Explicating the Urban Heat Island phenomenon using in-situ sensors

Priyadharshini Sakthivel

Department of Geography

McGill University, Montréal

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Abstract

Climate change, defined as long-term changes in global temperature and weather patterns primarily due to anthropogenic activities, affects ecosystems, biodiversity, and human health. As a result, urban populations are particularly at risk of heat-related illnesses, exacerbated by the Urban Heat Island (UHI) effect. Most UHI studies have utilized remotely sensed temperature data due to their easy availability and accessibility, but they only detect surface temperature differences and have been shown to portray urban areas as warmer than they actually are. In contrast, in-situ sensors can measure ambient air temperature, which impacts thermal comfort and is directly related to cardiovascular mortality. Currently, UHI can only be accurately measured using conventional in-situ weather stations, such as those operated by Environment and Climate Change Canada (ECCC). However, newer crowdsourced and Volunteered Geographic Information (VGI) approaches, such as using low-cost sensors, when combined with geographic technologies, have the potential to usher in a new era of micro-scale climate studies.

This thesis aims to assess the effectiveness of in-situ sensors in capturing and estimating UHI intensity within Canada. Through an extensive review of literature, the advantages of conventional and crowdsourced in-situ temperature data sources over other sources are identified. Furthermore, the challenges of utilizing data from in-situ sensors for UHI studies are also analysed. The analysis highlights the importance of considering spatial representativeness of in-situ sensors, whether conventional or crowdsourced, due to its influence on estimating UHI intensity. Overall, this thesis expands the current understanding of utilizing in-situ sensors to study UHI dynamics, which benefits policy-making and urban planning initiatives that aim to mitigate the adverse impacts of UHI and improve the resilience of cities to climate change.

Résumé

Le changement climatique, défini comme les changements à long terme de la température mondiale et des régimes climatiques principalement dus aux activités anthropiques, affecte les écosystèmes, la biodiversité et la santé humaine. En conséquence, les populations urbaines sont particulièrement exposées aux maladies liées à la chaleur, exacerbées par l'effet d'îlot de chaleur urbain (UHI). La plupart des études sur l'UHI ont utilisé des données de température télédétectées en raison de leur disponibilité et de leur accessibilité, mais elles ne détectent que les différences de température de surface et il a été démontré qu'elles donnent une image des zones urbaines plus chaudes qu'elles ne le sont en réalité. En revanche, les capteurs in situ peuvent mesurer la température de l'air ambiant, qui influe sur le confort thermique et est directement liée à la mortalité cardiovasculaire. Actuellement, l'UHI ne peut être mesurée avec précision qu'à l'aide de stations météorologiques conventionnelles in situ, telles que celles exploitées par Environnement et Changement climatique Canada (ECCC). Cependant, de nouvelles approches basées sur la participation de la population et l'information géographique volontaire (VGI), telles que l'utilisation de capteurs à faible coût, combinées à des technologies géographiques, ont le potentiel d'ouvrir une nouvelle ère d'études climatiques à micro-échelle.

Cette thèse vise à évaluer l'efficacité des capteurs in-situ dans la capture et l'estimation de l'intensité de l'UHI au Canada. Grâce à un examen approfondi de la littérature, les avantages des sources de données de température in-situ conventionnelles ou issues du crowdsourcing par rapport à d'autres sources sont identifiés. En outre, les défis liés à l'utilisation des données provenant de capteurs in situ pour les études sur les UHI sont également analysés. L'analyse souligne l'importance de la représentativité spatiale des capteurs in-situ, qu'ils soient conventionnels ou crowdsourcés, en raison de son influence sur l'estimation de l'intensité de l'UHI. Dans l'ensemble, cette thèse élargit la compréhension actuelle de l'utilisation des capteurs in-situ pour étudier la dynamique des UHI, ce qui profite aux initiatives d'élaboration de politiques et de planification urbaine qui visent à atténuer les impacts négatifs des UHI et à améliorer la résilience des villes face au changement climatique.

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List of Abbreviations

BUHI - Boundary Layer Urban Heat Island 15
CMA - Census Metropolitan Area 35
CUHI - Canopy Layer Urban Heat Island 15
CWS - Citizen Weather Stations 30
DNN - Deep Neural Network 37
ECCC - Environment and Climate Change Canada 13
GCC - Gulf Cooperation Council 17
GIS - Geographic Information Systems 13
GPS - Global Positioning System 21
IPCC - Intergovernmental Panel for Climate Change 10
LCZs - Local Climate Zones 29
LST - Land Surface Temperature 17
MENA - Middle East and North Africa 20
MODIS - Moderate Resolution Imaging Spectroradiometer 17
OSM - Open Street Map 22
ppm - parts per million 10
SUHI - Surface Urban Heat Island 15
UCI - Urban Cool Island 17
UGC - User Generated Content 21
UHI - Urban Heat Island 11
VGI - Volunteered Geographic Information 21

1. Introduction

The term "climate", derived from the Greek word "*klima*" which means inclination, describes the weather of a region averaged over a significant period of time (Heshmati, 2020). A change in either the average climate or the variability of the climate that continues for an extended period is referred to as "climate change". During the 1760s and 1840s, the Industrial Revolution changed rural agrarian societies into industrialised urban ones, as a result, the amount of carbon dioxide emissions started to increase with increased usage of fossil fuels (Britannica, 2023; Vries, 2008). All the carbon dioxide measurements taken over a century were later compiled in 1938 by British engineer George Callendar (Callendar, 1949), who discovered that carbon dioxide levels were rising along with temperatures. At that time, it was believed that this increase in temperature would be advantageous because it would prevent glaciers from returning and allow humanity to live in the future under a brighter sky and less barren landscape (*History of Climate Science Research*, 2023).

However, the amount of carbon dioxide in the air which was about 280 parts per million (ppm) before the Industrial Revolution, has now risen to over 400 ppm (NOAA, 2022). This increasing trend is confirmed by the Keeling Curve, a graph that records the daily changes of carbon dioxide concentration in Earth's atmosphere (Monroe, 2024). In the geological past, such extremely quick environmental shifts were often accompanied by mass extinctions because ecosystems could not adjust to the new conditions in time (*The History of Climate Science*, 2020). And contrary to earlier beliefs, more recent scientific evidence suggests that this warming might exacerbate the situation by melting permafrost and releasing trapped greenhouse gases from the oceans, which could amplify the warming. Amid such realizations of how things could go wrong disastrously, the Intergovernmental Panel for Climate Change (IPCC) was established in 1988.

1.1. Urban climate and Urban Heat Island effect

As stated above, industrialization changed the focus from agriculture to manufacturing and other industrial activities. This shift created more job opportunities in urban areas, drawing individuals from rural regions in search of employment. As a result, this increase in population helped to facilitate the development and spread of cities, a phenomenon known as urbanization (Berry, 2008). Since urban activities are significant contributors to greenhouse gas emissions, it is asserted that cities have a considerable role in climate change. According to estimates, cities account for

75% of all carbon dioxide emissions, with transportation and construction being the two biggest sources (Bazrkar et al., 2015). By 2050, 68% of the world's population, up from 55% today, is anticipated to reside in cities (UN DESA, 2018). This means that by 2050, an additional 2.5 billion people could live in urban regions due to urbanisation, with about 90% of this increase occurring in Asia and Africa (UN DESA, 2018). Further, people of lower social classes and racial and ethnic minorities are more likely to reside in warmer neighbourhoods than privileged ones, which causes a problem of environmental and climatic injustice (Fan & Sengupta, 2022; Schlosberg & Collins, 2014). Moreover, since climate change disrupts farm based livelihoods, it will continue to drive more climate refugees into urban areas (DePaul, 2012). These trends clearly demonstrate the importance of researching urban climate dynamics.

The local energy balance of a geographic space as well as its microclimatic characteristics and thermal environment are impacted by the alteration of a "natural" space to an urban space (Peng et al., 2020). When it comes to urban climate, the term 'Urban Heat Island' figures prominently. Urban Heat Island (UHI) effect is a climatic phenomenon characterized by temperature difference between the urban and the rural zones. The urban areas experience a higher temperature relative to their rural surroundings, especially at night (X. Yang et al., 2020; D. Zhou et al., 2019). UHI occurs due to heat accumulation resulted by the physical properties of urban landscape and anthropogenic heat released into the atmosphere (Oke, 1973). With recent developments in cities, there is no distinct borderline between 'urban' and 'rural' areas, therefore, the UHI can be considered in terms of the difference between the central parts of the city and its surrounding areas (Ngie et al., 2014). And it has been shown to exacerbate the effects of heatwaves, which relates it directly to global warming (Founda & Santamouris, 2017; Khan et al., 2021) adding to already important impacts of UHI such as higher energy use, exacerbation of energy poverty of vulnerable social groups during the hot months, and impaired air and water quality (Kousis et al., 2021).

The differences in the urban and rural temperatures were first observed by Luke Howard (1833) in the early 19th century, when studying the urban climate of London. The term 'Urban Heat Island' was later coined by Gordon Manley (1958) when he was investigating changes in snowfall patterns between urban London and its surrounding rural areas. UHI is measured by Urban Heat Island intensity (ΔUHI), which is the nocturnal difference between background the urban temperature and the background rural temperature (Oke, 1973). The intensity increases near sunset and is maintained until sunrise (X. Yang et al., 2020) and is usually used as an indicator for the magnitude of UHI (Jaber, 2022). The UHI effect is generated by a combination of factors, including the night-time release of heat absorbed by dark coloured rooftops, changes in shade and airflow brought on by urban architecture, and a lack of green space in the city (Fadhil et al., 2023).

It is directly associated with the degradation of public health and well-being due to increased urban temperatures. High temperatures have a variety of effects on human health, with mortality being the most severe. For instance, sixty-six casualties were reported in the city of Montreal in 2018 due to excessive urban heat (Lamothe et al., 2019). Other health implications include higher rates of asthma, complication of pre-existing medical condition of vulnerable populations and increased spread of diseases like malaria and dengue (Phelan et al., 2015). The ability to adapt to excessive heat exposure is essential to achieving improved health outcomes, and this ability is determined by the person's demographics, socioeconomic level, and geographic location. People of lower social classes and of racial and ethnic minorities are more likely to reside in warmer neighbourhoods than privileged ones, which causes a problem of environmental and climatic injustice (Fan & Sengupta, 2022; Schlosberg & Collins, 2014). It is important to identify the vulnerable populations at the community level, when developing policy interventions for this issue (Phelan et al., 2015).

Further, it has also been observed that energy consumption for residential cooling in the state of Texas increased due to UHI effect (Rong, 2006). A similar study was done for the residential area in Phoenix, Arizona found that urbanization has led to an increase in energy consumption from 7,888 kWh per year in the 1950s to more than 8,873 kWh per year in the 1990s (Golden et al., 2006). Extensive review of literature on the energy impacts of UHI by (Santamouris et al., 2015) identified the statistically significant role of UHI, which represents nearly 13% increase in energy consumption for cooling. This increased energy demand is tied with many other facets of society, thus impacting the economy, the environment and health (Phelan et al., 2015). Therefore, understanding the UHI effect is important for developing effective plans and policies to mitigate its impacts, promote public health, and build resilient and sustainable urban environments.

Currently, the only way to properly measure UHI is the use of conventional in-situ professional weather stations, such as those operated by Environment and Climate Change Canada (ECCC). These in-situ weather stations continuously measure near-surface (at a fixed 1.2m height) air temperatures and provide the data on an hourly basis (https://climateatlas.ca/important-data-notes-and-limitations). However, newer citizen science and Volunteered Geographic Information (VGI) approaches, for example through the Netatmo sensors (https://www.netatmo.com/) purchased from e-commerce sites like Amazon, combined with use of geographic technologies, has the potential to usher in a new era of micro-scale climate studies.

1.2. Geographic technologies in climate studies

With the ability to instantly plot, interpolate, and animate weather data across any level of the atmosphere, Geographic Information Systems (GIS) has emerged as a key management component in weather processing systems (Chapman & Thornes, 2003). It can be used as a decision support system because it i) offers a platform for displaying and analysing a vast combination of data from other sources (Chapman & Thornes, 2003); ii) aids decision makers in understanding the uncertainty of climate change impacts and managing the associated risks; and iii) helps in the planning and implementation of mitigation and adaptation strategies (Hassaan, 2021). Generally, geographic analysis and spatial visualization are valued in climate modelling as they help users evaluate results more accurately for a given area (Liu et al., 2011). The spatial variability of climatological and meteorological phenomena makes GIS an effective tool for managing enormous spatial climate datasets for a variety of purposes (Chapman & Thornes, 2003).

Additionally, to promote understanding, awareness, and action on climate change, it is essential to engage the general public in climate science. VGI represents a transformative approach to data collection compared to conventional methods typically employed by the government agencies. VGI platforms like Open Street Maps and eBird, provide opportunities for general public to contribute geospatial data voluntarily for mapping and environmental monitoring. It highlights life on a local level and draws attention on what often goes unnoticed in this huge world (Goodchild 2007). With a network of approximately eight billion people worldwide, VGI has the potential to provide dense and high-resolution datasets crucial for atmospheric observations. However, concerns about the data quality and reliability of VGI arise since the contributions are made by nonprofessional individuals.

1.3. Objectives

When measures are taken to reduce the UHI effect, it also helps address the effects of climate change and improve the quality of urban areas. This thesis is structured with the following objectives, each of which addresses certain research questions. The research objectives and questions are as follows,

i. To understand the abilities of in-situ sensors to capture the UHI phenomena

- What are the abilities of in-situ sensors to capture the UHI phenomenon?
- Can meteorological data volunteered by people be utilized in estimating UHI intensity (ΔUHI)?

ii. To identify the challenges associated with using in-situ sensors for UHI studies

- How representative are the crowdsourced sensors compared with the conventional sensors?
- What implications does representativity of in-situ sensors have on estimating UHI?

By accomplishing these objectives, this thesis provides a thorough understanding of using volunteered temperature datasets for quantifying ΔUHI, and contribute to the advancement of knowledge in the field.

2. Literature Review

This chapter of literature review is organized into two main sections related to the thesis: (i) a comprehensive review of Urban Heat Island (UHI) phenomena and (ii) Crowdsourcing/ Volunteered Geographic Information (VGI). The section on UHI delves into the types of UHI and global research initiatives on this phenomenon. The second section on Crowdsourcing/VGI begins with a summary of its origins and growth, followed by its application across various disciplines, and concludes with the issues associated with it.

2.1. Urban Heat Island

2.1.1. Methods to estimate intensity

Based on the surface or region of atmosphere being observed, three different types of UHI are identified namely Surface Urban Heat Island (SUHI), Canopy Layer Urban Heat Island (CUHI) and Boundary Layer Urban Heat Island (BUHI) (Branea et al., 2016). SUHI is based on the surface or skin (including grass, roofs, trees, and roads) temperatures (Martin et al., 2015), whereas CUHI and BUHI are based on the air (screen) temperatures (Mills et al., 2022). The air layer found between the ground and the roof of the building or the tops of the trees is referred to as the Urban Canopy Layer, and the air layer above this canopy layer is referred to as the Urban Boundary Layer (Bahi et al., 2019).

There are two common methods of obtaining temperatures to estimate the Canopy-level UHI (CUHI) identified above: i) in-situ sensors fixed at a stationary point (weather station) or as a traverse with the sensor fixed on a vehicle; and ii) model simulations (B. Zhou et al., 2020). Although expensive, the in-situ sensors provide accurate and continuous data and it has been found that the low-cost sensors are capable of monitoring weather conditions at high spatial and temporal resolutions (Fan & Sengupta, 2022). On the other hand, in-situ point measurements are limited by the number of locations monitored simultaneously and they are highly dependent on the interpolation parameters or techniques applied (B. Zhou et al., 2019). Whereas, data from mobile traverse comes with an advantage of spatial continuity in data but are highly influenced by the methodological design like route planning and mounting platform. For instance, at stop lights, the value recorded by the temperature sensors in mobile traverse is higher since exposed to the fumes of the adjacent vehicles' exhaust (B. Zhou et al., 2019).

On the other hand, SUHI is better captured by remote sensing, which uses information recorded in images from sensors that capture the ascending short and long wavelength radiation energy reflected from the earth's surface and measures the ground radiometric temperature which is based on the energy emitted and reflected from a surface (B. Zhou et al., 2019). The surface temperature of the permeable and impermeable materials of a landscape can be obtained from Stefan-Boltzmann's law that uses emissivity (Bahi et al., 2020). This surface temperature affects the air temperature along with other parameters like wind, moisture and turbulent mixing. Thermal remote sensing is capable of covering large geographic area at higher spatial resolution from tens of meters to several kilometers, yet they are limited to clear-sky conditions and to the complex physical structure of the buildings in urban area (B. Zhou et al., 2019). However, measurement in cities is difficult because of the complex structure of the urban–atmosphere interface since the surface temperature is influenced by surface slope and aspect, shading, and variations in surface thermal and radiative properties (Voogt & Oke, 1997). Moreover, there is no clear correlation obtained between surface temperatures obtained from satellites and the CUHI effect of higher nocturnal air temperatures in cities, and is the topic of ongoing research (Bechtel et al., 2014).

In general, therefore, SUHI is detected using surface temperature observed by airborne or satellite remote sensing (Martin et al., 2015), whereas, CUHI and BUHI are detected with air temperatures observed by in-situ sensors. While temperature observations for CUHI is typically obtained from in-situ sensors at standard meteorological height or from traverses of vehicle-mounted sensors, for BUHI, temperature observations are made from more specialized sensor platforms such as tall towers, radiosonde or tethered balloon flights, or from aircraft-mounted instruments. Due to the difficulty of placing sensors/instruments in the boundary layer, very few BUHI studies exist (Voogt & Oke, 2003). Moreover, we human beings exist within SUHI and CUHI, which is why more emphasis is given for these two phenomena and their impacts on human well-being in particular.

Finally, modelling of CUHI is also done at various scales like building scale, micro-scale and city scale models, according to the functions a model must perform (e.g., ENVIMet) (Tsoka et al., 2018). While, building and micro-scale models are accurate with higher resolution and are computationally expensive, city-scale models are easy to compute and covers a vast area, but do not have enough accuracy to provide details. So, spatially and computationally efficient models are needed to use them in the research of large urban area temperature anomalies (Mirzaei, 2015).

2.1.2. Research initiatives around the world

There have been a large number of studies on SUHI due to the relative ease of obtaining and using satellite data. In Canada, Rinner and Hussain (2011) used thermal images from Landsat sensor to identify SUHI for the city of Toronto and correlated the findings with land use density and land use type. Researchers from Montreal estimated SUHI intensity for the city with climatic models and validated the results with SUHI intensity found using Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature (LST) data (Roberge & Sushama, 2018). SUHI was also studied in several arctic cities with MODIS LST data, and the intensities were rather large in smaller arctic cities than those in significantly larger low- and mid-latitude cities (Esau et al., 2021). However, the seasonal differences in the intensities are not large, since the high incoming solar radiation is absorbed and stored by darker and dryer urban surfaces in summer; and in winter, snow cover and low solar angles make the Arctic cities insignificant energy source (Esau et al., 2021). Note that there exists a scarcity of research on CUHI with in-situ measurements in these cities (Esau et al., 2021; D. Zhou et al., 2019).

Outside of North America and Europe, the Middle East is a unique geographic area with different sociodemographic and geopolitical identities. Increased oil profit growth drove migrations into the region, resulted in the evolution of existing highly populated areas into megacities (Mirzaei & Aghamolaei, 2021). Surface temperature distribution studies of eight desert cities in the Middle East with MODIS data found that the urban temperature in general is cooler than the surrounding desert soils – giving rise to the Urban Cool Island (UCI) effect (Lazzarini et al., 2015). This occurs because the temperature is reduced further in daytime in cities with vegetation, due to the evapotranspiration of vegetation (oasis effect). Instead, the classic SUHI pattern, where cities are warmer than the surroundings rural areas, were exhibited during night time, since bare soil surfaces cool faster than man-made and vegetated surface. So hot desert cities are characterized by diurnal UCI phenomenon and nocturnal UHI phenomenon (Lazzarini et al., 2015). UHI studies using LST was also done for the time period from 2003 to 2018 in the countries participating in Gulf Cooperation Council (GCC). The night time temperatures were addressed but not the significant Urban Cool Island phenomenon of the arid zones (Al Fazari et al., 2021). Using a novel spatial correlation representative pixel approach, the association between different forms of land cover and LST was looked at in order to evaluate the Surface Urban Cool Island (SUCI) intensity in Isfahan. In arid environments, SUCI intensity is higher in the summer than in the winter, similar to SUHI in non-arid places (Masoodian & Montazeri, 2021). Since there were no meteorological station in Isfahan, surface temperature method was used to study the SUHI because MODIS LST data showed high correlation with the air temperature in the Iranian meteorological stations. At night, the urban area was about 3.5°C warmer than the non-urban areas, and temporal analysis showed that SUHI intensified in January and weakened in July (Montazeri et al., 2022). Despite these observations, the study of UHI is still in its infancy in the Arab world and further studies are needed (Jaber, 2022).

Researchers have consistently shown interest in understanding the dynamics of the CUHI. Oke's (1973) study investigates the relationship between city size and CUHI by recording air temperatures using a mobile traverse that extended across the St. Lawrence River in Quebec. City population served as a proxy for city size, and the traverse covered ten different settlements, including Montreal, each with a wide range of population sizes. The resulting ΔUHI values and population sizes of these ten Quebec settlements were then compared with other North American and European settlements. The analysis revealed that the size of a city is directly proportional to its UHI intensity (Oke, 1973). A study conducted in Detroit, U.S.A. examined the correlation between air temperature and factors including imperviousness and distance-to-water. Subsequently, kriging and linear regression techniques were utilized to predict air temperatures at unsampled locations and all kriging techniques outperformed the regression models. The results of this study when integrated with socio-demographic data helps identify population that are vulnerable to the impacts of UHI (K. Zhang et al., 2011). Eastin et al., (2018) studied the variability of CUHI in Charlotte, U.S.A at different temporal scales. On the diurnal scale, the intensity was maximum during night time due to the considerable influence of local weather conditions and air quality. When ideal conditions are present, CUHI is more pronounced in weekdays compared to weekends, and the elevated nitrogen dioxide concentrations indicate that this can be due to vehicular emissions. Seasonally, the intensity is greater during dry winter months, and annually, it continues to increase in accordance with increasing urbanization and anthropogenic activities (Eastin et al., 2018). Meanwhile, the CUHI of Berlin was simulated and higher intensity values were observed during night time as observed in Charlotte. This increased intensity is attributed to the differences in surface temperature and sensible heat flux between impervious and vegetated surface (H. Li et al., 2019). Similar seasonal and diurnal patterns of CUHI were observed in 86 major cities across China (D. Zhou et al., 2023). However, a significant uncertainty in studying CUHI in the Chinese context arises from the limited and uneven distribution of weather stations, most of which are situated neither in urban areas nor in rural areas. This may result in an underestimation of UHI intensity (D. Zhou et al., 2023).

While the majority of UHI research focuses on the summer or heat wave period, J. Yang & Bou-Zeid, (2018) examined CUHI in twelve U.S cities during the 2014 North American cold wave. The heat islands intensified during extreme cold periods, especially at nights. This is due to the release of heat stored in the urban fabric during warmer months and anthropogenic activities like regular snow removal in urban area and increased energy usage by residents for indoor heating. This heat can be advantageous during extreme-cold events and it is important to consider this aspect of UHI for developing effective heat action plans to mitigate the impacts of UHI during warmer times (J. Yang & Bou-Zeid, 2018).

Consistent with the findings of other studies, CUHI research in India with ground-based measurements shows that CUHI intensity is more during night-time, and it is due to increased human activities at night (Rajagopalan, 2021). India, one of the most populated nations, is anticipated to see the greatest increase in population worldwide in the near future. However, compared to China and the United States, UHI research is still underdeveloped in India (D. Zhou et al., 2019). Research on UHI is focused mainly on temperate climates and the climatic models developed for temperate cities won't be suitable in countries with unplanned cities like India (Rajagopalan, 2021). A meta-analysis reveals that only a small number of Indian cities have had UHI research done on them using conventional techniques, without taking seasonal and spatiotemporal variations in the tropical environment into account (Khan et al., 2021). In Kolkata Metropolitan Area, the usage of land has been significantly increased in central areas while simultaneously converting lands towards the periphery for urban uses. Air temperature profile obtained with twenty-five micrometeorological field observation sites showed that surface and air temperatures are related and correspond to the shape of trapezium, both being high between hour 13:00 and 15:00 and then drops to the minimum between the hours of 03:00 and 07:00, then later continue to increase. This case study in Kolkata is representative of the scenario in other Indian cities such as Mumbai-Pune and the nation's capital, Delhi. However, the policymakers and administrators will need greater understanding on UHI across multiple cities than on a single city, to enable them plan for the sustainable growth of metropolitan areas (Khan et al., 2021).

In Malaysia, researchers examined the seasonal and diurnal variation of UHI in Kuala Lumpur using air temperature data obtained from meteorological stations. They further explored the influence of meteorological parameters such as relative humidity and wind speed on UHI (Ramakreshnan et al., 2019). Jin et al., (2018) established a network of fixed sensors in Singapore's Jurong East area. By incorporating urban morphological parameters such as Sky View Factor and the plot ratio of vegetation and built-up areas, they analysed the effects of urban morphology in controlling UHI.

To summarize, UHI intensity is influenced by the data used, study area, weather conditions and data acquisition time (Sheng et al., 2017). UHI studies are primarily done in Asia, North America, and Europe with relatively fewer studies conducted in Middle East and North Africa (MENA) countries, and South and Central America (Mirzaei, 2015; D. Zhou et al., 2019). Moreover, studies on SUHI are more prevalent compared to those on CUHI, largely due to the widespread availability of satellite datasets.

2.2. Volunteered Geographic Information

2.2.1. Growth over time

Before the internet era, scientific knowledge was often limited to those in positions of power within government, prestigious universities, or wealthy countries with advanced technologies. This created a monopoly on scientific information generation and as a result, the general public had limited exposure to scientific findings. Citizen science represents a collaborative research approach that engages members of the general public, including volunteers, amateurs and enthusiasts (Goodchild, 2007; Muller et al., 2015). In citizen science, individuals who may lack formal expertise in the field they are contributing to, participate in collection, analysis and dissemination of scientific data (Haklay, 2013). This engagement of citizens shifts the traditional top-down model of science to a more democratized bottom-up approach (Goodchild, 2007; See et al., 2016). Although this approach is increasing in popularity in recent years, this form of data collection has in fact been around for a very long time. A classic example of this is the National

Audubon Society's longest running bird life survey program, the Christmas Bird Count, which has been going on since 1900 (Dunn et al., 2005). Note that the terms 'crowdsourcing' and 'citizen science' are often used interchangeably. Crowdsourcing is the process of information generation wherein data collection is outsourced by a company or an institute to a large network of people via an open call for voluntary undertaking of the task (Muller et al. 2015; See et al. 2016). While both refers to the process of information generation via a large group of individuals, the information generated as part of the citizen science programs are always of scientific nature (See et al. 2016).

With the advent of the internet, especially Web 2.0, an interactive version of Web 1.0 with two-way information exchange, and with improved tools like mobile phones with inbuilt Global Positioning System (GPS), non-professional individuals began involving in data collection. People have thus become 'produsers', where they not just use internet, but produce data as well (Haklay, 2013). This type of data are called User Generated Content (UGC) (Hecht & Stephens, 2014). Volunteered Geographic Information (VGI), is special case of UGC produced by crowdsourcing (See et al. 2016). The concept of VGI introduced by Michael Goodchild in 2007, refers to the voluntary production, gathering, and distribution of geographic data by individuals (Goodchild 2007). Through VGI, individuals can independently gather information, without having to wait to consult scientists or authorities (Hachmann et al., 2018). The prevalence of devices equipped with GPS, such as smartphones and personal computers, has enabled people to consume and produce a greater amount of VGI. For most of the VGI platforms, contributing to a good cause and/or earning a specific benefit from them were identified as the general participation incentives (See et al. 2016).

Haklay (2013) has categorized crowdsourced VGI using two main criteria: i) the role of volunteers, and ii) the nature of the geographical component. It can be either active or passive based on the role of volunteers. VGI is considered active when a volunteer continuously contributes it on their own, for example, individuals may actively contribute data by taking images of animal species, adding geotags and sharing them online. On the other hand, passive VGI involves volunteers serving as observation platforms, allowing their movements or actions to passively produce data. For example, volunteers may contribute when they voluntarily enable GPS while walking to track their walking pattern. Additionally, depending on the nature of the geographical component, VGI can be explicit, such as precise location information of where a bird species is spotted, or implicit, like geotagged images of the bird species. While all forms of VGI are capable of providing quantitative information, only active and explicit forms could give valuable qualitative information (Haklay, 2013).

2.2.2. Applications across disciplines

Major data sources for VGI include Open Street Map (OSM), Instagram, Twitter, Flickr, Foursquare, Weibo and Geo-wiki (Cui et al., 2021; Yan, Ma, et al., 2020). Data from these platforms are utilized extensively across various disciplines such as ecology, epidemiology, social sciences, emergency response, and disaster management. It also has a greater potential in the Global South, where rapid urbanization is prevalent since reliable data sources are scarce in these dense settlements. For example, using OSM data, Vahidnia (2022) determined the degree of deterioration of Iran's urban areas, and identified the worsening of conditions in some areas due to poor air quality, water supply, and traffic congestion as a result of the city's population growth. A review of literature by Hachmann et al., (2018) on the use of VGI in slums or informal settlement monitoring and development, highlights that VGI can provide data to prevent any new informal settlements from happening, and helps upgrade the already existing ones. Using data from Weibo and OSM, Miao et al., (2021) examined Beijing's spatial composition and found that the city is gradually suburbanizing. Forget et al., (2021) developed a machine learning model with OSM data and satellite imageries from multiple sensors to map the expansion of urban areas in Sub-Saharan Africa. With text based VGI from Twitter, Salazar-Carrillo et al., (2021) developed a model to forecast traffic jams and accidents in Mexico City.

Uses extend to the developed world as well, particularly in conjunction with existing survey or census datasets. For example, Heikinheimo et al., (2017) identified the preferences of visitors to a national park in Finland with the help of geotagged images from Instagram. It was found that while surveys provide insights of a specific point of time when they are filled up, social media data allows for continuous monitoring of park activities. Basiouka et al., (2015) explored the application of OSM data for cadastral mapping in Athens. This approach offers significant advantages, such as being user-friendly, widely accessible, and enabling public participation and information sharing. However, these benefits can turn into drawbacks if there are no rules in place, as it allows anyone to manipulate the cadastral datasets (Basiouka et al., 2015).

In urban areas, applications often include smart city development, urban transit, urban green space, and urban resilience following disasters (Cui et al., 2021; Olivatto, 2023). Vannoni et al., (2020) evaluated the effectiveness of COVID-19 countermeasures in limiting people's mobility in 41 global cities using data from Citymapper, a mobile application for public transportation. Data from Strava, a fitness tracking application, were utilized to generate elevation profiles for roads of Santa Barbara and Washington, DC (McKenzie & Janowicz, 2017). These elevation datasets can be frequently updated, unlike traditional expensive datasets, thus are beneficial in scenarios where up-to-date and high-resolution data are unavailable. They were also used to add an elevation feature to the existing OSM datasets (McKenzie & Janowicz, 2017). Through PhillyTreeMap, an open source database of the city's urban forest that enables the public to inventory trees in their neighbourhoods, the use of VGI for urban forest management was examined in Philadelphia (Foster & Dunham, 2015). The demographic variables had a significant effect on the coverage of VGI data, and recognizing these effects will help address concerns related to social and environmental justice (Foster & Dunham, 2015).

Until 2017, the adoption of VGI in environmental monitoring was at its lowest. However, the advent of affordable and portable sensors that exchange meteorological observations over Bluetooth and/or the internet, has increased the contributions to this field (Yan, Ma, et al., 2020). For example, data from inexpensive in-situ temperature sensors installed by the public were combined with satellite-based temperature data to predict the spatial distribution of summer air temperatures across Berlin (Vulova et al., 2020). In Norway, Grossberndt et al., (2020) found a positive correlation between the air quality modelled by a high-resolution air pollution dispersion model and the air quality perceived by people, which was obtained through a mobile application. Such emerging studies show that while the varying morphology of urban areas makes it difficult to predict temperature and other meteorological variables that change over short distances, it is beneficial to have access to data from a large network of these inexpensive sensors (Muller et al., 2015).

2.2.3. Potential challenges

Very recently, VGI based research has seen significant growth (Olivatto, 2023), especially with respect to GIS (Wu et al., 2023), due to its open approach in data collection. The majority of VGI contribution platforms require very little expertise in order to participate, other than a basic knowledge of Internet and smart phone literacy. Moreover, VGI is sometimes the cheapest and oftentimes the only source of geographic information, particularly in areas where access to such data is considered as a security concern (Goodchild 2007).

Because VGI-based data contributions have increased exponentially, this geospatial big data comes with its own set of challenges like data quality and uncertainty (Wu et al., 2023). The quality of VGI is obviously an issue, since they are voluntarily contributed by a large group of non-professionals. And the difficulties associated with assessing the data quality are often identified as one of the weakness of VGI (Olivatto, 2023; Yan, Feng, et al., 2020). Measures of data quality typically include data completeness, accuracy, and usability; an extensive discussion on this can be found in (Antoniou & Skopeliti, 2015). For example, researchers in the Philippines used machine learning on satellite images and OSM to develop a model to predict socio-economic indicators, since obtaining these through conventional approaches is challenging (Tingzon et al., 2019). Two different models were built, and when their respective performances were compared subsequently, both models were found to be equally efficient. However, due to the difficulties in evaluating the accuracy and completeness of the OSM dataset, the reliability of the predicted indicators was deemed uncertain.

This is even more evident with regard to weather-related VGI data, which requires that amateurs have knowledge about installation of weather stations, and must be in accordance with certain principles in order to satisfy quality concerns (See et al. 2016). The development of algorithms such as CrowdQC+ for quality-control of crowdsourced weather data also highlights these issues, and is a step in this direction (Fenner et al., 2021).

2.2.4. Representativeness and Bias

Much research attention has been directed towards quality and credibility of VGI, with a particular focus on OSM (Yan, Feng, et al., 2020). On the other hand, data representativeness, another important aspect of VGI, has received very little attention than it deserves and has been identified as a research gap (Basiri et al., 2019; G. Zhang & Zhu, 2018). In general, VGI has four key components: location (where), time (when), observer's identity (who), and the specifics of the observed attributes or phenomena (what) (G. Zhang & Zhu, 2018). One draws inferences about the population based on the sample and for these inferences to be valid, the sample needs to be representative of the population. Potential biases identified in VGI with respect to its components (Haklay, 2013) are: i) spatial bias, defined by the availability of more data in areas with a high population or intense outdoor activity; ii) temporal bias, which is defined by, for instance, more data availability during the summer months (G. Zhang & Zhu, 2018); and iii) demographic bias, characterized by participants who are mainly male and/or who are well-educated, have high income, and possess more leisure time (Spielman, 2014).

In geography, representativeness means how well the spatial variation of attributes captured by a sample represents the spatial variation of attributes over an entire study area. Volunteered ecological data reported for a lake monitoring program in Ontario were biased towards recreational sites and other places accessible from the population centers. This is referred to as the 'cottage effect', because density of sampling efforts was higher in the lakes close to cottages (Millar et al., 2018). Similar trends are observed in birdwatching programs, with increased instances reported in places easily accessible to birdwatchers and/or located close to highly populated areas (G. Zhang, 2020). Other VGI sources such as Twitter and Flickr exhibit a bias towards high-density urban areas, while Foursquare, which recommends places to visit based on a user's current location, completely fails to represent rural areas (Hecht & Stephens, 2014). This happens as a result of people's tendency to contribute data for locations where they reside (Haklay, 2016). This also holds true for OSM. Haklay et al., (2010) evaluated the validity of Linus' law (more the contributors, higher is the quality of a platform) with respect to the data accuracy of Open Street Maps (OSM). The maps of rural areas were found to have more positional errors, compared with those of urban areas (Haklay et al., 2010).

Temporal bias is also evident in VGI data. L. Li et al., (2013) examined the temporal patterns in georeferenced text and image data from Twitter and Flickr collected within the United States. The number of tweets peaked twice in a day at around 13:00–14:00 and 20:00–21:00, throughout a week. Conversely, Flickr users were more active during weekends, and the majority of photos were taken during the afternoon hours. When it comes to OSM, the majority of contributions were made in the evening, peaked between 20:00 and 21:00 hours. As previously seen, these contributions were also mostly made on Sundays (Neis & Zipf, 2012). This weekend bias is also observed in the field of ecology. G. Zhang (2020) observed that the eBird platform had the highest number of sampling events, globally during the bird migratory and breeding seasons.

While a large number of bird species were reported, it is advised not to assume that more birds were present during these seasons. Because of the limited sampling efforts outside this timeframe, it is meaningless to assume without considering the effects of the inconsistent sampling. Furthermore, compared to weekdays, weekends had a higher number of active birdwatchers who reported more species and sampling events. Furthermore, most observations in biodiversity monitoring are done at noon, which may cause the nocturnal species go unnoticed (Arazy & Malkinson, 2021).

Finally, understanding the demographic representation (and any demographic bias) of VGI is important to better reflect the perspectives of all demographic groups and create an inclusive decision-making environment. The availability of internet service in a particular area with a specific number of people is referred to as internet penetration; however, penetration does not imply extensive internet usage. This may be due to lack of knowledge, resources, infrastructure, technophobia and other factors (Pandita, 2017). While North America and Europe exhibit higher percentages of internet penetration, Asia and Africa have the least penetration percentage (Pandita, 2017; Sui et al., 2012). A country's population affects its overall internet penetration; the higher the population of a country, the lower its internet penetration (Pandita, 2017). Although the overall number of internet users increased by 2022, this digital divide between developed and developing countries still exists according to the report by United Nations' International Telecommunication Union (*Measuring Digital Development*, 2023) and this evidently impacts the VGI contribution from these countries. Apart from this, diverse sources of VGI are developed in Europe and North America, thus making VGI a Global North phenomenon. OSM, which started off in 2004 at University College London, is the most popular source of VGI data (Neis & Zielstra, 2014). At the individual level, the concept of participation inequality, as described by the 90-9-1 rule, applies to VGI data sources as well (Basiri et al., 2019; Haklay, 2016). This suggest that ninety percent of users are lurkers who only read or observe without contributing, nine percent of users occasionally contribute and, only one percent of users contribute regularly, accounting for the majority of contributions. Moreover, people who are educated with higher income and more leisure time are the major contributors, as it requires investing time and money in activities such as bird tracking or setting up weather stations (Haklay, 2013). Since most men have more leisure time and fewer caregiving responsibilities, they are the leading contributors, especially with respect to OSM

(Haklay, 2016). This causes some groups to be overrepresented while the under-represented groups who may already be nominally present, get completely neglected.

3. Spatial Representativeness of Weather Stations and Their Impact on Urban Climate Research: A Case Study of the Urban Heat Island Effect in Canada

Given the breadth of work on UHI and VGI as presented in the previous chapter, I next investigated the representativeness of both conventional and crowdsourced in-situ temperature sensors across Canada. The results highlight the importance of sensor representativeness in estimating UHI magnitude and the complementarity of both sensor types in urban climate research. The text maintains its original format as submitted to the journal "Urban Climate", from the abstract to the discussion and conclusion section.

3.1. Contribution of Authors

This work is co-authored by two people: Professor Raja Sengupta and myself. As the first author, I obtained necessary data from multiple sources, wrote Python scripts to process the acquired datasets, identified specific sensors for further analysis, estimated UHI intensity, analysed the results, prepared figures and tables, and drafted the manuscript.

Professor Raja conceptualized and supervised the work. He supported the development of research objectives, helped in data collection, and mentored the interpretation of the results. He also helped with structuring the manuscript, offered constructive feedback on its draft versions, and revised them.

3.2. Abstract

Citizen Weather Stations (CWS) are a source of Crowdsourced Geographic Information for urban climate research, which can provide extensive datasets in areas where data are scarce or unavailable. In this article, we explore the efficacy of using meteorological data from CWS in studying the Urban Heat Island (UHI) effect across Canada during late spring and summer of 2022. In particular, we evaluate the representativeness of CWS before relying on them for UHI intensity estimates, since potential spatial biases of these sensors can greatly affect canopy-level measurements. We compared the spatial distribution of Netatmo CWS with conventional sensors from Environment and Climate Change Canada (ECCC), and found that while the ECCC sensors better represented rural areas, the Netatmo sensors had wider representativeness for urban areas. We then computed UHI intensity using urban temperature from Netatmo sensors and peri-urban temperature from ECCC sensors. The resulting intensity values were higher than those estimated using either the Netatmo or the ECCC sensors individually, thus highlighting the influence of sensor representativeness in estimating UHI magnitude. Overall, our research explores the representativeness of both ECCC and CWS sensors, and highlights their potential complementarity in urban climate research.

Key Words: air temperature, crowdsourcing, spatial representativeness, urban climate, Urban Heat Island

3.3. Introduction

3.3.1. Urban Heat Island (UHI) and its variability

As climate change accelerates there is likely to be an increased occurrence of extreme weather events. Thus, spatially dense and temporally continuous observations are required to observe such phenomena, both in populous regions to mitigate risks and in less populous regions where essential data is insufficient (Muller et al., 2015). For example, the phenomenon of Urban Heat Islands (UHI) is accelerating globally with increased urbanization coupled with climate change (Chen et al., 2023). UHI, measured as the UHI intensity, is the difference after sunset between a temperature measured at the core of an urban space when compared to the temperature measured at a nearby rural reference (Oke, 1973). It is generated by a combination of factors, including increased heat absorption by dark coloured rooftops, changes in shade and airflow brought on by urban architecture, and a lack of green space in the city (Fadhil et al., 2023). Moreover, at a regional scale, it has been shown that the magnitude of UHI intensity is directly correlated to population size of the city (Oke, 1973).

However, a simple understanding of UHI intensity as the nocturnal urban-rural difference in canopy level air temperatures underestimates the complexities involved in urban climate, i.e., it does not accurately reflect the local conditions around each station (Fenner et al., 2017). A UHI study in London with citizen science sensors found that there is no single UHI core but instead a series of localized hot and cold anomalies (Chapman et al., 2017). To address this problem of oversimplification, Stewart & Oke (2012) proposed a climate-based classification of urban and rural areas, popularly known as 'Local Climate Zones' (LCZs). They identified seventeen LCZs, which are split into ten built-type zones and seven land cover-type zones. As a result, UHI is no longer the urban-rural air temperature difference; instead, it is the difference in temperature between LCZs. Thus, different sizes of in situ sensor networks are needed to capture this intra-city variability (Meier et al., 2017; Muller et al., 2013). Conventional weather stations are suitable for macro-scale synoptic observations, and hence not usually appropriate for intra-urban studies. These sensors are in a coarse array network, and most of the sensors in these networks are installed outside cities, and close to airports, to prevent urban temperature biases in weather forecasting and climate monitoring caused by the UHI effect (Castro Medina et al., 2024; Puche et al., 2023). Urban climate and UHI studies fall under city-scale, and requires dense sensor networks since they cannot be precisely captured by a single sensor (Muller et al., 2013).

Personal weather monitoring devices sold by third-party companies that individuals can install in their homes to record temperature and rainfall (i.e., Citizen Weather Stations or CWS) can thus be an important a source of data for use in urban climate research. These low-cost sensors are capable of monitoring weather conditions at high spatial and temporal resolutions (Fan & Sengupta, 2022) and provide a high spatial density of data continuously over a long time (Benjamin et al., 2021). They are useful to study weather patterns that change over short distances, particularly in urban areas with heterogeneous morphology (Muller et al., 2015). Due to the presence of a dense network of sensors, CWS effectively capture the variability in UHI intensity seen within cities, which opens the way to explore the relationship between temperature variation and other factors like land cover and urban morphology (Feichtinger et al., 2020; Meier et al., 2017).

However, since they are volunteered, there is a need to understand the presence of bias in their representativeness of the UHI phenomenon. For example, it has been noted that CWS don't represent urban greenspaces, and natural landscapes are not covered well since they are densely concentrated in the built-up areas (Chapman et al., 2017; Fenner et al., 2017; Meier et al., 2015). This bias has resulted in an overestimation of air temperature in vegetated areas away from the city center (Venter et al., 2020; Vulova et al., 2020). Thus, the impact of spatial biases on the reliability of data collected by the CWS largely depends on the objectives of every individual study (Geldmann et al., 2016). This can be due to the fact that scientific geographic sampling requires the careful selection of sites in a manner that the samples are representative. This is unlike volunteered sampling, where observations are ad hoc and opportunistic (G. Zhang & Zhu, 2018). So, carrying out any UHI intensity analysis only with CWS can be problematic due to the presence of bias.

3.3.2. Crowdsourced Geographic Information

In recent years, there has been a surge in the production of data from non-governmental sources (Wu et al., 2023). The development of Web 2.0, together with the exponential growth in processing power and performance of devices, has led to a scenario where people not just consumed data from the internet but contribute to it as well. These contributed data are referred to as User Generated Content (UGC) (Hecht & Stephens, 2014), with motivations to contribute ranging from incentives, gamification, a desire to share information publicly, or to a collective cause (See et al., 2016). Similarly, crowdsourcing is the process of information generation wherein data collection is outsourced by a company or an institute to a large network of people via an open call for voluntary undertaking of the task (Muller et al., 2015; See et al., 2016). Over the years, a variety of terms have evolved to describe these contributions, e.g., crowdsourced data, Citizen Science, and Volunteered Geographic Information (VGI) (See et al., 2016). Specific to geospatial data, VGI can be considered to be a special case of UGC produced by crowdsourcing that comes with an additional locational element. The term VGI was first used by Goodchild (2007), where the idea of people as mobile sensors was presented, each with five senses and an intelligence of their own to gather and process information. VGI thus throws light on what goes unnoticed in this huge world; it highlights life on a local scale, and it is at this that VGI is of great value to geographers (Goodchild, 2007). Research interest in the theme of VGI accounted for merely 1 percent and 2 percent in 1991 and 2001, respectively (Wu et al., 2023). However, more recently, it has surged to 13 percent in 2020. Thus, a network with more than 8 billion people (sensors) forms a useful source of data that can address data gaps in domains where there are few or no datasets available. This vast network can generate massive datasets that can be utilized in different scenarios. VGI thus should be understood in the context of "big data" that has gained much popularity very recently (Sui et al., 2012). Coincidentally, climate and atmospheric scientists, as well as geospatial scientists, have been acquainted with big data since its early stages, due to the processing of huge volumes of model outputs, both using raster and vector data (Muller et al., 2015). The difference, of course, is that VGI is considered as a non-conventional source of information, with concerns about whether it can achieve acceptable levels of accuracy, certainty and reliability.

Nevertheless, applications of crowdsourced Geographic Information (a term preferred by See et al., 2016), have become numerous over time, with applications in diverse fields such as ecology, epidemiology, social sciences, emergency response, and disaster management (Yan, Feng, et al., 2020). A study conducted by Millar et al., (2018) examined the nature of crowdsourced information about lakes, contributed by individuals for the Ontario Lake Monitoring Program in Canada. Using data from popular citizen science platforms such as iNaturalist and eBird, researchers have studied the spatial distribution of colour polymorphism in animal species (Farquhar et al., 2023), monitored the seasonal distribution and abundance of insects (Braz Sousa et al., 2022; Cull, 2022), analysed the online trade of birds (Fink et al., 2021), and developed models to predict the occurrence of protected bird species (Lin et al., 2022).

Meanwhile, Heikinheimo et al., (2017) utilized social media data to investigate the preferences of visitors to a national park in Finland. Benjamin et al., (2021) utilized crowdsourced air temperature datasets to examine temperature variations across London. They later used this dataset to analyse building energy consumption during summer and winter, based on the city’s morphology. (Chow et al., 2023) mapped the streets that were flooded after Hurricane Harvey struck Texas, in the United States. They then modelled a floodplain and compared it with the one that was modelled using the conventional dataset from the government. Researchers from Norway compared perceived air quality data collected through two crowdsourcing smartphone apps with the outputs from a high-resolution air quality model (Grossberndt et al., 2020). The results showed a positive correlation between the perceived air quality reported by app users and the modelled air quality. This indicates that the crowdsourced data accurately reflects the actual pollution levels, highlighting its reliability for monitoring air quality.

3.3.3. Measuring Urban Heat Island (UHI) intensity

Based on the surface or region of the atmosphere being observed, three different types of urban heat islands have been identified: Surface Urban Heat Island (SUHI), Canopy Layer Urban Heat Island (CUHI) and Boundary Layer Urban Heat Island (BUHI). SUHI is based on differences in the surface or skin (including grass, roofs, trees, and roads) temperatures, while CUHI and BUHI are based on the air temperatures in the Urban Canopy Layer and Urban Boundary Layer, respectively (Mills et al., 2022). The Urban Canopy Layer is the air layer found between the ground and the roof of the building or the tops of the trees, and the Urban Boundary Layer is located above the canopy layer (Bahi et al., 2019).

There are three common methods of obtaining temperatures to detect UHI of the three types identified above: i) in-situ measurements of air temperatures; ii) remote sensing from satellites and more recently, drones; and iii) model simulations (B. Zhou et al., 2020). Generally, CUHI and BUHI are detected by in situ sensors, whereas SUHI is estimated with remotely sensed data (Martin et al., 2015). In-situ or field measurements are either recorded at a stationary point (weather station) or as a traverse with the sensor fixed on a vehicle (B. Zhou et al., 2020). Although expensive and required in large numbers, they provide accurate and continuous data. Airborne remote sensing uses the information recorded in images from sensors that capture the ascending short and long wavelength radiation energy reflected from the earth's surface (B. Zhou et al., 2020). Although this method is capable of covering large geographic areas at higher spatial resolutions, from tens of meters to several kilometers, it is limited to clear-sky conditions and to the complex physical structure of the buildings in urban areas (B. Zhou et al., 2020). Due to the difficulty in placing sensors in the boundary layer, very few BUHI studies exist (Voogt & Oke, 2003). Besides, we human beings exist within SUHI and CUHI, which is why more emphasis is given to these two phenomena and their impacts on human well-being in particular. Additionally, studies on SUHI are more in number than CUHI, owing to the easy availability and accessibility of remotely sensed data (Mirzaei & Aghamolaei, 2021). However, airborne sensors record the surface temperature of the roofs of buildings and the ground, rather than the ambient air temperatures, thus representing the urban area as warmer than it normally is, and failing to recognize the different scales of climatic phenomena (Roth et al., 1989). Simulation of CUHI is also possible via models, and according to their function they can be at multiple scales, i.e., at the building scale, micro-scale and city scale models (Mirzaei, 2015). Building and micro-scale models are accurate with high resolution but are computationally expensive. Envi-Met, a three-dimensional micro-scale model based on the laws of fluid dynamics and thermodynamics, is a well-known example (Bruse & Fleer, 1998). It allows users to simulate complex interactions between built environment, vegetation, and atmosphere at a resolution of 0.5 to 10 m, and it is widely used to gain insights on UHI and thermal comfort of urban areas (Chatterjee et al., 2019; Cortes et al., 2022; Faragallah & Ragheb, 2022). On the other hand, city-scale models are easy to compute and cover a vast area, but their accuracy is not enough to provide details about the Urban Canopy Layer (Mirzaei, 2015). Moreover, simulations require data from in-situ sensors for model calibration and validation (Chatterjee et al., 2019).

Here, we explore the potential bias present in the use of CWS and traditional government-installed weather station data to estimate UHI Intensity.

3.3.4. Bias in VGI

Ideally, one draws conclusions about a population on the basis of a given sample, with the understanding that the sample is representative of the population in order to draw valid conclusions. In geography, representativeness means how well the spatial variation of attributes captured by a sample represents the spatial variation of attributes over an entire study area. Evaluation of crowdsourced Geographic Information's quality and reliability has received a lot of research attention (Basiri et al., 2019; See et al., 2016; Yan, Feng, et al., 2020), with a particular focus on Open Street Map (OSM) (Neis & Zielstra, 2014; Spielman, 2014). The widespread adoption of such crowdsourced information, whose primary contributors are non-professionals in a variety of disciplines, is the reason for this increased interest. Examining their representativeness has been recognized as a research gap (Basiri et al., 2019; Cui et al., 2021; Yan, Feng, et al., 2020; G. Zhang & Zhu, 2018). In general, crowdsourced Geographic Information has four key components: location (where), time (when), observer's identity (who), and the specifics of the observed attributes or phenomena (what) (G. Zhang & Zhu, 2018). Potential biases identified with respect to these components (Haklay, 2013) are: i) demographic bias, characterized by participants who are mainly male and/or who are well-educated, have high income, and possess more leisure time (Spielman, 2014); ii) spatial bias, defined by the availability of more data in areas with a high population or intense outdoor activity; and iii) temporal bias, which is defined by, for instance, more data availability during the summer months (G. Zhang & Zhu, 2018). Urban climate involves various spatial scales, so to effectively utilize crowdsourced data, it is crucial to understand which scales the data represent (Muller et al., 2015). The objectives of this paper are to examine the spatial representativeness of Citizen Weather Stations (CWS) as well as conventional government-installed weather stations across Canada, and to explore the potential influence of spatial representativeness on the estimation of CUHI intensity (hereafter ΔUHI). This study fills a research gap by being the first to investigate the data representativeness of CWS across Canada and its influence on estimating ΔUHI, which has been previously unexplored.

3.4. Research methodology

3.4.1. Study Area

With its vast territory spanning the upper half of North America, Canada is the second-largest country in the world, with ten provinces and three territories. Within this expanse, Census Metropolitan Areas (CMAs) are geographical units encompassing urban areas created by Statistics Canada to facilitate the collection and analysis of demographic data. According to Statistics Canada, "a CMA must have a total population of at least 100,000, based on data from the current Census of Population Program, of which 50,000 or more must live in the core based on adjusted data from the previous Census of Population Program" (Government of Canada, 2021). As of the 2021 census, Canada has forty-one CMAs distributed across its nine provinces, and these CMAs serve as study areas for this research (Table 1).

Table 1. CMA distribution across Canada.

Province/Territory	**CMA (*n*)**
Alberta	4
British Columbia	7
Manitoba	1
New Brunswick	3
Newfoundland and Labrador	1
Northwest Territories	0
Nova Scotia	1
Nunavut	0
Ontario	16
Prince Edward Island	0
Quebec	6
Saskatchewan	2
Yukon	0
Total	41

Nearly 74 percent of the country's population resides in these forty-one CMAs, with the top ten CMAs alone accommodating more than half of the country's total population (Statistics Canada, 2022). The census boundaries for CMAs and downtown areas were downloaded as a shapefile from Statistics Canada's 2021 census data (Statistics Canada, 2021). It was found that there were 42 CMA polygons, with Ottawa split into two parts—one on the Ontario side and the other on the Quebec side. They were then merged to get 41 CMAs.

3.4.2. Data sources, acquisition and processing

This study utilizes air temperature data from two different sources: conventional sensors installed across the country by Environment and Climate Change Canada (ECCC) and from Netatmo CWS. Temperature data collected by ECCC sensors owned and maintained by the government are openly available to the public at hourly, daily, and monthly time scales. Netatmo is engaged in the business of developing, manufacturing and selling electronic devices connected to the Internet, developing software and related data processing architecture including but not limited to artificial intelligence and learning algorithms. Netatmo especially products and distributes personal connected weather stations. Netatmo's devices have the capability to measure, monitor, record, collect, transmit, store and analyse data, related to temperature, wind speed, precipitation, air pressure, humidity, air quality, carbon dioxide content in the air (https://www.Netatmo.com/company). Each weather station records instantaneous air temperature at approximately five-minute intervals which can be retrieved in limited quantities via its Application Programming Interface (API). Both ECCC and Netatmo sensors across Canada that worked during the late spring and summer months of May to August 2022 (Budhiraja et al., 2021; National Research Council Canada, 2020) were considered for this study.

For the ECCC sensors dataset, data from three different government sources (https://climate.weather.gc.ca, https://www.canada.ca/en/environment-climate-change/services/climate-change/canadian-centre-climate-services.html, and https://climatedata.ca/) were combined. With more than 8500 sensors, the initial dataset had sensors that worked as early as 1840, that observed air temperature at different temporal scales. A Python script was created for cleaning this dataset. Sensors that recorded hourly temperature data throughout 2022 were extracted and were subsequently filtered based on their unique station IDs. After eliminating redundant sensors that were located within a distance of less than fifty meters from each other, a total of 1043 ECCC sensors were acquired. For Netatmo, the data file of all sensors and their locations across Canada was acquired through the Netatmo Weather Program for Education, which is a programme that gives university researchers access to the data to enable them to carry out specific analysis. These sensors have been reported to have an accuracy up to 0.3°C (Coney et al., 2022). Based on their unique station IDs, close to 3000 unique Netatmo CWS were identified for the year 2022. As mentioned earlier, on average, these sensors recorded air temperature at five-minute intervals. It was observed that some sensors operated under one ID for a specific period and then under a different ID for the rest of the period, in the same location. Either a device must have been replaced with another device or the ID of the original device must have been changed for this to happen. To address this issue, sensors that operated continuously under the same station ID during all 12 months of 2022 were extracted; 68 percent of the total Netatmo sensors were obtained as a result.

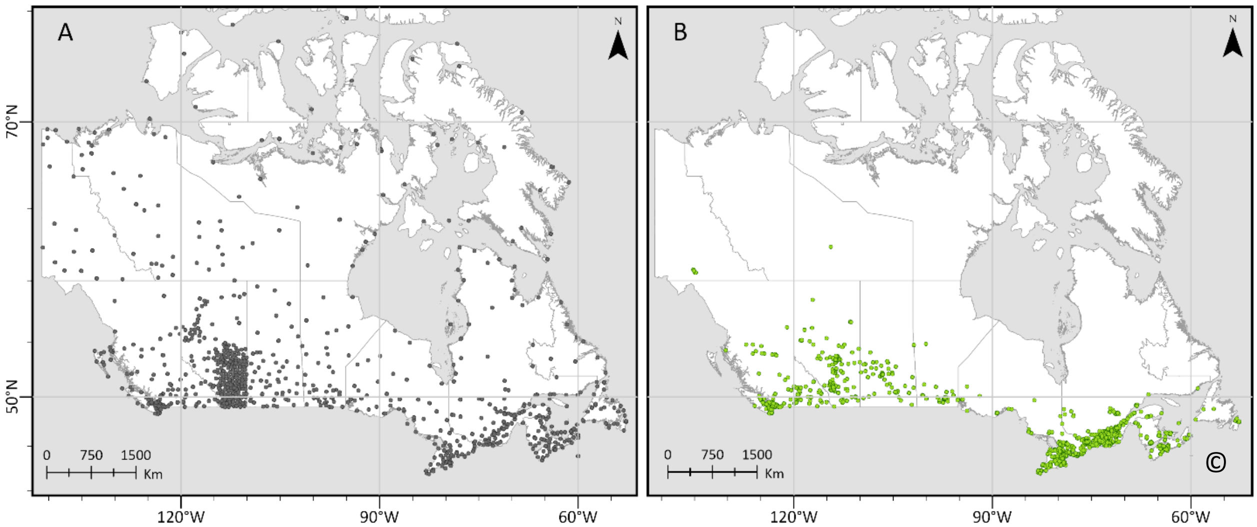

Figure 1. Overall distribution of (A) ECCC and (B) Netatmo sensors across Canada.

Other ancillary datasets were also utilized in this research. A shapefile with boundaries of primary and secondary downtowns of Canada was obtained from Statistics Canada (Sergerie et al., 2021); only primary downtowns were considered for this research. The most recent land use and land cover data for Canada at a 30 m spatial resolution was obtained through the Open Government Portal (Government of Canada, 2022; Latifovic et al., 2017). In order to facilitate analysis, sixteen land cover classes in the original dataset were reclassified into eight classes, namely, forest, grassland, wetland, cropland, barren, built-up, water, and snow. The building footprint dataset from Microsoft (2019) was also obtained. This dataset had nearly 12 million building footprint polygons extracted by Deep Neural Network (DNN) from aerial images and had a precision rate of 98.7%. Since this dataset had more building footprint polygons, it was chosen over the publicly available dataset provided by the Canadian government. All datasets were processed and then reprojected to Spherical Web Mercator projection (EPSG: 3857) in ArcGIS Pro 3.1.0.

Table 2. Distribution of ECCC and Netatmo sensors across Canada.

Provinces/Territories	ECCC (%)	Netatmo (%)
Alberta	23.59*	16.1
British Columbia	12.75*	17.46*
Manitoba	5.27	2.99
New Brunswick	2.01	1.52
Newfoundland and Labrador	4.12	0.6
Northwest Territories	5.66	0.05
Nova Scotia	4.51	2.99
Nunavut	7.86	0
Ontario	11.51	21.91*
Prince Edward Island	0.77	0.44
Quebec	12.85*	31.92*
Saskatchewan	6.04	3.75
Yukon	3.07	0.27

* Top three provinces with the highest share of sensors.

3.4.3. Analysis of spatial representativeness

In this study, the CMAs were considered as urban areas, and the entire sensor dataset was clipped to extract ECCC and Netatmo sensors located within these CMAs, thereby obtaining urban sensors to estimate ΔUHI. Additionally, 25 km buffers were created around each CMA to represent peri-urban areas located in the vicinity of each corresponding CMAs (i.e., the rural reference for measuring ΔUHI). Subsequently, the overlapping areas of CMA polygons were erased from these buffer polygons to get buffer rings that represent peri-urban areas. Sensors representing peri-urban areas were obtained by clipping the entire sensor dataset with these 25 km buffer rings, thereby providing peri-urban sensors to enable ΔUHI estimations (Figure 2). A 500 m buffer around each urban and peri-urban sensor, was created to calculate the percentage of each of the eight land cover classes within this area, as this distance has been shown to affect the measurement of heat islands by in-situ weather stations (Theeuwes et al., 2017).

A Python script was developed to compute these percentages and determine the dominant land cover surrounding each sensor. The quantity of ECCC as well as Netatmo sensors located within urban and peri-urban areas (as defined above) was tabulated. Graphs and charts were made to illustrate the distribution of sensors based on the predominant land cover class present within the 500 m radius. These were later used for analysing the spatial representativeness of the two temperature sensor categories.

3.4.4. Effect of spatial representativeness on UHI intensity

To explore the impact of the sensors' spatial representativeness on ΔUHI, a pair of sensors—one urban and one peri-urban—were selected from both ECCC and Netatmo sensor networks for every CMA. A reference sensor for the core urban area was selected from among the urban sensors based on its proximity to the downtown area, distance from large water bodies, and higher building ratio within its 500 m radius. For a peri-urban reference sensor, preference was given to the one located closer to the respective CMA, distant from large water bodies, and having a lower building ratio. Then, for every CMA, the distance between the urban reference sensor and the primary downtown area was estimated. CMAs that had (i) both urban and peri-urban sensors from ECCC and Netatmo and (ii) had their urban reference sensors located in downtown or within a distance of 2.5 km from downtown, were selected for further analysis.

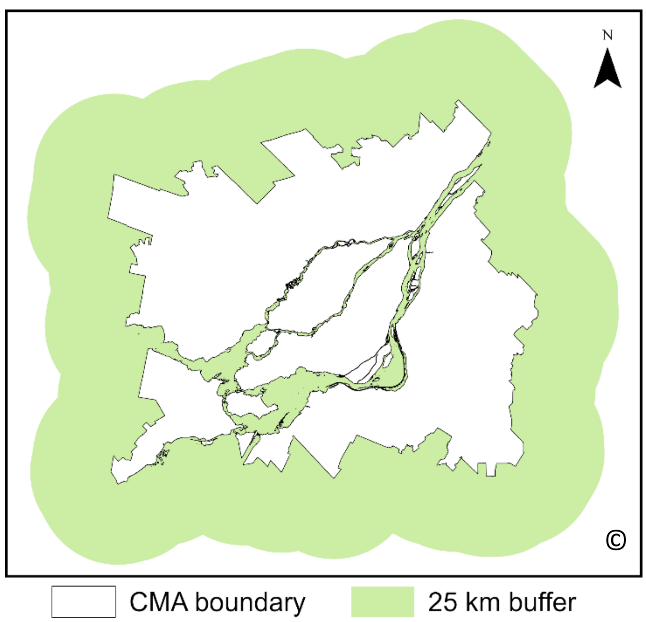

Figure 2. Urban and peri-urban extents of Montreal Census Metropolitan Area (CMA). The white region represents urban area and the green region represents peri-urban area.

The warmest day of each month, from May to August, was identified for each ECCC urban reference sensor. ΔUHI is greatest when skies are cloudless and winds are absent (Mills et al., 2022; Roth et al., 1989). Hence, the day that had the highest air temperatures, with minimum winds and with no precipitation in 48 hours prior was chosen. This is because atmospheric heat islands are best expressed under calm and clear conditions at night, when radiative cooling differences are maximized between urban and surrounding rural locations (Voogt & Oke, 2003). Since CUHI is more pronounced at night after sunset, ΔUHI was calculated using air temperature recorded by ECCC and Netatmo sensors at 1 a.m. for each CMA on their respective warmest days as identified above.

3.5. Results:

3.5.1. Spatial representativeness

Since bias could have a significant impact on the conclusions drawn from a sample, the representativeness of VGI has to be evaluated before utilizing it for any geographic application. One way of assessing it is to compare it with a reference dataset, which is considered representative of the population (G. Zhang & Zhu, 2018). It was observed that the ECCC sensors were widely distributed across Canada, while the Netatmo sensors were highly concentrated in the southern regions of the country (Figure 1). This spatial disparity highlights the need for a detailed understanding of the distribution pattern of these two sensor categories. On examining the overall distribution of sensors across each of Canada's provinces, Alberta, British Columbia, Quebec, and Ontario were found to have the highest number of both ECCC and Netatmo sensors (Table 2). Alberta, Quebec, and British Columbia were the top three provinces with the highest number of ECCC sensors at 23.59 percent, 12.85 percent, and 12.75 percent, respectively. However, with respect to Netatmo sensors, Quebec had the highest number of sensors (31.92 percent), followed by Ontario with 21.91 percent, and British Columbia with 17.46 percent of sensors. It is noteworthy that, while Netatmo sensors were scarce or not present in the Canadian territories of Northwest Territories, Nunavut, and Yukon, ECCC sensors were widely found in these areas.

With respect to the CMAs, 13 percent of the total ECCC sensors were within the CMAs as urban sensors, 5 percent were inside the 25 km buffer rings around the CMAs as peri-urban sensors, and the remaining 82 percent sensors were located beyond the 25 km buffer zone, classified as truly rural sensors. On the other hand, of the 69 percent of the total Netatmo sensors were urban sensors located within CMAs boundaries, 8 percent were peri-urban sensors were located inside the 25 km buffer rings, with only 23 percent of sensors located beyond the 25 km buffer zone. Thus, the majority of the ECCC sensors were located beyond the CMAs and their 25 km buffer zones, whereas most of the Netatmo sensors were located within the CMAs.

Of the forty-one CMAs, only twenty-three had both urban and peri-urban ECCC sensors (Figure 3). In the remaining CMAs, sixteen had either urban or peri-urban sensors, while two CMAs, namely Barrie and Guelph, lacked both urban and peri-urban sensors. On the other hand, thirty-one CMAs had both urban and peri-urban Netatmo sensors, and the remaining ten CMAs only had urban sensors. This already suggests a rural bias for ECCC sensors, and an urban bias for Netatmo sensors. This bias is further confirmed by analysing land cover distribution within a 500 m radius of each sensor (Figure 4). In urban areas, 37 percent of the ECCC sensors had built-up class as the primary land cover within their 500 m radius, slightly surpassing the cropland class in 31 percent of sensors, followed by water, grassland, and forest in 13 percent, 11 percent, and 8 percent of the sensors, respectively. In peri-urban areas, cropland was the dominant land cover class among 41 percent of the ECCC sensors, followed by water in 23 percent, forest in 13 percent, grassland in 11 percent of the sensors, and finally, built-up land cover prevailed only among 9 percent of the sensors. On the other hand, Netatmo sensors had a different distribution: an overwhelming 88 percent of the sensors were surrounded by built-up land cover, while a smaller portion of the urban sensors had forest (6 percent), cropland (3 percent), water (2 percent), and grassland (1 percent) as the primary land cover. Moreover, built-up cover was also the primary land cover class surrounding 45 percent of the peri-urban Netatmo sensors, with the prevalence of other land cover classes such as forest, cropland, water, and grassland in 23 percent, 18 percent, 9 percent, and 5 percent of the sensors, respectively. It was observed that, except for a few peri-urban ECCC sensors (4 percent) that had barren land cover, neither the ECCC nor the Netatmo sensors had any presence of barren, wetland, or snow classes as the dominant land cover.

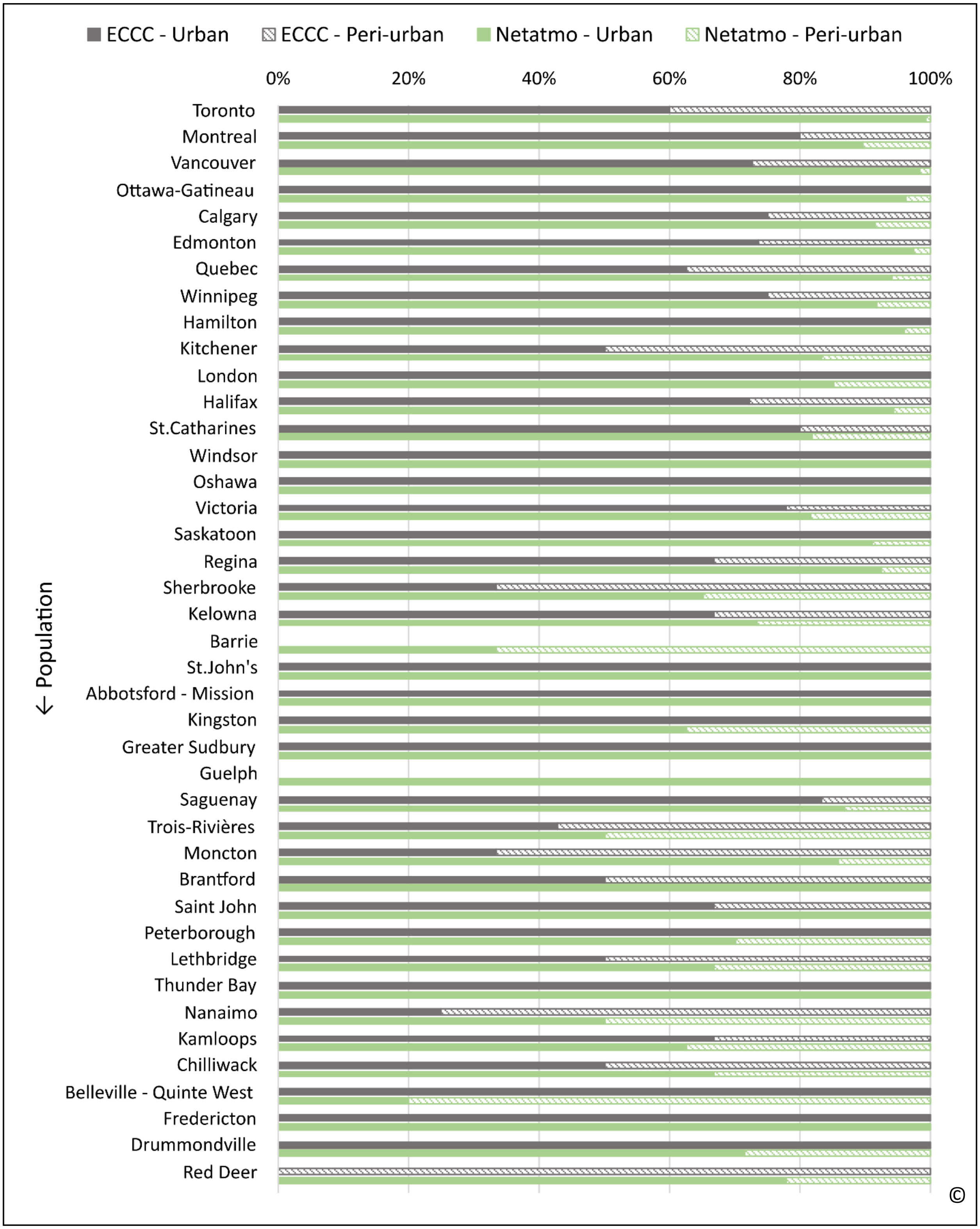

Figure 3. Distribution of urban and peri-urban sensors across forty-one Census Metropolitan Areas (CMAs) of Canada.

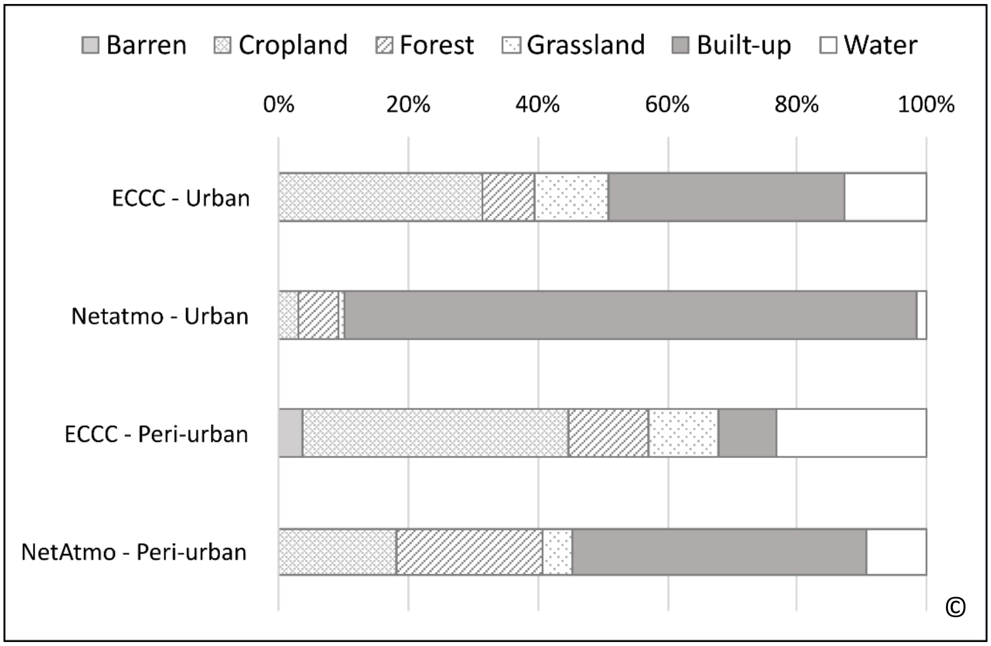

Figure 4. Percentage of dominant land cover classes within a 500 m radius of urban and peri-urban sensors.

3.5.2. Effect of representativeness on UHI intensity:

Twenty-one of the forty-one CMAs that were examined had both urban and peri-urban ECCC as well as Netatmo sensors. Among these, UHI intensity analysis was conducted only for seven CMAs namely, Toronto, Montreal, Vancouver, Quebec, Winnipeg, Halifax, and Victoria, where the urban reference sensors were either ideally located downtown, or at a distance of ≤2.5 km from the designated downtown areas (Table 3a). UHI intensities for these seven CMAs were estimated on the warmest days identified at their respective ECCC urban reference sensor location (Table 3b).

The estimated ΔUHI from just the ECCC sensors (ΔUHI_{ECCC}) across the seven selected CMAs varied between -1.9 °C and 5.7 °C during the four months of 2022 (Table 4). The data indicated that on the warmest days in at least one of the four months, Halifax, Toronto and Vancouver's urban areas were cooler than their peri-urban surroundings, and Victoria was cooler during all four months. ΔUHI estimated using just the Netatmo sensors ($\Delta UHI_{Netatmo}$) ranged from -1.7 °C to 10.1 °C across the same seven CMAs, and all of them exhibited a noticeable UHI effect during all four months, except Victoria (Table 4). In June 2022, Victoria's urban area was observed to be 1.7 °C cooler than its peri-urban surroundings on the warmest day.

Table 3a. Sensor distribution of top seven Census Metropolitan Areas (CMAs) that had both urban and peri-urban sensors, with their urban reference sensors located ≤2.5 km from downtown area.

CMA	**ECCC**			**Netatmo**		
	Urban (%)	**Peri-urban (%)**	**Urban reference to downtown distance (km)**	**Urban (%)**	**Peri-urban (%)**	**Urban reference to downtown distance (km)**
Toronto	60	40	0	99	1	0
Montreal	80	20	0	90	10	0
Vancouver	73	27	0.77	98	2	0
Quebec	63	37	1.5	94	6	0
Winnipeg	75	25	0	92	8	0.02
Halifax	72	28	0	94	6	0
Victoria	78	22	0	81	19	0

Table 3b. Dates of warmest days identified for the seven selected Census Metropolitan Areas (CMAs) at their respective ECCC urban reference sensor location.

CMA	**May**	**June**	**July**	**August**
Toronto	15	22	17	7
Montreal	26	15	21	1
Vancouver	23	27	29	19
Quebec	14	22	17	6
Winnipeg	24	11	9	22
Halifax	20	30	24	27
Victoria	22	26	26	7

Analysis of the CMA-wise mean (μ_{CMA}) of ΔUHI_{ECCC} revealed that of the seven CMAs, three – Victoria, Vancouver and Toronto - were colder during the four months and Montreal had the highest ΔUHI_{ECCC}. Conversely, the overall mean of $\Delta UHI_{Netatmo}$ for each of the seven CMAs showed that, all CMAs exhibited UHI effect, with Toronto, Vancouver, and Winnipeg as the top three CMAs with the most pronounced UHI effect. On examining the monthly averages, it was observed that the mean ΔUHI_{ECCC} was highest in June, whereas the mean $\Delta UHI_{Netatmo}$ was highest in July. Overall, except in the month of June, $\Delta UHI_{Netatmo}$ was consistently higher than ΔUHI_{ECCC} throughout the late spring and summer months from May to August.

Table 4. UHI intensity (ΔUHI) estimated with ECCC and Netatmo sensors. A positive value indicates that the Census Metropolitan Area (CMA) was warmer compared to its peri-urban surroundings.

CMA	ΔUHI_{ECCC}					$\Delta UHI_{Netatmo}$				
	May	**Jun**	**Jul**	**Aug**	**mean (μ_{CMA})**	**May**	**Jun**	**Jul**	**Aug**	**mean (μ_{CMA})**
Toronto	-1.5	-1.9	2.2	1.1	-0.025	6.4	2.1	10.1	7.1	6.425
Montreal	5.1	4.9	1.2	3.4	3.65	3.7	0.7	1.1	1.7	1.8
Vancouver	1.1	-2	-1.9	-2.3	-1.275	3.2	2.4	5.2	2.8	3.4
Quebec	0.6	1.6	3.5	0.6	1.575	1.7	0.3	2.3	1.6	1.475
Winnipeg	2.4	2.6	0.3	1.8	1.775	2.6	0.4	1.5	3.3	1.95
Halifax	0.2	5.7	-0.7	1.9	1.775	1.1	0.5	0.7	0	0.575
Victoria	-2	-4	-1.4	-4.1	-2.875	0.9	-1.7	0.5	1.8	0.375
mean (μ)	0.843	0.986	0.457	0.343		2.800	0.671	3.057	2.614	
S.D. (σ)	2.403	3.711	1.967	2.622		1.901	1.347	3.491	2.236	

To further explore the reasons for the results obtained above, the land cover percentages within a 500 m radius around the urban and peri-urban reference sensors of the seven selected CMAs were examined (Figure 5). In addition to the built-up class, urban ECCC sensors had significant portions of other land cover classes such as water and grassland. But nearly all the seven urban Netatmo reference sensors were surrounded by 100 percent built-up land cover. In peri-urban areas, ECCC reference sensors of the seven CMAs had a mixture of various land cover classes in different proportions, while except in Winnipeg, Netatmo reference sensors in the other six CMAs predominantly had built-up land cover class. Thus, regardless of their urban or peri-urban location, the Netatmo sensors had a higher presence of the built-up class compared to the ECCC sensors. This is most probably due to people's tendency to install their sensors in conveniently accessible locations with Wi-Fi access that are inevitably surrounded by buildings, like their backyards.

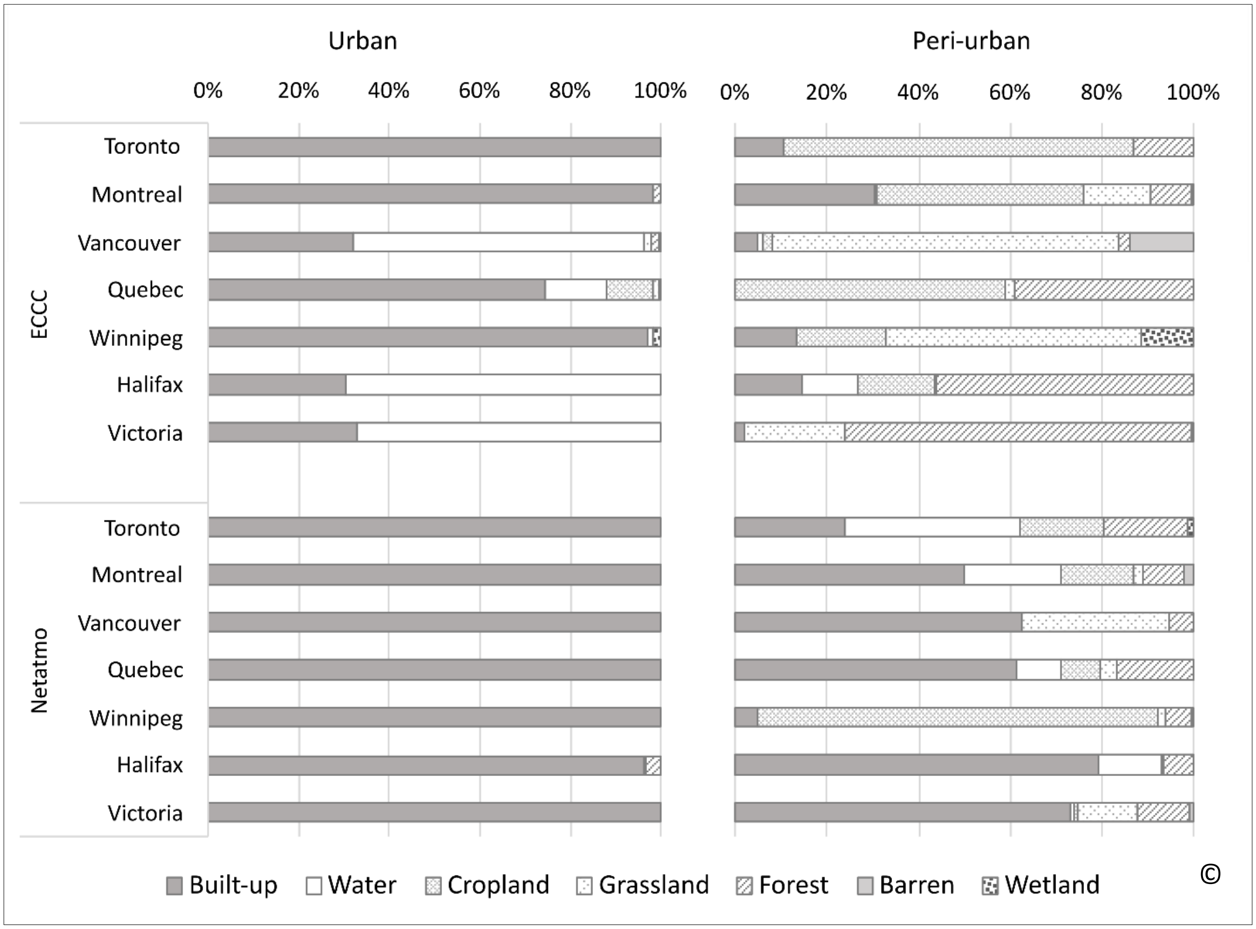

Figure 5. Land cover classes within a 500 m radius around both the urban and peri-urban reference sensors of the seven chosen Census Metropolitan Areas (CMAs).

Given that Netatmo sensors have extensive coverage in urban areas (Figure 6) and ECCC sensors better represented peri-urban areas, we also calculated ΔUHI by subtracting the temperatures observed by ECCC sensors in peri-urban areas from the temperatures observed by urban Netatmo sensors ($\Delta UHI_{Netatmo-ECCC}$). From the estimated values of $\Delta UHI_{Netatmo-ECCC}$, it was observed that during the warmest days of each of the four months from May to August 2022, all seven CMAs experienced higher temperatures compared to their peri-urban counterparts, indicating the presence of the UHI effect (Table 5). Furthermore, the μ_{CMA} of $\Delta UHI_{Netatmo-ECCC}$ were greater than the μ_{CMA} of both ΔUHI_{ECCC} and $\Delta UHI_{Netatmo}$ in almost all the seven CMAs. When the inverse is considered, UHI intensity ($\Delta UHI_{ECCC-Netatmo}$) values were all mostly negative and close to zero. And as expected, Vancouver, Toronto, and Quebec exhibited the most significant UHI effects (Oke, 1973). Among the four months, May had the highest mean $\Delta UHI_{Netatmo-ECCC}$, while June had the lowest.

Table 5. UHI intensity (ΔUHI) estimated with air temperatures from both ECCC and Netatmo sensors. A positive value indicates that the CMA was warmer compared to its peri-urban surroundings.

CMA	$\Delta UHI_{Netatmo-ECCC}$ (°C)					$\Delta UHI_{ECCC-Netatmo}$ (°C)				
	May	Jun	Jul	Aug	mean (μ_{CMA})	May	Jun	Jul	Aug	mean (μ_{CMA})
Toronto	3.8	0.3	11	8.6	5.925	1.1	-0.1	1.3	-0.4	0.475
Montreal	6.4	7	1.2	4.8	4.850	2.4	-1.4	1.1	0.3	0.600
Vancouver	6.5	6.1	9.4	5.2	6.800	-2.2	-5.7	-6.1	-4.7	-4.675
Quebec	12.6	3	4.4	2.8	5.700	-10.3	-1.1	1.4	-0.6	-2.650
Winnipeg	5.4	4	2.9	5.2	4.375	-0.4	-1	-1.1	-0.1	-0.650
Halifax	0.8	5	1.2	1.8	2.200	0.5	1.2	-1.2	0.1	0.150
Victoria	2.3	1.5	2.9	2.6	2.325	-3.4	-7.2	-3.8	-4.9	-4.825
mean (μ)	5.400	3.843	4.714	4.429		-1.757	-2.186	-1.200	-1.471	
S.D. (σ)	3.816	2.421	3.934	2.296		4.248	3.069	2.860	2.294	

3.6. Discussion and Conclusion

The aim of this study was to explore the efficacy of using meteorological data volunteered by individuals via Netatmo CWS for studying the UHI effect across Canadian CMAs, particularly with respect to bias that may be present due to the location of the sensors. As a first step, we assessed the spatial representativeness of Netatmo CWS by comparing it with conventional ECCC sensors, with the finding that ECCC sensors have equitable distributions nationally, which leads them to have better coverage in peri-urban and rural areas. Conversely, Netatmo sensors are more concentrated in urban regions, thus providing a better coverage for these areas (i.e., CMAs). Further, ECCC sensors were distributed across all provinces and territories but not all CMAs, whereas the Netatmo sensors were present in all CMAs but not across all provinces and territories. And a general observation from analysis of this distribution is that the number of peri-urban Netatmo sensors decreased with smaller CMA population. This suggests that there is geographic bias in both ECCC and Netatmo sensor locations.

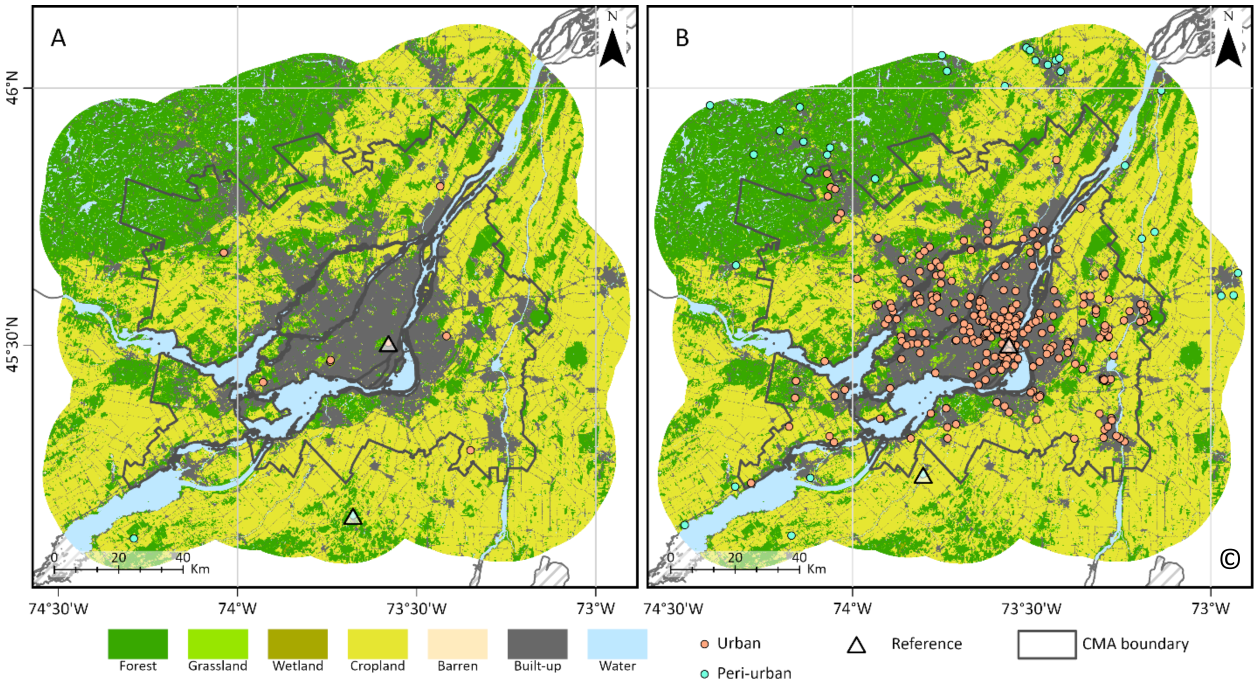

Figure 6. Land cover map with locations of (A) ECCC and (B) Netatmo sensors of Montreal Census Metropolitan Area (CMA). Compared to the ECCC sensors, a greater number of Netatmo sensors are found inside the CMA.

Additionally, we investigated how this spatial variability in the representativeness of sensors for both urban and peri-urban areas that represented the rural reference, affected the estimation of ΔUHI. Our findings revealed discrepancies in ΔUHI estimates with the ECCC and Netatmo sensors throughout late spring and summer from May to August 2022. The $\Delta UHI_{Netatmo}$ was consistently higher than ΔUHI_{ECCC} during all four months, and a higher magnitude of UHI intensity ($\Delta UHI_{Netatmo-ECCC}$) was observed when the Netatmo sensors served as the 'urban reference', and the ECCC sensors as the 'rural reference'. Conversely, $\Delta UHI_{ECCC-Netatmo}$ was much lower. This is obviously due to the representativeness of each of the sensor categories. Netatmo sensors, installed by individuals in easily accessible locations such as their backyards, represented urban areas better; whereas ECCC sensors, installed outside the urban centers by the Canadian federal and a few provincial governments were distributed uniformly across the country, better represented peri-urban and rural areas. Moreover, as expected from previous research (Oke, 1973), the highly populous CMAs exhibited higher $\Delta UHI_{Netatmo-ECCC}$.

These findings highlight the importance of taking bias into consideration when evaluating data from weather stations. As has been reported in the literature, bias has a significant impact on the conclusions drawn from a sample, potentially leading to inaccurate results. Therefore, as with other spatial data, it is essential to evaluate the representativeness of a dataset before using it for any geographic application. For example, launched in the UK in 2004, OSM is the most widely used crowdsourced geographic information, closely followed by Twitter, Instagram, Flickr, Weibo, and Geo-Wiki (Cui et al., 2021; Yan, Feng, et al., 2020). Research indicates that OSM is biased towards high-density urban areas (Hecht & Stephens, 2014; Neis & Zielstra, 2014), as contributors predominantly provide data for the cities where they live (Haklay, 2016). Twitter and Flickr also exhibit a similar bias toward urban perspectives. Consequently, studies and applications relying on these sources may have oversampled the urban population (Hecht & Stephens, 2014). Here, the same urban bias was observed with Netatmo data. More intriguingly, there was a rural bias present in the ECCC data, thus requiring the use of both Netatmo and ECCC sensors to obtain a balanced picture of UHI intensity.

Additionally, spatial bias has been extensively studied in other disciplines. For instance, Geldmann et al., (2016) examined spatial bias in ecology, analysing the influence of human infrastructure and land cover on observations from four different crowdsourcing programs in Denmark. The data provided by volunteers were highly representative of the areas where they resided or could commute, such as parks, hiking trails in woods, and fishing lakes. Similar findings were reported by Millar et al., (2018), who examined bias in the aquatic monitoring program in Ontario and termed the bias as 'Cottage effect'. Volunteers sampled lakes closer to their cottages and other recreational sites due to their attractiveness as a leisure spot and accessibility from population centers. This, taken with the fact that environmental monitoring demonstrated the lowest level of VGI adoption (Yan, Feng, et al., 2020), suggests the presence of bias in weather station data.

However, and as stated earlier, the urban bias of Netatmo data may be useful for UHI studies, particularly because there is significant intracity variability in UHI intensity, as demonstrated by the LCZ approach (Stewart & Oke, 2012). It is important to capture this variability and identify localities with higher UHI intensities as it is directly associated with the degradation of human health and well-being due to increased city temperatures. High temperatures have a variety of effects on human health, with mortality being the most severe. Moreover, people of lower social classes and of racial and ethnic minorities are more likely to reside in warmer neighbourhoods than privileged ones, which causes a problem of environmental and climatic injustice (Fan & Sengupta, 2022; Schlosberg & Collins, 2014). But while urban areas are exposed to a variety of meteorological phenomena, yet at least in the Canadian context, the presence of high-quality urban meteorological networks (i.e., ECCC sensors) is limited. This is due to the fact that installing conventional sensors in densely populated areas is not only expensive and challenging but also constrained by factors such as the need for approvals and concerns about vandalism (Muller et al., 2013). Crowdsourcing provides researchers with extensive datasets on environmental quality indicators in areas where monitoring is either scarce or non-existent (Grossberndt et al., 2020).

Thus, despite the presence of bias, CWS are well suited for obtaining air temperature from dense built-up city centers with urban canyons and reduced tree cover, where heat risk is high. Apart from air temperature, these CWS can observe other meteorological parameters, and hence it is a good idea to combine both conventional and CWS for urban climate studies. Conventional datasets are also biased in a certain way, but the bias may be complementary to the bias in crowdsourced datasets, as we see with the example of ECCC and Netatmo sensor locations. Hence, crowdsourcing can be used as an additional and complementary source of information to conventional methods of data collection (Chow et al., 2023; Cui et al., 2021; Heikinheimo et al., 2017; Millar et al., 2018), especially in studying temperature differences at a local scale (Fenner et al., 2017). As noted by See et al., (2016), this conflation is the key area of future research.

Note that this study has a few limitations. First, only the initial steps of data cleaning procedures identified in previous research (Coney et al., 2022; Meier et al., 2017) were done on the Netatmo dataset. As a result of this, sensors that did not record air temperature for all 24 hours of a day and on every day of a month were still considered for the analysis. Secondly, the study focused on volunteered meteorological datasets from a single source, Netatmo, which may restrict the breadth of the insights gained. Despite these limitations, this study provides a comprehensive understanding of the representativeness of CWS and highlights their potential in urban climate research. By including data from additional sources and implementing rigorous data cleaning procedures, these limitations will be addressed in the future. Despite these limitations, however, data from CWS remain a valuable complementary source for urban air temperature measurements for estimating UHI intensity.

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4. Discussion

Urbanization as a phenomenon is unavoidable in the near future. As a result of the increase in impervious surfaces, a surface energy imbalance between urban and rural areas is created, commonly known as Urban Heat Island effect, wherein the urban areas exhibit a higher temperature than their rural counterparts (Oke, 1973). Given that an increasing proportion of the population resides in urban areas, the residents are at risk of heat-related illnesses due to the elevated urban temperatures. Therefore, studying the UHI effect is important for understanding and mitigating the impact it has on public health and well-being.

Through the extensive literature review, three distinct types of UHI are identified based on the surface or atmospheric region being observed, i.e., Surface UHI (SUHI), Canopy-level UHI (CUHI) and Boundary Layer UHI (BLUHI). Further, these identified UHIs can be studied with data from different sources such as, in-situ sensors, remotely sensed data, and model simulations. In-situ sensors installed at a fixed location or mounted on a platform for traverse, are capable of providing accurate and continuous data on various meteorological parameters. Only they can measure ambient air temperature which has an impact on thermal comfort, which is directly related to health concerns such as cardiovascular mortality (Woeckel et al., 2023). While modeling can simulate ambient air temperatures on a larger city-scale, required for UHI research, the level of accuracy may not be sufficient to capture necessary nuances. Moreover, the accuracy of the simulated temperatures is dependent on the quality of the model's input parameters; this is known as the 'Garbage In, Garbage Out' problem of computational models (Hall, 2014). On the other hand, temperature measurements from airborne platforms can provide global data coverage at a spatial resolution of at least 60 m and are not affected by problems of input data quality. However, they can only detect the surface temperatures of roads, pavements, and building rooftops, thus portrays urban areas as warmer than they actually are. Thus, the in-situ sensors stand out as a reliable source for measuring ambient air temperature, which is important for understanding its implications on human health and well-being.

With the advent of advancements in Information and Communication Technology, a new era has emerged where individuals from the general public contribute data to the scientific community. Crowdsourced in-situ weather sensors are a prime example of this innovation. Unlike the conventional sensors, which are often always installed and maintained by the government, crowdsourced sensors are inexpensive and are often installed by the general public at their cost (e.g., Netatmo sensors can be purchased online from Amazon.ca). This approach not only expands the geographic coverage of temperature monitoring but also democratizes data collection and distribution, enabling communities to actively participate in environmental observation. However, since these datasets are volunteered by a diverse range of individuals, from amateurs to experts, it is important to assess their quality and representativeness. Moreover, bias could significantly influence the conclusions drawn from a sample, so the representativeness of these in-situ sensors has to be evaluated before utilizing them for any geographic application (G. Zhang & Zhu, 2018).

In this thesis, the spatial representativeness of conventional (Environment and Climate Change Canada or ECCC) and crowdsourced (Netatmo) in-situ sensors installed across Canada is assessed by comparing them with each other. The conventional ECCC sensors are found to have equitable distributions nationally, ensuring better coverage in peri-urban and rural areas. Conversely, crowdsourced Netatmo sensors are more concentrated in urban regions, thus providing a better coverage for these areas (i.e., CMAs). Further, ECCC sensors are distributed across all provinces and territories but not all CMAs, whereas the Netatmo sensors are present in all CMAs but not across all provinces and territories. This suggests that there is spatial bias in both in-situ sensor locations. These biases can affect the validity and generalizability of study findings, especially when attempting to understand larger geographical trends. For instance, almost all studies on data representativeness of OSM showed similar levels of data completeness and high data quality for densely populated urban areas compared to the conventional mapping datasets (Neis & Zielstra, 2014). However, this pattern does not apply to cities outside the European Context (Neis et al., 2013).

Furthermore, this thesis explores how the spatial representativeness of in-situ sensors affects the ΔUHI estimation in seven selected CMAs. The $\Delta UHI_{Netatmo}$ was consistently higher than ΔUHI_{ECCC} during all four months from May to August 2022. A larger magnitude of UHI intensity ($\Delta UHI_{Netatmo-ECCC}$) was observed when the Netatmo sensors served as the ‘urban reference’, and the ECCC sensors as the ‘rural reference’. Needless to say, the representativeness of each of the in-situ sensor categories is the reason for this. Moreover, a more accurate representation of urban areas (including intra-city variability of temperatures) is provided by Netatmo sensors, since the volunteers tend to set up these sensors in easily accessible locations, such as their own backyards. Meanwhile, ECCC sensors, installed outside urban centers at regular intervals by the Canadian federal and select provincial governments, offered better coverage of peri-urban and rural areas. This spatial bias is also seen in a study in Germany on air temperature modeling (Vulova et al., 2020). The crowdsourced sensors were densely concentrated in the built-up areas, resulting in inadequate coverage of natural landscapes. Consequently, the air temperatures of vegetated areas away from city centers were overestimated.

Apart from the sensor representativeness, another challenge identified from the literature is sensor overheating. Installing sensors in certain locations, such as proximity to a wall, leads to overheating of sensors during daytime (Varentsov et al., 2020). However, the temperature biases diminish at night, since the UHI effect becomes more pronounced during these hours. This problem arises due to inadequate protection from solar radiation and insufficient ventilation (Meier et al., 2015). The findings of this thesis emphasize accounting for bias when utilizing data from in-situ weather sensors, since bias has a significant impact on the conclusions drawn from a sample, potentially leading to inaccurate results. Despite the biases of crowdsourced sensors, they are useful for UHI studies, particularly due to the intra-city variability observed in UHI intensity, as highlighted by the LCZ approach (Stewart & Oke, 2012). These low-cost sensors are capable of monitoring weather conditions at high spatial and temporal resolutions (Fan & Sengupta, 2022), offering a dense and continuous stream of data over a long time (Benjamin et al., 2021). They are useful to study weather patterns that change over short distances, particularly in urban areas characterised by heterogeneous morphology (Muller et al., 2015).

More importantly, this intra-city variability in urban temperatures has to be monitored since rising urban temperatures are directly linked to decline in public health and well-being. High temperatures have a variety of effects on human health, with mortality being the most severe. Furthermore, it raises the need for energy, particularly during the summer, for cooling purposes, which results in higher electricity costs. As a result, individuals from marginalized communities, including those of lower social classes and racial and ethnic minorities, are more likely to reside in warmer neighbourhoods compared to the privileged ones. This causes a problem of environmental and climatic justice (Fan & Sengupta, 2022; Schlosberg & Collins, 2014), since the consequences of urban heat are more severe for these vulnerable populations. Urban green spaces serve as effective nature-based solutions for mitigating the heat impacts caused by UHI effect (W.

Zhou et al., 2023). They can significantly contribute to the urban micro climate, since they absorb incoming solar radiation, reduce the heat island effect through shading and evapotranspiration, and naturally filter dust and air pollutants, thereby reducing air pollution (Phelan et al., 2015).

Thus, despite the urban issues of health and energy demand linked to UHI effects, there is a dearth of professional urban meteorological sensor networks (i.e., ECCC sensors), in Canada. This is because installing conventional sensors in densely populated areas is difficult and expensive, and is also limited by obtaining approvals and potential vandalism concerns (Meier et al., 2017; Muller et al., 2013). Moreover, these sensors form a coarse observational network, since they are installed at uniform distances outside the urban centers to avoid the influence of urban core temperatures on synoptic weather observations. In contrast, crowdsourcing provides researchers with extensive datasets on environmental quality indicators in areas where monitoring is either scarce or non-existent (Grossberndt et al., 2020). It is cost-effective as it relies on volunteer contributions rather than expensive infrastructure and the volunteers always contribute for places which are easily accessible by them, often focussing on urban centers.

Therefore, crowdsourced sensors are well suited for predicting air temperature in built-up city centers where heat risk is high (Vulova et al., 2020). In addition to temperature, these in-situ sensors can observe other meteorological parameters like humidity and pressure, and hence it is a good idea to combine both conventional and crowdsourced sensors for urban climate studies (Chapman et al., 2017). Conventional datasets are also biased in a certain way, but the bias may be complementary to the bias in crowdsourced datasets, as we see with the example of ECCC and Netatmo sensor locations. To get a balanced picture of UHI intensity, both of these in-situ sensor categories have to be used together. Hence, crowdsourcing can be used as an additional and complementary source of information to conventional methods of data collection (Chow et al., 2023; Cui et al., 2021; Heikinheimo et al., 2017; Millar et al., 2018), especially for studying temperature differences at a local scale (Fenner et al., 2017). Specifically, conflating multiple data sources is a key area of research, since it enables researchers to leverage the advantages of various data sources (See et al., 2016).

Despite promising advances, this study has few limitations. Only the initial steps of data cleaning procedures identified in previous research (Meier et al. 2017; Coney et al. 2022) were done on the Netatmo dataset i.e., the sensors that did not record the air temperature every day of the month and for all 24 hours of the day were nonetheless taken into account for the analysis. This made it more difficult to estimate the UHI on the warmest days that were identified since, in the event that a Netatmo sensor is determined to have malfunctioned, the next warmest day was selected. As a result, the entire intensity estimation process had to be redone all again. Additionally, the scope of insights obtained may be limited, since the study was restricted to volunteered meteorological datasets from a single source. Despite the acknowledged limitations, this study provides a comprehensive understanding of the representativeness of in-situ sensors and highlights their potential in urban climate research. By including data from additional sources and implementing rigorous data cleaning procedures, the accuracy and reliability of intra-city UHI estimates will be improved in the future.

5. Conclusion

In this thesis, the efficiency of in-situ sensors of conventional (ECCC) and crowdsourced (Netatmo) sensor networks in capturing and estimating the UHI intensity has been investigated. It identifies the advantages of these in-situ temperature data sources over other sources through an extensive literature review. Furthermore, the analysis of these two datasets shows how important it is to consider representativeness when utilizing data from weather stations, whether conventional or crowdsourced. Although conventional sensors provide reliable measurements of the ambient temperature, their geographic coverage is limited and thus the intra-city variability of UHI cannot be effectively captured. On the other hand, crowdsourced sensors offer dense coverage in urban areas, but their placement by volunteers, introduce biases.

The inherent spatial bias of these two in-situ sensor categories influences the estimation of UHI intensity. When using crowdsourced sensors exclusively, the intensity values were higher compared to those obtained from conventional sensors. Crowdsourced sensors provide better representation of urban areas, while conventional sensors are more representative of peri-urban areas. Consequently, the UHI intensity calculated using these two datasets was higher than previously estimated values. This confirms that spatial representativity of sensors has an influence on the estimation of UHI intensity.

Moreover, this thesis highlighted the complementary nature of the spatial bias in both in-situ sensor categories and the potential of integrating data from both sources to obtain a thorough understanding of UHI intensity. The accuracy and reliability of UHI estimations can be improved by leveraging the strengths of each data source and by implementing rigorous data cleaning procedure. This approach captures the complexities of urban environments and policymakers can utilize these insights to design more effective mitigation and adaptation strategies. Overall, this thesis thus expands the current understanding of utilizing in-situ sensors to study UHI dynamics, which benefits policy-making and urban planning initiatives that aim to mitigate the adverse impacts of UHI and improve the resilience of cities to climate change.

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