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The effects of urban density on the provision of multiple health-related ecosystem services

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Abstract
Cities globally are expanding at an unprecedented rate, requiring an understanding of how to grow cities in a way that minimizes environmental impact while providing ecological benefits to people. Compact cities are often advocated for due to reduced impacts on biodiversity. However, increased development within an existing urban footprint may lead to loss of ecosystem services (ES) if accompanied by a loss of greenspace. We use spatial data and remote sensing approaches to explore relationships between urban form and indicators of health-related ES (temperature regulation, air pollution regulation, greenspace accessibility) at 250 study sites across a range of percent building cover in Montreal, Canada. We ask: 1) How does building cover and associated landscape structure affect multiple biophysical indicators linked to health-based ES? 2) Is population density (as a proxy for flow of ES to recipients) related to ES provision at the scale of investigation once building cover is accounted for? Relationships between building cover and indicators of ES provision varied across the studied indicators. Loss of greenspace accompanying increased building cover did not affect air quality, for example, which depended strongly on pollutant sources. However, increased building cover – and accompanying vegetation loss – was a strong driver of higher daytime temperatures. For ES provided by greenspace access, there was a trade-off between the ability to provide public vs. private greenspace; suggesting public greenspace should be prioritized to maximize ES provision. Overall, our findings support that urban densification must be pursued with consideration for the overall landscape structure, and prioritize maintenance of vegetation in particular.

Keywords Land surface temperature · Air quality · Urban greenspace · Ecosystem services · Urban densification

Introduction

By 2050, 68% of the global population is expected to live in cities (United Nations 2019). In many parts of the world, urban land area is expanding at a faster rate than urban populations are increasing (Seto et al. 2011), contributing to the phenomenon of urban sprawl (Nazarnia et al. 2016). This rapid expansion of built infrastructure has serious environmental implications, including habitat loss and reduced environmental quality due to land use conversion (McDonald et al. 2019). Therefore, the concept of compact cities – with dense and proximate development patterns – has gained popularity. Compact cities have many benefits, as emphasized by United Nations' Sustainable Development Goals (i.e., greater access to sustainable modes of transportation) (United Nations 2021). However, if urban densification is achieved via an increased number of buildings within an existing urban footprint, this can potentially lead to decreases in the provision of ecosystem services (ES, benefits people derive from nature) (MEA 2005) due to loss of urban greenspace (Lin et al. 2015).

Potential trade-offs between compact cities and those dominated by lower density development have frequently been examined under the 'land-sharing' vs. 'land-sparing' framework adapted from agriculture (Lin and Fuller 2013; Phalan et al. 2011) – particularly with respect to biodiversity conservation. 'Land-sharing' describes dispersed housing, interspersed with greenspaces across a wide area. The land-sharing model is frequently criticized as promoting urban sprawl, which eliminates natural habitats and puts many species at risk (Soga et al. 2014). For example, populations

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of both butterflies and ground beetles have been observed to decline in land-sharing environments at high levels of urbanization (Soga et al. 2014).

In contrast, 'land-sparing' describes a dense urban area with a small geographic footprint. Under the land-sparing model, biodiversity may benefit due to the presence of intact habitat outside the developed area (Geschke et al. 2018), but within densely built areas, there is potential for depleted environmental quality (Nelson et al. 2009). This suggests a potential trade-off between development scenarios that promote biodiversity conservation compared to ES provision, which has been less frequently examined in relation to urban density. Further, while the land-sharing vs. land-sparing framework provides a starting point to understanding potential benefits and drawbacks of different urban forms, it often relies on collapsing urban form into two categories, 'dense' or 'sprawling', which excludes many urban areas that fall between these two extremes. To understand ways in which cities can grow while supporting ES provision, research is needed that considers a more complete range of urban forms, including variation in building cover and the accompanying landscape structure.

A major challenge of the increased building cover often accompanying urban densification is the associated reduction in greenspace. This loss of greenspace has implications for urban ES related to human health, that are often produced in close proximity to where the impacts are felt (Koprowska et al. 2020; Tzoulas et al. 2007). Thus, as anthropogenic impacts associated with density increase, we are simultaneously losing the greenspace that may help to mitigate these impacts. For example, high temperature is a known issue in dense urban areas due to the urban heat island (UHI) effect, or hotter temperatures in cities relative to their rural counterparts (Arnfield 2003). Primarily a result of replacing vegetation with impervious surfaces, hot urban temperatures increase the vulnerability of urban residents to extreme heat events (Patz et al. 2005; Jenerette et al. 2016) with increased greenspace and canopy providing temperature mitigation services. Similarly, poor air quality may be exacerbated in dense areas, due to a high density of pollutant sources, such as vehicles or industry, combined with a lack of vegetation to filter pollutants from the air (Escobedo et al. 2011; Nowak et al. 2018). Air pollution is positively associated with increased prevalence of cardiovascular disease and death from all causes (Dominici et al. 2006; Rustgi et al. 2018). Disparities in physical access to urban greenspace, often measured both as distance to greenspace and amount of nearby greenspace is also a well-documented urban trend (Koprowska et al. 2020; Lin et al. 2015). While the drivers of these disparities can differ depending on the local context and include, for example, wealth, and racism, reduced access to greenspace is closely linked to urban form (Schell et al. 2020). Distributional inequities in greenspace access are concerning because reduced access and exposure to greenspace can lead to significant negative impacts on physical and mental health, particularly for children (Demoury et al. 2017; Engemann et al. 2019).

The effects of greenspace loss may also be non-linear, such that past a certain threshold, ecosystem services are not delivered. For example, temperature regulation has been observed to respond non-linearly to changes in canopy cover (Ziter et al. 2019), as well as park size (Cheng et al. 2015). The nonlinearity of these relationships can make it difficult to quantify the extent to which a reduction in greenspace may affect ES provision. This highlights a limitation of the land-sharing – land-sparing model. In real urban landscapes, the relative area occupied by built vs. green infrastructure exists along a gradient, which may interact with thresholds of ES provision.

Here, we use existing data and remote sensing techniques to determine how multiple biophysical indicators linked to ES provision vary along a gradient of urban building cover: comparing measurements of temperature, air pollution and greenspace accessibility (private and public) across the island of Montreal. These three environmental indicators were selected due to their importance for human health, and their expected sensitivity to changes in greenspace as a city densifies. Thus, while we did not measure ecosystem services directly, our chosen environmental indicators allow us to make inferences regarding changes in ES capacity.

As a key goal of quantifying ES is to consider how biophysical effects of nature benefit people, it is important to consider not only a landscape's capacity to produce a service, but the flow of that service to the people for whom it is in demand (Burkhard et al. 2012; Villamagna et al. 2013). While demand for ES can vary based on many factors (e.g., people's preferences, values, or vulnerabilities, Wolff et al. 2015), for the services considered here, we can consider the urban population an important proxy of the number of people who stand to benefit—particularly for non-consumed benefits. For example, the more people who are present in an area with clean air and comfortable temperature, the more efficient the provision of those services is. Consequently, we considered population density as an important factor in quantifying ES provision, because it takes a simple biophysical indicator or proxy, like amount of greenspace (which can be considered an indicator of supply or capacity) and provides additional context for the extent to which this service flows to people.

Specifically, we asked:

1. How does percent building cover and associated landscape structure affect multiple biophysical indicators linked to health-based ES?

2. Is population density related to the provision of ES at the scale of investigation once building cover is accounted for?

We hypothesized that there would be a negative, but non-linear, relationship between local building cover percentage and both temperature and air quality – due to reduced greenspace in dense neighbourhoods, and thus a decrease in the provision of both temperature regulation and air quality regulation services. We expected a linear negative relationship between percent building cover and the provision of greenspace accessibility. Our second hypothesis was that population density would not be related to air quality or temperature once percent building cover is accounted for but will be negatively related to access to greenspace because as more people must share the same greenspace, this translates to less greenspace per capita.

Methods

Study area and site selection

Montreal is a large Canadian city of approximately two million inhabitants (Statistics Canada 2016). It is an island in the St. Lawrence River in the province of Quebec (Fig. 1). The climate of Montreal is characterized by humid continental conditions, with cold winters and hot summers (Government of Canada 2021). Montreal has a long history of urban development that has led to its current urban form (Fougeres and MacLeod 2017). Compact, multifamily housing (e.g., multiplexes, townhouses, and low-rise apartments) is common compared to other North American cities, leading to many dense, walkable neighbourhoods; however, Montreal has also experienced exponential urban sprawl since the 1950s (Nazarnia et al. 2016). Thus, there is substantial variability in urban form throughout the city.

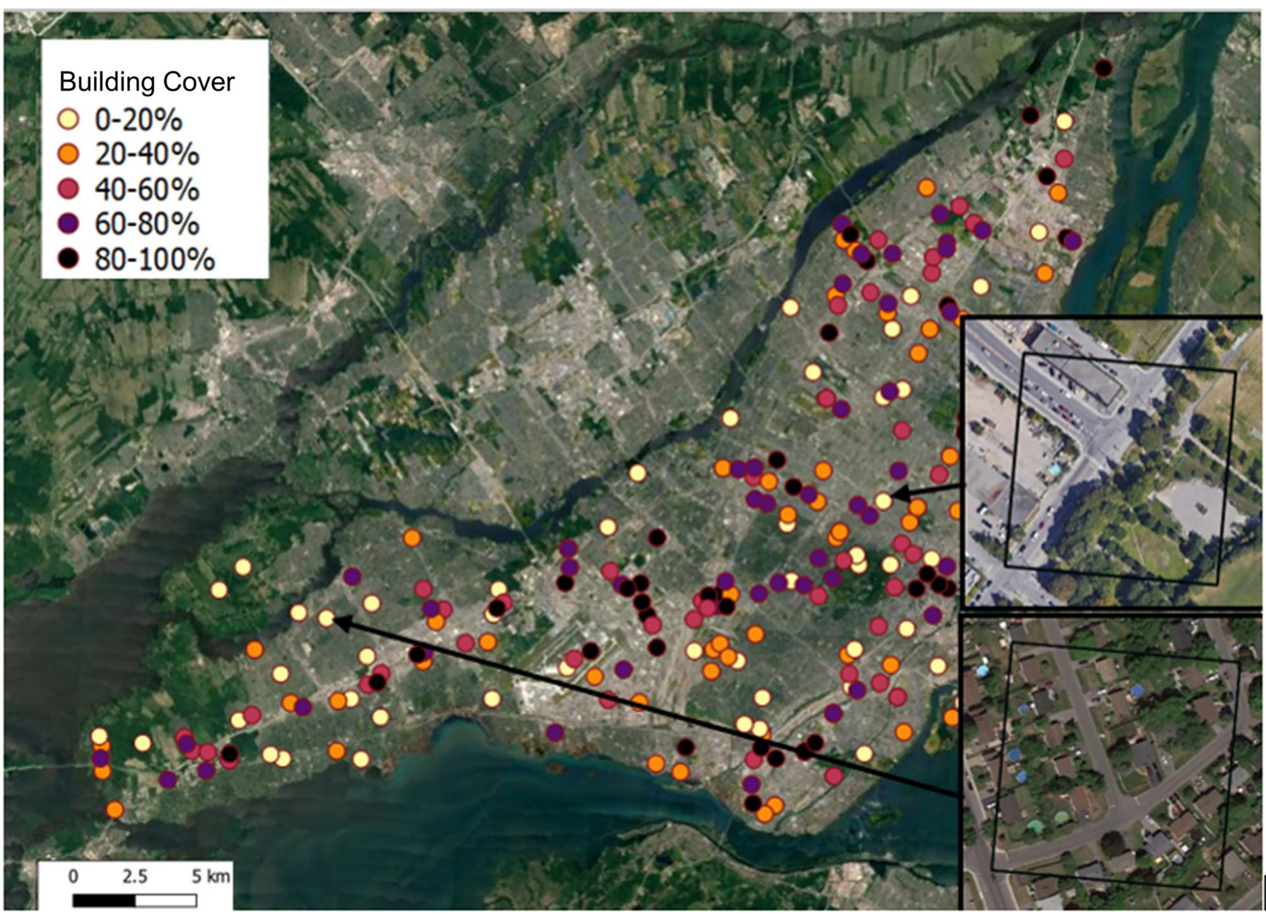

Fig. 1 Image of the Montreal area with dots indicating locations of 250 study sites (Google satellite image). The colour of the dot represents the percent building cover. Inset images represent two sites that illustrate the land-sharing (bottom) vs. land-sparing (top) concept

Two hundred fifty study sites were selected for analysis (Fig. 1). Each study site consists of a 120 m × 120 m cell, located on the Island of Montreal. This size was selected because it captures variability at the local scale (i.e., a few city blocks), which is a scale at which we can reasonably expect to see differences in the provision of, and access to, the selected ES. It is also a scale at which we see the full range of building cover, and often see densification via infill development or new development projects. All GIS analyses including site selection were done in QGIS 3.8, using the Quebec Albers projection (QGIS Development Team 2020). We created a 120 m × 120 m grid over the study area, and calculated percent building cover for each grid cell, using data from the Microsoft open layer of building footprints (Microsoft 2019). Site selection was done such that sites were evenly distributed across the island of Montreal and across the gradient of building cover (from 0–100% cover). To achieve this, we stratified sites by building cover in 10% increments (e.g., 0–10% building cover, 10–20% building cover, etc.), and geographically (by borough across the 34 boroughs on the island – the official term for the municipal subdivisions of the Island of Montreal). The result yielded 25 sites within each class of building cover, distributed geographically throughout the city to ensure sites were not clustered in areas subject to particular policies or governance (Fig. 1). No two sites were adjacent to each other or adjacent to water and no borough contained two of the same building cover strata.

To estimate how many people are potentially benefitting from ES (or susceptible to the lack of ES) provided at each site, we calculated the number of households within each study site (Ville de Montreal 2020). Number of individuals living within each site was not available due to privacy concerns, thus we considered number of households as the best available proxy for local population density. We selected the number of households over other common methods of estimating population density (e.g., census data), as data provided at larger scales would have been inaccurate at the scale of our study sites, as population is not evenly distributed over the wide area that many census tracts cover.

Environmental indicators

Land surface temperature (LST), an indicator strongly influenced by temperature regulation services, was obtained from a Landsat 8 image of the Montreal area with a resolution of 30 m × 30 m. The image used was a daytime image taken on July 27, 2019, and was selected based on time of year and minimal cloud cover. Mid-summer was chosen because this is when heat stress becomes a health concern, and when ecosystem services provided by vegetation are expected to be most pronounced. However, to ensure that the results obtained were robust, and not an artifact of the specific day selected, we also repeated our analysis for other days of the year (Appendix A). The image was pre-adjusted for brightness temperature and atmospheric correction. We calculated LST using the thermal band according to the method described by Parastidis et al. (Parastatidis et al. 2017). We measured LST as the mean LST value of pixels within each study site.

Concentrations of NO_2 were used as a representative measurement of air quality. This is a pollutant we would expect to be correlated with changes in building cover, since vegetation can reduce NO_2 through stomatal uptake (and there is likely to be more vegetation in less building dense areas). Secondly, it is frequently used in similar studies, making our results comparable to related studies in this field (Apparicio et al. 2016; Lee 2019). We obtained NO_2 concentrations from a SENTINEL 5P image of the Montreal area, taken on the same day as the LST image (Appendix A). The image has a resolution of 500 m × 1000 m. This product is pre-adjusted for clouds and provides values of mol/m^2 of NO_2 for each pixel. We measured NO_2 as the mean NO_2 concentration for each study site.

According to the World Health Organization (WHO) guidelines, individuals should live within a five-minute walk of the nearest public greenspace larger than 0.5 ha (WHO 2016). We thus identified all public greenspaces larger than 0.5 ha using publicly available data (Communauté métropolitaine de Montréal 2016). We verified the accuracy of each greenspace using Google Street View, and manually corrected for any inaccuracies in greenspace presence, size, or shape. We also digitized any barriers (i.e. fences) to ensure accuracy in greenspace entrances (Appendix B). Using QGIS, we calculated walking distance along the road network from each study site centroid to the entrance of the nearest qualifying public greenspace (Appendix B). We excluded greenspaces that require payment to enter and greenspaces that were blocked off to the public by physical barriers, because these did not meet our criteria of being accessible to the public. The greenspaces included in our final set consisted primarily of public city parks, which are maintained to provide a variety of recreational opportunities, but also include informal greenspaces (i.e., those not officially designated as parks) accessible to the public.

We also measured public greenspace access in terms of area of greenspace surrounding each study site at multiple spatial scales (300, 500, 800, and 1000 m radii). Spatial scales correspond to recommendations regarding urban mobility based on the greenspace accessibility literature (WHO 2016; Hogendorf et al. 2020), and transportation literature (Statistics Canada 2020; Castel and Farber 2017) – with the rationale that the distance considered appropriate for people to walk to a public transit stop should be similar to the distance they may regularly travel to access public greenspace.

To measure access to private residential greenspace, we clipped the Montreal Open Data Portal's map of land parcels to only include parcels of land that included at least one household. We then subtracted any impervious cover from the remaining layer using a custom generated impervious layer (Appendix C). This left us with only greenspace located on residential land parcels. The metric of private greenspace access used in analyses was the surface area of private greenspace per household for the study site. For example, in a case where a duplex existed on a lot with a private yard, we assumed each household had access to half of that private greenspace. However, it is conceivable that in practice, only one of these households would be allowed to use the yard. Therefore, our results regarding private greenspace access should be interpreted as potential access.

In addition to our independent variables (building cover and population density), we considered a range of covariates related to landscape structure and socio-economic factors anticipated to influence our environmental indicators of interest, as well as ES capacity. Euclidean distances to the river and nearest major road (class six or higher, i.e. two lanes of traffic in each direction) were calculated using the NNjoin plugin in QGIS. We also considered percent canopy cover of each study site (Montreal Open Data Portal 2015), and non-building impervious cover. We created a layer of ground-level impervious surfaces by compiling existing datasets on the locations of roads, sidewalks, and industrial sites, and then adding in missing features through hand digitization based on satellite imagery (Appendix C). This process ensured that types of impervious cover that are often excluded, such as impervious surfaces under canopy, were included for analyses. We calculated median household income from the most recent Canadian census (Statistics Canada 2016).

Statistical analysis

To determine the relationship between percent building cover and associated landscape structure on environmental indicators *(Question 1)*, we used a regression modelling approach. For each response variable, the specific model type (either linear mixed models (LMMs), or generalized additive models (GAMs) was selected to best reflect the nature of the data (Table 1). For responses including clear

Table 1 List of variables included in the final versions of all models regarding the effects of building cover and of population density

Dependant Variable	Independent Variables	Random Effects	Model Type
Models assessing the effect of building cover			
Model: Effect of building cover on land surface temperature			
Land surface temperature	Building cover, canopy cover, median household income, distance to the nearest river, impervious cover	Borough	LMM
Model: Effect of building cover on NO2 concentrations			
NO2 Concentration	Building cover, median household income, distance to the nearest major road, canopy cover	Borough	GAM
Model: Effect of building cover on access to public greenspace (distance-based)			
Walking distance along the road network to the nearest public green space	Building cover, median household income	Borough	LMM
Model: Effect of building cover on access to public greenspace (area-based)			
Area of public greenspace within a given radius of the study site (300 m, 500 m, 800 m, 1000 m)	Building cover, median household income	Borough	LMM
Model: Effect of building cover on access to private greenspace			
Surface area of private greenspace per household	Building cover, median household income	Borough	GAM
Models assessing the effect of population density			
Model: Effects of population density on land surface temperature			
Land surface temperature	Number of households, building cover	Borough	GAM
Model: Effects of population density on NO2 concentrations			
NO2 Concentration	Number of households, building cover	Borough	GAM
Model: Effects of population density on access to public greenspace (distance-based)			
Walking distance along the road network to the nearest public green space	Number of households, building cover	Borough	GAM
Model: Effects of population density on access to public greenspace (area-based)			
Area of public greenspace within a given radius of the study site (300 m, 500 m, 800 m, 1000 m)	Number of households, building cover	Borough	GAM
Model: Effects of population density on access to private greenspace			
Surface area of private greenspace per household	Number of households, building cover	Borough	GAM

non-linearities (NO_2, access to private greenspace), we used GAMs to flexibly account for the non-linear nature. In cases where the response was linear in nature (LST, access to public greenspace), such that using a GAM may have added additional complexity to model interpretation, we used the simpler to interpret linear mixed models. Covariates were selected based on a-priory hypotheses grounded in the literature, with all covariates tested for collinearity. For all models, we included borough as a random effect to account for potential spatial structuring, or influence of local policies on observed relationships. To ensure our models were representative and to avoid overfitting, model validation was performed using 10% of the data held out as a test (or validation) data set (Appendix D, Figs. 8 and 9). The models presented in the final analysis are complete models using all collected data. For all analyses, the p-value threshold used for statistical significance was alpha = 0.05, with alpha = 0.1 considered as marginally significant.

To determine the relationship between percent building cover and associated landscape structure on LST and access to public greenspace, we used linear mixed models (using the lme function in nlme in R (Pinheiro et al. 2020)). To model LST, we included canopy cover, log(income), log(distance to river), and impervious cover as covariates in addition to building cover. This analysis was repeated using LST from three other satellite images to ensure the observed relationships were robust to changes in satellite imagery and seasonal conditions (Appendix A). Prior to interpretation of model results, we also checked for spatial autocorrelation by assessing semivariograms of model residuals. To model access to public greenspace, log(income) was included as a covariate in addition to building cover. This was done in all models of public greenspace (one using distance as a response variable and four using surface area at various scales). Residuals were visually inspected for normality and homoscedasticity using diagnostic plots, and covariates were checked for collinearity using the VIF function in R. All variables were checked for inclusion through model comparison using likelihood ratio tests and Akaike weight ratios. For both LST and greenspace, all original covariates (above) were retained in the final models.

To test the relationship between percent building cover and associated landscape structure on NO_2 concentrations and access to private greenspace, we used generalized additive models (GAMs, using the gam function in MGCV in R (Wood 2011) to account for non-linearities. When modelling NO_2, we used the Spatial + approach described by Dupont et al. (2020) to account for spatial patterns beyond those accounted for by model covariates, identified via inspecting semivariograms of model residuals. In addition to percent building cover we included log(income), log(distance to a major road), and canopy cover as covariates. When modelling access to private greenspace, log(median household income) was included as a covariate in addition to percent building cover. For both NO_2 and private greenspace, model residuals were visually inspected for normality and homoscedasticity, and covariates were checked for concurvity (using plots the gam.check and concurvity functions in MGCV, respectively). The NO_2 model used 29 basis functions (the minimum number of basis functions that would allow for model residuals to be normally distributed and homoscedastic). Covariates included in preliminary models that were excluded from the final model were distance to a petrochemical facility in northeast Montreal, because it was no longer a significant predictor of NO_2 concentrations in the study area after adjusting the modeling approach, and removing it improved the model according to likelihood ratio tests and Akaike weight ratios. The private greenspace access model contained nine basis functions and was verified using the same techniques described above. Here, all original covariates were retained in the final model.

To determine the relationship between population density and environmental indicators (Question 2), we used GAMs (using the gam function in MGCV in R). We modelled each of LST, NO_2, area of private greenspace and public greenspace access as functions of the number of households per site. Once again, models of public greenspace access included one model using distance as a response and four using surface area. Model residuals were visually inspected for normality and homoscedasticity using the gam.check function in MGCV. For each of the LST model and the greenspace access models, there were nine basis functions. The NO_2 model had 29 basis functions. Each model was run once on its own, and again with percent building cover included as a covariate to determine whether household density significantly influenced environmental indicators beyond the influence of building cover. Determining whether household density was a strong predictor separate from building cover was necessary because household density and building cover were not closely correlated at our study sites. Models were validated using the same methods as described above and were compared using likelihood ratio tests as well as AIC comparisons).

Results

Temperature

The effect of building cover was different for each environmental indicator measured (Fig. 2). Land surface temperature (LST) is strongly, positively associated with percent building cover ($F_{5,200} = 107$, $p < 0.001$; Fig. 2a) with every 15% increment in building cover corresponding to ~1 °C increase in LST. LST is also associated with canopy cover, impervious cover, income, and distance to the river (Table 2). Canopy cover and log(income) are negatively associated with

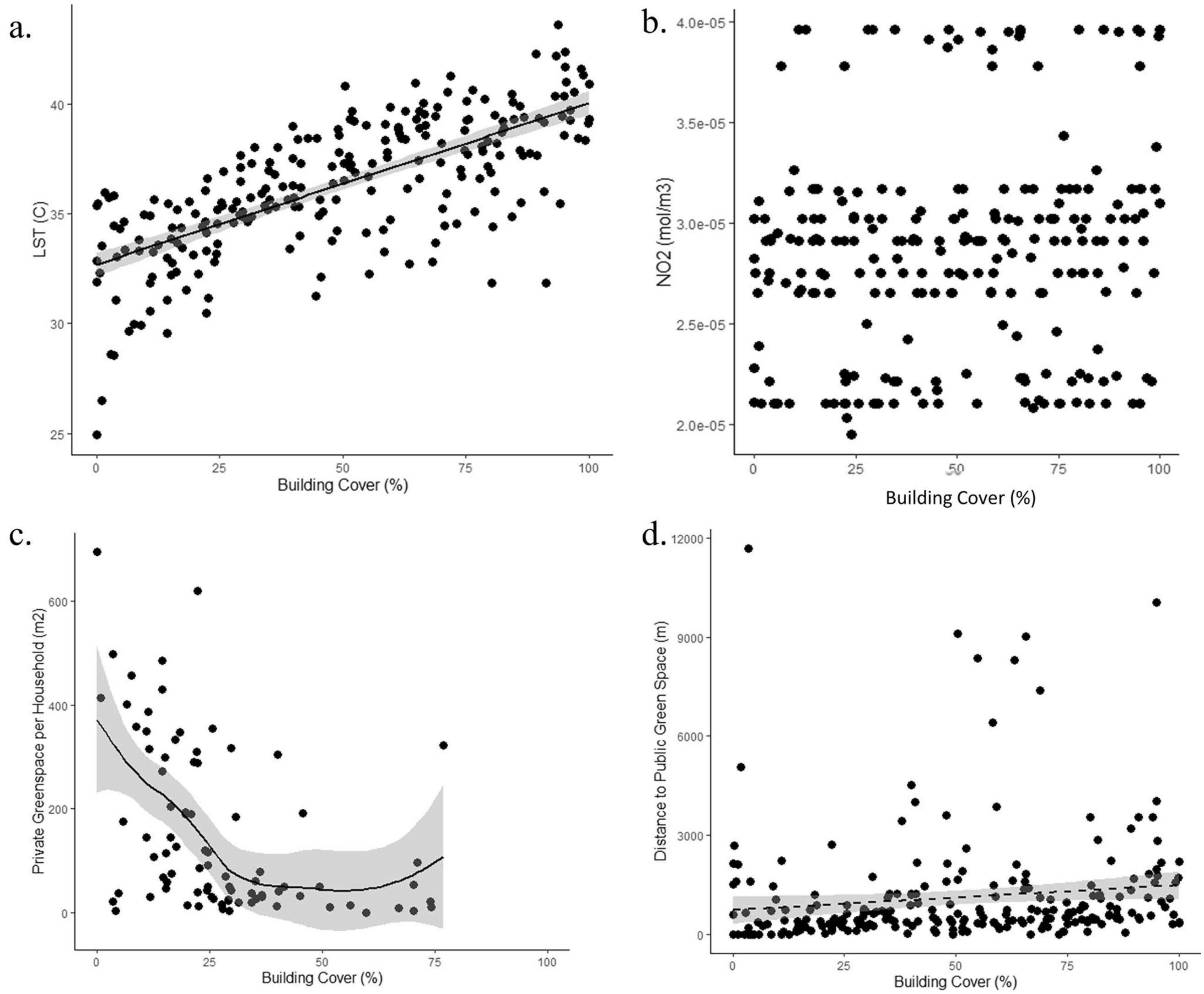

Fig. 2 **a** Land surface temperature (LST), **b** NO_2 concentration, **c** area of private residential greenspace per household, and (d) distance to the nearest public greenspace as functions of percent building cover (%) for 250 study sites. The plot of area of private greenspace has fewer points because private residential greenspace only exists on residential land parcels. Trend lines indicate statistical significance and dashed trend line indicates marginal significance. Shaded area represent 95% confidence intervals

Table 2 Fixed and random effects for linear mixed model predicting mean urban land surface temperature (LST) (°C) at site level (n = 250), based on percent building cover, canopy cover, impervious cover, log(median household income), and log(distance to the river)

	Estimate	Standard Error	t-value	p-value
Intercept	41.84	3.33	12.57	< 0.001
Building cover (%)	0.06	0.006	9.623	< 0.001
Canopy cover (%)	-0.06	0.01	-5.993	< 0.001
Log(Income)	-1.11	0.29	-3.769	< 0.001
Log(Distance to the River)	0.453	0.129	3.522	0.03
Impervious cover (%)	0.023	0.007	3.099	< 0.001
Random Effect				
Borough	1.03			

LST values with every 15% increase in canopy cover leading to ~1 °C decrease in LST ($F_{5,200} = 107$, $p < 0.001$) and every 10% increase in income equating to ~0.1 °C decrease in LST ($F_{5,200} = 107$, $p < 0.001$). While building cover and canopy cover were moderately negatively correlated, there were many examples of sites at equal building cover with very different levels of canopy cover (Appendix D). Distance to the river is positively associated with LST ($F_{5,200} = 107$, $p = 0.03$), as is impervious cover ($F_{5,200} = 107$, $p < 0.001$).

Study sites with fewer households showed higher variability in LST values (Fig. 3a). Sites with high numbers of households had consistently high LST values, however the relationship between number of households and LST was not significant once building cover was accounted for ($p = 0.11$). The majority of households measured were living in areas

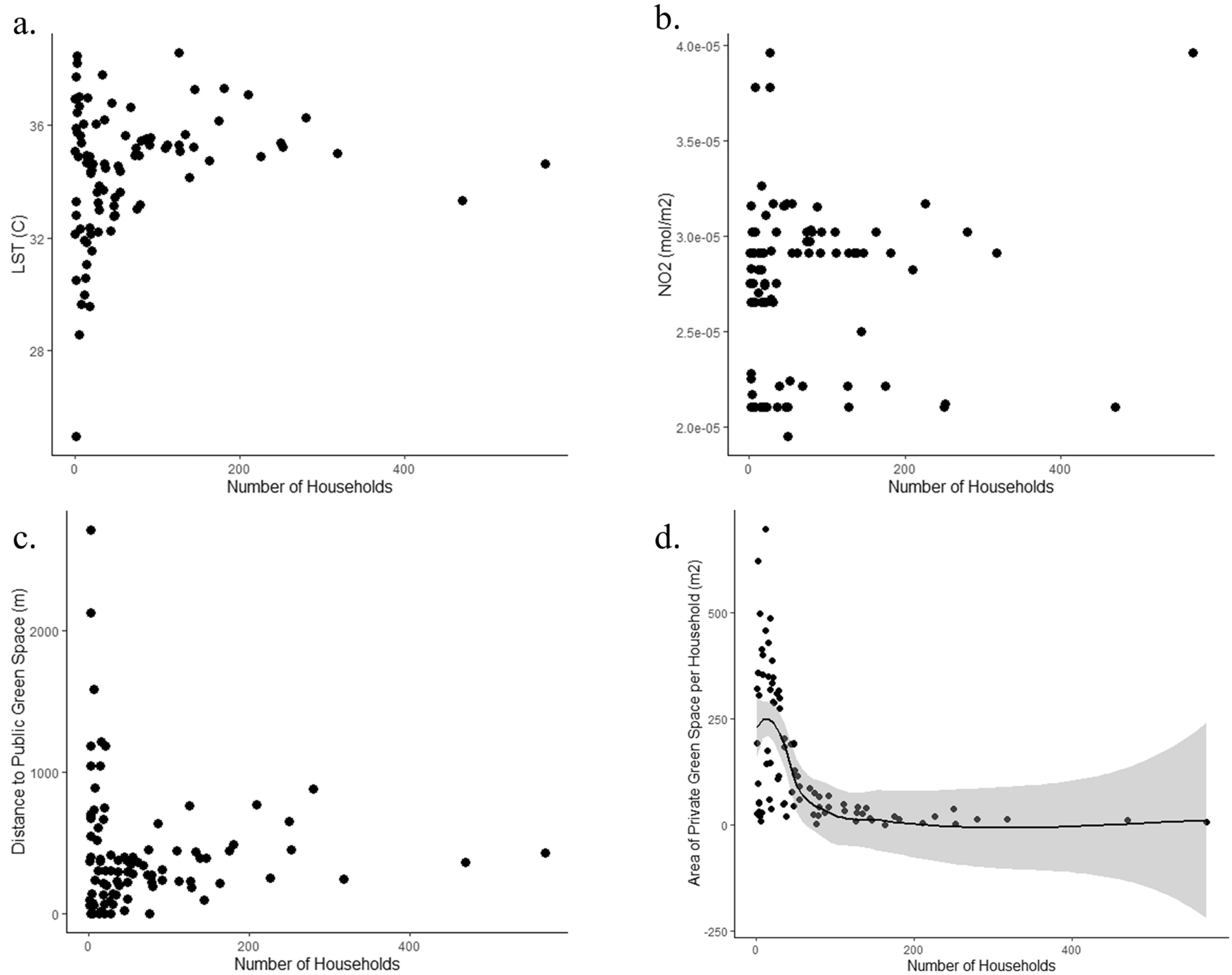

Fig. 3 **a** Land surface temperature (LST), **b** NO_2 concentration, **c** distance to the nearest public greenspace, and **d** area of private residential greenspace per household as functions of household density for study sites containing residential buildings. Trend lines indicate statistical significance. Shaded area represents 95% confidence intervals

of high LST (> 32 °C), however the majority of households exposed to lower LST (< 32 °C) were in areas with building density under 30% (Fig. 5b).

Air pollution

Concentrations of NO_2 were highly influenced by proximity to a large petrochemical refinery in our study region. When modelled as a non-spatial GAM, this effect was the strongest predictor of NO_2 concentrations of all measured covariates ($p < 0.001$). However, as substantial spatial autocorrelation was present in the model as measured by a semiovariogram, the Spatial + approach (Dupont et al. 2020) was applied, which meant distance to such point source pollutants was accounted for by use of the spatial model. Using this approach, NO_2 was significantly, negatively associated with distance to the nearest major road ($p = 0.003$) and median household income ($p = 0.006$) (Table 3); every 1% increase in distance from the nearest major road equated to ~3.8×10^{-9} mol/m^2 lower NO_2 concentration, with every 1% increase in income equating to ~1.2×10^{-8} mol/m^2 lower NO_2 concentrations. Neither percent building cover nor canopy cover were significant predictors of NO_2 concentrations ($p > 0.05$ for both). There was also no statistically significant relationship between household density and NO_2 concentrations ($p = 0.12$).

Public greenspace access

We found a marginally significant positive relationship between road network distance to the nearest public greenspace and percent building cover ($p = 0.06$). Further, twenty-four percent of all sampled residential sites did not meet the

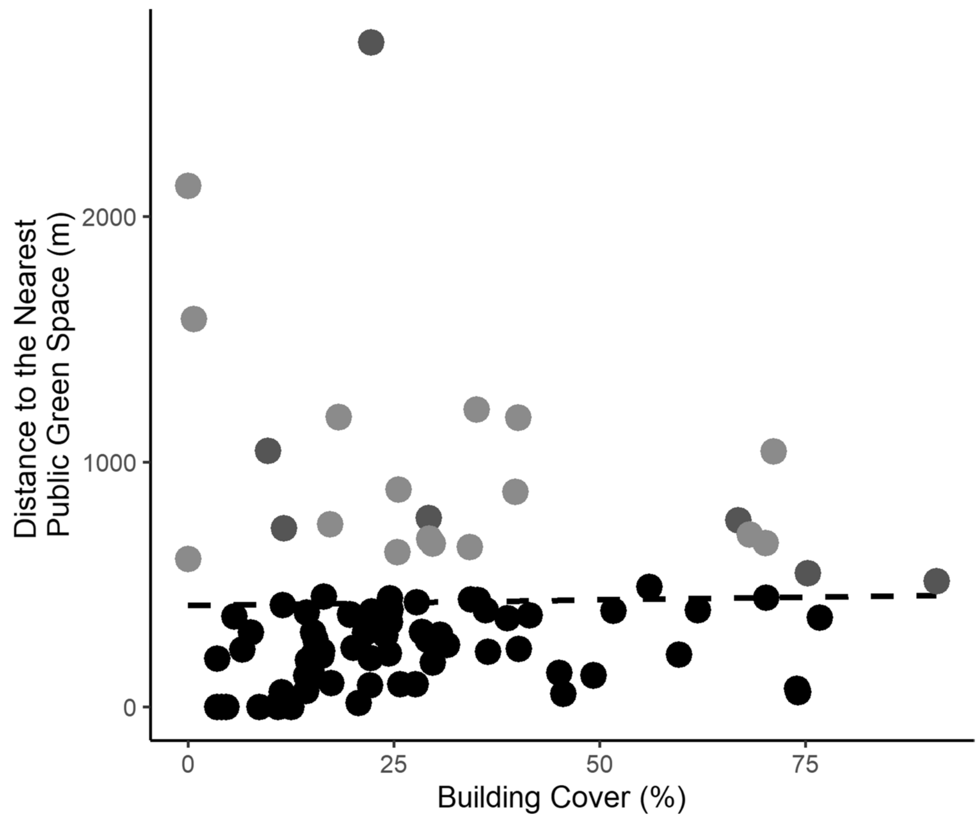

Fig. 4 Distance to the nearest public green space as a function of percent building cover for residential study sites. Light grey points indicate study sites that did not meet World Health Organization (WHO) guidelines of public green space access in terms of distance. Dark grey points indicate study sites that did not meet the WHO guidelines of distance to public green space and also do not have access to private green space (backyards)

WHO guideline that people should live within a five minute walk to the nearest public greenspace (WHO Regional Office for Europe 2016) (Fig. 4). The area of public greenspace surrounding a site was negatively correlated with building cover for buffer areas of 300 m ($p<0.001$), 500 m ($p=0.002$), 800 m ($p=0.009$), and 1000 m ($p=0.02$) radii. However, for all four buffer sizes the strength of this trend was very weak (Appendix D). Although sites dominated by high building cover had less public greenspace within a surrounding buffer on average, there were still many examples of highly built sites surrounded by a high area of greenspace. Study sites with high numbers of households tended to have less public greenspace within buffer areas than sites with fewer households, although this trend was not statistically significant at any scale ($p>0.1$ for all) for any of the buffer sizes (Appendix B).

Private greenspace access

Area of private residential greenspace was significantly reduced with increasing building cover ($p<0.001$), with the decline reaching a seeming threshold at approximately 25% building cover (Fig. 2c). Private greenspace is only available to some residents; only 18% of households included in study areas had access to a private yard (Fig. 5d). We also found a statistically significant non-linear relationship between household density and area of private residential greenspace per household in which the more households that were contained in a site, the less private greenspace was available to each household ($p<0.001$) (Fig. 3d).

Discussion

As global urbanization continues, it is increasingly important to consider how urban form influences environmental quality. Here, we assessed how environmental indicators important for human health vary along a gradient of building cover, with inferences for how this will influence capacity for and access to urban ecosystem services provided by local greenspace. We found that while indicators of some ES (i.e., temperature, access to private greenspace) are strongly influenced by percent building cover, other indicators (access to public greenspace, air quality) are only weakly, or not at all affected by changes in local building cover, providing insight into how urban densification may alter environmental determinants of health, and provision of multiple ES (Fig. 2). This finding was contrary to our initial hypothesis that as building cover increased, the impact on all measured indicators would be

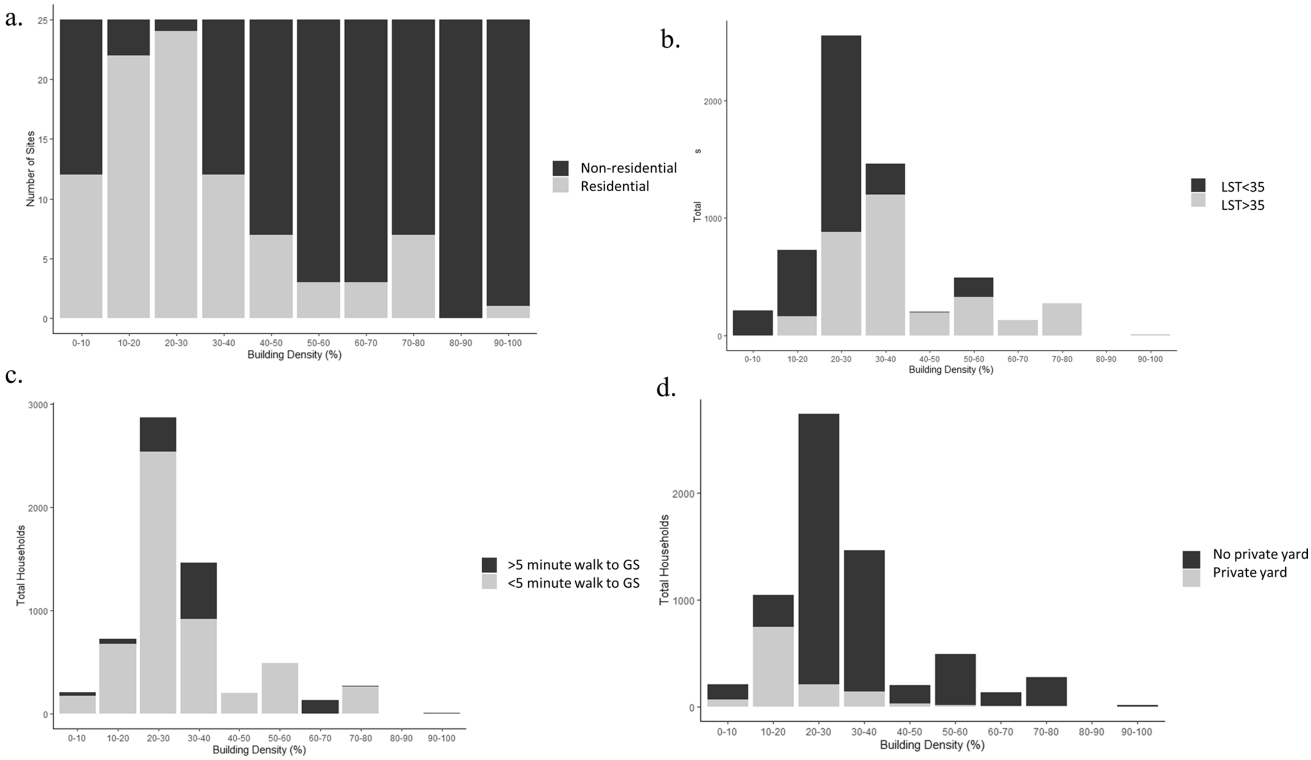

Fig. 5 **a** The proportion of study sites that were residential for each 10% increment in building cover. **b** The proportion of households benefitting from temperatures under 35 °C (the median temperature at our sites) for each density category. **c** The proportion of households benefitting from the WHO recommended access to public green space, and **d** the proportion of households benefitting from access to a private green space

negative, implying a loss of ES provided by greenspace or vegetation – and synergies among all ES indicators in their response to changes in urban form. Similarly, our results suggest that some ES are better provided at low population densities (e.g., those provided by private greenspace), limiting access to these services for urban dwellers living in heavily populated areas of the city, while other services can be provided at consistent levels across a range of population densities.

Table 3 Fixed effects for a general additive model predicting mean concentration of nitrogen dioxide (mol/m^2) at site level (n = 250), based on percent building cover, canopy cover, log(distance to the nearest major road), and log(median household income)

	Estimate	Standard Error	t-value	p-value
Intercept	2.8e^{-05}	1.1e^{-07}	249.71	< 0.001
Building cover (%)	-7.8e^{-10}	5.6e^{-09}	-0.14	0.89
Log(Income)	1.2e^{-06}	4.5e^{-07}	2.76	0.006
Log(Distance to Road)	3.8e^{-07}	1.3e^{-07}	3.03	0.003
Canopy cover (%)	6.0e^{-09}	1.1e^{-08}	0.56	0.58
Smooth Term	*edf*	*Ref.df*	*F*	*p-value*
S(Lat,Long)	27.41	28.84	63.77	< 0.001

Temperature

Our findings of higher LST in areas of the city with higher building cover and more additional impervious cover are unsurprising, given that impervious landscape features are known to contribute to intra-urban heat (Jenerette et al. 2016; Ziter et al. 2019). Our results suggest that in order to keep LST values below ~35 °C (a target drawn from the global LST literature Li et al. 2018; Parastatidis et al. 2017)), total impervious cover (including buildings) should remain below ~60%. While the relationship between total impervious cover and increased LST has been recorded by similar studies (Tran et al. 2017), the relationship between building cover and LST separate from other impervious surfaces has rarely been considered.

Our finding that not just impervious surfaces in general, but buildings in particular, are strongly positively associated with LST is important in that it speaks to a portion of impervious cover that is less easily modified. While other impervious cover types (i.e., parking lots, school grounds) can be converted to greenspace provided community support, or may be greatly reduced in some compact-city scenarios, it is much more difficult to eliminate or alter building footprints. By addressing buildings as their own urban category that significantly influences temperature, we can better address the core of the land-sharing vs. land-sparing question because we address the main part of the built environment that a land-sparing scenario often requires us to densify. This is particularly important in the context of building climate resilient cities. Our results suggest that compact cities – at least using conventional architecture – will present significant challenges for temperature regulation. However, future studies should continue to assess the influence of locally-appropriate green infrastructure interventions (e.g. green or cool roofs, green facades) on urban heat (Yang and Bou-zeid 2019). As cities increasingly invest in hybrid gray-green infrastructure as part of climate action plans, it is possible that building cover may exert less of an influence on local heat.

While buildings and additional impervious cover significantly increase urban temperature, this effect is moderated by canopy cover. Increasing canopy cover mitigates urban heat through several mechanisms, including increased surface reflectance, shade, and evapotranspiration, reducing thermal stress on the surrounding environment (Norton et al. 2015). Thus, our results confirm an increasingly well documented relationship between canopy cover and reduced air and land surface temperatures within urban areas. In a temperate city such as Montreal, maximizing canopy in areas where conventional buildings are already in place can help offset the increase in LST – maintaining some level of ES provision even as building cover increases. This type of change will require initiative on the part of both municipal decision-makers and private landowners, as privately owned greenspace contributes a large portion of the total urban forest in many cities (Hutt-Taylor and Ziter 2022). Benefits of canopy can be further increased in high building areas through replacement of other impervious surfaces with trees; for example, replacing a portion of each parking lot with vegetative cover. Large scale tree planting in an urban core is not, of course, without challenges (Cavender and Donnelly 2019). There are real barriers to planting in dense urban areas such as conflicting infrastructure, poor soil quality, and political pressure; exemplified by the lack of canopy cover – and thus a lack of temperature regulation services – at sites with very high building cover in our study. Future research on how to increase the growth and survival of urban trees despite these challenges is essential for moving forward. Despite these challenges, we find that at building cover of up to ~30%, we see a significant number of households benefitting from cool temperatures (Fig. 5b). This is contrary to sites of high building cover and high household density, which only experienced high LST values (Fig. 3a). Pursuing densification even to this moderate level of building cover could see a large increase in the number of people able to access temperature regulation services.

Canopy and impervious cover alone do not fully explain the trends we see in LST. Consistent with other studies, we observe higher temperatures in low-income areas (Table 3) (Hoffman et al. 2020; Jenerette et al. 2016; Norton et al. 2015). The link between temperature and income is often as a result of wealthier neighbourhoods having greater access to resources that lead to cooling (i.e., parks, trees) (Watkins and Gerrish 2018). Here, however, we find that income remains a significant driver of LST even when accounting for the effects of impervious and canopy cover, perhaps indicating that income is associated with characteristics of an urban area beyond what we were able to account for. This could be due to other physical characteristics of the built environment. For example, Alexander (2021) found that the height of buildings is positively correlated with LST, such that areas with taller buildings are hotter. While addressing building heights was beyond the scope of our study, lower income sites may be more likely to have taller buildings (e.g., large apartment buildings). Future studies should assess alternate measures of building density that go beyond simple building coverage, such as those that include floor area. There could also be effects related to the composition of vegetation, not considered here. In particular, wealthier urban areas often have higher species diversity than poorer areas (Leong et al. 2018), which could in turn influence temperature (Wang et al. 2021).

We do note here that strategies to increase access to ES must also consider the appropriate regional context of the city in question. For example, while our emphasis on the importance of maintaining high canopy cover is broadly applicable across temperate cities, increased canopy may introduce challenges in water-limited regions (Imhoff et al. 2010). Regionally appropriate solutions should always be considered when implementing nature-based solutions (Lin and Fuller 2013). Similarly, while we investigated daytime temperatures, the variables affecting nighttime LST and its health effects may differ from our findings (Jenerette et al. 2016). Future studies would benefit from incorporating a temporal perspective, particularly given the health implications of nighttime heat.

Air quality

In contrast to temperature, NO_2 concentrations were not related to building cover at the scale of our investigation (Fig. 2b), or to household density (Fig. 3b). Our hypothesis that increased greenspace at lower building covers would influence air quality was not supported, as vegetation was not influential. Yet, despite the lack of air quality regulation services observed in our study, our results still provide reason to be optimistic about compact city strategies. If densification can be achieved without sacrificing air quality, then it would make sense to do so and spare natural habitat in the process. However, this result speaks specifically to the densification of *buildings*, rather than increased cover of other built features, including roads.

Unlike building cover, major roads were important predictors of NO_2 concentrations in our study, consistent with other work in this field (Apparicio et al. 2016; Lee 2019; Yli-Pelkonen et al. 2017). Vehicles emit NO_2 as they travel, exposing the surrounding areas to the effects of this pollutant (Apparicio et al. 2016). This result aligns with previous studies of Montreal, with sites near major roads displaying higher levels of NO_2 than urban 'background' sites (Smargiassi et al. 2005; Crouse et al. 2009). Major roads can of course also be used by public transportation or other alternative transportation types, but it is the presence of cars and similar vehicles that currently make up the majority of traffic congestion and associated pollution (Duranton and Turner 2011; Venter et al. 2020). The sensitivity of air quality to particular built features, rather than building cover, indicates that it is not sufficient to simply discuss cities in terms of the arrangement of impervious vs. green cover. Rather, we must tease out which elements of a city are contributing to harmful environmental conditions, allowing us to highlight aspects of urban design that might need to be reimagined, such as automobile dependency. Dominant forms of transportation may also change in future cities (e.g., electric vehicles, increased public transit), and future studies should consider how changes in urban transportation will intersect with the ecology of our cities.

In addition to road infrastructure, the proximity to manufacturing facilities influenced NO_2 concentrations in our study area. The negative effects of industrial point sources on local air quality are well known (Oiamo et al. 2015). Similarly, the link between poverty and higher exposure to air pollutants is well established. A house near a busy road or industrial area may be considered lower value because of pollutants, noise, or lack of privacy, leading to occupancy by lower income families (Boehmer et al. 2013). Lower income areas also tend to have less vegetation cover (Schell et al. 2020). Although in our analyses we did not find vegetation to significantly impact NO_2 levels, previous work at different spatial scales has linked increased vegetative cover to lower pollutant concentrations (Nowak et al. 2018; Selmi et al. 2016; Yang et al. 2015).

While numerous studies have focused on air pollution mitigation by urban vegetation, results are highly variable depending on study methods and scale (Yli-Pelkonen et al. 2017). Studies that address whether increased tree cover reduces air pollution have found that the presence of trees can result in decreases (Nowak et al. 2018), increases (Fantozzi et al. 2015), or no change (Yli-Pelkonen et al. 2017) in levels of NO_2. The grain size at which sampling occurred may also have influenced our results, because variation within a pixel is not detected – thus, changes in very local air quality as a result of vegetation may not be easily detected by our methodology, which is a weakness of our work. Future research comparing spatial scales, or employing sensor networks, would improve our understanding of air quality regulation services provided by vegetation at local scales. An additional limitation of our work is that it is difficult to determine the magnitude of the biological implications indicated by the observed differences in NO_2 concentration, as measurements from Sentinel imagery do not easily convert into the units commonly used in the health literature (e.g., ppm, ppb). However, the general patterns observed were very close to those observed by other air quality studies in Montreal (Crouse et al. 2009; Smargiassi et al. 2005) that found biologically relevant results.

Greenspace access

Across a variety of metrics, access to public greenspace was only weakly influenced by urban density. We found no significant relationship between household density and distance to public greenspace, and although marginally significant, the relationship between building cover and distance to public greenspace was weak (Fig. 2d). The negative relationship with local building cover and surrounding surface area of greenspace (Appendix D) indicates that in Montreal, building cover does not greatly impact an individual's distance from the nearest greenspace, but may impact the sizes of those greenspace available to them. However, the difference in area of surrounding greenspace between sites with high and low building cover was small, with many examples of highly built sites surrounded by a high surface area of public greenspace (Appendix D). This general pattern held true when looking at greenspace availability between boroughs (neighbourhoods) as well. This demonstrates that it is possible to have dense local development with access to ample public greenspace, and that such areas already exist, a finding contrary to similar research in other cities (Koprowska et al. 2020). The minimal differences we observed in public greenspace access between areas of low and high building cover implies that in cities where dense areas do have lower access to public greenspace, this may be due to inequitable urban planning rather than an innate feature of densely built environments. However, the lack of a strong trend here doesn't necessarily imply equity in greenspace access overall, particularly when considering that some households have access to private greenspace while others do not.

Building dense, and densely populated, study sites have significantly less available private greenspace per household than their lower density counterparts. This was also true between different boroughs, with highly populated and building dense boroughs enjoying less private residential greenspace than less dense boroughs. This situation is likely unavoidable to a certain extent. As more people share the same amount of land, each person will inevitably get access to less of it. However, given that some neighbourhoods have significantly less private greenspace, it follows that those same neighbourhoods should be given higher access to public greenspace. These findings highlight a trade-off between the capacity of a city undergoing densification to provide private vs. public greenspace.

Disparities in access to greenspace can have significant consequences, given the importance of greenspace for physical and mental health (Demoury et al. 2017; Dennis et al. 2020; Sarkar et al. 2018). People who enjoy high access to greenspace are less likely to develop several health conditions including certain cancers and psychiatric illnesses (Demoury et al. 2017; Engemann et al. 2019; Frumkin et al. 2017). Especially over the course of the COVID-19 pandemic, the benefits of greenspace are being recognized by a broader audience (Park People 2020). While it is unsafe to gather indoors, parks have become increasingly important for maintaining mental health (Park People 2020). Yet, nearly one quarter of our sampled residential sites did not meet WHO recommendations for access to public greenspace, and nearly one in ten lacked access to both public and private greenspace (Fig. 4). This reality increases the urgency of the call for a greater total number of greenspaces to be implemented in cities, which would increase overall mental and physical health (Barbosa et al. 2007). Our focus on physical access to, and quantity of, greenspace also did not account for differences in greenspace type, or quality, which also plays an important role in ES provision (Arnberger 2012; Evans et al. 2022). Greenspaces with different vegetation types, features, and levels of use are likely to have differing affects on human wellbeing – and may be associated with levels of urban density – and future research should account for this possibility.

Conclusions

The relationship between urban building cover, environmental conditions, and ecosystem service provision is complex, and varies depending on the environmental factors under consideration. We found that the loss of greenspace accompanying increased building cover was less influential for air quality at the scale of our study, which depended much more strongly on major pollutant sources (e.g., factories, freeways) than on mitigation by vegetation. For temperature, however, increased building cover – and the accompanying lack of temperature regulation services provided by vegetation – was a strong driver of higher daytime temperatures, increasing the risk to human health. For ecosystem services provided by greenspace access, there is a trade-off between the ability of a compact city to provide public vs. private greenspace; suggesting public greenspace should be prioritized to maximize the provision of ES to people. Thus, while we expected to see clear synergies among health-related ES, such that urban form influenced each in a similar way, this was not true across our study sites – highlighting the importance of multi-ES studies in the same city. While this research was completed in the city of Montreal, we believe our findings are broadly applicable to other large cities, particularly in the North American context.

Overall, our findings support that urban densification must be pursued with consideration for the overall landscape structure, and prioritize the maintenance of vegetation in particular. Despite differences in the shape and strength of the relationships between different environmental indicators and building cover percentage, well-located green infrastructure represents a potential shared solution, particularly if prioritized over automobile-centric infrastructure. For example, access to greenspace would be improved by creating more public greenspace within walking distance of urban residents. The vegetation in these new greenspaces would in turn help mitigate temperature, achieving multiple benefits using a single approach. Thus, to maintain provision of, and access to, multiple ES under scenarios of urban densification, careful consideration should be given to where, and how, green infrastructure can be integrated into our cities without increasing sprawl (Norton et al. 2015). This will require interdisciplinary collaboration between ecologists, architects, designers, and engineers.

Appendix A: Comparisons of satellite imagery across different days

To ensure that results were not simply an artefact of the day chosen for analysis, we repeated our analyses for both LST and NO_2 concentrations using data from multiple days during different times of the year. We selected the least cloudy image for each of May, July and October (8th, 27th, 15th, respectively). Results for the relationship between building cover and LST (Fig. 6), and building cover and NO_2 (Fig. 7) are robust to differences in day of the year.

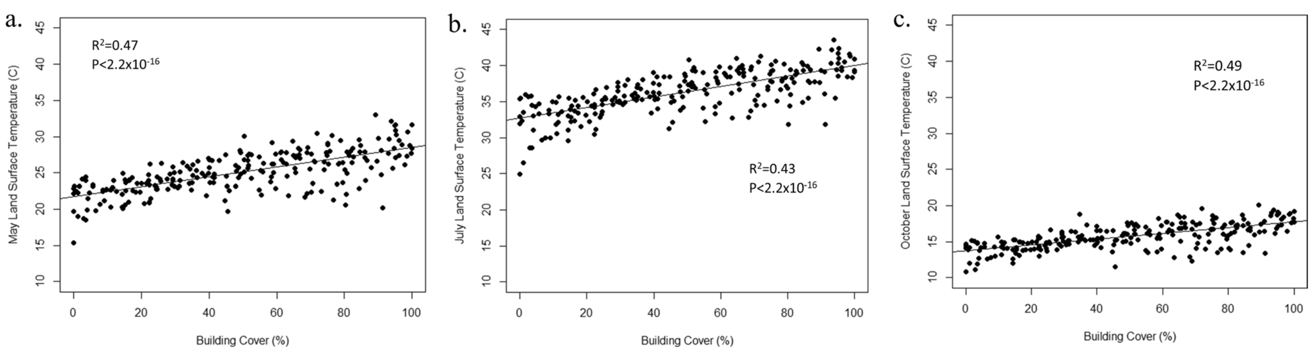

Fig. 6 The relationship between LST and percent building cover is consistent across multiple times of year that have leaves on trees. From left to right, these plots represent this relationship on the least cloudy day in May **a**, July **b**, and October **c**

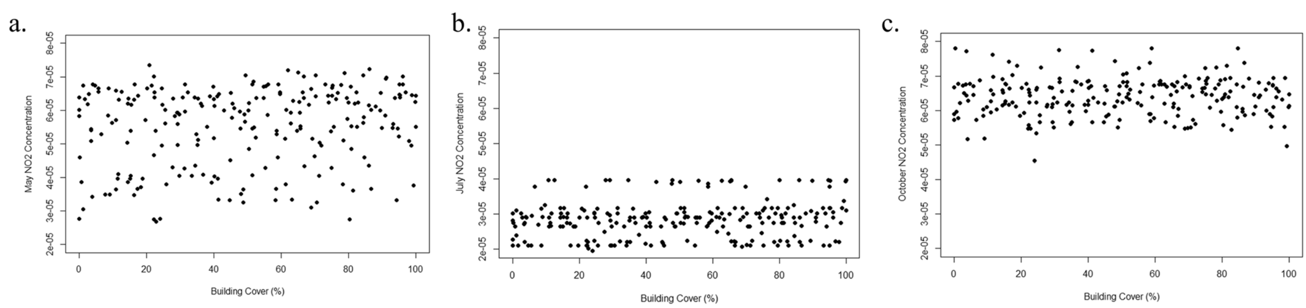

Fig. 7 The relationship between percent building cover and NO_2 concentrations (mol/m^2) is consistently uniform across multiple times of the year that have leaves on trees. From left to right, these plots represent this relationship on the least cloudy day in May **a**, July **b**, and October **c**

Details for images used in study results

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Appendix B: Creating the impervious cover layer

There is no existing layer of all impervious surfaces for Montreal at ground-level (i.e., existing LIDAR data does not differentiate the surface underneath canopy). The layer of impervious cover was created using a two-step process. The first step was to combine multiple existing GIS layers mapping specific portions of impervious cover. This included a layer of building footprints, the road network, sidewalks, bicycle paths, and intersections. The sources of these layers are listed and linked in the table below.

Resource	Description	Link
CMM Util-Sol	A layer classifying every land parcel in Montreal into land use types. We used classifications: 700, 710, 720, 725, 750, 760	http://observatoire.cmm.qc.ca/observatoire-grand-montreal/produits-cartographiques/donnees-georeferencees/
Montreal Open Data Portal Voirie-actif	A layer of all roadways, sidewalks and intersections	http://donnees.ville.montreal.qc.ca/dataset/voirie-actif
Montreal Open Data Portal Pistes-cyclables	A layer of all bicycle paths in Montreal	http://donnees.ville.montreal.qc.ca/dataset/pistes-cyclables
Microsoft Building Footprints	A layer rendering the building footprints of every building in Quebec	https://github.com/Microsoft/CanadianBuildingFootprints

Once these layers were combined, all remaining impervious surfaces (including buildings, parking areas, recreational areas, roads, and misc. impervious) were hand digitized onto the map. The final layer produced included all impervious surfaces in Montreal with the exception of minor impervious features such as driveways at private homes, which we were unable to digitize due to time constraints. A unique feature of this layer is that due to the hand digitizing process involved, impervious features that are under vegetation are included, even though they are often missed in remote sensing based impervious datasets.

Appendix C: Model validation

As a form of validation, all collected data was initially split into a training data set (90% of data) and a test, or validation, data set (10% of the data). To ensure our models were representative and to avoid overfitting, all models were initially run using the training dataset that excluded 10% of the collected data, with the 10% test data set visually inspected for fit to the training model (Fig. 8). The training data was also used to predict the values of the test data. The pearson correlation coefficients for predicted vs. observed vales of test data are 0.69 for LST, 0.43 for NO_2, 0.52 for distance to public greenspace, and 0.82 for amount of private greenspace. Residuals (observed – predicted values) were also inspected visually to assess model fit (Fig. 9). The models presented in the final analysis are complete models using all collected data. For all analyses, the p-value threshold used for statistical significance was alpha = 0.05, with alpha = 0.1 considered as marginally significant.

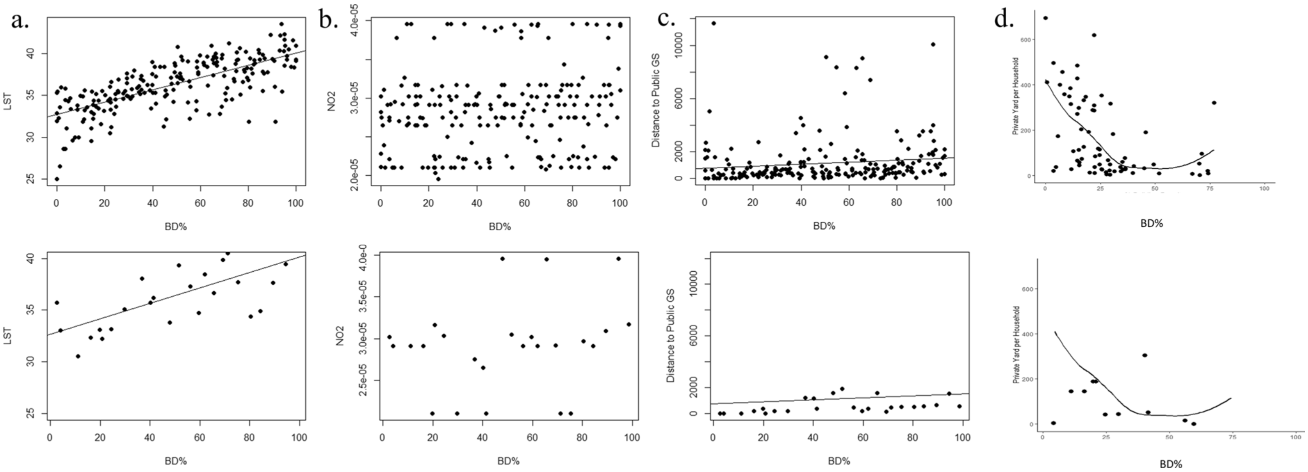

Fig. 8 Test vs. Training data for building cover percentage models for **a** LST, **b** NO_2, **c** distance to public greenspace, and d) amount of private greenspace. For each model, the data was split into a "training" dataset of 90% of the data (top row), and a "test" dataset of 10% of the data (bottom row). Each model was first run using the training data, then again using the test data, and finally as a complete model which was used in analysis. The regression lines represent the regression line for the training model

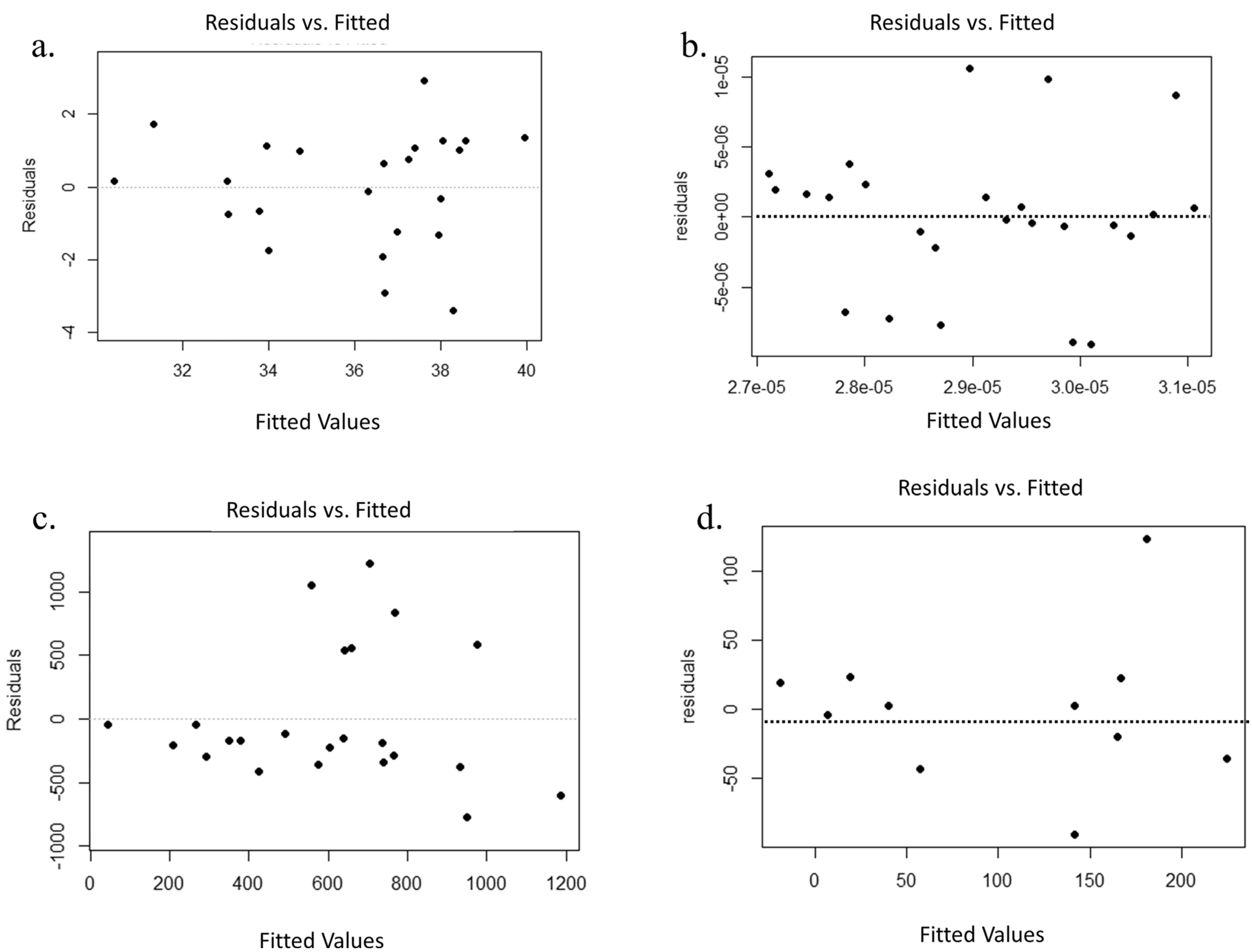

Fig. 9 Plots of residuals (observed – predicted values) vs. fitted values for models for the 10% test data set of **a** LST, **b** NO2, **c** distance to public greenspace and, **d** amount of private greenspace. The correlation coefficients for predicted vs. observed vales of test data are as follows: **a** 0.69, **b** 0.43, **c** 0.52, and **d** 0.82

Appendix D: Supplementary figures

Figures 10, 11 and 12.

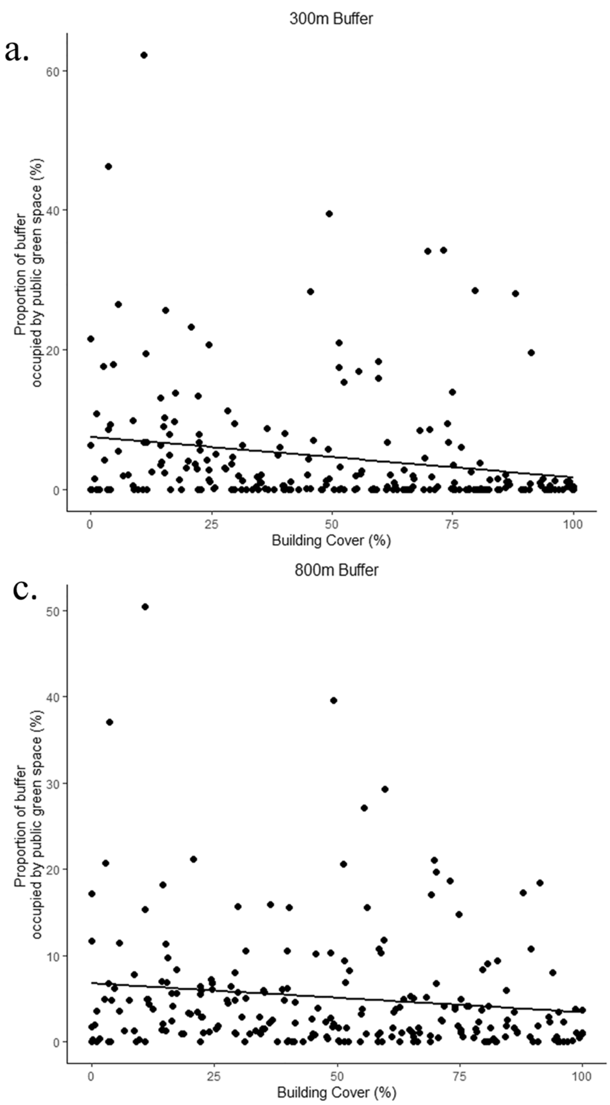

Fig. 10 Proportion (%) of publicly accessible greenspace within a buffer of **a** 300 m, **b** 500 m, **c** 800 m, and **d** 1000 m plotted against building cover percentage for 250 study sites. Trend lines indicate statistical significance. For all buffer sizes, there was a weakly negative relationship between building cover percentage and the amount of greenspace within the buffer

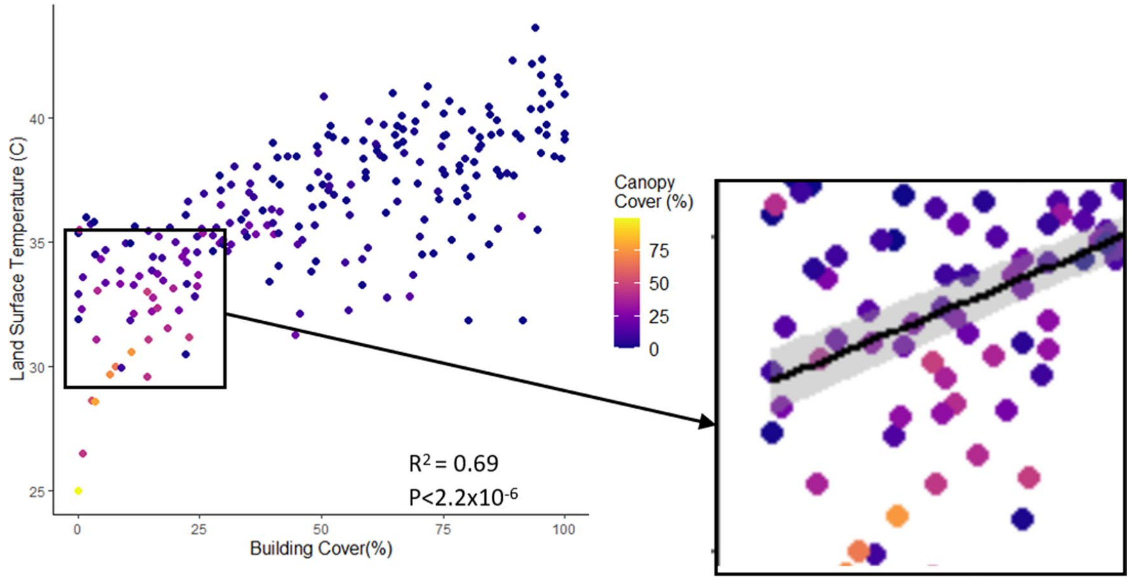

Fig. 11 Daytime land surface temperature (LST) as a function of building cover percentage for 250 sites across the Island of Montreal. Shaded area represents ± 2 SE. Colour represents percent canopy cover within each site. Some of the spread of the points in the building cover percentage – LST relationship can be explained by differences in canopy cover. When we zoom into the low building cover percentage section of the plot (inset figure) we can see that sites with lower LST tend to have higher canopy cover, even at the same level of building cover

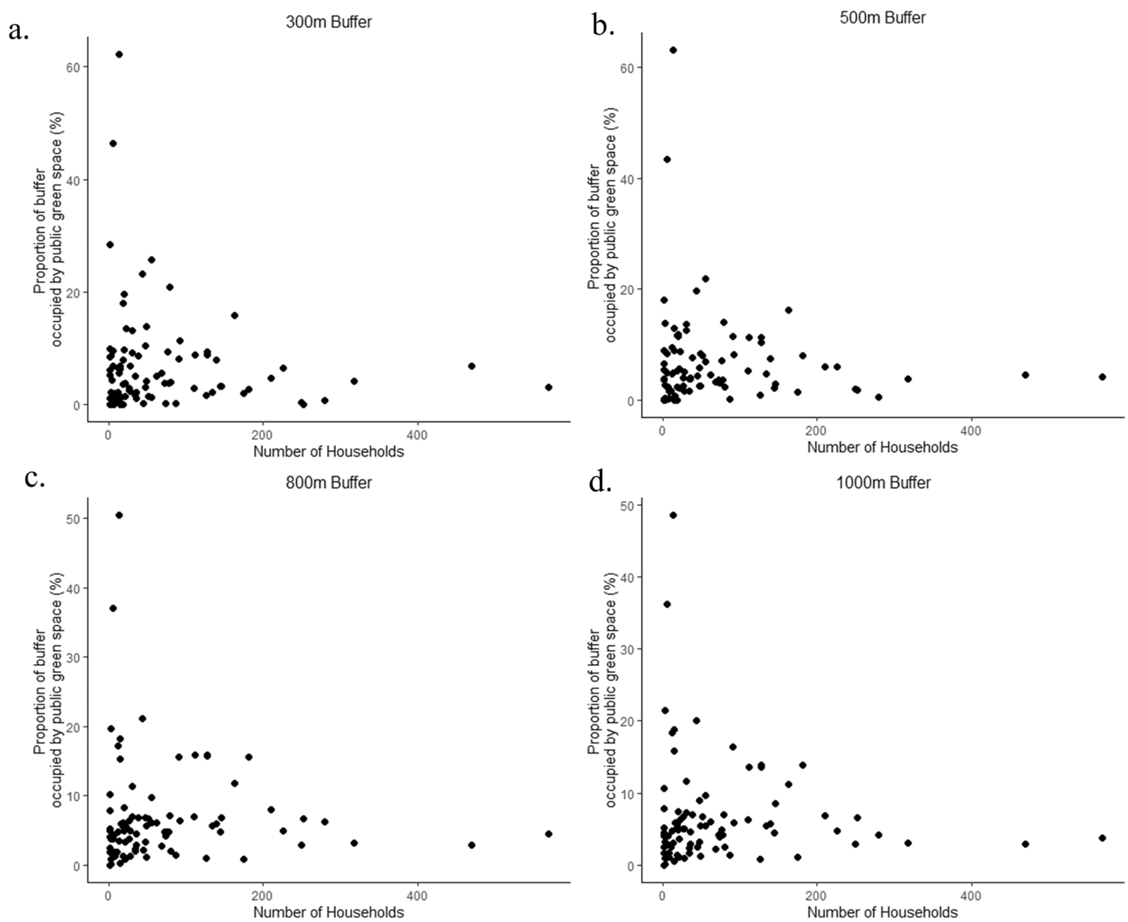

Fig. 12 Surface area of publicly accessible greenspace within a buffer of **a** 300 m, **b** 500 m, **c** 800 m, and **d** 1000 m plotted against the number of households at a study site. For all buffer sizes, there was a non-statistically significant negative relationship between the number of households at a site and the amount of greenspace within the buffer. All p-values > 0.1

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Authors' contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Emily Kroft under the supervision of Carly Ziter. The first draft of the manuscript was written by Emily Kroft and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials Data and materials for this research are available on GitHub repository urban_sprawl_stats.

Code availability Code for this project was done in R and is available on GitHub repository urban_sprawl_stats.

Declarations

Ethics approval Not Applicable.

Consent to participate Not Applicable.

Consent for publication Not Applicable.

Conflict of interest The authors have no competing interests to disclose.

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