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Impacts of land use and climate change on freshwater ecosystems in France

Basak Bayramoglu* Raja Chakir † Anna Lungarska‡

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Abstract

Pressures on freshwater ecosystems are mainly human-induced and driven by land use and climate change. We develop an empirical framework to estimate the impacts of land use (agriculture, forest, pasture, urban) and climate change on freshwater biodiversity, measured by a fish-based index, in France. Our estimation results reveal that rivers in areas with more intensive agriculture and steep pasture are associated to lower freshwater biodiversity compared to forest areas. Our simulations show that climate change will exacerbate these negative impacts through land-use adaptation. We discuss how two command-and-control policies could help improving freshwater biodiversity and cope with the adverse effects of land use and climate change.

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

JEL codes: C31, R14, Q22, Q53.

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15 **1 Introduction**

16 According to the Intergovernmental Science-Policy Platform on Biodiversity and Ecosys-
17 tem Services report (IPBES, 2018), more than 50% of *nature's regulating and non-*
18 *material contributions* to populations in Europe and Central Asia was lost between
19 1960 and 2016.¹ A World Wildlife Fund report (WWF, 2016) indicates that the 81%
20 global decline in freshwater species populations between 1970 and 2012, is more than
21 double the declines observed in land (38%) and marine (36%) populations. In 2015,
22 surface water bodies in 22 of European Union Member States did not achieve good
23 chemical status² and despite the few improvements accomplished only 53% of rivers and
24 lakes were considered to have good ecological status³ (IPBES, 2018).

25 Intensification of agriculture and forestry, and urban development are the major
26 direct drivers of loss of both biodiversity and ecosystem services in Europe (IPBES,
27 2018). However, the impact of climate change on biodiversity is becoming increasingly
28 rapid, and is likely to become one of the most important drivers in the future (Millennium
29 Ecosystem Assessment, 2005). By 2050, climate change could overtake land use change
30 as the main cause of biodiversity decline (IPBES, 2018). This confirms the conclusions
31 of the International Panel on Climate Change (IPCC) that water, and its availability
32 and quality will constitute the main pressure on societies and on the environment due
33 to climate change (Bates et al., 2008).

34 Climate change is likely to have both direct and indirect effects on freshwater biodi-
35 versity. The main direct impacts of climate change on freshwater biodiversity result from
36 changes in air and water temperatures, and changes in the timing, type and intensity of
37 precipitation (Kernan et al., 2011). Climate change also affects freshwater biodiversity
38 indirectly through societal and economic systems such as land use and land management
39 adaptations to climate change. It is important to take account of the effects of land use
40 and climate change and their interactions on the freshwater biodiversity (Allan, 2004,
41 p.258). Given the importance of both land use change and climate change for influencing

¹This report provides an overview of the state of biodiversity and ecosystem services, the benefits we derive from it, observed trends, future scenarios, and policy action recommendations.

²As defined by the European Union Water Framework Directive, EU WFD.

³Idem.

42 biodiversity, including only one or other driver could lead to an inadequate assessment
43 of their impacts (De Chazal and Rounsevell, 2009).

44 The objective of this paper is to evaluate the effects of both land use (agriculture,
45 forest, pasture, urban) and climate change on freshwater biodiversity in France mea-
46 sured by a fish-based index (FBI)⁴. Fish are considered as a useful indicator to assess
47 the ecological health of water bodies (Whitfield and Elliott, 2002). According to Ober-
48 dorff et al. (2002) “*among potential indicators, fish assemblages are of particular interest*
49 *because of their ability to integrate environmental variability at different spatial scales*”
50 (p.1720). The originality of the FBI is related to its use of multiple metrics based on
51 both occurrence and abundance data.⁵

52 The European Union Water Framework Directive (EU WFD) builds on two ele-
53 ments for the assessment of water quality, namely chemical and ecological status. Good
54 chemical status of a water body is attained when it complies with quality standards
55 in terms of substance concentration (established in the Directive 2008/105/EC on En-
56 vironmental Quality Standards, revised in 2013). Ecological status is the assessment
57 of the structure and functioning of aquatic ecosystems. It is determined by biologi-
58 cal quality (plant and animal species), and hydromorphological and physico-chemical
59 elements (macro-pollutants in particular) associated with the development of biologi-
60 cal cycles (Eaufrance, 2015). Its measurement is subject to interpretations by Member
61 States since each country has its specificities concerning freshwater biodiversity and
62 ecosystems. In our study, we focus on the ecological status of water bodies.

63 We estimate two models: a spatial econometric land use share model, and a statistical
64 spatial panel FBI model. The land use share model describes how land use is affected
65 by economic, pedo-climatic and demographic factors, while the FBI model explains
66 the spatial and temporal distribution of the FBI score by land use and pedo-climatic
67 variables. We use data on land use shares (agriculture, pasture, forest and urban) and

⁴Indice Poissons Rivière (IPR) in French.

⁵In the paper, we use the terms freshwater biodiversity and freshwater ecological health interchangeably. We are aware that the FBI does not perfectly represent freshwater biodiversity as it only concerns a part of the fish community living in rivers and not all species, and that the different metrics that make up the index do not reflect the whole characteristics of species in terms of biological traits. Nevertheless, FBI remains an interesting index for freshwater biodiversity as it is based on several metrics. Martinho et al. (2015) have shown that indicators based on multiple metrics of fish communities successfully reflect human pressures on a Portuguese estuary.

68 the FBI for various French rivers observed between 2001 and 2013. We use our estimation
69 results to simulate the impacts of two climate change scenarios on the FBI: a pessimistic
70 scenario A2, and an optimistic scenario B1 (IPCC, 2000, for the 2100 time horizon).
71 **The A2 scenario is associated with increasing greenhouse gas emissions and**
72 **a continuously growing world population with limited technological progress.**
73 **The B1 storyline builds on the assumption of a demographic peak in mid-**
74 **century followed by a decrease and greater technological innovation both**
75 **resulting in stabilized greenhouse gas concentrations in the atmosphere.**
76 **The two scenarios lead to a global temperature increase between 2° and**
77 **5.4°C (A2), and 1.1° and 2.9°C (B1).** Also, we discuss how two command-and-
78 control policies could help improve freshwater biodiversity and cope with the adverse
79 effects of land use and climate change. The two policy options considered are: (1) a
80 standard for nitrogen fertilizer use in agriculture, and (2) a standard for livestock density
81 on pastures.

82 **Related literature** There is a large economic literature on the effects of land use on
83 water quality and freshwater biodiversity. However, only a very small number of studies
84 deal with the impacts of climate change on freshwater biodiversity although the non-
85 economic literature on this subject is extensive. Finally, there is a small but growing
86 economic literature which focuses on the combined impacts of land use and climate
87 change on biodiversity and water quality.

88 Concerning the impacts of land use on **water quality**⁶, there is a vast body of
89 work. These studies simulate the performance of specific land use policies on water
90 quality indicators. For instance, Langpap et al. (2008) compares the relative efficiency
91 of local land use regulations and policies that affect the returns to land use from achieving
92 water quality improvements. Some studies in the literature focus on the effects of land
93 use on water quality, and in some cases, take account of a specific land use class: for
94 instance, Wu and Segerson (1995) and Wu et al. (2004) focus on agricultural land use,
95 while Atasoy et al. (2006) study the case of the urban land use. Other contributions

⁶There are also studies that link land uses to biodiversity indicators such as forest fragmentation (Lewis et al., 2011), wildlife habitat (Martinuzzi et al., 2015), or bird populations (Beaudry et al., 2013).

96 estimate the link between alternative land uses and indicators of water quality. The
97 case of the U.S. is studied by Hascic and Wu (2006), and Keeler and Polasky (2014),
98 the case of China by Xu et al. (2016), and the case of France by Figuepron et al. (2013)
99 and Abildtrup et al. (2013).

100 Among work that deals with the impacts of climate change on biodiversity, a recent
101 literature review (Runting et al., 2017) shows that there are a large number of ecological
102 studies assessing the impacts of climate change on ecosystem services. According to this
103 review, relatively few studies integrate decision making, or incorporate multiple drivers
104 of change such as economic drivers or local drivers (land use change). This is because
105 most studies do not use an economic framework that allows the inclusion for example,
106 of landowners' decisions and their reaction to market drivers or global drivers such as
107 climate change. Runting et al.'s review shows that the impact of climate change on most
108 types of services is predominantly negative (59% negative, 24% mixed, 4% neutral, 13%
109 positive) but varies across services, drivers and assessment methods.

110 Studies that include only either land use or climate change as drivers of freshwater
111 biodiversity are likely to assess their impacts inadequately (De Chazal and Rounsevell,
112 2009). These studies could suffer from either under- or over-estimation of the impacts
113 on biodiversity. A very small number of economic studies in the literature focus on
114 the simultaneous impacts of land use and climate change on biodiversity and water
115 quality. The closest to our work are the studies by Ay et al. (2014) and Fezzi et al.
116 (2015). Ay et al. (2014) propose a modeling framework that integrates simultaneously
117 the direct impacts of land use and climate change on the abundance of common birds
118 as an indicator of biodiversity, as well as the indirect impacts through climate change
119 effects on land use in France. They study the impacts of five different scenarios which
120 differ in the way they account for land use impacts and in the role played by economic
121 returns, public policies and climate on land use. Their results show that in France bird
122 community dynamics are projected to be more heavily impacted by climate change than
123 by land use. This result is in line with other local scale evidence (Martin et al., 2013)
124 but contradicts global studies which suggest that land use compared to climate change
125 will dominate biodiversity dynamics (Pereira et al., 2010). Fezzi et al. (2015) propose

126 an integrated framework linking a spatially explicit econometric model of agricultural
127 production to a statistical model of river water quality in the U.K. They examine how
128 adaptation to climate change in agriculture is expected to affect water quality. They
129 simulate how a spatially targeted afforestation regulation affects water quality when
130 accounting for the effect of climate change on land use adaptation. Their results show
131 that climate adaptation in the farming sector will generate fundamental changes to river
132 water quality. In some areas, policies that encourage adaptation are expected to conflict
133 with existing regulations aimed at improving freshwater ecosystems.

134 This paper makes several contributions to the literature. First, we study freshwater
135 biodiversity (an indicator of ecological water quality) unlike the extensive literature on
136 chemical water quality. Secondly, we take into account multiple land uses (including
137 agriculture, forest, pasture and urban land uses) unlike the literature focusing either
138 on agriculture or on urban land use. Third, we distinguish the impacts of intensive
139 and extensive land management in agriculture and pasture on freshwater biodiversity.
140 Fourth, we explicitly consider the spatial dimension by estimating a spatial panel model
141 to take account of individual heterogeneity as well as spatial autocorrelation of freshwater
142 biodiversity. Finally, and more importantly, we estimate the combined effects of land
143 use and climate, and we simulate the impacts of climate change scenarios and public
144 policies to improve freshwater biodiversity.

145 This study addresses the following questions: (i) How does land use and climate
146 change affect freshwater biodiversity in France? (ii) How could a public policy regulation
147 such as standards for nitrogen fertilizer use in agriculture or livestock density on pastures,
148 improve freshwater biodiversity? (iii) Would these policy options resolve the adverse
149 effects of land use and climate change on freshwater biodiversity?

150 The remainder of the paper is organized as follows. Section 2 provides background
151 information on freshwater biodiversity in France; section 3 presents the empirical model;
152 section 4 describes the data and section 5 presents the estimation and simulation results.
153 Section 6 concludes by summarizing our main results.

154 **2 Freshwater biodiversity in France**

155 In this section, we discuss first the status of water quality in France and the related
156 regulation in the European Union (EU), and second the FBI used in our study to indicate
157 freshwater biodiversity.

158 **2.1 Ecological status of water in France and European regulation**

159 In the IUCN⁷ – International Union for Conservation of Nature – Red List of Threat-
160 ened Species published in 2012, France is ranked fifth in the world for hosting the largest
161 number of endangered plant and animal species. **This list indicates that Spanish**
162 **toothcarp (*Aphanius iberus*) and Valencia toothcarp (*Valencia hispanica*)**
163 **have become extinct, and sturgeon (*Acipenser sturio*), European eel (*An-***
164 ***guilla anguilla*), Chabot du Lez (*Cottus petiti*) and Rhone streber (*Zingel***
165 ***asper*) are critically endangered in France** (UICN France, MNHN, SFI, ONEMA,
166 2010). The degradation of freshwater biodiversity is due to a decline in the quality and
167 quantity of water, and changes to the distribution and structure of aquatic biota in some
168 rivers in France (Oberdorff et al., 2002). French freshwater fish populations have suffered
169 from the degradation and destruction of natural environments as well as pollution.

170 France has been unable to comply with the objective of the EU WFD to achieve good
171 or very good surface water quality by 2015 for 60% of its national water resources. In
172 terms of chemical status, only 48.2% of French surface water resources were of acceptable
173 quality in 2013. In terms of ecological status, only 43.4% of surface water resources were
174 deemed to be good or very good quality (Onema/OIEau, 2015). Since 2015, two further
175 deadlines for meeting the environmental objectives in the EU WFD were issued – 2021,
176 and 2027 the final date for compliance.⁸

177 **2.2 Fish-based index**

178 Fish are considered a useful indicator to assess the ecological health of water bodies
179 (Whitfield and Elliott, 2002). **Fish-based indices are a method to assess water**

⁷<http://www.iucn.org/>

⁸http://ec.europa.eu/environment/water/water-framework/info/timetable_en.htm.

180 **quality status based on metrics derived from structure and function of fish**
181 **assemblages. The index proposed by Oberdorff et al. (2002) was explicitly**
182 **designed to evaluate for France the respect of the WFD. It** uses multiple metrics
183 based on both occurrence data and abundance data. The metrics based on abundance
184 data account for regional and local environmental factors (Oberdorff et al., 2002). A
185 FBI has been built for France for a large number of well-defined sites evenly distributed
186 across all available types of rivers monitored between 2001 and 2013.

187 The FBI employs seven metrics to calculate a site's current index score which is
188 compared to a reference (in the absence of stress) situation score. The value of the
189 index includes the sum of the deviations from the reference situation of seven metrics:
190 (1) Total number of species; (2) Number of lithophilic species (which require clean gravel
191 substrates for reproductive success); (3) Number of rheophilic species (which inhabit
192 lotic areas); (4) Total density of individuals (which measures individual abundance); (5)
193 Density of tolerant species (species with large water quality and habitat flexibility); (6)
194 Density of invertivorous species (species that feed mainly on invertebrates); (7) Density
195 of omnivorous species (species that can digest considerable amounts of both plants and
196 animals).

197 The closer the fish population to the reference situation, the lower the value of the
198 index. The index varies from 0 (meaning the reference situation prevails) to infinity.
199 In practice, in the most altered stations the FBI rarely exceeds 150. Defined by FBI
200 scores, Oberdorff et al. (2002) identify five classes of water quality for river basins: very
201 good (≤ 7); good ($[7 - 16]$); mediocre ($[16 - 25]$); bad ($[25 - 36]$); very bad (> 36).
202 This classification is used also by the decision makers (SOeS, 2012). Figures 1 and 2
203 respectively depict the evolution and spatial distribution of the FBI scores for French
204 hydrographic sectors.⁹

205 SOeS (2012) describes the evolution of the FBI index over the period 2001 to 2010
206 (see figure 1). The report notes that the index was mostly relatively constant over
207 the period considered with the exception of 2003 which experienced exceptionally high

⁹A hydrographic sector represents a smaller area than a hydrographic region. There are 187 hydrographic sectors in metropolitan France. This geographical scale has been used in other studies of water quality (Lungarska and Jayet, 2018).

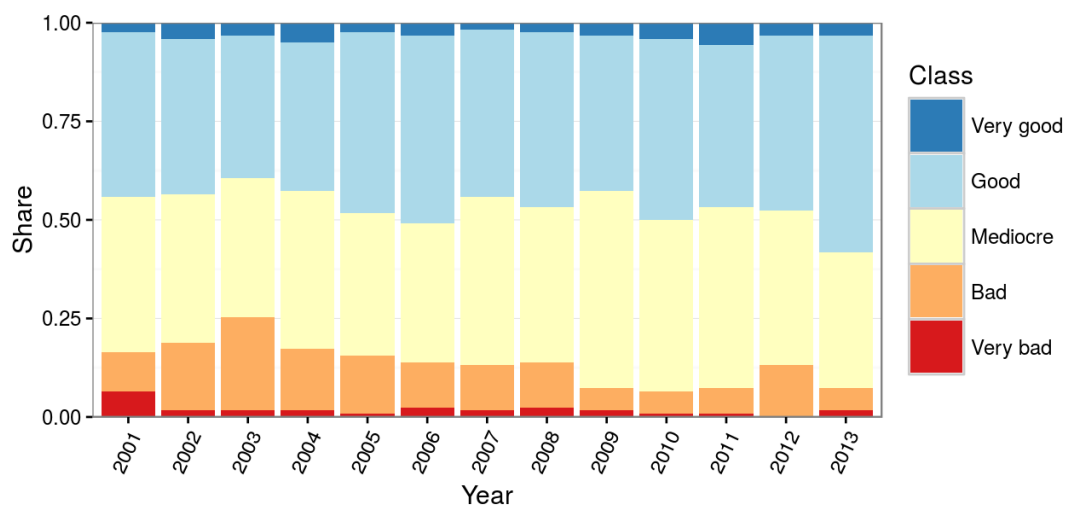


Figure 1: FBI scores for hydrographic sectors, time variation (2001 – 2013)

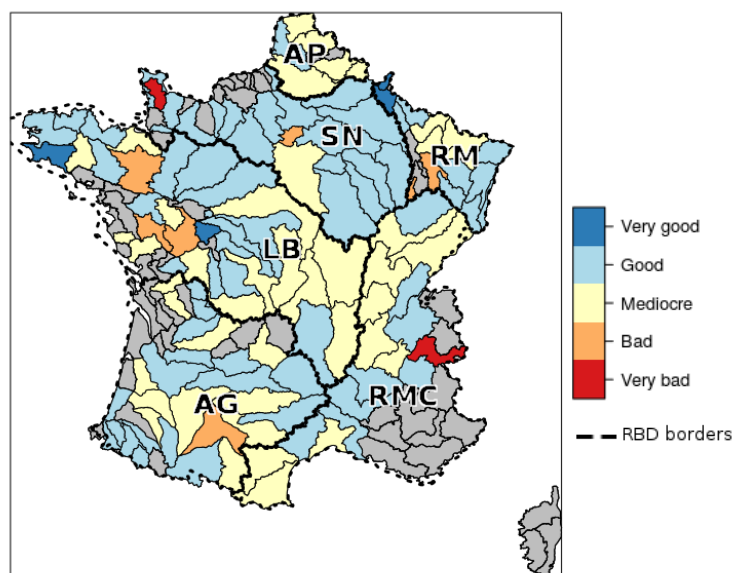


Figure 2: FBI scores for hydrographic sectors, space variation in 2013. French River Basin Districts (RBD) – Adour-Garonne (AG), Artois-Picardie (AP), Loire-Bretagne (LB), Rhône-Méditerranée-Corse (RMC), Rhin-Meuse (RM), and Seine-Normandie (SN).

208 temperatures and particular hydrological conditions. It highlights that slightly more
209 than half of the monitoring points recorded good or very good quality. However, to
210 meet the EU WFD water quality standards will require additional efforts. SOeS (2012)
211 proposes some explanations for the spatial heterogeneity of the FBI index for the six
212 river basin districts (RBD¹⁰, as defined in the EU WFD, presented on figure 2) in France.
213 The Artois-Picardie RBD which is very densely populated appears to be the district with
214 the highest number of points with low ecological quality. This is due to human-induced
215 pressures from industrialization and intensive agriculture. The Seine-Normandie RBD
216 is in the best position. The water quality is worst in the center regions of Picardie
217 and Région Parisienne due to urban development and intensive agriculture. Intensive
218 agriculture especially livestock production is at the origin also of the degradation of
219 river basin quality in Loire-Bretagne. In the Rhin-Meuse RBD, the FBI score indicates
220 that regions with more forest land have better water quality. The Adour-Garonne RBD
221 is affected negatively by hydro-electricity and intensive agricultural production. The
222 Rhône-Méditerranée RBD is affected by urban development, dam construction, and
223 hydro-electricity production. In sum, downstream points, and non-coastal water bodies
224 suffer more from human-induced disturbances.

225 **3 The empirical models**

226 In our study, we investigate the effects of land use and climate change on freshwater
227 biodiversity measured by the FBI index. We take also account of the impacts of climate
228 change on land use. These relationships are summarized in Equations 1 and 2 where FBI
229 is presented as a function (f) of land use (LU), climate (CL), and soil characteristics¹¹
230 (SQ), while land use is a function (h) of land rents ($\mathbf{R}(CL)$), which depend on climate
231 among others, and of other physical parameters (\mathbf{P}). In the FBI model, we use the
232 predicted land use shares derived from the land use model (\widehat{LU}). We develop these

¹⁰France is divided into six RBD: 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. See also figure 6 in the appendix.

¹¹When modeling nonpoint source pollution (as the one from agriculture) it is important to account for the pollutant fate and transport function Shortle and Horan (2002). In order to approximate this function, we control for the soil characteristics in the FBI model.

233 relationships further in sections 3.1 and 3.2.

$$\text{Land use model: } LU = h(\mathbf{R}(CL), \mathbf{P}) \quad (1)$$

$$\text{FBI model: } FBI = f(\widehat{LU}, CL, SQ) \quad (2)$$

234 Thus, we estimate two models: i) a spatial panel model explaining freshwater biodi-
235 versity measured by the FBI index, and ii) a spatial land use share model.

236 3.1 Land use share model

237 We estimate an econometric land use share model with cross-section data. Our econo-
238 metric model is based on econometric land use models estimated on aggregate data such
239 as Lichtenberg (1989); Stavins and Jaffe (1990); Plantinga (1996); Miller and Plantinga
240 (1999) for the U.S. case, and Chakir and Le Gallo (2013); Ay et al. (2017); Chakir and
241 Lungarska (2017) among others for the case of France.

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

$$S_{gl} = \frac{\exp(\mathbf{R}_g \beta_l^R + \mathbf{P}_g \beta_l^P)}{\sum_{l=1}^L \exp(\mathbf{R}_g \beta_l^R + \mathbf{P}_g \beta_l^P)}, \quad (3)$$

244 where \mathbf{R}_g is a vector of land use rents, β_l^R is the associated vector of the parameters
245 to be estimated; \mathbf{P}_g is a vector of physical characteristics and β_l^P is the associated vector
246 of the parameters to be estimated.

247 Linearizing the model in Equation 3 allows us to estimate Equation 4 with a reference
248 land use, L .

$$\tilde{S}_{gl} = \ln(S_{gl}/S_{gL}) = \mathbf{R}_g \beta_l^R + \mathbf{P}_g \beta_l^P + u_{lg}, \forall g = 1, \dots, G, \forall l = 1, \dots, L - 1 \quad (4)$$

249 We model spatial autocorrelation explicitly by employing the spatial Durbin error
250 model specification (SDEM, LeSage and Pace, 2009). This model specification allows

251 us to take account of the spatial autocorrelation in error terms as well as dependence
 252 between land use shares and the neighboring explanatory variables. Two neighbor struc-
 253 tures are included in order to represent the scale at which the explanatory variables are
 254 originally available (Equation 5).

$$\tilde{S}_{gl} = \mathbf{R}_g \beta_l^R + \mathbf{P}_g \beta_l^P + W'_L (\mathbf{R}_{g'} \beta_l^{R'} + \mathbf{P}_{g'} \beta_l^{P'}) + W''_L \mathbf{R}_{j'} \beta_l^{R''} + u_{lg}. \quad (5)$$

255 The error term $u_{lg} = \lambda W'_L \epsilon + \varepsilon$ corrects for spatial autocorrelation of the error
 256 terms through the λ coefficient given the spatial weight matrix W'_L (obtained here via
 257 a contiguity rule “queen” for the grid cells). The W'_L matrix is used to weight fine-scale
 258 rent variables ($\mathbf{R}_{g'}$), the physical parameters ($\mathbf{P}_{g'}$), and the grid level error terms. The
 259 W''_L matrix is applied to the regional scale land rents ($\mathbf{R}_{j'}$). Both matrices are defined
 260 following the “queen” contiguity rule.

261 3.2 FBI model

262 We estimate a model explaining the observed FBI score as a function of land uses
 263 (agriculture, forest, pasture, urban and other), land quality and climate. The spatial
 264 resolution chosen for the FBI model, is the hydrographic sector which is the most ap-
 265 propriate for observing fish populations in rivers. A hydrographic sector is a subdivision
 266 of the river basin districts (“bassin versant” in French) established by the EU WFD.

267 The double dimension of the panel data provides additional information in relation
 268 to cross-section data. It allows us to control the presence of individual effects in the
 269 model through random effects (RE). This structure of the error term makes it possible
 270 to account for the heterogeneity between hydrographic sectors. Moreover, considering a
 271 random-error specification rather than a fixed effects specification allows us to estimate
 272 effects for time invariant variables such as soil quality in our case.

273 Using spatial tools, we control for any spatially correlated unobserved factors that
 274 might influence water quality by estimating a spatial error model (SEM). The SEM posits
 275 that the error terms of a given location depend on the error terms of neighbors. This
 276 assumption can be justified on two grounds. First, there may be data measurement errors
 277 involving the water quality boundary differing from the boundaries of the hydrographic

278 sectors used for the measurement. This is quite plausible in our case since a river can
279 cross several hydrographic sectors. Second, omitted variables such as fish migration or
280 any local pollution which is not directly related to land use could be spatially correlated.

We assume that FBI_{it} in location i at time t ($i = 1, \dots, N$ and $t = 1, \dots, T$) is generated according to the following model:

$$\log(FBI_{it}) = \widehat{LU}_{it}\alpha + CL_{it}\beta + SQ_i\gamma + v_{it}, \quad (6)$$

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

$$\varepsilon_{it} = \lambda W_F \varepsilon_{it} + u_{it},$$

281 where for the i th hydrographic sector at time t , \widehat{LU}_{it} is a vector of predicted land use
282 shares, CL_{it} is a vector of climate variables, SQ_i is a vector of soil quality variables, μ_i
283 is the individual effect of location i assumed to be $IID(0, \sigma_\mu^2)$, ε_{it} is the autoregressive
284 spatial error term, W_F is the spatial weight matrix and u_{it} is an IID error term with
285 zero mean and variance σ_u^2 .

286 A variety of weighting schemes is possible; the choice depends on the process being
287 studied, the data and the estimated model. We first consider three weight matrices: the
288 contiguity matrix, the Delauney triangulation matrix and the upstream-downstream
289 matrix. In all three cases, the matrices are row-normalized. Given the close results
290 obtained for each of these neighboring structures, we opt for a combined contiguity-
291 upstream matrix as depicted in figure 3. In this neighbor structure, contiguous neighbors
292 located upstream have a greater weight in the weight matrix W_F . Some hydrographic
293 sectors are hydrologically independent and have no upstream-downstream neighbors
294 (mostly in coastal zones, see e.g. Brittany peninsula). However, main rivers cross
295 multiple hydrographic sectors and are thus the vector of upstream-downstream processes.
296 These processes are important for fish migration and for pollution spillovers.

297 4 Data description

298 In this section, we describe the datasets used for the land use share and the FBI models.
299 Summary statistics of the data used in the land use share model are described in table

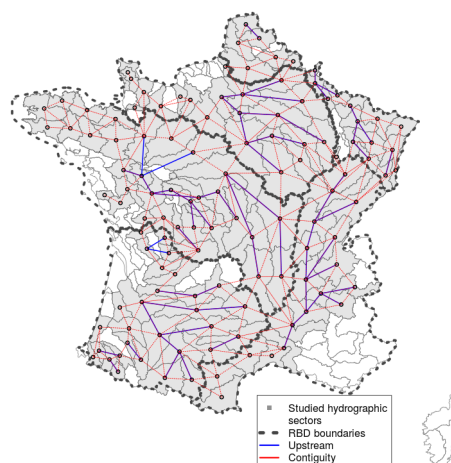


Figure 3: Neighbor relations following a contiguity-upstream rule

300 15 in appendix D. A summary of the data used in the FBI model is also provided in
 301 table 1.

302 4.1 Land use share model

303 **Land use shares** The land use share model is estimated for year 2000 using data
 304 derived from the Corine Land Cover (CLC) database and represented by aggregated
 305 land use classes for agriculture, pasture, forest, urban and other uses at a regular 8
 306 km × 8 km grid scale.¹² CLC is available also for the years 2006 and 2012. However,
 307 estimates for agricultural rent are available only for 2002, and forest rents are evaluated
 308 from 2006 onward. For these reasons, we can estimate land use shares only as a cross-
 309 section model. We decided to base our estimations on 2000 data which is the year closest
 310 to our agricultural land rent proxy.

311 For the area of metropolitan France, we observe approximately 9,000 grid cells.
 312 Crops and pastures are modeled together because of lack of dedicated land rent proxies
 313 for each use. However, we can distinguish the shares for the two uses (see more details
 314 in Construction of agricultural and pasture land use classifications in section 4.2).

¹²The aggregation rules are provided in table 14 in Appendix D.

315 **Agricultural and forestry rents** As in Lungarska and Chakir (2018), we proxy
316 agricultural and forestry rents by the results of two sector-specific mathematical pro-
317 gramming models. First, the agricultural supply-side model AROPAj (Jayet et al.,
318 2015) provides estimates for land shadow prices under current and future climate sce-
319 narios (Leclère et al., 2013). This model represents agricultural systems and accounts for
320 different autonomous adaptations available to farmers. Some of its features important
321 for this study are: i) endogenous choice of mineral fertilizer quantities, ii) land switch
322 between different crops and pastures, and iii) endogenous choice of animal husbandry
323 regime (feed or pasture). Second, the partial equilibrium French forestry sector model
324 (FFSM++, Cauria et al., 2013; Lobianco et al., 2016) optimizes forestry management
325 and evaluates expected revenues for the sector. Its estimates under climate change sce-
326 narios integrate a possible switch between tree species as adaptation by forest managers.
327 These two rent variables allow us to account for climate evolution following two climate
328 change scenarios (A2 and B1).

329 **Demography** Land rents in the case of urban use are approximated by demographic
330 information on population density and revenues.¹³ When we simulate the effects of
331 the climate change scenarios, we introduce predictions about demographic evolution in
332 France.¹⁴

333 **Soil quality and topography** In order to refine our land use predictions, we intro-
334 duce information on soil quality measured by texture classes (Panagos et al., 2012). For
335 instance, variable texture (cl. 1) represents the share of soil texture class 1 in the 8 x 8
336 km grid cell. In our model, we use this texture class as the reference since it describes
337 the worst soil quality. We control also for the average slope (derived from GTOPO30¹⁵
338 data) in the grid cell and in neighboring cells.

¹³Provided by the French statistical institute, INSEE.

¹⁴Up to 2040 we apply French statistical institutes's (INSEE) predictions at the French *département* level and then at the national level up to 2060 (http://www.insee.fr/fr/themes/detail.asp?reg_id=0&ref_id=donnees-carroyees&page=donnees-detaillees/donnees-carroyees/donnees_carroyees_diffusion.htm). Afterwards, we downscale and apply predictions from CIESIN for Western Europe (Center for International Earth Science Information Network, 2002).

¹⁵For more information: <https://lta.cr.usgs.gov/GTOPO30>.

339 **Accounting for climate change** Climate change has a direct impact on agricultural
340 and forest land uses. We use the results from the aforementioned sector-specific models
341 AROPAj and FFSM++ because both account for the effects of climate change on their
342 respective land based sectors. Furthermore, these models allow for some autonomous
343 adaptation to climate change. We build on the results for climate change in Leclère et al.
344 (2013) for agriculture and of Lobianco et al. (2016) for forestry. The predictions from
345 climate change scenarios A2 and B1 indicate an increase in the profitability of French
346 agriculture and a decrease in forestry. The results for land use indicate that we can
347 expect agricultural land use to expand at the expense of forest land use (Lungarska and
348 Chakir, 2018). More information on the climate change scenarios is provided in section
349 5.2.1.

350 **4.2 FBI model**

351 **Land use share estimates** Since the FBI model is based on panel data and the land
352 use share model is estimated for 2000 (as mentioned previously), we use information
353 from CLC for 2006 and 2012 to derive annual evolution rates for the different land
354 use classes in order to obtain land use share estimations for years 2001 to 2013 (the
355 time period covered by the FBI model). For instance, we calculate the evolution of the
356 urban area between two CLC observations in 2000 and 2006. Thus, we can deduce the
357 annual rate of increase or decrease for this land use and this period. We then apply this
358 evolution rate to the estimations of the land use share model.

359 The same technique is applied to all land use share estimations employed in the FBI
360 model. We use these inferred values rather than observed values in order to avoid bias
361 when simulating the effects of climate change and public policy (section 5.2.1).

362 **Construction of agricultural and pasture land use classifications** Agriculture
363 and pasture land uses have different environmental impacts depending on the intensity of
364 the land use and the slope of the plots. We account for slope since it matters for leaching
365 and soil erosion which have an impact on water pollution. To capture the effects of land
366 management on freshwater biodiversity, we distinguish four classes for each of these
367 two land uses. The distinction is made at the scale of the regular grid of the land use

368 share model (see section 3.1). For each grid cell, we combine information on land use
369 shares with average slope, and classify the agriculture/pasture land uses. We obtain
370 four classes for the two slope and two intensity category combinations (summarized
371 in table 1 and depicted in figure 4). The slope threshold is the first quartile value
372 of the grid cells (1.16% inclination), the nitrogen use threshold is the median value
373 (100 kgN/ha) and the livestock density threshold is the median value¹⁶ (0.7 livestock
374 units/ha). Data on nitrogen use and livestock density are derived from the AROPAj
375 agricultural supply model. The results from AROPAj allow us to distinguish agriculture
376 (crops) from pasture since the land use share model provides aggregate estimates of
377 these two uses.

378 **Soil quality and climate data** As in the land use share model, we control for topsoil
379 texture. Climate is summarized by annual average temperature (historical data from
380 Météo France) and a rain coefficient of variation. The direct effect of climate change
381 on the FBI is introduced using the projected values for these variables for 2100 in the
382 ARPEGE¹⁷ general circulation model for the International Panel on Climate Change
383 (IPCC) scenarios A2 and B1. The climate information is available at the 8 km × 8 km
384 regular grid (the same as in the land use share model) thanks to the downscaling of
385 ARPEGE results (Pagé et al., 2010; Pagé and Terray, 2010).

386 FBI values and all the regressors in the FBI model are aggregated (average values) at
387 the hydrographic sector level.¹⁸ We consider information for 122 of the 187 hydrographic
388 sectors for which we have yearly observations (see figures 1 and 2). Thus, we are modeling
389 two-thirds of the French metropolitan hydrographic sectors, covering a large spectrum of
390 French climatic situations, land use shares and soil characteristics. Only the Southeast
391 of France and Corsica are underrepresented. However, these regions are quite different in

¹⁶The median values are evaluated at the scale of the land use share model from Lungarska and Chakir (2018).

¹⁷For more details, please visit <https://www.umr-cnrm.fr/spip.php?article124&lang=en>.

¹⁸The aggregation of the FBI scores at the hydrographic sector level, allows us to smooth the selection bias introduced by the evolution in the FBI sample points. 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.

Variable	Definition	Unit	Year	
FBI	FBI score <i>Scale:</i> point; aggregated at the hydrographic sector level <i>Source:</i> 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, 2100	
• rain_cv	Coefficient of variation in monthly precipitation <i>Scale:</i> 8 x 8 km grid; aggregated at the hydrographic sector level <i>Source:</i> Météo France, ARPEGE (Pagé et al., 2010; Pagé and Terray, 2010).		1990, ..., 2013, 2100	
TXT1, ..., TXT4	Share of the texture class in the hydrographic sector <i>Scale:</i> 1:1,000,000; aggregated at the hydrographic sector level <i>Source:</i> Panagos et al. (2012), European Union Joint Research Center, JRC.	%	Invariant	
Slope	<i>Scale:</i> 30 arc sec; averaged at a regular grid level <i>Source:</i> GTOPO30, https://1ta.cr.usgs.gov/GTOP030	%	Invariant	
Land use	Share of each land use in the hydrographic sector			
• agr	Agriculture share	%	Interpolation using data for 2000, 2006, and 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			
	<i>Scale:</i> 1 ha; aggregated at the hydrographic sector level <i>Source:</i> Corine Land Cover.			
Intensity	Nitrogen use and livestock density <i>Scale:</i> Spatialized at 8 x 8 km regular grid scale <i>Source:</i> AROPAj, (Jayet et al., 2015)	kgN/ha, livestock units/ha		2002

Table 1: Data description of the FBI model

392 terms of agriculture and forestry, and their exclusion makes sense if we exclude outliers.

393 The summary statistics presented in table 1 show that the average FBI score in

394 the sample is 17.46, meaning that the ecological quality of water is poor on average.

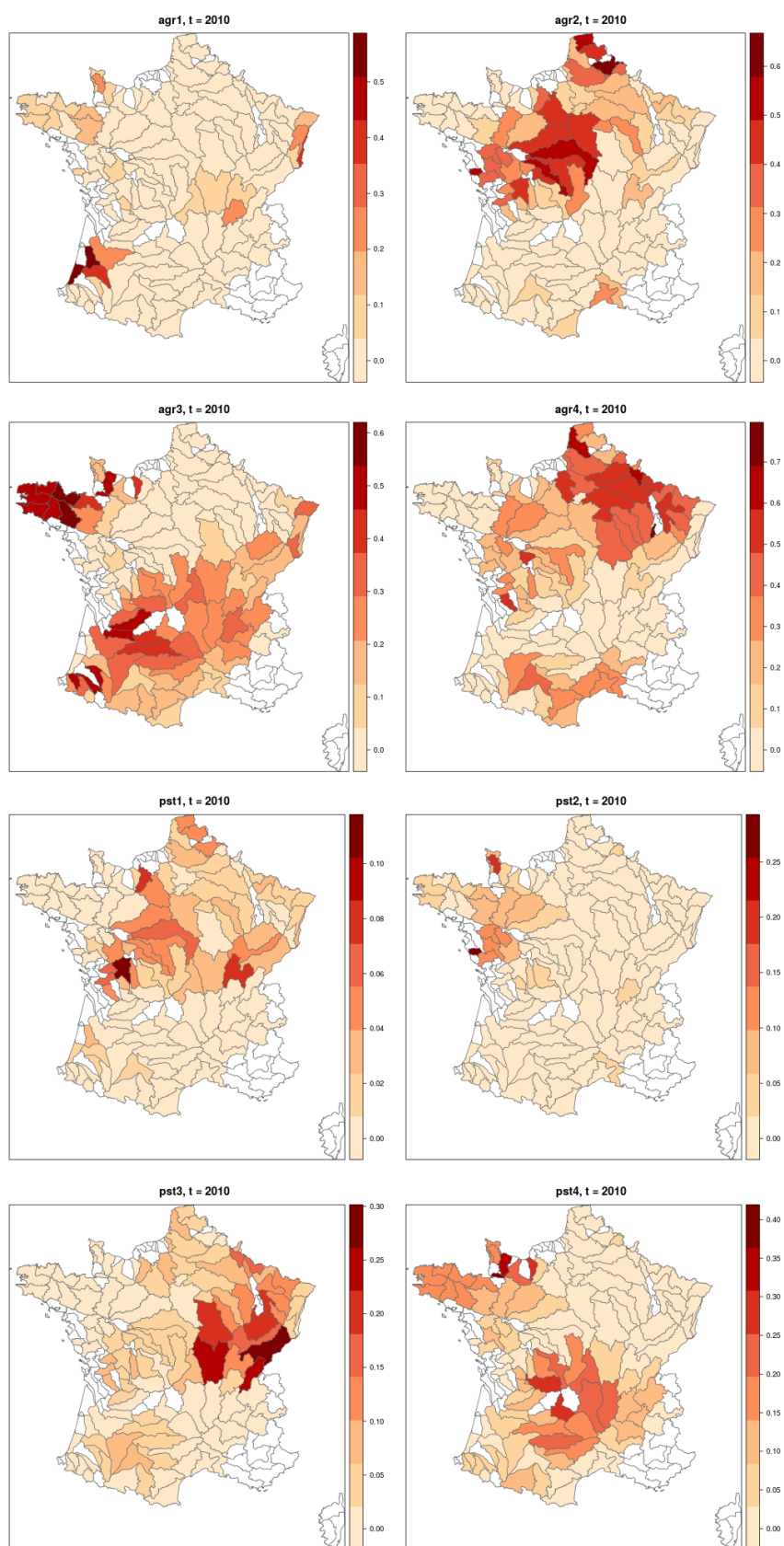


Figure 4: Land shares for the four agricultural and four pasture classes

395 Agricultural land (crops+pasture) accounts for the largest area in the sample (65%),
 396 followed by forests (25%), urban land (5%), and other land uses (4%).

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
Texture (cl. 2)	0	0.2233	0.4066	0.4506	0.7212	0.9595	0.26
Texture (cl. 3)	0	0.0381	0.1964	0.263	0.475	0.8639	0.25
Texture (cl. 4)	0	0	0.0495	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	0.0330	0.5582	0.094
agr2	0	0	0.0268	0.1225	0.2119	0.6237	0.165
agr3	0	0	0.1267	0.1633	0.2784	0.5874	0.174
agr4	0	0.0005	0.1488	0.1935	0.3321	0.7526	0.193
pst1	0	0	0.0047	0.0151	0.0235	0.1103	0.021
pst2	0	0	0	0.0165	0.0119	0.2739	0.039
pst3	0	0.0008	0.0259	0.0452	0.0665	0.2868	0.06
pst4	0	0	0.0306	0.0683	0.1134	0.3922	0.085
urb	0.0042	0.0184	0.0266	0.04296	0.0442	0.4422	0.053
oth	0.0029	0.0149	0.0281	0.05758	0.0672	0.4945	0.082

Table 2: Descriptive statistics of the variables in the FBI model

397 5 Estimation and simulation results

398 Section 5.1 presents the econometric results from the estimations of the impacts of land
 399 use on FBI. Section 5.2 presents the simulation results of the climate change scenarios
 400 and two command-and-control policies aimed at improving freshwater biodiversity in
 401 France.

402 5.1 Econometric estimation results

403 To compare estimations and to evaluate the gains from allowing for both spatial au-
 404 tocorrelation and individual heterogeneity, we consider the following estimators for the
 405 FBI model:

- 406 1. Pooled ordinary least squares (OLS) which ignores individual heterogeneity and
 407 spatial autocorrelation;

- 408 2. RE (random effects) estimator which accounts for random individual effects but
409 ignores spatial autocorrelation;
- 410 3. SEM which takes account of the autoregressive spatial error autocorrelation but
411 ignores individual heterogeneity;
- 412 4. SEM-RE estimator which accounts for both spatial error autocorrelation and ran-
413 dom individual heterogeneity.

414 In order to take account explicitly of spatial heterogeneity and possible differences
415 in public policies, we also include fixed effects (FE) for river basin districts (RBD).

416 The detailed results for the estimated models are provided in appendices B and C
417 (tables 8 to 13). Tables 8 to 10 present the results for the OLS, RE, SEM and SEM-RE
418 models for the three weight matrices: contiguity, contiguity-upstream and triangulation.
419 Tables 11 to 13 present the results for the same models with added RBD FE to account
420 for any individual specific characteristics of local water agencies.

421 We start by estimating the pooled OLS model and testing three weight matrix spec-
422 ifications: contiguity, triangulation and upstream. The Moran's I statistic significant
423 at the 1% confidence level for the two weight matrices, contiguity and triangulation,
424 and is not significant for the upstream weight matrix (see tables 6 and 7). Thus, the
425 FBI scores are subject to potential spatial autocorrelation. In several cases, elements of
426 the upstream weight matrix have no neighbors. This might explain why the Moran's I
427 coefficient in this spatial setting is not significant. Upstream relations are important for
428 hydrology. Hence, we combine information on upstream relations with the contiguity
429 matrix and define a new weight matrix called contiguity-upstream which assigns greater
430 importance to neighbors located upstream. The results in tables 6 and 7 show that the
431 Moran's I statistics are mostly higher for the contiguity-upstream matrix than for the
432 contiguity matrix.

433 We next estimate the SEM model which has a significant spatial autocorrelation
434 coefficient ranging from $\rho = 0.194$ to $\rho = 0.38$ for the three weight matrices and with
435 and without the RBD FE specifications (tables 8 to 13). These results indicate that
436 ignoring spatial autocorrelation could lead to inconsistent estimation.

437 The RE model results show that the fraction of the variance due to the differences
438 across hydrographic sectors ϕ is significant for all specifications (with and without RBD
439 FE). When we take account of both spatial autocorrelation and individual heterogeneity,
440 ρ and ϕ remain significant for all the specifications (with the three weight matrices, and
441 with and without RBD fixed effects). Since most of the results are stable for all the
442 specifications, we focus in what follows on interpreting the results of the SEM-RE model
443 based on the contiguity-upstream weight matrix presented in appendix C (table 12).

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

450 In order to compare the relative impacts of alternative land uses on the FBI score, we
451 calculate the elasticities of the FBI index with respect to each land use class at the mean
452 land uses value (table 3). These elasticities could be interpreted as follows: an increase
453 of 1% in the land use class agr2 will increase the FBI score by 0.158%. The results show
454 that the land use class that has the largest effect on the FBI score is low slope-high
455 intensity crops (agr2), followed by high slope-high intensity pasture (pst4), high slope-
456 high intensity crops (agr 4), high slope-low intensity pasture (pst3), and urban land
457 use. Our results are in line with those in Ministère de l'environnement (2017) which
458 mentions that water quality in France shows an overall marked increase in agricultural
459 and livestock pollution due mainly to nitrates and pesticides, and a decrease in industrial,
460 domestic and urban pollution since the creation 50 years ago of water agencies. Our
461 results for the adverse impacts in France of pasture located on steep slopes on nitrate
462 emissions from manure confirm those documented in Peyraud et al. (2014). The results
463 for urban use are in line also with the findings in Langpap et al. (2008) for four U.S.
464 states, and those in Fiquepron et al. (2013) for France.

465 The effects of soil, temperature and rain variability on the FBI are not significant.
466 Some river basin districts FE are significant, and year 2003 FE is significantly positive.

467 This indicates that the exceptional drought that occurred in 2003 reduced freshwater
 468 biodiversity. This suggests some intuitions concerning the potential impacts of climate
 469 change on FBI.

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

LS: low slope; HS: high slope; LI: low intensity; HI: high intensity.
 Note: *p<0.1; **p<0.05; ***p<0.01

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

470 Overall, the results show that the marginal effects of agricultural, pasture and urban
 471 land uses on FBI are larger than the marginal effect of forest land on FBI. This is as
 472 expected since the main factors that affect the abundance and diversity of aquatic life
 473 have been identified as nutrient loading, toxic pollution and habitat alteration (Hascic
 474 and Wu, 2006).

475 5.2 Simulation of climate change and public policies

476 In what follows, we first describe the simulated climate change and public policy sce-
 477 narios and then present the simulation results.

478 5.2.1 Simulated scenarios

479 **Climate change scenario simulations** We simulate the effects of land use and land
 480 use adaptation to climate change on freshwater biodiversity. We consider two IPCC sce-
 481 narios: an optimistic B1 scenario, and a pessimistic A2 scenario associated to a greater
 482 increase in temperature (IPCC, 2000, for the 2100 time horizon). An important differ-

483 ence between the two climate change scenarios is the hypothesis concerning demography.
484 The A2 scenario supposes a positive demographic evolution in France, while the B1 sce-
485 nario is based on an assumption of a more stable and even decreasing population. These
486 diverging hypothesis explain the difference in the predicted urban area and the resulting
487 difference in agricultural area whose expansion is more limited in the A2 scenario com-
488 pared to B1. In terms of land management, both climate change scenarios are associated
489 to increasing quantities of nitrogen fertilizer use (Leclère et al., 2013).

490 We build on the results in Lungarska and Chakir (2018) on the impact of climate
491 change on land use. Climate change affects the land rents of different land-based eco-
492 nomic activities such as agriculture, pasture and forestry. Two sector-specific models
493 capture these effects in biological modules. They account also for some land manage-
494 ment choices and other adaptation possibilities (input use, changes to varieties, sowing
495 and harvesting dates, etc.). We consider demography to be the main driver of urban
496 land use change.

497 Agriculture and forestry are the two land based sectors that are the most exposed
498 to climate change effects. Nevertheless, these two sectors have numerous options for
499 adaptation to the new climate conditions. In the sector-specific model for agriculture
500 (AROPAj) used in the present study, farmers can change crops or crop varieties, sowing
501 and harvesting dates, and intensity of their inputs (fertilizer) as well as the number of
502 animals per hectare in the case of pasture. Farmers also switch between pasture and
503 crops, and vice versa. Forestry managers modeled by the FFSM++ model have the
504 possibility to adapt through the choice of tree species. The land use share model allows
505 us to account also for possible adaptations through land use change. The estimated
506 coefficients of the land use share model are provided in appendix D.

507 Results concerning climate induced land use change indicate that we can expect crop
508 land to expand at the expense of forests and pastures (Lungarska and Chakir, 2018).

509 **Public policy simulations** We study two command-and-control policy options aimed
510 at limiting intensive agricultural land and intensive pasture. As our estimation results
511 show, intensive agriculture and pasture have the largest effects on freshwater biodiversity.
512 We thus exploit this information by simulating the effects of land management policies

513 on freshwater biodiversity. We consider a reduction in the intensity of nitrogen fertilizer
514 use on crops and a reduction in livestock density on pastures.

515 To control local water pollution problems, regulatory instruments such as standards
516 are more frequent in France than fiscal measures. This is because the precise location
517 of pollution is important, and can be considered only imperfectly by fiscal measures
518 (Ministère de l'environnement, 2017).

519 The policy options are designed in the following way. As explained before, agricul-
520 tural land and pasture land are each decomposed into four land use classes based on
521 intensification (high/low) and slope (high/low). In the case of agricultural land, the
522 intensification criterion is nitrogen fertilizer use per hectare, and in the case of pasture
523 the criterion is livestock density. The first regulation involves shifting from intensive
524 uses in favor of extensive uses for agricultural land in the same slope class. The second
525 policy involves the same shift for pasture.

526 As the FBI model estimation results show (see table 12), all intensive cropping and
527 pasture land uses (agr2, agr4, pst2, and pst4) have a positive and significant effect on
528 the FBI score, and thus, a negative impact on fish populations. Our simulations involve
529 shifting from intensive uses (in agriculture and pasture) to extensive uses for a given
530 slope type (high or low).

531 Table 4 summarizes the reductions in livestock units and nitrogen fertilizer use for
532 the different policy and climate change scenarios. Overall, a standard for intensive
533 pasture leads to a 32%-35% decrease in livestock units. The reduction in livestock units
534 for intensive farms (with more than 0.7 livestock units/ha) is 42%-44%. The associated
535 reductions in nitrogen fertilizer use in these scenarios (table 4) range between 49% and
536 58% overall, and from 57% to 62% for intensive farms (with more than 100 kgN/ha
537 fertilizer applications).

538 **5.2.2 Simulation results**

539 **Our simulation results are summarized in figure 5. As the estimations of the**
540 **FBI index are subject to prediction errors, the assignment in specific water**
541 **classes resulting from these FBI estimations is also subject to the prediction**

Policy scenario	Pasture policy		Agricultural policy	
Policy outcomes	Livestock units reduction	Livestock units reduction in intensive farms	Overall nitrogen reduction	Nitrogen reduction in intensive farms
Current climate	-32.12 %	-41.79 %	-49.44 %	-56.91 %
A2	-34.8 %	-43.66 %	-58.43 %	-62.5 %
B1	-34.54 %	-43.14 %	-55.28 %	-59.79 %

Table 4: Reductions in livestock units and nitrogen fertilizer use for the climate and policy scenarios

542 **errors. For this reason, we provide in appendix E (figures 7, 8, and 9),**
543 **the prediction intervals of FBI associated with each scenario and the water**
544 **quality classes.**

545 **The impact of climate change** on the FBI is shown clearly by comparing the maps
546 given at the three rows in the first column of figure 5. The predictions for the current
547 climate conditions are depicted at the top of the figure, those for climate change scenario
548 B1 are in the middle, and those for climate change scenario A2 are at the bottom of
549 the figure. It can be seen that the FBI is worse under the two climate change scenarios
550 compared to the current climate; scenarios A2 and B1 show more hydrographic sec-
551 tors registering “Mediocre”, “Bad” and “Very bad” quality (figures 9 and 8 in appendix
552 E). These results are driven by expansion in agriculture and urban land uses, and the
553 evolution of climate variables (increased temperature and coefficient of variation in pre-
554 cipitation). The maps in figure 5 show also that water quality is worse in the A2 scenario
555 compared to the B1. Recall here that the A2 scenario is considered a pessimistic sce-
556 nario, and thus, is associated to a greater temperature increase than the B1 scenario.
557 Also, the A2 scenario is supposed to lead to a greater increase in urban area since it
558 assumes a larger French population increase.

559 **The effects of a standard for livestock density** can be evaluated by comparing
560 the maps in the first column of figure 5 (“status quo”) with those in the second column of
561 the figure (“pasture policy” scenario). Under the current climate scenario (top of figure
562 5), the limitations on intensive pasture allow some hydrographic sectors to recover,

563 resulting in fewer observations of “Bad” and “Very bad” quality. Comparison of the
564 maps shows that in some sectors such as those located in the Massif Central (mid
565 Southern France) quality is worsened by the standard. In these sectors, pastures are
566 mostly steeply sloped and with high intensity (see figure 4), and the pasture policy
567 suggests that these pastures would shift to steep slope, low intensity. However, the FBI
568 coefficient of the latter is higher than the FBI coefficient of the former which results in
569 higher pressure on fish populations. Finally, this standard is not sufficient to compensate
570 for the adverse impacts of climate change on water quality. In fact, if the policy applies
571 to the two climate change scenarios, there are fewer “Good” and “Very good” water
572 quality hydrographic sectors than under the current climate regime.

573 **The effects of a standard on nitrogen fertilizer use for agriculture** represented
574 in the third column of figure 5 show that under the current climate the simulated policy
575 improves water quality, and some 60% of the hydrographic sectors are classed as “Good”
576 or “Very good”, while those classed as in a “Bad” state reduce from 10 to 3 sectors. **As**
577 **in the case of pasture policy, the agricultural policy is not able to fully offset**
578 **the adverse impacts of climate change on water quality.**

579 **Under which scenario does France comply with the EU WFD?** Table 5 sum-
580 marizes the simulation results for the different climate and policy scenarios. It repre-
581 sents the share of good and very good quality hydrographic sectors in terms of FBI
582 score. Recall that to comply with the objective of the EU WFD, France (like the other
583 EU member states) needs to achieve good or very good surface water quality for 60%
584 of its water resources by 2021. Regarding the effects of climate change and land use
585 adaptation, freshwater biodiversity deteriorates, and that loss of biodiversity would be
586 larger in the case of the pessimistic A2 climate change scenario. These results show
587 that land use adaptation to climate change could imply adverse effects for freshwater
588 biodiversity. Our results add to the findings in the literature on the unintended effects of
589 climate adaptation on chemical water pollution (Fezzi et al., 2015) and bird populations
590 (Beaudry et al., 2013; Ay et al., 2014)

591 In relation to the impacts of agricultural and pasture policies, both improve freshwa-

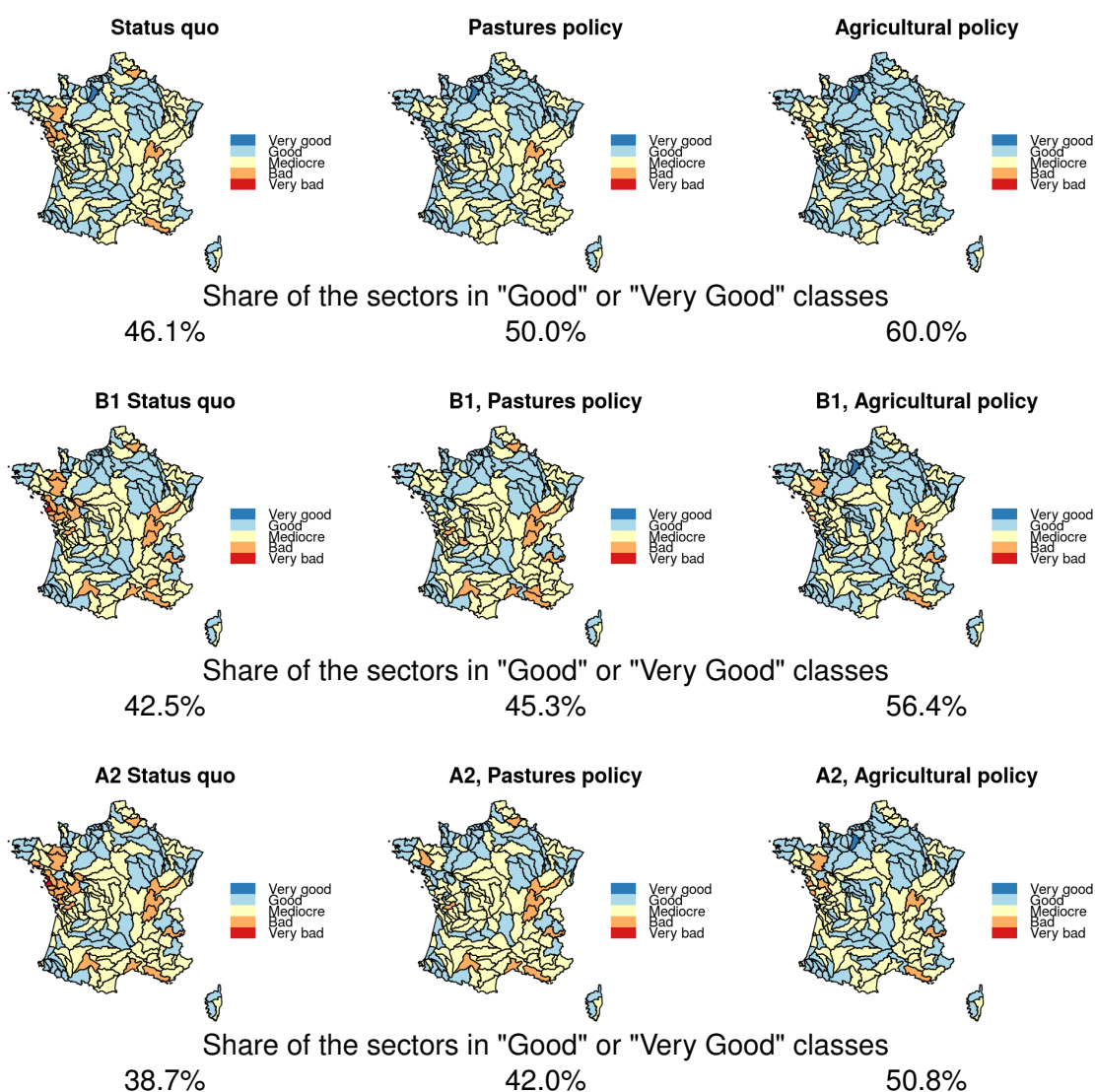


Figure 5: Simulation results for water quality based on FBI index under current climate (top row) and future climate change scenarios (B1 scenario, middle row; A2 scenario, bottom row), and for the two land use policies (Pasture policy, second column; Agricultural policy, third column). The agricultural policy outperforms the pasture policy for all climate scenarios. Water quality is worse under climate change. Moreover, the B1 scenario leads to better results than the A2 scenario regardless of the policy in place.

Scenario	Status quo	Pasture policy	Agricultural policy
Current climate	46.1%	50.0%	60.0%
B1 scenario	42.5%	45.3%	56.4%
A2 scenario	38.7%	42.0%	50.8%

Table 5: The share of hydrographic sectors with good and very good quality in terms of the FBI score

592 ter biodiversity compared to the status quo. When we take into account the combined
593 effects of the policies and the climate change scenarios, we note first that the two policies
594 do not fully compensate for the adverse impacts of climate change on biodiversity. The
595 better positioned sectors are still less than the 60% hydrographic sectors requirement to
596 conform to the EU WFD. Note also that the agricultural policy allows France to com-
597 ply with the EU WFD under the current climate but not under future climate change
598 scenarios.

599 **6 Conclusion**

600 The status of some rivers in France is highly degraded, exemplified by a decline in
601 the quality and quantity of water and changes in the distribution and structure of
602 aquatic biota (Oberdorff et al., 2002). French freshwater fish populations have suffered
603 from degradation and destruction of natural environments, and pollution. Pressures on
604 freshwater ecosystems are mainly human-induced and driven by land use and climate
605 change. The objective of this paper was to evaluate how land use and land use adaptation
606 to climate change affect freshwater ecosystems in France.

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

614 Regarding the effects of alternative land uses, our estimation results reveal that
615 rivers in areas with more agricultural, pasture and urban land relative to forest, are
616 associated to lower freshwater biodiversity. They also show that the harmful effect
617 of the agricultural sector (crops and pasture) is larger than that of the urban land
618 use on freshwater biodiversity. Regarding the effects of land management options, our
619 estimations provide interesting results. They show that intensive crops and high slope
620 pasture reduce freshwater biodiversity the most relative to forest land use.

621 Another result worthwhile to stress is that extensive pasture is not necessarily good
622 for freshwater biodiversity as usually mentioned in the literature. According to Ste-
623 infeld et al. (2006) extensive livestock systems may provide environmental services of
624 vegetation cover and biodiversity while intensive livestock production contributes to eu-
625 trophication of surface and ground water ecosystems. Our results show that extensive
626 pasture in steep areas reduce freshwater biodiversity relative to forest land use. This
627 is an important result as it is well known that steep slopes increase the speed of the
628 water flow leading to increasing run-off and soil erosion over time. These overall find-
629 ings highlight the importance of distinguishing crop and pasture land uses with respect
630 to intensive/extensive practices and topological characteristics when evaluating their
631 impacts on freshwater biodiversity.

632 Based on our estimation results, our simulations show that land use adaptation
633 to climate change reduces freshwater biodiversity. The loss in biodiversity is larger
634 in the case of the more pessimistic climate change scenario. We also discussed how
635 two command-and-control policy options might help to improve freshwater biodiversity
636 and mitigate the adverse impacts of climate change on this biodiversity. These policy
637 options are a standard for nitrogen fertilizer use in agriculture, and a standard for
638 livestock density on pasture. Our simulations show that the agricultural policy would
639 allow France to comply with the EU WFD under the current climate. However, neither
640 of the two policies makes compliance with the EU WFD under the climate change
641 scenarios. This indicates that simulating the mere effects of public policies without
642 including the climate change impacts would lead to the over-estimation of the benefits
643 from these policies. This, in turn, could introduce a bias in terms of the policy action
644 recommendations within the EU WFD.

645 The relatively poor performance of agricultural and pasture policies considered in
646 this paper needs to be nuanced. Our study considers only land regulations that do
647 not vary over the territory. The policies do not discriminate policy variables with re-
648 spect to pedo-climatic conditions. It could be interesting to consider the effectiveness of
649 spatially-differentiated regulations for freshwater biodiversity. For instance, policy might
650 recommend a reduction in the intensiveness of pasture in high slope areas, or an agri-

651 cultural policy might set some limits on intensive crop production located at upstream
652 points or in environmentally vulnerable areas. Furthermore, we focused on separate reg-
653 ulations for pasture and crop production but there are other possibilities. Mixed policies
654 can be investigated also by considering the interaction effects on freshwater biodiversity
655 between pasture and agricultural policies.

656 **Our analysis of the impacts of land use and climate change on FBI is**
657 **subject to uncertainties related mainly to climate scenarios. These uncer-**
658 **tainties are due to both incomplete and unknowable knowledge. The best**
659 **way to quantify some of these uncertainties is to use a probabilistic frame-**
660 **work. Using a statistical approach, Raftery et al. (2017) estimate an increase**
661 **in temperature by 2100 between 2°C and 4.9°C, with a median value of 3.2°C.**
662 **According to the same study, the probability of limiting global warming to**
663 **2°C by 2100 as set by the Paris agreement on climate is equal to 5% and the**
664 **chances of achieving the 1.5°C target, also contained in the same agreement,**
665 **are only 1%. The two scenarios considered in our paper assume global tem-**
666 **perature increase between 2°C and 5.4°C (A2), and 1.1°C and 2.9°C (B1).**
667 **This means that the pessimistic scenario is the most likely one and that our**
668 **chosen scenarios allow us to have a range of results on climate and land use**
669 **impacts on FBI taking into account uncertainties on climate scenarios. Our**
670 **simulations of the impacts of land use policies and climate change on fresh-**
671 **water biodiversity should be extended in the light of new climate scenarios**
672 **and new knowledge on global systems.**

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822 **Appendices**



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

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 6: 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 7: Moran's I for annual OLS models, RBD fixed effects

824 **B Models without fixed effects**

Variable	OLS	RE	SEM	SEM-RE
(Intercept)	1.5857 *** (0.1515)	2.0439 *** (0.2635)	1.6589 *** (0.1625)	2.073 *** (0.273)
Texture (cl. 2)	0.2778 *** (0.076)	0.4226 ** (0.1958)	0.2631 *** (0.0736)	0.4202 ** (0.191)
Texture (cl. 3)	-0.1082 (0.0739)	-0.0155 (0.1932)	-0.0886 (0.0769)	-0.0126 (0.1975)
Texture (cl. 4)	0.3317 *** (0.1036)	0.4389 (0.2742)	0.3719 *** (0.107)	0.467 * (0.2784)
rain_cv	-0.0101 (0.0442)	-1e-04 (0.0321)	-0.0031 (0.0541)	4e-04 (0.0371)
T	0.0225 ** (0.0095)	0.0161 (0.0122)	0.0163 (0.0111)	0.012 (0.0145)
agr1	1.3077 *** (0.1896)	0.8979 ** (0.4493)	1.2766 *** (0.1865)	0.9965 ** (0.4467)
agr2	1.6411 *** (0.1715)	1.2068 *** (0.3968)	1.635 *** (0.1739)	1.3257 *** (0.4053)
agr3	0.5659 *** (0.1614)	-0.0682 (0.3667)	0.6838 *** (0.165)	0.0316 (0.3762)
agr4	0.3807 *** (0.1239)	-0.1201 (0.2875)	0.4038 *** (0.1239)	-0.0808 (0.2914)
pst1	-3.7076 *** (0.9102)	-5.1257 ** (2.2187)	-3.3578 *** (0.9402)	-5.631 ** (2.2433)
pst2	2.0051 *** (0.386)	1.1779 (0.9645)	1.9849 *** (0.4161)	0.9209 (1.0056)
pst3	3.605 *** (0.3054)	2.7779 *** (0.7189)	3.0786 *** (0.3093)	2.5368 *** (0.7359)
pst4	1.0467 *** (0.2118)	0.5431 (0.4974)	0.9312 *** (0.2239)	0.4902 (0.5172)
urb00	1.6907 *** (0.2429)	1.0064 * (0.5865)	1.7578 *** (0.2535)	1.01 * (0.6084)
oth00	1.7594 *** (0.2667)	0.2513 (0.4727)	1.5262 *** (0.2654)	0.1616 (0.473)
y2003	0.0677 * (0.0358)	0.0709 *** (0.0266)	0.0722 (0.049)	0.0744 ** (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 8: Models based on the contiguity neighborhood matrix

Variable	OLS	RE	SEM	SEM-RE
(Intercept)	1.5857 *** (0.1515)	2.0439 *** (0.2635)	1.702 *** (0.1612)	2.1022 *** (0.2724)
Texture (cl. 2)	0.2778 *** (0.076)	0.4226 ** (0.1958)	0.2392 *** (0.073)	0.4065 ** (0.1903)
Texture (cl. 3)	-0.1082 (0.0739)	-0.0155 (0.1932)	-0.1174 (0.0775)	-0.0281 (0.1981)
Texture (cl. 4)	0.3317 *** (0.1036)	0.4389 (0.2742)	0.3402 *** (0.1065)	0.4548 (0.2774)
rain_cv	-0.0101 (0.0442)	-1e-04 (0.0321)	-0.0044 (0.0545)	-0.0018 (0.0372)
T	0.0225 ** (0.0095)	0.0161 (0.0122)	0.0158 (0.0111)	0.0118 (0.0146)
agr1	1.3077 *** (0.1896)	0.8979 ** (0.4493)	1.2281 *** (0.1845)	0.9632 ** (0.4442)
agr2	1.6411 *** (0.1715)	1.2068 *** (0.3968)	1.6156 *** (0.174)	1.3118 *** (0.4057)
agr3	0.5659 *** (0.1614)	-0.0682 (0.3667)	0.669 *** (0.1654)	0.0098 (0.3765)
agr4	0.3807 *** (0.1239)	-0.1201 (0.2875)	0.4121 *** (0.1242)	-0.0812 (0.2921)
pst1	-3.7076 *** (0.9102)	-5.1257 ** (2.2187)	-3.4194 *** (0.9364)	-5.6928 ** (2.2368)
pst2	2.0051 *** (0.386)	1.1779 (0.9645)	2.006 *** (0.4145)	0.9197 (1.0028)
pst3	3.605 *** (0.3054)	2.7779 *** (0.7189)	2.9243 *** (0.3075)	2.4342 *** (0.7343)
pst4	1.0467 *** (0.2118)	0.5431 (0.4974)	0.9426 *** (0.2234)	0.4961 (0.5173)
urb00	1.6907 *** (0.2429)	1.0064 * (0.5865)	1.7151 *** (0.2502)	0.9651 (0.6036)
oth00	1.7594 *** (0.2667)	0.2513 (0.4727)	1.4767 *** (0.2617)	0.1287 (0.4709)
y2003	0.0677 * (0.0358)	0.0709 *** (0.0266)	0.073 (0.0497)	0.0749 ** (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 9: Models based on the contiguity-upstream neighborhood matrix

Variable	OLS	RE	SEM	SEM-RE
(Intercept)	1.5857 *** (0.1515)	2.0439 *** (0.2635)	1.6205 *** (0.1676)	2.0737 *** (0.2738)
Texture (cl. 2)	0.2778 *** (0.076)	0.4226 ** (0.1958)	0.2034 *** (0.0741)	0.3746 ** (0.1907)
Texture (cl. 3)	-0.1082 (0.0739)	-0.0155 (0.1932)	-0.0718 (0.0786)	-0.0205 (0.1978)
Texture (cl. 4)	0.3317 *** (0.1036)	0.4389 (0.2742)	0.2825 *** (0.1064)	0.4097 (0.2748)
rain_cv	-0.0101 (0.0442)	-1e-04 (0.0321)	-0.0121 (0.056)	0.0031 (0.0375)
T	0.0225 ** (0.0095)	0.0161 (0.0122)	0.0235 ** (0.0116)	0.012 (0.0149)
agr1	1.3077 *** (0.1896)	0.8979 ** (0.4493)	1.1462 *** (0.1879)	0.9389 ** (0.4473)
agr2	1.6411 *** (0.1715)	1.2068 *** (0.3968)	1.3736 *** (0.1693)	1.212 *** (0.3984)
agr3	0.5659 *** (0.1614)	-0.0682 (0.3667)	0.6726 *** (0.1646)	0.0754 (0.3757)
agr4	0.3807 *** (0.1239)	-0.1201 (0.2875)	0.4973 *** (0.124)	0.0087 (0.2912)
pst1	-3.7076 *** (0.9102)	-5.1257 ** (2.2187)	-1.8795 ** (0.9058)	-4.6704 ** (2.1962)
pst2	2.0051 *** (0.386)	1.1779 (0.9645)	2.4822 *** (0.4023)	1.2225 (0.9785)
pst3	3.605 *** (0.3054)	2.7779 *** (0.7189)	2.6033 *** (0.3136)	2.2929 *** (0.7336)
pst4	1.0467 *** (0.2118)	0.5431 (0.4974)	0.9136 *** (0.2311)	0.4974 (0.5249)
urb00	1.6907 *** (0.2429)	1.0064 * (0.5865)	1.799 *** (0.2508)	1.0539 * (0.5983)
oth00	1.7594 *** (0.2667)	0.2513 (0.4727)	1.7154 *** (0.2676)	0.3347 (0.468)
y2003	0.0677 * (0.0358)	0.0709 *** (0.0266)	0.0696 (0.0552)	0.0754 ** (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 10: Models based on the triangulation neighborhood matrix

C Models with fixed effects per RBD

Variable	OLS	RE	SEM	SEM-RE
(Intercept)	1.6902 *** (0.1528)	1.8905 *** (0.2502)	1.7285 *** (0.1612)	1.94 *** (0.2623)
AgenceAG	0.1961 *** (0.0368)	0.1598 * (0.0871)	0.1918 *** (0.0391)	0.1576 * (0.0939)
AgenceAP	0.0198 (0.0543)	0.0437 (0.1307)	0.0413 (0.0605)	0.0557 (0.1466)
AgenceRM	0.1122 ** (0.0497)	0.1073 (0.1217)	0.1523 *** (0.0521)	0.1427 (0.128)
AgenceRMC	0.4046 *** (0.0424)	0.3909 *** (0.1022)	0.3937 *** (0.0448)	0.3802 *** (0.1089)
AgenceSN	-0.2935 *** (0.0384)	-0.2734 *** (0.0948)	-0.268 *** (0.0404)	-0.2432 ** (0.1003)
Texture (cl. 2)	-0.0512 (0.076)	0.0774 (0.1848)	-0.024 (0.0745)	0.1129 (0.1832)
Texture (cl. 3)	-0.1542 ** (0.0764)	-0.0696 (0.1884)	-0.1435 * (0.0778)	-0.068 (0.1936)
Texture (cl. 4)	-0.0063 (0.1135)	0.129 (0.2807)	0.0119 (0.1129)	0.1462 (0.282)
rain_cv	-0.0144 (0.0415)	-0.0014 (0.0321)	-0.0141 (0.0473)	-0.0012 (0.0366)
T	-0.0023 (0.0107)	0.0086 (0.0126)	-0.005 (0.0117)	0.0043 (0.0147)
agr1	1.1388 *** (0.1827)	0.8366 ** (0.4098)	1.1297 *** (0.1809)	0.9149 ** (0.4124)
agr2	1.4614 *** (0.1774)	1.1449 *** (0.3971)	1.5365 *** (0.1764)	1.3052 *** (0.4017)
agr3	0.8215 *** (0.1571)	0.2478 (0.3438)	0.8577 *** (0.158)	0.2961 (0.3513)
agr4	1.0714 *** (0.131)	0.586 ** (0.2891)	0.9826 *** (0.1301)	0.5151 * (0.2929)
pst1	0.5934 (0.916)	-1.1452 (2.1058)	0.1344 (0.9282)	-2.1728 (2.1414)
pst2	3.719 *** (0.3959)	2.7871 *** (0.9286)	3.4522 *** (0.41)	2.3473 ** (0.9689)
pst3	2.7934 *** (0.2957)	2.2973 *** (0.6534)	2.6781 *** (0.2979)	2.2211 *** (0.6732)
pst4	1.9861 *** (0.2156)	1.6212 *** (0.4986)	1.9021 *** (0.2239)	1.5279 *** (0.5233)
urb00	2.9445 *** (0.2567)	2.2645 *** (0.5941)	2.7912 *** (0.2611)	2.0658 *** (0.613)
oth00	1.4824 *** (0.2588)	0.4097 (0.4465)	1.3751 *** (0.2603)	0.3045 (0.4508)
y2003	0.0835 ** (0.0339)	0.0737 *** (0.0267)	0.0861 ** (0.0409)	0.0778 ** (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 11: Models based on the contiguity neighborhood matrix, RBD fixed effects (Loire-Bretagne as reference)

Variable	OLS	RE	SEM	SEM-RE
(Intercept)	1.6902 *** (0.1528)	1.8905 *** (0.2502)	1.7511 *** (0.1611)	1.9566 *** (0.2626)
AgenceAG	0.1961 *** (0.0368)	0.1598 * (0.0871)	0.198 *** (0.0397)	0.1607 * (0.0948)
AgenceAP	0.0198 (0.0543)	0.0437 (0.1307)	0.0401 (0.0608)	0.0539 (0.1468)
AgenceRM	0.1122 ** (0.0497)	0.1073 (0.1217)	0.1629 *** (0.0526)	0.1504 (0.1288)
AgenceRMC	0.4046 *** (0.0424)	0.3909 *** (0.1022)	0.4002 *** (0.0457)	0.3847 *** (0.1106)
AgenceSN	-0.2935 *** (0.0384)	-0.2734 *** (0.0948)	-0.2669 *** (0.0407)	-0.2417 ** (0.1009)
Texture (cl. 2)	-0.0512 (0.076)	0.0774 (0.1848)	-0.0271 (0.0739)	0.1129 (0.1818)
Texture (cl. 3)	-0.1542 ** (0.0764)	-0.0696 (0.1884)	-0.1495 * (0.078)	-0.0711 (0.1937)
Texture (cl. 4)	-0.0063 (0.1135)	0.129 (0.2807)	-0.0016 (0.1122)	0.1399 (0.2801)
rain_cv	-0.0144 (0.0415)	-0.0014 (0.0321)	-0.0152 (0.0478)	-0.0032 (0.0368)
T	-0.0023 (0.0107)	0.0086 (0.0126)	-0.0061 (0.0118)	0.0039 (0.0148)
agr1	1.1388 *** (0.1827)	0.8366 ** (0.4098)	1.1076 *** (0.1795)	0.8956 ** (0.4103)
agr2	1.4614 *** (0.1774)	1.1449 *** (0.3971)	1.5244 *** (0.176)	1.293 *** (0.4014)
agr3	0.8215 *** (0.1571)	0.2478 (0.3438)	0.8571 *** (0.1585)	0.2828 (0.352)
agr4	1.0714 *** (0.131)	0.586 ** (0.2891)	0.9825 *** (0.1304)	0.5101 * (0.2936)
pst1	0.5934 (0.916)	-1.1452 (2.1058)	0.1952 (0.929)	-2.1582 (2.1414)
pst2	3.719 *** (0.3959)	2.7871 *** (0.9286)	3.4851 *** (0.4109)	2.362 ** (0.969)
pst3	2.7934 *** (0.2957)	2.2973 *** (0.6534)	2.5914 *** (0.2971)	2.1452 *** (0.6724)
pst4	1.9861 *** (0.2156)	1.6212 *** (0.4986)	1.8969 *** (0.224)	1.5218 *** (0.5233)
urb00	2.9445 *** (0.2567)	2.2645 *** (0.5941)	2.7627 *** (0.2596)	2.0245 *** (0.6092)
oth00	1.4824 *** (0.2588)	0.4097 (0.4465)	1.3342 *** (0.2587)	0.2718 (0.4491)
y2003	0.0835 ** (0.0339)	0.0737 *** (0.0267)	0.0872 ** (0.0417)	0.0784 ** (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 12: Models based on the contiguity-upstream neighborhood matrix, RBD fixed effects (Loire-Bretagne as reference)

Variable	OLS	RE	SEM	SEM-RE
(Intercept)	1.6902 *** (0.1528)	1.8905 *** (0.2502)	1.7733 *** (0.1638)	1.9776 *** (0.2628)
AgenceAG	0.1961 *** (0.0368)	0.1598 * (0.0871)	0.1789 *** (0.0396)	0.1447 (0.0938)
AgenceAP	0.0198 (0.0543)	0.0437 (0.1307)	0.0372 (0.0605)	0.0491 (0.1448)
AgenceRM	0.1122 ** (0.0497)	0.1073 (0.1217)	0.1151 ** (0.0524)	0.1022 (0.1276)
AgenceRMC	0.4046 *** (0.0424)	0.3909 *** (0.1022)	0.3729 *** (0.0453)	0.3604 *** (0.1086)
AgenceSN	-0.2935 *** (0.0384)	-0.2734 *** (0.0948)	-0.2823 *** (0.0407)	-0.2608 *** (0.1001)
Texture (cl. 2)	-0.0512 (0.076)	0.0774 (0.1848)	-0.047 (0.0754)	0.0832 (0.1845)
Texture (cl. 3)	-0.1542 ** (0.0764)	-0.0696 (0.1884)	-0.1291 (0.0786)	-0.0598 (0.1937)
Texture (cl. 4)	-0.0063 (0.1135)	0.129 (0.2807)	-0.0191 (0.1129)	0.1244 (0.2801)
rain_cv	-0.0144 (0.0415)	-0.0014 (0.0321)	-0.0159 (0.0482)	0.0013 (0.037)
T	-0.0023 (0.0107)	0.0086 (0.0126)	-0.0039 (0.0119)	0.0036 (0.015)
agr1	1.1388 *** (0.1827)	0.8366 ** (0.4098)	1.063 *** (0.1819)	0.8622 ** (0.4138)
agr2	1.4614 *** (0.1774)	1.1449 *** (0.3971)	1.3426 *** (0.1753)	1.147 *** (0.3987)
agr3	0.8215 *** (0.1571)	0.2478 (0.3438)	0.8159 *** (0.1587)	0.2913 (0.3525)
agr4	1.0714 *** (0.131)	0.586 ** (0.2891)	0.9973 *** (0.1303)	0.5616 * (0.293)
pst1	0.5934 (0.916)	-1.1452 (2.1058)	0.7642 (0.9058)	-1.4384 (2.1006)
pst2	3.719 *** (0.3959)	2.7871 *** (0.9286)	3.7656 *** (0.4044)	2.6632 *** (0.952)
pst3	2.7934 *** (0.2957)	2.2973 *** (0.6534)	2.4554 *** (0.3004)	2.0268 *** (0.6726)
pst4	1.9861 *** (0.2156)	1.6212 *** (0.4986)	1.7912 *** (0.2267)	1.461 *** (0.5265)
urb00	2.9445 *** (0.2567)	2.2645 *** (0.5941)	2.7822 *** (0.2595)	2.1016 *** (0.6057)
oth00	1.4824 *** (0.2588)	0.4097 (0.4465)	1.4431 *** (0.2627)	0.4369 (0.4474)
y2003	0.0835 ** (0.0339)	0.0737 *** (0.0267)	0.0866 ** (0.0431)	0.0792 ** (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 13: Models based on the triangulation neighborhood matrix, RBD fixed effects (Loire-Bretagne as reference)

826 **D Land use model**

827 Land use shares are aggregated following the rules provided in Table 14. The data used for the land
 828 use model (Equation 5) is summarized in Table 15. Table 16 presents the estimated coefficients of the
 829 model.

Land Cover class	CLC value	LU class
1 Artificial Surfaces	1, ..., 11	Urban
2 Agricultural Areas	12, ..., 22	Agriculture
3.1 Forests	23, ..., 25	Forest
3.2 Shrub and/or herbaceous vegetation associations	26, ..., 29	Other
3.3 Open spaces with little or no vegetation	30, ..., 34	Other
4 Wetlands	35, ..., 39	Other
5 Water bodies	40, ..., 44	Other

Table 14: Extract from the CLC classification and the corresponding LU aggregation

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
<i>Source:</i> CLC 2000					
<i>Scale:</i> aggregated at 8 km x 8 km					
Shadow price	Land shadow price (k€/ha)	0.554	0.218	0	1.11
<i>Source:</i> AROPAj v.2 (2002)					
<i>Scale:</i> NUTS 2 and lower					
For revenue	Forestry revenues (€/ha)	137.683	66.509	28.934	308.043
<i>Source:</i> FFSM++, 2006					
<i>Scale:</i> NUTS 2 scale					
830 Pop revenues	Households' revenues (k€/ year/ household)	12.308	3.239	0	41.802
<i>Source:</i> INSEE, 2000					
<i>Scale:</i> French <i>commune</i>					
Pop density	Households density (households/ ha)	5.432	2.274	2.75	58.722
<i>Source:</i> INSEE, 2000					
<i>Scale:</i> 200 m x 200 m grid					
Slope	Slope (%)	4.325	6.155	0	47.721
<i>Source:</i> GTOPO 30					
<i>Scale:</i> 30 arc sec \sim 1 km					
Texture	Soils' texture classes	1	2	3	4
	Number of cells	1242	4820	3120	579
<i>Source:</i> JRC, Panagos et al. (2012)					
<i>Scale:</i> 1:1000000					

Table 15: Summary statistics of land use shares and the explanatory variables

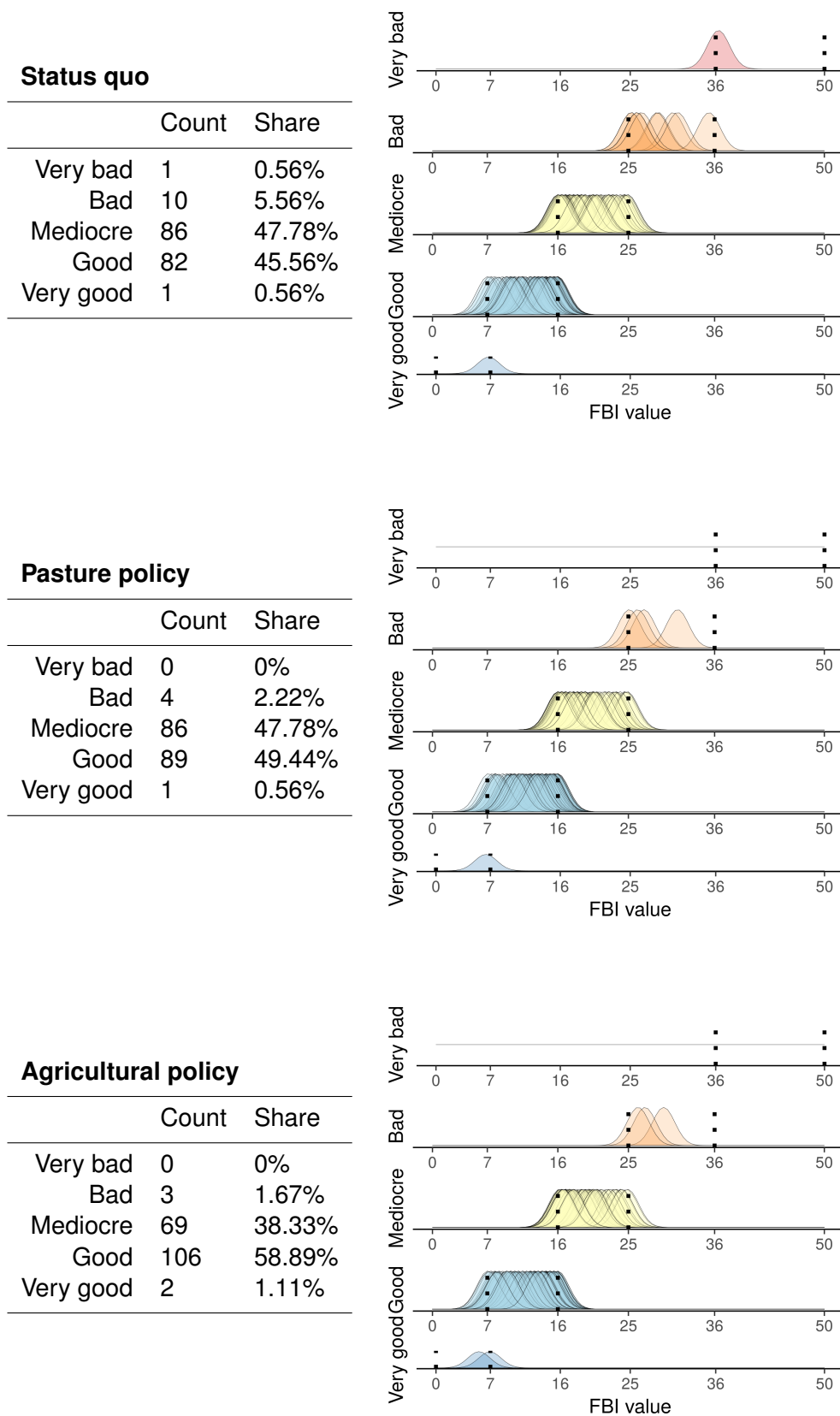
	<i>Dependent variable:</i>		
	ln(agr/oth)	ln(for/oth)	ln(urb/oth)
	(1)	(2)	(3)
Constant	2.644*** (0.618)	3.151*** (0.599)	-6.376*** (0.551)
Shadow price (spat)	0.888*** (0.303)	-0.406 (0.303)	0.568* (0.304)
For. revenues	0.003*** (0.001)	0.003*** (0.001)	0.004*** (0.001)
Pop. density	-0.131*** (0.013)	-0.145*** (0.014)	0.168*** (0.015)
Pop. Revenues	0.047*** (0.014)	0.062*** (0.014)	0.236*** (0.016)
Slope	-0.154*** (0.012)	0.027** (0.013)	-0.153*** (0.014)
Texture (cl.2)	0.668*** (0.098)	0.314*** (0.100)	0.509*** (0.111)
TXT2 Texture (cl.3)	1.186*** (0.115)	0.672*** (0.118)	0.896*** (0.129)
Texture (cl.4)	1.780*** (0.159)	0.980*** (0.163)	0.920*** (0.180)
Shadow price (W2)	1.542* (0.841)	-0.645 (0.820)	0.837 (0.765)
For. revenues (W2)	0.011*** (0.002)	0.008*** (0.002)	0.011*** (0.002)
Pop. density (W1)	-0.239*** (0.035)	-0.215*** (0.036)	-0.165*** (0.037)
Pop. Revenues (W1)	-0.011 (0.029)	-0.029 (0.029)	0.096*** (0.029)
Slope (W1)	-0.138*** (0.019)	-0.118*** (0.019)	-0.098*** (0.019)
Texture (cl.2, W1)	0.112 (0.096)	0.210** (0.098)	0.341*** (0.106)
Texture (cl.3, W1)	0.132 (0.094)	0.246** (0.095)	0.201** (0.103)
Texture (cl.4, W1)	0.245** (0.105)	0.083 (0.107)	0.194* (0.115)
<i>N</i>	9761		
R2	0.635	0.443	0.558
Moran's <i>I</i>	0.438***	0.402***	0.343***
λ	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 16: SDEM estimates for the land use model

831 E Simulations scenarios: water quality and prediction in- 832 tervals

833 Figures 7, 8 and 9 represent the number of hydrographic sectors in each water quality
834 class and for each climate change and policy scenario. The water quality class for each
835 sector is assigned given the estimated FBI index value for the sector. The latter estimates
836 are subject to prediction errors and for this reason we have also provided the distribution
837 of the predictions in each water quality class (second column in figures 7, 8 and 9). For
838 instance, in the “Status quo” case under current climate presented in the top row of figure
839 7, there are ten sectors that are classified as being in water quality class “Bad” which
840 represent 5.56% of all sectors (table on the left in the top row). The predicted intervals
841 for the FBI index for these ten sectors are represented on the right. We can see that in
842 this case there are two sectors that have an important part of their prediction distributions
843 below the threshold value of 25. There is also one sector that overlaps with the “Very bad”
844 class (values above 36).



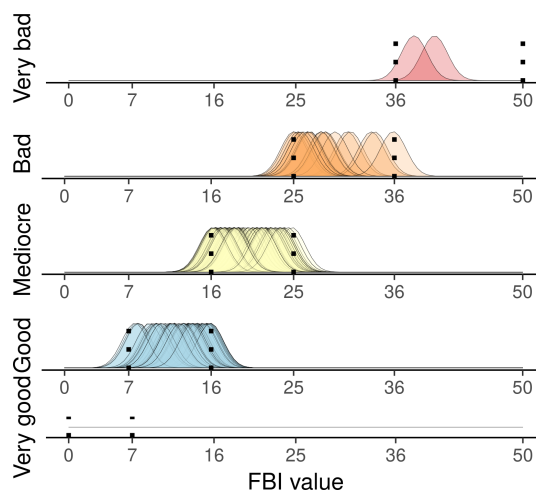
Water quality classes: "Very good" ($FBI \leq 7$); "Good" ($FBI \in]7-16]$);
 "Mediocre" ($FBI \in]16-25]$); "Bad" ($FBI \in]25-36]$); "Very bad" ($FBI > 36$).

49

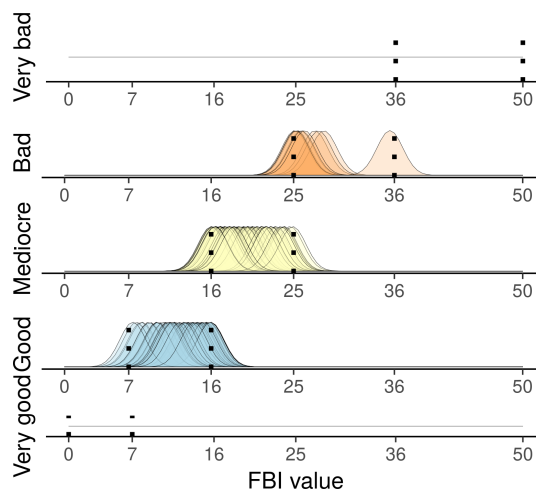
Figure 7: Summary results for water quality classes (first column) and FBI indexes' prediction intervals (second column) under current climate and for the two land use policies

B1, Status quo

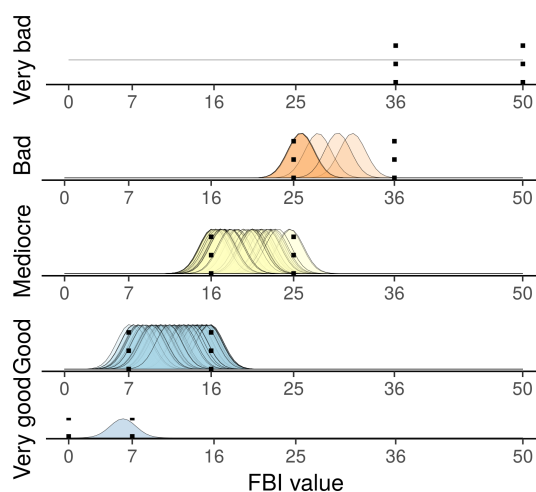
	Count	Share
Very bad	2	1.1%
Bad	19	10.5%
Mediocre	83	45.86%
Good	77	42.54%
Very good	0	0%

**B1, Pasture policy**

	Count	Share
Very bad	0	0%
Bad	11	6.08%
Mediocre	88	48.62%
Good	82	45.3%
Very good	0	0%

**B1, Agricultural policy**

	Count	Share
Very bad	0	0%
Bad	7	3.87%
Mediocre	72	39.78%
Good	101	55.8%
Very good	1	0.55%



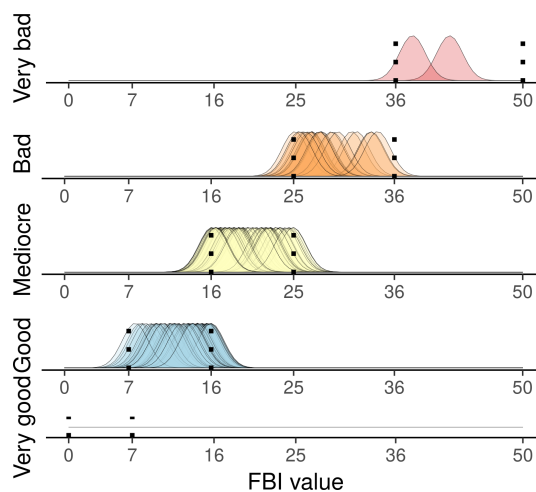
Water quality classes: "Very good" ($FBI \leq 7$); "Good" ($FBI \in]7-16]$);
 "Mediocre" ($FBI \in]16-25]$); "Bad" ($FBI \in]25-36]$); "Very bad" ($FBI > 36$).

50

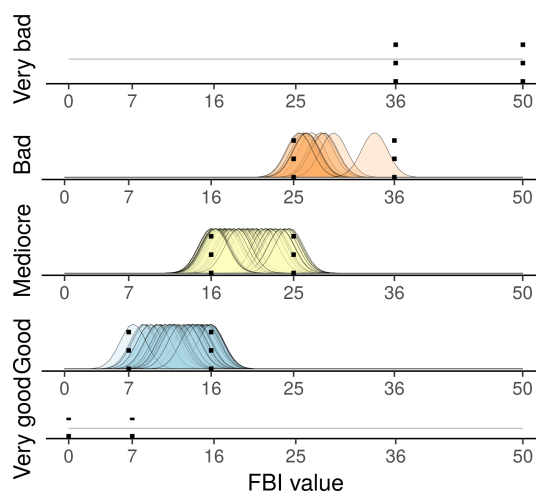
Figure 8: Summary results for water quality classes (first column) and FBI indexes' prediction intervals (second column) under B1 climate scenario and for the two land use policies

A2, Status quo

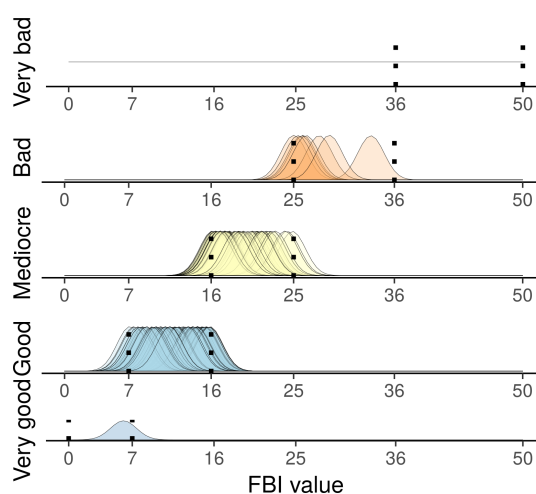
	Count	Share
Very bad	2	1.1%
Bad	21	11.6%
Mediocre	88	48.62%
Good	70	38.67%
Very good	0	0%

**A2, Pasture policy**

	Count	Share
Very bad	0	0%
Bad	12	6.63%
Mediocre	93	51.38%
Good	76	41.99%
Very good	0	0%

**A2, Agricultural policy**

	Count	Share
Very bad	0	0%
Bad	8	4.42%
Mediocre	81	44.75%
Good	91	50.28%
Very good	1	0.55%



Water quality classes: "Very good" ($FBI \leq 7$); "Good" ($FBI \in]7-16]$);
 "Mediocre" ($FBI \in]16-25]$); "Bad" ($FBI \in]25-36]$); "Very bad" ($FBI > 36$).

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Figure 9: Summary results for water quality classes (first column) and FBI indexes' prediction intervals (second column) under A2 climate scenario and for the two land use policies