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The recreational services value of the nearest periurban forest *versus* the global forest environment

Laetitia Tuffery*

Abstract

Most of previous forest recreational service valuation studies using hedonic methods have focused on direct proximity of housing to the nearest forest while treating the recreational services as homogeneous. However, households in urban and periurban areas may prefer diverse forest areas in their neighborhood. The main objective of this study is to estimate and compare the impacts of proximity to forest recreational services based on the nearest forest and the global forest environment, which includes spatially heterogeneous recreational quality. The global forest environment is computed from the forest recreational services with respect to travel time to the housing. Empirical results show that major differences exist between the forests' valuations and their recreational services depending on which forest environment is considered. The size of the nearest forest is the only characteristic with a positive and significant impact on housing prices. Conversely, the global forest environment positively impacts housing prices based on certain parameters, such as large forest size, no protected areas and the existence of hiking and biking paths, which implies public access and maintenance.

Jel codes: Q26, Q57, R14, R21

Keywords: recreational services; global forest environment; hedonic price method; spatial analysis

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1. Introduction

1.1 Current issues and motivations

The existence of large, highly populated urban areas often affects periurban and rural spaces by pressuring local land use. This pressure generates natural ecosystem changes, such as soil artificialization and natural habitat fragmentation, among other changes. The loss of well-being in various cities has been related to land degradation [1]. In addition, a survey [2] revealed that a significant percentage of the inhabitants of the Paris region believe that forested areas are shrinking, although such areas are actually expanding or remaining stable. This behavior suggests that an "urban man anxiety" exists regarding the disappearance of natural environmental spaces [2]. Hence, forest value near urban areas may be explained by the fact that people living in the city value natural environmental surroundings.

Urban and periurban forest ecosystems provide numerous ecosystem services. Among these services, cultural services (spiritual and religious, recreation and tourism, aesthetic, inspirational and educational [3]) play an important role in urban societies and are increasingly valuated. This article does not analyze all cultural ecosystem services but, rather, focuses on the non-material recreational aspects of human-nature relationships, i.e., the recreational periurban forest ecosystem services [4].

The main objective of this study is to spatially estimate and compare the impact of proximity to forest recreational services based on the nearest forest and the global forest environment.

1.2 Literature and methodology

Policymakers and land use managers need ecological and socio-economical information to develop land planning strategies and implement policies. However, these strategies often underestimate the value of ecosystem services, especially the recreational value. A comprehensive and realistic approach is needed that integrates this economic value into urban planning policies. Non-market valuation methods and geographic information systems (GIS) are increasingly and conjointly used as tools to implement land use management, urban planning and local public policy assessments [5]. Consumer preferences regarding environmental variables can be revealed by willingness to pay (WTP) studies. The housing market is a relevant proxy for the assessment of both the social and economic impacts of public actions in terms of land use and environmental amenities valuation. Accessibility, cost of housing and amenities are all considered when choosing a location, as highlighted by urban economics literature. The hedonic approach provides a suitable WTP method. This method evaluates housing prices based on property characteristics (location, environment, etc.) and defines implicit prices for each amenity by studying its effect on housing prices. Our model follows the basic framework of the hedonic price analyses established by Lancaster [6], Griliches [7] and Rosen [8].

Hedonic method studies of forest recreational service valuations generally include the direct proximity of housing to the nearest forest. These studies treat the recreational services as homogeneous within a forest environment. However, urban and periurban inhabitants may prefer diverse forest areas in their neighborhoods. Two main factors explain these preferences. First, from the household perspective, recreational and sports activities may differ between the week and the weekend. Second, amenity-based housing values are generally related to the quality of the amenity. The amenity can be multi-site and imply spatially heterogeneous quality levels in terms of recreational services. Indeed, forest quality is not homogeneous, having a positive impact associated with recreational amenities and a negative impact due to industrial activities, such as timber production or military land use [7,9]. Thus, considering only the nearest forest can generate an omitted variable bias, which negatively affects the land use strategies. The nearest forest is not necessarily the only forest considered by households when making a residential choice. The economic valuation of the global forest environment should provide a more comprehensive approach for assessing the recreational values of periurban forests.

Most empirical studies attempt to value the recreational properties of different ecosystems but only address the direct proximity to the ecosystem (e.g., distances to forests or trees in cities [10]) without fully integrating the ecosystem attributes and services. Local recreational services are not always known, which may explain this limitation. However, recent studies have estimated forest area values according to their ecosystem service attributes. Abildtrup *et al.* [11] and Termansen *et al.* [12, 13] used a choice experiment method to determine that spatial forest recreation preferences depend on recreational ecosystem services, such as hiking. Bestard *et al.* [14] and Clough and Meister [15] estimated the aggregate recreational forest service values at multiple sites using the travel cost method. Several articles have provided detailed estimates of natural site values using the hedonic price method with respect to the site's socio-ecological characteristics [9, 16, 17, 18] or ownership status (e.g., private *versus* institutional forest [19]). Panduro and Veie [17] provided a non-market valuation of green spaces (using a broad definition of the latter term). Their estimates are based on ecosystem services classification in those areas, as in Bell *et al.* [20], which include certain recreational ecosystem services, including parks, lakes, nature, sports fields, and others. The study showed that the impact on the housing price differs according to green area categories based on maintenance and accessibility. Ham *et al.* [9] estimated the marginal impact of proximity to the Pike National Forest when treating forests as heterogeneous goods. The study distinguished the housing proximities to the recreational and "working land" portions of the forest. The latter proximity exhibited a significant negative effect. Another heterogeneous recreational services study in national parks and lakes included the natural site proximity [18].

This study aims to improve the recreational services measurements of forests using a hedonic method valuation. To this end, we estimate the implicit price of the nearest forest recreational services and compare this price to the implicit price of the global forest environment near the housing areas. The global forest environment is computed from the forest recreational services based on the travel time to the housing. This work is conducted at the smallest national French statistical level using a large number of databases. This paper is organized as follows:

In the first part, we develop the data set and our geolocalized variables. Then, we present econometric models and estimation methods. Finally, we describe and discuss the results in part three.

2. Databases and variables

This hedonic price analysis requires a large number of databases and variables. All variables are presented in Appendix A.

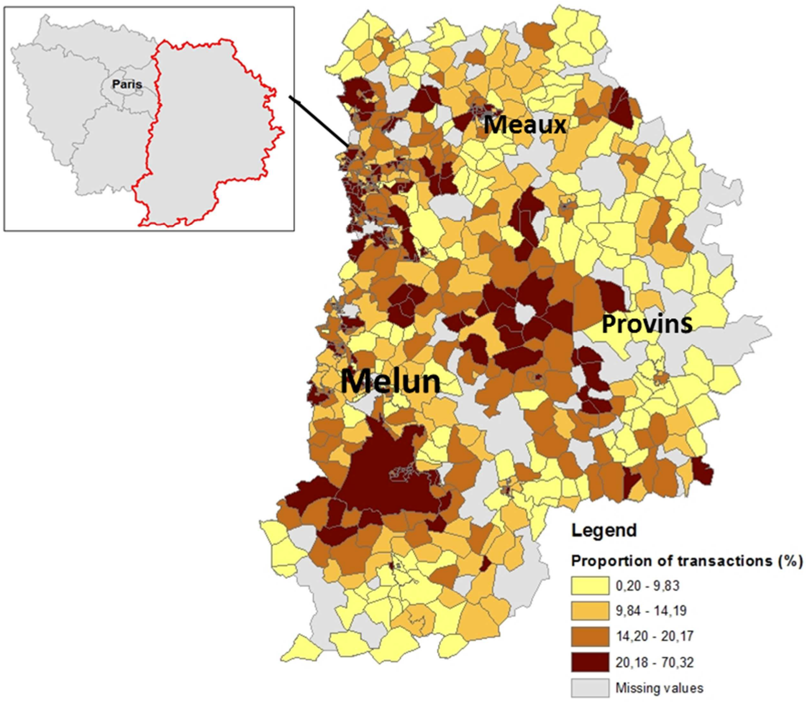
2.1 Housing specification database

Intrinsic housing characteristics are extracted from the BIEN database (Notarial Base for Paris region housing transactions) of the Chamber of Notaries of Paris. The BIEN database is an exhaustive database of housing transactions and characteristics in the Paris region. This database includes the prices and descriptions of properties sold (living area, number of rooms, number of bathrooms, garage, etc.) located in the smallest geographic area available at the French national statistics level (IRIS level)[1] from 1998 to 2015. More specifically, this study focuses on the Seine-et-Marne *département* transactions sub-database between 2001 and 2008 (apartments and houses). A total of 132 239 transactions were available during this period. Only 49 240 observations could be utilized due to missing values and outliers (e.g., business transactions, inheritance or parking lots). Figure 1 shows the proportion of housing market transactions (total dwellings in IRIS from the National Institute of Statistics - INSEE) at the IRIS level in the Seine-et-Marne *département*. The data are clearly affected by the proximity to Paris. The western portion of the *département* possesses a higher population density, higher prices and smaller units. The eastern portion is more rural.

The variables extracted from the BIEN database include the living area (in m²), housing age (dwelling built more or less than 5 years ago), dwelling type (1 if the observation is a house, 0 otherwise), number of garages and number of bathrooms.

[1] IRIS is the smallest national French statistics level. An IRIS includes approximately 2000 persons.

Figure 1: Proportions of transactions in the Seine-et-Marne *département*



Sources: BIEN (2001-2008) and INSEE (Population census, 2008)
Created by the author

2.2 Districts and neighborhood indicators

INSEE databases were used to define neighborhoods at the town and IRIS levels. Data were used from all 514 cities and 762 IRIS records in the Seine-et-Marne *département*. The socio-economic profiles of households and local amenities in the studied areas were extracted from those databases, including the median household income (city level); number of supermarkets, bakeries and cinemas (IRIS level); and travel time to the nearest high schools, hospitals, shops and urban parks.

The median household income was extracted from the household income database (2000 to 2007). The median household income (in constant euros) from the year preceding the transaction is used to obtain a time lagged variable and avoid accuracy issues in the econometric model. Trade, entertainment, culture, education, income distribution and health facility data were extracted from the Facilities database (2010) at the IRIS level. Facility supply data, such as for supermarkets and bakeries, and public institution data, such as for schools and hospitals, were also extracted from the 762 IRIS records. A road network analysis was conducted to integrate the distance and travel time from a dwelling to these public facilities and services.

2.3 Forest areas and their recreational characteristics

All forests, woodland areas and associated characteristics were used to create the best housing market profile based on the forest environment.

2.3.1 Forest area identification

This paper focuses on forests and their impact on housing prices; therefore, we integrated both private and public forests.

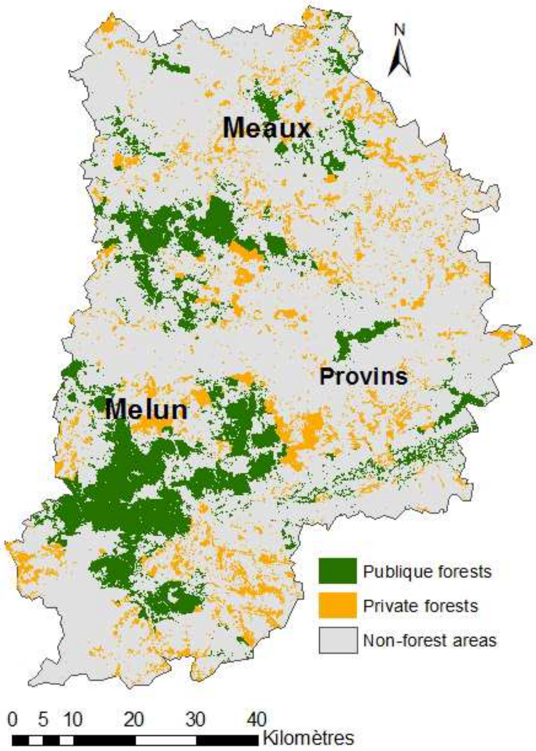
Two databases were used to geo-locate and map the forests at the *département* level. The Paris regional land use MOS/ECOMOS atlas (database 2008) is an exhaustive land use resource for the Paris region (Paris Region Institute for Urban Planning and Development - IAURIF, database 2000). ECOMOS is a similar database that only maps the natural environment and ecosystems. ECOMOS was produced from aerial photographs and satellite images. The database nomenclature is based on the CORINE *Land Cover* nomenclature. We used the "woods and forests" ECOMOS category, which includes all of the forests in the *département*. The public forests were identified using the definitions from the National Forestry Office (ONF, database 2012). The ONF protects and manages forests in France and provides geo-referenced databases for all public forest areas at a national level. Thus, our 46 public forests are also defined by the ONF. The private forests represent the remaining forests in the ECOMOS database, accounting for greater than 70 000 polygons in our database. Some forest polygons were regrouped to improve the processing capability. A city-level aggregation was most appropriate for our spatial analysis (i.e., all forest polygons belonging to the same city are considered one private forest). As a result, 360 private forests and 406 total forests were recognized (see Table 1).

Seine-et-Marne is composed of 60% agricultural land and 20% forest land. Public forests represent 27% of the total forest cover, and the remaining 73% are private forests (sources: MOS-2008, NFB-2012). Figure 2 illustrates the geographic forest distributions.

Table 1. Descriptive statistics of the Seine-et-Marne *département* forests

	Nb of forests	Part of forests (%)	Area (hectares)	Average area (Km²)
Public forest	46	27%	33600	18,57
Private forest	360	73%	91400	1,59
All forests	406	100%	125000	3,5

Figure 2. Public and private forests in the Seine-et-Marne *département*



Sources: MOS 2008, IAURIF and ONF
Created by the author

2.3.2 Recreational services

After forests areas have been identified, their recreational services can be determined. Each forest's attractiveness depends on its services quality, which includes planning, recreation, accessibility, and other factors. Data for identifying local recreational services in periurban forests were derived from the Crédoc survey [2], which focuses on forest area attendance in the Paris region.

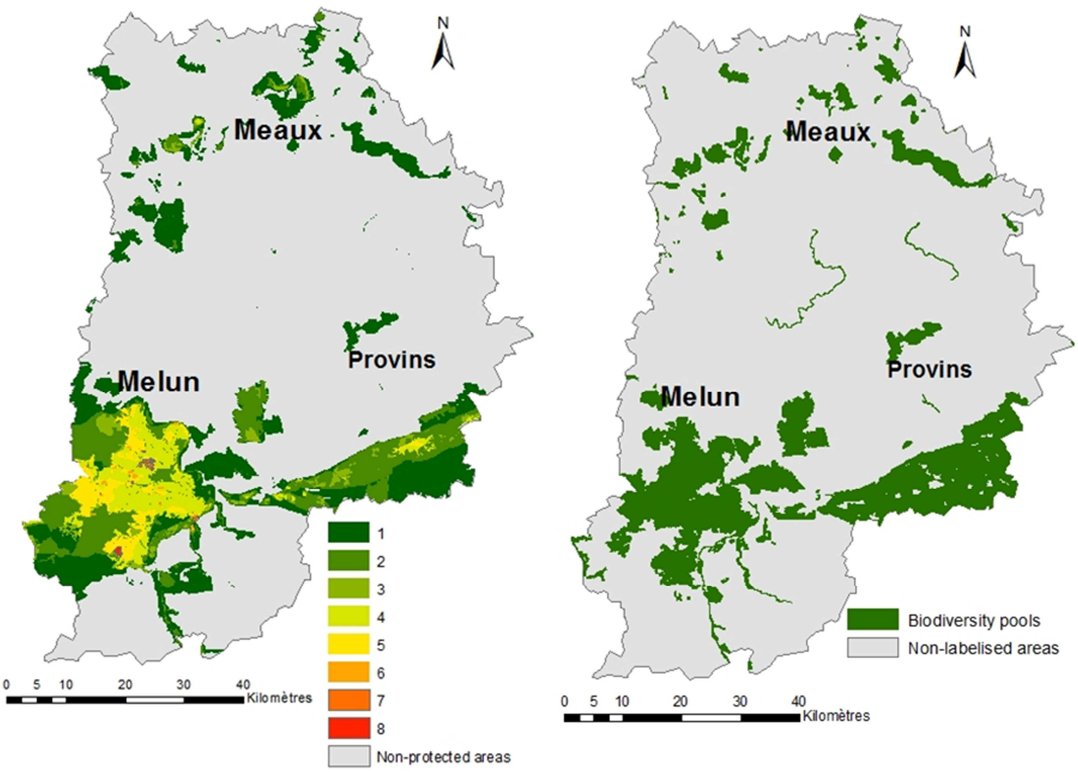
Our recreational services typology was constructed in two steps. First, four activities with the highest scores (walking and hiking, observations of plants and animals, biking and mountain biking, jogging and fitness trails) were selected from the Crédoc survey (see Table 2]). Five variables are then created: hiking paths, biking paths, protection index, biodiversity pools and leisure areas. Geo-localized surface shape variables were integrated to create the "protection index" and the "biodiversity pools" (see Figures 3). The protection index is based on a set of French biodiversity protection layers ranging from 0 to 8, including Natura 2000, Nature Reserve, Biological Reserve, Biosphere Reserve, Regional Nature Reserve, Biotope Protection or Natural Zone of Interest for Ecology, Flora and Fauna [21]. The more labels are present, the richer is the biodiversity of the space. The "biodiversity pools" classification was extracted from the IAURIF database and includes different natural areas, such as large forests, wetlands, natural or semi-natural areas and agricultural areas. Geo-localized data from the Seine-et-Marne plan for hikes and bikes database (PDIPR, database 2009) were used to define hiking paths, biking paths and leisure areas (see Figure 4). Only paths or labels inside forest areas were included in the analysis.

Table 2. Forest ecosystem services in the Paris region

What kind of activities do you practice in forest?		Variables
Walking and Hiking	75,50%	"Hiking path"
Observing plants and animals	24,10%	“Protection index” “Biodiversity pools”
Biking and Mountain biking	17,40%	"Biking path"
Jogging and Fitness trail	11,40%	"Leisure areas"

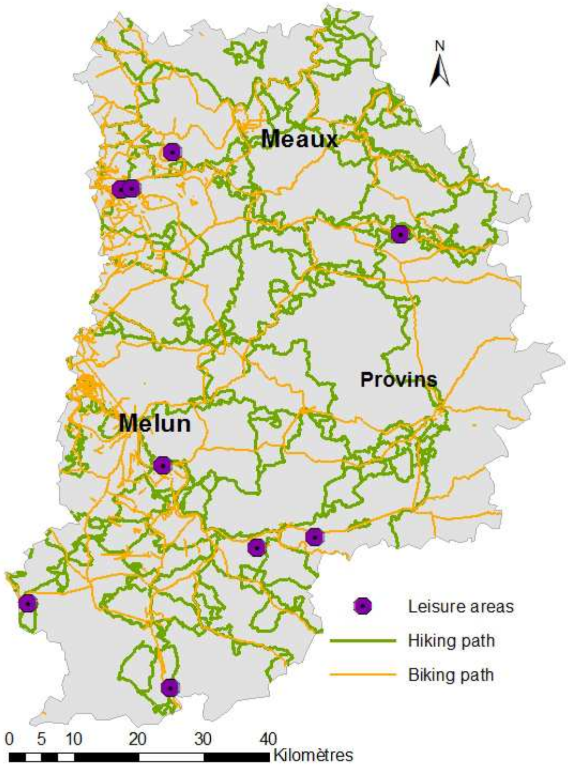
Sources: Attendance for the Paris region forests (1994-1999); characteristics and flow of visits [22]

Figures 3. Protection index and biodiversity pools



Sources: MOS 2008, IAURIF, Natureparif, Simon (2015)
Created by the author

Figure 4. Hiking paths, biking paths and leisure areas



Sources: MOS 2008, IAURIF, CG77 (PDIPR)
Created by the author

Based on the aforementioned recreational services typology, we defined a set of variables related to the recreational services of the forests:

- A forest area in km²;
- A proxy variable for the biodiversity richness, combining the protected areas index and the "biodiversity pools";
- A dummy variable for biking and hiking paths, which is 1 if paths are present in the forest area and 0 otherwise;
- A dummy variable for leisure areas, which is 1 if leisure areas are present in the forest area and 0 otherwise.

2.4 Global environment variables

An amenity can be multi-site and imply heterogeneous transportation costs and quality levels. Therefore, people do not always choose the closest forest. A typical example is accessibility to parks and forests in the vicinity of highly populated areas. People may visit the nearest forest during the week to participate in sports or other activities but visit other forest areas during the weekend. This study takes into account both the nearest forests and all of the forest areas and associated services within the housing environment.

The nearest forest model directly uses the recreational services of the nearest forest, as described in Section 2.3.2. However, the recreational global forest environment model weights the four forest recreational services by the travel time between each dwelling and each forest area and measures the accessibility to all of the forest areas in the territory. A travel time weight matrix is computed and applied to the recreational forest service variables.

The global forest environment estimation variables for each dwelling i and recreational service k are defined as follows:

$$N_{i,k} = \sum_{j=1}^{406}(e^{-T_{i,j}})^{*}n_{j,k} \text{ , with } j = 1, \dots, 406 \text{ and } k = 1, \dots, 4 \quad (1)$$

where $T_{i,j}$ is the travel time between each forest area j and dwelling i and $n_{j,k}$ is the set of k recreational services (size of the forest environment, biodiversity richness, leisure areas and hiking/biking paths) defined for j forest areas. Equation (1) represents the transformation of the variables of interest weighted by the inverse travel time. The weight of the variable will decrease as the travel time increases[2]. Thus, the variables are weighted by the housing proximity using the distance index $e^{-T_{i,j}}$. This transformation decreases the weights of extreme values and the variable dispersion. In addition, the relationship integrates the standard concept of hedonic pricing theory, which suggests that amenities have no significant effect on housing prices within a certain distance. Therefore, this transformation is most relevant for our study.

2.5 Distance computation

The majority of hedonic price studies integrate neighborhood proximity using "as the crow flies" distances. However, this distance metric is not representative of location strategies, especially in urban areas (transportation networks, road traffic, etc.). Therefore, we used travel time, which provides a more relevant accessibility measure. GIS software and distance computation methods were used to determine distance variables based on the existing road network (topographic database of French National Geographic Institute – IGN, 2011). A database of the Paris region was used to determine distance based on travel time according to daily and hourly average travel speeds *via* automobile. The average travel time was thus computed, distinguishing between working days and weekends[3].

2.6 Estimated sample

The existence of missing values[4] in the BIEN database may cause selection bias problems in our sample. One cannot conclude whether the parameters from the regression differ from those of the original database without controlling the randomness of missing values. However, our regression test results are not dependent on the

[2] Indeed, we can see that $\lim_{x\to 0} e^{-T_{i,j}} = 1$ and $\lim_{x\to\infty} e^{-T_{i,j}} = 0$

[3] Average travel speed is 76 km/h (website: sytadin.fr).

[4] For instance, observations for missing values such as IRIS or price/m² are, by definition, useless in our analysis.

sample size, as was also noted by Barthélémy *et al.* [23]. In addition, computational restraints make it impossible to utilize the Maximum Likelihood (ML) of the spatial econometric model (with a square spatial matrix of almost 50 000 observations) based on a sample with 49 240 observations. Therefore, a random subsample of approximately 11 000 observations was used. This subsample was constrained by the same spatial IRIS and transaction year parameters as the global sample, sufficiently representing the global sample. Student's t-test results for both the sample and subsample are presented in Appendix B.

3. Econometric model and estimation method

3.1 Analysis framework

The hedonic price model estimates the implicit and marginal prices of housing characteristics such as urban or environmental amenities in the neighborhood. Our model evaluates the marginal effects of each variable on housing prices (i.e., the forest and the recreational services it provides).

As in the theoretical model developed by Rosen [8], we consider that the price of differentiated goods, such as housing, depends on the associated attributes. Thus, hedonic prices are implicit attribute prices that are revealed to economic agents based on differentiated prices, which depend on the specific associated characteristics. Rosen treats dwellings as heterogeneous goods, which can be differentiated based on the prices of their characteristics. According to Lancaster, consumers derive their utility from the characteristics of goods. In the housing market, an agreement that leads to an exchange between buyers and sellers maximizes their marginal utility. Equilibrium occurs when the price perfectly matches the quality of the good so that individuals cannot maximize their well-being through another transaction. The equilibrium hedonic price function is as follows:

$$P = f(X_{j,}\beta) + \varepsilon \qquad (2)$$

where P is the price of the dwelling; X_j is the set of characteristics for $j = 1, \dots, m$; β is a coefficient; and ε is an error term.

The objective of this function is to determine the housing price according to its characteristics:

$$P = f(X_{1;}\, X_{2;}\, \dots ; X_m\,)$$

Per Equation (2), the marginal price for one single characteristic of a differentiated good can be written as follows:

$$P_j = \frac{\partial P}{\partial X_j} \text{ with } j = 1, \dots., m$$

The housing characteristics are typically organized according to three standard attribute classes: locational attributes (L), structural attributes (S) and neighborhood and environmental attributes (N), such that:

$$P = f(L; S; N) + \varepsilon$$

Our regression model sets the housing price as the dependent variable and the three attribute bundles as the explanatory variables. L represents a set of intrinsic characteristics used to specify the housing services [24]. S is a set of variables that includes the neighborhood and town characteristics or local extrinsic characteristics [25]. N includes the proximity, accessibility to the forest environment and recreational service variables.

The large number of explanatory housing price variables implies the possibility of non-linearity. Therefore, different functional forms are commonly used for this model. This model can be constructed as linear-linear, semi-log, log-log or a Box-Cox transformation [26]. The hedonic price function in this study is estimated using the semi-logarithmic functional form, which is widely used in the hedonic price method literature [10, 17, 27, 28]. Moreover, the log-linear transformation minimizes heteroskedasticity [29]. This functional form relates the logarithm of housing prices to the three categories of explanatory variables described above:

$$lnP = \alpha L + \beta S + \gamma N + \varepsilon$$

where P is the housing price per square meter for each observation.

A log-lin functional form is used for all discrete variables, including dummy variables (e.g., transaction year, house/apartment, number of bathrooms, garages, bakeries, supermarkets, etc.) [30]. A log-log functional form is used for all travel time variables and median income.

3.2 Estimation methods

Space and geographic localization are non-neutral in econometric models. Geo-referenced data (housing, neighborhood and accessibility attributes) consider the impacts of space on econometric models, accounting for spatial autocorrelation. Spatial autocorrelation can be defined as "*the coincidence of value similarity with locational similarity"* [22] or "*a situation where values observed at one location or region depend on the values of neighbouring observations at nearest locations*" [31].

Empirical spatial autocorrelation approaches have been applied to hedonic price method analyses of regional economics, spatial fields and urban fields [33]. Some real estate price studies, such as Can and Megbolugbe [33] and Pace and Gilley [34], also include controlled spatial autocorrelation. The spatial autocorrelation of hedonic pricing improves the model estimation and the environmental services assessment [35]. Thus, *"not only locations matter but interactions between locations matter too"* [36].

3.2.1 Environmental attributes in a spatial hedonic model

Empirical spatial hedonic pricing includes all accessibility and environmental services information in the housing price and can be interpreted as an implicit price. Thus, the hedonic price method represents a relevant method for evaluating the impacts of environmental services (recreational forest services in this study) on housing prices. Numerous accessibility and forest attribute variables are used in the estimation, including distance to public amenities (hospitals, high schools, shops and green parks), distance to train stations, distance to Paris, distance to forests, distance to recreational forest services, and other variables (as described in Section 2).

3.2.2 Spatial dependencies applied to the hedonic model for an environmental valuation

Baumont and Maslianskaia-Pautrel [25] developed four factors underlying spatial autocorrelation in the housing market. First, spatial autocorrelation often occurs because neighboring homes are frequently built during the same period and using the same architectural and technical methods (e.g., thermic and acoustic). Thus, houses share the same intrinsic characteristics. Second, urban public policies, such as urban renewal operations, homogeneously modify neighborhoods in terms of socio-economic and natural environments. Some of these public policies can improve a neighborhood's attractiveness and housing prices by developing transportation networks or urban parks. In contrast, other public policies can diminish the neighborhood environment *via* industrial or road network development. Third, private owners and real estate agencies compare the price of a dwelling to that of neighboring housing. Finally, environmental awareness and knowledge of sustainable development affect housing preferences and residential choices.

Thus, noting spatial element correlations can improve implicit price estimates. Models must account for the spatial structures of different variables, particularly the land use structures associated with housing and forest recreation environments.

3.2.3 Neighborhood structure and spatial weighting matrix

A weighting matrix W is used to measure spatial autocorrelation. The matrix represents the geographic proximity between observations, specifying the relative position of each observation with respect to the others. Due to the lack of GPS coordinates, all observations belonging to the same IRIS are located (for travel time and neighborhood analyses) at the center of the IRIS. Therefore, distance computations are irrelevant and inaccurate for this database. Administrative zoning or IRIS zoning seems more relevant. Thus, a binary contiguity matrix was used to appropriately reflect the housing market in this study. If two observations are located in the same IRIS, then the binary contiguity matrix value is 1 for these two observations, and it is 0 otherwise.

Spatial autocorrelation was tested using the Moran statistic. The autocorrelation coefficient, known as Moran's I, can be interpreted as the ratio of the covariance between contiguous observations and the total variance of the sample. Moran's I was significantly positive, which confirms the presence of spatial autocorrelation. Thus, neighboring observations are more similar in value than remote observations.

Ordinary Least Squares (OLS) estimators in the model are biased and non-convergent when lagged variables are ignored in the spatial hedonic specification [32]. Similarly, estimators become inconsistent if the model does not consider the spatial dependencies in the error term. Thus, the OLS estimators cannot be used with spatial autocorrelation.

3.2.4 Spatial econometric model: the spatial Durbin model (SDM)

The residuals ε depend on the dependent variable in the SDM model. The structural form is defined as follows:

$$lnP = \rho WlnP + \mathrm{X}\beta + W\mathrm{X}\sigma + \varepsilon \qquad (3)$$

The reduced form is as follows:

$$\mathrm{lnP} = \mathrm{A_n X\beta} + \mathrm{A_n WX\sigma} + \mathrm{A_n \varepsilon}$$
$$\text{with } \mathrm{A_n} = (\mathrm{I_n} - \mathrm{\rho W})^{-1}$$

where W is the spatial weighting matrix and $WlnP\rho$ and $WX\sigma$ are the spatial lag variables of the dependent and exogenous variables, respectively. The model (3) takes into account the spatial correlations of the lagged independent variable and dependent variable.

Spatial error models (SEM) and spatial autocorrelation models (SAR) are special cases of SDM [38]. According to Elhorst [37], the SDM model can be used as a starting point to reject the SAR or SEM models. A SAR model can be used if $\sigma = 0$, or a SEM can be used if $\sigma = -\rho\beta$[5]. A spatial lagged error issue exists in our model; thus, the spatial autoregressive model cannot be rejected. Therefore, the SDM is used. This model is estimated based on the ML. Thus, the model takes into account the presence of omitted variables and similar housing price trends. The SDM model results are presented in Section 4 (see Table 3).

4. Results

We estimated the hedonic functions of two different models. One function represents the proximity to the recreational services of the nearest forest, and the other represents the proximity to the global forest environment. These functions are estimated via a logarithmic regression of the housing price per square meter (in constant euros) based on the other control and interest variables. As described in Section 2, the models include discrete variables without specific transformations and independent variables with logarithmic transformations. The marginal price is the exponent of the coefficient minus one, which is then multiplied by one hundred. The transformation of a variable (see Equation (1)) may produce a negative coefficient, indicating that houses located farther from the global forest environment sell for less. The results of both models are presented in Table 3. The R^2 statistic is approximately 65%. In addition, these estimations require spatial autocorrelation control, which can be described by the “Rho” parameter. The spatial autoregressive parameter “Rho” for the housing price variable is a positive and significant coefficient for both models. Thus, if the average housing price of the closest IRIS to an observation increases by 1%, then the housing price of the observation increases by approximately 0.30%.

[5] “Due to the factor constraint σ=0 the spatial Durbin model simplifies to a spatial lag model while the factor constraint σ=-ρβ simplifies the spatial Durbin model to a spatial error model” [37].

Therefore, the impact of neighboring prices on a transaction is positive. All results for spatial lag explanatory variables are presented in Appendix C.

4.1 Proximity to nearest forest versus global forest environment and recreational services

The results show that housing valuation varies depending on the model.

A 10% increase in the area (in km²) of the nearest forest increases the housing price by 2% in the nearest forest model. The global forest size exhibits a weaker but positive coefficient in the global environment model. A 10% increase in the global forest environment size increases the housing price by 1%. Hence, the larger the forest area, the higher the valuation, suggesting that people value forest environments and prefer larger forested areas in or near their neighborhoods. However, the impact of the nearest forest area is twice that of the global forest environment (with a higher significance: 1% *versus* 5%). Thus, the forest area becomes particularly important if the analysis is restricted to the nearest forest.

The results are different between the two models, despite using the same recreational services. Certain recreational service (leisure areas, hiking and biking paths) parameters are not significant in the nearest forest model. Conversely, the hiking and biking path variable is significant and strongly positive in the global forest model. The presence of sports and recreational facilities increases the housing price by approximately 1%. Leisure areas have a no significant impact on housing prices in either model.

The biodiversity level parameter is negative and significant at 1% for both models. Biodiversity has a negative and significant impact on housing price (the higher the biodiversity level, the lower the forest valuation). Therefore, increased environmental protection is negatively valuated by agents. Biodiversity protection policies may limit or completely restrict access to forest areas (e.g., biological reserves restrict public access). Additionally, Lévêque [38] showed that urban and periurban populations prefer a controlled and domesticated nature rather than a wild nature with substantial biodiversity (e.g., insecurity and hygienic issues related to wild and natural ecosystems).

4.2 Business cycle, housing specifications and other amenities

As expected, differences exist between the estimated control variable parameters from the two models. Table 3 highlights the effects of analyzing variables based on the transaction year. These dummy variables provide information about the effects of business cycles on the housing market. The average price per square meter increased from 1336 euros/m² in 2001 to 2274 euros/m² in 2008, an increase of approximately 40% over 8 years. Thus, the transaction year encompasses inflation and business cycle effects on housing prices. As a consequence, binary variables are used to control this effect in the models. Both models estimated a positive and strongly significant business cycle impact.

The impact of intrinsic housing characteristics is significant for all variables. However, the coefficients of the nearest forest model are systematically higher, as shown in Table 3. The observed price is significantly and positively related to the living area. An elasticity of -0.36 implies that a living area increase of 10% will cause the price/m² to decrease by 3.6%. The housing age has a negative effect on the price, reaching 17.7% or 18.7% (depending on the model) for housing that is more than 5 years old. The dwelling type is also important, as house prices are positively impacted by approximately 16% or 17% compared to apartments. In addition, a garage increases the price by approximately 16% and an extra bathroom increases the price by 21% (with a decreasing marginal effect). These results are consistent with those previously reported in the literature.

Multiple neighborhood characteristic variables are used in this analysis. Based on the literature, we expected these variables to significantly affect property prices. However, supermarkets, bakeries and cultural amenities such as cinemas did not significantly impact housing prices. The location, distance and travel time variables between homes, public structures and employment areas vary according to the structure type. Some structures are perceived as amenities, including high schools and urban green parks, whereas other structures have no significant impact on housing values. Public service amenities (schools, hospitals, etc.) are generally spread throughout *départements* in urban areas. Hence, the presence of such amenities does not affect housing prices. The two models produced different results for the median income variable at the city level. There is a difference between the two models, with the global forest environment estimated to have a negative but non-significant impact on housing prices, whereas the nearest forest is estimated to have a negative and highly significant impact. This result can be explained by the negative relationship between housing price/m² and the living area. The housing price/m² tends to decrease with the median income, as wealthier households live in larger houses.

The travel time to the nearest train station and to Paris *via* public transport positively affects housing prices. A 10 minute increase in the train station travel time decreased the housing price by 0.6% in both models. A 10 minute increase in the travel time to Paris decreased the housing price by 0.6% in the global forest model and 0.8% in the nearest forest model. In contrast, decreasing the travel time required to reach employment areas reduces the housing price. These job locations correspond to major cities within a *département* or neighboring *départements*, suggesting that people do not value proximity to these cities.

Table 3. Housing price estimation results (price/m² in constant euros)

Method of estimation				Maximum Likelihood
Observations				11074
	Global forest environment		Nearby forest	
	Coeff	Std error	Coeff	Std error
R-squared	0,65		0,65	
Constant	9,218***	*0,168*	10,112***	*0,233*
Rho	0,302***	*0,006*	0,302***	*0,006*
Year of transaction				
2001(ref)	0,000		0,000	
2002	0,037	*0,031*	0,029	*0,233*
2003	0,171***	*0,030*	0,119***	*0,030*
2004	0,129***	*0,032*	0,220***	*0,032*
2005	0,339***	*0,031*	0,367***	*0,031*
2006	0,457***	*0,032*	0,423***	*0,032*
2007	0,463***	*0,031*	0,476***	*0,031*
2008	0,438***	*0,031*	0,460***	*0,031*
Housing specifications				
Living area (log)	-0,360***	*0,009*	-0,367***	*0,009*
Housing age (> 5 years)	-0,177***	*0,012*	-0,187***	*0,012*
House	0,157***	*0,009*	0,168***	*0,008*
Number of garage (log)	0,153***	*0,009*	0,159***	*0,009*
Number of bathroom (log)	0,206***	*0,017*	0,222***	*0,017*
Neighborhood characteristics				
Median income (log)	-0,064	*0,030*	-0,128***	*0,027*
Supermarket	-0,031	*0,011*	-0,017	*0,011*
Bakery	-0,018	*0,123*	-0,018	*0,134*
Cinema	0,077	*0,011*	0,061*	*0,006*
Location and amenities				
Travel time to nearby train station	-0,006***	*0,002*	-0,006***	*0,002*
Travel time to Paris by public transport	-0,006***	*0,001*	-0,008***	*0,001*
Travel time to nearest employment area	0,002*	*0,001*	0,002*	*0,001*
Travel time to high school	-0,004*	*0,002*	-0,005**	*0,002*
Travel time to hospital	-0,011***	*0,004*	-0,013***	*0,004*
Travel time to shops	-0,0001	*0,002*	-0,002	*0,002*
Travel time to urban park	-0,007***	*0,001*	-0,006***	*0,001*
Recreational Ecosystem Services				
Forest area (exp(-T))	0,001**	*0,0002*	-	-
Biodiversity pools*Protection index (exp(-T))	-0,006***	*0,002*	-	-
Leisure areas (exp(-T))	-0,029	*0,020*	-	-
Hiking*Biking path (exp(-T))	0,009***	*0,003*	-	-
Forest area	-	-	0,002***	*0,0004*
Biodiversity pools*Protection index	-	-	-0,021***	*0,007*
Leisure areas	-	-	-0,009	*0,031*
Hiking*Biking path	-	-	-0,003	*0,017*

5. Discussion and Conclusion

Various economic methods can be used to determine price estimates. However, the hedonic price method provides a relevant tool for assessing amenity valuations in urban and periurban areas. This method requires a large number of observations, geographic information and spatial econometrics. This study utilizes several original databases, new tools (such as the road network distance computation using GIS software) and a new amenity valuations approach to improve the hedonic estimates.

The majority of the forest recreational services valuation literature only considers the nearest amenity and the direct proximity of the housing to the forest, ignoring a potential preference for diverse forest areas in a neighborhood. This paper contributes to urban amenity valuation and specifically addresses the economic values of recreational activities in forest areas using a global environment approach based on heterogeneous recreational service qualities. Periurban forest areas and associated services are non-homogeneous commodities, which may include protected or unprotected land and public or private forests [19]. People may value proximity to forest areas depending on the recreational services provided by each specific area. Thus, individuals may prefer a diverse forest environment.

We compare the results from the standard nearest amenity approach and an original approach based on a preference for diverse forest areas (and recreational amenities). The hedonic function estimation results confirm the importance of "green and natural" surroundings to local populations. However, the global forest environment model results suggest that diverse recreational services more influence housing prices significantly than forest proximity. Conversely, only the nearest forest model was significantly influenced by a larger forested area. Thus, both models suggest that forests impact local economies and housing prices, particularly close proximity forests. However, the global forest environment results reveal additional preferences, as the recreational services in forest areas positively impact the housing price. This result is not significant in the nearest forest model.

Our study provides land use managers and planners original information regarding how people value the recreational benefits of forests in periurban areas (and in our case, metropolitan areas). This work sheds light on the importance of forest specifications, heterogeneities (diverse services) and global environment preferences (as opposed to only the nearest forest) when evaluating urban population decision making in the case of multi-sites amenity .

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A. Variable statistics

A.1 *Variable statistics*

	Mean	Std Error	Min	Max
Housing characteristics				
Price per square meter (in constant euros)	1826.85	636.99	105.77	9250.03
2001	0.16	9.02	0	1
2002	0.16	9.13	0	1
2003	0.16	9.13	0	1
2004	0.19	9.14	0	1
2005	0.20	9.14	0	1
2006	0.17	9.15	0	1
2007	0.17	9.15	0	1
2008	0.14	9.16	0	1
Housing age (> 5 years)	2.44	3.50	0	10.95
House	0.70	0.46	0	1
Living area (m²)	92	41.24	10	600
Number of garages	0.9	0.6	0	8
Number of bathrooms	1.23	0.5	0	8
Neighborhood characteristics				
Median income (in constant euros)	10882.33	1884.68	5821.06	19136.64
Supermarket	0.38	0.72	0	6
Bakery	0.82	1.67	0	11
Cinema	0.18	0.83	0	11
Travel time to urban amenities				
Travel time to nearby train station (min)	4.68	3.85	0.18	21.89
Traveltime to Paris by train (min)	52.21	14.28	23	90
Travel time to nearest employment area (min)	14.51	8.74	0.01	45.37
Travel time to high school (min)	6.32	4.73	0.05	25.76
Travel time to hospital (min)	2.34	1.85	0.00	11.82
Travel time to shops (min)	3.34	3.7	0.11	22.95
Travel time to urban parks (min)	9.46	6.32	0.17	36.42
Characteristics of natural and forest environment				
Nearby forest model				
Forest area	20.88	49.20	0.014	201.87
Biodiversity pools*Protection index	1.49	1.86	0	7
Leisure areas	0.18	0.38	0	1
Hiking*Biking path	0.69	0.46	0	1
Global forest environment model				
Forest area (exp(-T))	122.01	49.77	25.94	306.08
Biodiversity pools*Protection index (exp(-T))	23.48	6.62	7.02	39.59
Leisure areas (exp(-T))	1.68	0.76	0.27	3.47
Hiking*Biking path (exp(-T))	12.57	3.14	1.29	19.60

A.2 Forest variable statistics

	Average Distance (Km by car)	Average Travel time (min by car)	Average Travel time by walking (min)
Public forest	3.24	2.56	38.88
Std error	*3.4*	*2.7*	*41.3*
Private forest	1.85	1.46	22.2
Std error	*1.78*	*1.41*	*21.4*

	Average area (Km^2)
Public forest	18.57
Private forest	1.59
All forests	3.5

B. Comparison of the global sample and subsample (Student's statistics)

	Mean of global sample	Mean of subsample	T-stats	P-Value
Housing characteristics				
Price per square meter (in constant euros)	1826,85	1816,44	1,549	0,122
2001	0,16	0,12	-0,100	0,920
2002	0,16	0,12	-0,238	0,812
2003	0,16	0,12	-0,332	0,740
2004	0,19	0,14	0,274	0,784
2005	0,20	0,14	0,841	0,400
2006	0,17	0,13	0,291	0,771
2007	0,17	0,13	-0,119	0,906
2008	0,14	0,10	-0,761	0,447
Housing age (> 5 years)	92,00	92,17	-0,687	0,492
House	0,90	0,90	0,367	0,714
Living area (m²)	1,24	1,24	-0,043	0,966
Number of garages	0,91	0,91	-1,718	0,086
Number of bathrooms	0,66	0,66	-0,617	0,537
Neighborhood characteristics				
Median income (in constant euros)	10882,33	10873,83	0,438	0,661
Supermarket	0,38	0,32	0,408	0,683
Bakery	0,82	0,91	0,866	0,386
Cinema	0,18	0,02	0,323	0,347
Travel time to urban amenities				
Travel time to nearby train station (min)	4,68	4,72	-2,321	0,200
Traveltime to Paris by train (min)	52,21	52,52	-2,030	0,062
Travel time to nearest employment area (min)	14,51	14,40	0,227	0,821
Travel time to high school (min)	6,32	6,30	-0,996	0,319
Travel time to hospital (min)	2,34	2,37	-1,718	0,086
Travel time to shops (min)	3,34	3,38	-1,758	0,079
Travel time to urban parks (min)	9,46	9,47	1,830	0,067
Characteristics of natural and forest environment				
Nearby forest model				
Forest area	20,88	20,56	0,654	0,513
Biodiversity pools*Protection index	1,49	1,49	0,195	0,845
Leisure areas	0,18	0,17	0,255	0,255
Hiking*Biking path	0,69	0,68	0,799	0,799
Global forest environment model				
Forest area (exp(-T))	122,01	121,65	0,284	0,776
Biodiversity pools*Protection index (exp(-T))	23,48	23,48	0,183	0,855
Leisure areas (exp(-T))	1,68	1,68	1,731	0,084
Hiking*Biking path (exp(-T))	12,57	12,52	1,513	0,131

C. Spatial lag variable results

	Global forest environment		Nearby forest	
	Coeff	***Std error***	**Coeff**	***Std error***
Year of transaction				
2001(ref)	0,000		0,000	
2002	0,083**	*0,034*	0,086**	*0,033*
2003	0,086***	*0,033*	0,143***	*0,033*
2004	0,306***	*0,034*	0,205***	*0,034*
2005	0,334***	*0,033*	0,300***	*0,033*
2006	0,459***	*0,034*	0,493***	*0,033*
2007	0,583***	*0,033*	0,568***	*0,033*
2008	0,541***	*0,033*	0,516***	*0,033*
Housing specifications				
Living area (log)	-0,357***	*0,011*	-0,369***	*0,011*
Housing age (> 5 years)	-0,210***	*0,016*	-0,257***	*0,016*
House	0,102***	*0,012*	0,117***	*0,012*
Number of garage (log)	0,122***	*0,014*	0,138***	*0,014*
Number of bathroom (log)	0,226***	*0,026*	0,270***	*0,026*
Neighborhood characteristics				
Median income (log)	0,743***	*0,019*	0,796***	*0,027*
Supermarket	0,013	*0,031*	-0,018	*0,031*
Bakery	0,053***	*0,011*	0,050***	*0,011*
Cinema	-0,15	*0,120*	-0,202*	*0,119*
Location and amenities				
Travel time to nearby train station	0,006***	*0,002*	0,005**	*0,002*
Travel time to Paris by public transport	0,003***	*0,001*	0,003***	*0,001*
Travel time to nearest employment area	0,003***	*0,001*	0,003***	*0,001*
Travel time to high school	-0,0002	*0,003*	-0,005**	*0,002*
Travel time to hospital	-0,016***	*0,005*	-0,020***	*0,005*
Travel time to shops	-0,009***	*0,003*	-0,002	*0,003*
Travel time to urban park	0,005***	*0,002*	-0,002	*0,001*
Recreational Ecosystem Services				
Forest area (exp(-T))	0,001***	*0,0002*	-	-
Biodiversity pools*Protection index (exp(-T))	0,0003	*0,002*	-	-
Leisure areas (exp(-T))	0,099***	*0,021*	-	-
Hiking*Biking path (exp(-T))	0,011***	*0,003*	-	-
Forest area	-	-	0,001*	*0,0004*
Biodiversity pools*Protection index	-	-	-0,019**	*0,007*
Leisure areas	-	-	0,018	*0,033*
Hiking*Biking path	-	-	0,062***	*0,019*

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