# The Effect of Forest Land Use on the Cost of Drinking Water Supply: A Spatial Econometric Analysis

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**Abstract**

Forest land use is often associated with the protection of water resources from contamination and the reduced cost of drinking water supply. This study attempted to measure the value of the forest on the quality of water resources from a contingent market, namely drinking water supply, by estimating variations in drinking water costs as a function of variations in land uses. Spatial correlations were taken into account because of the use of different geographical scales (i.e., water service area and land uses) and the potential existence of organizational and technological spillovers between water services. We found a significant negative effect of forest land use on water costs. We found no evidence of spatial spillovers concerning the management regime but did find that organizational choices (i.e., grouping of municipalities within a water service) and factors related to the scarcity of resources in neighboring water services have an impact on water costs.

**Keywords:** Water quality; land uses; forest; water supply service; spatial spillovers.

**JEL classification:** C21; Q23; Q25; R14

## 1. Introduction

The overall objective of this article was to estimate the economic value of the ecological service provided by land uses on water quality and, in particular, by forest areas. Forests have an extensive root network and a great ability to generate porous and filtering soils. Recycling, especially of nitrogen, is important. Under forest cover, nitrate levels are low (see Jussy et al. 2002). Similar results are also observed for various pollutants (e.g., pesticides). Our hypothesis was that raw water from catchment areas with a large portion of forests is of higher quality, thus reducing the need for treatment of drinking water and, as a result, the associated costs of drinking water supply. In contrast, runoff from agriculture lands is the main cause of raw water pollution. In particular, nitrification is greater in an agricultural environment, and this property persists when agricultural land is planted with trees. The presence of agricultural land in the area surrounding the water supply service (WSS) may thus lead to sophisticated and costly treatments.

WSS have to produce water with sufficient quality from a resource (groundwater or surface water) and to distribute this water by continuously adapting supply with daily demand while preserving water quality during its transportation in transmission pipelines and distribution mains. Drinking water supply covers all operations from resource extraction to customer taps. Hence, the production process consists of several functions (i.e., production and treatment, stocking, pressurization, distribution), each one leading to specific costs (Garcia and Thomas 2001). Different factors related to the WSS (e.g., number of users connected to the distribution network, user water demand, network size) may then influence the technology and should be taken into account in the analysis of water supply costs.

Due to ecological processes (that go beyond the administrative boundaries), the system used to withdraw raw water, and the necessity of distributing water to consumers scattered over a given territory, the spatial aspects of drinking water supply and demand are quite obvious and need to be taken into account (Clark and Stevie 1981, Dale et al. 2005, Atosoy et al. 2006). For example, the costs of water supply may be influenced by local competition for scarce local water resources, implying displaced demand and (technological) spillovers between different WSS. If the demand for water is high in relation to available resources in a given region, the WSS may extend itself to neighboring regions to take advantage of their water resources, consequently increasing scarcity and water supply costs for neighboring WSS.

Technical spillovers may occur as a result of knowledge diffusion or the sharing of input factors (e.g., specialized labor). The organization of water supply and, as a result, the costs of water supply are also expected to be influenced by spillovers between neighboring WSS (Plunket et al. 2008, González-Gómez et al. 2009). Such spillovers may reflect the fact that a private company (in charge of the delegated WSS) will benefit from knowledge about the local resources (including information on hydrological, geological and climatic conditions) if they are already operating a WSS in the neighborhood. This may reduce their water supply costs. Moreover, WSS area and land uses generally do not coincide. The impact of the latter on service costs should thus be measured by taking both land distribution on the WSS and on its neighbors into account. Hence, in the case of econometric modeling, it is important to consider the spatial interaction on at least two different spatial scales that are based on the areas and the land uses of the WSS concerned.[1] Moreover, when evaluating ecosystem services, an analysis of the spatial scales covered by the identified service can be of use, for example, to determine how to compensate stakeholders (Hein et al. 2006).

Many scientific studies have been done on the relationship between forest and water quality but few have focused on economics and still fewer on the value of forests in supplying water for human consumption (Nuñez et al. 2006, Biao et al. 2010). Forest land use is normally associated with the protection of water resources from contamination and the reduced cost of drinking water supply (Abildtrup and Strange 2000, Willis 2002, Fiquepron et al. 2011, Ernst 2004). Some authors consider the economic contribution of forest ecosystem services in terms of soil and hydrological flow stabilization for farms (Pattanayak and Butry 2005). They focus on the complementarities between forests and farms by accounting for spatial dependence due to three main factors: (1) the ecological service "flow" across the forest system that affects its bio-geo-chemistry as well as its socioeconomic activities; (2) the fact that economic agents interact with, learn from and copy their neighbors; and (3) the impossibility of omitting some crucial variables with spatial correlation when collecting data, and the fact that different sources of data can lead to scale mismatches. Pattanayak and Butry (2005) found that the benefits of forest ecosystems would be substantially undervalued if spatial dependence was ignored.

In this study, we attempted to answer three questions: (i) Does forest, compared to other land uses, reduce the cost of drinking water supply? (ii) Do spatial dependences in the organization of WSS, mainly due to technological spillovers, exist? (iii) To what extent are the costs of providing drinking water affected by spatial interactions?

We addressed these questions by applying an econometric analysis of costs based on data collected in the Vosges department, a French administrative district located in the Lorraine region (in Northeastern France). Lorraine is a heavily wooded area. The forest is largely present in the Vosges department, with an afforestation rate of 48%. Both data on WSS and land uses were collected, making it possible to conduct a spatial analysis based on technical and economic conditions as well as ecological processes. The remainder of the article is organized as follows. Section 2 describes the cost model for drinking water supply by introducing the effect of land uses on water quality. Spatial econometric techniques used for the empirical application are also presented. Section 3 describes the data and Section 4 discusses the results. Section 5 concludes with a discussion of implications of spatial dependence for future research.

## 2. Theoretical model and empirical approach

### 2.1 Cost model

We assumed that forest land use has a (positive) impact on water (groundwater and surface water) quality and, more generally, that land uses affect raw waters. Improved water quality may have use as well as non-use values. The use values include the impact of water quality on drinking water supply and the recreational value of surface water. Non-use values may include the existence value of keeping water resources uncontaminated. Our analysis concentrates on the drinking water use. The service, i.e., protection of water, provided by forests is a non-market

[1] The watershed scale may be more relevant and interesting to consider, but these areas, even with assistance from other disciplines (such as hydrology), seem quite difficult to identify.

good. Forest owners are not remunerated for this service. However, we evaluated this service, applying a cost function approach. The basic idea is that raw water is an input in the production of drinking water. The cost of supplying drinking water decreases with increasing (raw) water quality.

We assume that the costs of providing drinking water to various users can be described by the following cost function:

$$C = C(Y, q, X, \varepsilon_c), \quad (1)$$

where $\varepsilon_c$ is a stochastic disturbance to WSS costs. The variable $Y$ denotes the drinking water demand of users $Y = D(P, \varepsilon_d)$, with $P$ the drinking water price and $\varepsilon_d$ a stochastic shock to the WSS demand. Raw water quality $q$ is represented as a function of land uses $L$:

$$q(L, \varepsilon_q), \quad (2)$$

where $\varepsilon_q$ is a stochastic shock to the water quality. Finally, $X$ is a vector of characteristics of the WSS (e.g., number of users, number of municipalities served by the WSS, number of intake stations).

We then estimate a reduced model of cost to directly measure the impact of forest land use on water costs. Combining Eqs. (1) and (2) and inserting the equation demand in the cost function yields the following expression:

$$C(L, X, \varepsilon), \quad (3)$$

where $\varepsilon$ represents the total random disturbance.

Many organizational choices exist for the WSS, involving different aspects such as the adoption of a specific technology related to the purification of raw water, the type of pressurization of water in the pipelines, or the grouping of several municipalities within the same WSS. Another relevant component of the organization is the management regime, which can be public or delegated to a private operator. In fact, delegation to a private operator depends, among others, on the complexity of the operation of the service (which can be due to the low level of raw water quality). This implies that water supply costs depend not only directly on the quality of the available raw water but also indirectly on the organization of the WSS. The interactions between management regimes (municipal vs. delegated) and operating costs of WSS can lead to selection biases (Boyer and Garcia 2008). Costs can be affected by the choice of management and, conversely, this choice can be explained by the cost differential between the two management regimes and other (un)observed factors. In our study, the number of services privately operated is low (less than 10% of the total sample). It is probably for this reason and contrary to other studies that no selection bias was detected.[2]

### 2.2 Spatial econometric methodology

The point of departure of this study is the approach used in Fiquepron et al. (2011). In other words, water quality, organization of water services, and water costs are modeled explicitly at the department level. This first study was an estimate of a simultaneous equation model describing the impact of land uses on water quality, the operation of WSS, and prices. It has been shown that forest has a positive effect on raw water quality compared to other land uses, with an indirect impact on water prices, making them lower for consumers. In our study, we

[2] Preliminary tests and econometric methods to correct the selection bias (Heckman 1976) were carried out. The associated results are available upon request from the authors.

used a more detailed and relevant spatial scale, the WSS area, as the geographical unit for measuring water costs and land use, and we explicitly included spatial effects in the estimation of the model.

Much interest has been expressed in spatial econometric modeling in recent years (Anselin 1988). Furthermore, Anselin (2001) has shown the importance of the use of spatial econometric methods in environmental and resource economics. An important source of spatially dependent and spatially heterogeneous observations are the scale mismatch and the inherent need to integrate data from different scales. In our study, cost observations were obtained at the WSS level that does not necessarily correspond to the land use territory.

LeSage and Pace (2009) promote the use of spatial techniques in regression models. First, the problem of an omitted variable bias may arise in spatial modeling because of unobservable factors that are spatially heterogeneous. In this study, resource accessibility or relationships between WSS (i.e., organizational and technological processes) can be non-observable and may exert a significant influence on water costs. Second, spatial dependence can be explained by the proximity of WSS that are subject to the same conditions of operation due to geographical, topographical factors or even the extraction of water in the same aquifer. Third, spatial (positive or negative) externalities may exist, arising from characteristics of neighboring WSS and/or land uses.

Spatial autocorrelation can be incorporated in a regression model in different ways. First, spatial autocorrelation can be limited to the error term in the regression model. This is known as the spatial error model (SEM). Following this specification, our cost model defined by Eq. (3) can be expressed as:

$$C = X\beta + L\gamma + \varepsilon \qquad \text{with} \qquad \varepsilon = \lambda W\varepsilon + u, \tag{4}$$

where $C$ is the dependent variable (i.e., cost), $X$ and $L$ are the explanatory variables (WSS characteristics and land uses, respectively), and $\beta$ and $\gamma$ their associated parameter vectors. The selection of neighbors is specified by the spatial weight matrix $W$, the term $W\varepsilon$ is referred to as the spatially-lagged error, and $\lambda$ the associated parameter to be estimated. The variable $u$ is the remainder error.

Second, the dependent variable for an individual can be partially determined by the observed values of neighboring individuals. The spatial lag model (LAG) can be written as follows:

$$C = X\beta + L\gamma + \rho WC + \varepsilon, \tag{5}$$

where $\varepsilon$ is a new (classical) error term and $\rho$ the parameter of the lagged dependent variable.

Third, the spatial relationship can be derived by adding spatially-lagged independent variables to the set of explanatory variables. This is the so-called spatially-lagged X model (SLX) that can be expressed as:

$$C = X\beta + L\gamma + WZ\delta + \varepsilon. \tag{6}$$

In this model, the dependent variable for a specific individual is regressed on the individual observation of $X$ and $L$, and the mean value of $Z$ for neighboring individuals. The set of independent variables $Z$ may be the same as the set of $X$ and $L$, or different. This latter model can be safely estimated by OLS, whereas models (4) and (5) must instead be estimated using maximum likelihood techniques (Anselin 1988) or IV-methods (Kelejian and Prucha 1998).

Due to nature of our data and, in particular, the mismatch between WSS area and land uses, we assumed that Eq. (6) gives the best fit to the data. However, it is possible that some unobservable heterogeneity remains present as well as a spatial distribution of costs related to similar technological constraints due to the same environment. This is why we adopted the following strategy for model choice: (i) regress a simple regression model without any spatial dependence (OLS); (ii) regress an SLX model and choose the model with the best fit;

(iii) implement Lagrange multiplier (LM) tests: SEM vs. OLS (the null being $\lambda = 0$) and LAG vs. OLS (the null being $\rho = 0$): if the null hypothesis is not rejected in either of the two models, keep the model of step (i); (iv) in the other case, according to the significance of the LM tests, keep the SEM model or the LAG model ; and (v) if both LM tests are significant, build a mixed model that takes the various dimensions of spatial relationships into account.

## 3. Data

The choice of the Vosges department in France (see Fig. 1) was motivated by a relatively complete dataset on WSS and water intake structures compared to other French departments in the Rhine-Meuse water basin. Moreover, maps established with the Geographic Information System (GIS) and localization of intake structures were essential for a spatial analysis. The department nevertheless presents difficulties because it is on two river basins: the Rhine-Meuse and the Rhone-Mediterranean-Corsica basins, and data are only available for the former.

There are 283 WSS in the Vosges that serve 515 municipalities (*communes*). Raw water (groundwater or surface water) is provided by 1,070 water intake structures. We were forced to eliminate certain municipalities from the analysis because we did not have the price of drinking water (56 out of the 515 municipalities). Our final sample contained 232 WSS that included the 459 remaining municipalities.

The prices of drinking water paid by users are used as a proxy for the average costs of supplying water. The prices of water paid by users and other data on WSS (e.g., water demand, number of users and organizational structure) are available from the Rhine-Meuse Basin Committee for the year 2008. A dummy variable was used for the organizational structure of the WSS, regardless of whether the management is delegated to a private operator or not (in our sample, only 21 WSS were privately operated). The land use is represented by variables describing the proportion of land in different land used in the WSS area. An average land use is calculated for each WSS. The approach chosen to calculate this land use is based on the land use in the municipalities supplied by a given WSS. Land use data are obtained from the CORINE Land Cover Map. We made four aggregated categories for different land uses: forest lands, agricultural lands, urban areas and the remainder areas (including grassland, swamplands, lakes and rivers). Table 1 presents descriptive statistics of main variables used in the empirical analysis. We also provide maps on the spatial distribution of drinking water prices and forest lands (see Figs. 1 and 2)

A WSS can have a distribution network that covers many different municipalities, each one with its own users. It may also have many intake sources, e.g., drilling, springs or wells).

[Table 1 here]

[Figure 1 here]

[Figure 2 here]

## 4. Results

Spatial weight matrices (denoted as $W$) are a tool that makes it possible to clarify the notion of neighborhood between spatial units. There are several kinds of weight matrices: they may be built on notions of contiguity, from definitions of distance or from the number of nearest neighbors. In a study on the relationship between regional growth and agricultural subsidies, Bivand and Brunstad (2006) attempted a number of weight definitions (e.g., full triangulation for the region centroids, distance threshold between region centroids, the K nearest neighbors to each region centroid). Finally, Gabriel neighbors, initially introduced by Gabriel and Sokal (1969), provide an adequate representation of the neighborhood relationship for a set of 93 EU regions. Since the WSS neighborhood presents geographic properties similar to the example of EU regions, we decided to use the Gabriel graph neighbor definition to build our weight matrix.

We followed the strategy of model selection described in Section 2.2. Once the SLX model defined by Eq. (6) was fitted, we carried out LM tests. The statistical value of the first test (SEM vs. SLX) is 0.8427 (compared to the theoretical value of a $\chi^2$ with one degree of freedom) and the p-value is equal to 0.3586. This result indicates the absence of spatial autocorrelation in the error term. The second test (LAG vs. SLX) gives a statistic with a value of 1.2387 and a p-value equal to 0.2657. Once again, the SLW model is preferable. Our estimation results are therefore those of the SLX model. They are presented in Table 2.

[Table 2 here]

First of all, it appears that the price of drinking water decreases with an increase of the proportion of forest lands in neighboring WSS. In contrast, the proportion of forests on the service area is found to have no significant impact on water supply costs. These results seem to confirm that land uses are of importance when applied to the raw water area, at the water catchment scale, and that forest must have a large cover to provide its ecological service of water protection. Moreover, in our sample, it is not uncommon that water intake sources are not located in the service area[3] but in neighboring municipalities served by other services because of the scarcity or poor quality of local water resources. This can also explain the positive influence of the proportion of forest land use in areas served by neighboring water services. Furthermore, even if the relationship is not significant, the portion of other lands (including grassland, swamplands, lakes and rivers) that potentially capture some positive effects of “non-polluting uses” seem to have a negative impact on water costs.

The estimate of forest land proportion can be directly used to assess the forest service on the water quality. An increase of one point in the proportion of forest (with respect to agricultural or other areas) leads to a decrease of approximately €0.006 of water price. This value is higher than the one (€0.004) found by Fiquepron et al. (2011), possibly revealing that the omission of spatial aspects may lead to an underestimation of the value of ecological services.

We observed that the coefficient of the variable urban area is (both directly and spatially) significantly negative (at a 10% level), indicating that water prices are lower in urban areas and possibly implying that economies of (customer) density may exist. Garcia and Thomas (2001) define economies of density as a decrease of average operation costs when an increase in water production makes it possible to satisfy the demand from new users for a given network size (and a constant demand per customer).

As shown in numerous studies, private operation (i.e., delegation of the WSS) leads to an increase in water prices. As explained above, the low number of privately-operated WSS does not make it possible to rigorously test a potential selection bias and to simultaneously estimate the choice of management (public vs. private) and

[3] Of the total number of water intake sources, almost 20% are not located in the service area they cover.

the variation of costs. However, we found no significance of the management regime observed in the neighboring WSS, and the model has thus been re-estimated without the dummy DELEG_lag. This result would indicate that there is no special (positive) effect, whereas we might expect that WSS copy their neighbors concerning the choice of delegating the operation of the water network to a private firm.

Concerning the number of municipalities grouped into the same WSS, the (positive) associated estimate indicates that a bigger WSS leads to an increase of prices and seems to show the limit of scale economies. However, we have a negative sign when the number of municipalities is higher for the neighboring WSS. An explanation of this effect could be that a municipality would be tempted to enter a large neighboring WSS (less work and responsibility for local delegates) if their costs are the same or higher than in the neighboring one. They will only remain independent if they observe that their costs are lower than the those of their neighbor WSS. The coefficient associated with the (average) number of neighboring WSS is significantly positive. The more users there are, the higher the water prices are. This result expresses the pressure on the water resource as the result of an increasing demand that directly affects (and negatively) the quality and the quantity of water availability.

It would not be surprising if the multiplication of water intake sources that provide drinking water for the service area increased the water price (by way of increasing fixed costs and energy costs). However, this spatially-lagged variable seems to have an opposite effect (but not significant). This result may indicate that a high number of intake sources in the neighboring regions is indicative of the fact that water in this raw water area is relatively easily available both in quantity and quality, leading to a decrease in average total costs.

As explained above, WSS do not necessarily use raw water from intake sources in their area and often look for water in neighboring WSS areas. Moreover, water quality is assumed to be better in deep ground waters than in surface (or less deep) waters. The positive coefficient of drilling (spatially lagged) means that it is more costly for the WSS to withdraw water from these specific intake sources. This would indicate that the access to raw water of good quality is difficult.

## 5. Conclusion

The first objective of this paper was to test whether forest land use reduces the cost of drinking water supply. Due to the limited use of pesticides and fertilizers in forests, it was expected that the water treatment costs and the costs of finding non-contaminated water resources would be lower in areas where forests cover a large portion of land in relation to land used for agriculture. This question is intrinsically spatial, implying knowledge about both the distribution of land uses (at the ecological scale) and the water network (at the stakeholder scale) for a given area. In two cities in Texas, Ernst et al. (2004) showed that an increase in the percentage of forested watershed areas from 10 to 60% induced a 2/3 decrease in treatment and chemical costs (per mil. gal.).

Our empirical results confirm this hypothesis, i.e., we found a significant negative effect of forest land use on water supply costs. These results are also consistent with the results of a national analysis (Fiquepron et al. 2011) on aggregated data. However, forest land use within the area supplied by a service did not have a significant effect on costs. Only the portion of forest cover in surrounding areas had a significant effect. This indicates that the spatial scale of the WSS (the municipalities supplied by a WSS) is not consistent with the spatial scale of the water resource considered by the WSS. It also confirms the importance of including spatial lags of the explanatory variables when modeling the determinants of water supply costs. Furthermore, we found that the number of intake sources, the difference in altitude between intake and exploitation, and intake sources requiring drilling (groundwater) had a positive effect on costs and is consistent with previous studies. We also found that the proportion of urban land reduces costs. Even though urban areas may in some cases be associated with water pollution, we found a negative effect of the proportion of urban land use. This may be a result of density economies, i.e., WSS that supply water to densely populated regions may have lower infrastructure costs.

Consistent with other studies, we found that delegating WSS management to private firms increases the costs (Boyer and Garcia, 2008). This could be due to a self-selection bias where the WSS with unobserved cost factors decide to delegate. We tested for self-selection bias but could not reject the absence of selection effects. However, this may be due to our data where only a small fraction of the WSS delegate the operation of their water network.

This brings us to the second objective in this study: to determine whether or not spatial factors influence the organization of WSS. It may be expected that spatial spillovers exist between WSS that may also influence the decision to delegate. This was also tested by including spatial lags in the delegation selection model. However, we did not find evidence of spatial spillovers. Before drawing definitive conclusions about this result, we would like to emphasize once again the relatively low number of WSS that were delegated in the study area. Our final objective was to apply a spatial econometric method to test if there were spatial spillovers in drinking water supply costs. In our case study, we neither found that spatially-lagged costs were significant (the spatial lag model) nor that spatial autocorrelation existed in the residuals (the spatial error model). This indicates that we did not omit any important spatial variables since such omitted variables would have induced spatial autocorrelation. These results also indicate that water supply costs are not influenced by unobserved spillovers that, for example, could be generated by knowledge diffusion. Another explanation for spatial correlation in water provision costs could be displaced demand where a WSS that experiences a high demand goes to neighboring areas to extract water to be able to comply with the demand. This would make the resource scarcer in the neighboring region and the price would consequently increase there as well. However, this effect was represented in our model that included the number of users in the neighboring regions: this variable had a positive effect on costs.

The results of this study suggest that further research is needed to refine the analysis of spatial aspects linking land uses and water quality. In particular, distant protection areas of water intake structures are defined on the basis of water catchment. If land uses (and specifically, forest lands) are known to exist in these areas, it would be possible to directly and more precisely measure their impact on water quality (by matching water and forest areas). Measurements of some targeted pollutants (e.g., pesticides, nitrates) would make it possible to have an indication of water quality and to estimate the value of specific land uses through water prices.

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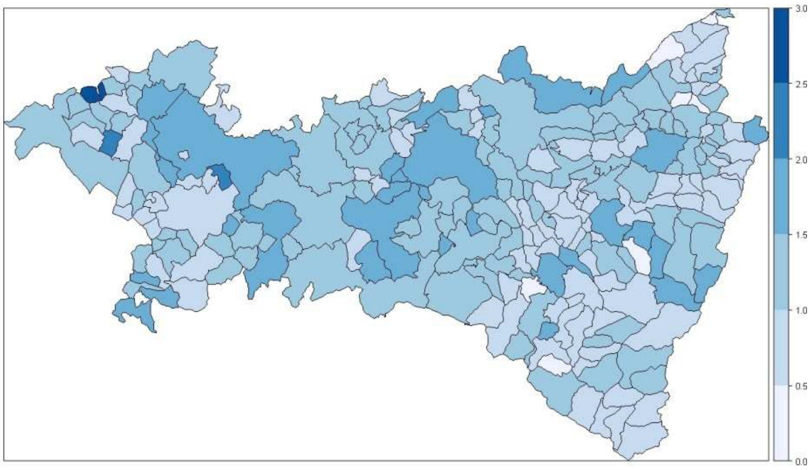
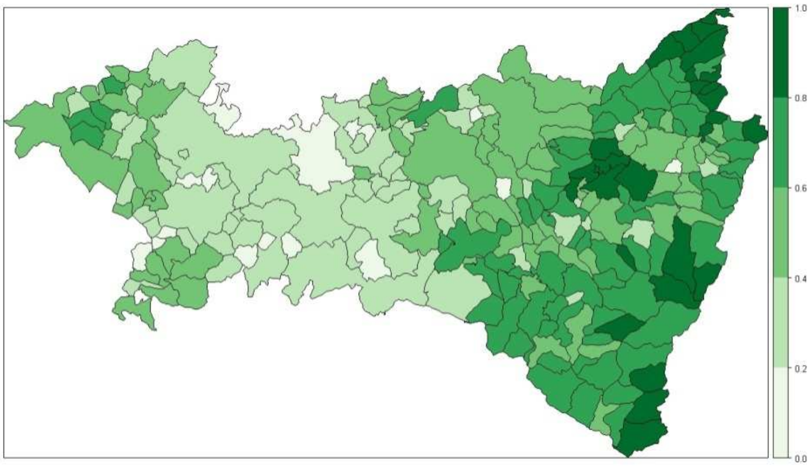
Figure 1: Spatial distribution of water prices




Note: the darker the blue, the higher the price.

Figure 2: Spatial distribution of forest lands




Note: the darker the green, the higher the proportion of forest lands.

Table 1: Definition of variables and descriptive statistics

| Variable | Definition of variable | MEAN | STD | MIN | MAX |
|---|---|---|---|---|---|
| FOREST | Proportion of forest lands | 0.54 | 0.223 | 0.047 | 1 |
| AGRI | Proportion of agricultural lands | 0.15 | 0.153 | 0 | 0.73 |
| URBAN | Proportion of urban area | 0.05 | 0.072 | 0 | 0.66 |
| OTHER | Proportion of other areas | 0.27 | 0.15 | 0 | 0.73 |
| USER | Number of users served by the WSS | 682 | 1,457 | 14 | 15,871 |
| MUNICIP | Number of municipalities served by the WSS | 1.87 | 3.269 | 1 | 30 |
| PRICE | Drinking water price (in €) | 1.08 | 0.358 | 0.21 | 2.56 |
| WATER_VOL | Delivered drinking water volume (in m3) | 104,676 | 254,019 | 1557 | 2,789,170 |
| DELEG | Dummy=1 if private operation | 0.09 | 0.29 | 0 | 1 |
| ALT_DIF | Altitude differential between the municipality and the water intake sources (in thousands of meters) | 0.07 | 0.086 | -0.234 | 0.448 |
| INTAKE | Number of water intake sources | 4.07 | 5.91 | 0 | 38 |
| DRILL | Type of intake (Dummy=1 if drilling) | 0.16 | 0.37 | 0 | 1 |
| WELL | Type of intake (Dummy=1 if well) | 0.14 | 0.35 | 0 | 1 |
| SOURCE | Type of intake (Dummy=1 if spring) | 0.81 | 0.39 | 0 | 1 |

Note: number of observations = 232 WSS.

Table 2: Estimation results of the SLX model

| Variable | Estimate | Std. Error | Pr(>\|t\|) | Significance level |
|---|---|---|---|---|
| (Intercept) | 1.376 | 0.1485 | < 2e-16 | *** |
| URBAN | -0.625 | 0.3752 | 0.097227 | * |
| OTHER | -0.250 | 0.1679 | 0.138389 | |
| ALTIT_DIF | -0.408 | 0.3133 | 0.194258 | |
| INTAKE | 0.0087 | 0.0042 | 0.041355 | ** |
| DRILL | -0.0670 | 0.0673 | 0.320489 | |
| DELEG | 0.352 | 0.1054 | 0.000993 | *** |
| MUNICIP | 0.0257 | 0.0098 | 0.009650 | *** |
| DELEG x MUNICIP | -0.0161 | 0.0134 | 0.231839 | |
| FOREST_lag | -0.551 | 0.1967 | 0.005531 | *** |
| URBAN_lag | -1.129 | 0.6780 | 0.097419 | * |
| USER_lag | 0.109 | 0.0438 | 0.014048 | ** |
| ALTIT_DIF_lag | 0.625 | 0.5029 | 0.214959 | |
| INTAKE_lag | -0.0125 | 0.0092 | 0.174290 | |
| DRILL_lag | 0.310 | 0.1359 | 0.023681 | ** |
| MUNICIP_lag | -0.0215 | 0.01219 | 0.078834 | * |

Note: ***: significant at 1%, **: at 5%, *: at 10%.