

The impact of spatial patterns of urban green infrastructure on urban microclimate and air quality

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Abstract

The impact of spatial patterns of urban green infrastructure on urban microclimate and air quality

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In response to the need for ecologically informed urban green space planning and design, the overall objective of my thesis is to evaluate how spatial patterns of urban green infrastructure (UGI) influence ecosystem service provision across various spatial and temporal scales. My first chapter explored the impact of UGI's spatial pattern on land surface temperature and its corresponding distributional inequity. My results show that aggregated tree clusters offer greater cooling benefits than fragments or dispersed green spaces during the day, especially at a larger spatial scale. Mapping mismatches in cooling supply and demand revealed that neighborhoods with higher proportions of visible minorities and low-income residents had significantly lower access to cooling services. My second chapter examined the effects of different spatial configurations of vegetation on microclimate conditions. The results indicated that aggregate tree clusters had stronger cooling effects than discrete tree clusters during daytime, but inhibited heat dissipation at night. However, relative humidity exhibited an inverse pattern compared to air temperature, moderating wet-bulb temperature differences among vegetation configurations. My third chapter assessed how tree cluster arrangements (linear vs. grouped) influence NO₂ and O₃ concentrations within urban parks. No significant differences in NO₂ concentrations were observed on either side of the tree clusters regardless of whether trees were planted in linear arrangements or grouped configurations, showing trees did not act as barriers to NO₂ dispersion. A slight “trap

effect” of trees on NO_2 concentrations was detected, while there was a significant decrease of O_3 concentrations under tree clusters of both configurations.

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Contribution of Authors

For this thesis, I am the first author on all manuscript chapters. I led the conceptualization, data curation and visualization, methodology development, statistical analysis and interpretation, thesis writing, review and revisions.

Chapter 3: This manuscript was co-authored with Angela Kross, Carly Ziter and Ursula Eicker. They supervised the project and contributed to thesis review and revisions, as well as project administration, funding acquisition, and conceptualization. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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List of Abbreviations

UGI: Urban Green Infrastructure

UHI: Urban Heat Island

O₃: Ozone

NO₂: Nitrogen Dioxide

P: Percent Cover of Vegetation

EMS: Effective mesh size

LPI: Largest patch index

MPSI: Mean patch shape index

LST: Land Surface Temperature

ES: Ecosystem Service

NDVI: Normalized Difference Vegetation Index

T_w: Wet-bulb Temperature

RH: Relative Humidity

Chapter 1: General Introduction

Only three percent of the world's land surface is covered with urban area, but urban environments support over half of the world population, account for 60-80% of global energy consumption, and generate about three quarters of carbon emissions, and the numerical values seem to be continuously increasing (United Nations. Department of Economic and Social Affairs. Population Division., 2019). The urbanization is still in progress currently. The global urban land area was detected to rise from 0.22% in 1992 to 0.69% in 2020 based on nightlight observations (M. Zhao et al., 2022). Compared with natural areas, urban areas with well-established human settlements and economic structures are more vulnerable to climate extremes (Ye & Niyogi, 2022). Climate change brings threats to urban areas in many aspects, including health impacts in periods of extreme heat; food insecurity linked to warming, drought, flooding, and uncertain precipitation; and the breakdown of infrastructure networks and critical services resulting from extreme weather events (Intergovernmental Panel on Climate Change (IPCC), 2013). Urban growth is not only associated with strong temperature rise, but could be greatly impacted by climate change as well (Chapman et al., 2019). Thus, there is a need to develop sustainable and safer cities to protect urban populations from hazards of climate change.

Urbanization leads to changes in the physical environment of cities, such as the increase of impervious areas and decrease of green spaces (Kim & Brown, 2021). The high thermal mass emitted by concrete and asphalt roads, the low ventilation capacity of urban canyons formed by high-rise buildings, the loss of vegetation, and the combined effect of heat released from vehicles on streets and air conditioners are some of the factors that contribute to temperature rise in cities (Akbari et al., 2016). Higher temperatures in cities are closely associated with adverse impacts for

human health and well-being, including increasing rates of illness and mortality directly related with temperature and indirectly through interactions with air pollution (Curriero et al., 2002; Darrel Jenerette et al., 2011; Filleul et al., 2006; Michelozzi et al., 2009). Social inequality in the distribution of resources and infrastructure also increases the exposure of vulnerable groups to a harmful environment (Schell, Dyson, Fuentes, Roches, et al., 2020).

However, remaining natural elements within urban areas also provide benefits to sustain and improve human livelihood and the quality of life through providing urban ecosystem services (ES) (Haase et al., 2014). ES are classified in a variety of ways, most commonly, they are divided into four categories: provisioning services (material outputs from ecosystems, including food, water, medicinal plants, and other resources), regulating services (functions, such as regulation of air pollution, temperature, floods, and disease), habitat or supporting services (providing living space for organisms), and cultural services (non-material, socio-ecological benefits people obtain from contact with nature, such as recreation, esthetic, spiritual, and psychological benefits and tourism) (Millennium Ecosystem Assessment (Program), 2005). Improving urban green infrastructure (UGI) - defined as “an interconnected network of greenspace that conserves natural ecosystem values and functions and provide associated benefits to human populations”(Benedict & MacMahon, 2002) - is an effective strategy to enhance the well-being of urban populations. In urban areas, neighborhood parks, community gardens, green roofs, street trees and private yards are common components of UGI (Coutts & Hahn, 2015).

High ambient temperature, absence of nighttime heat discharge, and low air quality in urban areas have short-term and long-term effects on human health (Singh et al., 2020). Thus, it is important to look at the urban heat mitigation and air quality improvement ecosystem services provided by UGI. Several studies have assessed the mechanisms by which urban greening can

regulate local microclimate and improve air quality (Beckett et al., 2000; Benedict & MacMahon, 2002; Hiemstra et al., 2017; Jenerette et al., 2016; Tomson et al., 2021; Y. Wang et al., 2014; Yun-Cai et al., 2018). The relationship between landscape patterns and the intensity of these ecosystem services provided by urban green infrastructure is also an important aspect. UGIs are part of landscape patterns, as they are embedded in a pattern of urban land cover types and they also have a spatial structure on a more detailed scale (L. Li et al., 2020). Spatial pattern, including composition and configuration of UGI, can influence the potential provision of ecosystem services, including regulation of urban microclimate and air quality (Alonzo et al., 2025; S. Du et al., 2016; Gourdji, 2018; Rui et al., 2018; X. Wang et al., 2021; Xiao et al., 2018; Y. Zhang et al., 2017; W. Zhou et al., 2011). Further understanding is needed on the effect of composition and configuration of urban greening on their ecosystem services intensity at different spatial and temporal scales, informing urban planning and improving ecosystem benefits.

In addition, reducing social inequality and inequity is a big goal of sustainability of the United Nations (*THE 17 GOALS | Sustainable Development*, n.d.). Prioritizing green equity in planning and design is reflected in policies in many countries/cities (Rigolon et al., 2024). Social inequality is the unbalanced distribution or allocation of wealth and resources to specific socio-cultural groups (Schell, Dyson, Fuentes, Des Roches, et al., 2020). Substantial inequalities, such as the uneven distribution of urban heat island (Huang & Cadenasso, 2016; Jenerette et al., 2011; Jesdale et al., 2013), vegetation and tree canopy cover (Clarke et al., 2013; Leong et al., 2018; Locke et al., 2021; Rigolon, 2016; Schwarz et al., 2015), and environmental pollutants (Bravo et al., 2016; Pope et al., 2016; Tessum et al., 2019), have been well documented in previous studies. However, these studies are predominately focused on the United States, and still less common in Canadian cities.

Improving the planning of UGIs for optimized supply of ecosystem services is a key strategy to mitigate potential climate change threats, and to improve the overall human –well-being in urban areas. There is a need to understand how the spatial patterns of UGI influence the supply of ecosystem services, and whether these ecosystem services are evenly distributed in urban areas. With a focus on heat mitigation and air quality improvement, the literature review in the following section explores these themes to provide a comprehensive foundation for the proposed research.

Chapter 2: General Literature Review

2.1 The Requirement for Urban Green Infrastructure Management

Rapid urbanization greatly alters the physical land surface properties in urban areas which correspondingly affects the surface-atmosphere coupling including the exchange of energy, water and momentum (Singh et al., 2020). Two significant changes are an increase in impervious areas by construction of roads and buildings and consequently a decrease in green spaces. Due to low albedo and high solar absorption, impervious surfaces absorb high solar radiation and reradiate it later (K. Wang et al., 2017). The materials used in construction have elevated thermal inertia and heat storage that is released at night causing a decrease in the difference between day and night temperature and thus consequent decrease in diurnal temperature range (Hardin & Vanos, 2018). The elevated temperature in urban areas relative to their rural surroundings is known as the urban heat island (UHI) effect. In large cities, high-rise buildings also prevent the dispersion of air pollutants contributed by burning of fossil fuels by power plants, automobiles, nonroad equipment, burning and incineration of municipal and agricultural wastes and industrial facilities (Leung, 2015).

With the development of urban areas, green spaces are often reduced in size or suffer from fragmentation. These changes can result in a decline of ecosystem service capacity (Andersson et al., 2015; McPhearson et al., 2015). As cities increase in population, there will be increased demand for the services provided by UGI, which means getting more ecosystem benefits under the constraint of space. To achieve this goal, we need to focus on improving the space utilization of UGI to mitigate urban heat and air pollutant concentration.

There is a growing global action to increase the urban greening level as response to climate change and the crisis of urbanization. Canada has proposed a 2 Billion Trees Program, aiming to plant 2 billion trees over a period from 2021-2031 (<https://www.canada.ca/en/campaign/2-billion-trees/2-billion-trees-program.html>). The city of Montreal has also committed to a plan to increase 500,000 new trees in heatwave-vulnerable areas by 2030 and is working toward a tree canopy target of 26 % by 2025 (Climate Plan 2020–2030) (<https://www.canada.ca/en/natural-resources-canada/news/2025/03/federal-investment-contributes-to-the-planting-of-500000-trees-in-montreal.html>). However, the corresponding question is: where and how to plant those trees?

There are some challenges and gaps in previous studies on the impact of spatial pattern of UGI on microclimate and air quality. For example, previous studies focused on increasing the quantity while paying less attention to the quality of UGI (Bowler et al., 2010; Gunawardena et al., 2017; Vaz Monteiro et al., 2016; Veerkamp et al., 2021). The relative extent to which configuration is important remains unclear, and the indicators are not consistent among studies (Fu et al., 2022; Hu et al., 2021; D. Zhao et al., 2020; Zhou et al., 2017). In addition, a comprehensive understanding of how much influence landscape pattern has on the variation in urban air temperature at multiple temporal and spatial scales is still lacking (Yan et al., 2014). Thus, it is urgent to improve the quality of UGI from the aspect of spatial pattern and optimize its ecosystem service provision.

2.2 Urban Green Infrastructure and Urban Heat Mitigation

‘Greening’ urban areas is an adaptation strategy that may mitigate additional increases in urban temperatures, mainly by increasing the cover and abundance of vegetation. The cooling influence of plants has been widely recognized (Alonzo et al., 2025; Bowler et al., 2010; Hiemstra

et al., 2017; Jenerette et al., 2016; Veerkamp et al., 2021; Winbourne et al., 2020). A key mechanism by which UGI cools the environment is evapotranspiration, which is composed of transpiration, wherein water is taken up by tree roots and moved through the stem and then evaporates through leaf stomates, and evaporation of water from all urban surfaces. The energy (i.e., latent heat) used to evaporate water transpired by trees consumes heat energy (i.e., sensible heat) in the local environment that would otherwise raise air temperature and, instead, cools leaf surfaces and nearby air temperatures by advection (Winbourne et al., 2020). In addition to evaporative cooling, shading from trees can act to cool the atmosphere by intercepting solar radiation and preventing warming of the land surface and air (Bowler et al., 2010). Further, trees can cool local air temperatures indirectly by reducing human dependence on and use of cooling services (e.g., air conditioners) (Winbourne et al., 2020).

Numerous studies have reported that the spatial pattern of green spaces can potentially influence the cooling effect (Beele et al., 2024; Hou & Estoque, 2020; Hu et al., 2021; Jayasinghe et al., 2024; L. Wu & Chen, 2023). The two fundamental aspects of land cover spatial pattern are composition and configuration. Composition refers to the abundance and variety of land cover features without considering their spatial character or arrangement; configuration, in contrast, refers to the spatial arrangement or distribution of land cover features (Gustafson, 1998). For land surface and air temperature modification, in addition to direct modification of surface characteristics, land cover pattern may also influence the temperature through its effects on the movements and flows of organisms, material, and energy in a landscape (Turner & Gardner, 2015). Thus, the total amount of vegetation, or percentage of different vegetation types (e.g., trees, grass, shrubs etc.) has a significant effect on the cooling intensity, while the size, shape or distribution of UGI also may play an important role in the magnitude of urban heat mitigation (Table 1). However,

there are relatively less study looking at the daytime VS nighttime differences when investigating the effect of spatial pattern of UGI on ambient air temperature. The knowledge of how configuration of different green infrastructures affects nighttime thermal comfort is still unclear, especially considering the heterogeneity of urban parks. Many of the vegetation indicators used in previous studies on trees' cooling effect are at the scale of individual trees; for example, canopy extension (e.g., crown diameter) (H. Wang et al., 2023), vertical size (e.g., tree height), leaf properties (e.g., leaf area index) or biological properties (e.g., transpiration rate) (J. Zhang, Khoshbakht, et al., 2022). The use of parameters related to tree groups is relatively rare and inconsistent in fine scale studies.

Table 1. Example of studies examining the impact of composition/configuration of UGI on urban temperatures, highlighting UGI types, key spatial pattern metrics, conclusions, and temperature types considered.

Spatial pattern	UGI type	Metrics	Conclusion	Temperature	Reference
Composition	Park	Green coverage, number of trees, park size.	Park area, perimeter, and shape index were significantly correlated with park cooling area and park cooling efficiency, with vegetation index significantly correlated with park cooling intensity and park cooling gradient.	LST	(Peng et al., 2021)
Composition	District	Tree coverage ratio, tree crown diameter	The cooling effect of trees gradually increased with increasing tree coverage. Small canopy trees have a better cooling effect than large canopy trees for the same level of coverage.	Air temperature	(H. Wang et al., 2023)
Composition	Park	Shrub cover, tree cover, sky view factor, distance from sea	Increase of shrub and tree cover reduce the air temperature in the parks.	Air temperature (All day)	(Cheung et al., 2021)
Configuration	Urban Space	Green Index of morphological spatial pattern analysis (MSPA) foreground classes	Core and bridge area are significantly positively related with the LST reduction.	LST	(Zhong, 2025)

Composition and configuration	Forest, woodland and shrub land with tree canopy VS Cropland and grassland, green spaces without tree canopy	Aggregation Index Largest Patch Index Mean patch area Mean shape index	Forest is the potential cooling land cover types while other vegetation, including crop and grass, failed to cool the LST in the daytime in Hangzhou. The cooling effects of forest differs in scale and configuration: cooling effect of forest could be detected in a rather larger scale (more than 690 m); aggregated forest with complex shape was preferred in cooling LST.	LST	(Hou & Estoque, 2020)
Composition and configuration	Urban trees	Deciduous vs evergreen trees Linear planting vs group planting vs individual planting	Regulation capacity: deciduous trees > evergreen trees, group planting > linear planting > individual planting.	Air temperature (Daytime)	(Zhao et al., 2020)
Composition and configuration	Urban Space	Green Tree canopy cover, grass and shrub cover, aggregation and shapes	Increase in tree cover mitigate daytime warming and aggregate trees further improved the cooling. The grass and shrubs offered significant nighttime cooling.	Air temperature (Daytime VS Nighttime)	(Beele et al., 2024)
Composition and configuration	Urban trees	Percent cover of tree canopy, Patch density, Edge density, Mean patch shape index, Patch cohesion index	Composition, configuration, and vertical structure of tree canopy were all significantly related to both daytime LST (stronger effect) and nighttime LST	LST	(J. Chen et al., 2020)

2.3 Urban Green Infrastructure and Air Pollution Mitigation

Vegetation helps to mitigate air pollution in multiple ways. Possible mechanisms include dispersion, interception, impaction, deposition or a combination. In this thesis, I focus on nitrogen dioxide (NO_2) and ozone (O_3) as both pollutants influence human health via the respiratory as well the cardiovascular systems (World Health Organization, 2006). At the individual plant scale, plants can literally uptake O_3 via both stomatal and nonstomatal processes (Fares et al., 2010). O_3 can be removed after entering the stomata and undergoing subsequent reactions within the intercellular region (Loreto & Fares, 2007). For NO_2 , plants can absorb some via the stomata simultaneously with carbon dioxide (CO_2) or oxygen (O_2) during photosynthetic and respiration processes, respectively (Figure 1) (Gourdji, 2018). However, the biogenic volatile organic compounds (BVOC) emitted by vegetation is a precursor of O_3 and O_3 could oxidize the NO to form NO_2 , which makes the role of urban vegetation on the local regulation of tropospheric O_3 concentrations very complex and largely influenced by species-specific emission rates of BVOCs and O_3 deposition rates (Fitzky et al., 2019).) Most of the studies exploring the effect of UGI on air quality focused on urban forests as a whole (a more general term that includes all the trees and associated vegetation in urban area) (Escobedo et al., 2011; Fantozzi et al., 2015; Maison et al., 2024; Yang et al., 2023). We will need more empirical evidence to explore the dominant mechanism of urban parks to affect the ambient air quality to better design the layout of the urban parks.

Several potential factors that influence the UGI's ability to mitigate air pollution have been explored by previous studies. Species and configuration of UGI are believed to be two major factors that affect this ES intensity of air quality regulation (Baldauf, 2017; Gourdji, 2018). The impact of vegetation on the concentration of gaseous air pollutants such as NO_2 and O_3 may largely depend on the type and structure of local vegetation, climatic conditions, proximity to traffic

pollution sources and regional and local ambient pollutant levels (Yli-Pelkonen et al., 2017). Thus, for ozone mitigation, deciduous broadleaf species tend to remove O₃ the most effectively (Alonso et al., 2011); and for NO₂ mitigation, plant species tolerant to NO₂ levels are good options. Further, BVOC emissions are strongly correlated to high temperature (Fitzky et al., 2019), which means more precursor of O₃. Research about the effect of tree configuration on air pollution mitigation is relatively limited. Some studies found lower O₃ concentrations in tree-covered habitats (Yli-Pelkonen et al., 2017), whereas other studies found the opposite (Buteau et al., 2017). To improve the empirical understanding of the effects of urban vegetation on local air pollution, Grundström & Pleijel (2014) compared NO₂ and O₃ near a major traffic route outside and inside a dense deciduous forest stand using passive diffusion samplers, and found that the effect of urban vegetation on NO₂ existed in a traffic polluted environment, but O₃ showed a more variable response. However, at the local scale, pollution concentrations can be increased if trees: 1) trap the pollutants beneath tree canopies near emission sources; 2) limit dispersion by reducing wind speeds, and/or 3) lower mixing heights by reducing wind speeds (Nowak et al., 2014).

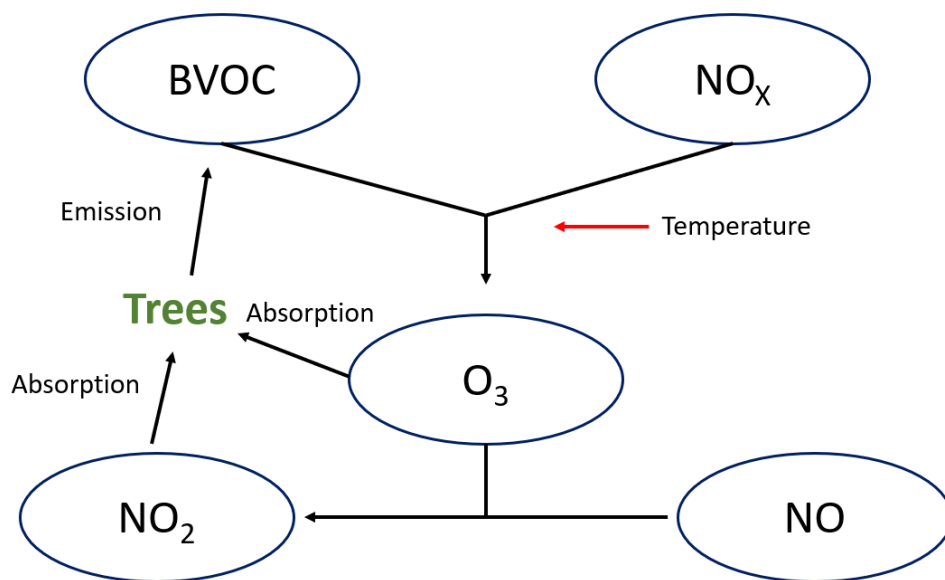


Figure 1. The interplay among O₃, NO₂ and trees

2.4 Environmental Justice

Social inequality is the unequal distribution or allocation of wealth and resources to specific socio-cultural groups, and such imbalances contribute to substantial injustices that privilege certain individuals over others (Schell, Dyson, Fuentes, Des Roches, et al., 2020). Urban social inequality stems from historical and contemporary power imbalances and produces deleterious effects that are often intersectional, involving race, economic class, gender, language, sexuality, nationality, ability, religion, and age (Winker & Degele, 2011). Inequality and inequity disproportionately affect which individuals own and access land, hence affect their accessibility to all kinds of ecosystem services. This issue can be discussed under a new concept: “environmental justice”. Environmental justice emerged as a normative concept and a social movement in the US in the

1970s (Schlosberg, 2007) and has often been referred to as the spatial distribution of environmental goods and ills amongst people, including the “fairness in the distribution of environmental wellbeing” (Low & Gleeson, 1998).

Urban ecosystems are complex systems that encompass various interactions between natural landscapes, built and planted infrastructures, and human activities (Alberti, 2015). Recently, several studies focused on informing sustainable solutions to promote urban biodiversity, human well-being, and urban resilience under the condition of global climate change. However, leveraging urban ecosystems to make connections of sustainability, conservation, and innovation, requires a comprehensive understanding of the underlying components, hierarchical structures, and key drivers of urban functions (Schell, Dyson, Fuentes, Des Roches, et al., 2020), such as social inequality.

Assessment of UGI is often viewed from three perspectives: quantity, quality, and accessibility of green spaces. All these factors play an important role in ecosystem service provision. However, for services such as air pollution mitigation and temperature reduction, ES providing and benefiting areas need to overlap spatially for their benefits to be delivered. Thus, recognizing potential mismatches between where ecosystem services are supplied and where demand is higher is essential when planning and creating policy for urban green infrastructure to ensure that benefits are provided where they are most needed so that investments can maximize impact (Herrerros-Cantis & McPhearson, 2021).

Household and neighborhood wealth and racial-ethnic disparities are currently the most common social variables that ecologists find are associated with within-city ecological patterns. Expanding urban vegetation has direct economic costs for its purchase, planting, and on-going maintenance, thus urban green space area and plant diversity are usually found to be positively

correlated with neighborhood wealth (Hepburn et al., 2025; Schell, Dyson, Fuentes, Des Roches, et al., 2020); and immigrants and visible minorities also usually have lower access to ecosystem services (Chaudhary et al., 2018, 2018; Jenerette et al., 2011). Previous studies used various indicators to indicate socioeconomic background as their study areas are under different social conditions (Chaudhary et al., 2018; Clarke et al., 2013; Locke et al., 2021; Song et al., 2021) and explored the injustice in the distribution of multiple ES (Table2). Those studies mainly focused on: the spatial distribution disparities of UGI, risk of exposure to environmental problems, and the potential spatial matches in supply & demand of ES. Notably, the distributional inequity of UGI in some developing countries, like China, is mainly due to physical geographic factors, changes in urban planning and development strategies rather than economic factors (Cao et al., 2024).

In conclusion, wealth and racial/ethnic groups explain the largest part of the environmental injustice. These drivers work together but in different forms or with different proportional impact in the process of driving environmental injustice in different countries and cities. Most environmental injustice studies are conducted in capitalist and developed countries, where both the government and individuals' activities contribute to the process, and disparities can be viewed at local scale; while for developing countries, especially socialist countries, the urban landscape patterns are mainly dependent on the budget and policy of local governments, and the disparities are usually studied at city or regional scale. Countries with a large proportion of immigrants, such as Canada, are typically faced with racial-ethnic disparities in the distribution of ecosystem services. Further, local climate conditions can either mitigate or aggravate the effects of these drivers. Thus, the study of environmental injustice should be spatially specific to make sure the solutions are applicable to the target city.

Table 2. Example of studies on environmental injustice research, with ecosystem service type, socio-demographic indicators, and environmental justice outcomes.

Ecosystem service type	Social demographic indicators	Conclusion	Reference
Mismatches of supply of and demand for ecosystem services (temperature reduction and runoff mitigation)	The percentage of different races and ethnicities The normalized median annual household income	Areas with lower supply–demand mismatch tend to be populated by a larger proportion of white residents with higher median incomes, and areas with high mismatch values have lower incomes and a higher proportion of people of color.	(Herreros-Cantis & McPhearson, 2021)
Supply-demand mismatch for UGI and heat exposure	Neighborhood economic status	Increased exposure observed among socio-economically disadvantaged communities, the elderly, and people with health issues. Areas associated with higher income levels show lower ES mismatches, indicating higher temperature regulation supply and reduced heat vulnerability.	(Aznarez et al., 2024)
Urban green space area and plant diversity Urban heat islands and air pollution	Neighborhood wealth, ethnic minority groups	Affluent urban residential neighborhoods generally have greater vegetation cover, canopy cover, and plant diversity than their less wealthy counterparts and ethnic minority groups. Heat is also unevenly distributed within cities: temperatures are typically greater in lower income neighborhoods than in higher-income areas, greater in ethnic minority community.	(Schell, Dyson, Fuentes, Des Roches, et al., 2020)

Urban heat health risk	Income, gender	High-income groups were able to disproportionately access the benefits despite the social equity provisions built into policy and institutional structures. Women have restricted access to decision making and thus to the ecosystem services.	(W. Zhu & Yuan, 2023)
urban park supply and resident demand	Age	The disparity between urban park supply and resident demand resulted from the spatial distribution of physical geographic factors, changes in urban planning and development strategies, and the diverse and dynamic demands of urban residents.	(Cao et al., 2024)
Multidimensional park qualities	Deprivation	Different types of parks have different relationships with deprivation. This paper demonstrate how examining park-type distribution reveals previously hidden inequities in green space provision.	(Hepburn et al., 2025)

Green infrastructure provision	Socioeconomic status (SES)	low-SES people tend to live closer to parks in urban and suburban areas, while the opposite occurs in rural areas. Study also showed that the quality of parks, including park amenities, maintenance and crime safety, is considerably lower in low-SES ethnic minority neighborhoods compared to white and wealthier areas.
Access to total vegetation and trees/shrubs on public lands and private yards	Income and race	Low-income populations have less access to both total vegetation and trees/shrubs on public land (in streets and alleys) than on private land (backyards). Visible minorities are found to have less access to trees/shrubs in all public lands, less access to total vegetation at the block and alley, but that they have slightly greater access to trees/shrubs in private yards. (Pham et al., 2012)
Air quality	Income and race	Air pollution sources are often located near low-income neighborhoods; consequently, low-income residents and ethnic minority groups frequently have higher risk of exposure to and vulnerabilities associated with air pollutants. (Chambliss et al., 2021)

2.5 Observation Method Used in Temperature/Air Quality mitigation Studies

Urban heat and air quality studies typically use two categories of data collection methods: in-situ methods and remote sensing methods. The in-situ measurements work well in providing us with high temporal resolution data and allow us to make observations at a relatively fine scale, which is very helpful in studies aiming to get detailed and accurate data. Although in-situ measurements can provide direct observation, in many cases, in situ measurements tend to be sparse and infrequent, and data collection can be difficult, time consuming, and expensive. Remote sensing (e.g. satellite or airborne imagery) complements in situ data collection by providing repetitive, consistent and spatially continuous measurements and characterization of habitat and biodiversity patterns, compositional, structural and functional attributes as indicators of vegetation condition over large areas on regular time intervals (Kowe et al., 2021). Landscape indicators and environmental variables such as altitude derived from Digital Elevation Models (DEM), vegetation cover from the Normalized Difference Vegetation Index (NDVI) products and Land Surface Temperature (LST) derived from remote sensing data are good data sources in mapping and monitoring the spatial structure of urban green spaces and vegetation fragmentation (Kowe et al., 2021).

Remote sensing with passive sensors has great potential to monitor the land use/land cover change, urban tree canopy, vegetation condition and leaf area index (H. Du et al., 2017; Hou & Estoque, 2020; Hu et al., 2021; Peng et al., 2021). However, bad weather conditions or large cloud cover can affect the quality of the images, which leads to the loss of information. In addition, it is hard to get both high spatial and high temporal resolution images from one single type of satellite

sensors, which requires the use of data processing methods like image fusion for certain scientific questions (Song et al., 2022). Remote sensing with active sensors has their own radiation source, which sends a pulse to objects on the earth's surface and measures the backscatter reflected back to the sensor, usually would not be influenced by cloud and other meteorological factors (airborne and below the cloud cover). They are also very useful in the assessment of green spaces. For example, Light Detection and Ranging (LiDAR) active sensors allows to measure the distance to the ground by calculating the time it takes for the light from its source to be reflected back to the sensor, thus allowing us to obtain the vertical dimensions of vegetation (LaRue et al., 2018; Nychka & Nadkarni, 1990). LiDAR data can be used to do in-depth vegetation analysis, like observation of vertical structure of green space and classification of species, which can be used in biodiversity research. However, the equipment is usually very expensive, and the measurement can be very time consuming, which is a limitation of this technology.

2.6 Synthesis and gaps

The reviewed literature highlights both the benefits of UGI and the limitations of existing research in fully capturing its role in providing urban ecosystem services. Urban green infrastructure plays an important role in shaping environmental quality and human well-being in cities, providing various ecosystem services, including urban heat mitigation and urban air pollution mitigation by various mechanisms (Winbourne et al., 2020; Bowler et al., 2010; Beckett et al., 2000; Hiemstra et al., 2017; Jenerette et al., 2016; Tomson et al., 2021; Y. Wang et al., 2014). Both the composition and configuration of green spaces influence urban heat mitigation (Beele et al., 2024; J. Chen et al., 2020; Hou & Estoque, 2020). Usually, the percent cover of green spaces is positively related with the cooling intensity, but the effect of configuration varies with the context of the area (e.g., local climate) (Turner & Gardner, 2015; Potchter et al., 2006; D. Zhao et al., 2020;

Bowler et al., 2010; Fu et al., 2022). Tree species and planting configuration are two main factors that affect air pollutant removal ability of the trees (Yli-Pelkonen et al., 2017; L. Chen et al., 2017; Baldauf, 2017; Xing & Brimblecombe, 2020). In terms of the distribution of urban green infrastructure, low-socioeconomic status and visible minorities tend to have reduced access to parks, and they are also frequently exposed to higher mismatches of the demand and supply of ecosystem services (Rigolon, 2016; Wen et al., 2013; Pham et al., 2012; Buyantuyev & Wu, 2010; Herreros-Cantis & McPhearson, 2021; Chambliss et al., 2021; Schell, Dyson, Fuentes, Des Roches, et al., 2020; Tessum et al., 2019).

Although these studies provide important insights, several important gaps remain in understanding the role of UGI in providing urban ecosystem services: 1) Lack of multiple spatial scale comparison. Researchers usually conducted studies at one specific spatial scale (i.e., local scale, city scale, or national scale), but the effect of UGI can change across different scales. 2) Lack of daytime and nighttime air temperature comparison with fine spatial resolution. Most of the studies about the impact of spatial pattern of UGI on ambient air temperature only focused on the daytime temperature, whereas the nighttime temperature is also an important factor for human health and well-being. 3) Lack of fine-scale empirical and paired site observations of air temperature and air pollutants. Due to the sparse weather stations in cities, scientists usually use models to simulate the distribution of air temperature or air pollutants in urban areas. However, model accuracy depends heavily on the quality of input data, and parameterizing the models for complex, heterogeneous urban environments (accounting for local variations in surfaces, vegetation, and emissions) remains a challenge. 4) Lack of consideration of green space configuration in the environmental justice research. Environmental injustice studies usually assess the quantity of UGI while overlooking the spatial characteristics.

These gaps directly inform the objectives of this study, which aim to provide a more comprehensive, multi-scale, and empirical assessment of UGI's role in urban cooling, pollutant mitigation, and environmental equity.

2.7 Objectives

1. Explore the relationship between land surface temperature and composition & configuration metrics of UGI at multiple spatial scales
2. Assess the spatial pattern of UGI in Montreal in terms of their cooling capacity and explore the corresponding environmental injustice.
3. Examine the differences in urban heat mitigation provided by various vegetation configurations between daytime and nighttime in small urban parks.
4. Provide detailed, empirical evidence of the impact of trees in urban parks on ambient NO₂ and O₃ concentration

This thesis is presented in a manuscript-based format. It consists of three manuscript chapters (Chapters 3-5). Chapter 3 addresses Objectives 1 and 2, chapter 4 addresses objective 3, and chapter 5 addresses objective 4.

Chapter 3: Analyzing spatial patterns of urban green infrastructure for urban cooling and social equity

3.1 Abstract

‘Greening’ urban areas is a key strategy to counteract rising urban temperatures and their negative impacts on human health and well-being. Efficient green space management is needed for optimizing ecosystem benefits in urban areas with limited space availability. Existing research often overlooks the spatial configuration of urban green infrastructure (UGI) and focuses on single scales, limiting its application. Our study evaluates how the composition and configuration of UGI impacts the supply of cooling services at two spatial scales. We also assess the equity of access to these cooling services in Montreal, considering socioeconomic factors. Using a statistical model based on three key predictors, percent cover of both high and low vegetation and the largest patch index of high vegetation, we predict the cooling supply of UGI during summer daytime with a moderately high accuracy ($R^2 = 0.80$). Our results showed that during the day, an increase of 10% in the percent cover of high vegetation, percent cover of low vegetation, or largest patch index of high vegetation would lead to a decrease in average land surface temperature of 1.41 °C, 0.76 °C, or 0.20 °C, respectively. To assess social equity, we developed a cooling demand index based on the proportion of vulnerable groups, focusing on older adults and young children. Mapping mismatches in cooling supply and demand revealed that neighborhoods with higher proportions of visible minorities and low-income residents had significantly lower access to cooling services. Conversely, access was significantly positively correlated with income and post-secondary education levels. Overall, our results offer practical guidance for designing UGI layouts that

maximize cooling supply and emphasize the need to prioritize underserved communities in urban greening efforts.

3.2 Introduction

Urbanization leads to changes in the physical environment of cities, such as the increase of impervious areas and decrease of green spaces (Kim & Brown, 2021). Temperature rise in cities is driven by the high thermal mass of concrete and asphalt roads, limited ventilation in urban canyons created by tall buildings, the reduction of vegetation, and the combined heat output from street vehicles and air conditioners (Akbari et al., 2016). Higher temperatures in cities are closely associated with adverse impacts on human health and well-being (Curriero et al., 2002; Filleul et al., 2006; Michelozzi et al., 2009).

‘Greening’ urban areas is a widely recognized strategy to mitigate high urban temperatures, through increasing the ecosystem service of temperature regulation (Alonzo et al., 2025; Bowler et al., 2010; Hiemstra et al., 2017; Veerkamp et al., 2021; Winbourne et al., 2020). In addition to providing shade, a key mechanism by which urban green infrastructure (UGI, defined here as all vegetated spaces within the urban area) cools the environment is evapotranspiration, which is composed of transpiration (by plants) and evaporation of water. Further, trees can cool the local environment in an indirect way, by reducing people’s reliance on and use of cooling services which release waste heat into the city (e.g., air conditioners) (Winbourne et al., 2020).

Numerous studies have reported that the spatial pattern of green infrastructure influences the magnitude of the cooling effect (Gustafson, 1998; Peng et al., 2021). Two fundamental aspects

of land cover spatial pattern are composition and configuration (Turner & Gardner, 2015). Composition refers to the abundance and variety of land cover features while configuration refers to the spatial arrangement or distribution of land cover features (Gustafson, 1998). Changes in surface characteristics involve changes in surface properties like albedo and thermal mass, which can directly alter the surface and air temperatures. Land cover pattern may also influence temperature through its effects on the movement and flow of air and energy in a landscape (Turner & Gardner, 2015). While many types of greening can confer cooling benefits, trees consistently demonstrate more effective reductions to land surface temperature compared to other plant functional types, such as shrubs or grass, particularly during the day (Alonzo et al., 2025; Y. Liu et al., 2021). This positive effect of tree cover on temperature mitigation includes both direct cooling of the local environment, as well as indirect cooling of surrounding areas, sometimes referred to as spillover effects (Smith et al., 2023). While the total amount of canopy or vegetation cover tends to make the largest contribution to temperature reduction, the spatial configuration can still significantly impact cooling in urban environments (Rakoto et al., 2021), with the size, shape or distribution of UGI playing an important role in the magnitude of urban heat mitigation (Hou & Estoque, 2020; Hu et al., 2021; X. Li & Zhou, 2019; Rakoto et al., 2021; Y. Wu et al., 2025; W. Zhou et al., 2017). However, the relative extent to which configuration is important remains unclear, as well as which configurations offer the most powerful cooling effect. For example, a recent review of the literature emphasizes that large, compact green spaces are consistently highly effective at reducing temperatures, particularly in terms of a greater distance of spillover effects. However, many distributed small patches - leading to increased edge effects - can also provide effective cooling, particularly in humid environments (Alonzo et al. 2025).

The composition and configuration of vegetation are also related to access to the benefits of green spaces. Unequal distribution of vegetation can restrict residents' access to cooling in certain neighbourhoods, therefore contributing to social inequalities within a city (Jenerette et al., 2011; McDonald et al., 2024; C. Wang et al., 2022; Z. Zhu et al., 2019). Reducing social inequality and inequity is an important component of achieving more sustainable cities (*THE 17 GOALS | Sustainable Development*, n.d.). Inequalities regarding urban heat usually take the form of uneven distribution of urban heat islands (Huang & Cadenasso, 2016; Jesdale et al., 2013), driven by uneven distribution of vegetation and tree canopy cover to communities with different socioeconomic status, where wealthier and whiter communities usually have access to larger or more diverse green spaces (Clarke et al., 2013; Gerrish & Watkins, 2018; Rigolon, 2016; Schwarz et al., 2015; Watkins & Gerrish, 2018). People of certain ages, such as the elderly and young children, are also physically more susceptible to the dangers of prolonged exposure to excessive heat, when compared to healthy young adults (Kovats & Hajat, 2008; McGeehin & Mirabelli, 2001). This is an important public health consideration in the context of an increasingly aging global population, where an anticipated one in six people will be over 65 by 2050 (Nations, n.d.). Thus, to better plan and manage future cities to reduce the impacts of urban heat, studies should integrate two key aspects: the capacity of vegetation to mitigate urban heat (cooling service supply) and the population's need for cooling based on vulnerability to heat island effects (cooling service demand). Understanding both supply and demand for cooling services – as well as whether there are mismatches between them, and the drivers of these mismatches – will help guide decisions on both how, and where, to intervene for more climate-resilient cities, where ecosystem services are accessible to urban residents who need them most.

Improving the planning of UGI to increase the supply of cooling services is a key strategy to adapt to potential climate change threats, and to improve overall human –well-being in urban areas. Given the limited availability of space for adding new green infrastructure in growing cities, there is a need to better understand how the spatial pattern of UGI influences the supply of cooling services. This will help practitioners and decision-makers to optimize greening efforts by carefully considering both the composition and configuration of vegetation. Equally important is considering whether these cooling services are equitably distributed in urban areas relative to people’s demand, to ensure that all residents can benefit. The assessment of demand for cooling service is often based on heat-related indices, such as heatwave days, heat index thresholds (Baró et al., 2015; Herreros-Cantis & McPhearson, 2021), or population density combined with consumption rates (Burkhard et al., 2012). These studies typically find that areas characterized by lower income communities or with a higher level of visible minorities usually receive less cooling service from urban green infrastructure than demand, due to distributional inequities in vegetation across cities (Wen et al., 2013). However, fewer studies assessing cooling supply also consider the increased need to deliver cooling services to physically vulnerable groups (i.e., the elderly and the young) in assessing demand (Aznarez et al., 2024; W. Zhu & Yuan, 2023). Recent studies highlight the importance of including the perspective of heat vulnerable populations in considering supply-demand mismatches in cooling services. Key drivers of supply-demand mismatches are often income, land-use history, and race, such that wealthier and more privileged communities have both higher supply of cooling services provided by vegetation, alongside reduced heat vulnerability (Cao et al., 2024; Leong et al., 2018).

Considering the role of green infrastructure composition and configuration on cooling supply in conjunction with demand is also an opportunity to further integrate the role of green

space configuration into distributional equity research (Guan et al., 2023). There is a broad literature describing the inequitable access to urban green space and associated benefits (Landry & Chakraborty, 2009; Leong et al., 2018; Nesbitt et al., 2019). However, environmental injustice studies often focus more on the presence or quantity of UGI within a particular area (Clarke et al., 2013; Jenerette et al., 2011; Locke et al., 2021; McDonald et al., 2024; Pham et al., 2012), while the configuration of the UGI at local scales (e.g., whether vegetation is locally clustered or distributed) is less explored (P. Chen, 2024; Wilson et al., 2024). However, there is increasing interest in the effects of changes in UGI configuration on a broad range of ecological benefits (Cimburova & Berghauser Pont, 2021; Lemoine-Rodríguez et al., 2022), which may also provide important opportunities to reduce inequities in access to cooling services.

The extent to which we see mismatches in supply and demand of cooling services may also vary with spatial scale, as the effect of UGI composition and configuration on temperature can change depending on the scale considered (Zhou et al., 2011). While multi-scale studies are increasing (S. Jia et al., 2024; Zhong, 2025), the majority of research on the effects of landscape structure on urban heat remains focused on a specific spatial scale (typically either local scale or city scale), limiting our understanding of the scales at which particular types of interventions are most powerful. Additionally, methodological differences in choice of spatial pattern metrics, the nuanced difference in defining cooling and the units that represent various spatial scales also creates difficulties in making comparisons among studies conducted at different scales. For example, at larger scales, satellite imagery and temperature retrieval techniques are widely used for their potential to provide repetitive, consistent and spatially continuous measurements (Kowe et al., 2021). However, bad weather conditions or large cloud cover might affect the quality of the images, which leads to loss of information. In addition, it is hard to get both high spatial and high

temporal resolution images from one single type of satellite sensors, which sometimes require technical processing like image fusion (Song et al., 2022). At fine scales, researchers often use modeling approaches, for example, ENVI-met (Bruse & Fleer, 1998), i-Tree (Nowak, 2024), and CFD (simulation software) (OpenFOAM Foundation, 2023) in studies that explore the effect of vegetation on temperature reduction (Aliabadi et al., 2017; Bowler et al., 2010; Y. Wu et al., 2025). These models are based on assumptions about trends derived from several pre-determined parameters and are often highly complex. There are also challenges in validation considering data availability and quality. Consideration of multiple scales within the same study can help overcome these difficulties in comparing results. Here, we focus on comparing census tract and a broader neighbourhood scale, which allows us to compare the effect of changing spatial scale, while also providing meaningful results for municipal interventions.

To enhance our understanding of how the spatial pattern of UGI impacts both cooling supply and the accessibility of vulnerable residents to cooling at various spatial scales, we address the following research questions:

1. How does the configuration and composition of UGI impact the supply of cooling services at two different spatial scales: borough (or neighbourhood), and census tract?
2. To what extent are there mismatches in supply and demand for cooling services for physically vulnerable residents, and are these mismatches driven by underlying inequities in terms of socioeconomic status, race, and education level?

Our study addresses critical gaps by examining the effects of UGI composition and configuration at multiple spatial scales, highlighting widely applicable landscape metrics associated with urban heat, and providing insights into scale-dependent impacts. Additionally, we

address the underexplored role of green space configuration in distributional equity research and environmental injustice assessments. Furthermore, we integrate a nuanced perspective on demand for cooling services by considering the needs of physically vulnerable age groups, which has emerged as a major public health concern (Vasconcelos et al., 2024), and may not be adequately addressed in studies relying solely on heat-related indices or population density metrics. By considering both the demand for cooling by physically vulnerable residents, and the extent to which supply-demand mismatches are driven by additional socio-economic factors, we interrogate how multiple aspects of inequity are embedded in access to a cool environment. Ultimately, we aim to provide actionable insights for optimizing UGI planning and facilitating equitable access to ecosystem services, enhancing urban resilience to climate change while addressing social inequalities.

3.3. Methods

3.3.1 Study area

Our study area is the Island of Montreal, Quebec, Canada, with a population of approximately 2 million people (Government of Canada, 2022), and containing Canada's 2nd largest city (Figure 2). Montreal is classified as a warm-summer humid continental climate (Köppen climate classification: Dfb). There are disparities in the distribution of vegetation in the city of Montreal which disfavor low-income people and, to a lesser extent, visible minorities (Pham et al., 2012). In recent years, Montreal has also experienced a concerning rise in the frequency and intensity of heat wave events, some of which have resulted in tragic and deadly consequences (Bustinza et al., 2013). The fact that Montreal is an island with a growing population

requires effective urban planning that prioritizes the development of UGI to maximize the supply of much needed cooling services to all residents.

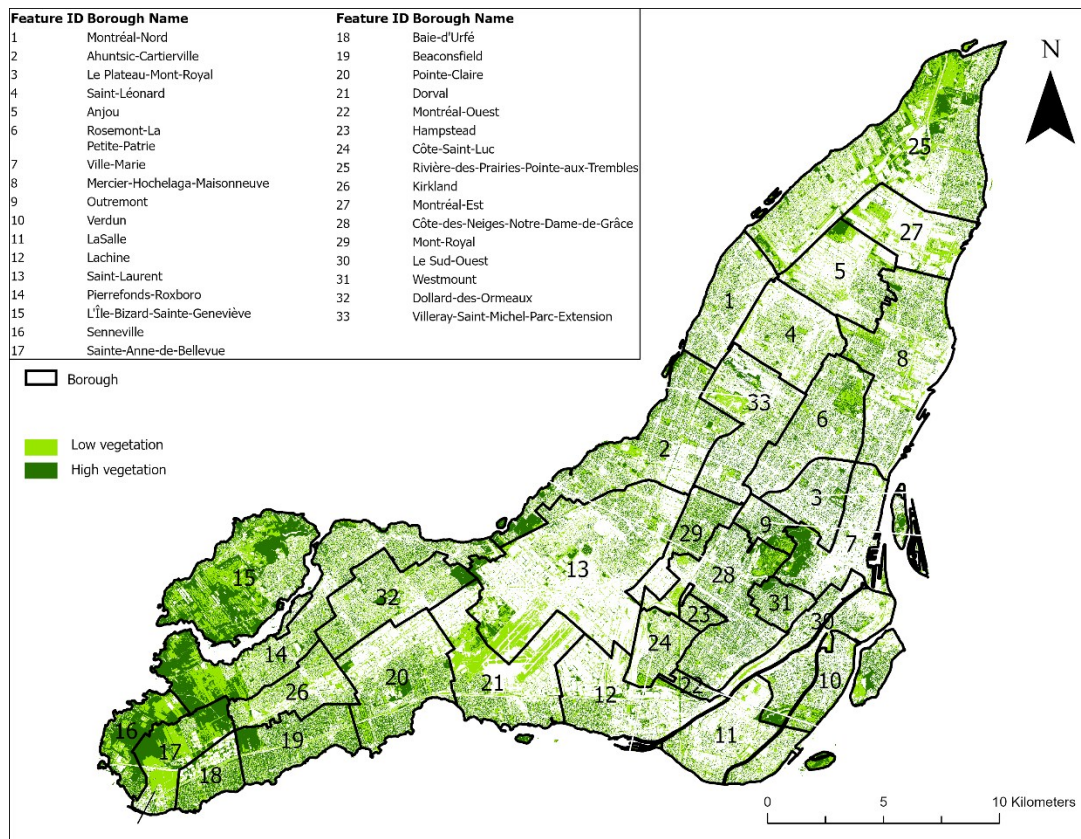


Figure 2. Map of the island of Montreal. The Island of Montreal is composed of 34 boroughs (the official term for the municipal subdivisions of the Island of Montreal), including 19 boroughs forming the City of Montreal, and 15 linked cities. Low and high vegetation are derived from the metropolitan canopy index (provided by the Communauté métropolitaine de Montréal, or Montreal Metropolitan Community, open data set: https://observatoire.cmm.qc.ca/produits/donnees-georeferences/#indice_canopee). This high spatial resolution (1m) dataset uses a combination of airborne LiDAR imagery and colour-infrared orthophotos to determine vegetation classes based on NDVI and height. Low vegetation (primarily grass or herbaceous vegetation cover) is identified based on the criteria that $NDVI \geq 0.3$ and < 3 m height, while high vegetation (tree cover) is identified as $NDVI \geq 0.3$ and > 3 m height.

3.3.2 Data

3.3.2.1 Land Surface Temperature Data

As we aim to conduct spatial scale mapping of the cooling supply at large scales, Landsat imagery is the most appropriate free data source to use. The LST data were derived from the land surface temperature product generated by the U.S. Geological Survey (USGS). The Landsat Collection 2 level 2 as released in 2020 and provides several improvements in the Landsat Science Products. A primary characteristic of Collection 2 is the substantial improvement in the absolute geolocation accuracy of the global ground reference dataset – which improves the interoperability of the Landsat archive through time. Collection 2 also includes updated global digital elevation modeling sources and calibration and validation updates. We used the collection 2 LST product generated from Landsat 8 Thermal Infrared Sensor (TIRS) for the island of Montreal on August 14th, 2020 and August 10th, 2021. The images are cloud free and atmospherically corrected and the dates are close to those of other datasets we used, such as Metropolitan canopy index data (2021) and demographic data (2021). The spatial resolution of the thermal band is 100 m but the product is adjusted to 30m-spatial resolution and the temporal resolution is 16 days.

3.3.2.2 Spatial pattern metrics

We used the metropolitan canopy index dataset (2021) as the reference for vegetation cover. This dataset is provided by The Montreal Metropolitan Community and derived from aerial photographs taken in August (<https://observatoire.cmm.qc.ca/produits/donnees-georeferences/>). The entire territory of greater Montreal is characterized into five major classes based on the nature of the territory and each class is assigned with a number: low mineralized surfaces (< 3 m height, e.g., roads, parking lots, etc.) (1), high mineralized surfaces(>3 m height, e.g., buildings) (2), low

vegetation (< 3 m height, e.g., grass, shrub, etc.) (3), high vegetation (e.g., > 3 m height, e.g., trees) (4) and aquatic (5). This classification is based on both the Normalized Difference Vegetation Index (NDVI) and LiDAR-derived height. With a very high spatial resolution of 1 m, this dataset fits well for measurement and monitoring purposes at multiple spatial scales.

3.3.2.3 Socio-economic data

A series of socio-economic datasets are derived from Canadian 2021 Census at census tract scale (<http://datacentre.chass.utoronto.ca/>). There are 533 census tracts on the island of Montreal, ranging from 3.7 to 1796.2 hectares (first quantile of 19.5 hectares and third quantile of 53.3 hectares). About 75% of the census tracts fall in the range between 10 to 100 hectares. We used 1) total population in each census tract, and population data of the age ranges 0-5 and 65+ respectively; 2) Median after-tax income of households in 2021 (\$); 3) total visible minority population (defined by the *Employment Equity Act* as “persons, other than Aboriginal peoples, who are non-Caucasian in race or non-white in colour”); 4) Highest certificate, diploma or degree and no certificate, diploma or degree for the population aged 25 to 64 years in private households. Those datasets reflect the age, economic and education status, and ethnic composition for each census tract, and have been used as important socioeconomic indicators to access the vulnerability to urban heat and accessibility to green space in previous studies (Chambliss et al., 2021; Herreros-Cantis & McPhearson, 2021; Rigolon, 2016; Schell, Dyson, Fuentes, Des Roches, et al., 2020; Wen et al., 2013).

3.3.3 Statistical Analysis of LST and UGI spatial pattern

To determine the impact of the configuration and composition of UGI on the supply of cooling services (Research question 1), we used a series of spatial pattern metrics and multiple linear regression models. Largest patch index and mean patch shape index (Table 3) are frequently used to quantify the fragmentation of green spaces (Connors et al., 2013; Hou & Estoque, 2020; X. Li & Zhou, 2019; Zhou et al., 2011, 2017). We also used an additional landscape metric, effective mesh size, which has been extensively used in landscape fragmentation studies, but has not been widely used in ecosystem service research. Effective mesh size is a measure of habitat connectivity. It is a more comprehensive measure of the size and structure of green spaces when compared to the mean patch size metric, which only refers to the average patch size and does not directly reflect the number and connection of green spaces. The mean patch size overemphasizes small but numerous patches by attributing equal weight to all patches, while the effective mesh size attributes weights that are proportional to the patch sizes. Effective mesh size is also independent of composition, allowing us to more clearly assess the relative impact of composition vs. configuration on urban cooling (Jaeger et al., 2008).

Table 3. Definition of spatial pattern metrics. A_U refers to total area of each unit (borough or census tract), A refers to the total area of one specific land cover type (high or low vegetation), a_i refers to the area of patch i for specific land cover type in each unit, n refers to the total number of patches of a specific land cover type in each unit, p_i refers to the perimeter of patch i for a specific land cover type in each unit.

	Metrics	Description	Equation
Composition	Percent Cover of high vegetation (P_{HV})	Percent cover of land cover feature with NDVI ≥ 0.3 and DEM ≥ 3.0 m (tree canopy)	$\frac{\sum_{i=1}^n a_i}{A_U} 100 (\%)$
	Percent cover of low vegetation (P_{LV})	Percent cover of land cover feature that NDVI ≥ 0.3 and DEM < 3.0 m (crops, grass, etc.)	
	Effective mesh size (EMS)	The size of the areas when the region under investigation is divided into n areas with the same degree of landscape division	$\frac{\sum_{i=1}^n a_i^2}{A}$
Configuration	Largest patch index (LPI)	The proportion of the largest patch to the total area of one land cover feature within an analysis unit	$\frac{\max a_i}{A} 100 (\%)$
	Mean patch shape index ($MPSI$)	The average shape index of patches within an analysis unit	$\frac{\sum_{i=1}^n \frac{0.25 * p_i}{\sqrt{a_i}}}{N}$

All the metrics are from McGarigal & Marks (1995) except for effective mesh size (Jaeger, 2000). The largest patch size was calculated differently by using the total area of one specific land cover type instead of the whole landscape unit. The effective mesh size also took a different format to the original equation by using the total area of one specific land cover type instead of the whole landscape unit (Roch & Jaeger, 2014).

For each borough (larger scale, on average 15 km²) and census tract (smaller scale, typically less than 1.5 km²), we calculated the mean LST as the response variable for statistical analyses, and composition and configuration parameters as predictor variables. While LST is not a perfect measure of human thermal comfort, research often uses LST as a proxy for air temperature in studies of vegetation cooling effects at broad spatial extents, where air temperature and humidity data are not available at sufficient spatial resolution (Hou & Estoque, 2020; Sanagar Darbani et al., 2025; Zhou et al., 2011, 2017). The calculation of composition and configuration parameters is based on the raster image of Metropolitan Canopy Index data. We calculated the spatial metrics and LST statistics in R studio. We used multiple-linear regression models to examine the relationships between LST and composition and configuration variables. We used LST datasets for the year 2020, and corresponding metropolitan canopy index datasets from the year 2021. The models describe LST as a function of:

- A) composition variables of high and low vegetation
- B) composition variables of high and low vegetation+ configuration variables of high vegetation
- C) composition variables of high and low vegetation+ configuration variables of low vegetation

The first model examines the effect of composition of high and low vegetation on LST. The next two models further investigate whether the combination of composition and configuration variables of urban greenery can better predict LST (Zhou et al., 2011). We calculated both the unstandardized regression coefficients and standardized coefficients for every variable in the models. The standardized coefficients are used to determine the relative importance of explanatory variables (Zhou et al., 2011). Larger absolute value of the standardized coefficient means the corresponding variable is more important. The regression coefficients in the models

indicate how the addition of the configuration variables alter the relationship between composition variables and LST. The statistical analysis was conducted using R statistical software (R4.3.1).

3.3.3.1 Environmental justice

To assess the equity of access to cooling services provided by UGI, we mapped both the supply and demand of these services across the Island of Montreal, aiming to identify and understand areas where demand and supply do not match for residents (research question 2). The supply of cooling service was calculated based on the predictor variables we derived in the previous analysis that show the relative importance for each spatial pattern metric to help mitigate urban heat. To assess the relationship between urban green infrastructure and their effects on land surface temperature (LST), we used the ΔLST (the maximum of the average LSTs in all census tracts minus the average LST in each individual census tract) as the dependent variable, the spatial pattern metrics (Table 3) of vegetation (both high and low vegetation) as the independent variables to build the model, where the intercept is settled as 0. Thus, when both the composition and configuration of vegetation equal 0, the anticipated ΔLST is also 0, and larger ΔLST indicates more cooling service provided by UGI.

$$\begin{aligned} \Delta LST = & \beta_1 P_{HV} + \beta_2 P_{LV} + \beta_3 EMS_{HV} + \beta_4 EMS_{LV} + \beta_5 LPI_{HV} + \beta_6 LPI_{LV} + \beta_7 MPSI_{HV} \\ & + \beta_8 MPSI_{LV} \end{aligned} \quad (1)$$

β s are the correlation coefficients. P_{HV} is the percent cover of high vegetation in each census tract, P_{LV} is the percent cover of low vegetation in each census tract, EMS_{HV} is the effective mesh size of high vegetation in each census tract, EMS_{LV} is the effective mesh size of low

vegetation in each census tract, LPI_{HV} is the largest patch index of high vegetation in each census tract, LPI_{LV} is the largest patch index of low vegetation in each census tract, $MPSI_{HV}$ is the mean patch shape index of high vegetation in each census tract, $MPSI_{LV}$ is the mean patch shape index of low vegetation in each census tract.

The model was calibrated using 80% of the 2020 data (around 350 samples, at census tract scale), which allowed for the adjustment and selection of the model variables and parameters. The remaining 20% of the census tracts was used to validate the model and to provide insights into its predictive accuracy. The model was also tested on 2021 data to assess the model's ability to generalize across different time periods or scenarios. This approach ensures that the model is well-calibrated, accurately validated, and robustly tested, making it more reliable for real-world applications. Subsequently, we removed the predictor variables (P_{LV} , EMS_{HV} , EMS_{LV} , LPI_{LV} , $MPSI_{HV}$, $MPSI_{LV}$) that showed no significance or detected by overall multicollinearity diagnostics and individual multicollinearity diagnostics from model 1 (*omcdiag* and *imcgiag* in R4.3.1). EMS_{HV} , LPI_{LV} show no significance in the model ($p > 0.05$) thus they were removed from the prediction model (Table 4). $MPSI_{HV}$, $MPSI_{LV}$ showed very high VIF values and they were not theoretically stronger variables compared to P_{HV} and P_{LV} , thus they were not selected to be included in the prediction model (Table 4). EMS_{LV} showed significance in the model, but at a margin ($p = 0.045$) and the estimate coefficient was 0.016, which is quite small (Table 4). The addition of this variable did not significantly improve the model, and this is why it was also removed. After removing the mentioned predictors, the VIFs of the predictors in the final model are below a threshold of 5 (Table 5). The differences between observed and predicted delta ΔLST were calculated and mapped, highlighting the spatial distribution of the model errors. Subsequently we obtained the relative importance of each indicator based on the correlation coefficients, we

calculated the predicted ΔLST in each census tract and normalized them to a number between 0 and 1 to produce an index of the supply of land surface temperature reduction by UGI in each census tract.

$$ES_{supply} = \frac{\Delta LST - \Delta LST_{min}}{\Delta LST_{max} - \Delta LST_{min}} \quad (2)$$

Table 4. Summary statistical indicators of the predictors in the multi-linear regression prediction model (for ΔLST) at census tract scale.

Predictors	P_{HV}	P_{LV}	EMS_{HV}	EMS_{LV}	LPI_{HV}	LPI_{LV}	$MPSI_{HV}$	$MPSI_{LV}$
coefficients	13.417	8.398	0.002	0.016	1.973	-0.422	2.569	-2.522
p-values	< 2e-16	< 2e-16	0.556	0.045	1.6e-7	0.387	0.007	0.008
VIF	10.34	9.96	2.30	2.23	3.57	3.66	890.24	906.16

Table 5. The VIF of the predictors in the model (1).

Predictors	P_{HV}	P_{LV}	LPI_{HV}
VIF	4.79	3.23	2.73

ES_{supply} is the supply index of cooling services provided by UGI, ΔLST is the predicted temperature difference between the target census tract and the census tract with highest average land surface temperature, ΔLST_{min} is the minimum predicted temperature difference, ΔLST_{max} is the maximum predicted temperature difference.

We calculated the demand of cooling services based on the age structure of the population in each census tract. Studies often use heat-related indices, such as heatwave days, or heat index thresholds as demand indicators (Fang et al., 2023; Herreros-Cantis & McPhearson, 2021). However, in this paper we focused on the receiver side of the cooling service, using an indicator of vulnerability to heat (the elderly and young children) that is anticipated to become increasingly important as global populations age. This means that areas with a higher proportion of this subset of the population have a higher demand for cooling services provided by UGI. As we are interested in citywide comparison for vulnerable groups, the proportion of the population of ages ≤ 5 and ages ≥ 65 (Harlan et al., 2006) is calculated relative to the total population of Montreal. We then normalized this proportion to a number between 0 and 1 to construct a demand index.

$$ES_{demand} = \frac{P - P_{min}}{P_{max} - P_{min}} \quad (3)$$

ES_{demand} is the demand index in each census tract, P is the proportion of vulnerable people in target census tract relative to the total population of Montreal (calculated as $P = \text{Percent}(\leq 5 \text{ years old}) + \text{Percent}(\geq 65 \text{ years old})$), P_{min} is the minimum proportion, P_{max} is the maximum proportion.

To assess the mismatch between supply and demand of cooling services across the island of Montreal, we generated a supply–demand mismatch value for each census tract, calculated as $ES_{supply} - ES_{demand}$. A supply–demand subtraction is suggested to represent the “budget” of cooling service per census tract. Finally, we explored the relationship between the mismatches and socio-economic indicators (median after-tax income of households in 2021 (\$), proportion of visible

minority to the total population in each census tract, proportion of people with highest certificate, diploma or degree and no certificate, diploma or degree to the total population in each census tract), using linear regressions, and thematic maps and Hot Spot Analysis (Getis-Ord Gi*) in ArcGIS Pro 3.2. We defined mismatch values which are above 0 as high mismatches, median income below \$34,555 as low income (Government of Canada, 2016), percent of people with postsecondary certificate above 55% (median value) as high number of higher education certificates, percent of visible minorities above 30% (median value) as high number of minorities, percent of people with no certificate above 15% (median value) as high number of non- certificates, and the rest values represent above-low income, low number of higher education certificates, low number of minorities, low number of non- certificates, respectively.

3.4 Results

3.4.1 Effects of the composition and configuration of UGI on LST

Both composition variables (percent cover of high and low vegetation) are significantly correlated with LST at both borough and census tract scale for the years 2020, indicating that the increase of either high or low vegetation will help to mitigate urban heat (Model A, Table 6). Temperature showed a decreasing trend from approximately 40°C in boroughs with 10% high vegetation to 30°C in those with 57% high vegetation in the year 2020. After adjusting for the effect of composition metrics, we can see the relative importance of each configuration variable on LST in the models (Models B and C, Table 6). Both the regression coefficients and the standardized coefficients show that high vegetation plays a more important role in cooling the land surface compared to low vegetation (Table 6). At the census tract scale, the effect of percent cover

of high vegetation on LST (-0.76) is weaker than at the borough scale (-0.83) if the model only includes the composition metrics, and it is the opposite for low vegetation (Model A, Table 6). However, when adding the configuration metrics of high vegetation to the model, the relative importance of composition metrics for both high and low vegetation becomes larger from borough scale to census tract scale (Models B and C). The negative relationship between largest patch index of high vegetation and LST remains significant across the borough to census tract scales. The negative relationship between effective mesh size, mean patch shape index of high vegetation and LST became significant at census tract scale, and the beta coefficients are much smaller than largest patch index. In addition, all configuration metrics (except for EMS of low vegetation at census tract scale) of low vegetation are not significantly correlated with LST (Model B and C, Table 6). This result indicates that the largest patch index of high vegetation has a relatively important impact on LST across multiple spatial scales. We also used the LST data from the year 2021 to test and the results are similar with those of the year 2020 (Table 7).

Table 6. Summary results for the three multi-linear regression models for the year 2020 at borough and census tract scales. For each of the three models, the response variable, LST, was predicted by composition variables, i.e., percent cover of high and low vegetation (model A), or a combination of those composition variables with the configuration variables of one type of land cover feature (Models B and C).

2020 Borough	Explanatory coefficient	variables/regression R-square (adjusted)	coefficient;	standardized	R2	
Model A	P_{HV}		P_{LV}		0.92	
	-17.4*** (-0.83)		-9.11*** (-0.27)		(0.91)	
Model B	P_{HV}	P_{LV}	EMS_{HV}	LPI_{HV}	$MPSI_{HV}$	0.95
	-11.97*** (-0.57)	-9.61*** (-0.28)	0.0007 (0.01)	-4.57* (-0.28)	-14 (-0.13)	(0.94)
Model C	P_{HV}	P_{LV}	EMS_{LV}	LPI_{LV}	$MPSI_{LV}$	0.94
	-16.68*** (-0.79)	-13.54** (-0.40)	-0.006 (-0.03)	0.24 (0.007)	13.57 (0.19)	(0.93)
2020 Census tract						R2
Model A	P_{HV}		P_{LV}		0.81	
	-15.27*** (-0.76)		-7.99*** (-0.33)		(0.81)	
Model B	P_{HV}	P_{LV}	EMS_{HV}	LPI_{HV}	$MPSI_{HV}$	0.83
	-12.43*** (-0.62)	-7.74*** (-0.32)	-0.008** (-0.07)	-1.87*** (-0.13)	-5.03*** (-0.09)	(0.83)
Model C	P_{HV}	P_{LV}	EMS_{LV}	LPI_{LV}	$MPSI_{LV}$	0.82
	-15.05*** (-0.75)	-7.87** (-0.32)	-0.03*** (-0.08)	-0.28 (-0.01)	1.95 (0.04)	(0.82)

P_{HV} : Percent cover of high vegetation, P_{LV} : Percent cover of low vegetation, EMS_{HV} : Effective mesh size of high vegetation, EMS_{LV} : Effective mesh size of low vegetation, LPI_{HV} : Largest patch index of high vegetation, LPI_{LV} : Largest patch index of low vegetation, $MPSI_{HV}$: Mean patch shape index of high vegetation, $MPSI_{LV}$: Mean patch shape index of low vegetation

Table 7. Summary results for the three multi-linear regression models for the year 2021 at borough and census tract scales. For each of the three models, the response variable, LST, was predicted by composition variables, i.e., percent cover of high and low vegetation (model A), or a combination of those composition variables with the configuration variables of one type of land cover feature (Model B and C).

2021 Borough	Explanatory coefficient	variables/regression R-square (adjusted)	coefficient;	standardized	R2	
ModelA	P_{HV}		P_{LV}		0.89	
	-17.5*** (-0.87)		-4.95* (-0.15)		(0.88)	
ModelB	P_{HV}	P_{LV}	EMS_{HV}	LPI_{HV}	$MPSI_{HV}$	0.93
	-12.54*** (-0.63)	-5.27* (-0.16)	0.003 (0.06)	-5.39* (-0.35)	-5.29 (-0.05)	(0.91)
ModelC	P_{HV}	P_{LV}	EMS_{LV}	LPI_{LV}	$MPSI_{LV}$	0.93
	-16.52*** (-0.82)	-9.78* (-0.3)	0.007 (0.03)	-1.84 (-0.06)	13.57 (0.19)	(0.91)
2021 Census tract	Explanatory coefficient	variables/regression R-square (adjusted)	coefficient;	standardized	R2	
ModelA	P_{HV}		P_{LV}		0.69	
	-14.05*** (-0.77)		-3.78*** (-0.17)		(0.68)	
ModelB	P_{HV}	P_{LV}	EMS_{HV}	LPI_{HV}	$MPSI_{HV}$	0.7
	-11.9*** (-0.65)	-3.48*** (-0.16)	-0.008** (-0.07)	-1.61*** (-0.12)	-2.12 (-0.04)	(0.7)
ModelD	P_{HV}	P_{LV}	EMS_{LV}	LPI_{LV}	$MPSI_{LV}$	0.7
	-13.88*** (-0.76)	-2.19* (-0.1)	-0.033*** (-0.12)	-1.17* (-0.06)	-0.34 (-0.008)	(0.7)

3.4.2 The supply of cooling services provided by UGI

Based on the Pearson correlation matrix, we identified high correlations between P_{LV} and $MPSI_{LV}$, as well as between EMS_{HV} and LPI_{HV} . Given that the standardized coefficients of P_{LV}

and LPI_{HV} are higher in Table 6, we removed $MPSI_{LV}$ and EMS_{HV} from the prediction model (1). After incorporating the remaining variables into the model, $MPSI_{HV}$ and LPI_{LV} were found to be non-significant, and the estimate coefficient of EMS_{LV} , was quite small. To reduce the number of the variables and improve the quality of the model, these variables were also removed. After verifying the collinearity within the model, we obtained the final prediction model to estimate the cooling value provided by specific composition and configuration of UGI, as follow:

$$\Delta LST = 14.12 * P_{HV} + 7.61 * P_{LV} + 1.95 * LPI_{HV} \quad (4)$$

We used the ΔLST data from the year 2021 as the observed data and the result of the model as estimated data to validate the model. We derived the diagnostics for the model, and it satisfied the assumptions of multiple linear regression in a series of plots (Normal Q-Q, Residuals vs Fitted, Residuals vs Leverage, etc.). The derived R^2 is 0.8, Root Mean Squared Error (RMSE) is 0.84, indicating a good performance of the model. Equation 4 shows P_{HV} , P_{LV} and LPI_{HV} are both positively related with the cooling intensity provided by UGI in each census tract, and the impact of P_{HV} is larger than P_{LV} and LPI_{HV} . We used the result of model 4 to determine the supply index of the cooling service provided by UGI from equation 2. This model indicated that during the day, an increase of 10% in the percent cover of high vegetation, percent cover of low vegetation, and largest patch index of high vegetation would lead to a decrease in average land surface temperature of 1.41 °C, 0.76 °C, 0.20 °C, respectively at census tract scale (10-100 hectares).

The highest supply index values are located in the west, southeast, and the Mont-Royal region of Montreal (Figure 3A), which are highly vegetated according to the metropolitan canopy index map.

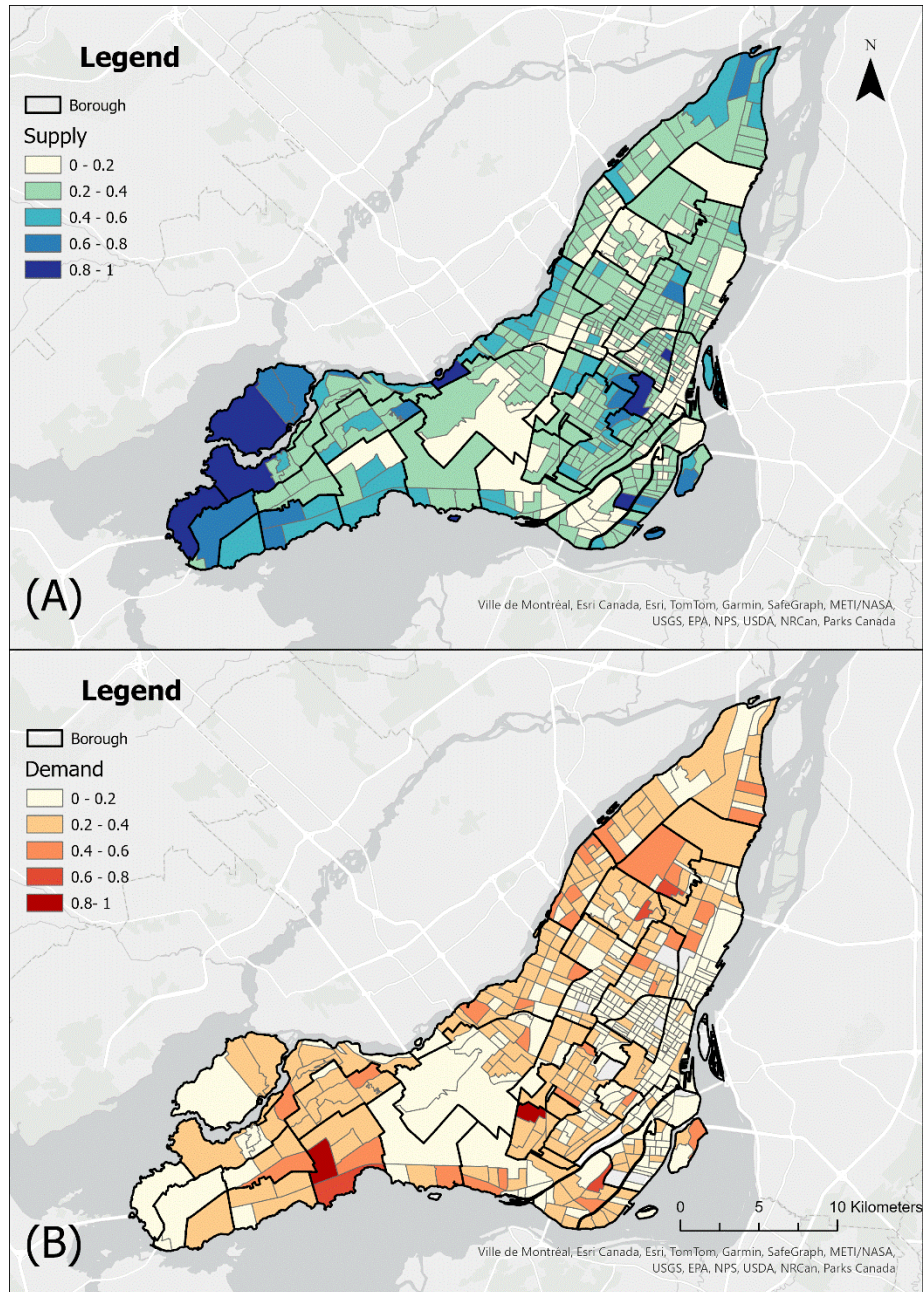


Figure 3. Supply index of the cooling service provided by UGI (A) and demand index in each census tract of Montreal (B). Values close to zero refer to low supply or demand, values close to 1 refer to high supply or demand.

We calculated the error between observed ΔLST and predicted ΔLST in each census tract of the year 2020 and 2021 (Figure 4). Positive value means our model has underestimated the cooling in that census tract, and vice versa. We found the places where we underestimated the most are the northeast and southeast of Montreal, to the maximum of $\sim 3.7^{\circ}\text{C}$, which might be due to the cooling impact of the river. On the other hand, we overestimated the cooling in some boroughs that are not close to the river and include large impervious surface area, such as Anjou, Saint-Léonard, and Le Plateau-Mont-Royal, to the maximum of $\sim 2.4^{\circ}\text{C}$. The reason is probably the influence of the surrounding impervious surfaces. This phenomenon indicates our model can separate the cooling effect provided by only green spaces from other land cover features.

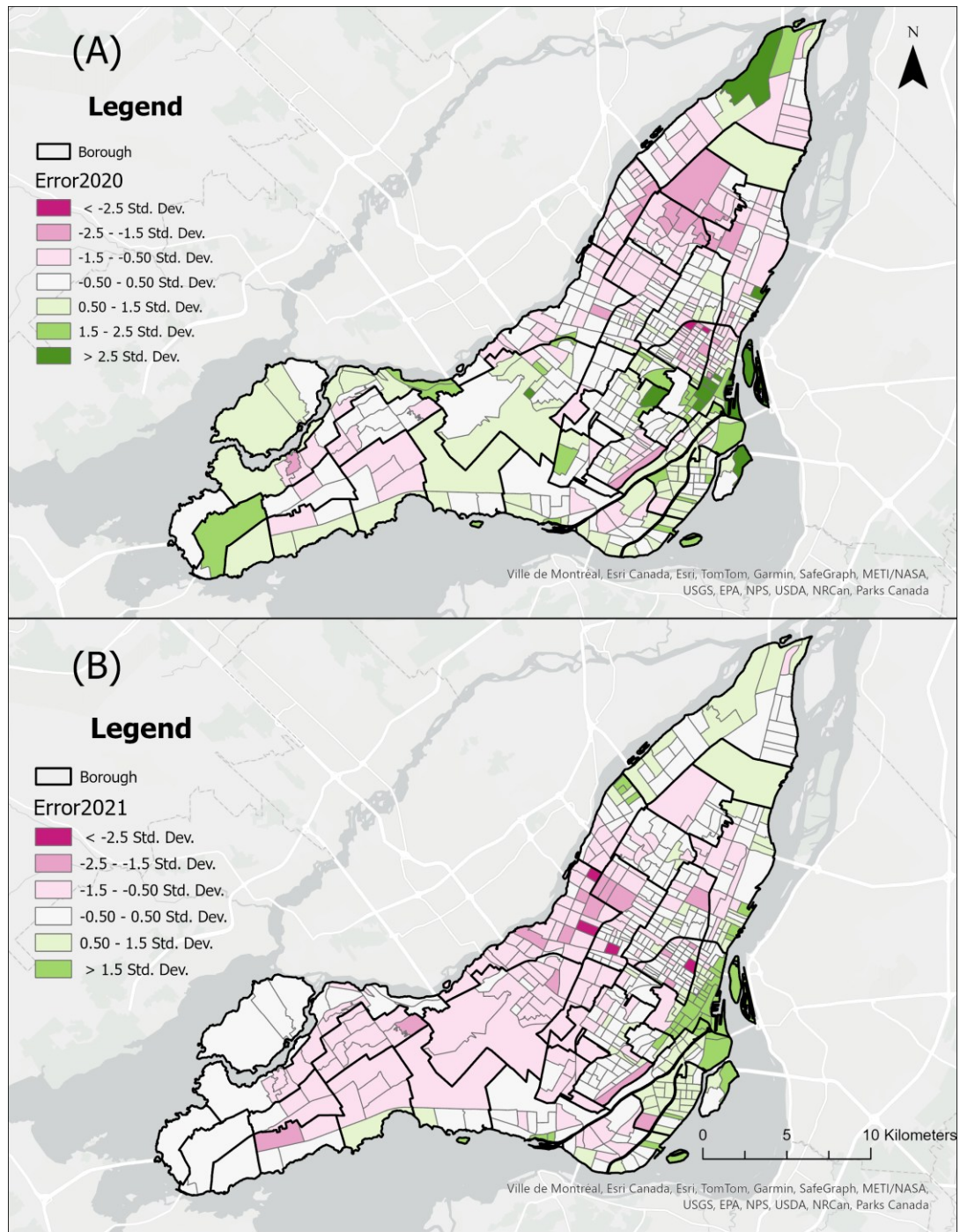


Figure 4. The standard deviation of the error between observed Δ LST and predicted Δ LST in each census tract of the year 2020 (A) and 2021(B) (calculated as observed minus predicted LST). The standard errors range from <-2.5 standard deviations (dark pink) to >2.5 standard deviations (dark green).

3.4.3 The demand for cooling services by vulnerable groups

Figure 3B. shows the demand index of the cooling service in each census tract of Montreal. Higher values correspond to a higher number of vulnerable individuals living in that census tract. We can see that the south and northeast parts of Montreal have higher demands for cooling services, especially Pointe-Claire, Côte-Saint-Luc, and Anjou.

3.4.4 The supply-demand mismatches of cooling services in Montreal

The supply-demand mismatches show wide spatial variation in Montreal across different census tracts (Figure 5). The distribution of positive and negative mismatches roughly aligns with the map of supply index of cooling service. The largest positive values are in the areas with high supply and low demand, such as Le Plateau-Mont-Royal, Outremont, L'Île-Bizard-Sainte-Geneviève, Senneville. The largest negative values fall in the boroughs with low supply and high demand, such as Anjou, Saint-Léonard, Côte-Saint-Luc, etc. However, some regions like Pointe-Claire, Montréal-Nord, with a high supply index, have a pronounced negative mismatch value. That is because the high proportion of vulnerable residents (i.e., elderly, children) living in those areas makes the demand index very large, which affects the overall mismatch values. Hot spots in Figure 4 show the areas that received less supply of cooling service provided by UGI than they demand, and cold spots are those places whose demand for cooling service is lower than the supply.

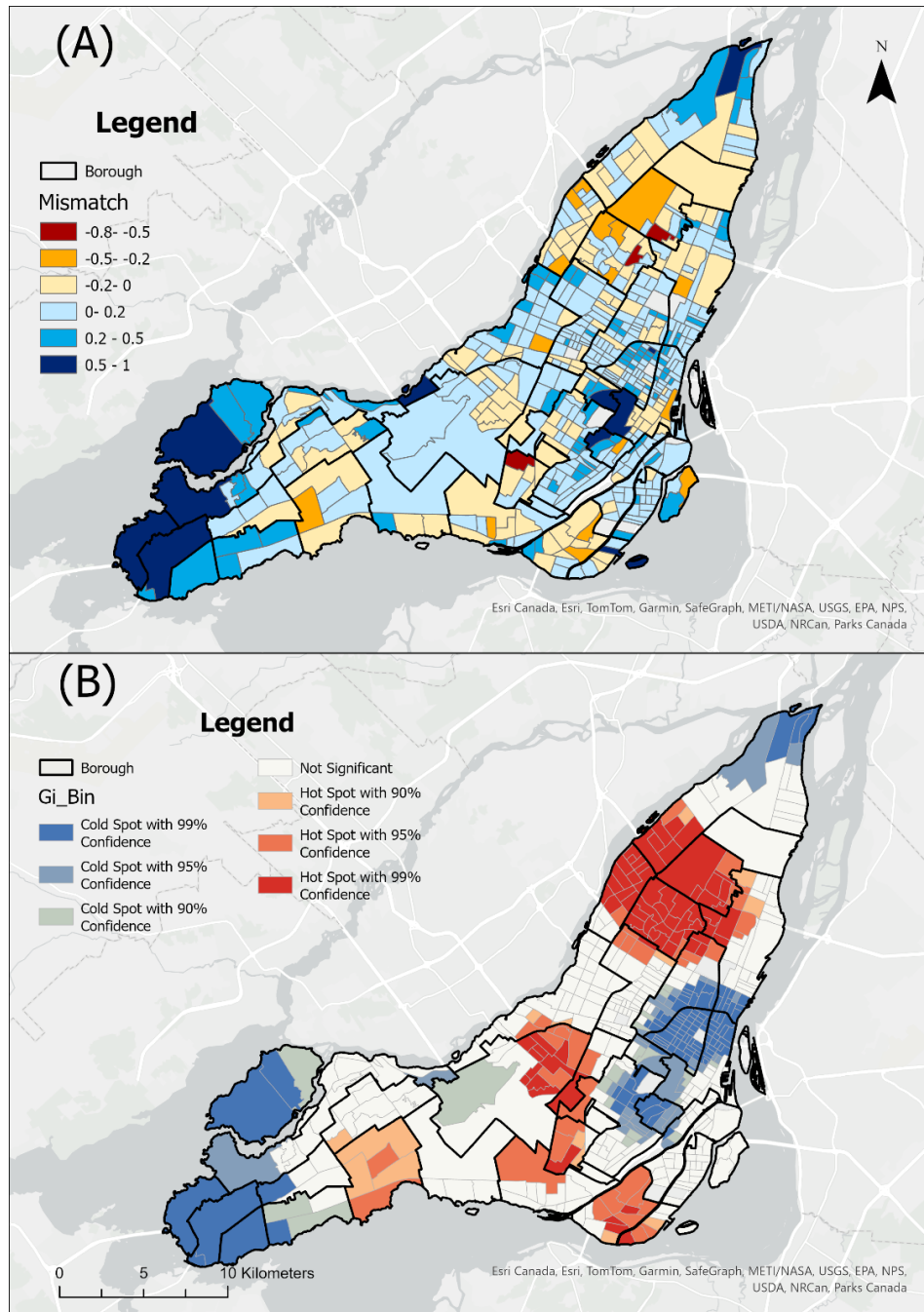


Figure 5. The supply-demand mismatches of cooling services in each census tract of Montreal. Positive value means the census tract that vulnerable residents receive more cooling service supply than demand, and vice versa (A). The hot and cold spots of the mismatches at different confidence level (implying a 90%, 95%, 99% probability that the clustering of high values or low values exist there). Hot spots are areas with high negative mismatches values, meaning that demand exceeds supply, and cold spots indicate areas with supply exceeds demand (B).

3.4.5 Environmental injustice

Supply-demand mismatches are correlated with socioeconomic drivers. Median after-tax household income and proportion of people with post-secondary certificates are positively related with supply-demand mismatches, the proportion of visible minority and the proportion of people with no certificate are negatively related with the supply-demand mismatches (Figure 6). Census tracts with higher median income and larger proportion of highly educated people were mostly associated with positive supply-demand values, indicating that their supply of cooling services as provided by UGI was higher than their demand. In contrast, census tracts with higher proportion of visible minorities and people with a low-level of education tend to have a higher demand for cooling services provided by UGI than what is supplied. The vulnerable population (young and elderly individuals) with a higher socio-economic status received more cooling services provided by the UGI, in contrast to those on the other end of the socio-economic spectrum. We also produced bivariate maps (Figure 7) to show the pairwise combination of cooling service supply-demand mismatches and socioeconomic factors. Some boroughs like Saint-Léonard and LaSalle, have especially severe issues, as they have large negative supply-demand mismatches and are at low socioeconomic status at the same time (as shown in Figure 5.).

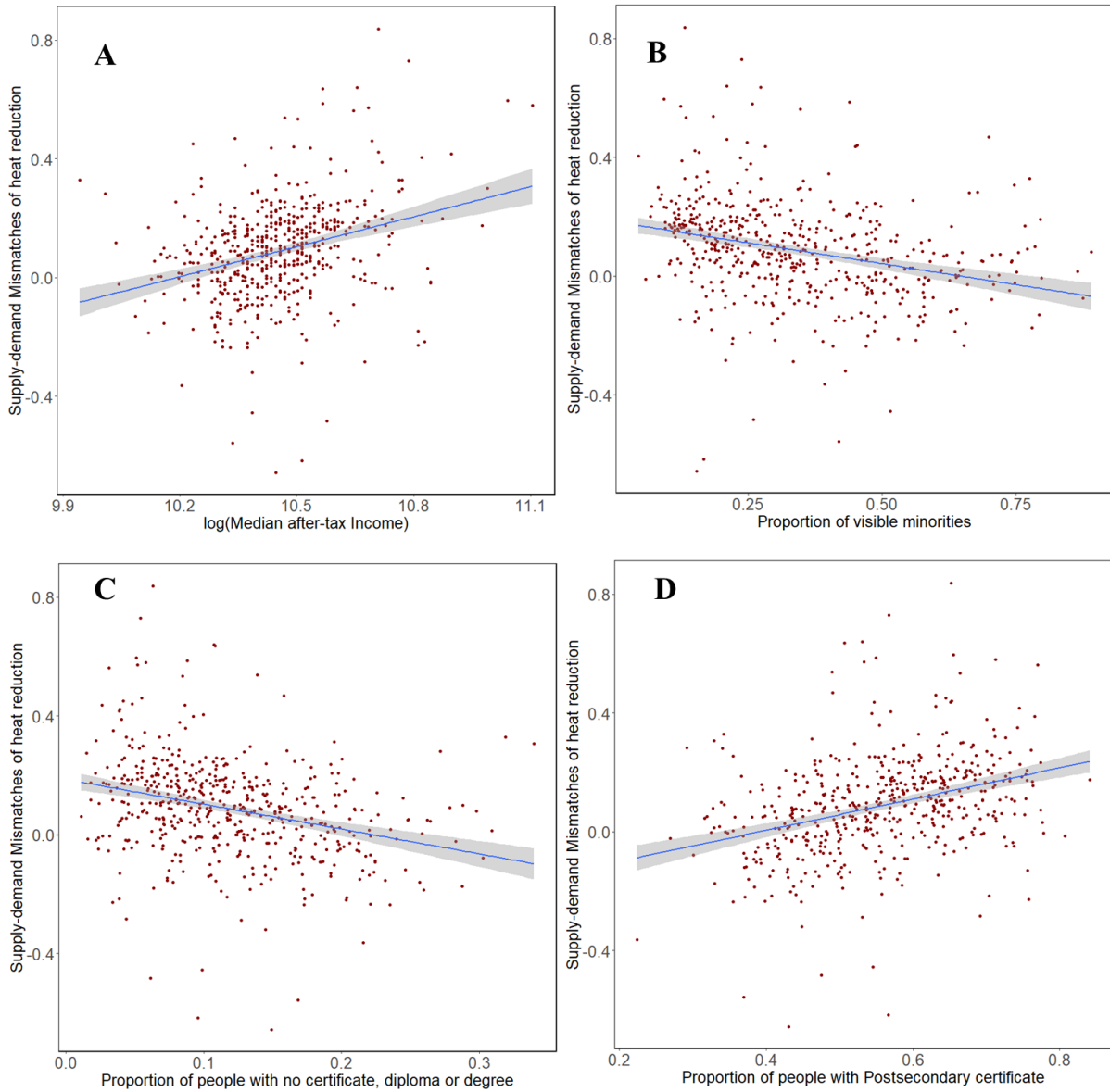
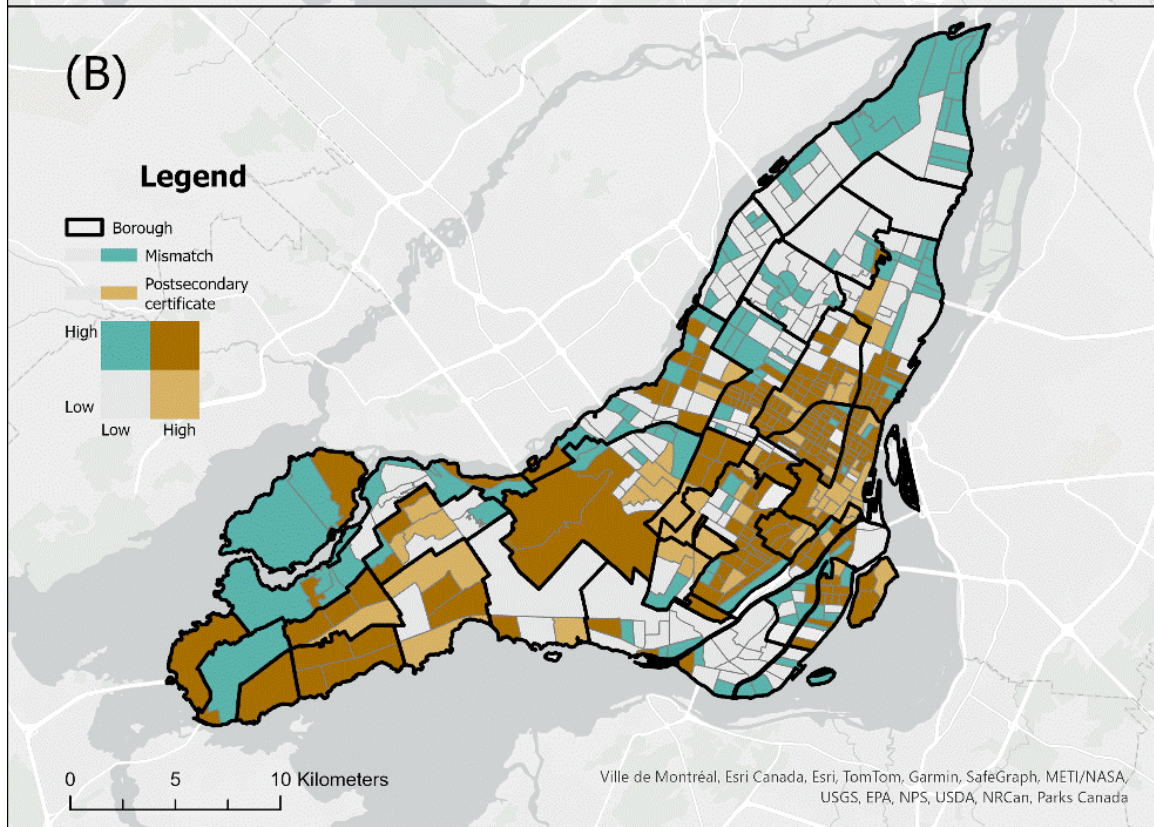
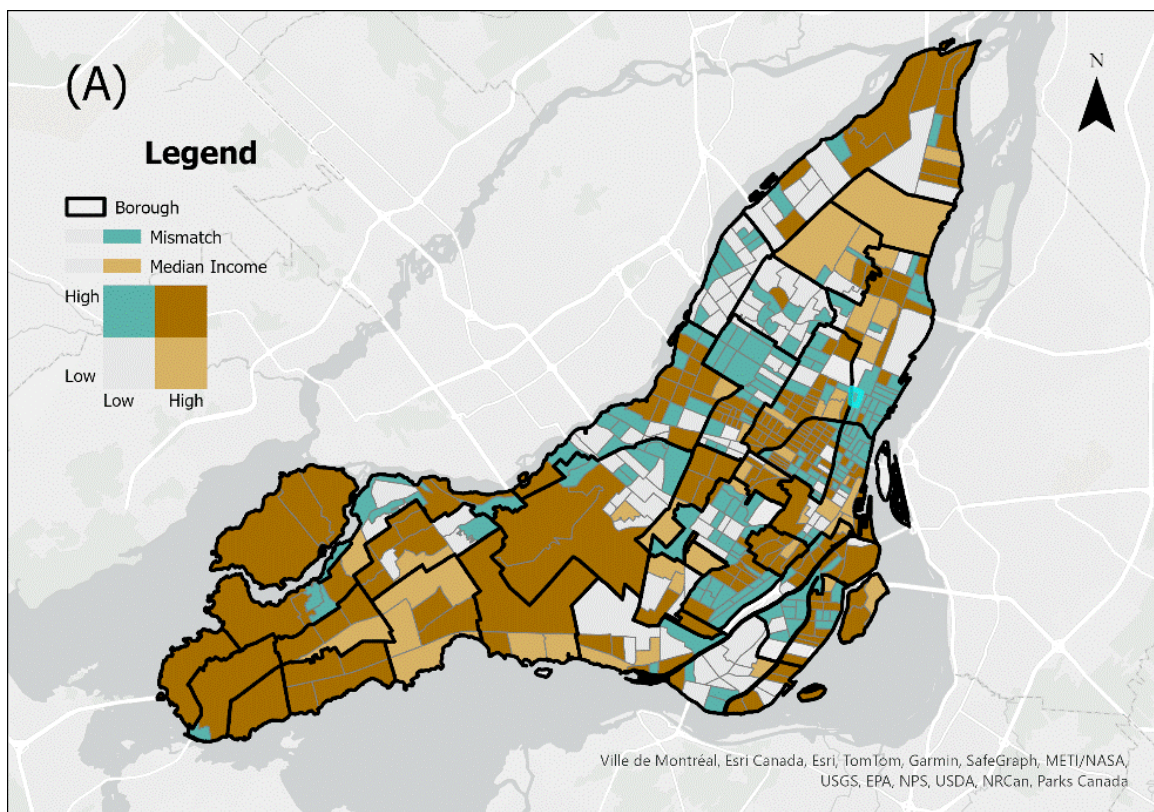


Figure 6. Figure of supply-demand mismatches and socioeconomic indicators. Relationship between supply-demand mismatches and the (A) log after-tax median household income ($y = -3.43 + 0.34x$, $R^2 = 0.1$, $p < 0.05$), the (B) proportion of visible minorities ($y = 0.18 - 0.28x$, $R^2 = 0.09$, $p < 0.05$), the (C) proportion of people with no certificate, diploma or degree ($y = 0.19 - 0.84x$, $R^2 = 0.09$, $p < 0.05$) and the (D) proportion of people with postsecondary certificate ($y = -0.21 + 0.53x$, $R^2 = 0.12$, $p < 0.05$)



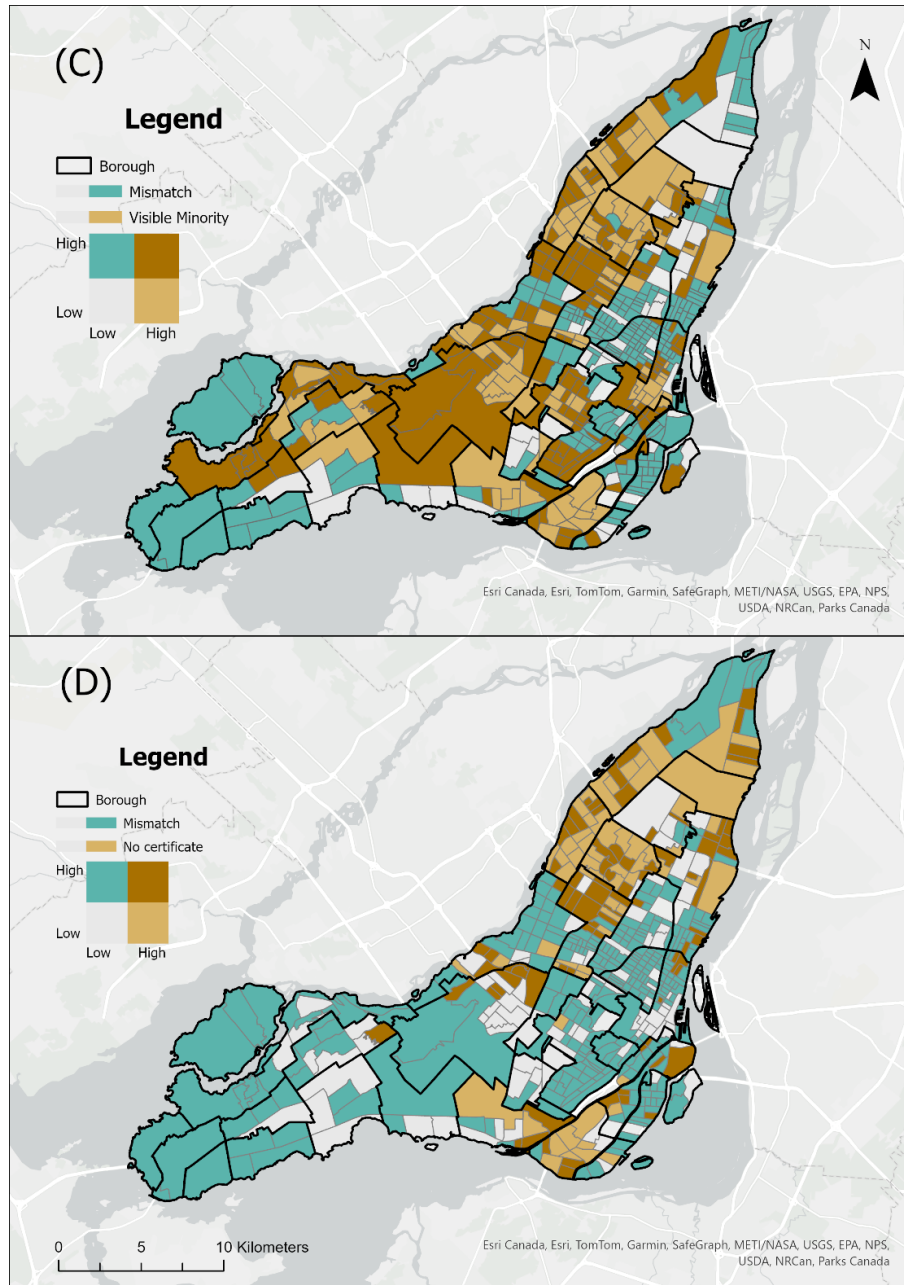


Figure 7. Bivariate maps of supply-demand mismatches and socioeconomic indicators. Bivariate maps of supply-demand mismatches and average household income (A), proportion of people with postsecondary certificate (B), proportion of visible minorities (C), proportion of people with no certificate, diploma or degree (D). Dark brown –Light grey–Light brown–Blue colors represent the high-high, low-low, high-low, low-high pairs of the indicators respectively.

3.5 Discussion

3.5.1 Research implications

Our results indicate that both the composition and configuration of UGI have a significant impact on LST. However, high vegetation has a larger effect than low vegetation, and composition is a more important factor than configuration for both high vegetation and low vegetation at both scales. These results are consistent with the conclusions of previous studies (Alonzo et al., 2025; Hu et al., 2021; X. Li & Zhou, 2019; Liu et al., 2021; Zhou et al., 2011, 2017). We attempted to improve on common configuration metrics that could more accurately describe the configuration of the land cover features. For instance, mean patch size used in previous studies can be strongly influenced by small but numerous patches, which is very common in cities. We used the effective mesh size to describe the average patch area while considering the relative areas of all patches in the area. The largest patch index used by some previous studies is defined by the area of the largest green space patch divided by the total area of a grid cell (Hu et al., 2021; X. Li & Zhou, 2019; Zhou et al., 2011, 2017). The largest patch index is thus often highly correlated with percent cover of UGI. In our study, we used the proportion of the largest patch relative to the total green space area and not the whole census tract area, so the index reflected the level of aggregation of green space.

The impact of UGI on LST varies across different spatial scales. We show that the percent cover of both high and low vegetation is negatively correlated with LST, indicating that increasing the composition of all kinds of UGI can significantly decrease LST, helping to mitigate urban heat. The effect of P_{HV} and P_{LV} on LST seems to be weaker at smaller than larger scales (Table 6). The effects of UGI configuration on LST were variable, depending on metric and scale. Largest patch index of high vegetation has a significant negative relationship with LST in all models. This

implies higher aggregation level of high vegetation provides a larger reduction of average LST during the daytime. This may be due to increased evapotranspiration rate of clustered trees compared to isolated trees or small clusters in the climate context of Montreal (W. Zhou et al., 2017). Effective mesh size (EMS) of UGI shows significant correlation with LST at census tract scale but not at borough scale. This may suggest that the impact of evapotranspiration from UGI on land surface temperature is more pronounced at smaller spatial scales. Higher EMS of low vegetation indicates that well-connected patches of low vegetation can still create cooler microenvironments by enhancing ground-level evapotranspiration and airflow. In addition, the relative importance of EMS and mean patch shape index (MPSI) are much smaller than that of LPI of UGI on LST. The reason could be that the aggregation level of high vegetation has a greater influence on evapotranspiration compared to factors like shape and average size under the climate of Montreal. Higher MSPI of high vegetation had a significant negative relationship with LST at census tract scale, indicating that tree patches with more irregular or complex shapes may enhance edge effects, increasing the interface between vegetated and non-vegetated areas (Table 6) (J. Yan et al., 2019; W. Zhou et al., 2017).

Our study proposed a simple model (compared to complicated models, such as ENVI-met, i-Tree, CFD, etc.) to predict the cooling effect of UGI based on three predictor variables that represent composition (percent cover) and configuration (largest patch index). The three variables in the model are not correlated with each other. We used the prediction model to estimate the cooling capacity of the vegetation, instead of only the changes of the absolute LST values. The model is with an intercept of 0 and the variables have the same unit, which has a practical meaning that if there's no vegetation in the area, there is no cooling capacity provided by the vegetation. The metrics are all percentage-based and are not easily influenced by the inevitable bias in land

cover data sources compared to the metrics based on edge or connectivity. While we see some large errors between the predicted ΔLST and the real ΔLST , these are expected in our model as our model only focused on the vegetation's cooling capacity, not considering the other factors that influence absolute temperature. For example, water sources such as the river provide extra cooling, which makes our model underestimate the ΔLST ; mineralized areas add extra heat, thus makes our model overestimate the ΔLST . That phenomenon aligns well with our expectation for our model - which was not meant to provide a comprehensive explanation of urban temperature.

The model concept suggests that by incorporating both the composition and configuration metrics of UGI into a simple multiple linear regression model, we can effectively predict vegetation cooling capacity in urban areas. City planners should consider the percent cover of both high and low vegetation, and the aggregation level of high vegetation specifically when they are making decisions on UGI management to tackle the crises of climate change. If applied in other locations, this approach could be valuable for making multi-city comparisons. Future research should extend assessment of the relative impact of composition and configuration under various climates or other local contexts, including differences in urban morphology (Alonzo et al., 2025). The integration of additional variables such as vegetation health would also be valuable to consider in future research, particularly as urban trees themselves are susceptible to the impacts of increased heat (Haase & Hellwig, 2022), which may in turn reduce their cooling potential.

It should also be noted that air temperature – or indices that integrate air temperature and humidity, such as wet-bulb temperature – are more directly related with human perception of heat than LST (Stull, 2011). Compared to air temperature, LST doesn't fully capture the effects of the surrounding environment, like atmospheric mixing, or microclimatic factors (e.g., humidity, wind speed). Thus, our supply index only captured relative cooling capacity of the vegetation in terms

of surface cooling and may not be fully representative of thermal comfort compared to, for example, physiological comfort indices. However, studies do show that air temperature and LST are strongly correlated (Berg & Kucharik, 2021; Naserikia et al., 2024; White-Newsome et al., 2013), particularly when assessing broad spatial extents where air temperature data is unavailable (Giannaros et al., 2014; Imran et al., 2022).

Unlike previous studies that use climate variables to derive the demand index for cooling service (Baró et al., 2015; Herreros-Cantis & McPhearson, 2021), we considered the demand for cooling services based on the increased susceptibility to heat of vulnerable age groups. By calculating largest patch index relative to the total green space, rather than total area, we also ensured that our metrics were appropriate for multi-scalar analyses. Our results indicate that there is indeed distributional inequity in cooling services in Montreal. The supply-demand mismatches map shows two main cold spots (where supply exceeds demand) in a dense downtown area and the lower-density, more highly vegetated west island, and two main hot spots (where demand exceeds supply) in industrial areas. The reasons for mismatches are different, positive mismatches can arise because of the high quantity and quality of UGI (i.e., mismatches driven primarily by supply), while others arise due to reduced demand for the cooling service (i.e., mismatches driven primarily by demand), and it's the same for the negative mismatches. According to our results, census tracts with higher median household income, fewer visible minorities and more people with postsecondary certificates are usually the places where supply of cooling services provided by UGI is higher than the demand by physically vulnerable populations, and vice versa. This result indicates an environmental inequity in Montreal, not only from the aspect of the distribution of green space (Pham et al., 2012), but also in terms of balancing supply and demand with respect to populations – such as older adults – who will be more greatly affected by increasing urban heat.

This phenomenon is not specific only to Montreal; for example, Aznarez et al. (2024) also observed higher temperature regulation supply and lower heat vulnerability in economically advantaged communities in their analysis in Basque Country.

3.5.2 Management implications

There is a growing global interest to develop green cities as a response to climate change. Canada, similar to other countries, has proposed ambitious tree planting (i.e., the 2 Billion Trees Program) over a period of 10 years by 2031, including new tree planting projects in cities to tackle the dual crises of climate change and biodiversity loss (<https://www.canada.ca/en/campaign/2-billion-trees/2-billion-trees-program.html>). The city of Montreal has committed to planting 500,000 new trees in heatwave-vulnerable areas by 2030 and is working toward a tree canopy target of 26% by 2025 (Climate Plan 2020-2030). However, a crucial question remains: where should these trees be planted? It is essential for people to understand which areas require trees the most and where they can yield the most ecosystem benefits. Our study offers further insights into these inquiries, considering factors such as configuration effects and supply-demand imbalances in urban design and planning. Based on the results, urban planners who want to reduce daytime heat should consolidate tree patches into large, continuous areas where possible, especially at larger spatial scales. It is also helpful to design smaller-scale interventions with more irregularly shaped tree patches and create enhanced connectivity, especially for low vegetation, to support micro-scale cooling. In addition to focusing on supply, we also suggest further actions need to be taken to mitigate environmental injustice in Montreal, particularly considering the demand for ecosystem services by vulnerable groups (e.g., young children and older adults), to help achieve sustainability goals.

Based on our findings, we suggest the development of a ranked action plan for Montreal's greening efforts, prioritizing areas based on cooling supply-demand mismatches and socio-demographic characteristics (Table 8). Boroughs such as Saint-Léonard and Montréal-Nord, which have high cooling demands by physically vulnerable residents, low amounts of green space, and lower socio-economic status, should be at the top of this priority list. For these priority areas (and all others), we suggest focusing on the creation of larger, connected green patches with high vegetation cover, as these provide the greatest cooling benefits. Smaller patches should be linked through parks, and linear parks, creating a cohesive network of cooling spaces.

Table 8. Top 7 boroughs with lowest average supply index and supply-demand mismatch index respectively

Ranking of boroughs according to the average supply and mismatch index	
Supply	Mismatch
Montréal-Est (0.17)	Pointe-Claire (-0.1)
Saint-Léonard (0.19)	Côte-Saint-Luc (-0.09)
Ville-Marie (0.20)	Anjou (-0.07)
Saint-Laurent (0.23)	Saint-Léonard (-0.06)
Villeray-Saint-Michel-Parc-Extension (0.23)	Montréal-Nord (-0.05)
Anjou (0.25)	Montréal-Est (-0.04)
Montréal-Nord (0.25)	Hampstead (-0.02)

Additionally, incentives should be offered to encourage the integration of low vegetation where tree planting may be constrained by space or soil conditions. This could include installing green roofs, grass strips, and ground cover vegetation in public and private spaces such as parking lots, walkways, and building perimeters.

3.6 Conclusions

This study examined how the composition and configuration of urban green infrastructure affects land surface temperatures. The composition variables (percent cover of high and low vegetation) are both significantly correlated with LST at both borough and census tract scale. Configuration variables have a stronger influence on LST at the smaller census tract spatial scale. Our study proposed a statistical model that used the percent cover of both high and low vegetation and largest patch index of only high vegetation as three main factors to predict the cooling ability of the UGI during summer daytime. Together with the demand index based on the proportion of physically vulnerable residents, we created a map of supply-demand mismatches to show their spatial variations, highlighting that communities dominated by lower income, less educated people and visible minorities receive less cooling service provided by the UGI than they demand compared with higher socioeconomic status communities in Montreal.

On a broader scale, the study's insights can inform climate resilience strategies, supporting the goal of adapting cities to the impacts of climate change. Cities with humid continental climates or similar urban heat profiles can apply these findings to shape their long-term urban greening and climate adaptation plans. This research also sets the groundwork for future studies that could address limitations of our approach and expand the model to different climates and scales. For example, it would be beneficial to consider additional LST products (beyond the August products used in this study) to understand the temporal dimensions of green infrastructure interventions, as well as finer-scale LST data to reduce scale mismatches between datasets that may have contributed to uncertainty here. Second, it should be noted that LST does not fully represent human thermal experience due to its limitation in capturing microclimate factors or physiological comfort indices. Third, though the metropolitan canopy index dataset has a fine spatial resolution, field

validation may improve future studies. The model also needs to be further tested for generality in cities with differing urban layout or climates. Last but not least, nighttime satellite images, such as Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data, could also be used to explore the effect of spatial pattern of UGI on LST during the night in the future. Similar approaches could also be applied in other cities with different climates, facilitating multi-city comparisons and enhancing our understanding of urban heat dynamics and UGI cooling service equity.

Connecting Statement 1.

Chapter 3 showed the various impact of composition and configuration of UGI on LST at borough and census tract scale in Montreal. Three key factors to predict the cooling capacity of UGI are percent cover of high vegetation, percent cover of low vegetation and largest patch index of high vegetation. The unequal distribution of UGI and vulnerable population leads to the unbalanced supply-demand for cooling service in Montreal. This chapter focused on the examination of LST at a relatively large spatial scale. However, advancing the effective management of UGI necessitates a more detailed examination of temporal variations in air temperature at the local scale, as these variations are more closely aligned with human thermal comfort perception.

Thus, in chapter 4, I narrow the study extent to the urban park scale, exploring the impact of presence and configuration of trees on air temperature, relative humidity and wet-bulb temperature during daytime and nighttime. Using mixed effect models and ordered contrasts, I quantified and compared the differences of air temperature, relative humidity and wet-bulb temperature among open grass area, discrete tree cluster and aggregate tree cluster in a series of urban parks in Montreal. The results are used to provide valuable guidance for city planners in urban park design.

Chapter 4: Tree Presence and Level of Aggregation in Urban Parks are Associated with Opposite Daytime and Nighttime Urban Cooling

4.1 Abstract

Urban parks, serving as “cool islands” for human activity in cities, play an important role among various urban green space types for regulating temperature. Effective management of green infrastructure within parks is essential for urban park design and planning. While effects of vegetation configuration on daytime air temperature are increasingly well studied, the specific effects of tree configuration on nighttime temperatures are less well understood, despite their importance for human health. Indices more relevant to human health (such as wet bulb temperature) also remain underexplored in the urban forestry literature. Our research aims to address the following question: Do different tree planting configurations (discrete planting versus aggregate planting) within parks affect daytime and nighttime air temperature, relative humidity, and wet-bulb temperature differently? We sampled air temperature and humidity in open grass areas, discrete tree clusters, and aggregate tree clusters in a series of urban parks in Montreal, Canada. Using mixed-effect models and ordered contrasts, we analyzed the impacts of tree configuration and time of day on park microclimate (air temperature and wet-bulb temperature). Our results indicated that aggregate tree clusters had stronger cooling effects than discrete tree clusters during daytime but inhibit heat dissipation at night. Our results also emphasize the importance of open grass areas for park cooling during nighttime. Relative humidity exhibited an inverse pattern compared to air temperature, moderating wet-bulb temperature differences among tree configurations, highlighting the importance of considering both temperature and humidity in urban

greening studies. A park that meets visitors' needs for temperature mitigation at different times of day should be structurally diverse, with a balance of dispersed, mature trees and open grasslands to optimize both daytime and nighttime thermal comfort. This study focuses on Montreal (a large city with a warm-summer humid continental climate) with potential to generalize our results to studies within similar climatic zones, as well as to generalize our study approach to cities more broadly.

4.2 Introduction

Climate change, leading to rising average air temperatures, more hot days and nights, and a higher frequency of heatwaves, has increased heat stress globally (Arnell et al., 2019; Chapman et al., 2019). Urban areas, which cover just three percent of the Earth's land surface but support over half of the global population, are especially vulnerable to increasing temperatures (United Nations. Department of Economic and Social Affairs. Population Division., 2019). The health impacts of extreme heat are particularly severe in cities, where heatwave events have been shown to increase mortality rates. For instance, the record-breaking heatwave in Europe during the summer of 2003 caused approximately 70,000 deaths due to heat-induced illnesses (Robine et al., 2007). The Pacific Northwest heat wave of 2021 led to 619 heat-related deaths in British Columbia in Canada, many occurring in the metro Vancouver area ([Government of Canada](#)) (Henderson et al., 2022). The mortality caused by extreme heat is likely to consistently increase in the future (J. Liu et al., 2023). In addition to affecting physical health, rising temperatures also have a negative

impact on mental health, with the impact being especially severe for already disadvantaged groups (Lawrance et al., 2022).

Rapid urbanization greatly alters the physical land surface properties in urban areas which correspondingly affects the surface-atmosphere coupling including the exchange of energy, water and momentum (Singh et al., 2020). Two significant changes are an increase in impervious areas by construction of roads and buildings and consequently a decrease in green spaces. Due to low albedo and high solar absorption, impervious surfaces absorb solar radiation, store heat in its thermal mass and reradiate it (K. Wang et al., 2017). The materials used in construction have elevated thermal inertia and heat storage that is released at night causing a decrease in the difference between day and night temperature and thus a consequent decrease in diurnal temperature range (Hardin & Vanos, 2018). The elevated temperature in urban areas relative to their rural surroundings is known as the urban heat island (UHI) effect. Compared with natural areas, urban areas with well-established human settlements and economic structures are more vulnerable to climate extremes (Ye & Niyogi, 2022). Thus, there is a need to protect urban populations from hazards of climate change.

There are multiple strategies to moderate the increased temperature in urban areas, including changes to vegetation, water surfaces, and urban geometry (Alonzo et al., 2025; Gago et al., 2013; Rizwan et al., 2008; J. Zhang et al., 2024). Urban greening is a nature-based solution to help mitigate urban heat. However, with the development of urban areas, green spaces are often reduced in size or experience increasing fragmentation. These changes can also result in a decline of the cooling potential of green spaces (Andersson et al., 2015; McPhearson et al., 2015). As urban populations grow, the demand for services offered by urban green infrastructure (UGI) will also rise, necessitating the maximization of ecosystem services within limited space. To achieve

this goal, we need to focus on improving the design and management of urban green infrastructure to mitigate urban heat.

Numerous studies have explored the effects of composition and configuration of UGI on their cooling capacity, focusing on both land surface temperature and air temperature (Beele et al., 2024; Hou & Estoque, 2020; Hu et al., 2021; Jayasinghe et al., 2024; L. Wu & Chen, 2023). Researchers have used multiple methods to investigate the impact of urban greening on urban thermal environments. Remote sensing (especially satellite) is frequently used in land surface temperature studies due to its ability to deliver repetitive, consistent, and spatially continuous measurements (H. Du et al., 2017; Hou & Estoque, 2020; Peng et al., 2021). In-situ measurements and modeling are more common methods to assess the effects of vegetation on air temperature (Cheung et al., 2021; Vaz Monteiro et al., 2016; J. Zhang, Gou, et al., 2022). Previous studies have explored the effects of green space size, shape and vegetation types on their cooling intensity or extent (J. Chen et al., 2020; Potchter et al., 2006; Vaz Monteiro et al., 2016; H. Wang et al., 2023; X. Wang et al., 2021). Results suggest that trees – particularly deciduous ones – contribute significantly to cooling, while grass can even increase greenspace temperatures relative to built-up area during the day (Beele et al., 2024; Potchter et al., 2006). In terms of configuration, group tree planting has a more pronounced effect in reducing air temperature compared to linear or individual tree planting (Lemoine-Rodríguez et al., 2022; J. Yan et al., 2019; D. Zhao et al., 2020b). However, despite this growing body of work on spatial patterns of cooling, the specific effects of tree configuration on air temperature – rather than surface temperature – remain understudied (Alonzo et al., 2025).

Compared to land surface temperature, air temperature is more closely related to human comfort in urban parks (Kirschner et al., 2025). A step further, wet-bulb temperature, which

integrates a combination of temperature and humidity, can even better represent how the human body experiences heat (Stull, 2011). There is a synergistic effect of high temperature and humidity on mortality risk (Bu et al., 2024), and wet-bulb temperature has been found to significantly influence people's activities, for instance, a reduction in visit frequency to urban green spaces (Wakayama et al., 2025). Numerous studies highlight the importance of wet-bulb temperature for heat stress mitigation (Kikumoto et al., 2016; Rahman et al., 2022; Ulpiani et al., 2020; Z. Zhou et al., 2024), interaction with green spaces (Boyle, 2023; Kirschner et al., 2025; C. Liu et al., 2025; Rahman et al., 2022; Wakayama et al., 2025), and understanding of thermal inequity (Boyle, 2023; Xu et al., 2025). However, wet-bulb temperature is more commonly used in modeling studies compared to local monitoring or paired-site field studies – where it is valuable to help account for both heat and humidity in situ. It is thus an essential indicator to include in studies of urban park management and design, which is at the intersection of heat mitigation, human thermal comfort and urban greening.

Additionally, most studies that examine the impact of spatial pattern of urban green infrastructure on temperature (including LST, ambient air temperature, or human thermal indices) have focused on daytime temperatures, whereas nighttime temperature is also an important factor for human health and well-being (He et al., 2022; Obradovich et al., 2017). The knowledge of how configuration of different green infrastructures affects nighttime thermal comfort is still unclear, especially considering the heterogeneity of urban parks. Several studies showed dense tree canopy can provide less cooling (or even warming) at night (Beele et al., 2024; Krayenhoff et al., 2021; Richmond et al., 2025). Further, many of the vegetation indicators used in previous studies on trees' cooling effect are at the scale of individual trees; for example, canopy extension (e.g., crown diameter), vertical size (e.g., tree height), leaf properties (e.g., leaf area index) or biological

properties (e.g., transpiration rate) (J. Zhang, Khoshbakht, et al., 2022). The use of parameters related to tree groups is relatively rare and inconsistent. In addition, relying only on weather station data, without incorporating in-situ air temperature sensors, brings several limitations (Lu et al., 2017).

Our review of the literature reveals a growing number of studies investigating the role of vegetation in mitigating urban heat. However, as outlined above, many of these studies emphasize daytime conditions, focus on surface temperature rather than ambient air temperature or wet-bulb temperature, use individual tree metrics rather than group-level spatial patterns, and often lack high-resolution in-situ monitoring, particularly for nighttime conditions.

To address these underexplored aspects, our study focuses on the effects of tree configuration within urban parks, specifically comparing discrete and aggregate planting patterns on ambient air temperature, relative humidity, and wet-bulb temperature across both day and night. Urban parks are particularly relevant settings for such investigations, given their frequent use by residents and their potential to serve as accessible cooling refuges during extreme heat events.

We aimed to answer the following question: Do different tree configurations (discrete planting versus aggregate planting) within parks affect daytime and nighttime air temperature, relative humidity, and wet-bulb temperature differently? We hypothesized that aggregate tree clusters will have a stronger effect on ambient air temperature during daytime and weaker effect at nighttime compared to discrete tree clusters, due to a higher evapotranspiration rate during the day and long wave radiation trapping effect at night. We expect the outcomes of this paper to offer a better understanding of how UGI configurations affect ambient air temperature and wet-bulb

temperature over time, as well as provide valuable insights for park designers to develop more effective strategies for managing UGI to optimize thermal comfort across time periods.

We conducted local-scale field measurement of both air temperature and relative humidity, examining the differences in urban heat mitigation provided by various tree configurations between daytime and nighttime, and interpreting the results through potential underlying mechanisms. To overcome the limitations of relying on sparsely distributed weather station data (Lu et al., 2017) – which may fail to capture fine-scale spatial variations and high-temporal-resolution fluctuations in air temperature – we developed a paired site design of in-situ sensors within urban parks to assess different tree configurations with shared background conditions. This allows us to specifically test our hypothesis without access to a city-wide dense sensor array. This research is particularly important given the increased risks associated with residential areas that fail to cool down during nighttime hours. Prolonged exposure to elevated nighttime temperatures can intensify heat stress, negatively impacting public health, particularly for vulnerable populations such as the elderly and individuals with pre-existing health conditions (He et al., 2022). Understanding the role of UGI in mitigating nighttime heat retention is essential for designing urban environments that promote resilience against extreme heat events.

4.3 Methodology

4.3.1 Study area

Our study area is the Island of Montreal, Quebec, Canada, with a population of approximately 2 million people (Statistics Canada 2021), and containing Canada's 2nd largest city. Montreal is classified as a warm-summer humid continental climate (Köppen climate classification:

Dfb). Summers are warm to hot and humid with a daily maximum average of 26 to 27°C (79 to 81°F), increasingly exceeding 30°C (86°F). Montreal, alongside other cities in Quebec, has experienced an increase in heat-related illness and mortality in recent years, with extreme heat a prominent public health concern (Boudreault et al., 2024). Heat events can extend into September. Heat events can extend into September. During the monitoring period in Montreal (August 20th to October 7th, 2022), daily average air temperatures ranged between 7.9 °C (46.22 °F, several days in October) and 25.6 °C (78.08 °F), with a total precipitation of 173 mm recorded (<https://montreal.weatherstats.ca/download.html>). In Montreal, a heatwave is defined as a period of three or more consecutive days during which the daily maximum temperature exceeds 30 °C and the minimum temperature remains above 22 °C (<https://climatedata.ca/extreme-heat-waves-in-quebec/#:~:text=The%20thresholds%20defining%20a%20heat,greater%20than%2030%C2%B0C.>). While our study did not capture heatwave conditions, we did capture multiple (non-consecutive) hot days (see Figure 10 for further information on baseline conditions).

Site selection

We selected 13 public parks in Montreal, Canada, with similar percent cover of high vegetation (trees) that vary in their spatial layout throughout the park (Figure 8). Previous studies found a strong correlation between air temperature at a point and land cover composition within a buffer zone of that location, and the extent of buffer zone varied greatly (10-300m) in different studies (H. Yan et al., 2014b; Ziter et al., 2019). We selected parks ranging from 1.4 to 10.5 hectares to ensure that background cooling effects based on park size remained relatively consistent. In all parks, the canopy cover is between 45-55%. This allows us to control for the effect of surrounding

canopy cover on temperature reduction and focus on the effect of tree configuration, which was our primary question of interest. This level of canopy cover also allowed for a variety of different land cover types and tree configurations within each park: open grass, discrete tree clusters and aggregate tree clusters. The main tree species in the parks are within the maple genus (*Acer spp.*), which account for 43% of all public trees in our study sites. More specifically, silver maple (*Acer saccharinum*), Norway maple (*Acer platanoides*), and sugar maple (*Acer saccharum*) are common (Table 9, 10). We excluded parks located within 1000 meters of major rivers to avoid potential influence on temperature regulation from the presence of water bodies (H. Du et al., 2016).

We installed three sensors (Credosense CSL-H2 T0.2 relative humidity and temperature loggers, described below) inside each park and one outside as a reference. We chose specific locations in each park for sensor installation at a height of approximately 1.8-2 m: one sensor was attached to a lamp post (or a fence in rare occasions where a lamp post was not available) in an area of open grass, one within a tree cluster with minimal crown overlap, and one in a tree cluster with significant crown overlap. For consistency among sites, the two sensors within discrete and aggregate tree clusters were attached to tree branches and were within the crown. This location (under the tree crown) is representative of where people are likely to be present within parks in an effort to gain cooling services provided by trees. Reference sensors were attached to infrastructures that do not provide large shade (e.g., a pole within a parking lot) to record consistent ambient air temperatures from an area with urban material, and to ensure comparability among reference locations across the study, as fully-sun exposed parking lots are consistently present throughout the urban landscape. We installed reference sensors in an open area at least 50 meters away from the park, following findings that the cooling extent of small to medium green spaces' extends at least 50 meters (Vaz Monteiro et al., 2016; D. Zhao et al., 2020b; S. Zhou et al., 2025). Some

distance variation between parks and reference sensors was inevitable due to the location of the parking lots available near our study parks.

Considering the scale of the parks we selected, we considered tree configuration within a 30-meter buffer of the sensors to designate tree clusters as either discrete or aggregate. Within this distance there is a strong relationship between air temperature and land cover composition, and similar buffer distance has been used in previous studies (Beele et al., 2024; Cheung et al., 2021; H. Yan et al., 2014b). We tried to keep the tree canopy cover and tree species similar between the discrete tree cluster and aggregate tree cluster within the entire buffer area, although canopy cover immediately surrounding the sensor is inevitably higher within an aggregate cluster due to spacing of the trees. When selecting sensor locations in the field, we ensured that trees within aggregate clusters were planted or naturally grown close together, forming a continuous canopy, and the sensor was placed on a tree that is part of such a cluster with continuous canopy. Trees in discrete clusters were spatially separated from other tree crowns by clear open spaces such as lawns, paths, or playgrounds. Each cluster is distinct and isolated, and may consist of a few trees or a short row of trees. Temperature sensors within discrete clusters were installed on a tree with open space on at least two sides, to ensure adequate air circulation and to represent conditions characteristic of discrete, partially exposed vegetation patches (as shown in Figure 8). This selection allowed us to capture distinct structural configurations with differing potentials for heat retention and release, particularly during nighttime, while holding canopy cover relatively constant in the broader park area.

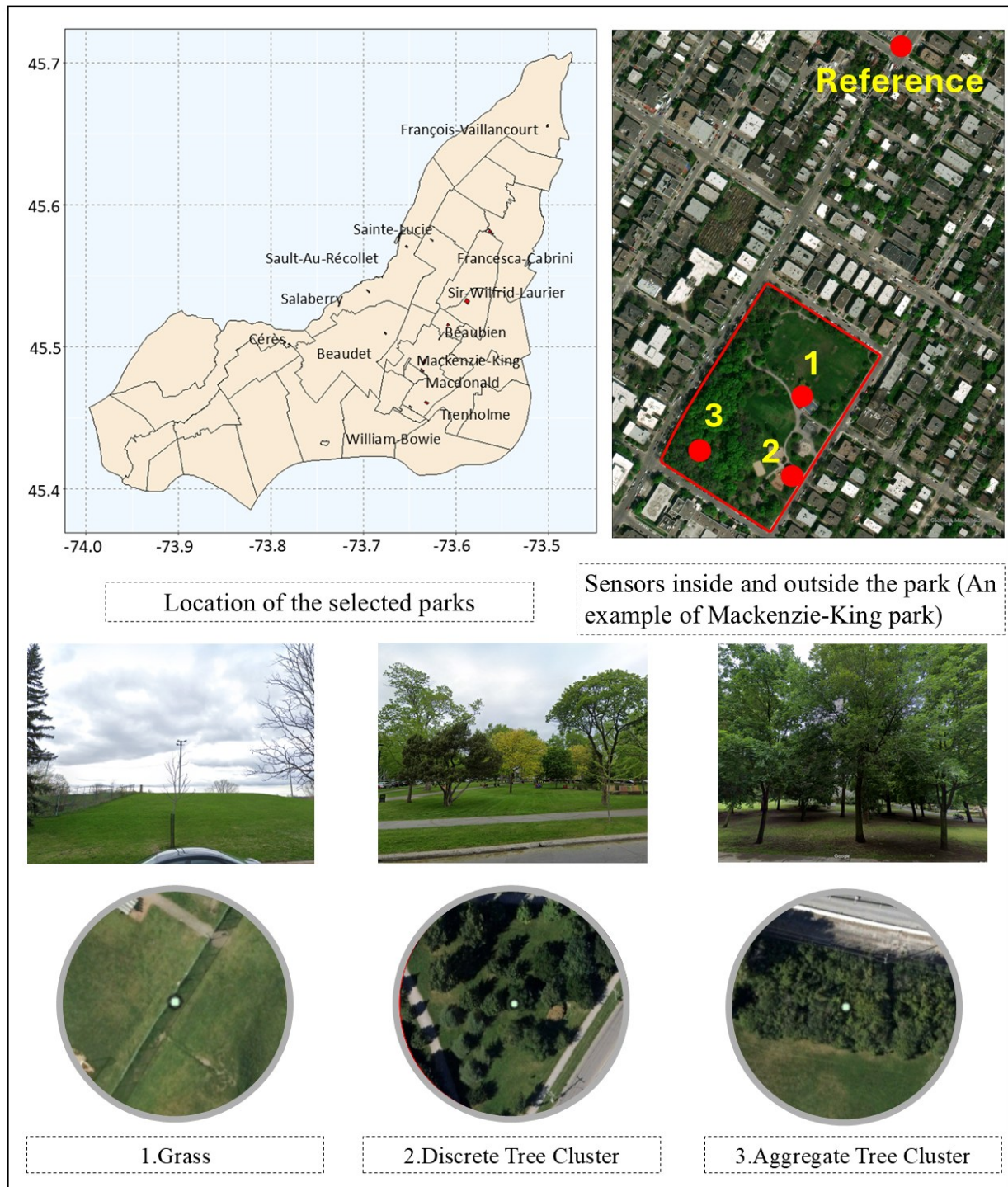


Figure 8. The location of the selected parks for air temperature and humidity monitoring in Montreal. An example of the location of the sensors installed inside and outside the parks. The appearance of the grass, discrete tree cluster and aggregate tree cluster.

Table 9. Summary of the number and proportion of top 10 tree species across all the parks

Tree Species (English)	Tree Species (Latin)	Number	Proportion
Silver Maple	<i>Acer saccharinum</i>	535	21.01%
Norway Maple	<i>Acer platanoides</i>	291	11.42%
Red Ash	<i>Fraxinus pennsylvanica</i>	141	5.54%
Sugar Maple	<i>Acer saccharum</i>	118	4.63%
Littleleaf European Linden	<i>Tilia cordata</i>	78	3.06%
Skyline Honey-Locust	<i>Gleditsia triacanthos</i>	71	2.79%
Colorado Spruce	<i>Picea pungens</i>	68	2.67%
Common Hackberry	<i>Celtis occidentalis</i>	62	2.43%
Basswood	<i>Tilia americana</i>	60	2.36%
Ivory Silk Japanese Tree Lilac	<i>Syringa reticulata</i>	51	2.00%

Table 10. Overview of the top 3 tree species in each park. (The park Beaubien is not included as the data is not available.)

Park Name	Area (ha)	Most common species	Second most common species	Third most common species
Sault-Au-Récollet	2.28	Red Ash <i>Fraxinus pennsylvanica</i> (53.7%)	Common Hackberry <i>Celtis occidentalis</i> (8.1%)	Crab Apple <i>Malus sylvestris</i> (6.5%)
William-Bowie	1.45	Norway Maple <i>Acer platanoides</i> (22.5%)	Littleleaf European Linden <i>Tilia cordata</i> (21.6%)	Silver Maple <i>Acer saccharinum</i> (15.7%)
Sir-Wilfrid-Laurier	10.51	Silver Maple <i>Acer saccharinum</i> (42.4%)	Norway Maple <i>Acer platanoides</i> (22.3%)	Columnare Norway Maple <i>Acer platanoides</i> 'Columnare' (5.9%)
Cérès	1.40	Red Ash <i>Fraxinus pennsylvanica</i> (25.4%)	Norway Maple <i>Acer platanoides</i> (14.4%)	Littleleaf European Linden <i>Tilia cordata</i> (12.7%)
Francesca-Cabrini	6.05	Ash <i>Fraxinus excelsior</i> (40%)	Norway Maple <i>Acer platanoides</i> (13.7%)	Basswood <i>Tilia americana</i> (11.3%)

Salaberry	2.06	American Ironwood <i>Ostrya virginiana</i> (18.2%)	Hop-Hornbeam	Black Maple <i>Acer nigrum</i> (10.0%)	Bitternut Hickory <i>Carya cordiformis</i> (6.1%)
Trenholme	4.71	Norway Maple <i>Acer platanoides</i> (36.8%)		Silver Maple <i>Acer saccharinum</i> (33.1%)	Littleleaf European Linden <i>Tilia cordata</i> (4.6%)
Macdonald	3.24	Silver Maple <i>Acer saccharinum</i> (31.7%)		Norway Maple <i>Acer platanoides</i> (13.6%)	Western Catalpa <i>Catalpa speciosa</i> (5.3%)
François-Vaillancourt	2.09	Pin Oak <i>Quercus palustris</i> (16.8%)		Sugar Maple <i>Acer saccharum</i> (16.1%)	Skyline Honey-Locust <i>Gleditsia triacanthos</i> (15.8%)
Beaudet	1.41	Silver Maple <i>Acer saccharinum</i> (34.5%)		Norway Maple <i>Acer platanoides</i> (19.3%)	Elm <i>Ulmus</i> (12.6%)

Mackenzie-King	2.68	Basswood <i>Tilia americana</i> (19.5%)	Sugar Maple <i>Acer saccharum</i> (11.3%)	Norway Maple <i>Acer platanoides</i> (9.4%)
Sainte-Lucie	1.88	Norway Maple <i>Acer platanoides</i> (21.9%)	Greenspire Littleleaf Linden <i>Tilia cordata Greenspire</i> (15.6%)	Ivory Silk Japanese Tree Lilac <i>Syringa reticulata</i> (15.6%)

4.3.2 Data

Air Temperature and Relative Humidity Data

We used CSL-H2 T0.2 temperature and relative humidity loggers (Credosense) which use small footprint sensors to offer highly accurate temperature measurements. The operating temperature is from -40 to $+85$ °C, with the accuracy of relative humidity of $\pm 2\%$ typical and $\pm 3\%$ minimum, temperature of ± 0.2 °C typical and ± 0.4 °C minimum; the resolution of temperature is 0.01 °C and of relative humidity is 0.01% . The logger can store up to 57,332 data points, and its battery can last for 17 months when set to a 30-minute recording interval (<https://credosense.com/temperature-and-relative-humidity-logger-csl-h2t2/>). In our study, the sensors logged air temperature and humidity data every 10 minutes. Each sensor was enclosed in a professionally tested Credosense radiation shield to avoid overheating by solar radiation and potentially biased measurements (Terando et al., 2017).

We collected data from August 20th to October 7th, 2022, during the period of full leaf out in in Montreal. Due to sensor malfunctions or unexpected factors common in urban areas (i.e., theft, vandalism), we were ultimately able to collect partial data for 12 of the 13 parks, and complete data (at all three locations for the full duration of the study) for 7 parks. We first did the analysis with incomplete data for all 12 parks. After that, we also re-did the analysis including the data from the 7 parks with complete monitoring for comparison (Table 17, 18). To focus on weather conditions where we would expect to see clear impacts of vegetation on urban heat, we extracted data from 13 clear sky (cloud free) days according to weather information from Environmental and Climate Change Canada and then conducted the analysis on this subset. We also extracted data from 10 cloudy days for comparison (results shown in Table 14,16), We summarized the hourly, daily maximum, and daily minimum temperature and humidity data for each sensor. For each

location within the park (Grass, Discrete Trees and Aggregate Trees), we derived the differences between the temperature within the parks and the reference sensors (i.e., park measure-reference measure, the cooling capacity provided at each location). There were some significant outliers in the temperature data caused by sensor malfunction (because of hardware issues). To account for this we used the Interquartile Range Method for outlier detection and removal (Tukey et al., 1977). Three percent of data points were removed.

Wet-Bulb Temperature

“Wet-bulb temperature” (T_w) combines heat and humidity, which takes evaporative cooling into account. It has been widely used in heat risk studies (Boyle, 2023; Kamal et al., 2024; Yang et al., 2024). We used an equation that is valid for relative humidities between 5% and 99% and for air temperatures between -22°C and 50°C to calculate the wet-bulb temperature as follows: (Stull, 2011). T_w is the wet-bulb temperature, RH is the relative humidity.

$$T_w = T * \arctan \left[0.151977 * (RH\% + 8.313659)^{\frac{1}{2}} \right] + \arctan(T + RH\%) - \arctan(RH\% - 1.676331) + 0.00391838 * (RH\%)^{\frac{3}{2}} * \arctan(0.023101 * RH\%) - 4.686035^{\circ}\text{C}$$

4.3.3 Statistical methods

The hourly air temperature, hourly relative humidity, daily maximum air temperature and daily minimum air temperature of each sensor were used to make within- and between-park comparisons, aiming to explore how different configuration of UGI affect the air temperature, humidity and wet-bulb temperature in daytime and nighttime.

We used linear mixed effects models in R to compare air temperatures within and across parks, to investigate the effect of planting configuration of trees on ambient air temperatures, and how daytime VS nighttime further influences these patterns (Zuur et al., 2009). As open areas, discrete, and aggregated tree clusters occur within a single park (raising a potential issue of non-independence between sample points, due to nesting of sites within park), we included parks as a random effect to account for differences in individual parks such as size and landscape context. The fixed effects we focused on are: configuration of trees and the time of the day.

$$T_{dif} \sim 1 + Configuration + Time + Configuration * Time + (1 + Configuration + Time + Configuration * Time | park) \quad (1)$$

$$RH_{dif} \sim 1 + Configuration + Time + Configuration * Time + (1 + Configuration + Time + Configuration * Time | park) \quad (2)$$

$$Tw_{dif} \sim 1 + Configuration + Time + Configuration * Time + (1 + Configuration + Time + Configuration * Time | park) \quad (3)$$

Model 1, 2 and 3 were used to explore how the configuration of trees affects the ambient air temperature, humidity and wet-bulb temperature relative to the surrounding impervious surface areas, and to test if time of the day has a significant influence on the air temperature and humidity difference respectively. The difference (dependent variable) is calculated as the average hourly air temperatures / humidity/ wet-bulb temperature of each site in the park minus the air temperature / humidity/ wet-bulb temperature of outside reference at the same time. We made the time of the day a categorical variable (“D” for daytime and “N” for nighttime) for the investigation of daytime and nighttime difference. The definition is based on sunrise (6:00 AM) and sunset (20:00 PM) time. To clearly differentiate the diurnal and nocturnal temperature in the statistical analysis, we selected the time window 10:00AM-16:00PM to represent the hottest daylight hours, and 22:00PM-4:00AM to represent coolest nighttime hours, consistent with other studies (Jayasinghe et al., 2024; H. Yan et al., 2014b; S. Zhou et al., 2025). Twilight hours were excluded because our objective was to capture representative periods of maximum daytime heating and minimum nighttime cooling. Temperatures during twilight fluctuate rapidly due to changing solar angles and surface energy exchange, which would introduce additional variability and reduce the ability to clearly distinguish between diurnal and nocturnal temperature patterns. However, we do show 24-hour data in Figures 12 to demonstrate differences at all times of day. For each sampling day we calculated the average air temperature and humidity within the time window for each site.

Ordered Contrast

Linear mixed effects models test for significant differences among groups. To test whether there is a significant temperature gradient in parks from open areas to aggregate tree clusters, we used ordered contrasts. The three-level ordered contrast was made following the mixed effect

models 1, 2 and 3, among open grass area (Level 1), discrete tree cluster (Level 2) and aggregate tree cluster (Level 3) during daytime and nighttime.

Mixed effect model analysis and ordered contrast were done in R studio (package: *lme4*) (Bates et al., 2015).

4.4 Results

4.4.1 The effect of configuration of trees on air temperature, relative humidity and wet-bulb temperature

During the daytime (especially 10:00AM-16:00PM), aggregate tree clusters showed the largest air temperature reduction compared to the outside park reference, while the open grass area was even hotter (Table 11, Figure 9). On the contrary, the open grass area was the coolest place in the park at night (22:00PM-4:00AM) and the aggregate tree cluster provided the smallest cooling effect, or even slight warming effect in some cases (Table 11, Figure 9; absolute values for temperature, humidity, and wet-bulb temperature are shown in Figure 10). The median humidity difference (RH_{dif_mean}) also showed opposite patterns between daytime and nighttime. Aggregate tree clusters are the most humid place in the park during the day but the driest at night. The open grass area had the lowest humidity during the day and the highest humidity at night. Due to these differences in humidity, the absolute value of mean wet-bulb temperature difference (Tw_{dif_mean}) of the open grass area was larger during the day and smaller during the night compared to the mean

air temperature difference ($T_{\text{dif_mean}}$). For the two types of tree clusters, the absolute values of $T_{\text{dif_mean}}$ were all smaller than that of $T_{\text{dif_mean}}$ during both daytime and nighttime. Furthermore, the gaps of $T_{\text{dif_mean}}$ between discrete tree cluster and aggregate cluster were smaller than that of $T_{\text{dif_mean}}$ (Table 11). In contrast with the clear sky days, the air temperature, relative humidity and wet-bulb temperature differences among open grass area, discrete tree clusters and aggregate tree clusters were much smaller during cloudy days (Table 12, Figure 11).

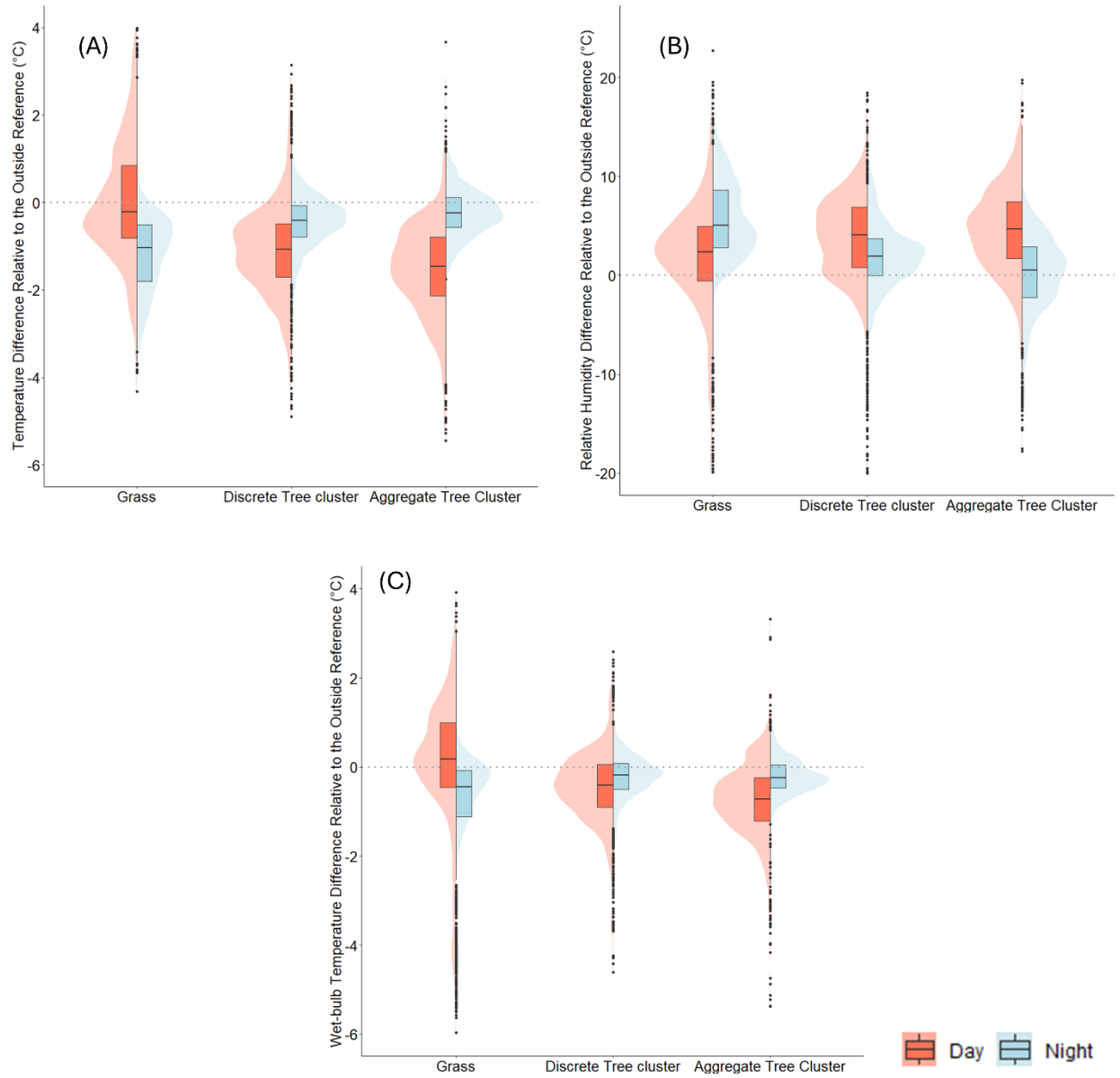


Figure 9. Boxplots and histograms of daytime (coral) and nighttime (light blue) air temperature (A), relative humidity (B), and Wet-bulb temperature (C) of grass, discrete tree clusters and aggregate tree clusters relative to the reference sites on 13 clear sky days.

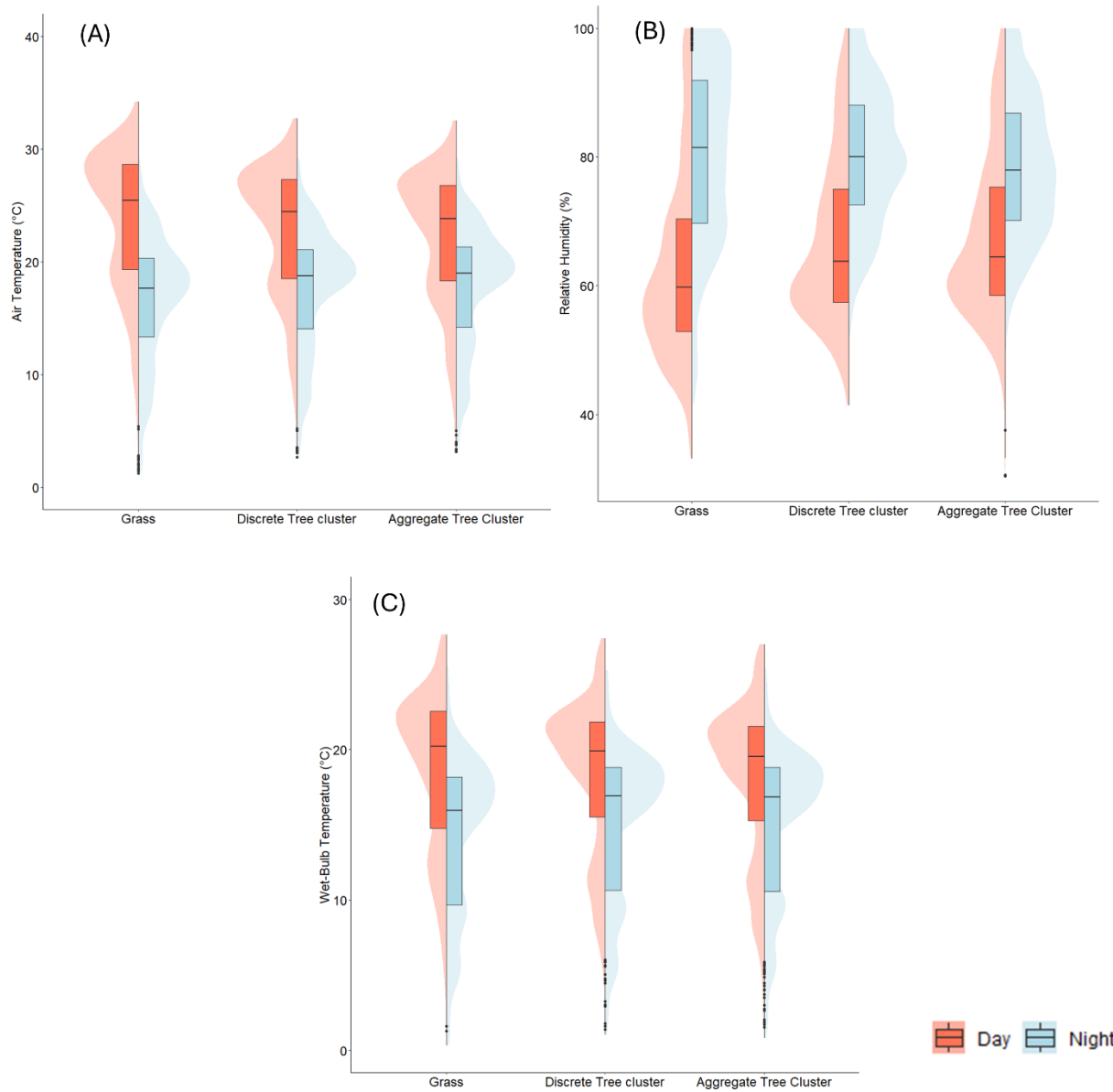


Figure 10. Boxplots and histograms of absolute daytime (coral) and nighttime (light blue) air temperature (A), relative humidity (B), and Wet-bulb temperature (C) of grass, discrete tree clusters and aggregate tree clusters on 13 clear sky days.

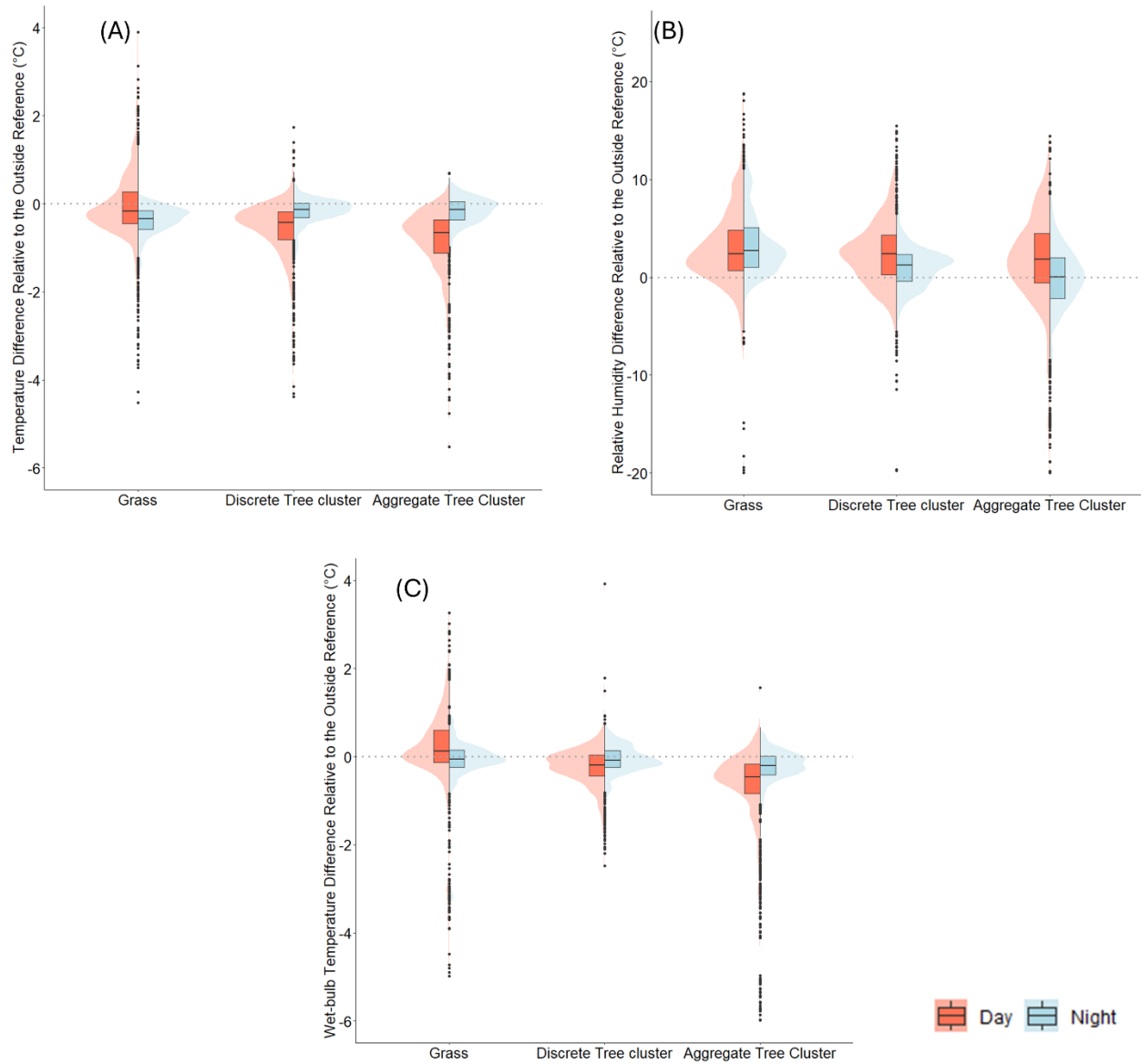


Figure 11. Boxplots and histograms of daytime (coral) and nighttime (light blue) air temperature (A), relative humidity (B), and Wet-bulb temperature (C) of grass, discrete tree clusters and aggregate tree clusters relative to the reference sites in 10 cloudy days.

Table 11. The average air temperature difference (T_{dif_mean}), humidity difference (RH_{dif_mean}), and wet-bulb temperature difference (Tw_{dif_mean}) between grass, discrete tree cluster, aggregate tree cluster in the parks and the outside park reference during the daytime (D) (10:00AM-16:00PM) and nighttime (N) (22:00PM-4:00AM).

		T_{dif_mean} (D)	T_{dif_mean} (N)	RH_{dif_mean} (D)	RH_{dif_mean} (N)	Tw_{dif_mean} (D)	Tw_{dif_mean} (N)
Open Grass Area		0.58°C	-1.15°C	1.73%	5.90%	0.77°C	-0.44°C
Discrete Tree Cluster		-1.26°C	-0.48°C	4.50%	1.94%	-0.48°C	-0.24°C
Aggregate Tree Cluster		-1.87°C	-0.23°C	5.47%	0.34%	-0.89°C	-0.18°C

Table 12. The average air temperature difference (T_{dif_mean}), humidity difference (RH_{dif_mean}), and wet-bulb temperature difference (Tw_{dif_mean}) between grass, discrete tree cluster, aggregate tree cluster in the parks and the outside park reference during the daytime (D) (10:00AM-16:00PM) and nighttime (N) (22:00PM-4:00AM) in 10 cloudy days.

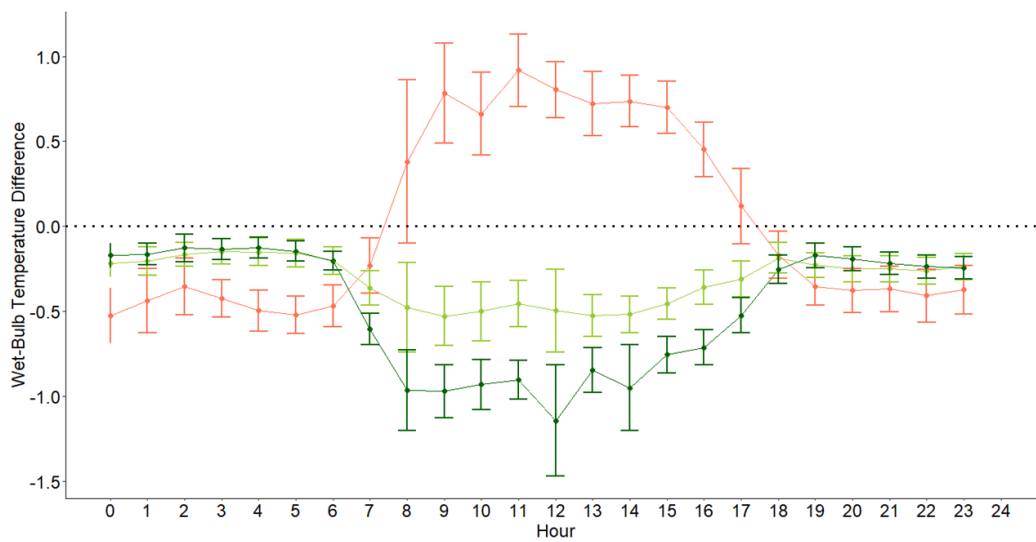
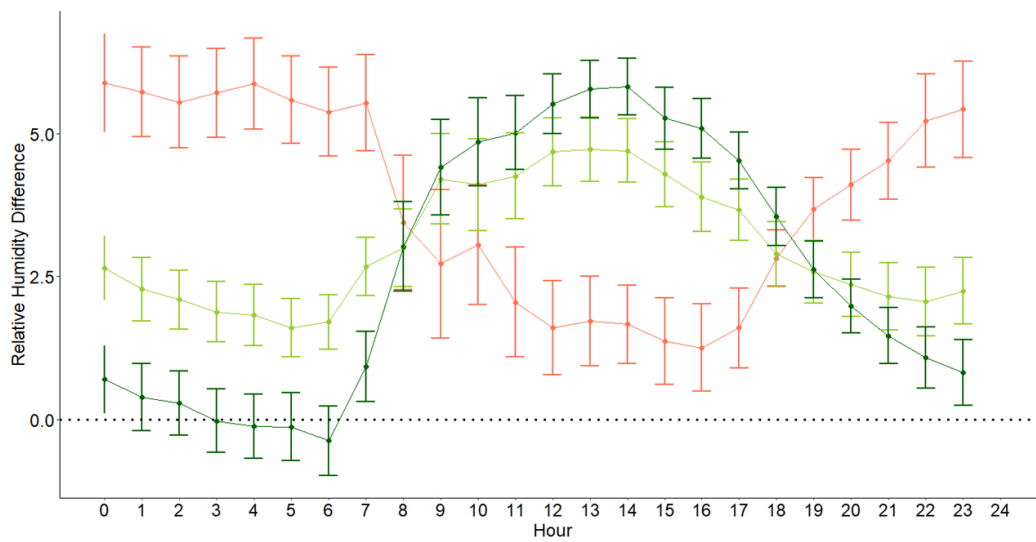
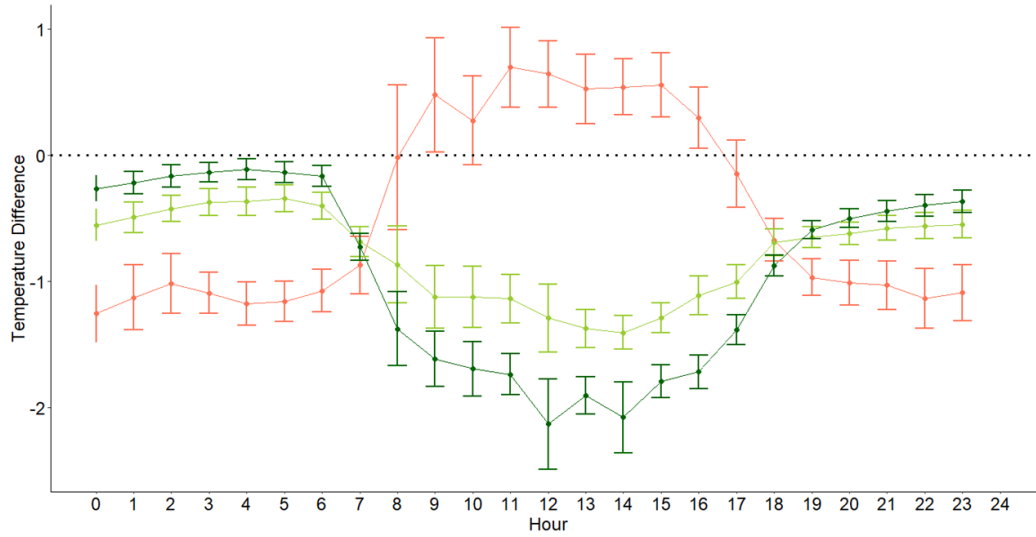
		T_{dif_mean} (D)	T_{dif_mean} (N)	RH_{dif_mean} (D)	RH_{dif_mean} (N)	Tw_{dif_mean} (D)	Tw_{dif_mean} (N)
Open Grass Area		0.13°C	-0.43°C	2.78%	3.38%	0.46°C	-0.04°C
Discrete Tree Cluster		-0.74°C	-0.22°C	3.15%	1.13%	-0.32°C	-0.07°C
Aggregate Tree Cluster		-1.09°C	-0.18°C	3.03%	0.10%	-0.67°C	-0.16°C

4.4.2 Hourly air temperature and relative humidity

We calculated the hourly average temperature differences (T_{dif}) between inside park sites and reference sites for all 12 parks (Figure 12). At 0:00 AM, the temperature differences between open grass area, discrete tree clusters, aggregate tree clusters and reference sites were -1.25°C , -0.55°C , -0.26°C , respectively. T_{dif} of discrete tree clusters and aggregate tree clusters rapidly decreased while T_{dif} of open area rapidly increased from 6:00 AM. At 11:00 AM, T_{dif} of open grass area peaked at 0.70°C , then it began to decrease. At 12:00 PM, a turning point was observed in the T_{dif} of the aggregate tree cluster line, with a recorded value of -2.13°C . At 14:00 PM, T_{dif} of discrete tree clusters reached the minimum values of -1.40°C , and then started to increase. From 19:00 PM to 7:00 AM, the open grass area was the coolest place compared to the outside reference, then the discrete tree clusters and the aggregate tree clusters. On the contrary, during the daytime from 7:00 AM to 19:00 PM, the aggregate tree clusters were the coolest sites. The relative humidity difference (RH_{dif}) showed an opposite pattern with the air temperature difference. During the night from 19:00 PM to 8:00 AM, the open grass area in the park was the most humid place, then came after the discrete tree clusters and aggregate tree clusters. RH_{dif} of open area was about to decrease while RH_{dif} of two tree clusters started to increase from 6:00 AM, which is the similar time point with the change of T_{dif} . At 14:00 PM, RH_{dif} of discrete tree clusters and aggregate tree clusters peaked at 4.70% and 5.83% respectively and then decreased. At 16:00 PM, RH_{dif} of the open grass area reached its turning point at 1.66% and then increased.

The changing pattern of wet-bulb temperature difference (Tw_{dif}) is similar to that of T_{dif} . However, the Tw_{dif} of open grass area, discrete tree cluster, and aggregate tree cluster are higher than T_{dif} during the whole day. The differences between Tw_{dif} among open grass area and two types of tree clusters were smaller during nighttime (19:00 PM-6:00 AM) than T_{dif} . The peak of

Tw_dif of open grass area was 0.92°C at 11:00 AM, while the troughs of discrete tree clusters and aggregate tree clusters were -0.53°C at 13:00 PM and -1.14°C at 12:00 PM, respectively. During the nighttime, the differences between Tw_dif of open grass area and the tree clusters were no larger than 0.37°C .



Grass Discrete Tree Cluster Aggregate Tree Cluster

Figure 12 . Line charts of mean and quantiles of hourly temperature difference (A), hourly relative humidity difference (B), and hourly wet-bulb temperature difference (C) between grass (coral red), discrete tree clusters (light green) and aggregate tree cluster (dark green) and reference sites. The bars refer to the 95% confidence intervals of the mean hourly temperature, relative humidity and wet-bulb difference for all the parks from 13 clear sky days in summer 2022 in Montreal, QC.

4.4.3 Mixed effect models

Air temperature

During the daytime, the open grass areas show a significant positive effect on ambient air temperature relative to the outside reference, with a magnitude of $0.69 \pm 0.24^{\circ}\text{C}$. The discrete tree clusters and aggregate tree clusters are associated with a significant decrease in relative air temperature compared to the open grass area, to an extent of $-1.96 \pm 0.26^{\circ}\text{C}$ and $-2.59 \pm 0.28^{\circ}\text{C}$, respectively (Table 13). At night, the open grass area shows a significant decrease in relative air temperature, to an extent of $-1.81 \pm 0.35^{\circ}\text{C}$ compared to daytime. The discrete tree clusters and aggregate tree clusters at night are associated with significant increase in relative air temperature, to an extent of $2.61 \pm 0.37^{\circ}\text{C}$ and $3.48 \pm 0.32^{\circ}\text{C}$ compared to daytime respectively (Table 13). During cloudy days, the T_{dif} between open grass areas and the outside reference was not significant, and the cooling effect of tree clusters were smaller (Table 14).

Humidity

During the daytime, the open grass area shows a non-statistically significant positive effect on ambient air humidity relative to the outside reference. The discrete tree clusters and aggregate tree clusters are associated with a significant increase in relative air humidity compared to the open

grass area, to an extent of $3.66 \pm 0.64\%$ and $4.79 \pm 0.57\%$, respectively (Table 13). At night, the open grass area shows a significant increase in relative air humidity, to an extent of $4.69 \pm 1.08\%$ comparative to it during daytime (Table 13). While the discrete tree clusters and aggregate tree clusters at night are associated with significant decreases in relative air humidity, to an extent of $-7.33 \pm 1.17\%$ and -9.97 ± 1.05

% compared to daytime respectively (Table 13). Under cloudy conditions, the impact of grass and tree clusters on daytime relative humidity was not as significant as on nighttime relative humidity (Table 14).

Wet-bulb temperature

During the daytime, the open grass area shows a significant positive effect on ambient wet-bulb temperature relative to the outside reference (Table 13). The discrete tree clusters and aggregate tree clusters are associated with a significant decrease in relative wet-bulb temperature compared to the open grass area, to an extent of $-1.25 \pm 0.16^\circ\text{C}$ and $-1.66 \pm 0.21^\circ\text{C}$, respectively (Table 13). At night, the open grass area shows a significant decrease in relative wet-bulb temperature, to an extent of $-1.13 \pm 0.20^\circ\text{C}$ in comparison to during daytime (Table 13). The discrete tree clusters and aggregate tree clusters at night are associated with significant increase in relative wet-bulb temperature, to an extent of $1.38 \pm 0.20^\circ\text{C}$ and $1.86 \pm 0.20^\circ\text{C}$ compared to daytime respectively (Table 13). Similar to T_{dif} , the Tw_{dif} between open grass area and outside reference was not significant and the cooling effect of tree clusters were smaller under cloudy conditions (Table 14).

Table 13. The results of the generalized linear mixed models exploring average hourly air temperature in grass, underneath discrete tree cluster and aggregate tree cluster relative to the outside reference at daytime (D) and nighttime (N) in 13 clear sky days. Estimated average coefficients $\pm$ S.E. are presented for all variables. p values are shown in the brackets.

Variables	T_dif	RH_dif	Tw_dif
	Coefficient $\pm$ SE	Coefficient $\pm$ SE	Coefficient $\pm$ SE
Grass (D)	0.69 $\pm$ 0.24 (0.02)	0.74 $\pm$ 0.87 (0.41)	0.75 $\pm$ 0.15 (0.000775)
Discrete tree cluster (D)	-1.96 $\pm$ 0.26 (5.97E-5)	3.66 $\pm$ 0.64 (0.000104)	-1.25 $\pm$ 0.16 (1.56E-05)
Aggregate tree cluster(D)	-2.59 $\pm$ 0.28 (1.57E-05)	4.79 $\pm$ 0.57 (0.000115)	-1.66 $\pm$ 0.21 (7.12E-06)
Grass (N)	-1.81 $\pm$ 0.35 (0.00065)	4.69 $\pm$ 1.08 (0.004740)	-1.13 $\pm$ 0.20 (0.001377)
Discrete tree cluster (N)	2.61 $\pm$ 0.37 (4.67E-05)	-7.33 $\pm$ 1.17 (0.001058)	1.38 $\pm$ 0.20 (0.000143)
Aggregate tree cluster (N)	3.48 $\pm$ 0.32 (1.17E-05)	-9.97 $\pm$ 1.05 (0.010323)	1.86 $\pm$ 0.20 (7.96E-05)

Table 14. The results of the generalized linear mixed models exploring average hourly air temperature in grass, underneath discrete tree cluster and aggregate tree cluster relative to the outside reference at daytime and nighttime in 10 cloudy days. Estimated average coefficients $\pm$ S.E. are presented for all variables. p values are shown in the brackets.

Variables	T_dif	RH_dif	Twb_dif
	Coefficient $\pm$ SE	Coefficient $\pm$ SE	Coefficient $\pm$ SE
Grass (D)	0.18 $\pm$ 0.14 (0.22307)	0.56 $\pm$ 1.18 (0.6501)	0.26 $\pm$ 0.22 (0.29520)
Discrete tree cluster (D)	-0.93 $\pm$ 0.11 (1.07e-05)	2.19 $\pm$ 0.70 (0.0282)	-0.62 $\pm$ 0.16 (0.02975)
Aggregate tree cluster(D)	-1.36 $\pm$ 0.08 (3.32e-11)	2.12 $\pm$ 1.41 (0.1689)	-1.06 $\pm$ 0.23 (0.00562)
Grass (N)	-0.62 $\pm$ 0.16 (0.00065)	1.42 $\pm$ 0.58 (0.0377)	-0.36 $\pm$ 0.15 (0.05250)
Discrete tree cluster (N)	1.16 $\pm$ 0.12 (0.00169)	-3.20 $\pm$ 0.57 (9.28e-08)	0.64 $\pm$ 0.13 (0.00754)
Aggregate tree cluster (N)	1.62 $\pm$ 0.12 (6.00e-11)	-4.45 $\pm$ 0.69 (3.80e-05)	0.95 $\pm$ 0.15 (0.00133)

Ordered Contrasts

We found a significant decreasing trend of both the relative air temperature and wet-bulb temperature along the gradient from open grass areas to discrete tree clusters to aggregate tree clusters during the day, with an estimate coefficient of -2.59 and -1.66 for air temperature and wet-bulb temperature respectively (Table 15). While at night, the contrasts show a significant increasing trend of air temperature difference from open grass areas to discrete tree clusters to aggregate tree clusters with an estimate coefficient of 0.90, but a non-significant increasing trend of wet-bulb temperature (Table 15). For relative humidity, there is a significant increasing trend from grass to discrete tree clusters and to aggregate tree clusters in the park during the daytime, with an estimate coefficient of 4.79 (Table 15). The nighttime result shows a statistically significant decreasing pattern among the relative humidity of the three sites in the park, with an estimate coefficient of -5.18. In contrast to the clear sky conditions, under cloudy conditions, no significant differences in relative humidity were observed among open grass areas, discrete tree clusters, and aggregate tree clusters. However, for both air temperature and wet-bulb temperature, the trend of reduced daytime temperature along the tree cluster gradient remained significant for both clear sky days and cloudy days, although differences were smaller under cloud cover (Table 16).

Table 15. Results of three-group ordered contrasts analysis for relative air temperature and relative humidity. This table presents the contrast analysis results comparing three ordered groups: open grass area (Level 1), discrete tree cluster (Level 2) and aggregate tree cluster (Level 3) during daytime (D) and nighttime (N). Coefficients represent the magnitude and direction of differences among groups, with open grass area (Level 1) as the reference level. Standard errors (SE) and p values are reported alongside coefficients

Level1-Level2-Level 3 Contrast	Estimate coefficient	SE	p value
T_dif (D)	-2.59	0.31	<0.0001
T_dif (N)	0.90	0.13	0.0007
RH_dif (D)	4.79	0.66	0.0001
RH_dif (N)	-5.18	0.95	0.0003
Tw_dif (D)	-1.66	0.23	<0.0001
Tw_dif (N)	0.19	0.16	0.26

Table 16. Results of three-group ordered contrasts analysis for relative air temperature and relative humidity in 10 cloudy days. This table presents the contrast analysis results comparing three ordered groups: open grass area (Level 1), discrete tree cluster (Level 2) and aggregate tree cluster (Level 3) during daytime (D) and nighttime (N). Coefficients represent the magnitude and direction of differences among groups, with open grass area (Level 1) as the reference level. Standard errors (SE) and p values are reported alongside coefficients

Level1-Level2-Level 3 Contrast	Estimate coefficient	SE	p value
T_dif (D)	-1.36	0.11	0.0001
T_dif (N)	0.26	0.09	0.02
RH_dif (D)	2.12	1.50	0.18
RH_dif (N)	-2.32	1.19	0.10
Twb_dif (D)	-1.06	0.25	0.0016

Twb_dif (N)	-0.11	0.13	0.43
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Table 17. The results of the generalized linear mixed models exploring average hourly air temperature in grass, underneath discrete tree cluster and aggregate tree cluster relative to the outside reference at daytime and nighttime in 13 clear sky days for 7 parks with complete data. Estimated average coefficients $\pm$ S.E. are presented for all variables. p values are shown in the brackets.

Variables	T_dif	RH_dif	Twb_dif
	Coefficient $\pm$ SE	Coefficient $\pm$ SE	Coefficient $\pm$ SE
Grass (D)	0.42 $\pm$ 0.29 (0.19781)	1.07 $\pm$ 1.27 (0.43367)	0.50 $\pm$ 0.29 (0.13195)
Discrete tree cluster (D)	-1.91 $\pm$ 0.27 (0.00035)	4.40 $\pm$ 0.96 (0.00386)	-1.05 $\pm$ 0.21 (0.00256)
Aggregate tree cluster(D)	-2.31 $\pm$ 0.25 (8.74e-05)	5.83 $\pm$ 1.43 (0.00697)	-1.21 $\pm$ 0.35 (0.01348)
Grass (N)	-1.61 $\pm$ 0.40 (0.00806)	5.65 $\pm$ 2.01 (0.05933)	-0.93 $\pm$ 0.37 (0.06851)
Discrete tree cluster (N)	2.51 $\pm$ 0.44 (0.00136)	-8.96 $\pm$ 2.28 (0.01857)	1.16 $\pm$ 0.36 (0.03346)
Aggregate tree cluster (N)	3.21 $\pm$ 0.30 (6.84e-05)	-10.61 $\pm$ 1.78 (0.01521)	1.58 $\pm$ 0.34 (0.01242)

Table 18. Results of three-group ordered contrasts analysis for relative air temperature and relative humidity in 13 clear sky days for 7 parks with complete data. This table presents the contrast analysis results comparing three ordered groups: open grass area (Level 1), discrete tree cluster (Level 2) and aggregate tree cluster (Level 3) during daytime (D) and nighttime (N). Coefficients represent the magnitude and direction of differences among groups, with open grass area (Level 1) as the reference level. Standard errors (SE) and p values are reported alongside coefficients

Level1-Level2-Level 3 Contrast	Estimate coefficient	SE	p value
T_dif (D)	-2.31	0.25	0.0001
T_dif (N)	0.90	0.13	0.0006
RH_dif (D)	5.83	1.44	0.0066
RH_dif (N)	-4.78	1.18	0.0070
Twb_dif (D)	-1.21	0.35	0.0134
Twb_dif (N)	0.36	0.17	0.0799

4.5 Discussion

We used mixed effect models and ordered contrasts to test the impact of tree planting strategies and temporal variation on ambient air temperature, relative humidity and wet-bulb temperature. Specifically, we tested whether open grass areas, discrete tree clusters, or aggregate tree clusters in parks performed differently with respect to cooling during daytime and nighttime. Our study reveals that both the configuration of tree clusters and time of the day have significant impacts on ambient air temperature, relative humidity and wet-bulb temperature, but that ignoring the impacts of humidity may result in overestimating the effects of tree configuration on perceived cooling effects.

4.5.1 The impact of tree configuration on ambient air temperature, relative humidity and wet-bulb temperature during daytime

Our data shows higher values of daytime air temperature in open grass areas compared to surrounding urbanized areas, which aligns with the findings in Yang et al. (2024) that short vegetation increases daytime air temperature in wet climates. Both discrete tree clusters and aggregate tree clusters significantly cool the surrounding air, with the aggregate tree cluster having a larger effect. This result is consistent with Zhao et al. (2020) who found a similar trend of the cooling effect: aggregate tree cluster > discrete tree cluster > open grass area in parks in Xi'an, China, and is broadly consistent with the consensus that higher canopy cover and multiple layers of vegetation enhance cooling (Alonzo et al. 2025). The difference between the air temperature of discrete and aggregate tree clusters might result from: 1) the higher evapotranspiration rate in aggregate tree clusters, which absorb more heat, and 2) the stronger shading effect of aggregate tree clusters, which reduces solar radiation from heating the air (Beele et al., 2024). The relative humidity of the three sites in the park are all higher than the outside reference, likely due to the evapotranspiration process of the vegetation. Inverse to their relationship with air temperature, the aggregate tree cluster shows the highest relative humidity, followed by the discrete tree cluster and open grass area. This suggests that planting trees in more concentrated clusters can enhance the daytime ambient air cooling, but also humidity.

The wet-bulb temperature, which combines the air temperature and relative humidity, better reflects how people perceive temperature, and is thus better representative of human thermal comfort (Pal & Eltahir, 2016). The significant decreasing trend of wet-bulb temperature from open

grass area to aggregate tree cluster relative to the outside reference is consistent with the air temperature results. However, the wet-bulb temperature difference between open grass area and outside reference is larger, and the difference between tree clusters and outside reference are smaller, compared to air temperature. This indicates that the temperature people experience within parks is likely higher than the measured air temperature due to the higher relative humidity – suggesting that studies considering only air temperature may be overestimating the cooling capacity of vegetation, particularly in more humid climates.

4.5.2 The impact of tree configuration on ambient air temperature, relative humidity and wet-bulb temperature during nighttime

Stationary monitoring of air temperature via sensors provides high temporal resolution nighttime air temperature and relative humidity data, which helps us to have a comprehensive understanding of urban greening's effect on urban microclimate.

Our results are consistent with a growing recognition that vegetation cooling mechanisms differ between daytime and nighttime (Gillerot et al., 2024). At night, the open grass area shows significantly lower air temperature in comparison to both discrete and aggregate tree clusters, indicating that trees have minimal cooling capacity at night, while open grass areas cool down quickly. This aligns with previous studies that show increasing grasses and shrubs can enhance nocturnal cooling while tree cover had a slight or even negative impact on nighttime heat mitigation (Beele et al., 2024; Gillerot et al., 2024; Kraemer & Kabisch, 2022). For example, Kraemer and Kabisch (2022) see similar results to ours in their study in Leipzig, Germany, where they observed a sparsely tree-covered park was warmer than an urban reference during the day,

but cooled the air more effectively than the reference areas over the course of the evening and night. Two studies of Belgian cities also reinforce this result. Gillerot et al. (2024) found that perceived nighttime temperatures were more strongly driven by regional-scale processes than local tree cover, while Beele et al. (2024) also noted a lack of tree-driven cooling at night, recommending trees interspersed in a mix of grasses and shrubs to promote release of nighttime heat. The nocturnal cooling effect of open grass areas could help mitigate the risk of heat-related illness and discomfort, especially for vulnerable populations (He et al., 2022; Obradovich et al., 2017). However, the fact that these nighttime differences were moderated when considering wet-bulb temperature suggests that further research incorporating perceived temperature is needed before concluding that there is a strong advantage to open areas.

The fact that aggregate tree clusters show slightly higher air temperature than the discrete tree clusters at night may be due to several reasons: the discrete tree cluster facilitating long-wave radiation release at night (Beele et al., 2024), the aggregate tree clusters' obstruction of heat exchange between underneath the tree and the cooler air above them (Chang & Li, 2014), or reduction of wind speed (Oshio et al., 2021). Most past studies have focused on the complexity of the tree cluster shape rather than aggregation level (Qian et al., 2018; Xiao et al., 2018), or overlooked the day-night difference (D. Zhao et al., 2020b), which makes multi-study comparison very difficult.

The increased humidity within open grass areas at night compared to the discrete and aggregate tree clusters aligns with the previous studies (Kuang, 2020). However, relatively few studies assess heat indices that combine temperature and relative humidity (but see Gillerot et al. 2024). Due to the reversal of relative humidity patterns at night compared to daytime, the wet-bulb temperatures relative to the outside reference are quite similar across the three sites in the parks at

night. The higher relative humidity of open grass area makes its cooling effect weaker at night, while the opposite relative humidity level between discrete tree clusters and aggregate tree clusters also weakens the wet-bulb temperature difference between them. This indicates that open grass areas may be more effective at nighttime cooling in cities under a dryer climate, compared to what we see in a relatively humid city. Future studies could compare cities across a range of climates to further explore variation in the impact of the type and configuration of vegetation on cooling services. Our results also emphasize the importance of considering the impact of relative humidity in urban greening studies, which often rely on low-cost sensors that are limited to measurements of temperature.

4.5.3 The 24-hour relative air temperature, humidity and wet-bulb temperature variations within parks

In addition to simply comparing the categories of daytime and nighttime (Alonzo et al., 2021; Beele et al., 2024; Jayasinghe et al., 2024; Yang et al., 2024), we made a more detailed 24-hour relative temperature, humidity, and wet-bulb temperature comparison among the three sites in the park, aiming to explore the dynamics of the cooling effect provided by trees as the environment changes throughout the day.

There are clearly two main turning points in our data: sunrise and sunset (Figure 12). Between sunrise and sunset (daytime), the temperature of open grass area in the park quickly transcended the outside reference and reached the peak at noon. The two types of tree clusters, in contrast, became increasingly cooler than the outside references until noon. The evapotranspiration

effect could explain the temperature differences between the two tree configurations, as the relative humidity line chart showed. The temperature differences between open grass area and tree clusters are likely explained by both shade and evapotranspiration.

Before sunrise and after sunset (nighttime), all three sites in the park remain cooler than the outside reference – thus, all configurations of green spaces are still providing cooling services at night – but relative cooling capacity follows a different order than daytime: open grass area > discrete tree cluster > aggregate tree cluster. As the relative humidity of open grass area is larger at night compared to the two types of tree clusters, the difference in wet-bulb temperature between them became smaller. People will not feel as cool in the open grass area as the air temperature implies, unless the humidity level of the region is very low.

4.5.4 Implications for park design and other urban green infrastructure

Our paired study design (with replicate configurations occurring within each park) provides insight into the role of local tree configuration while accounting for broader landscape factors known to affect temperature. Thus, the results of our study provide particularly pertinent insights into park design. Practitioners such as park managers, designers, and landscape architects should consider trade-offs of tree clusters' impact on ambient air temperature between daytime and nighttime. Leaving some open areas in the park – whether with grass, or incorporating more ecologically beneficial herbaceous species – could help to release heat at night, especially during heat waves. A park that meets visitors needs for temperature mitigation at different times of day should be structurally diverse, with a balance of dispersed, mature trees and open grasslands; thus,

we agree with the “savannah” approach advocated for by Kraemer and Kabisch (2022). Larger parks can also be structured spatially by vegetation type. For example, a well-designed park for cooling may include including open grass areas that could work as a cool island at night for people to do evening activities, a discrete tree cluster area where people could do some daytime walking or other activities that requires more space, and an aggregate tree cluster area to provide a cool daytime area to rest or for activities that don’t require much space to move. Thus, our study highlights the importance of heterogeneity within urban green spaces, and of considering vegetation structure beyond simply “greening” when designing for better public health outcomes. It should be noted that this suggestion is in the context of a relatively safe city, and advocating for nighttime park activity and dense plantings may not be suitable everywhere (Jansson et al., 2013; Sezavar et al., 2023). The cooling capacity of urban parks also underscores the importance of ensuring safe park environments at all times of day for city managers, to allow more people to benefit from the cooling services of urban parks – which will be a critical public health strategy as cities continue to warm (Park et al., 2024). Further, while our results likely generalize well to cities within a similar climatic zone, our findings may not generalize to more arid areas where the humidity would be different.

4.5.5 Limitations and recommendations

The observational nature of our study presents certain limitations. First, the tree species of discrete tree clusters and aggregate tree clusters are not exactly the same. Many tree crown characteristics can impact tree cooling capacity, such as crown diameter, crown height, sky view factor, leaf area index, which vary with species (J. Zhang et al., 2020; J. Zhang, Gou, et al., 2022). We tried our best to make sure that most of the trees were deciduous trees (and mainly maple trees

specifically, which is a dominant genus in our study area). While tree species composition does not differ in a consistent way between discrete vs. aggregate clusters – alleviating concerns of bias as a result of species – the consistency of more specific species could not be guaranteed using an observational study. Future studies could further explore the importance of urban forest composition for cooling (e.g., Li et al. (2024)), which is another important consideration for design and management practitioners. In addition, detailed vegetation characteristics and management practices such as tree density, leaf area index, grass height and irrigation practices were not incorporated in the model due to the limited sample size. Expanded studies that incorporate specific vegetation characteristics beyond tree configuration would be helpful for a more in-depth analysis in the future.

Second, we did not include detailed weather covariates in the model. We recognized that the solar radiation discrepancy between sunny days and cloudy days could lead to differences between the discrete tree cluster and aggregate tree cluster and so extracted the clear sky days and cloudy days for analysis. However, we were not able to capture variables such as wind speed, which could also influence the temperature difference between the two tree configurations. Future research should continue to explore how different solar radiation levels and wind speed affect the air temperature and relative humidity variation among various vegetation designs.

Third, due to unpredictable factors during urban fieldwork, we lost a few sensors during the monitoring period, which led to the incomplete dataset, which compounded an already relatively small sample size. In the future, wireless sensors could be more widely used in the city to provide real-time air temperature and relative humidity datasets, which could also reduce data loss.

Finally, the simplified park selection criteria and the potential sensor placement artifacts are two important aspects to be considered. While we are confident in the differences between aggregate and discrete clusters based on field observations, better quantification approaches can be developed to select different configurations of tree clusters prior to sensor deployment. Whether our observed differences in configuration hold at different levels of overall canopy (e.g. in parks or neighborhoods with higher or lower canopy cover) would also be a promising area for future work. Our sensors in open grass area and outside reference sites were also attached to metal posts or fences. While this is common practice in urban greening studies, it may introduce potential confounding effects from the thermal mass and properties of these artificial structures. We kept our use of these structure consistent across all parks so any confounding effect would be systematic across our study, but free-standing poles could be used in the future. Nevertheless, this study still provides valuable references for city planners and park designers working with urban greening, especially to deal with the crisis of increasing urban heat.

4.6 Conclusion

Our findings support the hypothesis that aggregate tree clusters have a stronger cooling effect during daytime and a weaker effect at nighttime compared to discrete tree clusters. Both the configuration of trees and time of the day have a significant impact on relative temperature and humidity in parks compared to reference sites in built-up urban areas. We also emphasized the importance of open grass areas for park cooling during nighttime, although the effect on perceived temperature is likely moderated by associated increases in nighttime humidity. These findings provide insight for city planners to better manage different layouts of urban green infrastructure to meet people's various needs under local context. In addition, this research could be used to improve urban canopy models by incorporating differential parameterizations for

discrete vs. aggregate tree clusters and explicit representation of open grass areas. In the future, multi-city comparisons should be made among cities with similar climate conditions and development patterns to confirm whether our findings could be applied to similar regions. (Yu et al., 2020). In addition, by comparing the findings with cities in different climate zones, we can further generate a broader view of how tree configuration affects daytime and nighttime air temperature under different climates. Furthermore, better quantification approaches can be developed to select different configurations of tree clusters prior to sensor deployment. We also suggest exploring factors such as vegetation traits and urban morphology to further expand this work, so more context-based conclusions can be drawn to benefit local residents.

Connecting Statement 2.

Chapter 4 showed presence and configuration of trees have opposite cooling effects during daytime and nighttime. More specifically, open grass areas within parks have stronger nighttime cooling potential than treed areas, and aggregate tree clusters cool the ambient air during the day but trap heat at night. This chapter also found relative humidity exhibited an inverse pattern compared to air temperature among different sites in urban parks, and humidity moderates urban cooling, with reduced variation in wet-bulb temperature versus air temperature.

Among the various ecosystem services in urban areas, cooling and the filtration of air pollutants are the ones of greatest concern to residents. After chapter 3 and 4's investigation on LST and air temperature, I extended the exploration of ecosystem services to air quality improvement services in chapter 5. Urban parks serve as a hotspot for residents' activities and air pollutant alleviation service is highly valued by the public. However, urban parks' effect on ambient air pollutants at a local scale is still unclear based on empirical evidence. In this chapter, I designed a paired-site experiment to examine how the presence and configuration of trees in urban parks affect ambient NO₂ and O₃ concentration.

Chapter 5: Exploring the Impact of Tree Presence and Configuration on Ambient NO₂ and O₃ Concentrations in Urban Parks

5.1 Abstract

Urban parks have gained increasing global attention for their role as key hubs of human activity within cities. Among the multiple ecosystem services they provide, air pollution alleviation is one of the most valued by the public, and the service is dominated by the trees in urban parks. However, previous studies have not reached a consensus on the impact of urban trees and their configuration on NO₂ and O₃ concentrations, particularly at the local scale, and empirical research examining how trees influence these pollutant levels remains limited. There is also a lack of empirical research that explores the details of the potential mechanism by which urban trees affect ambient NO₂ and O₃ concentrations. We designed an observational experiment to monitor the NO₂ and O₃ concentrations in six urban parks in Montreal within two periods in July and August 2023. We investigate the impact of tree presence and configuration on ambient NO₂ and O₃ levels at a local scale. Our results indicate that tree clusters located at the edges of parks did not act as barriers to the dispersion of NO₂ from adjacent roads into the park interiors, regardless of whether the trees were planted in linear arrangements or grouped configurations. However, there was a slight “trap effect” of the trees on NO₂ concentrations. On the contrary, we observed a significant decrease of O₃ concentrations under tree clusters. Our study highlighted the various effects of tree clusters in urban parks on the concentrations of different ambient air pollutants. We also emphasized that the presence of trees played a more important role in air pollutants modification than tree configuration at a local scale.

5.2 Introduction

Air pollution, including nitrogen dioxide (NO_2) and ozone (O_3), can negatively influence human health via the respiratory and cardiovascular systems (World Health Organization, 2006). Traffic-related sources of NO_2 and the corresponding reactions that generate ground-level O_3 lead to a higher level of NO_2 and O_3 in urban areas (Anttila et al., 2011; Calfapietra et al., 2013). Vegetation helps to mitigate the effects of air pollution in multiple ways and thus improves human health and well-being (Nowak et al., 2018; Shen & Lung, 2017; L. Wu & Chen, 2023). Possible mechanisms include dispersion, interception, impaction, deposition, or a combination of these. At the individual plant scale, plants can uptake O_3 via both stomatal and nonstomatal processes (Fares et al., 2010). O_3 can be removed after entering the stomata and undergoing subsequent reactions within the intercellular region (Loreto & Fares, 2007). Plants can also absorb NO_2 via the stomata simultaneously with carbon dioxide (CO_2) or oxygen (O_2) during photosynthetic and respiration processes, respectively (Gourdji, 2018). However, the biogenic volatile organic compounds (BVOC) emitted by vegetation are a precursor of O_3 and O_3 could oxidize the NO to form NO_2 , which makes the role of urban vegetation on the local regulation of tropospheric O_3 concentrations very complex and influenced by species-specific emission rates of BVOCs and O_3 deposition rates (Fitzky et al., 2019). Given the complexity of mechanisms underlying pollution mitigation, additional empirical evidence is needed to explore the dominant mechanisms by which urban vegetation affects ambient air quality.

Although there has long been a public consensus that vegetation plays an important role in cleaning the air, this well-accepted association of urban green infrastructure with better air quality is among the ecosystem services that is least empirically supported in the literature, with studies varying in the strength and direction of their conclusions (Xing & Brimblecombe, 2020).

From the mechanism aspect, due to the complex interaction between NO₂ and O₃ concentrations and urban greening, there is no clear consensus on whether urban greening impacts these pollutants positively or negatively. Several studies find that urban trees reduce O₃ concentrations (Fares et al., 2020; Harris & Manning, 2010; Kofel et al., 2024; Sicard et al., 2018; Yli-Pelkonen et al., 2017), while others report reductions only during specific seasons (Fantozzi et al., 2015). In contrast, other studies suggest that urban trees increase O₃ levels through the emissions of large amounts of BVOCs (Buteau et al., 2017; Maison et al., 2024; Ren et al., 2017). For NO₂ concentrations, conclusions also vary. Some studies point out the “trap effect” of urban trees on NO₂ concentrations (Harris & Manning, 2010; Maison et al., 2024), some do not find solid evidence supporting the influence of urban trees (Yli-Pelkonen et al., 2017, 2020), whereas some gave the opposite conclusion that there is a great decrease of NO₂ under the tree canopy (Fantozzi et al., 2015).

Studies that consider the roles of vegetation on air quality often focus specifically on the role of: 1) street trees (Y.-P. Jia et al., 2021; Maison et al., 2024), 2) urban parks (Fares et al., 2020; Xie et al., 2024) and 3) urban forests (a more general term that includes all the trees and associated vegetation in urban area) (Escobedo et al., 2011; Fantozzi et al., 2015; Maison et al., 2024; Yang et al., 2023). Studies of urban parks as an individual branch have a shorter publication history compared to those for urban forests and street trees, and much of the conceptual foundation for urban park studies comes from urban forest research, whereas street tree studies have had far less influence (Xing & Brimblecombe, 2020). As a result, urban parks are frequently regarded as regional pollutant sinks and mistakenly assumed to function like urban forests as a whole, with the internal heterogeneity of parks often overlooked (Janhäll, 2015). Urban parks are exposed to air pollution because of their proximity to roads and, in some cases, other sources such as industrial

activities. The heterogeneous distribution of pollutants from nearby traffic means that dispersion processes must be considered. (Viippola et al., 2018; Xing & Brimblecombe, 2019). Within parks, tree clusters vary in structure, some resemble street tree alignments, while others form dense forest-like patches. This heterogeneity in vegetation configuration not only distinguishes urban parks from street tree or urban forest studies but also influences how pollutants are intercepted, trapped, or dispersed within the park (Xing & Brimblecombe, 2020).

Considering the limited space for tree planting in urban parks, a deeper understanding of the impact of tree presence and their spatial arrangement on ambient air pollutant concentration levels is helpful for urban park design and planning. Research shows that physical characteristics of trees can influence pollutant removal capacity (Baldauf, 2017; Gromke et al., 2016; Hagler et al., 2012; Y.-P. Jia et al., 2021; Tong et al., 2016). At the individual tree scale, physical characteristics, such as the height, length and thickness of the vegetation barrier are found to be important to remove more air pollutants (Baldauf, 2017). At a larger scale (a group of trees), species and configuration of green infrastructure are two major factors that affect air quality regulation (Baldauf, 2017; Gourdji, 2018). The impact of vegetation on the concentration of gaseous air pollutants such as NO₂ and O₃ may largely depend on the type and structure of local vegetation, climatic conditions, proximity to traffic pollution sources and regional and local ambient pollutant levels (Yli-Pelkonen et al., 2017). For example, for ozone mitigation, deciduous broadleaf species tend to remove O₃ the most effectively (Alonso et al., 2011); and for NO₂ mitigation, plant species tolerant to NO₂ levels are good options. Further, BVOC emissions are strongly correlated to high temperature (Fitzky et al., 2019), which means more amount of precursor of O₃.

Research about the effect of tree configuration is relatively limited. Some studies found lower O₃ concentrations in tree-covered habitats (Yli-Pelkonen et al., 2017), whereas other studies found the opposite phenomenon (Buteau et al., 2017). Another study reported that increasing the spacing between tree crowns and/or lowering their cross-sectional areas can decrease pollutant concentrations in street canyons, which means we don't need high tree stand density (Abhijith & Gokhale, 2015). To improve the empirical understanding of the effects of urban vegetation on local air pollution, Grundström & Pleijel (2014) compared NO₂ and O₃ near a major traffic route outside and inside a dense deciduous forest stand using passive diffusion samplers, and found that the reduction effect of vegetation on NO₂ existed in a traffic polluted environment, but O₃ showed a more variable response. However, at the local scale, pollution concentrations can be increased if trees: 1) trap the pollutants beneath tree canopies near emission sources; 2) limit dispersion by reducing wind speeds, and/or 3) lower mixing heights by reducing wind speeds (Nowak et al., 2014). Another gap in the literature is the lack of empirical evidence to show the impact of air temperature on urban trees' capacity to reduce the pollutant concentration at a local scale. Though some studies showed that heat waves increased O₃ and NO₂ concentrations, with a stronger effect on O₃ than NO₂ (Kalisa et al., 2018; Lokoshchenko et al., 2022; Theoharatos et al., 2010; J. Wang et al., 2024), the combined influence of air temperature and tree configuration has rarely been studied.

The objective of this paper is to provide more empirical evidence of the air quality benefits of green infrastructure in urban parks, and to examine how tree configuration and air temperature influence the effects. Specifically, we aim to answer the following questions: 1) How do different tree planting configurations (linear planting VS group planting) affect the ambient NO₂ and O₃ concentration levels within parks? 2) Does temperature have an impact on

the air quality? This study presents a case study on the Island of Montreal, focusing on local-scale interactions between urban park trees, air pollutants and temperature. We expect the outcomes of this paper to offer detailed empirical evidence of how tree presence and configuration, together with air temperature, influence ambient O₃ and NO₂ concentrations, and to provide a foundation for future fine-scale studies.

We performed local-scale field measurements of NO₂ concentration, O₃ concentration, and air temperature in six urban parks, investigating the NO₂ and O₃ concentration variations in different sites around the tree clusters. To understand variation in pollutants at a local scale, we designed a paired site experiment with in-situ sensors within the parks to assess different tree configurations with shared background conditions. Urban parks are a hotspot for human activities often serving a critical outdoor space. A better understanding of how tree configuration affects local air pollutant distribution can inform the design of healthier, more effective green spaces, directly supporting public health and urban planning decisions.

5.3 Methods

5.3.1 Study area

The study area is the Island of Montreal, Quebec, Canada, with a population of approximately 2 million people (Statistics Canada 2021), and containing Canada's 2nd largest city. The spatial concentrations of NO₂ and O₃ show opposite patterns in Montreal, higher concentrations of NO₂ are along highway corridors and in the downtown of the city, whereas concentrations of ozone are higher at the edge of the suburbs with more vegetation cover (Buteau et al., 2017). We focused our research on NO₂ and O₃ hotspots by selecting 6 parks located close

to the Metropolitan Autoroute in Montreal: Sir-Wilfrid-Laurier, Félix-Leclerc, Villeray, Pie-Xii, Ladauversière, Nicolas-Tillemont (Figure 13). The main tree species in the parks are maple trees (*Acer spp.*), which account for 43% of all public trees. More specifically, Silver maple (*Acer saccharinum*), Norway maple (*Acer platanoides*), and Common Hackberry (*Celtis occidentalis*) are the top 3 tree species (Table 19).

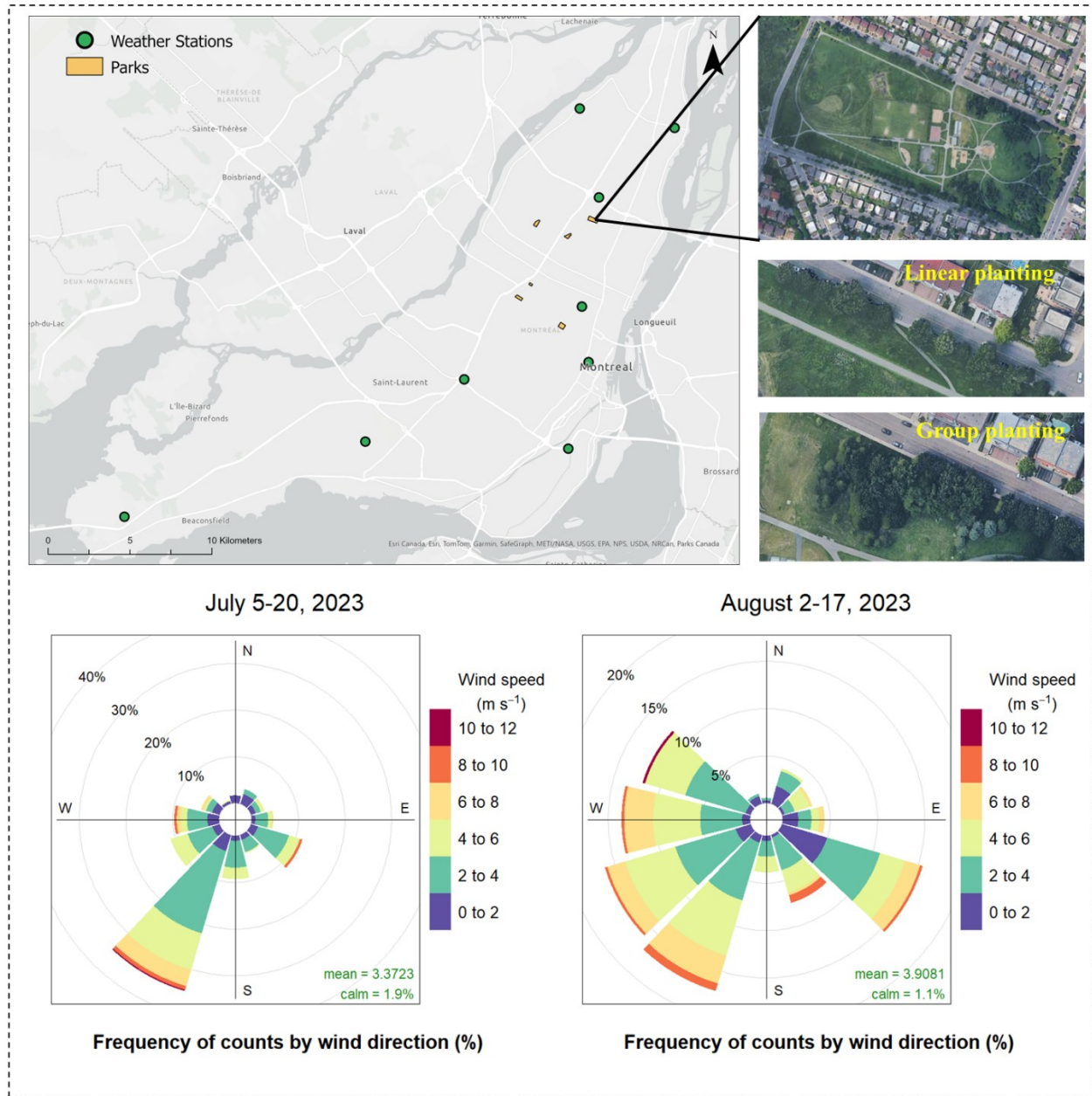


Figure 13. Study area and wind patterns during two observation periods. The top-left panel shows the spatial distribution of 6 parks (red outlines) and 9 weather stations (green points, called “ECCC weather station” later) in Montreal (installed by Environment and Climate Change Canada). The top-right insets illustrate two distinct tree planting configurations: linear planting and group planting. The bottom panels display windrose diagrams representing wind direction frequency and speed for July 5–20, 2023 (left), and August 2–17, 2023 (right). The dominant wind directions and mean wind speeds vary between periods, potentially influencing local pollutant dispersion patterns.

Table 19 Summary of the number and proportion of top 10 tree species across all the parks

Tree Species (English)	Tree Species (Latin)	Number	Proportion
Silver Maple	<i>Acer saccharinum</i>	562	21.08%
Norway Maple	<i>Acer platanoides</i>	310	11.63%
Common Hackberry	<i>Celtis occidentalis</i>	127	4.76%
Kentucky Coffee Tree	<i>Gymnocladus dioicus</i>	106	3.98%
Common Honey-Locust	<i>Gleditsia triacanthos</i>	98	3.68%
Spruce	<i>Picea</i>	77	2.89%
Littleleaf European Linden	<i>Tilia cordata</i>	74	2.78%
Sugar Maple	<i>Acer saccharum</i>	73	2.74%
Columnare Norway Maple	<i>Acer platanoides 'Columnare'</i>	66	2.48%
Colorado Spruce	<i>Picea pungens</i>	55	2.06%

Sample sites

The sample sites are in the parks close to a major highway (autoroute 40). Sensors were installed in 6 locations within each park (two sets of three sensors), to capture pollutant levels exterior to the park, within tree clusters (of two different configurations), and on the interior of the park, respectively (Figure 14). The first set corresponded to “linear planting” tree clusters (i.e., one line of trees) and included a sensor on the other side of the road outside of the park (A1), within the trees (A2), and inside the park in a non-treed area (A3). The second set mirrored the first, but focused on “group planting” (i.e., densely planted clusters of trees), again including an exterior-to-park sensor (B1), a sensor within the trees (B2), and in a non-treed area of the park interior (B3) (Figure 14). The sensors in A1, A3, B1, B3 sites were attached to lamp posts (or a fence on when lamp post was not available, $n = 2$) in an open area (not covered by the tree shadow). The distance from the inside park reference sites to the tree sites was between 5m and 15m (depending on the location of the lamp posts) (Fantozzi et al., 2015). Exterior sites were meant to capture ambient pollution surrounding the park, and were either placed in the road median, if present, or right on the other side of the road. We employed the passive samplers for two weeks each sampling period: from July 5th to July 20th 2023, and a second time from August 2nd to August 17th 2023. An air temperature and humidity sensor was installed beside each passive sampler to monitor the ambient air temperature and relative humidity. We also calculated the average temperature using the data from our installed sensors during the two periods.

5.3.2 Data

Air Quality Data

The use of passive samplers is one of the most commonly used approaches to determine spatial and temporal changes in concentrations of gaseous pollutants, though they only provide a single value during the monitoring period (Fan, 2011). To ensure reliability, we need to guarantee suitable exposure time in the field before the cartridges reach saturation. We chose to use OGAWA passive samplers to collect NO₂ and O₃ concentration data. The Ogawa Passive Sampler is accurate, easy to use and inexpensive, and is being used world-wide for the collection of NO-NO₂, NO_x, SO₂, O₃ and NH₃ (<https://ogawausa.com/>). Each passive sampler is composed of an end cap, two stainless steel screens, a pre-coated collection pad, a retainer ring, an inner base pad and a sampler body (one side). The pre-coated pad is the core part to collect the data, after ~two-weeks' observation period, the pre-coated pads are collected and analyzed followed the Ogawa protocol (Ogawa & Co., 2006). Due to the unpredictable factors, we lost one NO₂ passive sampler and two O₃ samplers in the end. We also collected hourly NO₂ and O₃ concentration data from 9 ECCC weather stations in Montreal from July 1st to August 31st, 2023. (<https://www.donneesquebec.ca/recherche/dataset/vmtl-rsqa-polluants-gazeux>).

Air Temperature Data

We attached CSL-H2 T0.2 relative humidity and temperature loggers (CredoSense) beside each OGAWA passive sampler to monitor the ambient air temperature. The operating temperature is from – 40 to + 85 °C, with the accuracy of relative humidity of ±2% typical and ±3% minimum, temperature of ±0.2 °C typical and ±0.4 °C minimum; the resolution of temperature is 0.01 °C and of relative humidity is 0.01%. Each sensor was enclosed in a professionally tested CredoSense radiation shield to avoid overheating by solar radiation and potentially biased measurements (Terando et al., 2017). In addition, we collected the hourly air

temperature data from ECCC weather stations in Montreal from July 1st to August 31st, 2023 (Figure 13) (<https://montreal.weatherstats.ca/download.html>).

5.3.3 Statistical Analysis

Before analysis, we used PlanetScope images (<https://www.planet.com/>) to verify the tree phenology in our sample sites between July 2023 and August 2023. This was to ensure that canopy conditions (e.g., leaf density, canopy cover) were comparable across the two measurement periods, minimizing the influence of phenological differences on pollutant concentrations under the tree canopy. We found that trees were fully in leaf during both sampling periods.

We first conducted a paired t-test to look at differences between A1 and B1 (exterior sensors associated with the same park) and A3 and B3 (interior sensors associated with the same park) to see if the ambient external and internal conditions are significantly different within each park.

We also examined the relationship between air temperature and NO₂ and O₃ concentrations using data from nine ECCC weather stations on the island to assess whether the correlations observed aligned with our field measurements, providing both a validation for our sensor data and a foundation for model development.

We used a mixed effect model to examine the effect of the tree configuration on the change of concentration of NO₂ and O₃ in Model (1), where C is the concentration of NO₂/O₃ in

each site, *Location* is 1(roadside), 2 (under trees), 3 (park interior), *Configuration* refers to two types of tree configurations (linear planting and group planting), *SamplePeriod* represent the cooler period (“L”) or the hotter period (“H”), *park* is the random effect.

To test whether there is a significant gradient in parks from outside to tree clusters and to park interior, we used ordered contrasts. The three-level ordered contrast was made following the mixed effect model, among roadside (Level 1), under tree clusters (Level 2) and park interior (Level 3) during hotter period (July) and cooler period (August). If the tree clusters act as a barrier to prevent NO₂ from spreading from the roadside to the park interior, the concentration gradient should follow this order: A1>A2>A3, B1>B2>B3. If the tree clusters act as the sink of the pollutant, the concentration of pollutants should be the lowest under the tree clusters compared to the two sides. Mixed effect model analysis and ordered contrast were done in R studio (package: *lme4*).

$$C \sim 1 + Configuration + Location + SamplePeriod + (1|park) \quad (1)$$

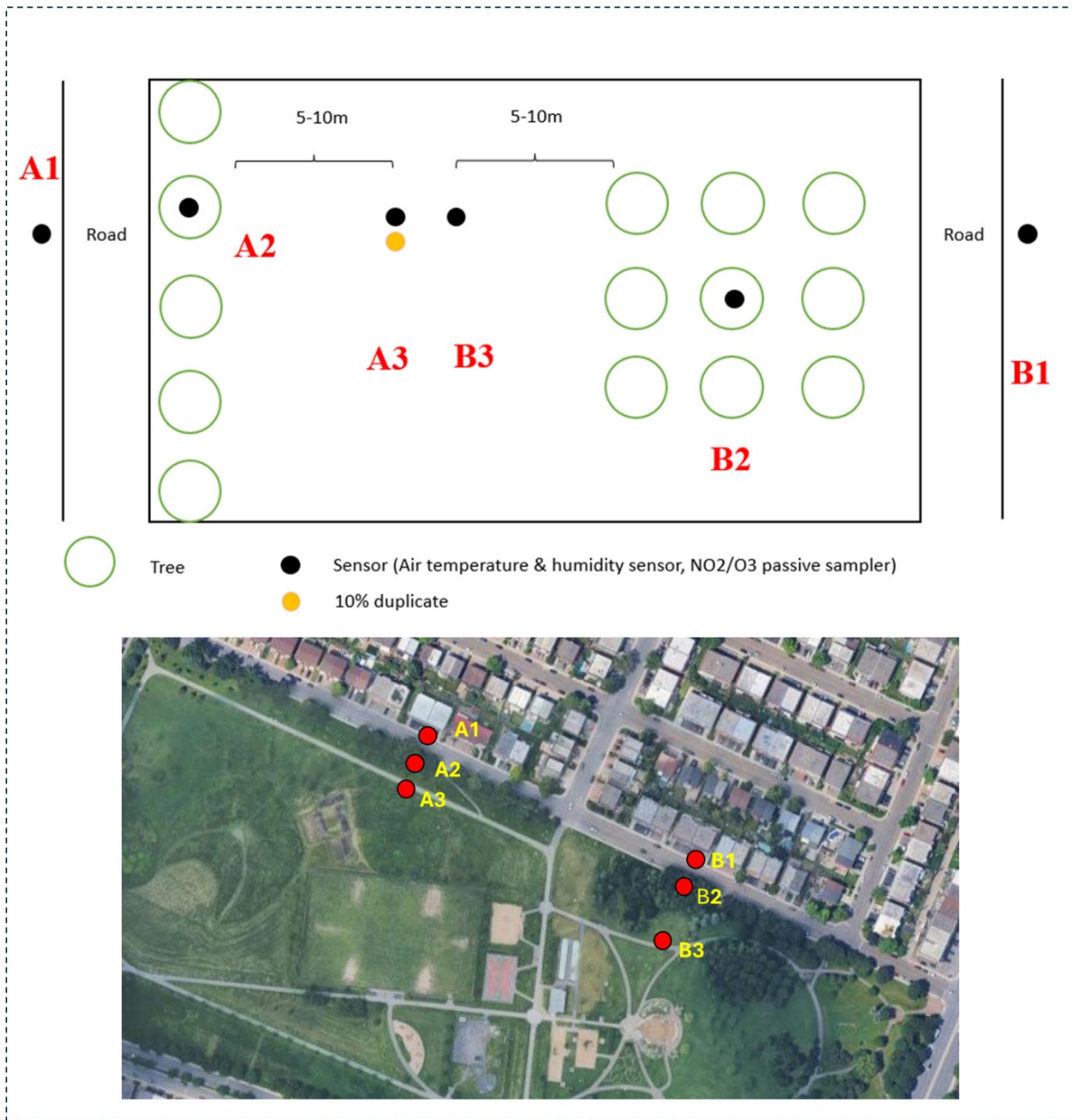


Figure 14 Upper is the schematic diagram of locations of the OGAWA passive samplers and CredoSense temperature & humidity sensors in each park and bottom is an example of Park Félix-Leclerc.

5.4 Results

5.4.1 The relationship between air temperature and pollutant concentrations

The linear regression analyses between the O₃/NO₂ concentration and air temperatures from the data collected from ECCC weather stations in Montreal showed significant positive relationships between O₃ concentrations and air temperatures (R² from across the 9 ECCC weather stations ranged from 0.25 to 0.51 for O₃ and air temperature) (Figure 15, Figure 16). However, the relationships between NO₂ concentrations and air temperatures were mostly negative and weak (R² from across the 9 ECCC weather stations ranged from 0 to 0.24 for NO₂ and air temperature). We found the average air temperature during period July 5th to July 20th, 2023 is higher than during August 2nd to August 17th, 2023 (Figure 17). The mixed effect model also revealed no significant difference in NO₂ concentrations between the hot and cool periods, while the difference in O₃ concentrations was significant (Table 21). Sample period strongly influenced O₃, with the cooler period showing 8.05 ± 0.55 ppb lower concentrations ($p < 0.001$).

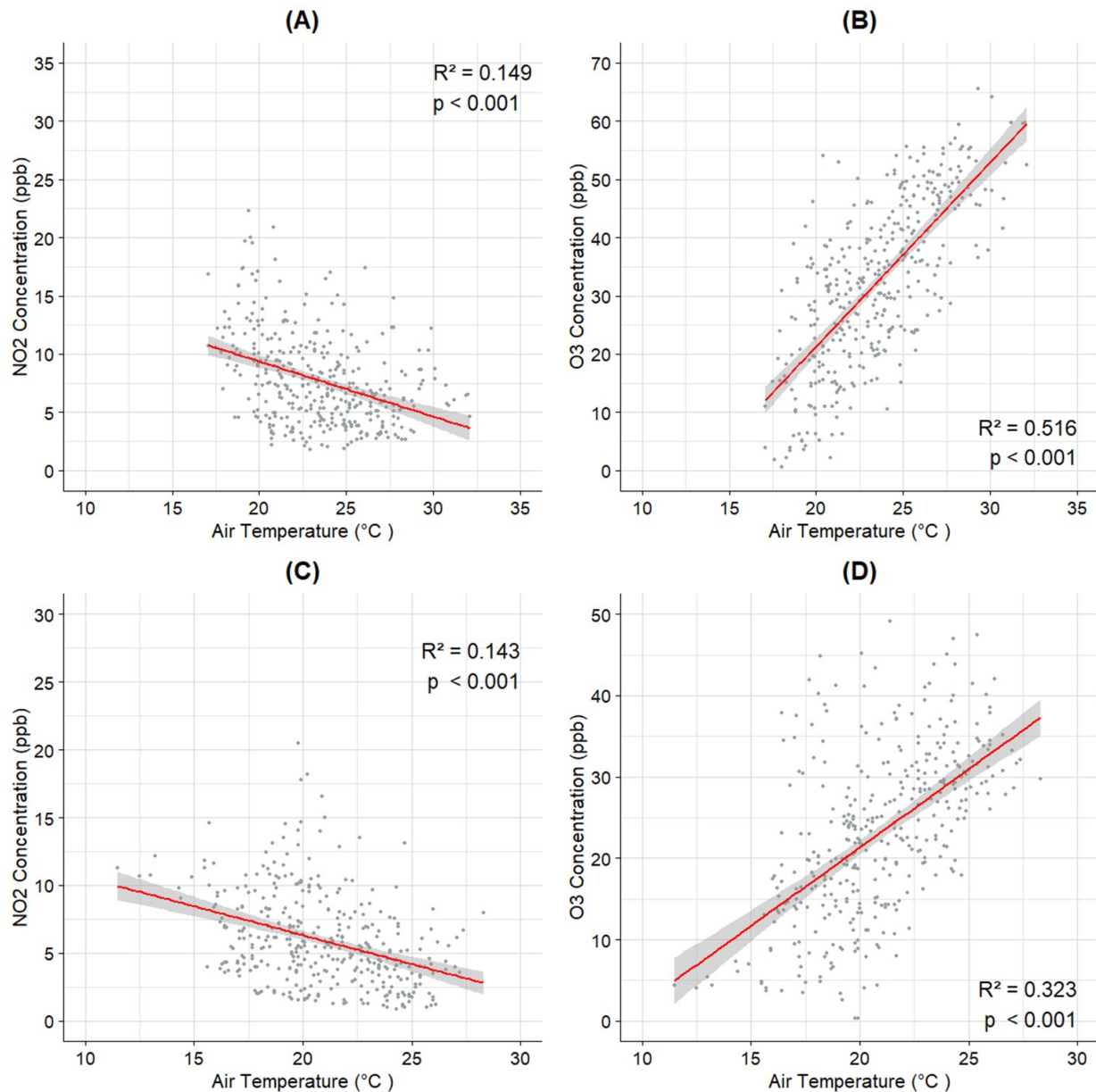
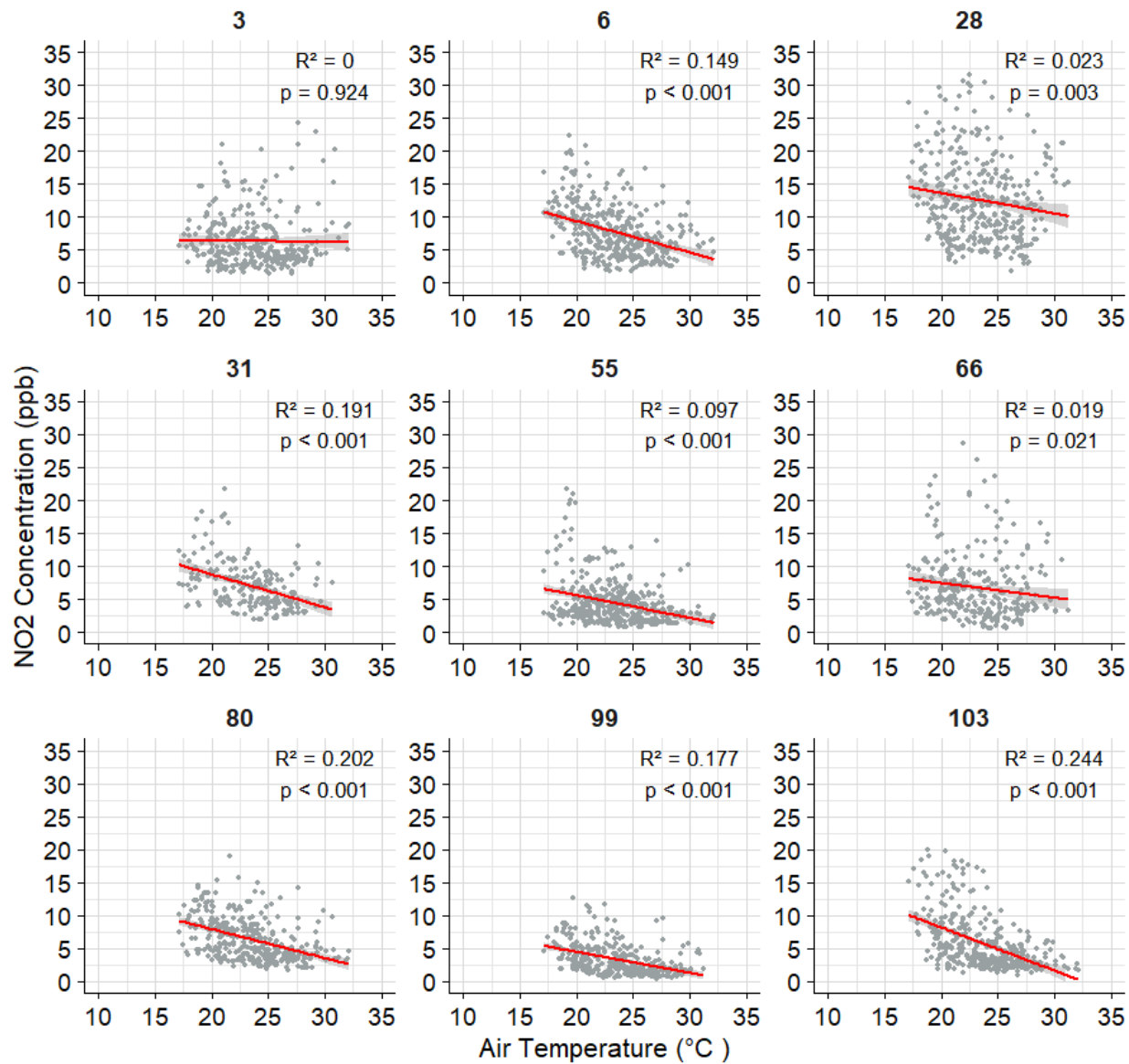
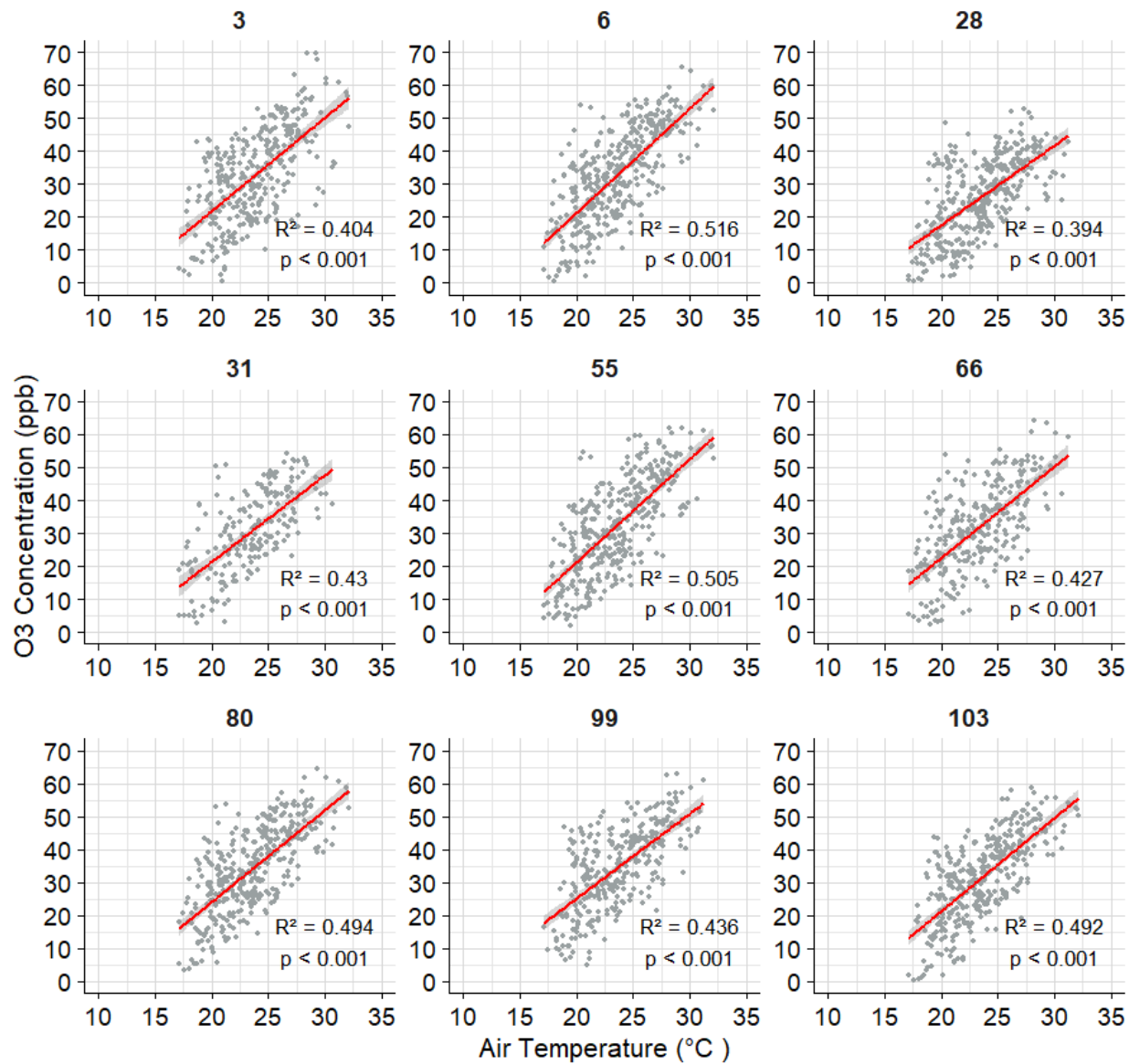


Figure 15 Scatterplots showing the relationship between NO₂ concentration (ppb) and temperature (°C) from one ECCC weather station in Montreal during July 5th, to July 20th (A), and during August 2nd to August 17th (C), 2023, between O₃ concentration (ppb) and temperature (°C) across nine ECCC weather stations in Montreal during July 5th, to July 20th (B), and during August 2nd to August 17th (D), 2023. The data is from the ECCC weather station No.6 installed by Environment and Climate Change Canada. Each point represents a NO₂/O₃ concentration record for an hour.

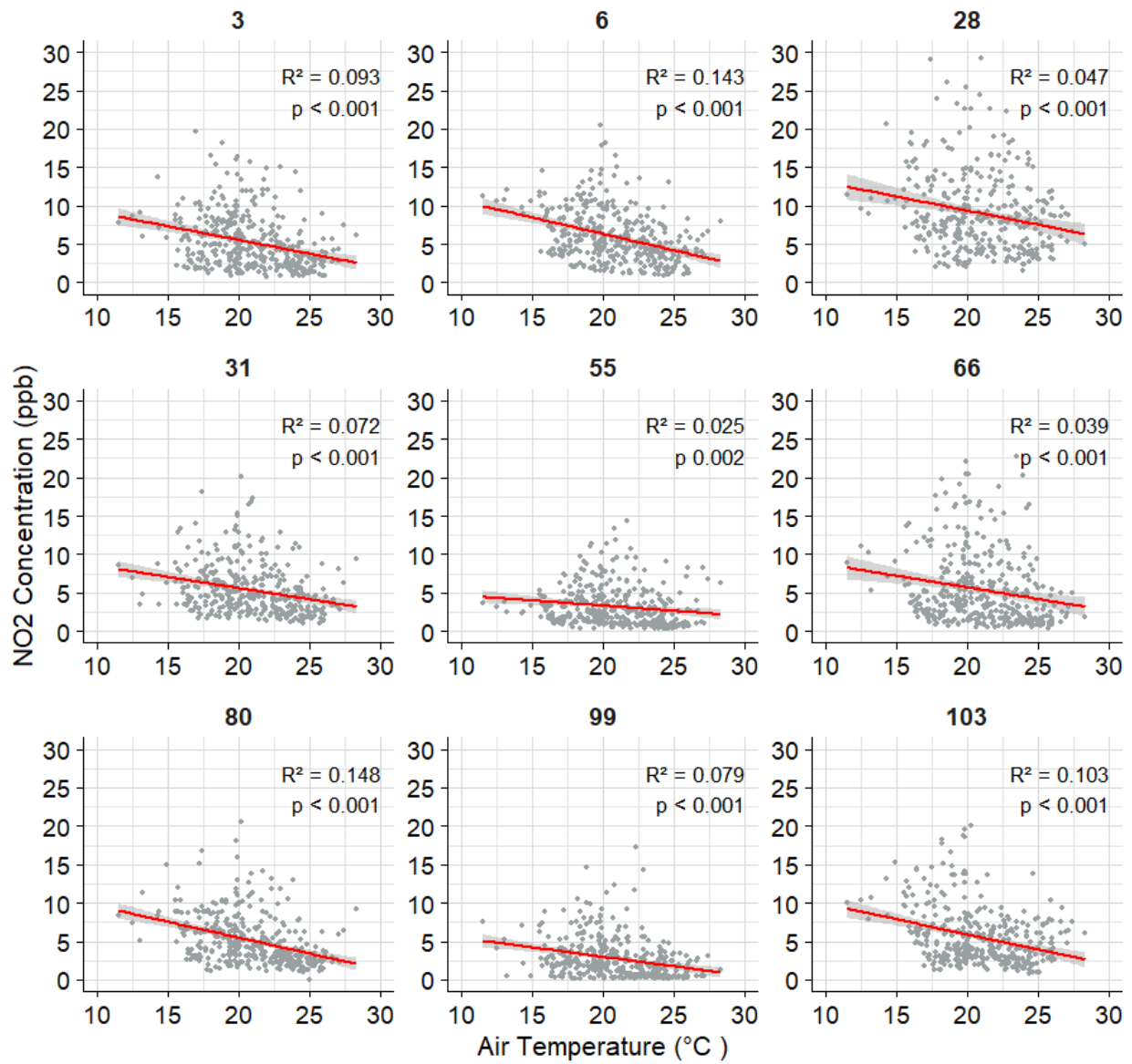
(A)



(B)



(C)



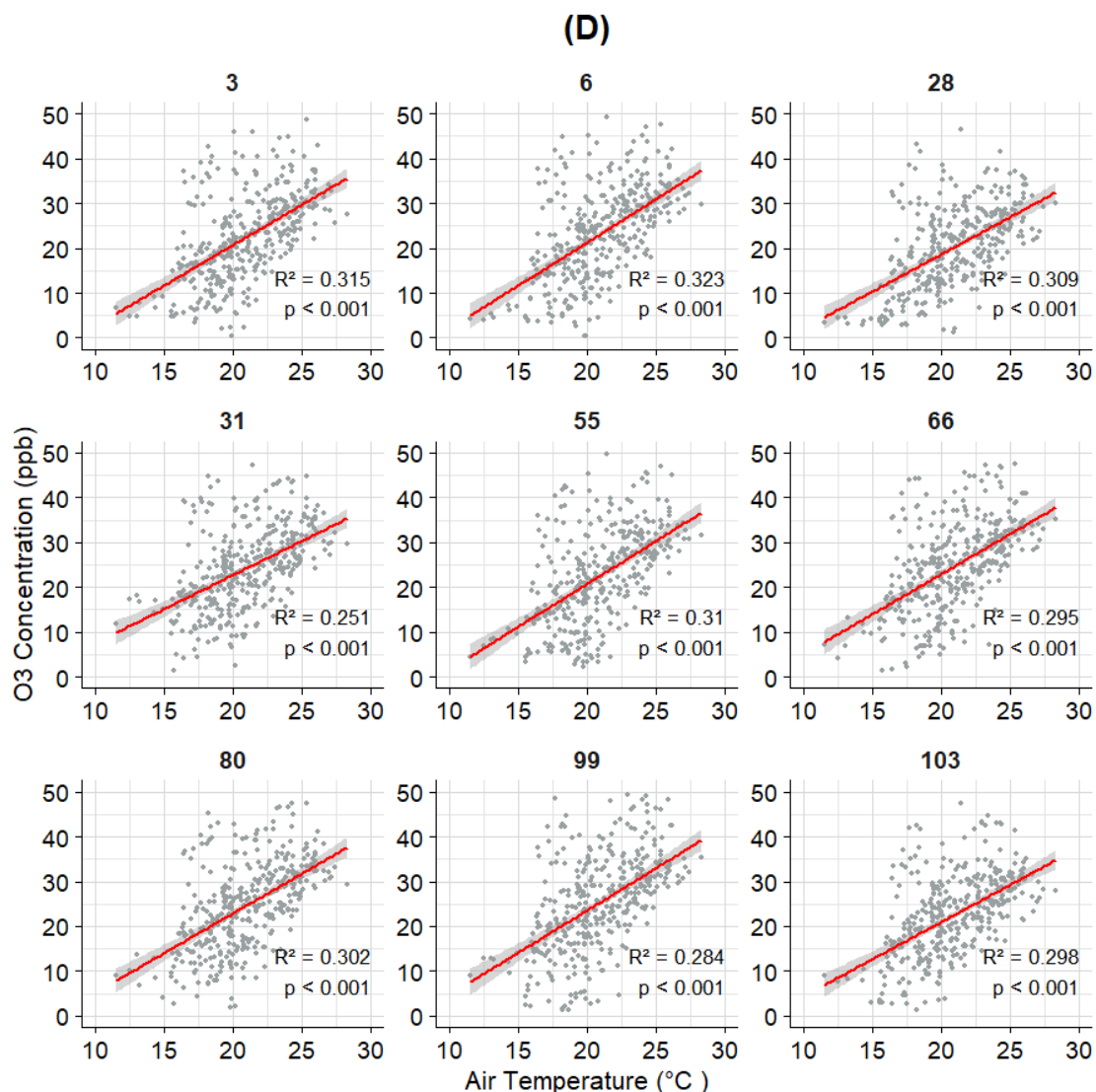


Figure 16 Scatterplots showing the relationship between NO_2 concentration (ppb) and temperature ($^{\circ}\text{C}$) across nine weather stations in Montreal during July 5th, to July 20th (A), and during August 2nd to August 17th (C), 2023, between O_3 concentration (ppb) and temperature ($^{\circ}\text{C}$) across nine weather stations in Montreal during July 5th, to July 20th (B), and during August 2nd to August 17th (D), 2023. Each panel represents a different weather station, with a linear regression line (red) and corresponding R^2 value indicating the strength of the association. Overall, the consistently moderate-to-strong positive correlations suggest a substantial influence of air temperature on O_3 levels; the associations between NO_2 concentrations and air temperatures are weak, as reflected by low R^2 values across all stations. Each point represents a NO_2/O_3 concentration record for an hour.

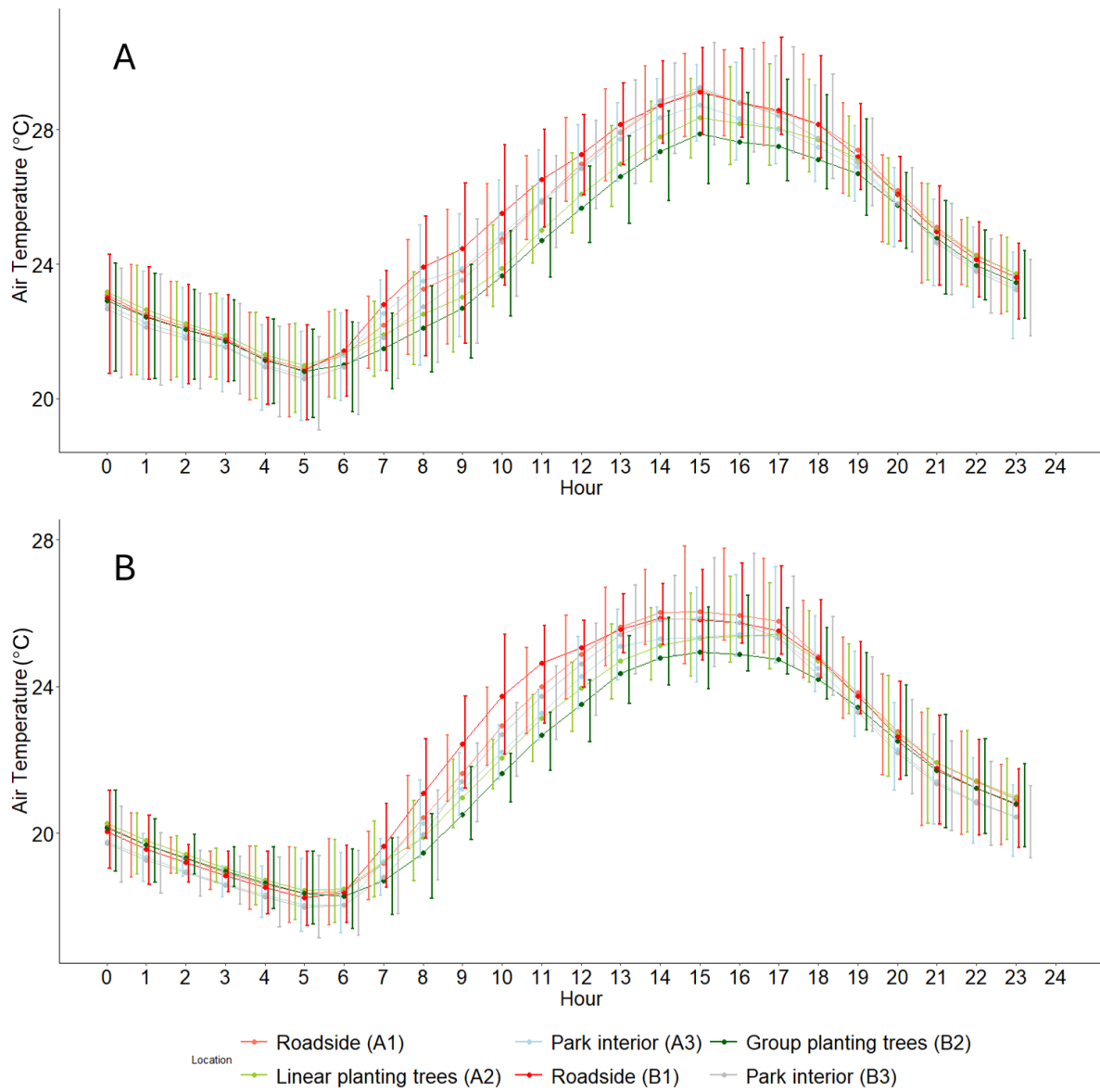


Figure 17 Line charts of mean and quantiles of hourly temperature between roadside (A1, coral red), linear planting trees (A2, light green), park interior (A3, light blue), roadside (B1, red), group planting trees (B2, dark green) and park interior (B3, grey). The bars refer to the 25th percentile and 75th percentile of the hourly temperature for all the parks during July 5th to July 20th, 2023 (A) and August 2nd to August 17th, 2023 (B).

5.4.2 The impact of park trees on ambient NO₂ and O₃ concentration

The results of the paired t-tests indicated that background concentrations of NO₂ and O₃ were similar, with the two roadside sampling locations and two interior sampling locations within each park showing no significant differences (Table 20). We observed a slightly higher concentration of NO₂ underneath the tree clusters in both July and August (except for the linear planting tree cluster in July), and a lower concentration of O₃ under the tree clusters during the same frame (Figure 18). NO₂ concentration under linear planting tree clusters was on average 5.32% higher than roadside concentrations, and 3.12% higher than park interior concentrations in July; in August it was on average 12.00% and 24.52% higher than roadside and park interior concentrations, respectively (Figure 18). NO₂ concentration under group planting tree cluster was on average 30.49% higher than roadside concentrations, and 18.14% higher than park interiors in July; in August it was on average 15.60% and 15.04% higher than roadside and park interior concentrations, respectively (Figure 18). O₃ concentration under linear planting tree cluster was on average 18.96% lower than roadside, and 11.56% lower than park interior in July; was on average 25.05% lower than roadside, and 15.03% lower than park interior in August, respectively (Figure 18). O₃ concentration under group planting tree cluster was on average 18.23% lower than roadside, and 21.55% lower than park interior in July; was on average 21.29% lower than roadside, and 20.64% lower than park interior in August, respectively (Figure 19). The concentrations of NO₂ and O₃ were not significantly different between roadside and park interior (Table 21). The configuration of trees did not significantly affect NO₂ (p value = 0.2278) but had a marginally

significant effect on O_3 ($P < 0.1$) which indicated that clustered trees have a stronger reduction effect on O_3 concentrations (Table 21).

Ordered contrasts showed that there's neither a significant linear trend for NO_2 nor O_3 concentration from roadside to tree clusters and to park interior (Table 22). However, there's a significant quadratic effect for both NO_2 and O_3 concentration. The negative coefficient of NO_2 concentration suggests a concave (inverted U-shaped) relationship—effects increase and then decrease from the roadside to tree clusters and to the park interior. While the large positive coefficient of O_3 concentration suggests a U-shaped pattern, which indicates the lowest values under the tree clusters.

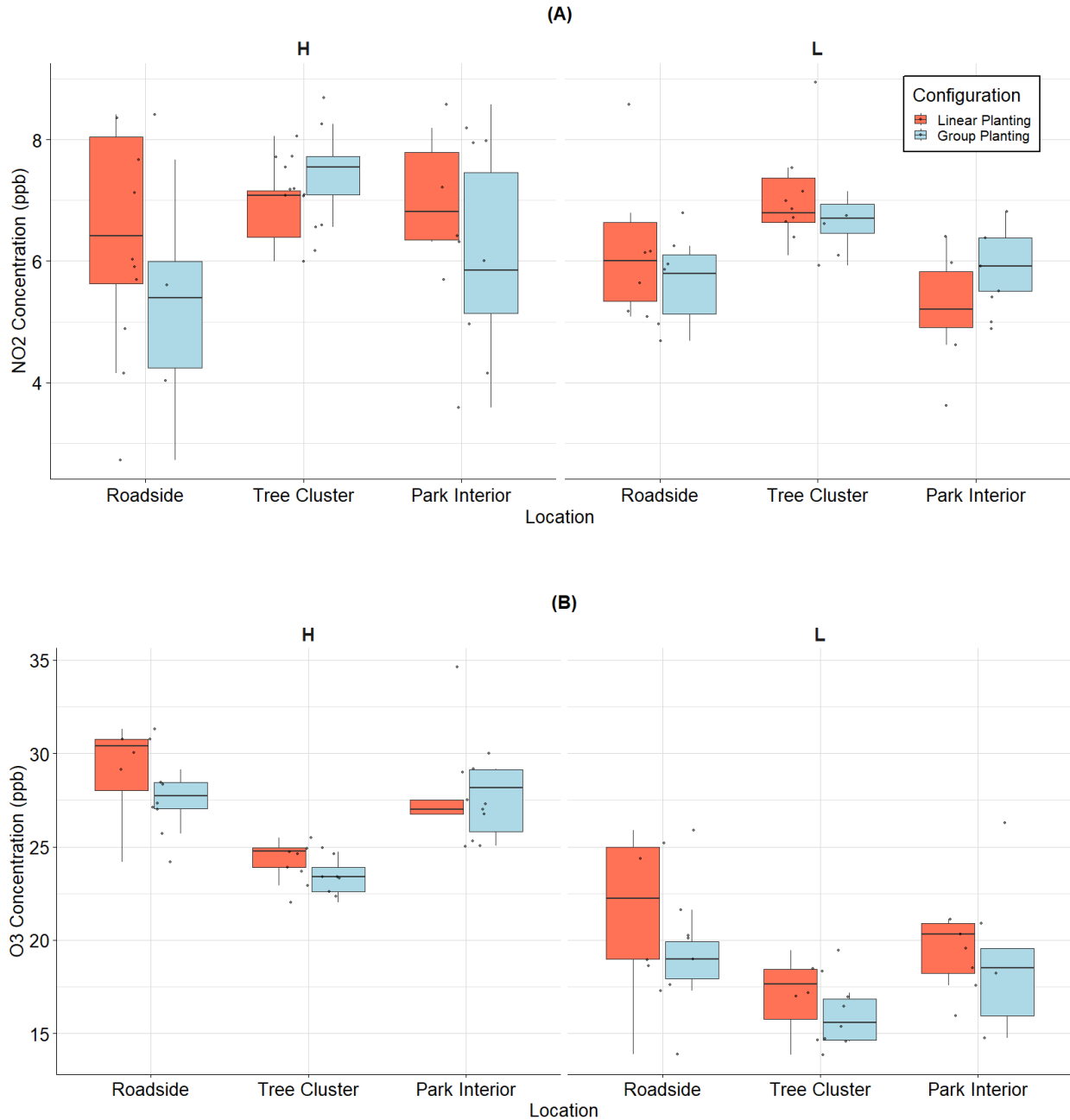


Figure 18 Boxplots of NO₂ concentration (A) and O₃ concentration (B), at roadside, under tree clusters and at park interior during July 5th, 2023 to July 20th, 2023 and August 2nd, 2023 to August 17th, 2023. Linear planting tree sets are all in green and group planting tree sets are all in orange. Coral color refers to linear planting tree pairs and light blue color refers to group planting tree pairs. H refers to the hotter period (July) and L refers to the cooler period (August).

Table 20 P-values from paired t-tests comparing pollutant concentrations (NO₂ and O₃) between paired roadside (A1-B1) and park interior (A3-B3) sites during July and August.

Pollutant	pairs	month	p-value
NO ₂	A1-B1	July	0.14
	A1-B1	August	0.25
	A3-B3	July	0.60
	A3-B3	August	0.46
O ₃	A1-B1	July	0.27
	A1-B1	August	0.19
	A3-B3	July	0.45
	A3-B3	August	0.81

Table 21 The results of the generalized linear mixed models exploring NO₂ and O₃ concentrations in roadside (reference), underneath linear planting tree cluster (A, reference) and group planting tree cluster (B), park interior during hotter period (“H”, July, reference) and cooler period (“L”, August). Estimated average coefficients $\pm$ S.E. are presented for all variables. p values are shown in the brackets.

Variables	NO ₂ concentration	O ₃ concentration
	Coefficient $\pm$ SE	Coefficient $\pm$ SE
Roadside	6.29 $\pm$ 0.34 ($< 2e-16$)	28.82 $\pm$ 0.69 ($< 2e-16$)
Under tree clusters	1.20 $\pm$ 0.32 (0.0005)	-4.20 $\pm$ 0.66 (2.4e-08)
Park interior	0.07 $\pm$ 0.34 (0.8412)	-0.70 $\pm$ 0.70 (0.3187)
Configuration (B)	-0.33 $\pm$ 0.27 (0.2278)	-1.00 $\pm$ 0.55 (0.0747)
SamplePeriod (L)	-0.42 $\pm$ 0.27 (0.1216)	-8.05 $\pm$ 0.55 ($<2e-16$)

Table 22 Results of three-group ordered contrasts analysis for NO₂ & O₃ concentration. This table presents the contrast analysis results comparing three ordered groups: roadside (Level 1), tree clusters (Level 2) and park interior (Level 3) with their linear and quadratic relationships tested. Coefficients represent the magnitude and direction of differences among groups, with roadside (Level 1) as the reference level. Standard errors (SE) and p values are reported alongside coefficients.

Level1-Level2-Level 3 Contrast	Estimate coefficient	SE	p value
NO ₂ (Linear)	0.07	0.34	0.84
NO ₂ (Quadratic)	-2.32	0.56	0.0001
O ₃ (Linear)	-0.70	0.70	0.32
O ₃ (Quadratic)	7.70	1.14	<0.0001

$$Y=kx^2+b$$

5.5 Discussion

We observed opposite distribution patterns of NO₂ and O₃ concentration in urban parks in Montreal. The NO₂ concentrations were significantly higher under the tree clusters compared to the exterior (i.e., roadside) or interior of the parks, while O₃ concentrations were significantly lower underneath the tree clusters. It is notable that the differences between roadside and park interior NO₂ concentrations were not significant within parks. This indicates that the tree clusters in our sample parks did not work as an obstacle to prevent NO₂ from spreading into the park from the exterior roadside environment.

In contrast to Yli-Pelkonen et al. (2020) and Yli-Pelkonen, Scott, et al. (2017), we found evidence of the trapping effect of the tree clusters on NO₂ concentration (Table 21 and 22). We see a significant peak under the tree clusters compared to the roadside and park interior, despite the different wind directions and speeds. This finding aligns with Harris & Manning (2010) and Viippola et al. (2018) that NO₂ concentrations are slightly higher inside the tree clusters or greenbelts compared to the open area. Our finding of significantly lower O₃ concentrations under tree clusters aligns with Yli-Pelkonen, Scott, et al. (2017), who found that the presence of tree cover could significantly reduce the O₃ concentrations but different with Grundström & Pleijel (2014) and Fantozzi et al. (2015) who did not find a significant reduction of O₃ concentrations or the decrease only found in one season (autumn).

Yli-Pelkonen et al. (2020) proposed that the lack of “trapping effect” in their study might be due to the size of the forest area or density of the patches. In our study, the concentration of NO₂ and O₃ under both linear planting and group planting tree clusters showed significant differences compared to the ambient open area. Our results also showed that the configuration of trees did not have a significant impact on NO₂ concentration, indicating that the presence of trees had a greater influence on NO₂ concentrations compared to their configuration. For O₃ concentrations, tree configuration exhibited a marginally significant effect ($p < 0.1$), potentially due to greater temperature reduction under group planting arrangements compared to linear (Pataki et al., 2011) (Figure 17). However, the relatively small size of the tree clusters in our study may have reduced the temperature contrast between these two configurations, which could explain the modest level of differences observed.

Different findings with respect to the impact of trees on O₃ concentration may be explained in part by tree species composition. Fantozzi et al. (2015) conducted their study under the *Q. ilex*

trees (evergreen) and found O₃ concentrations under the *Q. ilex* canopy were higher than that of open field in July. In our study, the two most common tree species were *Acer saccharinum* and *Acer platanoides*. *Acer sp.*, which are deciduous broadleaf species and among the top effective O₃-reducing tree species in North America, which have low ozone-forming potential (Sicard et al., 2018). However, *Acer platanoides* is an invasive species to Canada, this implies that except for the adverse impact, there can be ecosystem services provided by invasive species. Another reason for discrepancies in study results might be the spatial scale or size of the tree patches. Buteau et al. (2017) used several spatiotemporal prediction models to delineate the NO₂ and O₃ distribution in Montreal. The results indicated that concentrations of O₃ were higher at highly vegetated areas like the forests, which might be due to the emission of BVOC, the precursor of O₃ (Fitzky et al., 2019; Ren et al., 2017). The emission of BVOC might become a dominant factor that influences O₃ concentrations at mesoscale or macroscale, but at a local scale (e.g., within an urban park), the shade effect and the absorption effect of specific tree species may be stronger than the effect of BVOC emissions. In addition, the model conducted a spatial interpolation but didn't take account of the complexity of the land features, which might lead to the overlooking of the shade effect of tree canopy (Buteau et al., 2017).

Our analyses of both ECCC weather station data and local fine-scale measurements showed that O₃ concentration increased significantly with air temperature, whereas NO₂ showed no significant relationship, consistent with previous findings (Kalisa et al., 2018). Some studies have explored the complex effects of trees on NO₂ and O₃. For instance, Maison et al. (2024) quantifies the three main mechanisms of trees on NO₂, O₃ and other air pollutant concentrations using a multi-coupled model: dry deposition, aerodynamic effect and BVOC emissions. They found that dry deposition only provided very limited reduction of gaseous pollutants by at most a few percent.

The aerodynamic tree effect which modifies the air flow and limits the dispersion of air pollutants greatly increased the concentrations of NO₂ and thus increased O₃ concentration in streets. The emission of BVOC was found to have a slight increase effect on O₃ concentration, with a magnitude of 1-2%. In our study, the O₃ reduction rate mostly fell in 10%-30% between outside and inside tree canopy. The difference might be due to the monitoring context, where the model simulated the O₃ concentration on the streets (outside the tree canopy) and we directly monitored the O₃ concentration underneath the trees.

The simultaneous monitoring of NO₂ and O₃ concentration in our study also allowed us to have a deeper understanding on the impact of trees on ambient air pollutants in urban parks. The overall concentrations of O₃ were higher in July than in August, but the NO₂ concentrations did not show significant difference between the two months. Considering the connection between NO₂ and O₃ formation, the process of oxidization of NO by O₃ to generate NO₂ might not have made a significant contribution to NO₂ concentration under the tree clusters. Though Harris & Manning (2010) gave another explanation that the soil NO emission may play a role in higher level of NO₂ inside the urban tree canopy, our results seem not support this statement.

The differences between our result and model results emphasized the importance of field measurements and suggested current models may not be sufficient to simulate the complex uptake or increase effect of NO₂ and O₃ by urban trees at a local scale. More factors such as tree species diversity, vegetation vertical structure, or tree height need to be included in the analysis of the impact of urban trees on NO₂ and O₃ concentration, especially under specific local context.

Limitations and recommendations

First, this study took a case-study approach, conducted in six parks within Montreal. In our study, the selected parks were all located relatively close to major highways, where we expect to observe higher level of NO₂ concentration, potentially enhancing the observable effect of trees. Based on these criteria, relatively few parks are available for selection. Although the number of sites is limited, the study offers the advantage of capturing detailed information on pollutant concentrations and the role of tree clusters at a scale often missed in broader surveys. Building on these insights, future studies could expand the selection of urban parks across diverse environmental contexts (e.g., varying tree density, height of the trees, vertical structures) and increase the number of passive samplers to ensure a larger and more robust dataset. Second, the distance between tree clusters and two sides reference varied across different parks due to the random location of the lamp posts. This might cause some uncertainties in the result. In addition, the tree species of our tree clusters are not unified. Most of the trees in our selected parks were deciduous trees, especially maple trees, but the consistency of more specific species could not be guaranteed in an observational study. Furthermore, each passive sampler only provides one record during the monitoring period, which doesn't allow us to observe the temporal variation of the pollutants and consider more details under the context, such as wind speed, wind direction, etc. More real-time monitoring equipment could be used in the future to get more details on the impact of urban trees on NO₂ and O₃ concentration. This would be helpful to better understand the mechanisms and improve the air pollutant prediction models as well. Nevertheless, this study still provided valuable observations and references for researchers working on urban parks' impact on air quality improvement, for example, to determine what a minimum size of a close tree cluster needs to be to have any effect on the inside area, and include more factors like tree species, heights and vertical structure in future studies.

5.6 Conclusion

NO₂ and O₃ are among the most harmful urban air pollutants, linked to respiratory irritation, asthma aggravation, and reduced lung function. Understanding how urban trees can help mitigate these pollutants is therefore important for creating healthier, more livable cities. Using paired-site, local-scale empirical monitoring of the NO₂ and O₃ concentration, our results indicated that the tree clusters at the edge of the urban parks have limited impact to prevent the dispersion of NO₂ from the roadside to park interior whether the planting configuration of the trees is linear or in a group. We observed slight increase of NO₂ concentrations and a large decrease of O₃ concentrations under the tree clusters. The results also indicated a positive relationship between air temperature and O₃ concentrations. Though our results do not reveal the mechanisms by which urban trees influence spatial variations in NO₂ and O₃ concentrations, this study still provided valuable references for future work, whether it is field measurements or modeling process.

By comparing our findings with previous studies, we provide insights into how urban greening can be managed to improve air quality and how park design can be optimized to benefit residents within specific local contexts. Our study also lays the groundwork for future research which can address our current limitations such as the sample size and short monitoring periods, and by extending analyses to additional sites. Future studies should also incorporate tree species composition, vertical and canopy structure, and local weather conditions, which may play critical roles in shaping NO₂ and O₃ dynamics in urban parks.

Chapter 6: Overall Conclusions

Key findings

In this dissertation, I analyzed the relationship between spatial patterns of UGI and ecosystem services capacities, more specifically, urban cooling and air quality mitigation services across two spatiotemporal scales and explored the distributional inequity of UGI in terms of cooling supply-demand mismatches. I employed remote sensing, in-situ measurements, and statistical models to evaluate the cooling and air pollutant filtration services of UGI, addressing four main objectives.

The first objective is to explore the relationship between land surface temperature and composition & configuration metrics of UGI at multiple spatial scales. I found the composition variables (percent cover of high and low vegetation) are both significantly correlated with LST at both borough and census tract scale. Configuration variables have a more significant influence on LST at the smaller census tract spatial scale. Further, the percent cover of both high and low vegetation and largest patch index of only high vegetation are three main factors to predict the cooling ability of the UGI during summer daytime.

The second objective is to assess the spatial pattern of UGI in Montreal in terms of their cooling capacity and explore the corresponding environmental injustice. The supply index of cooling service was calculated based on the prediction model and the demand index was calculated based on the age structure of the population in each census tract. The mismatch analysis revealed the imbalance between the supply and demand of cooling services across the island of Montreal, representing the ‘budget’ of cooling services. Further incorporation between mismatches and

socio-economic indicators uncovered the underlying environmental injustice. This chapter showed that communities with lower income, lower education levels and higher proportions of visible minorities receive less cooling services provided by the UGI than they demand, compared to communities with higher socioeconomic status in Montreal.

The third objective is to examine the differences in urban heat mitigation provided by various vegetation configurations between daytime and nighttime in small urban parks. A paired site design of in-situ sensors within urban parks assessed detailed tree configurations with shared background conditions. Mixed effect models and ordered contrast presented the significant differences in urban heat mitigation provided by various tree configurations between daytime and nighttime. The potential underlying mechanisms were also deeply discussed in this chapter. I found that aggregate tree clusters have a stronger cooling effect during daytime and a weaker effect at nighttime compared to discrete tree clusters. Both the configuration of trees and time of the day have a significant impact on relative temperature and humidity in parks compared to reference sites in built-up urban areas. Further, this chapter also pointed out that humidity moderates urban cooling, with reduced variation in wet-bulb temperature versus air temperature.

The last objective is to provide detailed, empirical evidence of the impact of trees in urban parks on ambient NO_2 and O_3 concentrations. The result indicated tree clusters tend to trap NO_2 underneath while reducing O_3 concentrations at a fine scale. The extent of the impact is spatially limited but shows consistent influence under the canopy. This chapter underscored the importance of presence of trees rather than their configuration on air pollution mitigation while also informing the potential effect of configuration on air temperature regulation, which can indirectly influence the air pollution concentrations.

Overall, my research demonstrates that both the composition and configuration of urban green infrastructure (UGI) play an important role in regulating urban microclimates, with important implications for climate resilience, human well-being, and environmental equity. Across spatial scales, vegetation cover and patch structure significantly influenced land surface temperatures, with fine-scale configurations such as patch size or tree clustering showing more significant localized cooling effects. Tree arrangement further shapes park microclimates, with aggregated clusters providing greater daytime cooling than discrete clusters, but weaker nighttime effects. Open grass areas contribute to nighttime cooling although the effect is smaller with higher humidity. In addition to thermal regulation, UGI influences atmospheric chemistry: while tree clusters show limited effects on NO₂ concentrations, they consistently reduce O₃ levels. My paired-site experiment indicates that the presence of trees shows more significant effect than their planting configuration on air quality regulation at local scale.

Research and management recommendations

Taken together, these findings underscore the need for urban greening strategies that account for vegetation composition and configuration, as well as temporal variability between day and night. They also highlight social inequities in the distribution of cooling services, with vulnerable communities often experiencing higher unmet demand. The research provides practical guidance for city planners, particularly in humid continental climates, while laying the foundation for broader application through multi-city comparisons, refined canopy and air quality models, and integration of additional factors such as tree species, urban morphology, and human thermal comfort. More broadly, this work contributes to advancing climate adaptation planning by showing

how UGI design can simultaneously improve urban livability, reduce environmental inequalities, and enhance resilience to climate change.

Significant contributions

This study makes several significant contributions. The first paper demonstrates that both the composition and configuration of urban green infrastructure (UGI) influence land surface temperatures, with configuration effects becoming more pronounced at finer spatial scales. This increased importance of configuration at fine scales is important knowledge for urban planners and residents who often implement changes at local property or neighbourhood scales. By developing a predictive statistical model based on vegetation cover and patch metrics, the research also provides a transferable framework for estimating UGI cooling capacity. Importantly, it advances environmental equity research by integrating green space configuration and introducing a demand index that captures the needs of physically vulnerable age groups, revealing systematic mismatches in cooling service provision that disadvantage low-income and minority communities. Beyond these findings, the study delivers actionable insights for climate adaptation planning in humid continental and similar climates, while also establishing methodological groundwork for future research through recommendations on multi-temporal data, finer-resolution LST products, human thermal comfort indices, and multi-city comparative studies.

My second paper makes three key contributions to urban heat and green infrastructure research. First, it provides empirical evidence on how tree configuration within urban parks—discrete versus aggregate clusters—affects ambient air temperature, relative humidity, and wet-bulb temperature across both day and night, moving beyond the daytime-focused, surface-

temperature-centered studies common in the literature. Second, it highlights the interactive effects of tree arrangement and time of day, showing that aggregate clusters enhance daytime cooling but reduce nighttime cooling, while open grass areas contribute to nighttime cooling despite increasing humidity. Third, the findings offer practical guidance for urban planning and modeling, suggesting ways to design park vegetation layouts that optimize thermal comfort and informing improvements to urban canopy models through differential parameterization of tree configurations and explicit inclusion of grass areas.

My third paper makes several key contributions to air quality and urban park research. First, it makes up for the limited empirical observation of NO₂ and O₃ concentrations in tree configuration studies. It provides field observations at a fine scale and reveals the opposite impact of tree clusters on ambient NO₂ and O₃ concentrations. Second, it underscores the importance of tree presence on local scale air quality, further highlighting people's need for trees in urban areas. Third, the paired site design has provided valuable groundwork for future air pollution mitigation research at local scales and emphasised the essentiality of considering the heterogeneity within urban parks. It also stimulates new research directions to think about regarding urban park design, for example, to determine what a minimum size of a close tree cluster needs to be to have any effect on the inside area, and the impact of more factors like tree species, heights and vertical structure.

Together, my thesis findings advance understanding of how spatial patterns shape ecological processes in urban systems and inform practical strategies to enhance ecosystem service provision, while underscoring the importance of prioritizing underserved communities in urban greening efforts.

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