Part II: A Profile of Social Vulnerability in Canada

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Social Fabric

Recent disaster events in regions around the world and the shared experience of living through the COVID-19 global pandemic have raised awareness and concern about deep-rooted social inequities that exist in many societies and that are manifest here in Canada as well. While we are all exposed to the physical effects of hazard threats in the same way, certain groups within a community often bear a disproportionate burden of the risk associated with the impacts of floods, wildfire, illness and other disruptive events. This section shifts the focus of our investigation from the physical dimensions of urban systems to the complex set of social interactions that determine characteristics of both vulnerability and resilience for a particular place or region.

Social fabric describes the demographic characteristics of people living within a neighborhood or region and their relative capacities to weather the sudden shocks of hazard events that can disrupt the normal routines of day-to-day life. The threads of this complex and interwoven fabric of social interactions are often characterized through the lens of vulnerability and/or resilience. Vulnerability focuses on the underlying characteristics of social systems that exist prior to a disaster event that can predetermine levels of physical exposure to hazard threats and the degree to which members of a community may suffer harm as a result (Birkmann, 2006; S. Cutter, L., 2001; B. Wisner, 2004). Resilience refers to the inherent capabilities of social systems to withstand, recover from and adapt to the combined physical impacts and downstream consequences of disaster events (Adger et al., 2005; Folke et al., 2002; Walker et al., 2006).

Although useful in establishing a framework for understanding and describing characteristics of social fabric, it is important to bear in mind that vulnerability and resilience are not directly observable phenomena. Rather, they represent the manifestations of cause-effect relationships within a complex network of social and economic interactions that are relevant in the context of a particular place, and that can only be measured indirectly through a blend of qualitative and quantitative assessment (Rufat et al., 2019; Tate, 2012).

Qualitative assessment of social vulnerability is typically undertaken at a local scale in the context of academic studies and/or strategic planning initiatives that utilize ground-up methods of direct community engagement and deliberative dialog to identify the intrinsic characteristics of a particular neighbourhood or group of people. Examples of ground-up approaches include surveys and in-depth forensic studies of disaster events to better understand the differential impacts and downstream consequences that are influenced by underlying conditions and/or the driving forces of social inequity (e.g.,Burby, 2006; C. G. Burton et al., 2017; Canterbury District Health Board, 2018; Despotaki et al., 2017; Stevenson et al., 2014; K Tierney, 2006).

Quantitative assessments of vulnerability are typically undertaken through a top-down assessment of census-based demographic variables that are used as proxies to represent various dimensions of the social fabric. Examples of top-down social vulnerability assessments include the well-known ‘Hazards-of-Place’ model and subsequent variations that have been used to describe patterns of vulnerability with respect to various hazard threats at regional and national scales (e.g., Aroca-Jimenez et al., 2017; Boruff et al., 2005; Brooks et al., 2006; C. Burton & Cutter, 2008; J. Chakraborty et al., 2005; Cox et al., 2006; S. Cutter, L. et al., 2003; S. Cutter, L. et al., 2000; Dwyer et al., 2004; Tate, 2012; Vincent, 2004).

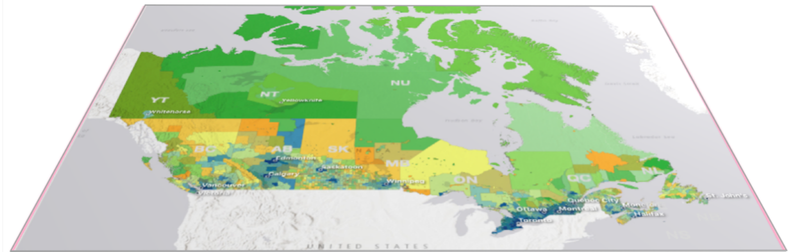
Studies of social vulnerability in a Canadian context include national surveys of inequity and marginalization (Matheson et al., 2012; Statistics Canada, 2019), and more focused studies of vulnerability in the context of natural hazard threats (Andrey & Jones, 2008; L. Chakraborty et al., 2020; Chang et al., 2018; Chang et al., 2015; Fox, 2008; Brenda Jones, 2003; Journeay et al., 2015; Oulahen et al., 2018; Oulahen et al., 2015). Equivalent regional and national level assessment frameworks have been developed to model dimensions of community resilience including capacities to respond, recover and adapt to the impacts of disaster events at regional and national scales (e.g., Adger et al., 2005; Bergstrand et al., 2015; Brechwald et al., 2015; S. L. Cutter et al., 2008; Oregon Seismic Safety Policy Advisory Commission, 2013; Paton et al., 2001; Peacock et al., 2010; Rockefeller Foundation, 2014).

Ground-up qualitative approaches generally result in a deeper and more nuanced understanding of the underlying conditions and drivers of social vulnerability, and the resilience capabilities of different groups that are required to inform disaster resilience planning in the context of a particular community or region. However, the assessment process can be resource intensive with output metrics that are context-specific and not easily aggregated or compared from one region to another. In contrast, top-down assessments provide a structured framework for measuring dimensions of social vulnerability using indicator-based metrics that are comparable from region to region, but that do not always reflect local knowledge about complex social interactions that ultimately determine local capacities to withstand, recover from and adapt to difficult situations.

In this study, we explore a complementary suite of methods and models to assess both intrinsic characteristics of social vulnerability at the census dissemination area level, and the underlying cause-effect relationships that help explain the interactions between social, economic and political factors and their influence on patterns of societal risk. Components of the study include (i) an adaptation of the 'Hazards-of-Place' inductive model for identifying and mapping underlying patterns of social vulnerability, (ii) a capacity-based hierarchical model to help make evident key determinants of social vulnerability through the lens of housing conditions, social capital, individual autonomy and financial agency, and (iii) preliminary results of a social vulnerability profile model that explores how causal factors intersect and influence capacities for response and recovery through the lens of specific neighbourhood archetypes. The following sections describe the overall framing and analytic methods used to develop each component of the social fabric layer for Canada and offer examples of how these models can be used to profile patterns of social vulnerability to natural hazard threats at regional and local scales.

Community Archetypes

The dimensions of vulnerability are context-specific and best understood through the lens of particular community types that reflect how social, economic and cultural characteristics may vary in response to differences in physical setting and/or socio-political influences. For example, demographic attributes that limit capacities to withstand the impacts of a damaging earthquake for a high-density urban neighbourhood may be the same attributes that promote resilience and adaptability of those living in more rural and remote settings. Conversely, attributes that



Community Archetype	Description	RI-mean	Human Settlements	Settled Area (km2)	Pop	People /km2
Metropolitan area	CSD's contained in metropolitan areas with a minimum population of 100,000, where at least 50,000 live in an urban core area defined as having at least 400 people/square kilometre. Population centres within this category are classified as Large (1000,000+), Medium (30,000-99,999) and Small (1,000-29,999) with adjacent rural fringe areas of less than 400 people /km2. Given a minimum of 100 commuters, at least 50% of the employed labour force living in the CSD works in the delineation core	0.17	77,593	28,585	24,948,619	2,398
Agglomeration area	CSD's contained in census agglomeration areas with a minimum population of 10,000, where at least 10,000 live in an urban core area defined as having at least 400 people/square kilometre. Population centres within this category are classified as Medium (30,000-99,999) and Small (1,000-29,999) with adjacent rural fringe areas of less than 400 people /km2. Given a minimum of 100 commuters, at least 50% of the employed labour force living in the CSD works in the delineation core	0.24	8,153	4,056	1,238,531	616
Agglomeration area with no census tracts	CSD's within census agglomeration having no census tracts or urban centres and characterized by low density rural settlements of less than 400 people /km2. Although geographically near large urban centres, limited access along established transportation routes limit availability of business services and the degree of economic influence.	0.32	29,495	11,944	3,050,850	363
Strong metropolitan influence	CSDs outside urban areas in provinces where at least 30% of the CSD's resident employed labour force commute to work in any CMA or CA. It excludes CSDs with fewer than 40 persons in their resident employed labour force.	0.24	73,516	26,241	1,986,849	66
Moderate metropolitan influence	CSDs outside urban areas in provinces where at least 5% but less than 30% of the CSD's resident employed labour force commute to work in any CMA or CA. It excludes CSDs with fewer than 40 persons in their resident employed labour force.	0.31	119,234	35,821	2,319,900	56
Weak metropolitan influence	CSDs outside urban areas in provinces where less than 5% of the CSD's resident employed labour force commute to work in any CMA or CA. It excludes CSDs with fewer than 40 persons in their resident employed labour force.	0.43	63,019	16,710	1,310,860	64
No metropolitan influenced	CSDs outside urban areas in provinces where none of the CSD's resident employed labour force commute to work in any CMA or CA. It also includes CSDs in provinces with fewer than 40 persons in their resident employed labour force.	0.48	17,325	4,247	230,994	59
Territories (outside CAs)	This category includes CSDs in the territories outside CAs	0.71	717	223	64,206	264
All Census subdivision		0.36	389,052	127,828	35,150,810	486

Figure 1: Community archetypes of Canada

correlate with access to health care and business services enhance the capacities of urban neighbourhoods to withstand the physical impacts of disaster events while diminishing those same capabilities in rural and remote communities.

To account for differences in social fabric across the range of settlement types in Canada, we assess profiles of vulnerability through a tapestry of eight community archetypes (See Figure 17). The archetypes are based on a statistical area classification (SAC) developed as part of the national census, which characterizes community typologies based on proximity to densely populated urban regions and associated centres of economic activity (Statistics Canada, 2016b). As summarized in Table X, community archetypes are defined in terms of population density, degree of urban influence and the proportion of residents that commute to work on a regular basis.

Additional measures of proximity and accessibility characterize each of the community archetypes and are recognized as important determinants of social vulnerability at the local level (Alasia et al., 2017). Variables include a remoteness Index (RI), measured in terms of travel distance costs along established transportation routes to the nearest population centre, and access to associated business services including health care, social assistance, financial and legal assistance and general goods and services (retail).

Linkages between the degree of remoteness and accessibility to services by different types of communities are especially relevant to the study of socio-economic vulnerability in large and sparsely populated countries like Canada and Australia. Studies in both countries have shown that populations in rural and remote settings are more likely to experience poor health, higher rates of mortality, lower life expectancy and higher levels of unmet healthcare needs (CIHI, 2012; Eckert et al., 2004; Subedi et al., 2019; Subedi et al., 2020). These factors are known to be key determinants of community health and can limit capacities to both withstand and recover from the impacts of hazard events (S. Cutter, L. et al., 2003; S. Cutter, L. et al., 2000).

Equivalent studies of environmental hazards in densely populated metropolitan regions have highlighted deep-rooted patterns of social inequity, displacement and exclusion from wealth-generating opportunities that disproportionally affect populations of different racial, cultural and ethnic backgrounds (Batty, 2013; Blaikie et al., 1994; Comfort et al., 1999; Cross, 2002; GFDRR, 2016; Klein et al., 2003; Matheson et al., 2012; Mileti, 1999; Pelling, 2003; Uitto, 1998; Ben Wisner, 2003). These patterns are amplified by pressures of rapid urban growth and the complexities of densification that disproportionally affect the most vulnerable in our communities.

The eight community archetypes and corresponding demographic variables outlined above provide both context and rationale for developing more detailed models of social vulnerability to natural hazard threats and their variability across the spectrum of urban and rural communities in Canada. Based on several iterations of model development, we have found that a tapestry of context-specific models is more effective than a single national model in measuring the dimensions of social vulnerability within each community type, and better reflects the diversity of settlements across Canada.

Model Development

Social vulnerability assessments focus on the question of who is most affected by the immediate impacts of a hazard event, and the underlying human and socioeconomic factors that may amplify the negative downstream consequences during recovery phases of a disaster. The roots of social vulnerability modeling can be traced back to a number of foundational studies that used composite indices and geostatistical analysis to detect and rank patterns of vulnerability based on representative demographic indicators that were known to be effective in profiling complex social and economic interactions at local and regional scales (Clark et al., 1998; S. Cutter, L. et al., 2000; Morrow, 1999; Tapsell et al., 2002).

There has since been a proliferation of social vulnerability models and important refinements in the methods used to measure the complexity of socio-economic interactions that influence capacities to withstand and recover from disaster events, and an increased scrutiny of model outputs based on forensic studies of recent disaster events (C. Burton et al., 2018; Rufat, 2013; Rufat et al., 2019; Tate, 2012). While these models vary widely in both the scope and the range of subjective judgments that are incorporated into the assessment process, the basic steps involved in developing the underlying indicators and related metrics are common to most. They include: (i) initial design of the indicator framework, (ii) selection and validation of demographic variables, (iii) transformation and reduction of redundant variables, and (iv) construction of indices used to measure specific dimensions of vulnerability that are relevant to the planning process.

Step 1: Model Design and Structure

As with other components of this study, the social vulnerability model (SVI) is focused on generating a base of evidence to support disaster risk reduction and sustainable land use planning in regions exposed to natural hazard threats in Canada. Important considerations in model design include the intended audience, how the outcomes of the assessment might be used to inform planning and policy development and the corresponding logic structure used to both generate and interpret model outputs.

The intended audience for this study includes community planners, emergency managers and policy analysts working in the context of a municipality or regional district authority who may have detailed knowledge about specific vulnerable populations and are able to build on the more general results of this study to promote disaster resilience using ground-up methods of qualitative assessment and targeted investments to help guide capacity development. It also includes other government and non-governmental organizations working on regional policy initiatives that may be focused on the more general needs of vulnerable populations in the context of emergency preparedness and response or disaster resilience planning.

An important decision in model design is the overall logic structure used to assess the dimensions of social vulnerability which can be based on any combination of deductive, inductive and/or knowledge-based based methods of reasoning and representation (Tate, 2012). Deductive models start with a pre-conceived hypothesis or assertion about the underlying drivers of vulnerability for a particular place, then use a pre-selected set of indicators to measure the relative contributions of relevant causal factors such as age, gender and income. They work well in situations where there is existing knowledge and clear understanding of underlying cause-effect relationships for a particular place but can be misleading if applied across different contexts of place or hazard exposure where these relationships may no longer be valid.

In contrast, Inductive models use geostatistical methods to identify trends and relational patterns in large multidimensional datasets that help explain observed behaviors or interactions. They generally start with a large set of twenty or more well-documented indicators, which are reduced to a smaller set of statistically significant factors that explain variability within the data using principal component and/or factor analysis. The resulting set of indicators are then assembled into a hierarchical structure (taxonomy) that reflects dimensions of vulnerability that are inferred to be relevant across a range of different hazard contexts. Relevant examples of this approach include inductive models developed around organizing principles of physical, social, and economic capital that have been used to explore both spatial and temporal dimensions of social vulnerability to coastal hazards in both urban and rural contexts across Canada (Andrey & Jones, 2008; Chang et al., 2018; Fox, 2008; Brenda Jones, 2003; Oulahen et al., 2018).

This study builds on the strengths of inductive and hierarchical models to identify and describe differences in social vulnerability within a particular place or region, and to detect similarities that may exist in overall social fabric across communities of different types in Canada. Physical dimensions of vulnerability, which include characteristics of susceptibility and capacities of different building types to resist the impacts of a hazard event are considered separately and integrated at a later stage in the assessment of hazard threats and/or risk.

Step 2: Selection of Relevant Indicators

As with all other metrics in the human settlement layer, social vulnerability indicators are quantitative variables used to represent the

Indicator Name	Description	Theme(s	Supporting Rationale	CIMD	SVI	CI	NVA
VFd_FamGT5	Proportion households with 5 or more persons	FS/IA	Blaikie et al., 1994; Morrow, 1999; Cutter et al. 2003	✓	✓	✓	
VFd_LonPar3Kids	Proportion of lone parent families with 3 or more children	FS/IA	Matheson et eal., 2012; Statistics Canada, 2019	✓	✓	✓	✓
VFd_LivAlone	Proportion of persons living alone	FS/IA	Matheson et eal., 2012; Statistics Canada, 2019	✓	✓	✓	
VFd_ImmLT5	Proportion of households who have immigrated in last 5 years	FS	Adger 1998, Cutter et al. 2003, Guillard-Gonçalves et al. 2015	✓	✓	✓	✓
VFd_MovedLT1	Proportion population who have moved within last year	FS	Clark et al. 1998, Jones and Andry 2007, Fekete 2009	✓	✓	✓	
VFd_NoWrkPlace	Proportion of population with no fixed workplace	FS	Matheson et eal., 2012; Statistics Canada, 2019	✓	✓	✓	
VAd_AgeGT65	Proportion of population who are 65 years and older	IA	Cutter et al. 2003; Burton 2015; Guillard-Gonçalves et al. 2015	✓	✓	✓	✓
VAdAgeLT6	Proportion children under 6 years of age	IA	Cutter et al., 2000; O'Brien and Mileti, 1992; Hewitt, 1997	✓	✓	✓	✓
VAd_AgeMedian	Median age of population	IA	Cutter et al., 2000; Hewitt, 1997				
VAd_NoEngFr	Proportion population with no working knowledge of English or French	IA	Matheson et eal., 2012; Statistics Canada, 2019	✓	✓	✓	✓
VAd_Indigenous	Proportion of population that identifies as Aboriginal	IA	Matheson et eal., 2012; Statistics Canada, 2019	✓	✓	✓	
VAd_VisMinority	Proportion of population who self-identify as a visible minority	IA	Matheson et eal., 2012; Statistics Canada, 2019	✓	✓	✓	✓
VAd_NoSecED	Proportion of population with no certificate, diploma or degree	IA	Cutter et al. 2003; Burton 2015	✓	✓	✓	✓
VAd_PubTrans	Proportion population who rely on public transit to commute to work.	IA	Cutter et al. 2010; Burton 2015		✓		
VAd_Health	Proportion labour force (15yr+) employed in healthcare/social assistance fields	IA	Hewitt,1997; Puente, 1999		✓		
VHd_Bus_ha	Number of businesses per hectare of settled area	HC	Burton 2015; Cutter et al. 2010; Cardona 2005		✓		
VHd_Pop_ha	Number of people per hectare of settled area	HC	Boruff and Cutter 2007; Birkmann 2007; Guillard-Goncalves et al 2014	✓	✓	✓	
VHd_Renter	Proportion of households that are tenants (or band housing)	HC	Matheson et eal., 2012; Statistics Canada, 2019	✓		✓	✓
VHd__Pre1975	Proportion of building stock that predate modern seismic safety guidelines	HC	Mendes 2009		✓	✓	
VHd_NSuit	Proportion of households living in non-suitable conditions	HC	Matheson et eal., 2012; Statistics Canada, 2019	✓	✓	✓	✓
VHd_Mntn1	Proportion of households with only 1 maintainer income	HC/EA	Cutter et al., 2000; Blake et al., 1994; Hewitt, 1997		✓	✓	
VHd_MntnAge	Proportion of households with primary maintainer either <25 years or > 65 years	HC/IA	Morrow, 1999; Hewitt, 1997		✓	✓	
VEd_IncHshld	Median household income value	EA	Cutter et al. 2003; Cutter et al. 2008; Burton 2015	✓	✓	✓	✓
VEd_IncIndiv	Median individual income value	EA/IA	Cutter et al. 2003; Cutter et al. 2008; Burton 2015	✓		✓	
VEd_ShltrGT30	Proportion of households that spend more than 30% of income on shelter costs	EA	Matheson et eal., 2012; Statistics Canada, 2019	✓	✓	✓	✓
VEn_IncLowDec	Proportion of family income in bottom half of decile distribution	EA	Cutter et al. 2003; Morrow 1999; Burton and Silva 2015	✓		✓	
VEd_Unemployed	Proportion of population (labour force) that is unemployed	EA/IA	Cardona 2005; Sherrieb et al 2010; Cutter et al. 2008	✓	✓		✓
VEd_WorkPart	Proportion of population that worked part time or for only part of the year	EA	Cutter et al., 2000; Blake et al., 1994; Hewitt, 1997		✓		
VEd_WorkNone	Proportion of population 15 and older that did not work in 2015	EA	Matheson et eal., 2012; Statistics Canada, 2019	✓		✓	
VEd_IncEmploy	Proportion of population who receive employment income	EA/IA	Matheson et eal., 2012; Statistics Canada, 2019	✓		✓	
VEd_Retail	Proportion of population that rely on work in retail trade	EA	Cutter et al. 2010		✓		

Themes include: Family Structure (SC);Individual Autonomy (IA), Housing Conditions (HC) and Economic Agency (EA). Methods that incorporate these metrics for use in a Canadian context include the Canadian Index for Multiple Deprivation (CIMD) and model components used in this study, including the baseline inductive social vulnerability index (SVI), the hierarchical capacity threshold index (CI) and neighbourhood vulnerability archetype profiles (NVA).

Figure 2: Demographic variables used to develop social vulnerability model for Canada

hazard threats. They are the means of operationalizing the social vulnerability model and communicating results through the use of maps, charts and tabulated results. Our selection of indicators is guided by questions about who might be impacted by hazard threats for a defined place or region, how this information might be used to inform planning and policy development and the availability of information for model development (See Figure 18).

For this study, we consider a broad range of vulnerability indices that reflect the potential impacts of both high probability/low consequences natural hazard threats which have resulted in significant disaster events over the past several hundred years (severe weather, floods, landslides and wildfire) -- and rare but potentially catastrophic hazard threats that occur over longer time frames and that pose a significant risk to Canadians living in both urban and rural settings (earthquakes and tsunami). Given our focus on actions that can be taken at a local level to reduce vulnerabilities and promote disaster resilience, we have selected a suite of indicators that are relevant at the scale of municipal-level planning using openly available demographic data reported by Statistics Canada at the dissemination area level (Statistics Canada, 2016a). This level of assessment also enables model outputs to be integrated with other dimensions of physical exposure and hazard susceptibility that are used in developing regional and/or national level risk assessments.

Several studies have shown that indicator selection can have a significant influence on the assessment process and resulting patterns of social vulnerability (B Jones & Andrey, 2007; Rufat et al., 2019; Tate, 2012). From an initial compilation and review of more than 60 candidate variables carried out in 2017, we selected a short list of 31 parameters that satisfied the overall model design criteria outlined above (See Table X). Significant omissions include a range of metrics on community health and wellbeing, which are known to be important determinants of vulnerability in the context of natural hazard threats. A suite of relevant health metrics included in a preliminary pilot study for the province of British Columbia were shown to have a significant influence on patterns of vulnerability at the community level. While this information is available through provincial and territorial health authorities and compiled at higher levels of aggregation by Statistics Canada, we were not able to source a consistent suite of metrics at a sufficient level of detail for all regions in Canada. Initial attempts at downscaling these national datasets were also not successful in replicating patterns detected with more granular datasets used in the initial pilot study. In some cases, the inclusion of these generalized measures of health and wellbeing overshadowed other significant measures of vulnerability considered relevant in the broader context of emergency management and disaster risk reduction planning.

Other important limitations of the model include well-known issues of under-reporting by socially marginalized groups in urban settings, and the exclusion of many indigenous communities and smaller settlements from dissemination area level reporting in situations where the global response rate exceeded 50% or where data have been suppressed for reasons of confidentiality (Statistics Canada, 2016a). It is worth noting that parallel and more focused studies of social marginalization carried out in support of the Canadian Index of Multiple Deprivation include many of the same variables and thematic dimensions used to explore patterns of social vulnerability in this study (Matheson et al., 2012; Statistics Canada, 2019; see Table X for details). Additional metrics on settlement patterns and housing characteristics used in the Canadian Index of Multiple Deprivation are covered separately in this study as part of the national physical exposure layer (See Section X).

Step 3: Variable Transformation and Reduction

Methods used to develop baseline values of social vulnerability follow well documented guidelines on the construction of multi-variate indices for inductive and hierarchical SVI models (C. Burton et al., 2018; C. G. Burton & Tourmene, 2017; S. Cutter, L. et al., 2003; Rufat, 2013; Tate, 2012; Yoe, 2002). After verifying accuracy and statistical characteristics of the data, values for missing data are interpolated using an Inverse Distance Weighting (IDW) algorithm and accompanying geospatial modeling tools made available as part of most standard Geographical Information Systems. Variables are then normalized into a common set of values of identical range between 0 and 1 using a MIN-MAX transformation through which a score of 0.0 indicates the lowest rank and a score of 1.0 indicates the highest rank. Indicators are then adjusted with respect to cardinality so that values all have a consistent meaning with respect to our conceptual framing of social vulnerability. It is important to note that higher normalized values represent an increased concentration of a parameter within a standard census dissemination area geometry and do not necessarily correlate with higher levels of intrinsic social vulnerability for a given indicator. Rather, it is the interaction of these variables within the context of a particular place that will determine relative degrees of influence.

Principal Components Analysis (PCA) is used to decompose the full set of parameters into a smaller number of characteristic factors that explain both interrelationships and variance within the data while minimizing the amplifying effects of highly correlated variables. Separate PCA analyses are carried out for each of the eight community archetypes using standard methods of varimax rotation to clarify relationships between the component factors. An eigenvalue threshold of 1.0 or greater to select a final set of 25 indicators considered statistically significant in explaining the majority of variance within each dataset.

While the degree of variance is different for each indicator across the eight community archetypes, a subset of eighteen variables consistently explains ~70% or more the variability within each archetype. Variability across archetypes is most evident for indicators that measure income, age, degree of mobility, housing characteristics and indigenous heritage. These patterns are interpreted to reflect characteristics of remoteness and the degree of socioeconomic influence from metropolitan regions that are inherent to the Statistical Area Classification (SAC) (Statistics Canada, 2016b).

Step 4: Indicator Framework

The standard approach to compare and analyze dimensions of social vulnerability is to aggregate relevant variables from a PCA analysis into a composite index that measures absolute values and spatial differences in magnitude from one place to another. This can be helpful in identifying hotspots of concern that may warrant further investigation at a local level, and in characterizing regional trends that may reflect underlying socioeconomic and/or political drivers of vulnerability. However, there are significant shortcomings in using a single composite index. The most obvious is that social vulnerability is the outcome of a complex set of system interactions that cannot be meaningfully reduced to an absolute value using statistical methods alone (Adger, 2006; Barnett, 2008; Rufat, 2013; Tate, 2012).

A related issue is the challenge of clearly explaining the meaning and significance of an absolute social vulnerability measure in the context of planning and policy deliberations that require a defensible rationale for how best to invest scarce resources in capacity development measures that increase the prospects of recovery and disaster resilience (Oulahen et al., 2015; Rufat, 2013; Rufat et al., 2019). An effective way of mitigating this challenge is to engage with practitioners at the beginning of the process to co-develop an index that reflects a shared understanding of model variables and intended outcomes (Bankoff et al., 2004; Barnett, 2008; Frazier et al., 2013), and to use context-specific weighting schemes that reflect local knowledge about the relative importance of specific dimensions of vulnerability in their community and their distribution from place to place (Greiving, 2006; Oulahen et al., 2015; Stern & Fineberg, 1996).

A shift from absolute to relative measures of vulnerability is one of several approaches taken in this study to increase transparency and help make evident the contributing influences and spatial relationships between dimensions of vulnerability that can interact in complex ways to either increase or decrease capacities to withstand and recover from a disaster event. (Adger et al., 2004; Blaikie et al., 1994; J. Chakraborty et al., 2005; Matheson et al., 2012; Mileti, 1999; Rufat, 2013; Turner et al., 2003). Rather than aggregating values into a composite index score, indicators are grouped into thematic pillars that reflect an understanding of likely causal effects. This allows both an interrogation of individual indicators within any particular dimension, and a comparison of relative performance metrics across dimensions. More importantly, a focus on relative vs absolute measures is more likely to encourage an exploration of why some places and population groups are more vulnerable than others -- and strategies that might be considered to inform investments in mitigation and capacity development.

Dimensions of Social Vulnerability

Baseline model outputs are used to explore relative dimensions of social vulnerability through the lens of social capital, individual autonomy, housing conditions and financial agency (Figure 19). Although one of many possible configurations, the choice of these particular dimensions and the arrangement of corresponding indicators reflect general aspects of vulnerability that are likely to be relevant at different stages of the disaster risk management cycle.

Social Capital reflects characteristics of household size, family characteristics, mobility and regular workplace relationships that are relevant for assessing capacities to anticipate and withstand the immediate impacts of a hazard event. These variables are common to many social vulnerability assessment frameworks (S. Cutter, L. et al., 2003; S. L. Cutter et al., 2008; S. L. Cutter et al., 2016; S. L. Cutter et al., 2010; Oulahen et al., 2015)

Individual autonomy encompasses characteristics of age, literacy, language barriers and socio-political capital that can influence capacities to both withstand, evacuate from and respond to the impacts of a hazard event (C. G. Burton & Silva, 2015; J. Chakraborty et al., 2005; S. L. Cutter et al., 2010). These indicators are also relevant in the context of evaluating dimensions of marginalization and social disadvantage (Matheson et al., 2012; Statistics Canada, 2019).

Housing conditions reflect the dimensions of ownership, population density, suitability of accommodation and relative capacities for maintenance and upkeep of physical assets. These are important when considering the effects of social disruption and household displacement in the weeks and months following a disaster event (S. L. Cutter et al., 2010; Matheson et al., 2012; K Tierney, 2006; Kathleen Tierney & Oliver-Smith, 2012) and will influence capacities for functional recovery.

Economic agency reflects the relative capacities of individuals and groups to take actions on their own behalf following a disaster event to arrange

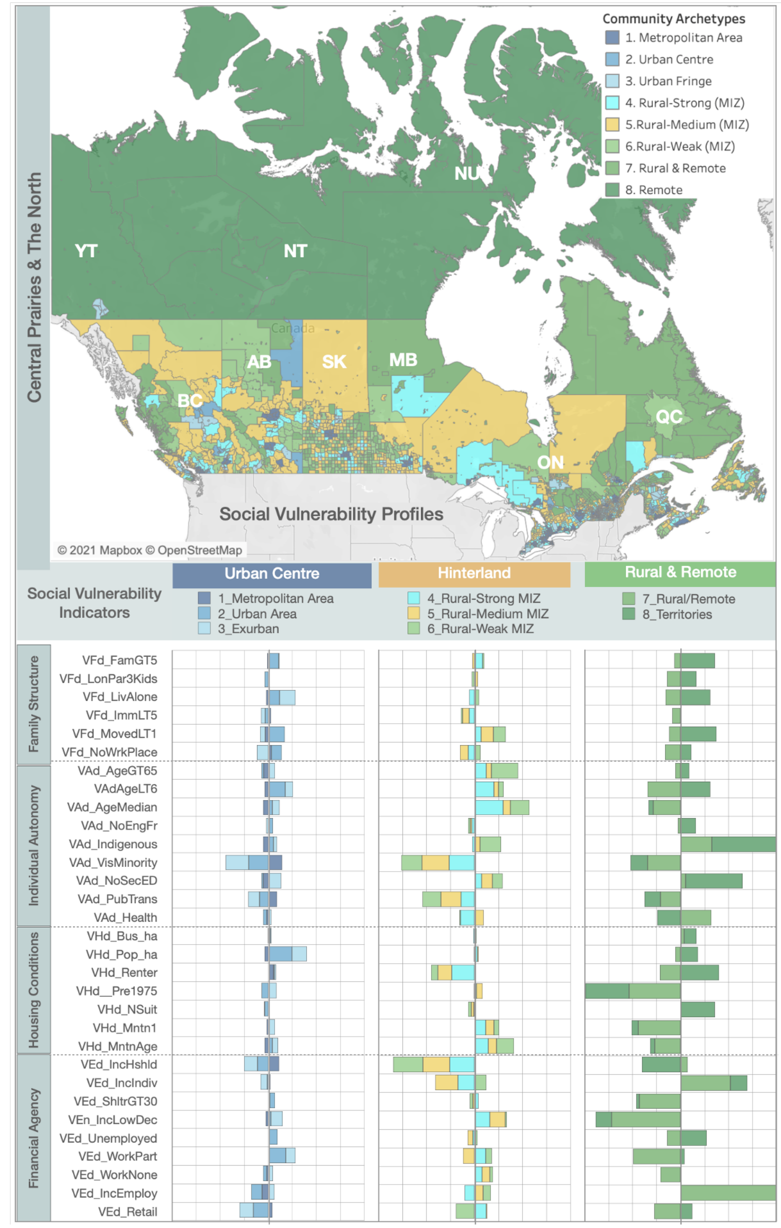


Figure 3: Social vulnerability profiles for representative community archetypes in Canada

for safe shelter, emergency supplies and to repair/replace capital assets that may have been damaged as a result. These indicators are often included when describing dimensions of economic capital or resilience (Blaikie et al., 1994; S. Cutter, L. et al., 2003; S. L. Cutter et al., 2008; Rose, 2004, 2016), and provide important insights on the potential downstream consequences of financial vulnerabilities during later stages of the recovery process.

Each dimension of the indicator framework serves as a prism of sorts, separating the overall measure of vulnerability into component parts that collectively represent a spectrum of unique characteristics for a particular place. We examine these threads of social fabric through the lens of broad community archetypes defined as part of the Statistical Area Classification (SAC) and corresponding physical characteristics of land use that describe the urban form of settlements across Canada. The integration of built environment and social fabric indicators helps to identify hotspots of concern across various scales of interest, and more directly addresses the question of why some communities are likely to be more vulnerable than others.

The resulting indicator profiles measure relative values of social vulnerability at the dissemination area level for each of the major community archetypes as a function of proximity to neighboring metropolitan areas, and the degree of influence by underlying socioeconomic and political forces that are unique to each province and territory. Differences in the relative dominance of vulnerability measures between community archetype are evaluated by comparing characteristic indicator values with respect to the national average (See Figure 19).

Metropolitan areas are characterized by densely populated urban centres with enveloping suburban and exurban regions that collectively account for ~77% of all dissemination areas in Canada. Dimensions of the social fabric that are relevant in this context include people living alone, those who have recently moved into the city, concentrations of visible minorities and lower income families in dense urban centres and higher than average rates of unstable employment.

The Canadian hinterland covers a broad geographic region and encompass rural communities of varying size that collectively account for ~20% of all dissemination areas in Canada. Rural communities are characterized by the degree of remoteness and corresponding levels of socioeconomic influence from neighboring population centres. Dimensions of social fabric that are more dominant in this context include increased numbers of people who have recently moved into the region and who may not have a strong sense of place, higher than average concentrations of elderly homeowners and indigenous populations, older homes with more limited capacity of residents to invest in maintenance, lower than average education levels and an increased number of lower-income families with unstable employment.

Rural and remote regions of Canada include sparse settlements along the coastline and interior portions of the northern territories that collectively account for the remaining ~3% of dissemination areas in Canada. Relevant characteristics of social fabric in these regions include significantly higher concentrations of indigenous communities, extremes in family structure that can influence social connections, lower overall levels of secondary education, and significantly lower levels of income and employment insecurity.

While these national comparisons are useful in understanding socioeconomic factors that can influence social vulnerability in different contexts, it is the convergence of vulnerability measures within each of the community archetypes that ultimately offer insights on relative capacities to withstand and recover from future disaster events. For example, the factors that influence patterns of social vulnerability in a dense urban setting will be different than those affecting rural and remote communities. Understanding the nuances of vulnerability profiles for a specific community type and how they vary from one region to another (similarities and/or differences) are important considerations for planning and policy development (C. Burton et al., 2018; Chang et al., 2018; Rufat et al., 2019).

Relative patterns of social vulnerability for each of the eight community archetypes can be measured using a combination of exceedance thresholds and vulnerability profiles that reflect the degree of influence

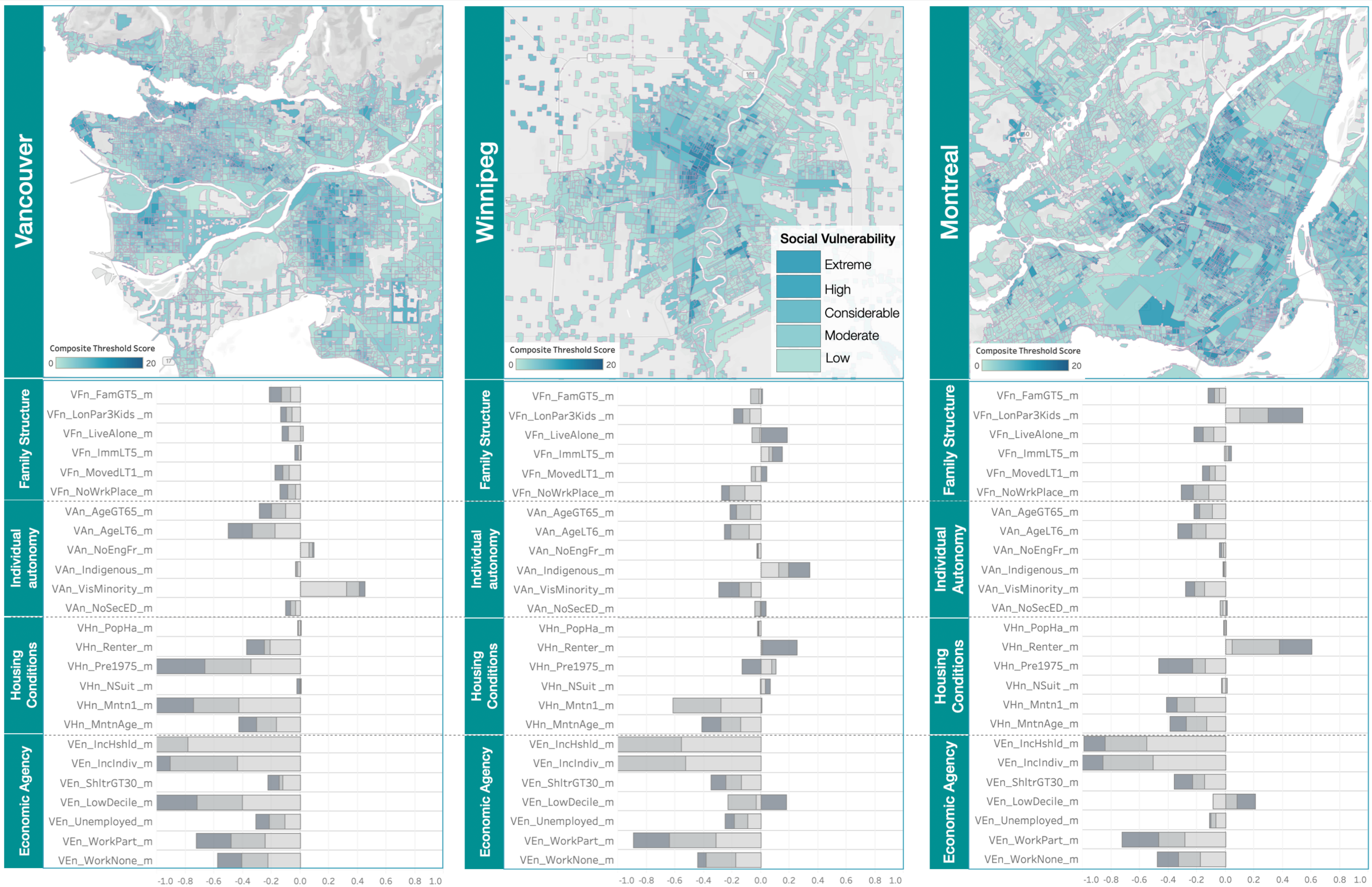


Figure 4: Social vulnerability profiles for representative urban centres in Canada

of local knowledge about the relative capacities of specific population groups, vulnerability thresholds are evaluated by assigning a threshold score of +1 to indicator measures that exceed the mean value plus one standard deviation. Indicator values that fall below this reference threshold are assigned a score of -1. This preserves overall framing of model results around the concept of vulnerability for a given community type and provides important insights into pre-existing conditions of social systems that can determine both the extent of physical exposure to hazard threats and the degree to which members of a community may suffer harm as a result.

Positive threshold scores reflect levels of social vulnerability that are considered above average for a given community archetype. They can be mapped separately to investigate vulnerability measures of interest and/or aggregated into composite indices to explore the contributing influence of family structure, autonomy, housing conditions and economic agency on the overall profile of vulnerability for a community or region (See Figure 19). The degree of interaction that any one measure has on the overall profile of social vulnerability can be explored in more detail by multiplying normalized baseline values (ranging from 0 to 1) by the corresponding threshold score of +1 or -1. Positive values show relative contributions for each indicator that tend to increase the overall profile of social vulnerability, while negative scores reflect increasingly lower degrees of influence.

Figure 20 provides an example of how this approach might be used to explore similarities and differences in social vulnerability between the greater metropolitan areas of Vancouver, Winnipeg and Montreal. The maps are based on composite threshold scores and are used to highlight regions in each metropolitan area where multiple dimensions of social vulnerability overlap. The accompanying profiles plot the relative degree of influence for each of the contributing vulnerability measures with respect to mean values for all metropolitan regions of this type across Canada.

Areas of increased vulnerability to natural hazards in the Metro Vancouver region occur in the West End and Eastside neighbourhoods of downtown Vancouver, in the Kingsway Corridor region of Burnaby and New Westminster, western regions of Surrey and northwest regions of Richmond. A deeper dive into the component threshold maps for the same area reveals the contributing influences across all four dimensions of vulnerability (See Figure 20). As is characteristic for densely populated urban regions of this type across Canada, the primary determinants of vulnerability include family structure, people who have recently moved into the city, higher concentrations of visible minorities and lower income families with unstable employment. The corresponding vulnerability profiles highlight additional factors in Vancouver that are above mean threshold values for metropolitan regions of this type. These include higher concentrations of visible minorities and people without knowledge or capacity to communicate in either of the official languages. The patterns are consistent with other studies of social vulnerability in the Metro Vancouver region and input received from practitioners working on the ground who understand the local neighborhood-level context and how these characteristics are likely to influence capacities to withstand and recover from future disaster events (Andrey & Jones, 2008; Oulahen et al., 2015).

Characteristics of social vulnerability are similar in the Winnipeg area, but concentrated in smaller geographic regions of the downtown core and along major transportation corridors leading into the city. This is particularly evident when evaluating overall threshold scores through the dimensions of economic disadvantage and family structure. Additional factors that are specific to the Winnipeg metropolitan area include higher proportions of people living alone, recent immigrants, indigenous populations, renters and low-income families. Although the focus of this study is on vulnerabilities to natural hazards, the overall profile is consistent with independent studies of social inequity carried out as part of a national index on marginalization in Canada (Matheson et al., 2012; Statistics Canada, 2019).

Composite vulnerability threshold scores are generally higher for most areas in Montreal area with hotspots located in the central, southwest and northeast regions of the city. The patterns reflect a more complex set of intersections across the various dimensions of social vulnerability with primary drivers including lone parent families with three or more children, tenants living in rental housing and higher concentrations of older buildings and family incomes in the lower half of the decile distribution. The patterns of economic agency and housing conditions are similar to those documented in the Winnipeg area. However, characteristics of family structure and individual autonomy in Montreal appear to be distinct from other urban regions of this type. These patterns are again consistent with the findings of studies that focused more specifically on determinants of social inequity across Canada (Matheson et al., 2012; Statistics Canada, 2019).

A Neighbourhood Profile of Vulnerability

We shift the focus in this section from place-based approaches that evaluate and compare levels of social vulnerability from the perspective of a community or region to a more specific assessment of neighborhood-level vulnerability archetypes that evaluate underlying drivers of vulnerability from the perspective of those most affected. This is a subtle but important shift in perspective. Re-framing the context of analysis in this way has the potential to bridge top-down quantitative approaches of measuring levels of social vulnerability with bottom-up qualitative approaches that reflect local knowledge and understanding of the many ways in which a particular community can be vulnerable to natural hazards and underlying causal factors.

This is particularly relevant for prioritizing planning and policy development efforts around those neighborhood archetypes that are likely to bear the greatest burden of risk, and the specific capacities and/or additional services they may need to enhance disaster resilience and related prospects of functional recovery. Our contribution to this emerging field of research is based on a pilot study carried out for the province of British Columbia. The study builds on and contributes to outputs of the national social vulnerability model described in previous sections. It also provides an opportunity to evaluate the usefulness of this approach in other regions of Canada where there may be potential to work with practitioners in bridging the gap between top-down and ground-up approaches to social vulnerability assessment in support of both disaster risk reduction and climate change adaptation.

Our assessment of neighborhood-level vulnerability archetypes uses machine learning and related pattern recognition techniques to detect and characterize relationships between distinct population groups and corresponding patterns of social vulnerability (Yip & Journeay, 2020). The methodology is similar in principle to hierarchical clustering techniques used in other equivalent studies of social vulnerability profiles (C. Burton et al., 2018; Chang et al., 2018; Rufat, 2013; Tuccillo & Buttenfield, 2016). Eight distinct neighborhood archetypes are defined based on a subset of twelve vulnerability measures from the national model (See Table X). Each dissemination area in the province of British Columbia is then assigned to one of the eight characteristic neighborhood archetypes based on similarity.

A subset of model results for the Lower Mainland region of southwest British Columbia is shown in Figure 21 along with a brief description of each neighborhood archetype. The map shows the distribution of neighborhood archetypes, while the corresponding bar charts profile the relative influence for each of the principle social vulnerability measures. Degrees of influence are measured with respect to provincial averages and associated standard deviations for each of the vulnerability measures. The results provide an additional dimension for interpreting broad patterns of vulnerability that were identified using capacity threshold scores (See Figure X). For example, there are spatial correlations between areas of higher vulnerability and concentrations of neighborhood types that are characterized by economic, social and housing insecurities, recent immigration into the city and high levels of racial and linguistic diversity.

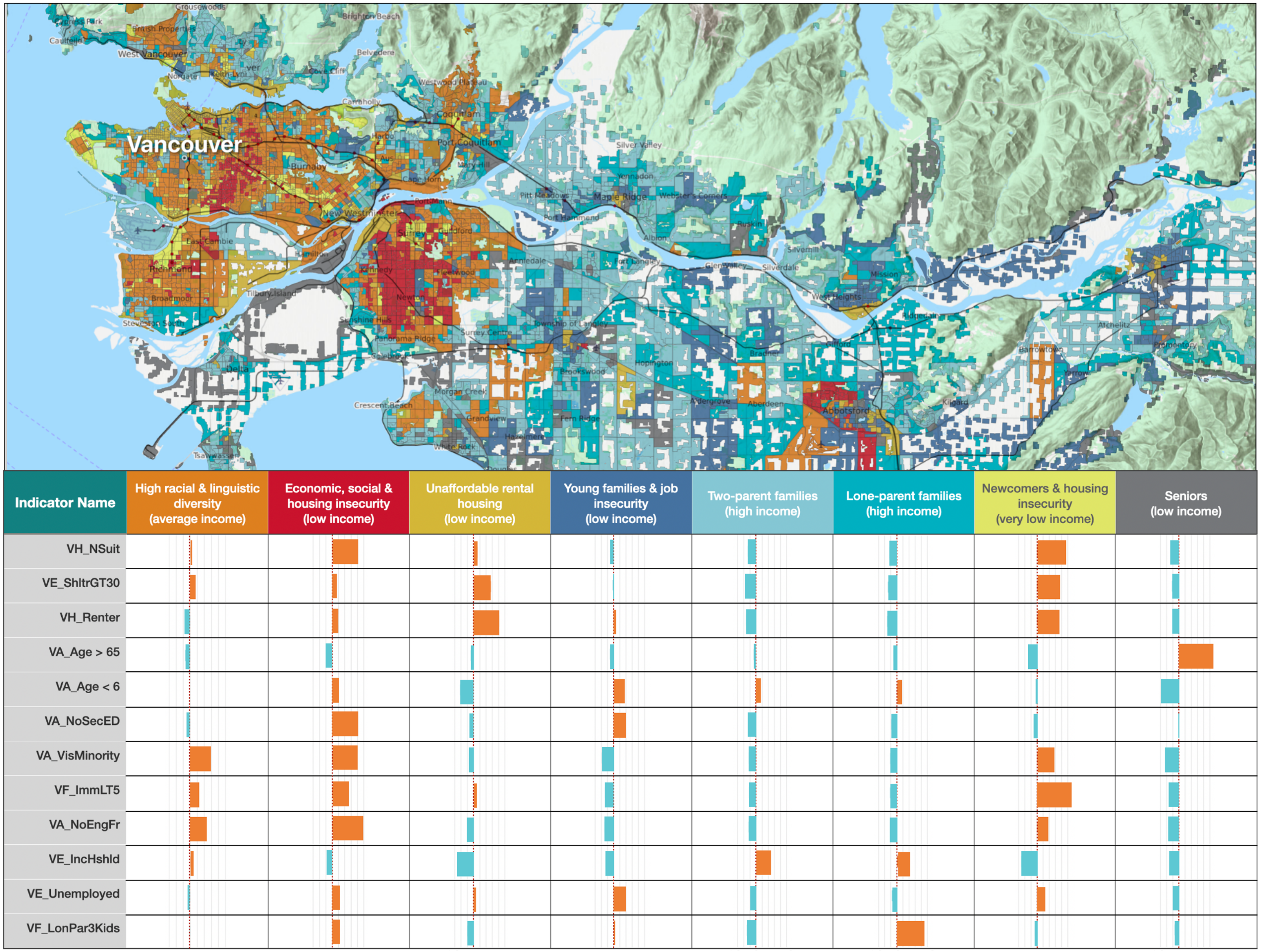


Figure 5: Neighbourhood archetypes for the Metro Vancouver region of southwest British Columbia

While the spatial patterns may be evident, specific measures of vulnerability will have different implications for each of the neighborhood archetypes depending on the type of hazard impact and associated downstream socioeconomic consequences. The profiles provide important insights to assist emergency managers and community planners in undertaking more detailed follow-up studies of specific neighborhood types to determine what resources and/or services may be needed by different population groups to increase capacities to withstand and recover from a disaster event. The goal is to anticipate who is likely to bear the greatest burden of risk and to prioritize scarce resources accordingly to promote disaster resilience of the community overall.

The potential of using neighborhood vulnerability archetypes to prioritize disaster resilience planning efforts is explored here in the context of a damaging earthquake scenario for our model community of Arcadia (See Figure 22). For context, Arcadia is a medium-sized community of ~184,500 people centered around an historic downtown business district that serves as an important link in the overall supply chain for the distribution of goods and services (Figure X).

The built environment is characterized by a mix of multi-family apartment complexes surrounding the downtown core with medium density residential developments clustered within an enveloping fabric of single-family neighbourhoods (Figure X). Primary hazards of concern for the community include riverine floods, wildfire and earthquakes. Of these, earthquakes pose the greatest risk with a potential for concentrated building damage, sustained social disruption during the recovery process and significant economic losses that would threaten economic security of small and medium-sized community businesses. Hotspots of damage and related losses are expected to be concentrated in the downtown core where there are higher concentrations of older buildings that predate modern seismic design codes.

From the perspective of social fabric, Arcadia is similar in demographic profile to other medium-sized Canadian municipalities situated in urban fringe areas. It is characterized by moderate levels of socioeconomic diversity with nearly half of all neighborhood archetypes (45%)

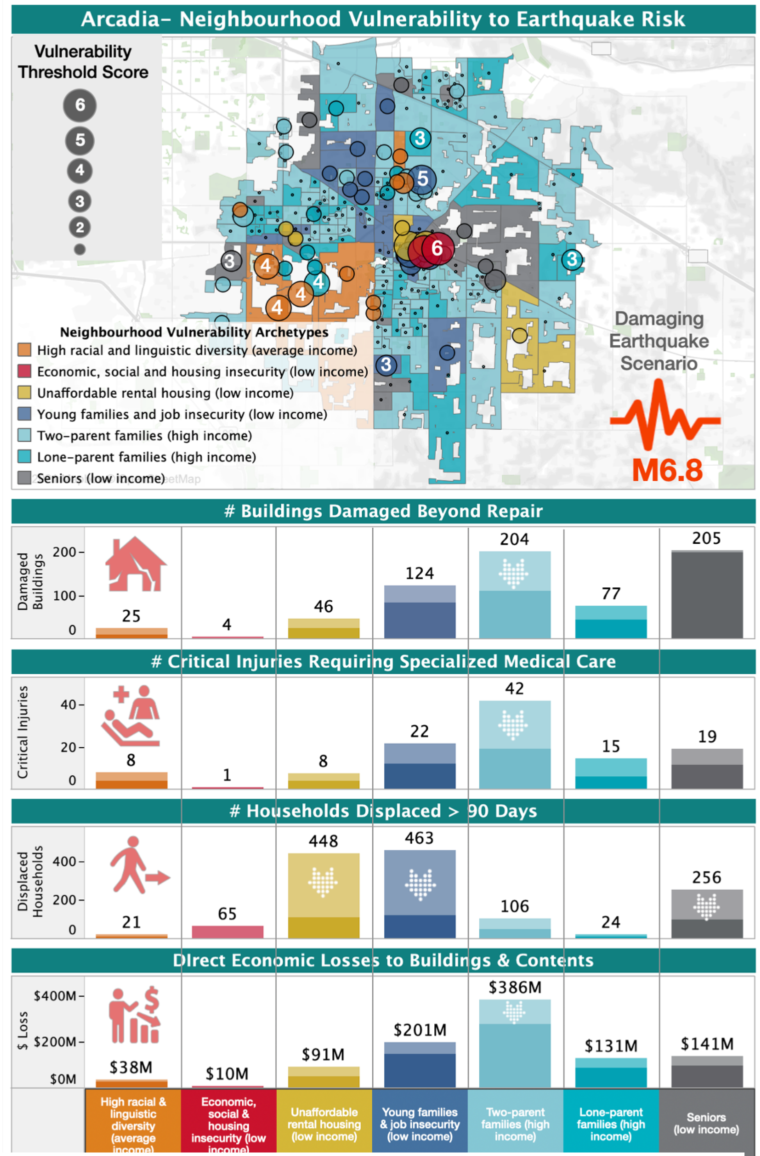


Figure 6: Neighbourhood vulnerability archetypes for the reference community of Arcadia

represented by two-parent family households of moderate and high income. Other dominant neighborhood archetypes include young families with lower income and unstable employment profiles (~20%) living in the downtown core and multi-family residential neighbourhoods, and seniors who have chosen to retire in Arcadia (~12%). Neighbourhoods characterized by unaffordable rental housing and lower income families (~9%) are also concentrated in the downtown area. Neighbourhoods of higher racial and linguistic diversity and average income represent ~3% of the total and occur in low-density residential areas in the southwest quadrant of the community.

Given the distribution and characteristics of neighborhood archetypes in Arcadia, emergency planning for initial stages of earthquake response would likely focus on the needs and requirements of families and seniors in the downtown core area. These would include both lower-income young families living in older condominiums and higher-income two-parent families in attached duplex, rowhouse and apartment complexes. These neighbourhoods would bear a disproportionate burden of the immediate physical impacts of earthquake damage with a particular concern for injuries to younger children and elder members of the community. Other areas of concern during these early stages of would include those neighbourhoods of higher racial and linguistic diversity where language barriers may present additional challenges for emergency response efforts.

Planning for sustained response and recovery stages would likely focus on emergency shelter requirements of younger families, seniors and others living in unaffordable rental housing who would likely be displaced for weeks and possibly several months following the earthquake event. The downstream economic impacts of the earthquake, including both loss of capital assets and disruption to employment income, would affect all neighbourhoods but in different ways. Building repair and replacement costs would be of primary concern for homeowners in higher income neighbourhoods, although much of this loss could be mitigated through proactive investments in seismic retrofits and/or earthquake insurance. Economic losses caused by employment disruptions and additional shelter costs incurred as a result of sustained household displacement would be a particular burden on lower income young families already managing job insecurity and those living in unaffordable rental housing.

The integration of neighborhood vulnerability profiles with outputs of a quantitative risk model provides important insights on who is likely to bear the burden of physical impacts and related socioeconomic consequences, the underlying causal factors, and strategies that might be considered to increase capacities of different neighborhood groups to both withstand and recover from future disaster events. This approach also establishes the necessary framework for evaluating the societal benefits of proactively investing in physical mitigation and/or adaptation measures in the broader context of sustainable community planning and development.

In many cases, the ancillary community benefits of investing in risk reduction measures far outweigh the financial costs. Strategic investments in seismic retrofit measures and/or redevelopment opportunities would not only make good sense from a business perspective but would also be effective in addressing underlying issues of social vulnerability for specific neighborhood groups. In our case study example of Arcadia, these would include lower income families living with housing and/or job insecurity, and seniors. While the context and characteristics of social vulnerability will be different for each community across Canada, the outputs of this study provide a framework to increase awareness and understanding of underlying causal factors and to inform strategies for disaster risk reduction.

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