


Article

Showcasing Relationships between Neighborhood Design and Wellbeing Toronto Indicators

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Abstract: Cities are the keystone landscape features for achieving sustainability locally, regionally, and globally. With the increasing impacts of urban expansion eminent, policymakers have encouraged researchers to advance or invent methods for managing coupled human–environmental systems associated with local and regional sustainable development planning. Although progress has been made, there remains no universal instrument for attaining sustainability on neither regional nor local planning scales. Previous sustainable urbanization studies have revealed that landscape configuration metrics can supplement other measures of urban well-being, yet few have been included in public data dashboards or contrasted against local well-being indicators. To advance this sector of sustainable development planning, this study had three main intentions: (1) to produce a foundational suite of landscape ecology metrics from the 2007 land cover dataset for the City of Toronto; (2) to visualize and interpret spatial patterns of neighborhood *streetscape* patch cohesion index (COHESION), Shannon’s diversity index (SHDI), and four Wellbeing Toronto indicators across the 140 Toronto neighborhoods; (3) to quantitatively assess the global collinearity and local explanatory power of the well-being and landscape measures showcased in this study. One-hundred-and-thirty landscape ecology metrics were computed: 18 class configuration metrics across seven land cover categories and four landscape diversity metrics. Anselin Moran’s *I*-test was used to illustrate significant spatial patterns of well-being and landscape indicators; Pearson’s correlation and conditional autoregressive (CAR) statistics were used to evaluate relationships between them. Spatial “hot-spots” and/or “cold-spots” were found in all *streetscape* variables. Among other interesting results, Walk Score[®] was negatively related to both tree canopy and grass/shrub connectedness, signifying its lack of consideration for the quality of ecosystem services and environmental public health—and subsequently happiness—during its proximity assessment of socioeconomic amenities. In sum, landscape ecology metrics can provide cost-effective ecological integrity addendum to existing and future urban resilience, sustainable development, and well-being monitoring programs.

Keywords: crime; data dashboard; landscape indicators; premature mortality; spatial autoregressive modeling; streetscapes; sustainable urbanization; Toronto; urban design; urban landscape; urban planning; walk score

1. Introduction

Cities are the keystone landscape features for achieving sustainability locally, regionally, and globally. In 2017, the United Nations predicted that the global population will grow to 9.7 billion

inhabitants by 2050, and 11 billion inhabitants by 2100; however, it will be cities that absorb a majority of the foreseen population growth in the developed and developing world [1]. As of 2008, *homo sapiens* became more of an urban species rather than rural [2], and now there are 28 megacities (population >10 million) and several nations with 100% urban population [3]. In a shocking prophecy by Michael Batty [4], the global population is predicted to be 70% urban in 2050 and 100% urban in 2092. Although cities have been recognized as leaders in socioeconomic well-being, catalysts for educational and technological growth, and centers for historic preservation, culture and the arts [5–7], their connected structure has been found to simultaneously degrade Earth’s life-supporting systems [8]. Urbanization, directly and indirectly, metabolizes Earth’s healthy environmental resources and disturbs life-supporting ecosystem services great distances from urban centers [9–16]. Consequently, land cover change associated with population growth, rural to urban migration, a desire for greater material well-being, and poor waste management are having the greatest impacts on Earth’s life-supporting biogeochemical systems and thus its planetary boundaries [10,15,17–25].

With the increasing impacts of urban expansion eminent [4,11,13,26], policymakers have encouraged researchers to advance or invent methods for managing coupled human–environmental systems associated with local and regional sustainable development planning [27]. Furthermore, for roughly two decades now, the planning community has seen a need for sustainable development initiatives that go beyond lip-service and put concepts into action [28–30]. Despite uncertainty about operationalization, the field of planning acknowledges that sustainable development is an influential concept and should shape future methodology and practice [31–33]. That said, although effort and progress have been made, there remains no universal instrument for attaining sustainability on neither regional nor local planning scales [34]. As suggested by Jianguo Wu [5–7], landscape ecology is likely the most relevant place-based and solution-driven discipline for moving humanity towards sustainability across space and time. Landscape ecology emphasizes two main principles of landscape: (i) patterns, or the physical configuration of its elements (i.e., urban land connectivity); and (ii) processes, or its biogeophysical functions (i.e., disrupted hydrological cycle) that modify or result from its spatial structure [35]. Despite numerous environmental management, conservation, restoration, urban and regional planning projects incorporating landscape ecology tools and methods, work remains for landscape sustainability science to move theory into everyday planning practice [36,37].

Indicators and their combined forms, indices, are essential tools for calibrating landscape structure during sustainable urbanization, urban resilience, environmental planning and management projects. At local and regional scales, indicator-based assessment of landscape function is a fundamental approach for evaluating relationships during sustainable landscape planning [38,39]. An evaluation metric takes the form of a rapidly employable single-number characterization of a location at a given time [40], which have been embraced widely for urban design, ecosystem management, natural resource conservation, sustainable urbanization, environmental and regional planning purposes [8,14,23,41]. Spatial planning investigations of human-dominated landscapes have been further understood using analytical tools for quantifying landscape structure (e.g., FRAGSTATS) and spatial analysis software (e.g., SAM) [14,41]. That said, few urban ecology studies serve as examples of how landscape *patterns* respond to indicators of urban well-being and resilience at local and regional scales. Lastly, because spatial autocorrelation [42] is inherently present during urban well-being assessments, appropriate inferential statistical methods (i.e., spatial autoregression) must be considered to correct for its accompanying errors.

Cultivating knowledge on how to optimize the urban mosaic is mandatory for creating urban resilience and sustainable cities. Urban patterns and processes offer both problems and solutions for sustainable development; however, they allow an opportunity to test questions related to what is the ‘optimal’ urban form [26]. Previous sustainable urbanization studies have revealed that landscape configuration metrics can supplement other measures of urban well-being (i.e., [43]), yet few have been included in public data dashboards or contrasted against local well-being indicators. To advance this sector of sustainable development planning, this study had three main intentions: (1) to produce

a foundational suite of landscape ecology metrics from the 2007 land cover dataset for the City of Toronto; (2) to visualize and interpret spatial patterns of neighborhood *streetscape* patch cohesion index (COHESION), Shannon's diversity index (SHDI), and four Wellbeing Toronto indicators across the 140 Toronto neighborhoods; and (3) quantitatively assess global collinearity and local explanatory power of the well-being and landscape measures showcased in this study. A goal of this study was to justify adding landscape ecology metrics into urban resilience, sustainable development, and well-being monitoring programs. This paper was also created to deliver sustainability scientists, spatial analysts, urban planners and designers an applied example for systematically assessing, describing, and monitoring sustainable landscape function across space.

2. Study Area

This research incorporated all 140 neighborhoods as individual *streetscapes* for the City of Toronto, located in the province of Ontario, Canada (Figure 1). The City is central to Southern Ontario's megalopolis, dubbed the "Golden Horseshoe," which is a band of ever-increasing population growth and subsequent urbanization wrapping the Provincial coastline of Lake Ontario [44–48]. As a leading port city on the Laurentian Great Lakes of North America, with access to the Atlantic Ocean by way of the Saint Lawrence Seaway, and land connections via major railways, Toronto was historically a place of mercantile prosperity and has grown into Canada's most populated, culturally diverse, and economically important city [49–52]. The 140 distinct neighborhoods have unique identities stemming from different demography and responding built and natural forms [52–55]. With an area of 641km², a population of 2.95 million in July 2018, and a density of 4457 persons/km², the City of Toronto shares similarities with other North American metropolises as Montreal, Chicago, Philadelphia, and Washington at 4916, 4594, 4512, and 4301persons/km², respectively [56–58]. However, Toronto is differentiated from other North American cities because it is seen as one of the fastest-growing urban centers, if not the fastest [51,59,60]. Increasing urbanizing pressures, the Greater Toronto Area (GTA) is encircled by 800,000 hectares of protected land, known as *the Greenbelt*, which includes such natural amenities as the Niagara Escarpment, Oak Ridges Moraine, and protected countryside [61].

The City of Toronto has been dubbed the most resilient city in the world [62], yet it is projected that its population growth will require innovative and adaptable urban sustainable development initiatives. Toronto's good reputation as a livable city and prosperous urban region is linked to its economic and social welfare and the goods and services that are provided to its citizens [63]. In example, an effort has been made to preserve its natural spaces and support Torontonians' connection to nature; the greenspace ravine systems and parks comprise nearly 17% of the city's net area [64–67]. However, over the last few decades Canadian societies, specifically in Toronto, have been changing. Economic, social, and environmental trends are posing significant challenges to securing improved well-being and promoting equitable and sustainable order within Canadian communities [68,69]. Toronto is beginning to show signs of distress (i.e., congested streets) and imbalance in areas such as housing and income security; without immediate action, the trends unfolding are likely to lead to a further decline in the City's well-being [51]. There is a need to evaluate current conditions and to determine the future path towards sustainability for Toronto's 140 neighborhoods using measurements of well-being. With its interesting human and physical geography, growing population, and confined limits to growth, Toronto's complex coupled urban landscapes are fashionable for examining how patterns of *streetscapes* relate to urban well-being.

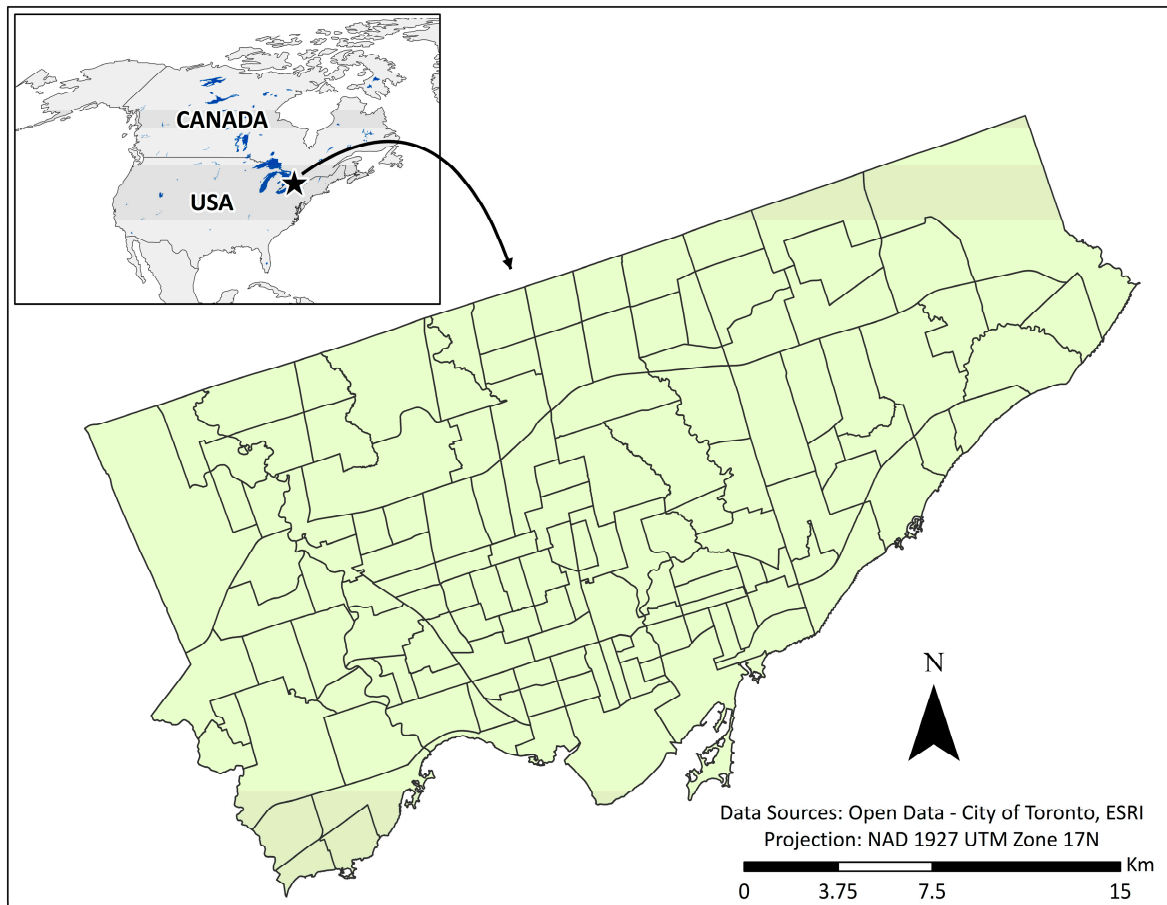


Figure 1. Study area map of the 140 neighborhood-landscapes (*streetscapes*) in Toronto, Canada ($43^{\circ}39'N$, $79^{\circ}20'W$). Source neighborhood Geographic Information System (GIS) data freely downloadable from the City of Toronto’s Open Data Portal website (<http://open.toronto.ca/>).

3. Materials and Methods

3.1. Wellbeing Toronto Indicators

Indicators and their composite versions indices are being used across spatial scales to address multiple planning and policy-making objectives, and are considered indispensable in the science and practice of sustainability [70–75]. These metrics are often quantitative expressions of spatial-temporal sustainability, resilience, or well-being in context to a system’s current state. At the international level, a call for these indicators happened at the Rio Earth Summit in 1992, which has resulted in a plethora of public and private organizations responding at all scales of application [33,72,76,77]. From Chapter 8.6 of Agenda 21 [78] “Countries could develop systems for monitoring and evaluation of progress towards achieving sustainable development by adopting indicators that measure changes across economic, social and environmental dimensions” (66). Regarding unifying methods for assessing sustainable urbanization, the International Organization for Standardization (ISO) is leading the way with ISO 37120:2018 [Sustainable cities and communities—Indicators for city services and quality of life] and ISO 37122:2019 [Sustainable cities and communities—Indicators for smart cities] initiatives [79,80]. Although not free of charge, ISO has organized and standardized a set of indicators for city quality of life, resilience, services and ‘smart cities’; furthermore, these standards act as proxies to help cities support policy creation and priority planning initiatives. Despite the aforementioned efforts, critical reviews of indicators and indices employed at the local level consider them ‘sub-optimal’ tools for technical assessment, public participation, and use [70,73]. Specifically, when using indicators and indices errors come from confusion or disagreement around variable selection, directionality,

normalization, weighting, and aggregation, as well as boundary delineation, stake-holder inclusion, spatial analysis needs, and best practices [71,72,75,81–85].

Specific to Canada, in 2016 and reiterated in 2018, the federal government has shown a strong commitment to developing technically sound evidence-based indicators for making progress toward Sustainable Development Goals [86]. This, of course, builds on a long-standing history of indicator creation and use in Canada from the internationally acclaimed Ecological Footprint [87] to the Canadian Index of Well-being [68] to the Wellbeing Toronto discussed more herein. In response to the growing need to measure well-being, the City of Toronto (the municipal government of Toronto) launched “Wellbeing Toronto” in 2011, a web-based measurement and visualization data dashboard that helps evaluate community well-being across a multitude of factors such as, crime, housing, and transportation (Figure 2). Wellbeing Toronto was developed to provide information to citizens and decision-makers and to enable a better understanding of how their communities function, based on the metrics provided [88]. This spatial decision-making tool uses a modified online geographic information system (GIS) to visualize a suite of well-being indicators across the City’s 140 neighborhoods. The free application allows users to select and/or combine various indicators, which appear instantaneously on a map of Toronto and produce a variety of graphs and tables, all of which are free to download. Without going into detail about its unresolved flaws, Wellbeing Toronto’s shortcomings impacting this study relate to: its inability to normalize count data (i.e., assaults) by even the most common method (i.e., population, area) circumventing the effects of different sized area units (i.e., Modifiable Areal Unit Problem; MAUP [89]); and its low representation of ecological integrity, environmental public health, ecological services, and biogeophysical indicators.

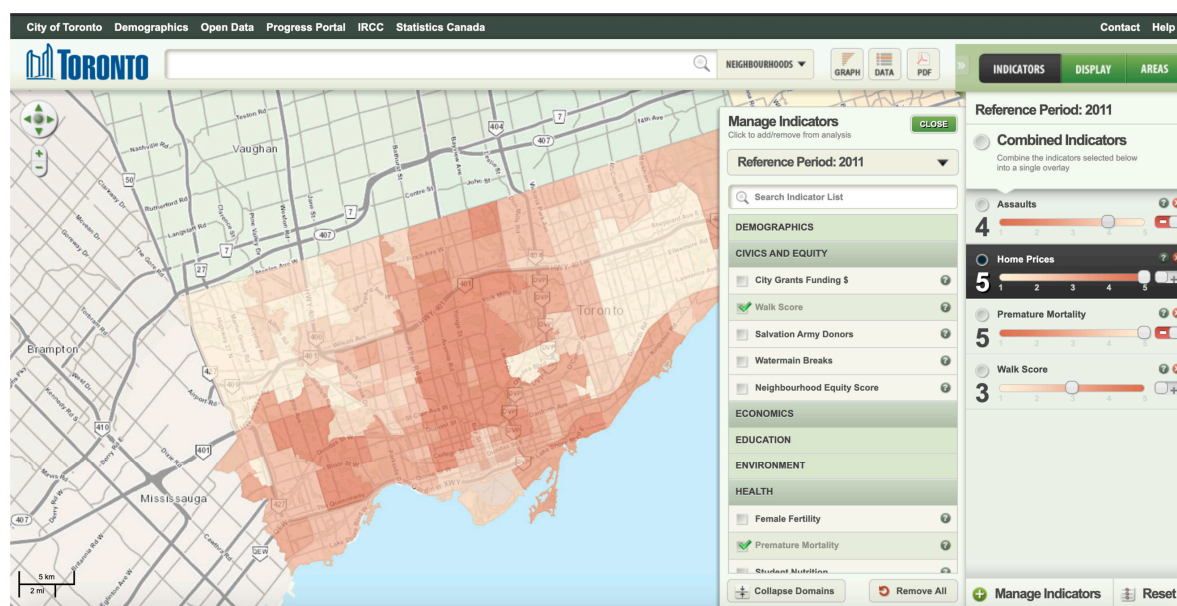


Figure 2. Screenshot of the City of Toronto’s mapping data dashboard, Wellbeing Toronto. Publicly accessible at: <http://map.toronto.ca/wellbeing/>.

To accomplish this study’s main intentions and supplementary goals, four of the 2011 Wellbeing Toronto indicators were selected from the data dashboard for contrasting against themselves and landscape ecology metrics. Specifically, the four urban well-being metrics chosen to showcase *streetscape* relationships were: assaults, home prices, premature mortality, and Walk Score. From the Safety domain, 2011 assaults were sourced from Toronto Police Service; there were 15,179 assaults in total across the City, with a minimum of nine, average of 108, and maximum of 712 in one neighborhood. To avoid spurious findings caused by MAUP, the 2011 assault counts were divided by their corresponding neighborhood population. From the Housing domain, home prices were sourced from Realosophy.com,

represents the average price (CAD) for residential real estate sold during the 2011–2012 timeframe. The average neighborhood home price minimum was \$204,104, the mean was \$548,193, and the maximum was \$1,849,084. From the Health domain, premature mortality was sourced from Toronto Public Health from the 2006–2008 period and represents all-cause premature mortality per 100,000 population. Population data used here come from Statistics Canada, 2006 Census of Canada. For clarification, Canada's premature mortality is a measure of unfulfilled life expectancy with an age expectation set to 70; the premature mortality rate is the sum of potentially lost years of individuals per 100,000 people [90]. Descriptive statistics for premature mortality reflected 108 (min), 217 (mean), and 615 (max). Lastly, from the Civics and Equity domain, Walk Score was sourced from walkscore.com; Walk Score is scaled from 0–100 based on walking routes and proximity to socioeconomic amenities such as grocery stores, schools, parks, restaurants, and retail. With increased values representing improved walkability, 2011 Walk Scores across the 140 neighborhoods had a minimum value of 42, average of 72, and maximum of 99.

3.2. Streetscape Configuration and Diversity

Neighborhood-landscapes (streetscapes) are inherently interconnected geophysical, biological, and socioeconomic systems, and connect to human behavior through geographical identity. Because of this, and the readily available well-being data from the Wellbeing Toronto data dashboard, this urban spatial aggregation scale was deemed suitable for this study. Although there is no omnipresent rule for “landscape scale,” or in this case streetscapes Richard T.T. Forman [91] suggested that a “landscape” is “a kilometers-wide mosaic over which local ecosystems recur.” The area descriptive statistics across the 140 Toronto neighborhoods are: 0.42 km² (min), 4.59 km² (mean), and 37.53 km² (max). Within each of the 140 neighborhood streetscapes, land cover class configuration and landscape diversity metrics were calculated using fine spatial and categorical resolution land cover data created for the City of Toronto in 2007 [92]. Produced from high-resolution QuickBird (Digital Globe) satellite imagery, combined with planimetric data, this land cover raster layer has 0.6 m (1.9685 ft) pixels allowing for single tree detection [93]. Although accuracy details for this data file could not be found, the same research group and methods applied to New York City rendered an overall classification accuracy of 96% [14,94]. This high-resolution land cover data set was classified into eight land cover categories: (1) tree canopy, (2) grass/shrub, (3) bare earth, (4) water, (5) buildings, (6) roads, (7) other paved surfaces, and (8) agriculture (Figure 3). The 2007 land cover yielded the following compositions for the Toronto categories: tree canopy (27.9%), grass/shrub (23.4%), other paved surfaces (16.9%), buildings (16.1%), roads (12.5%), water (1.6%), agriculture (0.9%), bare earth (0.7%).

Land cover configuration and landscape diversity metrics were computed using the freeware FRAGSTATS (ver. 4.2; [95]), which processes numerical expressions that correspond to a landscape's land use and land cover patterns. Hundreds of metrics for quantifying landscape composition, configuration, and diversity have been developed for use in a countless number of planning, socioeconomic and environmental science research applications [16,91,96,97]. Based on literature relevance and past experiences, for each of the 140 Toronto streetscapes, 130 landscape ecology metrics were computed to serve as a foundational suite for the City of Toronto (Data S1): 18 class configuration metrics across seven of the City's eight land cover categories and four landscape diversity metrics. Metrics for agriculture were not included due to very limited neighborhood representation. The 18 class configuration metrics computed for each of the seven land cover types were: class area (CA), percentage of landscape (PLAND), patch density (PD), largest patch index (LPI), landscape shape index (LSI), mean patch area (AREA_MN), area-weighted mean patch area (AREA_AM), area-weighted mean shape index (SHAPE_AM), area-weighted mean patch fractal dimension (FRAC_AM), perimeter-area fractal dimension (PAFRAC), area-weighted core area distribution (CORE_AM), area-weighted core area index (CAI_AM), area-weighted mean Euclidean nearest neighbor distance (ENN_AM), clumpiness index (CLUMPY), percentage-of-like-adjacency (PLADJ), patch cohesion index (COHESION), landscape division index (DIVISION), and effective mesh size (MESH). Additionally, the four landscape diversity

metrics were: Patch richness density (PRD), Relative patch richness (RPR), Shannon's diversity index (SHDI), and Shannon's evenness index (SHEI).

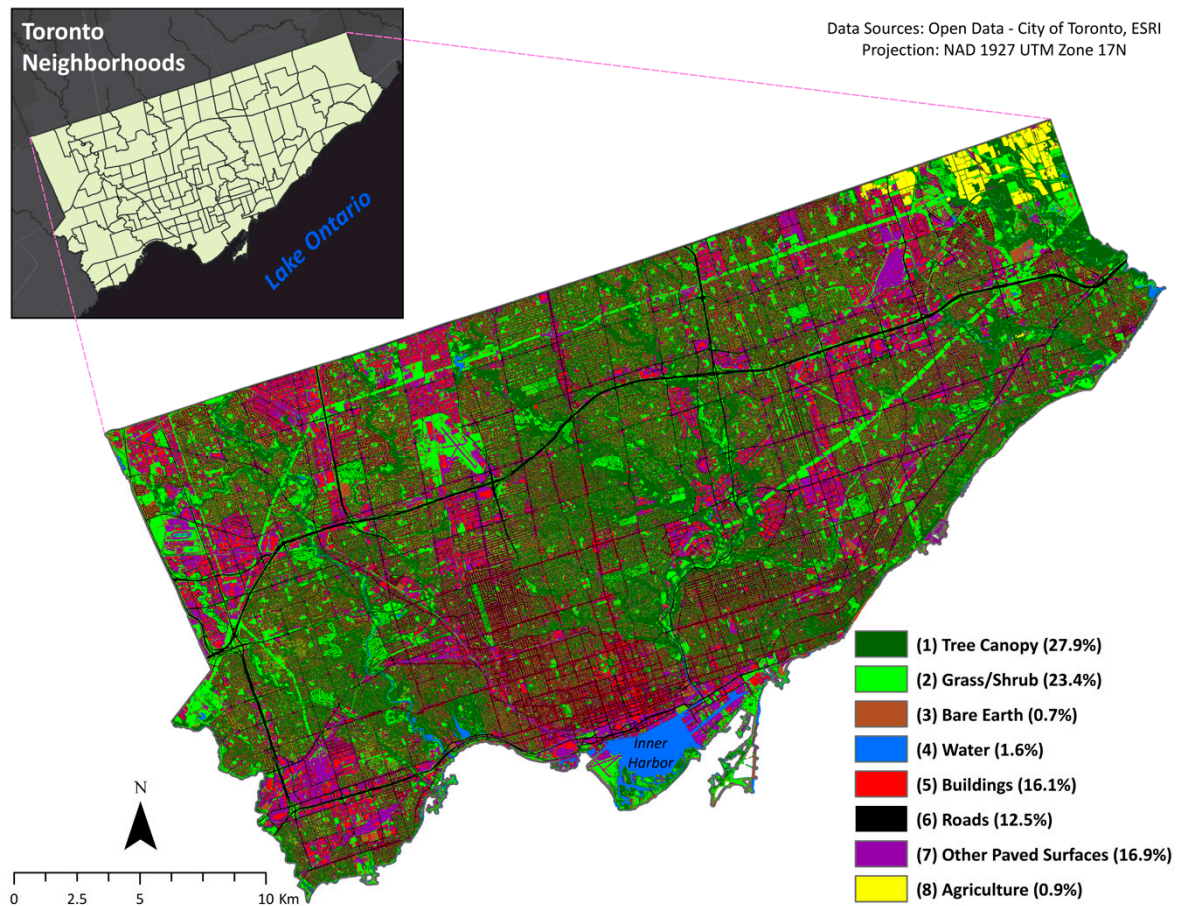


Figure 3. Map of 2007 land cover for Toronto, Canada. Source land cover data freely downloadable from the City of Toronto's Open Data Portal website (<http://open.toronto.ca/>).

To accomplish this study's intentions and goals, by showcasing how landscape ecology metrics relate to urban well-being, five land cover (tree canopy, grass/shrub, buildings, roads, other paved surfaces) class COHESION measures and the landscape diversity metric SHDI were showcased in the forthcoming data analysis section (Figure 4). Specifically, COHESION at the class-level measures the physical connectedness of the corresponding land cover type; its score ranges between 0 and 100 and increases as the patch type become more aggregated and physically connected [98]. Although other relationships await to be explored within the plethora of landscape ecology metrics computed herein, COHESION was chosen to showcase in this study due to its traction already gained in the sustainable development and spatial planning communities. To that end, Meerow and Newell [43] included forest cover COHESION as one of their model criteria to capture physical connectedness of wildlife habitat across census tracts during their spatial planning effort to improve urban resilience in Detroit. Precedingly, in a macroscale assessment of sustainable urbanization for Europe, Shaker [8] used COHESION to compute the physical connectedness of CORINE urban morphological zones for each country landscape. From that study, increased connectivity of urban cover COHESION was simultaneously linked to improved human well-being while deteriorating ecosystem well-being. SHDI [99], the most popular diversity index based on information theory and commonly used in landscape studies [23], is a rather abstract mathematical model that is most useful when comparing different landscapes or the same landscape over time [96]. The single number values of SHDI grow without limits; SHDI increases as the quantity of land cover classes present increases and/or their

proportions become more equal [96]. The premise behind showcasing relationships between SHDI and well-being indicators was centered around the increasing importance of understanding how landscape diversity of urban design relates to inhabitants’ living conditions. Accompanying maps and statistical figures for the five class COHESION metrics and SHDI are provided in Appendix A (Appendices A.1–A.3).

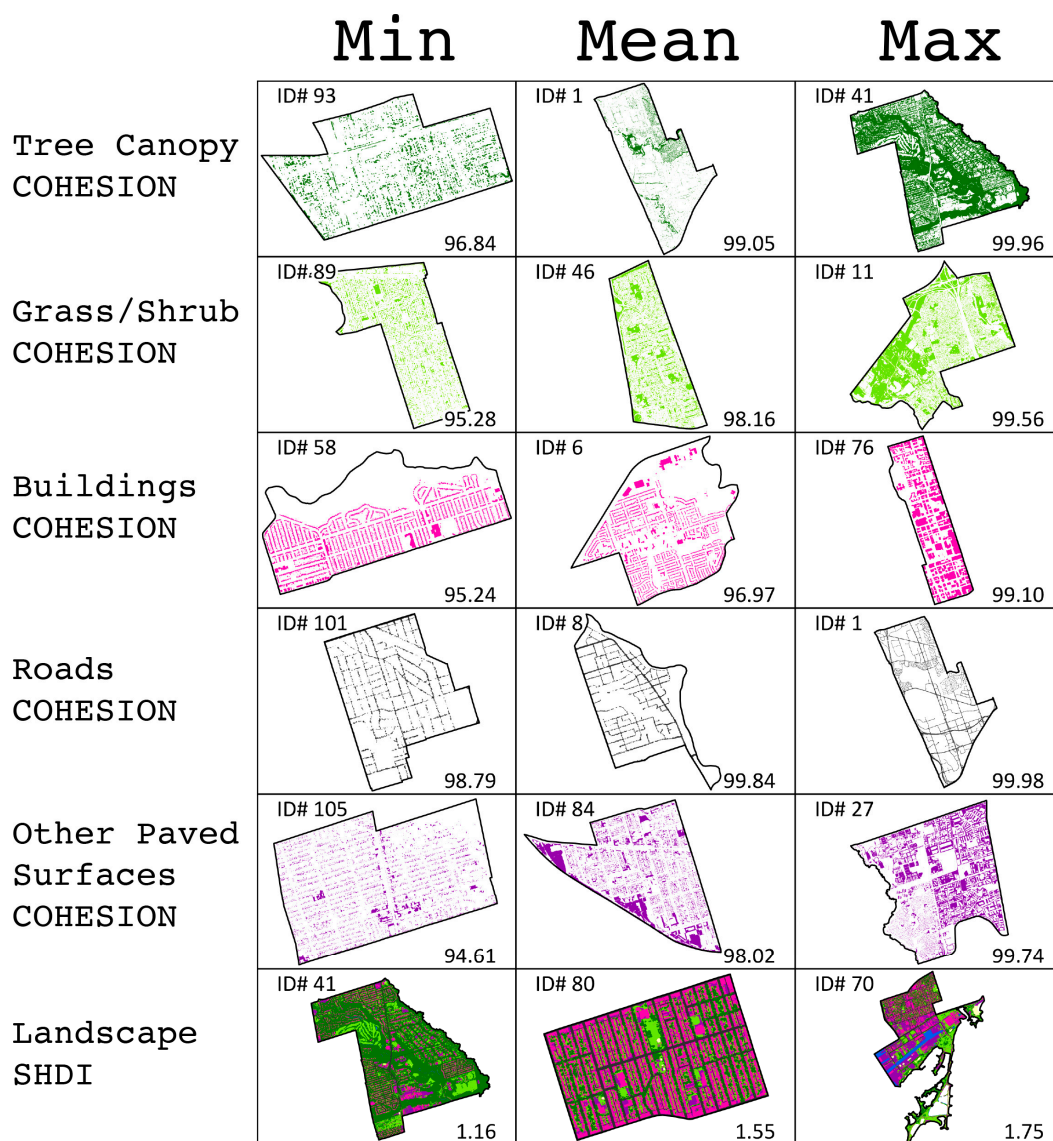


Figure 4. Streetscapes of the five land cover class COHESION metrics and one landscape diversity SHDI metric showcased in this study. Values in the lower-right corner are raw metric scores corresponding to its descriptive statistic. Upper-left corner labels match the City of Toronto’s universal neighborhood identification number enumerated in public spatial and tabular data. *Cartographic note:* Neighborhood-landscapes are not equal geographic scale.

3.3. Data Analysis

To accomplish the second and third intentions of this paper, and its complementary goals, a three-step analysis was created to visualize and showcase relationships between neighborhood COHESION, SHDI, and four Wellbeing Toronto indicators across the 140 Toronto streetscapes. Specifically, exploratory spatial data analysis (ESDA), global and local inferential statistical tests were used and will be explained in detail here. Prior to employing the statistical tests, to meet

parametric test requirement of Gaussian distributions, all variables evaluated in this study were appraised using the Shapiro–Wilk test due to its power for determining normality for all types of distributions and sample sizes [100]. In doing so, variables were determined if transformation was required, and which mathematical function was most appropriate for reaching a Gaussian frequency. For variables with straight values or counts, such as property values or number of assaults, log-transformation was used. For ratio or percentage variables ranging from 0 to 1 or 0 to 100, such as Walk Score, the empirical logit-transformation was used as it supersedes arcsine variants [101] and is an improvement over simple logit [102]. The statistical software SPSS (ver. 25, [103]) was used during this step of data preparation, and database used in the subsequent analysis provided here (Data S2).

First (1), to assess the level of spatial autocorrelation and to visualize local clustering an ESDA was conducted at global and local levels. Spatial autocorrelation, the lack of univariate stationarity or independence of an attribute over space, is the result of assessing the first law of geography [42]. Spatial autocorrelation should be seen as both beneficial and problematic in urban resilience, sustainable development, and well-being studies. Negatively, spatial autocorrelation violates the assumption of independence required by traditional parametric tests (i.e., ordinary least squares regression) [104,105]. Positively, nonstationarity (spatial autocorrelation) can provide statistically significant meaning to geographical patterns of sustainable development, and thus urban resilience and well-being investigations; furthermore, ‘hotspots’ maps are often created to reflect these spatial relationships [106]. Although other procedures have been created to assess spatial non-stationarity, the original global Moran’s I-test [107] was used to assess the level of spatial autocorrelation of the selected well-being and landscape measures across the study area. Additionally, to illustrate the geographic clustering of the six landscape ecology metrics and four well-being indicators, the local index of spatial association (LISA) Anselin Moran’s I [108] was conducted. Using ESRI’s ArcMap (ver. 10.4; [109]) Incremental Spatial Autocorrelation tool, a distance threshold of 3.5 km was established and used for both spatial autocorrelation tests.

Secondly (2), a two-tailed Pearson’s Product–Moment Correlation test (r) was used to assess relative statistical relationships between the five land cover class COHESION metrics, SHDI, and four Wellbeing Toronto indicators ($n = 140$). Pearson’s correlation coefficients range from 1 to -1 , with values closer to 1 indicating stronger bivariate association. Pearson’s Product–Moment Correlation test is one of the most common global (without considering geographic location and spatial influence) parametric tests for understanding bivariate inferential relationships, and a P-value accompanies the coefficient value signifying its statistical significance. The statistical software SPSS (ver. 25, [103]) was used during this step of the analysis.

Third (3), bivariate local (considering geographic location and spatial influence) conditional autoregressions (CAR) were conducted between- the five land cover class COHESION metrics and SHDI- with the four chosen Wellbeing Toronto indicators (assaults, home prices, premature mortality, and Walk Score). Since coupled human–environmental systems and data are impacted by a variety of processes over space, local methods that address the shortcomings of spatial autocorrelation should be used [105,110,111]. CAR corrects for spatial non-stationarity by calculating the spatial error terms of the model and adds a distance-weighted function between adjacent response variable values and the regression’s neighboring values for each explanatory variable [105,112,113]. Coefficient of determination (R^2) was used to compare and contrast relative explanatory power of the bivariate regressions; standardized beta coefficient (β) was used to corroborate association strength and interpret relationship directionality. CAR models used an estimated rho per regression and Alpha set to 1.0; CAR model residuals were assessed ex post facto by global Moran’s I statistic to confirm model independence. The freeware Spatial Analysis in Macroecology (SAM; ver. 4, [114]) was used during this step of the analysis.

4. Results

4.1. Exploratory Spatial Pattern Analysis

Spatial autocorrelation test results differ from each other; however positive scores indicate similar values are spatially clustered and negative scores indicate unlike values are systematically separated [115]. For this study, Global Moran's *I*-test divulged that all six landscape and four urban well-being measures used in the analysis had less than 1% chance of occurring randomly across space (Table 1). Across Toronto's 140 neighborhoods, Anselin Moran's-*I* [108] illustrated statistically significant spatial "hot-spots" and/or "cold-spots" for all streetscape variables showcased. Discrete categorical groupings of Local Anselin Moran's-*I* indicate that a geographic feature has statistically significant (0.05 level) clustering of neighboring features with similarly high (high-high; hot-spot) or low (low-low; cold-spot) attribute values within a defined distance; outliers are recorded when a high value is surrounded primarily by low values (high-low) or vice-a-versa (low-high) within that same defined distance [112].

Table 1. Spatial autocorrelation results derived from Global Moran's *I* analysis for four Wellbeing Toronto indicators (circa 2011) and the six showcased landscape configuration metrics.

	Global Moran's <i>I</i>	z-Score	P-Value
Wellbeing Toronto indicators			
Assaults	0.535	13.380 ***	< 0.001
Home Prices	0.479	12.038 ***	< 0.001
Premature Mortality	0.586	14.685 ***	< 0.001
Walk Score	0.837	20.826 ***	< 0.001
Landscape class metrics			
Tree Canopy (1) COHESION	0.399	10.048 ***	< 0.001
Grass/Shrub (2) COHESION	0.287	7.264 ***	< 0.001
Buildings (5) COHESION	0.388	9.740 ***	< 0.001
Roads (6) COHESION	0.261	6.982 ***	< 0.001
Paved Surfaces (7) COHESION	0.308	7.790 ***	< 0.001
Landscape diversity metric			
Shannon's Diversity Index (SHDI)	0.260	6.703 ***	< 0.001

Technical notes: Landscape ecology metrics computed on 2007 land cover data (COT, 2009) with 0.6 m (1.9685 ft) pixel resolution, and using queen contiguity (8-neighbor rule). COHESION: Patch cohesion index. See Leitão et al. (2006) and McGarigal et al. (2015) for landscape ecology metric details and equations. Spatial clustering was determined using an established 3.5 km search threshold. *** Denotes < 1% chance random pattern.

The local patterns of the five land cover class COHESION metrics and SHDI varied across Toronto's 140 streetscapes (Figure 5). Specifically, two statistically significant hot-spots and cold-spots resulted from the LISA analysis of tree canopy COHESION. The largest of the two hot-spots were found in the center of the City encompassing four neighborhoods while the other notable hot-spot was found in the west-center with two neighborhoods. The largest of the two cold-spots, on the south coast of the City, included 18 neighborhoods of more disconnected tree canopy. Regarding grass/shrub COHESION, LISA did not render any hot-spots; however, a larger, mildly-disjointed cold-spot was found in the south-center of the City incorporating over 15 streetscapes of more disconnected grass/shrub land cover. The LISA map of building COHESION revealed an expected hot-spot in the down-town core/central business district (CBD), while three small cold-spots showed through. The hot-spot of more connected buildings in the CBD included 11 neighborhoods. Road COHESION was illustrated via one larger cold-spot in the center of the City with 10 contiguous streetscapes with more disconnected roads; no hot-spots were revealed. For paved surfaces COHESION, one smaller significant hot-spot was found in the central-east part of the City and three main cold-spots also resulted. The LISA map of SHDI resulted in two prominent hot-spots and cold-spots, with 11 neighborhoods of contiguous low values in the central part of the City.

The local patterns of the four Wellbeing Toronto indicators varied across Toronto's 140 streetscapes (Figure 6). The LISA analysis for assaults resulted in one large hot-spot and one large cold-spot. More assaults were clustered in the down-town core/CBD, while less were found in the north-central neighborhoods. One major hot-spot and two larger cold-spots were illustrated for home prices, with a large notable cluster of higher-priced homes in the center of the City. The two low-priced clusters for home prices were found on either end of the City with eight neighborhoods each. The LISA analysis for premature mortality resulted in one large hot-spot and one large cold-spot. Increased premature mortality occurred on the south coast of the City, while decreased years lost were found in central-north streetscapes. One large hot-spot and two large cold-spots were revealed across the City for Walk Score. The cluster of neighborhoods with higher walkability was found in the center of the City, while two clusters of lower walkability found on both of its ends.

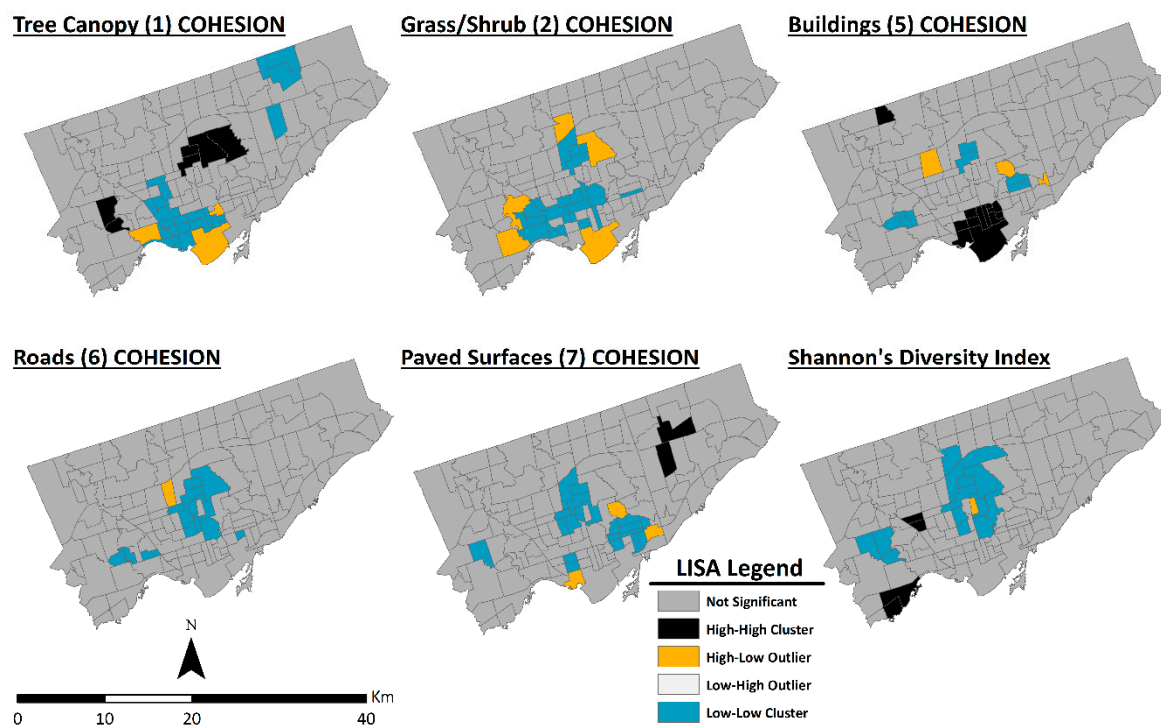


Figure 5. Local Anselin Moran's I index of spatial association for the five land cover class COHESION metrics and one landscape diversity SHDI metric showcased in this study. The spatial autocorrelation search threshold was set to a radius of 3.5 km; spatial clustering of high (high-high), low (low-low), or outliers (low-high, high-low) were statistically significant (0.05 level).

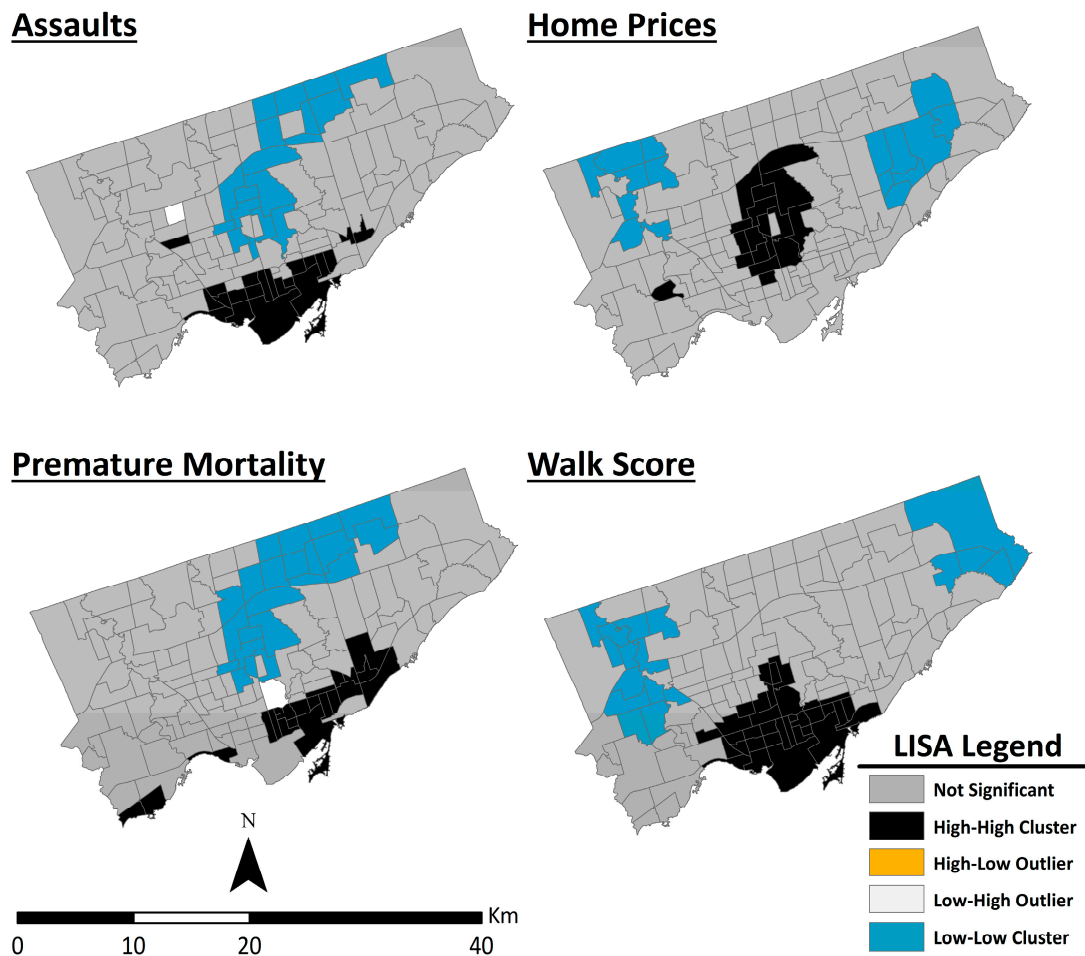


Figure 6. Local Anselin Moran’s *I* index of spatial association for the four Wellbeing Toronto indicators showcased in this study. The spatial autocorrelation search threshold was set to a radius of 3.5 km; spatial clustering of high (high-high), low (low-low), or outliers (low-high, high-low) were statistically significant (0.05 level).

4.2. Global Correlation Coefficients

Using Pearson’s Product–Moment Correlation test (r), statistically significant bivariate associations between the five land cover class COHESION metrics, SHDI, and four Wellbeing Toronto indicators were found (Table 2). Correlation coefficients are commonly classified into very positive (> 0.75), positive (0.75 to 0.50), neutral (0.50 to -0.50), negative (-0.50 to -0.75), or very negative (< -0.75). Since no statistical relationships were found within either of the “very positive” or “very negative” ranges, the seven “positive” and “negative” correlations are expounded here. With three coefficients recorded, home prices exhibited the highest degree of collinearity with significant negative relationships to: SHDI ($r = -0.61$, $P < 0.01$), roads COHESION ($r = -0.56$, $P < 0.01$), and paved surfaces COHESION ($r = -0.54$, $P < 0.01$). Another prominent negative coefficient came between Walk Score and grass/shrub COHESION ($r = -0.55$, $P < 0.01$). Three positive bivariate associations were noteworthy, with the strongest coefficient recorded between assaults and premature mortality ($r = 0.74$, $P < 0.01$). A positive correlation coefficient was also recorded between buildings COHESION and paved surfaces COHESION ($r = 0.62$, $P < 0.01$). Lastly, a positive statistical relationship was found between roads COHESION and SHDI ($r = 0.53$, $P < 0.01$).

Table 2. Pearson product-moment correlation coefficients (two-tailed) matrix of the four Wellbeing Toronto indicators (circa 2011) and six showcased landscape configuration metrics across Toronto neighborhoods ($N = 140$).

Variable	J	I	H	G	F	E	D	C	B	A
Description	Walk Score	Premature	Home Price	Assaults	SHDI	Paved Surf	Roads	Buildings	Grass/Shrub	Tree Canop
A) Tree Canopy (1) COHESION	−0.37 **	−0.26 **	0.22 **	−0.34 **	−0.39 **	−0.06	−0.25 **	−0.28 **	0.1	1
B) Grass/Shrub (2) COHESION	−0.55 **	−0.06	−0.42 **	−0.03	0.26 **	0.46 **	0.44 **	0.20 *	1	
C) Buildings (5) COHESION	0.23 **	0.22 **	−0.30 **	0.40 **	0.30 **	0.62 **	0.29 **	1		
D) Roads (6) COHESION	−0.24 **	0.20 *	−0.56 **	0.30 **	0.53 **	0.45 **	1			
E) Paved Surfaces (7) COHESION	−0.20 *	0.14	−0.54 **	0.21 *	0.45 **	1				
F) Shannon's Diversity Index (SHDI)	0.01	0.46 **	−0.61 **	0.44 **	1					
G) Assaults	0.34 **	0.74 **	−0.41 **	1						
H) Home Prices	0.30 **	−0.34 **	1							
I) Premature Mortality	0.29 **	1								
J) Walk Score	1									

Technical notes: Walk Score transformed using Empirical Logit; Home Prices, Premature Mortality, Assaults Log-transformed. COHESION: Patch cohesion index. ** Correlation is significant at the 0.01 level. * Correlation is significant at the 0.05 level.

4.3. Spatial Autoregressions

Results of the bivariate CAR analysis allowed for exploring relationships between the five land cover class COHESION metrics, SHDI and the four Wellbeing Toronto indicators (Table 3). Since many statistically significant relationships resulted, only the top two positive and negative correlations at the 99% confidence level are expounded for each Wellbeing Toronto indicator. Positively, assaults were best explained by SHDI ($R^2 = 0.24$, $P < 0.001$, $\beta = 0.46$), trailed by building COHESION ($R^2 = 0.20$, $P < 0.001$, $\beta = 0.42$). Assaults were only predicted negatively by tree canopy COHESION ($R^2 = 0.15$, $P < 0.001$, $\beta = -0.35$). At the aforementioned statistical level, home prices did not render positive correlations. However, negatively home prices and SHDI rendered the strongest model ($R^2 = 0.38$, $P < 0.001$, $\beta = -0.59$) of the study, followed by the second strongest roads COHESION ($R^2 = 0.31$, $P < 0.001$, $\beta = -0.49$). At the 99% statistical level, premature mortality was only positively correlated with SHDI ($R^2 = 0.25$, $P < 0.001$, $\beta = 0.47$); no negative models were rendered at this level. At the aforementioned statistical level, Walk Score did not render positive correlations. Conversely, Walk Score was best explained by grass/shrub COHESION ($R^2 = 0.25$, $P < 0.001$, $\beta = -0.43$) and then tree canopy COHESION ($R^2 = 0.14$, $P < 0.001$, $\beta = -0.31$). Lastly, Global Moran's I -test of CAR residuals bared randomness for all statistically significant regressions.

Table 3. Bivariate conditional auto-regressions (CAR) between four Wellbeing Toronto indicators (circa 2011) and the six showcased landscape configuration metrics ($N = 140$).

Wellbeing Toronto indicators	Tree Canopy (1) COHESION			Grass/Shrub (2) COHESION			Buildings (5) COHESION		
	β	P	R-square	β	P	R-square	β	P	R-square
Assaults	-0.35	***	0.15	–	–	–	0.42	***	0.20
Home Prices	0.26	**	0.09	-0.35	***	0.17	-0.32	***	0.12
Premature Mortality	-0.27	**	0.11	–	–	–	0.24	**	0.10
Walk Score	-0.31	***	0.14	-0.43	***	0.25	0.20	**	0.08
	Roads (6) COHESION			Paved Surfaces (7) COHESION			Shannon's Diversity Index (SHDI)		
	β	P	R-square	β	P	R-square	β	P	R-square
Assaults	0.32	***	0.14	0.25	*	0.10	0.46	***	0.24
Home Prices	-0.49	***	0.31	-0.49	***	0.28	-0.59	***	0.38
Premature Mortality	0.22	*	0.09	–	–	–	0.47	***	0.25
Walk Score	-0.13	*	0.06	-0.13	*	0.05	–	–	–

Technical notes: Landscape ecology metrics computed on 2007 land cover data (COT, 2009) with 0.6 m (1.9685 ft) pixel resolution, and using queen contiguity (8-neighbor rule). R-square values represent the full model including space (fit), rho: 0.989, Alpha: 1.0. Levels of significance: * $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$; – no relation observed. COHESION: Patch cohesion index. See Leitão et al. (2006) and McGarigal et al. (2015) for landscape ecology metric details and equations.

5. Discussion

5.1. Importance of Relationships

The results of the correlation matrix revealed noteworthy findings between the Wellbeing Toronto indicators. Walk Score (walkability) was positively correlated to assaults. It is presumed Walk Score measures the number of urban amenities within a distance as well as pedestrian affability. The more walkable a neighborhood is the more likely people use walking as their mode of transportation. This ultimately increases the number of human targets in public spaces as well as increased time they spend outdoors, therefore providing greater opportunities for assaults to occur [116]. Walk Score and home prices were also positively correlated, which is not surprising given the fact that proximity to amenities, schools, parks, retail, etc. are key characteristics associated with higher property value. Location and price are often considered to be the two most important factors when looking at real

estate; the more walkable an area is the more attractive it is perceived to be. Therefore, neighborhoods with a greater perceived quantity of socioeconomic amenities have improved market values [117]; however, seldom is the quality of those socioeconomic amenities or factors of environmental well-being considered. Home prices and assaults were found negatively associated. This can be attributed to safer neighborhoods having greater market demand and subsequent property values. Furthermore, several studies have found crime rates to be more prevalent in areas with lower socioeconomic status [118,119]. Home prices, a proxy for wealth, and premature mortality were found negatively associated. This corroborates the literature that people with low socioeconomic status have greater premature mortality than those with higher socioeconomic status [120]. Lastly, Walk Score and premature mortality were positively correlated. This is an interesting finding as it implies that risk of premature death from crime (i.e., assaults) and population-related accidents (i.e., pedestrian-car collisions) outweigh the health benefits of a walkable neighborhood. Of course, this finding is preliminary but suggests a fertile area for forthcoming research.

The results of the correlation matrix show interesting findings between the landscape ecology metrics. Tree canopy COHESION was negatively correlated with both COHESION of roads and buildings. This can be explained by the fact that tree canopy fragmentation and loss is often attributed to urban densification [121]. This is important as urban development lacking urban greenspace and subsequently tree canopy can have many social and physical health implications [122]. Furthermore, preserving urban tree canopy is important as it can also counter urban heat island effect, improve air quality, reduce the needs for heating and cooling of residential homes, and mitigate urban noise pollution [14,123]. Tree canopy COHESION and SHDI were also negatively associated. This is likely a result of spaces with denser tree canopy being disturbed less with regard to development and therefore tend to have fewer land cover classes. Moving on, grass/shrubs COHESION were positively correlated with COHESION of buildings, roads, paved surfaces, and SHDI. This can be explained by urban densification and urban greenspace becoming a key part of smart growth and new urbanist building standards. Research suggests that urban green spaces promote healthier communities as it facilitates physical activity, encourages better mental health and improvements in general well-being of people living in cities [124,125]. Lastly, buildings COHESION was positively correlated with COHESION of roads and paved surfaces, and SHDI. This finding was not surprising as buildings require the presence of infrastructure such as roads and paved sidewalks to support the populations utilizing these business, office, and residential spaces.

When looking at relationships between well-being and landscape indicators, the corroborating results of the global collinearity and local CAR analyses revealed several noteworthy findings. For example, Walk Score was negatively related to both tree canopy and grass/shrub connectedness, signifying its lack of consideration for quality of ecosystem services and environmental public health, and subsequently happiness, during its proximity assessment of socioeconomic amenities. This is reinforced by the fact that Walk Score was positively correlated to buildings COHESION. Consequently, the more connected buildings, the more built-related and contained amenities present, therefore higher Walk Score. These results convey the need for a “Green Walkscore” or “Walk Quality Index” that captures all spheres of urban sustainability. Tree canopy COHESION was negatively associated with premature mortality. As tree canopy becomes more connected streetscapes become cooler, local oxygen levels increase, and phytoremediation lessens toxic gasses and particulate matter reducing negative health effects [14]. Premature mortality experienced a positive correlation to COHESION of buildings and roads, and SHDI. Therefore, the more connected the built environment the greater likelihood for air quality issues such as higher concentrations of fine particulate matter [126]. Also noteworthy was the positive correlation between tree canopy COHESION and home prices. Several studies have indicated that greater presence of urban trees is significantly associated with higher home values [127–129]. This is explained by the presence of trees and dense canopy having improved ecological function and services; flora mitigating pollution levels that have a pernicious influence on property values. As expected with “not in my backyard” theory, lower home prices were found in more connected built

streetscapes as evident by negative correlations between home prices and COHESION of buildings, roads, and paved surfaces. Lastly, assaults were positively correlated to COHESION of buildings, roads, and paved surfaces; albeit, assaults negatively associated with tree canopy connectivity (tree canopy COHESION). The literature is mixed regarding relationships between urban vegetation patterns and crime, suggesting research is still needed [119,130].

5.2. Sustainable Urbanization: Building Resilience

Local, regional and global sustainability depends critically on cities. Cities are being exponentially stressed by increasing population density and the compounding effects of global climate change. Therefore, it is imperative that cities actively lead the way as forces of change for advancing the sustainable development effort. Despite relationships found among variables in this study, and the issues associated with urbanization mentioned, the big question is how results from studies like this one get operationalized in cities. Prevailing urban theorems acknowledge that natural and human systems are completely reliant on one another. *Homo Urbanus*, a taxonomy metonym for the urbanized human [2], depends on natural capital and ecological services. Similarly, Earth's natural systems now depend on humanity's willingness to create planning and policy strategies for conserving our life-supporting biogeochemical systems across space and time. If the urban footprint expands unchecked, through globalized metabolic scenarios of natural landscapes due to increased material well-being demand, it will lead to systematic collapse of life as we know it. To advance positive behavior changes, countries, regions, and cities have created data dashboards to share their governmental data with their stakeholders. These online indicator tools can serve as feed-back mechanisms for improving a location's condition, yet improvements remain. That said, the promise of open data portals, and larger what they stand for, are what will forever change the ways people view, visit, live, and die, within urban areas.

One of the greatest limitations to planning-based indicator programs is the low representation of ecological integrity, environmental public health, ecological services, and biogeophysical indicators. In doing so, the environmental sphere of sustainability is largely left out of the decision-making process. While communities are engaged in the enactment of policies and techniques consistent with sustainable development, if environmental metrics are not included equally in decision-making then results are biased toward socioeconomics. Since few local initiatives show evidence of successfully integrating all three spheres of sustainability, this study aimed to advance this sector of sustainable development planning by creating a foundational suite of landscape ecology metrics for the City of Toronto. These neighborhood design data are provided with this paper and will be given directly to city government, in hopes that landscape ecology metrics will be included in future decision-making and policy development. Although other urban resilience research has used landscape configuration to more fully capture environmental quality, landscape ecology metrics remain virtually nonexistent in public data portals or dashboards. At minimum, due to the importance of preserving, restoring, and connecting urban greenspace, and because of the results of this study, the five land cover (tree canopy, grass/shrub, buildings, roads, other paved surfaces) class COHESION measures should be added to Wellbeing Toronto. The truthful representation and understanding of built and natural environments through open data portals is an invaluable gift to the urban experience: as they are likely the best chance at creating city-wide resilience and strides towards sustainability. In sum, landscape ecology metrics can provide cost-effective ecological integrity addendum to existing and future urban resilience, sustainable development, and well-being monitoring programs.

Open-data platforms are so much more than just repositories of information. On the surface, they may appear to simply provide a pre-determined collection of demographic information, but when correctly taken up analytically as in this study, they can help us understand complex coupled human–environmental systems. Since Agenda 21's call for sustainable development monitoring and evaluation programs, leading cities and countries have created data dashboards and open data portal. In example, the Canadian cities of Montreal, Halifax and Vancouver; American cities of Houston and

New York; and country-wide efforts like in Denmark, practice thoughtful data dissemination. Although often scarce of environmental representation, these online data dashboards still provide brief snapshots into the inner-working of their locations. It is just a matter of time before these online tools include landscape pattern characteristics of their study areas, that span the individual to the neighborhood, city, province, and country-wide scale. Though, a data-driven approach to city-building is only being used in select cases. Within the site of this study, Toronto's Sidewalk Labs stands testament to district-wide sustainable development via a data-driven approach and smart city philosophy. If open data portals expanded to include more design-based indicators, such as those calculated and showcased in this study, it would drive more informed and reflexive decision-making when it comes to managing human-dominated landscapes. Beyond the two-dimensions evaluated with the landscape ecology metrics of this study, future urban well-being and sustainable urbanization research should consider all aspects of the space syntax [131]. Specifically, landscape surface metrics [132] and other urban analytics for describing and analyzing traits of spatial configuration [133,134] should be considered.

6. Conclusions

Sustainable development is the theme of our time, and Canada is poised to become a world-leader in reaching sustainability. Although Canada continues to move scientific theory into applied practice, work remains to achieve sustainable communities across Canada's cities and regions [135]. At the city-level, Toronto serves as an interesting site for examining both the inter-strata connectivity of human and natural systems in the wake of urbanization, as well as the current connectivity and spatial distributions of phenomena across historic and distinctly defined neighborhood identities. Due to its rapid population growth, restricted physical geography, overwhelmed infrastructure, poor air quality, increasing natural disasters (i.e., flooding), and already high density of people and urban structures, it is imperative that Toronto become the most sustainable city in Canada. Urban sustainable development in Canada is mandatory for the longevity of its regions, the country, and the world, as it would help to produce a long-term, mutually beneficial relationship between civilization and life-supporting planetary resources. Although true, there remains no unanimous method for achieving sustainability at neither regional nor local planning scales. Lastly, there remains no consensus regarding how best to design sustainable development index models or how best to use them for policy and decision-making across spatial scales, especially at the local government level [32,70,71,136].

A research study across the 140 neighborhood-landscapes (streetscapes) of Toronto was presented through three main intentions. Its foundational goal was to calculate landscape ecology metrics from the 2007 land cover dataset for the City of Toronto; for use in sustainable development planning strategies and to bolster its Wellbeing Toronto data dashboard. In doing so, 130 landscape indicators were generated: 126 land cover class configuration and four landscape diversity metrics. Note that other relationships await discovery using this free database; thus, forthcoming germane research should consider its adoption. To showcase the value of the data created, a three-step spatial analysis was created to accomplish the second and third intentions of this paper, and its complementary goals. Specifically, spatial patterns of streetscape COHESION, SHDI, and four Wellbeing Toronto indicators were spatially evaluated and visualized using Global and Local Moran's I, respectively across the 140 neighborhoods. Next, Pearson's Product-Moment Correlation test (r) was used to globally assess relative statistical relationships between the five land cover class COHESION metrics, SHDI, and four Wellbeing Toronto indicators. Third, to correct for errors caused by spatial autocorrelation and corroborate global coefficients, bivariate correlations between landscape and well-being indicators were made using local conditional autoregression. Lastly, it is hoped that this paper will serve sustainability scientists, spatial analysts, urban planners and designers an applied example for systematically assessing, describing, and monitoring sustainable landscape function across space.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2071-1050/12/3/997/s1>, **Data S1:** Three data items including CSV file, GIS shapefile, and source FRAGSTATS document for the raw FRAGSTATS metrics calculated ($n = 140$); **Data S2:** CSV file of non-transformed landscape class configuration

COHESION, landscape diversity SHDI, and four normalized and transformed Wellbeing Toronto indicators database ($n = 140$).

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Appendix A

Appendix A.1

Streetscapes of the five land cover class COHESION metrics and one landscape diversity SHDI metric showcased in this study. Values in the lower-right corner are raw metric scores corresponding to its descriptive statistic. Upper-left corner labels match the City of Toronto's universal neighborhood identification number enumerated in public spatial and tabular data. *Cartographic note:* Neighborhood-landscapes are set to the same geographic scale.

Appendix A.2

Choropleth maps illustrating the five land cover class COHESION metrics and one landscape diversity SHDI metric for Toronto, Canada. *Cartographic note:* Choropleth categories represent quantiles across the 140 neighborhood-landscapes (*streetscapes*).

Appendix A.3

Histograms and boxplots for the five land cover class COHESION metrics and one landscape diversity SHDI metric calculated for the 140 Toronto *streetscapes*. Boxplots illustrate quartiles and interquartile range (whiskers are $\pm 1.5 \times$ interquartile range), confidence diamond for mean value, and *shortest half* bracket. Observations beyond the whiskers are considered outliers.

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