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RESEARCH ARTICLE

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Spatial contagion structures urban vegetation from parcel to landscape

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Abstract

1. Residential yards are a significant component of urban socio-ecological systems; residential land covers 11% of the United States and is often the dominant land use within urban areas. Residential yards also play an important role in the sustainability of urban socio-ecological systems, affecting biogeochemical cycles, water and the climate via individual- and household-level behaviours.
2. Spatial contagion has been observed in yard vegetation in several cities, potentially due to social norms that compel neighbours to emulate or conform to specific aesthetic qualities or management regimes. Residents may feel obliged to mow their front yards or prune their trees, creating patterns of spatial autocorrelation in residential neighbourhoods.
3. In this study, we examined the spatial autocorrelation of several yard vegetation characteristics in both front and backyards in Boston, MA, USA. Our study area included 1,027 Census block groups (sub-neighbourhood areas) and 175,576 parcels with matched front-backyard pairings (n = 351,152 yards in total) across Boston's metropolitan area. We spatially defined 'neighbours' in five ways to better account for the potentially variable nature of how conformity or contagion manifests in empirical terms. We anticipated front yards to have stronger spatial autocorrelation due to the more publicly visible nature of these green spaces.
4. We found positive and significant spatial autocorrelation in all measured vegetation variables, in both front and backyards. Unexpectedly, spatial autocorrelation tended to be higher in backyards for tree canopy variables but higher in front yards for turf grass cover. Among block groups, different socio-economic variables, such as median household income, predicted spatial autocorrelation of vegetation characteristics. Our results were sensitive to how neighbours were spatially defined.
5. Our results further underscore the importance of backyards as critical areas for sustaining an urban tree canopy, and show that spatial patterns vary across different social groups. The importance of 'neighbour' definition indicates opportunities to think carefully about the mechanisms driving spatial autocorrelation and

the scales at which patterns develop. The identification of these mechanisms will have important implications for scales of policy and implementation for urban and suburban greening.

KEYWORDS

Boston, residential yards, spatial autocorrelation, spatial contagion, urban ecology, urban forestry

1 | INTRODUCTION

For many urban residents, yards may be their primary exposure to nature (Goddard et al., 2013). Yards are the non-building portions of residential land. In the United States, about 11% of all land is residential (Theobald, 2014), and within urban areas, residential land is often the dominant land use (Avolio et al., 2020b; Loram et al., 2007). Research has demonstrated that social norms and peer pressures are important drivers of yard management decisions and action, driving the vegetative diversity and structure of yards (Carrico et al., 2012, 2018; Fraser et al., 2013; Locke et al., 2018; Nassauer et al., 2009; Robbins, 2012; Visscher et al., 2016). The peer pressures to 'fit in' to a community and conform to a uniform, monoculture, mowed lawn can lead to intensive water and chemical use (Bormann et al., 2001; Hernke & Podein, 2011) and may have negative ecological consequences such as wasting potable water and water contamination from chemical inputs. These environmental impacts may aggregate to continental-scale environmental impacts (Groffman et al., 2017; Odum, 1982). Therefore, the drivers and outcomes of residential land management need to be better understood.

Reference group behaviour theory asserts that membership-seeking individuals adopt the behaviours, attitudes, standards and norms perceived as most desirable among the group they hope to join (Hyman, 1942; Merton & Kitt, 1950). This theory helps explain how social norms form via individuals seeking group acceptance. A complementary theory that may explain yard care is the *focus theory of normative conduct*. Drawing on previous work (Cialdini et al., 1990, 1991), Carrico et al. (2012, 5) explain that '*individuals have been shown to conform both to what they perceive to be desirable as well as typical behaviour to maintain a positive self-image and to garner social approval or to avoid negative attention from those around them*'. Social norms associated with reference group behaviour and/or focus theory of normative conduct may partially motivate neighbours to copy each other when managing their yards (Carrico et al., 2018; Harris et al., 2012, 2013; Julien & Zmyslony, 2001; Locke et al., 2018; Robbins, 2012). What constitutes the social reference group likely relates to the neighbourhood scale (Fraser et al., 2013; Grove et al., 2005; Nassauer et al., 2009; Visscher, Nassauer, Brown, et al., 2016).

Vegetation is the yard element most commonly managed through practices that include irrigation, fertilization, planting, pruning and mowing (Locke et al., 2019). Given strong social norms, nearby residential yards may become increasingly similar to each other with respect to vegetation structure, leading to higher spatial autocorrelation, or similarity of yard characteristics, among close yards. For example, yards with low levels of lawn cover may be near yards with similarly low levels of lawn cover, and parcels with abundant lawn cover would be near parcels with similarly abundant lawn cover. But some aspects of a yard are easier for residents to deliberately change than others. Moreover, when residents simply do nothing to modify yard vegetation (either actively choosing no management or via neglect), some yard vegetation types will change faster than others. For example, turf cover can be removed, enhanced or extended each growing season. When viewed from above, the spatial extent of tree canopy changes much more slowly over time, and the full extent of the land cover types beneath the canopy is unknown. When examining the spatial autocorrelation of vegetation, it is therefore important to consider vegetation type.

Yard-to-yard similarity within neighbourhoods, caused by human intervention or lack thereof, has been described as social contagion (Turner et al., 2015), and has been observed in a number of human-managed green spaces. For example, clustering of roadside gardens in Ann Arbor, MI has been observed between 30 and 610 m concentric ring buffers (peaking at 91 m) and may be due to spatial contagion (Hunter & Brown, 2012). A study of a single Montréal neighbourhood using Mantel multivariate correlograms found that vegetation and architectural styles in front yards were also highly spatially autocorrelated, which the authors highlighted as a potential example of mimicry (Zmyslony & Gagnon, 1998). When building materials, size and colour were similar, yards also had more similar vegetation characteristics (Zmyslony & Gagnon, 2000). The uptake patterns of green infrastructure in suburban Cleveland, OH, via apparent clustering (Turner et al., 2015), and Washington, DC, shown with spatial permutation tests (Lim, 2017), are also suggestive of social contagion. We use the term 'contagion' to refer to these types of spatial patterns throughout the paper and note that, unlike 'mimicry', contagion does not imply intention.

When considering social contagion, the location of vegetation within yards and yard size may also be important. The desire to 'fit in' and comply with neighbourhood norms maybe stronger where it is more readily visible (in front yards) than in more private and less-visible backyards. Indeed evidence from arid Phoenix, AZ (Larsen & Harlan, 2006; Larson et al., 2009) and mesic Baltimore, MD (Locke et al., 2018) suggests motivation for management, activities and vegetation-pertinent outcomes do vary by front and backyards. For example, among a sample of neighbourhoods in

Baltimore City and County, front yards had greater floral diversity, while backyards had more trees and greater tree diversity (Avolio et al., 2020b). In larger yards, mowing an entire yard can be less common, leaving more room for wooded areas (Visscher et al., 2014). The Zone of Care is the portion of a parcel frequently maintained and visible, such as flower beds or vegetable gardens (Nassauer et al., 2014). The type of vegetation and its location in the yard (e.g. front vs. backyard) and yard size are likely to affect the observed spatial patterns.

Appropriately spatializing reference group behaviour theory and social norms remains a significant methodological challenge in urban ecological research. Multiple factors complicate interpretation and comparisons of prior research on yard care, possible social contagion and front to backyard comparisons. First, studies have examined a variety of different outcomes based on different spatial analyses across plant species diversity (Avolio et al., 2020; Meléndez-Ackerman et al., 2014), roadside plantings and stewardship actions (Hunter & Brown, 2012), green infrastructure installations (Lim, 2017), vacant lot stewardship (Gobster et al., 2020) and exurban carbon storage (Nassauer et al., 2014; Visscher et al., 2014). Second, the influence of one neighbour on another could depend on the geographic distance between neighbours, whether yards abut, whether homes face each other across the street and/or whether they share a backyard. For example, the pattern of spatial autocorrelation of front yard landscaping across increasing distance classes has been shown to be similar on opposite sides of the street, and abutting front yards share 51% to 81% similarity (Zmyslony & Gagnon, 1998). There is not a clear way to operationalize a 'neighbour' in a social sense, and studies have used different approaches (Minor et al., 2016; Zmyslony & Gagnon, 1998), such as creating spatial weights matrices based on distance, nearness and contiguity. The definition of 'neighbour' affects how we measure spatial autocorrelation, and thus can influence the extent to which social contagion appears. Finally, the above-mentioned studies of yard-to-yard similarity may benefit from additional observations representing another climate, under a range of urbanicity conditions to help resolve some ambiguities that have emerged among prior foundational research.

In this paper, we build upon previous empirical research described above by examining spatial autocorrelation in both front and backyards and across neighbourhoods to examine patterns in vegetation cover across multiple scales. We do so to further test reference group behaviour theory and the focus theory of normative conduct in the context of vegetation structure on residential lands. We attempt to build on previous research in several ways. Remotely sensed data are used to examine both tree canopy and turf grass cover, which provides a standardized way of measuring and comparing vegetation structure and its spatial autocorrelation across yards. The definition of neighbour is operationalized with five measures to better understand the explanatory power of different spatial relationships. Focusing on the Boston metropolitan region (MA, USA), and using alternative methods of measuring spatial autocorrelation of yard vegetation, we ask the following research questions:

1. How does spatial autocorrelation of vegetation structure vary by front and backyards and vegetation type?

We expected to measure higher spatial autocorrelation in front yards when compared to backyards, because social norms associated with yard care appear to be stronger in front yards than backyards (Larsen & Harlan, 2006; Larson et al., 2009; Locke et al., 2018). We anticipated that spatial autocorrelation would extend beyond immediate, first-order neighbours to higher-order neighbours (e.g. a neighbour of a neighbour of your neighbour) because prior research has suggested high autocorrelation across neighbourhoods (Hunter & Brown, 2012; Lim, 2017; Zmyslony & Gagnon, 1998, 2000). We expected tree-based measures of vegetation to exhibit more spatial autocorrelation than turf, because trees are harder to change over time.

2. How does spatial autocorrelation differ across neighbourhoods composed of varied socio-economic and demographic populations?

We predicted that spatial autocorrelation would be similar across neighbourhoods with similar socio-economic characteristics—even if the neighbourhoods are not geographically proximate—and would be higher among social groups with more resources to enact social contagion (Daniels & Kirkpatrick, 2006; Grove et al., 2005, 2014). Tree canopy cover has been shown to be greater in high-income and predominantly White communities (Gerrish & Watkins, 2018; Watkins & Gerrish, 2018). We anticipated block groups with larger parcels to be more heterogeneous owing to the Zone of Care (Nassauer et al., 2014) and therefore have lower spatial autocorrelation.

3. How does the definition and operationalization of a 'neighbour' affect patterns of spatial autocorrelation in yard vegetation?

Finally, we thought autocorrelation would be highest when measured with contiguity-based neighbours (i.e. yard polygons that share borders), because abutting yards can share overhanging tree canopy, and lowest with distance-based measures (i.e. Euclidean distances). This is because distance-based measures in a Cartesian space are agnostic to the street network and urban morphology, and may relate spatially close, but socially less-salient yards to influence social contagion. A goal of this research is to understand how different operationalizations of spatial neighbours relate to the amount of observed spatial autocorrelation.

2 | METHODS

2.1 | Study area

This study focused on the Boston, MA, metropolitan region (42°21′29″N 71°03′49″W), an area of approximately 703 km^2. The region has a humid continental climate (mean annual temperature = 9.6°C; mean annual precipitation = 1,233 mm; PRISM Climate Group, 2015) and was historically covered with mesic forests. Forty-four per cent of the land area is residential (Ossola et al., 2019a), which is consistent with other urban areas in western countries such as Baltimore, MD (Avolio et al., 2020b), Chicago, IL (Lewis et al., 2019), Adelaide, (Australia; Ossola et al., 2021), Edinburgh (Scotland), Belfast (Northern Ireland), Cardiff (Wales) and Leicester and Oxford (England; Loram et al., 2007), and represents more than twice as much land area as parks and open spaces (18.43%; Ossola et al., 2019b). Backyards compose 14% of all urban land area and contain ~21% of all tree canopy cover; front yards cover ~8% of the area and have ~8% of the study area's tree canopy cover (Ossola et al., 2019b).

2.2 | Open data

Classified LiDAR point cloud data (year 2014) were obtained from the US Geological Survey ('MA Post-Sandy CMPG 2013–14', NPS = 0.7 m, vertical and horizontal accuracy = 0.05 m and 0.35 m respectively). High-resolution RGB-NIR imagery (1-m ground resolution, year 2014) were obtained from the National Agriculture Imagery Program (NAIP, USDA). Residential parcel polygons, building footprints and road centreline data were downloaded from the open data portals of the Commonwealth of Massachusetts (2017) and the City of Boston (2017).

2.3 | Geospatial analyses

All front, corner and backyards contained in all residential parcels with a house were located and classified in ArcGIS Desktop 10.5 (ESRI) by using the workflow described in the study by Ossola et al. (2019a, 2019b). Briefly, each house centroid was identified to fit an offset line perpendicular to the closest street centreline. Front and backyards were then located by splitting each parcel polygon with a dividing segment, perpendicular to the offset line, passing through the house centroid, and extending to the parcel's border. Yards were classified by attributing the front yard as the closest unit to the respective road centreline. Corner yards, which lack clear front/back sides, were assigned to all parcels located within 15 m from street intersections and were excluded from analyses. The workflow used to locate and classify yards exceeded 98% accuracy (Ossola et al., 2019a).

Vegetation maps detailing tree height, canopy volume and tree and grass covers were modelled and validated for their accuracy based on the LiDAR and RGB-NIR imagery as detailed in previous papers (Ossola et al., 2019a, 2019b). Briefly, tree canopy height was extracted from a canopy height model (1.5-m ground resolution) interpolated from the LiDAR data in ArcGIS Desktop 10.5 (ESRI). Tree and grass covers were modelled at 1.5-m resolution by using maximum likelihood supervised classification of ~100,000 pixels manually attributed to one of three land cover classes (i.e. tree, grass and non-vegetated cover), and based on the tree canopy height map and the RGB-NIR imagery (Singh et al., 2012). The average vertical accuracy of the tree height data, as recorded by the LiDAR point cloud, is 5.3 cm. The accuracy of the grass and tree canopy cover classification is 91.7% and 98.9% respectively (Ossola & Hopton, 2018b). Canopy volume was calculated as the product of tree canopy cover and height within each pixel, assuming this volume to be completely occupied by vegetation (Ossola & Hopton, 2018a, 2018b), which overestimates total volume. Because these remotely sensed data view the earth from above, and tree canopy overhangs turf, the turf estimates are plausibly underestimates (Akbari et al., 2003).

2.4 | Statistical analyses

2.4.1 | Yard and socio-economic variables

We operationalized the spatial autocorrelation of five vegetation metrics: (a) tree canopy cover as a percentage of yard area (m^2/m^2), (b) tree canopy volume (m^3/m^2), (c) average tree canopy height (m), (d) maximum tree canopy height (m) and (e) turf cover as a percentage of area (m^2/m^2). We used these measures of vegetation structure because prior research has identified these as important measures of vegetation structure for people through heat island reduction and storm water mitigation, and other species via habitat provision (insects, birds, etc. Beninde et al., 2015; Ossola et al., 2015).

Census block groups were used to represent different sub-neighbourhood areas, which is common in US Cities (Grove et al., 2014; Landry & Chakraborty, 2009; Locke & Grove, 2016). Census block groups are statistical divisions of Census tracts and are aggregates of blocks; blocks are the smallest US Census geography and (in urban areas) usually bounded by roads on all sides. Block groups are similar to Dissemination Areas produced by Statistics Canada, which have been used for similar studies of urban tree canopy in Montreal, QC (Pham et al., 2012; Pham et al., 2012) and Toronto, ON (Conway & Bourne, 2013; Greene et al., 2018). They usually contain between 600 and 3,000 people (United States Census Bureau, n.d.).

We removed 217 Census block groups from our dataset because they did not have a representative sample of at least 50 residential parcels, leaving 1,027 Census block groups in the analyses. These block groups ranged in size from 0.03 km^2 to 12.45 km^2 (mean = 0.44, median = 0.23, standard deviation = 0.79). Within those block groups, analyses were restricted to one- (65.52%), two- (25.58%) and three-family homes (8.9%) to help ensure that a limited number of residents could have actual control over yard management, leaving 175,576 parcels (perfectly matched front-backyard pairs) or 351,152 yards in total. Parcels ranged from 54.88 m^2 to 86,788 m^2 in area, the average backyard was 368.36 m^2, and the average front yard was 198.51 m^2. Summary statistics for each of the five vegetation characteristics by front and backyard are provided in Table S1.

Socio-economic variables were measured at the block-group scale, as this is the smallest area at which most data are available.

Block group-level variables were accessed from the 2010 to 2014 5-year American Community Survey (ACS) via the *get_acs* function in the TIDYCENSUS package (Walker, 2020) in R version 4.0.3 (2020-10-10). Like the Decennial Census, the ACS is also administered by the US Census Bureau, and collects socio-economic and demographic data about residents and households in the same geographic units. Unlike the Census, ACS data are collected monthly from a representative sample of US households. One-, three- and five-year aggregates of ACS data are released on an ongoing basis. For each block group, we extracted annual median household income, the percentage of the population identifying as White, and the percentage of housing units that are owner occupied. Income (Gerrish & Watkins, 2018) and race (Watkins & Gerrish, 2018) are among the best-studied correlates of urban tree canopy across neighbourhoods. Ownership was included as an indicator of control over yard care (Ossola et al., 2018). All data used in this paper and an *.Rmd file for replication are available via Locke et al., 2021.

2.4.2 | Spatial weights and spatial autocorrelation

All spatial autocorrelation analyses were conducted using R version 4.0.3 (2020-10-10). Spatial autocorrelation, as measured with global Moran's I, was calculated for each metric ($n = 5$) among front yards, and then again for backyards using the SPDEP package's *moran.test* function (Bivand et al., 2013; Bivand & Wong, 2018). Like correlation measures such as Pearson's r and Spearman's ρ, Moran's I varies from −1 to 1 (Moran, 1950). Negative values indicate negative spatial autocorrelation, which means that nearby observations are significantly more different than would be expected by random chance. Positive values indicate positive spatial autocorrelation, with nearby observations that are more similar than would be expected by random chance. A value that is not significantly different from zero indicates spatial randomness, such that the value of an observation cannot be predicted based on its neighbours' values. Also, like correlation coefficients, a p-value for each Moran's I is calculated assuming normality. Permutation tests can be conducted to assess significance but this is computationally intensive with large datasets such as ours.

The Moran's I test is sensitive to how neighbours are defined in a spatial weights matrix (Anselin, 2005). Spatial weights matrices define how the spatial location of observations are considered related to one another (Anselin, 2005). The weights matrix can be defined in several ways, and this reflects the conceptualization of spatial relationships (Figure 1). In this study, we used five types of weights matrices. Neighbours, in the spatial weights sense, can be defined by a specified distance between observations (Anselin, 2005). For our first weights matrix, we used a 40-m distance threshold to define neighbours (Figure 1a). Minor et al. (2016) found that similarity of front yards extended to around 67 m, and Hunter & Brown (2012) similarly found the greatest clustering of roadside gardens at 91 m. Forty metres ensures that these distance values would be captured in second- or third-order neighbours. This weights matrix is sensitive to parcel size, but the remaining weights matrices are not. For the second and third weights matrix, we defined neighbours by using a threshold number of nearest parcels, called K (Bivand et al., 2013). We used $K = 3$ and $K = 6$ so that each yard (of type front or back) was considered a neighbour to its three (Figure 1b) or six (Figure 1c) nearest parcels. This means that yards' neighbours depended on their configuration and proximity. In weights matrices 1–3, distances were computed using the yard centroids. In addition to these distance-based measures, neighbours can be defined from polygon contiguity (Bivand et al., 2013). Rook contiguity occurs when a yard's polygon edge touches another yard's polygon edge (Figure 1d), while Queen contiguity occurs when a yard's edge or corner touches the edge or corner of another yard (Figure 1e). Contiguity-based approaches define abutters as neighbours. By using several definitions of spatial weights, the analyses guard against spurious findings due to how the weights matrix is defined a priori.

To examine the differences in spatial autocorrelation by front and backyard, global Moran's I was calculated for each of the five vegetation structure measures using five types of spatial weights matrices: distance (40 m), k-nearest (three and six) and contiguity (edges only, called 'rook', and edges or vertices, known as 'queen').

To examine the decay of spatial autocorrelation across space, spatial correlograms were calculated for front and backyards separately, for each of the five vegetation variables, using each of the five types of weights matrices described above. This was facilitated by the *sp.correlogram* function in the SPDEP package (Bivand et al., 2013). Spatial correlograms calculate Moran's I at different spatial lags (i.e. between immediate neighbours, between neighbours' neighbours, etc.). A first-order lag, or lag 1, would include each yard's neighbours' neighbours' values (Figure 1f). Moran's I was calculated for 20 lags.

Because autocorrelation may vary by yard size (Nassauer et al., 2014; Visscher et al., 2014), local Moran's I for each parcel was calculated using the *localmoran* function in the SPDEP package (Bivand et al., 2013). Unlike the Moran's I described above which provides one statistic for an entire study area, the local Moran's I provides a measure of autocorrelation for each observation (Anselin, 1995, 1996). Then local Moran's I was correlated with yard size.

2.4.3 | Linking block group-specific autocorrelation to socio-economic conditions

To examine how autocorrelation covaries, or not, with neighbourhood socio-economic characteristics, global Moran's I was calculated again for front and backyards separately, for each block group ($n = 1,027$), using each of the five weights types, for all five variables. The result is 51,350 measures of Moran's I (2 yard types * 1,027 block groups * 5 vegetation variables * 5 spatial weights matrices). For each block group, we characterized income, race, ownership and parcel size using data described above.

Five mixed effects regression models were fit, one for each vegetation variable (Equation 1), using *lme4*'s *lmer* function (Bates

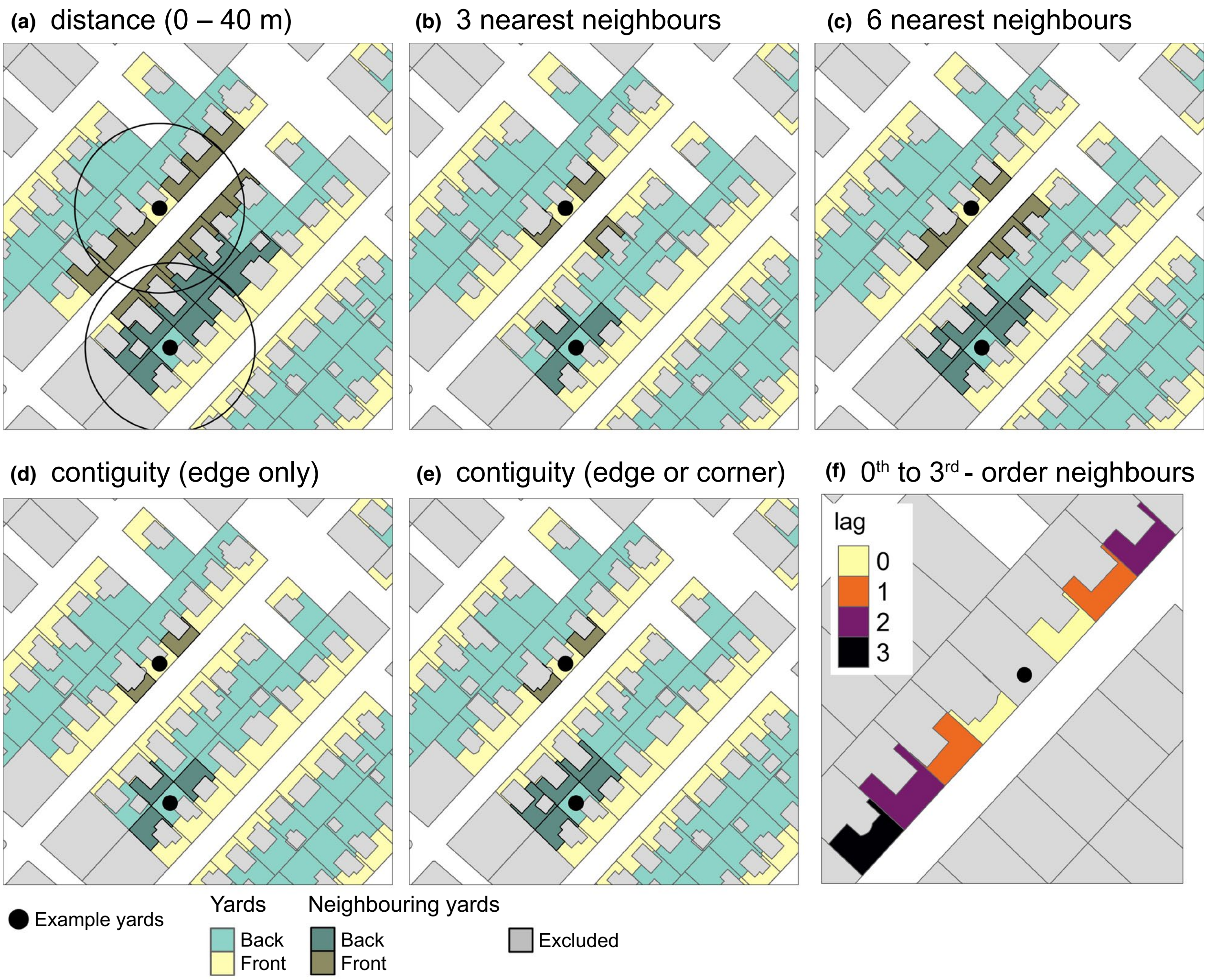

FIGURE 1 Five types of spatial neighbours are used in this paper: A radial distance of 40 m (a), the three nearest neighbours (b), the six nearest neighbours (c), the polygons who share an edge, called 'rook' (d) and polygons who share either an edge or a vertex, called 'queen' (e). Dots represent example yards: one front yard and one backyard to demonstrate how different types of neighbourhood definitions are operationalized. Using the front yard from panel e as an example (f), yards have queen-based neighbours (lag = 0), which in turn have neighbours (lag = 1), which also have neighbours (lag = 2), and so on. Neighbours' neighbours are higher order neighbours. Corner lots, whose front/back dichotomy is complicated, and non-residential-yards, are excluded

et al., 2015). For each vegetation variable, spatial autocorrelation in each block group (the dependent variable) was regressed against yard type (front or back), the block group's median income, the interaction between yard type and income, per cent White, per cent owner-occupied housing units and median parcel size, with the spatial weights matrix included as a random intercept:

$$Y_{ij} = \gamma_{00} + \gamma_{10} yard_{ij} + \gamma_{01} income_{0j} + \gamma_{02} pctWhite_{0j} + \gamma_{03} pctOwn_{0j} + \gamma_{04} medianParcelSize_{0j} + \gamma_{11} yard_{ij} \times income_{0j} + u_{0j} + e_{ij}, \quad (1)$$

where Y_{ij} is Moran's I of a vegetation variable (tree canopy cover, tree canopy volume, average tree canopy height, maximum tree canopy height or turf cover) in block group i, using the spatial weights matrix j. γ_{00} is the intercept and mean backyard value. γ_{10} is the back/front categorical variable with front yard as the contrast (with back as the reference) in block group i, γ_{01} is the coefficient for median household income (in \$1,000s), γ_{02} is the coefficient for per cent White, γ_{03} is the owner-occupied housing coefficient, γ_{04} is the median parcel size term and γ_{11} is the yard type–income interaction term. The u_{0j} term therefore represents the random effects per type of the spatial weights matrix, and e_{ij} are the block group-level residuals. Analyses were carried out using R version 4.0.3 (2020-10-10) and sjPlot facilitated making tables from lmer objects (Lüdecke, 2018).

3 | RESULTS

At lag 0 (i.e. immediate neighbours), spatial autocorrelation was always positive and statistically significant for all five measures of vegetation structure, for front and backyards, and with all five weights matrices (Figure 2). At lag 0, Moran's I ranged from a low of 0.235

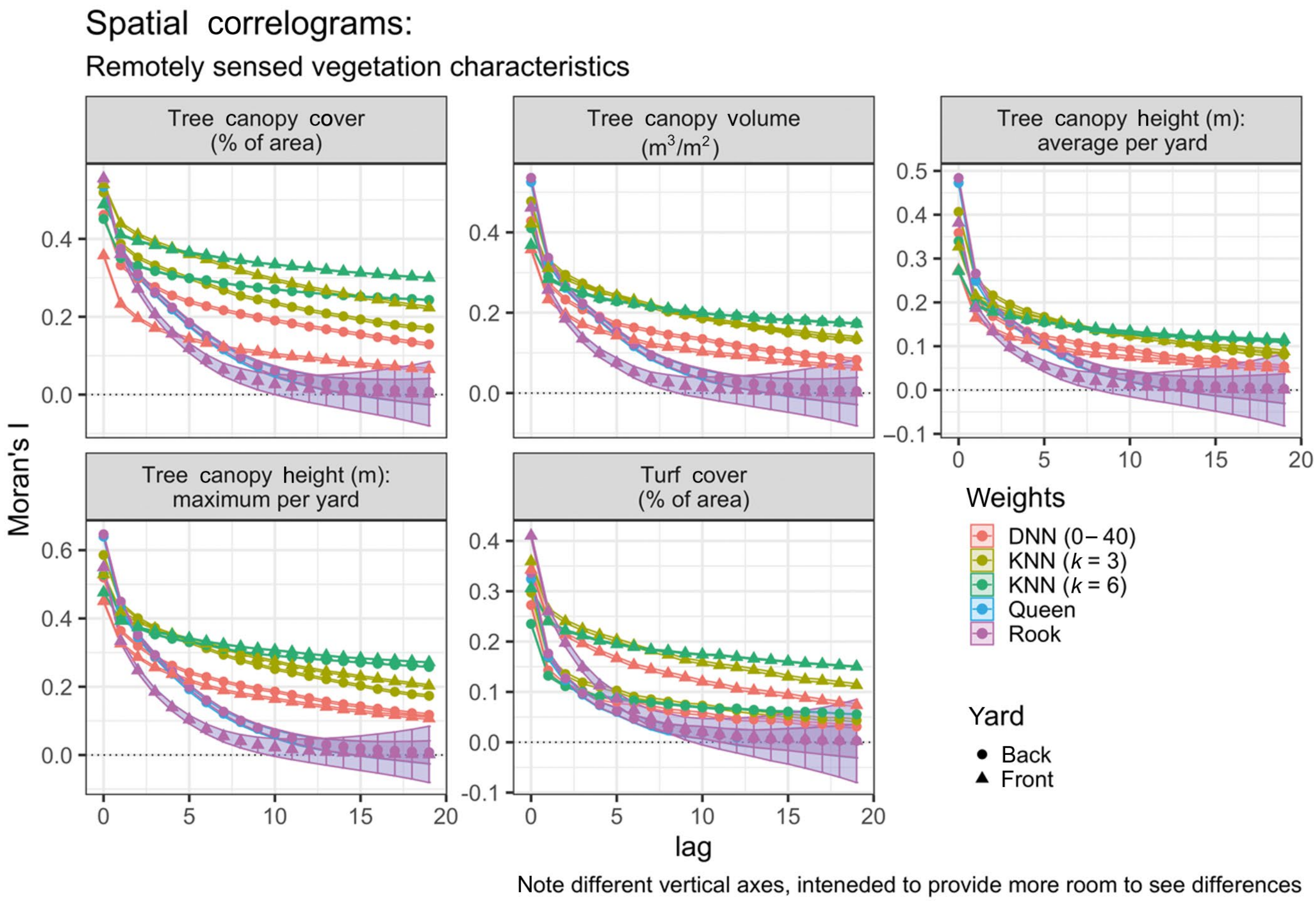

FIGURE 2 Spatial correlograms for remotely sensed vegetation characteristics by front and backyards ($n = 351{,}152$) using five different spatial weights definitions. Ribbon width shows the 95% confidence interval, which are very tight for non-contiguity-based definitions. Higher Moran's *I* values represent higher spatial autocorrelation of vegetation characteristics

(95% CI [0.232, 0.238]) for backyard turf with the $K = 6$ neighbours, to a high of 0.647 (95% CI [0.642, 0.651]) for backyard maximum tree height with neighbours defined by rook contiguity.

3.1 | Spatial autocorrelation of vegetation structure in front versus backyards and vegetation type

At lag 0, Moran's *I* was overall slightly higher in backyards (mean = 0.449, $SD = 0.11$) than that in front yards (mean = 0.420, $SD = 0.09$), and a paired *t*-test of Moran's *I* between front and backyards irrespective of vegetation variables and neighbour types showed higher autocorrelation in backyards ($p = 0.033$). Also at lag 0, and per each vegetation variable, paired *t*-test showed no differences between front and back for tree canopy ($p = 0.97$), greater autocorrelation in backyards for volume ($p < 0.001$), average height ($p < 0.001$), maximum height ($p = 0.0012$) and greater autocorrelation in front yards for turf cover ($p < 0.0001$).

For distance-based weight matrices, spatial autocorrelation remained high and statistically significant for all 20 lags examined. Contiguity-based measures show a faster decay rate, with spatial autocorrelation within the realm of chance after 10 lags. Contiguity-based measures have fewer available neighbours at higher order lags, consequently the 95% confidence interval is larger.

The correlation between local Moran's *I* for vegetation in each yard and its yard area is greater for front yards than backyards, and the difference is greater for trees than turf, while varying by vegetation and weights matrix type (Figure S1). In other words, larger front yards have greater spatial autocorrelation than backyards. The correlation between backyard area and the spatial autocorrelation of per cent tree canopy cover was the lowest, and not always significant; the backyard tree canopy cover autocorrelation appears relatively invariant with backyard area.

3.2 | Spatial autocorrelation and neighbourhood-level social characteristics

When examining the spatial autocorrelation per block group, front yards had less spatial autocorrelation for all five vegetation structure variables; this was true at both the scale of individual yards and also at the block group scale. Median household income was negatively associated with the spatial autocorrelation of tree canopy cover and positively associated with the spatial autocorrelation of maximum tree height and turf cover. The percentage of the population identifying as White in the US Census data had a positive statistically significant relationship with the spatial autocorrelation of turf cover. The percentage of the housing units that are owner occupied was positively related to the spatial autocorrelation of all of the vegetation structure variables except the percentage of tree canopy cover. Median parcel size was positively and significantly related to spatial autocorrelation of all vegetation measures. Finally, the interaction between income and yard type was always statistically significant (Figure 3). Spatial autocorrelation of front yard vegetation is positively related to income, and was greater than backyard spatial autocorrelation in the highest income block groups. However, the relationship between income and spatial autocorrelation of backyard vegetation depends on the vegetation variable; at higher income levels, backyard autocorrelation is lower (tree canopy cover), is greater (maximum tree canopy height) or does not vary at all (average tree canopy height, canopy volume and turf). The spatial weights matrix type accounts for 15% (turf) to 35% (maximum tree height) of the variation in Moran's *I* (Table 1). By construction, these block group-level correlates pertain to aggregates of households.

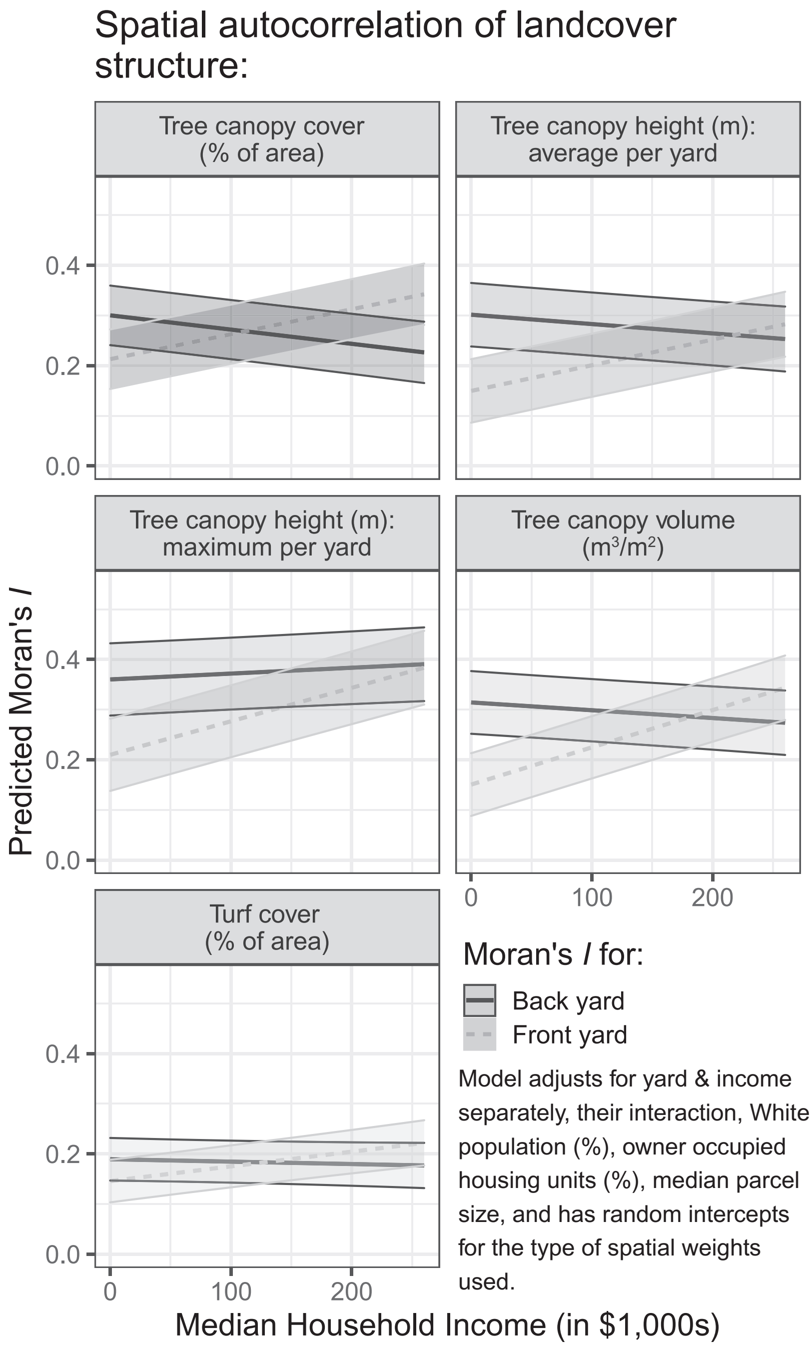

FIGURE 3 Front yard autocorrelation always rises with higher incomes, while the slope of backyard autocorrelation is smaller (max height, turf), is invariant to income (average canopy height, tree volume) or slightly negative (% canopy cover)

TABLE 1 Mixed effects regression models of Census Block Group-level vegetation structure spatial autocorrelation

	Tree Canopy Cover (% of area)				Tree Canopy Volume (m^3/m^2)			
Predictors	***Est.***	***std. Beta***	***std. CI***	***std. p***	***Est.***	***std. Beta***	***std. CI***	***std. p***
[illegible]: (Intercept)	0.26	0.10	−0.36 to 0.56	0.669	0.23	0.33	−0.11 to 0.77	0.142
V: Yard (Back as ref.)	−0.09	−0.20	−0.23 to −0.17	**<0.001**	−0.16	−0.66	−0.69 to −0.63	**<0.001**
γ_{00}: Median Household Income ($1,000s)	−0.00	−0.08	−0.11 to −0.06	**<0.001**	−0.00	−0.04	−0.07 to −0.02	**0.001**
γ_{10}: White (% of population)	0.00	0.01	−0.00 to 0.03	0.143	−0.00	−0.00	−0.02 to 0.01	0.726
γ_{01}: Owner Occupied Housing (% of housing units)	0.00	0.01	−0.00 to 0.03	0.119	0.00	0.03	0.01 to 0.04	**0.002**
γ_{02}: Median Parcel Size (m^2)	0.00	0.06	0.04 to 0.08	**<0.001**	0.00	0.14	0.12 to 0.15	**<0.001**
γ_{03}: Income-Yard interaction	0.00	0.23	0.20 to 0.27	**<0.001**	0.00	0.24	0.21 to 0.27	**<0.001**
Random effects								
σ^2	0.01				0.01			
τ_{00}	0.00_{type}				0.01_{type}			
ICC	0.27				0.29			
N	5_{type}				5_{type}			
Observations	10,270				10,270			
Marginal R^2/Conditional R^2	0.030/0.289				0.153/0.394			

4 | DISCUSSION

Urban residential land management is carried out in millions of households, with the cumulative environmental impacts potentially significant even at the continental scale (Groffman et al., 2017; Odum, 1982). Yet less attention has been paid to spatial patterns across a large metropolitan area. This paper investigated how the spatial autocorrelation of vegetation structure varies by front and backyards and across neighbourhoods composed of different socio-economic groups. Importantly, the analyses incorporated different spatial weights matrices that represent different spatial definitions of a 'neighbour'. We found strong patterns of positive spatial autocorrelation in all measured vegetation variables, in both front and backyards (Figure 2). Furthermore, these spatial patterns varied from one block group to another along with socio-economic variables such as income and home ownership. Finally, the spatial patterns we observed varied depending on how we operationalized 'neighbours', which suggests the need to better understand the choice of spatial weights in spatial analyses, and how residents may understand neighbours in a sociological sense. This work can inform attempts to influence resident planting behaviours on urban private land and complement public efforts to increase urban canopy cover and maximize ecosystem services such as landscape cooling and biodiversity conservation (Goddard et al., 2013; Ossola et al., 2021).

4.1 | Vegetation spatial autocorrelation across front and backyards and vegetation type

Contrary to our expectations, among immediate neighbours (i.e. lag 0), spatial autocorrelation of tree volume and average and maximum canopy height was greater in backyards than that in front yards. Social theory (Carrico et al., 2012; Cialdini et al., 1990, 1991; Grove et al., 2006; Hyman, 1942; Locke et al., 2018; Merton & Kitt, 1950) and prior empirical findings (Avolio et al., 2020a; Larsen & Harlan, 2006; Larson et al., 2009; Locke et al., 2018) suggest pressures for conformity are greater in more-visible front yards. Paradoxically, greater spatial autocorrelation in backyards is reasonable: in our study system, backyards have abundant tree canopy that form large contiguous patches that may partly explain the relative high autocorrelation (Ossola et al., 2019b). Moreover, the quickest, easiest and perhaps least-expensive types of vegetation for residents to modify, in order to achieve neighbourhood conformity, would be turf grass and lawns in front yards. Indeed, there was greater spatial autocorrelation in front yard turf cover, as compared to backyards, which is consistent with trying to achieve neighbourhood conformity and aesthetics of neatness in the most visible part of a home environment (Nassauer, 1988, 1995; Robbins, 2012; Visscher et al., 2016). In contrast to turf cover that can be more promptly modified once established, tree canopy is likely to increase more slowly, while being more challenging and expensive to remove. The contemporary distribution of urban tree canopy is a consequence of a blend of biophysical conditions and human decisions (Grove et al., 2018; Roman et al., 2018). It remains to be seen if legacy effects are stronger in backyards than front yards, and how legacy effects may interact with parcel or yard size. Yard size is a stronger correlate of spatial autocorrelation in front yards than backyards, and the relationships vary by vegetation and weights matrix type (Figure S1).

Positive spatial autocorrelation extended far beyond immediate, first-order neighbours for front and backyards and for all vegetation variables (Figure 2). Autocorrelation calculated based on distance

Tree Canopy Height (m): Average per yard				Tree Canopy Height (m): Maximum per yard				Turf Cover (% of area)			
Est.	*std. Beta*	*std. CI*	*std. p*	*Est.*	*std. Beta*	*std. CI*	*std. p*	*Est.*	*std. Beta*	*std. CI*	*std. p*
0.24	0.36	−0.11 to 0.83	0.131	0.27	0.36	−0.12 to 0.84	0.144	0.12	0.07	−0.27 to 0.40	0.698
−0.15	−0.72	−0.75 to −0.69	**<0.001**	−0.15	−0.71	−0.74 to −0.69	**<0.001**	−0.04	−0.13	−0.17 to −0.10	**<0.001**
−0.00	−0.05	−0.08 to −0.03	**<0.001**	0.00	0.03	0.01 to 0.05	**0.011**	−0.00	−0.01	−0.04 to 0.01	0.313
0.00	0.00	−0.01 to 0.02	0.612	0.00	0.01	−0.01 to 0.03	0.221	0.00	0.03	0.01 to 0.05	**0.008**
0.00	0.01	−0.00 to 0.03	0.073	0.00	0.02	0.00 to 0.03	**0.018**	0.00	0.02	−0.00 to 0.04	0.065
0.00	0.14	0.12 to 0.15	**<0.001**	0.00	0.19	0.18 to 0.21	**<0.001**	0.00	0.16	0.14 to 0.18	**<0.001**
0.00	0.20	0.17 to 0.23	**<0.001**	0.00	0.14	0.11 to 0.17	**<0.001**	0.00	0.10	0.07 to 0.14	**<0.001**
0.01				0.01				0.01			
0.01_{type}				0.01_{type}				0.00_{type}			
0.32				0.35				0.15			
5_{type}				5_{type}				5_{type}			
10,270				10,270				10,240			
0.160/0.431				0.189/0.471				0.042/0.182			

remained significant after 20 lags, whereas those calculated based on contiguity (i.e. queen and rook) started with greater autocorrelation among immediate neighbours then sharply decline and became insignificant after about 10 lags. Tree canopy overhanging from abutting parcels may explain the highest autocorrelation measured with contiguity-based neighbours. Since we are unable to attribute canopies to their stems, ownership cannot be ascribed. This issue might be more pronounced on smaller parcels. If social contagion is creating spatial autocorrelation in vegetation structure, the set of yards that constitute neighbours in the social sense is likely larger than only the yards that share an edge (rook), or edge or vertex (queen). What composes the social reference group is likely more inclusive, and likely relates to the neighbourhood scale (Fraser et al., 2013; Grove et al., 2006; Nassauer et al., 2009).

4.2 | Vegetation structure autocorrelation among neighbourhoods with different socio-economic characteristics

The block group to block group (our approximation of sub-neighbourhood areas) variation in tree-related autocorrelation varied by front and backyard, median household income, home ownership and parcel size. Block groups with larger median parcel size had greater spatial autocorrelation for all vegetation metrics (Table 1). Consistent with yard-scale findings, when aggregated to block groups, backyards had significantly greater spatial autocorrelation than front yards, too. Significant yard (front vs. back)–income interactions (Table 1; Figure 3) show that backyard spatial autocorrelation is relatively invariant by median household income, but spatial autocorrelation for front yards is greatest in higher income areas. Future analyses may explore additional cross-scalar interactions in greater depth as suggested by Roy Chowdhury et al. (2011) and Grove et al. (2005) and employed by Locke et al. (2016, 2019).

Different socio-economic characteristics predicted spatial autocorrelation of different vegetation characteristics. We expected that autocorrelation would be higher in high income areas, but we observed the opposite for tree canopy cover and maximum tree height. However, turf cover autocorrelation was positively associated with block group median household income. Furthermore, owner-occupied neighbourhoods generally had more spatial autocorrelation. It is possible that renters are less interested or able to modify vegetation, irrespective of their neighbours. The associations with income and home ownership, and the significant income–yard interaction, are collectively consistent with the notion of financially investing in lawns to signal membership and conformity with a uniform, monoculture, lawn-dominant landscape among White Americans (Robbins, 2012). Our single measure of race (% White) was not associated with any of the tree canopy spatial autocorrelation measures.

4.3 | Defining neighbours: Implications for theory, methods and practice

There is no clear process for studying spatial autocorrelation (or social contagion) of residential yards across spatial scales. The variety of methodological approaches that prior research has used to operationalize neighbours in spatial analyses has challenged comparisons of yard care studies. For example, using multiple distances or distance thresholds reveals a distance decay (Hunter & Brown, 2012; Zmyslony & Gagnon, 1998), but Euclidean distances are agnostic to street networks and urban form. Nearest neighbours often include abutters and visible yards across the street, but also can include distant yards in sparsely populated areas and may artificially limit the number of relevant yards in denser areas. Contiguity-based measures include abutters, but ignore yards across the street.

Our study demonstrates that spatial autocorrelation patterns depend on how neighbours are defined. Overall, 15 to 35% of the variation in autocorrelation at the block group scale was explained by the chosen weights type (Table 1). Similar variation was observed at the yard scale (Figure 2). Despite the lack of comparability among prior methods, future research may continue investigating how to best match what defines a neighbour in spatial analyses with what constitutes a neighbour in a social sense. Considering multiple conceptualizations—and even disciplinary approaches—of spatial neighbours will be important (Small & Adler, 2019) in subsequent analyses, because results are sensitive to how neighbours are defined. Relatively straightforward measures of distance, proximity, colocation and adjacency may not adequately capture the complexity of the social context of interest (Small & Adler, 2019). Neighbour definition is important and challenging, and invites further refinement that includes the dynamic nature of neighbours, as well as the interconnectedness and strength of social ties formed among residents.

Rather than defining one set or type of spatial neighbours for all households, neighbour definitions could also vary by geographic region or even household type. These methodological developments could allow for more refined testing of a spatialized reference group behaviour theory as it applies to residential landscapes. Ego-centric neighbours once only theorized (Hägerstrand, 1982) are increasingly possible with mobile GPS units (Kwan, 2013) and big data like cell phone- and social media-derived locations (Sampson & Levy, 2020; Wang et al., 2018). Individual behaviour tracked with these technologies can derive travel routes to and from home, work and places of recreation to derive person-specific neighbourhood definitions that are needed to refine future assessment of spatial autocorrelation patterns. Residents' personal and online social networks may also shape the reference group that in turn shapes yard care activities and outcomes like vegetation structure and its autocorrelative patterns. Finally, there could be interactions between population density, urban form and the conceptualization of neighbour. Future research can better operationalize the lived experience relevant for these kinds of questions.

4.4 | Limitations and future research

In this study, we used remotely sensed data to measure vegetation structure from a top-down perspective because they are consistent, spatially explicit and cover the entire area of interest. However, a limitation of this dataset is that shrubs and grasses under the tree canopy were undetected. If researchers and practitioners have questions about species, their conditions and their socio-ecological traits, alternatives to pixels will be needed. Additionally, if one wants to know if plants were intentionally planted or are the result of natural regeneration or inaction, then social surveys and resident interviews could complement and validate our approach. Analyses were limited to one-, two- and three-family homes, but intra-household motivations and decisions warrant further investigation. Another area of future research may include the spatial arrangement and configuration of yard vegetation. For example, does a yard have many small trees or one large tree with equal area? Both would lead to the same percentage cover value and therefore exhibit the same degree of spatial autocorrelation, even though the distribution and management could be very different, particularly when considering the identity and characteristics of species (e.g. aesthetic traits, etc.). Future research may use more detailed socio-ecological measures to examine spatial autocorrelation more directly, and how this might affect taxa other than plants.

An open question is the extent to which spatial autocorrelation in yards is caused by intentional mimicry between neighbours rather than decisions made by developers, planners, underlying environmental constraints and/or other drivers. To some extent, this question may be addressed by examining changes in spatial autocorrelation over time. In particular, there could be a 'founder's effect' whereby developers or prior residents plant trees but later move their residence (Ossola et al., 2018). Residents often fit into neighbourhoods by maintaining the landscape established by the developers (Harris et al., 2012). Do people who are able to move chose to move to neighbourhoods with particular vegetation structure and pattern, or do they move for other reasons and then create the landscape conditions they prefer after they have arrived? Additionally, home owners' associations influence yard care outcomes via their covenants, codes and restrictions (Fraser et al., 2013; Larson & Brumand, 2014; Turner & Ibes, 2011). If residents are mimicking their neighbours, we might expect to see an increase in spatial autocorrelation over time. Social bonds take time to form, and mimicry may be higher in certain social contexts than others. Similarly, as vegetation naturally grows over time, a better understanding of vegetation growth and interplay with mimicry are needed. Longitudinal data are required to address these questions.

Finally, it remains to be seen how our findings may or may not apply to other common types of green spaces in urban landscapes, and other countries and regions. This paper examined residential yards because they are a dominant land use, but future research could apply similar methods to examine allotment gardens, forested patches, parks and institutional campuses. Because autocorrelation is widespread, additional research may more closely investigate mimicry more directly, and examine the causes and consequences of yard care on residential socio-ecological systems over time.

5 | CONCLUSIONS

Residential yards are an important component of urban landscapes, and locally may represent residents' primary or only exposure to nature. Our study suggests that nearby yards are more similar to each other than would be expected by chance, producing patterns of positive spatial autocorrelation in all measured vegetation variables. Different types of vegetation, such as grasses, are easier to modify than others, while vegetation, such as trees and shrubs, with their different growth rates can influence how autocorrelation materializes at a specific point in time. The results underscored the importance of backyards as critical areas for sustaining an urban tree canopy as private land where tree vegetation is maintained. Furthermore, we found that different ways of operationalizing neighbours influenced the degree of spatial autocorrelation we observed. The spatial autocorrelation of residential vegetation structure may be purposefully or inadvertently influenced via social norms by neighbours, though spatial patterns from parcels to neighbourhoods are complex and likely related to socio-economic factors as well as yard and vegetation types. Understanding how spatial patterns materialize across scales can provide important insights on how to further urban greening by enriching current urban forestry strategies and plans with actions targeted at increasing structure and cover of private residential vegetation.

In complex modern urban socio-ecological systems, a broader focus on the private realm and the inclusion of residents through social mechanisms can significantly advance knowledge of how habitat is created, biodiversity is protected and landscapes are cooled during extreme heat. Future research could clarify how residential vegetation changes over time—from parcel to landscape—and how it is affected by changes in people's preferences and norms. It is necessary to further test our findings in other cities characterized by different environmental (e.g. climate), social and historical drivers. The use of big data and integrated analyses is needed to provide robust explanations on the possible mechanisms and processes underpinning complex and varied relationships between people and nature across residential forests. By better measuring and understanding autocorrelation, spatial contagion and ultimately social mimicry mechanisms, we can devise more effective planning and management actions to decisively increase vegetation cover and structure across private landscapes. We see the inclusion of the overlooked role of people and residents in urban greening as the ultimate tool to create greener cities and towns in the future.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHORS' CONTRIBUTIONS

D.H.L., A.O., E.M. and B.B.L. conceived of the ideas and designed the methodology; A.O. collected the data; D.H.L. conducted the analyses and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

DATA AVAILABILITY STATEMENT

Data are available on Dryad Digital Repository https://doi.org/10.5061/dryad.jdfn2z3bb (Locke et al., 2021).

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REFERENCES

Akbari, H., Shea Rose, L., & Taha, H. (2003). Analyzing the land cover of an urban environment using high-resolution orthophotos. *Landscape and Urban Planning*, *63*(1), 1–14. https://doi.org/10.1016/S0169-2046(02)00165-2

Anselin, L. (1995). Local indicators of spatial association – LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Anselin, L. (1996). The Moran scatterplot as an ESDA tool to assess local instability in spatial association. In M. Fischer, H. Scholten, & D. Unwin (Eds.), *Spatial analytical perspectives on GIS in environmental and socio-economic sciences* (pp. 11–125). Taylor & Francis.

Anselin, L. (2005). Exploring spatial data with GeoDa TM: A workbook. Retrieved from http://www.csiss.org/clearinghouse/GeoDa/geodaworkbook.pdf

Avolio, M. L., Blanchette, A., Sonti, N. F., & Locke, D. H. (2020a). Time is not money: Income is more important than lifestage for explaining patterns of residential yard plant community structure and diversity in Baltimore. *Frontiers in Ecology and Evolution*, *8*. https://doi.org/10.3389/fevo.2020.00085

Avolio, M. L., Blanchette, A., Sonti, N. F., & Locke, D. H. (2020b). Time is not money: Income is more important than lifestage for explaining patterns of residential yard plant community structure and diversity in Baltimore. *Frontiers in Ecology and Evolution*, *8*(April), 1–14. https://doi.org/10.3389/fevo.2020.00085

Bates, D. M., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using Lme4. *Journal of Statistical Software*, *67*, 1–48. Retrieved from http://lme4.r-forge.r-project.org/lMMwR/lrgprt.pdf

Beninde, J., Veith, M., & Hochkirch, A. (2015). Biodiversity in cities needs space: A meta-analysis of factors determining intra-urban biodiversity variation. *Ecology Letters*, *18*(6), 581–592. https://doi.org/10.1111/ele.12427

Bivand, R. S., Pebesma, E., & Gómez-Rubio, V. (2013). *Applied spatial data analysis with R* (2nd ed.). Retrieved from https://asdar-book.org/

Bivand, R. S., & Wong, D. W. S. (2018). Comparing implementations of global and local indicators of spatial association. *TEST*, *27*(3), 716–748. https://doi.org/10.1007/s11749-018-0599-x

Bormann, F. H., Balmori, D., & Geballe, G. T. (2001). *Redesigning the American lawn: A search for environmental harmony.* Yale University Press.

Carrico, A. R., Fraser, J., & Bazuin, J. T. (2012). Green with envy: Psychological and social predictors of lawn fertilizer application. *Environment and Behavior*, *45*(4), 427–454. https://doi.org/10.1177/0013916511434637

Carrico, A. R., Raja, U. S., Fraser, J., & Vandenbergh, M. P. (2018). Household and block level influences on residential fertilizer use. *Landscape and Urban Planning*, *178*(May), 60–68. https://doi.org/10.1016/j.landurbplan.2018.05.008

Chowdhury, R. R., Larson, K., Grove, M., Polsky, C., Cook, E., Onsted, J., & Ogden, L. (2011). A multi-scalar approach to theorizing socio-ecological dynamics of urban residential landscapes. *Cities and the Environment*, *4*(1), 1–19. Retrieved from http://digitalcommons.lmu.edu/cate/vol4/iss1/6/

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. *Advances in Experimental Social Psychology*, *24*(C), 201–234.

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology*, *58*(6), 1015–1026. https://doi.org/10.1037/0022-3514.58.6.1015

Conway, T. M., & Bourne, K. S. (2013). A comparison of neighborhood characteristics related to canopy cover, stem density and species richness in an urban forest. *Landscape and Urban Planning*, *113*, 10–18. Retrieved from http://www.sciencedirect.com/science/article/pii/S0169204613000121

Daniels, G. D., & Kirkpatrick, J. B. (2006). Comparing the characteristics of front and back domestic gardens in Hobart, Tasmania, Australia. *Landscape and Urban Planning*, *78*(4), 344–352. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S016920460600003X

Fraser, J. C., Bazuin, J. T., Band, L. E., & Morgan, G. J. (2013). Covenants, cohesion, and community: The effects of neighborhood governance on lawn fertilization. *Landscape and Urban Planning*, *115*, 30–38. https://doi.org/10.1016/j.landurbplan.2013.02.013

Gerrish, E., & Watkins, S. L. (2018). The relationship between urban forests and income: A meta-analysis. *Landscape and Urban Planning*, *170*, 293–308. https://doi.org/10.1016/j.landurbplan.2017.09.005

Gobster, P. H., Rigolon, A., Hadavi, S., & Stewart, W. P. (2020). Beyond proximity: Extending the 'greening hypothesis' in the context of vacant lot stewardship. *Landscape and Urban Planning*, *197*(February), https://doi.org/10.1016/j.landurbplan.2020.103773

Goddard, M. A., Dougill, A. J., & Benton, T. G. (2013). Why garden for wildlife? Social and ecological drivers, motivations and barriers for biodiversity management in residential landscapes. *Ecological Economics*, *86*, 258–273.

Greene, C. S., Robinson, P. J., & Millward, A. A. (2018). Canopy of advantage: Who benefits most from city trees? *Journal of Environmental Management*, *208*, 24–35. https://doi.org/10.1016/j.jenvman.2017.12.015

Groffman, P. M., Avolio, M., Cavender-Bares, J., Bettez, N. D., Grove, J. M., Hall, S. J., Hobbie, S. E., Larson, K. L., Lerman, S. B., Locke, D. H., Heffernan, J. B., Morse, J. L., Neill, C., Nelson, K. C., O'Neil-Dunne, J., Pataki, D. E., Polsky, C., Chowdhury, R. R., & Trammell, T. L. E. (2017). Ecological homogenization of residential macrosystems. *Nature Ecology & Evolution*, *1*(7). Retrieved from http://www.nature.com/articles/s41559-017-0191

Grove, J. M., Burch Jr., W. R., and Pickett, S. T. A. (2005). Social mosaics and urban community forestry in Baltimore, Maryland introduction: Rationale for urban community forestry continuities from rural to urban community forestry. In R. G. Lee and Field D. R. (Eds.), *Communities and forests: Where people meet the land* (pp. 248–273). Oregon State University Press. Retrieved from http://web.mac.com/jmorgangrove/Morgan/Products_files/Grove_et_al_SocialMosaics.pdf

Grove, J. M., Cadenasso, M. L., Burch, W. R. Jr, Pickett, S. T., Schwarz, K., O'Neil-Dunne, J., Wilson, M., Troy, A., & Boone, C. (2006). Data and methods comparing social structure and vegetation structure of urban neighborhoods in Baltimore. *Maryland. Society and Natural Resources*, *19*(19), 117–136. https://doi.org/10.1080/08941920500394501

Grove, J. M., Locke, D. H., O'Neil-Dunne, J. P. M., & O'Neil-Dunne, J. P. M. (2014). An ecology of prestige in New York City: Examining the relationships among population density, socio-economic status, group identity, and residential canopy cover. *Environmental Management*, *54*(3), 402–419. https://doi.org/10.1007/s00267-014-0310-2

Grove, M., Ogden, L., Pickett, S., Boone, C., Buckley, G., Locke, D. H., Lord, C., & Hall, B. (2018). The legacy effect: Understanding how segregation and environmental injustice unfold over time in Baltimore. *Annals of the American Association of Geographers*, *108*(2), 524–537. https://doi.org/10.1080/24694452.2017.1365585

Hägerstrand, T. (1982). Diorama, path and project. *Tijdschrift Voor Economische En Sociale Geografie*, *73*(6), 323–339. https://doi.org/10.1111/j.1467-9663.1982.tb01647.x/abstract

Harris, E. M., Martin, D. G., Polsky, C., Denhardt, L., & Nehring, A. (2013). Beyond 'Lawn People': The role of emotions in suburban yard management practices. *The Professional Geographer*, *65*, 345–361. https://doi.org/10.1080/00330124.2012.681586

Harris, E. M., Polsky, C., Larson, K. L., Garvoille, R., Martin, D. G., Brumand, J., & Ogden, L. (2012). Heterogeneity in residential yard care: Evidence from Boston, Miami, and Phoenix. *Human Ecology*, *40*(5), 735–749. https://doi.org/10.1007/s10745-012-9514-3

Hernke, M. T., & Podein, R. J. (2011). Sustainability, health and precautionary perspectives on lawn pesticides, and alternatives. *EcoHealth*, *8*(2), 223–232. https://doi.org/10.1007/s10393-011-0697-7

Hunter, M. C. R., & Brown, D. G. (2012). Spatial contagion: Gardening along the street in residential neighborhoods. *Landscape and Urban Planning*, *105*(4), 407–416. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S0169204612000291

Hyman, H. H. (1942). The psychology of status. *Archives in Psychology*, *296*, 5–38.

Julien, M., & Zmyslony, J. (2001). Why do landscape clusters emerge in an organized fashion in anthropogenic environments? *Landscape Research*, *26*(4), 337–350. https://doi.org/10.1080/01426390120090139

Kwan, M.-P. (2013). Gender, the home-work link, and space-time patterns of nonemployment activities. *Economic Geography*, *75*(4), 370–394.

Landry, S. M., & Chakraborty, J. (2009). Street trees and equity: Evaluating the spatial distribution of an urban amenity. *Environment and Planning A*, *41*(11), 2651–2670. Retrieved from http://www.envplan.com/abstract.cgi?id=a41236

Larsen, L., & Harlan, S. L. (2006). Desert dreamscapes: Residential landscape preference and behavior. *Landscape and Urban Planning*, *78*(1–2), 85–100. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S0169204605000800

Larson, K. L., & Brumand, J. (2014). Paradoxes in landscape management and water conservation: Examining neighborhood norms and institutional forces. *Cities and the Environment*, *7*(1), 1–24. Retrieved from http://digitalcommons.lmu.edu/cate/vol7/iss1/6/

Larson, K. L., Casagrande, D. G., Harlan, S. L., & Yabiku, S. T. (2009). Residents' yard choices and rationales in a desert city: Social priorities, ecological impacts, and decision tradeoffs. *Environmental Management*, *44*, 921–937. https://doi.org/10.1007/s00267-009-9353-1

Lewis, A. D., Bouman, M. J., Winter, A. M., Hasle, E. A., Stotz, D. F., Johnston, M. K., Klinger, K. R., Rosenthal, A., & Czarnecki, C. A. (2019). Does nature need cities? Pollinators reveal a role for cities in wildlife conservation. *Frontiers in Ecology and Evolution*, *7*, 1–8.

Lim, T. C. (2017). An empirical study of spatial-temporal growth patterns of a voluntary residential green infrastructure program. *Journal* *of Environmental Planning and Management*, 1–20. https://doi.org/10.1080/09640568.2017.1350146

Locke, D. H., Landry, S. M., Grove, J. M., & Roy, C. R. (2016). What's scale got to do with it? Models for urban tree canopy. *Journal of Urban Ecology*, *2*(1), juw006. https://doi.org/10.1093/jue/juw006

Locke, D. H., & Morgan Grove, J. (2016). Doing the hard work where it's easiest? Examining the relationships between urban greening programs and social and ecological characteristics. *Applied Spatial Analysis and Policy*, *9*(1), 77–96. https://doi.org/10.1007/s12061-014-9131-1

Locke, D. H., Ossola, A., Minor, E., & Lin, B. (2021). Yards, block groups, and vegetation cover measures. *Dryad Digital Repository*, https://doi.org/10.5061/dryad.jdfn2z3bb

Locke, D. H., Polsky, C., Grove, J. M., Groffman, P. M., Nelson, K. C., Larson, K. L., Cavender-Bares, J., Heffernan, J. B., Chowdhury, R. R., Hobbie, S. E., Bettez, N. D., Hall, S. J., Neill, C., Ogden, L., & O'Neil-Dunne, J. (2019). Residential household yard care practices along urban-exurban gradients in six climatically-diverse U.S. metropolitan areas. *PLoS ONE*, *14*(11), 1–14. https://doi.org/10.1371/journal.pone.0222630

Locke, D. H., Roy Chowdhury, R., Grove, J. M., Martin, D. G., Goldman, E., Rogan, J., & Groffman, P. (2018). Social norms, yard care, and the difference between front and back yard management: Examining the landscape mullets concept on urban residential lands. *Society & Natural Resources*, *31*(10), 1169–1188. https://doi.org/10.1080/08941920.2018.1481549

Loram, A., Tratalos, J., Warren, P. H., & Gaston, K. J. (2007). Urban domestic gardens (X): The extent & structure of the resource in five major cities. *Landscape Ecology*, *22*(4), 601–615.

Lüdecke, D. (2018). *SjPlot: Data visualization for statistics in social science*. https://doi.org/10.5281/zenodo.2400856. Retrieved from https://strengejacke.github.io/sjPlot/

Meléndez-Ackerman, E. J., Santiago-Bartolomei, R., Vila-Ruiz, C. P., Santiago, L. E., García-Montiel, D., Verdejo-Ortiz, J. C., Manrique-Hernández, H., & Hernández-Calo, E. (2014). Socioeconomic drivers of yard sustainable practices in a tropical city. *Ecology and Society*, *19*, 20. https://doi.org/10.5751/ES-06563-190320

Merton, R. K., & Kitt, A. (1950). Contributions to the theory of reference group behavior (with Alice Kitt Rossi). In R. K. Merton & P. F. Lazarsfeld (Eds.), *Continuities in social research* (pp. 40–105). The Free Press.

Minor, E., Belaire, J. A., Davis, A., & Franco, M. (2016). Socioeconomics and neighbor mimicry drive yard and neighborhood vegetation patterns. In *Urban landscape ecology: Science, policy and practice* (pp. 56–74). Routledge.

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, *2*(3), 17–23. https://doi.org/10.1093/biomet/37.1-2.17

Nassauer, J. I. (1988). *23 HortScience the aesthetics of horticulture neatness as a form of care*. Retrieved from http://deepblue.lib.umich.edu/handle/2027.42/49345

Nassauer, J. I. (1995). Messy ecosystems, orderly frames. *Landscape Journal*, *14*(2), 161–170. Retrieved from http://lj.uwpress.org/content/14/2/161.short

Nassauer, J. I., Cooper, D. A., Marshall, L. L., Currie, W. S., Hutchins, M., & Brown, D. G. (2014). Parcel size related to household behaviors affecting carbon storage in exurban residential landscapes. *Landscape and Urban Planning*, *129*, 55–64. https://doi.org/10.1016/j.landurbplan.2014.05.007

Nassauer, J. I., Wang, Z., & Dayrell, E. (2009). What will the neighbors think? Cultural norms and ecological design. *Landscape and Urban Planning*, *92*(3–4), 282–292. https://doi.org/10.1016/j.landurbplan.2009.05.010

Odum, W. E. (1982). Environmental degradation and the tyranny of small decisions. *BioScience*, *32*(9), 728–729. https://doi.org/10.2307/1308718

Ossola, A., Jenerette, G. D., McGrath, A., Chow, W., Hughes, L., & Leishman, M. R. (2021). Small vegetated patches greatly reduce urban surface temperature during a summer heatwave in Adelaide. *Australia. Landscape and Urban Planning*, *209*, https://doi.org/10.1016/j.landurbplan.2021.104046

Ossola, A., Hahs, A. K., & Livesley, S. J. (2015). Habitat complexity influences fine scale hydrological processes and the incidence of stormwater runoff in managed urban ecosystems. *Journal of Environmental Management*, *159*, 1–10. https://doi.org/10.1016/j.jenvman.2015.05.002

Ossola, A., & Hopton, M. E. (2018a). Measuring urban tree loss dynamics across residential landscapes. *Science of The Total Environment*, *612*, 940–949. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S0048969717321010

Ossola, A., & Hopton, M. E. (2018b). Climate differentiates forest structure across a residential macrosystem. *Science of The Total Environment*, *639*, 1164–1174. https://doi.org/10.1016/j.scitotenv.2018.05.237

Ossola, A., Locke, D. H., Lin, B., & Minor, E. (2019a). Greening in style: Urban form, architecture and the structure of front and backyard vegetation. *Landscape and Urban Planning*, *185*, 141–157. https://doi.org/10.1016/j.landurbplan.2019.02.014

Ossola, A., Locke, D., Lin, B., & Minor, E. (2019b). Yards increase forest connectivity in urban landscapes. *Landscape Ecology*, *34*(12). https://doi.org/10.1007/s10980-019-00923-7

Ossola, A., Schifman, L., Herrmann, D. L., Garmestani, A. S., Schwarz, K., & Hopton, M. E. (2018). The provision of urban ecosystem services throughout the private-social-public domain: A conceptual framework. *Cities and the Environment*, *11*(1), 1–15.

Pham, T.-T.-H., Apparicio, P., Landry, S., Séguin, A.-M., & Gagnon, M. (2012). Predictors of the distribution of street and backyard vegetation in Montreal, Canada. *Urban Forestry & Urban Greening*, *12*(1), 18–27. https://doi.org/10.1016/j.ufug.2012.09.002

Pham, T.-T.-H., Apparicio, P., Séguin, A.-M., Landry, S., & Gagnon, M. (2012). Spatial distribution of vegetation in Montreal: An uneven distribution or environmental inequity? *Landscape and Urban Planning*, *107*(3), 214–224. https://doi.org/10.1016/j.landurbplan.2012.06.002

PRISM Climate Group. (2015). *30-year normals*. Oregon State University.

Robbins, P. (2012). *Lawn people: How grasses, weeds, and chemicals make us who we are*. Temple University Press.

Roman, L. A., Pearsall, H., Eisenman, T. S., Conway, T. M., Fahey, R. T., Landry, S., Vogt, J., van Doorn, N. S., Grove, J. M., Locke, D. H., Bardekjian, A. C., Battles, J. J., Cadenasso, M. L., van den Bosch, C. C. K., Avolio, M., Berland, A., Jenerette, G. D., Mincey, S. K., Pataki, D. E., & Staudhammer, C. (2018). Human and biophysical legacies shape contemporary urban forests: A literature synthesis. *Urban Forestry & Urban Greening*, *31*, 157–168. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S1618866717307665

Sampson, R. J., & Levy, B. L. (2020). Beyond Residential segregation: Mobility-based connectedness and rates of violence in large cities. *Race and Social Problems*, *12*(1), 77–86. https://doi.org/10.1007/s12552-019-09273-0

Singh, K. K., Vogler, J. B., Shoemaker, D. A., & Meentemeyer, R. K. (2012). LiDAR-landsat data fusion for large-area assessment of urban land cover: Balancing spatial resolution, data volume and mapping accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing*, *74*(November), 110–121. https://doi.org/10.1016/j.isprsjprs.2012.09.009

Small, M. L., & Adler, L. (2019). The role of space in the formation of social ties. *Annual Review of Sociology*, *45*(1), 111–132. https://doi.org/10.1146/annurev-soc-073018-022707

Theobald, D. M. (2014). Development and applications of a comprehensive land use classification and map for the US. *PLoS ONE*, *9*(4). https://doi.org/10.1371/journal.pone.0094628

Turner, V. K., & Ibes, D. C. (2011). The impact of homeowners associations on residential water demand management in Phoenix, Arizona. *Urban Geography*, *32*(8), 1167–1188. https://doi.org/10.2747/0272-3638.32.8.1167

Turner, V. K., Jarden, K. M., & Jefferson, A. J. (2015). Resident perspectives on green infrastructure in an experimental suburban stormwater management program. *Cities and the Environment*, *9*(1), 1–32.

United States Census Bureau. *Glossary*. Retrieved from https://www.census.gov/programs-surveys/geography/about/glossary.html#par_textimage_4

Visscher, R. S., Nassauer, J. I., Brown, D. G., Currie, W. S., & Parker, D. C. (2014). Exurban residential household behaviors and values: Influence of parcel size and neighbors on carbon storage potential. *Landscape and Urban Planning*, *132*, 37–46. https://doi.org/10.1016/j.landurbplan.2014.08.004

Visscher, R. S., Nassauer, J. I., Brown, D. G., Currie, W. S., & Parker, D. C. (2016). Homeowner preferences for wooded front yards and backyards: Implications for carbon storage. *Landscape and Urban Planning*, *146*, 1–10. https://doi.org/10.1016/j.landurbplan.2015.09.001

Visscher, R. S., Nassauer, J. I., & Marshall, L. L. (2016). Homeowner preferences for wooded front yards and backyards: Implications for carbon storage. *Landscape and Urban Planning*, *146*, 1–10. https://doi.org/10.1016/j.landurbplan.2015.09.001

Walker, K. (2020). *Tidycensus: Load us census boundary and attribute data as 'tidyverse' and 'Sf'-ready data frames*. Retrieved from https://cran.r-project.org/package=tidycensus

Wang, Q., Phillips, N. E., Small, M. L., & Sampson, R. J. (2018). Urban mobility and neighborhood isolation in America's 50 largest cities. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(30), 7735–7740. https://doi.org/10.1073/pnas.1802537115

Watkins, S. L., & Gerrish, E. (2018). The relationship between urban forests and race: A meta-analysis. *Journal of Environmental Management*, *209*, 152–168. https://doi.org/10.1016/j.jenvman.2017.12.021

Zmyslony, J., & Gagnon, D. (1998). Residential management of urban front-yard landscape: A random process? *Landscape and Urban Planning*, *40*(4), 295–307. https://doi.org/10.1016/S0169-2046(97)00090-X

Zmyslony, J., & Gagnon, D. (2000). Path analysis of spatial predictors of front-yard landscape in an anthropogenic environment. *Landscape Ecology*, *15*(4), 357–371.

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