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When and How to Use Area-Level Measures for Health Analysis: A Review and Recommendation Report

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When and How to Use Area-Level Measures for Health Analysis: A Review and Recommendation Report

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Abstract

There has been growing interest in recent years to understand social and health inequalities in Canadian neighbourhoods using a variety of area-level measures. This report defines key concepts related to area-level analysis and introduces area-level measures developed and utilized at Statistics Canada for health analysis. It also provides a decision-making framework and practical recommendations to help researchers select appropriate methods. The goal is to guide readers on when area-level analysis is appropriate and what type of area-level measure is suitable to achieve research objectives. The report emphasizes that area- and individual-level measures are distinct constructs that independently influence health outcomes. While moderately correlated, they provide complementary perspectives, with their effects shaped by population demographics and neighbourhood context. The findings support the strategic use of area-level measures to enhance research quality and guide evidence-based decision-making.

Key words: methodology, area-level measure, inequality, level of analysis, decision framework

1 Introduction

In recent years, interest has grown in using area-level data analysis to better understand social and health inequalities in Canadian neighbourhoods. This method relies on aggregated data at geographic or administrative levels (e.g., neighbourhoods, postal codes, dissemination area) to identify patterns and outcomes across populations. Area-level measures are predefined tools used to perform area-level analysis by summarizing socioeconomic, demographic, geographic, or environmental characteristics of specific areas. At Statistics Canada, several such area-level measures have been developed and applied in health inequality research.

This review and recommendation report has three components. First, the report defines the concepts of area-level data analysis contrasting it with the individual-level data analysis (which involves examining data at the level of individual entities), evaluate existing literature on selecting an area-level analysis and highlights the key considerations for making such decisions. Second, the report reviews area-level measures that have been developed at Statistics Canada and used for health data analysis, outlining their advantages and disadvantages (e.g., Canadian Index of Multiple Deprivation, Canadian Social Environment Typology, Index of Remoteness and its Classification). Finally, the report provides practical guidelines, a decision-making framework, and recommendations for researchers in selecting appropriate levels of analysis and in selecting a suitable area-level measure for a specific type of research project.

2 Objectives

This report aims to guide researchers in understanding the conceptual differences of levels of analysis and selecting appropriate area-level measures. It has three specific objectives:

2.1 Characterize Analysis Levels

- Define area-level and individual-level analysis, highlighting their respective characteristics and strengths.
- Identify factors influencing the choice of analysis level, including types of research questions, data availability, and required level of aggregation.

2.2 Explore Area-Level Measures

- Highlight why area-level measures are important in data analysis.
- Discuss advantages and limitations of some area-level measures available at Statistics Canada.
- Provide real-world examples of research that have used area-level measures.

2.3 Provide Decision-Making Framework and Recommendations

- Offer a decision-making framework for researchers to determine optimal analysis levels and suitable area-level measures based on specific scenarios.
- Provide recommendations on the appropriate use of various area-level measures considering a variety of research contexts.

3 Definitions and Key Characteristics of Levels of Analysis

The appropriate level of analysis is crucial for analysts, researchers, and policymakers to derive accurate and meaningful conclusions from the data. The choice of an analytical method is primarily guided by research objectives and data availability. Different research questions and data characteristics may require distinct analytical methods. Within the domain of health, both area- and individual-level data are routinely used in analysis.

Area-level analysis involves examining data aggregated by geographic or administrative units, where the unit of analysis is the area (e.g., neighbourhood) rather than the individuals. Area-level analysis offers greater reliability in estimating population health outcomes by encompassing entire populations and their socioeconomic contexts; elements often missing in individual-level data. These data are accessible and effective for identifying disparities across subgroups within geographic boundaries and for comparing health outcomes between neighbourhoods with similar profiles.

In general area-level analysis has been used in two ways in public health research. Firstly, area-level analyses are often used as proxies for individual-level socioeconomic status or other social determinants of health (Kilgore, McClellan, Teigland, & Pulungan, 2018; Mustard, Derksen, Berthelot, & Wolfson, 1999). Secondly, they are used to incorporate the effect of contextual environmental factors on health (Moss, Johnson, Yu, Altekruse, & Cronin, 2021).

The social determinants of health framework recognizes that social influences on health operate through many different processes, one of which may be the types of areas or neighbourhoods in which people live. This analytical method uses aggregate data to examine the role of neighbourhood or community contexts (e.g., neighbourhood income, pollution levels, remoteness) in shaping the health of those who live there. The major advantages of area-level analyses are that they consider the total population for the area of study which yields statistically reliable and consistent estimates; helps to detect differences between groups and neighbourhoods; can assess the influence of multiple social determinants of health within communities; and can be tracked over time for a specific geographic location (Pampalon, Hamel, & Gamache, 2009; Peters, Oliver, & Carrière, 2012). Area-level analysis cannot evaluate the role of individual-level factors as confounders, mediators, or modifiers of the effect.

On the other hand, the individual-level analysis involves examining data at the level of individual entities, providing detailed insights into how specific individual behaviours and characteristics influence health outcomes. One of the key advantages of the individual-level analysis is that it provides a granular view, allowing researchers to understand how individual factors affect health outcomes. Furthermore, by examining individual data, researchers can identify patterns and differences across population subgroups leading to accurate and targeted findings and conclusions (Raily, et al., 2023). Individual-level analysis offers valuable insights for public health interventions by focusing on specific population subsets.

Table 1
Comparison of area-level and individual-level analysis at conceptual level

Concept	Area-Level Analysis	Individual-Level Analysis
Definition	Examines data aggregated by geographic or administrative units	Examines data at the level of individual persons, focusing on personal attributes and behaviors
Focus	Focuses on contextual or environmental factors like average income, pollution levels, or access to services in an area	Focuses on personal characteristics such as age, sex, education, health behaviours, and health outcomes
Data Source	Aggregated or summarized census, survey or administrative data by area	Microdata (e.g., Census, survey responses, administrative health records)
Use Cases	Urban planning, public health surveillance, resource allocation	Health risk assessments, epidemiological studies
Examples	Analyzing lung cancer rates across different regions to identify high-risk areas, and its relationship with poor air quality	Studying how smoking habits affect lung cancer risk among individuals
Limitations	Cannot infer individual-level relationships/causality	Reproducibility and generalizability of finding; requires detailed, often sensitive data; privacy concerns

However, individual-level analysis faces challenges, particularly around explaining social complexity, and data access and availability. Privacy concerns often limit access to individual-level data, and collecting enough cases for statistically reliable estimates can be difficult. For instance, while socioeconomic status is a key determinant of health, accurate data on it are frequently missing from administrative and survey sources (Dragano, et al., 2007; Pardo-Crespo, et al., 2013). Additionally, surveys may not fully capture the target population, introducing potential biases. Moreover, personal risk factors alone cannot explain geographic disparities in disease burden (Ben-Shlomo, White, & Marmot, 1996). Lastly, focusing solely on individual characteristics may overlook broader contextual influences—such as neighbourhood environments, social networks, and systemic inequalities—that significantly shape health and social outcomes (Lue, 2021; Public Health Agency of Canada, 2018).

4 Factors influencing analysis level selection

Numerous comparative studies have evaluated the comparability, effectiveness and applicability of area-level versus individual level analysis in the health domain. A comprehensive literature review was conducted to explore how findings from these comparative studies indicate when area-level analysis aligns, diverge, or interact with individual-level analysis (see Appendix A for a summary).

The review focused on research articles published within the past twenty-five years, primarily centered around health-related outcomes. Studies conducted in Canada, the United States, and Europe were specifically chosen for this analysis. To gather relevant literature, a biblioscan request was submitted to the Statistics Canada library. Various electronic resources and discovery tools, including Academic Search Premier, Scopus, Summon, JSTOR, PubMed, and Google Scholar, were utilized. As outlined in the table in Appendix A, the reviewed literature is grouped into three broad categories. The first category includes studies that found a degree of alignment between area-level and individual-level data analyses. The second category comprises studies that reported interactions or mixed results between the two levels of analysis. The third category consists of studies that found little or no agreement between area-level and individual -level data analyses.

4.1 Findings from the literature: comparing area- and individual-level health analysis

The primary objective of reviewing the literature was to investigate the alignment, divergence, or interaction between comparative studies of area-level analysis and those from individual-level analysis. The degree of agreement between area- and individual-level analyses varies based on the study subject, research area, and the specific health outcome chosen for investigation. However, listed below are the key takeaways from the literature listed in Appendix A:

- There is no definitive consensus among the literature's findings.
- Area- and individual-level socioeconomic status are distinct constructs and independently influence health outcomes. Findings from area- and individual-level analyses exhibit moderate correlation and offer complementary insights.
- While some studies have used area-level deprivation as a proxy for individual-level social risks (Brown, et al., 2023), others have indicated little or no agreement between the findings of individual-level and area-level analysis (Moss, Johnson, Yu, Altekruse, & Cronin, 2021). This suggests that area-level analysis can complement the findings of individual-level analysis, and it also can contribute uniquely to our understanding of health inequalities.
- The degree of variation resulting from using area-level analysis as proxies for individual-level analysis varies based on the sociodemographic composition of the population. In general, relying solely on area-level socioeconomic status as a proxy for individual-level socioeconomic status is not advisable (Buajitti, Chiodo, & Rosella, 2020). However, smaller geographic or administrative scales (such as Dissemination Areas) can be used for area-level analysis as they capture local variations and yield results similar to individual-level data.
- The social determinants of health and mortality associations were often found to be systematically underestimated when area-level analysis was used as proxy for individual-level analysis (Moss, Johnson, Yu, Altekruse, & Cronin, 2021).
- Aggregated area-level socioeconomic status provides more accurate health outcome assessments for urban areas, where geographic units are more homogenous compared to rural areas (Barnett, Roderick, Martin, Diamond, & Wrigley, 2002).
- Area-level studies diverge from individual-level analyses in their construction, leading to weaker correlations with outcomes. Integrating both area-level and individual-level data within a single multilevel study enables

the identification of how contextual neighbourhood characteristics impact health outcomes in addition to the personal risk factors. Extending analysis to incorporate both area- and individual-level outcomes using multilevel models enhances the ability to distinguish between contextual and compositional effects. However, this is often constrained by data availability (Jackson, Richardson, & Best , 2008).

- Administrative databases lacking individual socio-economic information makes the use of area-level data analysis crucial for monitoring social inequalities in health (Pampalon, Hamel, & Gamache, 2009).

The area- and individual-level analyses differ by construct. Complete agreement between findings from these two data analysis methods is unlikely. The moderate or poor agreement pattern between area- and individual-level analysis is likely due to variations in household level social determinants of health within a geographic area. It bares repeating that area-level data analysis represents the aggregate level of a concept within a geographic area rather than individual characteristics; assuming that all individuals in the same geography have same characteristics is an ecological fallacy. Care must be taken to interpret results with this in mind.

A clear limitation of area-level analysis is the application in rural areas. Rural postal codes typically cover larger geographical areas, which exhibit less homogeneity in terms of population socioeconomic composition compared to areas covered by urban postal codes (Pichora , et al., 2018). Therefore, the use of multi-factor indices may have too many factors to be effective in rural settings where there is greater socioeconomic heterogeneity. The literature suggests that the smaller the area of aggregation, the closer it aligns with individual-level characteristics of the population.

While there is no consensus in the literature regarding the findings from individual- and area-level analyses, the reviewed literature sheds light on when and where to use area-level or individual-level analysis in general. The next section specifically discusses why area-level measures are useful, outlines the available area-level measures at Statistics Canada, and illustrates different scenarios where single or multi-factor area-level measures are suitable.

5 Area-level measures used for area-level analysis

Area-level measures are pre-defined data tools specifically developed for conducting area-level analysis. They offer valuable insights for public health and urban planning by enabling targeted interventions based on neighbourhood dynamics. These measures are often linked to health indicators (e.g., mortality, morbidity) through residential postal codes, which can be mapped to census or administrative geographies using the Postal Code Conversion File Plus (PCCF+).[1] This integration allows users to conduct area-level analyses without needing to aggregate their own data, improving efficiency and comparability. Area-level measures are particularly useful when individual-level data are limited due to small sample sizes or missing socioeconomic information. They can provide aggregate estimates or facilitate comparisons across similar small areas. Additionally, they often rely on reliable administrative sources (e.g., the T1 Family File from the Canada Revenue Agency), which can overcome issues of inaccurate self-reporting in surveys and offer more reliable estimates of socioeconomic status. (Moore, Stinson, & Welniak, 2000; Pickett & Pearl, 2001)

Broadly speaking, there are two types of area-level measures used in area-level analysis to understand health inequalities.

1. Single-Factor Area-Level Measures: In this category, geographic areas are classified based on a single socioeconomic characteristic of the population or a single contextual environmental factor. For instance, neighbourhoods can be grouped into quintiles based on the proportion of the population in the neighbourhood with less than high school education (forming a “low-education quintile”) or assign the median family income of all the families living in that neighbourhood (resulting in an aggregate “neighbourhood income”) or classify neighbourhoods based on the access to healthcare facilities (e.g., proximity to healthcare measure).
2. Multi-Factor Area-Level Measures: These measures consider multiple socioeconomic, demographic, ethnocultural or environmental characteristics of neighbourhoods using a derived summary measure for each neighbourhood. Examples include the Canadian Index of Multiple Deprivation (CIMD), Remoteness classification, or the Canadian Social Environment Typology (CanSET) that incorporate various

1. For further information on how to use Statistic Canada’s area-level measures for health analysis please refer to the Area-level How to Guide, available upon request.

neighbourhood-level factors (e.g., income, education, employment status, housing status, family structure, access to services, population density etc.).

There are numerous area-level measures for health data analysis that offer significant advantages. Some of these measures are developed by Statistics Canada (e.g.; Proximity Measures Database, Canadian Social Environment typology, Canadian Index of Multiple Deprivation, Index of Remoteness and its classification, area level measure of income and education). Others are developed externally with support from Statistics Canada (e.g., Canadian Food Environment Data, Canadian Active Living Environment Data, Canadian Marginalization Index). Additionally, some measures are developed elsewhere but used by Statistics Canada for health analysis (e.g., Material and Social Deprivation Index). Lastly, numerous studies, both within and outside of Statistics Canada, have employed area-level analysis by defining their own geographic boundaries without applying preexisting area-level measures (Mah, et al., 2024; Ross, et al., 2007).

This availability and variety of area-level measures can make it difficult for a researcher to determine the most appropriate tool for their analysis. The following section provides an overview of the area-level measures developed by Statistics Canada that are used for health data analysis, describing their advantages and limitations, in advance of providing a decision-making framework to help guide researchers on selecting a measure for their health analysis.

6 Advantages and limitations of selected area-level measures developed by Statistics Canada and used for health data analysis

As outlined above, a variety of area-level measures are used for health data production and analysis. The area-level measures developed and utilized for health analysis at Statistics Canada fall into two categories discussed above: single factor (e.g., area-level income quintile, low education quintile) or multi-factor (e.g., CIMD, CanSET). In the following section, advantages and limitations of Statistics Canada's area-level measures in each category are elaborated, providing the context for a decision-making framework to aid researchers in selecting a specific area-level measure.

6.1 Area-level measure of income

The area-level measure of income at Statistics Canada is a single factor measure that classifies Census Dissemination Areas (DA) into neighbourhood quintiles/deciles based on the rank order of median household income for each household in Canada. To derive this measure, the average median income of all households within a dissemination area (DA) is used. This includes income from all sources, either before or after taxes and deductions, during the twelve-month period ending December 31 of the previous year. Household income data are adjusted using person-weights to account for household size.

The area-level measure of income data comes integrated with the PCCF+ data. The PCCF+ includes code scripts, a set of associated datasets derived from the Postal Code Conversion File (PCCF), a postal code population weight file, the geographic attribute file, the Health Region boundary file, and other supplementary data. A Reference Guide is available for each version of the PCCF+ file which provides more information on the area-level measure of income. The PCCF+ User guide is also a valuable resource to explore more about the area-level income and income quintiles.

The following area-level measures from the PCCF+ data are generally used in health inequality analysis:

a. Neighbourhood Income Quintile After Tax at CMA/CA Level (QAATIPPE).
b. Neighbourhood Income Quintile After Tax at National Level (QNATIPPE).
c. Neighbourhood Income Quintile Before Tax at CMA/CA Level (QABTIPPE).
d. Neighbourhood Income Quintile Before Tax at National Level (QNBTIPPE).

The area-level measure of income is useful to identify neighbourhood health inequalities. There is a body of evidence that has found a strong association between low household income and poor health outcomes in Canada, including higher all-cause mortality rates, lower life expectancy, lower health adjusted life expectancy, higher stroke fatality and higher COVID-19 mortality (Blair, et al., 2022; Statistics Canada, 2022; Bushnik, Tjepkema, & Martel, 2020; McLeod, Lavis, Mustard, & Stoddart, 2003; Saposnik, et al., 2008).

Area-level income measures are useful for comparing neighbourhoods across Canada, especially given the wide regional variation. The PCCF+ income measure provides both CMA/CA-specific quintiles for within-community comparisons and national quintiles for cross-community analysis. It is also one of the few measures that includes Canada's northern territories. Its main strength lies in capturing the collective economic status of neighbourhoods, making it valuable for assessing health outcomes.

While effective for examining income-related health and social inequalities, it's important to consider other socioeconomic factors that may influence outcomes. A multi-factor area-level measure may offer a more comprehensive understanding of these complex relationships. Additionally, this measure may be less suitable for rural areas, where large geographic units can mask significant income disparities among population groups.

6.2 Low-education measure: Proportion of the population with less than high school education

The low-education measure at Statistics Canada is a single factor area-level measure that ranks Canadian Census DAs into five equal-sized groups (quintiles) based on the age-standardized proportion of the population aged 20 years and over in private households whose highest level of educational attainment was less than high school on census day (Statistics Canada, 2023). The first quintile represents areas having the smallest proportion of the population with less than a high school education (highest education quintile), whereas the fifth quintile represents areas having the largest proportion of the population with less than a high school education (lowest education quintile). The area-level measure of the population with less than high school education data includes quintile values as well as continuous scores for all Census DAs in Canada except those having a total population less than 40.

There is an extensive body of research that demonstrates a positive association between higher education and health but many of these studies use individual level education or aggregate to household education. Across the literature, explanations of the drivers of the positive association range from individual factors (e.g., work conditions, personal resources, healthy lifestyles, literacy) to larger contextual factors (e.g., economic conditions, supports, unemployment rates). The neighbourhood-level education reflects the larger contextual factors like collective human capital and social well-being, impacting both mental and physical health of those in the area (Zhand, Chen, McCubbin, McCubbin, & Foley, 2011). Therefore, measuring education at the area-level can help better understand and address social inequalities, enabling more effective resource allocation.

This measure is best suited for Canadian studies in urban areas, working aged populations and areas with higher average education as they tend to have lower levels of educational inequality. Studies indicate that area-level education measures are particularly effective for examining health inequalities related to the top three pathways associated with education: work and economic conditions, social-psychological resources, and healthy lifestyle (Khalatbari-Soltani, Maccora, Blyth, Joannès, & Kelly-Irving, 2022). For instance, lower levels of education in Canada are linked to higher potentially avoidable mortality rates. Additionally, a higher proportion of individuals with higher education is correlated with lower obesity prevalence (Statistics Canada, 2023). Another advantage of the area-level education measure is that the proportions of population have been age-standardized, permitting the comparison across areas for a concept known to be impacted by age (e.g., older generations have lower education in general). This measure is a valuable tool in understanding health inequalities associated with low levels of education in Canada.

Much like the income quintile measure, the low education measure focuses on a single factor. It does not consider other crucial social determinants of health factors that significantly influence population health. These may include employment status, access to healthcare, and social support networks. By considering these multifaceted factors, researchers can better address the complexities of population health and design more effective interventions. Care should be taken when using this measure in combination with other individual-level or area-level measures known to be highly correlated (e.g., income). This measure may not be suitable for research targeting rural areas, DAs with small populations or populations under 20 years of age.

6.3 Proximity to Healthcare

Proximity to healthcare is one of the many proximity measures developed at Statistics Canada as part of the Linkable Open Data Environment. The healthcare proximity measure is a single-factor measure that evaluates the closeness of a dissemination block (DB) to a DB containing a healthcare facility within a 3-kilometre driving distance (Alasia, Newstead, Kuchar, & Radulescu, 2021). Healthcare facilities include ambulatory health care services, hospitals, and nursing and residential care facilities, derived using the North American Industry Classification System (NAICS) database. The healthcare proximity measure compiles and harmonizes open, publicly available, and directly provided data on healthcare facilities across Canada.

Proximity to healthcare is based on a gravity model that considers the network distance and size of the healthcare service available in the reference DB (Alasia, Newstead, Kuchar, & Radulescu, 2021). Both walking and driving networks are used to calculate proximity. The size of the service is determined by total employment and total revenue. This measure is a continuous scale of proximity to healthcare, normalized from 0 to 1, where 0 indicates the lowest proximity and 1 indicates the highest. The proximity measure database uses Census geographies and the OpenStreetMap road network (Proximity Measures Database (statcan.gc.ca)).

The key advantage of the healthcare proximity measure database is that it provides detailed information at the dissemination block level, which is a the most detailed level of geographic resolution available for standard Census geographies. The comprehensive coverage allows for precise analysis of proximity to essential services and amenities. Furthermore, the normalized index values make it easier to compare different areas and understand their relative accessibility. Since this measure is relatively new, there are no studies that have used it yet. However, other studies have applied similar concepts to identify neighbourhood level geographic disparities in accessing healthcare in Canada (Shah, Bell, & Wilson, 2016; Ge, Zhao, Huang, Shan, & Wei, 2021).

The proximity to healthcare data is an important area-level measure to understand accessibility to healthcare in Canadian neighbourhoods, however it does have some limitations. The most important limitation of this measure is that it does not have exhaustive coverage and may not contain all facilities in scope. Given that the inputs for this measure need to be available either under an open data licence (e.g., in an open government portal) or as publicly available data, there could be key data omitted resulting in biased analysis. Facility type classification and geolocation errors are also possible, although efforts have been made to minimize these. This type of proximity measure might not fully account for other factors affecting healthcare access, such as availability of transportation, socioeconomic status, or individual healthcare needs. In addition, this measure does not capture the healthcare access outside of 3-kilometre driving/walking distance, which may not capture the healthcare facilities in rural communities in Canada.

6.4 Canadian Index of Multiple Deprivation

The main objective of the Canadian Index of Multiple Deprivation (CIMD) is to measure neighbourhood deprivation and marginalization based on material and social disadvantages. This multi-factor area-level measure is useful to understand the social context influencing health inequalities between population groups or between geographic areas. The CIMD was first developed using 2016 Census of population data and was updated for the 2021 Census. Both the 2016 and 2021 version of the CIMD share a similar foundation to the 2006 Can-Marg index, however the CIMD is available at both national and regional/provincial level except for the territories (Statistics Canada, The Canadian Index of Multiple Deprivation: User Guide, 2019).

The CIMD uses microdata from the Census of Population, and the index is calculated at the DA geography. The CIMD was developed using a principal component analysis to reduce a large number of variables into four dimensions by grouping variables into distinct themes, namely Residential Instability, Economic Dependency, Situational Vulnerability and Ethnocultural Composition. The 2021 CIMD is based on 21 socioeconomic, sociodemographic and ethnocultural measures of social well-being contributing to the four dimensions of deprivation.

The CIMD's key strength lies in its recognition of multiple levels of social influence on health. It goes beyond economic factors to capture potent, context-specific components of marginalization in Canada such as ethnocultural identity, immigration status, economic status, and household composition. These dimensions have been used to identify spatial hotspots and sociodemographic profiles linked to various health outcomes, including injuries and breast cancer screening (Bentley, et al., 2023; Karbakhsh, Zheng, Rajabali, Yau, & Pike, 2024; Khudadad, et al., 2024). At the provincial level, the index serves as a valuable surveillance tool, informing healthcare decisions by regional health authorities and government agencies (Relova, et al., 2022).

The CIMD is a valuable area-level tool for analyzing the complex link between neighbourhood deprivation and health inequalities. However, it has limitations. As a cross-sectional measure, it may not reflect changes over time in its components, which evolve at different rates. Its multi-factor design adds interpretive complexity, and reliance on long-form Census data excludes certain populations, such as institutional residents, resulting in a healthier-than-average sample. Additionally, not all CIMD dimensions may be relevant to every health outcome, and conflicting factors within a dimension can obscure inequalities. Careful selection of dimensions is essential to ensure analytical relevance to the research question.

6.5 Canadian Social Environment Typology

The Canadian Social Environment Typology (CanSET) is a multi-factor geographic classification tool which uses multiple socioeconomic, demographic and ethnocultural variables from the Census of Population covering DAs from the Census Metropolitan Areas (CMA) and Census Agglomerations (CA) across Canada (Subedi, Aitken, & Greenberg, 2022). It classifies three levels of neighbourhood types based on the unique combination of 30 socioeconomic, demographic and ethnocultural variables representing the social environment within those DAs. The CanSET is a hierarchical clustering generated through cluster analysis. Each cluster can be taken as a social unit of analysis that indicates the geographic distribution of different kinds of combinations of population characteristics throughout CMAs and CAs. Each social environment cluster is a group of similar dissemination areas and represents a unique neighbourhood type.

The CanSET offers a nuanced view of the complex social makeup of Canadian CMAs and CAs, using a multilayered approach to reveal how intersecting dimensions of the urban social environment shape health and social outcomes. Unlike earlier measures focused solely on marginalization or health inequalities, CanSET enables intra- and inter-city comparisons, supports benchmarking, and helps track progress in reducing disparities. It was especially useful during the COVID-19 pandemic, highlighting elevated mortality rates in neighbourhoods with high proportions of seniors, institutionalized populations, immigrants, and low-income families (Subedi & Aitken, 2022). It also revealed unmet home care needs in low-SES suburban areas (Statistics Canada, The Daily, 2022). These findings underscore CanSET's value in identifying healthcare needs based on neighbourhood characteristics.

CanSET is a valuable tool for understanding neighbourhood health inequalities shaped by socioeconomic, demographic, and ethnocultural factors. However, it does not account for environmental conditions such as air quality, green space, or walkability, which limits its ability to fully capture the relationship between natural environment, built environments and health. For such analyses, complementary tools focused on natural and built environmental factors should be used. The CanSET is a cross-sectional clustering approach and is unique to each census year; therefore, the 2016 clusters do not match with 2021 CanSET clusters and are not directly comparable. Additionally, CanSET is limited to DAs within CMAs and CAs, making it unsuitable for rural areas. However, given its design, it remains a strong measure for assessing health inequalities in small, homogeneous urban settings.

6.6 Index of Remoteness and its classification

The Index of Remoteness (IR), developed by Statistics Canada's Centre for Special Business Projects, is a multi-factor continuous measure of remoteness for Canadian Census Subdivisions (CSDs). It incorporates geographic factors such as road access, distance to population centres, and the size of the nearest service-providing centre to assess accessibility (Alasia, Bédard, Bélanger, Guimond, & Penney, 2017). The IR uses census data and assigns each CSD a score from 0 (most accessible) to 1 (most remote). While the IR can be used as a continuous variable in statistical models, discrete categories like "easily accessible," "accessible," "less accessible," "remote," and "very remote" are often more practical for analyzing health outcomes and service access (Subedi, Roshanafshar, & Greenberg, 2020). Therefore, Statistics Canada developed the remoteness index classification that categorized the IR into discrete levels of remoteness geographies. These classifications help distinguish urban, rural, and remote communities. However, rural research emphasizes that rurality is not uniform and cannot be reduced to simple categories. With both continuous and categorical options, the IR offers flexibility for researchers to choose the most appropriate measure for their analytical needs. Although five classification methods are available

(Manual, Quintile, Equal Interval, Jenks Natural Break, and K-Means Cluster), it is recommended to use the Manual, Jenks Natural Break, or K-Means Cluster methods for most analytical work. These approaches produce categories more aligned with standard urban-rural classifications in Canada, such as population centres and the Statistical Area Classification.

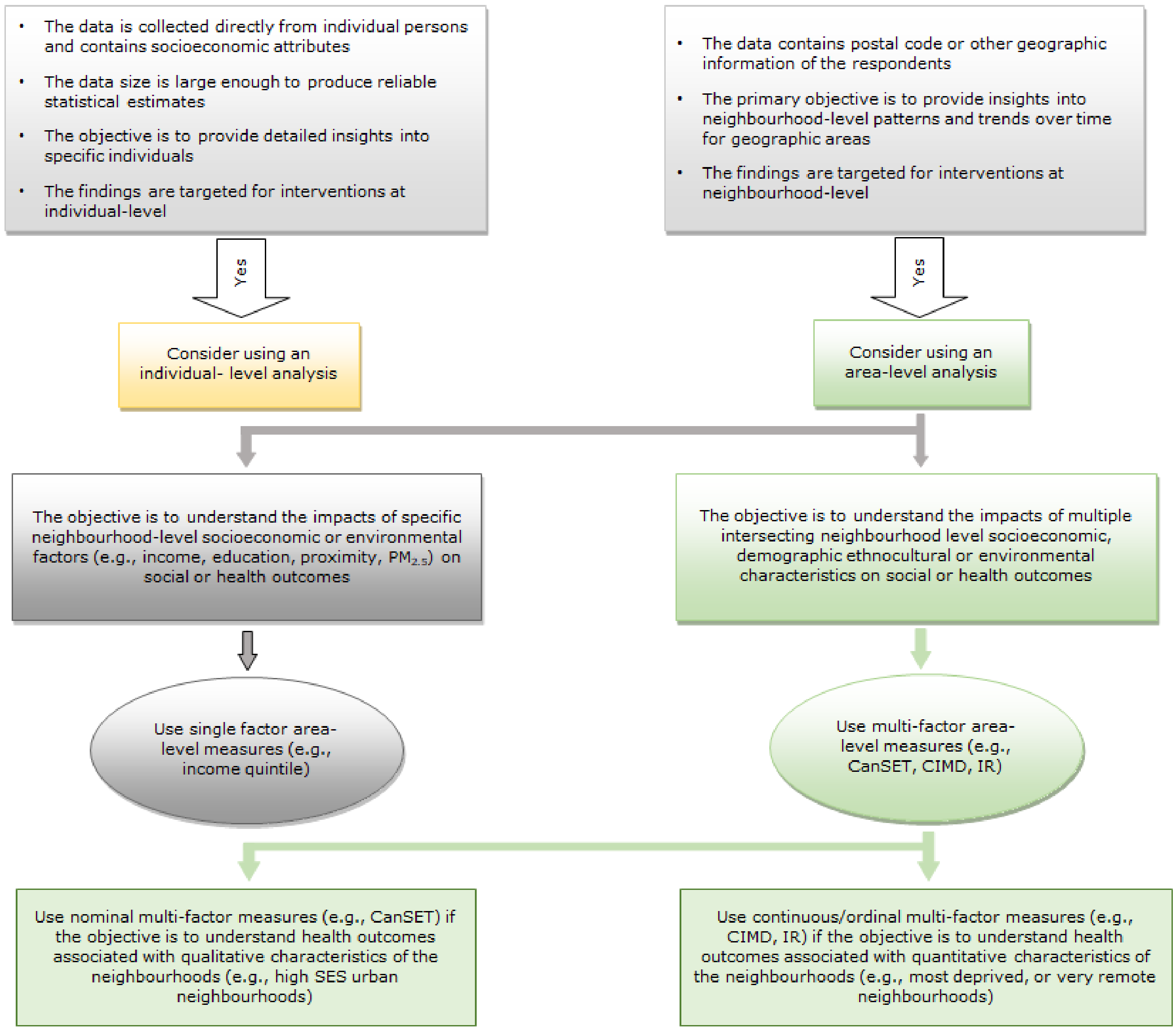
The Index of Remoteness (IR) and its classification system are valuable tools for examining disparities in health and socioeconomic outcomes across Canadian communities based on their relative accessibility. They are especially useful for analyzing rural and remote areas, which face distinct public health challenges such as limited healthcare access, travel costs, and isolation. For example, Melvin (2023) used the classification to study differences in postsecondary education and labour market outcomes among Indigenous populations, while Amini (2021) found lower self-reported health and higher suicide mortality rates among women and girls in very remote areas. Similar measures are often used to allocate health resources in hard-to-reach rural communities (Gupta, Gulliver, & Singh, 2023), particularly in Northern Canada, where individual-level health data is limited due to small populations and survey challenges (Stringer, Cheng, & Kim, 2023).

Like any measure, the IR has strengths and limitations. It helps fill gaps where individual-level data is unavailable, offering a way to compare urban and rural health outcomes. However, it primarily reflects physical distance to population centres and does not account for other dimensions of remoteness—such as healthcare access, social isolation, or economic opportunity. For instance, residents in Gatineau (Quebec) may live near Ottawa (Ontario) but face healthcare barriers due to provincial jurisdiction. Additionally, the IR provides a snapshot based on census-year data, while remoteness is dynamic and influenced by infrastructure, economic shifts, and population changes. Caution should be applied while applying IR to data not collected around the census year.

7 A decision framework for the selection of area-level measures

The choice of an appropriate measure for data analysis is crucial in capturing neighbourhood characteristics and their direct or indirect impact on population health outcomes. Furthermore, selecting the right area-level measure can improve analytical quality, leading to a better understanding of health disparities, complementing individual-level analyses, and informing effective policy decisions. Consequently, researchers benefit from a decision-making framework designed to guide them in selecting the appropriate analysis level and area-level measure for their studies. Guided by the literature discussed in the previous sections (listed in Appendix A), the following decision-making framework is designed to assist users in selecting the appropriate area-level measures.

Figure 1
A decision-making framework to select an appropriate analysis level and an area-level measure



Source: Statistics Canada.

8 Recommendations

There are numerous area-level measures for health data analysis that offer significant advantages. The following recommendations are provided to help guide researchers. Research on the relationship among socioeconomic, demographic, contextual environmental factors, and health outcomes highlights the importance of considering both area- and individual-level analyses in different contexts. Drawing from the literature and examples provided by studies that employ area-level measures, the following recommendations are offered for different analytical scenarios.

Table 2
Summary of Recommendations for the use of Area-Level Analysis and Measures

Analytical Scenario	Recommendation	Evidence
Individual-level data is readily available and the sample size is large enough for reliable statistical estimates. The objective is to understand individual differences and not to understand broader influences at the neighbourhood level.	Individual level data analysis is recommended.	Strong evidence in the literature.
The objective is to evaluate personal risk factors (e.g., smoking, drinking, exercise) associated with personal health outcomes (e.g., cardiovascular disease, obesity etc.)	Individual level data analysis is recommended.	Strong evidence in the literature.
The objective is to understand health outcomes among urban population having socioeconomic homogeneity (most of the people in the neighbourhoods have the same socioeconomic and ethnocultural background, similar work experience, education, etc.).	Area-level analysis using either a single or multi-factor area-level measure is recommended.	Strong evidence in the literature.
The objective is to evaluate structural, contextual, social risk factors associated with a health outcome (these factors include proximity to healthcare facilities, access to open space, community support, etc.).	Area-level analysis using a multi-factor area-level measure is recommended.	Strong evidence in the literature.
The objective is to examine influence of both personal (e.g., social determinants of health at individual level) as well as contextual environment on health (e.g., air, water or sound quality, access to parks and open spaces etc.).	Multi-level analysis (out of scope for this report) of both area- and individual-level data analysis is recommended.	Strong evidence in the literature.
Population of interest is small group (e.g., racialized group, indigenous, disable populations etc.), and data collection is biased or not fully captured in the survey or administrative data.	Area-level analysis using either a single or multi-factor area-level measure is recommended.	Some evidence in the literature.
Personal risk factors (e.g., drugs, smoking, drinking, poverty, personal values, or beliefs) are insufficient to account for the differences in health outcomes.	Multi-level analysis (not covered in this study) of both area- and individual-level data is suggested.	Some evidence in the literature.
Population of interest is rural, or the unit of analysis is relatively large (generally, rural DAs are large, and the population is often a mixed of different racial, cultural or economic status).	Individual level analysis or area-level analysis using a less heterogeneous single factor area-level measure is suggested.	Some evidence in the literature.
Population of interest is urban but has socioeconomic heterogeneity (generally, urban DAs are small, but some have a mixed population of different racial, cultural, and economic status).	Area-level analysis using a multi-factor area-level measure (if not individual-level) is suggested.	Some evidence in the literature.
The objective is to design Public Health interventions by identifying clusters of the populations of interest.	Area-level analysis using an area-level measure is suggested.	Little evidence in the literature.
The objective is to understand rare health outcomes.	Not enough information to make a recommendation.	Little to no evidence in the literature.
The objective is to make an international comparison of health outcomes.	Not enough information to make a recommendation.	Little to no evidence in the literature.

9 Conclusion

Area-level data analysis offers valuable insights into population health by capturing contextual socioeconomic and environmental factors that are often absent from individual-level analyses. Since area-level analysis typically represents entire populations within defined geographic boundaries, it provides consistent and reliable estimates.

Area-level measures further streamline this process by eliminating the need for researchers to aggregate data themselves, thereby improving efficiency and enabling comparability across neighbourhoods and over time. These measures are especially valuable in public health and urban planning, where they support targeted interventions based on neighbourhood-level dynamics. Their ability to highlight disparities among population subgroups and facilitate comparisons between communities with similar socioeconomic or environmental profiles makes them a powerful tool for evidence-based decision-making.

The decision-making framework and recommendations outlined in this report provide practical guidance for selecting appropriate analysis levels and area-level measures. Researchers benefit from a structured approach that aligns data sources with study objectives, enhancing the validity and impact of their findings. Understanding when and how to apply area-level versus individual-level analysis is essential for producing robust, actionable research. The framework is meant to empower researchers to make informed choices that strengthen the quality of their analyses and contribute to more equitable and targeted health interventions.

Appendix A: Summary of findings from area-level and individual-level comparative studies

Table A.1
Studies that found some degree of alignment between area- and individual-level analysis

Article Source	Article Title	Area/Country of Study	Findings/Conclusions
(Adams, Ryan, & White, 2004). *Public Health*, 27(1), 101-106.	How accurate are Townsend Deprivation Scores as predictors of self-reported health? A comparison with individual-level data.	United Kingdom	Area-level deprivation measures exhibited comparable predictive power for health outcomes as the individual-level measure of deprivation. Townsend deprivation scores computed at small areas (enumeration district) demonstrated a strong correlation with the deprivation measures calculated at the individual level and similarly predicted health outcomes.
(Marra, Lynd, Harvard, & Grubisic, 2011). *BMC Health Services Research*, 11(1), 1-7.	Agreement between aggregate and individual-level measures of income and education: a comparison across three patient groups.	Canada	Income and education measures at the census tract and dissemination area levels were most effective in approximating individual-level income for patients with diabetes. The alignment between individual-level and aggregate-level socioeconomic status measures may vary based on the patient group and their income. Further research is necessary to understand these differences among patient groups and to inform the selection of appropriate socioeconomic status measures.
(Pampalon, Hamel, & Gamache, 2009). *Health Reports*, 20(4).	A comparison of individual and area-based socio-economic data for monitoring social inequalities in health.	Canada	Area-based studies cover both material and social aspects, providing statistically reliable estimates that align with individual indicators. The association between health and socio-economic characteristics becomes more pronounced when measuring Socio Economic Status (SES) at the individual level. To gain deeper insights into health disparities, etiological studies should examine health determinants in both area- and individual-level contexts. Due to the lack of individual socio-economic data in administrative databases, relying on area-based indicators remains crucial for monitoring social health inequalities.
(Xia, et al., 2024). Journal of American Medical Association (JAMA).	Cardiovascular Risk Associated with Social Determinants of Health at Individual and Area Levels	United States of America	The study found that both personal and neighbourhood-level social disadvantages independently and cumulatively increase the risk of cardiovascular disease. Even after accounting for traditional health risk factors, individuals exposed to multiple adverse social determinants, such as low income, limited education, and living in high-poverty areas, faced significantly higher cardiovascular risk. The social and environmental contexts play a critical role beyond clinical risk factors.

Table A.2
Studies that found interaction or mixed results between area- and individual-level analysis

Article Source	Article Title	Area/Country of Study	Findings/Conclusions
(Boyle & Willms, 1999). *American Journal of Epidemiology*, 149(6).	Place Effects for Areas Defined by Administrative Boundaries.	Ontario, Canada	Multilevel modeling is useful for identifying locations with exceptional outcomes that cannot be attributed to the characteristics of the individuals living there. Studies that disregard multilevel structures and focus solely on individual-level or area-level data are flawed. The impact of place effects is generally smaller in large administrative areas compared to smaller ones.
(Diez Roux, et al., 2001). *Annals of Epidemiology, 11(6), 395-405*.	Area characteristics and individual-level socioeconomic position indicators in three population-based epidemiologic studies.	United States of America	Area- and individual-level indicators exhibited moderate correlation and offered complementary insights into living conditions. The extent of variation resulting from employing area-level measures as substitutes for individual-level measures varied across different racial and income groups.
(Fuller, et al., 2019). *CMAJ Open*, 7(1), E33-E39.	Individual- and area-level socioeconomic inequalities in diabetes mellitus in Saskatchewan between 2007 and 2012: a cross-sectional analysis.	Saskatchewan Canada	Area-level deprivation was associated with elevated risk of diabetes mellitus after adjustment for individual-level factors, however, the strength of this association varied between urban and rural communities. Area-based measures of deprivation were less similar to individual-level measures of deprivation in rural areas. Multifactor deprivation indices may have too many factors to be effective in rural settings in contrast to the single-factor area-based measures mainly because of larger geographic area- and greater heterogeneity.
(Jackson, Richardson, & Best, 2008). *Social Science & Medicine*, 67(12), 1995-2006.	Studying place effects on health by synthesising individual and area-level outcomes.	Greater London, United Kingdom	There was an association between area-level deprivation indicators and rates of hospital admission for cardiovascular disease and area-level rates of limiting long-term illness. Extending multilevel models to incorporate both individual and area-level outcomes increased power to distinguish between contextual and compositional effect. Area-level variation in health outcome observed were mainly by compositional characteristics of individual but not by the neighbourhood contextual characteristics.
(Jackson, Best, & Richardson, 2008). *Journal of the Royal Statistical Society Series A: Statistics in Society*, 171(1), 159-178.	Hierarchical related regression for combining aggregate and individual data in studies of socio-economic disease risk factors.	London, United Kingdom	The association between area-level socioeconomic status and hospitalization rates for cardiovascular diseases was primarily influenced by individual-level sociodemographic disparities. However, when aggregated data were considered, the results of cardiovascular disease hospitalization did not exhibit significant bias. To gain a more precise understanding of health disparities, examining deprivation and health at a finer geographical scale is recommended.
(Pichora , et al., 2018). *Canadian Journal of Public Health*, 109, 410-418.	Comparing individual and area-based income measures: impact on analysis of inequality in smoking, obesity, and diabetes rates in Canadians 2003–2013.	Canada	The agreement between the individual and area-level income was poor but both measures identified generally comparable levels of relative and absolute inequality in the rates of diabetes, smoking, and obesity for the selected study period in Canada.
(Tope, Morais, El-Zein, Franco, & Malagon, 2023). *International Journal of Cancer*, 153, 1766-1783.	Differences in site-specific cancer incidence by individual- and area-level income in Canada from 2006 to 2015.	Canada	Both individual and area-level income independently affect cancer incidents in Canada. Individuals who were both in the combined poorest individual- and area-level income quintiles had significantly higher overall age-standardized cancer incidence rates compared to those in the combined wealthiest individual- and area-level income quintiles.
(Xie, Hubbard, & Himes, 2020). *Annals of Epidemiology*, 43, 37-43.	Neighbourhood-level measures of socioeconomic status are more correlated with individual-level measures in urban areas compared with less urban areas.	United States of America	Individual and area-level socioeconomic status measure were correlated in urban neighbourhoods but were poorly correlation outside of urban settings.

Table A.3
Studies that found little or no agreement between area- and individual-level analysis

Article Source	Article Title	Area/Country of Study	Findings/Conclusions
(Buajitti, Chiodo, & Rosella, 2020). SSM – Population Health 10 (2020) 100553.	Agreement between area- and individual-level income measures in a population-based cohort: Implications for population health research.	Ontario, Canada	Agreement between area-level and individual-level income was low. Area- and individual-level socioeconomic status do not capture the same population groups, therefore using area-level measures as a proxy for individual-level socioeconomic status is not recommended.
(Hanley & Morgan, 2008). *BMC Health Services Research, 8*, 1-7.	On the validity of area-based income measures to proxy household income.	British Columbia, Canada	Limited consensus existed between area-level and household-level income measures. Interestingly, total prescription drug expenditures exhibited more equitable distribution when households were ranked based on neighbourhood income rather than individual household-level income. This observation implies that neighbourhood-level income may obscure the variations in individual household-level income.
(Ingleby, Atherton, Baker, Elliss-Brookes, & Woods, 2020). *BMJ Open*, 10(11).	Assessment of the concordance between individual-level and area-level measures of socio-economic deprivation in a cancer patient cohort in England and Wales.	England and Wales, United Kingdom	There was low level of agreement between individual-level and area-level indicators of deprivation. Individual and contextual deprivation are not matching with each other in a cohort of cancer patient. Area-level deprivation measures capture only part of the relationship between deprivation and health outcomes.
(Moss, Johnson, Yu, Altekruse, & Cronin, 2021), Population Health Metrics, 19(1), 1-10.	Comparisons of individual- and area-level socioeconomic status as proxies for individual-level measures: evidence from the Mortality Disparities in American Communities study.	United States of America	Individual-level socioeconomic status characteristics were closely linked to census tract- and county-level characteristics but correlations between individual- and area-level socioeconomic status characteristics were small. The magnitude of association with mortality was reduced with area-level data, and the direction of relationship was opposite in the case of employment and occupation.
(Southern, et al., 2005) Medical Care 43(11), 1116-1122	Individual-Level and Neighbourhood-Level Income Measures Agreement and Association With Outcomes in a Cardiac Disease Cohort.	Alberta, Canada	The area-based estimates of household income don't match well with patients reported income, especially for those with low incomes. However, both types of income data are still useful for predictions of survival, possibly because both individual and area-level income measure different things.

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