The landscape from home: a GIS-based hedonic price valuation[1]

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Abstract

We estimate the hedonic price of landscape seen from houses in the urban fringe of Dijon (France). The viewshed and the land cover as seen from the ground are analyzed by geographic methods from satellite images and from a digital elevation model. The landscape attributes are then used in an econometric model based on the sales of 2667 houses, which deals with endogeneity, multicollinearity, and spatial correlations. The results show that woodland and farmland in the immediate vicinity of houses have positive prices and roads a negative price when these features can be seen by an observer located on the ground, while those prices are clearly lower (or insignificant) when such features cannot be seen: the view itself matters. The arrangement of features in fragmented landscapes commands positive hedonic prices. Landscapes and objects seen more than 100–300 m away all have insignificant hedonic prices.

Introduction

Rural scenery, open spaces, forests, and farmland are all components of the lifestyle pursued by many households in most developed countries; this aspiration may contribute to the outward spread of cities into the countryside that has characterized urbanization for several decades now. Accordingly public authorities carefully manage open spaces and green areas in and around cities, and they are mindful of urban sprawl. This paper focuses on "periurban" green landscapes in France, as an amenity for people living there.

Of the various methods of evaluating non-market goods that of hedonic prices is adopted to estimate prices of landscapes in a periurban belt around Dijon, the capital of Burgundy (France), a commonplace rural setting featuring villages and small towns scattered over plains, hills and valleys covered by woodland and farmland. We analyze a landscape as seen "from within" instead of "from above" by taking account of objects and relief which may hide the view from the ground. In this way, the view from "home" can be reconstituted in a three-dimensional space. A hedonic estimation is then derived from data for 2667 house sales, by a model that deals with endogenous regressors and spatial correlation between the residuals.

The remainder of the paper is arranged into five parts. After a review of the literature (section 1), the economic and geographic models are set out along with the data (section 2); then come the results (section 3) and the discussion (section 4). Section 5 concludes.

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1. Landscape valuation

Landscape valuation employs stated preference methods (contingent valuation, choice experiment, etc.) and revealed preference methods (mainly hedonic pricing). Here the hedonic price method has been selected because adequate data is available. This is the method favored, then, in the brief state-of-the art review that follows.

Preference analysis from photographs. Photographs have long been used to analyze, by regression methods, a mark awarded to landscapes by a panel. The explanatory variables are objective attributes (objects, land use, visual arrangement, etc.), subjective attributes (mystery, atmosphere, etc.), and sometimes personal characteristics (social category, gender, age). Much of this work is old. Back in 1989 Gobster and Chenoweth [15] listed more than 80 references and recorded 1194 terms for describing esthetic preferences. For example, marks for photographs in the Great Lakes region (U.S.) are explained by physical, ground cover, "informational" (order, complexity, mystery, etc.), and perceptual (open, smooth, easy to cross) variables [23]. Recent research has been conducted in the same vein. For example, Johnston et al. [21] use maps and photographs of alternative developments to show that households choose fragmented, long and narrow housing subdivisions when density is low, but opt for more clustered forms for denser subdivisions.

Economic value of landscape seen from above. Land use within a certain radius around a house as seen from satellite or aerial photographs is used for landscape valuation. In most but not all cases positive hedonic prices are obtained for wooded land cover [24], particularly on woodland adjacent to the residential lot [37], and for nearby recreational forests [38] as well as, of course, for parkland, golf courses or greenbelts. Farmland has a less clear-cut impact with some studies concluding it has a positive effect on real-estate values [32] but others reporting either opposite [11] or insignificant effects [31]. Other contradictory, uncertain or unstable findings can be quoted. The legal status of land is sometimes included into the hedonic equation either because it affects expectations about subsequent development [19] or because the possibility of going into these areas for walks depends on that status [8].

Real-estate values generally decrease with the distance to a green area, a golf course, a forest park [38], a stretch of water [36] or to wetlands [28]. This effect is sometimes non-linear [5]. The proximity of open or green spaces has a substantial effect on prices when the distance is zero or very short (a few tens of meters), but the effect falls off rapidly with distance, and disappears beyond a few hundred meters at most. For example, Thorsnes [37] shows that housing with direct access to forests is worth 20–25% more and that this extra value vanishes if there is a road to cross to get to the forest. Therefore, the researchers must take into account precise features of the landscape and the exact locations of observers and objects alike.

Landscape ecology provides variables (seen from above) for characterizing the shape of patches formed by different types of land use: synthetic indexes (diversity, fragmentation, entropy, etc.), geometric variables (fractal dimension), or statistical summaries. For example, Geoghegan et al. [13] show that fragmentation and diversity of landscape have negative effects on real-estate values, except where very close and very far from Washington D.C.

Economic value of landscape seen from within. The view from the ground ("from within" as opposed to "from above") entails integrating the third dimension (i.e. relief and any tall objects) into the two-dimensional satellite image. This view, which is the actual view, has only recently been introduced into economic valuation models of which there are few as yet.

Firstly, Germino et al. [14] analyzed the landscape from satellite images and a digital elevation model to simulate a view, and Bastian et al. [3] used such variables to estimate hedonic prices of landscape. They concluded that in the Rocky Mountains (U.S.) landscape diversity, the only landscape variable that is significant, is highly appreciated. Second, Paterson and Boyle [31] compare a rural region of Connecticut (U.S.) seen from within and from above. The sign of their results varies with the specification and in particular contrasts the view from above and the view from within and the viewshed and its content. Some of these results are disappointing; for example, the hedonic price of the viewshed is negative (if alone) or insignificant (with the land cover) but then forests acquire a negative price. Lastly, Lake et al. [25] estimate the price of road noise and view in the urban area of Glasgow (Scotland). The viewshed was identified by a burdensome method (systematic visits to measure building heights). The findings show that the view of a road reduces the real-estate price, except from the backyard.

To sum up, whatever the method, findings are sometimes counterintuitive: unexpected signs, and insignificant or volatile values are sometimes reported. Now, it is acknowledged that people value open space and green landscape so the unstable results are paradoxical: why is the estimated value of green and open spaces surrounding houses not invariably positive? It is hard to say whether such fragile results reflect reality or derive from the coarseness of landscape variables. This unsatisfactory state-of-the-art prompts re-investigation of the matter. This is what is attempted in this paper using new geographical methods.

2. Geographical and economic models, study region, and data

2.1 Rosen's hedonic method

In evaluating the hedonic prices of the characteristics of houses, the first stage of the approach à la Rosen [33] is used. Its microeconomic foundations are well known, and thus they are reviewed succinctly here. A household k, with socio-economic characteristics α_k, maximizes a utility function $U = U(Z, H, \alpha_k)$ by consuming housing $H(x_1, ..., x_h)$, comprising a set of intrinsic (floor space, comfort, etc.) and extrinsic (accessibility, social or environmental quality of the location, etc.) attributes, x_h, and a composite good Z, taken as the numéraire, under the budget constraint $W_k = P(H) + Z$, where W_k is income and $P(H)$ the house price. The first order conditions of the standard microeconomic program give the hedonic price p_h of characteristic x_h, equal to the marginal rate of substitution of this characteristic for the composite good:

$$\frac{\partial}{\partial x_h} P(H) = \frac{\partial U / \partial x_h}{dU / \partial Z} = p_h \tag{1}$$

This price is a marginal price, from which neither a price for a quantity clearly different from x_h, nor a consumer's willingness to pay (WTP) can be derived, because the budget constraint is not linear and because sorting according to the characteristics of the buyers occurs on the market [34]. Nevertheless, this shadow price is an interesting finding, because it is extracted from the actual market. Among the econometric issues that the hedonic method raises, endogeneity, spatial correlation and multicollinearity are detailed in Section 2.4, (see also a detailed and recent presentation in [19])[2], after the presentation of the study region (Section 2.2) and the geographical model used to define the landscape variables (Section 2.3).

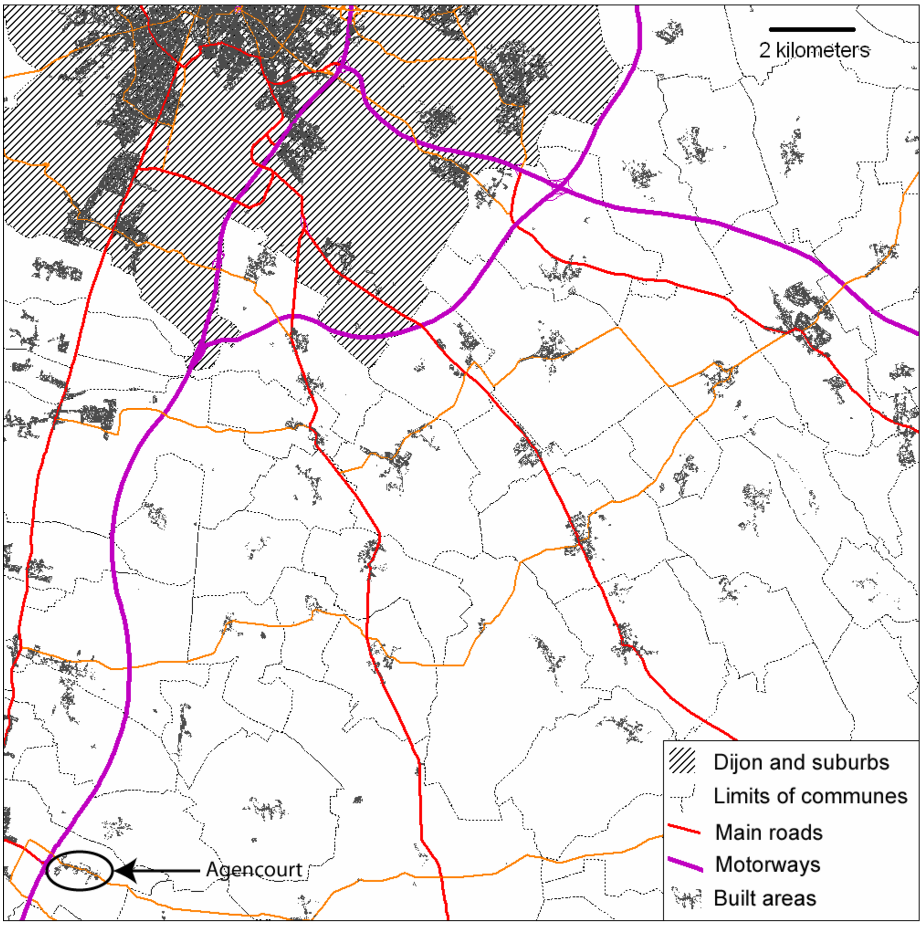
[2] The identification of the demand functions by Rosen's second stage is another issue not developed here because we cannot perform this stage: it assumes the provision of hedonic prices evaluated on different markets [7], which are not available for our single study area. Unfortunately, without this second stage the demand parameters cannot be estimated [34].

2.2 The study region

The study region is a periurban belt around Dijon (France). Its inner bound is the city of Dijon and its suburbs (250,000 inhabitants), which has been excluded from the study region because it would be difficult to apply our method of landscape analysis. Its outer bound is given by access time to Dijon of less than 33 minutes or a distance by road of less than 42 km (these limits were chosen by first fixing a threshold of commuters higher than 40%, and then rounding by adding some interspersed rural communes). The study region covers 3534 km² and includes 140,703 inhabitants. It is composed of 266 *communes* (a *commune* is the lowest tier of local government in France), with a mean population of 461 inhabitants (median: 229, standard deviation: 733). Built areas cover 2.4% of the land, farmland 59%, and woodland and natural formations 38%.

The settlement pattern of the region needs to be presented because the econometric model suits this situation. Figure 1 shows the south-east part of the study region (other quadrants are similar). Each village or small town is a densely populated cluster (population density is 1153 inhabitants per square kilometer[3]), isolated from its neighbors by broad expanses of farmland or woodland, where population density is close to zero, so that the mean population density of the study region is 41 inhabitants per square kilometer. Clearly, two different scales coexist: in a village, dwellings are tightly clustered, separated by just tens or a few hundreds of meters, but villages are separated by several kilometers.

Figure 1. South-east part of the study region



[3] Density is the ratio of population to the area of the village polygon, made of buildings (houses, public buildings, industrial or commercial facilities), streets and roads, open and green spaces (private and public gardens, squares, etc.).

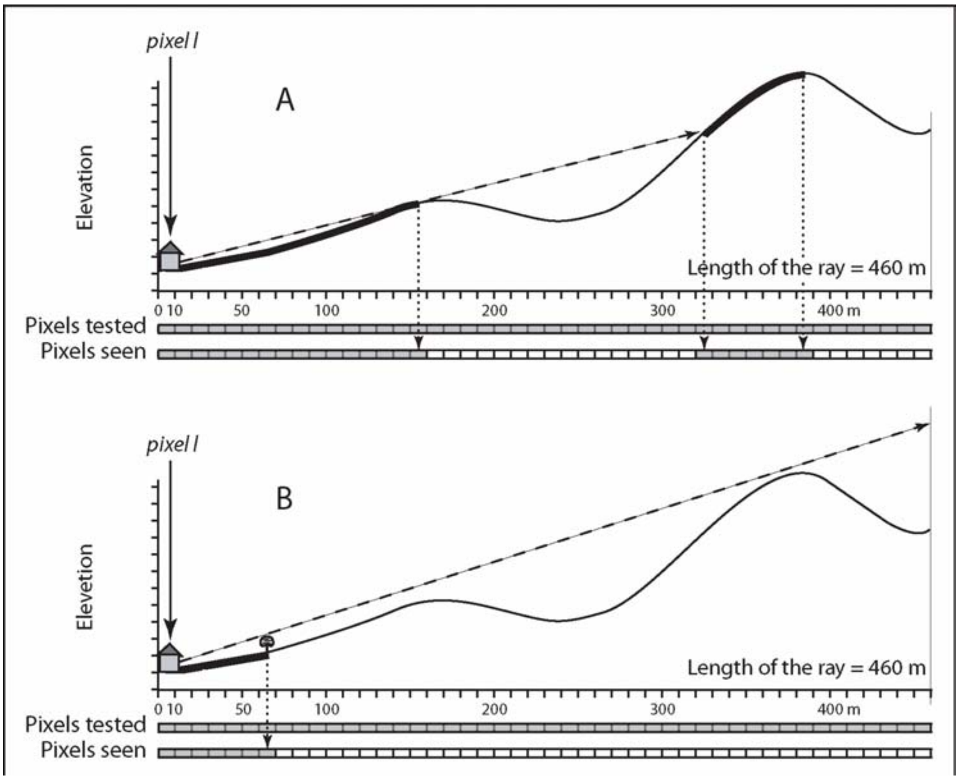
Moreover, each village may exhibit different features from the surrounding villages: from one commune to the next there are variations in population levels, household income, local public policy (tax, land zoning, etc.), and so on. Indeed, villages are local jurisdictions managed by local authorities, which are self-governing with regard to local policies, so that sharp differences often occur between neighboring communes. Of course, other characteristics vary smoothly in space, such as commuting distance from Dijon, where most jobs are located. A fixed-effect model, with a dummy variable associated to each commune, suits well to this geography.

2.3 A GIS-based geographic model of quantitative analysis of landscape

A landscape is a portion of space before one's eyes. Its quantification is based on its extent and content, which are here analyzed through a GIS-based model. The first factor depends both on the relief and the objects that may mask the view, whereas the second factor depends on the type of visible objects. The viewshed is measured by looking outward through 360 degrees: 120 rays (spaced at 3 degree intervals) are extended from each point in all directions and tests are conducted along the rays for each pixel encountered (a pixel is the smallest geographic object identified, here a square with 7 m sides). Depending on the relief and the type of object encountered, the area visible along the ray is determined (see Figure 2). Then, the number of pixels of each type in this area is calculated. Each point is also characterized by the longitude and latitude into a French system of Cartesian coordinates (the "Lambert" system), and the real-estate transactions are georeferenced in this system.

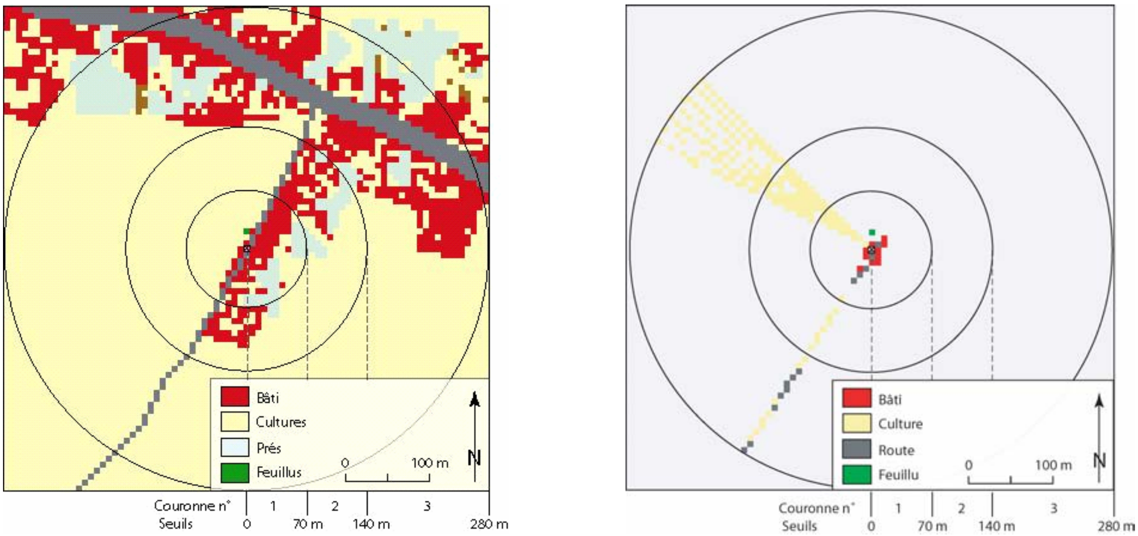
From the foregoing data, we model for each pixel the land use as seen from a satellite (from above) in concentric rings, and the landscape as seen at ground level (more exactly at a height of 1.80 m). Figure 3-A (from above) and 3-B (at ground level) provides the illustration for the village of Agencourt, located in the bottom-left corner of Figure 1.

Figure 2. Viewshed without and with objects hiding the view



In Figure 2-A, the view extends up to 155 m from the observer located at pixel ***l****; then it is cut by a hill between 155 and 325 m. The second hill is viewed between 325 and 385 m. In Figure 2-B, the tree 65 m from the observer masks the view beyond.*

Figure 3. Viewshed from the satellite (A) and from the ground (B)



(A) (B)

The results show that only 18% of the pixels visible from above are seen from within (the mean is 8.9%). However, it is important to notice that the model analyzes the view from a single pixel, the one where the real-estate transaction was georeferenced.[4] The actual viewshed from the residence is larger, because the observer can walk all around its residential lot, which extends on average over 15–20 pixels.

To analyze the "views" of landscapes defined in this way, a land use layer, which localizes and identifies objects, is combined with a digital elevation model, which models the topography and architecture of the space. First, data sources on land use, described by [22], are made up of images from two satellites: Landstat 7 ETM (30 m and 15 m spatial resolution) and IRS 1 (Indian Remote Sensing, images at 5.6 m spatial resolution). The model is based on the state of the landscape as it was at the time the satellites passed overhead (between June and September 2000). Thus it ignores agents' expectations about landscape changes.[5] Images were then processed by standard procedures in remote sensing science to correct their geometry, merge the two satellite images and classify the pixels (See Appendix B). Ultimately, 12 types of land use were identified: water, conifers, deciduous trees (these two are aggregated into woodland), crops, meadows, vineyards (these three are aggregated into agriculture), bushes, roads, railroads (these two are aggregated into networks), built areas, quarries, and trading estates. Some objects are ascribed a fixed height imposing a visual mask: 15 m for deciduous trees, 20 m for conifers, 3 m for bushes, 1 m for vineyards and 7 m for houses.[6] The other types (water, roads, railroads, fields) have zero height. Second, the digital elevation model provides altitudes to the nearest 0.1 meter for points 50 meters apart on the ground. It is dilated so it can be superimposed on the 7 m-resolution land-use image, and then the altitude of each pixel is determined by interpolation.

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[4] The margin of error of georeferencing being greater than one pixel, we checked that if the analyzed pixel is moved by 7 m or 14 m the econometric results are largely unchanged (the change becomes important with a move of 35 m).

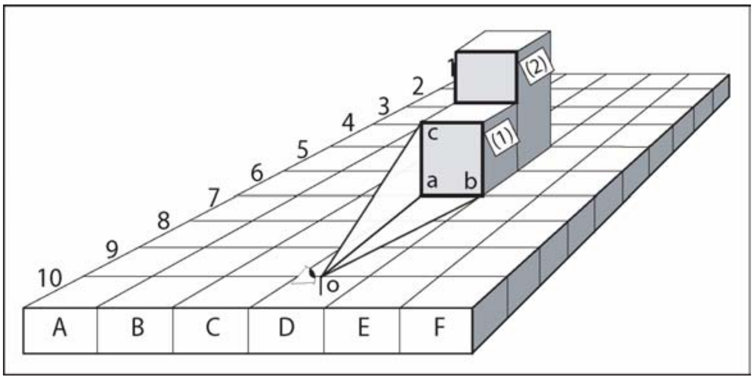
[5] The European database Corine Land Cover provides two comparable satellite images in 1990 and 2000, from which the land use change between the two dates can be calculated. In the study region, the polygons including all the 'urban' land uses (i.e. houses and private gardens, streets, public buildings and public open/green spaces) increased by 1.3% during the decade (the annual rate of growth was 0.00144). It is a sufficiently slow movement to assume that people cannot anticipate change. Even so, in some local situations, substantial changes may occur and may be foreseen by households. Some of these situations are taken into account by an interaction variable (see below) and the others are integrated into the residuals.

[6] The model may be sensitive to the height of the houses, which are the most common type of object blocking the view. They are mainly single-family detached houses without upper storeys: by assuming a standard height we make only a small error. We tested the effect of the chosen height (from 5 m to 9 m) on the econometric results; they are stable between 6 m and 9 m.

To take into account the depth of the viewshed, six buffers are distinguished: less than 70 meters from the observer, 70–140 m, 140–280 m, 280–1200 m, 1.2–6 km, and 6–40 km. In the latter, some types of objects do not exist (e.g. a road cannot be seen far off) and others are aggregated (e.g. bushes are included in forests). The viewshed perspective is taken into account by these distance buffers, from the next-door scenery to the remote skyline on the horizon.

Unfortunately, this method introduces multicollinearity between buffers and objects. That is why we also introduce an alternative method: we merge the six buffers into only one by measuring solid angles (or angular areas) for each type of object. As Figure 4 illustrates, the method consists in drawing a conic figure whose the observer's eye O is a vertex, and the visible section of an object is the base (i.e. the square with A, B, and C as three of its vertexes).

Figure 4. Solid angles



The solid angle measures the apparent size of an object by the "piece of the sky" that it shades [3b, 31b]. It is measured in steradian (sr), which is a geometric transformation of an angular area, such as the product of the angles AOB and AOC. The size of the solid angle depends both on the size of the objet and the distance from the observer.[7] This calculus is made of each visible pixels (as (1) and (2) in Figure 4), between 0 and 40 kilometers (particular trigonometrical rules are used for flat and sloping objets).

Solid angles reduce multicollinearity between buffers, but they have some drawbacks: (i) the landscape organization in successive planes disappears, (ii) findings are less intuitive (the steradian is not an usual unit of measure!) and (iii) multicollinearity of other type appears (the solid angle constituted by buildings is negatively correlated with the other ones). Therefore, we use this unit of measure as additional method, to compare the findings of two different geographical methods, and to deal with different collinearity (not between planes of vision, but between built-up pixels and other objects).

2.4 Economic model

We start with an econometric model that directly follows from the equation à la Rosen (1):

$$\ln P_i = X_i b + \varepsilon_i , \qquad (2)$$

[7] For example, a square house located at 7 m from an observer, which is seven meters high and occupies a square pixel of 7 m, forms a 45°*45°=2025 square degrees, or 0.4 sr. The same house located at 70 m from the observer forms a solid angle of 0.06 sr.

where P_i is the price of real-estate i, X_i the matrix of explanatory variables (including an intercept), b the vector of parameters to be evaluated, and ε_i an error term. We examines in turn: the links between variables x_is of X_i and the error ε_i, then spatial links inducing spatial correlation between neighbor residuals, and finally multicollinearity between regressors.

2.4.1 Endogeneity

The non-linearity of an attribute price (p_h in equation (1) is not a constant) may lead the consumer to choose both the price of housing and the quantity of this attribute at the same time, making the corresponding explanatory variable endogenous [9, 10]; for example, households simultaneously choose the price of the house and its living space (actually, living space is almost always endogenous in hedonic studies). Landscape variables may also be linked with the error either for the same reason (i.e. simultaneous choice) or because the market determines both the l.h.s. and some r.h.s. variables of the equation (2). For example, if urban pressure is high, residential values are high and thus open spaces are scarce and small; conversely, the quantity of open space determines residential prices through the land capitalization mechanism.

To deal with endogenous regressor(s) **the instrumental variable method** (IV) is used here. Hedonic theory shows that sorting of buyers and/or sellers on the market suggests using personal features of the agents as instruments do deal with endogenous housing attributes in the first stage (and with endogenous hedonic prices in the second stage; see [9], [10], [34]).[8] Other instruments are needed for landscape variables that may be endogenous ([19], [20]), chosen by the same rationale: exogenous variables linked with the potentially endogenous variables. The IV method requires an estimation of the main equation by the 2SLS. Statistical tests, presented below, are used to check endogeneity of the regressors and exogeneity of the instruments. We also present ordinary least squares (OLS) findings, although this method is rejected by the tests.[9]

2.4.2 Spatial correlations

It may be that for a spatialized good such as housing there are spatial links between explained/explanatory variables and the errors, which are generally taken into account by introducing a spatial autoregressive variable, or spatially lagged explanatory variables, or by modeling spatial correlations between the residuals in a spatial error model. For example, Brasington and Hite [6] use an auto-regressive term and spatially lagged explanatory variables. Irwin [19] and Geoghegan et al. [12] deal with the two problems of endogenous regressors and of spatial effects in estimating the hedonic price of green spaces. For example, Irwin, following [18], “creates a randomly drawn subset of the data in which nearest neighbour observations are dropped” [19: 474].

Here a different solution is applied to this problem by using a variable characterizing each commune, for two reasons:

- First, a distance-decay function between neighboring houses neither fits because distance is two-scaled (remember Figure 1), nor does a contiguity matrix function (some features change sharply from one village to the next depending on their size, local policies,

[8] Agents with certain characteristics buy certain quantities differing from other quantities bought by agents with other characteristics (e.g. large families buy large dwellings while single people buy studio apartments). The quantity of the attribute is thus correlated with family and agent’s characteristics (age, gender, qualifications, occupation, etc.). An exogenous regressor is obtained by projecting the endogenous variable on these exogenous instruments.

[9] The IV method is sensitive to the choice of the instruments: we can verify if the results are similar with IV and OLS methods.

geographic location). As said, observations in a commune share many characteristics not found in the database, etc., and they have equal access to markets for labor, goods, and services; they also share miscellaneous amenities, nuisances, and externalities.

- Secondly, we must deal with both an endogenous variable (namely: the living space) and spatial correlation. The living space may be endogenous as it is often the case in hedonic models, and it depends on spatial effects: distance from the CBD, population of the commune, etc. (moreover, the living space is the most influential variable in the model). Now, Irwin [18] shows that it is particularly difficult to deal with endogeneity in a spatial-lag model or a spatial error model.

To take into account these features, we transform (2) by introducing into the equation m_j, a variable characterizing the commune j:

$$\ln P_{ij} = X_{ij}b + m_j + \varepsilon_{ij} \tag{3}$$

The m_js capture all the characteristics shared by the observations located in each commune, including badly measured or omitted variables. Thus, there are no inter-commune correlations between the residuals. The variables m_js may be either dummies variables in a **fixed-effect model** ($m_j = I_j$), or random variables in a **mixed model** ($m_j = \varepsilon_j$), where I_j is a fixed dummy variable and ε_j a random intercept characterizing the commune j. The two models are used, because they present different advantages and disadvantages.

The fixed-effect model is the best to deal with omitted or poorly measured variables shared by observations in a commune. Nevertheless, it does not take into account inter-commune effects (e.g.: luxuriant woodland in some communes and rare in others), because these effects are captured by the I_js. Note that, for the variables used in the regressions, inter-commune standard deviations are about half the strength of intra-commune standard deviations (see Table A-1 in Appendix A). Intra-commune heterogeneity is therefore marked compared with the relative inter-commune homogeneity, suggesting that our estimators capture a large share of variance.

The mixed model uses a random intercept for each commune and three additional explanatory variables: distance to Dijon, population, and mean household income in the commune (it should also include other variables: school quality, etc.). This model allows taking into account inter-commune effects, particularly inter-commune changes in the landscape variables. Though, it has two drawbacks. First, it is econometrically very difficult, and out of the scope of this paper, to deal simultaneously with endogenous variables, spatial autocorrelations between the residuals and random intercepts. As Section 3 will show, we find nearby parameters for the landscape variables estimated by the OLS or the IV method; therefore we do not consider endogeneity of the living space in the mixed model. Second, this model would involve a high risk of bias, as an example shows. The proportion of forests in the land use increases with distance from Dijon; if distance were wrongly measured (e.g.: congestion, or travel time, or time opportunity cost badly evaluated), this measurement error would bias the woodland parameter. In the fixed-effect model, distance from Dijon is the same for all the houses of a commune and it is captured by the dummy I_j: a measurement error does not matter.

As a result, omitted variables or badly measured variables may entail correlation between explanatory variables and the communes' random intercepts in the mixed model. Moreover, they may entail spatial autocorrelation to occur between disturbances in different communes. To deal with these inter-commune autocorrelations, we follow Snijders and Bosker [35a: 199] and Littell *et al*. [25a: 303-330]: spatial autocorrelation between the disturbances of transactions taking place in communes j and s, $j \neq s$, is specified at the level of the individual transactions, as $\mathrm{cov}(\varepsilon_{ij}, \varepsilon_{rs}) = \sigma^2 \rho^{x_{js}}$, where σ^2 and ρ are random parameters to be estimated and x_{js} is the Euclidian distance between any two communes j and s.[10] Concurrently with this specification, we assume $\mathrm{cov}(\varepsilon_j, \varepsilon_s) = 0$.

Due to the limits of the mixed model, we had less confidence in its findings: we prefer the fixed-effect model, estimated by the 2SLS. Nonetheless, the mixed-model is also used, to check effects of inter-commune landscape variables and to compare the results by the two approaches.

Spatial links may also exist both in the fixed-effect model and in the mixed model, due to the location of the houses in the commune: central or peripheral situation, closeness to hazardous plants, etc. To reduce this problem, we introduce into the equation: (i) the distance from each transaction to the town hall (usually located at the center of the town or village), (ii) the situation vis-à-vis the zoning scheme, (iii) the location in zones liable to flooding. Nevertheless, other intra-commune links may exist, due to omitted variables (e.g.: hazardous plants): spatial correlation may remain between the residuals of observations located in the same commune. To check this possibility, a Moran's index between the neighbors ε_{ij} is computed, using a contiguity matrix where observations less than 200 m apart are neighbors.[11] Then, the significance of this index is tested. As we will see, it is insignificant.

2.4.3 Multicollinearity

It is easy to deal with some types of multicollinearity between regressors by transforming one of them to reduce or cut out the statistical link. In other cases, such as landscape variables, it is more difficult. Figure 2-A provides an illustration: the types of land uses are correlated, for three reasons: (i) complementarity, such as between roads and houses; (ii) dominant uses, such as farmland occupying the main part of an alluvial plain and limiting the space available for other uses; (iii) similar land uses entailing the presence of the same objects in adjacent buffers.

Figure 2-B suggests that the view from the ground reduces these statistical links, because the view is blocked by houses (elsewhere it may be trees, the relief, etc.). Houses, placed more or less randomly on the ground, break the regular arrangement of objects, by blocking the view in a quasi-random way. As a result, correlations are lower between objects viewed from the ground than from above. For example, the correlation between the rate of built-up and road land uses in the buffer 280-1200 m is 0.86 and it is only 0.10 when these objects are seen from the ground. This property is important for the econometric model: we chose the view from the ground because it is the actual view, and this choice entails a pleasant statistical property by reducing strongly multicollinearity.

Nevertheless, multicollinearity between certain regressors may subsist, which was managed as follow: (i) when a landscape variable exhibited a high correlation in two adjacent buffers and gave close parameters in the regression, the two buffers were merged; (ii) when the parameters were distinctly different one of the two correlated variables was transformed. By this method, we gather farmland and built-up pixels seen between 70 and 280 m, transport networks seen less than 280 m and the "green" land uses (farmland, woodland, and bushes)

[10] The distance is calculated from centre to centre of the communes. When j=s, the covariance between the disturbances becomes σ^2.

[11] The distance of 200 m between two houses is the threshold used in France to define urban morphology. Distance cut-off of 50 m and 100 m were also used, conducing to the same result: Moran's indexes are insignificant.

beyond 1.2 km. We introduced variables in share (i.e. percentage) for: farmland seen less than 70 m; woodland seen in the 70-280 m range; bushes and built pixels (seen between 70-280 m and 280-1200 m); and finally transport networks in the 280-1200 m range.

2.4.4 Statistical tests

The statistical tests were carried out as follows:

(i) Hausman's method is used to test whether variables are endogenous: first, a potentially endogenous variable is regressed on instruments (the residuals are written $\hat{\eta}$) and the equation of interest (in short: $Y = X\beta + \varepsilon$) is estimated by the 2SLS. The equation of interest is then modified by including $\hat{\eta}$: $Y = X\beta + \hat{\eta}\delta + \varepsilon$ (*increased regression*). If δ is statistically insignificant, the null hypothesis ($\mathrm{cov}(x,\varepsilon) = 0$) cannot be rejected.

(ii) Sargan's method is used to test the validity of the instruments. The residuals of the *increased regression* are regressed on the instruments (by OLS). Instruments whose coefficients are statistically different from zero are non-valid and eliminated. Sargan's test provides a statistic based on the χ^2 distribution to determine whether the instruments taken as a whole are valid.

(iii) A Moran's index between neighbors residuals (less than 200 m apart) is calculated and its significance is tested (the result shows that it is insignificant).

(iv) The homoscedasticity of the residuals is submitted to White's test.

2.5 Data and variables

The economic data come from real-estate lawyers (*notaires*), who are responsible for registering real-estate conveyances in France. The database is made up of 2757 sales of detached houses between 1995 and 2002, and records the price of the transaction and some characteristics of the property and the economic agents involved. Some 90 observations were excluded (atypical observations, shortcomings of the data base, etc.): evaluations were made from 2667 observations. The variables used in the regressions are defined in Table 1.

Note there are few property characteristics in the database (the type of heating, building materials, thermal insulation, etc. are unknown). Three variables, closely correlated with the living space (lot size, number of rooms and of bathrooms), were transformed into lot size/living space, average room size (also included in quadratic form), and number of bathrooms/living space. New houses resold before 5 years benefit from a reduced tax, which is captured by a dummy variable. Some of the variables in the database were excluded because of insignificant parameters (presence of outbuildings, parking spaces, cellars, lofts, terraces or balconies). Other variables characterize the transaction (type of operator, type of the previous transaction, house occupied or not either by the buyer or the seller, remoteness of the buyer's previous residence), the precise location of the real estate (proximity from a highway, location both in the zoning scheme and a floodable zone, distance from the town hall), and the topography of the parcel (slope, orientation, steep-sidedness).

This database also includes variables used as instruments, used in the instrumental equation: the gender, occupation, age, marital status, and nationality of the buyer and the seller. Other instruments were used to project landscape attributes that may be endogenous (namely: wood-covered and agricultural pixels that are closely located): slope, sun radiance, relative deepness, and orientation of the pixels.

The landscape variables are made up of land uses, according to the six distance buffers. Land uses are weighed up by number of seen pixels and unseen pixels (i.e. the difference between pixels seen from above and from within). As said, some variables in adjacent buffers are merged. Interaction variables are introduced between lot size and both woodland and agriculture (descriptive statistics show correlations between these land uses and lot size) and between agriculture and developable areas of the land zoning (to take into account households' expectations about development). Unseen pixels that are not introduced into the equations are the reference for the landscape variables. They are mainly made of pixels located beyond 1.2 km from the observer. Solid angles are used in a specific regression.

Lastly, landscape indices, currently used in landscape ecology, provide information about landscape composition and shape. They were calculated on land use images in 12 classes in a 70 m radius circle, for the view from above only. The computations were applied in the same way using Fragstats software [26], [27], with a new programming routine focused on transaction points to save calculation time. Appendix C presents some of them chosen among the numerous ones present in the literature [17], and their effect in the econometric regression. We selected the most significant by a forward stepwise method.

Table 1. Variables

ABBREVIATION	DEFINITION
LSPACE	Living space (m²) (logarithm)
LOT/LSPACE	lot size (m²) / living space (m²)
ROOMSIZE	average room size = living space / number of main rooms
(ROOMSIZE)²	average room size: square form
STORIES	number of stories in the house (included habitable attic or basement)
BATHROOMS	number of bathrooms / living space
ATTIC	presence of an attic
PERIOD OF CONSTRUCTION	period of construction: before 1850; 1850-1916; 1917-1949; 1950-1969 (reference); 1970-1980; 1981-1991; 1992-2002; unknown
LESS 5 YEARS	building constructed since less than 5 years, and reselled
BASEMENT	presence of a basement
AN1995 to AN2002	date of conveyance: dummies from 1995 to 2001 (2002 = reference)
PRIVATE	transaction without real estate offce (directly between private individuals)
SALE OFFICE	transaction by a real estate office
LAWYER OFFICE	transaction by a real estate lawyer office
BUYER OCC	property already occupied by the buyer
SELLER OCC	property already occupied by the seller
DIST BUYER	distance between the house and the buyer's location (logarithm)
FRENCH	buyer of French nationality
SUCC	previous transaction = succession
DIVISON	previous transaction = division of estate
NORMAL SALE	previous transaction = normal sale
100_200_ROAD	100-200 m from a major road
POS-UD	zone UD of the zoning scheme, i.e. located on periphery of the village
MIXED ZONE	mixed zone of the zoning scheme: residential and business zone
DIST TOWN HALL	distance from the town hall
SOUTH	south orientation of the parcel
FLOODING	liable to flooding
STEEP	steep sidedness
POPULATION	Population of the commune
DISTANCE DIJON	Distance from Dijon
(DISTANCE DIJON)²	Distance from Dijon: square form
INCOME	Household's commune mean income

Table 1 (continued)

Landscape variables:	**according to distance buffers: < 70 m, 70-140 m, 140-280 m 280-1200 m, 280-1200 m, 1.2-6 km, 6-40 km Pixels SEEN and UNSEEN are distinguished**
ABBREVIATION	**DEFINITION**
WOODLAND	number of pixels of wooded area (R_WOODLAND: rate of these pixels)
WOODLAND * LOT/LSPACE	number of pixels of wooded area * LOT/LSPACE
AGRI	number of pixels of agriculture (R_AGRI: rate of these pixels)
AGRI * LOT/LSPACE	number of pixels of agriculture * LOT/LSPACE
AGRI * POSUD	number of pixels of agriculture * class UD of the zoning scheme
NETWORK	number of pixels of road/railroad (R_NETWORKS: rate of these pixels)
BUILT	number of built pixels (R_BUILT: rate of these pixels)
BUSH	number of pixels of bush (R_BUSH: rate of these pixels)
WATER	number of pixels of water
DECID_PACHES	number of patches of deciduous trees within a 70 m radius
DECID_EDGE	length of deciduous wood edges within a 70 m radius (m)
AGRI_PACHES	number of patches of crops betwen 70 - 140 m
COMPACT	compactess index (0=compact forms; 1=elongate forms), < 70 m
BUILT ANGLE AREA	angle area made by built pixels (square degrees)
AGRI ANGLE AREA	angle area made by pixels of agriculture (square degrees)
WOODLAND ANGLE	angle area made by wooded pixels (square degrees)
BUSH ANGLE AREA	angle area made by pixels of bushes (square degrees)
NETWORK ANGLE	angle area made by pixels of roads and railroads (square degrees)
WATER ANGLE	angle area made by pixels of water (square degrees)

3 Results

3.1 Descriptive statistics

Table A-1 appended gives some descriptive statistics about the variables used in the model. The 2667 transactions are divided among 235 districts, averaging 11.3. The narrowness of the viewshed should be emphasized. The median area viewed from the pixel of observation is 1813 m². For 26.7% of the sample, the view is confined to the adjacent pixels; from the pixel at the third quartile of the distribution, one can see 21,420 m²; it exceeds 1 ha in 31.2% of cases and is 1 km² in 7.8%. The main reason for this restricted view is masking by buildings that are almost always only a few tens of meters apart.

In the immediate vicinity, that is less than 70 m from a house, people almost always see other buildings (500 m² on average in this buffer), trees from 36% of them (average tree-covered area is 370 m² if non zero), and open areas, fields or meadows, from 69% in the 70 m circle (2620 m² on average) and from 43% in the 70-280 m crown (1.6 ha on average). Roads are seen in the first 280 m from 44% of observations (1745 m² on average).

Table A-2 (See Appendix A) shows Pearson's correlation coefficients between the landscape variables used in the regressions (interaction variables are excluded, and values higher than 0.4 are emphasized in bold). Excepted for the variables of landscape ecology, whose large correlations had yet been underlined, five correlations higher than 0.4 remain, of which one reaches 0.71. The regressions have been made after cutting one member of these pairs, to verify that the estimated parameters were little changed.

Finally, Table A-3 shows the correlations between solid angles. Built solid angle is correlated (negatively) to three other ones (woodland, farmland and bushes).

3.2 Overall results: variables by distance buffers

Table 2 shows the results (See legend in table 1) obtained from the landscape variables ranked by buffers, estimated by the fixed-effect models, using either the OLS (column 1) or the IV method (column 2), and by the mixed model (column 3).

In the fixed-effect model, the adjusted R^2 is equal to 0.79 by the OLS and to 0.70 by the IV method; the -2 Log Likelihood is equal to -671.4 in the mixed model. The living space is endogenous (Student's t in the increased regression is –14.2) and Sargan's test shows there are no other endogenous variables. Moran's index between neighbor residuals is insignificant (threshold level: 28.1%) and White's test shows that the residuals are homoscedastic.

The results are briefly presented here and some of them, emphasized in bold, are discussed in section 4. The first finding is that, unlike in other studies [e.g. 19, 20], **landscape attributes are not endogenous**. As said, woodland and agriculture endogeneity were tested by specific instruments, using the IV method; Student's *t*s of the residuals in the increased regression (See Section 2.4.4) are insignificant: 1.4 (woodland seen at less than 70 m) and – 0.2 (agriculture seen between 70 and 280 m).

Table 2. Results: distance buffers

	(1)	(2)	(3)	(continued)	(1)	(2)	(3)
	fixed-effect		Mixed		fixed-effect		Mixed
	OLS	2SLS			OLS	2SLS	
INTERCEPT	12.18***	11.89***	12.50***	AN1998	-0.1963***	-0.1723***	-0.1956***
LSPACE	0.0070***	0.0126***	0.0069***	AN1999	-0.1296***	-0.1212***	-0.1326***
LOT/LSPACE	0.0180***	0.0169***	0.0167***	AN2000	-0.046*	-0.0369	-0.0410**
ROOMSIZE	-7.1E-4	-0.0175***	-0.0012	AN2001	0.0098	0.0118	0.00639
(ROOMSIZE)²	-8.2E-5	3.4E-5	-7.0E-5	AN2002	reference	reference	reference
STORIES	-0.0199**	-0.1349***	-0.0159*	SELLER OCC	0.0775***	0.0443***	0.0740***
BATHROOMS	2.943**	18.508***	2.639**	BUYER OCC	-0.1641***	-0.1653***	-0.1688***
ATTIC	0.0594***	0.1108***	0.0526***	DIST BUYER	0.0081***	0.0064***	0.00764***
BASEMENT	0.0652***	0.0428***	0.0690***	FRENCH	0.0691*	0.0997**	0.0366
PERIOD OF CONSTR.				PRIVATE	-0.0070	-0.0114	-0.0088
BEFORE 1850	-0.0848***	-0.0948***	-0.0832***	SALE OFFICE	0.0349***	0.0256*	0.0353***
1850-1916	-0.0646***	-0.0580***	-0.0628***	LAWYER OFFICE	reference	reference	reference
1917-1949	-0.0790***	-0.05288**	-0.0875***	SUCC	-0.0553***	-0.0391***	-0.0589***
1950-1969	reference	reference	reference	DIVISION	-0.0553***	-0.0583**	-0.0509***
1970-1980	0.0522***	0.017	0.0523***	NORMAL SALE	reference	reference	reference
1981-1991	0.0714***	0.0546***	0.0712***	100_200_ROAD	-0.0337	-0.0735***	-0.0430**
1992-2002	0.0596**	0.0104	0.0565**	POS-UD	-0.0374***	-0.0398***	-0.0230**
UNKNOWN	0.0222	0.0229	0.0204	MIXED ZONE	-0.0520**	-0.0642**	-0.0331
LESS5 YEARS	-0.0672**	-0.0451	-0.0613**	DIST TOWN HALL	-2.9E-5**	-4.0E-5***	-.0E-52
AN1995	-0.2725***	-0.2540***	-0.2694***	SOUTH	2.0E-4	0.00042**	4.5E-5
AN1996	-0.2171***	-0.1936***	-0.2158***	FLOODING	-0.0117	-0.0208	-0.0223
AN1997	-0.2287***	-0.2069***	-0.2305***	STEEP	1.5E-5	-7.E-5	-2.0E-5

Level of significance : *** 1%; ** 5%; * 10%,

Table 2. Results: distance buffers (continued)

	Distance Buffer	(1)	(2)	(3)	
		fixed-effect		Mixed	
		OLS	2SLS	dist.Dijon	
WOODLAND SEEN	< 70m	0.0053***	0.0057***	CLOSE	0.0031
				FAR	0.0073***
WOODLAND SEEN*LOT/LSPACE	< 70m	-1.42E-4	-1.7E-4		-1.5E-4*
WOODLAND UNSEEN	< 70m	0.0014***	0.0017***	CLOSE	0.0015***
				FAR	0.0008*
WOODLAND UNSEEN*LOT/LSPACE		-5.8E-5***	-6.0E-5***		-4.0E-5***
R_WOODLAND SEEN	70-140m	-3.0E-4	0.0010		0.00815
WOODLAND SEEN	140-280m	-0.0013***	-0.0007		-0.0011**
R-BUSHES SEEN	< 70m	0.0493	0.0264		0.040
R-BUSHES SEEN	70-140m	0.1642*	0.2448**		0.1351*
R-BUSHES SEEN	140-280m	-0.0021	0.0854		-0.0122
R_AGRI SEEN	< 70m	0.0281	-0.0130		0.0131
R_AGRI UNSEEN	< 70m	0.0015	0.00043		9.4E-4
AGRI SEEN	70-280m	1.23E-4***	1.7E-4***	CLOSE	0.0001***
				FAR	0.00012***
AGRI SEEN * LOT/LSPACE	70-280m	-0.0061***	-0.0064***		-0.0057***
AGRI SEEN * POSUD	70-280m	-2.4E-5	-5.0E-5*		-3.0E-5
AGRI UNSEEN	70-280m	4.0E-5***	3.6E-5***	CLOSE	3.5E-5***
				FAR	3.5E-5***
AGRI UNSEEN * LOT/LSPACE	70-280m	4.0E-5***	-0.0020**		-0.0023***
AGRI+WOODLAND SEEN	0.28-40km	3.9E-5	2.5E-5		5.1E-5
BUILT SEEN	< 70m	0.0015	0.00206		0.00128
R_BUILT SEN	70-280m	0.0014	-0.0018		0.00126
R_BUILT SEEN	0.28-1.2km	0.0172	0.00471		0.0356
NETWORKS SEEN	0-280m	-2.4E-4**	-0.0003**	CLOSE	-0.0004**
				FAR	-0.0003*
NETWORKS UNSEEN	0-280m	7.1E-5	4.5E-5	CLOSE	2.0E-5
				FAR	0.00011**
R_NETWORKS SEEN	0.28-1.2km	-0.1754	-0.2478		-0.159
WATER SEEN	0-40km	-0.0257	-0.0417**		-0.0324**
DECID_EDGE	< 70m	-3.2E-4***	-0.0005***		-0.0004***
DECID_PACHES	< 70m	0.0095***	0.0109***		0.0118***
AGRI_PACHES	< 70m	0.0022***	0.0025***		0.00172***
COMPACT	< 70m	0.1584	0.2313*		0.1507
POPULATION					2.6E-5***
DISTANCE FROM DIJON					-0.0551***
(DISTANCE FROM DIJON)²					0.00086***
INCOME					0.00002***

Level of significance : *** 1%; ** 5%; * 10%, The significance, sign and magnitude of the parameters estimated either by the fixed-effect model (MCO) or the mixed model are similar, except four of them. The differences are more numerous with the fixed-effect model (2SLS) regarding the characteristics of the house and of the transaction (area of the rooms, date of construction, etc.). Regarding the landscape variables, the signs are always the same whatever the model, and the significance at the 5% level is slightly different only for 4 variables (woodland seen in the range 140-280 m, share of bushes seen in the range 70-140 m, water, and compactness index).

A large number of inter-commune effects were tested with the mixed model: woodland, farmland, roads or built-up pixels seen according distance from Dijon, either continuous or dichotomous variable (closer or further than the median), or the share of these variables in the area of each commune, either continuous or dichotomous variable (sparser or more abundant than the median). The inter-commune effect significantly differs in two cases: transport networks seen less than 280 m and woodland seen less than 70 m. Any other inter-commune variable that was tested is insignificant. This is coherent with the weak inter-commune variance, which is always lower than the intra-commune one.

As said, we believe that the findings of the mixed model are less reliable than those of the fixed-effect model estimated by the 2SLS. Thus, we comment afterwards mainly the results of the latter.

The parameters evaluated for non-landscape variables (property, transaction and location attributes) are consistent with other French studies. Interestingly, two land zoning variables are significant: house prices are lower for locations either in mixed residential and business zones, or in zones at the periphery of the villages (i.e. zones UC and UD of the zoning scheme). Moreover, the prices are lower at the periphery of the towns or villages than close to the town hall.

For landscape attributes, table 2 shows that most objects located more than 70 m away have insignificant hedonic prices. Farmland, where it is the view between 70 and 280 m that matters and transport networks that are significant up to 280 m are the exceptions. Water is also significant whatever the distance (with a surprising negative parameter), but very few observations are involved. The hedonic price of other types of land use is insignificant beyond 70 m. A dummy variable indicating whether the different ranges beyond 70 m were seen or not was also tested, or a quantitative variable indicating the area viewed in those ranges when it was non zero. The results show that these variables are all insignificant. **It is as if households were short-sighted**. This indifference to the view of spaces beyond a few tens of meters, and in particular to open views with distant ranges, is a counterintuitive result.

3.3 Land uses: variables according to the distance buffers

<u>**Woodland**</u>. At the mean point of the residential lot, wooded areas in the first 70 m have a significantly positive hedonic price: the price of a house increases by 3% per additional standard deviation). Moreover, **the actual view of forests counts**, being valued more highly than their mere presence when they are not visible in this radius, where the price increases only by 0.2% per an additional pixel. The latter is the value of nearby groves, woods or forests for recreational (walking areas), protective (against noise), and ecological (air quality, fauna and flora, etc.) functions, but not for scenery seen from home, which is three times higher than unseen pixels.

The shape of areas covered by deciduous trees (landscape ecology indexes were not calculated for conifers, which are few) also exerts significant effects on house prices, which are added to the foregoing. An additional patch of this type within a 70 m radius has a positive contribution, which is 1.4% of the house price and conversely 100 additional meters of boundary of deciduous trees have a negative effect (-0.5%). The combination of these two variables gives an indication of the shapes valued: numerous patches with short edges correspond to rounded copses and not to massed forests or long and thin formations.

Surprisingly, the parameter of woodland seen at less than 70 m is higher in the periphery of the study area, and it is insignificant close to Dijon. One should think that its price was higher in this inner belt, due to its scarcity close to the city. Nevertheless, when woodland is present but unseen its value is higher close to Dijon: wooded surroundings are dearer close the city than in the periphery of the zone, where the parameter is barely significant at the 10% level.

Lastly, in fields of view more than 70 m away, tree-covered formations have insignificant prices, confirming the myopia of households.

Farmland. Farmland seen at less than 70 m has an insignificant parameter, but crops and meadows seen between 70 and 280 m from houses have a positive effect on the price of the house: 6.6% per standard deviation. It transpires from comparison with woodland that **the hedonic price of farmland seen is positive at distances somewhat greater than for trees**, although it remains confined to a radius of 300 m or so. This is consistent with other results [35], [21]. Farmland that is present but not seen within a 70–280 m radius commands a positive price, but only a fifth of that of farmland that is seen, confirming the importance of the view itself. The distance from Dijon has no effect on these parameters.

The interaction parameters between lot size and the area of both farmland seen and woodland seen are negative, showing that **agriculture and wooded areas in view are less valued when the lot size is large**, and conversely.[12] Moreover, we find a slight negative interaction between the area of farmland seen in the 70–280 m range and the location in a developable zone of the zoning scheme (POSU zones) (significant at the 12% level): **the view of farmland is slightly less valued when residences locate in a developable zone**. This result is consistent with others that show that the hedonic price includes expectations about a risk of conversion [4], [35]; nevertheless, it is a fragile result, because it is weakly significant and the same relation in the 70 m radius is insignificant. Interestingly, **the interaction parameter between developable zones and forest is insignificant**.

Transportation networks. Roads (and railroad tracks) in view at less than 280 m lower the price of a house by 1.3% per standard deviation. Networks within this radius but not in view have an insignificant price: it is less the presence of the road that is a nuisance when it is not seen (although it is a source of danger, air pollution, and noise) than the actual sight of it as it is a visual obstruction. This result is consistent with that for wooded and agricultural areas: **the presence of an object counts less than whether or not it can be seen**. Beyond the first 280 m, the sight of roads no longer significantly affects house prices, indicating that such nuisances remain confined to a narrow strip.[13] Transport networks seen in the 280 m circle have a parameter clearly more negative close to Dijon, where these networks are dense and crowded, than at the periphery of the region, where roads unseen but present in this circle have a positive sign (probably because they are correlated with omitted public goods variables).

[12] Remember that, with the fixed-effect model, the set of commune dummies capture commuting distance to Dijon, population, etc. and that location at the center or on the periphery of the villages is taken into account by the class "UD" of the zoning scheme and the distance from the town hall.

[13] A location close to a freeway or a major road is also a nuisance compounding that of the view. To reduce correlations between variables, we introduced into the equation both networks seen at less than 140 m and location in a strip 100–200 m from a freeway or a major road, which reduces the price by 7.8%.

Other land uses. Buildings are the most common land use close to housing. Its hedonic price is insignificant whatever the distance. Two opposite effects might explain this finding: on the one hand, close houses allow social relation with neighbors, and on the other hand the view of these structures may be less appreciated than green land uses. The parameter of bushes seen is insignificant (except in the 70-280 m range, with a positive sign), which can be explained by the heterogeneity of this type of land use (coppices, fallow land, groves, recent planting, etc.). Finally, the sight of rivers or lakes has a negative significant sign. It is not due to flooding risk (zones liable to flooding are controlled in the equation). This result is opposite to the usual finding of the literature; however it is based on a small number of observations.

Landscape composition variables (see also Appendix C) were introduced into the regression by a stepwise method, and four indices were kept: the number of patches of deciduous trees and their length within a 70 m radius (as said), a compactness index ranging from 0 (compact forms) to 1 (elongate forms), and the number of patches of farmland located in the 70–280 m range. For 1% of additional "elongation", the price rises by 0.23%, and by 0.2% per additional patch of farmland. The results, for the combination used here as for other indicators taken separately (Appendix C), show that **division, complexity, non-contiguity, landscape fragmentation, mosaic patterns, etc. have positive hedonic prices**.

3.4 Solid angles

Table 3 shows the solid angle results. To save space, only the landscape variables are kept in the Table; the variables characterizing the house, the transaction, and the location are the same that in Table 2. Solid angles unseen and the sky are the reference.

Table 3. Results: solid angles

	(1)	(2)	(3)
	fixed-effect		Mixed
	OLS	2SLS	
WOODLAND SEEN	0.2707***	0.2677**	0.2897***
(WOODLAND SEEN)²	-0.0093	-0.0141**	-0.0124**
WOODLAND SEEN*LOT/LSPACE	-0.0098***	-0.0093***	-0.0087***
AGRI SEEN	3.634***	2.5259*	1.9953
(AGRI SEEN)²	-2.594*	-1.5940	-0.9521
AGRI SEEN * LOT/LSPACE	-0.2492***	-0.2160***	-0.2007***
AGRI SEEN * POSUD	0.2746	0.2433	0.1625
BUSHES SEEN	0.1340	-0.2957	0.0176
(BUSHES SEEN)²	0.0812	0.2263	0.1517
BUILT SEEN	-0.0001	-0.0029	0.0550
NETWORKS	-1.878**	-1.6918*	-1.995**
WATER	2.765	-1.2531	0.0610
INDUSTRIAL ZONES	0.0330	0.0076	0.0571
POPULATION			0.0004***
DISTANCE FROM DIJON			-0.5076***
INCOME			0.0003***

Level of significance : *** 1%; ** 5%; * 10%,

Unit of measure: 10^4 sr

The main difference from the model with the buffer variables is the introduction of significant quadratic forms in several cases. When the quantity of a landscape type is measured by a solid angle, a saturation effect appears. It is particularly important with woodland: it is well known that in the vicinity of too many trees the viewshed is confined or closed; it is intelligible that this entails a depreciation of the real-estate.

In the comments of these results, we privilege as before the fixed-effect model estimated by the 2SLS. With this model, at the average point, the price of a house increases by 4.6% per standard deviation of woodland, by 3% per standard deviation of farmland (significant at the 10% level); it decreases by 1% by standard deviation more of roads. Water, bushes and buildings are insignificant. The interactions between woodland or farmland and the lot size are significant and have the same negative sign that with the variables according to the distance buffers.

All in all, these results are coherent with the previous ones. Now, the solid angle variables are calculated from a very different geographical model (even if the data are the same), and multicollinearity is different from that of the buffer distance model. The consistency of the results obtained by these two very different methods shows that they are robust.

Moreover, the findings obtained from the view from above are also coherent with the other estimations (See Table D-1 in Appendix D). Some differences can be noted. By the fixed-effect model and the IV method, the transport networks seen from above are insignificant, contrary when they are seen from the ground. But we noted that they were insignificant when unseen from the ground. Now, only 5.5% of the networks present less than 280 are seen: it is not surprising that this variable was insignificant when seen from above. Regarding the other variables, the sights from above and from the ground provide similar results, in spite of multicollinearity.

4 Discussion

4.1 General comments

The main advantage of our geographic model is that it can be used to calculate landscape variables from any of the 144 million pixels of the study region. The econometric model can thus be extended to new transactions if the economic data base is broadened. It is also possible to map results, as the following example shows. The price of a marginal loss of viewshed, due for example to new building obstructing 10% of the view, can be calculated at any point. Hedonic prices evaluated for each landscape attribute are used to calculate the price of this marginal loss of landscape, which is equal to the sum of the quantities weighted by prices. Figure 5 shows the result in Agencourt and the surrounding towns and villages.[14]

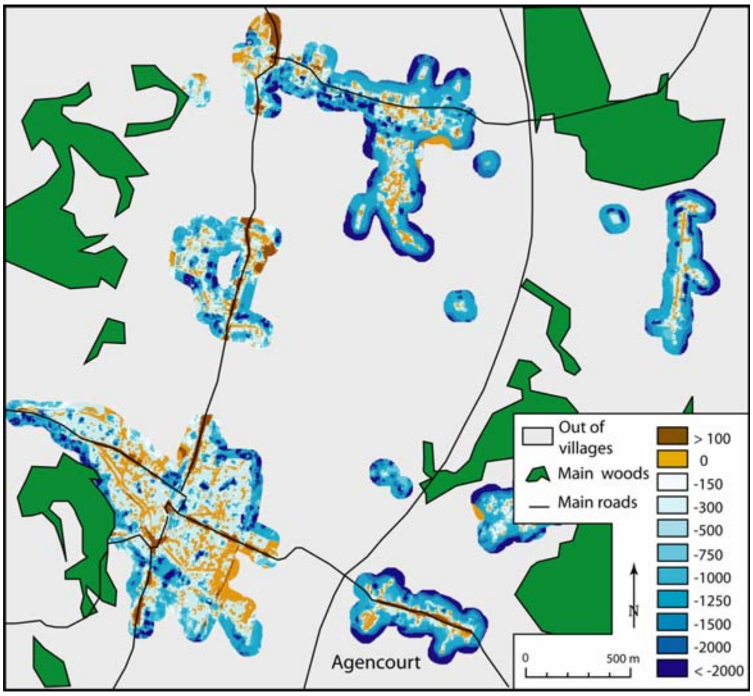
Obstruction of 10% of the viewshed entails a loss of value on the outskirts of villages, where the view is primarily of fields and woodland: sometimes €2000 or more (1.5-2% of the house price). It has a positive price where new building masks roads, for example in the centre of Nuits-Saint-Georges, the town at the West of Agencourt.

The main shortcoming of this geographic model is that it yields results which are approximations of the real situations and which may be biased if certain assumptions are inaccurate. Landscape variables, if poorly measured, would be endogenous and the estimated parameters would be biased. In particular, our model may underestimate the area seen by exaggerating the amount masked by buildings. As said, the narrowness of this area seen is real, especially as it is the view from a single pixel and not the view from the entire residential

[14] Only the built pixels and a 200 m buffer around the villages are analyzed as it would be absurd to calculate the price of loss of view from a house located in the middle of a field or a forest.

lot. However, the results for landscape variables are not called into question by this problem. Even if it was the view from above that prevailed, we have checked that one would obtain parameters that would remain significant at the 1 or 5% levels with the same signs. The model is therefore fairly robust to the measure of the viewshed (see also Footnote 4).

Figure 5. The price of an obstruction of 10% of the viewshed in and around Agencourt



The great advantage of the fixed-effect econometric model is that it takes into account all the factors depending on the distance from Dijon. Almost all the regressors, including those for landscapes, vary with this urban–rural gradient and the co-variations are almost impossible to take into account without the fixed-effect model. Thus, the mixed model is less reliable; its results are closely related to the fixed-effect one, and they show that the regional variability of landscape parameters is weak.

The main drawback of the model is one of identification problems. Whatever the precautions taken to avoid the effects of omitted variables or of multicollinearity, the method cannot guarantee freedom from bias related to these problems. This limitation must be accepted when dealing with real world observations, where the requirement that all else is equal cannot be met.

4.2 Public policies and markets

Landscapes are shaped by public policies. Significant landscape variables, mainly woodland and farmland, are not econometrically endogenous, meaning, in economic terms, that households do not simultaneously choose the quantities of these goods and the price of the housing and that the same market forces do not determine prices and these quantities. On the contrary, in the US results show that such variables are endogenous [e.g. 19, 20]. The difference probably arises from land use in France under more stringent public control than in the US, limiting market forces. Woodland is particularly well protected from any change in land use by a specific regulation requiring authorization for any forest clearance.[15]

[15] The Corine Land Cover European data base shows that, in the study region, no forest was converted to built land in the period 1990–2000 and that 64 ha out of 133,000 ha of forests were changed into communication networks.

It is the same in other European countries. For example, in the U.K. planning and land use are subject to the Town and Country Planning Act which has remained essentially unchanged since 1947 and "applying for planning permission often proves to be a lengthy, and very costly, process" [29]. In the Netherlands, for the last forty years, most building has taken place on land supplied by municipalities. This is quite unique for a market economy. This gives great control to the planning authorities [30].

Agricultural and forestry subsidies. French farmers long objected to being described as "nature's gardeners". They now promote their role in maintaining landscape and even want to be rewarded for it. One of the reasons for this change is the World Trade Organization talks: the Europeans argue that such aid does not distort competition. Our findings illuminate this debate in two ways.

First, the hedonic price of 100 m² of farmland seen within a radius of 70–280 m (that is €43) is less than 3% of that of 100 m² of woodland seen within a 70 m radius (€1460). And yet, public aid per 100 m² of forest is €0.28 and for farmland €3.86 [1], which is almost 14 times more. Admittedly, aid for farming is not justified by its landscape conservation role alone (it is also a matter of income support for farmers and so of maintaining employment, etc.). Nevertheless, the contrast is striking.

Secondly, public aid for farming is weakly related to the location of farmland relative to housing, or even totally unrelated in most cases, while households place a positive value on farmland only when it is very close to housing: a mere fraction of public support to farmland can be justified by its residential landscape value.[16] True, farming and forestry have other non-market functions, especially recreational (forest walks, tourist region landscapes), ecological and cultural functions, etc. However, local policies for enhancing villages and their immediate vicinity are justified by what we have termed "household myopia". Landscaping of public areas in villages, planting within the built environment, encouraging inhabitants to landscape their private gardens, etc. are "green" goods close to housing which command higher values than more remote farmland.

Agricultural policies and landscape shapes. The results for shape and landscape composition indices point in the same direction as the foregoing ones: over several decades, the re-parceling of farmland has formed large plots with simple geometric shapes to facilitate work with farm machinery, hedges have been torn up and tracks plowed up to enlarge production areas while crop rotations have been simplified. Forests have undergone comparable although less extensive change: same-age plantations on vast plots tend to replace coppices of different ages and varieties, with the same objective of increased productivity. The resulting landscapes are more uniform and made up of large contiguous patches. Now, the composition indexes we have introduced show that it is contrasted landscape forms that command high values: mosaics, small elongated patches, fragmentation and partitioning. There is a clear contrast between landscapes arising from the productive function of farming (and forestry) and landscapes valued for the non-market functions of these activities.

4.3 Consumer behavior

Short-sightedness. The indifference to the view of spaces beyond a few tens of meters, in particular to open views with distant ranges can be explained by the characteristics of the study zone, where distant horizons, when seen, are not formed by outstanding features, emblematic buildings, sea, or snow-capped lines of mountains, etc.; on the contrary they are

[16] By our calculations, the area within 200 m of the built pixels represents 23,000 hectares, or some 6.8% of the 3534 km² of the study region.

bluish-grayish in color, making them hard to distinguish against the skyline. However, it may be thought that these results are valid more widely than for just the Dijon area, because similar commonplace rural scenery is encountered in most parts of France.

Consumer demand for green landscape and for residential space. The interaction between both farmland/woodland and residential lot size indicates that the larger the lot size, the lower the marginal price of seen farmland or woodland. There may be a substitution relationship between green landscape and lot size, which cannot be estimated here because the consumer's demand function is unknown. If it is the case, green landscapes have a land-saving function in that they limit residential land uses.

Expectations. Due to population growth in the study region, farmland may be converted to urban uses, entailing the loss of the agricultural amenity. As said, taken as a whole the movement is weak (See Footnote 6), but it occurs mainly in the "U" category of the zone schemes, i.e. areas reserved for future urbanization. The significant and negative interaction AGRI*POSU (Table 1) shows that the hedonic value of farmland seen in the 70–280 m range is lower in these zones than elsewhere. The same result does not hold for the view of wooded pixels: their price is the same whether the zone is developable or not. The difference stems from the probability of conversion that, as said, is close to zero for forests.

5 Conclusions

A hedonic price model has been combined here with a GIS-based geographic model to evaluate the price of landscapes seen from houses in the urban fringe of Dijon (France). The geographic model is used to identify, with a resolution of 7 m, 12 types of land use from satellite images and to measure, by trigonometry, the viewshed taking into account the relief and obstacles that may block the view (houses, trees). The view of the landscape is quantified, in terms of viewshed and of the type of objects seen and unseen. The econometric model is the first stage of Rosen's approach, estimated from 2667 sales, which takes into account endogeneity by the instrumental method and spatial correlations by either a fixed-effect or a mixed model.

The results show, first, that it is above all the view of the tens of meters around a house which counts; beyond that distance, a few attributes remain significant up to 150–300 m, but no farther. Second, tree-covered formations have positive hedonic prices, as does farmland, while roads have negative prices. Thirdly, it is the view that influences the real-estate price and not the mere presence of certain types of land use: tree-covered areas or farmland close to a house but not visible from it have far lower hedonic prices than when they are seen, and nearby roads unseen have an insignificant hedonic price. Fourth, landscape shape indexes show that households prefer complex, fragmented shapes and mosaic patterns of scenery.

However, our method is reductive because it simplifies in the extreme what a landscape is and evaluates only use values related to residential consumption. The point that in spite of these limitations it yields significant results is encouraging. However, we are aware that other methods are also required to enhance knowledge in this difficult domain of the economic valuation of landscapes.

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Appendix A: descriptive statistics

Table A-1. Descriptive statistics

Number of observations	2667
Number of districts	235

Variable	Mean	Std	Variable	Mean	Std
LSPACE (ln m²)	110.7	34.13	YEAR1999	0.1631	0.3695
LOTSIZE (m²)	1027	1003	YEAR2000	0.1721	0.3775
ROOMSIZE (m²)	23.16	6.227	YEAR2001	0.1623	0.3688
STORIES (number)	1.636	0.5689	YEAR2002	0,05137	0,2208
BATH (number)	1,23	0,45	SELLER OCC	0.5991	0.4901
ATTIC	0.0483	0.2145	BUYER OCC	0.0210	0.1434
BASEMENT	0.3457	0.4756	DISTBUYER	8.3866	3.722
PERIOD OF			FRENCH	0.9868	0.1138
Before 1850	0.1124	0.3160	PRIVATE	0.2084	0.4062
1851-1916	0.1601	0.3667	SALE OFFICE	0.4372	0.4961
1917-1949	0.0757	0.2646	LAWYER OFFICE	0.0599	0.2375
1950-1969	0.0914	0.2883	SUCC	0.1496	0.3567
1970-1980	0.2268	0.4188	DIVISION	0.0446	0.2065
1981-1991	0.2084	0.4062	NORMAL SALE		
1992-2002	0.0704	0.2560	100-200M_ROAD	0.0896	0.2856
unknown	0.0543	0.2267	POS-UD	0.3254	0.4686
LESS 5 YEARS	0.0464	0.2105	MIXED ZONE	0.0547	0.2275
YEAR1995	0.0757	0.2646	DIST TOWN HALL	489.2	482.6
YEAR1996	0.0929	0.2904	SOUTH	83.66	30.30
YEAR1997	0.1301	0.3364	FLOOD	0.0704	0.2560
YEAR1998	0.1522	0.3593	STEEP	-92.79	228.2

(continued)

Variable	Buffer	Number of houses with the attribute	Value for houses with the attribute			
			mean	total std	intra-std	inter-std
Woodland seen	<70m	953	7.52	5.79	5.15	3.39
Woodland seen*lot size	<70m	953	98.68	154.0	131.2	64.25
Woodland unseen	<70m	1447	23.01	32.26	27.74	17.72
Woodland unseen*lot size	<70m	1447	299.8	914.5	819.2	389.7
Rate of woodland seen	70-140m	891	0.3279	0.3758	0.3335	0.1472
Woodland seen	140-280m	841	11.17	17.34	13.45	8.925
Rate of bushes seen	<70m	1176	0.1079	0.1727	0.1598	0.0434
Rate of bushes seen	70-140m	627	0.0571	0.0904	0.0832	0.0222
Rate of bushes seen	140-280m	461	0.0461	0.0814	0.0709	0.0277
Rate of farmland seen	<70m	1839	0.5073	0.2807	0.2485	0.1722
Rate of farmland unseen	<70m	2667	0.2740	0.1496	0.1267	0.0796
Farmland seen	70-280m	1160	322.6	441.0	387.5	195.7
Farmland seen*lot size	70-280m	1160	5.133	12.792	11.480	4.7102
Farmland seen*posU	70-280m	603	293.7	403.8	358.9	161.4
Farmland unseen	70-280m	2667	2614.8	780.32	550.6	552.9
Farmland unseen*lot size	70-280m	2667	26.19	27.60	22.99	15.27
Farmland+woodland seen	> 280m	814	96.35	161.93	146.9	53.04
Built seen	<70m	2494	10.87	5.059	4.606	2.446
Rate of built seen	70-140m	1000	0.1233	0.161	0.1502	0.0414
Rate of built seen	140-280m	231	0.1525	0.2219	0.2024	0.0349
Network transport seen	0-280m	1164	35.597	62.98	55.59	22.89
Network transport unseen	0-280m	2657	257.8	168.3	125.9	111.7
Rate of network transport se	> 280m	212	0.0390	0.0550	0.0509	0.0099
Water seen	0-40km	267	1	0	0.1842	0.1842
Decid_edge	<70m	1499	139.3	126.6	100.8	91.37
Decid_paches	<70m	1509	4.120	3.412	2.446	2.784
Agri_paches	<70m	2667	19.48	9.647	6.794	6.849
Compact	<70m	2667	0.6105	0.0408	0.0377	0.0158

Landscape variables	foret1	foret1_nv	txforet2	foret3	txbuiss1	txbuiss2	txbuiss3	txagri1	txagri1_nv	agri23	agri23_nv	vert_tot456	bati1	txbati23	txbati4	reso123	reso123_nv	txreso4	eau_vu	lisfeuil1	tachfeuil1	tachcult	compact
foret1	1,00																						
foret1_nv	***0,56***	1,00																					
txforet2	0,31	0,20	1,00																				
foret3	0,25	0,02	0,04	1,00																			
txbuiss1	0,12	0,09	0,11	0,00	1,00																		
txbuiss2	0,16	0,04	0,05	0,14	0,04	1,00																	
txbuiss3	0,18	0,01	0,03	0,21	0,01	0,14	1,00																
txagri1	0,19	-0,08	-0,01	0,31	-0,06	0,19	0,20	1,00															
txagri1_nv	-0,27	-0,03	-0,16	-0,23	0,05	-0,14	-0,12	***-0,56***	1,00														
agri23	-0,01	-0,11	-0,14	0,22	-0,10	-0,04	0,00	***0,60***	-0,34	1,00													
agri23_nv	-0,03	-0,16	-0,10	-0,04	0,00	0,02	0,03	0,21	0,22	0,03	1,00												
vert_tot456	-0,02	-0,08	-0,09	0,12	-0,07	-0,02	0,01	***0,41***	-0,23	***0,71***	0,04	1,00											
bati1	-0,31	-0,33	0,05	-0,11	-0,24	-0,01	-0,04	0,03	-0,22	-0,16	0,04	-0,11	1,00										
txbati23	0,04	-0,05	-0,02	0,00	0,02	0,20	0,02	0,20	-0,20	-0,10	0,03	-0,07	0,24	1,00									
txbati4	0,00	-0,05	-0,05	0,01	-0,03	-0,01	0,00	0,16	-0,11	0,15	0,03	0,02	0,07	0,03	1,00								
reso123	0,03	-0,06	-0,05	0,17	-0,08	0,01	0,00	0,07	-0,27	0,30	-0,07	0,19	0,20	0,03	0,18	1,00							
reso123_nv	-0,08	-0,05	0,00	-0,10	-0,02	0,01	-0,07	-0,22	-0,04	-0,21	-0,36	-0,15	0,08	0,04	-0,05	0,04	1,00						
txreso4	-0,05	-0,06	-0,05	0,01	-0,03	-0,01	0,05	0,15	-0,12	0,20	0,04	0,17	0,06	-0,03	0,10	0,20	-0,01	1,00					
eau_vu	0,16	0,01	-0,03	0,18	-0,03	0,02	0,03	0,30	-0,24	0,27	0,05	0,19	0,02	-0,01	0,10	0,11	-0,10	0,08	1,00				
lisfeuil1	***0,74***	***0,79***	0,29	0,13	0,13	0,12	0,10	-0,04	-0,07	-0,13	-0,12	-0,10	-0,37	-0,04	-0,05	-0,07	-0,03	-0,07	0,02	1,00			
tachfeuil1	***0,61***	***0,49***	0,32	0,18	0,14	0,12	0,12	-0,08	-0,04	-0,14	-0,09	-0,11	-0,30	-0,04	-0,06	-0,06	-0,02	-0,07	-0,03	***0,83***	1,00		
tachcult	-0,29	-0,26	-0,09	-0,21	0,03	0,00	-0,07	-0,07	0,05	-0,24	-0,09	-0,19	0,29	0,18	-0,04	-0,09	0,09	-0,03	-0,05	-0,38	***-0,40***	1,00	
compact	0,10	0,09	0,06	0,06	0,01	0,03	0,00	0,00	0,01	-0,02	0,10	-0,03	0,00	-0,02	0,02	0,06	0,01	0,03	0,03	0,12	0,12	-0,19	1,00

Table A-2. Correlation matrix between landscape variables (buffers of distance)

	foret	agri	buisson	bati	reso	eau
foret	1.00000					
agri	0.16308	1.00000				
buisson	0.29456	0.27391	1.00000			
bati	***-0.62409***	***-0.60702***	***-0.61010***	1.00000		
reso	-0.00742	-0.10461	-0.05069	-0.12361	1.00000	
eau	0.11498	0.01035	0.02051	-0.09622	-0.02368	1.00000

Table A.3 Correlation matrix between angle area variables

Appendix B: Geographical processing

The Landstat 7 ETM (30 m and 15 m spatial resolution) and IRS 1 (Indian Remote Sensing, images at 5.6 m spatial resolution) data were corrected geometrically to allow for deformations induced by the more or less oblique paths of the satellites, and then combined and transformed into "color spaces" to yield a spatial resolution of 7 m. These multi-channel images were then classified to identify relevant land uses (e.g. precedence was given to objects liable to mask the view; crops were not distinguished, because of yearly rotation, etc.). Each pixel was assigned to the most probable class from the composite signal; 12 types of land use were identified: water, conifers, deciduous trees, bushes, crops, meadows, vineyards, roads, built areas, quarries, railroads, and trading estates.

To reduce computation time, the 360 degree panorama was sampled by 120 rays spaced 3 degrees apart. In addition to the 7 m-resolution database, three other bases were constituted at resolutions of 30 m, 150 m and 1 km (the latter two images came from the *Corine Land Cover* database). First, tests were conducted along each ray up to a distance of 40 pixels (i.e. 280 m). A trigonometric calculation identifies the pixels seen depending on the relief and the objects encountered. The same process was then repeated to test the pixels between 280 m and 1200 m using the 30 m-resolution database; the 150 m base was used for testing pixels located from 1.2 km to 6 km away, and finally the 1 km base was used for testing beyond that range and up to 40 km away. This method reduced computation time by a factor of more than 35.

In addition, this operating procedure corresponds closely to the way a landscape is seen because it reflects the imperfections of the human eye. The closer an object is to the point of observation, the greater the proportion of the field of view it occupies. This "visual impact" declines with distance, until distant objects may be incorporated in part or in full in the field of view and then change nature: for example, it is a forest or a village that is seen instead of a tree or a house, or even a tract of farmland if the tree or house are small.

Results. Figure 6 compares the results (B) to an aerial photograph or orthophotograph (A) for Agencourt, the first *commune* in alphabetical order (arrowed in Figure 1, and which is typical of habitat in the study region).[17] The two roads in (B) are roughly aligned and are 1 or 3 pixels wide. The first real-estate transaction in the economic database is georeferenced in the center of the image. The landscape is therefore analyzed for this pixel. In both (A) and (B), its view is masked by other houses to the east and opens onto fields to the west. The built pixels south of this central point and to the right of the vertical road also have a masked view, although it remains relatively open as they are separated by meadows or fields (A), as found in (B) too. However, north of the central point and to the right of the road, the built pixels are contiguous and the view is completely masked in both representations. The same is true of most pixels on either side of the main road.

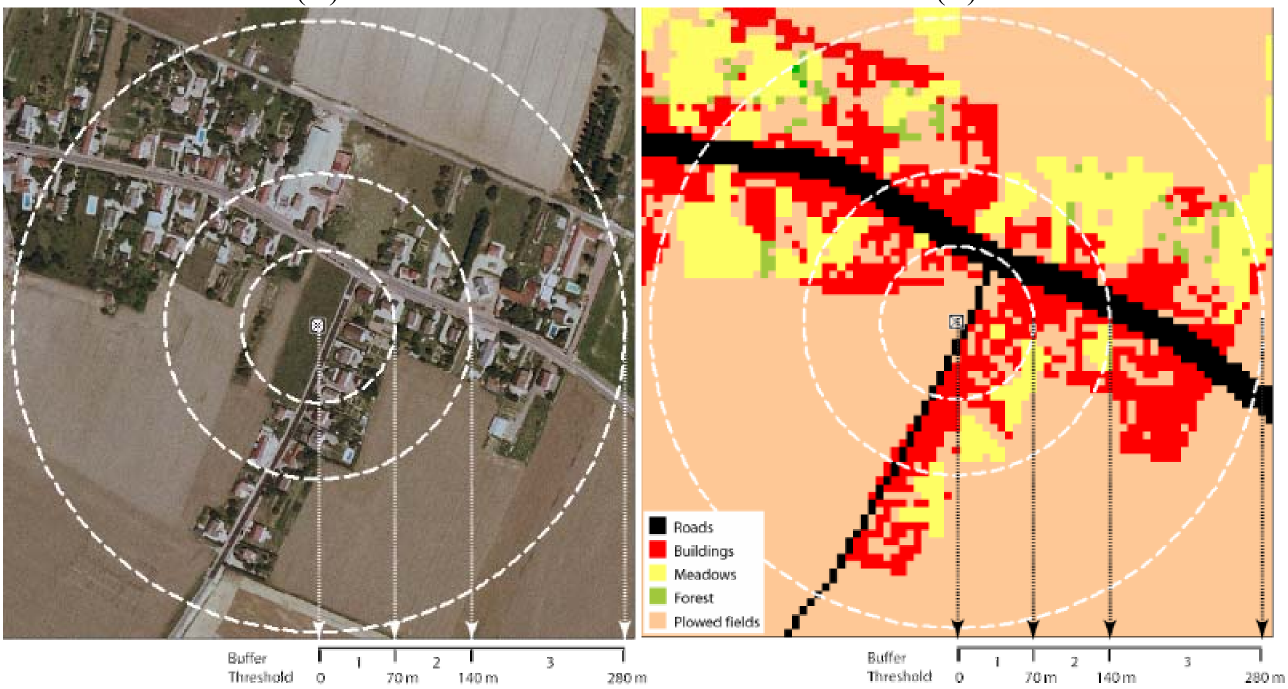
Despite this comparatively good overall match, differences appear between the two representations. The terraces around houses and drives are classified as built pixels because the building materials (probably paving stones) give off the same chromatic signals as the roofing tiles. The same is true of frontyards or paths, which are too small to be identified as lawns. Accordingly the built area shows up as a more compact mass in (B) than in (A). This leads to the viewshed being underestimated: terraces, drives and paths, small gardens, etc. are objects of zero height, allowing views which are not captured by the model.

[17] We did not have ortho-photographs at our disposal when the classification was made. Moreover, land use cannot be classified from such photos as the shots were taken at different dates and automatic classification is difficult: it provides only a panchromatic channel, which is less favorable for thematic discrimination than the 6 channels of the ETM image (blue, green, red, a near infrared, and two middle infrareds).

Notice too that one house, in the extreme south of the village and on the left of the road, is missing in (B): it escaped classification probably because its roof is not made of the same material as those in the rest of the village (as can be seen from the color orthophotograph); a few new buildings are found in (B) but not in (A), in particular on the eastern edge of the image (the satellite pictures are more recent than the aerial photograph).

Figure 6. Orthophotograph of Agencourt (A) compared to the geographical model (B)

(A) (B)



Appendix C: Landscape composition indices

As Table C-1 shows, the like-adjacency and aggregation indices take relatively high values (72–82 for a theoretical maximum of 100), which may be explained by the predominance of clustered dwellings. However, mosaics are preferred to uniformity: breaks in the built environment due to other land uses have positive hedonic prices, close to €1500 for one standard deviation. Contagion, interspection and division indices are insignificant.

Indices L24, L9 and L48 are significant, from €1300–1500 for an additional standard deviation, showing that elongate and non-compact shapes are preferred to closely packed shapes. In addition, the overall contiguity index shows that partitioning is valued more highly than shape connectivity, although only slightly so (significant at 10% level).

Many small patches provide landscapes that are more highly valued than those with a few large patches. This is consistent with the positive value attributed to the length of boundaries.

Table C-1. Landscape ecology indexes

fragstat code	Indice	Parameter	Descr. stat.: mean (std)
L114	Percentage of Like-Adjacence	-0.00171*	72.31(7.82)
L115	Contagion index	0.0017	92.78(1.84)
L116	Aggregation index	-0.0019**	81.14(7.88)

L117	Interspection and Juxtaposition index	0.0008	29.39(5.70)
L118	Division index	0.0011	0.681(0.169)
L24	Perimeter-Area Ratio Distribution	0.0357*	2.781(0.315)
L9	Landscape Shape Index	0.0207**	2.442(0.688)
L30	Shape Index Distribution	0.021	1.362(0.129)
L48	Related Circumscribing Circle Distribution	0.2131	0.610(0.040)
L54	Contiguity Index Distribution	-0.1643**	0.276(0.074)
L5	Patch number	0.0018	20.72(8.011)
L11	Patch area mean	-0.1591	0.091(0.062)
L7	Total edge	4.1E-5**	347.1(3.3E5)
L10	Largest Patch Index	0.00035	47.68(18.0)
L130	Shannon's Evenness Index	-0.0087	0.487(0.124)
L131	Simpson's Evenness Index	-0.0188	0.668(0.155)

*Fragstats codes are by McGarigal et al. (2002). The equations comprise the variables from Table 2 except the last four (DECID_PACHES, DECID_EDGE, AGRI_PACHES and COMPACT) plus each index introduced separately. It was estimate"ed by the IV method, by the 2SLS. The mean value, standard deviation and hedonic price are given only for indices significant at the 10% threshold.** and * indicate significance at the 5 and 10% levels respectively.*

Appendix D: View from above

Table D-1. Results: view from above

		(1)		(2)		(3)	
	DISTANCE BUFFER	fixed-effect MCO		fixed-effect 2SLS		Mixed	
		parameter	T	parameter	T	parameter	T
WOODLAND*LOT/LSPACE	<70m	0.00228	5.04	0.002709	4.91	0.002339	4.71
WOODLAND	<70m	-0.00006322	-5.82	-0.00007	-5.35	-0.00006	-4.95
R_WOODLAND	70-140m	-0.16703	-1.66	-0.15942	-1.30	-0.1751	-1.62
WOODLAND	140-280m	0.00001746	0.57	-8.2E-6	-0.22	0.000014	0.45
R-BUSHES	<70m	0.05897	0.52	-0.02589	-0.19	0.03391	0.27
R-BUSHES	70-140m	0.49404	2.93	0.664130	3.24	0.6353	3.35
R-BUSHES	140-280m	-0.32838	-1.16	-0.51487	-1.49	-0.4336	-1.49
R_AGRI	<70m	0.09012	1.56	0.106577	1.52	0.09685	1.50
AGRI	70-280m	0.00007636	3.20	0.000072	2.48	0.000071	2.68
AGRI*LOT/LSPACE	70-280m	-0.00414	-6.77	-0.00382	-5.14	-0.00342	-5.12
AGRI*POSU	70-280m	-0.00000176	-0.36	-2.2E-6	-0.37	-3.93E-6	-0.82
AGRI+WOODLAND	0,28-40km	0.00000617	0.10	0.000035	0.46	3.323E-6	0.08
BUILT	<70m	0.00015178	0.79	0.000285	1.21	0.000314	1.45
R_BUILT	70-280m	0.09544	1.75	0.101545	1.53	0.1102	1.80
R_BUILT	0,28-1,2km	0.36250	0.77	0.435067	0.76	0.4578	1.09
NETWORKS	< 280m	0.00007542	1.46	0.000055	0.88	0.000064	1.26
R_NETWORKS	0,28-1,2km	0.14767	0.17	0.010980	0.01	0.1449	0.21
WATER	0-40km	-0.00004063	-1.05	-0.00001	-0.28	-0.00004	-1.05
DECID_EDGE	<70m	-0.00032294	-2.73	-0.00054	-3.72	-0.00039	-3.03
DECID_PACHES	<70m	0.01097	3.50	0.012947	3.40	0.01476	4.38
AGRI_PACHES	<70m	0.00138	1.90	0.001367	1.54	0.000530	0.73
COMPACT	<70m	0.19314	1.72	0.292249	2.14	0.2478	1.97