International Journal of Disaster Risk Reduction 43 (2020) 101394

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: http://www.elsevier.com/locate/ijdrr

A place-based socioeconomic status index: Measuring social vulnerability to flood hazards in the context of environmental justice

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A R T I C L E I N F O

Keywords:
Socioeconomic status (SES) index
Vulnerability
Social inequality
Environmental justice
Flood risk management
Risk assessment

A B S T R A C T

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-important 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 components analysis. Our data revealed 11 statistically-significant multidimensional factors, which together explained 80.86% 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 across 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 scores 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.

1. Introduction

A combination of climate change, urbanization, population growth, and economic development have amplified flood risk in terms of augmented loss and damages [1]. 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 [2]. A better understating of socially-vulnerable communities and the flood risks they face is critical in developing schemes for societal response to flood disasters[1] and recovery mechanisms [3], identifying the fundamental root causes of vulnerability [4], and addressing the social indicators of flood vulnerability [5].

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 [6]. 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" [7]. Recognition of the places where the most socially vulnerable communities are located and their exposure to flooding (i.e., addressing geographic flood disadvantage) is a prerequisite to delivering a socially-just FRM approach [2]. 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 [8]' within FRM investment decisions [9].

Identification of geographic flood-disadvantaged communities or most vulnerable neighbourhoods provides further insights for the

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[1] 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" [80].

https://doi.org/10.1016/j.ijdrr.2019.101394
Received 24 July 2019; Received in revised form 18 October 2019; Accepted 12 November 2019
Available online 15 November 2019

distributional justice discourses within environmental planning and FRM decision-making processes. Distributional justice outcomes in FRM [9,10]—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[2] in human ecology [11,12]. 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 [13]. 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 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 [14].

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) [15]. 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 [16]. Communities with a higher SES index score are less vulnerable to environmental hazards and more resilient in coping with natural disasters [17,18]. 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 [19]. 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 [20].

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) [21]. 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,[3] CMA,[4] 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 outcomes 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. 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 natural hazards. This identification constructs a knowledge base that can enable more targeted solutions and strategies for effective mitigation and increasing future social capacity and resilience [20]. Social vulnerability emphasizes inequities in sensitivity and exposure (social equity) resulting from social-structural characteristics [22,23]. 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 [24], which led to the Social Vulnerability Index (SoVI), an empirical relative measurement of the social vulnerability of places [5]. 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 [25].

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 [7]. 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 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 [26]. Considering the EJ outcome, researchers in the United States and the United Kingdom have found that the most vulnerable groups to flood hazards consist of people who are poor, minorities, the elderly, children and the disabled [11,26–30].

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 [31]. 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 [26,32]. 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) [33]. 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 [30,34,35].

A few empirical studies have attempted to find the indicators of community and residential vulnerability to flood hazards [38–41]. However, it is still unclear whether people with different ethnic backgrounds, visible minorities, foreign-born, newly settled immigrants, Aboriginal Peoples, and Indigenous Peoples are among the most socially

[2] 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 [81].

[3] "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" [82].

[4] "A census metropolitan area (CMA) or a census agglomeration (CA) is formed by one or more adjacent municipalities centred on a population centre (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" [82].

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 hazard to major cities and urban residential neighbourhoods over the past two decades [36,37].

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 [38]. 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 [39]. Another study [42] 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 [43].

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 [5], 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) [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 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 focuse 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 (i) 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.

3. Data and methodology

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 in order 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.

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 vulnerability 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 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 [16,19,39,44–46].

3.2. Construction of the Canadian SES index

The paper adopted the Principal Components Analysis (PCA) tool to construct the SES index. In a multivariate context, PCA is a well-established data reduction technique developed by Pearson [47] and Hotelling [48]. 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 [49].

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 [50]. 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 [19,51–53]. 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 [54]. Fig. 1 depicts the detailed steps involved in the SES index construction.

4. Assessment and interpretation of PCA results

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 [55]. 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.

Table 1
Social vulnerability indicators and description of variables.

SoVI Indicators	Variable[a]	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[b]	Population with the first-generation status
	Foreign-born Canadian citizens	Canadian citizens not by birth
	Aboriginal Peoples[c]	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[d]	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
	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[e]
	Income	Median per capita income of census family for all persons aged 15 or older[f]
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

[a] 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.

[b] "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" [82].

[c] "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" [82].

[d] The Employment Equity Act defines visible minorities as 'persons, other than Aboriginal peoples, who are non-Caucasian in race or non-white in colour' [82].

[e] 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.

[f] 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.

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 [56]. 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, the CTs 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) [57].

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 [58]. 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 to 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 [59], 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 [57]. 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 [60]. 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

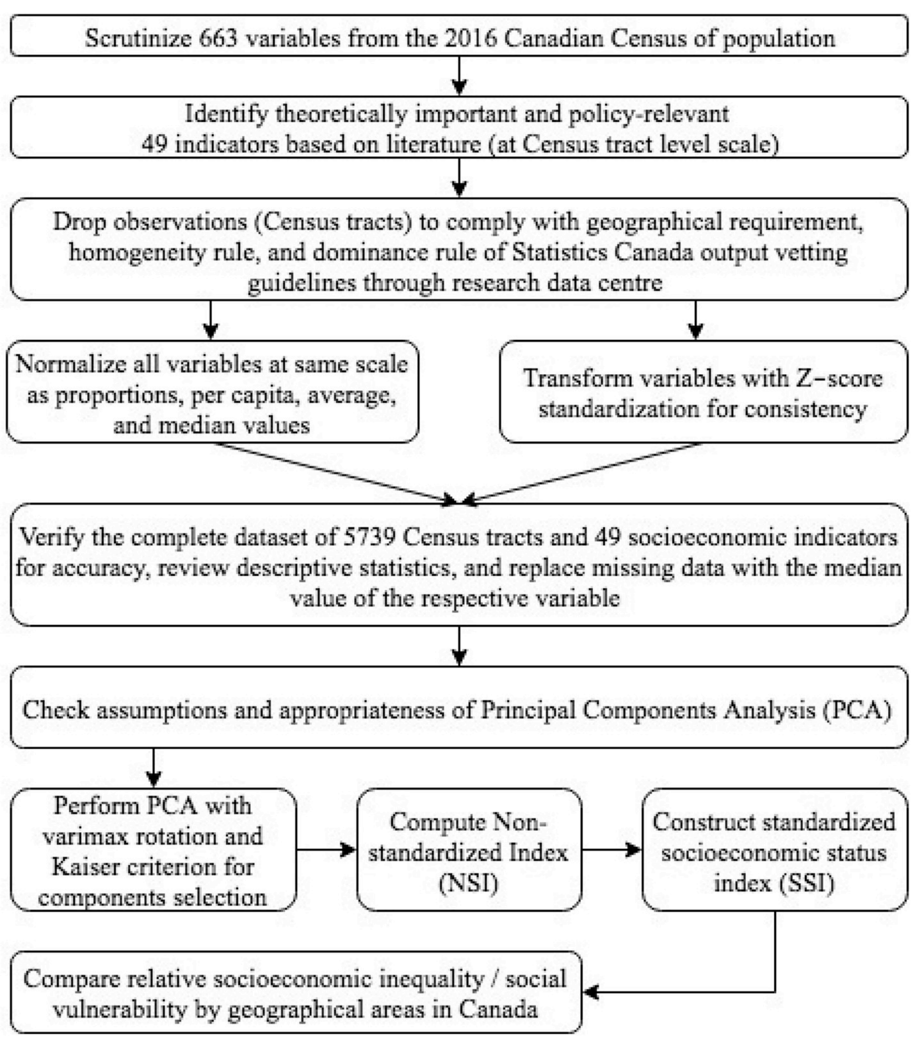

Fig. 1. Steps of the Canadian SES index construction.

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 [61]. 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 [62] 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.

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 [63] Scree plot was used as a graphical method to determine the number of factors (Fig. 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.

Factor rotations are usually helpful to facilitate the interpretation of the factors [64] and to reveal the *simple structure* (making the pattern of loadings more transparent, or more pronounced) [65]. The literature on the 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 [57]. 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 [66]. The results of promax rotation indicated a strong pattern of loadings and a simpler structure as suggested by Thurstone [65] in a sense that none of the variables have loadings above 0.30 on two or three factors at the same time [66]. 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 [57]. Component loading scores on individual variables are reported in Table 2.

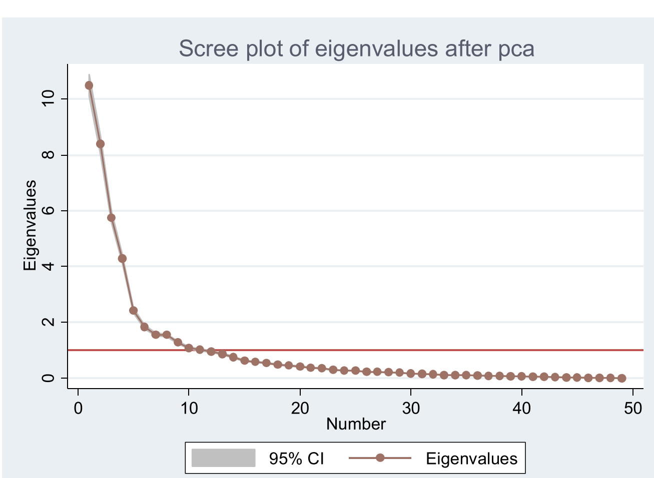

Fig. 2. Scree plot of eigenvalues of components.

The PCA with varimax rotation and the eigenvalue rule revealed 11 components, which together explained 80.86% 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% of the variance, respectively (Table 2). The first component accounted for 14.12% 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.

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 (i) 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 [67]. 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:

$$NSI_j = \sum_{i=1}^{11} W_i * PC_i \tag{1}$$

where,

$$W_i = \frac{Proportion\ of\ Variance\ for\ Factor_i}{Total\ Variance\ Explained}\ ; i = 1,\ 2,\ \ldots\ldots\ldots,\ 11 \tag{2}$$

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 [25]. The NSI index measures the SES of one geographical place (census tract in our data) relative to the other place on a linear scale [68]. 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 0–100, and are calculated using the following formula for census tract j [21,68]:

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

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

Table 2
Results of PCA: Component rotation matrix.

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7	Comp 8	Comp 9	Comp 10	Comp 11
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 [21].

socioeconomic status of a geographical place [21]. 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 [17,69].

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 [70]. 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 [71]. 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 [72]. 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 is 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.

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 [73]), we tested whether the SES index scores were normally distributed across CMAs and provinces/territories in Canada. Each dot above the boxes in Fig. 3 represents a higher SES index score corresponding to a CT. Numbers in the horizontal axis indicate provinces (1–10) and territories (11–13) in panel (a), whereas numbers (1–50) in the panel (b) represent 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 (Fig. 3). 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

[74]. 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.

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 [75]. 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 (Fig. 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 Fig. 4 visualize the spatial disparities of the SES scores on the three CMAs at the CT level.

Table 3 reports a ranking of the mean SES index scores by CMAs, and Table 4 discloses a ranking of the mean SES scores by province/territory, where the ranking value of "1" suggests at 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 [21]. We found that the difference in mean SES index scores between Oshawa and Toronto CMA

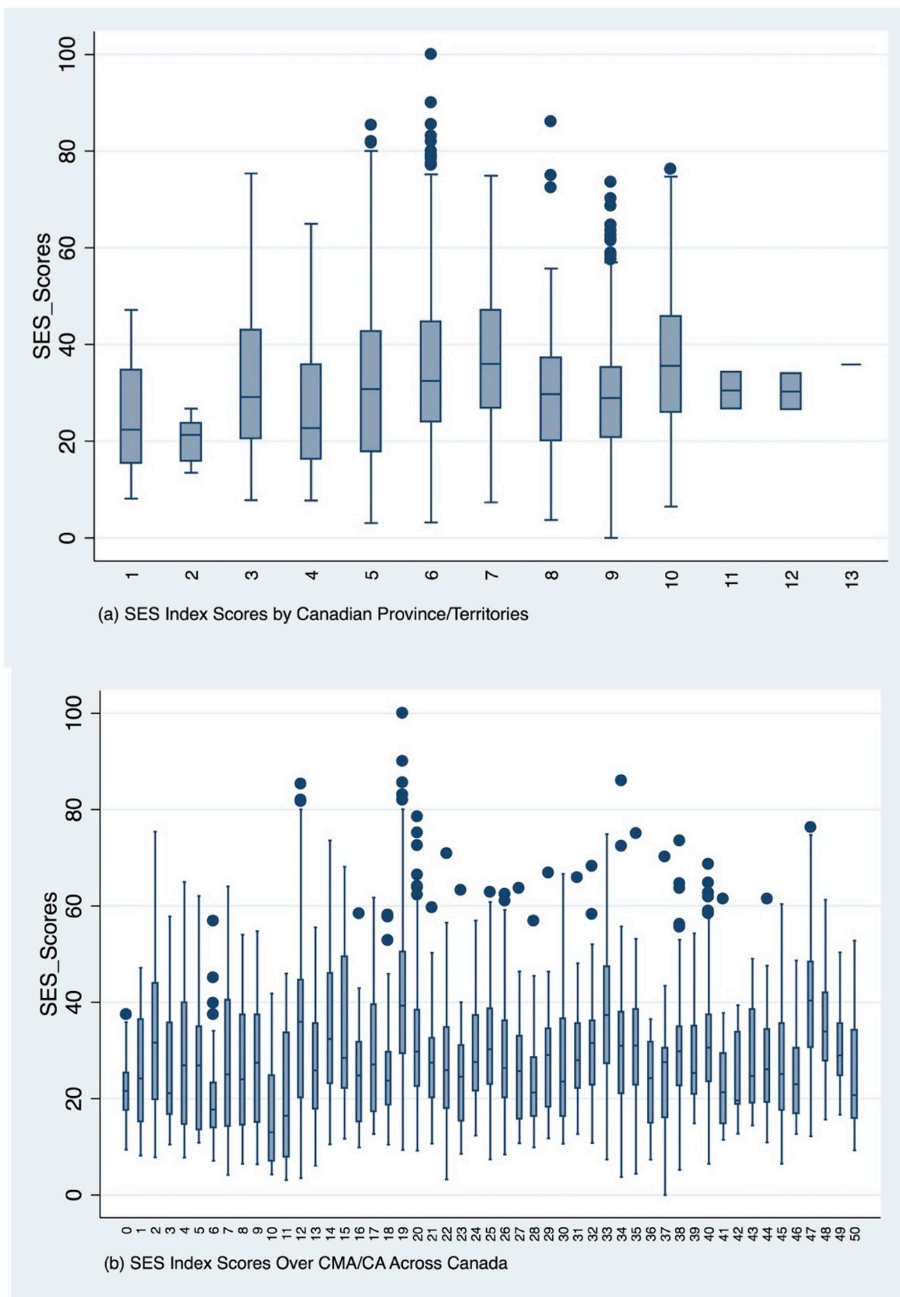

Fig. 3. Box plots of the SES index scores by CMA and Provinces/Territories.

as well as between Abbotsford – Mission and Vancouver CMA were higher than any other neighbouring CMA (Table 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 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 (Tables 3 and 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 [21,76]. 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.

5. Findings and conclusion

Place-based social vulnerability assessments at a small scale help identify places of high vulnerability [77] and aid in the planning processes of GIS-based environmental risk assessment [6]. 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

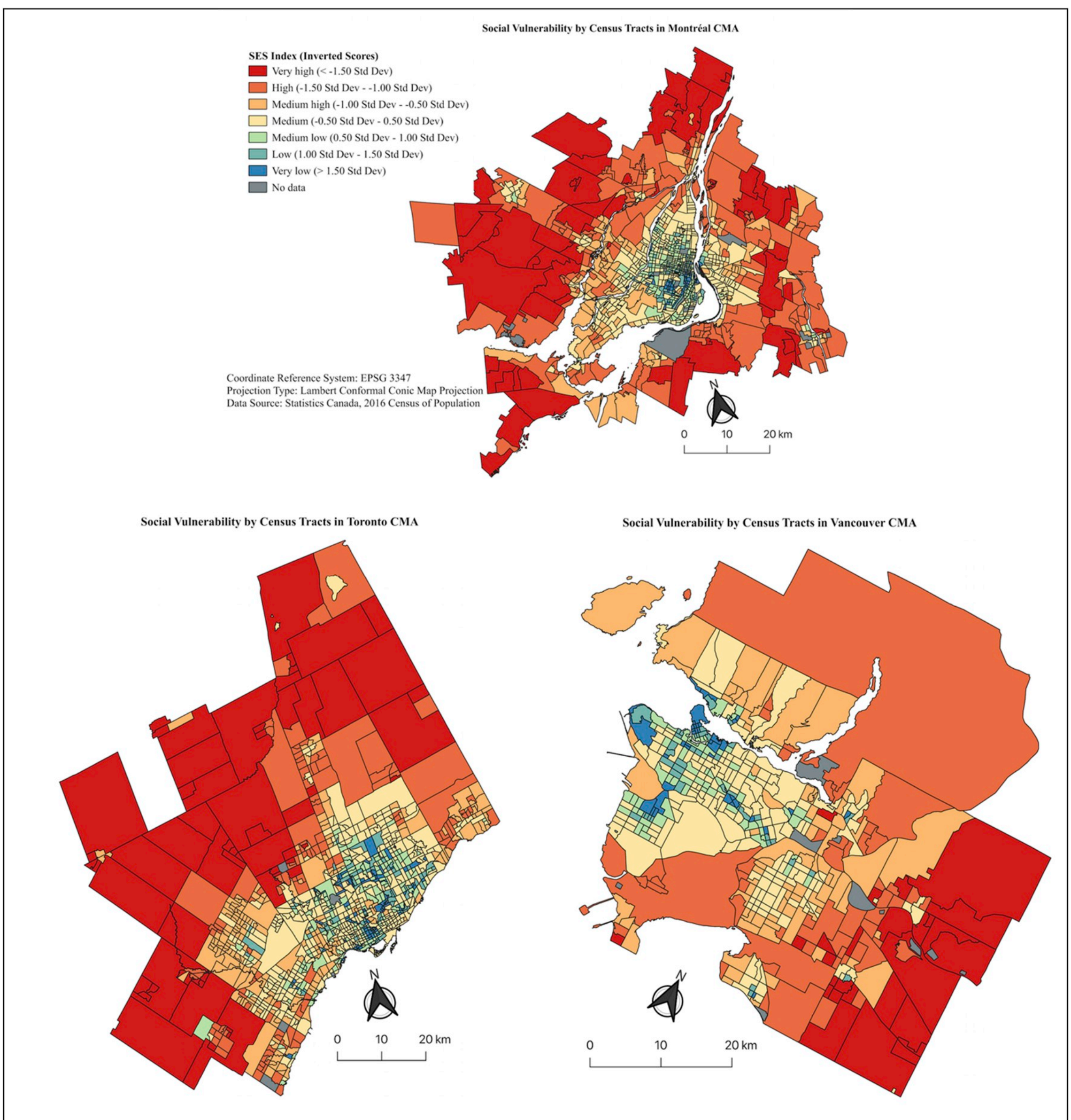

Fig. 4. Spatial variability of the SES index scores on Canada's three largest CMA.

Table 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 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

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 [19]. 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 [78]. 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 [26].

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 [2].

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 metres), 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 [5]. However, a number of 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 vulnerability between geographical places, but it cannot be utilized for understanding any absolute levels of socioeconomic and cultural attributes within a community [21]. 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) [79].

Nevertheless, the current study emphasizes a number of 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 [5].

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 [54]. 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.

Acknowledgement

The analysis presented in this paper was conducted at the South-Western Ontario Research Data Centre (SWORDC), which is a part of the Canadian Research Data Centre Network (CRDCN). The services and activities provided by the SWORDC are made possible by the financial or in-kind support of the Social Sciences and Humanities Research Council of Canada, the Canadian Institutes of Health Research, the Canadian Foundation for Innovation, Statistics Canada, and the University of Waterloo. The views expressed in this paper do not necessarily represent those of the CRDCN or its partners. We are also indebted to Dr. Pat Newcombe-Welch for her helpful comments to meet Statistics Canada RDC output vetting rules and guidelines, and to Andrea Minano for her support to clearly understand Canadian flood hazards extents data that helped us resolve cross-scale problem in the GIS-based SoVI mapping for flood risk assessment.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2019.101394.

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