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The Impact of Urban Green Space on Housing Value: A Combined Hedonic Price Analysis and Land Use Modeling Approach

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ABSTRACT

Urban green space (UGS) is increasingly considered as a nature-based solution to mitigate negative climate change effects and improve the quality of living environments. Although hedonic price (HP) modeling studies have yielded valuable insights about the UGS influence on housing value, from an area-development perspective the effects of UGS depend critically on the spatial allocation of UGS, which has not received much attention in the literature. In this paper, we combine HP analysis and land-use modeling to optimize the spatial allocation and evaluate the area-wide impact of UGS on housing value. Using transaction data from two middle-sized cities in the Netherlands, we estimate HP models considering different types of UGS and different types of housing. We show how the results can be incorporated into a housing land-use model and how the land-use model can be used to identify the spatial allocation of UGS that maximizes an area-wide (net) housing value. The results suggest that spreading green areas in neighborhoods results in higher housing value than centralizing green in a large urban park. Among the three housing types, detached houses benefit most from the UGS spreading strategy. Moreover, allocating UGS as green buffers is an effective way to increase housing value.

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1. Introduction

Nature-based solutions are receiving increasing attention as a way to make cities better adapted to climate change and to create high-quality living environments for citizens. These solutions involve the development of urban green space (UGS) which can take on various possible forms, such as parks, trees alongside streets, small forests, green buffers alongside infrastructure and allotments (Panduro and Veie, 2013; Czembrowski and Kronenberg, 2016). UGS has the potential to mitigate the negative effects of climate change related to heat (e.g., Oliveira et al., 2011; Razzaghmanesh et al., 2016), hydrology (Stovin et al., 2012), biodiversity and air quality (Jim and Chen, 2008). UGS can also contribute to improving the quality of living environments for residents by providing opportunities for leisure, sports, and social activities, and improving the aesthetics of the landscape (White and Gatersleben, 2011; Czembrowski et al., 2019).

Due to these benefits, greenification is high on the agenda of cities. To implement this policy, space for urban green is increasingly reserved in areas to be developed (or redeveloped) for housing (Zhao et al., 2024). Since UGS competes with other urban land uses (especially housing areas), the spatial allocation of green necessitates a trade-off, recognizing the diverse needs and preferences of residents, such as needs related to transport, shopping, and recreation (Huang and Yin, 2015). In the context of housing development, understanding these trade-offs and assessing the spatial effects on housing value is crucial for making optimal spatial allocation decisions regarding UGS from the perspectives of benefits of residents as well as financial feasibility of area development.

Hedonic Price (HP) modeling is a useful method to assess values residents assign to structural and location-related attributes of the dwelling. Based on transaction data, this method offers estimates of willingness-to-pay values for the various attributes considered in the analysis. In recent years, a large number of HP-studies have appeared, highlighting the valuations of various design and planning aspects of UGS. This has generated useful insights for

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developers, planners, and policymakers (Huang and Yin, 2015).

Additionally, land-use models offer a framework for adopting an area-wide perspective. These models consider the spatial allocation of demands for land-uses in an area in an integrated fashion (e.g., Bharath et al., 2021; Li et al., 2020; Ligmann-Zielinska et al., 2008). Koomen et al. (2015) show how the results of HP modeling can be used to specify the parameters of the local utility function of a land-use model. This offers a promising way to optimize the spatial allocation of land use considering an area-wide housing value.

The present study aims to develop an approach to optimize the spatial planning of UGS considering area-wide housing value and using HP modeling in combination with land-use modeling. The housing land-use model introduced by Arentze et al. (2010) offers a suitable framework for this aim. This model considers the optimization of the spatial allocation of a set of land-uses on the spatial scale of area development. Housing transaction data for two middle-sized cities (Eindhoven and Almere) in the Netherlands are used to estimate a hedonic price model with special attention to the impact of UGS on housing value. We implement the results of the HP analysis in the land-use model, to identify the optimal spatial distribution of UGS when housing value maximization is aimed for. We apply the model to a residential area development problem to demonstrate the approach.

The remainder of the paper is structured as follows. First, in Section 2, we review existing studies to position our approach in the existing literature. Then, in Section 3, we explain the methods used related to the two modeling techniques combined in this study - hedonic price analysis and land use modeling. Next, in Section 4, we describe the study area, data, and results of the hedonic price analysis. In Section 5, we then discuss the application of the resulting land use allocation model to an area development problem. Finally, in the last section, we summarize the major conclusions and discuss remaining problems for future research.

2. Literature Review

2.1. Hedonic Price Values for UGS

The impact of UGS on the value of housing has received much attention in HP-studies. Generally, it is recognized that UGS is not a homogeneous good, and approaches and findings stress the importance of distinguishing different types of urban green. Czembrowski and Kronenberg (2016) consider the impacts of various green space categories on apartment prices. They distinguish nine different types of green space in terms of area size (small and large) and function (e.g., parks, forests, cemeteries, allotments, gardens). Using a fixed effects regression model, they find that large forests and large parks have the most sizable impact on apartment prices. Panduro and Veie (2013) similarly use a detailed classification of the types of urban green. They distinguish eight different types and consider the impacts on the prices for family and non-family housing. Using a generalized additive model, they find that green buffers around infrastructure have little marginal value and that the two housing types differ in terms of the value associated with common green areas, the value being larger for non-family housing. Bockarjova et al. (2020) conducted a meta-analysis using the results of 37 hedonic pricing studies to estimate the effects of various forms of urban nature on housing prices. Urban parks, water bodies (blue), and other forms of UGS all have significant positive relationships with price. In an application, they found that depending on the urban nature intervention property prices can increase up to 20%.

Furthermore, various studies have focused on the impacts of accessibility and environmental characteristics of green space. Conway et al. (2010) show that each additional percentage of greenery coverage significantly increases the housing price. Melichar and Kaprová (2013) investigate the distance ranges in which UGS has positive effects on housing prices. They conclude that the size and type of green also have effects on residential building value. Furthermore, in terms of high-quality green open space, Łaszkiewicz et al. (2019) find that the estimated marginal willingness-to-pay (MWTP) for proximity to selected urban green spaces differs between price sub-segments of the real estate market. In the case of green parks, the estimated MWTP for their proximity increases with the wealth of the apartment buyers. Huang and Yin (2015) consider the importance of UGS relative to other sustainability elements competing for scarce space in cities. In an application in Wuhan, China, they found that among different forms of UGS, natural water sources have the largest positive effect on housing prices. However, Iqbal and Wilhelmsson (2018) argue that proximity of a green park can also have negative effects in relation to crime. In the Scandinavian context, they find evidence that crime in parks has a negative influence on apartment prices in the proximity.

Closely related to UGS, several studies have focused on the impact of landscape characteristics on house prices. In particular, open space and mixed-land use have received attention. In an early paper, Irwin and Bockstael (2001) find a significant influence of open space in a hedonic framework using an instrumental variables technique. Anderson and West (2006) use a neighborhood fixed effects specification and also find a positive impact of open space on housing values, and more so in high-density, high-income urban areas. Brander and Koetse (2011) conducted a meta-analysis of 52 hedonic pricing studies and found that the influence of open space is greater in areas with higher population density, indicating that the scarcity of open space plays a significant role. Koster and Rouwendal (2012) analyze the impact of mixed land use on housing values. In a semi-parametric hedonic price analysis, they find a positive effect of land use types that are compatible with residential use (e.g., business and leisure) and negative effects of others (e.g., manufacturing and wholesale). Gao and Changchun (2023) show however that mixed land use with predominance of commercial land may have a negative effect on prices. Teulings et al. (2018) show that the valuation of nature in the proximity strongly differs by population group.

2.2. Parametrizing Green in Land Use Models

Land-use models allocate land to specific uses based on a suitability (utility) function. The models use a classification of land uses, a function to evaluate the suitability of locations for various types of use, and a mechanism to determine land use change (dynamic models) or the optimal land-use allocation (static models). Irrespective of whether the goal of the model is to predict land use change or to find the optimal spatial allocation of land uses in a plan area, parameters of this function indicate marginal utility values of relevant accessibility and environmental characteristics of the location for each possible land-use. Traditionally, the parameters are set manually based on expert judgment. The manual approach has increasingly been replaced by more rigorous, data-driven methods that generally offer a better model fit (Koomen 2007). Different approaches have been applied. In the most commonly used approach, parameters are estimated based on observed land use changes using a discrete choice model or map comparison methods (e.g., Vliet et al., 2011). The parameters thus obtained represent land development decision-making of planners and developers. An alternative approach, which we use here, exploits property valuation methods. This approach was applied by Dekkers and Rietveld (2011) who estimated separate hedonic price models for the red (urban) and green (agriculture) submarkets and combined these with a model to predict transition probabilities of green to red. Similarly, Koomen et al. (2015) combined hedonic price analysis for urban land-use with the net-present-value method for agricultural land-use.

2.3. Research Gaps

In summary, HP-studies provide evidence for the importance of distinguishing different types of urban green and taking both accessibility and environment characteristics of UGS into account. Furthermore, evidence shows that the impacts of UGS on housing value may not be uniform for different housing types. Focusing on single houses (the home-owner perspective), the HP-studies do not answer the question of what the optimal spatial allocation of UGS is (the spatial planning perspective). Existing studies using HP-modeling in combination with land-use modeling do take the area perspective but have focused on land-use change prediction and the larger scale of a country or region and, hence, are not suited to address the (housing) area-development problem. The approach we develop in the present study addresses this research gap. We estimate a HP model that incorporates the different forms of UGS and estimate WTP-values for the three main housing types typically considered in area development. We use the results to specify a housing land-use allocation model and apply the model to a housing area development problem to evaluate spatial UGS policies on area-wide housing value.

3. Methods

In this section, we explain the hedonic price model and housing land use model we use, and the way in which the two models are combined.

3.1. Hedonic Price Model

Hedonic price modeling is a well-established method that uses regression analysis to estimate the contributions of location and structural attributes to the market value (price) of a dwelling. Our approach builds on the presumption that marginal values of structural and location attributes may differ between housing types. Therefore, we estimate a hedonic model separately for each housing type. To account for possible omitted variables, we use a spatial lag formulation (Anselin 1988) of the following form:

$$Y = \rho WY + S\beta_1 + L\beta_2 + D\beta_3 + \varepsilon \qquad (1)$$

where Y is a vector of observed housing prices, W is a spatial weight matrix, S is a matrix of observed structural variables (floor space, lot size, construction year, etc.), L is a matrix of observed neighborhood variables, D is a matrix of observed accessibility variables, ε is an error component, β_1, β_2, β_3 are vectors of coefficients related to these sets of variables, and ρ is the spatial-lag parameter. Following a commonly used approach, we use the natural log of price as the dependent variable ($Y = \ln(P)$, where P is the dwelling price). In this log-linear form, the coefficients represent the marginal effect of a unit change in the independent variable, measured as a percentage change in the price.

By including both L and D variables, the accessibility of green urban park and environmental green are both taken into account. By including relevant S variables, we control for structural attributes of the dwelling which may be correlated to the L and D variables of interest in this study. The spatial weights W represent spatial dependencies between the prices of properties (spatial autocorrelation); the shorter the distance, the larger the weight. The spatial-lag model accounts for a prominent feature of the real estate markets, namely the mutual dependence of the values of properties located in proximity of each other. Including the spatial lag term prevents estimates of the coefficients to be biased due to this spatial autocorrelation (Anselin 1988, Conway et al., 2010). To operationalize W, we define the neighbors of a property as the properties that lie within a pre-defined radius. Outside this radius, the weights are zero, while inside it, the weights are defined as the (row) standardized inverse of the distances (Tiefelsdorf et al. 1999). We set the pre-defined radius to be 300 m, implicitly assuming that beyond this range there are no spatial dependencies between the prices of properties (Di et al., 2010).

3.2. The Housing Land Use Model

We incorporate the results of the hedonic price analysis in the housing land use model (HLM) developed in Arentze et al. (2010) and used in several plan-scenario studies in Katoshevski-Cavari et al. (2010, 2011, 2014). HLM assumes that the plan area is represented as a regular grid of cells where each cell corresponds to a land parcel commanding a certain land use (White and Engelen, 2000). The model takes the land demands for a predefined set of land uses as given and assigns undeveloped cells to different land uses to accommodate the demands (Klosterman, 2001). The model mimics the behavior of an urban developer who seeks to maximize utility by developing locations to their best use. A so-called suitability function is used to compute for each undeveloped cell the utility for each possible land use. Allocation is performed based on an iterative procedure. After an initial allocation of land uses, feasible swaps of land uses between each two cells are evaluated and implemented if this increases the total utility across cells. This process is repeated until no further swaps are possible that increase the overall utility (for details of the algorithm and its properties, see Arentze et al., 2010).

In the context of a housing area development problem, the different housing types (e.g., detached houses, row houses, apartments) are considered developable land uses, and non-housing land uses (e.g., agriculture, industry, road infrastructure) are considered fixed land uses. To allow for mixed land-use solutions, also public buildings (e.g., schools, museums, etc.) are included as a developable land-use. Land-use demands are defined exogenously as well as the number of undeveloped cells that should be developed for that use. Given our interest in UGS, we assume that all undeveloped land will be used for housing, public buildings or UGS. Given this setting, the allocation mechanism is set at work to achieve an outcome that maximizes the total utility value.

We define the utility function as profit of a urban developer; it takes the following form:

$$Z_{ijk} = X_k \cdot \left(V_{ijk} - Cdev_{ijk}\right) - Clnd_{ij} \qquad (2)$$

where Z_{ijk} is the net value of use k in cell ij, V_{ijk} is the value of a dwelling of type k at location ij, $Cdev_{ijk}$ are the development costs per dwelling (including construction costs), X_k is a housing density (number of dwellings of type k per cell), and $Clnd_{ij}$ is the cost of land. The value of dwellings, V_{ijk}, consists of the following components:

$$V_{ijk} = Vcon_{ijk} + Vnbh_{ijk} + Vacc_{ijk} \qquad (3)$$

where $Vcon$ is a constant, $Vnbh$ is a value component depending on the direct neighborhood of the cell, and $Vacc$ is a value component depending on the accessibility of other locations from the cell.

The results of the hedonic price analysis (Eq. 1) are used to define the utility function of the HLM. That is, the estimates for structural characteristics ($S\beta_1$), neighborhood characteristics ($L\beta_2$) and accessibility characteristics ($D\beta_3$) are used to define the $Vcon_{ijk}$, $Vnbh_{ijk}$ and $Vacc_{ijk}$ terms, respectively, with proper handling of the log transformation of the price. Since all parameters in the HLM have housing type-specific values, the hedonic price model allows for housing type heterogeneity in the estimates.

4. Estimation of the HP Model

4.1. Study Area and Data

The hedonic price models (Eq. 1) are estimated based on 2014-2018 housing transaction data from the cities Eindhoven (240,000 citizens in 2023) and Almere (225,000 citizens in 2023), in the Netherlands. Together, these cities offer ample spatial variation in green, location and housing market characteristics, which we exploit for identification of generalizable effects.

The spatial land use data are provided by the Statistics Netherlands (CBS). The residential transaction data are provided by NVM - The Netherlands Association of Real Estate Brokers and Property Experts. The NVM data cover approximately 70% of all housing transactions in the country. The data set consists of 18,813 geocoded housing transactions. Table 1 provides a description of the structural dwelling variables, S, neighborhood land use variables, L, and accessibility variables, D, that are used in the model. The structural dwelling characteristics are included as control variables. The selection of variables for the model follows the standard hedonic pricing approach (e.g., Basu and Thibodeau 1998). We incorporated house characteristics (e.g., living area, lot size, construction year, maintenance situation and so on), neighborhood characteristics (e.g. UGS and other urban land-uses), and the accessibility characteristics (e.g. distance to city center, distance to train station, distance to big park). The selection of the four concentric retail rings were determined based on the general assumptions that 500 meters refer to walkable distances for daily activities and distances larger than 1500 meters fall outside the range of locations households in urban area consider as options in the Netherlands. We also tested other structural, neighborhood and accessibility variables, such as the direction of the dwelling, the presence of agricultural land or distance to the nearest entertainment site. As these variables were statistically insignificant, we did not include them in the final models.

The land use variables (L) related to each dwelling in the data are defined based on the HLM modeling framework. Each spatial observation is plotted on a land use map (we know the geolocation on an aggregation level of a 6-digit postcode, a statistical unit containing some 15 houses) and overlayed by a 100-by-100-meter cell grid. After this, the land use characteristics of each cell's direct neighborhood (eight cells) are calculated. For each particular land use, the share of the neighborhood covered by this land use is calculated.[1] The land use data offer a detailed classification into land use types. Not all land use types are relevant for the present analysis. Land use types that do not occur in residential neighborhoods with sufficient frequency were excluded. Furthermore, land uses that are strongly correlated with other land uses were excluded. Residential land use is taken as the reference and, hence, excluded from the regression.

The accessibility variables (D) include distances to the city center, public buildings, shopping areas, and city parks. For measuring accessibility (D), we considered two alternative methods, namely the number of facilities in several distance bands and the geographical distance to the nearest facility. For distance, we tried different transformations to account for possible non-linear relationships including no transformation (X), a log ($Ln(X)$, square root ($\sqrt{X}$) and square transformation (X^2). For each land-use, the measurement method (distance bands or nearest distance) and transformation method that maximized the goodness-of-fit (adjusted R^2) of the model was selected. For all land-uses except retailing, the nearest distance measure with log transformation appeared to yield the best fit. For shopping facilities, the distance-band method gave the best fit. Finally, we include transaction-year fixed effects to account for the general housing price developments.

The land uses 'recreation park' and 'water body' are both a form of environmental green and, hence, ways to implement the UGS. A city park is a form of central green and enters the model through an accessibility variable (distance to city park). Thus, this model specification allows us to estimate the valuations of both forms of UGS – environmental green and central green. The hedonic regression model is estimated separately for the three housing types. The transaction data used for the analysis after removing the outliers include 18,199 dwellings consisting of 5443 apartments, 9587 row houses, and 3169 semi-detached or detached houses.

4.2. Results

The Backward method was used to determine the selection of independent variables for each model

Table 1. Variables entering the hedonic model.

Panel A. Dwelling characteristics (*S*)		
Variable	Description	Measure
Log Transaction price	Dependent variable (continuous)	Continuous
Log Lot Size	Size of the parcel (continuous)	Continuous
Log Floor space	Size or residential floor space (continuous)	Continuous
#Dormers	Number of dormer windows (continuous)	Continuous
#Rooms	Number of rooms (continuous)	Continuous
#Floors	Number of rooms (continuous)	Continuous
Attic	Dwelling has an attic 1/0	Binary
#Balkonies	Number of balconies (continuous)	Continuous
Insulation degree	Low to high (categorical, 0-5)	Continuous
Building height	Height of the building in m (continuous)	Continuous
Construction year	Old to new (categorical, 1-7)	Categorical
Lift	Dwelling has a lift (0/1)	Binary
Central heating	Dwelling has central heating (0/1)	Binary
Parking space	0 = none, 1 = on street, 2 = garage, 3 = large garage (0 is base)	Categorical
Maintenance inside	Poor to good (1-4, 3 is base)	Categorical
Maintenance outside	Poor to good (1-4)	Categorical
Almere	Dwelling located in Almere 1/0	Binary
Panel B. Neighborhood land use characteristics (*L*)		
Quiet road	On a quiet road	Binary
Busy road	On a busy road	Binary
Recreation area (UGS)	Green area for recreation	% of neighborhood
Shopping area	Retail; restaurant; shopping mall, etc.	% of neighborhood
Road infrastructure area	Road related infrastructure	% of neighborhood
Park area	Parks, sports field	% of neighborhood
Water body (UGS)	Inland water	% of neighborhood
Industry and office	Industry area; business offices	% of neighborhood
Public buildings	Museum; city hall; school; hospital	% of neighborhood
Panel C. Accessibility (*D*) and temporal variables		
Variable	Description	Measure
Log Distance center	Distance to the city center	Continuous
Log Distance publ.b.	Distance to the public buildings	Continuous
# retail areas < 500 m	# retail areas in 0 – 500 m dist. band	Continuous
# retail areas 500 – 750 m	# retail areas in 500 – 750 m dist. band	Continuous
# retail areas 750 – 1000 m	# retail areas in 750 – 1000 m dist. band	Continuous
# retail areas 1000 – 1500 m	# retail areas in 1000 – 1500 m dist. band	Continuous
Log Distance city park (UGS)	Distance to city park (continuous)	Continuous
Transaction year	2014 – 2018 (categorical – dummy coded)	Categorical

(three housing segments) using a 5% statistical significance threshold. The spatial-lag model was specified accordingly and estimated using the Lagsarml method of the Spatialreg package in R. This method implements a maximum likelihood estimation with the spatial lag terms in the model.

Table 2 reports the estimation results related to the land use (*L*), and accessibility (*D*) variables, which are specifically relevant for the land use model. The spatial lag term (ρ) is strongly statistically significant in all three models which indicates that spatial interdependencies between dwelling prices within neighborhoods are relevant.

The values of the beta parameters reflect the impacts of the land use and accessibility variables on the log price. A first observation is that UGS in the form of environmental green has a positive impact on the housing value in all three housing segments. The size of recreation area has a positive relationship with housing price in all three segments and the size of water body for the apartments and detached houses segments. The estimated values of the coefficients indicate that for every 10 percentage point increase of green- (recreation park) or blue- (water body) space in the neighborhood the housing value increases by 2% for apartments and detached houses, and 0.5% for row houses. Distance to a city park appears to have an influence on house price only for row houses. The estimated value of -0.006 indicates that for every 10% decrease in distance to a city park, the average price of row houses increases by 6%. These results indicate clear differences between housing segments, whereby environmental green (recreation area or water body) seems to have a higher value in case of apartments and detached houses and central green (urban parks) has a higher value for row houses.

Secondly, in none of the segments we find a positive effect of mixing public buildings and residential use. The presence of public buildings in the neighborhood has no significant effect on house price in case

Table 2. Estimation results of the spatial-lag hedonic price models for apartments, row houses, and (semi-) detached houses[a].

	Apartments		Row houses		(semi-)Detached	
	coeff.	p-value	coeff.	p-value	coeff.	p-value
Quiet road	–	–	–	–	−0.012	0.021
Busy road	–	–	−0.039	0.000	−0.120	0.000
Shopping area	5.10e-04	0.000	−8.58e-04	0.001	–	–
Road infrastructure area	0.002	0.000	–	–	−0.003	0.000
Recreation area (UGS)	0.002	0.000	4.45e-04	0.001	6.01e-04	0.005
Water body (UGS)	0.002	0.000	–	–	0.002	0.000
Public buildings	−8.93e-04	0.000	–	–	–	–
Log Distance city center	−9.10e-06	0.000	−1.01e-05	0.000	−1.41e-05	0.000
Log Distance publ.build.	−6.10e-06	0.014	−1.75e-05	0.000	–	–
# retail areas < 500	0.019	0.000	0.023	0.000	0.015	0.000
# retail areas $500 - 750$	0.009	0.002	0.016	0.000	–	–
# retail areas $750 - 1000$	0.027	0.000	0.009	0.000	0.027	0.000
# retail areas $1000 - 1500$	–	–	0.004	0.003	–	–
Log Distance city park (UGS)	–	–	−0.006	0.000	–	–
Rho (ρ)	0.055	0.000	0.096	0.000	0.016	0.000
R-squared	0.800		0.799		0.827	

[a]Only land use and accessibility variables are reported.

of row and detached houses and a negative effect in case of apartments (β = -8.93e-04). Shopping area in the neighborhood also has a negative effect on housing price, at least, for row houses. The effect of this land-use is however positive in case of apartments. A busy road in the proximity reduces the value for row and detached houses. Particularly, a very busy road has a strong negative impact on housing price in these segments. The price of apartments is not significantly affected by the presence of busy road.

Turning to the accessibility variables, we see a negative effect of distance to the city center on housing price, as expected. The size of the effect is approximately the same for all three housing types and relatively small. The small effect we find can be attributed to the relatively small size of the cities studied, where distances rarely exceed 3 km. Within this range, residents tend to be indifferent to variations in distance, resulting in a diminished impact on property price. As for the retail facilities, the results show that the number of available shopping areas within certain distance bands have a positive effect on housing value; the positive effect decreases with distance, although not always monotonically.

These results suggest that environmental green generally increases the housing value. The overall findings are in accordance with Conway et al. (2010) who found similar marginal values for the percentage of greenery coverage. However, implementing this form of UGS means longer distances to central facilities with negative effect on housing value. The nature of the trade-off between accessibility and environmental green differs between the housing segments: for row houses accessibility of central facilities and for apartments and detached houses the presence of environmental green seems more important. This demonstrates that the area-wide impact of UGS on housing value depends on the spatial allocation of housing and UGS land-uses. In the next section, we show how these valuations can be used in an HLM model to generate an optimal land-use plan for area development.

5. Application of the HLM

In this section, we incorporate the estimated valuations of UGS as parameters in a housing land use model (HLM) and apply the HLM to solve a residential area development problem. As a plan area we consider the Meerhoven area - a city expansion area in Eindhoven, designated for residential use.

5.1. Parameters

The results of the hedonic price analysis are used to set the parameters of the HLM (Eq. 3). The value of the constant, *Vcon*, is determined for each housing type by calculating the hedonic value related to structural dwelling characteristics assuming an average dwelling with a high level of maintenance, a construction year after 2000, the 2018 price levels and dwelling sizes defined by the housing program in Meerhoven. The neighborhood (*Vnbh*) parameters are set based on the estimated values of the coefficients of land use variables in the hedonic model. The land-use of each cell is derived from the land-use map of the area and the neighborhood of each cell is defined as the eight neighboring cells. For each land-use and each developable cell, the size of the area covered by the land-use in the neighborhood is determined. The presence of a busy road in any of the adjacent cells is included as a binary value (quiet roads are not accounted for, as only main roads are known in this stage of development). The estimated marginal values of shopping area, public buildings, road infrastructure area and UGS land-uses are then used to calculate the total marginal value of land-use *Vnbh* for the cell. Assuming that water and green are both feasible forms of UGS and the best form is chosen once land is allocated to UGS, the UGS-environmental green parameter is set to the highest value of the two for each housing type (i.e., $\beta = 0.002$ for apartments and detached and $\beta = 4.45e\text{-}04$ for row houses). Similarly, the accessibility component, *Vacc*, for each developable cell is calculated based on the land-use map of the area and the model estimates. In line with the hedonic model, the distances to facilities including the (Eindhoven) city center, public buildings, and city park are calculated as straight-line distance and (after log transformation) the estimated parameters are used to calculate *Vacc* for the cell considered.

5.2. The Plan Area, Baseline, and Policy Scenarios

As a plan area, we take Meerhoven - a district of Eindhoven located on the western side of the city where new area development took place between 1995 and 2020. Meerhoven covers almost 300 hectares of land located around a large park. In the northeast of the park, a shopping center is situated. Outside Meerhoven, on the east side, the existing urban area of Eindhoven is located with the city center and an existing large urban park. The accessibility of these locations will also influence the housing value. Figure 1 shows the land-use map of Eindhoven and Figure 2 the existing land use pattern and developable land in the Meerhoven area district.

We consider two policy scenarios. Scenario 1 corresponds to the current situation in which a large neighborhood park is located in the center of Meerhoven. In scenario 2 (counterfactual) the area where the park is located is assumed available for residential development and the UGS in the park can be reallocated as environmental green. Comparing the performance of the two scenarios, conclusions can be made whether concentrated UGS (central green) is preferred over spatially distributed UGS (environmental green) when the goal is to maximize the net value of housing.

5.3. Model Assumptions

The assumptions used for the simulation are presented in Table 3. In Meerhoven, currently, 4500 dwellings have been realized and 600 more dwellings are planned. So, in total, the program involves the development of $(4500 + 600 \ =)$ 5100 dwellings. 25% of the dwellings are apartments and we assume that, in the segment of single-family houses, 60% are row houses and 15% are (semi-)detached. The assumed densities are 46 dwellings per ha (row) and 20 dwellings per ha (detached). For apartments, we take a density of 100 dwellings per ha, which is attainable in middle-high buildings. Table 3 also shows the assumptions regarding land costs, construction costs, and dwelling sizes. The numbers are representative for a location such as Meerhoven in The Netherlands. The dwelling sizes correspond to averages derived from the transaction data used in Section 3. In addition to housing, 4 ha of land is needed for public-building use.

5.4. Simulation Results

Figure 3 shows the HLM land-use allocation results for the two scenarios described above. In Scenario 1 (with the large park), the row houses are allocated near the park, due to the fact that the value of row houses benefits most from good accessibility to the park. Apartments are mainly located alongside a road; the reason is that the value of this housing type is not negatively affected by road proximity, in contrast to the other housing types. Green is largely allocated adjacent to a road where it can act as a buffer between the road and housing (row and detached). Also, public buildings are located alongside a road for the buffering function. In Scenario 1, all available environmental green is used as a green buffer along road infrastructure. In Scenario 2, the additional available space for green is used for complementary environmental green in the direct environment of dwellings, particularly of apartments and detached houses. Furthermore, in this scenario, row houses are predominantly located in the east side of the area because this location minimizes the distance to a large park outside Meerhoven, at the east side of the Meerhoven region.

5.4.1. Scenario 1 (with Big Park) scenario 2 (without the Big Park)

The model allows us to calculate the total net housing value for the plan area in each scenario. In Scenario 2, where green is implemented as environmental green,

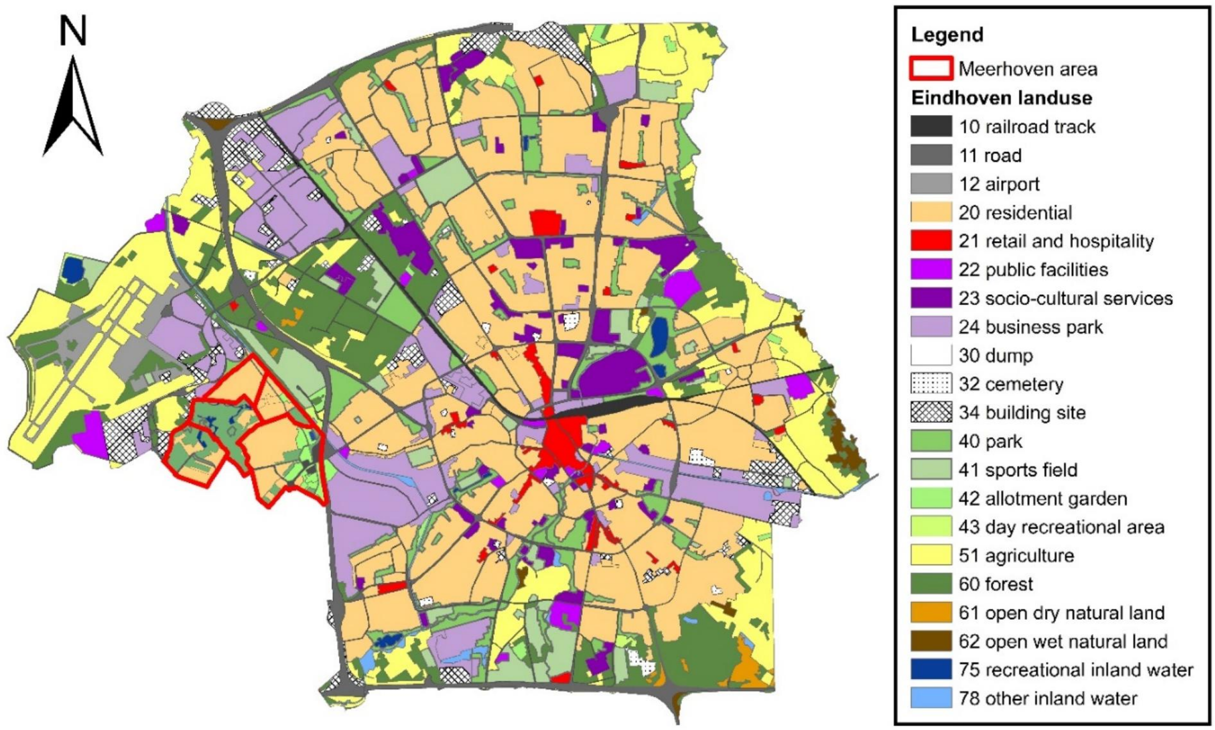


Figure 1. Land use map of Eindhoven city.

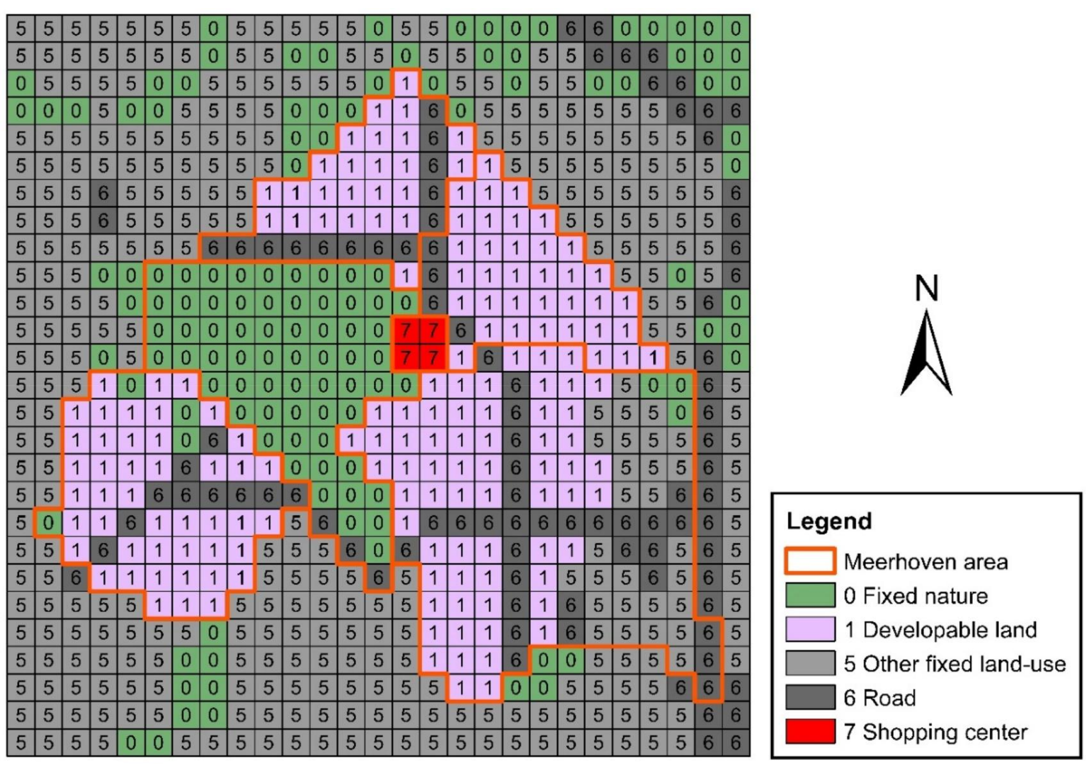


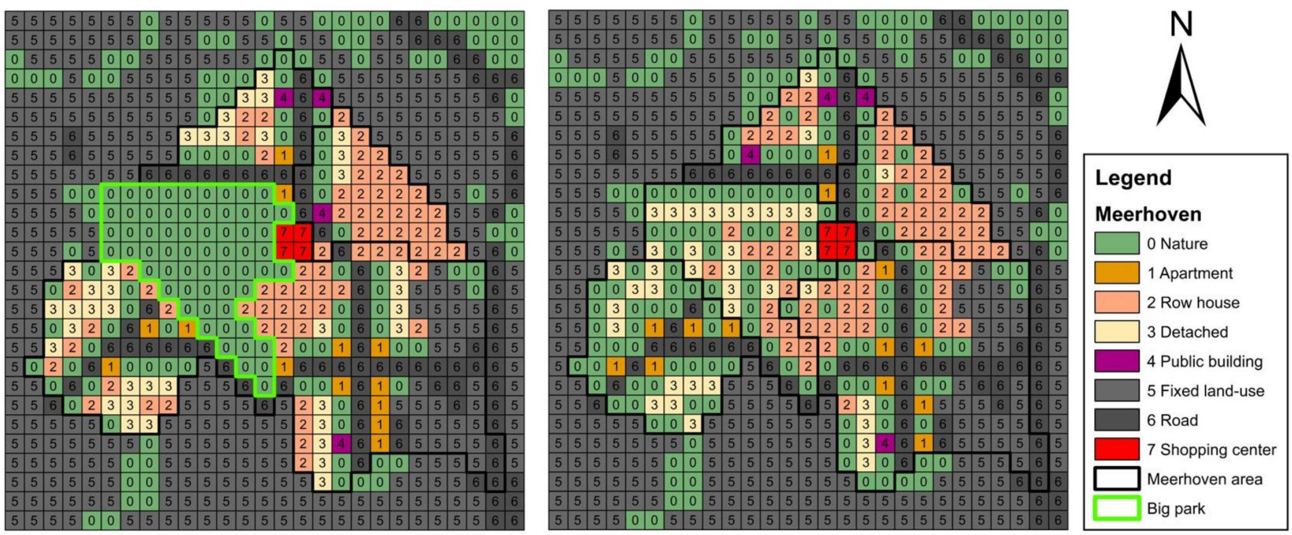
Figure 2. Meerhoven area land-use development plan.

the total net value is 3.1 percent higher compared to Scenario 1 (961 mEuro versus 932 mEuro). Table 4 shows mean dwelling prices in the HLM solution for different dwelling types for the two scenarios. The figures indicate that especially the detached and apartment housing types are responsible for the increase in the net value in Scenario 2. The average dwelling price is 1.11% higher for apartments and 3.28% higher for

Table 3. Housing program, housing densities, land demands and development costs assumed for the application.

Type of dwellings	Apartments	Row houses	(semi-) Detached*
Share in %	25	60	15
Number dwellings	1275	3060	765
Density in dwelling /ha	100	46	20
ha (number of cells)[a]	13	67	38
Land costs (€ / m2)	600	600	600
Construction costs (€ / m2 floor space)	2200	1700	1900
Dwelling size (m2 floor space)	80	120	160

[a]The figures are obtained by dividing the number of dwellings by the density (see Table 4).



Scenario 1 (with big park) *Scenario 2 (without the big park)*

Figure 3. Land use plans generated for the two scenarios.

Table 4. Model-based dwelling prices and development costs in the solutions for the two scenarios S1 (with big park) and S2 (without big park).

	Apartment			Row			Detached		
	S1	S2	Percent	S1	S2	Percent	S1	S2	Percent
Average Net value per cell (kEuro)	18612	19081	+2.52%	6392	6382	−0.16%	6883	7505	+9.04%
Average Net value per dwelling (kEuro)	186.12	190.81	+2.52%	138.97	138.75	−0.16%	344.17	375.25	+9.04%
Total costs / dwelling (kEuro)	236	236	Same	334	334	Same	604	604	Same
Average dwelling price (kEuro)	422.12	426.81	+1.11%	472.97	472.75	−0.05%	948.17	979.25	+3.28%

detached houses in Scenario 2; the average price of row houses is approximately the same in both Scenarios. Combining Table 4 with Figure 3, we can conclude that the added value in Scenario 2 is caused mainly by the mixed green land use in neighborhoods. Spreading UGS cells around residential blocks, increases the WTP value for the dwellings (in the adjacent eight cells) especially for apartments and detached houses. For example, compare an apartment with 3 out of the 8 neighboring cells (37.5% of the neighborhood area) covered by UGS and an apartment where all neighborhood cells have residential use. The former has a 1.67% (= 4.45 10^{-4} x 37.5) higher WTP value. In the same way, the model incorporates the influence of other neighborhood and accessibility characteristics of the cell on the WTP. The result is that, in Scenario 2 (without big park), the overall dwelling price increases with 1.11% and 3.28%, for departments and detached houses, respectively. Taking into account the costs of development, in this Scenario 2 developers can realize 2.52% and 9.04% higher profits on average for apartments and detached houses. In both scenarios, building apartments is more profitable than row houses, and due to the higher density, also more profitable than detached in each cell (1 hectare).

Note that these insights could not have been generated using only the underlying WTP-values for the different forms of UGS. The WTP-values for environmental green and accessibility of a park are approximately the same for detached houses and apartments whereas the value increase of detached houses in Scenario 2 is considerably larger. This is the consequence of assigning the land to the use that has the highest yield at a specific location. In the solutions for both scenarios, apartments are often located near roads, i.e., at locations which are not attractive for row houses and detached houses. As a consequence of these allocation decisions, the increase in neighborhood green is more limited for apartments compared to detached houses. For row houses the results indicate that, in the present spatial setting, a gain in environmental green (Scenario 2) is approximately equal to the loss (of accessibility) of central green.

To conclude, the results of the land use model indicate that, for the case of Meerhoven, a spatial strategy of spreading UGS across the area instead of concentrating UGS in a large urban park increases the value of housing overall and particularly in the detached housing segment.

6. Conclusions and Discussion

In this paper, we have developed and illustrated an approach to combine hedonic price modeling and a housing land use allocation model, to estimate the impacts of UGS on housing value and reveal the implications for the optimal spatial allocation of UGS in a housing area development perspective. We showed how a hedonic price model can be specified paying special attention to environmental green and central green as different forms of urban green space (UGS) and highlighted differences in impacts of these forms of UGS between housing types.

The results of the hedonic price analysis show that the WTP-values for the different forms of UGS differ between apartments, row housing and detached housing. For both apartments and detached housing, we find that the average housing value increases with approximately 2% for every 10 percent point increase in green coverage in the neighborhood of the dwelling. We do not find a statistically significant impact of the accessibility of a (large) urban park for these housing types. In the case of row housing, we do find an impact of accessibility of an urban park on the housing value: the housing price increases with 6% for every 10% decrease in distance. Environmental green appears to have a lower impact in case of row housing.

The differences in response between the housing types may possibly be explained by differences in household characteristics (e.g., age group, education, presence of children) and dwelling characteristics (e.g., presence of a private garden) between the segments, see also Teulings et al. (2018). Urban parks do not just offer green but, due to their larger scale, also locations for sports, play and social activities (Zhao et al., 2024). Our findings suggest that the added value this creates differs between housing types, possibly driven by the differences in household type and related specific activity needs (Panduro and Veie, 2013).

The results of the housing land use model that incorporates the estimated HP-models indicate that a location strategy where urban green is integrated in neighborhoods as opposed to concentrated in a (large) urban park may increase the overall housing value. The results further show that, when the aim is to maximize the housing value, it is optimal to allocate UGS alongside road infrastructure where it acts as a green buffer between a road and family housing to avoid a negative impact from road traffic. Next, the results suggest that under optimal land-use allocation decisions, detached housing experiences a larger increase in value than apartments in a distributed urban green scenario, even though the WTP-values for the different forms of UGS are the same. On the other hand, for row housing, the loss of central green and the gain of environmental green cancel each other out. We conclude that solely using estimated WTP-values for different forms of UGS overlooks important trade-offs in the optimal spatial allocation of these land uses. The land use model not only takes the WTP-values into account, but also the competition for land between different land uses. It appears that the land use competition effects, at least in the case considered, are substantial so that an integrated modeling approach is needed to reveal the implications for the optimal spatial allocation of UGS.

The approach developed in this study shows how housing transaction data and land use modeling can be combined to support spatial housing planning. To further develop this approach, several problems remain for future research. First, the existence of strong correlations between location characteristics generally imposes restrictions on the identifiability of land use effects on property value. In the application described, transaction data from two cities with different spatial and land use characteristics were combined to increase spatial variation that helps to identify generalizable effects of UGS and land use on housing values. Second, the data and model are focused on medium-sized cities in the Netherlands, which implies a limitation on the generalizability of the results. Our primary goal was to demonstrate the approach. For further applications, it is recommended to enlarge the sample of cities to increase the power of the analysis and generalizability of results. Further, it is worthwhile to consider alternative ways of collecting data about prices that do not suffer from the above identification problems. In housing research and urban planning, the stated choice experiment is a well-established method to estimate (housing) preferences of residents and eventually to derive willingness-to-pay estimates for housing attributes (e.g., Kim 2006, Wu and Zhao 2015, Ossokina et al, 2020). It may be useful to investigate this latter approach as an alternative way to obtain parameter estimates for the housing land use models. Despite the limitations, we believe the combined hedonic price analysis and land use modeling approach put forward in the present study has clear merits and has the ability to increase knowledge about the trade-offs in the spatial planning of UGS.

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Ethical Approval

At the time when the research was conducted, there was not yet an Ethical Review Board at the TU/e. Formally, the department itself was responsible for the ethical appropriateness of the research. However, a comparable study – using the same NVM data – conducted several years received ethical approval.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

Informed Consent

N/A: the data used was obtained from an existing source – NVM, the national association of brokers in the Netherlands

Note

1. Because the neighborhood contains 8 cells and a single cell can only have one land use, the shares are 1/8, 2/8, etc.

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References

Anderson, S. T., & West, S. E. (2006). Open space, residential property values, and spatial context. *Regional Science and Urban Economics*, *36*, 773–789. https://doi.org/10.1016/j.regsciurbeco.2006.03.007

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Kluwer.

Arentze, T. A., Borgers, A. W. J., Ma, L., & Timmermans, H. J. P. (2010). An agent-based heuristic method for generating land use plans in urban planning. *Environment and Planning B: Planning and Design*, *37*(3), 463–482. https://doi.org/10.1068/b35050

Basu, S., & Thibodeau, T. G. (1998). Analysis of spatial autocorrelation in house prices. *The Journal of Real Estate Finance and Economics*, *17*, 61–85. https://doi.org/10.1023/A:1007703229507

Bharath, H. A., Chandan, M. C., Vinay, S., & Akshit, S. (2021). Land allocation model using cellular automata to understand housing demand and supply. *Spatial Information Research*, *29*(3), 339–351. https://doi.org/10.1007/s41324-020-00350-w

Bockarjova, M., Botzen, W. J. W., Van Schie, M. H., & Koetse, M. J. (2020). Property price effects of green interventions in cities: A meta-analysis and implications for gentrification. *Environmental Science & Policy*, *112*(2020), 293–304. https://doi.org/10.1016/j.envsci.2020.06.024

Brander, L. M., & Koetse, M. J. (2011). The value of urban open space: Meta-analyses of contingent valuation and hedonic pricing results. *Journal of Environmental Management*, *92*(10), 2763–2773. https://doi.org/10.1016/j.jenvman.2011.06.019

Conway, D., Li, C. Q., Wolch, J., Kahle, C., & Jerrett, M. (2010). A spatial autocorrelation approach for examining the effects of urban greenspace on residential property values. *Journal of Real Estate Finance and Economics*, *41*(2), 150–169. https://doi.org/10.1007/s11146-008-9159-6

Czembrowski, P., Łaszkiewicz, E., Kronenberg, J., Engstro, G., & Andersson, E. (2019). Valuing individual characteristics and the multifunctionality of urban green spaces: The integration of sociotope mapping and hedonic pricing. *PLoS One*, *14*, 1–16. https://doi.org/10.1371/journal.pone.0212277

Czembrowski, P., & Kronenberg, J. (2016). Hedonic pricing and different urban green space types and sizes: Insights into the discussion on valuing ecosystem services. *Landscape and Urban Planning*, *146*, 11–19. https://doi.org/10.1016/j.landurbplan.2015.10.005

Dekkers, J., & Rietveld, P. (2011). Explaining land-use transition in a segmented land market: Potential input for Land Use Scanner. In *Land-use modelling in planning practice* (pp. 153–175). Springer Science & Business Media.

Di, W., Ma, j., & Murdoch, J. C. (2010). An Analysis of the Neighborhood Impacts of a Mortgage Assistance Program: A Spatial Hedonic Model. *Journal of Policy*

Analysis and Management, *29*(4), 682–697. https://doi.org/10.1002/pam.20530

Gao, Y., & Changchun, F. (2023). Impact of mixed land use on housing prices, spatial differentiation and implications: empirical analysis based on Qingdao. *Applied Spatial Analysis and Policy*, *16*, 1345–1370. https://doi.org/10.1007/s12061-023-09514-1

Huang, H., & Yin, L. (2015). Creating sustainable urban built environments: An application of hedonic house price models in Wuhan, China. *Journal of Housing and the Built Environment*, *30*, 219–235. https://doi.org/10.1007/s10901-014-9403-8

Iqbal, A., & Wilhelmsson, M. (2018). Park proximity, crime and apartment prices. *International Journal of Housing Markets and Analysis*, *11*, 669–686. https://doi.org/10.1108/IJHMA-04-2017-0035

Irwin, E. G., & Bockstael, N. E. (2001). The problem of identifying land use spillovers: measuring the effects of open space on residential property values. *American Journal of Agricultural Economics*, *83*, 698–704. https://doi.org/10.1111/0002-9092.00193

Jim, C. Y., & Chen, W. Y. (2008). Assessing the ecosystem service of air pollutant removal by urban trees in Guangzhou (China). *Journal of Environmental Management*, *88*(4), 665–676. https://doi.org/10.1016/j.jenvman.2007.03.035

Katoshevski-Cavari, R. T. A., Arentze., & H. J. P., Timmermans. (2011). Sustainable city-plan based on planning algorithm, planners' heuristics and transportation aspects. *Procedia Social and Behavioral Sciences*, *20*(2011), 131–139. https://doi.org/10.1016/j.sbspro.2011.08.018

Katoshevski-Cavari, R., Katoshevski, D., Arentze, T., & Timmermans, H. (2014). A multi-agent planning support system for assessing the role of transportation and environmental objectives in urban planning. *Journal of Transport and Land Use*, *7*, 29–42. https://doi.org/10.5198/jtlu.v0i0.333

Katoshevski-Cavari, R., Arentze, T., & Timmermans, H. (2010). A multi-agent planning support-system for assessing externalities of urban form scenarios: results of case studies. *Sustainability*, *2*, 2253–2278. https://doi.org/10.3390/su2072253

Kim, J. H. (2006). Amenity valuing differentiation in residential location choice among income groups: A stated preference approach. *International Journal of Urban Sciences*, *10*(1), 41–57. https://doi.org/10.1080/12265934.2006.9693586

Klosterman, R. E. (2001). The what if? Planning support system. Paper 10 of Planning Support Systems: Integrating geographic Information Systems, Models, and Visualization Tools. Excerpted and reprinted courtesy of ESRI Press.

Koomen, E. and Stillwell (2007). Modelling land use change: Theories and methods. In E. Koomen, J. Stillwell, A. Bakema, H. J. Scholten (Eds.), *Modelling land use change* (pp. 1–24). Progress and Applications, Springer.

Koomen, E., Diogo, V., Dekkers, J., & Rietveld, P. (2015). A utility-based suitability framework for integrated local-scale land use modelling. *Computers, Environment and Urban Systems*, *50*, 1–14. https://doi.org/10.1016/j.compenvurbsys.2014.10.002

Koster, H. R. A., & Rouwendal, J. (2012). The Impact of Mixed Land Use on Residential Property Values. *Journal Of Regional Science*, *52*, 733–761. https://doi.org/10.1111/j.1467-9787.2012.00776.x

Łaszkiewicz, E., Czembrowski, P., & Kronenberg, J. (2019). Can proximity to urban green spaces be considered a luxury? Classifying a non-tradable good with the use of hedonic pricing method. *Ecological Economics*, *161*, 237–247. https://doi.org/10.1016/j.ecolecon.2019.03.025

Ligmann-Zielinska, A., Church, R., & Jankowski, P. (2008). Spatial optimization as a generative technique for sustainable multiobjective land-use allocation. *International Journal of Geographical Information Science*, *22*(6), 601–622. https://doi.org/10.1080/13658810701587495

Li, F., Li, Z., Chen, H., Chen, Z., & Li, M. (2020). An agent-based learning-embedded model (ABM-learning) for urban land use planning: A case study of residential land growth simulation in Shenzhen, China. *Land Use Policy*, *95*, 104620. https://doi.org/10.1016/j.landusepol.2020.104620

Melichar, J., & Kaprová, K. (2013). Revealing preferences of Prague's homebuyers toward greenery amenities: The empirical evidence of distance-size effect. *Landscape and Urban Planning*, *109*(1), 56–66. https://doi.org/10.1016/j.landurbplan.2012.09.003

Oliveira, S., Andrade, H., & Vaz, T. (2011). The cooling effect of green spaces as a contribution to the mitigation of urban heat: A case study in Lisbon. *Building and Environment*, *46*(11), 2186–2194. https://doi.org/10.1016/j.buildenv.2011.04.034

Ossokina, I. V., Arentze, T. A., van Gameren, D., & van den Heuvel, D. (2020). Best living concepts for elderly homeowners: Combining a stated choice experiment with architectural design. *Journal of Housing and the Built Environment*, *35*, 847–865. https://doi.org/10.1007/s10901-019-09716-5

Panduro, T. E., & Veie, K. L. (2013). Classification and valuation of urban green spaces: A hedonic house price valuation. *Landscape and Urban Planning*, *120*, 119–128. https://doi.org/10.1016/j.landurbplan.2013.08.009

Razzaghmanesh, M., Beecham, S., & Salemi, T. (2016). The role of green roofs in mitigating Urban Heat Island effects in the metropolitan area of Adelaide, South Australia. *Urban Forestry and Urban Greening*, *15*, 89–102. https://doi.org/10.1016/j.ufug.2015.11.013

Stovin, V., Vesuviano, G., & Kasmin, H. (2012). The hydrological performance of a green roof test bed under UK climatic conditions. *Journal of Hydrology*, *414–415*, 148–161. https://doi.org/10.1016/j.jhydrol.2011.10.022

Tiefelsdorf, M., Griffith, D. A., & Boots, B. (1999). A variance-stabilizing coding scheme for spatial link matrices. *Environment and Planning A*, *31*, 165–180. https://doi.org/10.1068/a310165

Teulings, C.N., Ossokina, I.V. and H.L.F. de Groot (2018). Land use, worker heterogeneity and welfare benefits of public goods. *Journal of Urban Economics*, *103*, 67–82.

Tyrväinen, L., & Miettinen, A. (2000). Property prices and urban forest amenities. *Journal of Environmental Economics and Management*, *39*(2), 205–223. https://doi.org/10.1016/j.jue.2017.10.004

Vliet, van, J., A. K., Bregt., & A., Hagen-Zanker. (2011). Revisiting Kappa to account for change in the accuracy assessment of land-use change models. *Ecological Modelling*, *222*, 1367–1375. https://doi.org/10.1016/j.ecolmodel.2011.01.017

White, E. V., & Gatersleben, B. (2011). Greenery on residential buildings: Does it affect preferences and perceptions of beauty? *Journal of Environmental Psychology*, *31*(1), 89–98. https://doi.org/10.1016/j.jenvp.2010.11.002

White, R., & Engelen, G. (2000). high resolution integrated modelling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems*, *24*, 383–400. https://doi.org/10.1016/S0198-9715(00)00012-0

Wu, N., & Zhao, S. (2015). Impact of transportation convenience, housing affordability, location, and schooling in residence choice decisions. *Journal of Urban Planning and Development*, *141*(4), 05014028. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000258

Zhao, Y., van den Berg, P. E. W., Ossokina, I. V., & Arentze, T. A. (2024). How do urban parks, neighborhood open spaces, and private gardens relate to individuals' subjective well-being: Results of a structural equation model. *Sustainable Cities and Society*, *101*, 105094. https://doi.org/10.1016/j.scs.2023.105094