
# Assessing the direct and indirect impacts of breeding activities on residential values: a spatial hedonic approach in Brittany

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*Agriculture contributes to the production of a large range of externalities. Their valuation is a critical issue for the design of agro-environmental policies. Hedonic pricing method allows for such valuation using house prices and attributes. However, several endogenous biases affect the estimation. Some of these biases are due to spatial effects, which arise when observations are spatially correlated. The objective of the paper is to apply latest developments of spatial econometrics on a hedonic model to estimate the value of agricultural externalities from Brittany (France). We focused especially on externalities from breeding. We distinguish between direct and spatially indirect impacts of nitrogen pollution, but also on green algae presence, i.e. a nitrogen-related pollution arising on Breton seacoasts for years. Using a database of 8,075 transactions from 2010 to 2012, we run several linear and spatial hedonic models. A Spatial Durbin Error Model (SDEM) is selected as the best model. Our estimations reveal that swine and poultry breedings reduce house prices while cattle breeding has almost no impact on house prices. We highlight that the pollution from swine and poultry overlaps from the municipality where the production occurs. The green algae pollution of the closest beach decreases houses' prices by 13.5%.*

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## Abstract

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**Keywords:** Externalities; green alga; nitrogen; agriculture.

# 1. Introduction

Agricultural is a multifunctional activity ensuring the production of marketable goods jointly with non-marketable goods and services. This public good provision generates indirect effect on human welfare, which can be either positive (e.g. conservation of biodiversity) or negative (e.g. odor pollution, air pollution and eutrophication). The trend towards intensive and specialized agricultural systems has led to a gradual increasing of the negative indirect effects, with a decreasing of environmental quality. This is the case in Brittany. Brittany is the first breeding region of France with 8% of its GDP being agriculture. The intensification of breeding activities in Brittany generates several negative impacts. For example, permanent grassland turning has led to destruction of natural habitats and reduced the attractiveness of the landscape. Intensive breeding activities have also generated higher level of greenhouse gases emissions, agriculture accounting for 35% of these emissions in 2005 in Britany, i.e. a rate higher about 67% than the national one. The high animal density in Britany leads to a nitrogen surplus of 117KgN/Ha/year, i.e. 4 times more than the national average (Peyraud et al., 2012). It leads to high nitrogen released and pollution of water sources. It also generates pollution around the estuaries of Brittany, with 44% of the coastal municipalities of Brittany having been polluted by green algae in the last 15 years. These figures had led European Commission to threaten France by a 28 million euros fine for violating water quality standard in 2007. This fine have been abandoned in 2010 after France have conducted a 134 million euros plan to reduce nitrogen concentration in watercourses and pick up green alga. However, the proliferation of green algae on Breton shoreline still generates negative impacts on local inhabitant's welfare and tourism activities.

By definition, these externalities are ignored by the markets. To improve population's welfare, the authorities have to implement public policies to encourage the production of positive externalities at the expense of negative externalities. The role of the authorities is to select the most efficient instrument. The effectiveness of instruments depends on the costs faced by the farmers and the benefits captured by the population. If the costs can be estimated based on the agricultural technology and agricultural and input prices, specific methods are required to estimate the benefits that would capture the population. These methods rely on monetary valuation, a set of methods that allow attributing a monetary value to environmental characteristics based on their impact to the welfare of the populations. One way to estimate these externalities is the hedonic pricing method (Rosen, 1974). This method stands on the principle that goods, notably real estate properties, are a combination of attributes that influence buyers' welfare. Several empirical studies have used hedonic pricing method to estimate the willing-to-pay (WTP) of population to assess or improve air quality (Zabel and Kiel, 2000), water quality (Leggett and Bockstael, 2000), urban wetland (Frey et al., 2013) or urban green area (Panduro and Veie, 2013). The method is also applied to estimate the WTP to reduce negative externalities such as airport noise (Cohen and Coughlin, 2008) or traffic noise (Ossokina and Verweij, 2015).

Several studies have used hedonic pricing method to estimate the value of externalities from agriculture. Le Goffe (2000) has valued the impact of agricultural activities on renting price of rural bed and breakfast in Brittany. He found that one additional unit of livestock density and fodder crops decreases renting pricing by 24.1€ and 1€ respectively, whereas an additional unit of grassland increases renting pricing by 1€. Herriges et al. (2005) used Geographical Information System (GIS) data to estimate the impact of livestock activities, notably odor nuisance, on rural residential properties in Iowa. They found that properties values located downwind an animal facility at 0.25

and 0.5 miles are respectively reduced by 15% and 9%. Ready and Abdalla (2005) estimated both local amenities and disamenities impacts of agriculture in Berks county using GIS data. They found that a new livestock farm decreases house value by 6.4% and 4.1% when located at 500 and 800 meters respectively. Furthermore, they underlined that a house value would fall by 3% (respectively 5.8%) if a new poultry farm (respectively hog farm) settled within 800 meters around the house. Secchi (2007) examined the impact of landscape amenities on rural residential property values in Iowa. Her result suggests that increasing the distance of hog facilities with respect to a house by a mile increases the house value by 6.3%. Bontemps et al. (2008) assessed the impacts of agriculture activity on the price of residential property in Brittany using a non-parametric hedonic function. They found that house prices fall until 3.5% when the rate of converted permanent grassland in the municipality is over 20%. Furthermore, they found that the first units of released nitrogen decrease house prices by 7%. Each additional unit of nitrogen has no significant effect on house prices after 80 Kg/Ha. All these papers use standard linear econometric methods with cross sectional data.

The estimation of hedonic pricing model faces two empirical challenges: spatial effects due to the geographical location of each observation and potential endogenous problems (Feichtinger et al., 2016). The endogenous problems are notably due to unobserved heterogeneity in cross-sectional data but also from the confounding effects. These confounding effects may arise from spatial confounders. The spatial effects imply three different aspects: spatial autocorrelation, spatial diffusion and spatial heterogeneity. Spatial autocorrelation is the coincidence of value similarity across space (Anselin, 1988). Spatial diffusion is due to spatial processes that entails the formation of the dependent variable values. In particular, the presence of an activity in one place can impact houses' prices over a large geographical area. The spatial heterogeneity is linked to heterogeneous effect of the same cause over space. Spatial heterogeneity leads notably to heterocedasticity issues and instability of model parameters across space (Anselin, 1988). Thus, ignoring spatial effects can lead to irrelevant estimated parameters or misinterpretation of some economic processes (Anselin, 2003). A growing number of researchers have estimated hedonic pricing models using spatial econometric to deal with these issues. Spatial econometric provides useful tools to improve the quality of estimation by controlling for some spatial effects. Depending on the type of variables that are affected by spatial process, Elhorst (2014) describes three different of spatial interaction effects: (i) interaction effects among dependent variables, (ii) interaction effects among explanatory variables and (iii) interaction effects among the error terms. Each type of interaction introduced into hedonic model lead to a specific spatial model. Most of the hedonic spatial models have used the spatial autoregressive models (SAR), the spatial error models (SEM) and the Spatial Autoregressive Model with Autoregressive Disturbances models (SARAR). The SAR model specifies the hedonic model with spatial interaction effect on the depend variables while SEM model specifies a spatial interaction effect among the error terms. The SARAR model joins the SAR model and the SEM model.

Few studies on hedonic valuation of agricultural externalities have used these methods. Kim and Goldsmith (2009) used the SAR model to assess the impact of animal facilities on house prices. Their results revealed that the impact of swine facility with 10 000 head located at one mile to a house decreases its value by 11% when estimated with linear econometrics but only 8% when the spatial autocorrelation in sale prices is considered. In their case, the standard hedonic model without spatial econometric overestimates the impact of swine production on house prices by 23.5%. Yoo and Ready (2016) used the SEM model to examine the impact of forests and farmers' environmental contracts on house prices in Chester county (Pennsylvania). The linear estimation of the hedonic model revealed that one additional percentage of forest density within 800 meters around the house increases its price by 11.3 % with standard estimation of the hedonic model. The price increases by 9.6 % in the SEM model, suggesting an overestimation by 24.5% in the linear econometric estimation. Eyckmans et al. (2013) used SARAR model to estimate the disutility caused by odor from an animal waste processing facility in Flanders. The results of hedonic standard model showed that the prices of houses impacted by moderate and severe odor fall by 5% and 12% respectively, comparing to houses without nuisance. Comparing with spatial econometric results reveals that the spatial bias can lead to an underestimation of 10% of the parameters of interest.

SAR, SEM and SARAR are well suited to capture spatial autocorrelation and/or heterogeneity. However, there exist others spatial econometric models that can be used to address more complex form of spatial dependency such that the spatial diffusion effects. The spatial lag of exogenous variable models (SLX), the spatial Durbin models (SDM) and the spatial Durbin error models (SDEM) allow taking into account for such spatial spillovers. Their introduction allows correcting for some estimation biases. For example, Montero et al. (2011) concluded that SDM model was the most adapted model to estimate the impact of noise pollution on house prices and that SAR and SEM model underestimated this impact by 40% and 51.3% respectively. In addition, these models are well adapted to distinguish the economic cause of the externality (Halleck Vega and Elhorst, 2015). They notably allow measuring distance decay effects (the impact of the distnance on the strength of the externality) when specific spatial weighted matrix are used (Halleck Vega and Elhorst, 2015). Maslianskaïa-Pautrel and Baumont (2016) use these models to distinguish between the economic causes of houses' price determinants and to estimate the spatial and global externalities (Anselin, 2003).

SDM and SDEM models have been used in hedonic pricing studies within various fields but, they have never been used for estimating agricultural externalities to our knowledge. They could be useful for the estimation of externalities from agriculture. Indeed, agricultural activities are characterized by a high degree of spatial concentration, notably due to geological heterogeneity and industrial concentrations. In addition, even if several authors have highlighted that the externalities of breeding activities vary with the distance to the source of the disamenity (Ready and Abdalla, 2005; Herriges et al.,2005), the utilization of linear econometrics with GIS data does not prevent from biases due to spatial dependence (Mueller and Loomis, 2008).

The objective of this paper is to examine the direct and indirect impact of agricultural activities on residential values using spatial hedonic models. This study stands out among other studies focusing on agriculture externalities by applying new spatial econometric models (SDM and SDEM) to estimate the value of agricultural amenities and damages, especially those arising from breeding activities. Comparing the results of these models with those usually used (linear econometric, SAR, SEM and SARAR), we conclude about the strengthens of the two models for improving the quality of estimation and describing the spatial diffusion of the externalities.

The next section presents an analysis on the spatial biases arising in hedonic pricing model and the spatial econometric methods to overcome these biases. We present after the empirical model and descriptive analysis of the data. At last, we present the results of our estimation and discuss them.

## 2. Advanced in spatial hedonic pricing

### 2.a. Hedonic pricing method and spatial causality

Hedonic pricing is a monetary valuation method based upon a revealed preference approach aiming to assess monetarily non-marketable good values. The theory assumes that some goods are purchased for its attributes. Rosen (1974) underlined that the interactions of producers and consumers determine an equilibrium price of the marketable good, which can be used to determine the implicit price of each attribute constituting the good. These implicit prices being unobserved in real market, they can be only determined through statistical analyses. In particular, the house price can be considered as a function of its attributes (Freeman, 1981). A house price is a function of value of each of its attribute. In practice, the function that estimated provides a set of implicit prices of the house characteristics, these implicit prices being a transformation of the estimated parameters. The application of hedonic analysis requires the satisfaction of some assumptions related to market: (i) all buyers and sellers in the housing market are well informed of attribute levels at every possible housing location; (ii) all buyers in the market can move to utility-maximizing positions; (iii) the housing market is in equilibrium (Hanley et al., 2009). The implication of these assumptions in our study will be discussed in the last section.

Let $\mathbf{z}$ be a vector of house characteristics $(z_1,...,z_n)$, and $P$ the price of the house, the hedonic price function is expressed as:

$$P = P(\mathbf{z}) \qquad (1)$$

Assume that the consumer utility $U$ is a function of his composite consumption $x$ and the vector $\mathbf{z}$, the utility function $U$ of the consumer is defined as:

$$U = U(x,\mathbf{z}) \qquad (2)$$

Under the assumption of maximizing the utility of consumer with the constraint of his income $R$ [1], we reach the first derivate:

$$\frac{\partial U / \partial z_j}{\partial U / \partial x} = \partial P / \partial z_j \qquad (3)$$

The term $\partial P / \partial z_j$ is the implicit price of the house attribute $z_j$, corresponding to the marginal willingness to pay (WTP) of the consumer. The implicit price in hedonic analysis can be used to evaluate the impact of marginal change of environmental conditions on environmental amenities.

As the hedonic pricing method aims to determine the implicit prices of good attributes, the essential issue hedonic price studies seek to address is to reduce the estimation biases of the implicit price of $z_j$. The biased implicit prices could lead to failure of environmental policies. The estimation issues can arise from the model specification due to spatial effects but also to other endogenous bias thus that unobserved heterogeneity or misspecification of the functional form. We focus on the spatial biases.

As we have mentioned above, spatial biases raise when observations are spatially distributed, leading to empirical issues namely spatial autocorrelation, spatial diffusion and spatial

[1] Note that $R = p_x x + P$, $P$ being the hedonic price and $p_x$ the price of the composite good $x$.

heterogeneity. This indicates the house prices are not only a function of its attributes but also to neighboring houses' attributes (including environmental ones).

The spatial autocorrelation of house prices issue arise from the sharing of house market, notably a similar house demand within the same neighborhood. . This spillover refers to the information notably the prices, got by sellers and buyers about nearby properties with similar characteristics. Using this information, the prices of the properties in market are suggested in compliance with the price of its neighboring house. In addition, most of houses in the same street look alike, strengthening pricing similarity for houses belonging to the same neighborhood. Overall, the spatial spillover of house pricing implies market homogeneity. Ignoring this spatial autocorrelation in house prices leads to an endogeneity bias on the estimation of the implicit price of $z_j$ (Brady and Irwin, 2011). This interaction among house prices is usually controlled through the introduction of a spatial matrix on the dependent variable. The endogeneity of dependent variable in the model implies that Ordinary Least Square (OLS) estimates will be biased and inconsistent (Anselin and Bera, 1998).

The spatial diffusion is due to the price formation mechanism due to similarity of house attributes, notably environment variables, within the same neighborhood. The specification of this interaction is mainly motivated by the study of externalities (Halleck Vega and Elhorst, 2015). Since externalities do not have boundaries, the house properties belonging to the same neighborhood share the environmental externalities. Thus, the house prices in hedonic model is not only a function of its direct attributes but also a function of the attributes of neighbored houses. The closer a house is from the source of the externality, the higher the impact of the externality should be. The impact of neighbored houses' attributes is named indirect effect. The attribute $z_j$ can thus have a direct effect on the price of its house and an indirect effect due to spatial spillover on neighbored houses. These indirect impacts of explanatory variables are captured through the inclusion of a spatial lag on exogenous variables.

The omitted variable problems refer to unobserved factors influencing house prices. Although researchers have access to large dataset when estimating hedonic pricing model, it is almost impossible to measure every houses' attributes, including environmental ones (von Graevenitz and Panduro, 2015). This unobserved heterogeneity is captured in the error term. However, spatial autocorrelation of error terms appear if the omitted variables are spatially correlated. These can lead to endogenous biases if these omitted variables are spatially correlated with $z_j$. Usually, unobserved heterogeneity is controlled using panel (von Graevenitz and Panduro, 2015) but these methods are unavailable in cross-sectional data (Kuminoff et al., 2010). The omitted variable issue is linked to the heterogeneity of observations through space, which can only been partly captured with control variables. In addition, spatial heterogeneity can lead to heteroscedasticity problem or/and the instability of model parameters in space (Le Gallo, 2004).

### 2.b. Advanced in spatial econometrics

Spatial econometrics methods allow dealing with the spatial issues present above. We present the interest of spatial econometric models for the estimation of agricultural externalities.

The SAR model contains endogenous interaction effect accounting for spatial autocorrelation in housing prices. The model specifies the impact of prices of neighbored houses on a specific house thanks to the introduction of a spatial lag on house prices in the hedonic standard model, controlling for the direct spillovers between house prices of neighboring properties. The SEM model contains the interaction effect among the error term, controlling for spatial dependency in the error term. It is used to address to problem of misspecification that may occur due to improper functional, measurement error or omitted variables (Ham et al., 2012). Lastly, the SARAR model is used when both the interaction effect of dependent variables and the interaction effect among the structure of error are detected in the data. It allows both to quantify the intensity of the spillover arising from neighboring properties and take into account the effect generate by spatial dependency within disturbance term. These models control only the spatial spillover linked to the houses prices and the structure of the error terms. They do not take into account the interaction among the explanatory variables, justifying the utilization of new modelling approaches to estimate the impact of agricultural externalities on houses.

The SDM and SDEM models control for such interactions and are thus well adapted to estimate externalities that depend on the distance (Halleck Vega and Elhorst, 2015). The two models capture two different effects of houses attributes: the direct and indirect effects. The SDM contains simultaneously the interaction effect of houses pricing and the interaction effect of exogenous variables in addition to the impact of its own attributes. The SDEM model contains the interaction effect among exogenous variable and the interaction effect of the disturbance term. The SDM and SDEM models are well suited for our study because of both econometric and economic justifications. On the econometric side, the SDM is a quite general model including spatial lags of dependent and independent variables, that making it suitable to correct for spatial spillovers (Montero et al., 2011). In economic point view, the inclusion of the lag house pricing in the model allows homogenizing house markets in Brittany, a suitable property to respect the underlying assumption of homogeneity of market in the hedonic pricing model. The SDEM allows to address the spatial effect in the structure of the error such as omitted variables, justifying it econometric interest. Furthermore, both models allow determining the indirect effect of breeding activities on population welfare through the lag exogenous variables.

These models gain in popularity in hedonic valuation studies. Brasington and Hite (2005) used the SDM for both the hedonic and the demand estimation and showed that linear econometric estimation overvalue the demand elasticity for preventing environmental damages. They concluded that the omission of spatial effects lead to an underestimation of welfare losses, potentially leading to non-appropriate policy responses. Montero et al. (2011) used the SDM model to estimate the impact of noise pollution on housing prices of Madrid. They test the suitability of different spatial econometric models and conclude that the SDM model is the most suitable model to measure the noise externalities. They find notably that SAR and SEM models underestimated noise pollution by 40% and 51.3% respectively. Using the same database, Fernández-Avilés et al. (2012) estimated the impact of air pollution on houses prices. Using the SAR and SEM models, they found that air pollution increases housing prices. The indirect effects of air pollution explain this unexpected result. The SDM results do present a negative direct impact of air pollution on house prices. The introduction of a lag on independent variables allows estimating in a better way the indirect impact of noise pollution. The estimated indirect impacts were undervalued by 50 to 100 times in the SAR compared to the SDM. Using the same tests than Montero et al. (2011), Baumont and Legros (2013) concluded that the SDM model was more appropriate than the SEM models to evaluate the impact of building attributes on housing prices. Mihaescu and Vom Hofe (2013) used the SLX and SDEM models to assess the discount in housing prices due to proximity of brownfields. Maslianskaïa-

Pautrel and Baumont (2016) used SLX, SDM and SDEM models to distinguish between the economic causes of houses' price determinants and to estimate the spatial and global externalities (Anselin, 2003). They find notably that the high prices on the shoreline were more determinate by the impact of neighboring houses' prices than the positive amenities from seabord proximity. To our knowledge, only Brasington and Hite (2005), Mihaescu and Vom Hofe (2013) and Maslianskaïa-Pautrel and Baumont (2016) have used SDM and/or SDEM models for environmental externality evaluation.

# 3. Empirical model and data description

## 3.a. The study area

We examine the impact of agricultural activities on house prices of rural and non-coastal municipalities of three departments of Brittany: Finistere, Morbihan and Côte d'Armor. Brittany is the western region of France and the first agricultural region of France. In 2014, the utilized agricultural area covers over 1.6 million Ha, i.e. about 60% of the total region area. Livestock farming is the main agricultural activity in Brittany. Brittany represents 56% of French swine production and 44% of the national egg production. Farms are mainly oriented towards dairy production, 22% of French milk being produced in Brittany. Dairy production favors the maintenance of permanent grasslands and a typical "Bocage" landscape constituted of hedgerows and earth banks. Thanks to its landscape, its regional culture and its long seacoasts, Britany is the third French region for tourism, tourism contributing to 8% of Breton GDP. However, the 2,730 kilometers of seacoasts are threatened by the intensive breading activities. Indeed, swine, poultry and, to a less extent, dairy productions contribute to nitrogen and phosphate spills in Breton watercourses and groundwater. These releases have led to high nitrogen concentration in regional waters, up to 50 mg/L in 2010 and still 35 mg/L in 2016 (Figure 1a).[2] Among the various environmental issues due to high nitrogen concentration (e.g. acidification, eutrophication, dystrophication, greenhouse gas emissions or drinkable treatment costs), the proliferation of green algae on seacoasts is a source of major concern for Brittany (Figure 1b). The decomposition of beached green algae produces hydrogen sulfide. In addition to its malodorous smell, the hydrogen sulfide is potentially toxic and several wild and domestic animal deaths due to poisoning have affected media and population.[3] In addition to its impact on local residents, green algae proliferation threatens the sustainability of tourism in Brittany, tourists being sensitive to its presence (MEEM 2017). Green algae affects thus negatively the welfare of both residents and tourists. Local authorities have implemented several plans to reduce green algae pollution, notably in 2017 with the promulgation of a 55 million euros plan for the period 2017-2021. Reduction of nitrogen leaches has been a priority of Brittany and France for decades. Programs PMPOA 1 and 2 (from 1993 to 2007)[4] have targeted the modernization of 90 000 breading farms (principally in Brittany), 65% of

[2] Data provided by Bretagne Environment and available at http://www.observatoire-eau-bretagne.fr/Media/Donnees/Donnees/Evolution-des-concentrations-en-nitrates-dans-les-cours-d-eau-bretons. [consulted the 01/05/2017].

[3] In 2009, the death of a horse due to green algae decomposition have led authorities to launch the first green algae Plan. In 2011, 36 wild pigs have been found dead in a green algae zone. In 2016, the death of a jogger around the green algae zone has led authorities to command exams to determine the cause of the death. Today, no proof allows concluding to a death due to hydrogen sulfide inhalation but court actions are under processes, for the jogger and other potential victims (notably among the algae pickers).

[4] PMPOA is acronym of "Programme de Maîtrise des Pollutions d'Origine Agricole, literally "Program of Pollution Control of Agricultural Origin".

the investments being supported by public authorities. The development plan for Breton agriculture from 2002 have also insured 30% to 60% of treatment factory of swine manure.

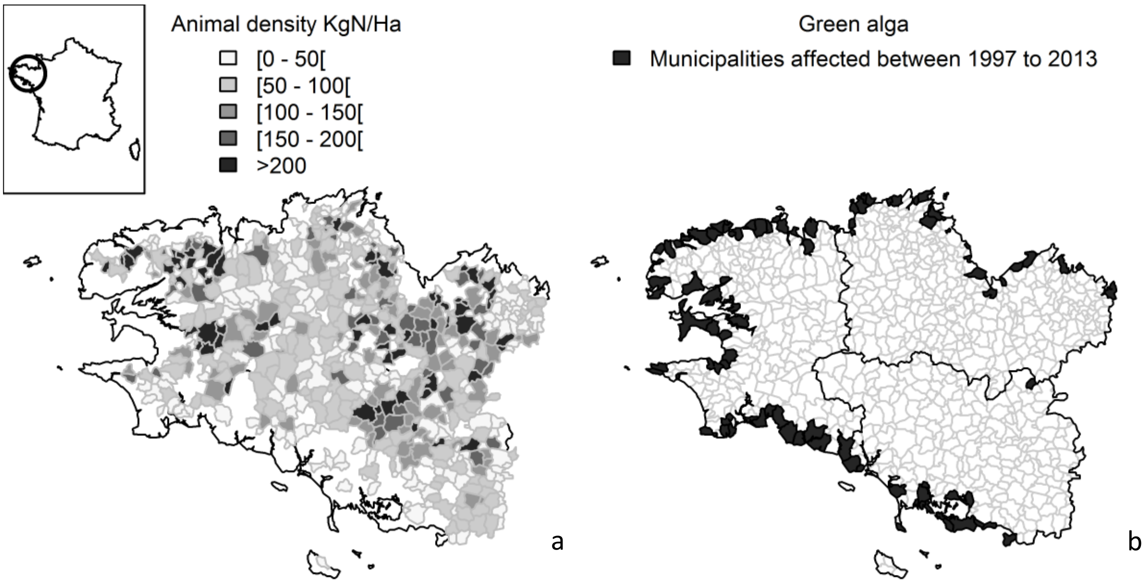


**Figure 1: Maps of used Breton municipalities with *(a)* nitrogen concentration and *(b)* green algae pollution of coastal municipalities**

## 3.b. Empirical models and econometric strategy

The purpose of the empirical study is to estimate the hedonic pricing model distinguishing the direct and indirect effects of agricultural activities, notably breeding ones, and controlling for any additional spatial effect. We estimate the hedonic pricing function through three different models: a hedonic model without spatial specification, a SDM model and a SDEM model. The three models are estimated using the log-log functional form to provide easily interpretable parameters.[5] We introduce departmental and temporal fixed effects in the three models.

We first estimate models based on the following log-log model:

$$ln\, P_{ijkt} = \boldsymbol{\gamma}\, ln\, \mathbf{I_i} + \boldsymbol{\xi}\, ln\, \mathbf{X_j} + \boldsymbol{\eta}\, ln\, \mathbf{CV_j} + \varepsilon_{ijkt} \qquad (4)$$

$P_{ijkl}$ is the price for house $i$ in municipality $j$ (department $k$) at year $t$, $\boldsymbol{\gamma}$, $\boldsymbol{\xi}$ and $\eta$ are vectors of parameters to be estimated with $\mathbf{I_i}$ being the vector of the intrinsic variables of the house $i$, $\mathbf{X_j}$ being the vector of agricultural variables in municipality $j$, $\mathbf{CV_j}$ the vector of control variables in municipality $j$ and $\varepsilon_{ijkl}$ being the error term. We first estimate the impact of the intrinsic variables, before to addition successively the set of agricultural and control variables. We then decompose the error term with the introduction a temporal fixed effect $\beta_t$ and a departmental fixed effect $\alpha_k$ such that $\varepsilon_{ijkt} = \alpha_k + \beta_t + \varepsilon_{ij}$. We estimate these successive models using Ordinary Least Square method. These models serve as reference for the spatial econometric estimations.

[5] We have also estimated the models with linear econometrics using the linear and the log-linear functional form. Results remain sensibly the same (see appendix 1).

In particular, we estimate the SDM and SDEM counterpart of (4) to capture the indirect impacts of agricultural externalities. The SDM model is written as:

$$\ln P_{ijkl} = \rho \mathbf{W} \ln \mathbf{P} + \boldsymbol{\gamma} \ln \mathbf{I_i} + \boldsymbol{\xi} \ln \mathbf{X_j} + \boldsymbol{\omega} \mathbf{W} \ln \mathbf{X_j} + \boldsymbol{\eta} \ln \mathbf{CV_j} + \boldsymbol{\zeta} \mathbf{W} \ln \mathbf{CV_j} + \alpha_k + \beta_t + \varepsilon_{ij} \tag{5}$$

Where $\mathbf{P}$ is a vector of $(n \times 1)$ dimension, $\mathbf{W}$ is the spatial weight matrix and $\rho$, $\boldsymbol{\gamma}$, $\boldsymbol{\xi}$, $\boldsymbol{\omega}$ and $\boldsymbol{\eta}$ are the vectors of parameters to be estimated. In particular, $\rho$, $\boldsymbol{\omega}$ and $\zeta$ are the parameters capturing respectively the autocorrelation of house prices and the indirect spatial effects of agricultural activities (i.e. the impact of agricultural activities on houses located on neighbored municipalities) and control variables. We affect a spatial parameter for agricultural and control variables that are not already defined as distance.

The SDEM model is written as follow:

$$\ln P_{ijkl} = \boldsymbol{\gamma} \ln \mathbf{I_i} + \boldsymbol{\xi} \ln \mathbf{X_j} + \boldsymbol{\omega} \mathbf{W} \ln \mathbf{X_j} + \boldsymbol{\eta} \ln \mathbf{CV_j} + \boldsymbol{\zeta} \mathbf{W} \ln \mathbf{CV}_j + \alpha_k + \beta_t + \varepsilon_{ij} \tag{6}$$

with $\varepsilon_{ij} = \lambda \mathbf{W} \boldsymbol{\varepsilon} + \mu_{ij}$ (7)

where $\lambda$ is the parameter capturing the spatial autocorrelation due to unobserved heterogeneity.

The estimation of spatial hedonic models requires the spatial weight matrix $\mathbf{W}$ that specifies the spatial relationship of each observation to each other. These matrices are $n \times n$ dimension (where $n$ is the number of observations), are both symmetric and non-stochastic matrix with exogenous elements $w_{ij}$ and diagonal elements set to zero. There are several spatial weight matrix, either the contiguity matrix, the inverse-distance matrix (Maslianskaïa-Pautrel and Baumont 2016) or the q-nearest neighbor matrix (Kim and Goldsmith 2009). Here, we use the q-nearest neighbor one.[6] The principle behind q-nearest neighbor's method consists of defining the q nearest neighbors to each observation (e.g. q equals 1 means that we only consider the closest neighbor of each observation). The matrix stands on the assumption that the level of interaction is identic for all q-neighbored observations. Then, the specification consists attribution the weight one for all the q nearest observations and zero for the others. The matrix is row-normalized by attributing the weight 1/q for the q closest observations.

In addition to the SDM and SDEM models, we also estimate the SAR, SEM and SARAR ones to provide some comparative analyses.

## 3.c. Descriptive statistics

We merge information from notarial house prices in Brittany (i.e. the MIN database), agricultural census of 2010, INSEE[7] population census of 2010, and from PIEB[8]. The descriptive statistics and the origins of the used variables are presented in table 1.

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[6] Note that this is an intermediatory work. We will perform the same analysis with contiguity matrix and inverse-distance matrix. We are notably interested to integrate the inverse-distance matrix with SDM and SDEM to compute distance decay effects for variables of interest, as suggested by Halleck Vega and Elhorst (2015).

[7] INSEE is French acronym of "Institut National de la Statistique et des Etudes Economiques", meaning in English " French National Institute for Statistics and Economic Research"

[8] PIEB acronym of "Portail de l'Information et l'Environnement en Bretagne", for « Information Website of Environnent in Brittany ».

**Table 1: Descriptive statistics and variables definitions (N=8,075)**

| Variables | Mean | Std-dev | Min | Max | Definitions | Sources |
|---|---|---|---|---|---|---|
| House_Price | 129193.4 | 60773.0 | 9361.7 | 450000 | House prices in 2012€ | MIN database |
| Intrinsic variables | | | | | | |
| Nb_bathroom | 1.33 | 0.47 | 1 | 2 | Number of bathrooms | |
| Nb_room | 5.01 | 1.37 | 3 | 9 | Number of rooms | |
| Nb_floor | 1.91 | 0.58 | 0 | 4 | Number of floors | |
| Garden_area | 2537.23 | 7556.7 | 1 | 252761 | Garden area (square meter) | |
| Variables of interest | | | | | | |
| Oilseeds_area | 0.03 | 0.04 | 0 | 0.18 | Oilseeds and proteins area (%UAA)[9] | Agricultural census |
| Cereals_area | 0.41 | 0.22 | 0 | 0.99 | Cereals arean (%UAA) | |
| Othercrops_area | 0.01 | 0.03 | 0 | 0.14 | Othercrops area (including industrial crops) (%UAA) | |
| Perm_grassland_area | 0.11 | 0.1 | 0 | 0.7 | Permanent grassland area (%UAA) | |
| Temp_grassland area | 0.22 | 0.2 | 0 | 0.94 | Temporary grassland area (%UAA) | |
| Fallow_area | 0.01 | 0.03 | 0 | 0.14 | Fallow_area (%UAA) | |
| Shannon index | 1.08 | 0.33 | 0.04 | 1.95 | Shannon index | |
| Swine_poultry_N | 47.71 | 74.29 | 0 | 534.12 | Quantity of nitrogen from swine and poultry (KgN/TAM)[10] | |
| Cattle_N | 33.55 | 23.74 | 0 | 281.88 | Quantity of nitrogen from cattle (KgN/TAM) | |
| D_algae | 17.94 | 11.38 | 0 | 49.48 | The minimum distance from municipalities to sea affected by green algae (Km) | PIEB |
| Ratio_algae | 0.86 | 0.16 | 0.22 | 1 | The ratio of the minimum distance to sea on the minimum distance to green alga | |
| Control variables | | | | | | |
| Waters_area | 0 | 0.01 | 0 | 0.19 | Water area (lake, rivers, etc.) (%TAM) | Corine Land Cover |
| Wetlands | 0 | 0.01 | 0 | 0.29 | Proportion of non-agricultural wetlands area (%TAM) | |
| Shrubs_area | 0.02 | 0.04 | 0 | 0.52 | Shrubs area (%TAM) | |
| Forest | 0.12 | 0.1 | 0 | 0.77 | Forest area (%TAM) | |
| Greenspace_area | 0 | 0.01 | 0 | 0.14 | Greenspace area (%TAM) | |
| Landfills_area | 0 | 0.01 | 0 | 0.14 | Landfill area (%TAM) | |
| Intdustries_area | 0.01 | 0.03 | 0 | 0.18 | Industrialized area (%TAM) | |
| Shops_area | 0.07 | 0.11 | 0 | 0.92 | Urbanized area (%TAM) | |
| D_sea | 17.95 | 12.99 | 2.22 | 51.56 | The minimum distance to sea (Km) | Euclidian distance calculation |
| D_city | 28.99 | 13.13 | 2.78 | 53.82 | The minimum distance to the closest city (Km) | |
| Pop_density | 1.2 | 1.98 | 0.08 | 20.43 | Population density (population/TAM) | INSEE census |
| Revenues | 20201.8 | 3157.9 | 12390.1 | 38818.2 | Average income (income / populations) | |
| Dummies | | | | | | |
| Dep_22 | 0.35 | 0.48 | 0 | 1 | Department of Côte d'Armor | - |
| Dep_29 | 0.28 | 0.45 | 0 | 1 | Department of Finistere | |
| Dep_56 | 0.37 | 0.48 | 0 | 1 | Department of Morbihan | |
| year2010 | 0.37 | 0.48 | 0 | 1 | Year of sale 2010 | |
| year2011 | 0.3 | 0.46 | 0 | 1 | Year of sale 2011 | |
| year2012 | 0.32 | 0.47 | 0 | 1 | Year of sale 2012 | |

[9] UAA : Utilized Agricultural Area.
[10] TAM: Total Area of the Municipality.

The dataset provides exhaustive information on 8,075 house transactions between 2010 and 2012. The prices range from €6,098 to €450,000 in 2012 €. Intrinsic variables are available for the 8,075 observations. Agricultural variables are available at the municipality scale, implying that the observation in the same municipality have the same explanatory variables (they share the same environment). They include the different crop cultivation, the nitrogen quantity released by each breeding activity notably hog, poultry and beef. We add the distance between the houses to the closest municipality affected by green alga.[11] We also constructed additional variables of interest. First, we compute the ratio of the minimal distance of municipalities to the sea on the minimal distance of municipalities to coast municipalities affected by green algae. It measures the relative proximity of municipality 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 alga. When it is under one, the nearest beach to municipalities is not affected by green algae. We also compute a Shannon index of farmland use in each municipality. The Shannon index is an entropy measure based on land shares. It increases with cultural diversity and decreases when there is a tendency towards monoculture. Finally, most of control variables was obtained from Corine Land Cover database and the French population census of INSEE. The control variables contain additional environmental and accessibility variables that influence the house pricing determination. Among the control variables, four variables are crucial in estimating hedonic pricing model: population density, municipalities' incomes, distance to the closest CDB[12] and distance to the sea. The two first variables are notably development and wealth indicator that influence house market. These two variables in the models allows to correct the heterogeneity of house market in Brittany.

To highlight the spatial nature of our data, we perform the statistic of Moran for house prices and agricultural variables in table 2. The statistic of Moran[13] (I of Moran) measuring the spatial autocorrelation of the observations. Its value ranges from -1 to 1. The value of -1 is a negative autocorrelation, meaning the value of neighboring observations are opposites. The value 1 is a positive autocorrelation meaning a similarity of the neighbored observations. The value of zero means the absence of spatial autocorrelation.

[11] The information on green algae pollution provide from the 2013 report of the CEVA (the French organism 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].

[12] The main city considered are: Rennes, Brest, Quimper, Saint-Brieuc, Guingamp, Vannes and Lorient.

[13] The statistic of Moran is expressed as: $I = \left( \frac{n}{\sum_i^n \sum_j^n w_{ij}} \right) \left( \frac{\sum_i^n \sum_j^n w_{ij} \left( X_i - \overline{X} \right) \left( X_j - \overline{X} \right)}{\sum_i^n \left( X_i - \overline{X} \right)^2} \right)$ Where $n$ is the number of observations, $X$ is the variable of interest, $\overline{X}$ : the average value of $X$ , $w_{ij}$ : The spatial weight describing the adjacency between $i-th$ and $j-th$ observations.

**Table 2: Statistic I of Moran of variables of interest**

| | I of Moran | P.value |
|---|---|---|
| House_price | 0.24 | <2.20e-16 |
| Othercrops_area | 0.35 | <2.20e-16 |
| Oilseeds_area | 0.43 | <2.20e-16 |
| Cereals_area | 0.68 | <2.20e-16 |
| Perm_grassland_area | 0.77 | <2.20e-16 |
| Temp_grassland_area | 0.8 | <2.20e-16 |
| Fallow_area | 0.35 | <2.20e-16 |
| Swine_poultry_N | 0.44 | <2.20e-16 |
| Cattle_N | 0.39 | <2.20e-16 |
| Shannon index | 0.55 | <2.20e-16 |

Moran tests on house prices highlight that house prices display spatial autocorrelation (Table 2). The Moran tests on variable of interests highlight that similar agricultural activities tend to agglomerate over space, which is partly highlighted in Figure 1a. Agricultural activities are more auto-correlated than house prices. Even if this may be due to the municipality scale source of agricultural data, it highlights that the SAR may undervalue the indirect spatial effects. These two sources of spatial autocorrelation can bias the estimated parameters if not taken into account.

Furthermore, we perform the statistic of Lagrange Multiplicator (and the robustness Lagrange Multiplicator) to determine the source of the spatial autocorrelation between house price autocorrelation and error autocorrelation. Finally, we perform the test of the common factor to assess the necessity of including a spatial lag on independent variables. The combination of the two tests indicates the most suitable spatial econometric model.

## 4. Results

Table 5 presents the results of the OLS estimation. The OLS results are corrected from heteroscedasticity issue with the White approach. Globally, the estimated model displays a $R^2$ of 0.511. The number of bathrooms, the number of rooms and the garden area are significant at the statistical significance level of 0.1% and are positively correlated with houses' price. Contrarily, the number of floors is negatively correlated at the statistical significance level of 5%. The estimated coefficients show that intrinsic variables have substantial effects on houses' price. For example, we find an elasticity of 50.8% for the number of rooms.

Regarding the variables of interest, the results reveal that Breton population is positively impacted by all agricultural areas except fallow lands. The oilseed, temporary grassland and other crops areas affect positively house prices at the 5% statistically significant level. Cereal area also increases houses' prices but at the 10% statistically significant level. These positive impacts are rather small compared to the negative impact of forest fallow. A relative increase of 1% of fallow area decreases house prices by 4.6% (effect statistically significant at the 0.1% level). The elasticity estimated of others agricultural areas comprised between 0.6% and 2.3%. Contrary to temporary grasslands, we find no effect of permanent grasslands on houses' prices.

Permanent grasslands in Brittany are mainly agricultural wetlands. Their presence improves the provision of some functionalities such as landscape beauty or biodiversity habitat. They can also affect negatively welfare inhabitants due to the presence of flood risk (e.g. Botzen and Van den Bergh, 2012). These combined effects can explain the non-significant impact of permanent grasslands on house prices in OLS model. Finally, the Shannon index has no statistically significant effect on houses' price. The diversity of the landscape is possibly already taken into account by the six agricultural land categories as independent variables.

Nitrogen effect in the model is controlled by swine, poultry and cattle impacts on house pricing. The combined effect of swine and poultry is statistically significant at the 0.1% level and is negative. This result is in line with all the studies on swine facilities' effects on houses' price (e.g. Le Goffe, 2000; Ready and Abdalla, 2005). On average, the combined effect of swine and poultry leads to a decreasing house pricing by 0.3% if we double animal density. Cattle nitrogen has however no impact on houses' price. Finally, our results show that the higher is the distance from green alga, the higher the prices are. This result holds even with the consideration of the distance to the nearest beach and with the interaction effect between the distances to closest green algae and beach. The log-linear functional form indicates the green algae pollution of the closest beach (when RATIO_ALGAE equals one) decrease houses' price by 9% (Appendix 1).

Regarding the control variables, the expected effects are found. Water areas increase houses' prices, reflecting the positive impact of recreational activities. Non-agricultural wetlands decrease house prices, reflecting the negative impact of flood risk. We find that Breton forests decrease residents' welfare. Le Goffe (2000) found the same results on tourists' welfare. He interpreted this negative impact due to the private property of the forests in Brittany, the forests being rarely accessible for tourists and inhabitants. The negative impact of forests could also reflect the preferences for open spaces than closed one. The population density and the revenues of the municipality increases houses' price. The distance to the main city impacts negatively house prices. The distance to the sea impacts three time more the prices of houses, an increase of 1% of the distance with the sea decreasing prices by 0.16% while it reduces it by 0,54% for the distance to the city.

**Table 3: Results of Moran and Lagrange multiplier tests**

| tests (K=80) | I of Moran | | LM test | | Robust of LM test | |
|---|---|---|---|---|---|---|
| | House_Price | Residuals | Lag | Error | Lag | Error |
| Coefficient | 0.24 | 0.03 | 372.35 | 396.28 | 87.429 | 111.36 |
| p.value | < 2.2e-16 | < 2.2e-16 | <2.2e-16 | <2.2e-16 | <2.2e-16 | <2.11e-15 |

Table 3 presents the results of the statistics I of Moran and the Lagrange Multiplier (LM) statistics. The statistics of Moran is statistically significant at 0.1%, highlighting the existence of spatial dependence of errors term and prices. The null hypothesis of ML-lag statistic tests non-spatial autocorrelation of dependent variable (house prices). The rejection of null hypothesis implies the presence of spatial autocorrelation of the house prices. By analogous, the ML-Error tests the non-spatial autocorrelation among the residuals. The LM test for both lag dependence variable and the residuals term are significant at the 0.1% statistically significant level. Their robust versions (RLM) are also highly significant. Thus, the omission of spatial dependence of observations surely leads to biased coefficient or inconsistent estimates of standard error (Lesage and Pace, 2009). The statistic of LM Error is 6.42% higher than the LM lag. At the other side, the RLM Error is 27.37% higher than RLM lag. These results imply that the spatial specification of the error term should capture more the spatial autocorrelation than the one on dependent variable. Table 4 present the performances of the five spatial hedonic models estimated. Their comparison provides additional information on the spatial correlation nature of the data.

**Table 4: Hedonic models performances**

| Models | OLS | SAR | SEM | SARAR | SDM | SDEM |
|---|---|---|---|---|---|---|
| n | 8075 | 8075 | 8075 | 8075 | 8075 | 8075 |
| $R^2$ | 50.91 | - | - | - | - | - |
| AIC | 6278.37 | 6055.8 | 6079.1 | 6050.7 | 6027,6 | 6027,3 |
| Log-likelihood | - | -2993.88 | -3005.528 | -2990.353 | -2948.782 | -2948.668 |

Based on the AIC and the log-likelihood values, the statistics indicate that the SDEM model is the best one to correct the spatial dependency (Table 4). The tests confirm thus the indications from the Lagrange multipliers (Table 3). Estimation results from the SDEM model are presented in table 5. Estimation results of other spatial models are presented in appendix 3.

The variables of interest and the control variable being at municipalities scale, the indirect impacts describe the impacts going beyond the municipality's boundaries. The parameters estimated for intrinsic variables are robust in the spatial model. All the intrinsic variables are significant at 0.1% and correlated positively to house pricing except the number of floor correlated negatively. These results are similar to the OLS ones. The indirect impact of the number of bathrooms and the number of rooms in one municipality influence the house pricing in the neighbored municipality, reflecting surely market homogeneity.

The SDEM model confirms that the quantity of nitrogen from swine and poultry decreases houses' price. The total effect (direct plus indirect parameters) indicates that a multiplication by two of nitrogen concentration from swine and poultry decreases prices by 0.5%. The consideration of the spatial dimension in the SDEM indicates that the OLS model underestimates the nitrogen effect by 36%. The indirect effect captures 89% of the total effect, the effect being statistically significant at 10% level. Thus, SDEM model indicates that the source of the externality overlaps from one jurisdiction to another. The distance between two neighbored municipalities being higher than the usual considered distance (less than 2 kilometers, e.g. Ready and Abdalla, 2005). The other spatial models (SEM, SAR, SARAR and SDM models) also confirm that nitrogen from swine and poultry decreases houses' prices (see Appendix 3). The SDEM and other spatial models confirm that the cattle nitrogen has no impact on prices. Additional estimation with cattle_N being at power 6 using OLS (Appendix 2) underlines that the first unit of nitrogen increases houses prices by 5%. After 35 kg/ha, nitrogen from cattle decreases house prices. The maximum negative impact is reached at 120 kg/ha, with a decrease of house prices by 3%. The difference of cattle and swine nitrogen may be due to the odor of swine and poultry manure compared to cattle one. The studies on odor pollution have only considered swine and poultry manures (e.g. Ready and Abdalla, 2005).

**Table 5: Estimation results of OLS model and the SDEM model**

| Variables | OLS | | | SDEM | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Direct impact | | | Indirect impact | | |
| | Coef | Std. Error | | Coef | Std. Error | | Coef | Std. Error | |
| Constant | 4.371 | 0.419 | *** | -0.057 | 1.368 | | | | |
| Intrinsic variables | | | | | | | | | |
| Nb_bathroom | 0.355 | 0.013 | *** | 0.347 | 0.013 | *** | 0.395 | 0.159 | * |
| Nb_room | 0.508 | 0.017 | *** | 0.513 | 0.016 | *** | -0.532 | 0.195 | ** |
| Nb_floor | -0.034 | 0.017 | * | -0.029 | 0.016 | ° | 0.100 | 0.195 | |
| Garden_area | 0.124 | 0.005 | *** | 0.125 | 0.004 | *** | 0.069 | 0.046 | |
| Variables of interest | | | | | | | | | |
| Oilseeds_area | 0.006 | 0.003 | * | -2.04e-04 | 0.004 | | 0.024 | 0.010 | * |
| Cereals_area | 0.018 | 0.009 | ° | 0.014 | 0.011 | | -0.003 | 0.029 | |
| Othercrops_area | 0.023 | 0.010 | * | 0.021 | 0.013 | ° | 0.004 | 0.033 | |
| Perm_grassland_area | 0.003 | 0.004 | | 0.009 | 0.006 | | -0.010 | 0.013 | |
| Temp_grassland area | 0.013 | 0.005 | ** | 0.002 | 0.006 | | 0.020 | 0.014 | |
| Fallow_area | -0.046 | 0.011 | *** | -0.022 | 0.015 | | -0.056 | 0.036 | |
| Shannon index | 0.026 | 0.020 | | -0.020 | 0.028 | | 0.049 | 0.064 | |
| Swine_poultry_N | -0.003 | 0.001 | *** | -0.001 | 0.001 | | -0.005 | 0.003 | ° |
| Cattle_N | -0.001 | 0.001 | | -0.001 | 0.001 | | 0.004 | 0.004 | |
| D_algae | 0.038 | 0.015 | * | -0.097 | 0.062 | | 0.138 | 0.071 | ° |
| Ratio_algae | -0.045 | 0.028 | | -0.158 | 0.073 | * | 0.097 | 0.104 | |
| Control variables | | | | | | | | | |
| Waters_area | 0.017 | 0.004 | *** | -0.004 | 0.005 | | 0.035 | 0.011 | *** |
| Wetlands | -0.012 | 0.005 | * | -0.011 | 0.007 | | 0.012 | 0.016 | |
| Shrubs_area | 0.006 | 0.002 | ** | 0.004 | 0.003 | | 0.010 | 0.007 | |
| Forest | -0.008 | 0.003 | ** | 0.003 | 0.005 | | -0.018 | 0.010 | ° |
| Greenspace_area | 0.002 | 0.005 | | -0.006 | 0.006 | | 0.015 | 0.015 | |
| Landfills_area | -0.003 | 0.004 | | -0.002 | 0.005 | | 0.001 | 0.012 | |
| Intdustries_area | 2,79e-04 | 0.003 | | -0.001 | 0.004 | | 0.006 | 0.008 | |
| Shops_area | -0.016 | 0.006 | ** | -0.008 | 0.006 | | -0.091 | 0.025 | *** |
| D_sea | -0.158 | 0.016 | *** | 0.053 | 0.061 | | -0.193 | 0.075 | ** |
| D_city | -0.054 | 0.009 | *** | -0.020 | 0.047 | | -0.013 | 0.054 | |
| Pop_density | 0.088 | 0.013 | *** | 0.095 | 0.015 | *** | 0.084 | 0.049 | ° |
| Revenues | 0.612 | 0.040 | *** | 0.349 | 0.058 | *** | 0.699 | 0.144 | *** |
| Dummies | | | | | | | | | |
| Dep_22 | -0.080 | 0.026 | ** | 0.009 | 0.066 | | -0.068 | 0.097 | |
| Dep_29 | -0.181 | 0.018 | *** | -0.047 | 0.072 | | -0.109 | 0.088 | |
| Year 2010 | 0.037 | 0.010 | *** | 0.034 | 0.009 | *** | 0.121 | 0.070 | ° |
| Year 2011 | 0.041 | 0.010 | *** | 0.034 | 0.010 | *** | 0.069 | 0.095 | |

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

The distance to the green algae influences positively houses' prices in the SDEM model, the total effect being similar to the parameters estimated in OLS. It confirms the negative effect of green algae on resident welfare. However, this effect is not robust over the other spatial models (Appendix 3). The variable RATIO_ALGAE is however significant in all the models and its effect is robust. The estimated total effect is negative, underlying the negative impact of the green algae pollution of the closest beach. The results of Table 3 highlight that the OLS overestimates the effects of the pollution by 26%, i.e. the green algae pollution of the closest beach decreases in fact house prices by 13.5%.

The direct and indirect estimated parameters of agricultural areas are almost all non-significant at the 10% statistical level. The only two significant effects are the indirect effect of oilseed area (5% statistical level) and the direct effects of other crop area (10% statistical level). The estimated total effect of other crop area in the SDEM is similar to the OLS one. However, the OLS underestimate the impact of oilseed by 73.6%. Indeed, most of the values of oilseed area is captured outside from the municipalities where they are produced. This could highlight the positive impact of oilseed on landscape, the beneficiaries of landscape being also the inhabitants of neighbored municipalities.

The SDEM estimation of the effects of the control variables confirms the sign of the impact found in the OLS one, but with sometimes high underestimation of the OLS estimation. For example, the negative impact of forest was underestimated by 48%. The impacts of resident density and revenues on house's prices were also underestimated by 51% and 42% respectively.

## 5. Discussion and final remarks

Our hedonic application aims to value the externalities generated by agriculture in Brittany considering both spatial dependence and spatial diffusion. Our results confirm that residents of Brittany value negatively swine and poultry activities, in line with the results of Le Goffe (2000) and Bontemps et al. (2008) in Brittany. The figure of the elasticity of house price on nitrogen (Appendix 2) confirms the result of Bontemps et al. (2008), i.e. nitrogen concentration has a negative impact on house's prices, but the impact is marginally decreasing. Contrary to Bontemps et al. (2008), we differentiate the impact between swine and cattle activities. To sum up, we find that swine and poultry impact greater houses prices than cattle activities. The figure of the elasticity of house price on cattle nitrogen (Appendix 2) suggests that cattle activities can be a source of amenities (for the first units of nitrogen) and desamenities (after 35 kgN/ha). The same figure for poultry and swine activities highlights that released of nitrogen from swine and poultry has a negative impact on houses prices but the impact is marginally decreasing. In other terms, the results of Bontemps et al. (2008) is driven by swine and poultry activities. This result is also supported by the robustness checks using spatial econometrics (Appendix 3). In addition, the SDEM results indicate that the impact of swine and poultry nitrogen overlaps from the municipality where the production occurs. The negative impact of swine activities is thus supposed to be larger than the distance decay that were estimated using linear econometrics with GIS data (e.g. Ready and Abdalla, 2005). Similar indirect effects were underlined for oilseed or for water areas, suggesting a spatial spillover from one place to neighbored municipalities. The positive impacts of agricultural areas (including the indirect effect of oilseeds) on houses' price highlight some positive amenities provided by agriculture.

The utilization of spatial econometrics is a necessity in hedonic valuation of environmental goods on cross-section data. Here, the SDEM appears to be the most suitable model to predict the data. The comparison between estimated parameters from SDEM and OLS (Table 5) shows that OLS have underestimated most of the effects of independent variables on houses' price. This is notably the case with two of our variables of interest, the swine nitrogen and the green algae pollution. The OLS underestimates the impact of swine nitrogen on houses' price by 36%. Similarly, the OLS underestimates the impact of the green algae pollution on the closest beach by 26%. The moves from the median value for RATIO_ALGAE (i.e. 0.91) to the lowest one (i.e. 0.22, meaning that the closest beach polluted by green algae is located 5 times farther than the closest beach) increases house prices by 25.5% using SDEM results but only 18.7% using the OLS results. Indeed, the polluted beaches by green algae are spatially correlated between each others, but also with others variables, leading to biased estimations with linear econometrics.

The presented results are intermediate ones. For the moment, we only use the q-nearest neighbor's matrix. This matrix is not the best one as it attributes the same weight for all the 80 neighbored observations. We have planned to run robustness checks using other spatial weight matrix. We notably plan to use the inverse–distance matrix with several threshold distance. The inverse-distance matrix appears to be the most suitable matrix in spatial hedonic studies (e.g. Baumont and Legros, 2013 ; Mihaescu and Vom Hofe, 2013 ; Maslianskaïa-Pautrel and Baumont, 2016). This method is a suitable one to measure distance-decay of the identified externalities (Halleck Vega and Elhorst, 2015). It would allow comparisons with studies measuring distance-decay of externalities from swine facilities using linear econometrics and GIS data. Indeed, the utilization of GIS with linear econometrics does not prevent from spatial autocorrelation effects, resulting in potential biased estimators (Mueller and Loomis, 2008).

Other potential limits come from our data and model. First, we have the same explanatory variables for observations located in the same municipality (except for intrinsic variables). We could have use GIS data for all the observation to compute unique variables for each observation. However, in addition to the obvious time saving of non-GIS data, the description of non-point source externalities such as nitrogen or wetlands is more adapted using concentration (or share) rather the closest distance to a potential source of a pollution. In case of the odor pollution valuation, the closest distance was a appropriated measure (e.g. Ready and Abdalla, 2005) but this is not the case for other externalities like road degradation. Second, we have used parametric methods. Even if we have used several functional forms (at least for OLS, Appendix 1), the utilization of non-parametric method can lead to substantial gains on the precision of the estimation (Bontemps et al., 2008). Finally, the results from the hedonic method are valid under several assumptions presented in section 2.1. The study of houses' price on 3 departments may question the assumption of homogenous market. To limit the heterogeneity of housing markets, we have focused on rural and non-coastal municipalities (see figure 1). We have added population density and revenues as additional explanatory variables in order to capture some heterogeneity. We have also added annual and departmental dummies to capture some of the unobserved heterogeneity. Finally, the mobilization of spatial econometrics (notably SAR and SDM models) "homogenizes" the Breton housing market. All these precautions should prevent from high unobserved heterogeneity in our data.

The correction of these spatial effects using the SDEM is of major importance in a context of green algae policies. Indeed, we have to recall that Brittany has spent over 200 million in 10 years to remove green algae from Breton shorelines. Brittany presenting a population of 3.3 million of inhabitants, the impact of green algae pollution on inhabitants' welfare exceeds largely the total amount of green algae plans. The consideration of green algae externalities allows improving the valuation of externalities from breeding. The single consideration of the nitrogen from cattle and swine underestimates the total impact from nitrogen by 90%. This figure is robust regarding the different econometric models. To our knowledge, we are the first to value green algae externalities using revealed preference methods.

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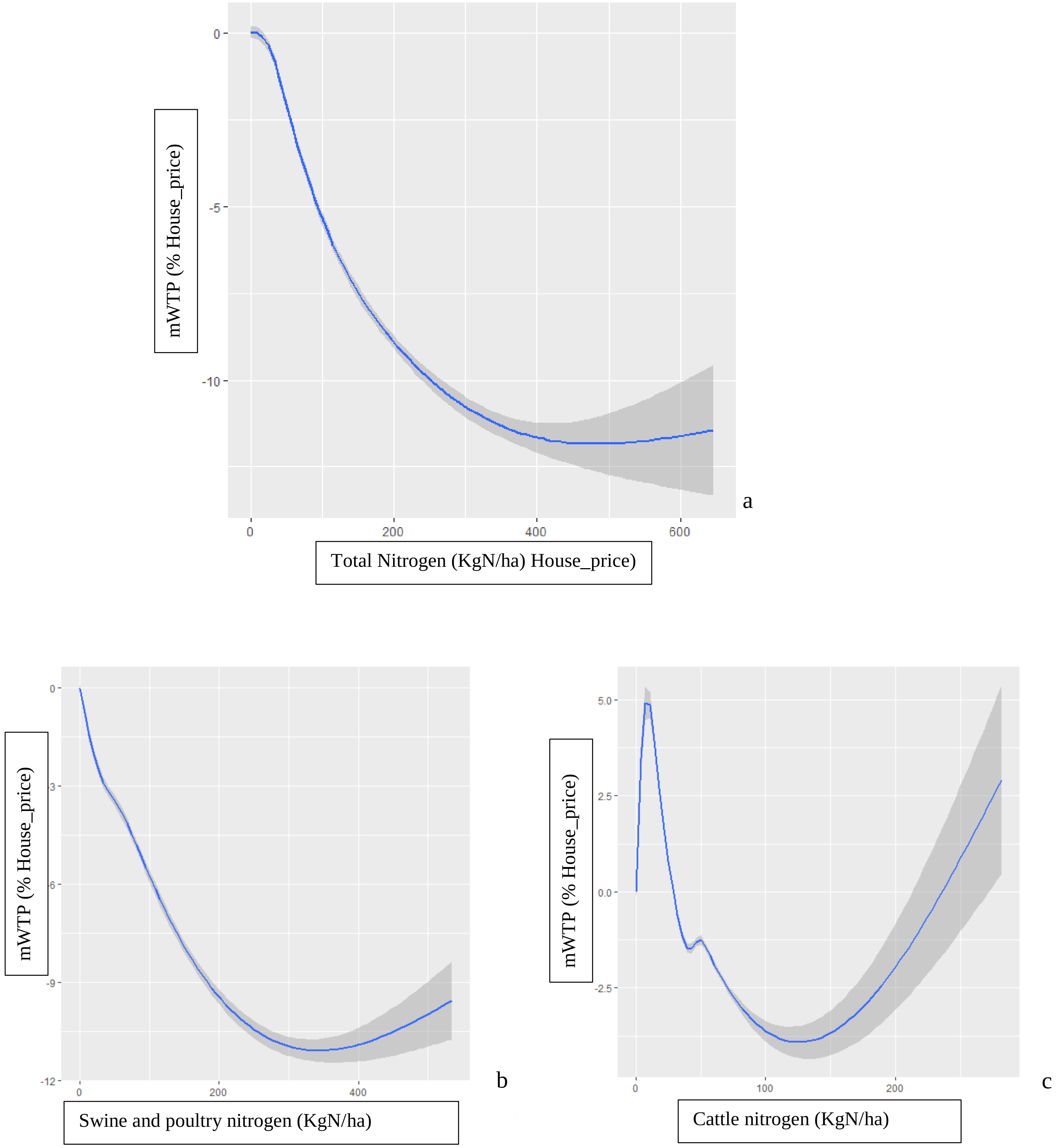
# APPENDICES

**Appendix 1: OLS estimation of hedonic model with linear and log-linear functional forms**

| Variables | OLS | | | | | |
|---|---|---|---|---|---|---|
| | Linear model | | | Log-linear model | | |
| | Estimate | Std. Error | | Estimate | Std. Error | |
| Constant | -23950 | 11569 | * | 10.48 | 0.09 | *** |
| Intrinsic variables | | | | | | |
| Nb_bathroom | 36385 | 1247,1 | *** | 0,28 | 0,01 | *** |
| Nb_room | 13023 | 443.2 | *** | 0.11 | 3.73e-03 | *** |
| Nb_floor | -4510.4 | 855.1 | *** | -0.04 | 0.01 | *** |
| Garden_area | 1.3 | 0.1 | *** | 8.46e-06 | 9.39e-07 | *** |
| Variables of interest | | | | | | |
| Oilseeds_area | 37890 | 30022 | | -0.17 | 0.26 | |
| Cereals_area | 6158.9 | 8404.9 | | 0.01 | 0.07 | |
| Othercrops_area | 158900 | 246150 | | 1.57 | 2.18 | |
| Perm_grassland_area | -14800 | 15908 | | -0.38 | 0.14 | ** |
| Temp_grassland area | 6486.4 | 9269.8 | | -0.07 | 0.08 | |
| Fallow_area | -269970 | 247060 | | -2.39 | 2.18 | |
| Shannon index | 14808 | 4640.5 | ** | 0.14 | 0.04 | *** |
| Swine_poultry_N | -28.5 | 7.4 | *** | -2.23e-04 | 6.52e-05 | *** |
| Cattle_N | -63.7 | 24.4 | ** | -4.97e-04 | 2.04e-04 | * |
| D_algae | -257.1 | 66.7 | *** | -1.35e-03 | 7.26e-04 | ° |
| Ratio_algae | -14393 | 4562.4 | ** | -0.09 | 0.03 | * |
| Control Variables | | | | | | |
| Waters_area | 256150 | 61732 | *** | 2.17 | 0.44 | *** |
| Wetlands | 55378 | 70601 | | -0.64 | 0.39 | ° |
| Shrubs_area | 85899 | 16823 | *** | 0.46 | 0.14 | *** |
| Forest | -29522 | 6049.2 | *** | -0.17 | 0.05 | ** |
| Greenspace_area | 174570 | 117800 | | 0.21 | 0.72 | |
| Landfills_area | -204470 | 85297 | * | -0.45 | 0.71 | |
| Intdustries_area | 2961.4 | 24790 | | 0.12 | 0.20 | |
| Shops_area | 26609 | 16582 | | 0.01 | 0.13 | |
| D_sea | -830.6 | 87.8 | *** | -0.01 | 8.38e-04 | *** |
| D_city | -240.2 | 51.5 | *** | -1.63e-03 | 4.14e-04 | *** |
| Pop_density | -1744.3 | 940.4 | ° | -4.45e-03 | 0.01 | |
| Revenues | 4.3 | 0.2 | *** | 3.36e-05 | 1.81e-06 | *** |
| Dummies | | | | | | |
| Dep_22 | -13207 | 3786.3 | *** | -0.10 | 0.03 | *** |
| Dep_29 | -25286 | 2939.4 | *** | -0.21 | 0.03 | *** |
| Year 2010 | 2136.1 | 1194.8 | ° | 0.04 | 0.01 | *** |
| Year 2011 | 3468.1 | 1283.8 | ** | 0.04 | 0.01 | *** |

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

**Appendix 2: House prices elasticity depending on (a) total nitrogen at municipality scale, (b) swine and poultry nitrogen at municipality scale and (c) cattle nitrogen at municipality scale.**



**Appendix 3: estimation results of other spatial hedonic models (SDM, SAR, SEM and SARAR)**

| Variables | OLS | | | SDM | | | | | | SAR | | | SEM | | | SARAR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | direct | | | indirect | | | | | | | | | | | |
| | Coef | Std. Error | | Coef | Std. Error | | Coef | Std. Error | | Coef | Std. Error | | Coef | Std. Error | | Coef | Std. Error | |
| Constant | 4.371 | 0.419 | *** | -0.324 | 0.871 | | - | | | 0.974 | 0.459 | * | 6.183 | 0.553 | *** | 1.659 | 0.621 | ** |
| Intrinsic variables | | | | | | | | | | | | | | | | | | |
| Nb_bathroom | 0.355 | 0.013 | *** | 0.345 | 0.013 | *** | 0.158 | 0.116 | | 0.350 | 0.013 | *** | 0.345 | 0.013 | *** | 0.348 | 0.013 | *** |
| Nb_room | 0.508 | 0.017 | *** | 0.516 | 0.016 | *** | -0.542 | 0.135 | *** | 0.509 | 0.016 | *** | 0.516 | 0.016 | *** | 0.513 | 0.016 | *** |
| Nb_floor | -0.034 | 0.017 | * | -0.030 | 0.016 | * | 0.092 | 0.134 | | -0.029 | 0.016 | ° | -0.032 | 0.016 | * | -0.030 | 0.016 | ° |
| Garden_area | 0.124 | 0.005 | *** | 0.125 | 0.004 | *** | 0.000 | 0.033 | | 0.124 | 0.004 | *** | 0.124 | 0.004 | *** | 0.124 | 0.004 | *** |
| Variables of interest | | | | | | | | | | | | | | | | | | |
| Oilseeds_area | 0.006 | 0.003 | * | -0.001 | 0.004 | | 0.016 | 0.007 | * | 0.004 | 0.003 | | -0.001 | 0.004 | | 0.002 | 0.003 | |
| Cereals_area | 0.018 | 0.009 | ° | 0.016 | 0.011 | | -0.012 | 0.021 | | 0.008 | 0.009 | | 0.014 | 0.010 | | 0.009 | 0.009 | |
| Othercrops_area | 0.023 | 0.010 | * | 0.025 | 0.013 | * | -0.021 | 0.028 | | 0.018 | 0.0097 | ° | 0.025 | 0.012 | * | 0.020 | 0.011 | * |
| Perm_grassland_area | 0.003 | 0.004 | | 0.008 | 0.006 | | -0.006 | 0.010 | | 0.002 | 0.004 | | 0.008 | 0.005 | | 0.003 | 0.004 | |
| Temp_grassland area | 0.013 | 0.005 | ** | 0.001 | 0.006 | | 0.016 | 0.010 | | 0.005 | 0.004 | | 0.007 | 0.005 | | 0.005 | 0.005 | |
| Fallow_area | -0.046 | 0.011 | *** | -0.026 | 0.015 | ° | -0.011 | 0.030 | | -0.033 | 0.011 | ** | -0.037 | 0.014 | ** | -0.033 | 0.012 | ** |
| Shannon index | 0.026 | 0.020 | | -0.014 | 0.028 | | 0.017 | 0.049 | | 0.015 | 0.021 | | 0.008 | 0.026 | | 0.013 | 0.023 | |
| Swine_poultry_N | -0.003 | 0.001 | *** | -0.001 | 0.001 | | -0.002 | 0.002 | | -0.002 | 0.001 | * | -0.002 | 0.001 | ° | -0.002 | 0.001 | * |
| Cattle_N | -0.001 | 0.001 | | -0.001 | 0.001 | | 0.003 | 0.003 | | 0.000 | 0.001 | | -0.002 | 0.001 | | -0.001 | 0.001 | |
| D_algae | 0.038 | 0.015 | * | -0.061 | 0.057 | | 0.086 | 0.062 | | 0.018 | 0.013 | | 0.008 | 0.030 | | 0.015 | 0.017 | |
| Ratio_algae | -0.045 | 0.028 | | -0.115 | 0.069 | ° | 0.089 | 0.085 | | -0.064 | 0.027 | * | -0.065 | 0.046 | | -0.069 | 0.032 | * |
| Control Variables | | | | | | | | | | | | | | | | | | |
| Waters_area | 0.017 | 0.004 | *** | -0.004 | 0.005 | | 0.022 | 0.008 | ** | 0.008 | 0.003 | * | 0.005 | 0.005 | | 0.007 | 0.004 | * |
| Wetlands | -0.012 | 0.005 | * | -0.009 | 0.007 | | 0.010 | 0.012 | | -0.010 | 0.005 | * | -0.010 | 0.006 | ° | -0.011 | 0.005 | * |
| Shrubs_area | 0.006 | 0.002 | ** | 0.003 | 0.003 | | 0.005 | 0.005 | | 0.005 | 0.002 | * | 0.005 | 0.003 | ° | 0.005 | 0.002 | * |
| Forest | -0.008 | 0.003 | ** | 0.003 | 0.005 | | -0.012 | 0.008 | | -0.004 | 0.003 | | -0.004 | 0.004 | | -0.004 | 0.003 | |
| Greenspace_area | 0.002 | 0.005 | | -0.007 | 0.006 | | 0.017 | 0.011 | | 0.003 | 0.004 | | -0.006 | 0.005 | | 0.000 | 0.005 | |
| Landfills_area | -0.003 | 0.004 | | -0.002 | 0.005 | | -0.002 | 0.009 | | -0.003 | 0.004 | | -0.001 | 0.004 | | -0.002 | 0.004 | |
| Intdustries_area | 2.79e-04 | 0.003 | | 0.000 | 0.004 | | 0.004 | 0.006 | | 0.002 | 0.003 | | -0.001 | 0.003 | | 0.001 | 0.003 | |
| Shops_area | -0.016 | 0.006 | ** | -0.006 | 0.006 | | -0.065 | 0.018 | *** | -0.007 | 0.006 | | -0.006 | 0.006 | | -0.006 | 0.006 | |
| D_sea | -0.158 | 0.016 | *** | 0.009 | 0.057 | | -0.095 | 0.064 | | -0.066 | 0.016 | *** | -0.127 | 0.030 | | -0.075 | 0.020 | * |
| D_city | -0.054 | 0.009 | *** | -0.037 | 0.042 | | 0.029 | 0.046 | | -0.020 | 0.009 | * | -0.060 | 0.020 | ** | -0.027 | 0.012 | * |
| Pop_density | 0.088 | 0.013 | *** | 0.092 | 0.015 | *** | 0.025 | 0.035 | | 0.069 | 0.013 | *** | 0.089 | 0.014 | *** | 0.075 | 0.013 | *** |
| Revenues | 0.612 | 0.040 | *** | 0.348 | 0.057 | *** | 0.242 | 0.112 | * | 0.344 | 0.043 | *** | 0.425 | 0.052 | *** | 0.378 | 0.048 | *** |
| Dummies | | | | | | | | | | | | | | | | | | |
| Dep_22 | -0.080 | 0.026 | ** | 0.032 | 0.064 | | -0.054 | 0.077 | | -0.044 | 0.027 | ° | -0.081 | 0.040 | * | -0.054 | 0.031 | *** |
| Dep_29 | -0.181 | 0.018 | *** | -0.011 | 0.070 | | -0.083 | 0.079 | | -0.091 | 0.018 | *** | -0.153 | 0.033 | *** | -0.108 | 0.023 | *** |
| Year 2010 | 0.037 | 0.010 | *** | 0.033 | 0.009 | *** | 0.052 | 0.049 | | 0.033 | 0.009 | *** | 0.032 | 0.010 | *** | 0.033 | 0.009 | *** |
| Year 2011 | 0.041 | 0.010 | *** | 0.033 | 0.010 | *** | 0.015 | 0.067 | | 0.034 | 0.010 | *** | 0.034 | 0.010 | *** | 0.034 | 0.010 | *** |