Cumulative air pollution indicators highlight unique patterns of injustice in urban Canada

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Abstract
Disparities in air pollution exposure are a form of distributional environmental injustice that has been documented in many jurisdictions around the world. In Canada, although there is a growing literature characterizing exposure inequalities, an important gap is research that captures the cumulative impact of the multiple air pollutants to which communities are exposed. Here, we present a screening-level analysis of inequalities in single pollutant and cumulative air pollution burdens in three major cities in Canada: Toronto, Montreal, and Vancouver. We construct three cumulative hazard indices (CHIs), using previously published national datasets for PM$_{2.5}$, NO$_2$, SO$_2$, and O$_3$ concentrations for illustrative year 2012. We describe the ways in which patterns of inequality differ between pollutants, between ways of calculating cumulative burden, and between cities. Different methods of constructing CHIs can yield different understandings of the spatial distribution of pollution, and in turn, inequality. We find the largest spatial variations for a CHI based on whether each pollutant exceeds an external benchmark (here, air quality guidelines), which translates into the largest calculated disparities in cumulative air pollution burdens for marginalized groups. We observe distinct patterns of inequality between the cities, in terms of which marginalized groups consistently experience higher cumulative air pollution burdens (Vancouver: Indigenous residents, Montreal: immigrant residents, Toronto: low-income residents). Results also highlight the importance of using a suite of socio-demographic indicators as patterns can differ between individual racialized/ethnic groups, and between different measures of socio-economic status. This work illustrates how a range of cumulative hazard screening indicators could be used in a policy context in Canada and elsewhere, while highlighting some of the methodological complexities in how environmental and social risks are characterized and combined. Given these complexities, we suggest that community input should inform the design of environmental justice indicators, as an important component of procedural justice.

1. Introduction

Environmental hazards are not distributed equally, spatially or socially. In the context of air pollution, a rich and growing body of literature with roots in the United States (US) has indicated that socially and economically marginalized groups, including low-income [1], racialized [2, 3], and Indigenous [4] communities, are often disproportionately exposed to ambient air pollution. Further, these same communities may experience existing vulnerability and susceptibility to air pollution health impacts, resulting from disparities in access to health care and political process, and other forms of structural oppression [5, 6]. These inequalities in exposure to environmental hazards are a form of distributional injustice, one facet of environmental injustice [7]. Here, we use the term injustice or inequity to refer to the subset of inequalities—that is, differences in exposure to environmental hazards between population groups—that arise from the systematic and intentional or unintentional marginalization of certain groups, and that are likely to reinforce or exacerbate disadvantage and vulnerability [8] (p 14).

Although there is a growing evidence base that characterizes air pollution exposure inequalities,
there remain important knowledge gaps that in turn can limit the extent to which environmental justice (EJ) is taken into account in decision-making (assessment and planning, permitting, enforcement). One of these is the continued need for more global coverage in EJ investigations [9–12]. Although EJ research has expanded in its geographic scope in the close to four decades since EJ discourse emerged through grassroots activism in the US, there remain important opportunities to increase the depth and breadth of research in other countries and regions. In Canada, scholars have argued that the shape of the EJ movement has differed compared to the US [13–15]. From a global perspective, ambient air pollution concentrations in Canada are relatively low, however, current understandings of concentration-response functions between exposure and health impacts suggest that small variations in exposure at lower concentrations can result in large health differences [16]. Although past research on air pollution and EJ in the form of case studies (e.g. Hamilton and Sarnia, Ontario [17–19]), comparisons across urban centres [1], and national-scale studies [20] have indicated some similarities to findings in the US and elsewhere, particularly around exposure for low socioeconomic status and racialized communities [14], researchers have also noted the need for further investigation into distributional impacts for Indigenous peoples, and interactions between racialization and immigrant status, for example [13, 14].

A second key gap, in Canada and elsewhere, concerns the methodological challenge of assessing and representing the multidimensional nature of EJ. Environmental injustice is a complex phenomenon: even when focusing only on distributional justice, there are multiple dimensions of risk, benefit, community vulnerability and individual susceptibility [21]. Although existing regulatory frameworks often target sources of environmental health harm from a pollutant-by-pollutant or source-by-source basis, in practice, people experience multiple environmental stressors simultaneously [22]. The term ‘cumulative impact’ is often used to acknowledge the interacting nature of these multiple stressors [23].

The ability to summarize cumulative impact in a single value (index) that can be geospatially visualized can be useful for policy and organizing. Further, given the current emphasis on evidence-based policy-making, summarizing real-world phenomena in standardized forms of measurement (indicators) has become directly tied to policy action (justifying its need, informing its design, and evaluating its impact) [24]. In California, for example, a cumulative impact index (CalEnviroScreen, California Environmental Protection Agency) is used as a screening tool to identify impact hotspots as priority areas for regulatory enforcement, and for allocation of government funds for environmental, health, and other social services [25]. However, creating these indicators requires that choices be made about what data are included, and how these different sub-measures should be aggregated [26–28]. Key methodological questions for designing a cumulative index include: whether the interactive effects of multiple stressors be treated additively or multiplicatively, how correlations between different stressors are taken into account, and whether and how different stressors are weighted relative to each other [22, 26, 27]. Expert input is critical in this discussion, for instance on epidemiological evidence of synergistic/multiplicative responses to co-exposures [22], and on the relative toxicity of different pollutants [29–31]. However, so are broader deliberations on community and policy priorities [32].

In light of these research needs, the objectives of this present study are, using air quality as an application case, to: (1) Expand on existing metrics of cumulative hazard and apply them to three cities in Canada; (2) Compare patterns of injustice across individual pollutants, cumulative impact indicators, and cities; (3) Demonstrate how different measures of cumulative hazard can yield different understandings of inequality. We aim to both characterize cumulative hazard and environmental injustice patterns in urban Canada, and illustrate the potential complexities that arise when considering the multidimensional nature of both environmental hazard and social vulnerability.

2. Methods

2.1. Air quality data

We use annual air quality datasets from 2012 for ground-level fine particulate matter (PM$_{1.3}$, annual average $\mu g\ m^{-3}$) [33, 34], ozone (O$_3$, annual average ppb) [35–37], nitrogen dioxide (NO$_2$, annual average ppb) [38, 39], and sulfur dioxide (SO$_2$, annual average ppb) [40–42] derived from previously published, peer-reviewed studies, described in detail in the Supplementary Information (SI) (available online at stacks.iop.org/ERL/15/124063/mmedia). Ambient air quality guidelines have been established for the selected pollutants in Canada due to their adverse impacts on human and ecosystem health. These adverse health impacts, relevant to EJ, include acute respiratory effects and premature mortality from heart disease, stroke, and lung cancer, estimated to contribute to 14 600 deaths and 2.7 million asthma symptom days in Canada per year [43]. Pollutant concentration datasets were accessed through the Canadian Urban Environmental Health Research Consortium (CANUE), which indexed all data to DMTI Spatial Inc. postal codes with a single link indicator (SIL, a single representative point location for the postal code population) [44].

2.2. Demographic data

We consider three large cities in Canada: Toronto, Montreal, and Vancouver. Although all three are
diverse urban centers, they also represent different geographic regions, with distinct land use and cover patterns, and distinct linguistic, social, economic, and governance histories. We obtained demographic data from the 2016 Canadian Census at the dissemination area (DA) level through Statistics Canada, accessed through the Canadian Census Analyzer [45]. DAs are the smallest geographic unit for which census data are provided publicly, with average populations sizes ranging from 400 to 700. In our illustrative analysis, we consider four census variables: low-income status (‘In low income based on the Low-Income Cut Offs’, LICO), Indigenous identity (‘Aboriginal Identity’), racialized group/ethnicity (‘Visible Minority’, further disaggregated into 12 categories), and immigrant status (‘Immigrant Status’). In addition to directly using census variables, we also use two derived indices for material and social deprivation, based on six socio-economic indicators from the 2016 Census [46], briefly described in the SI and fully in Pampalon et al [47]. We chose these variables and indices as example indicators of key social stratifiers that have been identified as policy priorities for addressing health inequity in Canada [8]. A more complete description of these census variables is provided in the SI, including a further discussion on our use of the term racialized in the Canadian context.

Pollutant concentrations at the postal code level, provided by CANUE, were linked to demographic data at the DA-level through spatial joins [48]. Pollutant concentrations were aggregated to the DA level by a simple average of postal code SLIs contained therein as a proxy for population-weighting. This method can contribute to exposure error but is appropriate for a screening-level analysis, as further explained in SI section 1.2.

2.3. Cumulative hazard indices

We construct three cumulative hazard indices (CHIs) to explore how different approaches to aggregating multiple pollutants affect estimates of inequality: additive (Add), multiplicative (Mult), and binary (Bin). For all three, we weight pollutants equally for analytical simplicity in this exploratory work, however, we discuss alternative approaches in the SI. Our approach to the additive and multiplicative CHIs draws from Su et al [26].

First, we normalized pollutant concentrations within each city to compare and aggregate them without scale effects. This process is described in SI section 1.4. Normalized ratios \( r_{ij}^{\text{norm}} \), for pollutant \( i \) and DA \( j \) are combined in the following ways to yield an additive and multiplicative index.

\[
CHI_{\text{Add}, j} = \sum_{i=1}^{4} r_{ij}^{\text{norm}}
\]

\[
CHI_{\text{Mult}, j} = \prod_{i=1}^{4} r_{ij}^{\text{norm}}
\]

For the binary index, for each DA, each pollutant is given a score of 0 or 1 based on whether the concentration, \( c_{ij} \), equals or exceeds the benchmark value, \( s_i \) (based on the Canadian Ambient Air Quality Guidelines for PM_{2.5}, NO_{2}, and SO_{2}, and the Canada-wide annual average concentration for O_{3}, see SI for description of benchmark values). The binary CHI is then the sum of these four scores:

\[
CHI_{\text{Bin}, j} = \sum_{i=1}^{4} x_{ij}
\]

where

\[
x_{ij} = \begin{cases} 
1 & \text{for } c_{ij} \geq s_i \\
0 & \text{for } c_{ij} < s_i 
\end{cases}
\]

2.4. Measures of inequality

There are numerous methods for quantifying environmental inequality, each with its tradeoffs [49, 50]. Here, we use two measures: (1) group differences in population-weighted, mean residential concentration and, (2) an absolute concentration index. This choice is further explained in the SI. Mathematically, the measures themselves indicate inequality, however, as noted in the Introduction, if the inequalities are considered unjust and likely to exacerbate existing vulnerability and disadvantage, they evince *inequality* in air pollution exposure [8, 49].

For each city, we calculate differences in population-weighted, mean residential pollutant concentrations and CHI scores between: low-income status and non-low income status, Indigenous and non-Indigenous, racialized/ethnicized and white, and immigrant and non-immigrant groups. The statistical significance \( (p < 0.05) \) of differences are determined with a two-sided Mann-Whitney U test.

Our second measure of inequality is an absolute concentration index. The concentration index, described in [49, 51, 52], is often used to characterize health inequality and has also been applied to characterize inequalities in environmental exposure [26, 27]. The index can be applied to individual or group-level (i.e. DA-level) data, as long as they can be rank ordered by degree of social marginalization. Construction of the index, based on a bivariate extension of a Lorenz curve, is detailed in SI section 1.5. In the remainder of the text, we refer to this as an Inequality Index (I), to avoid confusion around the word ‘concentration.’ If \( I = 0 \), we interpret this to mean there is equality in the dimension of marginalization (e.g. no difference in concentrations between DAs with higher or lower proportion of below LICO
3. Results

3.1. Cumulative air pollution and demographic descriptive statistics

Figure 1 shows the spatial distribution of the binary, additive, and multiplicative CHIs for each city, with additional descriptive statistics in tables S3–S5. The distribution of the underlying individual pollutants reflects location of emissions sources (including traffic and industry), chemistry (as some pollutants are emitted directly while others are formed in the atmosphere), meteorology and topography (which can impact the transport of pollutants), as well as the spatial resolution of the underlying datasets. These drivers and resulting concentration patterns for individual pollutants are described in SI section 2.1, and here we focus on cumulative air pollution patterns. At the dissemination area (DA) level, Toronto had the highest binary CHI score across the cities at 3, with above-benchmark values for PM$_{2.5}$, NO$_2$, and O$_3$ in Northwestern inner suburbs. For Montreal and Vancouver, the maximum was 2, for PM$_{2.5}$ and NO$_2$, though Montreal had the highest mean and media DA-level Binary CHI. The multiplicative and additive CHIs generally yielded the same spatial pattern, with clear traffic-related contributions to cumulative burdens, as well as some boundary artifacts for SO$_2$ satellite product resolution. However, additive CHIs were generally less spatially variable, with coefficients of variation ranging from 0.07 (Vancouver) to 0.14 (Montreal), compared to values ranging from 0.32 (Vancouver) to 0.58 (Montreal) for the multiplicative CHI.

Socio-demographic statistics are shown in tables S1 and S2. The populations of Toronto and Vancouver were majority racialized in the 2016 census, while Montreal’s non-white population represented 34.18% of the population. Immigrant populations ranged from 34.33% in Montreal to 47.02% in Toronto. All cities were similar in percentage of low-income (LICO) population, from 17.16% in Vancouver to 19.21% in Montreal. The DA with the highest percentage LICO population was in Vancouver (85.5%). Vancouver also had the highest city-wide percentage Indigenous population (2.24%), and also the highest DA-level Indigenous population (37.74%). The spatial distribution of scores for the two derived indices, SFS and MFS, are shown in figures S5–S7, along with maps of all other demographic variables. Figure 2 shows a subset of these variables, as an illustration.

We note a few key features of interest in figures 1 and 2. In Vancouver, Indigenous and low-income residents are highly concentrated in DAs east of the downtown core (peninsula), which have higher CHI scores, due to the presence of industry, marine and rail terminals, and associated traffic. In both Toronto and Vancouver, DAs with the highest proportions of racialized residents tend to be located in the inner suburbs (towards the Northwest and Northeast in Toronto and South in Vancouver). These areas correspond to regions of higher ozone in the former, and higher SO$_2$ in the latter, but are more mixed for the other pollutants. In Montreal, the eastern portion of the city contains DAs with high proportions of immigrant and racialized residents, and also high additive and multiplicative CHI scores due to the confluence of industrial and traffic-related pollutants, and photochemically produced O$_3$.

3.2. Group-weighted mean concentration differences

Inequality patterns, in terms of group-weighted mean exposure differences along dimensions of social marginalization, vary across pollutants, cumulative indices, and cities, reflecting the combination of where pollution burdens are highest (figure 1) and where vulnerable populations reside (figure 2). Figure 3 and tables S6–S8 show results for population-weighted mean residential concentration for different demographic groups. In figure 3, we plot the relative difference (in %) between the population in each city belonging to a demographic group and its complement (e.g. concentrations for racialized residents and concentrations for white residents), for each individual pollutant concentration and CHI. Almost all differences are statistically significant at p < 0.05, indicated with an asterisk.

Vancouver has the highest relative differences between socially advantaged and disadvantaged groups for individual pollutants and CHIs out of the three cities. In particular, concentrations and CHIs are consistently and statistically significantly higher for Indigenous compared to non-Indigenous residents (+0.47% for PM$_{2.5}$ to over +30% for the binary CHI), with the exception of SO$_2$. We observe a similar pattern for below LICO residents, with higher cumulative hazard burdens across all three CHIs (+1–6%), and higher or no difference in concentrations for individual pollutants (0–3%), with the exception of PM$_{2.5}$ (~2%). Results for racialization and immigrant status are more mixed across the four individual pollutants, and we find that cumulative hazard burdens are higher for white and non-immigrant populations. However, when disaggregated by racialized and ethnic groups (table S9), there are important
Figure 1. Cumulative Hazard Indices (CHI) by city.

Figure 2. Demographic data at the DA level, from the 2016 Canadian Census [45] for three variables of interest (% Indigenous residents, % racialized residents, % below LICO residents). Areas without reported data are shown in grey. These are typically DAs for which the number of residents corresponding to a given category are low enough that there could be identifiability concerns. Maps for all demographic variables are provided in the SI. Map tiles by Stamen Design, under CC BY 3.0. Data by OpenStreetMap, under ODbL. © OpenStreetMap contributors.
variations. For CHIs, Black, Latin American, Arab, West-Asian, Korean and other racialized groups not included elsewhere (NIE) have higher additive and multiplicative scores (1–12% higher than white residents), and binary CHI scores are higher than the white population for all groups except Chinese and Japanese populations.

Montreal exhibited different patterns of inequality compared to Vancouver: concentrations were modestly (up to 5%), but significantly, higher for racialized compared to white and immigrant compared to non-immigrant residents in the city across most individual pollutants and CHIs. For the additive and multiplicative CHIs, higher concentrations for the racialized over white population were due to inequalities for Black, Latin American, Arab, and Southeast Asian populations. Inequalities for the below LICO population were more mixed (in sign) across pollutants and CHIs, but also larger (up to 10%) than for racialized and immigrant groups. Indeed, the largest relative difference at (≈10%) observed in the city was between above and below LICO residents for the Binary CHI. Results for Indigenous communities in Montreal were similarly mixed, and no differences for CHIs were statistically significant.

Toronto tended to have lower inequalities, with some similarities to both Vancouver and Montreal in their patterns. As in Vancouver, below LICO households had consistently higher (0.13–3.35%) CHI scores than higher income households. Differences between racialized and white, and immigrant and non-immigrant residents were mixed in sign across the individual pollutants and additive and multiplicative CHIs (ranging from −1.70% to +9.19%), with the largest disparity for both being in the binary CHI (+9.19 and 6.21% for immigrant and racialized residents, respectively). More similarly to Montreal, individual pollutant concentrations for Indigenous residents were lower for some (O$_3$, NO$_2$), and higher for others (PM$_{2.5}$, SO$_2$), yielding mixed results across the CHIs.

### 3.3. Inequality index

Figure 4 presents a heat map of inequality indices for each city, with each cell representing the score for one dimension of social marginalization and pollutant/CHI. For the index, in addition to the four demographic groupings considered for group-weighted mean concentration differences, we also use social and material deprivation scores (SFS and MFS, respectively). Confidence intervals for the indices are provided in SI tables S12–S14.

Across all three cities, the largest inequality index values were for the binary CHI. These values occurred when ordering by proportion of Indigenous residents (−0.143), below LICO residents (−0.110), and MFS (−0.087) for Vancouver, Montreal, and Toronto, respectively. For the majority of dimensions of marginalization considered, the binary and multiplicative CHI yielded the largest magnitude inequality values (positive and negative), followed by various orderings of individual pollutants and the additive CHI. However, notable exceptions include the large inequality index values for O$_3$ in Vancouver, SO$_2$ in Montreal, and SO$_2$ in Toronto.

The inequality index results indicate similar patterns to the group-weighted mean differences in terms of which groups consistently experience inequalities in individual and cumulative air pollution hazards in each city. In Vancouver, inequality index values were consistently negative for Indigenous and below LICO composition, and SFS. Immigrant and racialized composition index values were more modest but consistently negative in Montreal, and MFS yielded some of the highest inequality values in the city, and were also predominantly negative. As with the group-weighted mean differences, taken as a whole, Toronto had the lowest inequality index values across the three cities. Below-LICO and racialized composition, as well as SFS yielded negative values for all CHIs, and two or more individual pollutants.
4. Discussion

Our findings illustrate the important ways in which cumulative air pollution burdens may differ from individual ones. Because individual air pollutants vary in their spatial distribution due to differences in emissions sources, chemistry, and transport, their combination may yield different spatial hotspots. In Montreal and Toronto, we find that inner suburbs are hot spots for the three CHIs considered: compared to urban cores, these areas can still have relatively high concentrations of traffic related air pollutants (e.g. NO\(_2\), PM\(_{2.5}\)), but also tend to have higher O\(_3\) (which is photochemically produced downwind of precursor emissions) and SO\(_2\) (due to industrial zoning). In Vancouver, we find that high-traffic, mixed-use industrial and residential zones east of the downtown core, which include marine and rail terminals, are cumulative pollution hot spots.

Different methods of constructing cumulative burden indicators can also be used to highlight different kinds of spatial ‘hot spots’ for air pollutants, and these hot spot differences in turn have implications for patterns of inequality. Our additive and multiplicative CHIs, which use normalized air pollution concentrations, are designed to showcase the relative distribution of cumulative burden within a city, whereas our binary CHI uses 0 or 1 scores based on comparison to external benchmarks. The binary approach could potentially be useful for identifying areas of concern based on regulatory exceedances; this may be a powerful approach in many jurisdictions where non-compliance has financial or other implications, though we note that in Canada, ambient standards are non-binding. In this work, the binary CHI emphasizes NO\(_2\) and PM\(_{2.5}\), as concentrations of these pollutants were most likely to be above 2020 air quality guidelines (used as benchmark values). Similarly, the additive CHI may indicate areas where individual pollutant concentrations are particularly high even when other pollutant concentrations are relatively low (compared to other regions in the city) as it assumes independence and no interaction between pollutants [28], whereas the multiplicative model emphasizes synergistic burdens with interactions between components [53]. These differences in what is emphasized in each CHI translate to the different magnitudes, and sometimes direction, of inequality for specific social groups shown in figures 3 and 4. For instance, methodologically we expect (and find) greater spatial variability in CHI values for the binary and multiplicative CHIs than the additive, and therefore larger inequalities in these CHIs between demographic groups. These results indicate that when choosing a CHI, careful consideration of the purpose of analysis is required to guide decisions on how individual pollutants are combined, weighted, and whether there are relevant thresholds to be considered.

We observe distinct patterns of inequity between cities, in terms of which socially marginalized groups experience higher cumulative air pollution burdens. In Vancouver, Indigenous, low-income, and high social deprivation score residents had higher CHIs across all three indices. Inequalities in the binary CHI for Indigenous residents of Vancouver were the largest observed across all three cities (binary CHI 30% greater than that for non-Indigenous population, inequality index = −0.143), driven by high spatial concentration of Indigenous residents in neighbourhoods with above-benchmark PM\(_{2.5}\) and NO\(_2\). In contrast, in Montreal, immigrant, racialized, and high material deprivation score residents had elevated cumulative hazard burdens (for at least 2 out of 3 CHIs). Inequalities in Toronto tended to be more modest in magnitude than in Vancouver or Montreal, and were most consistently observed for low-income, racialized, and high social deprivation index groups. Results were largely, but not always, consistent between the two measures of inequality considered.

However, our results also indicate the importance of unpacking indicators of social stratification to better understand how and why inequalities emerge. For instance, although we find that racialized residents as a whole do not experience larger cumulative air...
pollution burdens in DAs in Vancouver than white residents (measured through group-weighted mean exposure differences), while they do in Montreal, in both cities, areas with higher proportions of Black, Latin American, and Arab residents have higher concentrations of individual pollutants and cumulative burdens. These variations emphasize the criticality of capturing how individual racialized communities differ in their experience of air pollution burdens in cities and across cities, a finding also demonstrated in the US [54]. We also find inconsistencies between results for our two indicators of socio-economic status: below LICO status, and the material deprivation score (MFS), which combines educational attainment, unemployment, and income [47]. This finding echoes previous studies in suggesting that, as with hazard, there is a need to adopt a multi-faceted understanding of social marginalization by using a suite of indicators (e.g. tenancy), even when considering a concept such as socio-economic status [1].

Taken together, these results reflect the complex social geographies and histories of each of these cities [55, 56]. For example, different histories of immigration have implications for inequalities related to immigrant status and racialization. All three cities have historically been gateway cities for newcomer settlement [57]. However, Vancouver and Toronto have larger immigrant populations (in the 2016 census, close to 50%). In Vancouver, since the 1990s, newcomers have come predominantly from East and South Asia, while newcomers to Toronto and Montreal tend to be from more geographically diverse origins, including Central and South America, the Caribbean, and Africa [57, 58]. In all cities, patterns of settlement for newcomers, some of high socioeconomic status, has tended towards suburbs rather than inner city areas over time [57, 58]. In short, every city has its own story, and these stories are constantly evolving. In Canada, as in many other jurisdictions, EJ indicators are not yet routinely incorporated into policy decision-making at the local, provincial, or federal level in processes such as impacts assessment for new projects or regulations [49, 50, 59]. Even in cases where consideration of equity dimensions is encouraged in planning [60], guidance on how to measure and monitor these dimensions can be limited, particularly from the perspective of cumulative hazards. The screening indicators developed and demonstrated in this work are one approach for incorporating EJ dimensions in policy analysis and effectiveness evaluation. Our findings highlight that if such indicators are applied in Canada, a place-based approach should be adopted, as the interactions between the distribution of pollutants and residents from different vulnerable groups can vary substantially from city to city, and conclusions from one context may not be generalizable to another.

This paper illustrates the potential application of CHIs for screening-level analysis of patterns of inequity in three Canadian cities for a single year; however, this initial demonstration should be followed by more detailed analysis. Here, we have used a range of input datasets, focusing on those that are nationally consistent to enable comparison across cities; however, this results in mismatches in spatial resolution between pollutants. In particular, we use coarser spatial resolution products with concentrations derived from satellite and larger-scale chemical transport modelling for regional pollutants such as O₃ and SO₂. Although these concentration surfaces are validated against ground-based observations [36, 37, 41, 42], and represent the best available national-scale data, there are opportunities to adopt approaches that better capture intra-city variations for EJ analysis. Also, we use residential mean concentration as an easy-to-apply proxy exposure metric, acknowledging that it is not a measure of personal exposure. To more fully understand inequities in air pollution burdens, it is critical to capture what people breathe not only where they live, but also where they work, learn, and play [61]. Although we weighted all pollutants equally for analytical simplicity in this illustrative analysis, alternative weighting schemes tailored for use-case should be developed before application of this approach in a decision-making context—for instance, based on relative toxicity given health endpoints of interest [29–31]. Finally, future analysis could benefit from more finely resolved socio-demographic data. Our results suggest that a more intersectional analysis, one that considers how different social stratifiers may combine (e.g. immigration status, racialization, socio-economic status), is necessary to better understand drivers of observed disparities. Analysis of individual-level census microdata would therefore be a valuable next step, as would the use of regression models to analyze how individual social stratifiers predict cumulative air pollution burdens net of key control variables (including other stratifiers).

Although the focus of this paper was to document and describe patterns of inequality, EJ research must also elucidate and transform the systems and structures that produce them. This includes research on systemic drivers [4, 6], EJ organizing and activism [62, 63], and quantitative analysis that evaluates the potential impact of intervention strategies [64–66]. In all of these threads of research though, attention should be paid to how inequality is characterized and measured. This exploratory descriptive analysis illustrates the complexity of that characterization in the context of cumulative air quality impacts and EJ in Canada. Importantly, by bringing attention to the ways in which different choices about how environmental risks and social stratifiers are chosen, characterized, and combined can change our understanding of inequality, this work emphasizes the need for place-based, community-engaged approaches to EJ analysis to ensure that analytical
choices reflect the priorities and perspectives of marginalized communities. Indeed, recognizing that procedural justice can be a means to address distributive injustice [63], we suggest that an environmental data justice perspective—one that concerns itself with how, by whom, and for whom environmental data is governed and produced [67, 68]—should inform the design of environmental justice indicators.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: 10.5281/zenodo.4007391.

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