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Spatial Analysis of Risk Exposure of Urban Trees: A Case Study from Bologna (Italy)

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Abstract: In Europe, more than two-thirds of the population live in urban areas. The management of urban green areas and trees is becoming increasingly relevant involving different players and stakeholders, as well for keeping a focus on the Sustainable Development Goals. Society and policy makers are often unaware of the disservices that neglecting these areas can cause. Appropriate monitoring interventions can protect both citizens and trees themselves. The aim of the study was to assess the risk potential in urban trees in Bologna suburbs (Italy). For each tree in the city of Bologna, three target variables identifying the number and categories of streets, buildings, and walking and cycle paths near the tree were considered and used as covariates. A multiple regression model assessing the relationship between a dependent synthetic spatial variable (digital number, DN), proxy of the likelihood of tree failure, and the three independent covariates was estimated. Both the number of streets and walking and cycle paths in the area surrounding a tree are shown to be significantly associated with the DN value. The use of open data can assist in monitoring and maintaining urban green areas. The tool supports a virtuous circle between stakeholders in urban systems through sustainability and efficiency.

Keywords: open data; risk exposure; spatial analysis; tree failure; urban green infrastructure; urban planning; urban trees

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1. Introduction

During the past few decades, society has gained a greater understanding and awareness of how nature operates [1,2].

According to the recent literature, in the next decades, the urban green areas, currently providing home to around 10 billion trees around the world [3], will play an increasingly important role in maintaining liveable and resilient cities [4] in the face of demographic [5] and climatic pressure [6,7]. Despite the growing importance and urgency of this issue, this still does not translate into the concrete adoption of specific policies and promotion activities that can effectively increase and improve the lifespan of urban trees. Indeed, several studies conducted in large cities demonstrated that the greater the human impact on the environment, the shorter the life expectancy of trees [8,9]. Furthermore, according to the recent literature, trees are increasingly threatened by climate change [10], pests, and diseases [11,12]. Despite this topic being widely discussed in the literature and there being a large body of studies on the subject, one of the main barriers to tackle this issue and concretely intervene remains the consistent economic costs related to the management of urban trees [13,14]; thus, it is neglected by local administrators and policy-makers, who favour other relevant aspects of public expenditure. Indeed, conflicting land uses [15] and cost–benefit trade-offs [16] cause strife in many levels of the society [17].

The complexity and mess of urban landscapes can be mitigated by a better understanding of the trees in them [18]. As widely known in the literature, urban trees are renowned for improving livability in cities through their ecosystem services [19–21]. Nevertheless, long-lasting benefits can only be provided if the responsible local authorities properly manage the trees [22]. It should also be considered that urban trees are particularly vulnerable to extreme climate conditions such as precipitation, wind rips, and elevated temperatures [23], which can result in tree failure, an increasingly frequent occurrence throughout the world, posing the threat of property damage, financial losses, citizen injury, and, albeit remotely, mortal accidents [22,24,25].

Assessing tree failure then should play a crucial role in preventing these damages [26], but this is a challenging task. Indeed, early signs are often not visible and require a detailed evaluation of each tree (e.g., requiring specific tests and instruments), which is limiting considering the management of all the trees across a whole modern city [27].

Moreover, one of the major critical issues for the management of urban trees is the lack of information on the disruptions caused by the death of urban trees [28]. In order to protect both trees and citizens, it is essential to identify (a limited number of) dangerous trees and to adopt appropriate monitoring and management interventions [29].

According to this, the measure and assessment of the risk associated with the failure of urban trees represent a prominent problem in the urban reality.

Tree failure poses a risk to the provision of ecosystem services [30], the quality of surrounding infrastructure, and the integrity of the population [31,32]. In large urban realities, such as that of Bologna, extensive tree management is required by the competent authorities [22], whose activities are often limited by political, technical, and economic issues [14]. This task requires a pragmatic, professional, and skillful approach, in which technologies are employed capable of providing effective support to local authorities by defining guidelines and frameworks and prioritizing interventions that optimize the resources available for the preventive maintenance of road trees and reduce the risks associated with the failure of urban trees [33].

According to the literature, a number of recent studies have been carried out so far discussing the assessment of the trees' risk of failure and suggesting proper evaluation tools [34,35].

Tree risk research currently focuses on predicting defects and structural impact principles from accidental causes [36–38]. Despite the fact that systematic risk assessment is an effective and economical method of determining tree risk at the outset, data acquisition for assessment metrics remains predominantly subjective [34], and further research is needed. Therefore, (i) adding evaluation tools for objectivity, (ii) combining modern technologies such as computer vision for accurate data collection, and (iii) using machine learning to determine metric weights and develop a professional tree risk assessment website or application that makes the initial risk assessment a simple, quick, and reusable assessment method are all prospective research directions for determining tree risk [39].

In addition, tree risk assessment through visualized methods allow for further quantification and comprehensive objective evaluation of the complex factors affecting tree risk [40–43]. Other studies have instead focused on the development and measurement of specific indicators for the assessment of tree-fail hazard [44–46]. Other studies have proposed different risk monitoring systems [47–50].

Finally, to this end, it is necessary to use tools capable of comprehensively quantifying and monitoring the presence, abundance, age, and health status of trees in urban areas [51,52] in a more rapid and reliable way. On the other hand, governments are always looking for low-cost targeted ways to manage and engage the public on urban trees [53–55].

Moreover, evaluation studies in urban areas as a support for public decisions [56–58] could be useful for this issue. Nevertheless, evaluation studies can be difficult to implement and conduct since they require a higher spatial resolution and multiple scale of analysis in sampling particular resources in specific places all within the typically heterogeneous urban landscape [59].

In this context, it appears important, despite being very complex, to involve researchers and citizens in the evaluation of potential risks associated with trees and to define the critical issues and the consequent priorities for intervention [60,61].

New insights on this topic could be provided by the use of open-source data, which could be a useful and free resource to provide support to the design and implementation of new policies on tree management. Open-source data have become increasingly widespread in smart cities as citizens are provided with tools that help creating new services and platforms [62,63] and can more easily collect a wide variety of information. Open-source data contain information of considerable potential, which could make it possible to improve the efficiency of the public administrations [64,65] in this complex topic. This kind of information has various advantages, allowing for progressive improvement and innovation of research [66]; moreover, according to recent studies, they can represent a useful tool in the support of decision-making processes [67] and finally allow better access to data for citizens [68]. Furthermore, the opening and the use of public data will allow increased participation by citizens in the social and political life [69] and could contribute to strategic areas such as the environment [70].

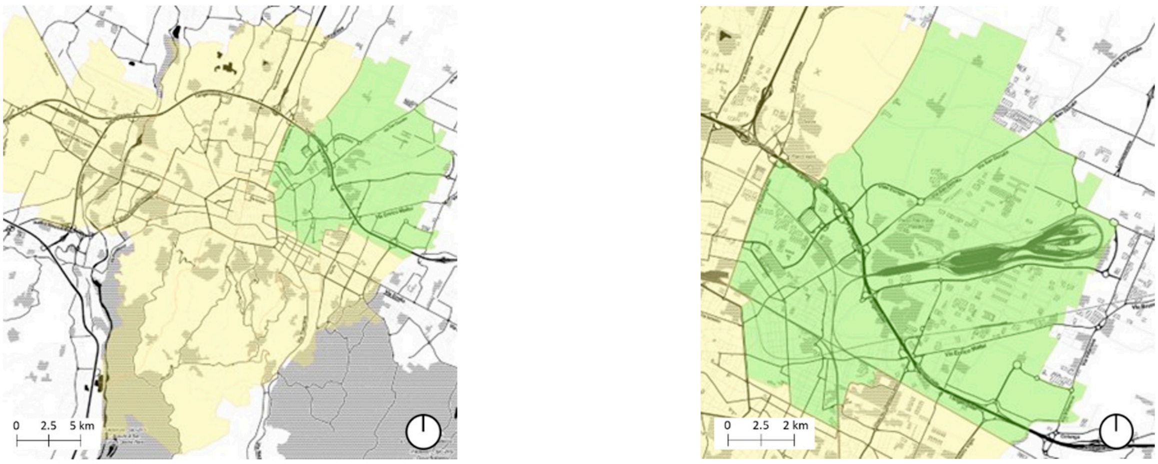
Specifically, this study aims at assessing the risk exposure of urban trees, by using open-source data, in Bologna suburbs (Italy).

2. Materials and Methods

2.1. Study Area

The catchment area considered for the study analyses is the metropolitan city of Bologna (44°29′38″ N 11°20′34″ E). It is located in the province of Bologna, in the Emilia-Romagna region, a region located in north-eastern Italy. According to the Italian National Institute of Statistics, Bologna has an area of around 140.9 km^2 and nearly 390,000 inhabitants in 2022 [71], with a density population of 2754 inhabitants/km^2.

The municipality of Bologna is divided into six districts: Borgo Panigale-Reno (surface area 31 km^2 and 61,200 inhabitants); San Donato-San Vitale (26 km^2 and 66,697 inhabitants); Navile (25 km^2 and 69,545 inhabitants); Porto-Saragozza (15 km^2 and 69,783 inhabitants); Santo Stefano (30 km^2 and 65,047 inhabitants); and Savena (11 km^2 and 59,890 inhabitants) [72]. To perform this study, we chose to divide the city areas in districts instead of a random grid because the districts have an administrative meaning and may better support policies on street trees. This study focused on the San Donato-San Vitale district (Figure 1).



(**a**) (**b**)

Figure 1. Location of the study area. (**a**) Classification of the Municipality of Bologna (yellow color; 44°29′38″ N 11°20′34″ E); (**b**) focus on the district of San Donato (green color; 44°30′13.68″ N 11°22′04.44″ E).

The city of Bologna was chosen as the case study for two reasons. First of all, the datasets provided by the public administration containing open data on municipalities and green urban areas are available, and moreover, there is the possibility of being physically present on the site in the event of future study developments.

2.2. Data Collection

2.2.1. Open-Source Data

For the analysis, open-source data were retrieved, in shapefile format (.shp) from a specific database of the Municipality of Bologna in 2022. This database is freely accessible from the website of the Municipality [73] and usable by any user for any purpose.

Firstly, all the data underwent an interpretation and evaluation phase for explorative purposes (i.e., it was decided how to proceed and for each variable, how to deal with any missing values). Observations with missing values or incomplete codes were excluded from the analyses.

2.2.2. Urban Tree Data

The tree species and specimens considered were elaborated starting from the "Public green areas of Bologna" dataset. Only the public trees located in the study area (e.g., San Donato-San Vitale district) were considered; the private ones were excluded from the analyses. The resulting population was composed of 84,611 statistical units (i.e., each unit corresponding to a tree) belonging to the study area under examination.

2.2.3. Covariates

For each tree included in the analyses, various independent target variables were considered for the analyses. According to the literature, three variables related to traffic conditions (roads and cycle–pedestrian paths) and buildings were selected [74]. Thus, three variables identifying the number and categories of streets, walking and cycle paths, and buildings near each tree were considered and used as independent covariates in the statistical analyses.

2.3. Data Analysis

The downloaded datasets underwent a pre-processing, cleaning, and data manipulation phase. This phase was necessary to understand the data structure, the entity of the different starting datasets, and subsequently to clean data and decide how to treat them (and any missing values).

The values related to the height and diameter of the tree specimens were reassigned, and the initial nominal scale was converted into categories following an ordinal scale. Once the values of the height and trunk diameter, measured at a height of 1.30 m from the ground, had been reassigned to different scales, we proceeded with the creation of a new scale of classes consisting of the ratio between the height and diameter (h/D ratio). The evaluation of the stability of the trees was formulated on the basis of the height–diameter ratio (h/D ratio) [75,76]. The decision was taken with the aim of using, according to the available data, a well-known index, although opinions have recently been provided regarding the use of this index that would see it more correctly associated with the forest area, with refined and regular layouts, rather than with the urban area [77].

Subsequently, geo-spatial analyses were conducted through the QGIS software, aimed at aggregating the vector data necessary for the composition of the dataset for subsequent processing and the formulation of the value of the digital number (DN value), a synthetic spatial variable characterizing each tree included in the study [78]. The DN value of each tree is related to the propensity of the tree itself to collapse (please see below) and can be likely considered as a proxy of the risk of failure of the tree.

2.4. Statistical Analysis

Various descriptive analysis tools and summary measures, such as position indexes, were used in order to explore, describe the data, and to visualize their distribution.

The variables included in the analyses as covariates, as previously mentioned, were those identifying the number of (i) streets, (ii) walking and cycle paths, and (iii) buildings located in the area around each considered tree. These variables were expressed as count data.

As outcome, or dependent variable, we used the DN value. As previously described, the DN value is related to the propensity for failure of each tree and can be considered a proxy of the risk of the tree's failure, i.e., the higher the DN value of the tree, the higher the likelihood to experience a failure of the tree itself. Similarly, the lower the DN value of the tree, the lower the likelihood of experiencing a failure episode for the tree. DN values can vary from 0 (minimum likelihood of experiencing a failure episode) to 255 (maximum likelihood of experiencing a failure episode), and the use of this proxy of the risk of tree's failure allows us to perform a spatial analysis, considering each tree in its geographical context.

A multiple adjusted linear regression model was used in order to evaluate whether there is a linear relationship between the DN value and the considered independent covariates [79,80]. A multiple linear regression model was estimated since we considered the average value of the dependent variable (DN value) as a linear function of the regressors relating to the targets. Thus, the multiple regression model was estimated in which the DN value was assumed as the dependent variable and the following variables as explanatory variables: number of buildings; streets; ans walking and cycle paths.

2.5. Additional Notes

All the analyses were carried out with the SAS software (version 9.4; SAS Institute, Cary, NC, USA), the Excel software (of Microsoft Office Personal Productivity Software Suite, version 2019 16.0.6742.2048), and the QGIS Software (3.24.0).

For all the hypotheses tested, p-values were considered significant when the two-tailed values were below the alpha significance level of 0.05.

3. Results

Table 1 shows the position indices relating to the four variables included in the model. For the DN value, the observed minimum value is equal to 57, while the maximum value is equal to 255. The average DN value is equal to 154.50. Instead, the average number of geometries of buildings (variable buildings) is equal to 762.77. In this case, the median value, equal to 3.50, suggests a possible asymmetric distribution of the values. The number of building geometries varies between a minimum value of 0 and a maximum value of 5791. The average number of street geometries (variable streets) is equal to 2249.17, and the median value, equal to 619.50, suggests that in this case also the underlying distribution could be asymmetrical. The minimum number of road geometries is 1, while the maximum is 12,582 in this case. Finally, the average number of walking and cycle path geometries is equal to 717.36. The number of cycle–pedestrian lane geometries is between a minimum value of 0 and a maximum value of 5454.

Table 1. Summary measures referring to the variables included in the analyses.

Variable	Mean	Median	Min	Max	Standard Deviation
DN value	154.53	154.50	57.00	255.00	56.77
Buildings	762.77	3.50	0.00	5791.00	1500.59
Street	2249.17	619.50	1.00	12,582.00	3346.41
Walking and cycle path	717.37	127.00	0.00	5454.00	1299.36

From Supplementary Table S1, it can be noted that all the considered independent variables are correlated with the DN value, these correlations being between 0.62 and 0.68, and are statistically significant (associated p-values < 0.0001).

Concerning the regression model, the resulting F-test (Supplementary Table S2) signals that the model is statistically significant, with a p-value < 0.0001. In other words, at least one of the three independent covariates turns out to be on average statistically different from 0.

Based on the R-squared estimate reported in Table 2, it is possible to conclude that approximately 57% of the overall variability of the dependent variable (DN value) is explained by the model, i.e., the relationship with the other regressors. In particular, the R-squared value of 58% suggests a good fit of the model to the data.

Table 2. Statistics of the dependent variable and value of the linear coefficient of determination.

MSE Root	3.711.777	**R-Squared**	0.5791
Mean dependent variable	15.452.551	**R-squared corrected**	0.5725
Coefficient variable	2.402.048		

From Supplementary Table S2, referring to the estimation of the model parameters, it is possible to conclude that both the covariates related to streets and walking and cycle paths are significantly associated with the dependent variable (*p*-value < 0.0001). Furthermore, the relationship existing between the streets variable and the DN value proves to be positive. Consequently, as the number of road geometries near the tree increases, the value associated with the DN value increases. That is, as the number of street geometries around a tree increases, the propensity of experiencing a death of the tree increases. More specifically, with the other regressors being equal, a unit increase in the number of road geometries of the dependent variable corresponds to an average increase of 4% in the propensity of experiencing a tree's failure. Otherwise, a negative relationship is observed between the variable relating to the number of pedestrian and cycle path geometries (walking and cycle paths) and the dependent variable (DN value). It follows that, the higher the number of pedestrian and cycle path geometries around a tree, the lower the risk of experiencing an episode of subsidence by the tree.

Instead, from Table 3, the variable relating to the number of building geometries (buildings) does not appear to be statistically significant (*p*-value equal to 0.63); thus, the number of buildings around the tree is not associated with its risk of experiencing a failure episode.

Table 3. Estimation of model parameters.

Variable	**DF**	**Sum of Squares**	**Mean-Squared**	**F-Value**	***p*-Value**
Intercept	1	115.97	3.76088	30.84	<0.0001
Buildings	1	0.00461	0.00956	0.48	0.6300
Street	1	0.04569	0.00490	9.32	<0.0001
Walking and cycle path	1	−0.09442	0.01518	−6.22	<0.0001

4. Discussion

In line with this task, open-source data were used to examine the association between the dependent spatial variable describing the trees' propensity to failure (DN value) and three independent categories using a multiple linear regression model. Based on the results, both the number of streets and walking and cycle paths are significantly associated with the DN value, showing a positive and negative association, respectively. Thus, in our study, we used open-source data to estimate the likelihood of the tree failing associated with independent variables, describing various features of the urban structure.

Furthermore, it can be observed that there seems to be a positive association between the street variable and the DN value. Consequently, the level of failure propensity that each tree is exposed to increases as the number of road geometries around the tree increases. In the literature, similar studies have been conducted, which examine the relationship between trees and streets. The findings of this study appear to be consistent with those from similar studies already published in the literature [47,81].

Instead, a negative relationship is observed between the variable walking and cycle paths and the DN value. It follows that a unit increase in the number of geometries of cycle–pedestrian tracks around the tree is associated with an average decrease of 9% in the risk of experiencing a subsidence episode by the tree. In other words, as the number of geometries of walking and cycle path increases, the tree's propensity to subsidence decreases. This result could be supported by the work of North et al.; the increase in the risk connected to the sagging of the trees could be due to a lack of design in the sixth planting of the trees [82].

The number of building geometries from the analysis was not statistically significant (p-value equal to 0.63) and showed no association with the dependent variable. There are no studies at the moment that validate this lack of association; however, recent studies indicate the level of failure propensity in urban trees related to the building [32,83,84].

In order to understand the results obtained, it is necessary to discuss this study's strengths and limitations.

This study has several strengths. This is one of the most recent studies defining the priorities of trees' monitoring and intervention activities in Bologna.

As described in the Introduction section, assessing the priority of tree monitoring is a challenging task as early signs are often not visible and require detailed assessment of each tree, which is limiting considering citywide tree management [33,85]. It is then necessary to provide several tools that optimize the management of urban trees (e.g., by programming interventional interventions identifying the tree with a higher propensity to experience a failure event) and provide support to local governments in managing the tree heritage (e.g., by forecasting the risk of trees experiencing failure episodes).

Proper tree selection, management, and care treatments are equally important. Ensuring a high level in these three areas is essential to obtain the optimal benefits of tree planting.

This article presents a valid tool to carry out long-term monitoring, which allows the development of good practices based on reliable data in a given environment, thus ensuring good prospects for improving the growth conditions of trees [86]. Furthermore, for our purposes, we used open-source data, which were proven to be a valid resource to provide evidence supporting the decisions and policies related to tree management. Furthermore, the use of existing and freely available open-source data would avoid costs associated with the collection of data in the field by operators, saving expenditures, thus making this approach more sustainable and attractive for public administrations, enabling them to more easily adopt optimized and concrete programs for the urban tree management.

This study provides evidence, combined with other precautions, that specific analyses performed on open data could help in the optimization process of the management of urban trees. Below are some inputs and suggestions on how to optimize the urban tree management: maximize the positive effects of vegetation on the urban environment through integrated and innovative management capable of combining environmental needs with economic ones [87–89]; promote knowledge and monitoring of the natural heritage of urban greenery through innovative mapping and representation tools [90,91]; make the management interventions of the urban greenery system systematic and homogeneous by preparing appropriate plans and programs [92,93]; carry out maintenance interventions according to the most up-to-date criteria and in compliance with scientifically based cultivation techniques aimed at reducing external inputs [94–96]; guarantee transparency in every action and make citizens an active part in the knowledge and care of greenery through communication, information, teaching, and active discussion actions [97,98]. Among these, the implementation of a tool using open data and providing quantitative evaluation for the assessment of trees' failure risk could provide an interesting contribution to the scientific discussion on this topic.

However, the study suffers from several shortcomings. As emerged from the literature, the failure of a tree in the urban environment can be due to a number of predictive factors. These factors often occur at the same time, resulting in interactions and negative synergies.

The study did not consider factors related to wood degradation, inappropriate pruning, presence/absence of xylophagous organisms [99,100], and constriction of the trunk by sidewalks, which in urban environment can overall increase the probability and type of tree fall (trunk breakage or uprooting) [101] in adverse weather conditions [102]. Thus, further studies are needed, since our results need to be integrated with this kind of information, in order to provide a more comprehensive analysis of this phenomenon.

The second limitation is due to the open-access format tools that although have considerable advantages [103] are characterized by the presence of various limits. Among which are: (i) the incompleteness of the information, several variables presented blank cells (missing values); (ii) heterogeneity of the nature of the information (the presence of non-unique data compromises any comparisons); (iii) the strong heterogeneity of data collection methodologies, which combined with the lack of complete metadata has made it impossible to interpret the data (i.e., the presence of acronyms not known in the literature and lacking an appropriate description) [104].

Furthermore, it should be considered that a limited set of open-source data has been entered in the open format and must now be inserted into a standard data set. Field operators should be trained in data collection typology, measurement units, and acronyms used by everyone in the field. The data that cannot always be used for this type of application would require a good standard of metadata accessories, which would include explicit information about the use, measurement units, and any other information that can help the analyst in elaborating the collected data in a proper way, without introducing any incomprehension or bias.

Despite that, the increasing use and collection of this kind of data in the next years will allow the research community to access more precise and detailed information, providing more detailed analysis and evidence. This study aims also to provide a useful insight into this topic, acting as a starting point for further future analysis.

Another limitation is attributed to data manipulation and the consequent arbitrary choices related to the treatment of missing values. A high degree of subjectivity on the part of the evaluator is implicit in this phase, as he is required to interpret the data available and decide how to proceed both in the case of missing values and during the phases of composition of the starting dataset for the analyses [105].

Therefore, the estimated regression model provided information relating to the first simple exploratory analysis, with the aim of verifying if any relationship exists between the risk of experiencing a tree's failure episode (DN value) and variables related to urban geometries. Due to the peculiarities of the distributions underlying these explanatory variables, additional analyses will be required in the future.

5. Conclusions

The following study provides information on the risk associated with the likelihood of tree failure. Naturally, upstream of risk management, it is important to consider different conditions for the correct design and subsequent management of the trees themselves [32].

Through the use of open-source data, this study demonstrated that the potential association between the risk of experiencing a tree's failure episode (DN value) and variables related to urban geometries (i.e., street, walking and cycle paths, and buildings) could be estimated, providing useful evidence. The study supports a virtuous circle model among stakeholders by providing a valid, unique, and sustainable tool for the management of urban green areas. In addition, these tools, combined with the use of free and already collected open data, would reduce costs associated with data collection, which would be particularly beneficial to public administrations. This study provides an interesting example on how open data could be used as a support to the optimization of urban tree management through an improved approach. Through data availability and intuitive visualization dashboards, leaders can quickly understand the current state of their services, identify areas that require improvement, and make informed decisions to optimize urban tree management [106]. Despite this ambitious aim, in order to obtain more precise results, it will be necessary to continue the analysis and to expand the study. In this way, it would be possible to obtain an effective and efficient tool for the public administrations, not only for the urban reality under examination [107], but also for other realities in the national and international territory. By doing so, it would be possible to have a valid and unambiguous tool available in the urban context, which in addition to satisfying the criteria of sustainability, effectiveness, and efficiency, promotes a virtuous circle model among the three stakeholders in the urban system [77,108].

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/urbansci7040123/s1, Supplementary Table S1: Pearson correlation matrix; Supplementary Table S2: Analysis of variance.

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