YES	0.080	0.161	0.025	NO
Disability (physical)	0.023	0.045	0.251	YES	0.093	0.187	0.014	NO
Persons living alone	0.032	0.064	0.464	YES	0.116	0.233	0.008	NO
Black	0.020	0.040	0.199	YES	0.066	0.132	0.021	NO
South Asian	0.020	0.041	0.364	YES	0.072	0.144	0.012	NO
Other Visible Minorities	0.020	0.040	0.185	YES	0.077	0.153	0.019	NO
Indigenous	0.016	0.032	0.320	YES	0.058	0.115	0.015	NO
Instability	0.035	0.070	0.353	YES	0.125	0.250	0.006	NO
Economic Insecurity	0.019	0.038	0.177	YES	0.081	0.162	0.014	NO
Coastal Flood Hazard Exposure								
Female	0.017	0.033	0.000	NO	0.089	0.177	0.035	NO
Age 65 and over	0.019	0.038	0.000	NO	0.084	0.168	0.072	NO
Disability (physical)	0.023	0.046	0.000	NO	0.120	0.239	0.122	NO
Persons living alone	0.033	0.065	0.003	NO	0.171	0.343	0.170	NO
Black	0.020	0.041	0.000	NO	0.257	0.514	0.320	NO
South Asian	0.021	0.042	0.000	NO	0.098	0.196	0.042	NO
Other Visible Minorities	0.021	0.041	0.000	NO	0.192	0.384	0.083	NO
Indigenous	0.017	0.033	0.000	NO	0.145	0.289	0.365	YES
Instability	0.036	0.072	0.000	NO	0.188	0.376	0.292	NO
Economic Insecurity	0.020	0.039	0.000	NO	0.093	0.185	0.039	NO

4.4.4 Spatially Varying Relationships

As suggested by Kim and Nicholls (2016), geospatial mapping of local GWR coefficients and location-specific R^2 values are essential to understand how local coefficients are distributed across space, particularly for those statistically significant in the global OLS models (Matthews & Yang, 2012; Mennis, 2006). Although several options exist for mapping GWR results, we followed the mapping techniques published in Tooke et al. (2010) and Kim and Nicholls (2016) that support the paper's core objective of highlighting flood-related socioeconomic inequities in Canada. GIS-based choropleth maps (**Figure 4.1-4.3**) show how the statistical associations between flood risk exposure and residents' racial, ethnic, and socio-demographic status spatially vary by CTs in Canada's three biggest census metropolitan areas (CMA).

Due to the enormous geographical scope in the analysis, we selected a small subset of locations to focus on for this exercise. Since the majority of populations and residential properties are located in geographically large urban areas in Canada, we created geospatial maps for three largest CMAs, such as Toronto, Montreal, and Vancouver, where more than one third (35.9%) Canadians reside (Statistics Canada, 2020). Since the analysis was conducted at the national scale for 4458 CTs, we could utilize estimated GWR regression results from this study to create maps for all neighbourhoods under consideration and improve further our understanding of socioeconomic inequities in exposure to flood hazards. The estimated local coefficients were joined to the 2016 census tract cartographic boundary file and then mapped using natural breaks (Jenks)" classification method (six classes) and graduated classification style in QGIS 3.16 (Wang & Wu, 2020). Statistics Canada's Lambert conformal conic map projection was used to produce all maps at the CT level as it is the most common map projection type used for standard maps of Canada at small scales (Statistics Canada, 2018b). A summary of both GWR and GWLR regression results are included in the *supplementary material***.**

Figure 4.1 displays GWR analysis results, which portray the relationships between pluvial flood risk and racial or ethnic and other socio-demographic variables at the CT level in Toronto CMA. The positive association between a variable and pluvial flood exposure is displayed by dark and green-shaded areas in the maps of **Figure 4.1** for the respective variable. For example, a few CTs in western Toronto show a positive and significant relationship between neighbourhood instability and pluvial flood exposure (**Figure 4.1.G**). In contrast, a few CTs in eastern Toronto show positive and significant relationships between economic insecurity and pluvial flood exposure (**Figure 4.1.H**). Estimated GWR parameters in this study, as displayed in **Figures 4.1-4.3**, clearly exhibit spatial-nonstationarity of covariates that explain a variety of relationships between SES and flood risk.

The global value of R^2 is 0.09 for the OLS models of both fluvial and pluvial flood risk. However, the local R^2 value varies from 0.07 to 0.66 for the pluvial GWR model (mean: 0.25) and from -9.37 to 0.96 for the fluvial GWR model (mean: 0.31) across the study area (**Figure 4.1.A and 4.2.A**). Most of the CTs (97% of 4458) had higher local R^2 values from the GWR models than global R^2 values from the OLS models. The statistical association between fluvial flood risk exposure and socioeconomic covariates is best explained in parts of Montreal and Wood Buffalo CMAs using local GWR model, whereas GWR coefficients seem to explain best in Red Deer and Granby CMAs considering pluvial flood risk exposure. Consistent with the findings of Kim and Nicholls (2016), our results suggest that the equity implications in exposure to flood hazards could be better explored using GWR-based models as they provide significantly better goodness-of-fit measures compared to OLS-based models.

To examine flood-related socioeconomic inequities, non-stationary relationships between variables were also confirmed by comparing strengths, directions, and statistical significance of OLS coefficients with their respective local GWR coefficients (Kim & Nicholls, 2016). For example, the fluvial OLS coefficient of *Indigenous* was 0.27 ($p < 0.01$), indicating greater fluvial flood exposure regarding the proportion (%) of Indigenous peoples in Canada (**Table 4.3**). However, **Figure 4.2.F** shows that the local *Indigenous* coefficient values range from -1.77 to 4.3 in the fluvial GWR model with a mean of 0.04, indicating a non-stationary relationship between variables.

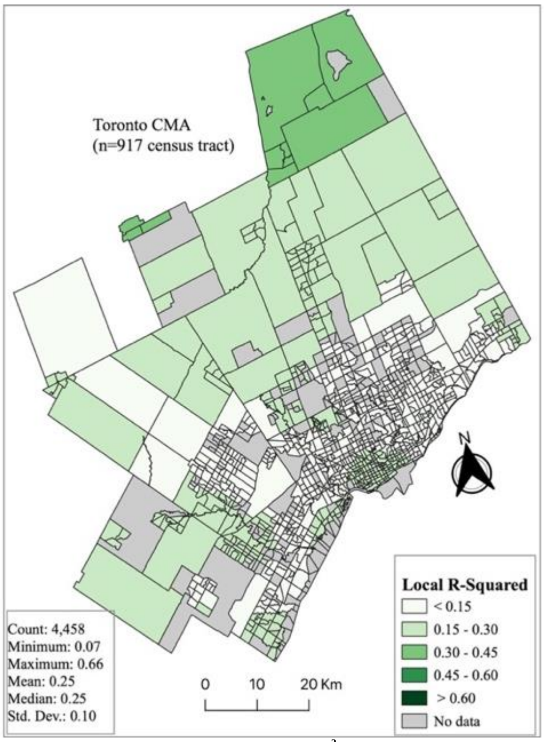


Fig 5.1.A: Local R^2

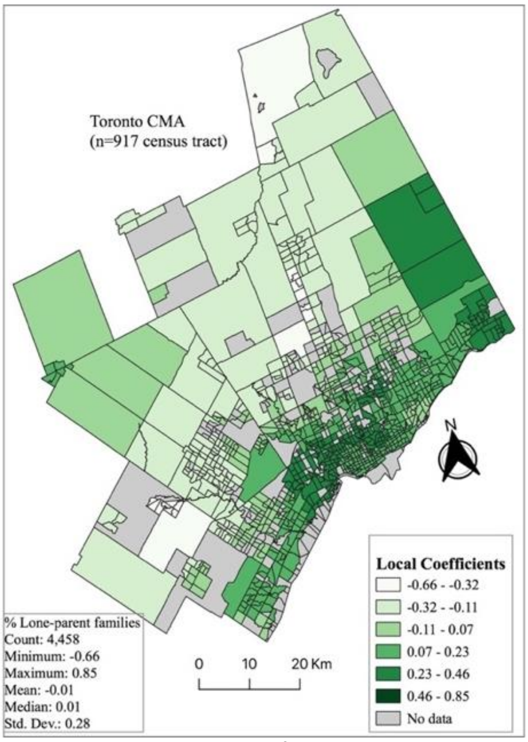


Fig 5.1.B: Proportion (%) of Lone-Parent Families

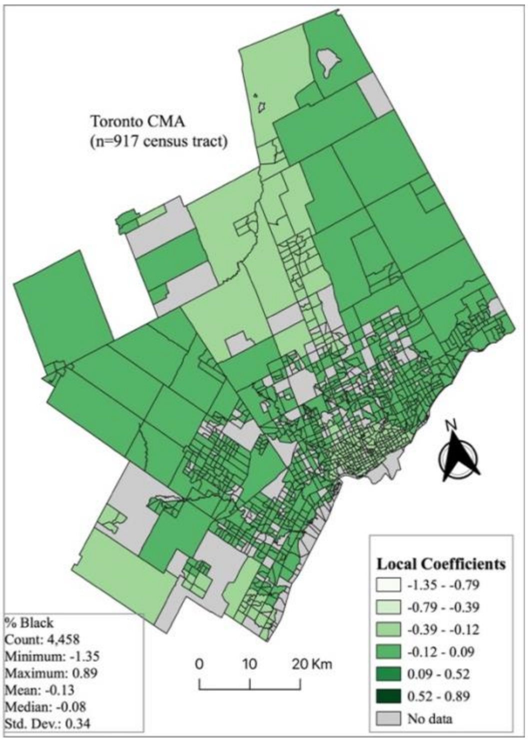


Fig 5.1.C: Proportion (%) of Black

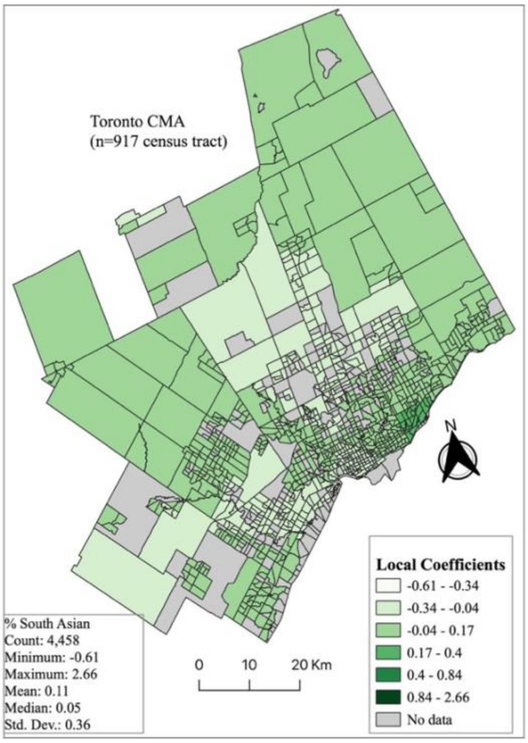


Fig 5.1.D: Proportion (%) of South Asian

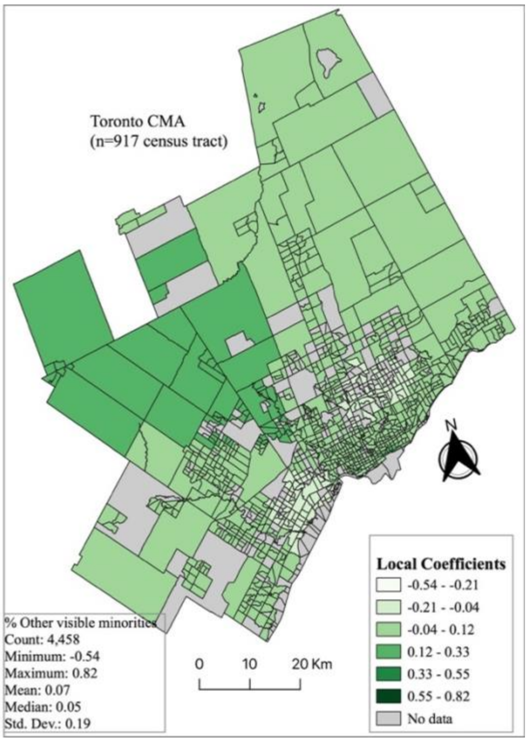


Fig 5.1.E: Proportion (%) of Other Visible Minorities

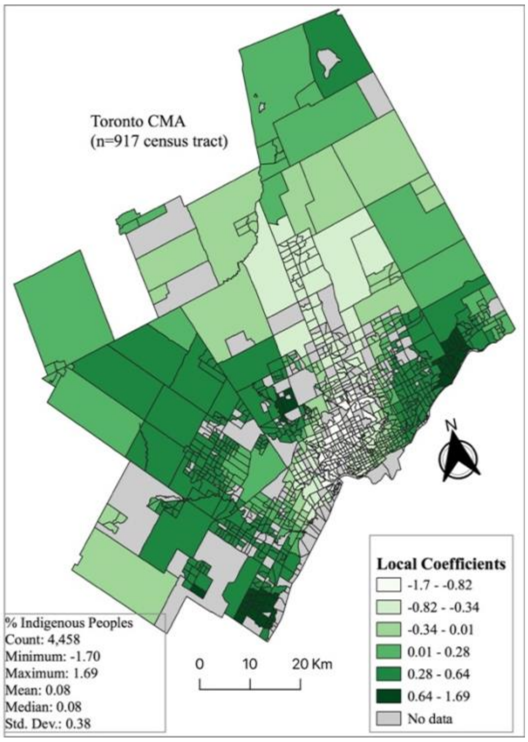


Fig 5.1.F: Proportion (%) of Indigenous Peoples

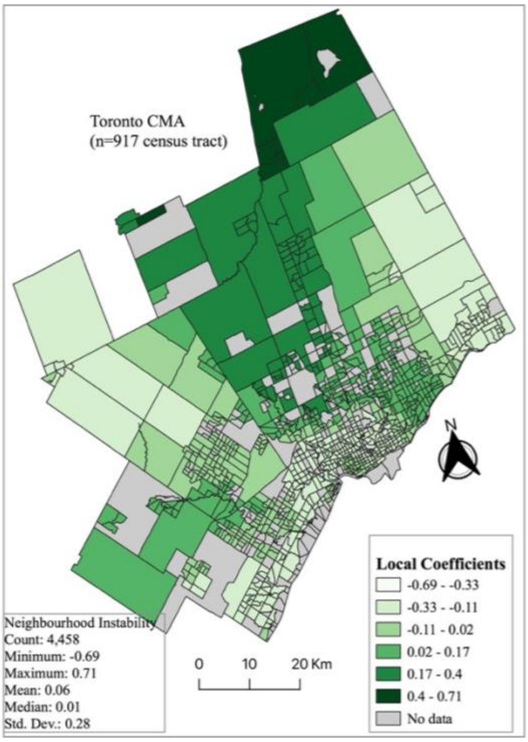


Fig 5.1.G: Neighbourhood Instability Index

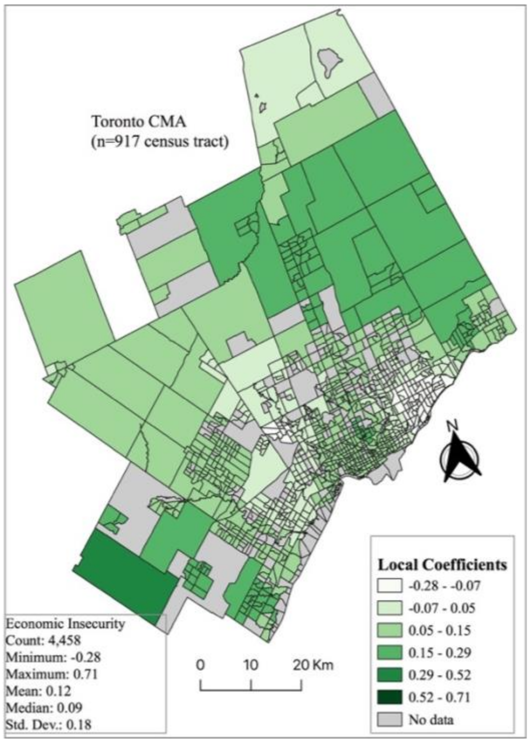


Fig 5.1.H: Economic Insecurity Index

Figure 4.1 Spatial Distribution of Local GWR Parameters of Pluvial Flood Risk Model in Toronto CMA

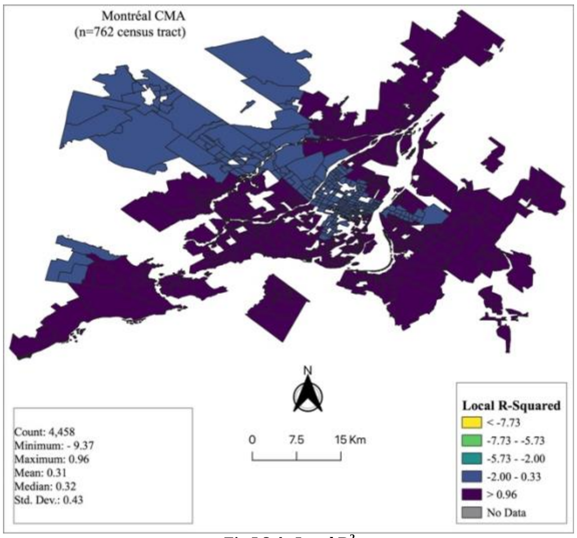


Fig 5.2.A: Local R^2

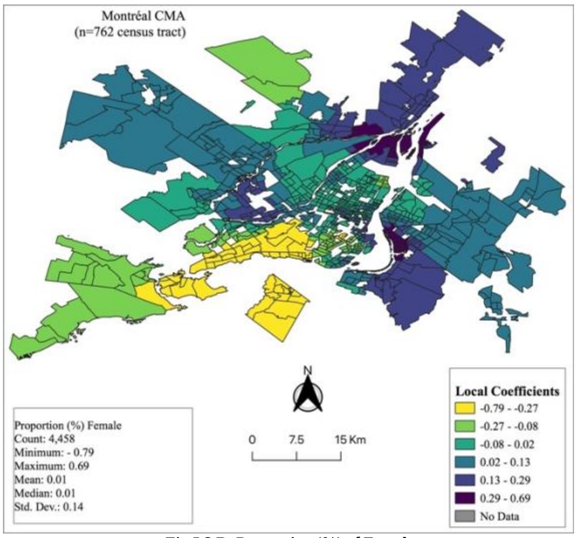


Fig 5.2.B: Proportion (%) of Female

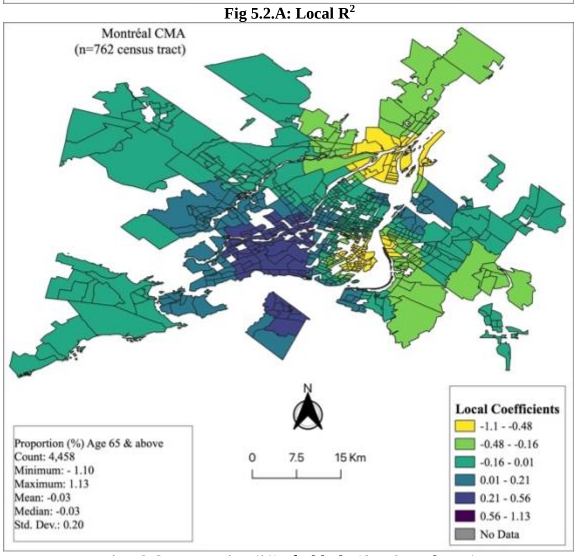


Fig 5.2.C: Proportion (%) of Elderly (Age 65 and over)

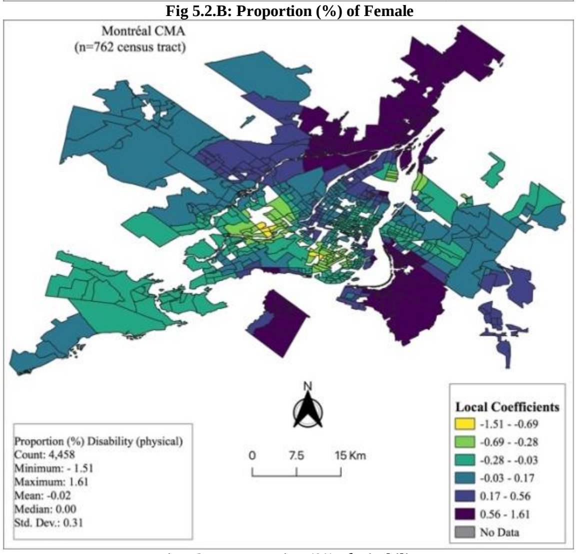


Fig 5.2.D: Proportion (%) of Disability

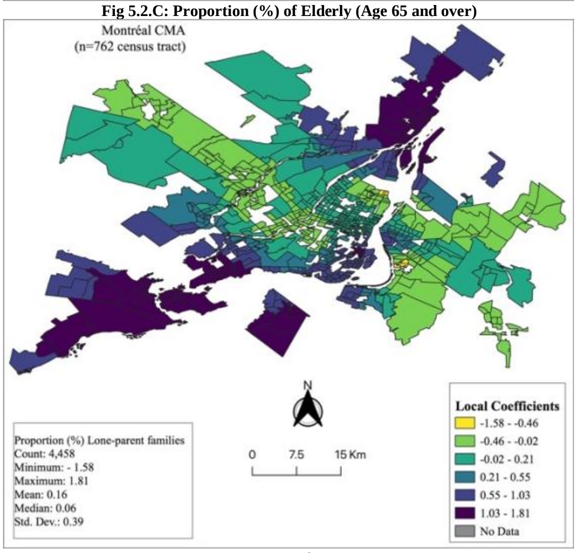


Fig 5.2.E: Proportion (%) of Lone-Parent Families

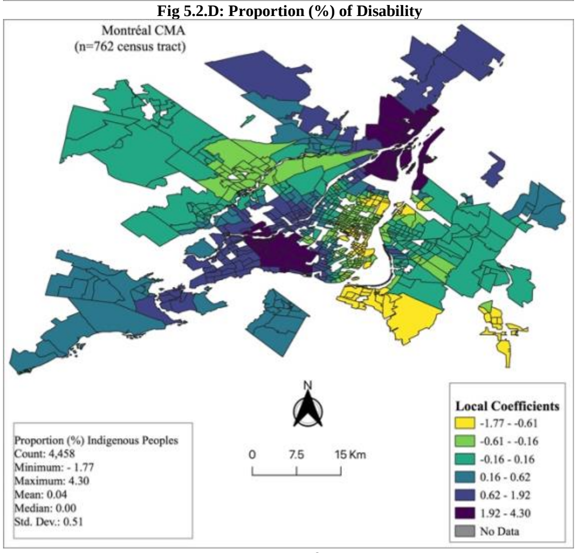


Fig 5.2.F: Proportion (%) of Indigenous Peoples

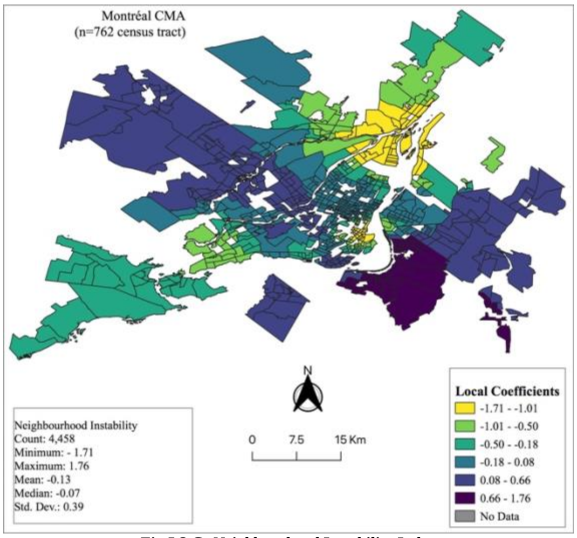


Fig 5.2.G: Neighbourhood Instability Index

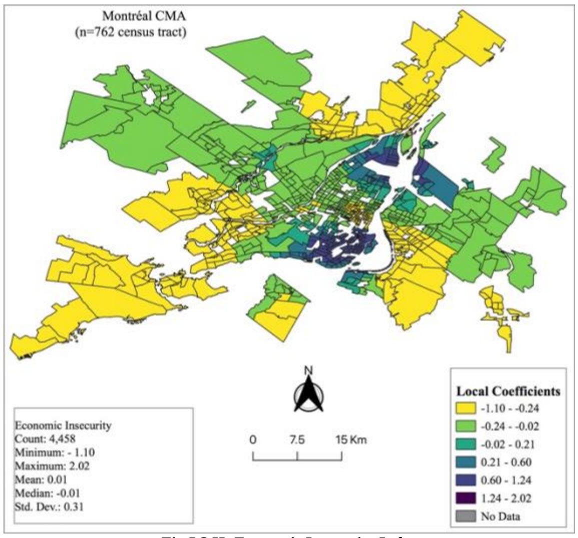


Fig 5.2.H: Economic Insecurity Index

Figure 4.2 Spatial Distribution of Local GWR Parameters of Fluvial Flood Risk Model in Montreal CMA

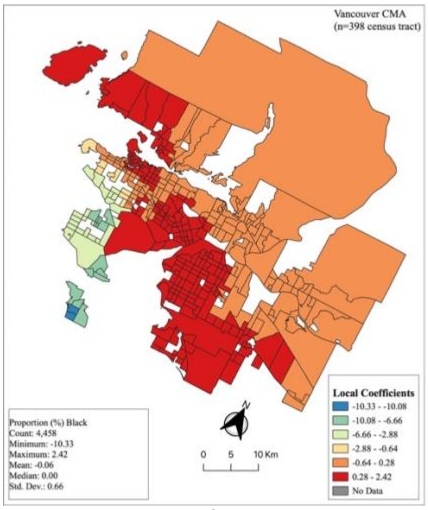


Fig 5.3.A: Proportion (%) of Black in Coastal GWR model

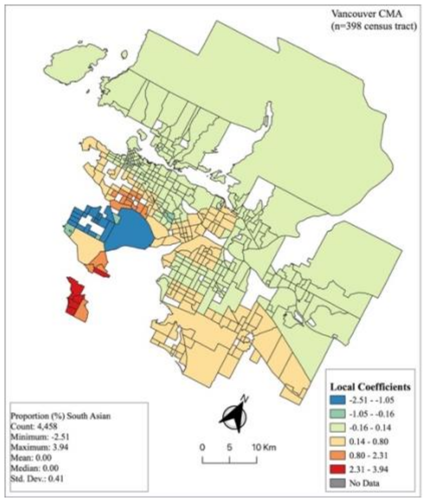
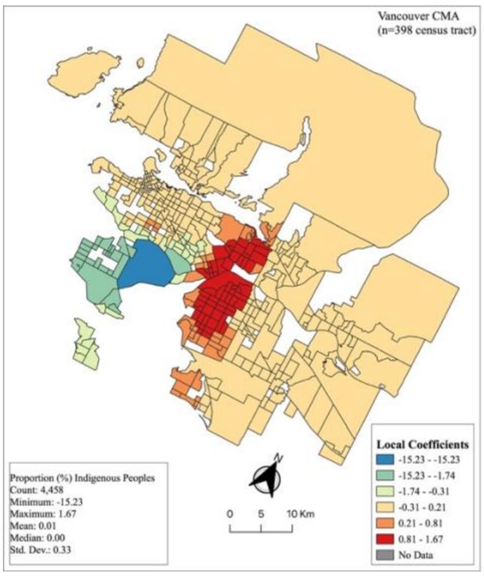


Fig 5.3.B: Proportion (%) of South Asian in Coastal GWR model



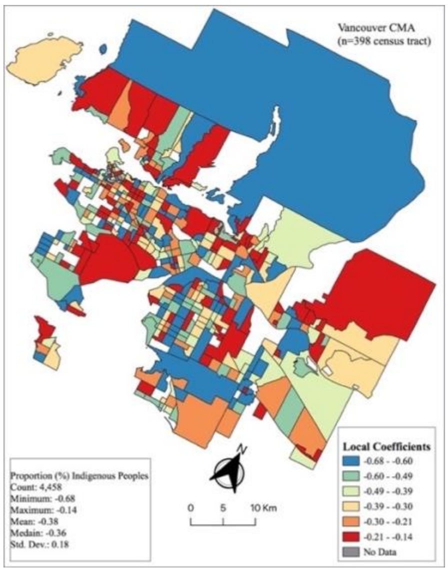


Fig 5.3.C: Proportion (%) of Indigenous Peoples in Coastal GWR model **Fig 5.3.D: Proportion (%) of Indigenous Peoples in Coastal GWLR model**

Figure 4.3 Spatial Distribution of Local Parameters of Coastal Flood Risk Model in Vancouver CMA

4.5 Discussion

This study extends analyses on flood-related distributive environmental justice research by exploring racial/ethnic, demographic, and socioeconomic inequalities in the areal extent of fluvial, pluvial, and coastal flooding across Canada, estimated at the 100-year return period. We find that neighbourhood-level racial or ethnic, economic, social, and demographic factors play a significant explanatory role in the distribution of flood risk across Canadian neighbourhoods, even after controlling for spatial effects. Specifically, we find that flood risk is significantly increased in Canadian neighbourhoods predominantly comprising certain vulnerable groups such as females, persons living alone, Indigenous peoples, South Asians, the elderly (age 65 and over), other visible minorities, and economically insecure residents.

These findings are similar to other Canadian research on environmental inequities in noise exposure and/ air pollution hazards (Buzzelli & Jerrett, 2007; Carrier et al., 2016b; Crouse et al., 2009; Dale et al., 2015; Pinault et al., 2016; Tooke et al., 2010). For instance, noise exposure in Montreal is found to be strongly associated with low-income households, visible minorities, persons spending over 30% of their income on housing, and social deprivation index (Carrier et al., 2016b; Dale et al., 2015). Similar studies on air pollution exposure find a significant and positive association between NO_2 concentrations and socioeconomic deprivation indicators such as percent lone-parent households, percent renters, and percent unmarried residents in Canada (Crouse et al., 2009; Pinault et al., 2016).

Our results of flood-related socioeconomic inequities are also congruent with a few US and UK-based findings that racial or ethnic and social disparities are significantly over-represented in the neighbourhoods of inland flood risk zones, and these disparities are under-represented in coastal flood risk zones of Canada (J. Chakraborty et al., 2014; J. L. Fielding, 2012; Walker, 2012; Walker & Burningham, 2011). This is perhaps because of our data limitation considering water-based amenities are often significantly and directly correlated with the exposure to coastal flood risk (J. Chakraborty et al., 2019) – a limitation that future studies can address using proximity to beach or waterbodies and percent vacant or recreational homes as predictor variables. However, the findings of this study are still useful in tracing local areas where flood-related socioeconomic inequalities are of concern in Canada.

Pearson's bivariate correlation coefficients and their corresponding statistical significance results were used to measure the magnitude and strength of associations between all outcome and explanatory variables. Model specification for each flood risk type was started with the ordinary least square (OLS) regression approach. OLS model diagnostic results for all models demonstrated the need to control for spatial dependence. The results from all OLS models showed a weak relationship among variables with lower R-squared and higher AIC values. GWR-based results suggested disparities in exposure to inland flood risk that vary over space with higher R-squared and lower AIC (better goodness-of-fit) that clearly indicated significant spatial non-stationarity of socioeconomic covariates.

GWR models demonstrated the importance of accounting for spatial differences in risk factors of flood exposure and showed some consistency in identifying certain racial or ethnic factors related to environmental injustices. This study is the first attempt to explore the factors associated with the socio-geographic distribution of flood risk using GWR in Canada. The GWR technique improves the OLS approach by identifying local differences in socioeconomic inequalities and flood risk determinants, which help policymakers correctly identify the spatially varying association between flood exposure and racial or ethnic and socioeconomic characteristics. The generated GWR estimates, and their geospatial maps represent a critical starting point for a more detailed investigation of the disproportionate impacts of flood risk at Canada's local level.

Since all local GWLR coefficients are found to be stationary, statistical inferences and predictions about the socioeconomic determinants of flood risk based on the corresponding non-spatial binary logistic regression model coefficients could also be valid. Moreover, there is no essential difference in performance between global and local GWLR models considering the binary outcome of inland flood exposure, since the difference of AIC or AICc values is less than two for both fluvial and pluvial flood exposure models (see **Table 4.3**, AIC values). As a rule of thumb, an absolute differential AIC value of 3 or more suggests an improved model performance (Fotheringham et al., 2002). Based on these comparisons, we find an improvement of goodness-of-fit in the local GWLR model over the global logistic model in the case of coastal flood risk exposure. However, GWLR models have failed to reveal spatial heterogeneity in the relationships between variables. The study finds that GWR models could be more powerful to demonstrate local variations in model predictors that capture environmental inequities and are critical for evidence-informed decision-making processes at the local level. Overall, all local GWR models have performed better than their global counterparts, such as traditional OLS and logistic regression models.

A growing body of environmental justice research has extensively used the GWR approach to analyze socioeconomic inequities in the distribution of toxic air releases (Gilbert & Chakraborty, 2011), air pollution (Jephcote & Chen, 2012), land use such as public open spaces (Kim & Nicholls, 2016), access to parks and physical activity sites (Maroko et al., 2009), the spatial distribution of vegetation (Tooke et al., 2010), and accessibility to public playgrounds, tourism sites, and outdoor recreational sites to name a few (Porter & Tarrant, 2001; Smoyer-

Tomic et al., 2004; Talen, 1997). This is a first attempt to compare GWR and GWLR analyses with other traditional regression methods for modelling spatial heterogeneity and/ nonstationarity in the distribution of flood hazards across Canada. The study emphasized spatial relationships between the outcome and predictor variables that may vary across Canada's local areas (C. Brunsdon et al., 2002). Aligned with other environmental equity studies (Gilbert & Chakraborty, 2011; Pugh, 2016; Saefuddin et al., 2012; Tooke et al., 2010), the study finds that the GWR is a superior model to logistic regression for fitting spatially referenced socioeconomic data and the best method for analyzing socioeconomic inequities in the distribution of flooding. Hence, the study represents a methodological contribution in terms of extensive model selection criteria and a substantive contribution in addressing spatial heterogeneity of flood risk.

Moreover, congruent with the well-established EJ literature on flood hazards, the present study demonstrates the critical importance of dealing with fluvial, pluvial, and coastal flood risks separately while assessing flood-related socio-environmental inequities (Montgomery & Chakraborty, 2015). The paper shows how the spatially varying distribution of flood hazards and socioeconomic deprivation, or social vulnerability indicators could inform Canada's equitable flood management approach that complements Federal Government's Gender-based Analysis Plus (GBA+)[26] priorities in flood-related disaster and emergency management across Canada. Thus, the findings of the paper promote a socially just flood risk management approach emphasizing the need to acknowledge socio-economic heterogeneity within various racial, ethnic, and socio-demographic groups.

[26] The Government of Canada defines "GBA+" as "an analytical process used to assess how diverse groups of women, men and people of all genders may experience policies, programs and initiatives. The 'plus' in GBA+ acknowledges that GBA goes beyond biological (sex) and socio cultural (gender) differences, and considers many other identity factors, like race, ethnicity, religion, age and mental or physical disability" (Government of Canada, 2020).

Our findings suggest that policymakers must consider the spatial heterogeneity of racial or ethnic and socio-demographic covariates in the design of FRM strategies that optimize scarce resource allocation (Koks et al., 2015). Indeed, many scholars have argued that accommodating spatial non-stationarity over local regions is required to avoid invalid models and misleading statistical inference or conclusions (Saefuddin et al., 2012). Geospatial mapping of GWR results is a powerful tool for motivating initiatives to target population subgroups for effective flood risk communication as it provides a scientific basis for the location-specific allocation of public resources to reduce socioeconomic inequalities (Tooke et al., 2010). A broad research implication from the stated objectives can be drawn such as how to distribute the liabilities of flood damages or to promote non-governmental activities in adaptation and risk diversification such as designing flood insurance schemes with premiums depending on the flood risk extents and socioeconomic status.

4.6 Conclusion

This paper contributes to the existing body of quantitative EJ research on flooding with a thorough demonstration of statistically valid and novel methods of addressing flood-related socioeconomic inequities across Canada. Specifically, we demonstrate the application of global and local regression analysis techniques for assessing spatial non-stationarity in relationships between socioeconomic covariates and flood risk. By adding a GWR and GWLR approach in equity analysis of flood hazards, the study assists emergency managers in identifying community sub-groups most susceptible to flood damages. Such an approach helps distribute the scarce FRM resources where needed and increase resilience across local communities. The study provides preliminary and national-scale evidence of racial or ethnic and socioeconomic differences in model-based estimates of flood risk exposure across Canada that can be further explored in more racially/ethnically concentrated areas of poverty and flood vulnerable neighbourhoods both after and before a real flooding event for considering socio-temporal consequences of flooding. Our findings may inform decision-makers addressing systemic socioeconomic inequities in exposure to flood hazards that could help them develop practical guidelines for an equitable flood risk management approach.

Notably, this study's results could be useful for implementing a risk-based flood management approach. For example, this could entail relocating those at the highest concentration of flood-related vulnerability and determining flood insurance premiums based on neighbourhood-level socioeconomic capacities of population and flood damage estimates. Our findings also support the "Minister of Public Services and Procurement Supplementary Mandate Letter" that the decision-makers must develop policies to reduce potentially disproportionate impacts of flooding on most vulnerable communities that complement GBA+ consideration in decision-making processes at the Federal level (Trudeau, 2021).

Future research could address if differences in flood risk contribute to socio-environmental inequities in Canada. It is also critical to investigate temporal relationships between socioeconomic variables and extent of flood exposure, integrate climate change scenarios in the flood exposure analysis and deconstruct environmental inequities considering all racial or ethnic minorities groups. Adding post-event characteristics (such as potential loss and damage estimates in the aftermath of flooding) to social vulnerability assessment and scrutinizing temporal relationships between socioeconomic variables and the extent of flood exposure could provide valuable insights for tackling the inequity trends of flood risk distribution.

Chapter 5: Dissertation Research Implications and Conclusion

5.1 Summary of Dissertation Findings

This dissertation has addressed a series of interconnected research questions to inform environmental justice considerations for FRM policy in Canada. First, it analyzed which indicators of social vulnerability are significant and relevant in Canada, where vulnerability is geographically concentrated in the country, and whether the socioeconomic status of groups of people varies by geographical areas across Canada. The thesis argued that social, economic, racial/ethnic background and built environment characteristics of population subgroups underpin differential socioeconomic inequality and social vulnerability across geographic places. The driving forces of social vulnerability in Canada are consistent with the social, economic, and cultural factors identified in the environmental justice literature, including race and ethnicity, income, built environment, elderly populations, education, occupation, family structure, and access to resources (J. Chakraborty et al., 2014, 2019; Collins & Grineski, 2017; J. Fielding & Burningham, 2005; Sayers et al., 2018; Walker & Burningham, 2011). Social vulnerability is geographically stratified in Canada. Large metropolitan areas are substantially less vulnerable than small metropolitan areas, perhaps due to more access to resources, education, and employment opportunities, the state of their built environments, and more coping capacity that fosters resilience.

Second, the thesis investigated the extent of exposure of residential properties to flood hazards in Canada and whether socioeconomic vulnerability and flood exposure of residential properties vary spatially across census tracts in Canada. It sought to identify hotspots of flood risk and which neighbourhoods are at an elevated risk of flooding and highly vulnerable to flood hazards. The thesis completed the first nationwide spatial assessment of flood risk by integrating flood hazard, social vulnerability, and exposure of residential properties at the CT level in Canada. Social vulnerability and flood exposure of residential properties was found to vary considerably across Canadian geographical regions. The thesis revealed results consistent with the Insurance Bureau of Canada's evidence that 1.7 million properties (or 19% of the population) occupy flood-prone areas of Canada (Insurance Bureau of Canada, 2019a). Most of the CTs and the CMAs in southern and southwestern parts of Canada are in high to very high flood risk areas. Most of the urban regions in Central Canada and Western Canada were geographically concentrated in flood-disadvantaged areas that are susceptible to high and very high flood risk. Flood risk hotspots are geographically concentrated in 18 census tracts and nine census metropolitan areas across five provinces. No hotspots were detected in the provinces of Newfoundland and Labrador and Nova Scotia.

Finally, the thesis explored social and spatial injustices in flood risk by investigating whether socially vulnerable groups are disproportionately exposed to fluvial, pluvial, and coastal flood risk at the CT (neighbourhood) level across Canada. The dissertation shows evidence of significant differences in the geographical distribution of socially vulnerable groups between fluvial, pluvial (inland or surface water), and coastal flood risk. Based on empirical evidence, the thesis argues that socioeconomically deprived residents predominantly occupy inland flood zones more than coastal flood zones. Inland flooding-related socioeconomic inequities in Canada are non-stationary, spatially heterogeneous, and vary across space. The thesis has concluded that spatially varying relationships exist between flooding and socioeconomic characteristics of populations so that geospatial disparity in exposure to inland flood risk is significantly related to social deprivation factors in Canada.

5.2 Research Implications for FRM Policy and Contributions

There is a growing body of flood-related post-disaster research evidence that flooding affects peoples and communities differentially and area-based pre-existing inequalities in terms of gender, race, education, income, ability or disability and socioeconomic status exacerbate the impacts of flooding (Adger et al., 2005; Emrich et al., 2020; Fatemi et al., 2017; von A. Fekete, 2009; Tate et al., 2021; D. S. K. Thomas et al., 2013; Yoon, 2012). However, Canadian FRM decision-making processes often neglect social vulnerability in disaster preparedness and recovery discussions and decisions, and fail to address socioeconomic inequalities to flooding that make people, communities, and places more socially vulnerable to flood hazards and disasters (J. Chakraborty et al., 2019; Collins, Grineski, Chakraborty, et al., 2019; Griego et al., 2020).

The existing flood risk assessment and management framework in Canada is fundamentally incomplete without assessing and addressing social vulnerability to flood hazards. This is because FRM-related decision-making and policy lacks sufficient geographical precision to manage social-economic vulnerability to flooding. This thesis evidence that urban (e.g., inland) flooding is much more substantial when considering social vulnerability in the risk assessment process (**Chapter 4**). Findings of this thesis reinforce the need for incorporating measures of social vulnerability into Canadian flood risk assessment and management framework, which offers multiple benefits. First, it provides a better understanding of flood risk with a more comprehensive and robust method of assessing risk through three intersectional components, including hazard, physical exposure, and social vulnerability. Second, it offers a significant benefit of expanding Canada's traditional approach to risk assessment beyond hazard, exposure, and physical vulnerability to include social vulnerability. Third, subsequent analysis of social vulnerability characteristics and the distribution of flood risk across marginalized populations highlights the environmental injustices associated with flood risk. Such an analysis helps target flood mitigation and recovery resources to communities for whom public investment reduces flood vulnerability. Finally, comprehensive risk assessment that incorporates social vulnerability measures helps decision-makers prioritize government policies for people and communities that would benefit most from flood risk reduction.

This dissertation research contributes to the emerging literature on social vulnerability, flood risk assessment, and environmental justice. It offers a systematic and statistically-sound methodology, grounded in existing scholarship, to assess social vulnerability, flood risk, and social inequity to flood risk exposure in the context of environmental justice. It employs GIS-based methods to leverage hazard, vulnerability, and exposure data for delineating the concentration of flood risk and vulnerability at the local level. This type of analysis is critical to designing FRM policies that support GBA+ considerations in decisions and help prevent environmental racism.

The Government of Canada's ongoing commitment and mandate to GBA+ across federal departments requires decision-makers must ensure that the differential impacts of people of all genders and diverse groups of people are considered when government policies, programs, regulations, and legislation are developed (Government of Canada, 2020). Notably, the "Minister of Public Safety and Emergency Preparedness Supplementary Mandate Letter" fully supports the implementation of GBA+ in policy decisions to address systemic inequities, including systemic racism; unconscious bias; gender-based discrimination; barriers for persons with disabilities; discrimination against LGBTQ2 communities; and inequities faced by all vulnerable populations (Trudeau, 2021). Thanks to the federal mandate to GBA+ that supports Canada's equitable policy development practices congruent with distributive justice principle.

This dissertation's analytical approach is beneficial to understand flood-related distributive inequities that support the federal mandate to GBA+ considerations in FRM policy decisions, including designing flood insurance schemes, strategic relocations, and property buyout programs.

The thesis also considers some potential risks of publicizing neighbourhood-level social vulnerability or SoVI of Canada. Although residential-level fluvial flood exposure in Canada is mostly concentrated in CTs along with rivers and lakes, the social vulnerability adds to the complexity of flood risk assessment as the pluvial flood risk primarily intersects with socioeconomic vulnerability in dense downtown neighbourhoods. The incorporation of social vulnerability may entirely shift the scale and location of fluvial and pluvial flood risks that policymakers should address for effective policy development, including flood mitigation and recovery policies. Moreover, as this dissertation exhibited, certain marginalized and racialized groups may experience disproportionate flood risk due to higher flood exposure and social vulnerability. Subsequent and repeated analysis on the distribution of flood risk across vulnerable populations is required at a lower level of census geography, such as DAs, to achieve a more granular analysis of social vulnerability to ensure that flood mitigation and recovery resources are allocated to areas that need most.

However, establishing a statistically valid relationship between flood risk exposure and the attributes of social vulnerability [such as gender, age, immigration status, health and disability, language and literacy, homeownership status, educational attainment, and occupation (Susan L. Cutter et al., 2003; Tapsell et al., 2010)] has policy implications for integrated FRM. For example, this analysis could inform how liabilities for flood damages are distributed or to promote non-governmental activities in adaptation and risk diversification, such as developing insurance schemes with premiums that could be subsidized and tailored to high-risk zones and lower socioeconomic status. Such an analysis also justifies for risk-based flood hazard mitigation measures (e.g., flood insurance and relocation strategies) in the existing Canadian flood risk management paradigm.

In the context of the sustainability of flood risk reduction, incorporating and understanding different aspects of social equity and fairness is crucial (Sayers et al., 2014), since the distribution of flood hazard impacts in a society results from social, economic and political processes and structures (Montgomery & Chakraborty, 2015). Strengthening social equity and considering social vulnerability in Canada's FRM policy decisions could enhance the legitimacy of, and compliance with, various flood risk reduction policies, such as national commitments towards developing flood insurance and relocation programs. Analyzing, assessing, and comprehensively understanding social vulnerability to flood hazards could be a vehicle to strengthen the sustainability of FRM policy in the current era of climate change.

5.3 Conclusions and Future Research

A core challenge in research on the social vulnerability to disasters is to find appropriate spatial, quantitative, and qualitative data to represent comprehensive characteristics of social well-being and socioeconomic capacities of people at the local level (Fernandez et al., 2016). Methodological inconsistencies also arise in combining hazardous locations, hazard extents, assessing exposure and measuring social vulnerability indicators (J. Chakraborty et al., 2005). A few authors argue that these pitfalls are avoidable to a greater extent by incorporating GIS-based multi-criteria decision analysis (MCDA) rather than depending on the statistical methods (e.g., Principal Component Analysis) only (Fernandez et al., 2016; Kuhlicke et al., 2011; Scheuer et al., 2011).

Irrespective of the differences in opinions about risk assessment methodology, a consensus view among disaster management scholars and practitioners is that assessing and effectively addressing social vulnerability decreases both human suffering and economic loss. Identifying socially vulnerable populations, better understanding risks to these populations, and aiding in mitigating, preparing for, responding to, and recovering from that risk are all essential ingredients (Flanagan et al., 2011). Vulnerabilities are the root causes of disasters, and they are socially constructed phenomenon rather than objective conditions (Shreve & Kelman, 2014). Therefore, the assessment of social vulnerability needs to be an integral part of the disaster risk management domain.

Toward sustainability in FRM policy and practices, future research must incorporate stakeholders and citizens in the decision-making processes of FRM, to ground-truth pre-existing vulnerabilities and social inequalities to both pre- and post-flood disasters. It is also important to measure multistakeholder and citizen preferences for a sustainable FRM policy and flood risk reduction that future research could address by employing a state-of-the-art non-market-based environmental valuation method. A stated preference method, such as a choice experiment approach, could serve both as a basis for decisions concerning flood risk reduction policy measures (e.g., comparing, and eliciting preferences of homeowner vs environmental managers to measure the willingness to pay for flood insurance) and as a source of legitimacy for socially just policy choices in Canada. Future research could also explore the possible interactions between social vulnerability and flooding by integrating socioeconomic characteristics and flood risk perceptions of residents and stakeholders in designated flood-prone areas and using different flood risk reduction scenarios.

A growing body of research argues that socially vulnerable populations and communities are most likely to be disproportionately impacted by global climate change and climatic hazards due to geographic location-related disadvantages, and inseparable associations between unique cultural and other social characteristics of human populations and climate-sensitive environments (Birkmann et al., 2014; Bjarnadottir et al., 2011; Susan L. Cutter et al., 2009; Ford & Smit, 2004; Lynn et al., 2012; Perkins, 2011; Tucker et al., 2015). Due to changes in climatic conditions, more frequent and intense extreme weather events are likely to occur (X. Zhang et al., 2019). These events could be more frequent, severe, and disastrous for some communities than others, amplifying uneven impacts on populations and places in Canada (Ford et al., 2006). Assessing and addressing social vulnerability and equity in the context of climate change is important not only because some populations may have less coping capacities to deal with climatic hazards and their impacts, but also due to the prevalence of historical policy and governance-related environmental racism where certain vulnerable groups are inequitably exposed to other hazards and toxic waste (I. Waldron, 2020; I. R. G. Waldron, 2018). Without government intervention, disproportionate exposure to climatic hazards will get worse for some people and communities, such as Indigenous, Black, and other racialized communities who are already most vulnerable to the impacts of climate change (Ford et al., 2010; I. R. G. Waldron, 2018).

In an era of accelerating climate change, it is essential to understand why some peoples and communities are differentially vulnerable to climate threats and why they are disproportionately exposed to climatic hazards (K. Thomas et al., 2019). Understanding and using social dimensions of vulnerability is equally or more important than using technology or engineering-based solutions to deal with natural hazard processes (Haque & Etkin, 2007), as an understanding of socioeconomic vulnerability is crucial for decision-makers to implement equitable policies that consider differences in the socioeconomic status of people when allocating resources. The findings of this thesis strongly support growing calls and the need for direct government intervention, a national strategy and relevant public policy development, and law enactment to redress longstanding impacts of environmental racism and/ climatic injustices on vulnerable communities across Canada, such as Black and Indigenous communities (House of Commons of Canada, 2020; Reid, 2021; I. Waldron, 2020).

In the current paradigm of vulnerability/resilience-based approach to flood risk management policy and practices worldwide (A. Fekete et al., 2014; McClymont et al., 2020; Serra-llobet, 2015), integrating social vulnerability and equity dimensions to the development of Canadian public policy and federal and provincial funding programs would be timely, practical, equitable, socially justifiable, and more economical than investing in the traditional approach of emergency and disaster management that prioritizes visualization of flood risk through hazard extents-based mapping and exposure analysis, technological intervention and control of the physical environment. Flood risk can be effectively reduced using social safety programs that target the economic determinants of social vulnerability that define affordability, such as income, the prevalence of low income, employment status, and shelter costs to income ratio. For example, funding targeted to flood vulnerable communities made available through Disaster Financial Assistance Arrangements (DFAA), subsidies, or vouchers could improve the affordability of flood insurance and property buyout programs could help relocate populations occupying high-risk zones. These strategies would ultimately enhance the community and social resilience of these communities to repeated flooding while reducing overall social vulnerability.

There might also remain co-benefits between FRM and social welfare policies, and FRM policy instruments need to be adjusted to take advantage of these co-benefits (e.g., insurance subsidies) that further research could address. Moreover, FRM could be a public good for Canada when all levels of government consider offering subsidized and ‘affordable’ flood insurance policy (Geaves & Penning-Rowsell, 2016). Future research could help develop an affordability framework for Canadian vulnerable populations to complement the national flood insurance and relocation plan. Finally, further research should foster flood risk communication among government officials, environmental planners, and disaster management professionals who engage flood vulnerable communities through environmental education and promote practical benefits of adopting subsidized and/ incentivized property level flood protection measures for sustainability in FRM.

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Appendices: Supplementary Materials of Manuscript # 3

A.1 Flood Risk Exposure Analysis at the Census Tract (CT) Level

This supplementary document presents the data sources (**Table 7.1**), and methods used for calculating the number of residential properties exposed to fluvial, pluvial, or coastal flood hazards in Canada. The study uses a national flood hazard dataset created by JBA Risk Management — an expert global flood modelling firm. The flood hazard dataset spatially delineates flood hazard areas across Canada. The 2018 flood hazard datasets (i.e., Canada Flood Maps at 30-meter horizontal resolution in GeoTIFF format of raster datafile) capture land areas exposed to fluvial, pluvial, and coastal flooding for various flood return periods, such as 20, 50, 100, 200, and 500-years. We focused on the geospatial analysis of flood hazard exposure to residential properties using 100-years of the flood return period, without accounting for fluvial-flood defenses.

Table A.1 Social and Flood Data Sets Utilized

Dataset	Format	Purpose	Source
Flood hazard area at 30m horizontal resolution	Raster datafile (GeoTIFF)	Identify flood hazard extents (e.g., 1-in-100-year flood recurrence scenario)	JBA Risk Management 2018
Address points of residential properties (counts)	Spatial layer in point shapefile (.shp)	Estimate flood exposure of residential properties	DMTI Spatial 2018
The 2016 census of population microdata	Stata datafile (.dta)	Construction of neighbourhood deprivation indices, selection of race/ethnicity indicators and other socio-demographic characteristics	Statistics Canada, 2016 Census
The 2016 CT cartographic boundary	Spatial layer in polygon shapefile (.shp)	Flood exposure and unit of analysis	Statistics Canada, 2016 Census

Exposure refers to the "people or assets, including residential properties and critical infrastructure, that are likely to be affected by a hazard" (UNDP, 2004, p. 136). Flood exposure is typically measured by identifying populations and communities that would be affected by a specific flood scenario, such as the 100-year flood recurrence interval (i.e., a flood the magnitude of which has a 1-in-100 (1%) chance of occurring in any given year) (Holmes & Dinicola, 2010). IPCC (2012) defines 'exposure' as the assets and values located in flood-prone areas. Following the methods used by Qiang (2019), this study estimated the flood exposure of residential properties across Canada. We determined flood exposure in three main phases: (1) quantifying the total number of residential properties within each dissemination block (DB); (2) aggregating DB-level total number of residential properties to find the totals at the CT level, and then (3) calculating the percentage of residential properties (as described in equations 1) and spatially join them to the 100-year flood hazards at the CT level.

$$\%\ Residential\ Properties\ Exposed\ to\ Flood_{CT} = \frac{Number\ of\ Residential\ Properties\ Exposed\ to\ Flood_{CT}}{Total\ Residential\ Properties_{CT}} \quad \text{------ (1)}$$

The exposure analysis was presented at the CT level, and the analysis was conducted for 5,721 CTs in Canada. CTs are "small, relatively stable geographic areas that usually have a population of less than 10,000 persons, based on data from the previous census of population program. They are located in census metropolitan areas and in census agglomerations that had a core population of 50,000 or more in the previous census" (Statistics Canada, 2018a). JBA's flood hazard extent datasets were first imported into ArcMap 10.7.1 to visualize flood-prone areas identified by JBA's Canada Flood Maps (**Figure A.1**).

The national address points dataset on "residential properties (count)" (spatial layer in point shapefile) was collected from the DMTI Spatial Inc., a company with world-renowned expertise in location analytics (DMTI Spatial Inc., 2018). DMTI's CanMap address points dataset covers the entire Canadian territory and includes residential and non-residential addresses. Only address points that had primary use of "residential" were included as part of the exposure analysis. Out of all address points in the database, 11,051,056 address points were classified as "residential properties", and these properties were included in the flood exposure analysis. An address point represents a single unit (e.g., apartment, unit). Therefore, there remained cases where multiple addresses were in the same geographic location (e.g., condo building, duplex).

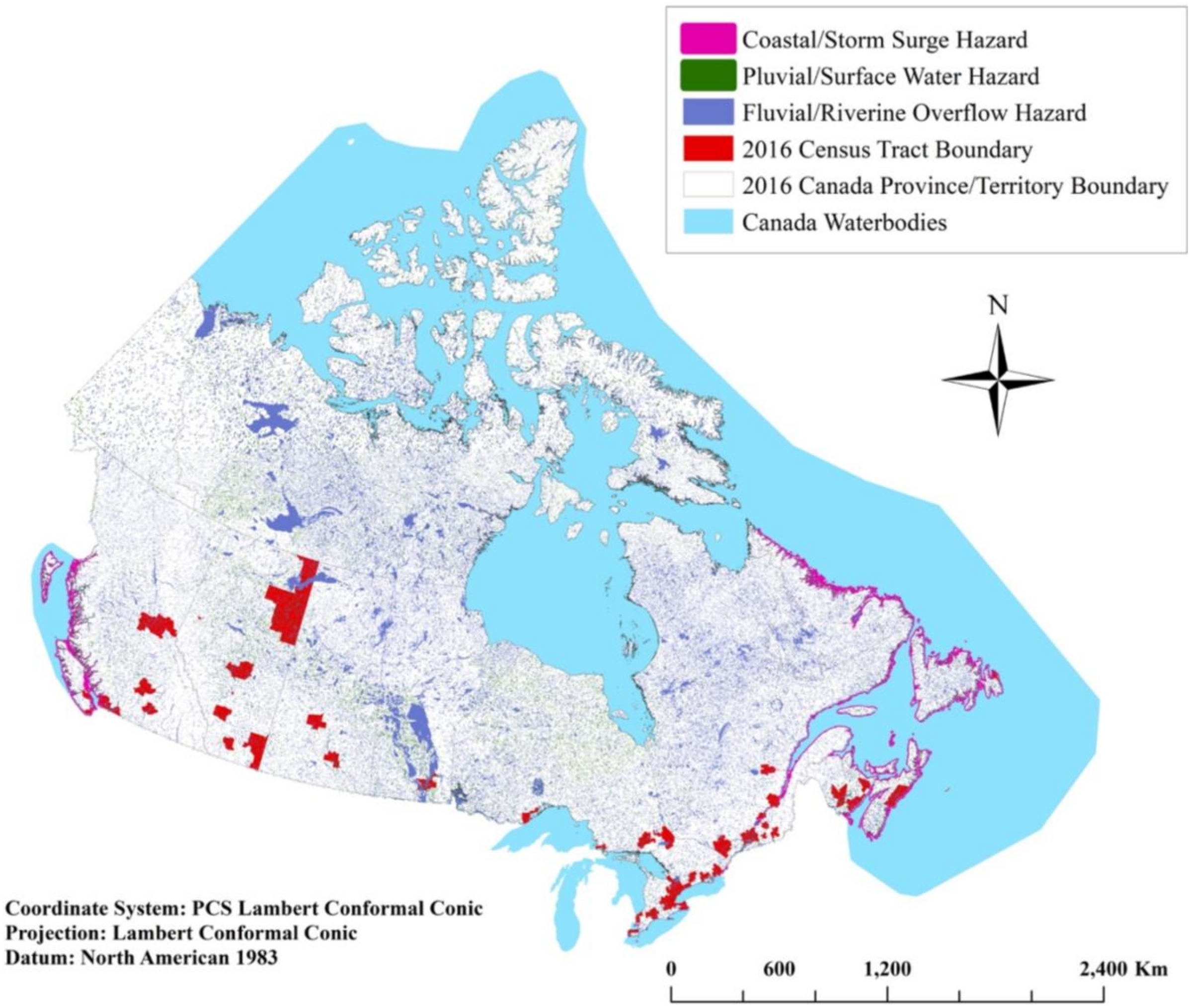

Figure A.1 CT-Level Flood-Prone Areas as Determined by JBA's Canada Flood Maps

The 11 million residential address points were spatially joined to Statistics Canada's 2016 dissemination block (DB) boundary to detect the total number of residential properties located within each DB. "A dissemination block (DB) is an area bounded on all sides by roads and/ boundaries of standard geographic areas. The dissemination block is the smallest geographic area for which population and dwelling counts are disseminated. Dissemination blocks cover all the territory of Canada (Statistics Canada, 2018a, p. 90)." The points dataset contained a total of 15,947,485 addresses in Canada, including industrial, commercial, and residential addresses. For all address points, data attributes of LAT (latitude), LON (longitude), and PRIM_USE (primary use) were also included in the dataset. A 15m buffer was generated for all the residential properties in the absence of building footprint data for residential property point locations (**Figure A.2**).

Using the output buffer polygons of residential properties, a binary analysis (yes/no) was used to indicate if properties intersected with the flood hazard area receiving a 1 if they did and 0 if they did not. As the CTs do not cover the entire Canadian territory, only a portion of residential properties was located inside the CT boundary. There were 8,342,118 residential properties located inside CTs. The majority of CTs had at least 1 residential property. However, 51 of the 5,721 CTs did not intersect with any residential addresses. The GIS-based exposure analysis results were summarized in an excel file (see **Table A.1** as a sample of exposure data summarized at the CT level) and then spatially joined with the 2016 CT level cartographic boundary.

(A) Original Property Points Locations Vs. 15m Buffer Results **(B) Fluvial-Undefended Flood Exposure of Residential Properties in Vancouver**

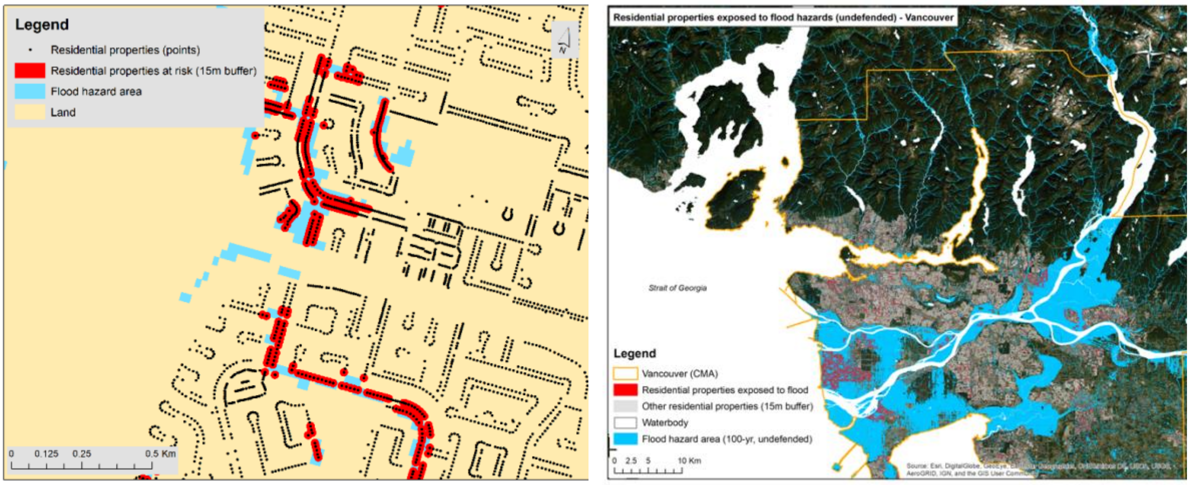

Figure A.2 Residential Properties Exposed to 100-Year Fluvial-Undefended Flood Hazard

Table A.2 Sample CT-Level Flood Exposure Data Record of Residential Properties

CTUID	FLRF_Q100	FLSW_Q100	STSU_Q100	TOT PROP	FLRF_Q100_RP	FLSW_Q100_RP	STSU_Q100_RP
933014800	0	1	1	2440	0	180	2294
933014101	1	1	1	2210	37	196	2210
933014002	1	1	1	1999	1068	200	1995
933016102	1	1	1	1992	1927	307	1992
933014203	1	1	1	1988	4	281	1974
933020000	1	1	1	2738	2723	298	1949
933016106	1	1	1	1789	1750	362	1785
933014201	1	1	1	1771	1	160	1771
933014304	1	1	1	1664	30	107	1664
539020100	1	1	1	1770	182	200	1559
933016103	1	1	1	2058	646	471	1468
933014303	1	1	1	1457	600	118	1455
933014707	0	1	1	2630	0	196	1448
933014902	0	1	1	1450	0	167	1444
933014704	0	1	1	1881	0	145	1438
933014301	1	1	1	1433	141	84	1432
933016105	1	1	1	1671	477	545	1344
933014406	0	1	1	1477	0	67	1339
933014404	0	1	1	1578	0	285	1326
933015106	1	1	1	1334	907	629	1305
933014710	0	1	1	1386	0	57	1300

The flood risk exposure analysis presented in this study has some limitations that can be addressed in the future study. The exposure analysis was exclusively based on residential address points location and hazard-based flood extent areas. If residential properties are in an area exposed to flood hazards, then these are classified as being at risk of flooding. The same applies to condo units, regardless of whether they are on an upper floor of a building and may not directly be impacted by a flood (instead, the main floor lobby or basement parking would be flooded). This analysis is not an indication of the severity of flood damages that would be incurred if a property were flooded. The amount of damage produced for an individual property could be driven by location, floodwater depth, velocity, and duration. This analysis is a conservative view of flood exposure in Canada, and other estimates show that about 10% of Canadian properties are at risk of flood, while here, the total is closer to 15% of the total housing stock.

The study cannot "ground-truth" exposure and vulnerability due to the unavailability of both pre-event and post-event data and limited local information related to exposure, sensitivity, and adaptive capacity that are often collected through specific site visits and qualitative survey methods (Albano et al., 2017). Moreover, JBA's Canada Flood Map hydrology datasets are based on historical data that do not incorporate future climate change projections.

A.2 Neighbourhood Socioeconomic Deprivation Indices

Table A.3 shows the rotated component loading matrix after applying Principal Component Analysis (PCA), and some PCA post-estimation results for extracted variables. The two components explain 72.39% of the total variance. All standardized variables were used in the PCA for 4458 CTs with at least 250 residents in a CT. The first component constitutes the instability index with five variables (42.10% variation), and the second component constitutes the economic insecurity index with four variables (30.29% variation).

Table A.3 PCA Neighbourhood Deprivation Component Loading and PCA Postestimation

Variables	Components		PCA postestimation		
	Instability	Economic Insecurity	SMC	KMO	Cronbach's Alpha
Low-income households	0.429	0.113	0.795	0.879	0.818
Renter-occupied private dwelling	0.421	0.139	0.809	0.833	0.815
Shelter cost over 30 % of income	0.433	-0.045	0.726	0.734	0.841
No access to private vehicle	0.453	-0.174	0.621	0.809	0.853
Not lived in the same house a year ago in 2015	0.435	-0.082	0.624	0.820	0.845
Median household income (rescaled)	0.216	0.426	0.825	0.738	0.817
Median home value (rescaled)	0.017	0.435	0.705	0.526	0.858
No high school diploma	-0.095	0.547	0.603	0.664	0.864
Households on public or social assistance	0.039	-0.509	0.482	0.822	0.858

These indices provide a more detailed and multidimensional assessment of socioeconomic vulnerability indicators rather than using poverty or prevalence of low income status only to represent social deprivation (Grineski et al., 2015; Montgomery & Chakraborty, 2015). Following the PCA post-estimation methods of Chakraborty et al. (2020), we also tested for Kaiser–Meyer–Olkin (KMO)'s sampling adequacy test, Bartlett's Test of Sphericity, test for scale reliability using Cronbach's Alpha (α), and squared multiple correlations (SMC) between each variable and all other variables (**Table A.3**). Results from these diagnostic tests suggest that PCA was appropriate for those selected socioeconomic variables that are valid, reliable, and consistent for constructing deprivation indices at the CT level.

A.3 Ordinary Least Squares (OLS) Regression Diagnostics

As suggested by Patrick (1980, p. 51), conventional regression procedures of non-spatial OLS models for spatially referenced data are “not a reliable representation and should be avoided when there is a spatial phenomenon to be analyzed”. Hence, we used GeoDa-based OLS diagnostic procedures to detect spatial autocorrelation. Jarque-Bera test for all three OLS models (**Table A.4**), suggests a statistical rejection of the null hypothesis of normality in errors (as indicated by low probability). A Breusch-Pagan test and Koenker-Bassett test of heteroskedasticity (that is, random regression errors do not have constant variance over all CT-level observations) point out the need for more explicit inclusion of spatial autocorrelation or spatial effects as our data consist of irregular spatial units. The GeoDa program reports the results of several Lagrange Multiplier (LM) tests and Moran’s I (error) test to address spatial dependence in the variables under investigation – “a situation where the dependent variable (or the error term) at each location is correlated with observations on the dependent variable (or values for the error term) at other locations” (Matthews, 2006, p. 26). The results of LM tests and Moran’s I (error) test show that all three OLS models’ residuals are autocorrelated across space. Since the LM (SARMA) statistic is statistically significant, we find that any of the Spatial Autoregressive (SAR) models, including Spatial Lag Model (SLM) or Spatial Error Model (SEM) is appropriate for a further model specification that controls spatial autocorrelation (Anselin, 2005; Matthews, 2006).

The GeoDa program also generates two kinds of SAR model diagnostic tests, including the Breusch-Pagan test for heteroskedasticity and a Likelihood Ratio test on the SAR coefficient.

High statistical significance of these tests suggest there remains specification problems in both SLM and SEM models (Anselin, 2005; Anselin & Griffith, 1988). It is also quite challenging to interpret the SLM coefficients due to endogenous spatial dependence (Golgher & Voss, 2016; Grineski et al., 2015).

Table A.4 OLS Regression Diagnostics

	Fluvial		Pluvial		Coastal	
TEST ON NORMALITY OF ERRORS	VALUE	PROB	VALUE	PROB	VALUE	PROB
Jarque-Bera	21814.7	0.0000	8105.1	0.0000	2833437.4	0.0000
HETEROSKEDASTICITY						
Breusch-Pagan test	2049.2	0.0000	761.1	0.0000	11133.7	0.0000
Koenker-Bassett test	356.7	0.0000	200.3	0.0000	180.0	0.0000
SPATIAL DEPENDENCE (row-standardized weights)						
Moran's I (error)	63.0	0.0000	30.9	0.0000	81.1	0.0000
Lagrange Multiplier (lag)	4228.2	0.0000	1037.9	0.0000	6586.8	0.0000
Robust LM (lag)	303.8	0.0000	106.5	0.0000	70.2	0.0000
Lagrange Multiplier (error)	3925.2	0.0000	940.7	0.0000	6523.0	0.0000
Robust LM (error)	0.7	0.3887	9.3	0.0023	6.4	0.0116
Lagrange Multiplier (SARMA)	4229.0	0.0000	1047.2	0.0000	6593.2	0.0000
MULTICOLLINEARITY CONDITION NUMBER			5.4			

A.4 GWR Regression Summary Output From GWR4 Program

A.4.1 Fluvial Flood Risk Exposure

```
*****************************************************************************
*            Semiparametric Geographically Weighted Regression              *
*                      Release 1.0.90 (GWR 4.0.90)                          *
*                             12 May 2015                                   *
*               (Originally coded by T. Nakaya: 1 Nov 2009)                 *
*                                                                           *
*         Tomoki Nakaya(1), Martin Charlton(2), Chris Brunsdon (2)          *
*         Paul Lewis (2), Jing Yao (3), A Stewart Fotheringham (4)          *
*                     (c) GWR4 development team                             *
* (1) Ritsumeikan University, (2) National University of Ireland, Maynooth, *
*        (3) University of Glasgow, (4) Arizona State University            *
*****************************************************************************

Program began at 11/20/2020 10:52:44 AM

*****************************************************************************
Session:
Session control file: C:\Users\l2chakra\OneDrive - University of Waterloo\1.
PhD Projects\Project 3\StataReg\Final Shape File\GWR_Results_All
Models\GWR_Fluvial\FLRF_GWR.ctl
*****************************************************************************
Data filename: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\gwr_data_new.csv
Number of areas/points: 4458

Model settings---------------------------------
Model type: Gaussian
Geographic kernel: adaptive bi-square
Method for optimal bandwidth search: Golden section search
Criterion for optimal bandwidth: AICc
Number of varying coefficients: 11
Number of fixed coefficients:   0

Modelling options---------------------------------
Standardisation of independent variables: OFF
Testing geographical variability of local coefficients: OFF
Local to Global Variable selection: OFF
Global to Local Variable selection: OFF
Prediction at non-regression points: OFF

Variable settings---------------------------------
Area key: field9: NCT
Easting (x-coord): field74 : COORD_X
Northing (y-coord): field75: COORD_Y
Cartesian coordinates: Euclidean distance
Dependent variable: field69: zPFLRF
Offset variable is not specified
Intercept: varying (Local) intercept
Independent variable with varying (Local) coefficient: field59: zpfemale
Independent variable with varying (Local) coefficient: field60: zpag65ov
Independent variable with varying (Local) coefficient: field61: zpdisable
Independent variable with varying (Local) coefficient: field62: zplivealon
Independent variable with varying (Local) coefficient: field63: zpblack
Independent variable with varying (Local) coefficient: field64: zpsouthasi
Independent variable with varying (Local) coefficient: field65: zpothervis
Independent variable with varying (Local) coefficient: field66: zpindigen
Independent variable with varying (Local) coefficient: field67: zInstabili
Independent variable with varying (Local) coefficient: field68: zInsecurty
*****************************************************************************

*****************************************************************************
  Global regression result
*****************************************************************************
  < Diagnostic information >
Residual sum of squares:                    4042.863326
Number of parameters:                         11
 (Note: this num does not include an error variance term for a Gaussian model
ML based global sigma estimate:               0.952302
Unbiased global sigma estimate:               0.953479
-2 log-likelihood:                          12215.499608
Classic AIC:                                12239.499608
AICc:                                       12239.569800
BIC/MDL:                                    12316.329075
CV:                                           0.916417
R square:                                     0.092870
Adjusted R square:                            0.090626

Variable                    Estimate    Standard Error      t(Est/SE)
-------------------- --------------- --------------- ---------------
Intercept                   0.000094        0.014280        0.006591
zpfemale                    0.048064        0.016088        2.987675
zpag65ov                   -0.041781        0.018748       -2.228532
zpdisable                  -0.112381        0.022582       -4.976507
zplivealon                  0.150141        0.031880        4.709530
zpblack                    -0.026600        0.019819       -1.342173
zpsouthasi                  0.031666        0.020418        1.550862
zpothervis                 -0.054787        0.020143       -2.719848
zpindigen                   0.276128        0.016225       17.018394
zInstabili                 -0.133600        0.035226       -3.792650
zInsecurty                  0.059883        0.019178        3.122415

*****************************************************************************
  GWR (Geographically weighted regression) bandwidth selection
*****************************************************************************

Bandwidth search <golden section search>
  Limits: 62,  4458
 Golden section search begins...
 Initial values
  pL            Bandwidth:    62.000 Criterion:  10514.543
  p1            Bandwidth:   306.981 Criterion:  10008.108
  p2            Bandwidth:   458.387 Criterion:  10310.283
  pU            Bandwidth:   703.368 Criterion:  10572.706
 iter    1 (p1) Bandwidth:   306.981 Criterion:  10008.108 Diff:     151.406
 iter    2 (p1) Bandwidth:   213.406 Criterion:   9724.990 Diff:      93.574
 iter    3 (p1) Bandwidth:   155.574 Criterion:   9704.747 Diff:      57.832
 iter    4 (p1) Bandwidth:   119.832 Criterion:   9482.498 Diff:      35.742
 iter    5 (p2) Bandwidth:   119.832 Criterion:   9482.498 Diff:      22.090
 iter    6 (p2) Bandwidth:   133.484 Criterion:   9421.200 Diff:      13.652
 iter    7 (p1) Bandwidth:   133.484 Criterion:   9421.200 Diff:       8.438
 iter    8 (p2) Bandwidth:   133.484 Criterion:   9421.200 Diff:       5.215
 iter    9 (p1) Bandwidth:   133.484 Criterion:   9421.200 Diff:       3.223
 iter   10 (p2) Bandwidth:   133.484 Criterion:   9421.200 Diff:       1.992
 iter   11 (p1) Bandwidth:   133.484 Criterion:   9421.200 Diff:       1.231
 iter   12 (p1) Bandwidth:   132.724 Criterion:   9419.283 Diff:       0.761
Best bandwidth size 132.000
Minimum AICc      9419.283

*****************************************************************************
  GWR (Geographically weighted regression) result
*****************************************************************************
  Bandwidth and geographic ranges
Bandwidth size:                    132.723583
Coordinate                Min              Max            Range
--------------- --------------- --------------- ---------------
X-coord          3932028.809524  8980877.717450  5048848.907926
Y-coord           701775.609685  2542101.874819  1840326.265134

  Diagnostic information
Residual sum of squares:             1368.360616
Effective number of parameters (model: trace(S)):                    826.6750
Effective number of parameters (variance: trace(S'S)):               615.2474
Degree of freedom (model: n - trace(S)):                            3631.3249
Degree of freedom (residual: n - 2trace(S) + trace(S'S)):           3419.8973
ML based sigma estimate:                0.554026
Unbiased sigma estimate:                0.632548
-2 log-likelihood:                   7385.970815
Classic AIC:                         9041.320956
AICc:                                9419.283089
BIC/MDL:                            14340.473775
CV:                                     0.537031
R square:                               0.692970
Adjusted R square:                      0.599744
```

```
*************************************************************
 << Geographically varying (Local) coefficients >>
*************************************************************
Estimates of varying coefficients have been saved in the following file.
    Listwise output file: C:\Users\l2chakra\OneDrive - University of
Waterloo\1. PhD Projects\Project 3\StataReg\Final Shape File\GWR_Results_All
Models\GWR_Fluvial\FLRF_GWR_listwise.csv

Summary statistics for varying (Local) coefficients
Variable                        Mean             STD
-------------------- --------------- ---------------
Intercept                   0.065412        0.865866
zpfemale                    0.005310        0.135233
zpag65ov                   -0.034402        0.194991
zpdisable                  -0.022961        0.307008
zplivealon                  0.159143        0.393129
zpblack                    -0.077259        0.349510
zpsouthasi                  0.036798        0.660471
zpothervis                  0.053351        0.266900
zpindigen                   0.043155        0.509826
zInstabili                 -0.127884        0.385275
zInsecurty                  0.008867        0.307381

Variable                         Min             Max           Range
-------------------- --------------- --------------- ---------------
Intercept                  -4.488219        4.204630        8.692848
zpfemale                   -0.794480        0.692922        1.487402
zpag65ov                   -1.095824        1.134385        2.230209
zpdisable                  -1.510219        1.612943        3.123163
zplivealon                 -1.583664        1.809522        3.393186
zpblack                    -2.712753        1.317042        4.029796
zpsouthasi                 -5.871127        4.981761       10.852888
zpothervis                 -0.686543        2.449779        3.136321
zpindigen                  -1.770817        4.300143        6.070960
zInstabili                 -1.705501        1.762610        3.468111
zInsecurty                 -1.096842        2.023511        3.120353

Variable                Lwr Quartile          Median    Upr Quartile
-------------------- --------------- --------------- ---------------
Intercept                  -0.329780       -0.173922        0.133174
zpfemale                   -0.048023        0.013296        0.068825
zpag65ov                   -0.089537       -0.025260        0.046162
zpdisable                  -0.117765        0.000890        0.117177
zplivealon                 -0.031997        0.062011        0.288269
zpblack                    -0.177426       -0.019044        0.059492
zpsouthasi                 -0.075533        0.043000        0.199057
zpothervis                 -0.067852        0.019298        0.115797
zpindigen                  -0.184063        0.002837        0.194121
zInstabili                 -0.277033       -0.069392        0.087157
zInsecurty                 -0.154630       -0.007531        0.119237

Variable               Interquartile R      Robust STD
-------------------- --------------- ---------------
Intercept                   0.462954        0.343183
zpfemale                    0.116848        0.086618
zpag65ov                    0.135700        0.100593
zpdisable                   0.234942        0.174160
zplivealon                  0.320265        0.237410
zpblack                     0.236918        0.175625
zpsouthasi                  0.274590        0.203551
zpothervis                  0.183649        0.136137
zpindigen                   0.378184        0.280344
zInstabili                  0.364190        0.269970
zInsecurty                  0.273867        0.203015
 (Note: Robust STD is given by (interquartile range / 1.349) )

*****************************************************************************
 GWR ANOVA Table
*****************************************************************************
Source                             SS          DF             MS           F
----------------- ------------------- ---------- -------------- ----------
Global Residuals             4042.863    4447.000
GWR Improvement              2674.503    1027.103          2.604
GWR Residuals                1368.361    3419.897          0.400    6.507912

*****************************************************************************
Program terminated at 11/20/2020 11:15:40 AM
```

A.4.2 Pluvial Flood Risk Exposure

```
******************************************************************************
*             Semiparametric Geographically Weighted Regression              *
*                        Release 1.0.90 (GWR 4.0.90)                         *
*                               12 May 2015                                  *
*                 (Originally coded by T. Nakaya: 1 Nov 2009)                *
*                                                                            *
*           Tomoki Nakaya(1), Martin Charlton(2), Chris Brunsdon (2)         *
*           Paul Lewis (2), Jing Yao (3), A Stewart Fotheringham (4)         *
*                         (c) GWR4 development team                          *
* (1) Ritsumeikan University, (2) National University of Ireland, Maynooth, *
*        (3) University of Glasgow, (4) Arizona State University             *
******************************************************************************

Program began at 11/20/2020 12:40:49 PM

******************************************************************************
Session:
Session control file: C:\Users\l2chakra\OneDrive - University of Waterloo\1.
PhD Projects\Project 3\StataReg\Final Shape File\GWR_Results_All
Models\GWR_Pluvial\FLSW_GWR.ctl
******************************************************************************
Data filename: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\gwr_data_new.csv
Number of areas/points: 4458

Model settings---------------------------------
Model type: Gaussian
Geographic kernel: adaptive bi-square
Method for optimal bandwidth search: Golden section search
Criterion for optimal bandwidth: AICc
Number of varying coefficients: 11
Number of fixed coefficients:   0

Modelling options---------------------------------
Standardisation of independent variables: OFF
Testing geographical variability of local coefficients: OFF
Local to Global Variable selection: OFF
Global to Local Variable selection: OFF
Prediction at non-regression points: OFF

Variable settings---------------------------------
Area key: field9: NCT
Easting (x-coord): field74 : COORD_X
Northing (y-coord): field75: COORD_Y
Cartesian coordinates: Euclidean distance
Dependent variable: field70: zPFLSW
Offset variable is not specified
Intercept: varying (Local) intercept
Independent variable with varying (Local) coefficient: field59: zpfemale
Independent variable with varying (Local) coefficient: field60: zpag65ov
Independent variable with varying (Local) coefficient: field61: zpdisable
Independent variable with varying (Local) coefficient: field62: zplivealon
Independent variable with varying (Local) coefficient: field63: zpblack
Independent variable with varying (Local) coefficient: field64: zpsouthasi
Independent variable with varying (Local) coefficient: field65: zpothervis
Independent variable with varying (Local) coefficient: field66: zpindigen
Independent variable with varying (Local) coefficient: field67: zInstabili
Independent variable with varying (Local) coefficient: field68: zInsecurty
******************************************************************************

******************************************************************************
  Global regression result
******************************************************************************
  < Diagnostic information >
Residual sum of squares:                  4040.073864
Number of parameters:                       11
 (Note: this num does not include an error variance term for a Gaussian
model)
ML based global sigma estimate:             0.951973
Unbiased global sigma estimate:             0.953150
-2 log-likelihood:                      12212.422652
Classic AIC:                            12236.422652
AICc:                                   12236.492843
BIC/MDL:                                12313.252118
CV:                                         0.913486
R square:                                   0.093565
Adjusted R square:                          0.091322

Variable                    Estimate    Standard Error      t(Est/SE)
-------------------- --------------- --------------- ---------------
Intercept                  -0.000013        0.014275       -0.000906
zpfemale                   -0.035673        0.016082       -2.218198
zpag65ov                   -0.009381        0.018742       -0.500565
zpdisable                  -0.016604        0.022575       -0.735538
zplivealon                  0.109221        0.031869        3.427161
zpblack                    -0.066791        0.019812       -3.371259
zpsouthasi                 -0.047329        0.020411       -2.318805
zpothervis                  0.110941        0.020136        5.509505
zpindigen                   0.083609        0.016220        5.154792
zInstabili                  0.102965        0.035214        2.923997
zInsecurty                  0.128316        0.019172        6.693031

******************************************************************************
  GWR (Geographically weighted regression) bandwidth selection
******************************************************************************

Bandwidth search <golden section search>
  Limits: 62,  4458
 Golden section search begins...
 Initial values
  pL          Bandwidth:    62.000 Criterion:  13154.495
  p1          Bandwidth:  1741.123 Criterion:  11874.762
  p2          Bandwidth:  2778.877 Criterion:  11960.361
  pU          Bandwidth:  4458.000 Criterion:  12172.118
 iter    1 (p1) Bandwidth:  1741.123 Criterion:  11874.762 Diff:   1037.755
 iter    2 (p1) Bandwidth:  1099.755 Criterion:  11734.519 Diff:    641.368
 iter    3 (p1) Bandwidth:   703.368 Criterion:  11643.847 Diff:    396.387
 iter    4 (p1) Bandwidth:   458.387 Criterion:  11578.184 Diff:    244.981
 iter    5 (p1) Bandwidth:   306.981 Criterion:  11559.783 Diff:    151.406
 iter    6 (p2) Bandwidth:   306.981 Criterion:  11559.783 Diff:     93.574
 iter    7 (p1) Bandwidth:   306.981 Criterion:  11559.783 Diff:     57.832
 iter    8 (p2) Bandwidth:   306.981 Criterion:  11559.783 Diff:     35.742
 iter    9 (p1) Bandwidth:   306.981 Criterion:  11559.783 Diff:     22.090
 iter   10 (p2) Bandwidth:   306.981 Criterion:  11559.783 Diff:     13.652
 iter   11 (p1) Bandwidth:   306.981 Criterion:  11559.783 Diff:      8.438
 iter   12 (p2) Bandwidth:   306.981 Criterion:  11559.783 Diff:      5.215
 iter   13 (p2) Bandwidth:   310.204 Criterion:  11559.412 Diff:      3.223
 iter   14 (p1) Bandwidth:   310.204 Criterion:  11559.412 Diff:      1.992
 iter   15 (p2) Bandwidth:   310.204 Criterion:  11559.412 Diff:      1.231
Best bandwidth size 310.000
Minimum AICc    11559.412

******************************************************************************
  GWR (Geographically weighted regression) result
******************************************************************************
  Bandwidth and geographic ranges
Bandwidth size:                    310.203556
Coordinate                Min             Max           Range
--------------- --------------- --------------- ---------------
X-coord          3932028.809524  8980877.717450  5048848.907926
Y-coord           701775.609685  2542101.874819  1840326.265134

  Diagnostic information
Residual sum of squares:              2898.044945
Effective number of parameters (model: trace(S)):
377.758369
Effective number of parameters (variance: trace(S'S)):
281.301942
Degree of freedom (model: n - trace(S)):
4080.241631
Degree of freedom (residual: n - 2trace(S) + trace(S'S)):
3983.785204
ML based sigma estimate:                  0.806274
Unbiased sigma estimate:                  0.852913
-2 log-likelihood:                    10731.356371
Classic AIC:                          11488.873109
AICc:                                 11559.411676
BIC/MDL:                              13913.856717
CV:                                       0.814756
R square:                                 0.349791
Adjusted R square:                        0.272374
```

```
*****************************************************************************
 << Geographically varying (Local) coefficients >>
*****************************************************************************
Estimates of varying coefficients have been saved in the following file.
    Listwise output file: C:\Users\l2chakra\OneDrive - University of
Waterloo\1. PhD Projects\Project 3\StataReg\Final Shape File\GWR_Results_All
Models\GWR_Pluvial\FLSW_GWR_listwise.csv

Summary statistics for varying (Local) coefficients
Variable                       Mean              STD
-------------------- --------------- ---------------
Intercept                  0.073263        0.646954
zpfemale                  -0.000196        0.118328
zpag65ov                   0.026597        0.175370
zpdisable                  0.110529        0.213911
zplivealon                -0.014633        0.280189
zpblack                   -0.134862        0.338568
zpsouthasi                 0.112549        0.357810
zpothervis                 0.074129        0.186401
zpindigen                  0.083551        0.377202
zInstabili                 0.064957        0.282911
zInsecurty                 0.120876        0.184398

Variable                        Min              Max           Range
-------------------- --------------- --------------- ---------------
Intercept                 -1.137742        2.598799        3.736542
zpfemale                  -0.270117        0.369389        0.639507
zpag65ov                  -0.550403        0.451389        1.001792
zpdisable                 -0.636578        0.906904        1.543482
zplivealon                -0.655571        0.853213        1.508784
zpblack                   -1.346321        0.887130        2.233451
zpsouthasi                -0.606009        2.655859        3.261868
zpothervis                -0.543662        0.820498        1.364161
zpindigen                 -1.703789        1.690554        3.394343
zInstabili                -0.693048        0.708389        1.401437
zInsecurty                -0.284428        0.713807        0.998235

Variable               Lwr Quartile          Median    Upr Quartile
-------------------- --------------- --------------- ---------------
Intercept                 -0.341091       -0.113283        0.281678
zpfemale                  -0.074432       -0.007269        0.077113
zpag65ov                  -0.064637        0.049709        0.130868
zpdisable                 -0.030713        0.084878        0.220199
zplivealon                -0.228235        0.010995        0.236205
zpblack                   -0.192523       -0.080473        0.006503
zpsouthasi                -0.094335        0.047863        0.269380
zpothervis                -0.019720        0.046137        0.165516
zpindigen                 -0.083206        0.075959        0.236674
zInstabili                -0.097075        0.009324        0.255791
zInsecurty                 0.014106        0.092969        0.191292

Variable             Interquartile R      Robust STD
-------------------- --------------- ---------------
Intercept                  0.622769        0.461652
zpfemale                   0.151545        0.112339
zpag65ov                   0.195506        0.144926
zpdisable                  0.250913        0.185999
zplivealon                 0.464439        0.344284
zpblack                    0.199025        0.147536
zpsouthasi                 0.363715        0.269618
zpothervis                 0.185236        0.137314
zpindigen                  0.319880        0.237124
zInstabili                 0.352866        0.261576
zInsecurty                 0.177186        0.131346
 (Note: Robust STD is given by (interquartile range / 1.349) )

*****************************************************************************
 GWR ANOVA Table
*****************************************************************************
Source                          SS          DF              MS           F
----------------- ------------------- ---------- --------------- ----------
Global Residuals           4040.074    4447.000
GWR Improvement            1142.029     463.215           2.465
GWR Residuals              2898.045    3983.785           0.727    3.389109

*****************************************************************************
Program terminated at 11/20/2020 12:52:15 PM
```

A.4.3 Coastal Flood Risk Exposure

```
*****************************************************************************
*            Semiparametric Geographically Weighted Regression
*                       Release 1.0.90 (GWR 4.0.90)
*                               12 May 2015
*                  (Originally coded by T. Nakaya: 1 Nov 2009)
*
*             Tomoki Nakaya(1), Martin Charlton(2), Chris Brunsdon (2)
*             Paul Lewis (2), Jing Yao (3), A Stewart Fotheringham (4)
*                         (c) GWR4 development team
* (1) Ritsumeikan University, (2) National University of Ireland, Maynooth,
*         (3) University of Glasgow, (4) Arizona State University
*****************************************************************************

Program began at 11/20/2020 1:40:52 PM

*****************************************************************************
Session:
Session control file: C:\Users\l2chakra\OneDrive - University of Waterloo\1
PhD Projects\Project 3\StataReg\Final Shape File\GWR_Results_All
Models\GWR_Coastal\STSU_GWR.ctl
*****************************************************************************
Data filename: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\gwr_data_new.csv
Number of areas/points: 4458

Model settings---------------------------------
Model type: Gaussian
Geographic kernel: adaptive bi-square
Method for optimal bandwidth search: Golden section search
Criterion for optimal bandwidth: AICc
Number of varying coefficients: 11
Number of fixed coefficients:   0

Modelling options---------------------------------
Standardisation of independent variables: OFF
Testing geographical variability of local coefficients: OFF
Local to Global Variable selection: OFF
Global to Local Variable selection: OFF
Prediction at non-regression points: OFF

Variable settings---------------------------------
Area key: field9: NCT
Easting (x-coord): field74 : COORD_X
Northing (y-coord): field75: COORD_Y
Cartesian coordinates: Euclidean distance
Dependent variable: field71: zPSTSU
Offset variable is not specified
Intercept: varying (Local) intercept
Independent variable with varying (Local) coefficient: field59: zpfemale
Independent variable with varying (Local) coefficient: field60: zpag65ov
Independent variable with varying (Local) coefficient: field61: zpdisable
Independent variable with varying (Local) coefficient: field62: zplivealon
Independent variable with varying (Local) coefficient: field63: zpblack
Independent variable with varying (Local) coefficient: field64: zpsouthasi
Independent variable with varying (Local) coefficient: field65: zpothervis
Independent variable with varying (Local) coefficient: field66: zpindigen
Independent variable with varying (Local) coefficient: field67: zInstabili
Independent variable with varying (Local) coefficient: field68: zInsecurty
*****************************************************************************

*****************************************************************************
  Global regression result
*****************************************************************************
  < Diagnostic information >
Residual sum of squares:                  4257.148391
Number of parameters:                         11
 (Note: this num does not include an error variance term for a Gaussian
model)
ML based global sigma estimate:              0.977213
Unbiased global sigma estimate:              0.978421
-2 log-likelihood:                       12445.739079
Classic AIC:                             12469.739079
AICc:                                    12469.809270
BIC/MDL:                                 12546.568545
CV:                                          0.960134
R square:                                    0.044888
Adjusted R square:                           0.042525
```

```
Variable                    Estimate   Standard Error      t(Est/SE)
-------------------- --------------- --------------- ---------------
Intercept                  -0.000194        0.014654       -0.013259
zpfemale                    0.021453        0.016508        1.299504
zpag65ov                    0.056772        0.019239        2.950908
zpdisable                  -0.009942        0.023173       -0.429027
zplivealon                  0.020033        0.032714        0.612373
zpblack                    -0.058453        0.020337       -2.874180
zpsouthasi                  0.206591        0.020952        9.860094
zpothervis                 -0.068410        0.020670       -3.309583
zpindigen                  -0.015899        0.016650       -0.954893
zInstabili                 -0.010583        0.036148       -0.292764
zInsecurty                  0.015473        0.019680        0.786218

*****************************************************************************
  GWR (Geographically weighted regression) bandwidth selection
*****************************************************************************

Bandwidth search <golden section search>
  Limits: 62,  4458
 Golden section search begins...
 Initial values
  pL            Bandwidth:    62.000 Criterion:   9171.722
  p1            Bandwidth:   155.574 Criterion:   9194.744
  p2            Bandwidth:   213.406 Criterion:   9886.034
  pU            Bandwidth:   306.981 Criterion:  10797.163
 iter    1 (p1) Bandwidth:   155.574 Criterion:   9194.744 Diff:      57.832
 iter    2 (p1) Bandwidth:   119.832 Criterion:   8917.492 Diff:      35.742
 iter    3 (p2) Bandwidth:   119.832 Criterion:   8917.492 Diff:      22.090
 iter    4 (p2) Bandwidth:   133.484 Criterion:   8906.223 Diff:      13.652
 iter    5 (p1) Bandwidth:   133.484 Criterion:   8906.223 Diff:       8.438
 iter    6 (p2) Bandwidth:   133.484 Criterion:   8906.223 Diff:       5.215
 iter    7 (p1) Bandwidth:   133.484 Criterion:   8906.223 Diff:       3.223
 iter    8 (p1) Bandwidth:   131.493 Criterion:   8900.576 Diff:       1.992
 iter    9 (p2) Bandwidth:   131.493 Criterion:   8900.576 Diff:       1.231
 iter   10 (p2) Bandwidth:   132.253 Criterion:   8898.292 Diff:       0.761
Best bandwidth size 132.000
Minimum AICc     8898.292

*****************************************************************************
  GWR (Geographically weighted regression) result
*****************************************************************************
  Bandwidth and geographic ranges
Bandwidth size:                    132.253372
Coordinate                  Min             Max           Range
--------------- --------------- --------------- ---------------
X-coord          3932028.809524  8980877.717450  5048848.907926
Y-coord           701775.609685  2542101.874819  1840326.265134

  Diagnostic information
Residual sum of squares:            1217.435913
Effective number of parameters (model: trace(S)):
826.675071
Effective number of parameters (variance: trace(S'S)):
615.247441
Degree of freedom (model: n - trace(S)):
3631.324929
Degree of freedom (residual: n - 2trace(S) + trace(S'S)):
3419.897300
ML based sigma estimate:                0.522580
Unbiased sigma estimate:                0.596646
-2 log-likelihood:                   6864.980152
Classic AIC:                         8520.330293
AICc:                                8898.292427
BIC/MDL:                            13819.483112
CV:                                     0.490157
R square:                               0.726862
Adjusted R square:                      0.643928
```

```
*************************************************************
 << Geographically varying (Local) coefficients >>
*************************************************************
Estimates of varying coefficients have been saved in the following file.
    Listwise output file: C:\Users\l2chakra\OneDrive - University of
Waterloo\1. PhD Projects\Project 3\StataReg\Final Shape File\GWR_Results_All
Models\GWR_Coastal\STSU_GWR_listwise.csv

Summary statistics for varying (Local) coefficients
Variable                        Mean             STD
-------------------- --------------- ---------------
Intercept                  -0.065427        0.591183
zpfemale                   -0.012636        0.125828
zpag65ov                    0.002699        0.202448
zpdisable                  -0.028559        0.467595
zplivealon                  0.059461        0.385238
zpblack                    -0.062289        0.662405
zpsouthasi                  0.001051        0.413008
zpothervis                  0.001683        0.252369
zpindigen                   0.006395        0.334196
zInstabili                 -0.076958        0.423281
zInsecurty                  0.001607        0.294801

Variable                         Min              Max           Range
-------------------- --------------- --------------- ---------------
Intercept                  -3.088191        9.201468       12.289659
zpfemale                   -1.643117        1.430789        3.073906
zpag65ov                   -1.335956        2.907169        4.243126
zpdisable                  -5.705748        6.445455       12.151202
zplivealon                 -1.196913        5.089043        6.285956
zpblack                   -10.328238        2.416192       12.744431
zpsouthasi                 -2.505904        3.936454        6.442358
zpothervis                 -2.530087        6.143308        8.673394
zpindigen                 -15.230070        1.674863       16.904933
zInstabili                 -4.787894        0.267352        5.055247
zInsecurty                 -3.873170        4.573419        8.446589

Variable                Lwr Quartile          Median    Upr Quartile
-------------------- --------------- --------------- ---------------
Intercept                  -0.106000       -0.106000       -0.106000
zpfemale                    0.000000        0.000000        0.000000
zpag65ov                    0.000000        0.000000        0.000000
zpdisable                  -0.000024        0.000000        0.000000
zplivealon                  0.000000        0.000000        0.003370
zpblack                     0.000000        0.000000        0.000000
zpsouthasi                  0.000000        0.000000        0.000000
zpothervis                  0.000000        0.000000        0.000000
zpindigen                   0.000000        0.000000        0.000000
zInstabili                  0.000000        0.000000        0.000000
zInsecurty                 -0.000044        0.000000        0.000000

Variable             Interquartile R      Robust STD
-------------------- --------------- ---------------
Intercept                   0.000000        0.000000
zpfemale                    0.000000        0.000000
zpag65ov                    0.000000        0.000000
zpdisable                   0.000024        0.000018
zplivealon                  0.003370        0.002498
zpblack                     0.000000        0.000000
zpsouthasi                  0.000000        0.000000
zpothervis                  0.000000        0.000000
zpindigen                   0.000000        0.000000
zInstabili                  0.000000        0.000000
zInsecurty                  0.000044        0.000032
 (Note: Robust STD is given by (interquartile range / 1.349) )

*****************************************************************************
 GWR ANOVA Table
*****************************************************************************
Source                         SS           DF              MS            F
----------------- ------------------- ---------- --------------- ----------
Global Residuals          4257.148    4447.000
GWR Improvement           3039.712    1027.103            2.960
GWR Residuals             1217.436    3419.897            0.356    8.313532

*****************************************************************************
Program terminated at 11/20/2020 1:53:00 PM
```

A.5 GWLR Regression Summary Output From GWR4 Program

A.5.1 Fluvial Flood Risk Exposure

```
*****************************************************************************
*            Semiparametric Geographically Weighted Regression              *
*                       Release 1.0.90 (GWR 4.0.90)                         *
*                               12 May 2015                                 *
*                 (Originally coded by T. Nakaya: 1 Nov 2009)               *
*                                                                           *
*           Tomoki Nakaya(1), Martin Charlton(2), Chris Brunsdon (2)        *
*           Paul Lewis (2), Jing Yao (3), A Stewart Fotheringham (4)        *
*                         (c) GWR4 development team                         *
* (1) Ritsumeikan University, (2) National University of Ireland, Maynooth, *
*         (3) University of Glasgow, (4) Arizona State University           *
*****************************************************************************

Program began at 11/24/2020 10:45:31 AM

*****************************************************************************
Session:
Session control file: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\GWLRM_All Models\1. Fluvial\fluvial_gwblm.ctl
*****************************************************************************
Data filename: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD Projects\Project
3\StataReg\Final Shape File\gwr_data_new.csv
Number of areas/points: 4458

Model settings---------------------------------
Model type: Logistic
Geographic kernel: adaptive Gaussian
Method for optimal bandwidth search: Golden section search
Criterion for optimal bandwidth: AIC
Number of varying coefficients: 11
Number of fixed coefficients:   0

Modelling options---------------------------------
Standardisation of independent variables: OFF
Testing geographical variability of local coefficients: OFF
Local to Global Variable selection: OFF
Global to Local Variable selection: OFF
Prediction at non-regression points: OFF

Variable settings---------------------------------
Area key: field9: NCT
Easting (x-coord): field74 : COORD_X
Northing (y-coord): field75: COORD_Y
Lat-lon coordinates: Spherical distance
Dependent variable: field54: FLRF_BIN
Offset variable is not specified
Intercept: varying (Local) intercept
Independent variable with varying (Local) coefficient: field59: zpfemale
Independent variable with varying (Local) coefficient: field60: zpag65ov
Independent variable with varying (Local) coefficient: field61: zpdisable
Independent variable with varying (Local) coefficient: field62: zplivealon
Independent variable with varying (Local) coefficient: field63: zpblack
Independent variable with varying (Local) coefficient: field64: zpsouthasi
Independent variable with varying (Local) coefficient: field65: zpothervis
Independent variable with varying (Local) coefficient: field66: zpindigen
Independent variable with varying (Local) coefficient: field67: zInstabili
Independent variable with varying (Local) coefficient: field68: zInsecurty
*****************************************************************************

*****************************************************************************
  Global regression result
*****************************************************************************
  < Diagnostic information >
Number of parameters:                        11
Deviance:                             4612.079811
Classic AIC:                          4634.079811
AICc:                                 4634.139191
BIC/MDL:                              4704.506822
Percent deviance explained               0.175360

Variable                    Estimate  Standard Error      z(Est/SE)       Exp(Est)
-------------------- --------------- --------------- --------------- ---------------
Intercept                   0.896337        0.037504       23.899793        2.450609
zpfemale                    0.071851        0.041578        1.728087        1.074495
zpag65ov                   -0.135475        0.048264       -2.806942        0.873301
zpdisable                  -0.062901        0.057698       -1.090163        0.939037
zplivealon                 -0.085877        0.079203       -1.084274        0.917707
zpblack                    -0.101701        0.047162       -2.156446        0.903299
zpsouthasi                 -0.128560        0.049847       -2.579064        0.879361
zpothervis                 -0.233310        0.048715       -4.789310        0.791908
zpindigen                   0.046583        0.052833        0.881698        1.047685
zInstabili                 -0.909795        0.089562      -10.158284        0.402607
zInsecurty                  0.102449        0.048848        2.097304        1.107881

*****************************************************************************
  GWR (Geographically weighted regression) bandwidth selection
*****************************************************************************

Bandwidth search <golden section search>
  Limits: 72,  4458
 Golden section search begins...
 Initial values
  pL             Bandwidth:   648.137 Criterion:   4633.681
  p1             Bandwidth:  2103.375 Criterion:   4632.804
  p2             Bandwidth:  3002.762 Criterion:   4633.230
  pU             Bandwidth:  4458.000 Criterion:   4633.695
 iter    1 (p1) Bandwidth:  2103.375 Criterion:   4632.804 Diff:     899.387
 iter    2 (p1) Bandwidth:  1547.523 Criterion:   4631.947 Diff:     555.852
 iter    3 (p1) Bandwidth:  1203.988 Criterion:   4631.392 Diff:     343.535
 iter    4 (p2) Bandwidth:  1203.988 Criterion:   4631.392 Diff:     212.316
 iter    5 (p1) Bandwidth:  1203.988 Criterion:   4631.392 Diff:     131.219
 iter    6 (p2) Bandwidth:  1203.988 Criterion:   4631.392 Diff:      81.098
 iter    7 (p2) Bandwidth:  1254.109 Criterion:   4631.337 Diff:      50.121
 iter    8 (p1) Bandwidth:  1254.109 Criterion:   4631.337 Diff:      30.977
 iter    9 (p2) Bandwidth:  1254.109 Criterion:   4631.337 Diff:      19.145
 iter   10 (p1) Bandwidth:  1254.109 Criterion:   4631.337 Diff:      11.832
 iter   11 (p1) Bandwidth:  1246.797 Criterion:   4631.306 Diff:       7.313
Best bandwidth size 1246.000
Minimum AIC      4631.306

*****************************************************************************
  GWR (Geographically weighted regression) result
*****************************************************************************
  Bandwidth and geographic ranges
Bandwidth size:                      1246.796778
Coordinate                Min             Max           Range
--------------- --------------- --------------- ---------------
X-coord           3932028.809524  8980877.717450    10388.828752
Y-coord            701775.609685  2542101.874819      696.418322
 (Note: Ranges are shown in km.)

  Diagnostic information
Effective number of parameters (model: trace(S)):                      28.492641
Effective number of parameters (variance: trace(S'WSW^-1)):             0.272472
Degree of freedom (model: n - trace(S)):                             4429.507359
Degree of freedom (residual: n - 2trace(S) + trace(S'WSW^-1)):       4401.287189
Deviance:                             4574.320392
Classic AIC:                          4631.305675
AICc:                                 4631.685181
BIC/MDL:                              4813.728543
Percent deviance explained               0.182111

*****************************************************************************
 << Geographically varying (Local) coefficients >>
*****************************************************************************
Estimates of varying coefficients have been saved in the following file.
    Listwise output file: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\GWLRM_All Models\1.
Fluvial\fluvial_gwblm_listwise.csv

Summary statistics for varying (Local) coefficients
Variable                        Mean             STD
-------------------- --------------- ---------------
Intercept                   0.900069        0.024361
zpfemale                    0.067221        0.017980
zpag65ov                   -0.140031        0.018715
zpdisable                  -0.057240        0.045072
zplivealon                 -0.081244        0.026232
zpblack                    -0.099438        0.032078
zpsouthasi                 -0.128435        0.020285
zpothervis                 -0.232931        0.026599
zpindigen                   0.032199        0.063103
zInstabili                 -0.927363        0.074247
zInsecurty                  0.114235        0.027097

Variable                         Min             Max           Range
-------------------- --------------- --------------- ---------------
Intercept                   0.855393        0.946611        0.091218
zpfemale                    0.028796        0.092586        0.063790
zpag65ov                   -0.178534       -0.101144        0.077390
zpdisable                  -0.156878        0.008440        0.165318
zplivealon                 -0.138275       -0.022065        0.116210
zpblack                    -0.154879       -0.044927        0.109952
zpsouthasi                 -0.173034       -0.090507        0.082526
zpothervis                 -0.288599       -0.196352        0.092247
zpindigen                  -0.076595        0.164117        0.240712
zInstabili                 -1.076401       -0.816484        0.259918
zInsecurty                  0.059413        0.163437        0.104024

Variable                Lwr Quartile          Median    Upr Quartile
-------------------- --------------- --------------- ---------------
Intercept                   0.879506        0.899220        0.921633
zpfemale                    0.053560        0.074512        0.081036
zpag65ov                   -0.152256       -0.136396       -0.127487
zpdisable                  -0.091570       -0.050398       -0.018263
zplivealon                 -0.101627       -0.080968       -0.062817
zpblack                    -0.127639       -0.099858       -0.069726
zpsouthasi                 -0.141995       -0.127141       -0.113813
zpothervis                 -0.256629       -0.229773       -0.207995
zpindigen                  -0.014833        0.024708        0.078500
zInstabili                 -0.988356       -0.908605       -0.865769
zInsecurty                  0.091987        0.120157        0.134561

Variable             Interquartile R      Robust STD
-------------------- --------------- ---------------
Intercept                   0.042127        0.031228
zpfemale                    0.027476        0.020368
zpag65ov                    0.024770        0.018361
zpdisable                   0.073307        0.054341
zplivealon                  0.038810        0.028770
zpblack                     0.057913        0.042931
zpsouthasi                  0.028181        0.020891
zpothervis                  0.048635        0.036052
zpindigen                   0.093333        0.069187
zInstabili                  0.122587        0.090873
zInsecurty                  0.042575        0.031560
 (Note: Robust STD is given by (interquartile range / 1.349) )

*****************************************************************************
 GWR Analysis of Deviance Table
*****************************************************************************
Source                     Deviance         DOF     Deviance/DOF
------------ ------------------- ---------- ----------------
Global model               4612.080    4447.000            1.037
GWR model                  4574.320    4401.287            1.039
Difference                   37.759      45.713            0.826

*****************************************************************************
Program terminated at 11/24/2020 11:29:07 AM
```

A.5.2 Pluvial Flood Risk Exposure

```
*****************************************************************************
*            Semiparametric Geographically Weighted Regression              *
*                     Release 1.0.90 (GWR 4.0.90)                           *
*                            12 May 2015                                    *
*             (Originally coded by T. Nakaya: 1 Nov 2009)                   *
*                                                                           *
*        Tomoki Nakaya(1), Martin Charlton(2), Chris Brunsdon (2)           *
*        Paul Lewis (2), Jing Yao (3), A Stewart Fotheringham (4)           *
*                       (c) GWR4 development team                           *
* (1) Ritsumeikan University, (2) National University of Ireland, Maynooth, *
*        (3) University of Glasgow, (4) Arizona State University            *
*****************************************************************************

Program began at 11/24/2020 11:35:19 AM

*****************************************************************************
Session:
Session control file: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\GWLRM_All Models\2. Pluvial\GW
Logistic\pluvial_gwlrm.ctl
*****************************************************************************
Data filename: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\gwr_data_new.csv
Number of areas/points: 4458

Model settings---------------------------------
Model type: Logistic
Geographic kernel: adaptive Gaussian
Method for optimal bandwidth search: Golden section search
Criterion for optimal bandwidth: AIC
Number of varying coefficients: 11
Number of fixed coefficients:   0

Modelling options---------------------------------
Standardisation of independent variables: OFF
Testing geographical variability of local coefficients: OFF
Local to Global Variable selection: OFF
Global to Local Variable selection: OFF
Prediction at non-regression points: OFF

Variable settings---------------------------------
Area key: field9: NCT
Easting (x-coord): field74 : COORD_X
Northing (y-coord): field75: COORD_Y
Lat-lon coordinates: Spherical distance
Dependent variable: field55: FLSW_BIN
Offset variable is not specified
Intercept: varying (Local) intercept
Independent variable with varying (Local) coefficient: field59: zpfemale
Independent variable with varying (Local) coefficient: field60: zpag65ov
Independent variable with varying (Local) coefficient: field61: zpdisable
Independent variable with varying (Local) coefficient: field62: zplivealon
Independent variable with varying (Local) coefficient: field63: zpblack
Independent variable with varying (Local) coefficient: field64: zpsouthasi
Independent variable with varying (Local) coefficient: field65: zpothervis
Independent variable with varying (Local) coefficient: field66: zpindigen
Independent variable with varying (Local) coefficient: field67: zInstabili
Independent variable with varying (Local) coefficient: field68: zInsecurty
*****************************************************************************

*****************************************************************************
  Global regression result
*****************************************************************************
  < Diagnostic information >
Number of parameters:                   11
Deviance:                          2086.665399
Classic AIC:                       2108.665399
AICc:                              2108.724779
BIC/MDL:                           2179.092410
Percent deviance explained            0.077160

Variable                    Estimate    Standard Error        z(Est/SE)       Exp(Est)
-------------------- --------------- --------------- --------------- ---------------
Intercept                   2.828174        0.070598        40.060143       16.91454
zpfemale                   -0.014766        0.058063        -0.254306        0.98534
zpag65ov                    0.034255        0.080359         0.426275        1.03484
zpdisable                   0.165540        0.093271         1.774829        1.18003
zplivealon                 -0.302414        0.116250        -2.601413        0.73903
zpblack                    -0.275970        0.066161        -4.171176        0.75883
zpsouthasi                 -0.383560        0.072101        -5.319759        0.68143
zpothervis                 -0.035846        0.076685        -0.467438        0.96478
zpindigen                  -0.147046        0.057631        -2.551497        0.86325
zInstabili                 -0.286222        0.124940        -2.290876        0.75109
zInsecurty                  0.248932        0.080928         3.075965        1.28265

*****************************************************************************
  GWR (Geographically weighted regression) bandwidth selection
*****************************************************************************

Bandwidth search <golden section search>
  Limits: 72,  4458
 Golden section search begins...
 Initial values
  pL            Bandwidth:   648.137 Criterion:   2122.382
  p1            Bandwidth:  2103.375 Criterion:   2109.652
  p2            Bandwidth:  3002.762 Criterion:   2108.684
  pU            Bandwidth:  4458.000 Criterion:   2108.317
 iter    1 (p2) Bandwidth:  3002.762 Criterion:   2108.684 Diff:     899.387
 iter    2 (p2) Bandwidth:  3558.613 Criterion:   2108.510 Diff:     555.852
 iter    3 (p2) Bandwidth:  3902.148 Criterion:   2108.428 Diff:     343.535
 iter    4 (p2) Bandwidth:  4114.465 Criterion:   2108.375 Diff:     212.316
 iter    5 (p2) Bandwidth:  4245.684 Criterion:   2108.347 Diff:     131.219
 iter    6 (p2) Bandwidth:  4326.781 Criterion:   2108.329 Diff:      81.098
The upper limit in your search has been selected as the optimal bandwidth size.
Best bandwidth size 4458.000
Minimum AIC      2108.317

*****************************************************************************
  GWR (Geographically weighted regression) result
*****************************************************************************
  Bandwidth and geographic ranges
Bandwidth size:                  4458.000000
Coordinate                  Min             Max           Range
--------------- --------------- --------------- ---------------
X-coord           3932028.809524  8980877.717450    10388.828752
Y-coord            701775.609685  2542101.874819      696.418322
 (Note: Ranges are shown in km.)

  Diagnostic information
Effective number of parameters (model: trace(S)):                          12.736309
Effective number of parameters (variance: trace(S'WSW^-1)):                 0.141979
Degree of freedom (model: n - trace(S)):                                 4445.263691
Degree of freedom (residual: n - 2trace(S) + trace(S'WSW^-1)):           4432.669360
Deviance:                            2082.844027
Classic AIC:                         2108.316645
AICc:                                2108.395376
BIC/MDL:                             2189.860298
Percent deviance explained              0.078850

***********************************************************
 << Geographically varying (Local) coefficients >>
***********************************************************
Estimates of varying coefficients have been saved in the following file.
    Listwise output file: C:\Users\l2chakra\OneDrive - University of Waterloo\1. Ph
Projects\Project 3\StataReg\Final Shape File\GWLRM_All Models\2. Pluvial\GW
Logistic\pluvial_gwlrm_listwise.csv

Summary statistics for varying (Local) coefficients
Variable                        Mean             STD
-------------------- --------------- ---------------
Intercept                   2.829098        0.005738
zpfemale                   -0.015143        0.006336
zpag65ov                    0.033978        0.013158
zpdisable                   0.164800        0.007707
zplivealon                 -0.302417        0.005606
zpblack                    -0.276267        0.011323
zpsouthasi                 -0.383762        0.006835
zpothervis                 -0.036096        0.010262
zpindigen                  -0.147272        0.008185
zInstabili                 -0.286017        0.004353
zInsecurty                  0.248699        0.008436

Variable                         Min             Max           Range
-------------------- --------------- --------------- ---------------
Intercept                   2.819789        2.839160        0.019371
zpfemale                   -0.027416       -0.002691        0.024725
zpag65ov                    0.009915        0.052558        0.042642
zpdisable                   0.151265        0.177039        0.025773
zplivealon                 -0.312259       -0.288135        0.024124
zpblack                    -0.293927       -0.256752        0.037175
zpsouthasi                 -0.394104       -0.370680        0.023424
zpothervis                 -0.052569       -0.017708        0.034860
zpindigen                  -0.159987       -0.129522        0.030465
zInstabili                 -0.297676       -0.277466        0.020211
zInsecurty                  0.232746        0.263608        0.030862

Variable                Lwr Quartile          Median    Upr Quartile
-------------------- --------------- --------------- ---------------
Intercept                   2.823790        2.828850        2.834028
zpfemale                   -0.020017       -0.015217       -0.010190
zpag65ov                    0.021906        0.035434        0.047035
zpdisable                   0.157666        0.165792        0.172073
zplivealon                 -0.306908       -0.303066       -0.298440
zpblack                    -0.286929       -0.276947       -0.265613
zpsouthasi                 -0.390052       -0.384133       -0.377743
zpothervis                 -0.046227       -0.035708       -0.026841
zpindigen                  -0.154882       -0.147431       -0.140220
zInstabili                 -0.289017       -0.285643       -0.282664
zInsecurty                  0.241716        0.249312        0.255658

Variable               Interquartile R      Robust STD
-------------------- --------------- ---------------
Intercept                   0.010238        0.007590
zpfemale                    0.009827        0.007284
zpag65ov                    0.025129        0.018628
zpdisable                   0.014408        0.010680
zplivealon                  0.008468        0.006277
zpblack                     0.021316        0.015801
zpsouthasi                  0.012310        0.009125
zpothervis                  0.019386        0.014371
zpindigen                   0.014662        0.010869
zInstabili                  0.006353        0.004709
zInsecurty                  0.013942        0.010335
 (Note: Robust STD is given by (interquartile range / 1.349) )

*****************************************************************************
 GWR Analysis of Deviance Table
*****************************************************************************
Source                   Deviance        DOF     Deviance/DOF
------------ ------------------- ---------- ----------------
Global model             2086.665   4447.000            0.469
GWR model                2082.844   4432.669            0.470
Difference                  3.821     14.331            0.267

*****************************************************************************
Program terminated at 11/24/2020 12:25:52 PM
```

A.5.3 Coastal Flood Risk Exposure

```
****************************************************************************
*            Semiparametric Geographically Weighted Regression            *
*                     Release 1.0.90 (GWR 4.0.90)                          *
*                             12 May 2015                                  *
*             (Originally coded by T. Nakaya: 1 Nov 2009)                  *
*                                                                          *
*       Tomoki Nakaya(1), Martin Charlton(2), Chris Brunsdon (2)           *
*       Paul Lewis (2), Jing Yao (3), A Stewart Fotheringham (4)           *
*                     (c) GWR4 development team                            *
* (1) Ritsumeikan University, (2) National University of Ireland, Maynooth, *
*         (3) University of Glasgow, (4) Arizona State University          *
****************************************************************************

Program began at 11/24/2020 12:57:01 PM

****************************************************************************
Session:
Session control file: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\GWLRM_All Models\3.
Coastal\coastal_GWRLM.ctl
****************************************************************************
Data filename: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\gwr_data_new.csv
Number of areas/points: 4458

Model settings---------------------------------
Model type: Logistic
Geographic kernel: adaptive Gaussian
Method for optimal bandwidth search: Golden section search
Criterion for optimal bandwidth: AIC
Number of varying coefficients: 11
Number of fixed coefficients:   0

Modelling options---------------------------------
Standardisation of independent variables: OFF
Testing geographical variability of local coefficients: OFF
Local to Global Variable selection: OFF
Global to Local Variable selection: OFF
Prediction at non-regression points: OFF

Variable settings---------------------------------
Area key: field9: NCT
Easting (x-coord): field74 : COORD_X
Northing (y-coord): field75: COORD_Y
Lat-lon coordinates: Spherical distance
Dependent variable: field56: STSU_BIN
Offset variable is not specified
Intercept: varying (Local) intercept
Independent variable with varying (Local) coefficient: field59: zpfemale
Independent variable with varying (Local) coefficient: field60: zpag65ov
Independent variable with varying (Local) coefficient: field61: zpdisable
Independent variable with varying (Local) coefficient: field62: zplivealon
Independent variable with varying (Local) coefficient: field63: zpblack
Independent variable with varying (Local) coefficient: field64: zpsouthasi
Independent variable with varying (Local) coefficient: field65: zpothervis
Independent variable with varying (Local) coefficient: field66: zpindigen
Independent variable with varying (Local) coefficient: field67: zInstabili
Independent variable with varying (Local) coefficient: field68: zInsecurty
****************************************************************************

****************************************************************************
  Global regression result
****************************************************************************
  < Diagnostic information >
Number of parameters:                  11
Deviance:                         1616.077850
Classic AIC:                      1638.077850
AICc:                             1638.137229
BIC/MDL:                          1708.504861
Percent deviance explained           0.143333

Variable                 Estimate    Standard Error      z(Est/SE)        Exp(Est)
-------------------- ------------- --------------- --------------- ---------------
Intercept               -3.768471        0.142379      -26.467970        0.023087
zpfemale                 0.055220        0.088646        0.622930        1.056773
zpag65ov                 0.485318        0.083916        5.783368        1.624692
zpdisable                0.206204        0.119740        1.722095        1.229004
zplivealon              -0.457642        0.171255       -2.672277        0.632774
zpblack                 -1.010604        0.256777       -3.935719        0.363999
zpsouthasi               0.241282        0.097901        2.464550        1.272880
zpothervis              -1.089803        0.191939       -5.677849        0.336283
zpindigen               -0.356876        0.144571       -2.468518        0.699859
zInstabili               0.356024        0.188091        1.892833        1.427642
zInsecurty              -0.190180        0.092658       -2.052493        0.826810
```

```
****************************************************************************
  GWR (Geographically weighted regression) bandwidth selection
****************************************************************************

Bandwidth search <golden section search>
  Limits: 72,  4458
 Golden section search begins...
 Initial values
  pL            Bandwidth:   526.007 Criterion:   1654.662
  p1            Bandwidth:  2027.895 Criterion:   1634.775
  p2            Bandwidth:  2956.112 Criterion:   1635.493
  pU            Bandwidth:  4458.000 Criterion:   1636.472
 iter    1 (p1) Bandwidth:  2027.895 Criterion:   1634.775 Diff:    928.218
 iter    2 (p2) Bandwidth:  2027.895 Criterion:   1634.775 Diff:    573.670
 iter    3 (p1) Bandwidth:  2027.895 Criterion:   1634.775 Diff:    354.548
 iter    4 (p2) Bandwidth:  2027.895 Criterion:   1634.775 Diff:    219.122
Best bandwidth size 2027.000
Minimum AIC      1634.775

****************************************************************************
  GWR (Geographically weighted regression) result
****************************************************************************
  Bandwidth and geographic ranges
Bandwidth size:                  2027.894740
Coordinate                Min             Max           Range
--------------- --------------- --------------- ---------------
X-coord          3932028.809524  8980877.717450    10388.828752
Y-coord           701775.609685  2542101.874819      696.418322
 (Note: Ranges are shown in km.)

  Diagnostic information
Effective number of parameters (model: trace(S)):                        19.368601
Effective number of parameters (variance: trace(S'WSW^-1)):               0.084855
Degree of freedom (model: n - trace(S)):                               4438.631399
Degree of freedom (residual: n - 2trace(S) + trace(S'WSW^-1)):         4419.347652
Deviance:                           1596.037582
Classic AIC:                        1634.774784
AICc:                               1634.952587
BIC/MDL:                            1758.781392
Percent deviance explained             0.153957

**************************************************************
 << Geographically varying (Local) coefficients >>
**************************************************************
Estimates of varying coefficients have been saved in the following file.
    Listwise output file: C:\Users\l2chakra\OneDrive - University of Waterloo\1. PhD
Projects\Project 3\StataReg\Final Shape File\GWLRM_All Models\3.
Coastal\coastal_GWRLM_listwise.csv

Summary statistics for varying (Local) coefficients
Variable                        Mean             STD
-------------------- --------------- ---------------
Intercept                  -3.787559        0.110397
zpfemale                    0.053148        0.022214
zpag65ov                    0.487163        0.037848
zpdisable                   0.210219        0.061448
zplivealon                 -0.459363        0.107032
zpblack                    -1.029826        0.164329
zpsouthasi                  0.241975        0.027955
zpothervis                 -1.093044        0.054289
zpindigen                  -0.384113        0.184533
zInstabili                  0.358958        0.149490
zInsecurty                 -0.188262        0.024638

Variable                         Min             Max           Range
-------------------- --------------- --------------- ---------------
Intercept                  -3.968334       -3.640189        0.328144
zpfemale                    0.013690        0.097689        0.083999
zpag65ov                    0.424017        0.553756        0.129740
zpdisable                   0.118817        0.303305        0.184488
zplivealon                 -0.665894       -0.263106        0.402789
zpblack                    -1.304754       -0.817173        0.487581
zpsouthasi                  0.188262        0.295587        0.107325
zpothervis                 -1.199851       -0.991798        0.208053
zpindigen                  -0.677483       -0.142071        0.535412
zInstabili                  0.126563        0.602353        0.475791
zInsecurty                 -0.235866       -0.142265        0.093601
```

```
Variable                Lwr Quartile          Median    Upr Quartile
-------------------- --------------- --------------- ---------------
Intercept                  -3.895119       -3.771358       -3.679207
zpfemale                    0.035037        0.051486        0.070193
zpag65ov                    0.451707        0.485798        0.523221
zpdisable                   0.150161        0.207248        0.271928
zplivealon                 -0.543512       -0.456531       -0.373953
zpblack                    -1.186679       -1.006364       -0.866938
zpsouthasi                  0.221698        0.242155        0.263436
zpothervis                 -1.133950       -1.091180       -1.051353
zpindigen                  -0.569059       -0.359349       -0.203568
zInstabili                  0.212811        0.350807        0.504839
zInsecurty                 -0.207449       -0.188631       -0.168397

Variable                Interquartile R      Robust STD
-------------------- --------------- ---------------
Intercept                   0.215913        0.160054
zpfemale                    0.035156        0.026060
zpag65ov                    0.071514        0.053012
zpdisable                   0.121767        0.090264
zplivealon                  0.169559        0.125692
zpblack                     0.319741        0.237021
zpsouthasi                  0.041738        0.030940
zpothervis                  0.082597        0.061228
zpindigen                   0.365491        0.270935
zInstabili                  0.292028        0.216477
zInsecurty                  0.039052        0.028949
 (Note: Robust STD is given by (interquartile range / 1.349) )

****************************************************************************
 GWR Analysis of Deviance Table
****************************************************************************
Source                  Deviance       DOF    Deviance/DOF
------------ ------------------- --------- ---------------
Global model            1616.078  4447.000           0.363
GWR model               1596.038  4419.348           0.361
Difference                20.040    27.652           0.725

****************************************************************************
Program terminated at 11/24/2020 1:44:44 PM
```