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Contents

REVIEW NOTES

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Identifying spatial variation in the values of urban green at the city level

A case study in Thessaloniki, Greece

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Abstract

Analyzing the benefits/values of urban green spaces (UGS) to local citizens is necessary in order to make these areas more visible, as well as to support future planning decisions related to the development of new green infrastructure in the urban environment. This paper aims to examine the values associated with the UGS in the city of Thessaloniki, Greece, by using a Hedonic Pricing Method, which examines the effect of urban green areas and amenities on housing prices. Furthermore, the study attempts to examine if the proximity to green spaces has a fixed/homogenous effect on residential property values across the city. A global regression analysis was first applied to explore which structural, locational and green/environmental characteristics are likely to have a statistically significant effect on housing prices. Then, a semi-parametric geographically weighted regression analysis, was applied to identify how the implicit prices of the environmental/green attributes vary within the city. The study revealed that the values of several environmental attributes vary significantly spatially, having in most cases a positive influence on home sale prices. These findings reveal that when making planning decisions about urban green spaces, it is necessary to consider the heterogeneity of citizens' preferences, facilitating thus a more targeted planning for new green infrastructures.

Keywords

Economic valuation; Spatial hedonic pricing model; Urban green spaces; Urban sustainability; Geographically weighted regression.

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1. Introduction

By their nature, cities are particularly vulnerable to natural hazards and climate change impacts. Furthermore, cities are exposed to several human pressures caused by the continuous growth in the size and the population of the urban areas. Specifically, according to data of the United States Department of Economic and Social Affairs, in 2007 for the first time in human history, 50% of the entire global population lived in urban areas and it is now predicted to reach 69% by 2050 (Zali et al., 2016). Consequently, the living conditions in cities deteriorate, and several problems are encountered. It has to be noticed that even though the cities represent only the 4% of the Earth's land, they consume about the 67% of the global primary energy and, due to urban lifestyle and economy, they are responsible for more than the 70% of greenhouse gas (GHG) emissions (Papa et al., 2015). Cities are also highly vulnerable to climate change, as they represent concentrations not only of people but also of assets and infrastructures (De Gregorio Hurtado et al., 2015). Thus, the sustainability and the resilience of cities are increasingly challenged and the necessity to find solutions and to take action is more urgent than ever.

Furthermore, urban density is now commonly considered as a fundamental characteristic of sustainable urban form and thus a prime goal of urban planning. Namely, compact cities have the potential to reduce the use of land and optimize the flow of people, energy, and good, while they may increase the proximity between dwellings, workplaces, and public facilities. Consequently, compact cities are likely to demand fewer resources and produce fewer greenhouse gases (Palacio et al., 2018). Even though compact cities are trying to solve the problems of rapid urbanization and urban sprawl, some negative effects may also exist (e.g. overcrowding, lower living quality, etc.). A major issue which is necessary to be addressed is the lack of urban green space in densified urban areas and the removal of green space when densifying an urban area (Haaland & Van den Bosch, 2015).

Hence, the development of green spaces is likely to strengthen the resilience of the cities, enabling them to overcome many future shocks and pressures. Furthermore, urban green spaces (UGS) are integral elements of cities' living environment, ensuring a higher quality of everyday life, as well a safe and friendly environment for citizens. Therefore, beyond the environmental benefits that citizens could gain from green infrastructures, there are also benefits related to many other sectors such as the economic, the social, and the cultural ones. Some examples are the management of the stormwater through the green and blue roofs (Foster et al., 2011) and the mitigation of the urban heat island effect (Onishi et al., 2010; Tsilini et al., 2015). Other advantages include the reduction of air pollutants (Foster et al., 2011), the cooling of the interior of buildings, especially during summer months (Wang et al., 2014), the improvement of the urban and peri-urban ecosystems' health and ecosystems' services (Tzoulas et al., 2007), as well as the contribution to the mental and physical health by creating positive feelings (Chiesura, 2004). All these benefits have been widely recognized but they are even more important in compact cities.

Finally, as a result of the above-mentioned benefits, proximity to green spaces increases property values, although this increase varies depending on the type of green space and the type of properties (Skouras & Arvanitidis, 2008). For all these reasons, several recent movements in urbanism, such as ecological urbanism, ecological landscape urbanism and landscape urbanism, emphasize that it is vital for the quality of life of cities to prioritize nature and ecological considerations (Latinopoulos, 2022).

The present study highlights the value of green spaces in the urban fabric, by using the hedonic pricing approach. In particular, a spatial hedonic analysis model was used in order to determine the value of green spaces with housing prices, as well as to examine how the proximity to green space influences the value of a property in the study area. Another question that the study attempt to answer, is whether this influence is homogeneous throughout the study area, or if there are regions/neighborhoods where urban green has a more significant (positive) impact on property values (i.e. if there are regions/neighborhoods where the value of green infrastructure is higher as compared to the rest of the city). For the spatial analysis, the Municipality of Thessaloniki in Greece was selected as a study area, which has up to now a very low rate of proportional green space per capita.

2. Literature Review

2.1 UGS and Green Infrastructure

The term "green areas" is used in various ways even within the same discipline and the same culture, based on the research question (and on their interpretation/expression), as well as on the characteristics of those areas (Taylor & Hochuli, 2017). The classification of green spaces could be done with many different criteria, such as according to: 1) their size (Choi et al., 2020); 2) the quality and the quantity of the provided services; 3) the accessibility (Panduro & Veie, 2013); 4) their dominant functions; 5) the different kind of administration (Liu et al., 2020). Even though at the national level (i.e. in Greek legislation) there is no strict distinction between the concepts of "UGS" and "free public spaces", in the study area (Municipality of Thessaloniki), green spaces are considered according to the city's "Green Regulation" as: urban spaces covered by vegetation, including: public parks, gardens, cemeteries, planted trees in historic sites, green belts, street/sidewalk trees, and groves (Municipality of Thessaloniki, 2017).

A new term for urban green is that of green infrastructure, the definition of which varies among studies, according to the context, the stakeholders, and/or the spatial scale in which it is examined (Salata & Yiannakou, 2016). Green infrastructures are usually considered as an interconnected network of green space that conserves natural ecosystem functions and provides associated benefits to human populations (Benedict & McMahon, 2002). Respectively to green spaces, green infrastructure can be also classified into categories. The simplest classification is the urban, peri-urban and rural division, while several attributes/criteria can be used for this purpose: a) land uses; b) accessibility; c) land ownership (public/private); d) physical characteristics (e.g. morphology); e) spatial configuration (Koc et al., 2016), scale (Barker et al., 2019), etc.

Recent studies tend to use classified land cover (CLC) data, from satellite imagery to measure greenspace in urban areas. Other studies are measuring vegetation's health and density by means of vegetation indices, which are based on the biophysical functions of plants, as well as on high-resolution aerial photos (Li et al., 2015). One of the most well-known indices is the Normalized Difference Vegetation Index (NDVI), which is usually obtained from Landsat imagery (with a 30m resolution) to quantify green areas and to show the status (density and condition) of green vegetation on the landscape.

2.2 Economic valuation of UGS

Many reasons make necessary the estimation of the economic value of UGS. First of all, despite their multiple benefits, the critical role of UGS is often neglected or overlooked in the urban/regional development and planning policies (Sandstrom et al., 2006; Latinopoulos et al., 2016). Besides, as pointed out by More et al. (1988), UGS are subject to development pressures because planners have been more or less unable to articulate its value in economic terms. Furthermore, the valuation of UGS is also necessary in order to understand/assess the economic benefits of the various ecosystem services provided by these areas.

When market prices are not available for environmental and natural resource valuation (as in the case of the valuation of UGS), the value is measured by the citizens' (direct or indirect) willingness to pay (WTP) for the goods and/or services (whether or not actual transactions take place). The valuation of such non-market benefits of UGS are not a simple task, as it necessitates to assess various social and ecological services. Several economic valuation techniques have been developed to quantify such values. These techniques are rigorously based on either stated preferences (SP) in surveys with respect to the non-marketed goods/services or on observed behavior towards some marketed goods/services (revealed preference - RP) (Navrud, 2000).

Stated preferences (SP) techniques, such as the contingent valuation method, are trying to infer the value of non-market goods by asking people to state their WTP for a benefit in a hypothetical scenario (Bouma & Van Beukering, 2015). These techniques are the most frequently cited for the valuation of environmental values as they enable the estimation of both use and non-use values. As a consequence, they are also very commonly used within the context of UGS and urban parks. On the other hand, there is a great controversy over whether people would actually pay the amounts stated in the survey responses (Barbier et al., 1997) and they are also prone to several biases questioning their applicability in decision making processes (Mitchell & Carson, 1989; Venkatachalam, 2004).

On the other hand, revealed preference techniques are based on actual consumer (or producer) behavior and identify how non-marketed environmental services, influence the actual market for some related economic goods (Bouma & Van Beukering, 2015). Therefore, these techniques are mainly applied to elicit preferences for direct and indirect use, as revealed in complementary or surrogate markets. The most important indirect methods are the travel cost method, the hedonic pricing method, and the averting behavior method (Mendelsohn & Olmstead, 2009).

The present work focuses on the application of the hedonic pricing method (RP technique), which is based on the assumption that people's demand for composite marketed goods (e.g. housing prices), which among others, incorporates environmental characteristics is likely to reveal the value that people attach to each particular environmental characteristic (Pearce & Özdemiroglu, 2002). According to Gargiulo & de Ciutiis (2009), the market value of residential houses depends on many neighborhood/location characteristics, such as the accessibility, the density of services in the vicinity and the urban quality (i.e. the quality of the urban environment). Regarding the latter, the role of urban green spaces (UGS) is fundamental and for this reason there is an increasing literature on their effect on housing prices (e.g. Tyrväinen, 1997; Luttik, 2000; Morancho, 2003; Kong et al, 2007; Donovan & Butry, 2011; Saphores & Li, 2012; Liebelt et al., 2017).

For example, according to the U.S. Environmental Protection Agency (EPA), green infrastructure can contribute to land value increases up to 30% (Zucaro & Morosini, 2017). More specifically, Morancho, 2003 examined the effect of distance and size of UGS, in the city of Castellon in Spain, concluding that the most important factor affecting property prices is the distance from green spaces. Cho et al (2006) and Poudyal et al (2009) estimated the price increase with respect to the property's distance from the nearest park. In a similar study in the district of Salo in Finland, Tyrväinen and Miettinen (2000) estimated that increasing the distance of a property from an urban forest by 1 km, reduces its value by 5.9%. Other studies, focused on how property prices are affected by: the UGS size (e.g. park size) (e.g. Hoshiro & Kuriyama, 2010), the aggregate UGS area within a radius from home, as a landscape metric (e.g. Kong et al., 2007), the percentage of a town district covered by forested land (Tyrvainen, 1997), the diversity of UGS (e.g. Kong et al., 2007), the view of a green space (Morancho, 2003; Jim & Chen, 2006; Tyrväinen & Miettinen, 2000). All this information, coming from the valuation of different UGS variables/characteristics is likely to provide valuable insights into the values that citizens attain from these spaces and may thus support future urban planning processes and decisions (Panduro & Veie, 2013).

3. Methodology

3.1 Hedonic pricing method

The hedonic pricing method measures the implicit price (i.e. the value of an individual characteristic) of an environmental good or service, which is not traded on a market, as revealed through the observed price of a product that is traded on markets (Bouma & Van Beukering, 2015). Hedonic pricing may be used to estimate economic benefits or costs associated with environmental quality (e.g. air pollution, noise) and/or environmental amenities (e.g. aesthetic views, proximity to recreational sites). It is usually applied to variations in housing prices that reflect - among others - the value of local environmental attributes. Houses are multi-attribute goods, so their price is determined by characteristics, which can be classified into the following categories:

$$P = f\,(S, N, L, E) \tag{1}$$

P is the vector of the rent or the price of the house; S is the matrix of the property-related (structural) attributes (e.g. number of rooms, age, floor, size, etc.); N is the matrix of neighborhood's socio-economic characteristics (e.g. quality of services, quality of the schools, quality of transport system, etc.); L is the matrix of locational variables (e.g. distance to schools, distance from the central business district, distance from bus/metro stations, etc.); E is the matrix of environmental characteristics (e.g. UGS variables), which are usually considered as a separated category (Saphores & Li, 2012).

In most studies, the market price is considered to be the selling price and not the rent value, because rent values are problematic since different apartments may have different terms in the rental agreement. For example, some might include heat and hot water supply or parking spaces (Sopranzetti, 2010). The partial derivative of P (Eq. 1) with respect to any of the selected attributes (dP/dz_i) is an implicit price, that equals its marginal contribution to the housing price, representing thus consumers' marginal willingness to pay for the corresponding characteristic/attribute (Saphores & Li, 2012). According to Gómez-Baggethun & Barton (2013) the hedonic pricing method is widely used for the assessment of the UGS (e.g. open spaces, parks, trees in public spaces) through a regression analysis (Herath & Maier, 2010). The most common method for estimating the function above is the application of a linear regression model, which is solved by means of an ordinary least squares (OLS) method (Latinopoulos, 2018):

$$P_i = \alpha + \beta Z_{i,j} + e_i \tag{2}$$

P_i is the price of house i, α is the intercept term; β is the vector of regression coefficients, Z is the Matrix of j attributes of each house and e is the random error, which is assumed that it follows the normal distribution. The functional form of the hedonic regression equation can either be linear, semi-log, or log-log form (Herath & Maier, 2010), thus differentiating the way the results are interpreted (Mallios et al., 2009). For example, in the case of the linear model, any coefficient β_i represents the marginal value of the *j-th* characteristic while in the log-linear model the same coefficient β_j represents the elasticity of demand for this specific characteristic (Mallios et al., 2009). Thus, log-linear models are commonly used to make better interpretation of the results, as well as to minimize the problem of heteroskedasticity.

3.2 Geographically weighted regression

Traditional OLS hedonic pricing models are based on various assumptions. For example, it is assumed that there is sufficient information about the conditions in the market, as well as about the environmental issues (people are supposed to be aware of the link between the environmental good and their welfare). It is also assumed that when using an OLS model, the random error e in Eq.2 follows a normal distribution with mean zero and constant variance, so there is no autocorrelation in the data. However, in some cases, there is (spatial) autocorrelation between the values of a variable due to the spatial nature of the sampling (e.g. property values are dependent on property values of neighboring locations) and this may violate the assumption of independence of observations in the traditional hedonic price model (Latinopoulos, 2018).

Another drawback of traditional hedonic-pricing models is that the fail to detect and account for the non-stationarity of the effects of space/location on real estate prices. Spatial non-stationarity means that the relationship between the variables is not constant across the study area (Páez & Wheeler, 2009), indicating thus a heterogeneous relationship between dependent and independent variables across the geographic space. As non-stationarity is not taken into account when using a traditional OLS model, the resulting statistics/estimations are assumed to be constant across space (Brunsdon et al., 1996). This means that wherever a house is located, the value added for an additional floor or for a closer proximity to an UGS, for instance, will be the same (global estimate) in the whole study area. However, this may not be the case and it might be more reasonable to assume that price determinants are spatially varying parameters with different marginal price functions across space. And this clarifies why a global (OLS) model is not always possible to explain the relationships between all sets of variables (Brunsdon et al., 1996). Hedonic regression models, in order to better explain the real estate prices across space, integrate new approaches for modeling spatial heterogeneity. The most popular ones are the following: a) spatial error models, which are appropriate if it appears to be structure in the residual term, b) spatial lag models which are appropriate when a spatial structure is present in the model's variables (Charlton & Fotheringham, 2009), c) OLS models using dummy variables to represent distinct geographic areas/submarkets, and d) geographically weighted regression (GWR) models, which allow the regression parameters to vary over space, being also able to explore the issue of spatial parametric non-stationarity.

In this study, a geographically weighted regression (GWR) model was developed to take into account the variable nature of relationships in geographical space. There is a good reason to expect that the price of housing attributes will exhibit spatial heterogeneity within large metropolitan areas (i.e. large housing markets) due to different preferences (demand by households based on socioeconomic characteristics), location attributes and neighborhood characteristics (supply of certain types of housing and neighborhood characteristics. So, it is very likely that supply and demand imbalances may result in spatial heterogeneity within a large metropolitan area (Bitter et al., 2007). In fact, recent applications of GWR models demonstrated that property prices premiums varied in terms of the effect and magnitude across space for the demand of explanatory variables that are spatial in nature (Dziauddin et al., 2015).

The basic difference between the traditional OLS models and the GWR model is the fact that the latter (a) assumes that the association between the property price and the independent variables can be spatially variant and (b) provides a set of equations to estimate the coefficients at any given location (local coefficients). In other words, the GWR model aims to capture spatial variations (i.e. to address spatial heterogeneity and spatial autocorrelation) in the relations between housing prices and the selected attributes. The geographically weighted regression model is expressed as follows:

$$P_i = \alpha(u_i, v_i) + \Sigma_j \beta_j (u_i, v_i) Z_{i,j} + \varepsilon_i \tag{3}$$

All the elements are the same with the Eq. 2 above, but the only difference is that they are location specific. Namely, *Pi* is the dependent variable (price of house) at location *i*, the coefficients *α* and *β* are non-stationary but also correspond to the location *i* of each observation (where u_i and v_i are the x-y coordinates at location *i*) and ε_i is the random error at location *i*. Data located near to point *i* are assumed to have more influence in the estimation of the *j-th* attribute's β-coefficient [$\beta(u_i, v_i)$] than data located farther from *i*. Thus, in GWR an observation is weighted in accordance to its proximity to point *i* so that the weighting of β-coefficients is no longer constant in the calibration but varies with i, that is (Fotheringham et al., 1998):

$$\hat{\beta}(u_i, v_i) = [X^T W(u_i, v_i) X]^{-1} X^T W(u_i, v_i) P] \tag{4}$$

where the bold type denotes a matrix, $\hat{\beta}$ represents an estimate of *β* and $W(u_i, v_i)$ is a n×n matrix whose off-diagonal elements are zero and whose diagonal elements denote the geographical weighting of observed data for point *i*. Usually these weights (for any given observation) are estimated by means of a kernel function (based on the rule that closer observations have a higher effect on the estimation of the coefficients than those further apart). The most commonly used kernel functions are the fixed Gaussian and the adaptive bi-square kernel functions[1].

There are different formations of GWR, one of which is the semi-parametric. The semi-parametric models allow to mix simultaneously some globally fixed variables (i.e. effects that are independent of location) and some locally varying variables (Nakaya, 2007). In this way, the analysis can be separated into global (stationary) and local (non-stationary), instead of the traditional OLS regression analysis where all variables are considered to be global. In this case, the geographically weighted regression model is expressed as follows:

$$P_i(u_i, v_i) = \alpha(u_i, v_i) + \Sigma_j \gamma_j Z_{i,j} + \Sigma_j \beta_j (u_i, v_i) Z_{i,j} + \varepsilon_i \quad (5)$$

It should be also noted that spatial heterogeneity can also be captured by means of other non-parametric (e.g. local polynomial regression models) or semi-parametric methods (e.g. generalized additive model) which allow a more flexible modeling between the regressor and the predictor without any a priori assumptions regarding the underlying data generating process. These models expand the traditional hedonic model by identifying nonlinear effects and thus, by allowing covariates to take nonlinear functional form in order to enhance the model quality (Cajias & Ertl, 2018). However, this kind of analysis has large computation and data requirements to achieve reliable estimation, so its attractiveness is limited in our study due to the limited dataset availability. Besides, the type of the methodology to be employed depends on the research problem, the research objectives, the data availability and not on the merits of a particular research approach, as no particular approach is superior to others (Creswell, 2007).

4. Study area description, data collection and pre-processing

4.1 Study area description

The Municipality of Thessaloniki was selected as the study area for the present study. It is the second most populated municipality in Greece (according to the 2011 Greek census the population is about 325,000 inhabitants) while its total area is equal to 19.31 km^2. It is also the center of the metropolitan area of Thessaloniki (Fig.1), where the historic city center is located. Consequently, it is a typical compact city facing various environmental problems (e.g. air quality, traffic noise), and particularly, facing a lack of open and green spaces.

The urban form of the metropolitan area of Thessaloniki has undergone several changes, and the most important reasons for these changes were the natural disasters and the refugee crises that had occurred from time to time. According to the current General Urban Plan, some areas have been characterized as "purely residential" especially in the southeastern part and others as "general residence". In the northwestern part, the main public transport hubs (port and railway station) are located close to the sub-urban and peri-urban industrial zone/sites. Finally, the Metropolitan area of Thessaloniki has on average 2.6m^2 of green area per person, while the World Health Organization (WHO) recommends having 10 to 12 square meters.

Especially for the UGS, the Municipality of Thessaloniki has developed an "Observatory of Urban Green Siting" under the Geospatial Information Infrastructure. In this Observatory, the location of green spaces and trees are recorded with the aid of Geographical Information System (G.I.S.), while the green adequacy index is calculated through the normalized vegetation index from Sentinel-2 satellite data (Municipality of Thessaloniki, 2016). According to the index data, only two neighborhoods ("Upper Town" and "Troxiodromikon") appear to have high adequacy index values, while in the rest of the study area the index values are significantly low,

1 A Gaussian function assigns the weight as a continuous function of distance, while the adaptive bi-square kernel function uses the same number of nearby points for modeling, and therefore, it does not coerce the bandwidth into a constant but permits the spatial extent (bandwidth) to vary across space (Yang et al., 2020).

and in many cases, a critical green deficit is identified. Additionally, it is important to mention that the share of green area per person – which was estimated based on census data on the population from the Hellenic Statistical Authority (www.statistics.gr) and on land-use data from the Urban Atlas (https://land.copernicus.eu/) – is slightly higher than the average share of the Metropolitan area (3.14m^2/person) but still quite low. It should be noted that according to a ministerial order, the need for green spaces on Greek cities has been set to 8 m^2/resident. So, there is a deficit of such spaces of 4.86 m^2/resident, based on the Greek legislation or equal to 6.86 m^2/resident, based on WHO standards.

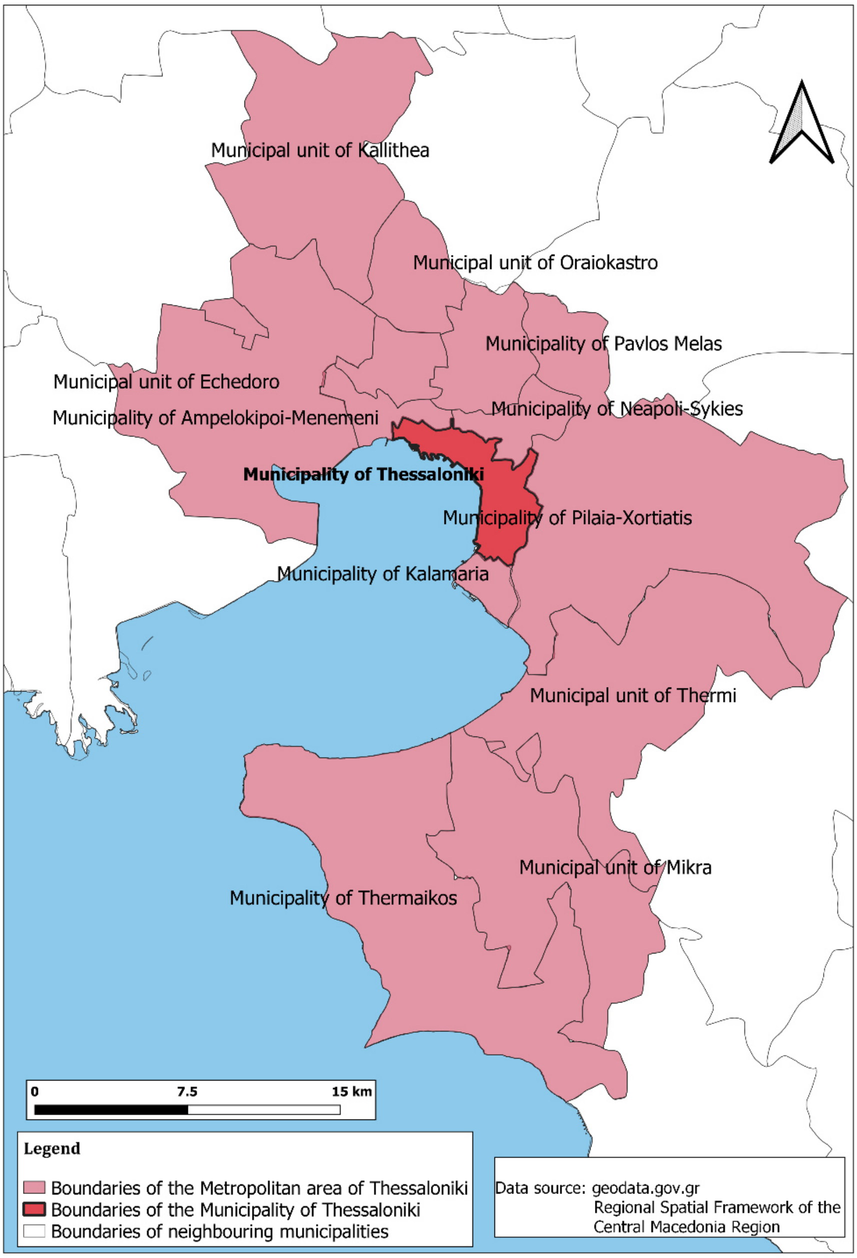


Fig.1 Location of the Municipality of Thessaloniki within the Metropolitan area

In this context, a study has been conducted by Latinopoulos et al. (2016), aiming to value (through a contingent valuation method) the benefits of an urban park regeneration project in the location of the Thessaloniki International Fair (TIF). The survey proved that on average households would be willing to pay significant amounts of money for the regeneration of the TIF area and the creation of a large metropolitan park.

4.2 Data collection

The data for this study were collected from a real estate online database (www.spitogatos.gr), over a one-month period, aiming to identify properties under the same demand conditions and thus to exclude any seasonal variation. We used a data collection method aiming to select (from the available database) only the properties that met the following criteria:

- properties had to be for sale and not for rent (i.e. we only examined property values and not rental values);
- only residential properties have been considered;
- properties had to be in the boundaries of the Municipality of Thessaloniki and their location (coordinates) should be available;
- properties had to be well (evenly) distributed over the study area;
- properties should have been entered into the database no later than six months earlier than the data collection period.

Following these criteria, a sample of 295 apartments were collected. All properties were then imported in the GIS environment (QGIS 3.18 software), for visualization (Fig.2) and for further analysis. Subsequently, by using the Urban Atlas database (edition 2012), land-use and land cover data were extracted for the green spaces in the study area. The Urban atlas distinguishes 21 thematic classes of land cover, including diverse classes of open/green spaces. In our study area, we initially used the following categories of land uses to classify the available green spaces: (1) Urban Green Spaces (UGS), (2) Arable Land, (3) Pastures, (4) Forests, (5) Herbaceous vegetation associations (natural grassland, moors, etc.), (6) (rows/corridors of) Trees (e.g. street trees).

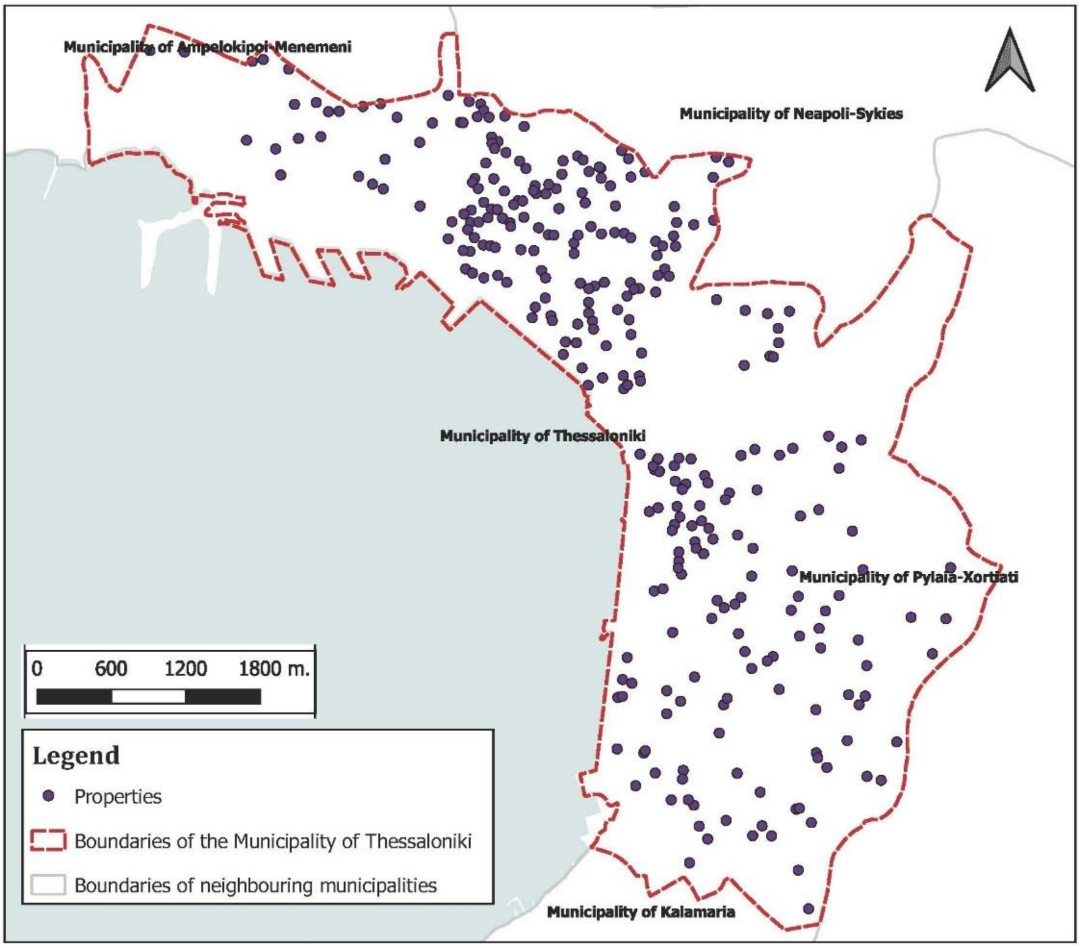


Fig.2 Map of the spatial distribution of properties

Some of these categories were combined to avoid using categories with very small number of cases, to obtain more efficient estimates and thus, to have a well-fitted model. So, urban green spaces, which are bordered by suburban natural areas and/or forests were studied as a separate category (Green other spaces). Arable land, pastures, forests, and herbaceous vegetation associations were also included in this category. A separated category was also used for the case of trees, which include contiguous rows or patches of trees, covering 500m² or more and with a minimum width of 10 m over "Artificial surfaces" (Rows of trees). All the rest were considered as UGS (Fig.3).

Then, for each individual property, the shortest (Euclidean) distance was calculated from: (a) all the above-mentioned categories of green spaces, (b) the coastline, (c) the historic center (the historic center was mapped in QGIS, according to the ministerial order: "Characterization as a historical place of the historical center of Thessaloniki", which describes in detail the city's districts.

Finally, we calculated, by using the QGIS software the vegetation index (NDVI) all over the study area and we assigned the corresponding value to each observation (according to the location of each property). The reasoning for using NDVI index is to represent vegetation's health and density in the study area, as well as to evaluate green space regardless of the land-use type (and then to use this evaluation as an attribute to the hedonic model). For the NDVI calculation the satellite Landsat 8 images were used from Landsat Collection 1 Level-1 and Landsat 8OLI/TIRS C1 Level 1. The date those images were taken was 20/6/2020 and their analysis was 30m, which were both considered very satisfactory. NDVI values range from [-1,1]. Low NDVI values indicate moisture-stressed vegetation and higher values indicate a higher density of green vegetation (Gessesse & Melesse, 2019). According to Fig.4, it is obvious that most of the study area represents a sparse and moderate vegetation, while there are only few areas where the vegetation index values are high.

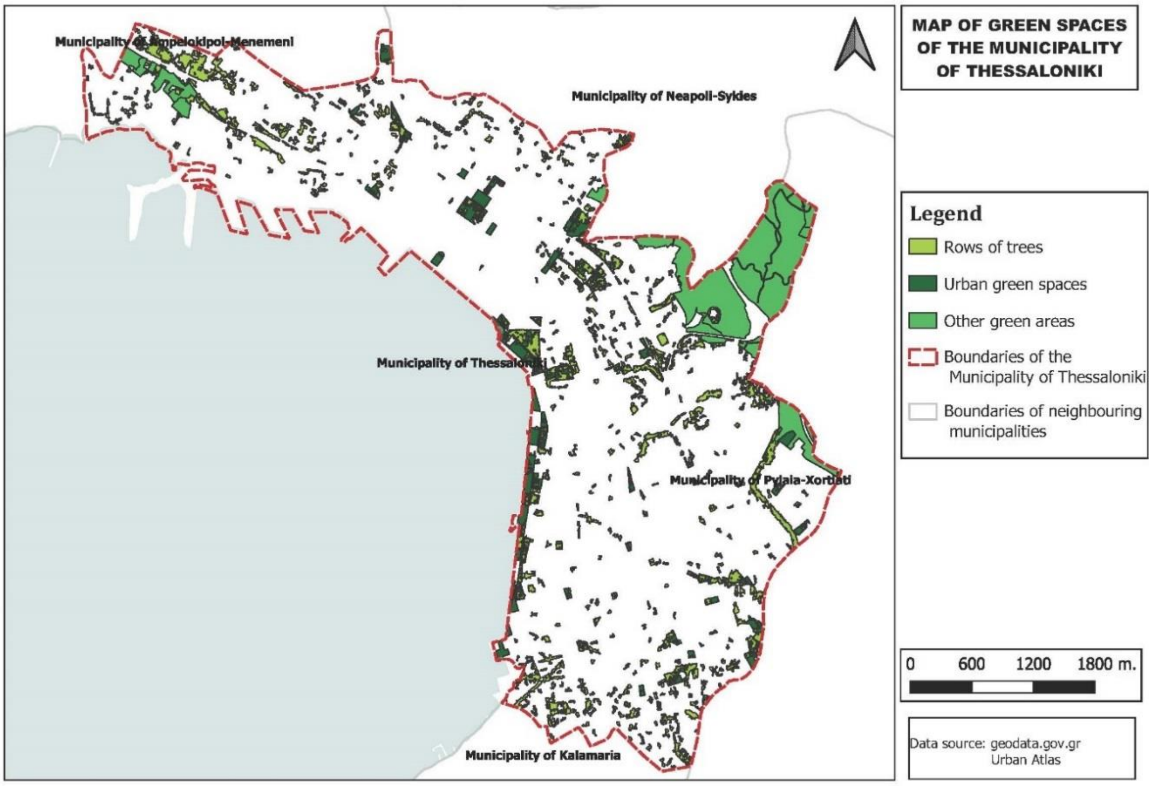


Fig.3 Map of green spaces of the Municipality of Thessaloniki

Explanatory variables were selected based on previous relevant studies, as well as on the suggested data availability for the study area. Accordingly, 13 attributes were finally selected as factors that may affect the dependent variable (i.e. the housing prices).

Most of these factors are related to the structural characteristics of the housing units/observations in the data, while four different factors were used to fully consider the role of green areas on residential property (real estate) values. Tab.1 lists and describes each of the selected variables and Tab.2 provides the summary statistics and the expected sign (effect of each variable on housing prices).

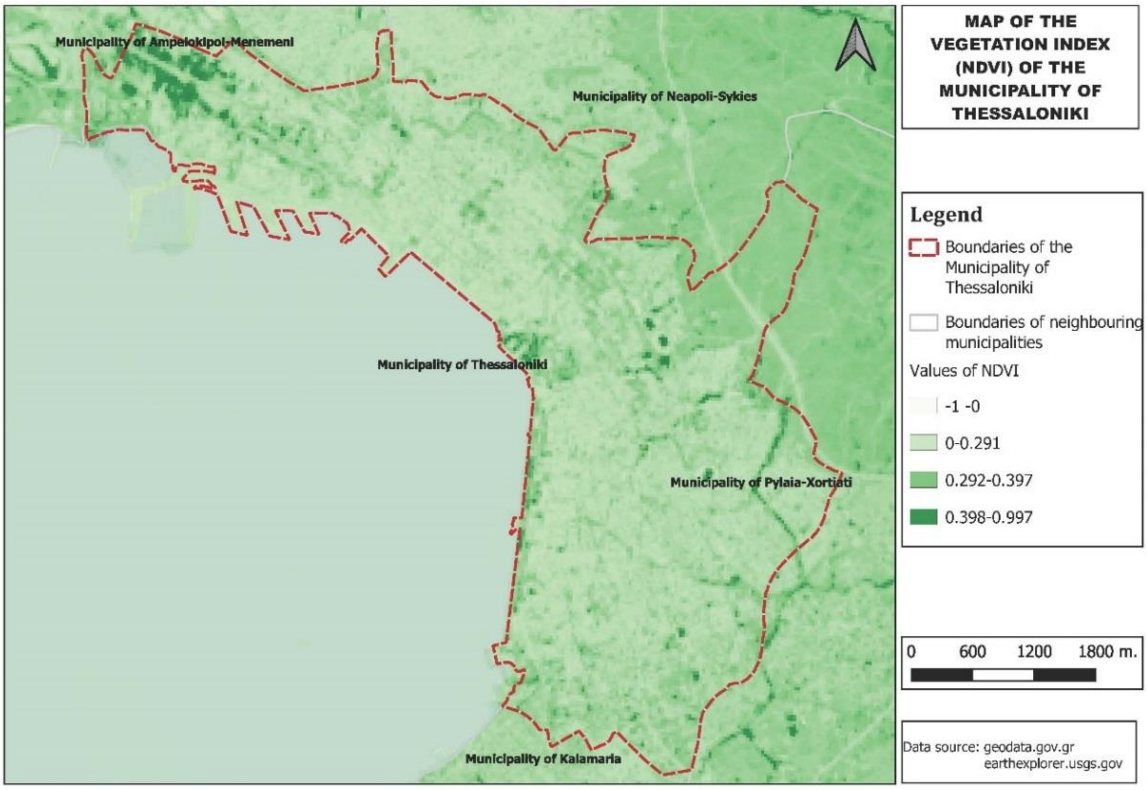


Fig.4 Map of the vegetation index (NDVI) of the Municipality of Thessaloniki

Variable	Category	Description
PRICE	Dependent variable	- Offered price of each housing unit/apartment (in €) – used as dependent variable in the OLS model - Offered price per square meter of each housing unit (€/m2) – used as dependent variable in the GWR model
AREA	Structural	Usable area of a flat (m^2)
AGE	Structural	Age of the apartment
FLOOR	Structural	Floor level on which the apartment is situated
NBEDROOM	Structural	Number of bedrooms in the apartment
TYPEHEAT	Structural	Type of apartment's heating system 0: Heating with all types of fuel except gas, 1: Heating with gas
ELEVATOR	Structural	(Dummy) - 1: The elevator is available
ORIENT	Structural	Apartment's orientation 0: North orientation, 1: All other orientations (except the north)
UGSDIST	Environmental	Distance to the closest urban green space (m)
TREESDIST	Environmental	Distance to the closest rows of trees (m)
OGADIST	Environmental	Distance to the closest "other green area" (m)
CENTDIST	Accessibility	Distance to the city center (m)
COASTDIST	Environmental	Distance to the coastline (m)
NDVI	Environmental	Vegetation index values [ranging from -1 to 1]

Tab.1 Attributes used in the analysis and descriptions

Variable	Mean value	Standard deviation	Min value	Max value	Expected sign
PRICE	122,289	79,908	6,000	530,000	DV[1]
PRICE per m^2	1574.73	627.70	142.86	4,240.00	DV[2]
AREA	76.65	33.69	25	240	+
AGE	43.25	19.45	0	120	-
FLOOR	2.61	1.93	-1	8	+
NBEDROOM	1.81	0.77	1	4	+
TYPEHEAT	0.63	0.48	0	1	-
ELEVATOR	0.70	0.45	0	1	+
ORIENT	0.99	0.09	0	1	-
UGSDIST	238.62	244.84	1.16	2,047.83	-
TREESDIST	86.34	76.35	0.43	453.47	-
OGADIST	1,364.04	698.40	10.77	3,250.02	-
CENTDIST	1,196.64	1,192.20	0.00	4,581.48	-
COASTDIST	947.36	542.40	51.06	2,659.31	-
NDVI	0.11	0.06	0.03	0.39	?

[1]= Dependent variable in the OLS model, [2]=Dependent variable in the GWR model

Tab.2 Descriptive statistics of the selected variables

5. Results

5.1 OLS regression model results

Before implementing the regression analysis, the correlation between independent variables was checked by using a correlation table (with threshold value r > 0.70). In our sample of observations, the variables of AREA and *NBEDROOM* were found to be positively correlated as the value of the correlation coefficient was found equal to +0.79. Consequently, the variable *NBEDROOM* was not used in the regression analysis. For the rest of the independent variables the values of the correlation coefficient range from -0.01 to +0.36, well below the threshold value, indicating thus, that the regression models will not suffer from multicollinearity.

The next step was to import the data into the GEODA software tool (Anselin et al., 2006) to apply the regression analysis. Tab.3 represents the results for the OLS regression analysis, which corresponds to a global model with fixed (in space) coefficients. According to Tab.3, the variables "*ORIENTATION*", "*ELEVATOR*" and "*TREESDIST*" were not found statistically significant, thus, in contrast with all the other variables they do not affect the price variance. Concerning the environmental attributes, it is interesting to note that 3 out of 4 variables were found to be statistically significant at the 1% level, with the expected sign. Namely, the *UGSDIST* (distance from green urban spaces) coefficient reveals a strong negative relationship, according to which housing prices are likely to decrease by 71.6€ if the distance between the residential area and the nearest UGS increases by 1 meter. Respectively, for an-one-meter increase in distance to other green areas (*OGADIST*) the housing price is likely to decreased by 16.2€, indicating that the implicit value of UGS is more than 4 times higher than the implicit value of other green areas (OGAs). It is also worth mentioning that, the NDVI variable is statistically significant with a positive coefficient, which shows that residential areas with higher NDVI values are expected to have higher property values. It should be underlined that the extreme value of the *NDVI*'s β-coefficient is mainly due to the low mean value of NDVI in the study area, as well as to the small variance around this value. The fact that the vegetation index is statistically significant indicates that except for the distance from green spaces, the environmental quality of those spaces (e.g. vegetation cover, tree cover, etc.) is also important. Finally, concerning the structural characteristics, the findings are consistent with previous research and expectations. Specifically, higher prices are expected in bigger, newer and higher floor level apartments.

Variable[1]	Coefficient	Probability
Constant	-29,985.5	0.358
AREA	1,469.0	0.000
AGE	-360.89	0.038
FLOOR	5,321.98	0.001
ELEVATOR	17,463.1	0.011
TYPEHEAT	27,177.9	<0.001
ORIENT	39,295.9	0.144
TREESDIST	68.171	0.133
UGSDIST	-71.561	<0.001
OGADIST	-16.166	<0.001
CENTDIST	25,210.4	<0.001
COASTDIST	-20.408	0.002
NDVI	185,291	0.001
Number of observations	295	
R-squared	0.682	
Adjusted R-squared	0.669	
F-statistic	50.51	

[1] Dependent variable = PRICE

Tab.3 Results of the linear regression analysis

5.2 Geographically Weighted Regression (GWR) model results

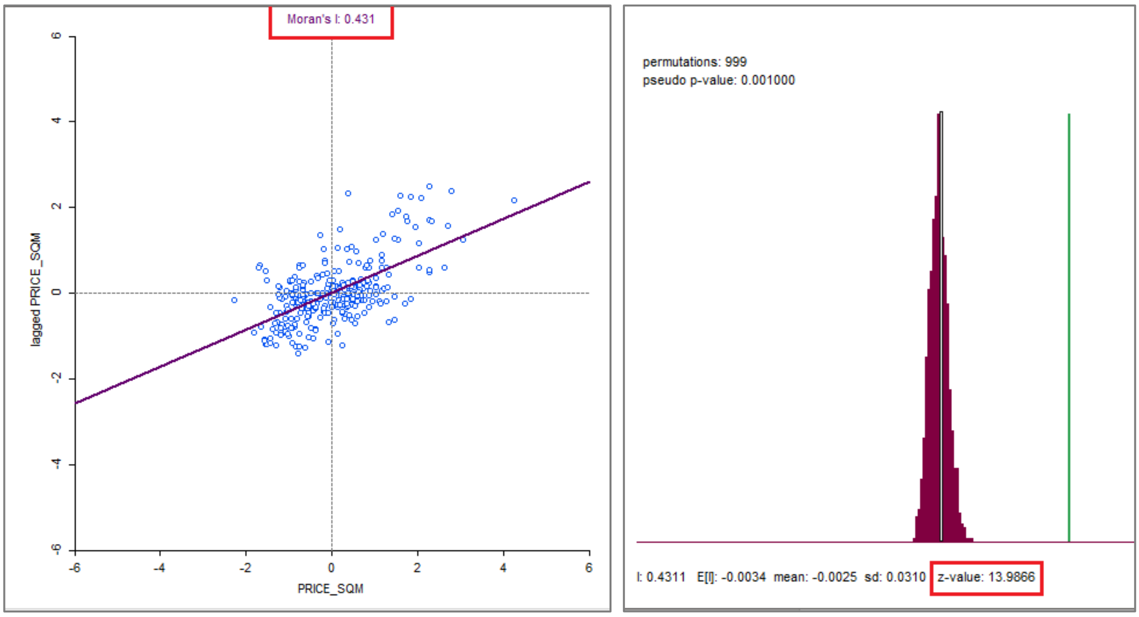
As aforementioned, spatial autocorrelation refers to the correlation of a variable's values due to spatial closeness (Griffith, 2003). The purpose of this study was to check if spatial autocorrelation exists between the dependent variable's values.

Specifically, it was checked if the variations in the properties' prices are the same in the whole study area or if there are areas where some (local) characteristics may affect more or less these prices. In order to additionally control for a possible non-linearity regarding the 'living space', we use the 'housing price per square meter' as a dependent variable (Gröbel, 2019). The first step was to test for spatial autocorrelation by using the GEODA software tool in order to perform a Moran's I test.

For this purpose, nearest neighbor weights were used, as the sample of the properties consisted only of points that didn't have a natural neighbor (after running lots of tests, the 6-nearest neighbors were considered). The Moran's I value is found equal to 0.43 which indicates the existence of spatial autocorrelation (Fig.5a). Also, according to Fig.5b, the Moran statistic is found significant ($z= 13.99$, $p<0.001$) so that the null hypothesis of no spatial pattern of residuals was rejected. This is an indication that the coefficients have been incorrectly specified, maybe as a result of non-stationarity and that a local modeling framework may result to a better specification.

The existence of spatial autocorrelation was further examined through the Local Indicators of Spatial Autocorrelation (LISA), by creating the corresponding thematic map in the environment of GEODA (Fig.6). As it can be observed in Fig.6, spatial autocorrelation (statistically significant) is observed in two areas in the study area. The first area is located in the historic center of Thessaloniki, where the house units (observations) have a positive spatial autocorrelation, in the High-High (HH) LISA category (red points).

The second area is located in the western part of the Municipality, at the entrance of the city and near the two main transportation hubs (port, railway station) and quite close to the industrial zone. In this cluster, the observations are included in the Low-Low (LL) LISA category, implying thus a negative spatial autocorrelation. It would be interesting thus to further examine the impact of the selected attributes in these High-High and Low-Low clusters.



(a) (b)

Fig.5 Moran's I test: (a) scatter plot, (b) z and pseudo-p value for the Moran's index

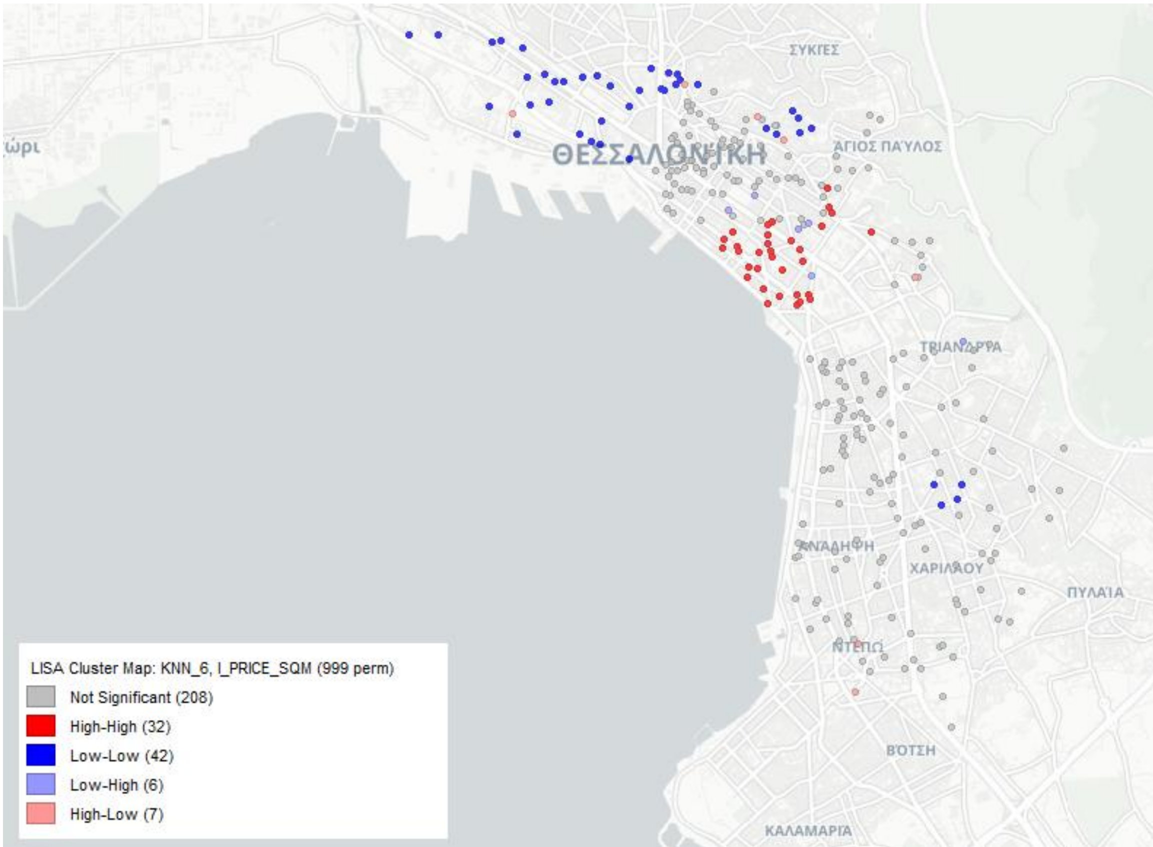


Fig.6 Local Indicators of Spatial Autocorrelation (LISA) cluster map

Having confirmed the existence of spatial autocorrelation, the next step was to examine which variable(s) influence(s) this autocorrelation. In this framework we used the GWR 4.0 software for spatial modeling and analysis (Nakaya et al., 2009).

Namely, a geographically weighted regression analysis with a fixed Gaussian kernel weighting function was used and the fitting technique for automated variable selection model, called "local to global" (L to G), was chosen. In this technique (L to G), all the variables are initially considered to present variation in space and are included in the local field, and then with successive iterations, the variables that remain constant are considered global (following a similar concept to the stepwise regression models). The independent variables that were included in this procedure were the same as in the case of the OLS model.

Tab.4 represents the GWR results for the "L to G" model (mean, median, lower quartile, and upper quartile for local variables, as well as the estimated coefficients for the global variables). It should be noticed that all environmental attributes were found as non-stationary variables, varying across space, while only two structural attributes were considered as fixed in space (stationary): i.e. *FLOOR* and *TYPEHEAT*. The mean coefficients of the environmental attributes reflect the following overall effects: a) a 1-meter increase in the distance from an UGS will decrease the housing price by 0.36€/m^2; b) a 1-meter increase in the distance from "rows of trees" will decrease the price by 0.59€/m^2; while c) a 1-meter increase in the distance from the coastline will decrease the housing price by 0.21€/m^2.

In Tab.4, it is also interesting to notice that all the mean and median values have the expected sign (as in the OLS results). However, by observing the lower (25^{th}) and upper (75^{th}) quartile coefficients some of them seem to be counterintuitive. Specifically, despite the fact that most of the local coefficients of *OGADIST* (distance from other green areas), *COASTDIST* (distance from the coastline) and *CENTDIST* (distance from the city center) are negatively correlated with housing prices, there is also a positive relationship for some properties (corresponding to the upper quartile).

	Non – stationary variables				Stationary variables
Variable[1]	**Lower Quartile**	**Mean**	**Median**	**Upper Quartile**	**coefficients**
Intercept	1,866.79	2,516.77	2,483.27	3,330.47	
UGSDIST	-0.725	-0.356	-0.342	-0.025	
TREESDIST	-0.879	-0.586	-0.362	-0.036	
OGADIST	-0.552	-0.0896	-0.279	0.223	
COASTDIST	-1.108	-0.211	-0.271	0.275	
CENTDIST	-0.561	-0.228	-0.205	0.200	
AREA	-4.774	-3.003	-3.160	-1.405	
AGE	-10.135	-6.969	-7.192	-3.177	
TYPEHEAT	-	-	-	-	222.39***
FLOOR	-	-	-	-	70.30***
Number of observations		295			
R-squared		0.523			
Adjusted R-squared		0.483			
AIC_c		4,524.6			

***=statistically significant at the 1% level [1]Dependent variable = PRICE per m^2

Tab.4 Results of geographically regression analysis

The estimated local regression coefficients (for the selected attributes) and their associated t-test values can be also mapped by using a GIS-software.

In this study, we used the QGIS software and the Inverse Distance Weighted (IDW) interpolation method[2] in order to visualize the local coefficients of the environmental/green attributes. Fig.7 illustrates the spatial distribution of the parameter estimates for the UGSDIST (distance from UGS) variable and the associated interpolated t-test variables.

There are two areas where the proximity to UGS was found to have a significant impact on housing prices (i.e. the local coefficients were statistically significant at the 10% level or higher). Specifically, the first area is located in the city center (between Aristotelous Square and the Courthouse area), while the second one is located in the southeastern part of the Municipality, where small and medium green urban spaces are scattered

2 IDW interpolation method weights the points of the sample according to the distance. In this way, as the distance increases from unknown points, the influence from the sample points tends to decrease. Comparatively with the Triangulated Irregular Network (TIN) interpolation method, which is mainly used for calculating elevation, the first was chosen as it fitted better in the sample.

throughout the urban environment (according to Fig.3). Particularly, in both areas, an increase of a property's distance from an UGS by 1-meter is likely to decrease the housing price on a range from 0.72€/m^2 to 1.18€/m^2 (while in all other areas/neighborhoods the price effect is insignificant and much lower).

Fig.8 shows a similar map for the attribute TREESDIST (distance from trees). This variable is found statistically significant at the local level only in a neighborhood, situated in the southern part of the Municipality. In this neighborhood, according to Fig.3, there is a higher (as compared to the study area) density of street trees. Proximity to trees in that particular neighborhood has a strong influence on housing prices (e.g. a 1-meter increase of a property's distance from street trees, could decrease the housing price from 0.87€/m^2 to 4.94€/m^2).

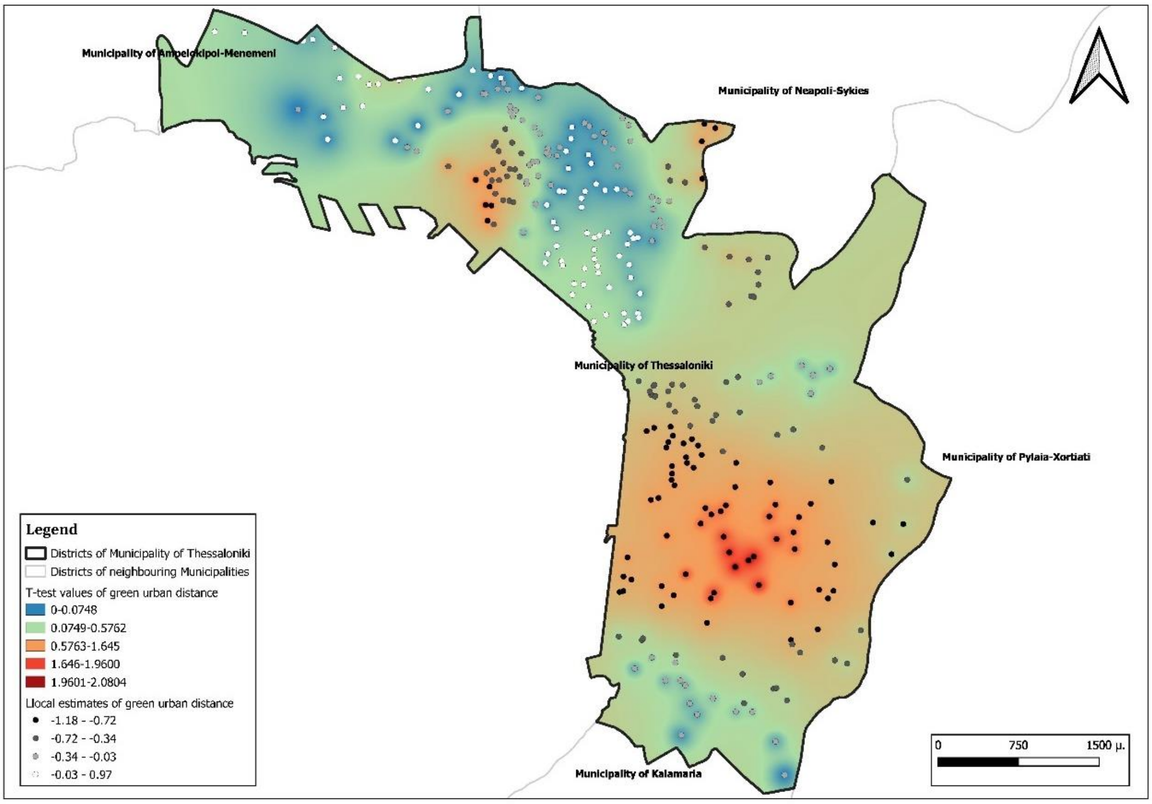


Fig.7 Map of local estimates and t-test values for green urban distance variable

Another variable with spatially heterogenous impacts on the properties' values of the study area is the distance from the coastline (*COASTDIST*). In Fig.9, is obvious that this attribute has a statistically significant effect in the historic city center, where the proximity to the "Old Waterfront" has an important and statistically significant impact on housing (e.g. a 1-meter increase of a property's distance from the coastline, is likely to decrease the property's value from 1.13€/m^2 up to 1.51€/m^2).

Something similar is not observed in the areas near the "New Waterfront", where the local parameters were not found statistically significant. Based on the previous maps (Fig.7 and Fig.8), property values of houses which are close to the "New Waterfront" (southern coastal regions) are likely to be more affected by their proximity to green spaces.

This may be attributed to the fact that the "New Waterfront" is structured by the coastline and the linear zone of green spaces that develops along the coastline. In this zone green spaces/areas are dense (as compared to the rest of the study area), causing thus some collinearity at the local level with the COASTDIST attribute. Therefore, in that part of the city, it is likely that our results may ultimately underestimate the implicit price of properties' proximity to the sea (coastline).

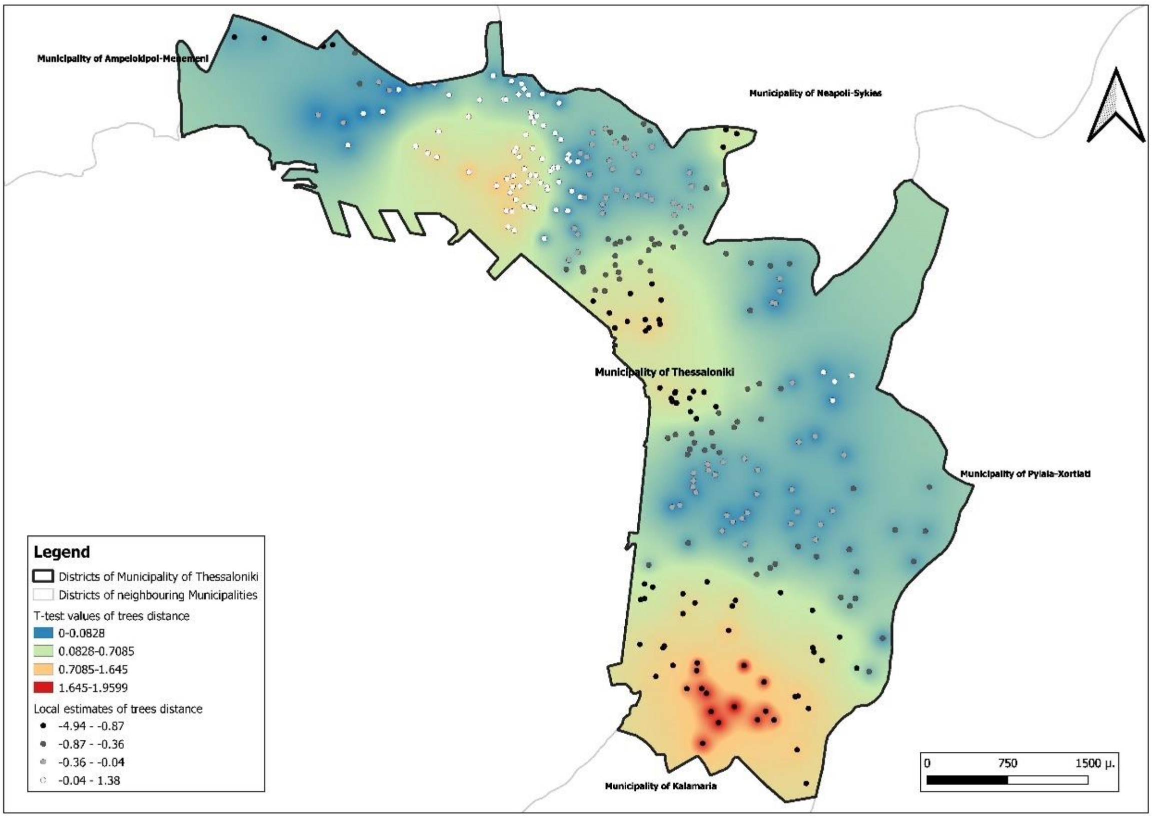


Fig.8 Map of local estimates and t-test values for trees distance variable

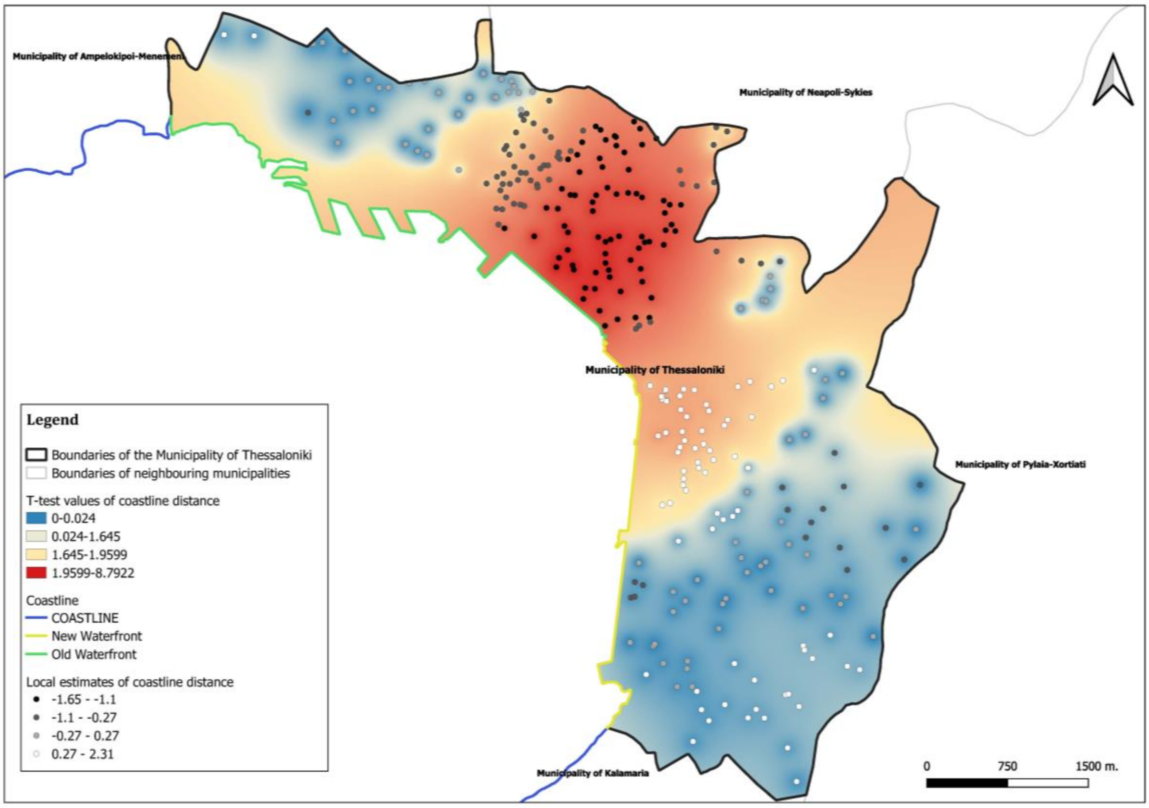


Fig.9 Map of local estimates and t-test values for coastline distance variable

6. Discussion and conclusions

In this study, a hedonic pricing model based on Geographically Weighted Regression (GWR) analysis is used to explore the spatial heterogeneity of environmental/location characteristics on properties values. A semi-parametric tool, such as the mixed GWR model was applied aiming to understand how different characteristics and different locations of green areas/amenities may affect the price of houses at the city level. An OLS analysis was also performed, but not for comparison purposes, but only in order to initially distinguish the main structural characteristics, as well as the green/environmental characteristics that are likely to have a statistically significant marginal effect on the selected property values. Both linear regression (OLS) and GWR models' results reveal that there is a proximity effect between urban green amenities and housing prices, with differences across space and across different typologies of green areas/amenities. Urban green amenities were found to have a positive and spatially heterogeneous impact on the residential real estate market in the Municipality of Thessaloniki. According to the OLS model, the distance from UGS, as well as the distance from other green areas/amenities (OGAs) (e.g. peri-urban green areas, arable land, herbaceous vegetation associations, etc.) can negatively affect the housing prices. Namely, as distance from the nearest UGS or OGA increases by one meter, the (average) housing price is expected to decrease by 71.56€ and 16.16€ respectively. Furthermore, it should be mentioned that in the OLS model, a statistically significant premium was estimated for the "vegetation index" (NDVI) variable, highlighting thus, the necessity to maintain/improve the quality (extent and health) of green vegetation in the urban area (e.g. the vegetation cover, the tree cover, etc.). As already stated, according to the GWR results, the impact of green/environmental attributes on housing prices is not constant over the study area. Particularly, the proximity to UGS was found to significantly increase the property values in the south-eastern regions/neighborhoods of the study area, as well as in a small neighborhood in the city center. Concerning the proximity to (rows of) street trees, the marginal impact on housing prices seems to be more intense in the southern part of the Municipality, on the border with the Municipality of Kalamaria. It is also important to mention that property values in the western part of the municipality, are not impacted by the proximity to any category of green areas. Apart from the green areas/amenities, the present study also examined the marginal price effects due to the properties' proximity to the coastline. According to the GWR results, the "distance from the sea (coastline)" attribute seems to have a significant influence on the real estate market, mainly in the area of the "Old Waterfront", located in the city center. Namely, a one-meter distance increase from the coastline of the "Old Waterfront" is expected to decrease the housing price on a range from 1.13€/m^2 to 1.51€/m^2. On the other hand, in neighborhoods situated near the "New Waterfront", the proximity to green areas/amenities seems to have a more significant effect on housing prices than the distance from the coastline, maybe due to the fact that in those neighborhoods UGS are mostly located in the waterfront (representing thus a local collinearity effect).

It is interesting also to note that in the Low-Low cluster areas (i.e. areas with negative spatial autocorrelation of the dependent variable) the environmental attributes have no significant impact on property values, while in the High-High clusters (i.e. areas with positive spatial autocorrelation of the dependent variable) the property values are significantly affected by the coastline distance and in some cases by the distance to green areas. Therefore, the implicit prices for the environmental attributes were found higher (and significant) in neighborhoods with higher residential prices.

The analysis highlights the importance of green infrastructures and the urgent need to integrate them into the urban fabric of Thessaloniki. Their potential benefits, such as the mitigation of the phenomenon of urban heat island, the air filtration, the (flood)water management, and the improvement of citizens' health and quality of life, are expected to be huge. Some of these benefits can be also internalized by the market values of houses, offering thus an economic incentive to city planners, especially in areas where land values are higher (and the associated UGS development costs may be initially considered to be too expensive). Furthermore, as the concept of compact cities is gaining popularity, it is even more urgent to include green spaces in the urban planning procedure, because this concept is based on the belief that public spaces and parks can lead to the flourish of neighborhoods (Zali, 2016). At the same time ensuring proximity, access and exposure to UGS is usually considered of great importance for health and well-being in the design of compact urban environment (Lennon, 2021). In this context, citizens of Thessaloniki have already expressed the need for new UGS and are very supportive of the development of new green projects (Latinopoulos, 2022). Certainly, the integration of new green projects into the urban fabric should take into consideration the potential gentrification effects that may arise, in terms of increasing property values that could result to higher rental prices, and therefore, to the displacement of economically vulnerable residents. Hence, hedonic pricing methods should be used as a monitoring tool for future green infrastructure development goals, aiming to examine both positive (in real estate markets) and negative (in terms of gentrification) externalities.

Future research efforts could focus on adding more cases in the initial dataset of housing prices in order to achieve greater spatial heterogeneity among the location attributes, which would also allow more explanatory variables/attributes to be used (e.g. view on green areas, size of UGS, socioeconomic characteristics of the neighborhood, etc.). Future studies could also broaden the typologies of urban green areas/amenities and take into account accessibility and fairness/equity considerations with regard to urban green spaces.

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Image Sources

Fig.1: Location of the Municipality of Thessaloniki within the Metropolitan area;

Fig.2: Map of the spatial distribution of properties;

Fig.3: Map of green spaces of the Municipality of Thessaloniki;

Fig.4: Map of the vegetation index (NDVI) of the Municipality of Thessaloniki;

Fig.5: Moran's I test: (a) scatter plot, (b) z and pseudo-p value for the Moran's index;

Fig.6: Local Indicators of Spatial Autocorrelation (LISA) cluster map;

Fig.7: Map of local estimates and t-test values for green urban distance variable;

Fig.8: Map of local estimates and t-test values for trees distance variable;

Fig.9: Map of local estimates and t-test values for coastline distance variable.

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