Land Use and Freshwater Ecosystems in France
(*First Unfinished Draft*)

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Abstract

Freshwater ecosystems have experienced over the last three decades larger declines in biodiversity than terrestrial and marine ecosystems. In France, this degradation is represented by a decline in the quality and quantity of water, and by changes in the distribution and structure of aquatic biota for some rivers. These human-induced pressures are mainly driven by land use changes such as urban development and intensive agriculture. In this paper, we estimate a spatial panel data model to measure the effects of alternative land uses on a selected indicator of the ecological status of surface water, namely a fish-based index. This model allows us to control for both spatial autocorrelation and unobserved individual heterogeneity which may influence water quality. We study the value of the fish-based index in various French rivers at the level of hydrographic sectors observed between 2001 and 2013. Our preliminary estimation results first reveal that spatial autocorrelation coefficients are significant. More importantly, they indicate that the urban land is the land use with the greatest adverse impact on freshwater fish populations. These results suggest that urban development tends to degrade more freshwater bioversity than the other land uses.

Keywords: freshwater biodiversity, freshwater ecosystems, fish-based index, land use, water quality, spatial panel data model, France.

JEL codes: C31, R14, Q22, Q53.

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1 Introduction

Freshwater ecosystems have experienced over the last three decades larger declines in biodiversity than terrestrial and marine ecosystems. This is due to alterations of habitat, water pollution problems, overexloitation of water resources, exotic invasions, water extraction and flow regulation (Mantyka-Pringle et al. (2014)). These human-induced pressures are mainly driven by land use changes. The increased urbanization and development cause the alteration of habitat in rivers. The agricultural sector is at the origin of diffuse pollution problems due to discharges of nitrogen, phosphorus and pesticides in soil and water. Some rivers in France are highly degraded because of these various land uses and their changes. This degradation is represented by a decline in the quality and quantity of water, and by changes in the distribution and structure of aquatic biota for some rivers in France (Oberdorff et al. (2002)). This has led us to ask what land uses are at the origin of the spatial heterogeneity of the "health" of water bodies in France, and which public policies are best in improving it.

France is constrained by the European Union Water Framework Directive since 2000. This Directive indicates that the quality of surface water must be good or very good by 2015 for 60% of water resources in all member states. However, France has failed to fulfill its obligation to comply with this Directive. The decision of the European Court of Justice in September 2014 censured France, for the third time since 2001, for the insufficient measures taken. In France in 2013, only 48,2% of surface water resources are in a good position regarding the chemical status. Regarding the ecological status, only 43,4% of surface water resources are in a good or very good situation (Onema/OIEau (2015)).

In order to reach the ecological objective of the Directive, France needs information on the human-induced pressures on freshwater ecosystems. The objective of this study is to estimate the effects of alternative land uses on a selected indicator of the ecological status of surface water, namely a fish-based index (FBI[1], hereafter). Fish is considered as a useful indicator to assess the ecological health of water bodies "*. . . since they respond predictably to changes in both abiotic factors, such as habitat and water quality, and biotic factors, such as human exploitation and species additions (Davis and Simon 1995)*" (Hascic and Wu (2006), p. 218). Oberdorff et al. (2002) also note that "*among potential indicators, fish assemblages are of particular interest because of their ability to integrate environmental variability at different spatial scales*" (p.1720). The originality of the fish-based index is related to the use of multiple metrics based on occurrence data as well as on abundance data. The metrics based on abundance data account for regional and local environmental factors (Oberdorff et al. (2002)). Such an index is built in France for a large number of well-defined sites evenly distributed across all available types of rivers monitored from 2001 to 2013.

Land use changes that trigger the degradation of water quality come either from agricultural production or from urbanization. One strand of the literature (among others, Wu and Segerson (1995), Wu et al. (2004), and Atasoy et al. (2006)) measures the effects of sectoral activities on the extent of water pollution. Regarding agricultural land use, Wu and Segerson (1995) have proposed an empirical model to quantify the extensive margin effects of alternative agricultural policies on "potential" groundwater pollution[2] in Wisconsin in the U.S. The estimated acreage responses are used to evaluate the potential pollution along with information on the joint distribution of crops and land quality. In a different vein, Wu et al. (2004) have used simulated environmental data[3] to measure the extent of water pollution due to agricultural runoff for 42 000 agricultural sites in the upper-Mississippi river basin in the U.S. In a first step, a model of crop choice and tillage practice is estimated. In a second step, environmental production functions (nitrate leaching and runoff, water and wind erosion) are estimated by regressing the simulated environmental data on the

[1] Indice Poissons Rivière (IPR) in French.

[2] The amount of acreage that is vulnerable to pollution (by land characteristics) and that grows a chemical-intensive crop is assumed to measure the groundwater pollution.

[3] The methodology used is "metamodelling" as in Wu and Babcock (1999).

vector of crop management practices and land quality. This framework enables them to evaluate the effect of crop management practices on the estimated environmental production functions. These papers use either an approximate pollution indicator or simulated environmental data, and not effective pollution, to measure the extent of water pollution. In contrast, as concerns urban land use, Atasoy et al. (2006) have proposed a spatial econometrics model to estimate the impact of residential development on water quality[4] in the upper Neuse River and its tributaries in the U.S. They have found that both the density of residential land use and the rate of land conversion have a negative impact on water quality.

Another strand of the literature analyzes the link between alternative land uses and indicators of water quality (among others, Hascic and Wu (2006), Langpap et al. (2008), Fiquepron et al. (2013), Abildtrup et al. (2013), Martinuzzi et al. (2014), and Fezzi et al. (2015)).[5] The case of the U.S. is studied by Hascic and Wu (2006), Langpap et al. (2008), and Martinuzzi et al. (2014), the case of Great Britain by Fezzi et al. (2015), and the case of France by Fiquepron et al. (2013) and Abildtrup et al. (2013). Hascic and Wu (2006) have proposed an econometric model that estimates the impact of alternative land uses[6] on the chemical and ecological status of water quality. The analysis is applied to a cross-section of 2100 watersheds in the lower 48 states of the U.S. The chemical status of water quality is represented by the conventional ambient water quality and the toxic ambient water quality. The empirical analysis is also carried out to measure how the two predicted values of water pollution indicators along with a vector of land-use and habitat variables, affect the ecological status of watersheds.[7] The estimation results, based on the negative binomial (NB2) model, indicate that only the conventional water pollution variable has a positive and significant effect on the number of endangered species in an average watershed. Langpap et al. (2008) have extended the work of Hascic and Wu (2006) by estimating a land use choice model on pooled data. The multinomial logit model explains the determinants of alternative land uses in 4 states in the U.S.[8] Langpap et al. (2008) have also estimated three NB2 models of water health's indicators (the same indicators as used in Hascic and Wu (2006)[9]). The estimations results show that watersheds with more urban land relative to forest area are associated with more species at risk.

As concerns the case of France, Fiquepron et al. (2013) estimate a system of simultaneous equations to assess the impact of alternative land uses on two measures of chemical status of water quality (pesticides, nitrates), and on the price of drinking water in France. This analysis is carried out for 93 Departments in France. They have shown that the forest land use has a positive effect on raw water quality compared to other land uses. This, in turn, induces a decrease in the price of drinking water. Abildtrup et al. (2013) obtain similar results in their reduced model of cost of drinking water estimated for 232 water supply services in the Vosges Department in France. They estimate a spatial econometric model to take into account the effects of the land uses by neighbor water services on the cost of drinking water of a given water supply service.

The previous work on France has studied exclusively the effects of land uses on the chemical status of water quality. In this work, we close the gap in the literature by analyzing how alternative land uses affect the ecological status of water quality. To this end, we estimate the effects of land uses on the fish-based index which is an indicator of the ecological status of water bodies.

[4]Three measures of water quality considered are total nitrogen (TN), total phosphorus (TP), and total suspended solids (TSS).

[5]There exist also an empirical literature that explains terrestrial biodiversity by alternative land uses, see for instance Lewis and Plantinga (2007) on habitat fragmentation, and Ay et al. (2014) on bird populations.

[6]Land-use categories considered are: Cultivated cropland, non-cultivated cropland, forest land, pasture land, rangeland, urban land, rural transportation land, minor land (comprising mining land and land concerned by the Conservation Reserve Program), and federal land.

[7]The ecological status is measured by the species-at-risk indicator, more precisely by the number of aquatic and wetland species at risk of extinction in a given watershed.

[8]These determinants are the returns of five land uses (range land, urban land, agricultural land, forest land and other) and the indices of local land use regulations.

[9]Unlike Hascic and Wu (2006), the indicators of chemical water pollution do not directly enter in the equation to estimate the species-at-risk indicator.

As these effects are conditional to the location of water body and to its climatic and edaphic characteristics, it is important to take into account the spatial heterogeneity of the fish-based index in the econometric strategy. To this end, unlike the previous literature, we use a spatial panel data model to explain the score of the fish-based index registered for various monitoring points in France observed between 2001 and 2013. This model allows us to control for both spatial autocorrelation and unobserved individual heterogeneity which may influence water quality. The explanatory variables considered are five land uses (agriculture, forest, pasture, urban and other), climatic and edaphic factors as well as information on terrain relief. The spatial resolution chosen is the hydrographic sector[10] which is the most appropriate one for observing fish populations in rivers. We will discuss the implications of the results for the design of agricultural and land use policies that improve the health of freshwater ecosystems.

This national-scale, hydrographic sector-level analysis aims to answer the following questions: (i) Do land-use, habitat and environmental variables explain the spatial heterogeneity of the fish-based index in France? (ii) What land uses, at the expense of others, are at the origin of the degradation of river ecosystems in France? (iii) Do spatial dependences in the score of the fish-based index exist? (iv) To what extent is the score of this index affected by spatial interactions?

In what follows, we provide an overview of the state of freshwater fish resources in France and describe the fish-based index in Section 2. Section 3 sets out the empirical model and the estimation method. Section 4 describes the data, and presents the estimation results. Section 5 summarizes our main results and draws some policy conclusions.

2 Freshwater Fish in France

2.1 Context

Freshwater fish are not only important for biodiversity concerns but also in economic terms. The volume and value of catches of commercial inland fisheries amount to 1186 tons and €10 470 000 respectively (2007-2008 average). The average price of these catches is €8.8 per kg, with a significant contribution of glass eel and adult eels. The commercial catches of inland fisheries is marked by a strong specialization in ells in France. The sector is specialized in small-scale fishing: the number of fishing boats is 621 with an average size of 6 m and average power of 40 HP. Fish are caught from Alpine lakes, Loire, Gironde, Adour and Rhône estuaries and rivers. Even though the share of commercial inland fishing in national catches is small, namely 0.2%, the sector offers specially niche market products, such as ells, mostly to local and regional markets (Ernst&Young (2011)). The main species in catches are houting, lamprey, eel, perch and white fish (International (2009)).

The French exports of freshwater fish including trout, salmon and eel amount to €226 million in 2013 (FranceAgriMer (2014)) (for a comparison, the exports of marine fish are €713 million in 2013). The most important species in terms of exports is eel whose catches represent 65 to 70% of European production. Indeed, France is the first producer of eels in Europe. The farmed production of eels is non existent in France (EU report). Since 60s, there has been a decreasing trend in the stocks of eels due to alterations of habitat and pollution problems. This is why this species is classified in Annex II of the list of CITES as a species whose trade should be controlled. Since 2010, the exports of eels outside of the EU is forbidden. Domestic demand has dropped too due to Polychlorinated biphenyl (PCB) pollution concerns in eels. French authorities, such as ANSES (French Agency for Food, Environmental and Occupational Health & Safety) have

[10] A hydrographic sector is a subdivision of the river basin districts ("*bassin versant*" in french) established in the EU Water Framework Directive. France is divided into six river basin districts: Rhône-Méditerranée-Corse, Rhin-Meuse, Loire-Bretagne, Seine-Normandie, Adour-Garonne and Artois-Picardie. They correspond respectively to five large rivers (Rhône, Rhin, Loire, Seine et Garonne), and la Somme river. A hydrographic sector represents a smaller area than a hydrographic region. There are 187 hydrographic sectors in metropolitan France. See Figure 1 in the Appendix. This geographical scale has been used in other studies of water quality (Lungarska and Jayet, 2014).

recommended the non consumption of freshwater species most accumulated with PCB pollution (namely, eel, barbel, bream, carp, sheatfish). Large retailers do not offer any eels in France due to these information campaigns. Despite decreasing supply of eels, prices have been low, around €8.4 per kg due to the decreasing trend in demand.

More generally, the freshwater fish populations in France have suffered from the degradation and destruction of natural environments as well as from pollution problems. The inventory of the Red List of Threatened freshwater species in France, conducted by the International Union for Conservation of Nature (IUCN) French National Committee and the National Museum of Natural History indicates the following: 15 freshwater fish species over 69 are threatened, 4 species are critically endangered, 2 species have disappeared at the global level and 2 species have been extincted at the France metropolitan. The species which have been extincted at the France metropolitan are Spanish toothcarp and Valencia toothcarp, and those that are critically endangered are sturgeon, european eel, Chabot du Lez, and Rhone streber (UICN France (2010)).

2.2 Fish-based index

Fish-based index employs seven metrics to calculate the current index score at a site which is then compared to the score which would prevail at the reference situation (at the absence of stress). The value of the index includes the sum of the deviations from the reference of the following seven metrics:

- Total number of species
- Number of lithophilic species (which require clean gravel substrates for reproductive success)
- Number of rheophilic species (which inhabit in lotic areas)
- Total density of individuals (which measures individual abundance)
- Density of tolerant species (species having a large water quality and habitat flexibility)
- Density of invertivorous species (species which mainly feed on invertebrates)
- Density of omnivorous species (species that can digest considerable amounts of both plant and animal foods).

The more the fish population is close to the reference situation, the lower the value of the index. The index varies from 0 (meaning that the reference situation prevails) to the infinity. In practice, FBI rarely exceeds 150 in the more altered stations.

SOeS (2012) draws a description of the evolution of this index over the period 2001 to 2010.[11] It is highlighted that slightly more than half of the monitoring points have good or a very good quality, except in 2003, which is marked by exceptionally high temperatures and particular hydrological conditions. The report notes that the index stayed relatively constant over the period of consideration. However, in order to meet the water quality standards of the European Water Framework Directive, additional efforts should be undertaken. There exists a high degree of heterogeneity in the score of the fish-based index for the six river basin districts. Artois-Picardie appears to be the river basin district with the highest number of points with low ecological quality. The Seine-Normandie is in the best position. In fact, upstream points are usually in a better situation than downstream ones. The big river basin districts suffer more from human-induced disturbances. Coastal water bodies are more preserved.

SOeS (2012) provides some explanations for the spatial heterogeneity of the FBI index for watersheds in France. Artois-Picardie watershed is a very populated one, receiving human-induced pressures from industrialization and intensive agriculture. In Rhin-Meuse watershed, the FBI score indicates a better quality in the regions with more forest land. Regarding the Seine-Normandie

[11]Note that the stations where measures are made have evolved through time. In the period 2001- 2004, data only cover RHP (Réseau Hydrobiologique et Piscicole) while data also concern reference situation in the period 2005-2006. This explains the over-estimation of points with very good quality in the latter period. Finally, the number of monitoring stations has almost doubled after 2007, which decreased the preponderance of points with very good quality.

watershed, the quality of water is worst in the center regions, namely in Picardie and Région Parisienne. The human-induced pressures mainly come from urban development and intensive agriculture. The latter factor is also at the origin of the degradation of the river basin quality in Loire-Bretagne watershed. Adour-Garonne watershed is negatively affected by the hydro-electricity and intensive agricultural production. FBI scores best at the regions with more forest land and grassland. Rhône-Méditerranée watershed suffers from urban development, dam construction, and from hydro-electricity production.

Our objective is to check if the precedent insights provided by SOeS (2012) could be validated by data. To this end, we estimate a spatial panel data model covering the period 2001-2013 for the sites included in the FBI index.

3 The empirical model

In order to assess the impact of pedo-climatic variables as well as land uses on the quality of water, we estimate an econometric model explaining observed FBI at a monitoring point located throughout French rivers as a function of land use, land quality and climate to each monitoring point. By using spatial tools, we control for any spatially correlated unobserved factors which may influence water quality. We assume that FBI_{it} in location i at time t ($i = 1, ..., N$ and $t = 1, ..., T$) is generated according to the following model:

$$FBI_{it} = x_{it}\beta + v_{it}, \tag{1}$$

$$v_{it} = \mu_i + \varepsilon_{it}, \tag{2}$$

where x_{it} is a $k \times 1$ vector of observed regressors on the ith cross-section unit at time t, μ_i is the random individual effect of location i assumed to be $IID(0, \sigma_\mu^2)$, and v_{it} is an IID[12] error term with zero mean and variance σ_v^2.

3.1 Random-effects vs fixed-effects

Conditional on the specification of the variable μ_i, the model can be estimated as fixed or random effects model. In the fixed-effects (FE) model, a dummy variable is introduced for each spatial unit as a measure of the variable intercept. In the random-effects (RE) model, the variable μ_i is treated as a random variable that is IID with zero mean and variance σ_μ.

The random effects specification assumes that $E(\mu_i x_{it}) = 0$ and $E(\mu_i \varepsilon_{it}) = 0$ for all i and t. If the hypothesis that the individual-specific component is orthogonal to the explanatory variables does not hold, estimates from the RE model suffer from possible bias due to the correlation between the error term and the regressors.

The choice between the (RE) or the (FE) specification depends on the model and data.[13] In a spatial setting, using individual fixed effects might induce an incidental parameter problem as the asymptotics in the cross-sectional dimension is necessary.[14] In addition, in a FE model, time-invariant spatial clusters will be "swept away" by the within estimator and the associated coefficient cannot be identified. For this reason we choose to model individual effects through random effects. This choice imposes that the individual effects are independent of exogenous regressors.

3.2 Spatial specification

The standard approach in most spatial analyses is to start with a non-spatial linear regression model and then to test whether or not this model needs to be extended with spatial interaction

[12]Independent and identically distributed.

[13]See Hsiao (1986) and Baltagi (1995) for a discussion on the choice between random effects and fixed effects models in the non spatial case and Lee and Yu (2010b) in the spatial case.

[14]See Lee and Yu (2010a) for a recent overview on the estimation of spatial panel models.

Model name	Model presentation
SEM	$FBI_{it} = x_{it}\beta + \mu_i + \varepsilon_{it}$
	$\varepsilon_{it} = \lambda W \varepsilon_{it} + u_{it}$
SAR	$FBI_{it} = \rho W FBI_{it} + x_{it}\beta + \mu_i + \varepsilon_{it}$

Table 1: Spatial autocorrelation models tested

effects. This approach is known as the specific-to-general approach, which we adopt in this paper. Starting with a standard linear regression model, three different types of interaction effects could be introduced in a spatial econometric model: endogenous interaction effects among the dependent variable (FBI) known as the spatial autoregressive (SAR) model, exogenous interaction effects among the independent variables (X) known as the spatial lag of X (SLX) model, and interaction effects among the error terms (ε) called the spatial error model (SEM). The three models (SAR, SEM, SLX) could be combined to have the SDM and SAC models. We focus on the SEM and SAR spatial models.

3.3 Weight matrix

Neighbor relationships are defined by the elements of the weight matrix W. A variety of weighting schemes could be considered and the choice depend on the data and the estimated model. We consider the neighbor matrix based on contiguity rule and row-normalized.

4 Data description and estimation results

4.1 Data description

In our study, we combine information on fish population (the FBI index), climate, edaphic conditions, terrain relief, and land use. Summary information on the data is provided in Table 2. FBI values are aggregated (average values) at the scale of the hydrographic sector [15]. There is information for each year for 122 sectors (represented on Figure 2). Land uses are derived from the Corine Land Cover (CLC) and represented by aggregated land use classes for agriculture, pastures, forest, urban, and other uses. The share of each land use is evaluated at the scale of the hydrographic sector. Edaphic conditions are given by the topsoil texture and the subsoil available water capacity (Panagos et al., 2012). For instance, variable TXT1 represents the share of the soil texture class 1 at the hydrographic sector, class 1 being the worst one in terms of soil quality. In the same way, variable AWC1 is the share of the available water capacity class 1 at the hydrographic, with again class 1 representing the worst one. Climate is summarized by the annual average temperature. Terrain relief is given by altitude and slope. Land use data are available only for some of the years covered by our study. The intermediate values are thus interpolated with respect to observation.

[15] We are using the terms hydrographic sector and hydrosector interchangeably.

Variable	Definition	Unit	Year
FBI	FBI index value for the observation *Scale:* point; *Source:* Oberdorff et al. (2002), The French National Agency for Water and Aquatic Environment, ONEMA.	-	2001, ..., 2013
t	Annual average temperature *Scale:* 8 x 8 km grid; *Source:* Météo France.	°C	1990, ..., 2013
TXT1, ..., TXT5	Share of the texture class in the hydrographic sector	%	Invariant
AWC1, ..., AWC5	Share of the available water capacity class in the hydrographic sector *Scale:* 1:1,000,000; *Source:* Panagos et al. (2012), European Union Joint Research Center, JRC.	%	Invariant
slope	Slope *Scale:* 30 arc sec ($\sim$ 1 km); *Source:* GTOPO30.	%	Invariant
Land use classes • agr • pst • for • urb • oth	 Agriculture share Pasture share Forest share Urban share Other *Scale:* 1 ha; *Source:* Corine Land Cover.	 %	 1990, 2000, 2006, 2012

Table 2: Data description

4.2 Estimation results

In order to compare the estimations and to evaluate the gains associated with allowing for spatial autocorrelation as well as for individual heterogeneity (in the form of random individual effects) we consider the following estimators:

1. The pooled OLS, which ignores individual heterogeneity and spatial auto-correlation.
2. The RE (Random-Effects) estimator of a standard panel data model with random effects. This estimator accounts for random individual effects but takes into account neither spatial autocorrelation nor correlation across equations.
3. The SEM (Spatial Error Model) which takes into account the autoregressive spatial error autocorrelation but ignores individual heterogeneity.
4. SEM-RE estimator, which accounts for both spatial error autocorrelation and random individual heterogeneity.
5. The SAR (Spatial Autocorrelation Model) which takes into account the autoregressive effects between the dependent variable across the spatial units, but does not account for individual heterogeneity.
6. SAR-RE estimator, which accounts for both spatial autocorrelation in dependent variable and random individual heterogeneity.

The detailed results for the estimated models are provided in the Appendix. We start by estimating the pooled OLS model (Table 3). The Moran's I statistic associated with this model specification and the contiguity neighbors matrix is significant at the 1% confidence level. Thus, the FBI scores are potentially subject to spatial autocorrelation. Consequently, we estimate two alternative model specifications accounting for the spatial autocorrelation. Both the SEM and the SAR models (Table 5, 7 and 8) have significant spatial autocorrelation coefficients, λ and ρ respectively. This result indicates that the estimation results from the OLS model which ignores spatial autocorrelation are biased. The coefficients of land use classes are significant for the two models. The estimates presented in Tables 5 and 8 indicate that the urban land use is affecting the most the FBI value (highest coefficient for this land use). We should remind here that the higher the FBI value, the greater is the difference between the reference situation and the observed fish population. Hence, our estimation results suggest that urban development tends to degrade more freshwater bioversity than the other land uses.

The estimation of the SEM and the SAR models (Table 5, 7 and 8) also shows that the effects of the slope and temperature on the FBI score are significantly negative. This means that low FBI values are associated with steep topography and high temperatures. The positive effect of temperature on freshwater biodiversity could be related to individual hetorogeneity: southern regions (with high average temperatures) have less intensive agriculture activities, hence less pollution in rivers compared to northern regions. The estimation results also show that the soil quality is generally not significant (except TXT1 in some specifications) while the subsoil available water capacity is. The estimation of the SEM and the SAR models points out that the positive coefficient of AWC1 is always larger than that of AWC5. This means that better subsoil water capacity degrades less the freshwater biodiversity. More the subsoil has the ability to retain water, less will be leaching and pollution problems in rivers. Direct effects for the SAR model are all significant except for the soil texture class variables TXT2, TXT3 and TXT4 (Table 9). This is also the case for the indirect and total effects as Tables 10 and 11 show.

The RE model (no spatial autocorrelation, Table 4) reports that an important fraction of the variance is due to the differences across panels. The sole significant and positive land use coefficient in this model is the one associated with the urban use. The subsoil water capacity has also a significant effect on the FBI value. When we take into account both the spatial autocorrelation and the individual heterogeneity, the SEM-RE model (Table 6) performs better than the SEM model (Table 5). Both λ and θ are significant. The value of θ is close to 1 meaning that the most of the information is contained in the within estimator. For this model, the coefficients for agricultural and other land uses are not significant while those for urban and pasture land are. Slope, temperature, and soil texture classes are not significant (except the first texture class), while subsoil water capacity classes are significant. The SAR-RE model (Table 12) performs slightly better in terms of log likelihood than the SEM-RE model (Table 6). The value of θ for the former model is also significant but lower. The urban and pasture land uses, and the subsoil water capacity have a significant positive impact on the FBI value.

5 Conclusion

In the IUCN Red List of Threatened Species published in 2012[16], France ranks fifth in the world for hosting the largest number of endangered plant and animal species. Regarding freshwater ecosystems, their degradation is represented by a decline in the quality and quantity of water, and by changes in the distribution and structure of aquatic biota for some rivers in France (Oberdorff et al. (2002)). The French freshwater fish populations have suffered from the degradation and destruction of natural environments as well as from pollution problems. This has led us to ask what land uses are at the origin of the spatial heterogeneity of freshwater ecosystems in France. To this end, we estimated a spatial panel data model to measure the effects of alternative land uses on a selected indicator of the ecological status of surface water, namely a fish-based index. This model allows us to control for both spatial autocorrelation and unobserved individual heterogeneity which may influence water quality. We studied the value of the index in various French rivers at the level of hydrographic sectors observed between 2001 and 2013.

Our preliminary estimation results first reveal that spatial autocorrelation coefficients are significant. This means that there are spatial interactions in the value of the fish-based index, and ignoring them would lead to biased estimates. Secondly, our results indicate that the urban land is the land use with the greatest adverse impact on freshwater fish populations. Hence, these results suggest that urban development tends to degrade more freshwater biodiversity than the other land uses. Finally, our estimations show that better freshwater biodiversity is associated with steep topography and high temperatures.

Further work is needed to study the following aspects. We first plan to use a different weight matrix for spatial interactions which takes into account the upstream and downstream points at the level of hydrographic sectors (Atasoy et al. (2006)). We will also study the effects of the exceptional drought that took place in 2003 on the value of the fish-based index. Another extension is to test the predictive power of our model for the year 2013, by estimating it for the period 2001-2012. Our ultimate aim is to discuss the implications of our results for the design of land use policies, such as urban zoning or agro-chemicals tax policies, that could improve the health of freshwater ecosystems. This discussion is important given the necessity for France to comply with the ecological objectives of the European Union Water Framework Directive.

[16]http://www.iucn.org/

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Appendices

Figure 1: Hydrographic sectors and River bassin districts (RBD, water agencies) in France

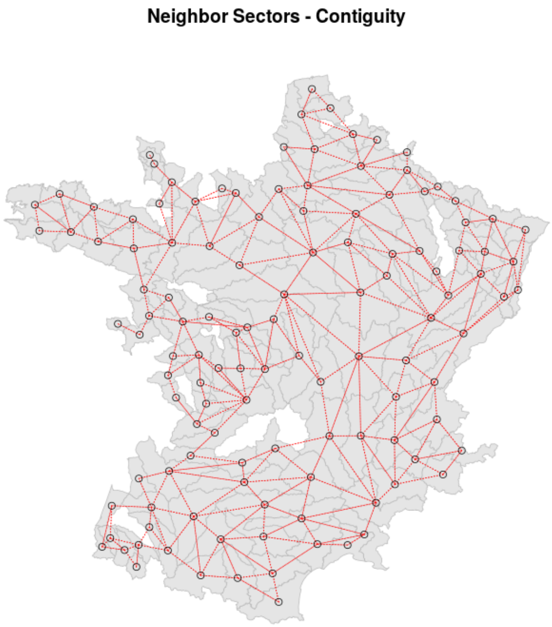

Figure 2: Hydrographic sectors and neighbor relations

Dependent Variable – FBI

Variable	Coefficient	t-statistic	t-probability
constant	-7.438301	-0.811752	0.417057
Slope	-0.312818	-4.222254	0.000026
TXT1	22.221365	2.696912	0.007073
TXT2	14.105795	1.779235	0.075395
TXT3	12.586843	1.651005	0.098937
TXT4	10.694753	1.373719	0.169725
AWC1	20.613727	7.590725	0.000000
AWC3	19.415048	7.092030	0.000000
AWC4	12.388609	5.694745	0.000000
AWC5	10.326612	3.855989	0.000120
t	-0.572336	-3.472110	0.000530
agr	5.348438	3.259786	0.001139
pst	7.309840	3.962582	0.000077
urb	34.980648	4.750370	0.000002
oth	16.303870	3.478211	0.000519

R-squared = 0.1095

Rbar-squared = 0.1015

$\sigma^2 = 44.5282$

Durbin-Watson = 1.4850

Nobs, Nvars = 1586, 15

Moran's I test = 0.1792, H_0 probability = 0

Table 3: Ordinary Least-squares Estimates

Dependent Variable – FBI

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
constant	33.17905	37.91925	0.87	0.382	-41.14131	107.4994
Slope	-.1625688	0.1891438	-0.86	0.390	-0.5332838	0.2081462
TXT1	-24.29879	37.10904	-0.65	0.513	-97.03117	48.43358
TXT2	-34.73945	37.42375	-0.93	0.353	-108.0886	38.60976
TXT3	-33.51741	36.58624	-0.92	0.360	-105.2251	38.1903
TXT4	-36.15189	36.96529	-0.98	0.328	-108.6025	36.29873
AWC1	25.29604	8.011504	3.16	0.002	9.593785	40.9983
AWC3	22.43901	7.852149	2.86	0.004	7.049077	37.82893
AWC4	15.618	6.333761	2.47	0.014	3.204057	28.03195
AWC5	10.7814	7.534955	1.43	0.152	-3.986836	25.54964
t	-0.0666236	0.3227135	-0.21	0.836	-0.6991305	0.5658833
agr	3.398396	4.848217	0.70	0.483	-6.103936	12.90073
pst	5.798709	5.285086	1.10	0.273	-4.559869	16.15729
urb	39.8174	22.34316	1.78	0.075	-3.97439	83.60919
oth	5.86615	13.85592	0.42	0.672	-21.29096	33.02326
σ_u	5.2484778					
σ_e	4.750234					
Interclass correlation	0.54970738 (fraction of variance due to u_i)					
R-sq:						
within	0.0041				Wald χ^2 (14)	28.83
between	0.1950				corr(u_i, X)	0 (assumed)
overall	0.1225				Prob > χ^2	0.0110

Table 4: Random-effects GLS regression

Dependent Variable – FBI

Variable	Coefficient	t-stat	probability
constant	0.402528	0.043439	0.965352
Slope	-0.341204	-3.869768	0.000109
TXT1	12.705221	1.551204	0.120853
TXT2	6.707693	0.842249	0.399649
TXT3	5.730441	0.740894	0.458758
TXT4	2.349118	0.295030	0.767971
AWC1	14.533713	4.998511	0.000001
AWC3	16.918103	5.986646	0.000000
AWC4	11.586969	5.204175	0.000000
AWC5	7.880436	2.904474	0.003679
t	-0.668858	-3.127307	0.001764
agr	9.249959	5.357404	0.000000
pst	11.292615	5.578202	0.000000
urb	28.819483	3.914568	0.000091
oth	28.713942	5.784481	0.000000
λ	0.403117	4.427677	0.000010
R-squared	0.1999		
Rbar-squared	0.1927		
GM σ^2	39.7212		
σ^2	39.6301		
Nobs, Nvars	1586, 15		

Table 5: SEM: Generalized Moments Estimation of Spatial Error Model

Dependent Variable – FBI

Variable	Coefficient	Asymptot t-stat	z-probability
constant	-35.143311	-1.602578	0.109028
slope	-0.052129	-0.309753	0.756749
TXT1	38.848604	1.884867	0.059448
TXT2	27.747289	1.397467	0.162273
TXT3	25.925479	1.359437	0.174008
TXT4	25.435806	1.312037	0.189508
AWC1	23.181073	3.298804	0.000971
AWC3	22.915428	3.220442	0.001280
AWC4	14.384432	2.573129	0.010078
AWC5	15.936419	2.350892	0.018728
t	0.305652	1.238132	0.215667
agr	3.209854	0.736469	0.461445
pst	8.030179	1.657975	0.097323
urb	50.325898	2.764300	0.005705
oth	6.938818	0.611459	0.540896
λ	0.213675	5.351218	0.000000
θ	0.963502	7.111260	0.000000
R-squared	0.5455		
corr-squared	0.0911		
σ^2	22.5087		
Nobs,Nvar	1586, 15		
log-likelihood	-4884.8961		

Table 6: SEM-RE: Pooled model with spatial error autocorrelation and spatial random effects

Dependent Variable – FBI

Variable	Coefficient	Asymptot t-stat	z-probability
constant	0.822584	0.089152	0.928961
slope	-0.342851	-3.829603	0.000128
TXT1	11.964826	1.470881	0.141323
TXT2	6.111653	0.771624	0.440337
TXT3	5.178569	0.672457	0.501293
TXT4	1.582819	0.199527	0.841850
AWC1	14.086251	4.837639	0.000001
AWC3	16.711162	5.929509	0.000000
AWC4	11.529976	5.195277	0.000000
AWC5	7.708500	2.853672	0.004322
t	-0.668786	-3.050860	0.002282
agr	9.698135	5.611798	0.000000
pst	11.830462	5.807797	0.000000
urb	28.414985	3.883738	0.000103
oth	29.860190	6.010034	0.000000
λ	0.440954	13.590973	0.000000
R-squared	0.0929		
corr-squared	0.0955		
σ^2	38.7953		
log-likelihood	-5183.7989		
Nobs,Nvar,#FE	1586, 15, 15		

Table 7: SEM : Pooled model with spatial error autocorrelation, no fixed effects

Dependent Variable – FBI

Variable	Coefficient	Asymptot t-stat	z-probability
constant	-9.543563	-1.099249	0.271660
Slope	-0.254406	-3.622936	0.000291
TXT1	15.882940	2.032366	0.042117
TXT2	10.163756	1.353208	0.175989
TXT3	9.505721	1.316456	0.188021
TXT4	7.530800	1.021290	0.307117
AWC1	14.026536	5.355187	0.000000
AWC3	15.782927	6.061390	0.000000
AWC4	10.287517	4.985732	0.000001
AWC5	7.342736	2.887427	0.003884
t	-0.456896	-2.925582	0.003438
agr	6.357376	4.092912	0.000043
pst	8.038776	4.605442	0.000004
urb	30.128810	4.316324	0.000016
oth	19.468218	4.385462	0.000012
ρ	0.380989	12.642222	0.000000
R-squared	0.0982		
Rbar-squared	0.0902		
σ^2	39.8025		
Nobs, Nvars	1586, 15		
log-likelihood	-4645.2137		

Table 8: SAR : Spatial autoregressive Model Estimates

Direct	Coefficient	t-stat	t-prob	lower 01	upper 99
Slope	-0.262986	-3.589942	0.000341	-0.446140	-0.109653
TXT1	16.215906	2.053694	0.040169	-4.000597	34.828633
TXT2	10.287518	1.360598	0.173834	-10.220248	28.286205
TXT3	9.636180	1.328718	0.184132	-8.794489	27.182521
TXT4	7.670016	1.031457	0.302484	-11.874460	25.624961
AWC1	14.489330	5.197862	0.000000	7.254987	21.616689
AWC3	16.249906	5.842998	0.000000	8.678265	23.179715
AWC4	10.608792	4.759029	0.000002	4.325034	15.916627
AWC5	7.541558	2.720444	0.006591	0.231220	14.293188
t	-0.469623	-2.875557	0.004087	-0.886515	-0.059722
agr	6.630084	4.041392	0.000056	2.517298	10.602779
pst	8.411621	4.592223	0.000005	3.434474	12.845518
urb	30.929278	4.376706	0.000013	11.217390	47.530677
oth	20.111527	4.553169	0.000006	9.390131	31.229027

Table 9: SAR : Direct effects

Indirect	Coefficient	t-stat	t-prob	lower 01	upper 99
slope	-0.150186	-3.355936	0.000810	-0.273977	-0.059768
TXT1	9.258515	1.995395	0.046171	-2.283834	20.713030
TXT2	5.879615	1.335346	0.181955	-5.761310	16.796808
TXT3	5.515553	1.303462	0.192606	-5.566361	16.751048
TXT4	4.388114	1.015915	0.309825	-7.581830	15.606926
AWC1	8.263252	4.732009	0.000002	4.155594	13.062374
AWC3	9.283592	4.973262	0.000001	5.059055	14.118791
AWC4	6.065426	4.177756	0.000031	2.693069	10.105774
AWC5	4.300806	2.611404	0.009102	0.125611	8.941905
t	-0.268088	-2.758320	0.005877	-0.535506	-0.035723
agr	3.795507	3.601245	0.000326	1.278073	7.116728
pst	4.817088	3.985422	0.000070	1.894519	8.073660
urb	17.696764	3.867609	0.000114	6.796883	30.033102
oth	11.507852	4.032788	0.000058	5.070892	19.889034

Table 10: SAR : Indirect effects

Total	Coefficient	t-stat	t-prob	lower 01	upper 99
Slope	-0.413172	-3.576201	0.000359	-0.706059	-0.164070
TXT1	25.474422	2.048005	0.040724	-6.284431	54.369520
TXT2	16.167134	1.357110	0.174939	-16.227975	45.721043
TXT3	15.151734	1.324868	0.185406	-13.635360	44.156086
TXT4	12.058130	1.028874	0.303696	-19.183124	40.131427
AWC1	22.752582	5.234001	0.000000	11.514441	33.932228
AWC3	25.533498	5.768429	0.000000	13.766355	36.936144
AWC4	16.674218	4.681997	0.000003	7.077126	25.541097
AWC5	11.842364	2.714074	0.006718	0.356832	23.265002
t	-0.737711	-2.874403	0.004102	-1.415210	-0.096033
agr	10.425591	3.963368	0.000077	3.876654	17.535479
pst	13.228709	4.481725	0.000008	5.503805	20.660285
urb	48.626042	4.294862	0.000019	18.236048	74.654231
oth	31.619379	4.486063	0.000008	14.717835	49.339915

Table 11: SAR : Total effects

Dependent Variable – FBI

Variable	Coefficient	Asymptot t-stat	z-probability
constant	-35.794514	-1.760628	0.078301
Slope	-0.037230	-0.240139	0.810223
TXT1	35.119357	1.827746	0.067588
TXT2	26.152020	1.401440	0.161082
TXT3	25.243642	1.407388	0.159312
TXT4	24.308200	1.332140	0.182814
AWC1	17.473317	2.612345	0.008992
AWC3	19.082844	2.840833	0.004500
AWC4	12.943652	2.430809	0.015065
AWC5	12.261614	1.902314	0.057130
t	0.275171	1.353136	0.176012
agr	4.872257	1.215664	0.224113
pst	9.019610	2.012542	0.044163
urb	47.710434	2.803214	0.005060
oth	12.795058	1.154456	0.248313
ρ	0.242992	6.467484	0.000000
θ	0.287207	11.424163	0.000000
R-squared	0.5473		
corr-squared	0.0927		
σ^2	22.4209		
Nobs,Nvar	1586, 16		
log-likelihood	-4877.4783		

Table 12: SAR-RE: Pooled model with spatially lagged dependent variable and spatial random effects

Variable	Direct	t-stat	indirect	t-stat	total	t-stat
Constant	-37.6222	-1.9674	-11.7894	-1.7701	-49.4116	-1.9439
Slope	-0.0414	-0.2598	-0.0128	-0.2572	-0.0542	-0.2601
TXT1	36.9845	2.0394	11.5683	1.8406	48.5528	2.0185
TXT2	28.0194	1.5750	8.7954	1.4630	36.8148	1.5631
TXT3	27.0474	1.5759	8.4893	1.4597	35.5368	1.5632
TXT4	25.9741	1.4896	8.1672	1.3979	34.1413	1.4810
AWC1	17.6839	2.5045	5.4673	2.2845	23.1512	2.5007
AWC3	19.2300	2.8966	5.9561	2.5502	25.1861	2.8834
AWC4	12.9249	2.4243	3.9873	2.2139	16.9121	2.4211
AWC5	12.1855	1.9032	3.7680	1.7626	15.9535	1.8933
t	0.2729	1.3136	0.0838	1.2670	0.3567	1.3136
agr	4.9332	1.1741	1.5446	1.1262	6.4777	1.1709
pst	9.3030	1.9965	2.8982	1.8138	12.2012	1.9785
urb	49.4130	3.0543	15.4276	2.5181	64.8406	2.9894
oth	13.2611	1.1565	4.1521	1.1053	17.4132	1.1532

Table 13: SAR-RE: Direct, indirect and total effects