

Integrated models and scenarios of climate, land use and common birds dynamics

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Abstract

Reconciling food, fiber and energy production with biodiversity conservation is among the greatest challenges of the century, especially in the face of climate change. Model-based scenarios linking climate, land use and biodiversity can be exceptionally useful tools for decision support in that perspective. Here we present a modeling framework that links climate projections, private land use decisions including farming, forest and urban uses and the abundances of common birds as an indicator of biodiversity. One of the major originalities is to integrate the effect of climate change on the economic drivers of land use using fine-scale data from France. Different economic and conservation scenarios, coupled with a regionalized projection of climate change (IPCC SRES A1B) are compared in terms of impacts on land use and biodiversity over the next four decades. Our analysis indicates that the effect of climate dominates the effects of land use and conservation policy on bird abundances at the national scale. Moreover, global environmental changes turn out to be globally detrimental for biodiversity. Only a moderate number of bird species and locations appear to profit from habitat-based conservation.

Keywords: Climate change ; land use ; conservation policy ; econometrics ; common birds.

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Contents

1	Introduction	3
2	Material and methods	5
2.1	Data	5
2.1.1	Bird abundances	5
2.1.2	Land Use Changes	6
2.1.3	Economic returns	7
2.1.4	Biophysical attributes	8
2.2	Models	9
2.2.1	Species Distribution Models	9
2.2.2	Econometric model of Land Use Changes	10
2.2.3	Models of economic returns	12
2.2.4	Simulation of scenarios	13
3	Results	16
3.1	Climate change impacts on birds without LUC (scenario S0)	16
3.2	Climate change with extrapolated trends of LUC (scenario S1)	18
3.3	Climate change with climate-induced LUC (scenario S2)	20
3.4	Climate change with conservation policy (scenarios S3 and S4)	22
4	Discussion	24
4.1	Ecological models	24
4.2	Econometric models	26
4.3	Climate scenario	27
4.4	Conservation policy	28
4.5	Conclusion	29
5	Acknowledgements	30

1 Introduction

Climate and Land Use Changes (LUC) are considered to be two of the main drivers of past and future changes in terrestrial biodiversity (MA 2005, Pereira et al. 2010; Willis and MacDonald 2011). For medium-term prospective analyses (ca. 50 yrs) these two drivers can be treated very differently in terms of scenarios and possibilities for intervention for biological conservation policy. At this temporal horizon, global warming can reasonably be considered as exogenous since climate projections foresee that most of the climate change over this period is already committed (i.e., are relatively independent of greenhouse gas emissions scenarios, IPCC 2007; Rogelj et al. 2012). By contrast, LUC are potentially under much greater control of national and local decision makers and therefore seen as more controllable drivers for conservation policies. However, some of these present and future LUC are likely to be influenced by climate change. It is clear that local opportunities and constraints appear when climate changes and that humans adapt their use of land resources. For example, there are already signs of negative impacts of recent climate warming on corn and wheat yields, and models foresee that future climate change will result in projected northward shifts of maize area in the United States, or rice area in China (Brisson et al., 2010; Lobell et al., 2011; Tubiello et al., 2002; Xiong et al., 2009). Consequently, an efficient conservation policy has to be based both on the direct climate effect on species communities and the indirect effects induced by human adaptations, strategies and public policies (Hannah et al., 2002; Berrang-Ford et al., 2011). It requires the integration of ecological, environmental and anthropogenic dimensions accounting in particular for economic mechanisms. This paper presents an integrated bio-economic model as a way of exploring these interactions. We use a fine-scale analysis of continental France as a case study to demonstrate the insights that can be provided by this type of model.

We use the abundance of common bird species as our biodiversity metric, since birds are often regarded as good general indicators of the state of wildlife and of the countryside,

27 for both scientific and practical reasons (Furness and Greenwood, 1993; Gregory et al.,
28 2005). For our analysis, bird abundance data were extracted from a standardized, volunteer-
29 based monitoring program with a random initial selection of sites that results in habitat-
30 representative sampling efforts. Compared with threat status, population trends are updated
31 more frequently and thus have a higher temporal resolution. Habitat representativity is
32 crucial because it provides coherence with the land use mapping of all cover types in the
33 econometric model about LUC (agricultural areas, semi-natural areas but also urban areas.)
34 A high temporal resolution is necessary for both model calibration and extrapolation to the
35 future. In our analysis, the dynamics of bird species populations are related to climate and
36 habitat changes, based on the principals of Species Distribution Models (SDM). However, we
37 have modeled species population size rather than the probability of presence that is typically
38 predicted by SDM (Araújo et al., 2005; Guisan and Thuiller, 2005; Brotons et al., 2012;
39 Renwick et al., 2012). These models are based on ecological niche theory (Hutchinson, 1978),
40 and assume that habitat and climate requirements can be deduced from current distributions
41 and then distributions and population size can be extrapolated using projections of future
42 climate and habitat changes (Peterson et al., 2011).

43 To simulate future land use dynamics, an econometric model is used to estimate spatially
44 explicit LUC based on the assumption that land use decisions are functions of economic
45 returns as assessed by private decision makers (Stavins and Jaffe, 1990; Plantinga, 1996;
46 Nelson et al., 2008; Radeloff et al., 2012). Such models have been shown to be consistent
47 with classical economic theory and observations (Lubowski et al., 2008; Lewis et al., 2011).
48 Nevertheless, such models are very demanding in terms of data because knowledge of
49 potential economic return is required for each sampled land plot and each possible land use.
50 We circumvent this constraint by combining aggregated but exhaustive data about land prices
51 and precise data at each sampled land plot about biophysical attributes including topography,
52 land quality and climate. The econometric model is estimated on observed LUC (France,
53 1993–2003) in order to simulate spatially explicit LUC for different economic scenarios (for a

54 similar exercise in the U.S. but with different data choices, see [Radeloff et al. 2012](#)).

55 The third component of our bio-economic model takes into account the effect of climate
56 change on the economic returns of land within a Ricardian analysis. Based on the seminal
57 work of [Mendelsohn et al. \(1994\)](#) and extended for different regions of the world (see [Mendel-
58 sohn and Dinar, 2009](#) for a review), this consists in evaluating the consequences of climate
59 change on land profitability on the basis of the correlations between current land prices and
60 climate variables. Because land price is considered as the net present value of an infinite
61 flow of economic returns, the effect of projected climate on land prices is a proxy for its net
62 effect on the economic returns of land. With this structure in three modelling blocks (SDM,
63 LUC and Ricardian analysis), this integrated bio-economic model is used to simulate future
64 land uses and birds' distributions from the present to 2053 in 10 years time slices.

65 **2 Material and methods**

66 **2.1 Data**

67 **2.1.1 *Bird abundances***

68 We used bird data from the French Breeding Bird Survey (FBBS), a standardized monitoring
69 scheme in which skilled volunteer ornithologists identify breeding birds by song or visual
70 contact in spring ([Jiguet et al., 2012](#)). In FBBS, each observer provides the name of her
71 municipality, and a 2×2 km square to be prospected is randomly selected within a 10 km
72 radius from the gravity center of this municipality. In each square, the observer monitors
73 10 point counts separated by at least 300 m twice per spring (4 to 6 weeks between the
74 sessions, 5 minutes each). Counts were repeated yearly by the same observer at the same
75 points, on about the same date (with a maximum difference of 7 days within April to mid
76 June) and at the same time of day (with a maximum difference of 15 minutes). FBBS data

77 contribute to European official index of biodiversity and have been extensively used to study
78 the effects of climate and LUC on bird populations (Barbet-Massin et al., 2011; Barnagaud
79 et al., 2012), as well as the effects of farmers' preferences (Mouysset et al., in press) and the
80 effects of agro-environmental policies (Mouysset et al., 2011, 2012). To simultaneously smooth
81 annual noise and model the observed dynamics, FBBS data are used at two points of time,
82 2003 and 2009. For each species and each FBBS square, bird abundances are respectively
83 defined as the maximum number of counts 2002–2004 ($n = 1,031$) and 2008–2010 ($n = 1,380$).
84 FBBS provides also a description of the habitats of the surveyed squares. Even if this
85 information cannot be used to describe the national dynamics of LUC, they appear to be
86 better predictors of the bird population than the aggregation of more exhaustive data at the
87 scale of FBBS squares. So the SDM are estimated with FBBS habitats description and each
88 FBBS observation is weighted in the regressions according to its significance in terms of local
89 land use.

90 **2.1.2 Land Use Changes**

91 Data about LUC are extracted from the TERUTI survey which was carried out every year
92 1992–2003 by the statistical services of the French Ministry of Agriculture. The TERUTI
93 survey counts about 550,000 points for which we know the location in terms of French
94 municipalities: the finest administrative delineation ($n \approx 36\,500$, median area: 10.73 km^2).
95 The TERUTI survey uses a systematic area frame sampling with a two-stage sampling
96 design. In the first stage, the total national area is divided into a $12 \times 12 \text{ km}$ grid. For each
97 of these 4,700 regular meshes there are 4 aerial photographs which cover 3.5 km^2 each. In
98 the second stage, on each photograph, a 6-by-6 grid determines the 36 points to be surveyed
99 in June by an agent on the ground. Each point corresponds to a homogeneous unit in terms
100 of land use and statistically represents about 100 hectares (ha) at the *département* scale
101 ($n = 95$, median area: $5,880 \text{ km}^2$). On the basis of the detailed classification of land uses (81
102 items) we attribute to each plot a use among 5 more aggregate items: annual crop, pasture,

103 perennial crop, forest or urban. These data have already be used to estimate econometric
104 LUC models by [Chakir and Parent \(2009\)](#) and [Chakir and Le Gallo \(2012\)](#) but not for the
105 whole of France and at a such disaggregate level. They have been similarly merged with a
106 subset of the avian data that are used here, at the national scale ([Devictor et al., 2007, 2008](#)),
107 but not in relation with the economic incentives of landowners' choices.

108 **2.1.3 *Economic returns***

109 For the estimation of the econometric model of LUC, the price of land is used to compute the
110 expected net returns from different agricultural land uses. Defining land price as the net
111 present value of expected future rents is standard in the economic theory ([Ricardo, 1817](#);
112 [Goodwin et al., 2003](#)). This approach, detailed in [subsubsection 2.2.3](#), uses data about land
113 prices that also come from the statistical services of the French Ministry of Agriculture. Yearly
114 prices 1990–2005 are available for three land uses (annual crops, pastures and perennial
115 crops) and for the 713 Small Agricultural Regions (SAR) of France. SAR size ranges from
116 11 to 4,413 km² with an homogeneity in terms of both agro-ecological and economic levels,
117 reducing intra-SAR heterogeneity ([Mouysset et al., 2012](#)). For the two others considered land
118 uses – forest and urban – the approximations of economic returns are computed differently
119 and at different geographic scales. For the expected net returns from forest, we use data
120 about wood raw production (in m³), total forest area (in ha) and wood prices (in current euro
121 per ha), all available annually at the scale of the French *départements*. We compute the
122 expected returns from forest by multiplying the aggregate production by its unitary price
123 and dividing the result by the total forest area of each *département*. Because this calculation
124 provides the net returns per total forested area, it implicitly takes into account that only a
125 part of the forest area is harvested each year (with a harvested share closely related to the
126 length of rotations). It is nevertheless based on the assumption of a myopic agent who makes
127 decisions based on the hypothesis that future returns will be the same as today and neglect
128 production costs. The urban returns are approximated by the population densities at the fine

129 scale of the municipalities on the basis of the national census of French population (source:
130 <http://www.insee.fr/en/bases-de-donnees/default.asp?page=recensements.htm>, last accessed:
131 February 18, 2013).

132 **2.1.4 Biophysical attributes**

133 Biophysical attributes of sampled TERUTI plots include both topographic and climate
134 variables. Topography of each plot was generated by coupling a Digital Elevation Model
135 of France (resolution of 250 meters, see <http://professionnels.ign.fr/rgealti>, last accessed:
136 February 18, 2013) with the spatial geo-referencement of plots. Within a Geographical
137 Information System (GIS), we calculated the elevation, the slope, the roughness and the
138 exposition of each TERUTI sampled plot. Soil quality variables were extracted from the
139 French soil database developed by the National Institute for Agricultural Research and
140 matched by GIS. The initial data are available at the 1:1,000,000-scale ([Jamagne et al. 1995](#),
141 <http://www.gissol.fr/programme/bdgsf/bdgsf.php>, last accessed: February 18, 2013) and they
142 were downscaled to a 1-km grid with pedotransfert rules ([Cheaib et al., 2012](#)). They provide
143 measures of the agricultural fertility of plots: plant available water capacity and soil depth.

144 We use historical (1990–2010) and projected (2010–2053) climate data, both available
145 at the same spatial resolution (8×8 km rasters) with a smooth transition between his-
146 torical and future climate. Climate data include 13 variables about temperatures (annual
147 means, maximum and minimum, bird breeding period means April–August and seasonality
148 approximated by standard deviation), precipitations (annual means, maximum and min-
149 imum, breeding period means and seasonality), solar radiation (breeding period means),
150 relative humidity (breeding period means) and wind (breeding period means). Regionalized
151 climate scenarios are based on the Intergovernmental Panel of Climate Change’s SRES A1B
152 greenhouse gas emissions scenario A1B coupled with the *Météo-France Arpège* climate model
153 ([Déqué, 2007](#)). Regionalized climate projections were produced with a multivariate statistical
154 downscaling methodology, which is able to generate local time series of temperature and

155 precipitation, and other climatic variables at different sites (Boé et al., 2009). The model is
 156 based on large-scale circulation predictors, here the mean sea-level pressure field, as well as
 157 the 2-meter temperature averaged over France. It starts from regional climate properties to
 158 establish discriminating weather types for the chosen local variable. Intra-type variations
 159 of the relevant forcing parameters are then taken into account by multivariate regression
 160 using the distances of a given day to the different weather types as predictors. The final step
 161 consists of conditional re-sampling (for further details in climate downscaling see Boé et al.,
 162 2009 and Cheaib et al., 2012).

163 2.2 Models

164 2.2.1 Species Distribution Models

165 Bird populations are modeled with Species Distribution Models (SDM) that are viewed as
 166 providing a first approximation of the potential impact of climate and habitat changes on
 167 biodiversity (Pearson and Dawson, 2003). For a general description of the method, we note
 168 μ_{tqs} the abundance of species s in the FBBS square q at the time t and we assume the
 169 following relationship between the outcome and its predictors:

$$\log(\mu_{qst}) = \lambda_s(\mathbf{c}_{qt}, \mathbf{h}_{qt}, \mathbf{x}_q, \mathbf{z}_q) + \delta_s \cdot t, \quad (1)$$

170 where the $\lambda_s(\cdot)$ are spline-based smoothing functions with an endogenous structure as
 171 it is common for Generalized Additive Models (Hastie and Tibshirani, 1990). They have to
 172 be estimated, as the scalars δ_s that capture the linear growth 2003–2009 for each species
 173 s , all other things equal. \mathbf{c}_{qt} stands for the values at location q and time t of the two first
 174 axes of a principal component analysis on the matrix of climatic variables. The Figure SM1
 175 of Supplementary Material (SM) shows the locations of the initial variables in terms of
 176 their principal axes that account for 87% of variance. \mathbf{h}_{qt} is the vector of habitat variables

177 including a fragmentation index, \mathbf{x}_q represents a vector of topographic variables while \mathbf{z}_q
178 is the spatial coordinates of the gravity center of each FBBS square. Including the spatial
179 coordinates inside the smoothed function allows us to separate the unobserved contextual
180 effects (i.e., inter-species competition, spillovers from anthropogenic perturbations) from the
181 direct topographic, climatic and habitat effects. Because birds' abundances are over-dispersed
182 positive integers, they are modeled as a distribution from the negative binomial family. The
183 function `gam()` from the R package `mgcv` 1.7 was used to estimate such models (Wood, 2006).

184 **2.2.2 *Econometric model of Land Use Changes***

185 We have reduced land use types to five ($L = 5$) exhaustive and mutually exclusive categories.
186 In our case study, land uses refer to annual crop, perennial crop, pasture, forest and urban.
187 Landowners are assumed to choose LUC in order to maximize their utility and these choices
188 are assumed to be independent for each parcel. With this latter assumption, we can associate
189 each plot of land with a distinct decision maker. In particular, a stylized landowner i chooses
190 the use ℓ_{it}^* on a plot if this provides the highest utility from all uses that are possible. The
191 following formula:

$$\ell_{it}^* = \arg \max_{\ell} \{u_{i\ell t}\} \quad (2)$$

192 is connected to the behavioral assumption of rationality. But rationality is not a necessary
193 condition, as Train (2009) explains: “The models can also be seen as simply describing the
194 relation of explanatory variables to the outcome of a choice, without reference to exactly how
195 the choice is made.” Utility $u_{i\ell t}$ is net of conversion costs from the previous land use (in
196 period $t - 1$), we comment this point later. This formulation for utility is forward-looking and
197 allows the possibility of multi-year LUC as perennial crop, forest or urban. In the literature
198 (Plantinga, 1996; Lubowski et al., 2008), utility is assumed to be the expected one-period
199 net returns that come from a dynamic optimization problem. We exploit this result here

200 by assuming a parametric but nevertheless flexible structure between the expected returns
 201 and utility. At t , for each land use ($\forall \ell = 1, \dots, L$) and for each sampled plot ($\forall i = 1, \dots, I$), we
 202 assume:

$$u_{i\ell t} = \alpha_\ell + \widehat{\mathbf{r}}_{it}\boldsymbol{\beta}_{1\ell} + \mathbf{c}_{it}\boldsymbol{\beta}_{2\ell} + \mathbf{x}_i\boldsymbol{\beta}_{3\ell} + \widehat{\mathbf{r}}_{it}(\mathbf{c}_{it} + \mathbf{x}_i)\boldsymbol{\beta}_{4\ell} + \mathbf{h}_{it-1}\boldsymbol{\eta}_\ell + \epsilon_{i\ell t}. \quad (3)$$

203 Where $\widehat{\mathbf{r}}_{it}$ is the computed vector of net returns in t for each possible land uses on plot
 204 i . Because these variables are only available at the scale of the SAR, they are crossed with
 205 climate \mathbf{c}_{it} and biophysical variables \mathbf{x}_i to allow plot-level deviations from the aggregate
 206 returns. These two latter vectors come from a dimension reduction of initial variables by
 207 principal component analysis (see Figure SM1 of SM). Conversion costs between uses are
 208 taken into account (and proved to be strong determinants) by including $L - 1$ dummy variables
 209 representing the previous land use of plot i : \mathbf{h}_{it-1} . So, the vector $\boldsymbol{\eta}_\ell$ provides estimates of
 210 the costs to change to land use ℓ . Each vector of coefficients to estimate $[\alpha_\ell; \boldsymbol{\beta}_{\cdot\ell}; \boldsymbol{\eta}_\ell]$ is proper
 211 to a land use category ℓ . This means that expected economic returns, climate, biophysical
 212 variables and conversion costs could have heterogeneous effects on the utility, depending on
 213 the considered land use.

214 Because all the sources of landowner's utility cannot be observed, an error term $\epsilon_{i\ell t}$
 215 is included in eq.(3). The stochasticity of the model is only related to these unobserved
 216 components of utilities and their associated densities. [McFadden \(1974\)](#) identifies three
 217 standard hypothesis about errors that allow to obtain a multinomial logit model: indepen-
 218 dence, homoscedasticity and extreme value distribution (i.e., Gumbel). With these hypothesis,
 219 one can show that the probabilities have simple closed forms, which correspond to the logit
 220 transformation of the deterministic part of the utility ($\bar{u}_{i\ell t} \equiv u_{i\ell t} - \epsilon_{i\ell t}$). The probability that
 221 the land plot i is in use ℓ at the period t is:

$$p_{i\ell t} = \frac{\exp(\bar{u}_{i\ell t})}{\sum_k \exp(\bar{u}_{ikt})} = f_\ell(\widehat{\mathbf{r}}_{it}, \mathbf{c}_{it}, \mathbf{x}_i, \mathbf{h}_{it-1}). \quad (4)$$

222 The estimation was performed using `nnet` 7.3 and `mlogit` 0.2 on R. Another critical
 223 part of the model is that the unobserved factors have to be uncorrelated over alternatives
 224 and periods, as well as having the same variance for all alternatives and periods. These
 225 assumptions, used to provide a convenient form for the choice probability, are found to be not
 226 restrictive (homoscedasticity cannot be rejected by a score test, p -value= 0.283). Moreover,
 227 these hypothesis are associated with the classical restriction of Independence of Irrelevant
 228 Alternatives for which Hausman-McFadden specification tests are performed, with mixed
 229 evidence. The independence is not rejected for three uses: pasture, perennial crop and
 230 urban (p -values are respectively 0.001, 0.005 and 0.036) but rejected for annual crop and
 231 forest at 5%. This means that the 3 formers choices can be dropped from the choice set
 232 without modifying significantly the parameters of the model (i.e., they are robust to the IIA
 233 restriction) a property which is not true for the 2 latter.

234 **2.2.3 Models of economic returns**

235 As noted above, the price of land is used to compute the expected net return from land use.
 236 To understand this, land is considered as a classical fixed asset. This implies that its price
 237 $v_{\ell t}$ at time t for the use ℓ is equal to the net present value of all expected future rents that
 238 keeping it in its current use allows to earn. Assuming flat interest rates $\tau_t = \tau$ and flat rates
 239 of capital gains $g_t = g$, this reads as follows:

$$v_{\ell t} = \sum_{s=1}^{\infty} \frac{\mathbb{E}_t(r_{\ell t+s})}{\prod_{j=1}^s (1 + \tau_{t+j})} = \sum_{s=1}^{\infty} \frac{\mathbb{E}_t(r_{\ell t+s})}{(1 + \tau)^s} = \sum_{s=1}^{\infty} \frac{\mathbb{E}_t(r_{\ell t+1})(1 + g)^s}{(1 + \tau)^s} = \frac{\mathbb{E}_t(r_{\ell t+1})}{(\tau - g)}, \quad (5)$$

240 The expectation operator at t is noted \mathbb{E}_t , and previous equalities use the well-known
 241 property of the sum of infinite geometric series. Thus, knowing or making an assumption
 242 about the difference between the interest rate and the rate of capital gains ($\tau - g$) is sufficient
 243 to compute the expected return of a land plot on the basis of its observed price: $\hat{r}_{\ell t} = (\tau - g) \cdot v_{\ell t}$.
 244 This result depends strongly on well-functioning (i.e., competitive and balanced) markets

245 and so has to be considered as a theoretically-consistent first approximation.

246 To model the effect of climate change on land prices $v_{\ell t}$ or, equivalently, on the expected
247 net returns $\hat{r}_{\ell t}$ of annual crop, pasture, perennial crop and forest, we use a Ricardian analysis
248 (Mendelsohn et al., 1994). The Ricardian equations relate the economic returns of land to
249 climate, other biophysical variables and geographical coordinates. The relation is specified
250 as follows:

$$\log(\hat{r}_{i\ell t}) = y_{\ell}(\mathbf{c}_{it}, \mathbf{x}_i, \mathbf{z}_i) + \gamma_{\ell} \cdot t, \quad (6)$$

251 with $y_{\ell}(\cdot)$ is a spline-based smooth function with endogenous structure which depends
252 of the considered land use. Thus, these GAM functions and the γ_{ℓ} are estimated on the
253 cross-sectional variations between SAR and the time series 1993–2003, accounting for the
254 capitalized value of climate and time in land returns. The models are estimated separately
255 for annual crop, pasture, perennial crop and forest using GAM with a distribution from
256 the Gaussian family with natural logarithm link (Wood, 2006). For the dynamics of the
257 urban returns, we use the spatialized previsions of population growth by INSEE. Because
258 demographic data are available at the *département* scale, they are downscaled by assuming
259 that each municipality keep a constant proportion of the aggregate values.

260 **2.2.4 Simulation of scenarios**

261 Our scenarios differentiate themselves by the dynamics of the deterministic part of utilities
262 of eq.(4). The estimated logit regression function $\hat{f}_{\ell}(\cdot)$ and the biophysical variables \mathbf{x}_i stay
263 constant between scenarios. But, depending on the considered scenario, the economic returns
264 $\hat{\mathbf{r}}_{it}$ and/or the climate variables \mathbf{c}_{it} are allowed to change. We consider 5 scenarios that are
265 presented in Table 1. They vary according to three dimensions: the extrapolation of current
266 trend, the inclusion of climate change and the presence of a conservation policy.

Table 1: The differences between scenarios in terms of factors from species distribution and land use change models

Scenario	Factors accounted for in models	
	Bird abundances	Land Use Changes (LUC)
S0	Trend + Climate Change	Constant
S1	Climate + Trend + LUC	Continued trend only
S2	Climate + Trend + LUC	Trend + Climate Change
S3	Climate + Trend + LUC	Trend + Payments for pasture
S4	Climate + Trend + LUC	Trend + Climate Change + Payments

Notes: Simulations of bird population by SDM pursue the observed 2001–2009 trends and integrate climate change in all scenarios. In scenario S0, land use is constant. In scenario S1, the model of LUC is used to extrapolate the temporal trends to obtain a kind of business-as-usual scenario. In scenario S2, the effects of climate change on the returns from land and, consequently, on LUC are taken into account. Scenario S3 and S4 are respectively equivalent to S1 and S2 with a conservation policy focusing on permanent pastures. See in the text for the details of the conservation policy.

267 Once the LUC econometric model is estimated, the direct predictions (without changing
268 exogenous variables) consist, for each plot i , in a fitted probability vector $\hat{\mathbf{p}}_{it}$ of being in
269 each use at t . Because the model is estimated on LUC 1993–2003, we consider 1993 as
270 the period $t = 0$ and 2003 as the period $t = 1$: our model is recursive with decennial steps.
271 Remembering that each TERUTI observation counts for 100 ha, the predicted probabilities
272 can be easily converted into predicted LUC. As an example, consider a plot i which counts
273 for 100 ha of annual crop in period 0 and has a predicted probability vector for period 1 of
274 $\hat{\mathbf{p}}_{i1} = (0.8, 0.15, 0.03, 0.01, 0.01)$. This means that 80 ha are predicted to not change their use,
275 15 ha to be converted to pasture, 3 ha to perennial crop, 1 ha to forest and 1 ha to urban
276 (probabilities $\hat{\mathbf{p}}_{i1}$ are in the order annual crop, pasture, perennial crop, forest, urban). Land
277 use at $t = 1$ is common to all scenarios and, for S0, it is the same at $t = 2$ (2013), $t = 3$ (2023),
278 $t = 4$ (2033), $t = 5$ (2043) and $t = 6$ (2053).

279 For the others scenarios, LUC simulation for $t = 2$ is performed by substituting the dy-
280 namics of certain exogenous variables in regression equations. For S1, only t is implemented
281 in the Ricardian equation (6) to obtain the economic returns $\hat{\mathbf{r}}_{i2}^{S1}$ that are plugged into the lo-
282 gistic equations (4). For S2, climate variables \mathbf{c}_{it} are implemented in the Ricardian equations

283 (6) as in the logistic equations (4). For both scenarios, we predict a probability matrix of land
 284 use in $t = 2$ conditionally on previous land use: $\hat{\mathbf{h}}_{i2} = \hat{\mathbf{p}}_{i2}(\mathbf{h}_{i1})$. One has nevertheless to note
 285 that this step in the simulation is facilitated by the knowledge of the previous use for each
 286 surveyed plots by the 2003 wave of the TERUTI survey: \mathbf{h}_{i1} . Things are different to simulate
 287 LUC after the period $t = 2$ for which we do not have a single previous use for each plot: we
 288 only know a vector of probabilities: $\hat{\mathbf{h}}_{i2}$. So the next LUC, for $t = 3$ but equally for $t = 4$, $t = 5$
 289 and $t = 6$, are computed differently. For each potential use ℓ on a plot i , the simulated land
 290 use is:

$$\hat{h}_{i\ell t} = \hat{\mathbf{p}}_{it}(\mathbf{h}_{it-1} = \mathbf{1}_\ell) \cdot \hat{\mathbf{h}}_{it-1}, \quad (7)$$

291 where $\mathbf{1}_k$ is a $1 \times L$ vector with the k -component equals to 1 and the others to zero. In
 292 other words, variables describing land use are still dummies to predict transition probabilities
 293 but they are values inside the unit interval to simulate land use. Because LUC transition
 294 probabilities are functions of expected returns of each land use, the inclusion of an incentive-
 295 based conservation policy (for S3 and S4) is straightforward. Here, to keep the paper short, we
 296 describe only the results to a permanent payment of 200 euros/ha for the pasture. Different
 297 taxes and/or subsidies on other land uses can also be implemented with our model, we let it
 298 for future researches. This conservation policy consists, for $t > 1$, in increasing the rents for
 299 pastures ($\ell = 3$) used to fit transition probabilities:

$$\hat{r}_{i3t}^{S3} = \hat{r}_{i3t}^{S1} + 200 \quad \text{and} \quad \hat{r}_{i3t}^{S4} = \hat{r}_{i3t}^{S2} + 200. \quad (8)$$

300 For the others uses, the respective economic returns of S3 and S4 are the same as S1 and
 301 S2. For all scenarios, LUC are used in the SDM of eq.(1) to predict bird abundances at the
 302 same spatial and temporal scales. At this final stage, these LUC effects are coupled with
 303 the direct effect of climate change on bird distribution. To evaluate the effects on birds we

304 use an abundance-based index: the geometric mean of current abundances normalized by
305 the abundances of the year 2003 ($t = 1$):

$$BI_{mt} = \prod_{s \in S} \left(\frac{\hat{\mu}_{ms}(t)}{\mu_{ms}(1)} \right)^{1/|S|} \quad (9)$$

306 where m is the geographical scale at which the index is computed, principally the France
307 to obtain national dynamics or the 12×12 km TERUTI mesh to obtain maps. Applied to
308 farmland specialists species, this index is the well-used European Farmland Bird Index
309 but we use it equally on birds species as a whole and for different habitat specializations:
310 generalist, forest and urban. Because this index aggregates potentially heterogeneous species'
311 trends, we use the formula from [Gregory et al. \(2005\)](#) to compute the associated standard
312 errors.

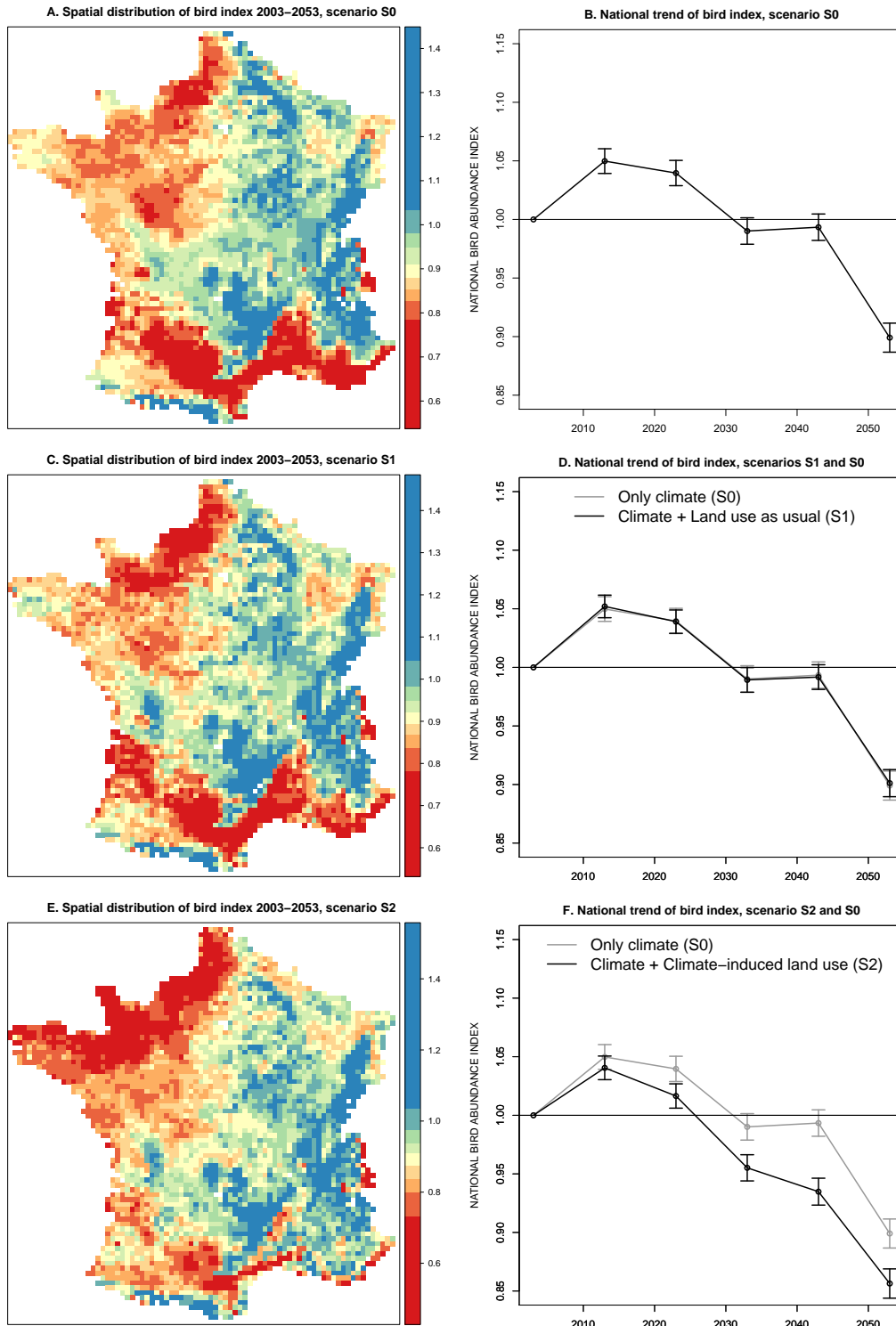
313 **3 Results**

314 **3.1 Climate change impacts on birds without LUC (scenario S0)**

315 The first scenario consists in predicting the effect of climate change on bird populations,
316 modifying only climate in the SDM. This means that land use is considered as constant.
317 Under the IPCC SRES A1B regionalized climate projection used here ([Cheaib et al., 2012](#)),
318 the annual temperature of France is projected to increase by $+ 2.02^\circ\text{C} \pm 0.23$ s.d. up to 2053.
319 The annual cumulative precipitation is projected to decrease by $- 13.40$ mm ± 6.3 s.d., the
320 relative humidity to decrease by $- 1.69$ % ± 1.2 s.d. and the solar radiation to increase by +
321 17.10 J ± 14.4 s.d. As displayed in the Panel B of [Figure 1](#) from a national viewpoint, the
322 effect of climate change on the aggregate bird index is first positive (+ 5% up to 2020), not
323 significant for 2030–2040 and strongly negative from 2040 onward ($- 10\%$ at 2053).

324 The spatial precision of the projected climate (8×8 km) allows us to model more precisely

Figure 1: The effects of climate and land use changes on the index of bird abundances for the scenarios without conservation: S0, S1 and S2.



325 than usual the geographical shifts in bird distributions. As the panel A of **Figure 1** shows,
326 the Mediterranean coast at the southeast and the center of the southwest are two regions
327 of important decline in bird populations. Some important (even if less strong) detrimental
328 effects appear as well in the northwest of France. In contrast, bird populations in the
329 continental part of the country – the east and the center – have high positive growth rates
330 (up to + 40%). These dynamics of bird populations are best explained by average 2003
331 temperatures and average elevation (respective Pearson’s correlations of – 0.51 and + 0.42,
332 both p -values < 0.001).

333 In this scenario, land use is constant but plays an important role in determining bird
334 population dynamics. The Figure SM2 of SM differentiates the direct effect of climate
335 according to species’ preference in terms of habitats. It shows that climate change up to
336 2053 is significantly detrimental for generalist species (about – 10%), forest specialists
337 (about – 30%) and urban specialists (about – 2.5%). In contrast, the model predicts that the
338 abundances of farmland specialists increase by about + 10% over this period, even if the
339 confidence interval is larger than the others. The mechanisms driving this effect are that
340 climate-induced shifts in bird species distributions are toward areas of more favorable land
341 uses for farmland specialists. Pastures are generally at higher elevation than annual crops.
342 The Figure SM3 provides the individual rates of variation for each bird species abundances
343 2003–2053. Climate change significantly impacts the large majority of species: the variations
344 of only 2 species are not significant, 21 species increase and 39 decrease.

345 **3.2 Climate change with extrapolated trends of LUC (scenario S1)**

346 This first scenario of LUC was simulated by extrapolating the 1993–2003 trends of economic
347 returns (see **subsection 2.2.4**). It is coupled with the previous S0 effect of climate change
348 on birds. Panel (a) of **Table 2** presents the national land allocation 2003–2053 with decennial
349 steps. The main insights are, as for the previous decade, the increase of annual crop, forest

350 and urban area (respectively + 3.17%, + 9.11% and + 33.4%) and the decrease of pasture
 351 and perennial crop area (both of - 17.7%). In relative terms, the urbanization of land is the
 352 most notable trend, as in Haim et al. (2011). The dynamic of annual crops is the more subtle
 353 with a small loss 2003–2013, an increase 2013–2033 and a stagnation 2033–2053.

Table 2: National acreages of land uses (in thousand hectares) and the associated growth rates for scenarios S1, S2, S3 and S4

Extrapolating current trends of land use changes										
YEAR	(a) S1: Without conservation					(b) S3: With conservation				
	PECR	ANCR	PAST	FORE	URBA	PECR	ANCR	PAST	FORE	URBA
2003	141.3	1,573.5	1,529.8	1,580.4	315.7	141.3	1,573.5	1,529.8	1,580.4	315.7
2013	135.1	1,571.7	1,472.6	1,610.1	351.3	130.3	1,397.2	1,718.2	1,561.3	333.8
2023	128.2	1,606.6	1,390.0	1,643.9	371.9	119.9	1,334.1	1,789.1	1,555.3	342.4
2033	123.2	1,621.5	1,332.4	1,673.6	389.9	112.4	1,292.8	1,832.7	1,551.2	351.6
2043	119.3	1,625.4	1,290.2	1,700.1	405.6	106.8	1,265.3	1,859.5	1,548.2	361.0
2053	116.2	1,623.0	1,258.1	1,724.2	419.3	102.6	1,246.4	1,875.7	1,546.0	370.1
$\Delta(\%)$	- 17.7	+ 3.17	- 17.7	+ 9.11	+ 33.4	- 27.6	- 20.79	+ 22.6	- 2.15	+ 17.5

Climate-induced land use changes										
YEAR	(c) S2: Without conservation					(d) S4: With conservation				
	PECR	ANCR	PAST	FORE	URBA	PECR	ANCR	PAST	FORE	URBA
2003	141.3	1,573.5	1,529.8	1,580.4	315.7	141.3	1,573.5	1,529.8	1,580.4	315.7
2013	185.8	1,687.0	1,327.5	1,593.6	346.9	184.1	1,611.6	1,436.0	1,573.8	325.2
2023	181.4	1,833.4	1,146.0	1,614.0	365.9	176.2	1,579.8	1,519.7	1,541.6	333.4
2033	198.5	1,935.6	973.9	1,630.8	401.8	183.2	1,635.8	1,477.2	1,514.8	339.7
2043	217.4	2,096.6	754.8	1,625.9	446.1	193.7	1,836.2	1,278.5	1,486.4	345.9
2053	306.6	2,038.6	680.8	1,607.5	507.3	259.7	1,827.1	1,233.5	1,431.3	389.1
$\Delta(\%)$	+ 177	+ 27.15	- 55.5	+ 1.71	+ 60.1	+ 83.7	+ 16.15	- 19.36	- 9.43	+ 23.5

Notes: In columns: ANCR for Annual Crops, FORES for Forests, PECR for Perennial Crops, PAST for pastures and URBA for urban. The two last rows, named $\Delta(\%)$, present the growth rates 2003–2053.

354 The effect of LUC in the scenario S1 is globally neutral concerning the dynamics of the
 355 national bird index: the differences with S0 are small and not significant (see Panel D of
 356 **Figure 1**). In S1, the aggregate bird index is shaped exclusively by climate change. Spatially,
 357 the general structure is maintained but there is some mitigation at certain parts of the south
 358 of France and an amplification at the northwest (see Panel C of **Figure 1**). To disentangle
 359 the effects of S1 LUC from the climate effects, the Figures SM4 and SM5 present the net

360 effects of S1 LUC with constant climate. It appears that S1 LUC effects are much more
 361 smooth and homogeneous between species with the same habitat preferences (relatively to
 362 the effects plotted in Figure SM2). They are positive and significant for urban specialists and
 363 generalists, not significant for forest specialists and negative and significant for farmland
 364 specialists. From individual species point of view, populations grow significantly for 15
 365 species as a result of S1 LUC, 10 decrease significantly and 37 do not exhibit any significantly
 366 evolution.

367 **3.3 Climate change with climate-induced LUC (scenario S2)**

368 The endogenisation of the effects of climate on the economic returns of land by the Ricardian
 369 models is presented in **Table 3**. Up to 2053, the returns are predicted to increase for annual
 370 crop (md= + 116.8%), for pastures (md= + 73.81%) and perennial crop (md= + 13.35). The
 371 median increase of the density of population is + 28.31% but the median rate of variation
 372 for returns from forest is negative: – 13.18%. Climate change is also found to increase the
 373 heterogeneity (measured by Standard Errors) in terms of economic returns for annual crops,
 374 pastures and urban.

Table 3: The Ricardian effects of climate change on the economic returns from land: amounts in money and in variations

Land Use	2003		2053		Variations 2003–2053				
	Mean	SE	Mean	SE	Min	Q1	Q2	Q3	Max
ANCR	265.4	92.27	587.7	346.2	– 100.0	+ 72.05	+ 116.8	+ 159.4	+ 323.5
PAST	113.9	73.35	191.7	103.8	– 24.10	+ 52.62	+ 73.81	+ 98.21	+ 341.7
PECR	177.3	730.1	185.6	699.4	– 75.18	+ 4.474	+ 13.35	+ 19.01	+ 196.0
FORE	80.90	60.07	69.92	53.31	– 44.76	– 16.25	– 13.18	– 8.742	+ 45.36
URBA	81.98	291.8	103.0	386.8	– 29.10	+ 13.99	+ 28.31	+ 46.81	+ 109.4

Notes: The mean values of returns are in current euros/ha for the first 4 rows and hab/km² for the last. SE is for Standard Errors and variations are expressed in %. In row: ANCR for Annual Crops, FORES for Forests, PECR for Perennial Crops, PAST for Pastures and URBA for Urban.

375 The Panel (c) of **Table 2** presents the consequences of such variations of economic returns

376 in terms of LUC. Except for perennial crops, climate-induced LUC are in the same directions
377 as in the scenario S1: annual crops, forests and urban increase and pastures decrease. The
378 effect of climate change on perennial crops is strong (+ 177%) and is mainly explained by
379 the high growth rate at the top of the distribution of returns. As a consequence, this growth
380 concerns few locations already specialized in perennial crops (southeast in particular). The
381 important decrease of pastures (– 55.5%) is mainly explained by the substitution for annual
382 crops and urban. The growth rate of urbanization in S2 is twice the rate of S1 even if the same
383 scenario in terms of population growth is used. This can be explained by the fact that higher
384 temperatures are in general associated with bigger houses and bigger gardens in France (to
385 enjoy warmer temperatures), so global warming is projected to increase urbanization (Haim
386 et al., 2011).

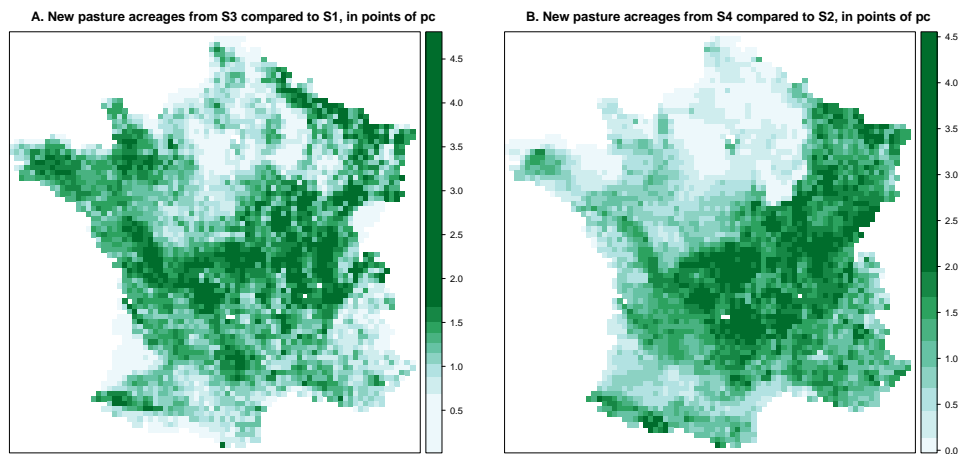
387 The Panel F of Figure 1 shows that climate-induced LUC amplifies the negative effect
388 of climate change on the aggregate bird index. With climate-induced LUC, the national
389 bird index shows a decrease of 14% of abundances in 2053, relatively to 10% in the case of
390 constant land use S0. Panel E of Figure 1 indicates a strong spatial redistribution of the loss
391 in terms of abundances. An important part of the most detrimental effects of climate change
392 in the southeast are mitigated by climate-induced LUC. In contrast, an amplification of the
393 effect of climate change appears in the northeast. Climate change implies a northern shift of
394 annual crops and an increase of urban and perennial crops in the south that explain these
395 results.

396 The isolated effects of S2 LUC on birds are shown in Figures SM6 and SM7, according to
397 habitat preferences of bird species and for each species separately. It appears that only urban
398 specialists benefit from climate-induced LUC: + 10.5%. The others present a significant
399 decrease in abundance for 2053: respectively – 5%, – 7.5% and – 8.5% for generalist,
400 farmland and forest specialists. The raw effects of S2 LUC are negative and significant for
401 41 species and positive for only 12 species. The latter are all urban specialists except the
402 Eurasian skylark (*Alauda arvensis*) that is a farmland specialist.

403 **3.4 Climate change with conservation policy (scenarios S3 and S4)**

404 Coupled with S1 to produce S3, the annual payment of 200 euro/ha for pasture is sufficient
405 to reverse the predicted decline of pasture in the next decades, see the Panel (b) of **Table 2**.
406 This payment involves a net increase of + 22.6% of pastures in the period 2003–2053. In S3,
407 the urbanization is still positive but moderate (+ 17.5%) relative to S1. Pastures induced by
408 such a conservation strategy (new pastures but also pastures that are not converted) replace
409 principally annual and perennial crops in the scenario S1. Even if the conservation scenario
410 negatively affects forest acreages, the loss is small: – 2.15%. The spatial distribution of these
411 conservation-induced pastures are presented in the Panel A of **Figure 2**. Areas of annual crop
412 specialization (around *Paris* at the northern center) and of forest specialization (extremes
413 southwest and southeast) are not heavily impacted by the conservation which are well spread
414 over locations.

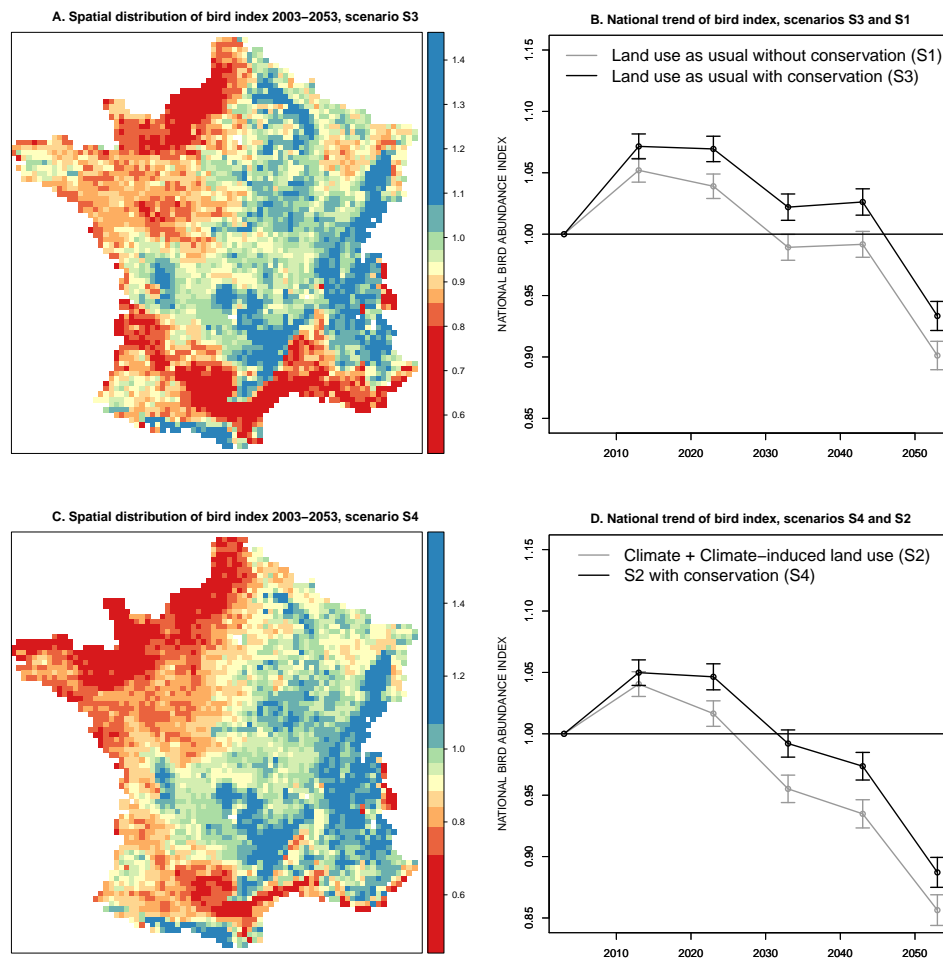
Figure 2: The net effects of the conservation payments of 200 euro/ha on pastures in scenarios S3 and S4, relative to S1 and S2 respectively



415 However, coupled with S2 to obtain S4 (i.e., taking into account climate change impacts on
416 LUC), the same payments for conservation are not able to reverse the loss of pastures, see the
417 Panel (d) of **Table 2**. Nevertheless, the predicted loss is highly mitigated relatively to S2, and
418 the 2053 acreages of pasture with conservation policy (S4) are near than twice the acreages

419 without conservation (S2). The payments for pasture coexist with an increase of annual crops
 420 because, as we have already seen, crops returns increase both by the extrapolation of trends
 421 and the benefit from climate change by the Ricardian effect. Conservation payments decrease
 422 urbanization even though this land conversion remains high (+ 23.5%). This scenario S4
 423 presents the highest loss of forest acreages (− 9.4%) both because of the decrease of the
 424 returns of forests from climate change and the competition with pastures that come from
 425 conservation. In this scenario, conservation-induced pastures are clearly spatially segregated
 426 (see the Panel B of Figure 2). The east and the center of France concentrate the principal
 427 part of these pastures, leaving the northwest weakly impacted by the conservation.

Figure 3: The effects of climate, land use changes and conservation policy on the index of birds abundances for scenarios S3 and S4.



428 For both conservation scenarios S3 and S4, the payments for pasture allow to significantly
429 increase the national bird index but not sufficiently to counteract the negative effects of
430 climate change (Panels B and D of **Figure 3**). The national trend stays shaped by climate
431 change (i.e., first a small increase then a bigger decrease) even if the differences that come
432 from conservation are statistically significant. For S3, the negative effects of climate
433 are delayed to 2045 instead of 2030 for S1. For S4, the conservation implies 2053 birds'
434 abundances close to S0 (about - 10%), indicating that conservation allows to counteract
435 globally the negative effects of climate-induced LUC. It is also interesting to show that the
436 effects of the 200 euros/ha conservation on the differences between S3 and S1 and between
437 S4 and S2 are relatively similar: about + 2.5 points of the national bird index.

438 Figures SM8 and SM9 present the net effects of both scenarios with conservation on bird
439 species individually. For S3, the effects of conservation are generally positive. They involve
440 detrimental effects only for 10 species of all habitat preferences, and species with negative
441 effects from S1 are not particularly targeted. The biggest improvements due to conservation
442 concern farmland specialists: Whinchat (*Saxicola rubetra*), Hoopoe (*Upupa epops*), European
443 Stonechat (*Saxicola rubicola*) and Red-backed Shrike (*Lanius collurio*). For S4, conservation
444 negatively affects 20 species from all habitat preferences. But strong positive effects are
445 found for certain species, in particular species of the bottom of the Figure SM9 that are
446 declining strongly in S2. This is a kind of mitigation effect from habitat-based conservation,
447 but clearly insufficient to counteract the patterns implied by climate change.

448 **4 Discussion**

449 **4.1 Ecological models**

450 We show that the dynamics of bird populations facing climate change vary according to
451 both their location within their current climatic niches and the land use corresponding to

452 their future climatic niches. Our results clearly show that the former source of variation is
453 stronger than the latter. A first explanation for this result is simply that climatic variables
454 have stronger effects in SDM than habitat and topographic variables. So, the climate side
455 of our scenarios is the most important driver of the spatial dynamics of common birds. The
456 second explanation is that LUC of our scenarios are not directly operated in relation to
457 birds dynamics. LUC and conservation policy could potentially have stronger effects if they
458 were deliberately shaped for bird conservation and if the climate-induced shifts in bird
459 distributions were taken into account in land use decisions. But, even if conservation policy
460 could be better designed, the observed magnitude of differences between scenarios suggests
461 that it would be very difficult for land use allocation schemes to overcome the large climate
462 signal. This result is in contrast to the commonly held belief that land use change will remain
463 the dominant driver of bird diversity dynamics (Jetz et al. 2007) or biodiversity dynamics in
464 general (Periera et al. 2010) over the coming century. While this land use may remain the
465 dominant driver at global scales, our work suggests that this may not be the case in many
466 areas where land use and biodiversity dynamics are not mediated by large scale deforestation
467 and conversion of natural systems to production systems.

468 Omitting large parts of a species range when modeling its distribution can overestimate
469 the risk of local decline or extinction, as it does not consider all possible environmental
470 conditions where a species can survive. Current developments of SDM for animals try to
471 disentangle the effects of various environmental variables on population dynamic parameters,
472 e.g., climatic impacts on survival, reproductive success and dispersal. Developing such
473 models will provide more efficient inferences for policy decision, by better targeting potential
474 expected improvements. A few studies already tried to consider realistic dispersal scenarios
475 for birds predicted to shift their range polewards, but accounting for dispersal did not change
476 the estimates of impact predictions at a national scale (Jiguet et al., 2013). As regards
477 biodiversity metrics, the use of geometric mean of current abundances (e.g., taxonomic
478 diversity) is not totally satisfying. The current biodiversity crisis could impact the future

479 potential of evolutionary processes, so that the impacts of global change on phylogenetic
480 diversity should be estimated. Similarly, as long as ecosystem processes are those important
481 for the resilience of the global biological diversity, future investigations should concern the
482 potential impacts of global change on functional diversity. Species interactions are shaping
483 community dynamics and functions, and integrating the architecture of mutualistic or trophic
484 networks will necessarily improve predictions ([Thébault and Fontaine, 2010](#)).

485 **4.2 Econometric models**

486 Our empirical model of LUC provides a means to examine the effects of returns from land
487 and economic-based policies (i.e., acreage payments) on land use decisions. We show that
488 changing the returns from land is sufficient to induce significant variations in terms of LUC,
489 relative to the scenario with extrapolated trends. Through their influence on capitalized
490 values into land returns, climate variables are also proved to be strong determinants of
491 LUC. With our regionalized projections, the net effect of climate change is to increase urban,
492 annual and perennial crop acreages, at the expense of pastures and forests. These results
493 are shared by many projections about LUC but the fine resolution of the initial data and the
494 extrapolation by the modelisation of landowners' choices allow us to obtain a particularly
495 high spatial resolution.

496 Although our LUC model provided promising results, it could be enhanced in several
497 ways. An area for future research is the development of data and methods that could help to
498 estimate more precise econometric models of LUC. One possible improvement of our model is
499 to take explicitly into account spatial autocorrelation of the outcome variables, the residuals
500 or both. The challenge, then, is for land use modeling to take into account time and space
501 within a unified framework. In this perspective, the methods developed by [Sidharthan and](#)
502 [Bhat \(2012\)](#) seem to be promising and are a good alternative to a Bayesian framework or
503 an estimation by simulation methods which are quite intensive in terms of computation.

504 Concerning the Ricardian models, there is legitimate concern that extrapolation too far into
505 the future may exceed the valid range of use of econometrics. It is especially striking when
506 applied to novel climates that do not occur in the data used to estimate the model. However,
507 alternatives such as process-based modeling approaches often suffer from a lack of data to
508 properly constrain parameterization and may suffer from overtuning, so choosing between
509 modeling approaches is not clear-cut. These issues are very similar to those that arise when
510 comparing empirical and process-based SDM, for which model selection is difficult to make
511 based on objective criteria (Cheaib et al., 2012). A recent multi-study analysis of climate
512 change impacts on African agriculture indicates econometric approaches give results that
513 are coherent with statistical and processes-based approaches over the time frame examined
514 in our analysis (Müller et al., 2011).

515 **4.3 Climate scenario**

516 For this analysis, we have used a single climate projection and, therefore, there is a sub-
517 stantially broader range of projected climate changes than we have explored. This means
518 that there is also substantially higher uncertainty in projections of bird population change
519 and LUC than presented here. As noted in the introduction, climate projections from the
520 present to mid-century differ more between climate models than between emissions scenar-
521 ios, especially in the IPCC AR4 SRES-based climate model ensemble (Knutti and Sedláček,
522 2012). The most recent IPCC AR5 RCP-based climate model ensemble projections give even
523 broader ranges of warming and precipitation than the AR4 projections, but the multi-model
524 ensemble averages are very similar to AR4 projections at both global and French scales
525 (Knutti and Sedláček, 2012; Diffenbaugh and Giorgi, 2012). Large uncertainty, especially
526 concerning future precipitation regimes must be kept in mind, since modeled populations
527 and distributions of birds and LUC appear to depend on temperature and precipitation (see
528 Table SM1 and SM2 of SM). The climate projections that we have used are, however, close to

529 the mean of the AR4 and AR5 multi-model climate projection ensembles over the period that
530 we have studied.

531 It has been shown that climate impacts are highly dependant on the spatial scale of
532 climate projections, especially in mountainous areas (Franklin et al., 2013). Thus, given
533 the importance of altitudinal related climate variation in determining both bird and LUC
534 responses to climate change, regionalized climate is an essential component of analyses of
535 interactions between climate, LUC and policy in this type of study. The statistical climate
536 downscaling method used in this study provides a much finer spatial scale for time series
537 climate data (ca. 8 km) than global scale ($0.5^\circ =$ ca. 110 km latitude for high resolution
538 data sets) or many regional scale projections (ca. 20 km, Mitchell and Jones, 2005). The
539 downscaled climate is also much better tested against French climate data (Boé et al., 2009)
540 than frequently used downscaling methods based on the WorldClim dataset (e.g., Franklin
541 et al., 2013).

542 **4.4 Conservation policy**

543 Our results suggest that projections of future species distributions, and also management
544 options and conservation assessments, cannot be based on the assumption of a uniform
545 response to climate change across a species range or at range edges only. This illustrates
546 a challenge for the conservation policy that has to reflect this heterogeneity of bird and
547 LUC responses. Incorporating the uncertainty that comes from the data and the models is
548 another policy challenge that will complicate conservation schemes and highlights the need
549 for conservation schemes that leave substantial flexibility for corrections over time. However,
550 the conservation policy has to be simple in order to be understandable for landowners and to
551 avoid prohibitive implementation and monitoring costs. The economic incentives proposed
552 in this paper are in line with these objectives. Here, we limit the conservation policy of a
553 fixed-amount payment for pasture at the national scale. We have also tested another amounts

554 of payments for pasture (100 euro/ha and 300 euro/ha) without observing any change in the
555 relative spatial distribution of effects. The national acreages of pasture are growing with the
556 amounts of payment but the relative shares at different scales stay constants. Determining
557 the optimal level of payments for pasture is outside the scope of this paper.

558 In contrast to the incentive-based, national policy studied here, at least two main al-
559 ternative conservation policies could be implemented at low cost. The first possibility is to
560 keep the economic logic of conservation payments but apply varying payments to landowners
561 based on the location of their parcels or the presence of vulnerable species (current or future).
562 The second possibility is the well-used command-and-control approach that implies external,
563 regularly and not generally compensated constraints on LUC. Both would require more eco-
564 nomics and ecological information than the conservation policy implemented here, reinforcing
565 the interest of prospective tools like the models that we develop here. In particular because
566 climate-induced LUC could have positive effects on biodiversity locally, they have to be
567 anticipated by conservation policies so that they do not target areas that are not vulnerable.
568 In the same vein, spatially targeted conservation policies need to take into account the shift
569 in species distributions as a result of climate change, to not target areas that would not be
570 viable.

571 **4.5 Conclusion**

572 We have compared 5 different integrated scenarios from now to the next 4 decades, using
573 IPCC climate, economic and conservation projections. The explicit structure of our bio-
574 economic model allows to study the climate-induced LUC resulting from the economic returns
575 of land and a conservation policy consisting of annual payments to promote permanent
576 pastures. Three main questions have been addressed:

577 (i) What are the probable effects of climate on common bird abundances?

578 (ii) Does climate-induced LUC mitigate or amplify the effects of climate?

579 (iii) What are the effects of payments in order to have more eco-friendly LUC?

580 For (i), we found a negative national effect of climate change on bird abundances at
581 2053. This effect is strong relative to the effect of projected LUC. Locally, it causes a greater
582 elevation shift than northern shift in the distribution of birds. For (ii), we found that climate-
583 induced LUC amplify the negative direct effect of climate on birds. This is not the case
584 everywhere, with some, particularly southern, locations that could benefit from such LUC.
585 The answer to question (iii) is more complex, because we found that a conservation policy
586 based on relatively high payments to promote pastures can not counteract the globally
587 negative effect of climate on certain locations and certain species. We do not find any
588 significant correlation between the growth of bird abundances with and without conservation,
589 both at the spatial and the species scales. We interpret that as the positive effects of
590 incentive-based conservation do not match particularly the vulnerable locations and species.

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References

- 601 **Araújo, M. B., R. G. Pearson, W. Thuiller and M. Erhard** (2005). Validation of species-climate
602 impact models under climate change. *Global Change Biology* 11: 1504–1513.
- 603 **Barbet-Massin, M., W. Thuiller and F. Jiguet** (2011). The fate of european breeding birds under
604 climate, land-use and dispersal scenarios. *Global Change Biology* .
- 605 **Barnagaud, J.-Y., V. Devictor, F. Jiguet, M. Barbet-Massin, I. Le Viol and F. Archaux** (2012).
606 Relating habitat and climatic niches in birds. *PLoS One* 7.
- 607 **Berrang-Ford, L., J. D. Ford and J. Paterson** (2011). Are we adapting to climate change? *Global*
608 *Environmental Change* 21: 25 – 33, doi:10.1016/j.gloenvcha.2010.09.012.
- 609 **Boé, J., L. Terray, E. Martin and F. Habets** (2009). Projected changes in components of the
610 hydrological cycle in French river basins during the 21st century. *Water Resources Research* 45:
611 W08426.
- 612 **Brisson, N., P. Gate, D. Gouache, G. Charmet, F.-X. Oury and F. Huard** (2010). Are wheat
613 yield stagnating in Europe? A comprehensive data analysis for France. *Field Crop Research* 119:
614 201–212.
- 615 **Brotons, L., M. De Cáceres, A. Fall and M.-J. Fortin** (2012). Modeling bird species distribution
616 change in fire prone mediterranean landscapes: incorporating species dispersal and landscape
617 dynamics. *Ecography* 35: 458–467, doi:10.1111/j.1600-0587.2011.06878.x.
- 618 **Chakir, R. and J. Le Gallo** (2012). Predicting land use allocation in France: A spatial panel data
619 analysis. *Ecological Economics* in press.
- 620 **Chakir, R. and O. Parent** (2009). Determinants of land use changes: A spatial multinomial probit
621 approach. *Papers in Regional Science* 88: 327–344.
- 622 **Cheaib, A., V. Badeau, J. Boe, I. Chuine, C. Delire, E. Dufrêne, C. François, E. S. Gritti,**
623 **M. Legay, C. Pagé, W. Thuiller, N. Viovy and P. Leadley** (2012). Climate change impacts on
624 tree ranges: Model intercomparison facilitates understanding and quantification of uncertainty.
625 *Ecology Letters* 15: 533–544.
- 626 **Déqué, M.** (2007). Frequency of precipitation and temperature extremes over france in an anthro-
627 pogenic scenario: Model results and statistical correction according to observed values. *Global and*
628 *Planetary Change* 57: 16–26.
- 629 **Devictor, V., R. Julliard, J. Clavel, F. Jiguet, A. Lee and D. Couvet** (2008). Functional biotic
630 homogenization of bird communities in disturbed landscapes. *Global Ecology and Biogeography* 17:
631 252–261.
- 632 **Devictor, V., R. Julliard, D. Couvet and F. Jiguet** (2007). Functional homogenization effect of
633 urbanization on bird communities. *Conservation Biology* 21: 741–751.
- 634 **Diffenbaugh, N. S. and F. Giorgi** (2012). Climate change hotspots in the cmip5 global climate
635 model ensemble. *Climatic Change* 114: 813–822, doi:10.1007/s10584-012-0570-x.
- 636 **Franklin, J., F. W. Davis, M. Ikegami, A. D. Sypard, L. E. Flint, A. L. Flint and L. Hannah**
637 (2013). Modeling plant species distributions under future climates: How fine scale do climate
638 projections need to be? *Global Change Biology* 19: 473–483, doi:10.1111/gcb.12051.
- 639 **Furness, R. W. and J. J. D. Greenwood** (1993). *Birds as Monitors of Environmental Change*.

- 640 London: Chapman & Hall.
- 641 **Goodwin, B. K., A. K. Mishra and F. N. Ortalo-Magné** (2003). What's wrong with our models of
642 agricultural land values? *American Journal of Agricultural Economics* 85: 744–752.
- 643 **Gregory, R. D., A. van Strien, P. Vorisek, A. W. G. Meyling, D. G. Noble, R. P. B. Foppen and**
644 **D. W. Gibbons** (2005). Developing indicators for european birds. *Phylosophical Transactions of the*
645 *Royal Society B* 360: 269–288.
- 646 **Guisan, A. and W. Thuiller** (2005). Predicting species distribution: Offering more than simple
647 habitat models. *Ecology Letters* 8: 993–1009.
- 648 **Haim, D., R. J. Alig, A. J. Plantinga and B. Sohngen** (2011). Climate change and future land use
649 in the United States: An economic approach. *Climate Change Economics* 2: 27–51.
- 650 **Hannah, L., G. F. Midgley and D. Millar** (2002). Climate change-integrated conservation strategies.
651 *Global Ecology and Biogeography* 11: 485–495.
- 652 **Hastie, T. and R. Tibshirani** (1990). *Generalized additive models*. Chapman and Hall.
- 653 **Hutchinson, G. E.** (1978). *An Introduction to Population Ecology*. Yale University Press.
- 654 **IPCC** (2007). *Climate Change 2007: Mitigation of Climate Change*. Fourth Assessment Report.
655 Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.
- 656 **Jamagne, M., R. Hardy, D. King and M. Bornand** (1995). La base de données géographique des
657 sols de france. *Étude et Gestion des Sols* 2: 153–172.
- 658 **Jiguet, F., M. Barbet-Massin, V. Devictor, N. Jonzén and Åne Lindströme** (2013). Current
659 population trends mirror forecasted changes in climatic suitability for Swedish breeding birds. *Bird*
660 *Study* .
- 661 **Jiguet, F., V. Devictor, R. Julliard and D. Couvet** (2012). French citizens monitoring ordinary
662 birds provide tools for conservation and ecological sciences. *Acta Oecologica* 44: 58–66.
- 663 **Knutti, R. and J. Sedláček** (2012). Robustness and uncertainties in the new CMIP5 climate model
664 projections. *Nature Climate Change* : 1–5doi:10.1038/nclimate1716.
- 665 **Lewis, D. J., A. J. Plantinga, E. Nelson and S. Polasky** (2011). The efficiency of voluntary
666 incentive policies for preventing biodiversity loss. *Resource and Energy Economics* 33: 192–211.
- 667 **Lobell, D. B., W. Schlenker and J. Costa-Roberts** (2011). Climate trends and global crop produc-
668 tion since 1980. *Science* 333: 616–620, doi:10.1126/science.1204531.
- 669 **Lubowski, R. N., A. J. Plantinga and R. N. Stavins** (2008). What drives land-use change in the
670 United States? A national analysis of landowner decisions. *Land Economics* 84: 529–550.
- 671 **McFadden, D.** (1974). *Conditional logit analysis of qualitative choice behavior*. New York: Academic
672 Press, chap. 2 in *Frontiers in Econometrics*. 105–142.
- 673 **Mendelsohn, R. and A. Dinar** (2009). *Climate change and agriculture: An economic analysis of*
674 *global impacts, adaptation and distributional effects*. Northampton: Edward Elgar.
- 675 **Mendelsohn, R., W. D. Nordhaus and D. Shaw** (1994). The impact of global warming on agricul-
676 ture: A Ricardian analysis. *American Economic Review* 84: 753–771.
- 677 **Millennium Ecosystem Assessment** (2005). *Ecosystems and human well-being: Biodiversity syn-*
678 *thesis*. Tech. rep., World Resources Institute, Washington, DC, USA.
- 679 **Mitchell, T. D. and P. D. Jones** (2005). An improved method of constructing a database of monthly

680 climate observations and associated high-resolution grids. *International Journal of Climatology* 25:
681 693–712, doi:10.1002/joc.1181.

682 **Mouysset, L., L. Doyen and F. Jiguet** (2012). Different policy scenarios to promote various targets
683 of biodiversity. *Ecological Indicators* 14: 209–221.

684 **Mouysset, L., L. Doyen and F. Jiguet** (in press). How does economic risk aversion affect biodiver-
685 sity? *Ecological Applications* .

686 **Mouysset, L., L. Doyen, F. Jiguet, G. Allaire and F. Leger** (2011). Bio-economic modeling for
687 sustainable management of biodiversity and agriculture. *Ecological Economics* 70: 617–626.

688 **Müller, C., W. Cramer, W. L. Hare and H. Lotze-Campen** (2011). Climate change risks for African
689 agriculture. *Proceedings of the National Academy of Sciences* doi:10.1073/pnas.1015078108.

690 **Nelson, E., S. Polasky, D. J. Lewis, A. J. Plantinga, E. Lonsdorf, D. White, D. Bael and**
691 **J. J. Lawler** (2008). Efficiency of incentives to jointly increase carbon sequestration and species
692 conservation on a landscape. *Proceedings of the National Academy of Science* 105: 9471–9476.

693 **Pearson, R. G. and T. P. Dawson** (2003). Predicting the impacts of climate change on the distribution
694 of species: Are bioclimate envelope models useful? *Global Ecology and Biogeography* 12: 361–371.

695 **Pereira, H. M., P. W. Leadley, V. Proença, R. Alkemade, J. P. W. Scharlemann, J. F.**
696 **Fernandez-Manjarrés, M. B. Araújo, P. Balvanera, R. Biggs, W. W. L. Cheung, L. Chini,**
697 **H. D. Cooper, E. L. Gilman, S. Guénette, G. C. Hurtt, H. P. Huntington, G. M. Mace,**
698 **T. Oberdorff, C. Revenga, P. Rodrigues, R. J. Scholes, U. R. Sumaila and M. Walpole**
699 (2010). Scenarios for global biodiversity in the 21st century. *Science* 330: 1496–1501, doi:
700 10.1126/science.1196624.

701 **Peterson, A. T., J. Soberón, R. G. Pearson, R. P. Anderson, E. Martínez-Meyer, M. Nakamura**
702 **and M. B. Araújo** (2011). *Ecological Niches and Geographic Distributions*. Princeton University
703 Press.

704 **Plantinga, A. J.** (1996). The effect of agricultural policies on land use and environmental quality.
705 *American Journal of Agricultural Economics* 78: 1082–1091.

706 **Radeloff, V., E., A. Plantinga, D. Lewis, D. Helmers, J. Lawler, J. Withey, F. Beaudry, S. Mar-**
707 **tinuzzi, V. Butsic, E. Lonsdorf, D. White and S. Polasky** (2012). Economic-based projections
708 of future land use in the conterminous United States under alternative policy scenarios. *Ecological*
709 *Applications* 22: 1036–1049.

710 **Renwick, A. R., D. Massimino, S. E. Newson, D. E. Chamberlain, J. W. Pearce-Higgins and**
711 **A. Johnston** (2012). Modelling changes in species' abundance in response to projected climate
712 change. *Diversity and Distributions* 18: 121–132, doi:10.1111/j.1472-4642.2011.00827.x.

713 **Ricardo, D.** (1817). *Principles of political economy and taxation*. Great minds series, London.

714 **Rogelj, J., M. Meinshausen and R. Knutti** (2012). Global warming under old and new scenarios
715 using IPCC climate sensitivity range estimates. *Nature Climate Change* 2: 248–253.

716 **Sidharthan, R. and C. R. Bhat** (2012). Incorporating spatial dynamics and temporal dependency in
717 land use change models. *Geographical Analysis* 44: 321–349, doi:10.1111/j.1538-4632.2012.00854.x.

718 **Stavins, R. N. and A. B. Jaffe** (1990). Unintended impacts of public investments on private decisions:
719 The depletion of forested wetlands. *American Economic Review* 80: 337–352.

720 **Thébault, E. and C. Fontaine** (2010). Stability of ecological communities and the architecture of
721 mutualistic and trophic networks. *Science* 329: 853–856, doi:10.1126/science.1188321.

722 **Train, K.** (2009). *Discrete Choice Methods with Simulation, Second Edition*. Cambridge University
723 Press.

724 **Tubiello, F. N., C. Rosenzweig, R. A. Goldberg, S. Jagtap and J. W. Jones** (2002). Effects of
725 climate change on US crop production: Simulation results using two different GCM scenarios. part
726 I: Wheat, potato, maize, and citrus. *Climate Research* 20: 259–270.

727 **Willis, K. and G. MacDonald** (2011). Long-term ecological records and their relevance to climate
728 change predictions for a warmer world. *Annual Review of Ecology, Evolution, and Systematics* 42:
729 267–287, doi:10.1146/annurev-ecolsys-102209-144704.

730 **Wood, S.** (2006). *Generalized Additive Models : An introduction with R*. Chapman & Hall / CRC, 1st
731 ed.

732 **Xiong, W., D. Conway, E. Lin and I. Holman** (2009). Potential impacts of climate change and
733 climate variability on China’s rice yield and production. *Climate Research* 40: 23–35.

734 List of Tables

735	1	The differences between scenarios in terms of factors from species distribution and land	
736		use change models	14
737	2	National acreages of land uses (in thousand hectares) and the associated growth rates	
738		for scenarios S1, S2, S3 and S4	19
739	3	The Ricardian effects of climate change on the economic returns from land: amounts in	
740		money and in variations	20

741 List of Figures

742	1	The effects of climate and land use changes on the index of bird abundances for the	
743		scenarios without conservation: S0, S1 and S2.	17
744	2	The net effects of the conservation payments of 200 euro/ha on pastures in scenarios S3	
745		and S4, relative to S1 and S2 respectively	22
746	3	The effects of climate, land use changes and conservation policy on the index of birds	
747		abundances for scenarios S3 and S4.	23