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Decoupling values of agricultural externalities according to scale: a spatial hedonic approach in Brittany

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Abstract

Agricultural activities jointly generate various externalities. Hedonic pricing method allows for their valuation. Previous hedonic studies have estimated the value of the externalities generated by a given agricultural activity in a single parameter. Based on simple theoretical model, we illustrate that this parameter captures the sum of the different externalities generated by the activity. We explain that this parameter can differ at different spatial scale. Using specific spatial econometric models with spatial lags on the explanatory variables, we distinguish between the value of infra-municipal agricultural externalities and the value of extra-municipal agricultural externalities with larger spatial range arising from the same agricultural source. Among the estimated models, the spatial lag of the exogenous variable and the general nested spatial models are selected as the best models. We find that swine activities present negative effects at all scales whereas dairy cattle activities, including grassland management, present negative effects at the infra-municipality scale but positive spillovers.

Externalités et distances: une spatialisation de l'approche hédonique en Bretagne

Résumé

Les activités agricoles produisent diverses externalités dont la valeur peut être théoriquement estimée à l'aide de la méthode des prix hédoniques. Les études hédoniques antérieures ont toutefois estimé la valeur des externalités générées par une activité agricole à travers un paramètre unique. Sur la base d'un modèle théorique simple, nous montrons que ce paramètre capture la somme des différentes externalités générées par l'activité. Nous expliquons que ce paramètre peut différer à différentes échelles géographiques. En utilisant des modèles économétriques spatiaux spécifiant un effet spatial spécifique pour chaque variable explicative, nous distinguons la valeur moyenne des externalités agricoles capturée à l'échelle infra-communales (où les résidents et les activités agricoles sont localisés dans la même municipalité) et celle capturée à l'échelle extra-municipale (où les résidents et les activités agricoles sont localisés dans des municipalités différentes). Parmi les modèles estimés, les modèles SLX et GNS apparaissent statistiquement comme les meilleurs modèles. Nous montrons que les activités d'élevages porcins et avicoles affectent négativement les résidents à toutes les échelles, tandis que les activités d'élevages bovins, incluant la gestion des prairies, présentent des effets négatifs à l'échelle infra-municipale, mais des effets positifs à l'échelle extra-municipale.

Mots-clés : externalités, azote, agriculture, économétrie spatiale

Code JEL : Q51, Q53, H41

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1. Introduction

Agriculture is a multifunctional activity that ensures the joint production of marketable and non-marketable goods. These externalities impact the population's utility, either positively (e.g. conservation of biodiversity) or negatively (e.g. odor pollution), and present public good features: non-rivalry between consumers and/or non-excludability, especially for nuisances. The modernization of agriculture in Europe during the 20st century has increased the negative agricultural externalities (e.g. Sutton et *al.*, 2011). The authorities have thus implemented several policies to internalize these effects. For example, the Common Agricultural Policy (CAP) offers payments to maintain specific areas (e.g. permanent grasslands) or to help European farmers to modernize their farms and buildings to reduce pollution. The role of the authorities is to establish the most efficient instruments and to allocate an appropriate agro-environmental budget, which notably depends on the benefits captured by the population.

These benefits should be estimated using monetary valuation methods. The hedonic pricing method is a cornerstone of this literature (Rosen, 1974). Based on Lancaster's theory (1966), the hedonic pricing method is based on the principle that prices of marketable goods are defined by the combination of their attributes, which allows the value of each attribute to be determined. This method has been frequently used to estimate the population's willingness to pay (WTP) to improve environmental conditions, such as water quality (Leggett and Bockstael, 2000), or to reduce negative externalities, such as noise pollution (Fernández-Avilés et *al.*, 2012). The hedonic pricing method is often applied to real estate observations, the theory being that, *ceteris paribus*, houses with superior amenities (negative externalities) have a higher (lower) price corresponding to the capitalization of the externality in the houses' value.

Several studies have valued agricultural externalities using this method. Le Goffe (2000) found that to double nitrogen concentration at the municipality scale decreases Breton Bed and Breakfast renting prices by 3%. Ready and Abdalla (2005) found that a new livestock farm located 500 meters from a house decreases its value by 6.4%. Herriges et *al*. (2005) stated that animal facilities reduce property values by 15% when they are located 0.25 miles upwind from houses. Bontemps et *al*. (2008) found that nitrogen surplus at the municipality scale decreases Breton house prices up to 7% but has no additional effect after 80 kg/Ha. They also found that

the municipal share of temporary grassland decreases house prices up to 3%. Cavailhès et *al*. (2009) found that farmed activities have higher impacts when they are visible from the house.

Even if these papers provide remarkable insights on the impacts of agriculture on residents' utility, they have estimated the hedonic function at a given spatial scale, either the municipal scale (Bontemps et *al*., 2008; Le Goffe, 2000) or a lower one (Cavailhès et *al*., 2009; Ready and Abdalla, 2005). They do not provide information on the impacts of agriculture at higher scales, which is however important when designing agro-environmental policies. Indeed, using declared preference methods, several papers highlights that residents are willing to pay to conserve distant sources of amenities (even located from more than one hour to their house), even if the WTP decreases with the distance to the amenity source (e.g., Ay et *al*., 2017; Pate and Loomis, 1997). As rural households use to move over larger distance than urban ones to reach a place (for their job or leisure activities), agricultural activities can influence the housing market at larger scales than the previously examined ones, at least in neighboring municipalities. In addition, farms are dispersed over space and operate rarely on a single municipality. For example, Breton swine farmers are willing to apply manure at 70 kilometers from their headquarters (Gaigné et *al*., 2011), which imply that the externalities should not be contained in the municipality where the swine production occurs.

Previous papers have also ignored that agriculture supports the joint provision of several public goods and bads. For example, agricultural wetlands provide habitat for remarkable biodiversity, which can be valorized by hikers, hunters and anglers, but agricultural wetlands are also located in areas with higher flooding risk. One can thus consider that an agricultural activity is a proxy of several public goods, whom quantities are unobserved in the usual datasets. As papers on the distance-decay of WTP highlight that each public good affects agents under its own spatial range of impacts (e.g. Ay et *al*., 2017; Rolfe and Windle, 2012), one can even consider than an agricultural activity at a given localization is the proxy of several externalities, each of them impacting differently the residents' utility over space. The consequence is that one agricultural activity can have a positive impact at a narrow scale and a negative impact at a larger scale, and vice versa.

The objective of our paper is to distinguish the value of the agricultural externalities arising from the same agricultural activity at two different scales: the infra-municipal scale (where the residents and the agricultural activities are localized in the same municipality) and the extra-municipal scale (where the residents and the agricultural activities are localized in different municipalities), the distance to the considered activity being smaller in the infra-municipal

scale. Our results could inform policymakers on the strengths and forms of the agricultural externalities over space, which should impact the design of agro-environmental policies.

For our purpose, we estimate a spatial hedonic model on the rural housing market of Brittany between 2010 and 2012. Spatial hedonic studies has been developed since the seminal work of Leggett and Bockstael (2000) (see Anselin and Lozano-Gracia, 2009 for a review) but have mainly relied on the spatial autoregressive (SAR) model or the spatial error model (SEM), which capture the whole spatial effect in a single parameter (McMillen, 2012). Here, we use econometric models that specify spatial effects for each of the explanatory variable, which are more flexible in modeling spatial spillover effects, i.e. the impact of a change in the variable level at one localization on the dependent variables of other places (Halleck Vega and Elhorst, 2015). The distinction between direct (i.e. the impact of a change in the variable level at one localization on the dependent variables of this localization) and spillover effects allow disentangling the value of agricultural effects at the different identified scales. We test the statistical performance of eight theoretically consistent spatial hedonic models, with four models that include the spatial effects on the explanatory variables. We find that the best specifications are the ones that include the spatial effects on the explanatory variables and in particular the spatial lag of exogenous variable model (SLX) and the general nested spatial model (GNS). This suggest that the principal source of spatial interactions is due to the spillovers of the agricultural externalities. The introduction of these spatial interactions suites better our data than the specifications of the spatial interactions due to price diffusion (captured by SAR and its developments) or due to spatial heterogeneity (captured by SEM and its developments). In particular, we find that swine and poultry breeding activities impact house prices even in neighboring municipalities, suggesting a larger spatial impact than what had been previously estimated. We find that cattle activities (animal density, areas of temporary and permanent grasslands) have a direct negative impact on house prices but a positive spillover on neighboring house prices.

The next section presents a brief theoretical analysis on the measure of agricultural externalities at different scales and explain in more details the interest of the used spatial econometric models. The third section presents the empirical model and the descriptive statistics of the data. The fourth section presents the results of our estimations and the sensitivity analysis. We discuss the results in the last section.

2.   Advances in spatial hedonic pricing

This section first explains the signification of the estimated parameters in hedonic method when considering a given agricultural activity as the support of different externalities with specific spatial range of impacts. We then present the developments of spatial econometrics to capture the spillover effects at the extra-municipal scale arising from the explanatory variables.

2.1.   Hedonic pricing method in a spatial framework

This part departs from the hedonic pricing model developed by Rosen and add successively the different source of spatial interactions that have been identified in the literature: the price diffusion effect, the spatial heterogeneity effect and the diffusion of externalities. The modeling of the diffusion of externalities in a hedonic model have not been theoretically examined to our knowledge.

2.1.1.   Hedonic pricing method: basic features

The hedonic pricing method considers that goods, and in particular houses, are functions of their attributes (Ball, 1973; Rosen, 1974). Denoting $\mathbf{y}_i$ as a vector of n characteristics $(y_{1i},...,y_{ni})$ of house i ($i \in [1;I]$) , which can be considered as marketable attributes, $\mathbf{z}_j$ as a vector of m characteristics $(z_{1j},...,z_{mj})$ of localization j ($j \in [1;J]$), including the agricultural activities at the source of the externalities, and P_{ij} as the price of house i in localization j, the hedonic price function is classically written as follows:

$$P_{ij} = P(\mathbf{y}_i, \mathbf{z}_j) \tag{1}$$

Assuming that the consumer utility U_{ij} localized in house i in municipality j is a function of the consumer's composite consumption (x), $\mathbf{y}_i$ and $\mathbf{z}_j$, U_{ij} is defined as follows:

$$U_{ij} = U\left(x, \mathbf{y}_i, \mathbf{z}_j\right) \tag{2}$$

Under the assumption that consumers maximize their utility under their income constraint $R = p_x x + P_{ij}$, with R being the income of the consumer and p_x the price of the composite good x , we reach the following first-order condition:

$$\frac{\partial U_{ij}/\partial z_{kj}}{\partial U_{ij}/\partial x} = \frac{\partial P_{ij}}{\partial z_{kj}} \tag{3}$$

The term $\partial P_{ij}/\partial z_{kj}$ represents the consumer's marginal WTP for the attribute z_{kj} (the kth element of $\mathbf{z}_j$). In particular, z_{kj} can be an agricultural attribute, whom values follow a continuous distribution (e.g. an area or an animal density). Previous studies have focused on the estimation of $\partial P_{ij}/\partial z_{kj}$, providing information on the household valuation of z_{kj}. Assuming a negligible impact of agricultural contractible labor on residents' localization choices, it means that z_{kj} support the provision of goods and/or services with public good characteristics.

2.1.2. Hedonic pricing method: the price diffusion effect

Relation (3) is valid under some assumptions, namely that (i) all buyers and sellers on house market have perfect information about the attributes' levels associated to each property's location, (ii) all buyers in the market are able to move to utility-maximizing positions, (iii) the housing market is in equilibrium and (iv) that the house supply is fixed in the short term (Hanley et al., 2009). The hedonic valuation literature has paid attention to the first assumption by considering that sellers and buyers obtain information about nearby properties and use it to determine the prices of other houses (e.g. Kim et al., 2003). One way to incorporate this information is to consider that the hedonic function depend on the vector $\mathbf{P}$ of house prices in the considered market such that $P_{ij} = P(\mathbf{y}_i, \mathbf{z}_j, \mathbf{P})$. This reflects that buyers and sellers could use similar neighboring sales as a reference for determining a transaction price (Osland, 2010). Thus, a marginal change in z_{kj} will indirectly impact P_{il} ($j \neq l$) through price reorganization. Assuming that I_l is the number of houses in localization l (such that $I = \sum_{l=1}^{J} I_l$), the total effect of a marginal change of z_{kj} is:

$$\underbrace{\sum_{l=1}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{total impact} \\ \text{of attribute } k \\ \text{in location } j}} = \underbrace{\sum_{i=1}^{I_j}\frac{\partial P_{ij}}{\partial z_{kj}}}_{\substack{\text{direct impact} \\ \text{of attribute } k \\ \text{in location } j}}\left(1 + \sum_{l=1}^{J}\sum_{m=1}^{I_l}\sum_{n=1}^{J}\sum_{o=1}^{I_n}\underbrace{\frac{\partial P_{on}}{\partial P_{ml}}\frac{\partial P_{ml}}{\partial P_{ij}}}_{\text{price diffusion}}\right) \tag{4}$$

Such price diffusion effect in housing prices is sometimes subject to criticism (e.g. Anselin and Lozano-Gracia, 2009) because it implies theoretically that all buyers and sellers take simultaneously into account the prices in other transactions, which is unlikely to arise in real settings. Based on this explanation, Anselin and Lozano-Gracia (2009) suggest that the adjacency effect (i.e., the fact that a house price tends to be similar to the prices of neighboring houses) is not due to information diffusion on prices but rather to spatial heterogeneity or to the diffusion of externalities.

2.1.3. Hedonic pricing method: the spatial heterogeneity effect

As already stated, relation (3) means that z_{kj} support the provision of goods and services with public good characteristics. We note $\{z_{kj}^{(1)}, ..., z_{kj}^{(Q)}\}$ the set of Q public goods and bads supported by z_{kj}, the elements could being be null for some agricultural activities and non-null for the others. The element $z_{kj}^{(q)}$ is thus the level of public good q supported by the activity k in the municipality j. We assume that the production of $z_{kj}^{(q)}$ depends on z_{kj} such that $z_{kj}^{(q)} = f_k^{(q)}(z_{kj}, \mathbf{l_j})$, where $f_k^{(q)}$ is the production function of the public good q supported by the activity k, and $\mathbf{l_j}$ the vector of local conditions (e.g. wind, soil or slope) that may influence the provision of public goods by the agricultural activity k in location j. These local conditions imply that the provision for any public goods supported by k would be heterogeneous over space.

We assume that each of the Q public goods is valued by the households such that $U_{ij} = U(x, \mathbf{y}_i, \mathbf{z}_j^{(1)}, ..., \mathbf{z}_j^{(Q)})$, with $U(\cdot)$ being linear. In this framework, $\partial P_{ij}/\partial z_{kj}$ is in fact the sum of the value of all Q externalities supported by the attribute z_{kj}. Indeed, relation (3) gives:

$$\frac{\partial U_{ij}/\partial z_{kj}}{\partial U_{ij}/\partial x} = \sum_{q=1}^{Q} \frac{\partial P_{ij}}{\partial z_{kj}^{(q)}} f_k'^{(q)}(z_{kj}, \mathbf{l_j}) \qquad (5)$$

where $f_k'^{(q)}$ is the marginal productivity of z_{kj} for the production of the public good q, which is independent to the distance, and $\partial P_{ij}/\partial z_{kj}^{(q)}$ is the value of the externality q supported by activity z_{kj} on house i. This value can be positive or negative. Relation (4) highlights that the estimated WTP for a specific agricultural activity in previous studies is equal to the sum of the

values attributed to the externalities jointly produced by the activity. However, as $z_{kj}^{(q)}$ is often unobserved by the econometrician, the $\partial P_{ij}/\partial z_{kj}^{(q)}$ cannot be measured independently and the econometrician can only measure the WTP for a specific activity z_{kj}.

The econometrician could assume that $\mathbf{l_j}$ does not influence the public good provision such that he could directly estimate relation (3). In particular, a positive value in relation (3) implies that z_{kj} provides more positive externalities than negative ones. Alternatively, the econometrician could recognize that $\mathbf{l_j}$ does influence the public good provision and thus estimates:

$$\frac{\partial U_{ij}/\partial z_{kj}}{\partial U_{ij}/\partial x} = \frac{\partial P_{ij}\left(\mathbf{z_j},\mathbf{l_j}\right)}{\partial z_{kj}} \tag{6}$$

where $\partial P_{ij}\left(\mathbf{z_j},\mathbf{l_j}\right)/\partial z_{kj}$ reflects the WTP for the attribute k in j that depends on the local conditions. For example, the value of odor nuisance induced by swine density depends on the wind. As these local conditions tend to be correlated over space (see e.g. wind strength or soil quality), the WTP for the activity k could be heterogeneous over space. The econometrician could control for this heterogeneity, which otherwise would lead to biased estimated WTP.

In the case where both the spatial heterogeneity and the price diffusion effect appears in the data, the hedonic specification would capture the total effect of a marginal change of z_{kj} as:

$$\underbrace{\sum_{l=1}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{total impact}\\\text{of attribute }k\\\text{in location }j}} = \underbrace{\sum_{i=1}^{I_j}\frac{\partial P_{ij}\left(\mathbf{z_j},\mathbf{l_j},\mathbf{P}\right)}{\partial z_{kj}}}_{\substack{\text{direct impact}\\\text{of attribute }k\\\text{in location }j}}\left(1+\sum_{l=1}^{J}\sum_{m=1}^{I_l}\sum_{n=1}^{J}\sum_{o=1}^{I_n}\underbrace{\frac{\partial P_{on}}{\partial P_{ml}}\frac{\partial P_{ml}}{\partial P_{ij}}}_{\text{price diffusion}}\right) \tag{7}$$

2.1.4. Hedonic pricing method: the diffusion of externalities

Finally, some papers on the distance-decay effect on WTP illustrate that each public good q supported by activity z_{kj} can impact the residents' utility in other locations (i.e.

$U_{ij} = U(x, \mathbf{y}_i, \mathbf{z}_j^{(\mathbf{q})}, \mathbf{z}_{\mathbf{l}}^{(\mathbf{q})})$ with $\mathbf{z}_{\mathbf{l}}^{(\mathbf{q})}$ being the matrix of the $J-1$ vectors of the set of public goods $\mathbf{z}_l^{(\mathbf{q})}$ in the other locations than j).[1] The total effect of a marginal change of z_{kj} is:

$$\underbrace{\sum_{l=1}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{total impact} \\ \text{of attribute } k \\ \text{in location } j}} = \underbrace{\sum_{i=1}^{I_j}\sum_{q=1}^{Q}\frac{\partial P_{ij}}{\partial z_{kj}^{(q)}}\,f_k'^{(q)}\left(z_{kj},\mathbf{l_j}\right)}_{\substack{\text{direct impact} \\ \text{of unobserved} \\ \text{externality } q \\ \text{supported by } k \\ \text{in location } j}} + \underbrace{\sum_{\substack{l=1 \\ l\neq j}}^{J}\sum_{i=1}^{I_l}\sum_{q=1}^{Q}\frac{\partial P_{il}}{\partial z_{kj}^{(q)}}\,f_k'^{(q)}\left(z_{kj},\mathbf{l_j}\right)}_{\substack{\text{local spillovers} \\ \text{of unobserved} \\ \text{externality } q \\ \text{supported by } k \\ \text{in location } j}} \quad (8)$$

where $\partial P_{il}/\partial z_{kj}^{(q)}$ is the spillover of the externality generated by $z_{kj}^{(q)}$ in the localization l. Indeed, due to data limitation on the spatial distribution of the agricultural activities, we can only know the municipal implantation of the different activities but, contrary to houses, we ignore their precise localization in the considered municipality.[2] Hence, the modeling framework integrates the insights from the distance-decay effect by considering two discrete zones: the municipality j where the agricultural activity z_{kj} occurs (i.e. the infra-municipal scale) and all the other municipalities (i.e. the extra-municipal scale), the infra-municipal scale being localized closer to the externality sources than extra-municipal scale but representing a smaller area than the extra-municipal scale.[3]

According to the papers on the distance-decay of WTP, the direct impact of the marginal change of $z_{kj}^{(q)}$ should be stronger than any spillover effect, i.e. $\left|\partial P_{ij}/\partial z_{kj}^{(q)}\right| > \left|\partial P_{il}/\partial z_{kj}^{(q)}\right|$. For example, a permanent grassland would impact more the utility of hunters that live in the same location than the utility of the hunters that live in other locations. However, as the number of hunters outside from j is supposed greater than the number of hunters in j, the sum of the spillover effects can be higher than the sum of the direct impact depending on the strength of the distance-decay effect, i.e. $\sum_{i=1}^{I_j}\left|\partial P_{ij}/\partial z_{kj}^{(q)}\right| \leq \sum_{\substack{l=1 \\ l\neq j}}^{J}\sum_{i=1}^{I_l}\left|\partial P_{il}/\partial z_{kj}^{(q)}\right|$. This means that the sum of the utility of hunters derived from the conservation permanent grasslands at the infra-municipal scale can be lower than the sum of the utilities of the hunters that live in other locations (i.e. at the extra-municipal scale).

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[1] For sake of simplification, we note $\bigcup\left(\mathbf{z}_j^{(\mathbf{q})}, \mathbf{z}_{\mathbf{l}}^{(\mathbf{q})}\right) = \mathbf{z}^{(\mathbf{q})}$ and $\bigcup_{j=1}^{J}\mathbf{z_j} = \mathbf{z}$.

[2] We here assume that the $\mathbf{z}_j$ are localized on the centroid of the municipality.

[3] Given our assumptions, one can thus consider that the houses of municipality j are closer to the source of the externalities $\mathbf{z}_j$ than the houses located in other municipalities. Of course, there are cases where houses located in neighbored municipalities can be closer to at least one house of j but this is true on average.

As the public goods and bads are jointly produced by z_{kj} and given their wide range of forms and values over space, we can observe cases where the direct and spillover impacts have the same sign and other where they have opposite ones. This feature is presented in Figure 1. In this theoretical example, the activity z_{11} provides one public good $z_{11}^{(1)}$ and one public bad $z_{11}^{(2)}$. Figure 1 highlights that, even if the average effect of z_{11} is negative in the first municipality (because the effects of $z_{11}^{(2)}$ on the prices of the first municipality are greater than the effects of $z_{11}^{(1)}$), the form of the distance-decay explains that the average spillover effect of z_{11} is positive. Taking an illustrative case, permanent grasslands in one localization provide suitable conditions to hunters over a large range of space (corresponding to $z_{11}^{(1)}$) but also represent an area with higher flooding risks (which corresponds to $z_{11}^{(2)}$). Flooding risk affects houses on a smaller range of space than the suitable hunting conditions but present a higher marginal value in the short range.

Figure 1: joint production of public goods and the distance-decay effect of consumers' willingness to pay
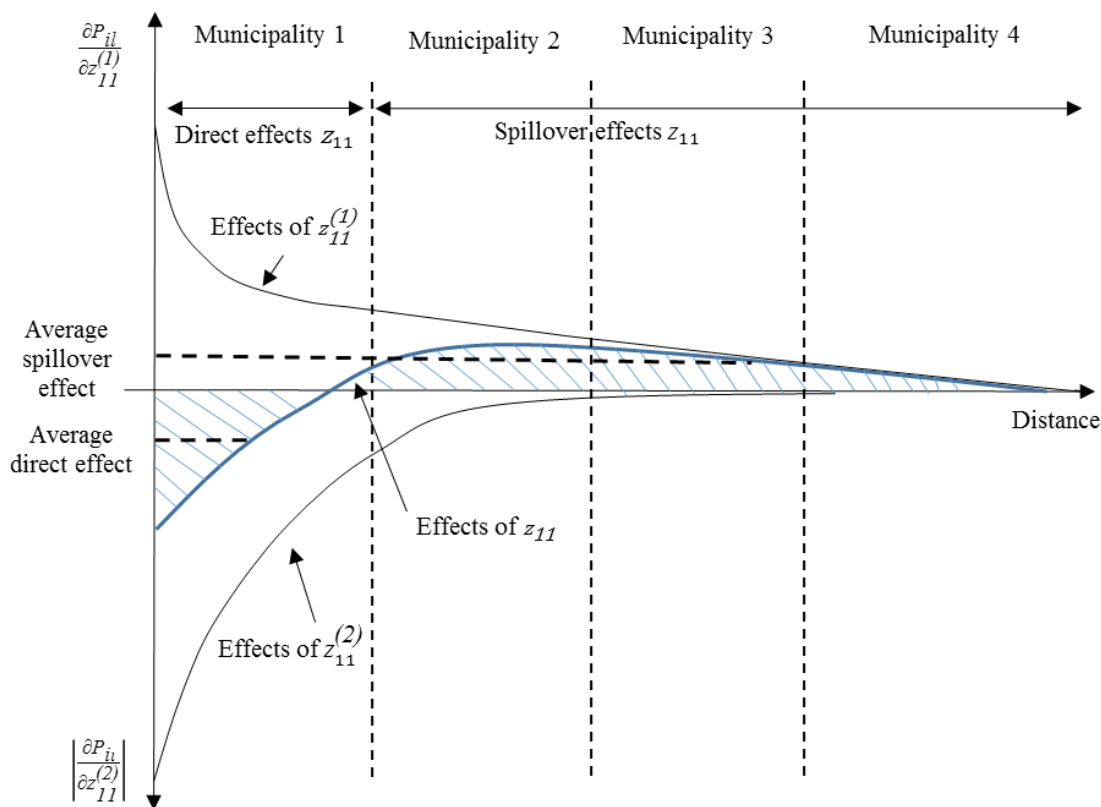
Even if $z_{kj}^{(q)}$ is unobserved, the econometrician can assess $\partial P_{ij}/\partial z_{kj}$ and $\partial P_{il}/\partial z_{kj}$

($\forall l \in [1;J]$ - j) summing over the Q public goods and bads. In this case, relation (8) leads to:

$$\underbrace{\sum_{l=1}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{total impact}\\\text{of attribute }k\\\text{in location }j}} = \underbrace{\sum_{i=1}^{I_j}\frac{\partial P_{ij}}{\partial z_{kj}}}_{\substack{\text{direct impact}\\\text{of attribute }k\\\text{in location }j}} + \underbrace{\sum_{\substack{l=1\\l\neq j}}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{spillovers}\\\text{of attribute }k\\\text{in location }j}} \tag{9}$$

in case where the econometrician assumes that local conditions does not affect the public good provision. Alternatively, if the econometrician considers that the local conditions could affect the public good provision, relation (8) leads to:

$$\underbrace{\sum_{l=1}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{total impact}\\\text{of attribute }k\\\text{in location }j}} = \underbrace{\sum_{i=1}^{I_j}\frac{\partial P_{ij}\left(\mathbf{z},\mathbf{l_j}\right)}{\partial z_{kj}}}_{\substack{\text{direct impact}\\\text{of attribute }k\\\text{in location }j}} + \underbrace{\sum_{\substack{l=1\\l\neq j}}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}\left(\mathbf{z},\mathbf{l_j}\right)}{\partial z_{kj}}}_{\substack{\text{spillovers}\\\text{of attribute }k\\\text{in location }j}} \tag{10}$$

Relations (9) and (10) present the hedonic specifications without the price diffusion effect. Assuming that such process are at stake in the observations, the econometrician could measure:

$$\underbrace{\sum_{l=1}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{total impact}\\\text{of attribute }k\\\text{in location }j}} = \underbrace{\sum_{i=1}^{I_j}\frac{\partial P_{ij}}{\partial z_{kj}}}_{\substack{\text{direct impact}\\\text{of attribute }k\\\text{in location }j}}\left(1+\underbrace{\sum_{l=1}^{J}\sum_{m=1}^{I_l}\sum_{n=1}^{J}\sum_{o=1}^{I_n}\frac{\partial P_{on}}{\partial P_{ml}}\frac{\partial P_{ml}}{\partial P_{ij}}}_{\text{price diffusion}}\right) + \underbrace{\sum_{\substack{l=1\\l\neq j}}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{spillovers}\\\text{of attribute }k\\\text{in location }j}}\left(1+\underbrace{\sum_{l=1}^{J}\sum_{m=1}^{I_l}\sum_{n=1}^{J}\sum_{o=1}^{I_n}\frac{\partial P_{on}}{\partial P_{ml}}\frac{\partial P_{ml}}{\partial P_{ij}}}_{\text{price diffusion}}\right) \tag{11}$$

in case he assumes spatial homogeneity. Alternatively, in case of spatial heterogeneity, the econometrician could measure:

$$\underbrace{\sum_{l=1}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}}{\partial z_{kj}}}_{\substack{\text{total impact}\\\text{of attribute }k\\\text{in location }j}} = \underbrace{\sum_{i=1}^{I_j}\frac{\partial P_{ij}\left(\mathbf{z},\mathbf{l_j},\mathbf{P}\right)}{\partial z_{kj}}}_{\substack{\text{direct impact}\\\text{of attribute }k\\\text{in location }j}}\left(1+\underbrace{\sum_{l=1}^{J}\sum_{m=1}^{I_l}\sum_{n=1}^{J}\sum_{o=1}^{I_n}\frac{\partial P_{on}}{\partial P_{ml}}\frac{\partial P_{ml}}{\partial P_{ij}}}_{\text{price diffusion}}\right) + \underbrace{\sum_{\substack{l=1\\l\neq j}}^{J}\sum_{i=1}^{I_l}\frac{\partial P_{il}\left(\mathbf{z},\mathbf{l_j},\mathbf{P}\right)}{\partial z_{kj}}}_{\substack{\text{spillovers}\\\text{of attribute }k\\\text{in location }j}}\left(1+\underbrace{\sum_{l=1}^{J}\sum_{m=1}^{I_l}\sum_{n=1}^{J}\sum_{o=1}^{I_n}\frac{\partial P_{on}}{\partial P_{ml}}\frac{\partial P_{ml}}{\partial P_{ij}}}_{\text{price diffusion}}\right) \tag{12}$$

The three spatial processes (the price diffusion, the spatial heterogeneity and the diffusion of externalities) are at stake in relation (12). To our knowledge, the measure between direct impacts at the infra-municipal scale and spillover impacts at the extra-municipal scale as presented in equations (9) to (13) has never been done in hedonic valuation of agricultural externalities. This is the aim of this paper.

2.2.   Advances in spatial econometrics: integrating spillovers

The different hedonic specifications that we developed in 2.1 correspond to different spatial econometric models. Indeed, Elhorst (2014) considered three types of spatial interactions to address the spatial effects: (i) the interactions among dependent variables, (ii) the interactions among explanatory variables and (iii) the interactions among the error terms. In the context of the hedonic valuation, the first type of interactions refers to the price diffusion effect (equation (4)), the second type of interactions refers to the diffusion of the externalities (equation (9)) and the third type of interactions refers to the spatial heterogeneity effect (equation (6)). All these interactions can be present in a given set of observations.

To our knowledge, three studies have used spatial econometrics to assess the value of agricultural externalities: Kim and Goldsmith (2009) used the SAR model (equation (4)), Eyckmans et *al*. (2013) used the spatial autoregressive model with autoregressive disturbances (SARAR) model (equation (7)) and Yoo and Ready (2016) used the SEM (equation (6)). These models do not considered interactions among explanatory variables, i.e. do not consider the diffusion of externalities. Indeed, if the SEM does not consider any indirect impact, the spillovers from SAR and SARAR due to price diffusion are defined as the global spillovers, i.e. the impact of a change in the level of z_{kj} that is transmitted to all other locations based on the infinite series expansion of the defined diffusion processes over all localizations (LeSage and Pace, 2009).[4] Even if we can compute a spillover effect for each attribute, the SAR and the SARAR models impose an *a priori* restriction on the spillover effects because they capture the whole spatial effect in a single parameter (McMillen, 2012). The consequence is that two distinct activities present the same relative spillover impacts relatively to the direct ones. The SAR, the SEM and the SARAR models are thus not adapted to measure the defined spillovers in (9), which are defined in the spatial econometric literature as local spillovers.[5] The spatial lag of exogenous variable (SLX) model (equation (9)), the spatial Durbin error model (SDEM) (equation (10)), the spatial Durbin model (SDM) (equation (11)) and the general nesting spatial (GNS) model (equation (12)) allow to measure the defined spillovers in the section 2.1.4 because they consider the interactions among the explanatory variables (LeSage and Pace, 2009). These models are thus well suited to study the forms and strengths of externalities over

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[4] Basically, a marginal change of z_{kl} impacts house prices in localization l, which in turn, impact house prices in other locations, whom marginal change impact house prices in other locations, etc.

[5] Contrary to the global spillovers, local spillovers do not disperse recursively through prices and concern only the impact of a change of z_{kj} on neighbored observations.

space (Halleck Vega and Elhorst, 2015). For this reason, Halleck Vega and Elhorst (2015) suggested taking the SLX model as the point of departure when estimating a spatial model and to successively develop it, if necessary, using the SDEM, the SDM or the GNS model.

To the best of our knowledge, Brasington and Hite (2005) were the first to use the SDM in a hedonic analysis for environmental attributes. Comparing the OLS model, the SAR model, the SEM and the SDM, Montero et *al.* (2011) showed that the SDM was the most suitable model for valuing noise pollution in Madrid. In particular, Fernández-Avilés et *al.* (2012) highlighted that the consideration of local spillovers correct for the nonlinearities of air pollution over space. Some more recent spatial hedonic studies have also tested the SLX model and the SDEM. Mihaescu and Vom Hofe (2013) were the first to use these specifications in the hedonic valuation of environmental attributes. Maslianskaïa-Pautrel and Baumont (2016) used the SLX model, the SDM and the SDEM to estimate the spillovers of environmental attributes. Notably, they found that the high prices on the shoreline are more determined by the impact of diffusion of prices than by the diffusion of externalities. To the best of our knowledge, no hedonic study on environmental valuation has ever used the GNS model, despite its apparent generality at first glance.

The developed specifications in 2.1, corresponding from linear (equation (3)) to GNS (equation (12)) models, could all be right from the theoretical point of view and depend only on the spatial process at stake in the observations. The choice of the best specifications is an empirical issue that we treat in the following sections.

3. Empirical models and data description

We measure the direct and spillover impacts of agricultural activities on the house prices of rural and noncoastal municipalities of three departments of Brittany: Finistere, Morbihan and Côte d'Armor. We present the agriculture of Brittany and its environmentally related issues in the first part of this section. We then present the descriptive statistics of our sample. Finally, we introduce the econometric strategy.

3.1. Presentation of the study area

Brittany is the western region of France (Figure 2). In 2014, the utilized agricultural area covered 1.6 million ha, i.e. approximately 60% of the total region area. Breeding is the main agricultural activity in Brittany, a region where it is produced about 56% and 44% of national

swine and egg production respectively. Breton farms are mainly oriented toward dairy production, with 22% of French milk being produced in Brittany. Dairy production favors the maintenance of permanent grasslands and a typical "Bocage" landscape composed of hedgerows and earth banks. Owing to its countryside, its regional culture and its long seacoasts, Britany is the third highest French region for tourism. However, the environmental qualities of the region are threatened by intensive breading activities. Indeed, swine, poultry and, to a lesser extent, dairy productions contribute to nitrogen and phosphate spills in Breton watercourses and groundwater. The average nitrogen surplus of Brittany is 117 kg/Ha/year, i.e. approximately four times more than the national average (Peyraud et *al.*, 2014). These surpluses led to high nitrogen concentrations in regional waters, which lead to several environmental negative effects such as water acidification, eutrophication, dystrophication and greenhouse gas emissions. In addition, the high nitrogen concentration rates have led to the proliferation of green algae on Breton seacoasts, whom decomposition produces the malodorous and potentially toxic hydrogen sulfide. It is suspected that several wild and domestic animal deaths have been due to hydrogen sulfide poisoning in recent years.[6] Thus, green algae negatively impacts the utility of local residents and tourists (MEEM, 2017). Local authorities have implemented several plans to reduce green algae pollution, notably in 2017 with the promulgation of a 55 million euro plan for the period 2017-2021, who followed the 134 million euro plan for the period 2010-2016.

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[6] In 2009, the death of a horse due to green algae decomposition led authorities to launch the first green algae plan. In 2011, 36 wild pigs were found dead in a green algae zone. In 2016, the death of a jogger around the green algae zone led authorities to demand tests to determine the cause of the death. Today, no proof makes it possible to conclude that his death was due to hydrogen sulfide inhalation, but court actions are under process for the jogger and other potential victims.

Figure 2: Maps of *(a)* **the localization of the observations and** *(b)* **average house prices by municipality (***Source***: authors' own computation)**
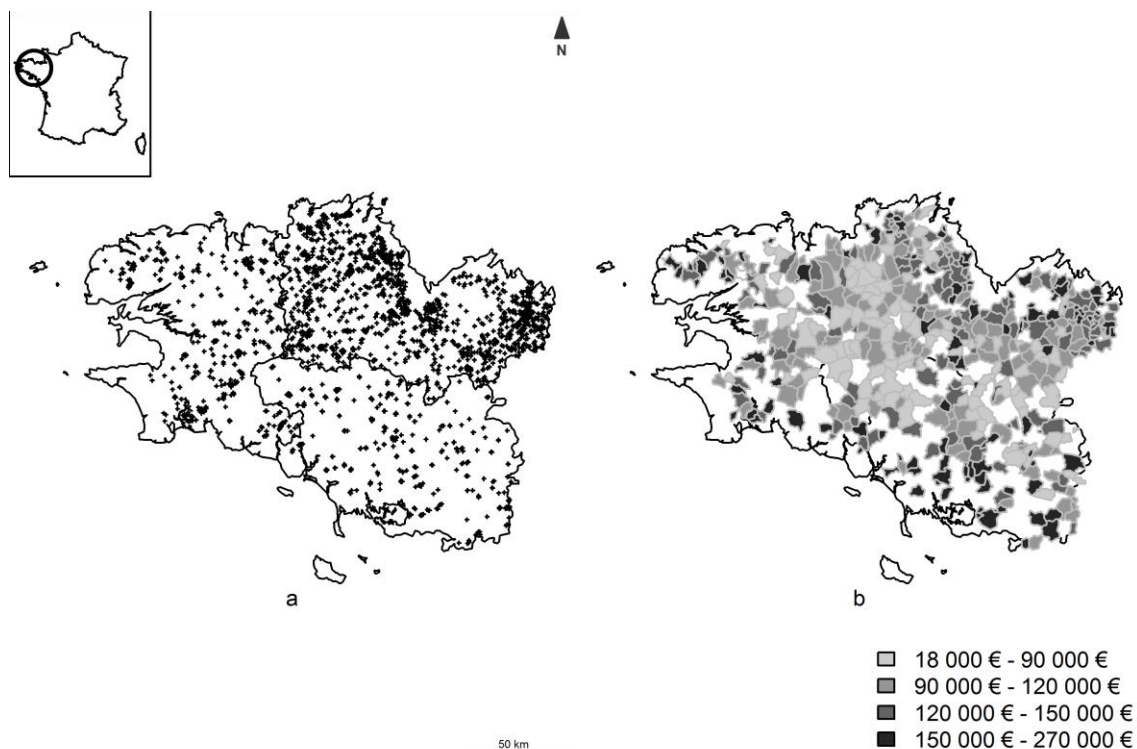
3.2. Descriptive statistics

Our dataset merges information from the notarial house prices in the 3 western NUTS3 regions of Brittany between 2010 and 2012 (i.e., the MIN database), the agricultural census of 2010, Corine Land Cover, the INSEE population census of 2010 and the PIEB.[7] In order to focus on the representative Breton rural market, the sampling of the houses was performed on three criteria: (i) the house should not be located in a coastal municipality, which is a major driver of house prices, (ii) the house should belong to a municipality with less than 4,000 inhabitants, removing from the urban market effect and (iii) the address and the coordinates of the house should be available (Figure 2a). The selection of a homogenous submarket should prevent most issues of spatial heterogeneity [Anselin and Lozano-Gracia, 2009]. In particular, the buyers of a homogenous market are expected to behave the same way. The temporal heterogeneity of the housing market is addressed using the observations for three consecutive years (2010 to 2012).

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[7] INSEE is the French acronym of "Institut National de la Statistique et des Etudes Economiques". PIEB is the acronym of "Portail de l'Information et l'Environnement en Bretagne".

We do not have to report any significant exogenous shocks to agricultural activities (i.e., similar agricultural and environmental policies), but the average prices slightly decrease over the period from 124,122 to 121,853 all in €2012. The descriptive statistics and the origins of the used variables are presented in Table 1.

Table 1: Descriptive statistics and variable definitions (N=2,476)

Variables	Mean	Std.dev	Min	Max	Description	Sources
House price	124214.50	57488.01	10000	448000	House prices in 2012€	MIN Dada
Intrinsic variables						
Nb_bathroom	1.31	0.46	1	2	Number of bathrooms	
Nb_room	4.96	1.38	3	9	Number of rooms	MIN Dada
Nb_floor	2.95	0.58	1	6	Number of floors	
Garden_area	2487.91	6334.04	42	178349	Garden area (square meter)	
Variables of interest						
Oilseeds_area	0.03	0.04	0	0.18	Oilseeds and proteins area (%UAA – Usable Agricultural Area -)	
Cereals_area	0.35	0.19	0	0.99	Cereals area (%UAA)	
Othercrops_area	0.01	0.04	0	0.14	Othercrops area (including industrial crops) (%UAA)	
Perm_grassland_area	0.16	0.10	0	0.45	Permanent grassland area (%UAA)	
Temp_grassland area	0.13	0.18	0	0.72	Temporary grassland area (%UAA)	
Fallow_area	0.01	0.04	0	0.14	Fallow_area (%UAA)	Agricultural
Shannon index	1.15	0.31	0.04	1.95	Shannon index	cencus
Swine_poultry_N	49.21	72.72	0.00	534.12	Quantity of nitrogen from swine and poultry (KgN/TAM - Total Area of the Municipality)	
Cattle_N	34.39	23.76	0.00	100.22	Quantity of nitrogen from cattle (KgN/TAM)	
D_algae	19.06	11.48	3.22	50.48	The minimum distance from municipalities to sea affected by green algae (Km)	
Ratio_algae	0.87	0.16	0.31	1	The ratio of the minimum distance to sea on the minimum distance to green algae	
Control variables						
Waters_area	0	0.01	0	0.19	Water area (lake, rivers, etc.) (%TAM)	
Wetlands	0	0.01	0	0.29	Proportion of non-agricultural wetlands area (%TAM)	Corine
Shrubs_area	0.01	0.03	0	0.29	Shrubs area (%TAM)	Land Cover
Forest	0.10	0.09	0	0.77	Forest area (%TAM)	
Greenspace_area	0	0.01	0	0.07	Greenspace area (%TAM)	

Landfills_area	0	0.01	0	0.05	Landfill area (%TAM)	
Industries_area	0.01	0.02	0	0.18	Industrialized area (%TAM)	
Shops_area	0.08	0.14	0	0.92	Urbanized area (%TAM)	
D_sea	17.67	12.49	2.22	51.08	The minimum distance to sea (Km)	Authors'
D_city	27.94	13.18	2.78	51.67	The distance to the closest city (Km)	calculations
Pop_density	1.43	2.65	0.09	20.43	Population density (population/TAM)	
Revenues	20.04	3.21	12.39	38.82	Average income (income / populations in k€)	INSEE
Services	21.54	14.57	1.00	69	Number of services (e.g. school) in the municipality	
Dummies						
Year 2010	0.27	0.44	0	1	Sale in 2010	
Year 2011	0.47	0.50	0	1	Sale in 2011	
Year 2012	0.26	0.43	0	1	Sale in 2012	

The dataset provides exhaustive information on 2,476 house transactions between 2010 and 2012. The prices range from €10,000 to €448,000 in 2012 and appear to be spatially correlated (Figure 2b). The intrinsic variables are available at the house level. The agricultural and control variables are only available only at the municipality scale, implying that the observations in the same municipality have the same explanatory variables. Our variables of interests notably inform on the different types of crop cultivation and the nitrogen quantity released by each breeding activity. We also have information on green algae pollution, with the Euclidean distance between the houses to the closest municipality affected by green algae.[8] We compute the ratio of the minimal distance of municipalities to the sea to the minimal distance of municipalities to coastal municipalities affected by green algae. This ratio measures the relative proximity of municipalities to coastal municipalities polluted by green algae to the closest coastal municipality; its value ranges between zero and one. When the value is equal to one, the nearest coastal municipality of the house (and thus the closest beach) is polluted by green algae. When it is less than one, the nearest beach to municipalities is not affected by green algae. High values of this ratio express the loss of households' opportunity to enjoy nonpolluted beaches in their area. We also compute a Shannon index of farmland use in each municipality to represent land-use diversity, which may be considered as a proxy of landscape quality. The Shannon index is an entropy measure based on land shares; it increases with cultural diversity

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[8] The information on green algae pollution is provided by the 2013 report of the CEVA (the French organization for algae studies). The report is available at: http://www.ceva.fr/fre/MAREES-VERTES/Connaissances-Scientifiques/Marees-Vertes-en-Chiffres/Denombrement-des-sites-touches-par-des-echouages-d-ulves [consulted the 01/08/2017].

and decreases when the crop diversity tends toward monoculture. The control variables contain additional environmental and accessibility variables that should influence the house price determination. Among the control variables, four variables are crucial for estimating the hedonic pricing model: the population density, the municipalities' incomes, the distance to the closest CDB and the distance to the sea.[9] Because the first two variables are development and wealth indicators, their introduction in the model make it possible to correct for the heterogeneity of the considered market. The two last variables are major drivers of house prices. Based on the correlation matrix in appendix A1, we estimate that most variables do not present excessive correlation between each other. Most notable correlations concern for example the areas of temporary and permanent grasslands or the area of oilseeds with the areas fallows and other crops.

3.3.   Empirical models and econometric strategy

We estimate the eight spatial hedonic models presented above (equations (3), (4), (6), (7) and equations (9) to (12)), which are summarized in Appendix 2. The hedonic models are estimated under the semi-log form, which according to Cropper et *al.* (1988) and Wooldridge (2015), is the best specification to mitigate the issue of heteroskedasticity and to limit unobserved heterogeneity biases.[10] The linear hedonic model we estimate is:

$$\ln\left(P_{ijt}\right) = \beta_0 + \boldsymbol{\beta_1}\mathbf{y_i} + \boldsymbol{\beta_2}\mathbf{z_j} + \varepsilon_{ijt} \tag{13}$$

where P_{ijt} is the selling price of house i located in municipality j in year t, $\mathbf{y_i}$ is the vector of the intrinsic variables of house i, $\mathbf{z_j}$ is the vector of variables in municipality j, including our variables of interest (the agricultural activities) and our control variables. We decompose the error term ε_{ijt} of (13) such that $\varepsilon_{ijt} = \boldsymbol{\alpha}t + \varepsilon_{ij}$, where $\boldsymbol{\alpha}$ is the vector of the temporal fixed effects. $\left(\beta_0, \boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \boldsymbol{\alpha}\right)$ is the set of vectors to be estimated. The $n \times n$ matrix $\mathbf{W}$ is the spatial weight matrix that is required to estimate the seven spatial hedonic models, which is symmetric and constituted of exogenous off-diagonal elements and null diagonal elements. The set of parameters $\left(\lambda, \rho, \boldsymbol{\eta}\right)$ is the specific parameters of the spatial econometric models, with

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[9] The main cities considered are Rennes, Brest, Quimper, Saint-Brieuc, Guingamp, Vannes and Lorient.
[10] We have also estimated the model using linear and log-log specifications. The results remain sensibly the same; they are available from the authors upon request.

$\boldsymbol{\eta} \equiv \left(\boldsymbol{\eta_1}, \boldsymbol{\eta_2} \right)$. The successive introduction of these parameters leads to the different spatial econometric models. We estimate the linear hedonic model using the OLS and use the maximum likelihood estimation for the spatial hedonic models (Ord, 1975). The coefficients are corrected for issues of heteroskedasticity using the White approach for the OLS. The spatial models are estimated using the maximum likelihood method. It implies that the error terms have not been corrected for heteroskedasticity, which may bias the inference.

As stated in section 2, the eight economic specifications of the hedonic model can be valid depending on the spatial processes at stake in our data. We first use the specific-to-general approach first presented by Florax et *al.* (2003) and extended by Halleck Vega and Elhorst (2015) to select the best hedonic model specification. This approach consists in testing the spatial autocorrelation in the models by starting from simple models (OLS or SLX models) to more general models. However, it prevents the comparison between the SLX model and the SAR model, the SEM and the SARAR (Halleck Vega and Elhorst, 2015). For this reason, we then use two alternative criteria to select the most suitable model, namely, the goodness of fit (measured here by the log likelihood, the Akaike information criterion (AIC) and the Nagelkerke R² tests (1991)) and the quality prediction (measured here by the normalized root mean square error – NRMSE –).[11] The combination of these two criteria and the specific-to-general approach has been used by Chakir and Lungarska (2017) to determine the best specification.

We estimate our models using the 40-nearest neighbor matrix (noted W1). Indeed, if the inverse-distance matrix is often used in environmental valuation studies within urban housing market, it is considered to be ineffective in rural housing markets where houses are less connected than in urban markets (Kim and Goldsmith, 2009). By contrast, the K-nearest neighbor matrix is more adapted to the larger daily journeys and the larger geographic area of rural housing markets (Kim and Goldsmith, 2009). The K-nearest neighbor matrix is specified such that the k number of neighbors accounts for at least one house located in a neighboring municipality. As, in our data, the municipality with the highest number of sold houses is 35 (the average number of sales per municipality is 5), we define K=40 neighbors. W1 assumes that

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[11] We compute the NRMSE as NRMSE= $\sqrt{\frac{\sum_{i=1}^{n}(\hat{P}_i - P_i)^2}{n}} / \sigma_P$ where $\hat{P}_i$ is the predicted value of the estimated model, P_i is the observed value of the dependent variable of the model, and σ_P is the standard deviation of the observed dependent variable.

the 40 closer neighbors have the same impact on each other. On average, the observations are located to 5.5 km to the 40th nearest neighbor.

In addition to W1, we also run the eight models with six alternative matrices (see appendix A3): the inverse of the Euclidean distance (denoted W2, with d_{mn} being the distance between observations m and n), the inverse of the Euclidean distance with the threshold (denoted W3 and W4), the square of the inverse of the Euclidean distance with the threshold (denoted W5 and W6) and the "queen" contiguity matrix between municipalities (denoted W7). [12] We use the contiguity weighting matrix W7 for municipality-aggregated data, decreasing the GNS number of observations but controlling for the fact that houses in the municipality share the similar environmental and control variables. This should limit a "double-counting" effect for the measure of the spillovers, even if the number of sales is less than 10 for 85% of the municipalities.

4.   Results

The Moran's I for the residuals of the OLS model is significantly positive (p-value of 1.31E-10 with W1, see Table A4), highlighting the spatial autocorrelation in our data. Section 4.1 presents the selection of the most suitable spatial models with W1 and section 4.2 presents the estimated parameters of the selected models with W1. We present the robustness checks in section 4.3.

4.1   Selection of the model for the 40 nearest neighbors matrix

Table 2 provides (i) the results for the LM tests for the residuals of the OLS and SLX models, (ii) the goodness-of-fit criteria for the eight models and (iii) the prediction quality criteria for the eight models. The LM tests on OLS residuals indicate that SARAR specification is the most relevant to correct for the spatial autocorrelation of our data when the diffusion of externalities is ignored. With respect to the SLX residuals, the LM tests display the non-significance of the spatial parameters for both the lagged dependent variable and the disturbance term, indicating that it is less appropriate to extend the SLX model to the SDM, the SDEM and the GNS model. This suggest that the spatial interactions on the externalities suites better our data than the

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[12] Note that the maximum distance between the 40 closer neighbors is 25 kilometers, explaining the setting of the threshold in W4 and W6 to 25 kilometers. However, 75% of the observations present an average distance to the 40th closer neighbor that is less than 10 kilometers, explaining the setting of the threshold in W3 and W5 to 10 kilometers.

spatial interactions on price diffusion (captured by SAR and its developments) or on spatial heterogeneity (captured by SEM and its developments).

Table 2: Lagrange Multipliers, goodness-of-fit and prediction quality of the different model specifications with W1

LM test	LM test	Model	R²	LL	AIC	NRMSE
OLS versus SEM (Ho: λ=0) - *LM error*	20.89***	**OLS**	0.421	-1101.9	2267.7	76.1
OLS versus SAR (Ho: ρ=0) - *LM lag*	51.49***	**SEM**	0.426	-1090.8	2247.6	75.5
OLS versus SARAR (Ho: ρ= λ=0) - *LM lag + error*	52.43***	**SAR**	0.430	-1083.2	2232.3	75.4
SLX versus SDEM (Ho: λ=0) - *LM error*	0.07	**SLX**	0.447	-1045.1	2214.2	74.3
SLX versus SDM (Ho: ρ=0) - *LM lag*	2.16E-04	**SARAR**	0.431	-1081.0	2230.0	75.1
SLX versus GNS (Ho: ρ= λ=0) - *LM lag + error*	1.17	**SDM**	0.447	-1045.1	2216.2	74.3
SAR versus SAC (Ho: λ=0) - *LM error*	2.97°	**SDEM**	0.447	-1045.1	2216.2	74.3
SDM versus GNS (Ho: λ=0) - *LM error*	1.18	**GNS**	0.448	-1044.3	2216.5	74.0

***, **, *, ° stands for p-value of 0.1%, 1%, 5%, and 10% respectively.

The results on the prediction quality of the model indicates that the smallest value of the NRMSE is provided by the GNS specification. Although it is not the smallest value, the NRMSE of the SLX model ranks second with the SDM and SDEM. Similarly, the goodness-of-fit criteria reveal that SLX, SDM, SDEM and GNS specifications improve the estimation quality compared to the OLS, SEM, SAR and SARAR models. The results show that the GNS specification provides the highest R² and maximum likelihood estimation values. However, the results show that the SLX model provides the smallest value of the AIC, i.e., the SLX model minimizes the loss of information. The R² values of the SLX and GNS models are the highest. The tests thus indicate that either the SLX or the GNS models are the best specifications and confirm that the specifications of the spatial diffusion of the externalities capture most of the spatial interactions at stake in our data.

4.2   Spatial hedonic results using the 40 nearest neighbors matrix

Table 3 presents the results of the OLS, SLX and GNS specifications. The structure of the GNS model implies that the estimated coefficients are not the marginal effects. Table 4 summarizes the marginal effects for the SLX and the GNS models. The results on the linear model displays

some similar counterintuitive results than those found in the literature. For example, similar to Bontemps et *al.* (2008), the OLS estimator on temporary grasslands is negative (-0.17). Similar to Le Goffe (2000), we find that the municipal share of cereals increase house prices in the considered municipality (the OLS estimator is 0.16). These two result are counterintuitive but disappear in the SLX and the GNS, once considered the spatial diffusion of the externalities.

Table 3: Coefficients for the linear and selected spatial hedonic models with W1

Variables	OLS model			SLX model					GNS model					
	Est. Coef	Std. Err		Coef.	Std. Err		Coef. (lag)	Std. Err		Coef.	Std. Err		Coef. (lag)	Std. Err	
Constant	10.63	0.14	***	9.70	0,47	***	-	-		6,20	1,91	**	-	-	
Nb_bathroom	0.26	0.02	***	0.26	0,02	***	0.11	0.14		0.25	0.02	***	0.02	0.13	
Nb_room	0.11	0.01	***	0.11	0,01	***	-0.07	0.05		0.11	0.01	***	-0.10	0.04	*
Nb_floor	-0.06	0.01	***	-0.06	0,01	***	-0.01	0.10		-0.06	0.01	***	0.01	0.07	
Garden_area	9.41E-06	1.64E-06	***	9.80E-06	1,23E-06	***	2.54E-07	1.00E-05		9.79E-06	1.21E-06	***	-3.30E-06	8.25E-06	
Oilseeds_area	-0.11	0.52		-0.43	0,58		-0.63	2.02		-0.48	0.58		-0.61	1.66	
Cereals_area	0.16	0.09	°	-0.34	0,14	*	1.33	0.27	***	-0.33	0.14	*	1.00	0.26	***
Othercrops_area	1.49	3.52		4.33	4,82		-41.26	21.61	°	4.51	4.80		-33.56	17.95	°
Perm_grassland_area	-0.17	0.21		-0.63	0,29	*	1.41	0.61	*	-0.58	0.29	*	1.04	0.53	*
Temp_grassland area	-0.17	0.09	°	-0.51	0,15	***	0.78	0.32	*	-0.52	0.15	***	0.71	0.27	**
Fallow_area	-1.14	3.59		-4.76	4,90		43.29	22.09	°	-4.85	4.87		35.17	18.39	°
Shannon index	-4.53E-03	0.06		0.03	0,08		-2.76E-03	0.17		0.04	0.08		-0.02	0.14	
Swine_poultry_N	-3.62E-04	1.25E-04	**	-6.78E-05	1,43E-04		-8.60E-04	3.58E-04	*	-5.86E-05	1.42E-04		-5.60E-04	3.44E-04	°
Cattle_N	-8.46E-04	4.06E-04	*	-1.13E-03	4,62E-04	*	2.29E-03	1.40E-03	°	-1.14E-03	4.61E-04	*	1.94E-03	1.14E-03	°
D_algae	-4.61E-04	1.50E-03		-4.59E-03	0,01		0.01	0.01		-4.47E-03	4.91E-03		0.01	0.01	
Ratio_algae	-0.13	0.07	°	-0.12	0,12		0.05	0.20		-0.12	0.12		0.10	0.17	
Waters_area	-0.16	0.81		-3.60E-04	1,12		-1.43	2.22		-0.03	1.11		-1.08	1.84	
Wetlands	-0.55	0.56		-0.69	0,79		0.74	2.71		-0.65	0.79		0.48	2.24	
Shrubs_area	0.37	0.27		0.32	0,35		-0.44	1.03		0.29	0.34		-0.22	0.86	
Forest	-0.11	0.10		-0.04	0,11		0.04	0.27		-0.04	0.11		0.01	0.22	
Greenspace_area	0.29	1.33		-0.32	1,41		-1.23	4.15		-0.06	1.41		-1.31	3.41	
Landfills_area	0.56	1.88		-0.49	1,77		5.94	5.78		-0.61	1.77		3.64	4.70	
Industries_area	0.25	0.33		-0.22	0,45		-0.93	1.14		-0.30	0.45		-0.65	0.94	
Shops_area	-0.34	0.22		-0.39	0,26		0.05	0.61		-0.42	0.27		0.29	0.53	
D_sea	-0.01	1.69E-03	***	2.29E-04	0,01		-0.01	0.01		-2.00E-04	0.01		-0.01	0.01	
D_city	-5.93E-04	7.29E-04		-3.55E-03	3,82E-03		3.27E-03	4.30E-03		-4.80E-03	3.63E-03		4.91E-03	4.03E-03	
Pop_density	0.02	0.01	°	0.02	0,01	°	0.02	0.03		0.02	0.01	°	0.01	0.03	
Revenues	0.03	3.08E-03	***	0.01	4,69E-03	**	0.04	0.01	***	0.01	4.65E-03	**	0.02	0.01	°
Services	1.77E-04	7.30E-04		1.80E-03	8,00E-04	*	-3.97E-03	1.83E-03	*	2.19E-03	8.06E-04	**	-4.17E-03	1.57E-03	**
Time FE	Yes			Yes						Yes					
R²	0.421			0.447						0.448					
LL	-1101.86			-1045.121						-1044.267					
AIC	2267.7			2214.241						2216.533					
ρ	-			-						0.358 *					
λ	-			-						-0.533 °					

***, **, *, ° stands for p-value of 0.1%, 1%, 5%, and 10% respectively

Indeed, we find in the SLX and GNS models that both the direct and spillover effects of the cereals and the temporary grassland areas are significant. Our results show that they are negatively correlated with the selling prices of the houses within their municipality boundaries but that their spillover effects are positive and higher in absolute term than the direct effects, meaning that they positively influence the utility of the inhabitants living in neighboring municipalities. These results suggest a negative direct effect of temporary grasslands and cereals at the infra-municipal scale, which may be due to short range nuisances (smell, noise, flies associated to grazing cows), but positive local spillovers at the extra-municipal scale, which may be attributed to the landscape attractiveness and amenities. These results are more consistent with the common feeling and stress the utility of the decomposing the effects of agricultural externalities at different scales. We find a similar effect for permanent grasslands, with a negative direct effect and a positive and higher local spillover effects. As permanent grasslands are mainly agricultural wetlands in Brittany, this effect could reflect the local disutility of permanent grasslands due to the presence of flood risk but the positive effects of other externalities, such as biodiversity and landscape beauty, at a larger scale. In the linear model, the result for permanent grasslands was non-significant at the 10% level. This result could indicate that we have disentangled the scale effects of the different externalities by the management of permanent grasslands.

Table 4: Direct, indirect and total impacts of the SLX and GNS models with W1

Variables	SLX model						GNS model					
	DE		IE		TE		DE		IE		TE	
Nb_bathroom	0.256	***	0.112		0.368	*	0.283	***	0.056		0.340	***
Nb_room	0.113	***	-0.065		0.048		0.122	***	0.000		0.122	***
Nb_floor	-0.062	***	-0.012		-0.074		-0.146	***	0.054		-0.092	
Garden_area	9.80E-06	***	2.54E-07		1.01E-05		7.55E-06	**	6.11E-06	°	1.37E-05	**
Oilseeds_area	-0.434		-0.632		-1.067		-0.816		0.454		-0.362	
Cereals_area	-0.343	*	1.328	***	0.985	***	0.009		0.093		0.102	
Othercrops_area	4.326		-41.261	°	-36.935	°	3.520		-33.228	*	-29.708	
Perm_grassland_area	-0.631	*	1.405	*	0.774		-0.552		-0.297		-0.849	
Temp_grassland area	-0.509	***	0.780	*	0.271		-0.446	*	0.128		-0.318	
Fallow_area	-4.763		43.294	*	38.531	°	-3.582		33.830	*	30.248	°
Shannon index	0.032		-0.003		0.029		0.093		-0.037		0.056	
Swine_poultry_N	-6.78E-05		-0.001	*	-0.001	**	-3.36E-04	°	-0.001	**	-0.001	***
Cattle_N	-0.001	*	0.002	°	0.001		-0.001	*	0.001		-1.58E-04	
D_algae	-0.005		0.007		0.002		0.001		-0.002		-0.001	
Ratio_algae	-0.124		0.046		-0.078		0.093		-0.214		-0.121	
Waters_area	-3.60E-04		-1.427		-1.427		-0.677		1.959		1.282	
Wetlands	-0.690		0.742		0.052		-0.663		0.875		0.212	
Shrubs_area	0.321		-0.439		-0.118		0.537		0.007		0.545	
Forest	-0.045		0.042		-0.002		-0.184		0.040		-0.144	
Greenspace_area	-0.323		-1.232		-1.555		0.691		-1.802		-1.111	
Landfills_area	-0.493		5.938		5.446		0.752		2.698		3.451	
Industries_area	-0.216		-0.928		-1.144		-0.718		1.356		0.637	
Shops_area	-0.395		0.047		-0.347		-0.632		-0.772		-1.403	
D_sea	2.29E-04		-0.009		-0.008	**	-0.012		0.004		-0.008	*
D_city	-0.004		0.003		-2.83E-04		0.003		-0.005		-0.002	
Pop_density	0.023	°	0.019		0.042		0.028		0.004		0.032	
Revenues	0.014	**	0.036	***	0.050	***	0.018	**	0.016		0.035	***
Services	0.002	*	-0.004	*	-0.002		0.002		-0.001		0.001	
Time FE	Yes						Yes					

***, **, *, ° stands for p-value of 0.1%, 1%, 5%, and 10% respectively.

We find in the SLX and the GNS models that the spillover effects of the swine and poultry is negative and significant at the 5% level. This result suggests that the negative externalities of swine breeding are perceived at the extra-municipality scale and thus potentially far from the production zone. Table 4 underlines that the marginal direct impact is negative and significant

in the GNS model. The results reveal that the direct impact of swine breeding tends to be negative but, as it is not significant in SLX, may not be robust. This result could represent that the recent investments of swine and poultry farms in renovating their buildings (notably with the PMPOA 1 and 2 programs). Indeed, one consequence of these investments is that farmers must transport and spread manure out of their farms, which could explain why the spillovers of the swine and poultry density are negative and significant. Overall, using the SLX and GNS results, we find that if we double the swine and poultry density, house prices are reduced by 5.38%, i.e., approximately three times what was estimated in the linear model (the estimated average impact of doubling density on house prices was estimated at -1.80%). The results of the SLX and GNS models are more in line with what we find in the literature [e.g. Bontemps et *al.*, 2008].

We find in the SLX model that both the direct and spillover effects of the cattle density are significant at the 10% level. The direct effect is negatively correlated with house prices, but the local spillover effect is positive. This result could illustrate the negative effect of the odor nuisance at the infra-municipality scale and the positive impact at higher scale could represent the contribution of pastures to landscape attractiveness. In addition, we find that the positive externalities of the cattle density have an impact that is twice greater than the impact of the negative externalities. In the GNS model, the direct impact of the cattle density is also significant and negative, showing that the direct effect is robust. The indirect impact in the GNS model is nonsignificant, suggesting that only the local spillover impacts residents' utility. Similar to the swine and poultry density, we find that the effects of the cattle density are underestimated in the OLS model compared to the SLX and GNS models.

While the result is negative and significant in the linear model, we find that the D_ALGAE and RATIO_ALGAE variables are non-significant at the 10% level in both the SLX and GNS models. The result from the linear model seems to be not robust when correcting for spatial autocorrelation. Indeed, even in the SEM (see Appendix 5), we find that this effect disappears. This result suggests that green algae pollution is spatially correlated with an omitted variable that influences residents' utility.

Finally, our results for the control variables reveal that population income is positive and significant at the 1% level and positive for both the direct and the spillover impacts for both SLX and GNS models. The population density is also significant in the SLX model but only for the direct effect. As in the linear model, the direct effects of the intrinsic variables are significant at the 1% level in both the SLX and GNS models. The spillover effects of the

intrinsic variables are non-significant except for the garden area in the GNS model. This indicates that the houses' own characteristics look more to private goods.

4.3   Robustness checks

Our results in 4.1 and 4.2 highlight that the specification of the spatial diffusion of the externalities capture most of the spatial interactions at stake in our data and that it allows to estimate the effects of the same activity at the infra-municipality and the extra-municipality scales. If these results are consistent with our theoretical part, they are valid with the spatial matrix W1. We test here the impact of alternative spatial matrices.

4.3.1. Distance-based spatial matrix

We provide here the robustness analyses to examine the sensitivity of our results to the different distance-based spatial matrices (W2 to W6). All criteria in appendix (Tables A6 and A7) indicate that the GNS model is the most suitable for specifying spatial autocorrelation for the five matrices. We find that the direct impact of cattle breeding is robust (see Table A8 in the appendices), while both the direct and spillover impacts of swine and poultry are not significant. Even if we find the same sign and amplitude for the indirect effect for cattle than in W1, this result is no longer statistically significant. These results show that our previous insights depend on the specified matrices. Furthermore, our sensitivity analysis reveals that the impacts of D_ALGAE are significant for matrices W3 and W5 and increase house prices while the impacts of RATIO_ALGAE are significant for matrices W4 and W6 and decrease house prices. Utilizing alternative matrices than W1 confirms our linear results that green algae pollution decreases house prices, even if the significance of the impacts depends on the matrix used.

4.3.2. Results at the municipal aggregated database

One of the limits of our approach is that, even if we know the specific location of each observation, the information on the agricultural variables is available at the municipal scale. Therefore, neighboring observations share similar agricultural and control variables. This feature is common to several hedonic studies [e.g. Bontemps et *al.*, 2008] could represent a limit when considering a spatial framework. Tables A5 in the appendices presents the goodness-of-fit models and the prediction quality criteria for W7. The SDEM and the GNS model provide

the highest R² and log likelihood values and the smallest values for NRMSE. The results of LM indicate that in this case, the SEM and/or SDEM are the most suitable (see Table 2). Using these criteria, we select the SDEM specification as the most appropriate for the aggregated model, suggesting that both the diffusion of the externalities and the spatial heterogeneity processes are at stake in our data. Table A9 in the appendices presents the results of the OLS model and the SDEM with W7. We notably confirm the results for swine, poultry and cattle breeding activities and, to a lesser extent, we confirm our results for grasslands.

Regarding the selection of the spatial matrix, we find that W1 present the second highest R² and the second lowest log-likelihood (after W4). Overall, we agree with Kim and Goldsmith [2009] that the 40-nearest spatial matrix presumably provides the most interesting results in rural housing market. These robustness test also confirm that distance-based spatial matrix tend to provide less consistent results in rural housing markets (Kim and Goldsmith, 2009).

5. Discussion

5.1 Contributions

Our hedonic application aims to value the externalities generated by agriculture in Brittany at different spatial scales, taking into account the spillover effects at the extra-municipal scale. Our results confirm that, on average, the residents of Brittany negatively value breeding activities, which is in line with the results of Le Goffe (2000) and Bontemps et *al.* (2008) in Brittany. However, in contrast to those studies, we distinguish between cattle and swine activities, allowing to examine separately the effect of the two types of breeding. The results of the linear model highlight that swine and poultry activities negatively impact residents' utility more than do cattle activities.

Our spatial econometric results show that the externalities arising from these two types of breeding activities have opposite forms over space. First, the direct impact at the infra-municipal scale of the cattle density is negatively correlated with house prices, but the local spillover effect at the extra-municipal scale is positive, meaning that the effect of cattle breeding on residents' utility depends on the scale of the demand to the different externalities generated by cattle farms. At the infra-municipal scale, the negative impact could illustrate the impact of the odor nuisance. At the extra-municipal scale, the positive impact could represent the impact of grazing on landscape attractiveness, with landscape attractiveness impacting the resident

inhabitants to a larger extent than the odor nuisance. We find similar results for temporary and permanent grasslands, where the direct impacts are negative but the local spillover impacts are positive. We interpreted the negative impacts by the increase in flood risks at the infra-municipal scale and the positive impacts at the extra-municipal scale as the provision of some cultural and recreational services such as landscape attractiveness and biodiversity habitat that could benefit hunting activities (Mensah and Elofsson, 2017). As these areas are primarily managed by cattle farms, the tradeoff faced by residents in regard to cattle farms is reinforced: cattle farms reduce the utility of residents at a narrow scale but increase it at a larger scale. Second, in line with all the studies on effects of swine facilities on house prices, we find that swine and poultry activities have negative impacts on residents' utility. On average, the combined effect of swine and poultry leads to a 5.4% decrease in house prices if we double the animal density, which is quite similar to previous results [e.g., Bontemps et *al.*, 2008]. However, our spatial approach indicates that the negative impacts overlap with the municipality where the production occurs. The distance to swine activities has already been stressed to highlight the large impact of swine activities on house prices, but our results are larger than those previously estimated using linear econometrics with GIS data (e.g., Ready and Abdalla, 2005). In addition, we find that the direct impacts at the infra-municipal scale are lower than the local spillover impacts at the extra-municipal scale. We interpret this result as the reallocation of the odor nuisance due to the renovation of swine and poultry buildings and its replacement by manure spreading, sometimes far from buildings (Gaigné et *al.*, 2012; Peyraud et *al.*, 2014). Overall, the spillover effects suggest that agricultural externalities overlap on neighbored municipalities, meaning that instruments design by municipal governance should be not optimal and that higher level of governance should be privileged.

Our results highlight the necessity of using spatial econometrics in the hedonic valuation of environmental goods. Correcting for the spatial autocorrelation of the observations modifies the significance, the sign and the amplitude of the parameters. For example, we find that permanent grasslands have a negative impact on residents' house in the linear specification, which could question the involvement of the Common Agricultural Policy for their conservation. However, when controlling for the effect of the diffusion of the externalities, we find a positive impact of the grasslands, but this impact appears at larger scales than the infra-municipal one. Regarding cattle farms, we find a negative impact in the linear specification but a potentially positive impact in the SLX specification, as the positive externalities are valued as twice greater than the negative externalities. Regarding swine and poultry activities, we find

that the non-specification of the spatial correlation leads to an underestimation of their negative impacts on house prices by 2.5 in the case of the SLX model and even by three in case of the GNS model. These figures highlight the usefulness of spatial autocorrelation correction for the unbiased estimations of the parameter of interest when panel data are unavailable, the unbiased estimation of externalities being crucial for agro-environmental policy design. As repeat sales are rarely provided in real estate databases (at least for a short period of time such as ours), we advocate for a generalization of the utilization of spatial econometrics in hedonic valuation studies.

In particular, in line with Halleck Vega and Elhorst (2015), we advocate for a generalization of the utilization of spatial econometric models that specify the spatial relationships between the explanatory variables. Indeed, our results reveal that these models are the most appropriate for the seven tested matrices. The *a priori* restrictions between the direct and the spillovers effects in the SAR and the SARAR models reduce the explanatory power of the explanatory variables, without mentioning that these restrictions reduce the information on the forms of externalities over space. In addition, we find that the SDM was not the most suitable model for specifying spatial dependence for the seven tested matrices. This result is particularly interesting, as, except for Maslianskaïa-Pautrel and Baumont (2016), all the environmental hedonic studies specifying the spatial relationships between the explanatory variables have used the SDM. Similar to Halleck Vega and Elhorst (2015), we call for a generalization to take the SLX model as the point of departure when estimating the spatial hedonic model and to then test for additional spatial effects using the specific-to-general approach (or any other procedure). Finally, in line with Chakir and Lungarska (2017), our results stress that the GNS model is often the best model for specifying the spatial autocorrelation of the observations. This result suggests that the three types of spatial interactions (autocorrelation, diffusion, heterogeneity) appears in our hedonic study. In the specific case of W1, the statistical tests suggest that both the SLX and the GNS could represent the best specifications, highlighting that spatial diffusion of externalities are the main type of spatial interactions in our data. Indeed, we find that the levels of the SLX and the GNS estimators were fairly similar in the case of W1. However, we find estimated parameters that are less significant than those in other models, which is a common feature of GNS models due to the complexity of the modeled spatial relationships [Halleck Vega and Elhorst, 2015].

5.2   Limits

Our work suffers from some potential limitations. First, the results from the hedonic method are valid under several assumptions presented in section 2.1.2. We already explained in section 2.1.2 that the introduction of the spatial settings can better fit the assumption of perfect information by incorporating the information on other house transactions, notably the prices, in the hedonic function. This feature is one on the main motivation to use the SAR model and its developments (Osland, 2010). The three other assumptions, namely that (i) the buyers can move to utility-maximizing positions, (ii) the housing market is in equilibrium and (iii) the house supply is fixed in the short term seems to not be modified by the introduction of spatial settings in the hedonic model. The validity of our results remains subject to the validity of these three assumptions.

Second, other limits may arise from the econometric point of view. Indeed, our study of house prices in three NUTS3 departments may question the assumption of a homogenous market. On such a large territory, we may face an issue of market heterogeneity, which could imply that buyers behave differently over the territory. This would affect the quality of the estimation because of heteroscedasticity issue. To limit the heterogeneity of housing markets, we have focused on the rural housing market (see 3.2). We have also added population density and revenues as additional explanatory variables to capture some heterogeneity. We have limited temporal heterogeneity by using time fixed effects. Finally, one interest of the spatial econometrics models with a spatial effect on house prices is that it fully integrates the adjacency effect and thus artificially reduces the heterogeneity of the Breton housing market. The models including a spatial effect on the error term reduce also the unobserved heterogeneity if this one is spatially correlated (Anselin and Lozano-Gracia, 2009; LeSage and Pace, 2009). All these measures should prevent high heterogeneity in our data and improve the quality of our estimated parameters.

Third, the choices of the spatial matrices can impact the results. We have proved that some of our results are robust to the different matrices but others only appears for some matrices. This suggests that the different matrices lead to different integration of space viscosity that could be more or less suitable for the capture of spatial processes. We agree with Kim and Goldsmith (2009) that the K-nearest spatial matrix presumably provides the most interesting results in rural housing market.

Fourth, observations from the same municipality share the same agricultural variables, which partly explains why we have tried several spatial weighted matrices. As the matrices based on the inverse distance attribute more weight on neighboring observations, this could explain why the results from W2-W6 are less interpretable. It could be interesting to use GIS data for all observations to compute unique variables for each observation. However, the description of nonpoint source externalities such as nitrogen pollution is more adapted using the concentration (or share) rather than the closest distance to a potential source of a pollution (Bontemps et *al.*, 2008). Overall, we agree with Kim and Goldsmith (2009) that distance-based spatial matrix are apparently not appropriate for hedonic valuation in rural housing markets.

Finally, our results relied only on parametric functional forms. The utilization of a nonparametric method in a spatial framework (McMillen, 2012) can lead to substantial gains in the precision of the estimation (Bontemps et *al.*, 2008). Similarly, other developments in the spatial econometrics literature, such as the mobilization of an endogenous spatial weighted matrix (Halleck Vega and Elhorst, 2015), should be considered in future hedonic valuations of agricultural and environmental externalities.

6.   Conclusion

We carried out the commonly used hedonic pricing method on house prices to estimate the value of the agricultural externalities in Brittany (Bontemps et *al.*, 2008; Le Goffe, 2000). Our contributions are threefold. First, we explain theoretically that spatial hedonic models enables to measure the value of the agricultural externalities both at the infra-municipality and at the extra-municipality scales. We explain that, given that an agricultural activity support the provision of multiple public goods and bads and that consumers' willingness-to-pay present a distance-decay, the value of the agricultural at the two scales can be different and even of opposite signs. It means that shot range and long range externalities of one agricultural activity correspond to different biophysical processes. Second, the estimations of the different specifications of the spatial hedonic model highlights that the spatial interactions are mainly due to the spatial diffusion of the externalities. Our results suggest that the effects of price diffusion and spatial heterogeneity are less important factors. This explain why the GNS model present fairly similar results than the SLX models. Third, we find that swine activities present negative effects at all scales whereas dairy cattle activities, including grassland management, present negative direct effects but positive local spillovers.

References

Anselin, L., Lozano-Gracia, N. (2009). Spatial hedonic models. In *Palgrave Handbook of Econometrics*, Springer, p. 1213–1250.

Ay, J.S., Chakir, R., Marette, S. (2017). Distance Decay in the Willingness to Pay for Wine: Disentangling Local and Organic Attributes. *Environmental and Resource Economics*, 68(4): 997–1019.

Ball, M.J. (1973). Recent empirical work on the determinants of relative house prices. *Urban studies*, 10: 213–233.

Bontemps, C., Simioni, M., Surry, Y. (2008). Semiparametric hedonic price models: assessing the effects of agricultural nonpoint source pollution. *Journal of Applied Econometrics*, 23(6): 825–842.

Brasington, D.M., Hite, D. (2005). Demand for environmental quality: a spatial hedonic analysis. *Regional science and urban economics*, 35(1): 57–82.

Cavailhès, J., Brossard, T., Foltête, J.C., Hilal, M., Joly, D., Tourneux, F.P., Wavresky, P. (2009). GIS-based hedonic pricing of landscape. *Environmental and Resource Economics*, 44(4): 571–590.

Chakir, R., Lungarska, A. (2017). Agricultural rent in land-use models: comparison of frequently used proxies. *Spatial Economic Analysis*, 12(2-3): 279–303.

Cropper, M.L., Deck, L.B., McConnell, K.E. (1988). On the choice of funtional form for hedonic price functions. *The Review of Economics and Statistics*, 70(4): 668–675.

Elhorst, J.P (2014). *Spatial Econometrics: from Cross-Sectional Data to Spatial Panels.* Springer.

Eyckmans, J., De Jaeger, S., Rousseau, S. (2013). Hedonic Valuation of Odor Nuisance Using Field Measurements: A Case Study of an Animal Waste Processing Facility in Flanders. *Land Economics*, 89(1): 53–75.

Fernández-Avilés, G., Minguez, R., Montero, J.M. (2012). Geostatistical air pollution indexes in spatial hedonic models: the case of Madrid, Spain. *Journal of Real Estate Research*, 34(2): 243–274.

Florax, R.J., Folmer, H., Rey, S.J. (2003). Specification searches in spatial econometrics: the relevance of Hendry's methodology. *Regional Science and Urban Economics*, 33(5): 557–579.

Gaigné, C., Le Gallo, J., Larue, S., Schmitt, B. (2011). Does regulation of manure land application work against agglomeration economies? Theory and evidence from the French hog sector. *American Journal of Agricultural Economics*, 94(1): 116–132.

Halleck Vega, S., Elhorst, J.P. (2015). The SLX model. *Journal of Regional Science*, 55(3): 339–363.

Hanley, N., Barbier, E.B., Barbier, E. (2009). P*ricing Nature: Cost-Benefit Analysis and Environmental Policy*. Edward Elgar Publishing, 360 p.

Herriges, J.A., Secchi, S., Babcock, B.A. (2005). Living with hogs in Iowa: the impact of livestock facilities on rural residential property values. *Land Economics*, 81(4): 530–545.

Kim, C.W., Phipps, T.T., Anselin, L. (2003). Measuring the benefits of air quality improvement: a spatial hedonic approach. *Journal of Environmental Economics and Management*, 45(1): 24-39.

Kim, J., Goldsmith, P. (2009). A spatial hedonic approach to assess the impact of swine production on residential property values. *Environmental and Resource Economics*, 42(4): 509–534.

Lancaster, K.J. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2): 132–157.

Le Goffe, P. (2000). Hedonic pricing of agriculture and forestry externalities. *Environmental and Resource Economics*, 15(4): 397–401.

Leggett, C.G., Bockstael, N.E. (2000). Evidence of the effects of water quality on residential land prices. *Journal of Environmental Economics and Management*, 39(2): 121–144.

LeSage, J.P., Pace, R.K. (2009). *Introduction to Spatial Econometrics*. Boca Raton, CRC Press, 374 p.

Maslianskaïa-Pautrel, M., Baumont, C. (2016). Environmental Spillovers and their Impacts on Housing Prices: A Spatial Hedonic Analysis. *Revue d'Economie Politique*, 126(5): 921–945.

McMillen, D.P. (2012). Perspectives on spatial econometrics: linear smoothing with structured models. *Journal of Regional Science*, 52(2): 192–209.

MEEM. (2017). *Green algae and tourism frequentation (Analyse)*. French Ministry of Environment, Energy and Sea (MEEM).

Mensah, J.T., Elofsson, K. (2017). An empirical analysis of hunting lease pricing and value of game in Sweden. *Land Economics*, 93(2): 292–308.

Mihaescu, O., Vom Hofe, R. (2013). Using spatial regression to estimate property tax discounts from proximity to brownfields: A tool for local policy-making. *Journal of Environmental Assessment Policy and Management*, 15(1): 1–23.

Montero, J.M., Fernández-Avilés, G., Mínguez, R. (2011). Spatial Hedonic Pricing Models for Testing the Adequacy of Acoustic Areas in Madrid, Spain. *Investigaciones Regionales*, 21: 157-181.

Nagelkerke, N.J. (1991). A note on a general definition of the coefficient of determination. *Biometrika*, 78(3): 691–692.

Ord, K. (1975). Estimation methods for models of spatial interaction. *Journal of the American Statistical Association*, 70(349): 120–126.

Osland, L. (2010). An application of spatial econometrics in relation to hedonic house price modeling. *Journal of Real Estate Research*, 32(3): 289-320.

Pate, J., Loomis, J. (1997). The effect of distance on willingness to pay values: a case study of wetlands and salmon in California. *Ecological Economics*, 20(3): 199–207.

Peyraud, J.L., Cellier, P., Aarts, F., Béline, F., Bockstaller, C., Bourblanc, M., Durand, P. (2014). Nitrogen flows and livestock farming: lessons and perspectives. *Advances in Animal Biosciences*, 5(1): 68–71.

Ready, R.C., Abdalla, C.W. (2005). The amenity and disamenity impacts of agriculture: estimates from a hedonic pricing model. *American Journal of Agricultural Economics*, 87(2): 314–326.

Rolfe, J., Windle, J. (2012). Distance decay functions for iconic assets: assessing national values to protect the health of the Great Barrier Reef in Australia. *Environmental and Resource Economics*, 53(3): 347–365.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy*, 82(1): 34–55.

Sutton, M.A., Oenema, O., Erisman, J.W., Leip, A., van Grinsven, H., Winiwarter, W. (2011). Too much of a good thing. *Nature*, 472(7342): 159–161

Yoo, J., Ready, R. (2016). The impact of agricultural conservation easement on nearby house prices: Incorporating spatial autocorrelation and spatial heterogeneity. *Journal of Forest Economics*, 25: 78–93.

Appendix 1: Correlation matrix of the variables
Table A1: Correlation matrix of the variables

	House prices	Bath room	room	floor	garden	oilseeds	cereals	Other crops	Permanent grasslands	Temporary Grasslands	Fallow	Shannon	Swine Poultry N	Cattle N	D algae	Ratio algae	Waters	Wetlands	Shrubs	Forest	Green space	Landfills	Industries	Shops	D_sea	D_city	Pop density	Rev	Services
House prices	1,00																												
Bathroom	0,41	1,00																											
Room	0,46	0,39	1,00																										
Floor	0,05	0,14	0,22	1,00																									
Garden	0,13	0,05	0,02	-0,03	1,00																								
Oilseeds	0,09	0,05	0,03	0,08	-0,07	1,00																							
Cereals	0,06	0,02	0,01	-0,02	-0,05	-0,11	1,00																						
Othercrops	0,10	0,03	0,04	0,09	-0,08	0,87	-0,32	1,00																					
Permanent grassland	-0,12	-0,02	-0,06	-0,01	0,12	-0,16	-0,61	-0,07	1,00																				
Temporary grassland	0,02	-0,02	0,03	0,00	-0,08	-0,07	0,00	0,03	-0,63	1,00																			
Fallow	0,10	0,03	0,04	0,09	-0,07	0,87	-0,32	0,99	-0,07	0,03	1,00																		
Shannon index	0,06	0,01	0,04	0,08	-0,05	0,67	-0,60	0,77	0,17	0,07	0,78	1,00																	
Swine poultry N	-0,06	0,00	0,00	-0,03	0,00	-0,11	0,27	-0,21	-0,13	-0,07	-0,21	-0,14	1,00																
Cattle_N	-0,14	-0,02	0,00	-0,06	0,03	-0,40	-0,05	-0,45	0,10	0,04	-0,45	-0,23	0,16	1,00															
D_algae	-0,32	-0,03	-0,09	-0,04	0,08	-0,06	-0,01	-0,08	0,17	-0,09	-0,08	-0,16	-0,05	0,13	1,00														
Ratio_algae	-0,21	-0,03	-0,03	-0,06	0,09	-0,20	-0,04	-0,23	0,09	0,00	-0,23	-0,15	0,07	0,34	0,26	1,00													
Waters_area	0,06	0,00	0,02	0,04	-0,03	0,33	-0,13	0,40	-0,02	0,02	0,40	0,31	-0,11	-0,21	-0,11	-0,24	1,00												
Wetlands	0,09	0,03	0,02	0,04	-0,03	0,09	0,02	0,11	-0,09	0,08	0,11	0,05	-0,08	-0,09	-0,09	-0,08	0,34	1,00											
Shrubs_area	-0,01	-0,01	-0,01	0,02	0,03	-0,09	0,00	-0,07	-0,07	0,28	-0,07	-0,06	-0,11	-0,05	0,06	0,00	0,03	0,08	1,00										
Forest	0,00	0,00	0,00	0,01	0,03	-0,04	0,02	0,00	-0,11	0,20	0,00	-0,08	-0,18	-0,18	0,02	0,02	-0,08	-0,01	0,19	1,00									
Greenspace	0,12	0,02	0,03	0,01	-0,04	0,06	0,01	0,14	-0,06	0,00	0,14	0,10	-0,09	-0,20	-0,12	0,03	0,08	0,02	0,08	0,12	1,00								
Landfills	0,02	-0,02	0,01	0,04	-0,02	0,28	0,02	0,21	-0,07	-0,03	0,21	0,15	0,00	-0,08	-0,05	-0,02	0,12	0,07	0,04	-0,08	0,05	1,00							
Industries	0,09	-0,01	0,03	0,01	-0,08	0,19	0,00	0,27	-0,14	-0,01	0,27	0,15	-0,12	-0,22	-0,06	-0,18	-0,01	-0,01	-0,09	-0,03	0,02	0,01	1,00						
Shops_area	0,11	0,02	0,05	0,08	-0,10	0,63	-0,23	0,76	-0,10	0,04	0,76	0,56	-0,22	-0,38	-0,13	-0,24	0,45	0,11	-0,07	-0,15	0,26	0,25	0,31	1,00					
D_sea	-0,35	-0,04	-0,08	-0,06	0,10	-0,07	0,03	-0,13	0,20	-0,14	-0,13	-0,21	0,02	0,20	0,85	0,46	-0,13	-0,10	0,07	0,02	-0,12	-0,06	-0,11	-0,18	1,00				
D_city	-0,15	0,00	-0,03	0,02	0,00	0,06	-0,01	0,03	0,08	-0,02	0,03	0,04	-0,08	-0,03	0,37	-0,16	0,02	-0,07	0,07	0,04	-0,14	-0,06	-0,03	-0,06	0,44	1,00			

Pop_density	0,11	0,01	0,05	0,07	-0,09	0,60	-0,21	0,72	-0,10	0,04	0,72	0,53	-0,20	-0,35	-0,16	-0,24	0,51	0,11	-0,06	-0,14	0,24	0,28	0,31	0,96	-0,21	-0,10	1,00	
Revenues	0,37	0,09	0,14	0,00	-0,11	0,01	0,09	0,08	-0,25	0,18	0,08	0,05	-0,01	-0,12	-0,51	-0,21	-0,01	0,18	-0,09	0,03	0,20	-0,03	0,17	0,08	-0,53	-0,26	0,04	1,00
Services	0,00	-0,01	0,05	-0,02	-0,14	0,10	-0,07	0,14	-0,19	0,29	0,14	0,17	-0,06	0,04	0,02	-0,04	0,10	-0,02	-0,07	-0,06	0,01	-0,01	0,30	0,36	-0,01	0,00	0,34	0,04

Appendix 2: Summary of the estimated spatial models

Table A2: Summary of the estimated spatial models (Source: adapted from Halleck Vega and Elhorst, 2015)

Models	Description	Direct effects	Spillover effects
Linear	$\ln(\mathbf{P}) = \beta_0 \boldsymbol{\iota} + \boldsymbol{\beta_1} \mathbf{y} + \boldsymbol{\beta_2} \mathbf{z} + \boldsymbol{\varepsilon}$	Elements of $\boldsymbol{\beta}$	0
SEM	$\ln(\mathbf{P}) = \beta_0 \boldsymbol{\iota} + \boldsymbol{\beta_1} \mathbf{y} + \boldsymbol{\beta_2} \mathbf{z} + \boldsymbol{\varepsilon}$ with $\boldsymbol{\varepsilon} = \lambda \mathbf{W} \mathbf{u}$	Elements of $\boldsymbol{\beta}$	0
SAR	$\ln(\mathbf{P}) = \rho \mathbf{W} \ln(\mathbf{P}) + \beta_0 \boldsymbol{\iota} + \boldsymbol{\beta_1} \mathbf{y} + \boldsymbol{\beta_2} \mathbf{z} + \boldsymbol{\varepsilon}$	Diagonal elements of $(\mathbf{I} - \rho \mathbf{W})^{-1} \boldsymbol{\beta}$	Off-diagonal elements of $(\mathbf{I} - \rho \mathbf{W})^{-1} \boldsymbol{\beta}$
SLX	$\ln(\mathbf{P}) = \beta_0 \boldsymbol{\iota} + \boldsymbol{\beta_1} \mathbf{y} + \boldsymbol{\eta_1} \mathbf{W} \mathbf{y} + \boldsymbol{\beta_2} \mathbf{z} + \boldsymbol{\eta_2} \mathbf{W} \mathbf{z} + \boldsymbol{\varepsilon}$	Elements of $\boldsymbol{\beta}$	Elements of $\boldsymbol{\eta}$
SARAR	$\ln(\mathbf{P}) = \rho \mathbf{W} \ln(\mathbf{P}) + \beta_0 \boldsymbol{\iota} + \boldsymbol{\beta_1} \mathbf{y} + \boldsymbol{\beta_2} \mathbf{z} + \boldsymbol{\varepsilon}$ with $\boldsymbol{\varepsilon} = \lambda \mathbf{W} \mathbf{u}$	Diagonal elements of $(\mathbf{I} - \rho \mathbf{W})^{-1} \boldsymbol{\beta}$	Off-diagonal elements of $(\mathbf{I} - \rho \mathbf{W})^{-1} \boldsymbol{\beta}$
SDM	$\ln(\mathbf{P}) = \rho \mathbf{W} \ln(\mathbf{P}) + \beta_0 \boldsymbol{\iota} + \boldsymbol{\beta_1} \mathbf{y} + \boldsymbol{\eta_1} \mathbf{W} \mathbf{y} + \boldsymbol{\beta_2} \mathbf{z} + \boldsymbol{\eta_2} \mathbf{W} \mathbf{z} + \boldsymbol{\varepsilon}$	Diagonal elements of $(\mathbf{I} - \rho \mathbf{W})^{-1} (\boldsymbol{\beta} + \mathbf{W} \boldsymbol{\eta})$	Off-diagonal elements of $(\mathbf{I} - \rho \mathbf{W})^{-1} (\boldsymbol{\beta} + \mathbf{W} \boldsymbol{\eta})$
SDEM	$\ln(\mathbf{P}) = \beta_0 \boldsymbol{\iota} + \boldsymbol{\beta_1} \mathbf{y} + \boldsymbol{\eta_1} \mathbf{W} \mathbf{y} + \boldsymbol{\beta_2} \mathbf{z} + \boldsymbol{\eta_2} \mathbf{W} \mathbf{z} + \boldsymbol{\varepsilon}$ with $\boldsymbol{\varepsilon} = \lambda \mathbf{W} \mathbf{u}$	Elements of $\boldsymbol{\beta}$	Elements of $\boldsymbol{\eta}$
GNS	$\ln(\mathbf{P}) = \rho \mathbf{W} \ln(\mathbf{P}) + \beta_0 \boldsymbol{\iota} + \boldsymbol{\beta_1} \mathbf{y} + \boldsymbol{\eta_1} \mathbf{W} \mathbf{y} + \boldsymbol{\beta_2} \mathbf{z} + \boldsymbol{\eta_2} \mathbf{W} \mathbf{z} + \boldsymbol{\varepsilon}$ with $\boldsymbol{\varepsilon} = \lambda \mathbf{W} \mathbf{u}$	Diagonal elements of $(\mathbf{I} - \rho \mathbf{W})^{-1} (\boldsymbol{\beta} + \mathbf{W} \boldsymbol{\eta})$	Off-diagonal elements of $(\mathbf{I} - \rho \mathbf{W})^{-1} (\boldsymbol{\beta} + \mathbf{W} \boldsymbol{\eta})$

Appendix 3: Definition of the used spatial weight matrices

Table A3: Definition of the used spatial weight matrices

Specifications	Matrices	Description
K-nearest weighting	W1	$\mathbf{W} = w_{mn} = \begin{cases} 1/K & \text{if } n \in [1;K] \\ 0 & \text{if } n \notin [1;K] \end{cases}$ with $K = 40$
Inverse distance weighting	W2	$\mathbf{W} = w_{mn} = d_{mn}^{-1}$
Inverse distance weighting with threshold	W3	$\mathbf{W} = w_{mn} = \begin{cases} d_{mn}^{-1} & \text{if } d_{mn} \leq 10\text{km} \\ 0 & \text{if } d_{mn} > 10\text{km} \end{cases}$
	W4	$\mathbf{W} = w_{mn} = \begin{cases} d_{mn}^{-1} & \text{if } d_{mn} \leq 25\text{km} \\ 0 & \text{if } d_{mn} > 25\text{km} \end{cases}$
Squared-inverse distance weighting with threshold	W5	$\mathbf{W} = w_{mn} = \begin{cases} d_{mn}^{-2} & \text{if } d_{mn} \leq 10\text{km} \\ 0 & \text{if } d_{mn} > 10\text{km} \end{cases}$
	W6	$\mathbf{W} = w_{mn} = \begin{cases} d_{mn}^{-2} & \text{if } d_{mn} \leq 25\text{km} \\ 0 & \text{if } d_{mn} > 25\text{km} \end{cases}$
Contiguity weighting	W7	$\mathbf{W} = w_{op} = \begin{cases} 1 & \text{if munipalities } o \text{ and } p \text{ are contiguous} \\ 0 & \text{if not} \end{cases}$

Appendix A4: Spatial autocorrelation of the OLS residuals with W1-W7

Table A4: Spatial autocorrelation of the OLS residuals in the seven matrices

	W1	**W2**	**W3**	**W4**	**W5**	**W6**	**W7**
I of Moran	0.02	0.03	0.09	0.06	0.10	0.10	0.09
p-value	1.31E-10	1.17E-09	1.70E-09	1.38E-14	1.52E-09	3.15E-12	0.0011

Appendix 5: SEM, SAR, SARAR, SDM and SDEM results with W1

Table A5: SEM, SAR, SARAR, SDM and SDEM results with W1

Models / Variables	SEM		SAR		SAC		SDM X		SDM Lag.X		SDEM X		SDEM Lag.X	
Constant	10.894	***	6.531	***	5.100	***	9.713	***	-		9.703	***	-	
Nb_bathroom	0.256	***	0.256	***	0.254	***	0.256	***	0.113		0.256	***	0.118	
Nb_room	0.115	***	0.115	***	0.113	***	0.113	***	-0.065		0.113	***	-0.067	
Nb_floor	-0.062	***	-0.060	***	-0.057	***	-0.062	***	-0.012		-0.062	***	-0.012	
Garden_area	9.51E-06	***	9.56E-06	***	9.58E-06	***	9.80E-06	***	2.62E-07		0.000	***	0.000	
Oilseeds_area	-0.336		-0.269		-0.277		-0.435		-0.631		-0.441		-0.598	
Cereals_area	-0.035		0.096		0.167	*	-0.343	*	1.329	***	-0.342	*	1.320	***
Othercrops_area	3.523		2.510		1.260		4.325		-41.277	°	4.329		-40.973	°
Perm_grassland_area	-0.412	°	-0.152		-0.015		-0.631	*	1.406	*	-0.627	*	1.392	*
Temp_grassland area	-0.263	*	-0.133		-0.073		-0.509	***	0.781	*	-0.510	***	0.782	*
Fallow_area	-3.426		-2.228		-0.918		-4.762		43.309	*	-4.758		42.942	*
Shannon index	0.012		0.008		0.013		0.032		-0.003		0.032		-0.003	
Swine_poultry_N	-2.24E-04	°	-2.48E-04	*	-2.68E-04	*	-6.78E-05		-0.001	*	0.000		-0.001	*
Cattle_N	-0.001	*	-0.001	*	-0.001	*	-0.001	*	0.002	°	-0.001	*	0.002	°
D_algae	-0.001		1.62E-05		4.92E-04		-0.005		0.007		-0.005		0.007	
Ratio_algae	-0.151	°	-0.082		-0.044		-0.124		0.045		-0.123		0.047	
Waters_area	0.053		0.075		0.075		-0.001		-1.428		-0.009		-1.432	
Wetlands	-0.635		-0.437		-0.307		-0.690		0.741		-0.689		0.714	
Shrubs_area	0.380		0.325		0.270		0.321		-0.438		0.318		-0.409	
Forest	-0.094		-0.081		-0.071		-0.045		0.042		-0.044		0.034	
Greenspace_area	0.111		0.170		0.143		-0.323		-1.236		-0.306		-1.309	
Landfills_area	-0.209		0.449		0.976		-0.492		5.944		-0.497		5.869	
Industries_area	0.265		0.279		0.234		-0.216		-0.927		-0.225		-0.909	
Shops_area	-0.302		-0.260		-0.234		-0.395		0.046		-0.398		0.049	
D_sea	-0.007	**	-0.005	**	-0.004	***	2.28E-04		-0.009		0.000		-0.009	
D_city	-0.001		-4.59E-04		-2.89E-04		-0.004		0.003		-0.004		0.003	
Pop_density	0.017		0.014		0.013		0.023	°	0.019		0.023	°	0.020	
Revenues	0.023	***	0.020	***	0.017	***	0.014	**	0.036	***	0.014	**	0.036	***
Services	0.001		0.001		0.001		0.002	*	-0.004	*	0.002	*	-0.004	*
Time FE					0.045	*	0.048	*	0.383	**	0.048	*	0.380	**
R²	0.426		0.430		0.431		0.447				0.447			
LL	-1090.8		-1083.167		-1080.987		-1045.121				-1045.08			
AIC	2247.576		2232.334		2229.974		2216.241				2216.16			
ρ	-		0.36 ***		0.48 ***		-0.001				-			
λ	0.43 ***		-		-0.37 *		-				-0.03			

***, **, *, ° stands for p-value of 0.1%, 1%, 5%, and 10% respectively.

Appendix 6: Goodness-of-fit and prediction quality of the different model specifications with W2-W7

Table A6: Goodness-of-fit and prediction quality of the different model specifications with W2-W7

	W2				W3				W4				W5				W6				W7			
	R²	LL	AIC	NR MSE	R²	LL	AIC	NR MSE	R²	LL	AIC	NR MSE	R²	LL	AIC	NR MSE	R²	LL	AIC	NR MSE	R²	LL	AIC	NR MSE
OLS	0.421	-1101.9	2267.7	76.1	0.421	-1101.9	2267.7	76.1	0.421	-1101.9	2267.7	76.1	0.421	-1101.9	2267.7	76.1	0.421	-1101.9	2267.7	76.1	0.494	-51.4	186.13	71.1
SEM	0.428	-1088.0	2242.1	75.4	0.428	-1088.3	2242.6	75.5	0.431	-1081.5	2229.0	75.2	0.428	-1087.5	2241.0	75.4	0.430	-1083.1	2232.1	75.2	0.502	-47.6	161.13	70.2
SAR	0.429	-1084.5	2235.0	75.4	0.431	-1081.0	2228.0	75.2	0.436	-1071.0	2208.0	74.8	0.431	-1081.3	2228.6	75.2	0.434	-1075.2	2216.3	75.0	0.494	-51.3	168.66	71.1
SLX	0.440	-1060.2	2244.4	74.8	0.433	-1076.3	2276.5	75.3	0.443	-1053.8	2231.6	74.6	0.432	-1078.7	2281.3	75.4	0.436	-1069.3	2262.6	75.1	0.534	-31.1	186.13	68.2
SARAR	0.430	-1084.4	2236.9	75.3	0.432	-1078.7	2225.5	74.5	0.437	-1067.3	2202.6	74.1	0.431	-1080.2	2228.3	74.8	0.435	-1073.0	2214.1	74.3	0.502	-47.5	163.04	70.2
SDM	0.443	-1053.6	2233.2	74.5	0.439	-1064.3	2254.7	74.8	0.448	-1042.3	2210.7	74.1	0.439	-1065.0	2256.1	74.8	0.444	-1053.1	2232.3	74.4	0.534	-31.1	188.12	68.2
SDEM	0.444	-1052.9	2231.8	74.4	0.438	-1064.8	2255.7	74.8	0.448	-1043.2	2212.3	74.1	0.438	-1065.3	2256.5	74.8	0.443	-1053.9	2233.9	74.4	0.537	-29.3	184.67	67.8
GNS	0.444	-1052.8	2233.8	74.5	0.439	-1062.6	2253.1	72.9	0.449	-1041.5	2211.0	73.5	0.439	-1064.1	2256.2	73.3	0.445	-1050.5	2228.9	72.6	0.537	-28.9	185.77	67.7

Appendix 7: Results for the spatial autocorrelation tests for the hedonic models with W2-W7.

Table A7: Results for the spatial autocorrelation tests for the hedonic models with W2-W7

LM Test	W2	W3	W4	W5	W6	W7
OLS versus SEM (Ho: λ=0) - *LM error*	27.35***	28.44***	44.32***	29.39***	39.14***	6.183*
OLS versus SAR (Ho: ρ=0) - *LM lag*	39.08***	45.69***	74.25***	43.57***	57.97***	0.050
OLS versus SARAR (Ho: ρ= λ=0) - *LM lag + error*	39.13***	48.64***	78.41***	45.03***	59.95***	6.266
SLX versus SDEM (Ho: λ=0) - *LM error*	12.51***	24.20***	22.79***	27.75***	31.94***	2.679°
SLX versus SDM (Ho: ρ=0) - *LM lag*	12.332***	25.48***	25.034***	28.40***	34.233***	0.009
SLX versus GNS (Ho: ρ= λ=0) - *LM lag + error*	12.59***	27.82***	25.94***	28.85***	37.25***	4.185
SAR versus SAC (Ho: λ=0) - *LM error*	0.12	3.76°	6.47*	1.92	3.36°	6.253*
SDM versus GNS (Ho: λ=0) - *LM error*	1.78	3.87*	1.5	1.45	5.40*	4.256

***, **, *, ° stands for p-value of 0.1%, 1%, 5%, and 10% respectively.

Appendix 8: GNS results for W2 – W6 (direct, indirect and total impact)
Table A8: GNS results for W2 – W6 (direct, indirect and total impact)

Variables	W2			W3			W4		
	DE	IE	TE	DE	IE	TE	DE	IE	TE
Nb_bathroom	0.253 ***	0.212	0.465 **	0.257 ***	0.097 **	0.354 ***	0.256 ***	0.157 °	0.413 ***
Nb_room	0.113 ***	-0.025	0.088	0.114 ***	0.016	0.130 ***	0.113 ***	0.021	0.134 ***
Nb_floor	-0.057 ***	0.023	-0.035	-0.060 ***	-0.054 *	-0.114 ***	-0.057 ***	-0.060	-0.117 *
Garden_area	0.000 ***	0.000	0.000	0.000 ***	0.000	0.000 *	0.000 ***	0.000	0.000 °
Oilseeds_area	-1.104	2.089	0.985	-0.682	0.486	-0.196	-0.094	-1.537	-1.630
Cereals_area	-0.157	1.027	0.870	-0.033	0.221	0.187	-0.390 *	0.978 ***	0.587 **
Othercrops_area	0.553	3.618	4.171	23.742 °	-23.582 °	0.160	22.455	-40.677	-18.222
Perm_grassland_area	-0.821 *	1.539	0.718	-0.323	0.278	-0.045	-0.686 °	0.935	0.249
Temp_grassland area	-0.335 °	0.512	0.177	-0.248	0.133	-0.115	-0.296	0.248	-0.048
Fallow_area	-1.342	1.428	0.085	-24.459 °	25.061 *	0.602	-23.988	44.879 °	20.890
Shannon index	0.135	-0.264	-0.129	0.038	-0.058	-0.020	0.075	-0.076	-0.001
Swine_poultry_N	0.000	-0.001	-0.001	-0.000	-0.000	-0.000 °	-0.000	-0.000	-0.000
Cattle_N	-0.002 **	0.004	0.002	-0.001 °	0.001	-0.001	-0.001 *	0.001	0.000
D_algae	0.001	-0.005	-0.004	-0.011	0.011	0.000	-0.017 *	0.019 *	0.003
Ratio_algae	0.021	-0.407	-0.386	-0.062	-0.073	-0.134	-0.093	0.046	-0.047
Waters_area	-1.582	5.094	3.512	-3.848 *	4.626 *	0.778	-0.664	1.102	0.438
Wetlands	-3.781 °	25.730	21.949	-0.754	0.048	-0.706	-3.125 °	5.565	2.440
Shrubs_area	0.310	-0.109	0.201	-0.068	0.498	0.430	0.300	-0.304	-0.004
Forest	0.023	-0.818	-0.795	0.023	-0.140	-0.117	-0.039	-0.041	-0.080
Greenspace_area	0.972	-1.422	-0.450	0.777	-0.502	0.275	-0.344	-0.112	-0.455
Landfills_area	0.691	-3.687	-2.996	0.169	1.544	1.714	-0.806	4.236	3.430
Industries_area	0.504	-1.505	-1.001	-0.592	1.087	0.495	0.110	-0.153	-0.044
Shops_area	-0.516	-0.177	-0.694	0.021	-0.348	-0.327	-0.221	-0.216	-0.436
D_sea	-0.010 **	0.013	0.003	0.007	-0.015	-0.008 ***	0.012	-0.022 *	-0.010 ***
D_city	-0.003 °	0.003	0.000	-0.012 °	0.011	-0.001	-0.010	0.010 °	0.000
Pop_density	0.025	-0.007	0.017	0.014	0.000	0.014	0.018	0.002	0.020
Revenues	0.019 **	0.048 °	0.067 **	0.011	0.017 °	0.028 ***	0.006	0.030 **	0.036 ***
Services	0.003 *	-0.006	-0.003	0.001	-0.001	0.000	0.001	-0.001	0.000
Time FE	Yes			Yes			Yes		
R²	0.444			0.439			0.449		
LL	-1052.892			-1062.567			-1041.501		
AIC	2233.783			2253.133			2211.001		
ρ	0.046			0.313 ***			0.362 ***		
λ	0.273			-2.773 **			-0.207 °		

Table A8 (continuation): GNS results for W2 – W6 (direct, indirect and total impact).

Variables	W5			W6		
	DE	IE	TE	DE	IE	TE
Nb_bathroom	0.258 ***	0.076 **	0.333 ***	0.261 ***	0.107 *	0.368 ***
Nb_room	0.114 ***	0.012	0.127 ***	0.113 ***	0.011	0.124 ***
Nb_floor	-0.061 ***	-0.046 *	-0.107 ***	-0.058 ***	-0.055 *	-0.113 ***
Garden_area	0.000 ***	0.000	0.000 **	0.000 ***	0.000	0.000 *
Oilseeds_area	-0.910	0.861	-0.048	-0.695	0.639	-0.056
Cereals_area	0.127	0.037	0.164	-0.154	0.402	0.248 °
Othercrops_area	22.823	-22.142 °	0.681	44.260 °	-46.577 °	-2.317
Perm_grassland_area	-0.095	0.014	-0.080	-0.401	0.410	0.010
Temp_grassland area	-0.010	-0.131	-0.141	0.046	-0.164	-0.119
Fallow_area	-23.110	23.010 °	-0.100	-45.559 °	48.644 *	3.085
Shannon index	0.009	-0.022	-0.013	0.153	-0.182	-0.029
Swine_poultry_N	-0.000	-0.000	-0.000 *	-0.000	-0.000	-0.000 °
Cattle_N	-0.002 *	0.001	-0.001	-0.001 °	0.001	-0.001
D_algae	-0.009	0.009	0.000	-0.017 *	0.018 *	0.001
Ratio_algae	-0.089	-0.058	-0.148 °	-0.013	-0.111	-0.124
Waters_area	-3.562 *	4.096 *	0.534	-1.866	2.431	0.565
Wetlands	3.394	-4.123	-0.730	-2.280	1.729	-0.551
Shrubs_area	-0.142	0.619	0.478	0.487	-0.129	0.358
Forest	-0.031	-0.073	-0.104	-0.033	-0.065	-0.097
Greenspace_area	0.528	-0.039	0.489	0.628	-0.676	-0.048
Landfills_area	-1.277	3.052	1.774	-0.996	3.657	2.661
Industries_area	-0.148	0.625	0.477	0.297	0.086	0.383
Shops_area	0.056	-0.353	-0.297	-0.173	-0.130	-0.304
D_sea	0.007	-0.014	-0.008 ***	0.012	-0.020	-0.008 ***
D_city	-0.010 °	0.010	-0.001	-0.010	0.009 *	-0.001
Pop_density	0.011	0.003	0.013	0.014	0.000	0.014
Revenues	0.013	0.015	0.028 ***	0.005	0.026 **	0.031 ***
Services	0.001	-0.001	0.000	0.001	-0.001	0.000
Time FE		Yes			Yes	
R²		0.439			0.445	
LL		-1064.086			-1050.460	
AIC		2256.171			2228.920	
ρ		0.262 ***			0.345 ***	

Appendix 9: OLS and SDEM results with W7 in the aggregated model

Table A9: OLS and SDEM results with W7 in the aggregated model

Variables	OLS Model			SDEM Model		
	Coef.	Std. Err		DI	II	TI
Constant	11.174	0.228	***	-	-	-
Nb_bathroom	0.295	0.055	***	0.284 ***	0.060	0.344 ***
Nb_room	0.116	0.021	***	0.121 ***	-0.001	0.120 ***
Nb_floor	-0.153	0.039	***	-0.149 ***	0.030	-0.119
Garden_area	7.91E-06	2.26E-06	***	7.47E-06 **	6.11E-06	1.36E-05 **
Oilseeds_area	-0.508	0.727		-0.861	0.498	-0.363
Cereals_area	0.052	0.122		0.025	0.008	0.033
Othercrops_area	4.691	6.977		3.862	-35.155 *	-31.293
Perm_grassland_area	-0.704	0.319	*	-0.543	-0.474	-1.017
Temp_grassland area	-0.353	0.153	*	-0.437 *	0.052	-0.385
Fallow_area	-4.529	7.017		-3.983	35.772 *	31.789
Shannon index	0.064	0.082		0.113	-0.066	0.047
Swine_poultry_N	-0.001	2.16E-04	*	-3.26E-04 °	-0.001 **	-0.001 ***
Cattle_N	-0.001	0.001	*	-0.001 *	0.001	-2.85E-04
D_algae	-4.97E-04	0.003		0.003	-0.005	-0.002
Ratio_algae	-0.066	0.119		0.124	-0.285	-0.161
Waters_area	-0.507	1.069		-0.758	2.268	1.510
Wetlands	0.084	0.597		-0.812	0.991	0.179
Shrubs_area	0.705	0.316	*	0.568	0.037	0.605
Forest	-0.166	0.138		-0.192	0.024	-0.167
Greenspace_area	0.842	1.943		0.851	-1.939	-1.088
Landfills_area	0.483	1.842		0.757	2.427	3.184
Industries_area	-0.514	0.727		-0.679	1.433	0.753
Shops_area	-0.566	0.387		-0.623	-0.784	-1.407
D_sea	-0.009	0.003	***	-0.014	0.006	-0.007 °
D_city	-0.001	0.001		0.005	-0.007	-0.002
Pop_density	0.024	0.018		0.029	-7.49E-05	0.029
Revenues	0.024	0.005	***	0.020 *	0.013	0.033 **
Services	0.002	0.001	°	0.002 °	-0.001	0.001
Time FE	Yes			Yes		
R²	0.494			0.53699		
LL	-51.35			-29.33534		
AIC	186.13			184.67		
λ	-			0.123 °		

***, **, *, ° stands for p-value of 0.1%, 1%, 5%, and 10% respectively.

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