Supporting Online Material for

Climate change impacts on tree ranges: model inter-comparison facilitates understanding and quantification of uncertainty

Alissar Cheaib [*], Vincent Badeau, Julien Boe, Isabelle Chuine, Christine Delire, Eric Dufrêne, Christophe François, Emmanuel S. Gritti, Myriam Legay, Christian Pagé, Wilfried Thuiller, Nicolas Viovy and Paul Leadley

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Contents

SA1: Model description

BIOMOD (Thuiller 2003; Thuiller *et al.* 2005; Thuiller *et al.* 2006; Thuiller *et al.* 2009) is a package implemented in R software for ensemble forecasting of species distributions, enabling the treatment of a range of methodological uncertainties in species distribution models and the examination of species-climate relationships. Here, we used the nine models implemented BIOMOD: Generalised Linear Models GLM (McCullagh & Nelder 1989), Generalised Additive Models GAM (Hastie & Tibshirani 1990), Multivariate Adaptive Regression Splines MARS (Freidman 1991), Classification Tree Analysis CTA (Breiman *et al.* 1984), Mixture Discriminant Analysis MDA (Hastie *et al.* 1994), Artificial Neural Networks ANN (Ripley 1996), Generalised Boosted Models GBM (Ridegeway 1999), Random forests (Breiman 2001), and one Rectilinear Envelope Similar to BIOCLIM (Busby 1991). Seven climatically derived variables considered critical to plant physiological function and survival were used as input data in BIOMOD: mean annual, winter, and summer precipitation, mean annual temperature and minimum temperature of the coldest month, growing degree days (GDD>5°C) and an annual potential evapotranspiration. Mean monthly values were averages for the period of 1971-2000 and of 2046-2065.

For each species and for all models, 70% of the original data were used for the model calibration, while 30% were kept for model evaluation using the True Skill Statistics (TSS) method (Allouche *et al.* 2006). This procedure was repeated ten times to make sure the model predictive accuracy was not influenced by the random-splitting procedure.

To account for the fact that different models are used altogether, we applied a committee averaging method to extract a single output from the 9 models X 10 repetitions of outputs per model. The committee averaging method is an ensemble forecasting method (Thuiller *et al.* 2009) based on the use of different model algorithms (e.g. regressions, classification trees, machine learning). The rationale of ensemble forecasting is that different algorithms have different levels of accuracy under different circumstances and there is no single perfect algorithm (Elith* *et al.* 2006). In the committee averaging method, predicted probability maps of species' presences from the different algorithms are not averaged, but instead transformed into binary maps (using for each model the threshold that maximizes TSS) which are then summed to obtain one single map of the final output. In other words, each model "votes" for each site whether it forecasts species presence or not. It is therefore not a probability of occurrence that is measured but rather a percentage of agreement on species presence between the various algorithms and repetitions (90 binary maps). The main advantage of the committee averaging method is the use of "comparable outputs" (binary presence-absences) instead of the raw algorithm outputs (continuous probabilities) that do not necessarily have the same meaning or the same range of variation. Note that we did not necessary use the 90 binary maps as we only kept the models having a TSS higher than 0.3 (to make sure bad models were excluded). The final committed averaging outputs were transformed into binary presence-absence using a threshold maximizing the TSS.

Another advantage of the committee averaging procedure is that the raw output (not binary transformed and standardized between 0 and 1) gives the likelihood of being true given the data and models. Values close to 0 mean that all models and repetitions agree that predict an absence. Values close to 1 mean that all models and repetitions agree to predict a presence. Intermediate values give the uncertainty associated with the projection.

N-NBM (Badeau *et al.* 2010) investigated the relationship between the binary responses of trees and the explanatory variables with a logit function (proc logistic SAS 9.2, 2002). No climatic variable was considered *a priori* critical, so N-NBM used a wide set of potential explanatory effects: minimum, maximum and mean temperatures; precipitations; wind speed; relative humidity and vapor pressure deficit; atmospheric pressure; global solar irradiance; potential evapotranspiration (based on Turc’s formula, Penman’s formula and Penman-Monteith’s formula corrected by the CO_2 concentrations); growing degree days (>0°C, >5° and >10°C); number of days of frost (<0°C, <-5°C, <-10°C). A daily water balance model (Granier *et al.* 1999) was also used to quantify the water stress intensity, the number of days of water stress; the start date of water stress. Each of these three variables was calculated for deciduous and evergreen forests using the three PET calculations. Monthly, seasonal and annual values were computed from daily data covering the 1971-2000 period. Effects in the models were selected according to a stepwise method and a significance level of the score chi-square ≤0.0001. The compromise between the number of variables and the model performance was evaluated step-by-step with the Nagelkerke R^2, AIC values, Khi^2 score, variance inflation factor, collinearity and TSS. Because numerous explanatory variables can be added to the models with very low significance levels, an expert-based selection was also used: each new variable entering into the model should have a “physiological sense” otherwise the procedure stops (e.g. the significance of November atmospheric pressure is not obvious); at each step the new variable should improve significantly the TSS (better ranking of one hundred points at least); the number of explanatory variables was strongly limited (no more than five variables for the species studied here). Calibration / validation procedures were done three times at least (i.e. if the order of the variables was consistent) on randomly selected points (70% / 30% of the original data). Final parameter estimates were averaged from the three calibrations.

STASH (Sykes *et al.* 1996; Sykes 2001) is a bioclimatic model that simulates the biogeography of individual plant species at the continental scale. This model estimates the bioclimatic envelope of the considered species by comparing its native distribution with gridded bioclimatic data. The bioclimatic envelope consists of a minimum set of physiologically constraining environmental parameters to plant growth and regeneration (i.e. mean temperature of the coldest month, mean temperature of the warmest month, accumulated growing season warmth (GDD), chilling requirement for budburst and a drought index). These parameters associated to physiological mechanisms are assumed to control species' distribution limits. Some of these parameters act as on-off switches on the growth index calculated by STASH, other parameters act as multipliers of the growth index and determine the degree of presence of the species in a grid cell (See Sykes *et al.* 1996 for further details).

STASH requires monthly mean values of temperature, precipitation and percentage of cloudiness, to generate gridded bioclimatic parameters over i) the time period corresponding to the native distribution dataset to define the bioclimatic envelope of the focal species ii) the considered time periods of the study to compute specialised growth index by comparison with the previously defined bioclimatic niche.

PHENOFIT (Chuine & Beaubien 2001; Morin & Chuine 2005) is composed of several sub-models: different phenological models (leafing, flowering, fruiting, and leaf senescence), a frost injury model, a survival model and a reproductive success model. Every sub-model works at a daily time-step. The model outputs a mean probability of presence of an adult tree of the studied species. This probability is assessed by the fitness of the individual, calculated as the product of its probability to survive until the next reproductive season and to produce viable seeds before the end of the annual cycle (reproductive success). In this study, fitness was averaged over the time slice. Parameter estimates are either directly measured (e.g. LT_{50}, temperature inducing 50% frost damage on leaves or buds or twigs) or fitted on observations of the species traits. The inputs are daily climate variables (daily maximum and minimum temperatures, precipitation, relative humidity, total incoming shortwave radiation, wind speed) and the holding water capacity of a site. The version used for this study used the leaf senescence model of (Delpierre *et al.* 2009) and a daily water balance calculated with a Penman PET.

CASTANEA (Davi *et al.* 2005; Dufrêne *et al.* 2005) is an eco-physiologically multi-layer process-based model, simulating carbon, energy and water balance, and stand growth in an even-aged monospecific forest stands. For most processes the stand is represented by an average tree. As far as mortality is concerned, a gaussian tree distribution is considered for the key state variables (notably carbon reserves).

Tree structure is subdivided into four functional compartments: foliage, aboveground and belowground woody biomass (stem, branches and coarse roots), fine roots, and carbohydrates reserves pool located in sapwoods of woody biomass. The canopy is considered homogeneous horizontally and vertically subdivided into a variable number of layers, each of them enclosing a constant (small) amount of leaf area. The main processes simulated are: (i) at half-hourly timescale, the canopy photosynthesis, maintenance and growth respiration (autotrophic respiration), soil heterotrophic respiration, transpiration and evapotranspiration. (ii) and at daily timescale, the carbon allocation, growth of organs, leaf area index and water content. Tree mortality was taken into account and estimated from the carbohydrates reserve pool (when reserves reached a low level, a corresponding fraction of the trees was considered dead). The effect of CO_2 concentration is directly taken into account by the photosynthesis model. The model reproduces the observed enhancement of photosynthesis and the reduction of stomatal conductance both due to CO_2 increase. This is the only direct effect of CO_2 increase that is assumed. All phenological events (budburst, leaf expansion and growth, start of leaf yellowing and leaf fall) are modelled daily depending on degrees-days and day duration (Delpierre *et al.* 2009). The present version of CASTANEA was used for two species: European beech and sessile oak. CASTANEA uses many input parameters; some of them are taken from literature, other ones estimated from field measurements, interpolation or theoretical evaluation.

Input meteorological driving variables at hourly temporal scale are global radiation, rainfall, wind speed, air humidity, air temperature and CO_2 air concentration.

The duration of each simulation corresponds to the period of the forest management cycle according to a medium scenario of forest exploitation (The first cut occurs when the trees reach 40 years old, then a cut is made approximately every 10 years). For each simulation, we replicated the climate time series (1970 to 2001 for current climate, 2046 to 2065 for future climate) until the end of the forest management cycle (150 years for both species).

To analyse the predictions of the model in forest vigour and productivity, we chose as main output the sum of wood harvested during the management cycle, seen as an indicator of tree fitness.

LPJ (Smith *et al.* 2001; Bonan *et al.* 2003; Sitch *et al.* 2003; Hickler *et al.* 2004; Gritti *et al.* 2006; Miller *et al.* 2008). The version of LPJ used here is described in (Gritti *et al.* 2006) and does not include any modifications of the model since then (e.g. Hickler *et al.* 2006, Miller *et al.* 2008). We ran LPJ with only one species instead Plant Functional Type (PFTs) in order to compare LPJ with the species-based models used in this study. LPJ is a generalized ecosystem model that combines mechanistic representations of plant physiological and biogeochemical processes with explicit formulations of the dynamic processes controlling vegetation structure, such as plant establishment, mortality, and competition inter and/or intra species/PFTs (although no competition was accounted for in the version used in this study), The model simulates the growth of individual trees on a number of replicate patches, corresponding approximately in size to the area of influence that one large adult tree has on its neighbours. Climate changes influence plant growth in LPJ via temperature effects on the kinetics of photosynthesis and maintenance respiration; influence of soil water content on stomatal conductance and photosynthesis; and changes in phenology (in association with an increased GDD during the growing season). Increased atmospheric CO_2 concentrations result in biochemical stimulation of photosynthesis, and can lead to improved water balance due to enhanced water-use efficiency.

Climatic factors, expressed as monthly mean temperature, precipitation and cloudiness, as well as a prescribed disturbance regime (which can be used to represent land management) and soil characteristics, directly influence vegetation distribution and dynamics.

Simulations are performed across a grid. Within each grid cell the focal species performance is described as yearly or monthly production indices such as Net Primary Production or Leaf Area Index. Each species is defined by a set of parameters describing plant physionomy, allometry, physiology, phenology and bioclimatic limits. The species sets used in the present study were based on the set of the corresponding PFTs defined in the global version of LPJ-Guess (Smith *et al.* 2001). However species-specific values were used when available. In this study LPJ predicts potential or ‘natural’ distribution of vegetation described by climate and intraspecific interactions within an ecosystem.

ORCHIDEE (De Noblet-Ducoudré *et al.* 2004; Krinner *et al.* 2005) is a terrestrial biosphere model based on three different sub-models simulating explicitly processes of water and energy exchange between atmosphere and vegetation, terrestrial carbon cycle linked vegetation and soil decomposition processes, as well as changes in vegetation distributions in response to climate change as well as short time scale interactions between vegetation and biosphere. ORCHIDEE includes (i) a hydrological model which operates at 30 minutes time step and describes water and energy exchanges between land vegetated and atmosphere, (ii) a carbon model which operates at a one day time step and simulates the different sub-processes of the carbon cycle and their interactions: phenology, photosynthesis, respirations, carbon allocation, litter decomposition and soil carbon dynamics, and (iii) a vegetation dynamics model which operates at one year time step, and includes the parameterization of vegetation dynamics that determine the distribution of species based on bioclimatic criteria for the introduction or elimination of PFTs, fire, sapling establishment, light competition and tree mortality.

The variables used by ORCHIDEE are: minimum and maximum air temperature, shortwave and long wave incoming radiations, specific air humidity, precipitations, surface pressure and wind speed. Time step is 30’. Data are then interpolated from daily to 30’ timestep using a weather generator that allows reproducing the diurnal cycle of main parameters. The model outputs (fraction of PFT occupied by grid cells) are averaged over the time slice (20 years around 2001 and 2055).

In this study and compared to initial parameterization of (Krinner *et al.* 2005), some changes in vegetation dynamics have been made:

1) Climate constraints are used to define adaptation and regeneration of PFTs. Theses climatic parameters are applied to define the rate of PFT expansion and eventually the death of PFT if certain thresholds are reached. These constraints were originally only based on mean annual temperature. A new constraint on minimum soil water was introduced to account for constraints water stress on PFT distribution. Average yearly minimum soil water is calculated based on 20 years climatology. The adaptation factor is then modulated by the ratio of average climatologic minimum soil water to its threshold in a similar way to what is done with temperature.

2) Another modification was done for calculation of the rate of PFT expansion. In the initial formulation PFT expansion rate was independent of the NPP of this PFT. This rate was only depending on regeneration factor. NPP was then only taken into account in the light competition process when sum of fractional cover of all PFT was over 95%, then PFT with highest NPP are dominant over the others PFT. The rate of expansion of each PFT is now modulated by the ratio of NPP of the PFT to the NPP of the most productive PFT.

IBIS (Foley *et al.* 1996; Kucharik *et al.* 2000) is a terrestrial biosphere model designed around a hierarchical, modular structure and consists of four modules which operate at different time steps. The land surface module operates at relatively short time step (here 60 min) and simulates water, CO_2, and energy exchanges. The vegetation phenology module operates on daily time step and describes vegetation cycle (budburst and senescence) in relation to seasonal climatic conditions. The carbon balance module simulates gross photosynthesis, maintenance and growth respiration and net primary productivity. The vegetation dynamic module simulates at a yearly time-step the time-dependent changes in vegetation cover resulting from changes in NPP, carbon allocation, mortality and biomass turnover of each plant functional types and PFTs competition.

The energy, water and carbon fluxes simulated by IBIS have been validated against site-specific biophysical measurements from fluxes towers (Delire & Foley 1999), field-level ecological studies (Senna *et al.* 2005; Kucharik *et al.* 2006), as well as spatially extensive ecological and hydrological data (Costa & Foley 1997; Kucharik *et al.* 2000; Coe *et al.* 2002). IBIS is forced by hourly values of air temperature and humidity, precipitation, wind speed, downward solar visible and infrared radiation. We present here quasi-equilibrium results. For the current climate, the model was spin up for 500 years using the 1951-2000 climate forcing repeatedly. The last 30 years were used for the analysis. Similarly for the 2055 time slice, the model was run for 200 years looping through the 2046-2065 climate forcing and we analyzed the last 20 years. We chose to analyze results in terms of NPP because IBIS is mainly a vegetation carbon balance model and this variable best reflects the inner workings of the model.

For this study, we modified the very simple winter leaf phenology parameterization based on temperature for the deciduous trees to allow them to grow on the Western part of the country. With the original parameterization, coniferous trees would systematically win competition in the Western half of the country because the growing season of deciduous trees was too short. We also increased the specific leaf area index of broadleaved evergreen trees to better represent Holm Oak. The original parameterization was better suited for species like Eucalyptus trees. We also had to lower the minimum bioclimatic temperature limit to allow the species in France in the current climate. The very high resolution climate data used in this study includes temperatures extremes that are not present in the climatologies at 0.5 degrees resolution used to develop the model at global scale.

SA2: Regionalized Climate

Regionalized climate scenarios were produced with a multivariate statistical downscaling methodology, which is able to generate local time series of temperature and precipitation, and other variables at different sites based on large-scale circulation predictors, here the mean sea-level pressure, 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 resampling. For further details in climate regionalization see (Boé *et al.* 2009)

SA3. Model comparison in the future climate

To respond to the question “For a given simulated distribution of a tree species under current climate, what fraction is projected to disappear in the future?", we calculated a relative rate of gain or loss for each species for each of the 14 bioclimatic regions as: (sum of 2055 grid cells with presence - sum of current grid cells with presence) / sum of current grid cells with presence. Negative values correspond to loss of area for a species, positive values to gain (Tables S1-S5). In regions with very limited current presence we do not present relative change. Because the Holm oak presence is currently confined to the Mediterranean region, it is difficult to calculate a relative rate of gain or loss for the other ecological regions, since the current presence is zero.

However, if a tree species is simulated to be present in 10% of a region and to disappear entirely in the future, this is not at all the same as situation where it is present in 90% of a region and the completely disappears in the future. The relative change calculated above assigns the same value of both situations (i.e., -1). For this reason, we calculated an absolute change metric as (sum of grid cells with presence in 2055 - sum of grid cells with presence in current climate) / sum of grid cells (Table S1-S6). This absolute change works better in some ways (i.e., it accounts for the % current presence in a region), but fails to respond to the important question about relative change. For example, if one model simulates 30% presence under current climate and another simulates 50% presence and both simulate total loss under the future, an absolute change metric tells us that models disagree, when in fact they both agree that climate will be unfavorable for the species throughout the entire region.

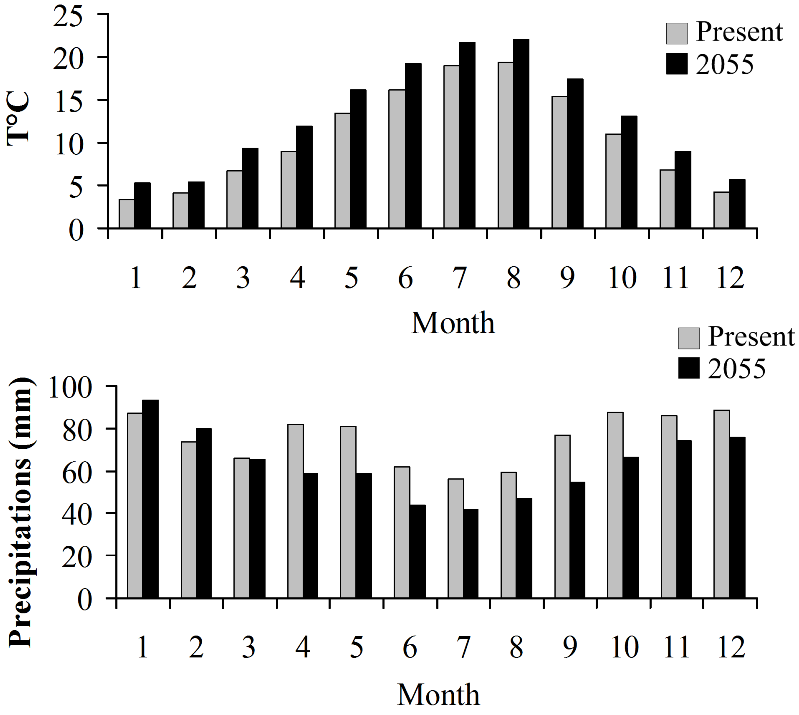

Fig. S1. Monthly mean temperatures and sum of precipitation averaged over the current climate (1970-2001) and the 2055 climate (2046-2065) across France.

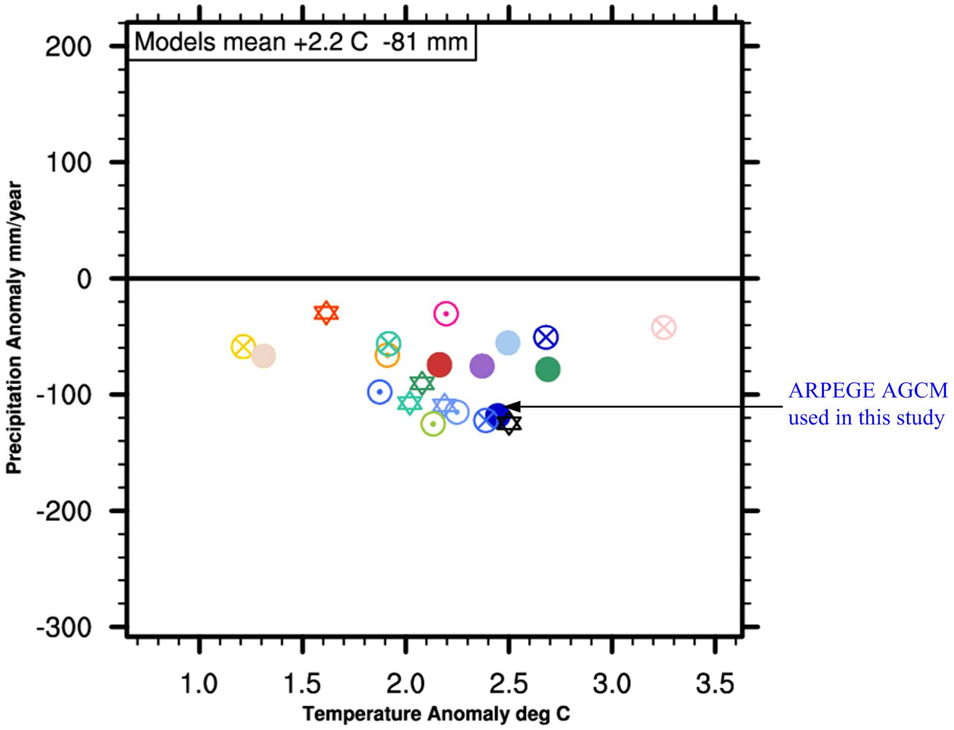

Fig. S2. Anomalies of Temperature (°C) versus Precipitation (mm. year^{-1}) of 2046-2065 period compared to 1961-1990 reference climate for 14 CMIP3 IPCC models downscaled scenarios, and 7 Meteo-France ARPEGE model downscaled scenarios. The ARPEGE downscaled scenario used in this study is the dark blue filled circle.

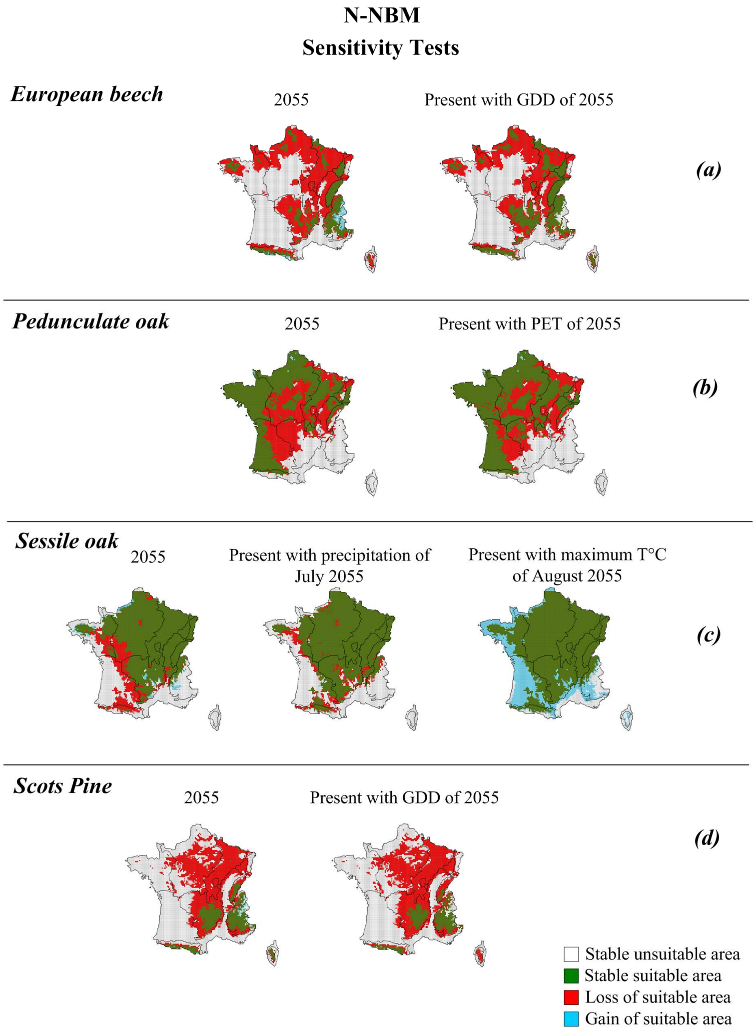

Fig. S3. N-NBM sensitivity tests: (a) For European beech, the sum of growing days GDD (sum of days with Temperature > 10°C) can explain entirely the future distribution since holding all other climatic variables to current values and maintaining only the future values of GDD leads to the same distribution than in 2055; (b) For Pedunculate oak, the potential evapotranspiration PET of July can explain entirely the future distribution since holding all other climatic variables to current values and maintaining only the future values of PET leads to the same distribution than in 2055; (c) For Sessile oak, NBM shows contrasting and weak sensitivity to climate; (d) For Scots pine as for beech, temperature (GDD) seems to play the dominant role on the future distribution. Red = predicted to be present in the current climate but absent in 2055; Blue = predicted to be absent in the current climate but present in 2055; Green = predicted to be present in the current and 2055 climates and White = predicted to be absent in the current and 2055 climates.

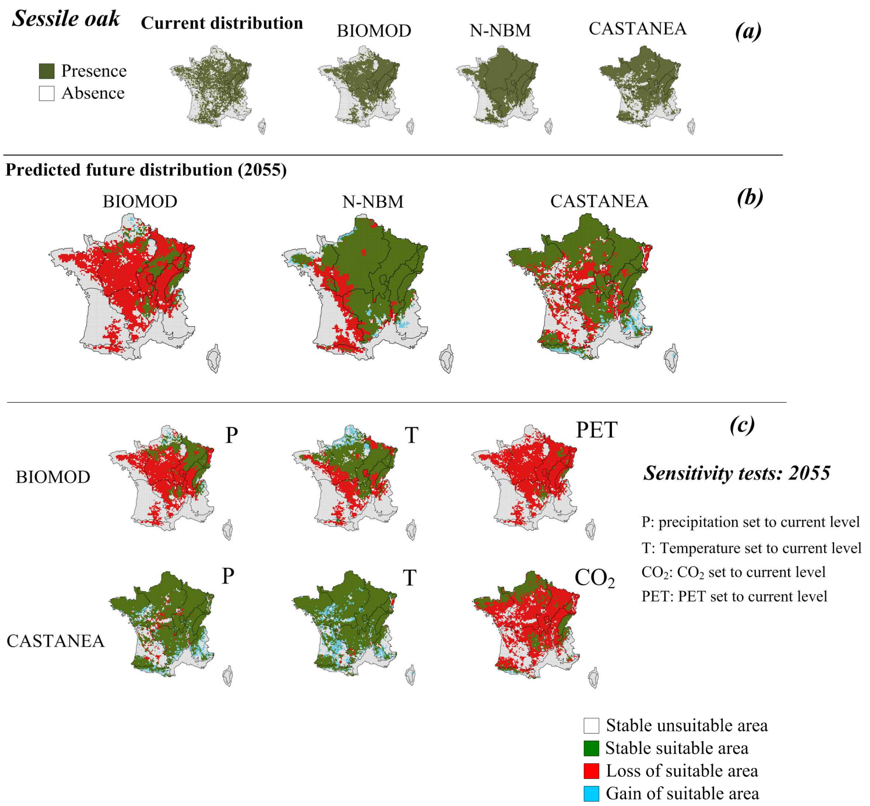

Fig S4. Modeled Sessile oak distribution under present and future climate: (a) Current spatial patterns of Sessile oak simulated by models and observed current distribution based on NFI data. Green indicates presence; white indicates absence. (b) Model projections of changes in Sessile oak distribution by mid-century. Red = predicted to be present in the current climate but absent in 2055; Blue = predicted to be absent in the current climate but present in 2055; Green = predicted to be present in the current and 2055 climates and White = predicted to be absent in the current and 2055 climates. (c) Sensitivity tests carried out by setting one climate variable to current levels and all others to 2055 levels. CO_2 = atmospheric CO_2 concentration set to current value. T = Temperature set to current climate. P = Precipitation set to current climate. PET = potential evapotranspiration set to current climate.

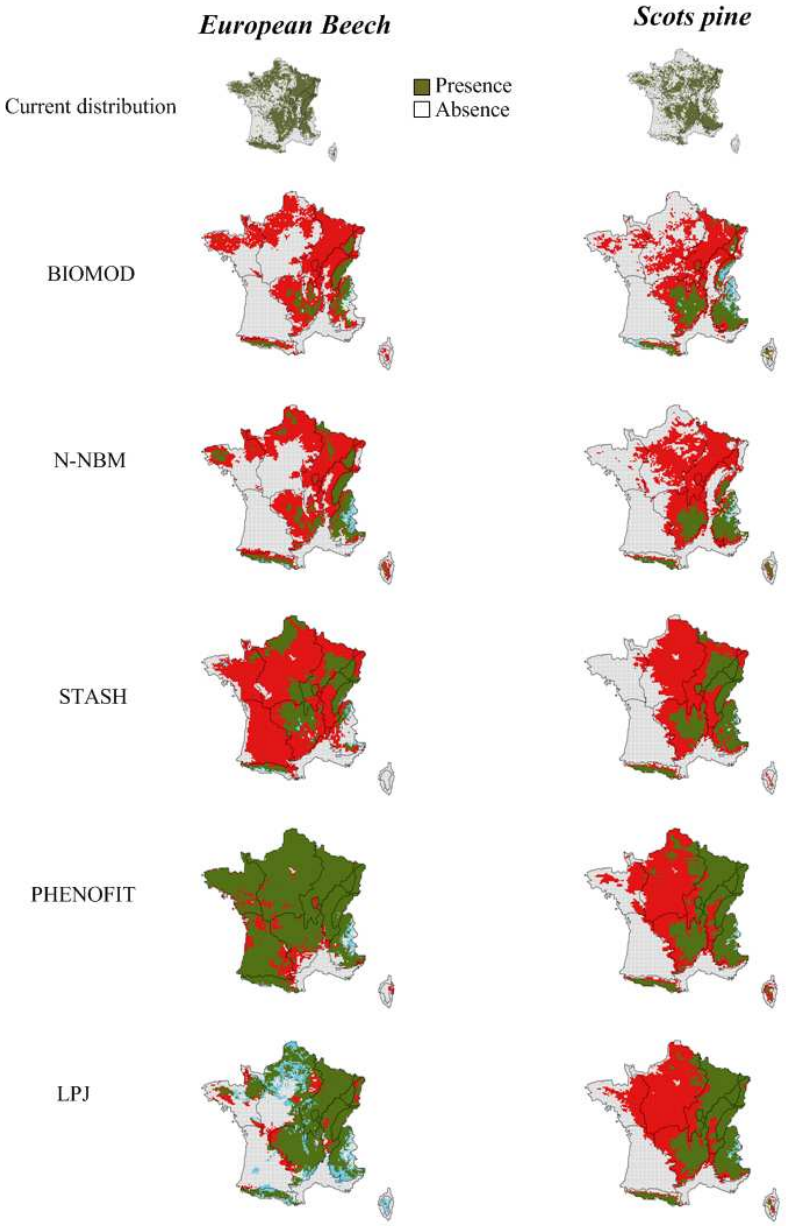

Fig S5. Model projections of changes in European beech and Scots pine distribution by mid-century. Red = predicted to be present in the current climate but absent in 2055; Blue = predicted to be absent in the current climate but present in 2055; Green = predicted to be present in the current and 2055 climates and White = predicted to be absent in the current and 2055 climates.

Tables

Table S1. Relative and absolute rates of loss or gain of presence of European beech projected by different models for each bioclimatic region.

		BIOMOD	N-NBM	STASH	PHENOFIT	CASTANEA	LPJ
Alps	Relative change	-0.41	0.04	-0.46	0.15	0.19	0.62
	Absolute change	-0.26	0.03	-0.20	0.09	0.12	0.32
Jura	Relative change	-0.29	-0.14	-0.04	0.02	-0.01	0
	Absolute change	-0.29	-0.14	-0.03	0.02	-0.01	0
Saône	Relative change	-0.99	-0.97	-0.69	-0.03	-0.33	-0.14
	Absolute change	-0.78	-0.77	-0.69	-0.03	-0.32	-0.13
Alsace	Relative change	-1	-0.99	-0.77	0	-0.68	-0.35
	Absolute change	-0.65	-0.62	-0.77	0	-0.64	-0.35
Vosges	Relative change	-0.52	-0.34	-0.16	-0.02	-0.09	0
	Absolute change	-0.52	-0.34	-0.16	-0.02	-0.09	0
NE	Relative change	-1	-0.89	-0.55	0	-0.13	0.04
	Absolute change	-0.94	-0.81	-0.55	0	-0.12	0.03
NW	Relative change	-1	-0.94	-0.76	-0.04	-0.23	0.29
	Absolute change	-0.43	-0.45	-0.74	-0.04	-0.22	0.13
Brittany	Relative change	-0.99	-0.84	-0.93	-0.09	-0.23	-0.25
	Absolute change	-0.57	-0.37	-0.70	-0.09	-0.21	-0.09
SW	Relative change	-1	-1	-1	-0.25	-0.62	-0.28
	Absolute change	-0.02	-0.04	-0.87	-0.25	-0.31	-0.02
Pyrenees	Relative change	-0.62	-0.36	-0.31	-0.07	-0.09	0.40
	Absolute change	-0.42	-0.27	-0.22	-0.06	-0.07	0.23
Center	Relative change	-0.78	-0.80	-0.57	-0.25	-0.47	-0.02
	Absolute change	-0.67	-0.68	-0.55	-0.23	-0.42	-0.02

Table S2. Relative and absolute rates of loss or gain of presence of Pedunculate oak projected by different models for each bioclimatic region.

		BIOMOD	N-NBM	STASH	PHENOFIT	LPJ
Alps	Relative change	-0.13	-0.78	-0.48	1	0.17
	Absolute change	-0.02	-0.03	-0.06	0.30	0.12
Jura	Relative change	0.12	-0.38	0.48	0.71	0
	Absolute change	0.08	-0.26	0.24	0.41	0
Saône	Relative change	-0.76	-0.68	-0.94	-0.06	0
	Absolute change	-0.71	-0.54	-0.94	-0.06	0
Alsace	Relative change	-0.83	-0.35	-0.99	-0.03	0
	Absolute change	-0.83	-0.35	-0.86	-0.03	0
Vosges	Relative change	-0.18	-0.45	-0.06	0.47	0
	Absolute change	-0.16	-0.34	-0.04	0.30	0
NE	Relative change	-0.72	-0.41	-0.86	0.05	0
	Absolute change	-0.71	-0.40	-0.86	0.05	0
NW	Relative change	-0.58	-0.38	-0.84	-0.03	0.01
	Absolute change	-0.56	-0.38	-0.74	-0.03	0.01
Brittany	Relative change	-0.37	-0.03	-0.78	-0.14	0.14
	Absolute change	-0.37	-0.03	-0.73	-0.14	0.11
SW	Relative change	-0.84	-0.42	-0.87	-0.32	0.08
	Absolute change	-0.73	-0.38	-0.80	-0.32	0.07
Pyrenees	Relative change	-0.91	-0.13	-0.15	0.01	0.13
	Absolute change	-0.34	-0.04	-0.08	0.01	0.10
Center	Relative change	-0.93	-0.92	-0.78	-0.09	0
	Absolute change	-0.59	-0.51	-0.58	-0.06	0

Table S3. Relative and absolute rates of loss or gain of presence of Sessile oak projected by different models for each bioclimatic region.

		BIOMOD	N-NBM	CASTANEA
Alps	Relative change	-0.59	0.25	0.56
	Absolute change	-0.12	0.06	0.21
Jura	Relative change	-0.37	0	-0.01
	Absolute change	-0.35	0	-0.01
Saône	Relative change	-0.94	-0.06	-0.30
	Absolute change	-0.89	-0.06	-0.28
Alsace	Relative change	-0.81	0	-0.80
	Absolute change	-0.81	0	-0.62
Vosges	Relative change	-0.63	0	-0.07
	Absolute change	-0.63	0	-0.07
NE	Relative change	-0.69	-0.01	-0.11
	Absolute change	-0.68	-0.01	-0.11
NW	Relative change	-0.82	-0.11	-0.27
	Absolute change	-0.65	-0.10	-0.24
Brittany	Relative change	-1	-0.27	-0.18
	Absolute change	-0.52	-0.16	-0.15
SW	Relative change	-1	-0.96	-0.65
	Absolute change	-0.13	-0.33	-0.25
Pyrenees	Relative change	-1	-0.86	0.26
	Absolute change	-0.31	-0.43	0.14
Center	Relative change	-0.87	-0.1	-0.34
	Absolute change	-0.65	-0.09	-0.28

Table S4. Relative and absolute rates of loss or gain of presence of Temperate broad leaf summer-green PFT (TeBS) projected by different models for each bioclimatic region.

		BIOMOD	N-NBM	IBIS	ORCHIDEE
Alps	Relative change	-0.45	0.15	0.40	-0.3
	Absolute change	-0.25	0.09	0.18	-0.15
Jura	Relative change	-0.30	0	0.10	-0.19
	Absolute change	-0.30	0	0.09	-0.18
Saône	Relative change	-0.87	-0.30	-0.01	-0.28
	Absolute change	-0.81	-0.30	-0.01	-0.28
Alsace	Relative change	-0.81	0	0	-0.24
	Absolute change	-0.81	0	0	-0.23
Vosges	Relative change	-0.41	0	0.01	-0.44
	Absolute change	-0.41	0	0.01	-0.41
NE	Relative change	-0.81	-0.01	0	-0.29
	Absolute change	-0.80	-0.01	0	-0.26
NW	Relative change	-0.73	-0.05	-0.02	-0.35
	Absolute change	-0.66	-0.05	-0.02	-0.32
Brittany	Relative change	-0.45	0	-0.05	-0.64
	Absolute change	-0.44	0	-0.05	-0.55
SW	Relative change	-0.95	-0.38	-0.37	-0.78
	Absolute change	-0.72	-0.37	-0.34	-0.28
Pyrenees	Relative change	-0.77	-0.09	0.17	-0.44
	Absolute change	-0.56	-0.07	0.10	-0.22
Center	Relative change	-0.85	-0.41	-0.12	-0.49
	Absolute change	-0.75	-0.40	-0.10	-0.27

Table S5. Relative and absolute rates of loss or gain of presence of Scots pine projected by different models for each bioclimatic region.

		BIOMOD	N-NBM	STASH	PHENOFIT	LPJ
Alps	Relative change	0.03	-0.14	-0.21	-0.08	-0.03
	Absolute change	0.02	-0.11	-0.19	-0.07	-0.02
Jura	Relative change	-0.1	-0.53	-0.01	0	0
	Absolute change	-0.07	-0.45	-0.01	0	0
Saône	Relative change	-0.99	-0.98	-0.59	-0.41	-0.29
	Absolute change	-0.48	-0.34	-0.59	-0.41	-0.29
Alsace	Relative change	-1	-1	-0.56	0	-0.06
	Absolute change	-0.68	-0.25	-0.56	0	-0.06
Vosges	Relative change	-0.56	-1	-0.16	0	0
	Absolute change	-0.53	-0.90	-0.16	0	0
NE	Relative change	-0.96	-0.99	-0.61	-0.25	-0.26
	Absolute change	-0.88	-0.91	-0.61	-0.25	-0.26
NW	Relative change	-1	-1	-1	-0.83	-0.91
	Absolute change	-0.38	-0.51	-0.76	-0.80	-0.86
Brittany	Relative change	-1	-0.99	-1	-0.99	-1
	Absolute change	-0.28	-0.10	-0.07	-0.39	-0.48
SW	Relative change	-1	-1	-1	-1	-1
	Absolute change	-0.01	-0.04	-0.03	-0.07	-0.05
Pyrenees	Relative change	-0.22	-0.32	-0.34	-0.34	-0.23
	Absolute change	-0.13	-0.18	-0.24	-0.26	-0.15
Center	Relative change	-0.56	-0.65	-0.59	-0.46	-0.45
	Absolute change	-0.53	-0.55	-0.55	-0.45	-0.44

Table S6. Absolute rates of gain or loss of presence of Holm oak (for BIOMOD, N-NBM, STASH and LPJ) and temperate broad leaf evergreen PFT (TeBE for IBIS and ORCHIDEE) projected by models for each bioclimatic region.

		BIOMOD	N-NBM	STASH	LPJ	IBIS	ORCHIDEE
Alps	Absolute change	0.01	0.04	0.06	0.16	0.07	0.33
Jura	Absolute change	0.25	0.09	0.14	0	-0.01	0.15
Saône	Absolute change	0.63	0.60	0.89	0.04	0.19	0.23
Alsace	Absolute change	0.21	0.83	0.94	0	0.71	0.17
Vosges	Absolute change	0.31	0.19	0.05	0	0.16	0.13
NE	Absolute change	0.32	0.19	0.73	0.17	0.06	0.37
NW	Absolute change	0.33	0.33	0.79	0.75	0.12	0.81
Brittany	Absolute change	0.49	0.47	0.41	0.86	0.05	0.48
SW	Absolute change	0.75	0.81	0	0.30	0.35	0.46
Pyrenees	Absolute change	0.66	0.54	0.19	0.36	-0.08	0.24
Center	Absolute change	0.76	0.59	0.50	0.35	0.20	0.41
Mediterranean	Absolute change	0	-0.08	0.01	-0.22	0.01	0.09

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