

Online Resources for: Integrated models, scenarios and dynamics of climate, land use and common birds

April 13, 2014

Contents

OR1 Data	2
OR1.1 Bird abundances	2
OR1.2 Land Use Changes	2
OR1.3 Economic returns	3
OR1.4 Biophysical attributes	3
OR2 Figures and Tables	5

List of Tables

ORT1	Results of Species Distribution Models for the 65 common bird species	6
ORT2	Coefficients and Student t from the Multinomial Logit about land use changes	7
ORT3	Summary of the results from the 4 econometric Ricardian models	8
ORT4	The different spatial entities used to match the data, areas in km ²	9
ORT5	Robustness results of Species Distribution Models I	10
ORT6	Robustness results of Species Distribution Models II	11

List of Figures

ORF1	Principal Component Analysis for climate and land quality variables	5
ORF2	Effect of scenario S0 on bird index for 4 different habitat speciality	12
ORF3	Effect of scenario S0 on bird species of interest	13
ORF4	Effect of only S1 LUC on bird index according to habitat speciality	14
ORF5	Effect of scenario S1 on considered bird species	15
ORF6	Effect of scenario S2 on bird index according to habitat speciality	16
ORF7	Effect of scenario S2 on considered bird species	17
ORF8	Net effect of 200 euro conservation payments with LUC as usual (S1 → S3)	18
ORF9	Net effect of 200 euro conservation payments with climate-induced LUC (S2 → S4)	19

ORF10	Robustness checks I for bird distributions for scenarios S0, S1 and S2	20
ORF11	Robustness checks II for bird distributions according to the SDMs	21

OR1 Data

OR1.1 Bird abundances

We used avian data from the French Breeding Bird Survey (FBBS), a standardized monitoring scheme in which skilled volunteer ornithologists identify breeding birds by song or visual contact in spring (Jiguet et al., 2012). In FBBS, each observer provides the name of her municipality, and a 2×2 km square to be prospected is randomly selected within a 10 km radius from the center of gravity of this municipality. In each square, the observer monitors 10 point counts separated by at least 300 m twice per Spring (4 to 6 weeks between the sessions, 5 minutes each). Counts were repeated yearly by the same observer at the same points, on about the same date (with a maximum difference of 7 days within April to mid June) and at the same time of day (with a maximum difference of 15 minutes). FBBS data contribute to European official index of biodiversity and have been extensively used to study the effects of climate and LUC on bird populations (Barbet-Massin et al., 2011; Barnagaud et al., 2012), as well as the effects of farmers’ preferences (Mouysset et al., 2013) and the effects of agro-environmental policies (Mouysset et al., 2011, 2012). To simultaneously smooth annual noise and model the observed dynamics, FBBS data were averaged over two 3-year time windows, 2003 (the average 2002–2004, $n=1,031$) and 2009 (the average 2008–2010, $n=1,380$). For each species and each FBBS square, bird abundances are defined as the maximum number of counts. FBBS provides also a description of the habitats of the surveyed squares. The SDM are estimated with FBBS habitat descriptions (which were transformed to equivalent land use categories based on the simplified TERUTI classification, see OR1.2) and each FBBS observation is weighted in the regressions according to its significance in terms of local land use. On their own, FBBS habitat descriptions are not representative of the local land use.

OR1.2 Land Use Changes

Data about LUC are extracted from the TERUTI survey which was carried out every year 1992–2003 by the statistical services of the French Ministry of Agriculture. TERUTI data count about 550,000 points for which we know the location in terms of French municipalities.¹ The TERUTI survey uses a systematic area frame sampling with a two-stage sampling design. In the first stage, the total national area is divided into a 12×12 km grid. For each of these 4,700 regular meshes there are 4 aerial photographs which cover 3.5 km^2 each. In the second stage, on each photograph, a 6-by-6 grid determines the 36 points to be surveyed in June by an agent on the ground. Each point corresponds to a homogeneous unit in terms of land use and statistically represents about 100 hectares (ha) at the *département* scale ($n = 95$, median area: $5,880 \text{ km}^2$, see Table OR1.4). On the basis of the detailed classification of land uses (81 items) we attribute to each plot a use among 5 more aggregate categories: annual crops (wheat, corn, sunflowers, etc.), pasture (a rather large

¹the finest administrative delineation ($n \approx 36\,500$, median area: 10.73 km^2), see Table OR1.4.

definition including grasslands, rangelands, productive fallows, moors), perennial crops (vineyards, orchards and greenhouses), forest (both productive and recreative, including plantations, hedgerow) or urban area (cities and exurban houses but also roads, highways, airports, etc.) These data have already be used to estimate econometric LUC models by Chakir and Parent (2009) and Chakir and Le Gallo (2013) but not for the whole of France and at a fine spatial scale. They have been similarly merged with a subset of the avian data that are used here, at the national scale (Devictor et al., 2007, 2008), but not in relation with the economic incentives of landowners' choices.

OR1.3 Economic returns

The price of land is used to compute the expected net returns from different agricultural land uses. Defining land price as the net present value of expected future rents is standard in the economic theory (Ricardo, 1817; Goodwin et al., 2003). This approach, detailed in the main text, uses data about land prices that also come from the statistical services of the French Ministry of Agriculture. Yearly prices 1990–2005 are available for three land uses (annual crops, pastures and perennial crops) and within the 713 Small Agricultural Regions (SAR) of France. SAR size ranges from 11 to 4,413 km² (see Table ORT4) with a homogeneity in terms of both agro-ecological and economic factors, reducing intra-SAR heterogeneity (Mouysset et al., 2012). For the two other land uses – forest and urban – the approximations of economic returns are computed differently and at different geographic scales. For the expected net returns from forest, we use data about wood raw production (in m³), total forest area (in ha) and wood prices (in current euro per ha), all available annually at the scale of the French *départements*. We compute the expected returns from forest by multiplying the aggregate production by its unitary price and dividing the result by the total forest area of each *département*. This simplification is based on the assumption of a myopic agent who makes decisions based on the hypothesis that future returns will be the same as today and neglect production costs. The urban returns are approximated by the population densities at the scale of the municipalities (number of people per total area) on the basis of the national census of French population. In France, the municipality is the administrative body where development planning choices (constructibility, servicing) are operated.

OR1.4 Biophysical attributes

Biophysical attributes of sampled TERUTI plots include both topographic and climate variables. Topography of each plot was generated by coupling a Digital Elevation Model of France (resolution of 250 meters) with the spatial reference of plots. Within a Geographical Information System (GIS), we calculated the elevation, the slope, the roughness and the exposition of each TERUTI sampled plot. Soil quality variables were extracted from the French soil database developed by the National Institute for Agricultural Research and matched by GIS. The initial data are available at the 1:1,000,000-scale (Jamagne et al., 1995) and they were downscaled to a 1-km grid with pedo-transfer rules (Cheaib et al., 2012). They provide measures of the agricultural fertility of plots: plant available water capacity and soil depth.

We use historical (1990–2010) and projected (2010–2053) climate data, both available at the same spatial resolution (8 × 8 km rasters) with a smooth transition between historical and future

climate. Climate data covers 13 variables including temperatures (annual means, maximum and minimum, bird breeding period means April–August and seasonality approximated by standard deviation), precipitation (annual means, maximum and minimum, breeding period means and seasonality), solar radiation (breeding period means), relative humidity (breeding period means) and wind (breeding period means). Regionalized climate scenarios are based on the Intergovernmental Panel of Climate Change’s SRES A1B greenhouse gas emissions scenario A1B coupled with the *Météo-France Arpège* climate model (Déqué, 2007). Regionalized climate projections were produced with a multivariate statistical downscaling methodology, which is able to generate local time series of temperature and precipitation, and other climatic variables at different sites (Boé et al., 2009). The model is based on large-scale circulation predictors, here the mean sea-level pressure field, as well as the 2-meter temperature averaged over France. It starts from regional climate properties to establish discriminating weather types for the chosen local variable. Intra-type variations of the relevant forcing parameters are then taken into account by multivariate regression using the distances of a given day to the different weather types as predictors. The final step consists of conditional re-sampling (for further details in climate downscaling see Boé et al., 2009 and Cheaib et al., 2012).

References

- Barbet-Massin, M., W. Thuiller and F. Jiguet** (2011). The fate of european breeding birds under climate, land-use and dispersal scenarios. *Global Change Biology* .
- Barnagaud, J.-Y., V. Devictor, F. Jiguet, M. Barbet-Massin, I. Le Viol and F. Archaux** (2012). Relating habitat and climatic niches in birds. *PLoS One* 7.
- Boé, J., L. Terray, E. Martin and F. Habets** (2009). Projected changes in components of the hydrological cycle in French river basins during the 21st century. *Water Resources Research* 45: W08426.
- Chakir, R. and J. Le Gallo** (2013). Predicting land use allocation in France: A spatial panel data analysis. *Ecological Economics* in press.
- Chakir, R. and O. Parent** (2009). Determinants of land use changes: A spatial multinomial probit approach. *Papers in Regional Science* 88: 327–344.
- Cheaib, A., V. Badeau, J. Boe, I. Chuine, C. Delire, E. Dufrière, C. François, E. S. Gritti, M. Legay, C. Pagé, W. Thuiller, N. Viovy and P. Leadley** (2012). Climate change impacts on tree ranges: Model intercomparison facilitates understanding and quantification of uncertainty. *Ecology Letters* 15: 533–544.
- Déqué, M.** (2007). Frequency of precipitation and temperature extremes over france in an anthropogenic scenario: Model results and statistical correction according to observed values. *Global and Planetary Change* 57: 16–26.
- Devictor, V., R. Julliard, J. Clavel, F. Jiguet, A. Lee and D. Couvet** (2008). Functional biotic homogenization of bird communities in disturbed landscapes. *Global Ecology and Biogeography* 17: 252–261.
- Devictor, V., R. Julliard, D. Couvet and F. Jiguet** (2007). Functional homogenization effect of urbanization on bird communities. *Conservation Biology* 21: 741–751.
- Goodwin, B. K., A. K. Mishra and F. N. Ortalo-Magné** (2003). What’s wrong with our models of agricultural land values? *American Journal of Agricultural Economics* 85: 744–752.
- Jamagne, M., R. Hardy, D. King and M. Bornand** (1995). La base de données géographique des sols de france. *Étude et Gestion des Sols* 2: 153–172.
- Jiguet, F., V. Devictor, R. Julliard and D. Couvet** (2012). French citizens monitoring ordinary birds provide tools for conservation and ecological sciences. *Acta Oecologica* 44: 58–66.
- Mouysset, L., L. Doyen and F. Jiguet** (2012). Different policy scenarios to promote various targets of biodiversity. *Ecological Indicators* 14: 209–221.

Mouysset, L., L. Doyen and F. Jiguet (2013). How does economic risk aversion affect biodiversity? *Ecological Applications* .

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

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

OR2 Figures and Tables

Figure ORF1: **Principal Component Analysis for climate and land quality variables:** For *climate variables* (left panel), RHB: mean relative humidity during breeding, WDB: mean wind during breeding, TMN: minimal monthly temperature, TME: mean monthly temperature, TBR: mean temperature during breeding, TMX: maximal monthly temperature, PMN: minimal monthly precipitation, PBR: mean precipitation during breeding, PCM: mean monthly precipitations, PMX: maximal monthly precipitation, PSD: seasonality of precipitations, TSD: seasonality of temperatures, SRB, mean solar radiation during breeding. For *land quality* (right panel), DMX: maximal soil depth, DMN: minimal soil depth, DME: mean soil depth, WMN: minimal water holding capacity of soils, WMX: maximal water holding capacity, WME: mean water holding capacity, EXP: exposition, ELV: elevation, SLP: slope, RGH: roughness. The two main axes for climate variables are used, but only the first axis for land quality variables

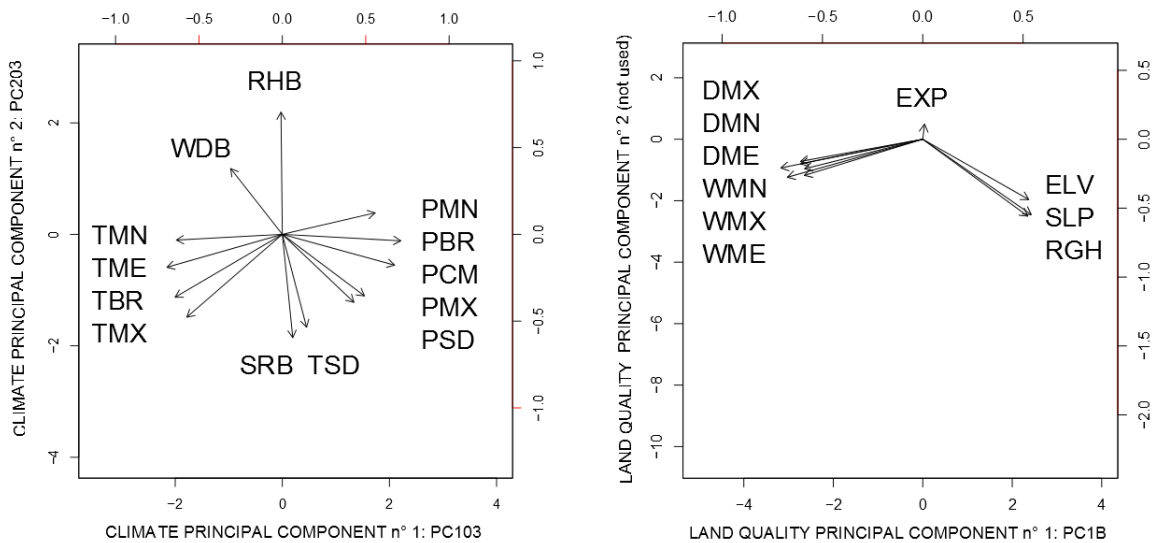


Table ORT1: **Results of Species Distribution Models for the 65 common bird species:** 65 Species Distribution Models are estimated, one for each bird species of interest. The top panel of the Table presents the distribution of the adjusted R-squares and of the correlations between observed and predicted abundances. The two principal components of climate variables (left panel of Figure ORF1) are included in SDM with bivariate smoothing functions. Land use shares (ANCR for annual crops, PAST for pasture, FORE for forest and URBA for urban, perennial crop is the reference land use) have each their own additive smooth functions. The bottom panel of this Table presents the results about the 1% statistical significance of each smoothed terms (both bivariate and univariate)

Generalized Additive Models with Negative Binomial distributions					
N= 65	Min	Q1	Q2	Q3	Max
Adj.-R ²	.15	.29	.37	.43	.87
Corr($\mu, \hat{\mu}$)	.43	.57	.62	.67	.94
Statistical significance of explanatory variables					
VAR	CLIMATE	ANCR	PAST	FORE	URBA
<i>p</i> -value < .01	56/65	52/65	25/65	62/65	52/65
% of species	(86)	(80)	(38)	(95)	(80)

Table ORT2: **Coefficients and Student t from the Multinomial Logit about land use changes**

* marks the 1% significant coefficients. McFadden $R^2 = 0.683$. Perennial crop is used as the reference modality, so the coefficients have to be interpreted relative to the effects of the variables on this choice. After the intercept, the first 4 rows accounts for the previous land uses. PC1B, PC103 and PC203 are principal component axis respectively for biophysical attributes and climate (see Figure ORF1). The next 5 variables are the economic returns: RTANCR for the returns from annual crop, RTPAST from pasture, RTFORE from forest, RTPECR from perennial crop and POPULA for population. Because the returns interact with biophysical and climate variables (see the eq. (3) in the main paper), the remaining rows indicates the coefficients associated with these interactions

Variables	ANCR		PAST		FORE		URBA	
	Coefficient	Stud. t	Coefficient	Stud. t	Coefficient	Stud. t	Coefficient	Stud. t
(intercept)	-1.76595 *	-31.57	-1.21581 *	-22.57	-3.76205 *	-38.48	-3.08081 *	-40.89
UinitANCR	6.37053 *	148.69	4.53382 *	104.13	3.72674 *	38.63	3.42914 *	50.99
UinitPAST	4.87827 *	107.31	6.54125 *	148.27	5.91267 *	65.44	4.56686 *	70.18
UinitFORE	3.22036 *	30.59	4.73351 *	48.85	11.07261 *	90.27	5.11910 *	46.25
UinitURBA	2.48644 *	23.69	3.95471 *	43.29	5.05943 *	39.66	8.33810 *	85.25
PC1B	0.02298	1.21	0.14045 *	7.59	0.14755 *	7.15	0.06694 *	3.11
PC103	0.01766	0.83	0.26168 *	12.65	0.20597 *	9.32	0.06954 *	2.97
PC203	0.14177 *	6.36	0.29133 *	13.82	0.01880	0.80	0.18356 *	7.59
RTANCR	0.00166 *	6.85	-0.00252 *	-10.46	-0.00011	-0.42	0.00038	1.37
RTPAST	-0.00151 *	-4.78	0.00170 *	5.43	-0.00132 *	-3.81	-0.00051	-1.43
RTFORE	0.00416 *	5.63	0.00025	0.34	0.00219 *	2.81	-0.00123	-1.49
RTPECR	-0.00188 *	-14.46	-0.00141 *	-11.15	-0.00091 *	-6.45	-0.00104 *	-6.93
POPULA	-0.00002 *	-10.5	-0.00000 *	-2.58	-0.00001 *	-3.88	0.00001 *	4.38
PC1B:RTANCR	-0.00003	-0.31	-0.00022 *	-2.31	-0.00027 *	-2.49	-0.00006	-0.52
PC1B:RTPAST	-0.00032 *	-2.90	-0.00006	-0.53	0.00013	0.99	-0.00002	-0.18
PC1B:RTFORE	0.00015	0.41	-0.00072	-1.95	-0.00091	-2.24	-0.00144 *	-3.36
PC1B:RTPECR	-0.00000	-0.00	0.00014 *	4.19	0.00011 *	3.20	0.00010 *	2.52
PC1B:POPULA	-0.00000 *	-2.40	-0.00000 *	-5.11	-0.00000 *	-4.44	-0.00000 *	-4.91
PC103:RTANCR	0.00007	0.71	-0.00028 *	-2.86	-0.00014	-1.28	-0.00042 *	-3.76
PC103:RTPAST	-0.00015	-1.10	0.00034 *	2.61	0.00024	1.62	0.00057 *	3.71
PC103:RTFORE	0.00157 *	3.42	-0.00062	-1.37	-0.00013	-0.27	0.00165 *	3.20
PC103:PXPECR	0.00015 *	5.29	-0.00003	-1.09	-0.00001	-0.31	-0.00000	-0.09
PC103:POPULA	-0.00000	-0.50	-0.00000	-1.63	-0.00000	-1.45	0.00000	1.5
PC203:RTANCR	0.00069 *	6.65	-0.00004	-0.35	0.00032 *	2.83	0.00049 *	4.35
PC203:RTPAST	-0.00006	-0.50	-0.00038 *	-2.96	0.00003	0.19	-0.00058 *	-3.90
PC203:RTFORE	0.00229 *	3.18	0.00008	0.11	0.00116	1.47	-0.00130	-1.58
PC203:PXPECR	-0.00029 *	-5.84	-0.00030 *	-6.67	-0.00030 *	-6.18	-0.00029 *	-5.61
PC203:POPULA	-0.00001 *	-9.59	-0.00000 *	-5.25	-0.00000 *	-5.16	-0.00000 *	-4.53

Table ORT3: **Summary of the results from the 4 econometric Ricardian models:** Only 4 Ricardian models (in rows) are estimated because the proxy for urban returns is predicted from deterministic national projections. ** stands for 0.01% of statistical significance, * for 1%. The table gives the values of F-tests for statistical significance. Climate variables, \mathbf{c}_{tq} , are accounted for by including the two principal components in bivariate smoothing functions. Land quality variables, \mathbf{x}_q , are accounted for by their first principal component in univariate smoothing functions. Human population (*POP*) is also included in these Ricardian models, as are the spatial coordinates \mathbf{z}_q of the centroids of each Small Agricultural Regions. The latter two factors are also included as arguments of bivariate smoothing functions. The fifth column gives the coefficients for the annual trends and their significance. The table also contains the cross-sectional and temporal dimensions of the data used to estimated Ricardian models. They are principally determined by data availability: $n=713$ where the estimation is at the scale of Small Agricultural Regions and $n=93$ for the French *départements*, see Table ORT4. Three of these models are estimated on pooled data from three points in time: 1993, 1998 and 2003. Because of data limitations, the Ricardian model for perennial crops is estimated for only two periods: 1993 and 1998. The last column contains the adjusted R-squares associated with each model

	F- \mathbf{c}_{tq}	F- \mathbf{x}_q	F- <i>POP</i>	F- \mathbf{z}_q	γ_ℓ	(n, t)	Adj.R ²
ANCR	4.95**	11.6**	29.6**	14.8**	.028**	(713, 3)	.785
PAST	4.13**	11.6**	17.5**	6.11**	.012**	(713, 3)	.766
PECR	3.62**	0.43	2.90*	20.6**	.007*	(93, 2)	.914
FORE	6.46**	1.68	0.65	19.9**	.000	(93, 3)	.361

Table ORT4: **The different spatial entities used to match the data, areas in km²:** TERUTI points are used to match the biophysical information (slope, elevation, land quality) to land use observation and to fit the land use model. Municipalities are used to compute population density, proxy the urban returns and make prediction about future urban return. TERUTI meshes are used to aggregate the predictions from land use change and map the results (as in Figure 1–3 in the main paper). Small Agricultural Regions are used to obtain returns from agricultural land use (crop, pasture and perennial crops) and *départements* for the returns from forest

NAME	NUMBER	MEAN AREA	MIN AREA	MAX AREA
TERUTI points	514,074	1	1	1
Municipalities	36,368	15	0.5	760
TERUTI meshes	3,578	144	144	144
Small Agricultural Regions	713	780	11	4,413
Départements	96	5,800	600	10,525

Table ORT5: Robustness results of Species Distribution Models I: The number of bird species treated falls from 65 in the negative binomial GAMs to 55 using mixed models with negative binomial distributions because there was no convergence of estimation process for 10 species. The random effects are specified at the *départements* scale, see table ORT4. The covariates are specified as second order polynomials (the bottom panel of the Table reports joint statistical significance). The geographical coordinates are not included as covariates, to stress the differences with the other SDMs. In comparison to the results from Table ORT1, the predictive abilities are smaller, and the climate and land use variables are less often significant. The simulations from these SDMs are presented in the Figure ORF10

Mixed Models with Negative Binomial distributions					
N= 55	Min	Q1	Q2	Q3	Max
Corr($\mu, \hat{\mu}$)	.22	.40	.47	.56	.78
Statistical significance of explanatory variables					
VAR	CLIMATE	ANCR	PAST	FORE	URBA
<i>p</i> -value < .01	34/55	37/55	16/55	52/55	39/55
% of species	(62)	(67)	(29)	(95)	(71)

Table ORT6: **Robustness results of Species Distribution Models II:** SDMs are also fitted using zero inflated hurdle models (from the R package psc1) with and without geographical coordinates as regressors. The joint effect of longitude and latitude is significant for 49 species (77%). The other covariates are specified as second order polynomials (the bottom panel of the Table reports joint statistical significance)

Zero Inflated Hurdle Models					
N= 64	Min	Q1	Q2	Q3	Max
Without Geographical Coordinates					
Corr($\mu, \hat{\mu}$)	.10	.36	.41	.51	.76
With Geographical Coordinates					
Corr($\mu, \hat{\mu}$)	.19	.42	.49	.57	.79
Statistical significance of explanatory variables					
VAR	CLIMATE	ANCR	PAST	FORE	URBA
Without Geographical Coordinates					
<i>p</i> -value < .01	55/64	51/64	49/64	57/64	49/64
% of species	(86)	(80)	(77)	(89)	(77)
With Geographical Coordinates					
<i>p</i> -value < .01	53/64	51/64	43/64	55/64	46/64
% of species	(83)	(80)	(67)	(86)	(72)

Figure ORF2: **Effect of scenario S0 on bird index for 4 different habitat specialization:** Each partially-linear curve represents a bird species. The thicker curves with confidence intervals represent the geometric means (i.e., the aggregate bird index). Standard deviations are computed by the delta method

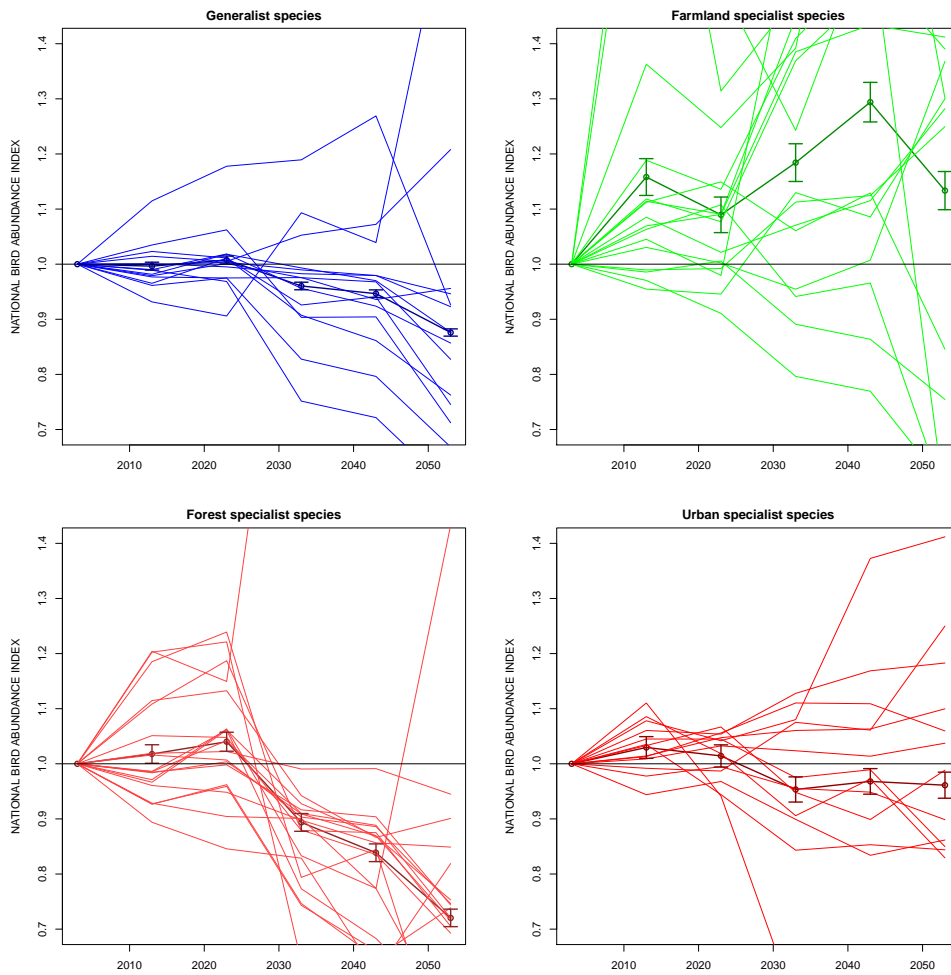


Figure ORF3: **Effect of scenario S0 on abundance of bird species of interest:** Habitat specialization are in parentheses, at the right of species' names: AGR for agriculture, GEN for generalist, FOR for forest and URB for urban. Confidence intervals are at 95%, a positive growth is marked in blue, a negative in red and the absence of significant growth in gray

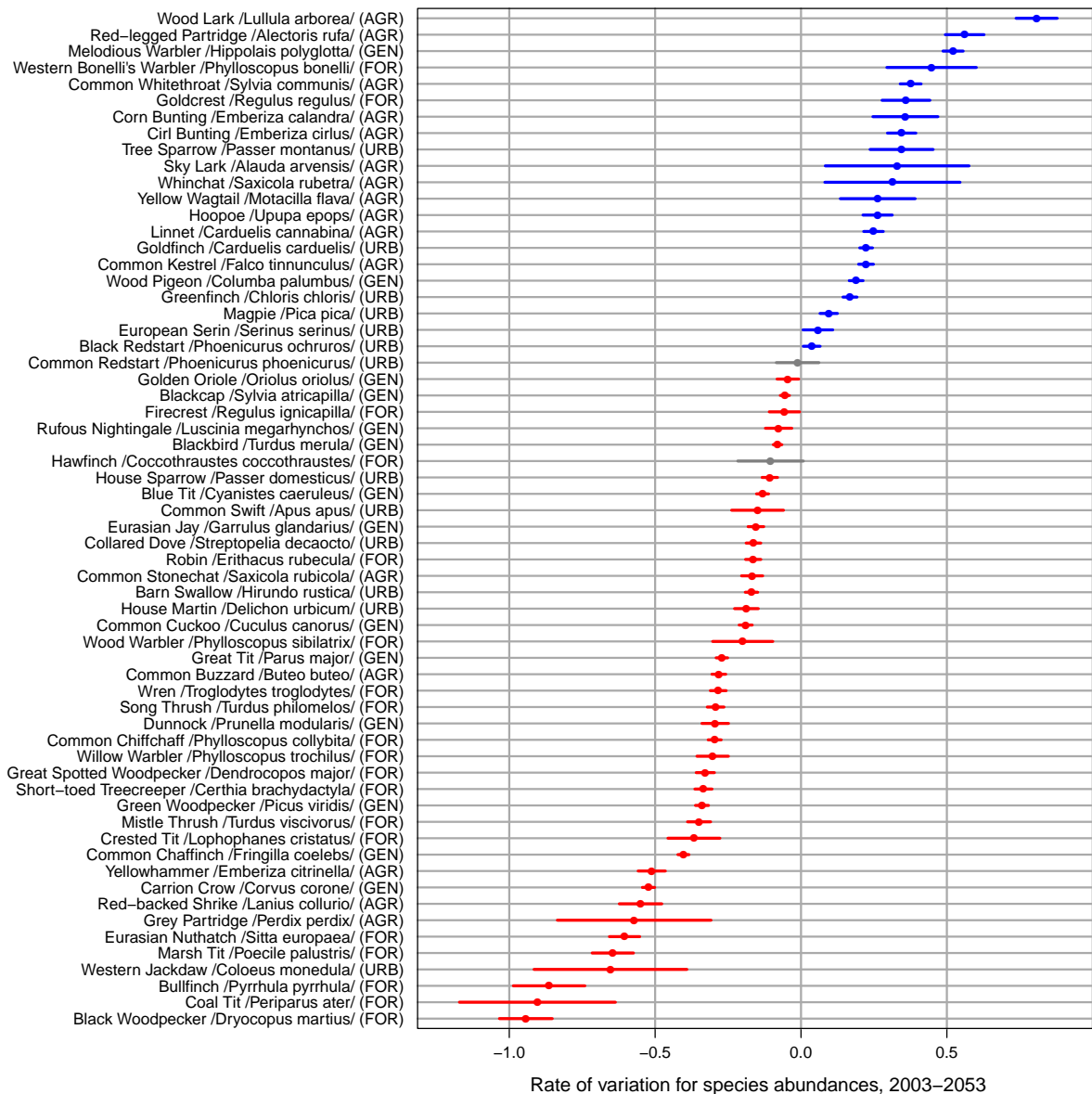


Figure ORF4: **Effect of only S1 LUC on bird index according to habitat specialization:** Each partially-linear curve represents a bird species. The thicker curves with confidence intervals represent the geometric means (i.e., the aggregate bird index). Standard deviations are computed by the delta method

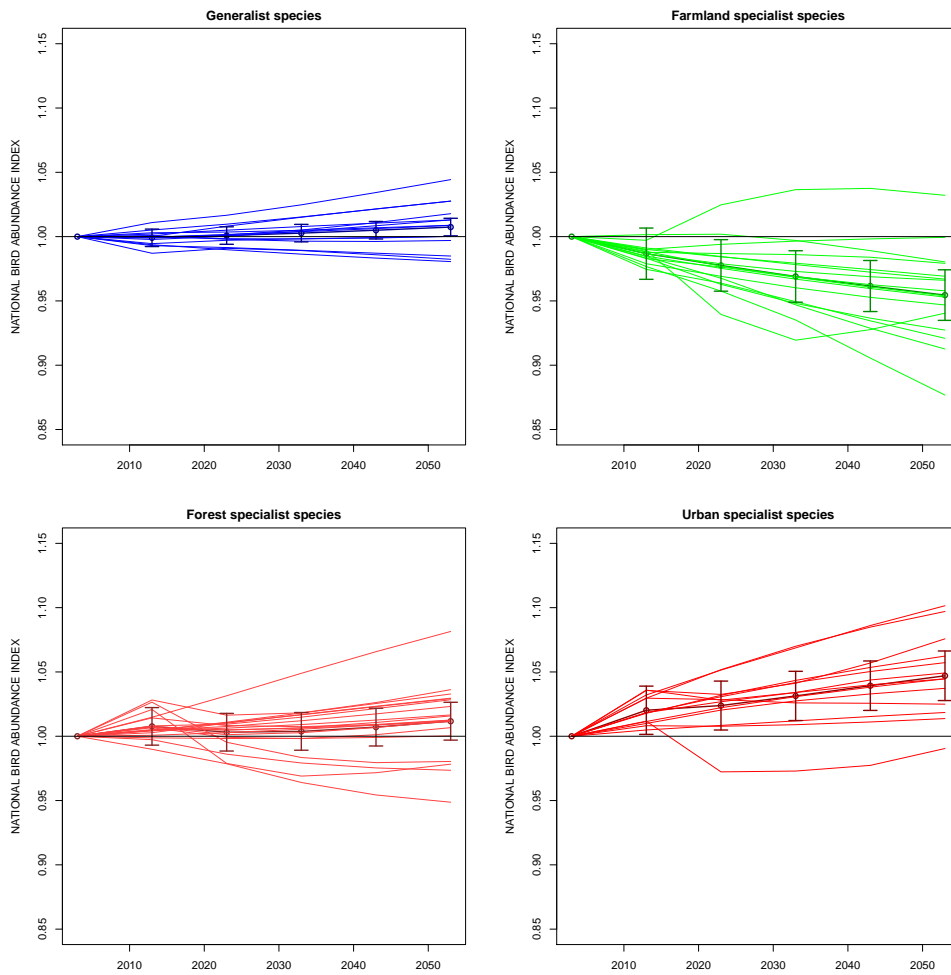


Figure ORF5: **Effect of scenario S1 on considered bird species:** Habitat specialization are in parentheses, at the right of species' names: AGR for agriculture, GEN for generalist, FOR for forest and URB for urban. Confidence intervals are at 95%, a positive growth is marked in blue, a negative in red and the absence of significant growth in gray

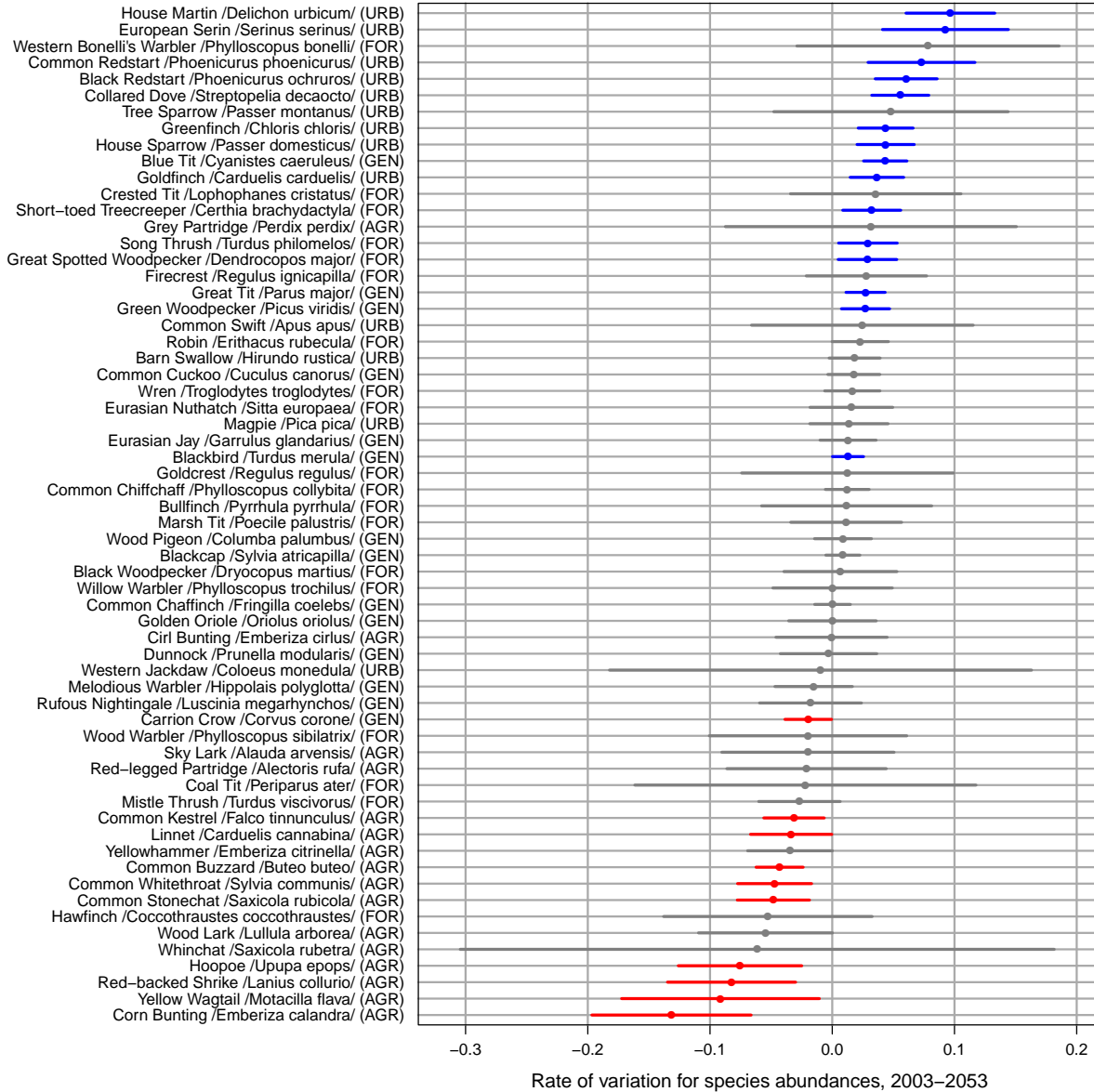


Figure ORF6: **Effect of scenario S2 on bird index according to habitat specialization:** Each partially-linear curve represents a bird species. The thicker curves with confidence intervals represent the geometric means (i.e. the aggregate bird index). Standard deviations are computed by the delta method

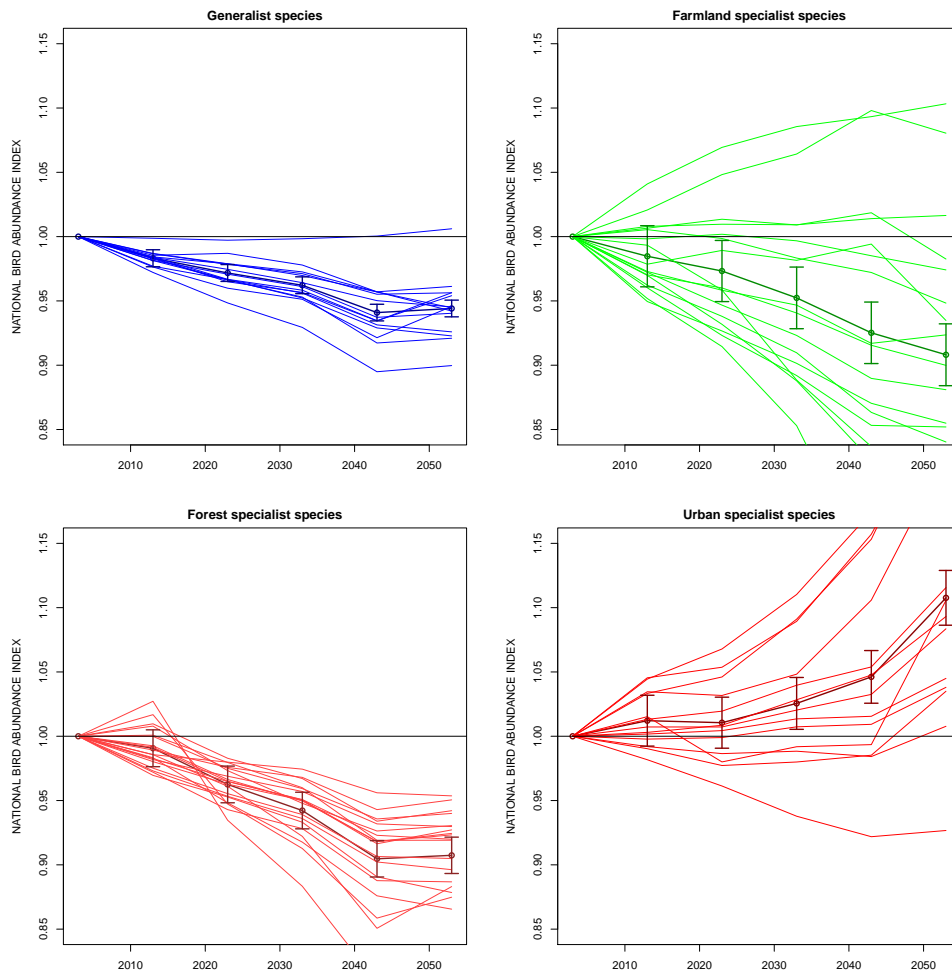


Figure ORF7: **Effect of scenario S2 on considered bird species:** Habitat specialization is reported in parenthesis, at the right of species' names: AGR for agriculture, GEN for generalist, FOR for forest and URB for urban. Confidence intervals are at 95%, a positive growth is marked in blue, a negative in red and the absence of significant growth in gray

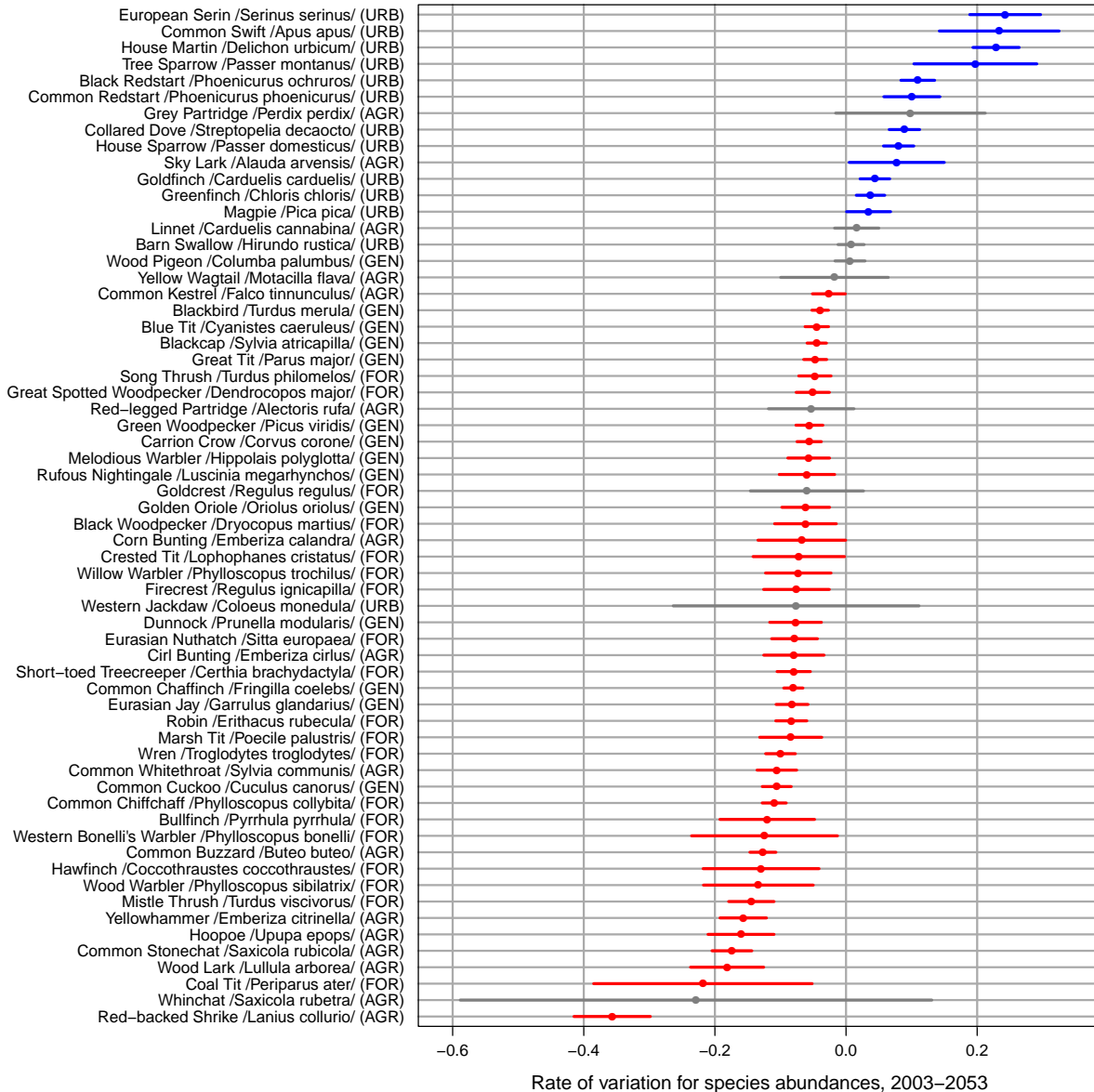


Figure ORF8: **Net effect of 200 euro conservation payments with LUC as usual (S1 → S3):** habitat specialization is reported in parentheses, at the right of species' names: AGR for agriculture, GEN for generalist, FOR for forest and URB for urban. Confidence intervals are at 95%, a increase of abundances following payment for pasture is marked in blue, and a decrease in red

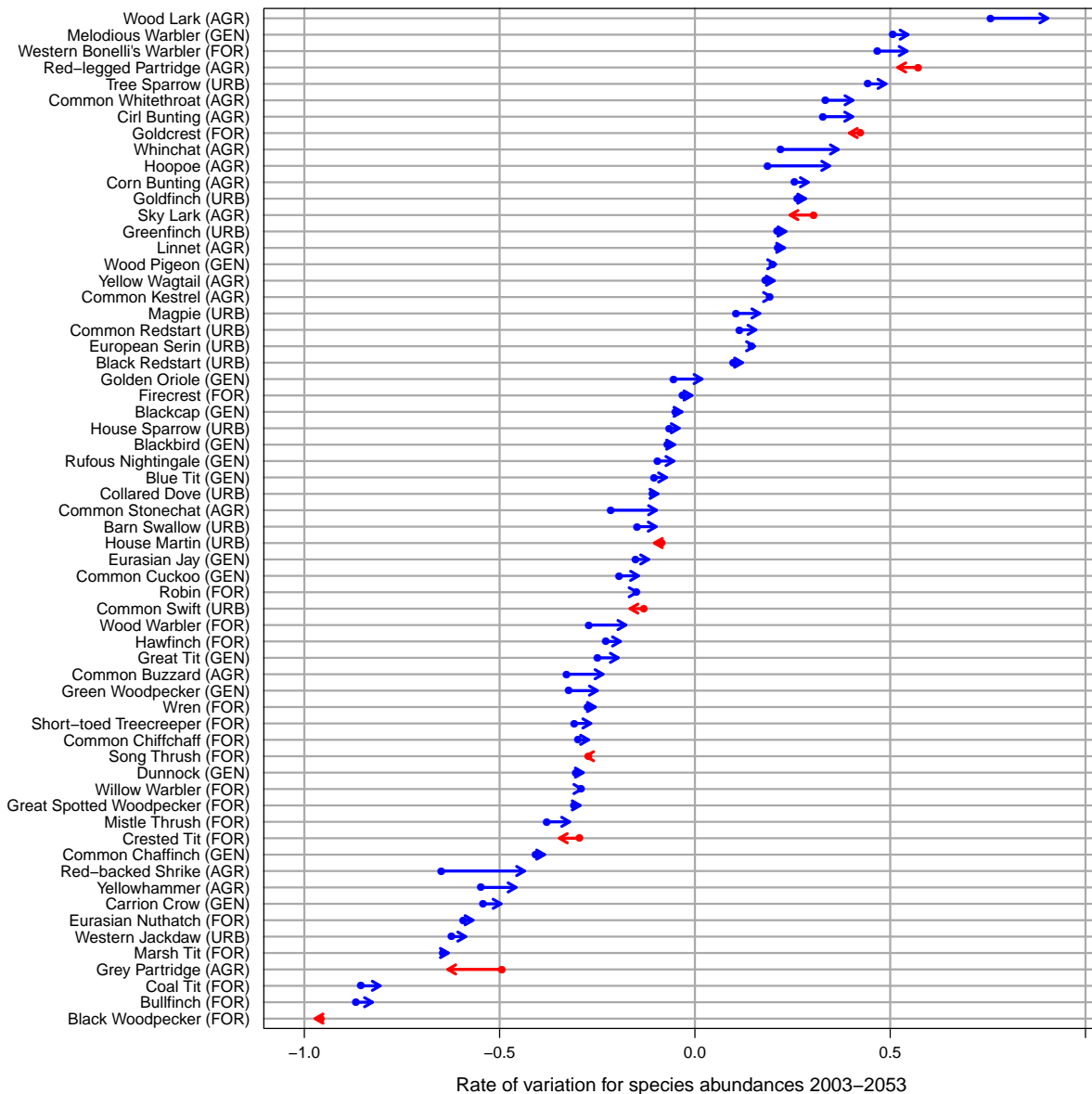


Figure ORF9: **Net effect of 200 euro conservation payments with climate-induced LUC (S2 → S4):** Habitat specialization is reported in parentheses, at the right of species' names: AGR for agriculture, GEN for generalist, FOR for forest and URB for urban. Confidence intervals are at 95%, a increase of abundances following payment for pasture is marked in blue, and a decrease in red

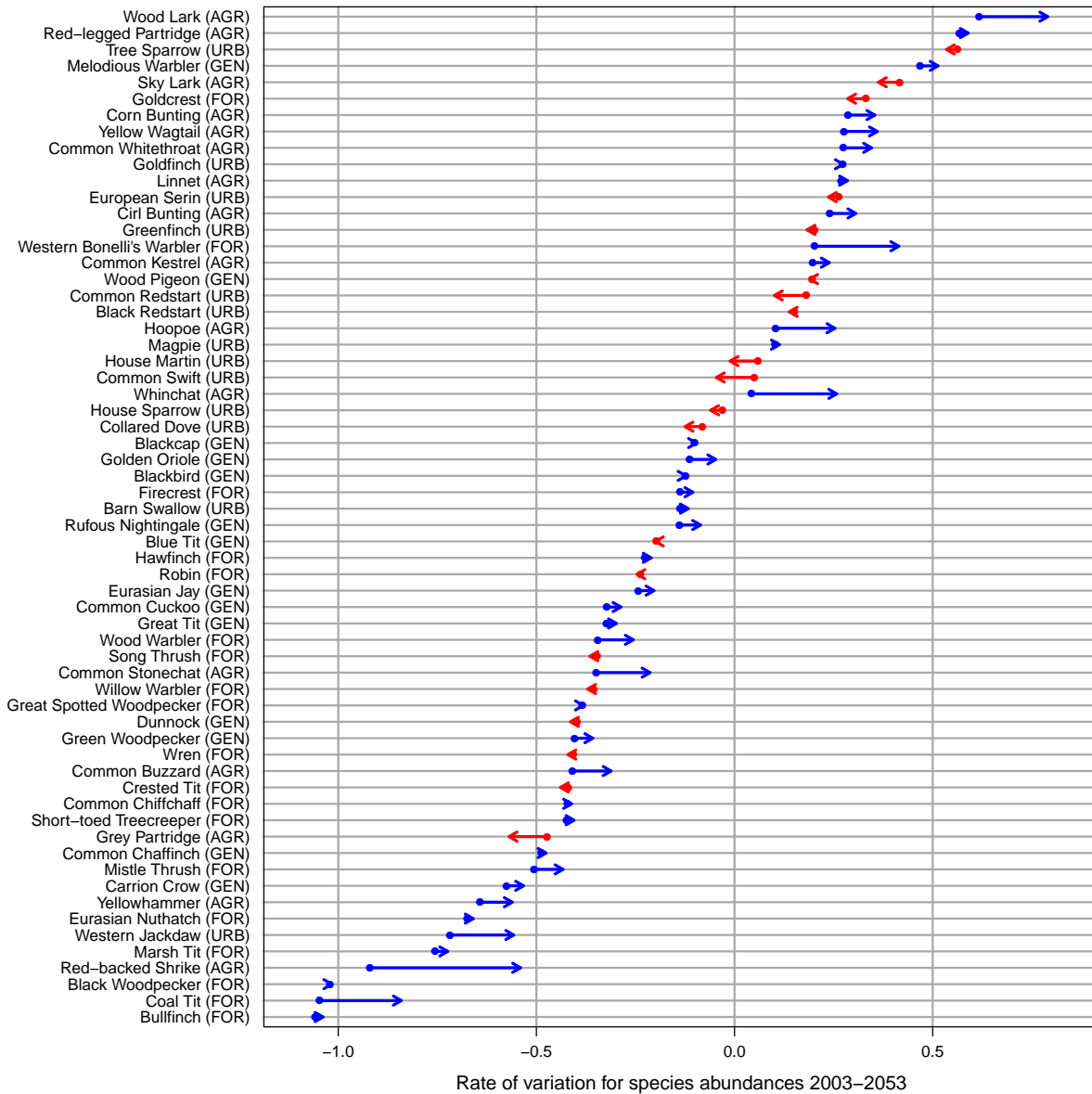
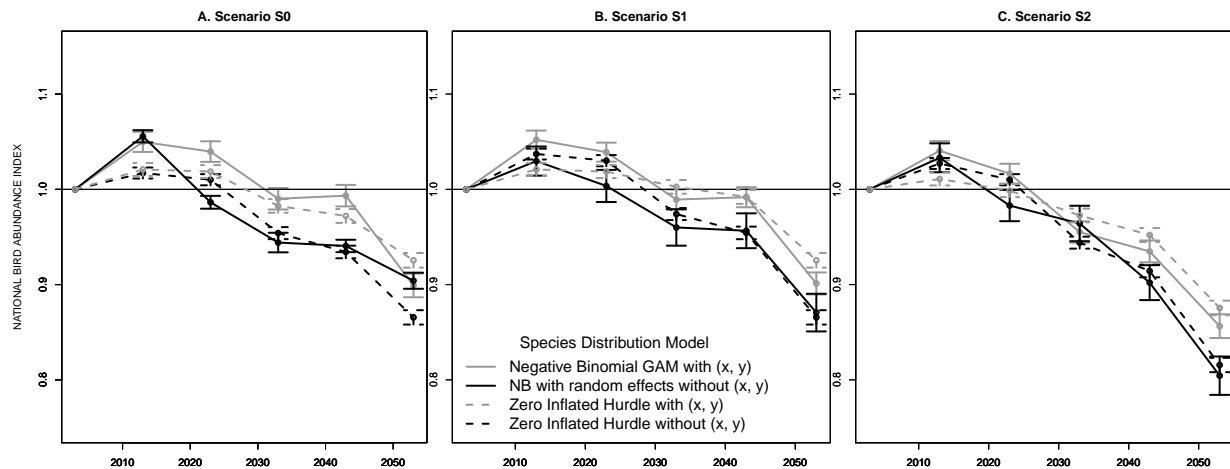
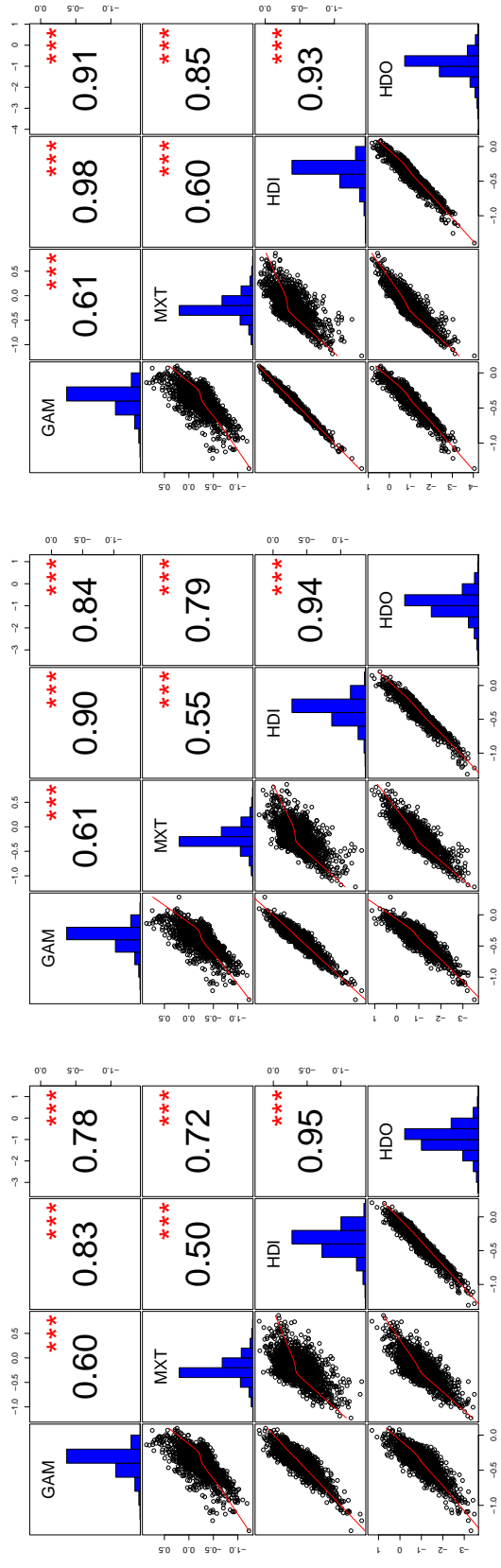


Figure ORF10: **Robustness checks I for bird distributions for scenarios S0, S1 and S2:** This figure presents the predictions of bird index from scenarios S0, S1 and S2 (see Figure 1 in the main paper). Each plot contains the predictions using Negative Binomial GAM (as in the main paper) and the alternative predictions from Mixed Negative Binomial without geographical coordinates as a covariate but with *département* random effects. The projections are similar, except that the effect of climate change seems greater for the latter. The uncertainty of the projections is in general greater for random effect model





(a) Scenario S0

(b) Scenario S1

(c) Scenario S2

Figure ORF11: **Robustness checks II for bird distributions according to the SDMs:** This figure presents the projections of bird abundances variations for scenario S0, S1, and S2 between SDMs. Four SDMs are reported, GAM: GAM negative binomial with geographical coordinates; MXT: Mixed negative binomial without geographical coordinates; HDI: Zero Inflated Hurdle models with geographical coordinates; HDO: Zero Inflated Hurdle models without geographical coordinates. The projected variations are highly correlated, which illustrates the robustness of our results to the choice of the SDMs