# Land Use and Freshwater Ecosystems in France

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**Abstract**

Since the mid 1980s, freshwater ecosystems have experienced larger declines in biodiversity than terrestrial and marine ecosystems. Pressures on freshwater ecosystems are mainly human-induced and driven by land use changes. The objective of this paper is to evaluate how land-use adaptation to climate change affects freshwater ecosystems in France. For this purpose, we use data on land use shares (agriculture, pasture, forest and urban) and on an indicator of the ecological status of surface water, namely a fish-based index (FBI) measured for various French rivers observed between 2001 and 2013. We estimate two models: a spatial econometric land use share model and a statistical spatial panel FBI model. The land use share model describes how land use is affected by economic, physical and demographic factors, while the FBI model explains the spatial and temporal distribution of the FBI score by land use and pedo-climatic variables. Our estimation results indicate that land-use adaptation to climate change reduces freshwater biodiversity. We use our estimation results to analyze how two command-and-control policy options could help France to comply with the EU Water Framework directive and mitigate the adverse impacts of climate change on freshwater biodiversity.

*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

Since the mid 1980s, freshwater ecosystems have experienced larger declines in biodiversity than terrestrial and marine ecosystems. This is due to habitat changes, water pollution problems, overexploitation of water resources, exotic invasions, and water extraction and flow regulation (Mantyka-Pringle et al., 2014). A recent World Wildlife Fund report (WWF, 2016) indicates that the global decline in freshwater species populations, 81% between 1970 and 2012, is more than double that observed in land (38%) and marine (36%) populations. In relation to rivers, the report underlines that almost half of global river flows are subject to alterations (e.g. abstraction or channel modifications), or fragmentation (e.g. weirs and dams). Migratory fish species are particularly vulnerable to the fragmentation of river courses which impairs their reproduction capacities. Indeed, the abundance of migratory fish populations dropped by 41% between 1970 and 2012 (WWF, 2016).[1]

Freshwater fish populations in France have suffered from the degradation and destruction of natural environments as well as from pollution problems. The Red List inventory of threatened freshwater species in France[2] indicates that 15 out of 69 freshwater fish species are threatened, 4 species are critically endangered, 2 have disappeared at the global level and 2 species have become extinct at the French metropolitan level. The species which have become extinct are Spanish toothcarp and Valencia toothcarp, and those that are critically endangered are sturgeon, European eel, Chabot du Lez and Rhone streber (UICN France, MNHN, SFI, ONEMA, 2010).

France has been subject to the European Union Water Framework Directive (EU WFD) since 2000. This Directive imposed good or very good surface water quality by 2015 for 60% of water resources in all member states. France failed to fulfill this obligation and the European Court of Justice issued a ruling against France in 2014. In terms of chemical pollution, only 48.2% of French surface water resources were of acceptable quality in 2013. In terms of ecological status[3], only 43.4% of surface water resources were deemed good or very good quality (Onema/OIEau, 2015).[4] After 2015, there are two further deadlines for meeting the environmental objectives of the Directive, 2021 and 2027 - the final date for

[1]https://freshwaterblog.net/2016/10/27/freshwater-species-populations-fall-by-81-between-1970-and-2012/

[2]This inventory is conducted by the International Union for Conservation of Nature (IUCN) French National Committee and the National Museum of Natural History.

[3]As the biodiversity of aquatic species constitutes one of the main determinants of the ecological status of water quality, in the paper, we use the two terms interchangeably.

[4]The chemical status is the assessment of the quality of a water on the basis of the concentrations of each of the families of substances called "priority" or "dangerous priority". The good chemical status of a station is achieved when the concentrations (maximum concentration and annual average) do not exceed the environmental quality standards set by the Directive 2008/105/EC on Environmental Quality Standards, revised in 2013. Ecological status is the assessment of the structure and functioning of aquatic ecosystems. It is determined from biological quality (plant and animal species), and hydromorphological and physico-chemical elements (macro-pollutants in particular) associated with the development of biological cycles (Eaufrance, 2015).

meeting these objectives.[5]

To comply with the Directive's objectives, France needs information on the causes of pressures on freshwater ecosystems in different locations. Human-induced pressures on freshwater ecosystems are driven mainly by land use and land use changes (Allan, 2004; Haines-Young, 2009; Martinuzzi et al., 2014). Increased urbanization and land developments cause alterations to river habitats. The agricultural sector is responsible for a variety of pollution problems due to discharges of nitrogen, phosphorus and pesticides in soil and water. Some rivers in France are highly degraded, exemplified by a decline in the quality and quantity of water and changes in the distribution and structure of aquatic biota (Oberdorff et al., 2002).

While both land-use change and climate change are recognized as the main drivers of loss of biodiversity – terrestrial, marine and freshwater biodiversity taken together (Mantyka-Pringle et al., 2014), - human land use changes are recognized as the greatest future threat to freshwater biodiversity (Martinuzzi et al., 2014). However, it is important to take into account the effects of the interactions between land use and climate change on the ecological quality of rivers since: "*In addition to its direct influences, land use interacts with other anthropogenic drivers that affect the health of stream ecosystems, including climate change*" (Allan, 2004, p.258). Land-use changes constitute an important adaptation strategy to combat climate change. Climate change mainly modifies the rents associated with each land use. These modified rents in turn, can induce economic agents to change their land use strategies. This can result for instance, in more agricultural land to the detriment of grassland, with related impacts on freshwater ecosystems. The objective of this paper is to evaluate the effects on freshwater biodiversity of these adaptation-induced land-use changes in the case of France.

We use data on land use shares (agriculture, pasture, forest and urban) and an indicator of the ecological status of surface water, namely the fish-based index (FBI)[6] measured for various French rivers observed between 2001 and 2013. Fish is considered a useful indicator to assess the ecological health of water bodies (Whitfield and Elliott, 2002). Oberdorff et al. (2002) notes 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 FBI is related to the use of multiple metrics based on both occurrence data and abundance data.[7] The metrics based on abundance data account for regional and local environmental factors (Oberdorff et al., 2002). Such an index is built for France for a large number of well-defined sites evenly distributed across all available types of rivers monitored from 2001 to 2013.

To conduct our analysis, we estimate two models: a spatial econometric land use share model, and a statistical spatial panel FBI model. The land use share model describes

[5] http://ec.europa.eu/environment/water/water-framework/info/timetable_en.htm.

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

[7] Martinho et al. (2015) have shown that indicators based on multiple metrics of fish communities succesfully reflect human pressures on a Portuguese estuary.

how land use is affected by economic, physical and demographic factors, while the FBI model explains the spatial and temporal distribution of the score of FBI by land use and pedo-climatic variables. The land use share model allows us to investigate how land uses are modified by climate change (i.e. "land-use adaptation"). The FBI model helps the evaluation in turn, of the effects of land uses on freshwater biodiversity. To our knowledge, this is the first analysis in the literature applied to the case of France.

Our paper is related to two streams of literature. Firstly, there is large body of work on estimating the effects of land uses on water quality. Some of these contributions take into account a specific land use class: for instance, Wu and Segerson (1995) and Wu et al. (2004) focus on agricultural land use in the U.S., while Atasoy et al. (2006) studies the case of the urban land use in the U.S. Other contributions estimate the link between alternative land uses and indicators of water quality. The case of the U.S. is studied by Hascic and Wu (2006), Langpap et al. (2008), and Keeler and Polasky (2014), the case of Great Britain by Fezzi et al. (2015), the case of China by Xu et al. (2016), and the case of France by Fiquepron et al. (2013) and Abildtrup et al. (2013).

Secondly, there is a literature that estimates the effects of land uses on freshwater biodiversity which includes contributions by Hascic and Wu (2006), Langpap et al. (2008), and Martinuzzi et al. (2014) all applied to the case of the U.S.[8] These studies simulate the performance of specific land use policies on biodiversity indicators. For instance, Langpap et al. (2008) compares the relative efficiency of local land use regulations and policies that affect the returns to land use from achieving water quality improvements. Fezzi et al. (2015) simulates how a spatially targeted afforestation regulation affects water quality when accounting for the effect of climate change on land use adaptation.

We use our estimation results also to discuss how two command-and-control policy alternatives could help improve freshwater biodiversity. The two policy options considered are: (1) a standard on nitrogen fertilizer use in agriculture, and (2) a standard on livestock density on pastures. The policy options are designed in the following way. Agricultural land and pasture land are decomposed to four land use classes each, with respect to intensification (high/low) and slope (high/low). We take into account soil slope as it allows to take into account soil erosion and leaching which have an impact on water pollution. In the case of the agricultural land, the intensification criteria is the use of nitrogen fertilizers per hectare, and in the case of pastures the criteria is the livestock density. The first regulation consists in shifting the intensive uses in favor of extensive ones for the agricultural land for the same slope class. The second policy does the same for pastures land. In line with Fezzi et al. (2015), we also use our estimation results to discuss whether these policy options could help mitigate the adverse impacts of climate change on freshwater biodiversity. For this purpose, we simulate the impact of the policy alternatives under two climate change scenarios: a pessimistic scenario A2 and an optimistic scenario B1 (IPCC, 2000, for the

[8]There are also studies that link land uses to other biodiversity indicators such as forest fragmentation (Lewis and Plantinga, 2007), wildlife habitat (Martinuzzi et al., 2015), or bird populations (Beaudry et al., 2013; Ay et al., 2014).

2100 time horizon).

Climate change has two effects on freshwater biodiversity in our framework: a direct effect through the FBI model, and an indirect land-use adaptation effect through the land use choice model. As these effects are conditional on the location of the water body and its pedologic and climatic characteristics, it is important in the modeling strategy to take account of the spatial heterogeneity of the FBI. As climatic conditions evolve over time and these changes in turn, affect nitrogen runoff in water bodies, it is important to consider the evolution of the FBI over time. To this end and in contrast to Fezzi et al. (2015), we use a spatial panel data model to explain the FBI score registered for various monitoring points in France observed between 2001 and 2013. This model allows us to control for both spatial autocorrelation and unobserved hydrographic sectoral heterogeneity which can influence water quality. The explanatory variables considered are five land use classes (agriculture, forest, pasture, urban and other), and pedo-climatic variables. The spatial resolution chosen is the hydrographic sector[9] which is the most appropriate for observing fish populations in rivers.

This national-scale, hydrographic sector-level analysis aims to answer the following questions: (i) How does land-use adaptation to climate change affect freshwater ecosystems in France? (ii) Could standards on nitrogen fertilizer use in agriculture, and livestock density on pastures improve water quality and allow France to comply with the EU WFD? (iii) Do these policy options overcome the adverse effects of climate change on freshwater biodiversity?

Section 2 describes the two empirical models and the estimation method; section 3 describes the data, and section 4 presents the results of the estimations and simulations. Section 5 summarizes our main results and draws some policy conclusions.

# 2 The empirical models

We estimate two models to evaluate the effects of land use and climate-induced Land Use Change (LUC) on water quality. We estimate a statistical spatial panel model describing the relation between land use and water quality measured by the FBI index, and a spatial econometric land use share model.

[9]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 the Somme river. A hydrographic sector represents a smaller area than a hydrographic region. There are 187 hydrographic sectors in metropolitan France. See figure 6 in the appendix. This geographical scale has been used in other studies of water quality (Lungarska and Jayet, 2016).

## 2.1 FBI model

In order to assess the impact of pedo-climatic variables and land uses on water quality, we estimate a model explaining the observed FBI score aggregated at the level of hydrographic sectors located throughout France as a function of land use, land quality and climate. Using spatial tools, we control for any spatially correlated unobserved factors that might influence water quality by estimating a Spatial Error Model (SEM). 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:

$$\begin{aligned} log(FBI_{it}) &= LU_{it}\alpha + CL_{it}\beta + SQ_i\gamma + v_{it}, \\ v_{it} &= \mu_i + \varepsilon_{it}, \\ \varepsilon_{it} &= \lambda W_F \varepsilon_{it} + u_{it} \end{aligned}$$

where for the $i$th hydrographic sector at time $t$, $LU_{it}$ is a vector of observed land use shares, $CL_{it}$ is a vector of climate variables, $SQ_i$ is a vector of soil quality variables, $\mu_i$ is the individual effect of location $i$ assumed to be $IID(0, \sigma_\mu^2)$, $\varepsilon_{it}$ is the autoregressive spatial error term, $W_F$ is the spatial weight matrix (see Figure 1) and $u_{it}$ is an $IID$ error term with zero mean and variance $\sigma_v^2$.

A variety of weighting schemes are available; the choice depends on the data and the estimated model. We first consider three weight matrices: the contiguity matrix, the Delauney triangulation matrix and the upstream-downstream matrix. In the three cases, the matrices are row-normalized. For the results obtained from each of these neighboring structures, we opt for a combined contiguity-upstream matrix as depicted in Figure 1. In this neighbor structure, contiguous neighbors located upstream have a greater weight in the weight matrix $W_F$.

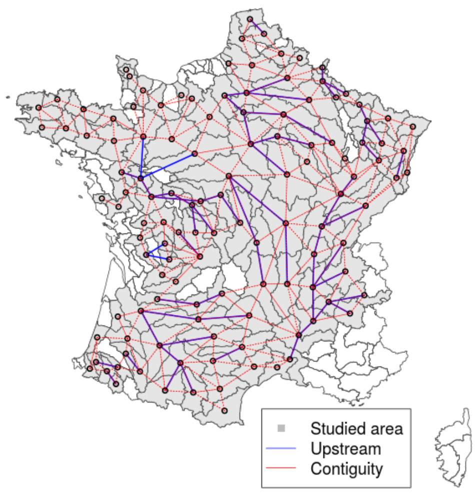



Figure 1: Neighbor relations following a contiguity-upstream rule

## 2.2 Land use share model

We estimate an econometric land use share model. Our econometric model is based on the literature on econometric land use models estimated on aggregated data for the case of the U.S. such as Lichtenberg (1989); Stavins and Jaffe (1990); Plantinga (1996); Miller and Plantinga (1999), and for the case of France including Chakir and Le Gallo (2013); Ay et al. (2017); Chakir and Lungarska (2017).

As in Chakir and Lungarska (2017), our econometric land use model is estimated at the 8 x 8 km homogeneous grid scale covering the area of metropolitan France. We observe approximately 9,000 grid cells for the year 2000. Four land use classes are considered: i) agriculture (crops and pastures); ii) forest; iii) urban; and iv) others. We model spatial autocorrelation explicitly by employing the spatial Durbin error model specification (LeSage and Pace, 2009) as in Lungarska and Chakir (2016). This model specification allows us also to take account of the spatial dependence between land use shares and the neighboring explanatory variables. Two neighbor structures are included in order to represent the scale at which the explanatory variables are originally available (more details are provided in Appendix D).

The land use share $S_{gl}$ is computed as the share of the areas in grid $g$ ($\forall g = 1, ..., G$) with land use $l$ ($\forall l = 1, ..., L$). These shares are written as:

$$S_{gl} = \frac{\mathbf{R}_g \boldsymbol{\beta}_l^R + \mathbf{S}_g \boldsymbol{\beta}_l^S}{\sum_{l=1}^{L} \exp\left(\mathbf{R}_g \boldsymbol{\beta}_l^R + \mathbf{S}_g \boldsymbol{\beta}_l^S\right)} \tag{1}$$

where $\mathbf{R}_g$ is a vector of land use rents, $\boldsymbol{\beta}_l^R$ is the associated vector of the parameters to be estimated; $\mathbf{S}_g$ is a vector of the soil characteristics and $\boldsymbol{\beta}_l^S$ is the associated vector of the parameters to be estimated.

Linearizing the model in Equation 1 allows us to estimate Equation 2 with a reference land use, $L$

$$\tilde{S_{gl}} = ln(S_{gl}/S_{gL}) = \mathbf{R}_g \boldsymbol{\beta}_l^R + \mathbf{S}_g \boldsymbol{\beta}_l^S + u_{lg}, \forall g = 1, ..., G, \forall l = 1, ..., L-1 \tag{2}$$

The error term $u_{lg} = \lambda W_L \epsilon + \varepsilon$ corrects for spatial autocorrelation of the error terms through the $\lambda$ coefficient given the spatial weight matrix $W_L$ (obtained here via a contiguity rule “queen” for the grid cells).

The rents from each land use are approximated by the results of two sector-specific economic models for agriculture and forestry, and demographic and economic indicators for the urban land use. We control also for soil quality (texture) and terrain slope. For the agricultural land rents, we use the shadow price estimates from the agricultural supply-side model AROPAj (Jayet et al., 2015) which accounts for climatic (through coupling procedures with the crop model STICS, Brisson et al., 2003; Leclère et al., 2013) and economic conditions, namely the EU Common Agricultural Policy. For forest rents, we use the expected net returns estimated by the French forestry FFSM++ partial equilibrium model (Caurla et al., 2013; Lobianco et al., 2016).

# 3 Data description

## 3.1 Fish-based index

The FBI employs seven metrics to calculate a site's current index score, and this is compared to the score that would prevail at the reference situation (in the absence of stress). The value of the index includes the sum of the deviations from the reference situation 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 lotic areas);
- Total density of individuals (which measures individual abundance);
- Density of tolerant species (species with large water quality and habitat flexibility);
- Density of invertivorous species (species that feed mainly on invertebrates);
- Density of omnivorous species (species that can digest considerable amounts of both plants and animals).

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 infinity. In practice, FBI rarely exceeds 150 in the more altered stations. Defined by FBI scores, we can identify five classes of water quality for river basins: very good ($\leq 7$); good (]7-16]); poor (]16-25]); bad (]25-36]); very bad (>36). Figures 2 and 3 represent respectively the time and spatial distribution of the FBI scores for French hydrographic sectors.

SOeS (2012) describes the evolution of the FBI index over the period 2001 to 2010.[10] The report notes that the index was mostly relatively constant over the period considered with the exception of 2003 which experienced exceptionally high temperatures and particular hydrological conditions. It highlights that slightly more than half of the monitoring points recorded good or a very good quality. However, to meet the EU WFD water quality standards will require additional efforts. SOeS (2012) proposes some explanations for the spatial heterogeneity of the FBI index for the six river basin districts in France. The Artois-Picardie watershed which is very populated appears to be the river basin district with the highest number of points with low ecological quality. This is due to human-induced pressures from industrialization and intensive agriculture. The Seine-Normandie watershed is

[10]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.

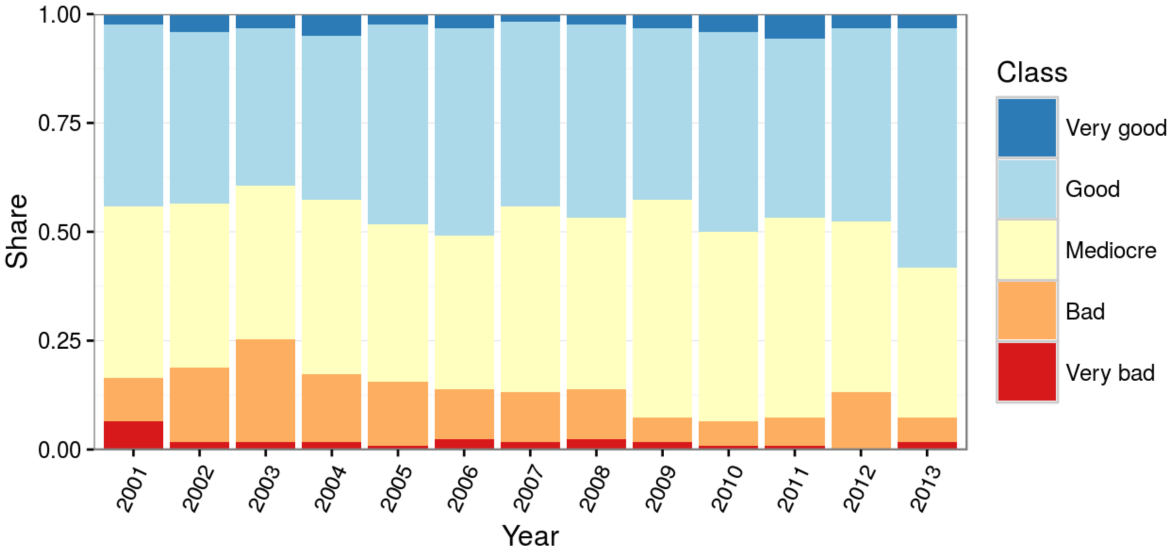



Figure 2: FBI scores for hydrographic sectors, time variation (2001 – 2013)

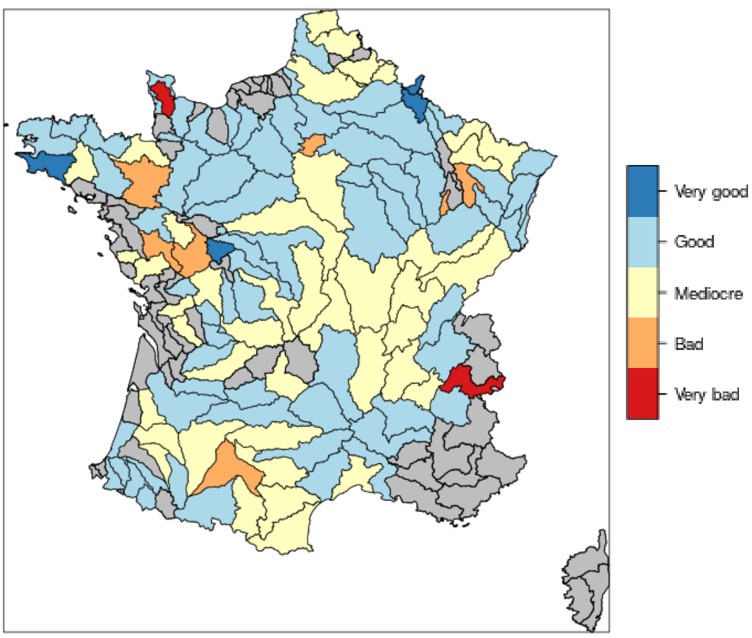



Figure 3: FBI scores for hydrographic sectors, space variation (2013)

in the best position. The water quality is worst in the center regions of Picardie and Région Parisienne due to urban development and intensive agriculture. Intensive agriculture especially livestock production is at the origin also of the degradation of river basin quality in the Loire-Bretagne watershed. In the Rhin-Meuse watershed, the FBI score indicates that regions with more forest land have better water quality. The Adour-Garonne watershed is affected negatively by hydro-electricity and intensive agricultural production. The Rhône-Méditerranée watershed is affected by urban development, dam construction, and hydro-electricity production. In sum, downstream points, big river basin districts, and non-coastal water bodies suffer more from human-induced disturbances.

Our objective is to check if the findings in SOeS (2012) can be quantitatively validated by data. We estimate a spatial panel data model for the period 2001-2013 for the sites included in the FBI index, and take account explicitly of spatial heterogeneity by including fixed effects for river basin districts (RBD).

## 3.2 Other data

In our study, we combine information on FBI, climate, pedologic conditions, and land use. Tables 1 and 2 present summary information and descriptive statistics of the data. FBI values and all of the regressors are aggregated (average values) at the hydrographic sectors level. We consider information for 122 of the 187 hydrographic sectors for which we have observations each year (represented in Figure 1). Land uses are derived from the Corine Land Cover (CLC) database and represented by aggregated land use classes for agriculture, pastures, forest, urban, and other uses. Land use data are available only for some of the years covered by our study.[11] Thus, intermediate values are interpolated with respect to observations. Land quality is measured by topsoil texture (Panagos et al., 2012).

For instance, variable TXT1 represents the share of soil texture class 1 at the hydrographic sector level where class 1 is the worst soil quality. Climate is summarized by annual average temperature and rain indicators. Summary statistics show that the average FBI score in the sample is 17.46, meaning that the ecological quality of water is poor on average. Agricultural land (crops+pasture) accounts for the largest area in the sample - 65%, followed by forests 25%, urban land 5%, and other land uses 4%. The data used for the land use share model are described in Table 13 in Appendix D.

**Construction of agricultural and pasture land use classifications** Agricultural land use and pasture have different environmental impacts depending on the intensity of the land use and the slope of the plots. To capture this diversity, we distinguish four classes for each of these two land uses. The distinction is made at the scale of the regular grid of the land use shares model. For each grid cell we combine the information on land use shares with the average slope (GTOPO30[12]), and classify the agriculture/pasture land

[11] The data are available for the years 1990, 2000, 2006 and 2012.

[12] For more information: `https://lta.cr.usgs.gov/GTOPO30` .

uses. We obtain four classes for the two slope and two intensity categories combinations (summarized in Table 1 and presented in Figure 4). The slope threshold is the first quartile value of the grid cells (1.16%), the nitrogen use threshold is the median value (100 kg$N$/ha), and the livestock density threshold is the median value (0.7 livestock units per ha). Data on nitrogen use and livestock density are derived from the AROPAj agricultural supply model (Jayet et al., 2015). Furthermore, the results of this model allow us to distinguish agriculture (crops) from pastures since the land use shares model provides estimates of the aggregate of these two uses.

# 4 Estimation and simulation results

To compare the estimations and to evaluate the gains from allowing for both spatial autocorrelation (SEM) and individual heterogeneity (random individual effects) we consider the following estimators for the FBI model:

1. Pooled ordinary least squares (OLS) which ignores individual heterogeneity and spatial auto-correlation;

2. RE (random effects) estimator which accounts for random individual effects but ignores spatial autocorrelation;

3. SEM (spatial error model) which takes account of the autoregressive spatial error autocorrelation but ignores individual heterogeneity;

4. SEM-RE estimator, which accounts for both spatial error autocorrelation and random individual heterogeneity.

The detailed results for the estimated models are provided in Appendices B and C (Tables 7 to 12). Tables 7 to 9 present the results for the OLS, RE, SEM and SEM-RE models for the three weight matrices: contiguity, contiguity-upstream and triangulation. Tables 10 to 12 present the results for the OLS, RE, SEM and SEM-RE models for the three weight matrices - contiguity, contiguity-upstream and triangulation – with added RBD fixed effects to account for any individual specific characteristics of local water agencies.

We start by estimating the pooled OLS model. The Moran's $I$ statistic associated with this model is significant at the 1% confidence level for the two weight matrices contiguity and triangulation, and not significant for the upstream weight matrix (see Tables 5 and 6). Thus, the FBI scores are subject to potential spatial autocorrelation. In several cases, elements of the upstream weight matrix have no neighbors. This might explain why the Moran's $I$ coefficient in this spatial setting is not significant. Upstream relations are important for hydrology. Hence, we introduce information on upstream relations in the contiguity matrix and assign greater importance to neighbors located upstream. The results in Tables 5 and 6 show that the Moran's $I$ statistics are mostly higher for the contiguity-upstream matrix than for the contiguity matrix.

| Variable | Definition | Unit | Year |
| --- | --- | --- | --- |
| FBI | FBI score<br>*Scale:* point; aggregated at the hydrographic sector level<br>*Source:* Oberdorff et al. (2002), The French National Agency for Water and Aquatic Environment, ONEMA. | - | 2001, ..., 2013 |
| Weather | | | |
| • T | Annual average temperature in the hydrographic sector | °C | 1990, ..., 2013 |
| • rain_mean | Monthly average precipitation | mm | 1990, ..., 2013 |
| • rain_var | Variation in monthly precipitation | mm | 1990, ..., 2013 |
| • rain_cv | Coefficient of variation in monthly precipitation<br>*Scale:* 8 x 8 km grid; aggregated at the hydrographic sector level<br>*Source:* Météo France. | | 1990, ..., 2013 |
| TXT1, ..., TXT4 | Share of the texture class in the hydrographic sector<br>*Scale:* 1:1,000,000; aggregated at the hydrographic sector level<br>*Source:* Panagos et al. (2012), European Union Joint Research Center, JRC. | % | Invariant |
| Slope | <br>*Scale:* 30 arc sec; averaged at a regular grid level<br>*Source:* GTOPO30, `https://lta.cr.usgs.gov/GTOPO30` | % | Invariant |
| Land use | Share of each land use in the hydographic sector | | |
| • agr | Agriculture share | % | 1990, 2000, 2006, 2012 |
| – agr1 | low slope, low intensity | | |
| – agr2 | low slope, high intensity | | |
| – agr3 | high slope, low intensity | | |
| – agr4 | high slope, high intensity | | |
| • pst | Pasture share | | |
| – pst1 | low slope, low intensity | | |
| – pst2 | low slope, high intensity | | |
| – pst3 | high slope, low intensity | | |
| – pst4 | high slope, high intensity | | |
| • for | Forest share | | |
| • urb | Urban share | | |
| • oth | Other<br>*Scale:* 1 ha; aggregated at the hydrographic sector level<br>*Source:* Corine Land Cover. | | |
| Intensity | Nitrogen use and livestock density<br>*Scale:* Spatialized at 8 x 8 km regular grid scale<br>*Source:* AROPAj, (Jayet et al., 2015) | kg$N$/ha<br>LU/ha | 2002 |

Table 1: Data description

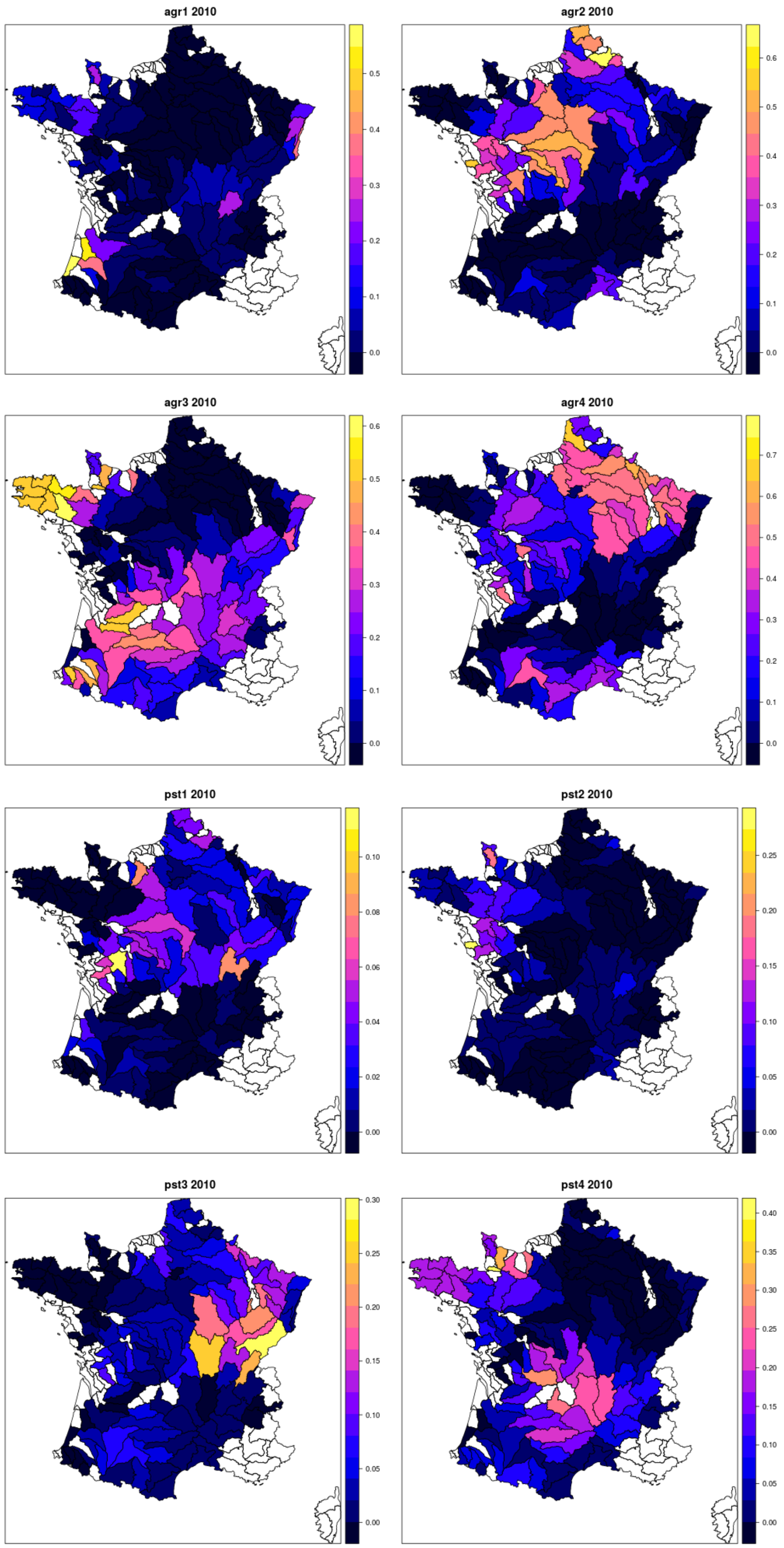



Figure 4: Land shares for the four agricultural and four pastures classes

| Variable | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. | St. Dev. |
|---|---|---|---|---|---|---|---|
| FBI | 3.373 | 12.68 | 16.56 | 17.46 | 21.18 | 63.44 | 7.04 |
| TXT2 | 0 | 0.2233 | 0.4066 | 0.4506 | 0.7212 | 0.9595 | 0.26 |
| TXT3 | 0 | 0.03814 | 0.1964 | 0.263 | 0.475 | 0.8639 | 0.25 |
| TXT4 | 0 | 0 | 0.04946 | 0.1181 | 0.1652 | 0.727 | 0.16 |
| rain_cv | 18.8 | 50.33 | 65.07 | 67.88 | 81.99 | 162.8 | 23.651 |
| T | 3.903 | 10.48 | 11.3 | 11.27 | 12.19 | 15.56 | 1.507 |
| agr1 | 0 | 0 | 0 | 0.0397 | 0.03299 | 0.5582 | 0.094 |
| agr2 | 0 | 0 | 0.02684 | 0.1225 | 0.2119 | 0.6237 | 0.165 |
| agr3 | 0 | 0 | 0.1267 | 0.1633 | 0.2784 | 0.5874 | 0.174 |
| agr4 | 0 | 0.000516 | 0.1488 | 0.1935 | 0.3321 | 0.7526 | 0.193 |
| pst1 | 0 | 0 | 0.00472 | 0.01514 | 0.02347 | 0.1103 | 0.021 |
| pst2 | 0 | 0 | 0 | 0.01652 | 0.01191 | 0.2739 | 0.039 |
| pst3 | 0 | 0.0007672 | 0.02589 | 0.04523 | 0.06653 | 0.2868 | 0.06 |
| pst4 | 0 | 0 | 0.03059 | 0.06829 | 0.1134 | 0.3922 | 0.085 |
| urb | 0.004234 | 0.01843 | 0.02656 | 0.04296 | 0.04423 | 0.4422 | 0.053 |
| oth | 0.00291 | 0.0149 | 0.0281 | 0.05758 | 0.06724 | 0.4945 | 0.082 |

Table 2: Descriptive statistics of the variables in the model

We next estimate the SEM model which has a significant spatial autocorrelation coefficient ranging from $\rho = 0.194$ to $\rho = 0.38$ for the three weight matrices and with and without the RBD fixed effects specifications (Tables 7 to 12). These results indicate that ignoring spatial autocorrelation could lead to inconsistent estimation.

The RE model results show that the fraction of the variance due to the differences across hydrographic sectors $\phi$, is significant for all specifications (with and without RBD fixed effects). When we take account of both spatial autocorrelation and individual heterogeneity, $\rho$ and $\phi$ remain significant for all the specifications (with the three weight matrices, and with and without RBD fixed effects). Since most of the results are stable for all the specifications, we focus in what follows on interpreting the results from the SEM-RE model based on the contiguity-upstream weight matrix presented in Appendix C (Table 11).

The results from this model show that most of the coefficients associated with agricultural land, urban land and pasture are statistically significant and positive. Since forest is our reference land use, this result means that the marginal effects of agricultural, pasture and urban land uses on FBI are larger than the marginal effect of forest land on FBI. Recall here that the higher the FBI score, the greater is the difference between the reference situation (in the absence of stress) and the observed fish population.

In order to compare the relative impacts of alternative land uses on the FBI score, we calculate the elasticities of FBI index with respect to each land use class at the mean value of land uses (Table 3). These elasticities could be intrepreted as follows: an increase by 1% in the land use class agr1 will increase the FBI index by 0.036%. The results show that the land use class that has the biggest effect on the FBI value is low slope-high intensity crops (agr2), followed by high slope-high intensity pasture (pst4), high slope-low intensity pasture (pst3), and urban land use. Our results are in line with Ministère de l'environnement (2017) who mention that water quality in France shows overall a marked decrease in industrial, domestic and urban pollution since the creation of water agencies 50 years ago, but an increase in agricultural and livestock pollution, mainly due to nitrates and pesticides. Moreover, the adverse impacts in France of pasture located on steep slopes, on nitrate emissions from manure have been well documented (see for instance Peyraud et al. (2014). The result for the urban use is in line with the findings in Langpap et al. (2008) for four U.S. states, and those of Fiquepron et al. (2013) in the case of France.

The effects of soil, temperature and rain variability on the FBI are not significant. Some river basin districts fixed effects are significant and year 2003 fixed effect is significantly positive. This indicates that the exceptional drought occurred in 2003 reduced freshwater biodiversity. This suggests some intuitions concerning the potential impact of climate change on FBI.

| Variable | SEM-RE coefficient | Mean land use share | FBI elasticity wr to land use |
|---|---|---|---|
| agr1 | 0.896* | 0.040 | 0.036* |
| agr2 | 1.293** | 0.123 | 0.158** |
| agr3 | 0.283 | 0.163 | 0.046 |
| agr4 | 0.510* | 0.194 | 0.099* |
| pst1 | -2.158 | 0.015 | -0.033 |
| pst2 | 2.362* | 0.017 | 0.039* |
| pst3 | 2.145** | 0.045 | 0.097** |
| pst4 | 1.522** | 0.068 | 0.104** |
| urb00 | 2.025*** | 0.043 | 0.087*** |
| oth00 | 0.272 | 0.058 | 0.016 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | |

Table 3: Elasticities of the FBI index with respect to the different land use classes calculated at the mean of land uses

## 4.1 Discussion of results

Here, we discuss the intuitions behind the relationships between land use and FBI. The results overall show that the marginal effects of agricultural, urban and pasture land uses on FBI are larger than the marginal effect of forest land on FBI. This is as expected since the main factors that affect the abundance and diversity of aquatic life have been identified as nutrient loading, toxic pollution and habitat alteration (Hascic and Wu, 2006).

**Agricultural and Pasture Land** SOeS (2012) reports that some of the adverse impacts of agricultural land use on fish populations are due to irrigation. Water withdrawals for irrigation have adverse impacts on fish populations, especially in hot, dry periods when water levels are already low. In riverbeds, degradation can result from substrate blockage, and reductions in or disappearance of gravel areas needed by certain species such as trout for spawning. However, the biggest impacts on fish populations are from nutrient loading through discharges of fertilizers and pesticides.

Commissariat Général au Développement Durable (Commissariat Général au Développement Durable, 2016) provides information on the evolution of nitrogen and phosphate pollution in rivers. Phosphate levels in watercourses have fallen sharply since 1998 thanks to improved treatment of urban wastewater, lower levels of phosphates in detergents and a significant decline in the use of phosphate fertilizers. Despite slightly reduced use of mineral nitrogen fertilizers, nitrate levels in rivers remained stable between 1998 and 2013. The report notes also that inter-annual nitrogen pollution trends are influenced strongly by rainfall. In terms of geographical sources of nitrogen pollution, the highest concentrations of nitrates in 2013 were in the north / north-west of the territory upstream of the Rhone valley, due to intensive livestock production, and in the south-west due to intensive agriculture. Nearly 6% of the points exceed the average vigilance threshold of 40 mg/l, and 1.9% exceed 50 mg/l. These points are located in the north of Brittany, in Poitou-Charentes, in the Ile de France / Center and locally in Languedoc Roussillon. Conversely, mountainous areas such as the Massif Central, the Alps and the Pyrenees, the Aquitaine and Mediterranean coasts, Corsica and parts of northeastern France have average concentrations below 10 mg/l, considered to be natural for aquatic environments.[13]

In the case of pesticide concentrations in rivers, Commissariat Général au Développement Durable (2016) underlines that pesticides are present in almost all rivers. In 2012, only 1 out of 191 hydrographic areas was pesticide free, while 54 sectors had average concentrations greater than 0.5 micrograms per liter, 8 of which exceeded 2 micrograms per liter. This contamination is due mainly to herbicides use. Commissariat Général au Développement Durable (2015) provides detailed geographical information on the sources of pesticide pollution. The most affected basins correspond to cereal and oil crops production areas such as the Beauce, the Bassin Parisien, Nord-Pas-de-Calais and the Midi-Pyrénées region, and the wine-producing regions in the Mediterranean perimeter. The less polluted regions include regions with little intensive agriculture and those close to relief zones in the south-east quarter of metropolitan France near the Alps, on the edge of the Massif Central, and the Vosges and Jura mountains.

In what follows, we provide a brief review of the effects of nitrogen and pesticide pollution on freshwater fish populations. The presence of pesticides in freshwater can damage fish in various ways (Pimentel, 2005). First, high concentrations of pesticides can kill the fish directly, while low levels of pesticides can kill fish fry. Also, pesticide pollution can affect fish populations indirectly by eliminating fish food such as insects and other invertebrates. Finally, reductions in fish populations imply economic losses for fishermen. Pimentel (2005) estimates that the sum of all these costs in the U.S. is US$ 100 million

[13] http://www.statistiques.developpement-durable.gouv.fr/lessentiel/ar/2000/0/contamination-cours-deau-nitrates.html

per year.

Camargo (2005) reviews published data on nitrate (NO3-) toxicity for freshwater animals. They highlight several results related to the adverse effects of nitrogen pollution on fish populations. First, the toxicity[14] of nitrates to aquatic animals increases with increasing nitrate concentrations and increasing exposure times. Second, freshwater animals appear to be more sensitive than marine animals to nitrate. In the case of freshwater invertebrates, if nitrate concentrations exceed 10 mg NO3-N/l (USA federal maximum level for drinking water) over a long period of time, damage to the fish population will occur. Camargo recommends a maximum of 2 mg NO3-N/l in order to avoid the most sensitive freshwater species from being adversely affected.

**Urban Land Use** In the case of France, SOeS (2012) documents the sources of anthropogenic pressures on freshwater fish populations. In the case of urban land use, the report stresses that territory development and planning modify aquatic environments through the simplification or destruction of habitat mosaics necessary for the life cycles of many species. Some species are sensitive to slowdown and homogenization of water flows, and disturbance to sediment transport associated with hydropower facilities. Land use planning not only standardizes river banks and reduces shelters, it leads also to discontinuities between the river and side annexes such as water meadows which are used for example, by pike for their reproduction. The connection with wetlands is important for many other species, and dams induce breaches in the longitudinal continuity of rivers. Deterioration in the status of fish populations has been observed over quite long distances downstream of dams.

Migratory species such as Atlantic salmon, sea trout, European sturgeon, shad and marine and fluvial lampreys are especially sensitive to land use changes. These species spawn in fresh water and grow in the sea. Obstacles on rivers and degradation of breeding sites, as in the case of sturgeon in the Gironde, can jeopardize their survival. Eels are highly migratory; they spawn in the Sargasso Sea and grow in freshwater. They suffer from the presence of barriers to upstream and downstream migration, transit through turbines, decline in wetlands, and water pollution.

## 4.2 Simulation of climate change and land use policies

## 4.3 Simulated scenarios

**Climate change scenario simulations** We simulate the direct and indirect effects (based on the land rents related to different land-based economic activities) of climate change on freshwater biodiversity. We consider two IPCC scenarios: an optimistic B1 scenario, and a pessimistic A2 scenario associated with a greater increase in temperature. We build on Lungarska and Chakir (2016), which studies the impact of climate change on

[14] Nitrate toxicity provokes the conversion of oxygen-carrying pigments to forms that are incapable of carrying oxygen (Camargo, 2005).

land use in the same way. Climate change affects the land rents of different land-based economic activities such as agriculture, pasture and forestry. Two sector-specific models capture these effects in biological modules. They account also for some land management choices and other adaptation possibilities (input use, changes to varieties, sowing and harvesting dates, etc.). We consider demography as the main driver of urban land use change. The estimated coefficients of the land use share model are provided in Appendix F.

**Public policy simulations** We study two command-and-control policy options aimed at limiting intensive agricultural land and intensive pasture. In the case of agriculture, we consider a reduction in the intensity of nitrogen fertilizer use on crops, and in the case of pasture, we consider a reduction in livestock density.

Regulatory instruments such as standards are used more frequently in France than fiscal measures for controlling local water pollution problems. The reason is that the precise location of pollution is important and can only be considered imperfectly by fiscal measures (Ministère de l'environnement, 2017).

We distinguish intensive uses at the base of the median values[15] which are about 100 kgN/ha for fertilizer use for agriculture, and 0.7 livestock units/ha for pasture. As the estimation results for the FBI model show (see Table 11), intensive cropping and pasture land uses (agr2, agr4, pst2, and pst4) all have a positive and significant effect on the FBI score, and thus have a negative impact on fish populations. Our simulations consist of shifting intensive uses (in agriculture and pasture) to extensive uses for a given slope type (high or low).

Table 4 summarizes the reductions in livestock units and nitrogen fertilizer use for the different scenarios. Overall, a standard on intensive pastures is associated to a 32% – 35% decrease in the number of animals. When this reduction applied to farms with more than 0.7 livestock units/ha, the reduction in livestock units for these farms is of 42% – 44%. The associated reductions in use of nitrogen fertilizers in these scenarios (Table 4) range from 49% to 58% overall, and from 57% to 62% for intensive farms.

| Climate scenario | Overall animal reduction | Animal reduction in intensive farms | Overall nitrogen reduction | Nitrogen reduction in intensive farms |
|---|---|---|---|---|
| CTL | -32.26 % | -41.89 % | -49.28 % | -56.81 % |
| A2 | -34.93 % | -43.71 % | -58.35 % | -62.44 % |
| B1 | -34.65 % | -43.19 % | -55.17 % | -59.7 % |

Table 4: Reduction in animal number and nitrogen fertilizer use for the climate scenarios

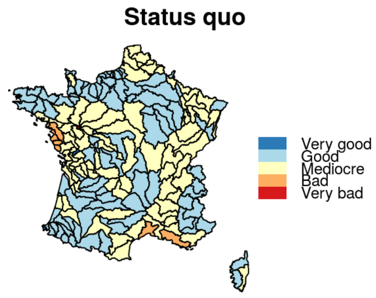
[15] The median values are evaluated at the scale of the land use share model from Lungarska and Chakir (2016).

## 4.4 Simulation results

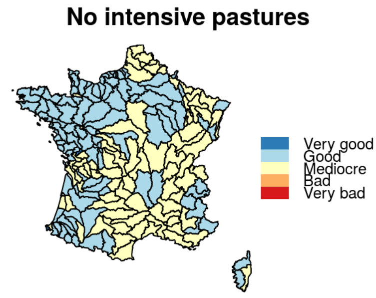
**The impact of climate change** on the FBI index is clear if we compare the maps on the left side of Figure 5. The predictions for the current climate conditions ("status quo") are depicted at the top, those for the climate change scenario A2 are in the center, and those for the climate change scenario B1 are at the bottom of the figure (simulations conducted at the 2100 time horizon). We note that the FBI index is worse under the two climate change scenarios compared to the status quo; there is a higher number of hydrographic sectors registering "Mediocre", "Bad" and "Very bad" quality. These results are driven by expansions of agriculture and urban land uses as well as the evolution of climate variables (increased temperature and coefficient of variation in precipitation). The maps show also that water quality is worse in the A2 scenario compared to the B1. Recall here that the A2 scenario is considered a pessimistic scenario, and thus is associated with a greater increase in temperature than the B1 scenario. Also, the A2 scenario is supposed to lead to a greater increase in urban area since it assumes a bigger French population increase. These overall results indicate that land-use adaptation to climate change deteriorates freshwater biodiversity, and that the loss in biodiversity would be larger in the case of the pessimistic A2 climate change scenario.

**The effects of a standard on livestock density** can be seen if we compare the maps in the left side of Figure 5 with those in the center of the figure ("no intensive pastures" scenario). Under the current climate (at the top of Figure 5), the limitations on intensive pastures allow the hydrographic sectors to recover, resulting in fewer "Bad" and "Very bad" quality observations. However, this improvement in water quality is not sufficient. The sectors in a good position are still less than 60% of the total hydrographic sectors required to conform to the EU WFD. Comparison of the maps shows also that in some sectors such as those located in the Massif Central area (middle of southern France) quality is worsened by the standard. Finally, the standard is not sufficient to compensate for the adverse impacts of climate change on water quality.

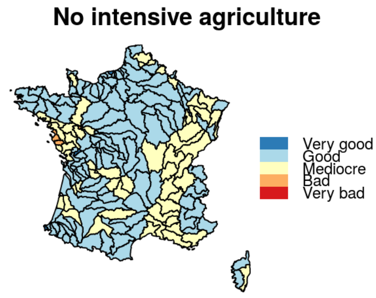
**The effects of a standard on nitrogen fertilizer use in agriculture** represented in the right side of Figure 5 show that the simulated policy is improving water quality, and almost 68% of the hydrographic sectors are classed as "Good" or "Very good", while those in a "Bad" state have reduced from 6 to 3 sectors. In contrast to the situation of a standard on pasture, this policy compensates for the adverse impacts of climate change on water quality in both climate change scenarios. In the pessimistic scenario A2, the sectors in a good position represent 60% of observations, which corresponds to the EU WFD target.



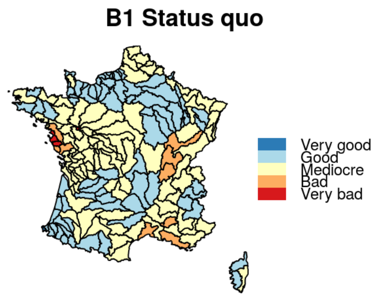

| | Count | Share |
|---|---|---|
| Very bad | 1 | 0.53% |
| Bad | 6 | 3.21% |
| Mediocre | 82 | 43.85% |
| Good | 91 | 48.66% |
| Very good | 7 | 3.74% |



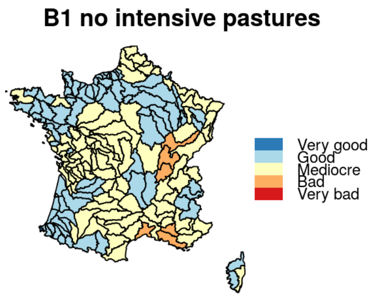

| | Count | Share |
|---|---|---|
| Very bad | 0 | 0% |
| Bad | 0 | 0% |
| Mediocre | 79 | 42.25% |
| Good | 101 | 54.01% |
| Very good | 7 | 3.74% |



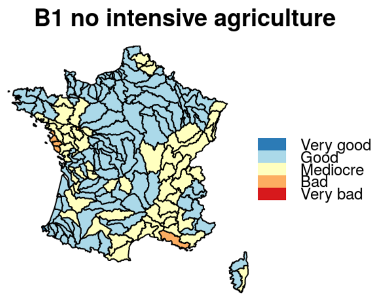

| | Count | Share |
|---|---|---|
| Very bad | 0 | 0% |
| Bad | 3 | 1.6% |
| Mediocre | 57 | 30.48% |
| Good | 119 | 63.64% |
| Very good | 8 | 4.28% |



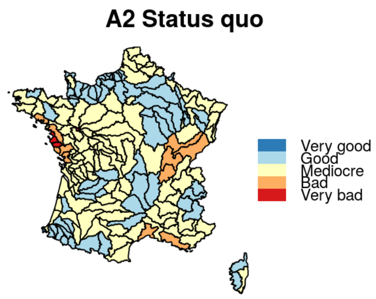

| | Count | Share |
|---|---|---|
| Very bad | 3 | 1.6% |
| Bad | 9 | 4.81% |
| Mediocre | 92 | 49.2% |
| Good | 77 | 41.18% |
| Very good | 6 | 3.21% |



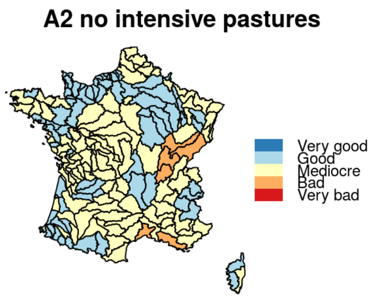

| | Count | Share |
|---|---|---|
| Very bad | 0 | 0% |
| Bad | 6 | 3.21% |
| Mediocre | 90 | 48.13% |
| Good | 85 | 45.45% |
| Very good | 6 | 3.21% |



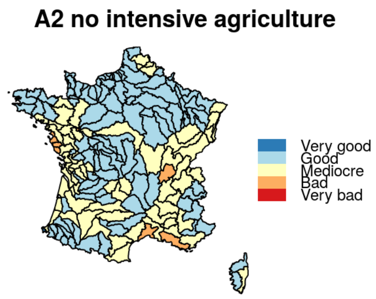

| | Count | Share |
|---|---|---|
| Very bad | 0 | 0% |
| Bad | 5 | 2.67% |
| Mediocre | 56 | 29.95% |
| Good | 120 | 64.17% |
| Very good | 6 | 3.21% |




| | Count | Share |
|---|---|---|
| Very bad | 3 | 1.6% |
| Bad | 11 | 5.88% |
| Mediocre | 101 | 54.01% |
| Good | 66 | 35.29% |
| Very good | 6 | 3.21% |




| | Count | Share |
|---|---|---|
| Very bad | 0 | 0% |
| Bad | 7 | 3.74% |
| Mediocre | 101 | 54.01% |
| Good | 73 | 39.04% |
| Very good | 6 | 3.21% |




| | Count | Share |
|---|---|---|
| Very bad | 0 | 0% |
| Bad | 7 | 3.74% |
| Mediocre | 67 | 35.83% |
| Good | 107 | 57.22% |
| Very good | 6 | 3.21% |

Figure 5: Simulation results for the FBI index under present and climate change scenarios, and for the two land use policies

# 5 Conclusion

In the IUCN Red List of Threatened Species published in 2012[16], France is ranked fifth in the world for hosting the largest number of endangered plant and animal species. The degradation of freshwater ecosystems is due to a decline in the quality and quantity of water, and changes in the distribution and structure of aquatic biota in some rivers in France (Oberdorff et al., 2002). French freshwater fish populations have suffered from the degradation and destruction of natural environments as well as pollution problems. Pressures on freshwater ecosystems are mainly human-induced and driven by land use changes. The objective of this paper was to evaluate how land-use adaptations to climate change are affecting freshwater ecosystems in France.

We used data on land use shares (agriculture, pasture, forest and urban) and an indicator of the ecological status of surface water, the FBI measured for various French rivers observed between 2001 and 2013. We estimated two models: a spatial econometric land use share model, and a statistical spatial panel FBI model. The land use share model describes how land use is affected by economic, physical and demographic factors, while the FBI model explains the spatial and temporal distribution of the score of FBI by land use and pedo-climatic variables.

Our estimations provide some interesting results. They reveal that rivers in areas with more agricultural, pasture and urban land relative to forest are associated with lower freshwater biodiversity. They show also that low slope-intensive crops and high slope (intensive/extensive) pasture reduce the most freshwater biodiversity, related to forest, Our estimation results indicate also that land-use adaptation to climate change reduces freshwater biodiversity. The loss in biodiversity is larger in the case of the more pessimistic climate change scenario.

Based on our estimation results, we discussed how two command-and-control policy options might help to improve freshwater biodiversity and mitigate the adverse impacts of climate change on this biodiversity. These policy options were a standard on nitrogen fertilizer use in agriculture, and a standard on livestock density on pasture. Our findings show that the first policy would allow France to comply with the EU WFD under the current climate and future climate change scenarios.

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

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# Appendices


Figure 6: Hydrographic sectors and River bassin districts (RBD, water agencies) in France

# A Moran's I

| Year | Contiguity | Upstream | Contiguity-Upstream | Triangulation |
|---|---|---|---|---|
| 2001 | -0.023 | 0.041 | 0.001 | 0.017 * |
| 2002 | 0.016 * | 0.003 | 0.029 * | 0.043 ** |
| 2003 | 0.136 *** | 0.066 | 0.152 *** | 0.137 *** |
| 2004 | 0.055 ** | 0.003 | 0.074 ** | 0.056 *** |
| 2005 | 0.122 *** | -0.004 | 0.128 *** | 0.182 *** |
| 2006 | 0.116 *** | 0.04 | 0.124 *** | 0.144 *** |
| 2007 | 0.044 ** | -0.004 | 0.034 * | 0.055 *** |
| 2008 | 0.156 *** | 0.02 | 0.153 *** | 0.115 *** |
| 2009 | 0.043 ** | 0.027 | 0.054 ** | 0.054 *** |
| 2010 | 0.143 *** | 0.042 | 0.145 *** | 0.127 *** |
| 2011 | 0.12 *** | 0.038 | 0.116 *** | 0.088 *** |
| 2012 | 0.194 *** | 0.125 | 0.21 *** | 0.138 *** |
| 2013 | 0.095 *** | 0.077 | 0.095 *** | 0.091 *** |

Table 5: Moran's I for annual OLS models, no fixed effects

| Year | Contiguity | Upstream | Contiguity-Upstream | Triangulation |
|---|---|---|---|---|
| 2001 | -0.106 | 0 | -0.09 | -0.035 |
| 2002 | -0.042 | -0.05 | -0.041 | 0.01 ** |
| 2003 | 0.016 ** | -0.001 | 0.022 ** | 0.043 *** |
| 2004 | 0.017 ** | -0.043 | 0.022 ** | -0.006 ** |
| 2005 | 0.073 *** | -0.022 | 0.081 *** | 0.119 *** |
| 2006 | 0.021 ** | -0.024 | 0.018 ** | 0.051 *** |
| 2007 | -0.017 | -0.053 | -0.032 | -0.041 |
| 2008 | 0.099 *** | 0.005 | 0.116 *** | 0.033 *** |
| 2009 | -0.013 * | -0.014 | -0.001 * | 0.002 ** |
| 2010 | 0.038 ** | -0.001 | 0.045 ** | 0.052 *** |
| 2011 | 0.033 ** | -0.028 | 0.024 ** | -0.039 |
| 2012 | 0.044 *** | 0.141 * | 0.089 *** | 0.011 ** |
| 2013 | -0.014 * | 0.059 | 0.001 * | 0.022 ** |

Table 6: Moran's I for annual OLS models, RBD fixed effects

# B Models without fixed effects

| Variable | OLS | RE | SEM | SEM-RE |
|---|---|---|---|---|
| (Intercept) | 1.5857 *** | 2.0439 *** | 1.6589 *** | 2.073 *** |
| | (0.1515) | (0.2635) | (0.1625) | (0.273) |
| TXT2 | 0.2778 *** | 0.4226 ** | 0.2631 *** | 0.4202 ** |
| | (0.076) | (0.1958) | (0.0736) | (0.191) |
| TXT3 | -0.1082 | -0.0155 | -0.0886 | -0.0126 |
| | (0.0739) | (0.1932) | (0.0769) | (0.1975) |
| TXT4 | 0.3317 *** | 0.4389 | 0.3719 *** | 0.467 * |
| | (0.1036) | (0.2742) | (0.107) | (0.2784) |
| rain_cv | -0.0101 | -1e-04 | -0.0031 | 4e-04 |
| | (0.0442) | (0.0321) | (0.0541) | (0.0371) |
| T | 0.0225 ** | 0.0161 | 0.0163 | 0.012 |
| | (0.0095) | (0.0122) | (0.0111) | (0.0145) |
| agr1 | 1.3077 *** | 0.8979 ** | 1.2766 *** | 0.9965 ** |
| | (0.1896) | (0.4493) | (0.1865) | (0.4467) |
| agr2 | 1.6411 *** | 1.2068 *** | 1.635 *** | 1.3257 *** |
| | (0.1715) | (0.3968) | (0.1739) | (0.4053) |
| agr3 | 0.5659 *** | -0.0682 | 0.6838 *** | 0.0316 |
| | (0.1614) | (0.3667) | (0.165) | (0.3762) |
| agr4 | 0.3807 *** | -0.1201 | 0.4038 *** | -0.0808 |
| | (0.1239) | (0.2875) | (0.1239) | (0.2914) |
| pst1 | -3.7076 *** | -5.1257 ** | -3.3578 *** | -5.631 ** |
| | (0.9102) | (2.2187) | (0.9402) | (2.2433) |
| pst2 | 2.0051 *** | 1.1779 | 1.9849 *** | 0.9209 |
| | (0.386) | (0.9645) | (0.4161) | (1.0056) |
| pst3 | 3.605 *** | 2.7779 *** | 3.0786 *** | 2.5368 *** |
| | (0.3054) | (0.7189) | (0.3093) | (0.7359) |
| pst4 | 1.0467 *** | 0.5431 | 0.9312 *** | 0.4902 |
| | (0.2118) | (0.4974) | (0.2239) | (0.5172) |
| urb00 | 1.6907 *** | 1.0064 * | 1.7578 *** | 1.01 * |
| | (0.2429) | (0.5865) | (0.2535) | (0.6084) |
| oth00 | 1.7594 *** | 0.2513 | 1.5262 *** | 0.1616 |
| | (0.2667) | (0.4727) | (0.2654) | (0.473) |
| y2003 | 0.0677 * | 0.0709 *** | 0.0722 | 0.0744 ** |
| | (0.0358) | (0.0266) | (0.049) | (0.0325) |
| phi | | 1.0162 *** | | 0.9788 *** |
| rho | | | 0.3012 *** | 0.199 *** |
| N | 1586 | 1586 | 1586 | 1586 |
| McFadden pseudo R2 | 0.195 | 0.646 | 0.236 | 0.667 |
| McFadden pseudo R2 (adj.) | 0.175 | 0.626 | 0.216 | 0.647 |
| Log. Lik. | -669.86 | -294.4 | -635.84 | -276.76 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 7: Models based on the contiguity neighborhood matrix

| Variable | OLS | RE | SEM | SEM-RE |
|---|---|---|---|---|
| (Intercept) | 1.5857 *** | 2.0439 *** | 1.702 *** | 2.1022 *** |
| | (0.1515) | (0.2635) | (0.1612) | (0.2724) |
| TXT2 | 0.2778 *** | 0.4226 ** | 0.2392 *** | 0.4065 ** |
| | (0.076) | (0.1958) | (0.073) | (0.1903) |
| TXT3 | -0.1082 | -0.0155 | -0.1174 | -0.0281 |
| | (0.0739) | (0.1932) | (0.0775) | (0.1981) |
| TXT4 | 0.3317 *** | 0.4389 | 0.3402 *** | 0.4548 |
| | (0.1036) | (0.2742) | (0.1065) | (0.2774) |
| rain_cv | -0.0101 | -1e-04 | -0.0044 | -0.0018 |
| | (0.0442) | (0.0321) | (0.0545) | (0.0372) |
| T | 0.0225 ** | 0.0161 | 0.0158 | 0.0118 |
| | (0.0095) | (0.0122) | (0.0111) | (0.0146) |
| agr1 | 1.3077 *** | 0.8979 ** | 1.2281 *** | 0.9632 ** |
| | (0.1896) | (0.4493) | (0.1845) | (0.4442) |
| agr2 | 1.6411 *** | 1.2068 *** | 1.6156 *** | 1.3118 *** |
| | (0.1715) | (0.3968) | (0.174) | (0.4057) |
| agr3 | 0.5659 *** | -0.0682 | 0.669 *** | 0.0098 |
| | (0.1614) | (0.3667) | (0.1654) | (0.3765) |
| agr4 | 0.3807 *** | -0.1201 | 0.4121 *** | -0.0812 |
| | (0.1239) | (0.2875) | (0.1242) | (0.2921) |
| pst1 | -3.7076 *** | -5.1257 ** | -3.4194 *** | -5.6928 ** |
| | (0.9102) | (2.2187) | (0.9364) | (2.2368) |
| pst2 | 2.0051 *** | 1.1779 | 2.006 *** | 0.9197 |
| | (0.386) | (0.9645) | (0.4145) | (1.0028) |
| pst3 | 3.605 *** | 2.7779 *** | 2.9243 *** | 2.4342 *** |
| | (0.3054) | (0.7189) | (0.3075) | (0.7343) |
| pst4 | 1.0467 *** | 0.5431 | 0.9426 *** | 0.4961 |
| | (0.2118) | (0.4974) | (0.2234) | (0.5173) |
| urb00 | 1.6907 *** | 1.0064 * | 1.7151 *** | 0.9651 |
| | (0.2429) | (0.5865) | (0.2502) | (0.6036) |
| oth00 | 1.7594 *** | 0.2513 | 1.4767 *** | 0.1287 |
| | (0.2667) | (0.4727) | (0.2617) | (0.4709) |
| y2003 | 0.0677 * | 0.0709 *** | 0.073 | 0.0749 ** |
| | (0.0358) | (0.0266) | (0.0497) | (0.0328) |
| phi | | 1.0162 *** | | 0.9761 *** |
| rho | | | 0.3149 *** | 0.2073 *** |
| N | 1586 | 1586 | 1586 | 1586 |
| McFadden pseudo R2 | 0.195 | 0.646 | 0.241 | 0.671 |
| McFadden pseudo R2 (adj.) | 0.175 | 0.626 | 0.221 | 0.65 |
| Log. Lik. | -669.86 | -294.4 | -631.5 | -274.18 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 8: Models based on the contiguity-upstream neighborhood matrix

| Variable | OLS | RE | SEM | SEM-RE |
|---|---|---|---|---|
| (Intercept) | 1.5857 *** | 2.0439 *** | 1.6205 *** | 2.0737 *** |
| | (0.1515) | (0.2635) | (0.1676) | (0.2738) |
| TXT2 | 0.2778 *** | 0.4226 ** | 0.2034 *** | 0.3746 ** |
| | (0.076) | (0.1958) | (0.0741) | (0.1907) |
| TXT3 | -0.1082 | -0.0155 | -0.0718 | -0.0205 |
| | (0.0739) | (0.1932) | (0.0786) | (0.1978) |
| TXT4 | 0.3317 *** | 0.4389 | 0.2825 *** | 0.4097 |
| | (0.1036) | (0.2742) | (0.1064) | (0.2748) |
| rain_cv | -0.0101 | -1e-04 | -0.0121 | 0.0031 |
| | (0.0442) | (0.0321) | (0.056) | (0.0375) |
| T | 0.0225 ** | 0.0161 | 0.0235 ** | 0.012 |
| | (0.0095) | (0.0122) | (0.0116) | (0.0149) |
| agr1 | 1.3077 *** | 0.8979 ** | 1.1462 *** | 0.9389 ** |
| | (0.1896) | (0.4493) | (0.1879) | (0.4473) |
| agr2 | 1.6411 *** | 1.2068 *** | 1.3736 *** | 1.212 *** |
| | (0.1715) | (0.3968) | (0.1693) | (0.3984) |
| agr3 | 0.5659 *** | -0.0682 | 0.6726 *** | 0.0754 |
| | (0.1614) | (0.3667) | (0.1646) | (0.3757) |
| agr4 | 0.3807 *** | -0.1201 | 0.4973 *** | 0.0087 |
| | (0.1239) | (0.2875) | (0.124) | (0.2912) |
| pst1 | -3.7076 *** | -5.1257 ** | -1.8795 ** | -4.6704 ** |
| | (0.9102) | (2.2187) | (0.9058) | (2.1962) |
| pst2 | 2.0051 *** | 1.1779 | 2.4822 *** | 1.2225 |
| | (0.386) | (0.9645) | (0.4023) | (0.9785) |
| pst3 | 3.605 *** | 2.7779 *** | 2.6033 *** | 2.2929 *** |
| | (0.3054) | (0.7189) | (0.3136) | (0.7336) |
| pst4 | 1.0467 *** | 0.5431 | 0.9136 *** | 0.4974 |
| | (0.2118) | (0.4974) | (0.2311) | (0.5249) |
| urb00 | 1.6907 *** | 1.0064 * | 1.799 *** | 1.0539 * |
| | (0.2429) | (0.5865) | (0.2508) | (0.5983) |
| oth00 | 1.7594 *** | 0.2513 | 1.7154 *** | 0.3347 |
| | (0.2667) | (0.4727) | (0.2676) | (0.468) |
| y2003 | 0.0677 * | 0.0709 *** | 0.0696 | 0.0754 ** |
| | (0.0358) | (0.0266) | (0.0552) | (0.0338) |
| phi | | 1.0162 *** | | 0.9532 *** |
| rho | | | 0.3871 *** | 0.2302 *** |
| N | 1586 | 1586 | 1586 | 1586 |
| McFadden pseudo R2 | 0.195 | 0.646 | 0.249 | 0.667 |
| McFadden pseudo R2 (adj.) | 0.175 | 0.626 | 0.228 | 0.646 |
| Log. Lik. | -669.86 | -294.4 | -625.09 | -277.36 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 9: Models based on the triangulation neighborhood matrix

# C Models with fixed effects per RBD

| Variable | OLS | RE | SEM | SEM-RE |
|---|---|---|---|---|
| (Intercept) | 1.6902 *** | 1.8905 *** | 1.7285 *** | 1.94 *** |
| | (0.1528) | (0.2502) | (0.1612) | (0.2623) |
| AgenceAG | 0.1961 *** | 0.1598 * | 0.1918 *** | 0.1576 * |
| | (0.0368) | (0.0871) | (0.0391) | (0.0939) |
| AgenceAP | 0.0198 | 0.0437 | 0.0413 | 0.0557 |
| | (0.0543) | (0.1307) | (0.0605) | (0.1466) |
| AgenceRM | 0.1122 ** | 0.1073 | 0.1523 *** | 0.1427 |
| | (0.0497) | (0.1217) | (0.0521) | (0.128) |
| AgenceRMC | 0.4046 *** | 0.3909 *** | 0.3937 *** | 0.3802 *** |
| | (0.0424) | (0.1022) | (0.0448) | (0.1089) |
| AgenceSN | -0.2935 *** | -0.2734 *** | -0.268 *** | -0.2432 ** |
| | (0.0384) | (0.0948) | (0.0404) | (0.1003) |
| TXT2 | -0.0512 | 0.0774 | -0.024 | 0.1129 |
| | (0.076) | (0.1848) | (0.0745) | (0.1832) |
| TXT3 | -0.1542 ** | -0.0696 | -0.1435 * | -0.068 |
| | (0.0764) | (0.1884) | (0.0778) | (0.1936) |
| TXT4 | -0.0063 | 0.129 | 0.0119 | 0.1462 |
| | (0.1135) | (0.2807) | (0.1129) | (0.282) |
| rain_cv | -0.0144 | -0.0014 | -0.0141 | -0.0012 |
| | (0.0415) | (0.0321) | (0.0473) | (0.0366) |
| T | -0.0023 | 0.0086 | -0.005 | 0.0043 |
| | (0.0107) | (0.0126) | (0.0117) | (0.0147) |
| agr1 | 1.1388 *** | 0.8366 ** | 1.1297 *** | 0.9149 ** |
| | (0.1827) | (0.4098) | (0.1809) | (0.4124) |
| agr2 | 1.4614 *** | 1.1449 *** | 1.5365 *** | 1.3052 *** |
| | (0.1774) | (0.3971) | (0.1764) | (0.4017) |
| agr3 | 0.8215 *** | 0.2478 | 0.8577 *** | 0.2961 |
| | (0.1571) | (0.3438) | (0.158) | (0.3513) |
| agr4 | 1.0714 *** | 0.586 ** | 0.9826 *** | 0.5151 * |
| | (0.131) | (0.2891) | (0.1301) | (0.2929) |
| pst1 | 0.5934 | -1.1452 | 0.1344 | -2.1728 |
| | (0.916) | (2.1058) | (0.9282) | (2.1414) |
| pst2 | 3.719 *** | 2.7871 *** | 3.4522 *** | 2.3473 ** |
| | (0.3959) | (0.9286) | (0.41) | (0.9689) |
| pst3 | 2.7934 *** | 2.2973 *** | 2.6781 *** | 2.2211 *** |
| | (0.2957) | (0.6534) | (0.2979) | (0.6732) |
| pst4 | 1.9861 *** | 1.6212 *** | 1.9021 *** | 1.5279 *** |
| | (0.2156) | (0.4986) | (0.2239) | (0.5233) |
| urb00 | 2.9445 *** | 2.2645 *** | 2.7912 *** | 2.0658 *** |
| | (0.2567) | (0.5941) | (0.2611) | (0.613) |
| oth00 | 1.4824 *** | 0.4097 | 1.3751 *** | 0.3045 |
| | (0.2588) | (0.4465) | (0.2603) | (0.4508) |
| y2003 | 0.0835 ** | 0.0737 *** | 0.0861 ** | 0.0778 ** |
| | (0.0339) | (0.0267) | (0.0409) | (0.0321) |
| phi | | 0.7605 *** | | 0.7652 *** |
| rho | | | 0.1939 *** | 0.1839 *** |
| N | 1586 | 1586 | 1586 | 1586 |
| McFadden pseudo R2 | 0.319 | 0.664 | 0.335 | 0.682 |
| McFadden pseudo R2 (adj.) | 0.293 | 0.638 | 0.309 | 0.656 |
| Log. Lik. | -566.61 | -279.48 | -553.15 | -264.65 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 10: Models based on the contiguity neighborhood matrix, RBD fixed effects (Loire-Bretagne as reference)

| Variable | OLS | RE | SEM | SEM-RE |
|---|---|---|---|---|
| (Intercept) | 1.6902 *** | 1.8905 *** | 1.7511 *** | 1.9566 *** |
| | (0.1528) | (0.2502) | (0.1611) | (0.2626) |
| AgenceAG | 0.1961 *** | 0.1598 * | 0.198 *** | 0.1607 * |
| | (0.0368) | (0.0871) | (0.0397) | (0.0948) |
| AgenceAP | 0.0198 | 0.0437 | 0.0401 | 0.0539 |
| | (0.0543) | (0.1307) | (0.0608) | (0.1468) |
| AgenceRM | 0.1122 ** | 0.1073 | 0.1629 *** | 0.1504 |
| | (0.0497) | (0.1217) | (0.0526) | (0.1288) |
| AgenceRMC | 0.4046 *** | 0.3909 *** | 0.4002 *** | 0.3847 *** |
| | (0.0424) | (0.1022) | (0.0457) | (0.1106) |
| AgenceSN | -0.2935 *** | -0.2734 *** | -0.2669 *** | -0.2417 ** |
| | (0.0384) | (0.0948) | (0.0407) | (0.1009) |
| TXT2 | -0.0512 | 0.0774 | -0.0271 | 0.1129 |
| | (0.076) | (0.1848) | (0.0739) | (0.1818) |
| TXT3 | -0.1542 ** | -0.0696 | -0.1495 * | -0.0711 |
| | (0.0764) | (0.1884) | (0.078) | (0.1937) |
| TXT4 | -0.0063 | 0.129 | -0.0016 | 0.1399 |
| | (0.1135) | (0.2807) | (0.1122) | (0.2801) |
| rain_cv | -0.0144 | -0.0014 | -0.0152 | -0.0032 |
| | (0.0415) | (0.0321) | (0.0478) | (0.0368) |
| T | -0.0023 | 0.0086 | -0.0061 | 0.0039 |
| | (0.0107) | (0.0126) | (0.0118) | (0.0148) |
| agr1 | 1.1388 *** | 0.8366 ** | 1.1076 *** | 0.8956 ** |
| | (0.1827) | (0.4098) | (0.1795) | (0.4103) |
| agr2 | 1.4614 *** | 1.1449 *** | 1.5244 *** | 1.293 *** |
| | (0.1774) | (0.3971) | (0.176) | (0.4014) |
| agr3 | 0.8215 *** | 0.2478 | 0.8571 *** | 0.2828 |
| | (0.1571) | (0.3438) | (0.1585) | (0.352) |
| agr4 | 1.0714 *** | 0.586 ** | 0.9825 *** | 0.5101 * |
| | (0.131) | (0.2891) | (0.1304) | (0.2936) |
| pst1 | 0.5934 | -1.1452 | 0.1952 | -2.1582 |
| | (0.916) | (2.1058) | (0.929) | (2.1414) |
| pst2 | 3.719 *** | 2.7871 *** | 3.4851 *** | 2.362 ** |
| | (0.3959) | (0.9286) | (0.4109) | (0.969) |
| pst3 | 2.7934 *** | 2.2973 *** | 2.5914 *** | 2.1452 *** |
| | (0.2957) | (0.6534) | (0.2971) | (0.6724) |
| pst4 | 1.9861 *** | 1.6212 *** | 1.8969 *** | 1.5218 *** |
| | (0.2156) | (0.4986) | (0.224) | (0.5233) |
| urb00 | 2.9445 *** | 2.2645 *** | 2.7627 *** | 2.0245 *** |
| | (0.2567) | (0.5941) | (0.2596) | (0.6092) |
| oth00 | 1.4824 *** | 0.4097 | 1.3342 *** | 0.2718 |
| | (0.2588) | (0.4465) | (0.2587) | (0.4491) |
| y2003 | 0.0835 ** | 0.0737 *** | 0.0872 ** | 0.0784 ** |
| | (0.0339) | (0.0267) | (0.0417) | (0.0324) |
| phi | | 0.7605 *** | | 0.7643 *** |
| rho | | | 0.2109 *** | 0.1927 *** |
| N | 1586 | 1586 | 1586 | 1586 |
| McFadden pseudo R2 | 0.319 | 0.664 | 0.339 | 0.685 |
| McFadden pseudo R2 (adj.) | 0.293 | 0.638 | 0.313 | 0.658 |
| Log. Lik. | -566.61 | -279.48 | -549.99 | -262.25 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 11: Models based on the contiguity-upstream neighborhood matrix, RBD fixed effects (Loire-Bretagne as reference)

| Variable | OLS | RE | SEM | SEM-RE |
|---|---|---|---|---|
| (Intercept) | 1.6902 *** | 1.8905 *** | 1.7733 *** | 1.9776 *** |
| | (0.1528) | (0.2502) | (0.1638) | (0.2628) |
| AgenceAG | 0.1961 *** | 0.1598 * | 0.1789 *** | 0.1447 |
| | (0.0368) | (0.0871) | (0.0396) | (0.0938) |
| AgenceAP | 0.0198 | 0.0437 | 0.0372 | 0.0491 |
| | (0.0543) | (0.1307) | (0.0605) | (0.1448) |
| AgenceRM | 0.1122 ** | 0.1073 | 0.1151 ** | 0.1022 |
| | (0.0497) | (0.1217) | (0.0524) | (0.1276) |
| AgenceRMC | 0.4046 *** | 0.3909 *** | 0.3729 *** | 0.3604 *** |
| | (0.0424) | (0.1022) | (0.0453) | (0.1086) |
| AgenceSN | -0.2935 *** | -0.2734 *** | -0.2823 *** | -0.2608 *** |
| | (0.0384) | (0.0948) | (0.0407) | (0.1001) |
| TXT2 | -0.0512 | 0.0774 | -0.047 | 0.0832 |
| | (0.076) | (0.1848) | (0.0754) | (0.1845) |
| TXT3 | -0.1542 ** | -0.0696 | -0.1291 | -0.0598 |
| | (0.0764) | (0.1884) | (0.0786) | (0.1937) |
| TXT4 | -0.0063 | 0.129 | -0.0191 | 0.1244 |
| | (0.1135) | (0.2807) | (0.1129) | (0.2801) |
| rain_cv | -0.0144 | -0.0014 | -0.0159 | 0.0013 |
| | (0.0415) | (0.0321) | (0.0482) | (0.037) |
| T | -0.0023 | 0.0086 | -0.0039 | 0.0036 |
| | (0.0107) | (0.0126) | (0.0119) | (0.015) |
| agr1 | 1.1388 *** | 0.8366 ** | 1.063 *** | 0.8622 ** |
| | (0.1827) | (0.4098) | (0.1819) | (0.4138) |
| agr2 | 1.4614 *** | 1.1449 *** | 1.3426 *** | 1.147 *** |
| | (0.1774) | (0.3971) | (0.1753) | (0.3987) |
| agr3 | 0.8215 *** | 0.2478 | 0.8159 *** | 0.2913 |
| | (0.1571) | (0.3438) | (0.1587) | (0.3525) |
| agr4 | 1.0714 *** | 0.586 ** | 0.9973 *** | 0.5616 * |
| | (0.131) | (0.2891) | (0.1303) | (0.293) |
| pst1 | 0.5934 | -1.1452 | 0.7642 | -1.4384 |
| | (0.916) | (2.1058) | (0.9058) | (2.1006) |
| pst2 | 3.719 *** | 2.7871 *** | 3.7656 *** | 2.6632 *** |
| | (0.3959) | (0.9286) | (0.4044) | (0.952) |
| pst3 | 2.7934 *** | 2.2973 *** | 2.4554 *** | 2.0268 *** |
| | (0.2957) | (0.6534) | (0.3004) | (0.6726) |
| pst4 | 1.9861 *** | 1.6212 *** | 1.7912 *** | 1.461 *** |
| | (0.2156) | (0.4986) | (0.2267) | (0.5265) |
| urb00 | 2.9445 *** | 2.2645 *** | 2.7822 *** | 2.1016 *** |
| | (0.2567) | (0.5941) | (0.2595) | (0.6057) |
| oth00 | 1.4824 *** | 0.4097 | 1.4431 *** | 0.4369 |
| | (0.2588) | (0.4465) | (0.2627) | (0.4474) |
| y2003 | 0.0835 ** | 0.0737 *** | 0.0866 ** | 0.0792 ** |
| | (0.0339) | (0.0267) | (0.0431) | (0.0331) |
| phi | | 0.7605 *** | | 0.7524 *** |
| rho | | | 0.2381 *** | 0.209 *** |
| N | 1586 | 1586 | 1586 | 1586 |
| McFadden pseudo R2 | 0.319 | 0.664 | 0.338 | 0.681 |
| McFadden pseudo R2 (adj.) | 0.293 | 0.638 | 0.312 | 0.654 |
| Log. Lik. | -566.61 | -279.48 | -550.59 | -265.64 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 12: Models based on the triangulation neighborhood matrix, RBD fixed effects (Loire-Bretagne as reference)

# D Land use model

The land use model is defined at the 8 × 8 km grid cell. The estimated land shares are then aggregated at the hydrographic sector level. We model four land use classes: i) agriculture (crops and pastures); ii) forestry; iii) urban; and iv) other. More details on the model specification are provided in Chakir and Lungarska (2017). We use a spatial Durbin error model (SDEM) that takes account of the interactions between non-observed factors that affect the land use allocation decision (equation 3).

$$\begin{aligned} \widetilde{y} &= X\beta + W_1 X'\beta' + W_2 X''\beta'' + \varepsilon \\ \varepsilon &= \lambda W_1 \varepsilon + u \end{aligned} \tag{3}$$

$W_1$ is an $n \times n$ spatial weight matrix for grid cell neighbors, $W_2$ is a $m \times m$ spatial weight matrix for regional neighbors, $X'$ are the fine scale explanatory variables, $X''$ are regional variables, $\beta'$ and $\beta''$ are the associated parameters, and the parameter $\lambda$ expresses the interaction between residuals and $u$ is an independent and identically distributed ($iid$) random variable error term such that $u \sim iid(0, \sigma^2 I)$.

The data used for the model is summarized in table 13

| Variable | Description | Mean | St. dev. | Min | Max |
|---|---|---|---|---|---|
| Land use | | | | | |
| $s_{ag}$ | Share of crops and pastures | 0.601 | 0.289 | 0 | 1 |
| $s_{fo}$ | Share of forest | 0.264 | 0.225 | 0 | 1 |
| $s_{ur}$ | Share of urban | 0.049 | 0.093 | 0 | 1 |
| $s_{ot}$ | Share of other uses | 0.086 | 0.173 | 0 | 1 |
| | *Source*: CLC 2000 | | | | |
| | *Scale*: aggregated at 8 km x 8 km | | | | |
| Shadow price | Land shadow price (k€/ha) | 0.554 | 0.218 | 0 | 1.11 |
| | *Source*: AROPAj v.2 (2002) | | | | |
| | *Scale*: NUTS 2 and lower | | | | |
| For revenue | Forestry revenues (€/ha) | 137.683 | 66.509 | 28.934 | 308.043 |
| | *Source*: FFSM++, 2006 | | | | |
| | *Scale*: NUTS 2 scale | | | | |
| Pop revenues | Households' revenues (k€/ year/ household) | 12.308 | 3.239 | 0 | 41.802 |
| | *Source*: INSEE, 2000 | | | | |
| | *Scale*: French *commune* | | | | |
| Pop density | Households density (households/ ha) | 5.432 | 2.274 | 2.75 | 58.722 |
| | *Source*: INSEE, 2000 | | | | |
| | *Scale*: 200 m x 200 m grid | | | | |
| Slope | Slope (%) | 4.325 | 6.155 | 0 | 47.721 |
| | *Source*: GTOPO 30 | | | | |
| | *Scale*: 30 arc sec ∼ 1 km | | | | |
| Texture | Soils' texture classes | *1* | *2* | *3* | *4* |
| | Number of cells | 1242 | 4820 | 3120 | 579 |
| | *Source*: JRC, Panagos et al. (2012) | | | | |
| | *Scale*: 1:1000000 | | | | |

Table 13: Summary statistics of land use shares and the explanatory variables.

| | *Dependent variable:* | | |
|---|---|---|---|
| | ln(agr/oth) | ln(for/oth) | ln(urb/oth) |
| | (1) | (2) | (3) |
| Constant | 2.644$^{***}$ | 3.151$^{***}$ | $-$6.376$^{***}$ |
| | (0.618) | (0.599) | (0.551) |
| Shadow price (spat) | 0.888$^{***}$ | $-$0.406 | 0.568$^{*}$ |
| | (0.303) | (0.303) | (0.304) |
| For. revenues | 0.003$^{***}$ | 0.003$^{***}$ | 0.004$^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| Pop. density | $-$0.131$^{***}$ | $-$0.145$^{***}$ | 0.168$^{***}$ |
| | (0.013) | (0.014) | (0.015) |
| Pop. Revenues | 0.047$^{***}$ | 0.062$^{***}$ | 0.236$^{***}$ |
| | (0.014) | (0.014) | (0.016) |
| Slope | $-$0.154$^{***}$ | 0.027$^{**}$ | $-$0.153$^{***}$ |
| | (0.012) | (0.013) | (0.014) |
| Texture (cl.2) | 0.668$^{***}$ | 0.314$^{***}$ | 0.509$^{***}$ |
| | (0.098) | (0.100) | (0.111) |
| Texture (cl.3) | 1.186$^{***}$ | 0.672$^{***}$ | 0.896$^{***}$ |
| | (0.115) | (0.118) | (0.129) |
| Texture (cl.4) | 1.780$^{***}$ | 0.980$^{***}$ | 0.920$^{***}$ |
| | (0.159) | (0.163) | (0.180) |
| Shadow price (W2) | 1.542$^{*}$ | $-$0.645 | 0.837 |
| | (0.841) | (0.820) | (0.765) |
| For. revenues (W2) | 0.011$^{***}$ | 0.008$^{***}$ | 0.011$^{***}$ |
| | (0.002) | (0.002) | (0.002) |
| Pop. density (W1) | $-$0.239$^{***}$ | $-$0.215$^{***}$ | $-$0.165$^{***}$ |
| | (0.035) | (0.036) | (0.037) |
| Pop. Revenues (W1) | $-$0.011 | $-$0.029 | 0.096$^{***}$ |
| | (0.029) | (0.029) | (0.029) |
| Slope (W1) | $-$0.138$^{***}$ | $-$0.118$^{***}$ | $-$0.098$^{***}$ |
| | (0.019) | (0.019) | (0.019) |
| Texture (cl.2, W1) | 0.112 | 0.210$^{**}$ | 0.341$^{***}$ |
| | (0.096) | (0.098) | (0.106) |
| Texture (cl.3, W1) | 0.132 | 0.246$^{**}$ | 0.201$^{**}$ |
| | (0.094) | (0.095) | (0.103) |
| Texture (cl.4, W1) | 0.245$^{**}$ | 0.083 | 0.194$^{*}$ |
| | (0.105) | (0.107) | (0.115) |
| $N$ | 9761 | | |
| R2 | 0.635 | 0.443 | 0.558 |
| Moran's $I$ | 0.438$^{***}$ | 0.402$^{***}$ | 0.343$^{***}$ |
| $\lambda$ | 0.759$^{***}$ | 0.738$^{***}$ | 0.658$^{***}$ |
| Log Lik. | -22128.97 | -22391.3 | -23449.36 |
| AIC | 44295.95 | 44820.61 | 46936.71 |
| (AIC for LM) | 48524.05 | 48493.73 | 49569.55 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 14: Spatialized dual value, 4 LU