

Reliable predictions of forest ecosystem functioning require flawless climate forcings

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Abstract:	Climate change affects various aspects of ecosystem functioning, especially photosynthesis, respiration and carbon storage. We need accurate modelling approaches (impact models) to simulate forest functioning and vitality in a warmer world so that forest models can estimate multiple changes in ecosystem service provisions (e.g., productivity and carbon storage) and test management strategies to promote forest resilience. Here, we aimed to quantify the bias in these models, addressing three questions: (1) Do the predictions of impact models vary when forcing them with different climate models, and how do the predictions differ under climate model vs. observational climate forcings? (2) Does the climate impact simulation variability caused by climate forcings fade out at large spatial scales? (3) How does using simulated climate data affect process-based model predictions in stressful drought events? To answer these questions, we present historical results for 1960-2010 from the CASTANEA ecophysiological forest model and use the data from three climate models. Our analysis focuses on monospecific stands of European beech (Fagus sylvatica), temperate deciduous oaks (Quercus robur and Q. petraea), Scots pine (Pinus sylvestris) and spruce (Picea abies) in French forests. We show that prediction of photosynthesis, respiration and wood growth highly depends on the climate model used and species and region considered. Predictions were improved after a monthly mean bias or monthly quantile mapping correction for the three models considered. The processes simulated by the impact model exhibited large variability under different climate forcings at the plot scale (i.e., a few hectares). This variability faded out at larger scales (i.e., an ecological region, 100 km²), owing to an aggregation effect. Moreover, process predictions obtained under different climate forcings were more variable during the driest years. These results highlight the necessity of quantifying the bias correction effect on process predictions before predicting flux dynamics with a process-based model.

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TITLE: Reliable predictions of forest ecosystem functioning require flawless climate forcings.

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Abstract

Climate change affects various aspects of ecosystem functioning, especially photosynthesis, respiration and carbon storage. We need accurate modelling approaches (impact models) to simulate forest functioning and vitality in a warmer world so that forest models can estimate multiple changes in ecosystem service provisions (e.g., productivity and carbon storage) and test management strategies to promote forest resilience.

Here, we aimed to quantify the bias in these models, addressing three questions: (1) Do the predictions of impact models vary when forcing them with different climate models, and how do the predictions differ under climate model vs. observational climate forcings? (2) Does the climate impact simulation variability caused by climate forcings fade out at large spatial scales? (3) How does using simulated climate data affect process-based model predictions in stressful drought events? To answer these questions, we present historical results for 1960-2010 from the CASTANEA ecophysiological forest model and use the data from three climate models. Our analysis focuses on monospecific stands of European beech (*Fagus sylvatica*), temperate deciduous oaks (*Quercus robur* and *Q. petraea*), Scots pine (*Pinus sylvestris*) and spruce (*Picea abies*) in French forests.

We show that prediction of photosynthesis, respiration and wood growth highly depends on the climate model used and species and region considered. Predictions were improved after a monthly mean bias or monthly quantile mapping correction for the three models considered. The processes simulated by the impact model exhibited large variability under different climate forcings at the plot scale (i.e., a few hectares). This variability faded out at larger scales (i.e., an ecological region, 100 km²), owing to an aggregation effect. Moreover, process predictions obtained under different climate forcings were more variable during the driest years. These results highlight the necessity of quantifying the bias correction effect on process predictions before predicting flux dynamics with a process-based model.

Key words: Process-based models, climate change, regional scale, photosynthesis, respiration, French forest

1 Introduction

In the Northern Hemisphere, climate change will lead to increased temperature and spatially heterogeneous changes in the precipitation regime as well as more frequent and intense extreme climatic events in the forthcoming decades (Pachauri et al., 2014), particularly with strong drought and/or thermal stresses. Such changes, and notably extreme drought events (Tramblay et al., 2020), may be very damaging for European ecosystem functioning (Maracchi et al., 2005), especially for forests. Warmer and drier conditions can lead to medium- or long-term damage (Bréda et al., 2006; Linares et al., 2010). They impact fundamental biological processes involved in the energy, carbon and water cycles (Anderegg et al., 2012; Dusenge et al., 2019; van der Molen et al., 2011) and may lead to massive dieback, as already reported (Ogaya et al., 2020; Senf et al., 2020). Moreover, stressful climatic events can also increase the vulnerability of forest stands to pathogen attacks (Desprez-Loustau et al., 2006) and fire risks (Dale et al., 2001).

It has become critical to take an interest in forest functioning changes in the coming decades to maintain forest cover and ecosystem services over the long term. It is particularly important to quantify forest productivity at scales ranging from the plot (sylvicultural unit) to regional scales (wood supply basin) taking into account the climate. This would help in decision-making and quantification of the contribution of forests to carbon neutrality. Many studies have already addressed climate change effects on the fundamental processes governing forest ecosystems (Lindner et al., 2010; Sperry et al., 2019), describing positive effects (Gunderson et al., 2009) and, in more extreme conditions, negative effects (Sperry et al., 2019). Most studies have used data from the last few decades (second half of the last century) (Zimmermann et al., 2015) or spatial stress gradients (latitudinal, Frenne et al., 2013; Pretzsch et al., 2010; altitudinal, Marcora et al., 2017) to represent process evolution during the intensification of stressful climatic conditions. These approaches are limited in terms of the studied ecosystems, precise and extensive climatic datasets are quite short (e.g., only a few decades long for SAFRAN, Durand et al., 1993), and spatial gradients are limited to existing conditions. These approaches are very useful but remain rare because such experiments are difficult to implement and manage and/or are limited to young trees.

Simulation models are a promising tool, and their contributions are crucial, going beyond the intrinsic limits of field studies. Modelling future climate effects on productivity has already fuelled scientific debate (García- Valdés et al., 2020) and provided keys for forest management practices (Gupta & Sharma, 2019;

Lindner et al., 2000). In many studies, this type of forecasting is carried out in the contemporary period with empirical growth models (BICAFF project, Valade et al., 2018; MARGOT model, Wernsdörfer et al., 2012), without integrating climate change. These models have proven relevant at short time scales and for constant climate conditions, but they are not able (by construction) to take into account the influence of climate change on the processes of forest functioning (ignoring the fertilizing CO2 effect on photosynthesis, (A. P. Walker et al., 2020), or the increasing temperature effect on photosynthesis and respiration (Dusenge et al., 2019), especially forest productivity (Boisvenue & Running, 2006; Reyer et al., 2014), as well as photosynthesis and respiration. On the other hand Dynamic Vegetation Models (such as LPJmL or JeDi, Nishina et al. 2015) are able to take into account climate change but in the majority of cases deal with Plant Functional Type instead of species, and operate at large scales (not at the plot scale, see resolution in Table 1 in Nishina et al. 2015).

Alternatively, process-based models could provide many advances that could strengthen forest functioning predictions. Indeed, they allow us to integrate the direct effects of the climate (temperature, precipitation, radiation or relative humidity) on the processes involved in the functioning of ecosystems (photosynthesis and respiration, for example) and therefore make it possible to project their functioning under changing conditions, which are not yet observable in the field. Even though this topic has already been studied (Zhao et al., 2012) there is no consensus regarding how process-based model outputs are affected by climate forcings derived from climate models. For example, Palma et al. (2018) suggested little process uncertainties due to the climate data used (with the BiomeBGC model), while Stéfanon et al. (2015) and Glotter et al. (2014) conversely suggested a strong effect of uncertainties due to climate input. Thus, it is important to understand the uncertainty level associated with the climate model that is used. However, uncertainties accumulate along a "cascade of uncertainty" (Lindner et al., 2014; Reyer, 2013) composed of uncertainty at each step in the chain. In the first step, assumptions about the development pathways of future societies have been developed in IPCC reports (Pachauri et al., 2015). These storylines have allowed the development of representative concentration pathway (RCP) scenarios (Moss et al., 2010; van Vuuren et al., 2011). The projected greenhouse gas emissions then drive global climate models (GCMs) to provide global climate change scenarios, which are downscaled to lower resolutions using regional climate models (RCMs) (called uncorrected climate model data in our study). To use that data at the forest stand level, further downscaling to the forest stand scale is required (8 km resolution in our corrected climate model data). Then, the data can be used as input into a

stand-level forest model. In our work, we try to quantify the uncertainty due to climatic input data, i.e., this step of the cascade of uncertainty. In fact, GCM and RCM outputs are often used as climate forcing for ecological impact models, which potentially results in large cumulative errors because information and error are passed sequentially along the modelling chain from GCM to RCM to impact model.

It is especially important to study these cumulative errors when moving from local (plot) to regional scales (environmental and sylvicultural units). Indeed, the change in scale involves other factors that vary (age, total biomass, soil fertility), which can compensate for the errors and thus limit the contribution of the climate to the predictability of the process. Moreover, it is crucial to evaluate and decrease the bias in process estimation (gross primary production, *GPP*, or aboveground wood biomass increment, *AWBI*) during stressful years to correctly predict further changes because (1) extremely stressful conditions are predicted to be more frequent in the next decades (Polade et al., 2017); (2) climate models have more difficulty reproducing extreme climatic conditions (Iizumi et al., 2017) and impact models have difficulties estimating their effects (Albrich et al., 2020); and (3) ecosystem responses can vary greatly when a threshold is exceeded (Dorman et al., 2015; Meir et al., 2015), which is a situation that is most often encountered during stressful years. There are at least two steps to this assessment work: estimating the error induced by the quality of the climate data used as input and estimating the quality of the stress response in the impact model (van Horssen et al., 2002). Here we will focus on only the first part.

Our objective in this study is to evaluate the ability of different climate simulation models (as opposed to observational data) to be used as input data for process-based model simulations. We propose here to evaluate process-based model simulation over a historical period (1960-2010) to estimate error predictions, comparing results with three climate models. Several studies conducted similar work (Nishina et al., 2015; Palma et al., 2018; Stéfanon et al., 2015). In contrast to these studies, our work using climate models includes comparisons between measured and simulated flux from the process model, using historical climatic data and modelling climate simulations, as opposed to forest distribution or forest stock considered in these previous works. Understanding bias allows for improving predictions. With improved predictions, there would be multiple applications for forest process-based modelling in the context of climate change: deepening our knowledge of process variations, estimating changes in ecosystem services (such as productivity or carbon storage) or testing different forest management practices (e.g.,Garcia-Gonzalo et al., 2014; Palma et al., 2015)

to promote resilience. In this study, we answered the following questions: (1) Do the predictions of impact models vary when forcing them with different climate models, and how do the predictions differ under climate model vs. observational climate forcings? (2) Does the variability in the impact climate simulations caused by climate forcings fade out at large spatial scales? (3) How does the use of simulated climate data affect process-based model predictions in the case of stressful drought events?

Our analysis focuses on French forests, studying monospecific stands of European beech (*Fagus sylvatica* L.), temperate deciduous oaks (*Quercus robur* and *Q. petraea*), Scots pine (*Pinus sylvestris*) and spruce (*Picea abies*). These dominant and representative stands of temperate forests in Europe and France (50% of French wood volume according the French Forest National Inventory, IFN, https://inventaire-forestier.ign.fr/) are important for timber or patrimonial reasons. To address this topic, we used the stand process-based model CASTANEA (Dufrêne et al., 2005), and not large-scale model (like in Palma et al. 2018 or Nishina et al. 2015,), to test the relevance of 3 different climate models (including correction or not, i.e., six climate cases) in the past period compared with historical climatic data (French mesoscale SAFRAN analysis system, Durand et al., 1993). By definition this type of model allows to understand and predict the functioning at forest plot level. Then, we aggregated the simulation at regional scale. Comparison of CASTANEA simulations using different climate models (with and without bias corrections) as input allows us to quantify the percentage of bias associated with different climate model data and evaluate their relevance in prediction with process-based models. Comparing corrected and uncorrected model data effects on CASTANEA prediction allows us to assess the importance of correction.

2 Materials and Methods

2.1 Process-based model description

The process-based model CASTANEA (Dufrêne et al., 2005) aims at simulating carbon and water fluxes and stocks of even-aged regular monospecific forest stands at the rotation timescale (several decades). In this study, CASTANEA was used to simulate the annual stand photosynthesis, respiration and wood growth in monospecific stands (as in Delpierre et al., 2012; Guillemot et al., 2014b), but other studies focused on allocation (Davi et al., 2009a; Guillemot et al., 2017) and water fluxes (Davi et al., 2006).

In brief, light interception and photosynthesis submodels are implemented in CASTANEA by using a multilayer canopy description. The canopy is considered to be horizontally homogeneous and is vertically sub-divided into a given number of layers (i.e., approximately 30), each of them enclosing a constant leaf area (typically less than 0.1 m2 m−2). Three different radiative balances are performed, in the PAR (400–700 nm), in the NIR (700–2500 nm), and in the thermal infrared. In the PAR and global regions, incident light is split into direct and sky diffuse radiation using equations given by Spitters (1986) and Spitters et al. (1986). In the thermal infrared, the diffuse atmospheric radiation is computed from air temperature according to Idso (1981).

The leaf photosynthesis is represented using a C3 plants biochemical process-based model, according to Farquhar et al. (1980). The respiration is composed of maintenance respiration and growth respiration, with maintenance respiration computed from the nitrogen content of living biomass and assuming an exponential relationship to account for temperature dependence (Ryan, 1991).

After accounting for leaf growth and need of carbohydrate for maintenance respiration, the available carbon is allocated. Growth and allocation submodels comprised four functional compartments: foliage, woody biomass (stems, branches and coarse roots), fine roots and a pool of carbohydrate reserves. One average tree is considered as representative of the whole stand (i.e the variability between trees is not taken into account). Two time steps, half-hourly and daily, are used in the model. Most variables involving fluxes are simulated half-hourly; all state variables, growth and phenology are daily simulated, for example carbon allocation. The model performs well in simulating the interannual fluctuations in forest-atmosphere CO2 exchanges (Delpierre et al., 2012) and the spatial and interannual variations in wood growth (Guillemot et al., 2014b). A complete description of CASTANEA is given in Dufrêne et al. (2005), with subsequent modifications from Davi et al. (2009), Delpierre et al. (2012) and Guillemot et al. (2014, 2017).

Carbon allocation coefficients (from *NPP*) are related to stand age and species, as well as to the current and previous year water stress (Guillemot et al., 2014). The module of C allocation to wood growth was preliminarily calibrated and validated at the plot scale on the RENECOFOR (French national network monitoring forest ecosystems) tree ring series (over the 1970-1990 period, see Guillemot et al., 2014b) and IFN inventory (see A.1).

2.2 Input data

2.2.1 Studied species

We considered five species in this study: common beech (*Fagus sylvatica*), Norway spruce (*Picea abies*), pedunculate and sessile oaks (*Quercus robur* and *petraea*) and Scots pine (*Pinus sylvestris*). These species are widespread in French territory, but they are also major species in European temperate forests (San-Miguel-Ayanz et al., 2016) and are widely studied. They represent an important percentage of forest volume (IFN, *Le Memento*, 2019): 10% for beech, 11% for pedunculate oak, 11% for sessile oak, 5% for Scots pine and 8% for spruce (i.e., 45% of the total volume of French forests). These five species are also economically important, with 18.4 ± 2.9 Mm^3/y between 2009 and 2017 (IFN, *Le Memento*, 2019).

Beech and oaks are broadleaved species, while spruce and Scots pine are coniferous species. Beech and spruce are late-successional and shade-tolerant species. Spruce is very sensitive to high temperatures during summer. Beech and sessile and pedunculate oaks (Lobo et al., 2018) are sensitive to water stress, while Scots pine tolerates drier conditions (Pasta et al., 2016) and is an earlier succession and more light-demanding species. These five species allowed us to study various types of forest due to the physiological and ecological differences between the species.

In the model, pedunculate and sessile oaks have the same parameterization, but they were distinguished in this study because their spatial distributions and local stations in France are different.

2.2.2 Climate data

The CASTANEA model works at an hourly time step. It can be forced with daily climatic data that are internally rescaled at an hourly time step. The daily data used here were radiation (*Rg*), precipitation (*Prec*), daily mean, minimum and maximum temperature (*T, Tmin,* and *Tmax*, respectively), relative humidity (*RH*) and mean wind speed (*W*). We used two types of data. First, we used a reference dataset that comes from the French mesoscale SAFRAN analysis system (Système d'Analyse Fournissant des Renseignements Atmosphériques à la Neige or in English System of Analysis Providing Atmospheric Information to Snow, Vidal et al., 2010). Second, we also used modelled climate series extracted from EURO-CORDEX model data with the MPI (GCM MPI-ESM-LR downscaled with RCM RCA4), Hadgem (GCM MOHC-HadGEM2-ES downscaled with RCM RCA4) and CNRM (GCM CNRM-CERFACS-CNRMCM5 downscaled with RCM

RCA4) models (see the next two paragraphs and A.2) over all of Metropolitan France for the 1960-2010 period.

Historical climate data: SAFRAN

The SAFRAN product is a mesoscale analysis system developed by Météo-France that reconstructs vertical atmospheric profiles on a regular horizontal 8 km grid. It spatializes large-scale general circulation model data, combined with observed data. SAFRAN first analyses temperature, wind, air humidity, incident solar radiation and cloudiness (Quintana-Seguí et al., 2008). For each geographic unit, a draft model is compared to the observations to verify the consistency of the observations. The analysis is then performed using valid observations (Vidal et al., 2010). SAFRAN analyses therefore have the advantage of providing all the climatic variables necessary for the simulation with CASTANEA at high spatial resolution over the period 1960-2010 and can serve as climatic references in our study. SAFRAN has already been validated over the French metropolitan territory and produces unbiased estimates of precipitation, solar radiation, wind speed, relative humidity and temperature (Quintana-Seguí et al., 2008).

Modelled climate data

We decided to work on daily climate data produced in the frame of the EURO-CORDEX initiative (Kotlarski et al., 2014) and processed by Fargeon et al. (2020). CORDEX simulations result from dynamic downscaling by the coupling of GCMs with RCMs. The selection of the GCM-RCM couples that we used was based on the availability in the archiving system of CORDEX simulations (Earth System Grid Federation, ESGF), antecedent model validation for the area of interest, and maximization of the expected differences between models while remaining in the plausible zone.

Finally, we worked with model data from three GCMs (MPI-ESM-LR, MOHC-HadGEM2-ES, CNRM-CERFACS-CNRMCM5), downscaled with one RCM (RCA4) at 50 km (De Cáceres et al., 2018; Fargeon et al., 2020; McSweeney et al., 2015). We used only one RCM since these models have marginal effects compared to GCMs on modelling climate data (Glotter et al., 2014). The three selected runs, as well as a description of their projected climatic changes, are summarized in A.2.

To summarize, Fargeon et al. (2020) identified a significant bias in uncorrected climate simulations over the past period (1995-2015) for meteorological variables of interest (*T*, *RH*, *Rg*, *Prec* and *W*) for our study

compared to SAFRAN (Vidal et al., 2010). Hence, projections based on biased data might misestimate anomalies and scenario impact. Consequently, statistical downscaling and bias corrections were performed by Fargeon et al. (2020) using the SAFRAN reanalysis as reference observational data (8 km resolution) and standard methods based on monthly mean bias or monthly quantile mapping (Bedia et al., 2014; Ruffault et al., 2014), which strongly reduced the bias in model outputs. Temperature and radiation were corrected using a mean bias, and precipitation, wind speed and relative humidity were corrected using quantile mapping.

In this study, we wanted (objective n°1, see above) to compare CASTANEA simulations using six different climate datasets (MPI, CNRM and Hadgem, with and without corrections) to evaluate the outputs of the process-based model CASTANEA with different climate model data.

2.2.3 Inventory

To initialize the state variables and stand characteristics of the CASTANEA model, we used a sub-dataset of the French National Forest Inventory. Because CASTANEA models only monospecific, regular and even-aged stands, we considered only stands that constituted more than 70% of the objective species (in basal area and density). In addition to having regular inventories, we kept only trees of the dominant stratum in the plot of the IFN inventory. Plot stands younger than 20 years were excluded (less than 8% of previously selected monospecific plots) because CASTANEA did not manage the youngest stands. We used inventory data (over 2005-2017, available at https://inventaire-forestier.ign.fr/)

In the final dataset, we have 2379 plots of pedunculate oak, 2178 plots of sessile oak, 2196 plots of beech, 1364 plots of spruce and 1834 plots of Scots pine.

Two regional scales, SER (meso-regional scale, “Sylvo-Eco-Region”, i.e., regions with forest and ecological coherence, Cavaignac, 2009) and GRECO (macro-regional scale, Grande Region ECOlogique, Bonheme, 2021), are used to aggregate the results at the plot scale.

2.3 Simulation design and process studied

CASTANEA simulations are performed over the period 1960-2010, initialized with the inventories previously detailed and the soil water holding capacity (SWHC) from the Q-div project (Badeau, 2011). Each species is treated separately. Because we want to look at only the effect of the climate, it is necessary to minimize evolving factors, as age and biomass. Stressful years will not occur at the same time for SAFRAN and for climate model data, so trees would respond differently depending on their age and biomass; therefore,

age and biomass are kept constant for each decade (i.e., 1960-1970, 1970-1980, 1980-1990, 1990-2000, 2000-2010), with a reinitialization of stand age and biomass at each decades. This duration makes it possible to have minimal changes in age and biomass and to be able to take into account the lag effects of climate.

We focused on several output variables of CASTANEA to evaluate the use of the climate models described earlier (see section 2.2.2), characterizing ecosystem functioning and the added value of the process-based model: photosynthesis (*GPP*) and maintenance respiration (*Resp*), which allow us to study the carbon cycle, and aboveground wood biomass increment (*AWBI*), which interests managers (in the context of an applied use of climate models).

2.4 Analyses

2.4.1 CASTANEA calibration in French territory

First, we evaluated CASTANEA in French territory by comparing the simulated annual radial increment (RI_{sim}) and annual radial increment of the IFN inventory (RI_{obs}) between 2006 and 2017.

The evaluation was performed for each species by comparing RI_{sim} and RI_{obs} for each SER, averaging the values in each plot to decrease the relative weight of the outlier structure (i.e., very low density or age or extreme SWHC). We also compared $AWBI_{sim}$ and $AWBI_{obs}$ (see Fig. 1) using the radial increment to *AWBI* conversion developed in Guillemot et al. (2014a). The total observed volume is computed based on the observed radial increment, diameter and allometries used in CASTANEA: the relationship between age and dominant height for beech stands is from Bontemps et al. (2007), for oaks is from (Bontemps et al., 2012), for spruce is from Seynave et al. (2005), and for Scots pine is from Palahí et al. (2004), and the relationships of diameter, height and volume are from Vallet et al. (2006) among others. With this volume and the wood density used in the model (660 trees for oaks, 550 trees for beech, 379 trees for spruce and 440 trees for Scots pine), we can compute $AWBI_{obs}$ and compare it with $AWBI_{sim.}$

2.4.2 Climate models vs. SAFRAN: bias of impact model outputs for non-extreme years

Plot scales

We wanted to compare impact model outputs (*AWBI*, *GPP*, *Resp*) resulting from simulations with climate models (*mod*) (corrected: $MPI_{corrected}$, $CNRM_{corrected}$, $Hadgem_{corrected}$; uncorrected: MPI_{raw}, $CNRM_{raw}$, $Hadgem_{raw}$) and impact model outputs from simulations with SAFRAN data (*saf*) for each species separately.

For each plot, impact model outputs were averaged over 1960-2010 to allow statistical comparison between climate models and SAFRAN data.

To quantify the percentage of prediction bias, we computed the bias between simulations with the climate model and simulations with SAFRAN by variable (*V*), model (*mod*) and species (*sp*) for each plot *i*:

$$\delta_{mod,p,sp,i} = V_{mod,sp,i} - V_{saf,sp,i} \qquad (3)$$

We compared absolute variable bias when simulations were performed with uncorrected simulated climate data (δ_{raw}) or with corrected simulated climate data ($\delta_{corrected}$), plotting $\delta_{corrected}$ as a function of δ_{raw}.

Although validation was performed at the plot scale, we decided to work at the SER (Sylvo-Eco-Region or Ecological Forest Region) scale for each species (see Fig. A.3) to reduce the statistical effects of marginal stands (with very low or very high density, for example).

We computed the bias percentage to quantify the percentage of bias using the climate model compared to the reference (simulation with SAFRAN data) for every model (with and without correction):

$$p.bias_{mod,p,sp,i} = \delta_{mod,p,sp,i}/V_{saf,sp,i} \quad (4)$$

Regional scales

To study the scale effect on the quality of prediction (objective n°2, see above), we focused on two regional scales, SER and GRECO, to understand the aggregation effect on these two scales. At the regional level, stand age distribution could have a strong effect on prediction because processes are strongly affected by stand age in CASTANEA and can interact with climate effects. In the following analyses, we considered four age classes (20-60 years, 60-120 years, 120-180 years, >180 years). For more details, see A.4.

We compute the proportion of bias compared to the variable level at the regional scale as in eq. 3, using the total surface of the species (S_{sp}), mean level per hectare of variable V for all plots *i* of a given age class, species, model and SER ($mean_i(V_{mod,sp,s,age})$) and proportion of that age class ($p_{sp,s,age}$):

$$\delta_{mod,v,sp,s} = V_{mod,sp,s} - V_{saf,sp,s} \quad (6a)$$

$$\delta_{mod,v,sp,s} = \sum_{age} S_{sp} * p_{sp,s,age} * mean_i(V_{mod,sp,s,age}) - \sum_{age} S_{sp} * p_{sp,s,age} * mean_i(V_{saf,sp,s,age})$$

which reduces to:

$$\delta_{mod,v,sp,s} = S_{sp} * \sum_{age} p_{sp,s,age} * mean_i(\delta_{mod,v,sp,s,age}) \quad (6b)$$

The bias percentage was also calculated:

$$p.biais_{mod,v,sp,s} = \delta_{mod,v,sp,s}/V_{saf,sp,s} \quad (7)$$

We also computed the percentage of bias at larger scales (GRECO level and France level). Appendix 4 presents details of equations (6) and (7).

2.4.3 Process bias in SAFRAN simulation for driest years

For this part (objective n°3, see above), we decided to test the effects of climate forcings on CASTANEA predictions during extreme events. Then, we focused on bias estimation in the driest years over the period 1960-2010. We selected the driest years of our study period for each dataset, each model and each GRECO (Table A.5). We use the standardized precipitation-evapotranspiration index (*SPEI*) to identify these years (Vanoni et al., 2016). The *SPEI* is derived from the standardized precipitation index (*SPI*, Guttman, 1999) and represents a climatic water balance (Thornthwaite, 1948) calculated at different time scales using the monthly (or weekly) difference between precipitation and potential evapotranspiration (*PET*) (Vicente-Serrano et al., 2013; Vicente-Serrano et al., 2010). Using the *R* package *SPEI* (Vicente-Serrano et al., 2010), we calculated the annual *SPEI* between February and July (i.e., the growth period), hereafter identified as $SPEI_{07}$ (Vanoni et al., 2016; Jourdan et al., 2019). This allowed us to determine the years with the driest growth season in a dataset for each climate model and SAFRAN dataset (Fig. A.6 and Table A.5).

For this sub-dataset, we also compared $\delta_{corrected}$ and δ_{raw} (following eq. 2) and computed the percentage of variable bias simulated with climate model data (following eq. 3), as described in section 2.4.2.

3 Results

3.1 Climate models vs. SAFRAN: bias of impact model outputs

The simulated photosynthesis was on average 1500 gC/m²/y for oaks, 1250 gC/m²/y for beech, 1750 gC/m²/y for Scots pine and 2250 gC/m²/y for spruce (Fig. 1). Photosynthesis simulated with the Hadgem

climate model without correction was lower than that in other simulations for every species (except for spruce).

The simulated respiration was on average 700 gC/m²/y for oaks, 500 gC/m²/y for beech, 600 gC/m²/y for Scots pine and 1500 gC/m²/y for spruce. Respiration simulated with the *CNRM* climate model without correction was lower than that simulated with the other models for every species, except for spruce (Fig. 2).

The simulated wood growth averaged 150 gC/m²/y for oaks, 150 gC/m²/y for beech, 120 gC/m²/y for Scots pine and 160 gC/m²/y for spruce. Wood carbon simulated with the Hadgem climate model without correction was lower than that simulated with the other models for every species, except for pedunculate oak (Fig. 1).

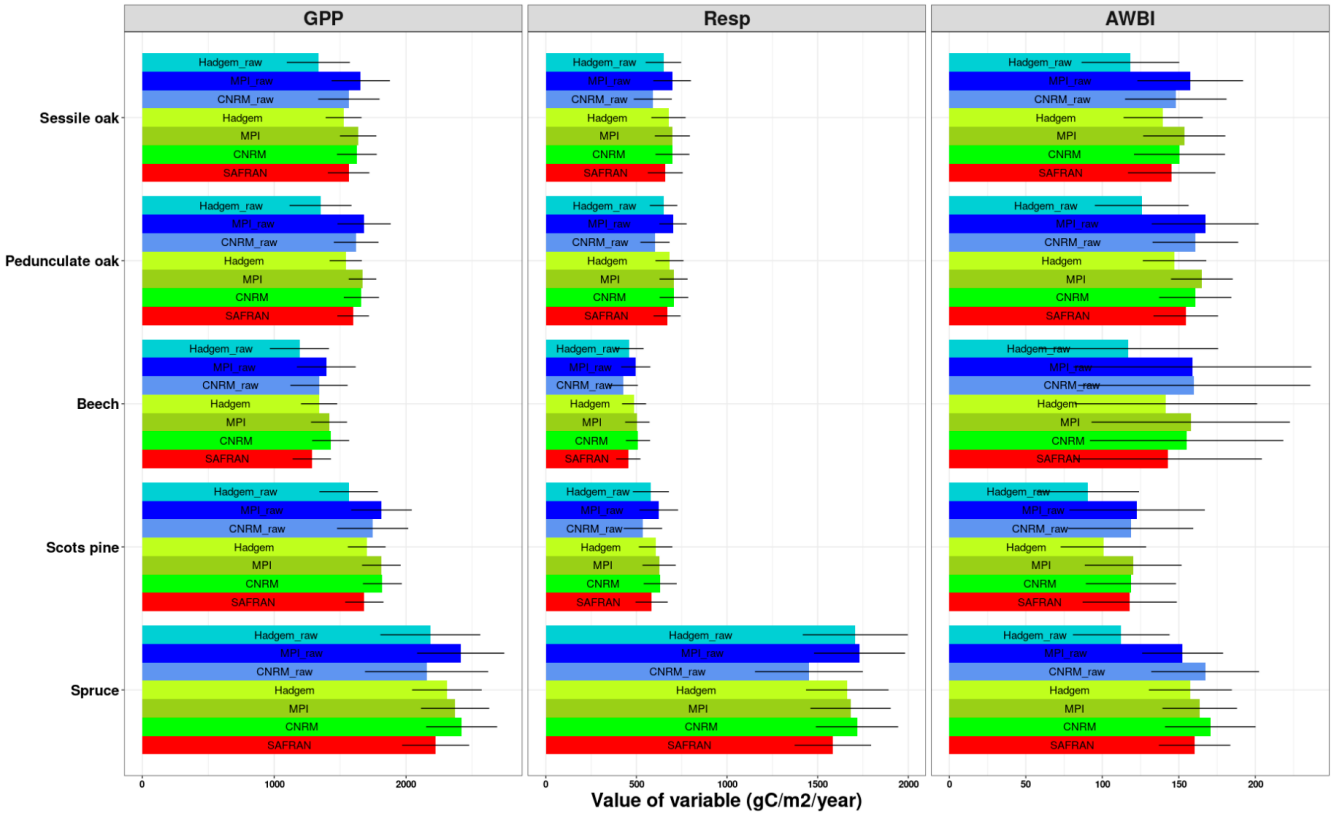


Figure 1: Mean values of NPP_{wood}, GPP and Resp for 1960-2010 by species and origin of data used from simulations with SAFRAN (red), models before correction (blue) and models after correction (green). The origin of the climate data are also indicated on the barplot. Error bars represents spatial heterogeneity of SER.

Bias before vs. after correction

Process biases decrease overall when the climate data are corrected (on average 17 gC/m²/y for *AWBI*, 113 gC/m²/y for *GPP* and 40 gC/m²/y for *Resp*) and reach an error of 8% on average at the plot level. The absolute value of the bias between simulation with SAFRAN and with uncorrected models is greater than the absolute

bias with corrected models for the MPI and Hadgem models (averages of 84% and 85% for all combinations of processes, respectively), meaning that climatic corrections reduce bias relative to SAFRAN simulations (Fig. 2). This result is more nuanced for the CNRM model (only 58% of *SER* shows a bias improvement for photosynthesis and 60% for respiration).

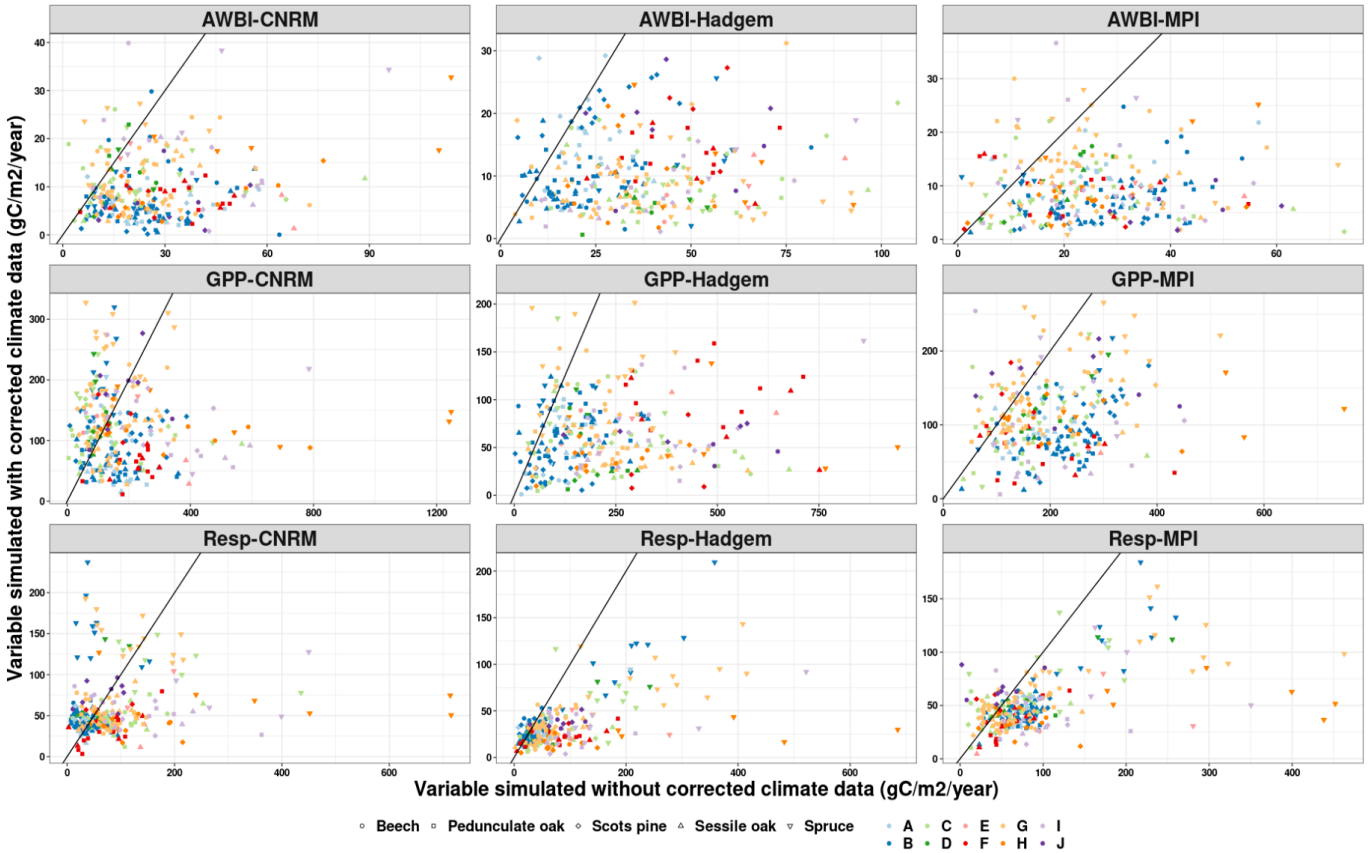


Figure 2: Comparison of process bias between simulations with uncorrected data and corrected data for each process and each model. Shapes represent species, and GRECOs are indicated by colour. The black line is the 1:1 line. Points below the line indicate less bias in uncorrected data. Points above the line indicate an increase in bias between uncorrected and corrected climate data.

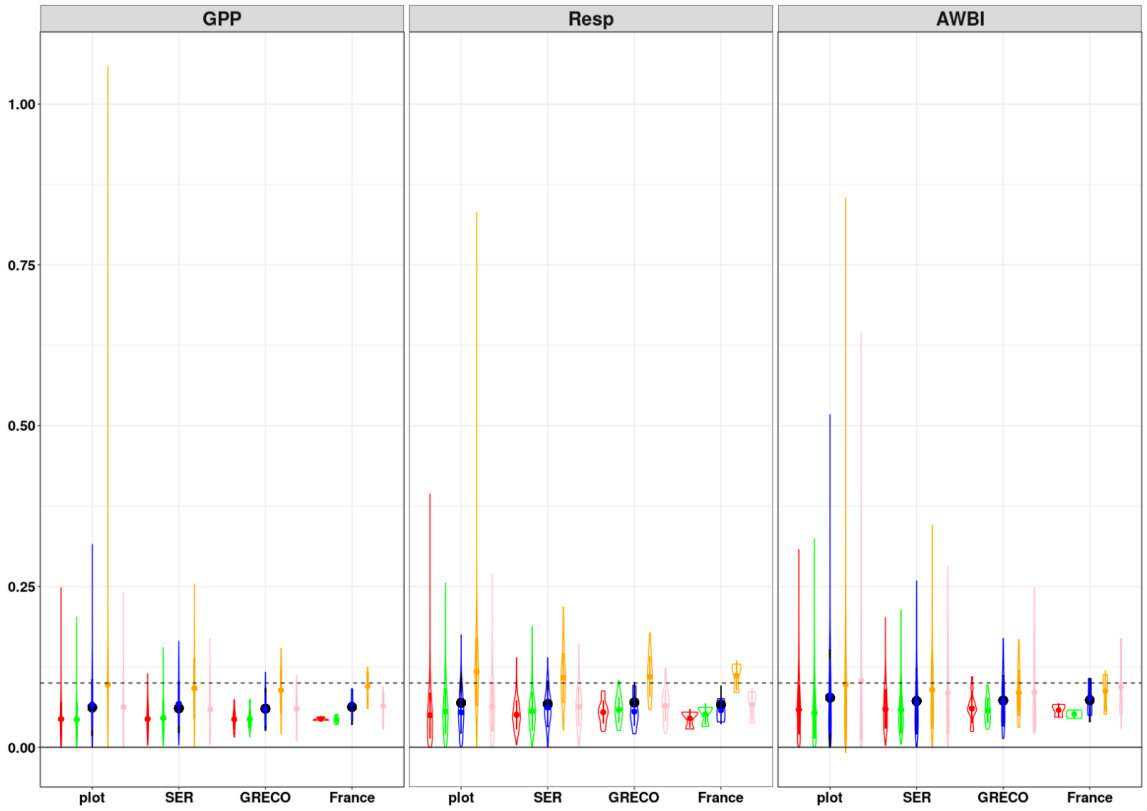
In a few cases, the correction of climate bias did not improve the impact model simulations. Then, in these cases, the impact model simulation appeared less accurate after climate de-biasing. For the CNRM model, the climate bias correction increased the bias for *GPP* and *Resp* in beech stands, for *GPP* in spruce stands, for *Resp* in Scots pine stands and for *AWBI* in sessile oak stands.

Does the percentage of bias depend on aggregation levels?

The correction of climate model data decreases the percentage of variable bias that is induced by using raw climate model data by a factor of more than two for each scale and each process (Table A.7). The percentage of variable bias simulated with corrected climate model data differs among scales (plot, SER,

GRECO and France), processes (Fig. 3a) and species. At the plot level, the percentages of variable bias are on average 6% for *GPP*, 7% for *Resp* and 8% for *AWBI* (Table A.7) but can reach more than 90% for *AWBI, Resp* and *GPP* in monospecific beech stands. At the regional scale (SER, GRECO and France), percentages of variable bias are quite similar, with averages of 6% for *GPP*, 7% for *Resp* and 7% for *AWBI* for SER, GRECO and France (with a weaker standard error). The difference in the percentages of variable bias among scales varies depending on monospecific stands, from the highest percentages of variable bias for beech stand *AWBI* (from 10% for plot scales to 9% for France scales) to the lowest percentages of variable bias for sessile oak stand *GPP* (from 4% for plot and France scales). The percentage of *AWBI* bias is higher than the percentages of *GPP* and *Resp* biases at every scale.

a)



b)

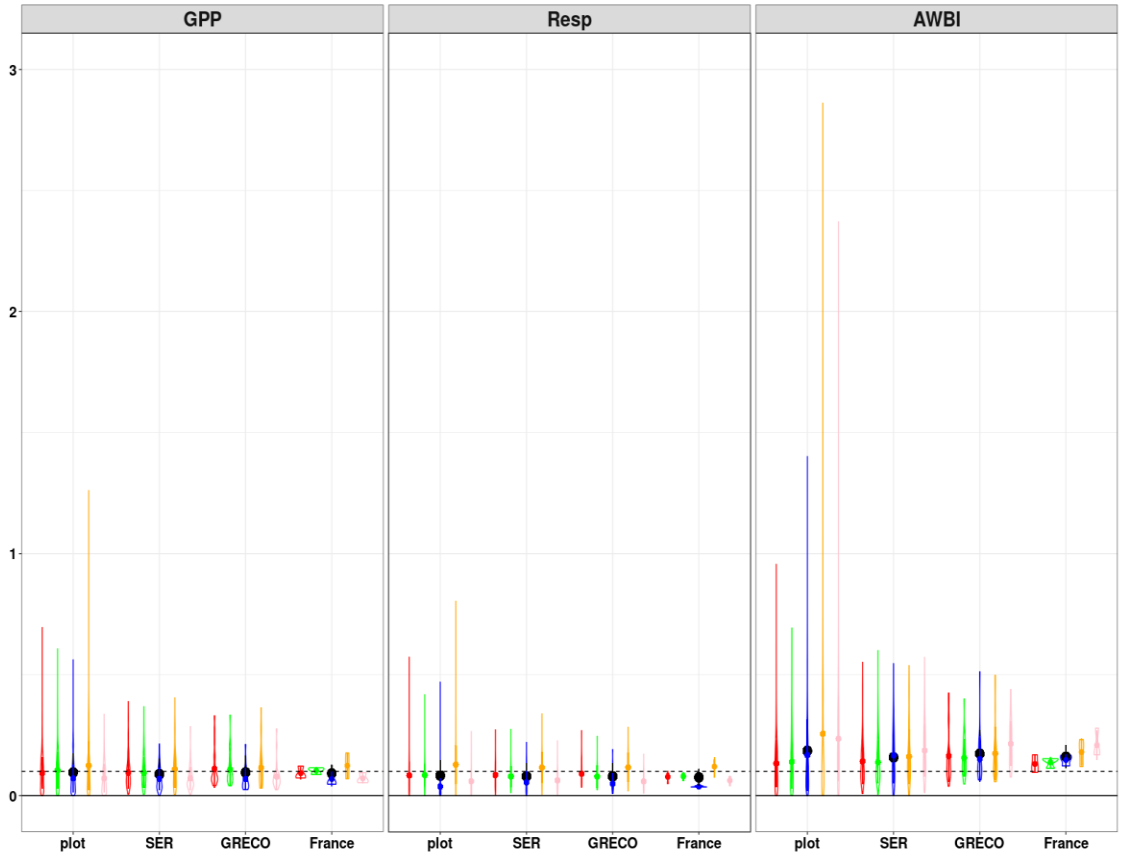
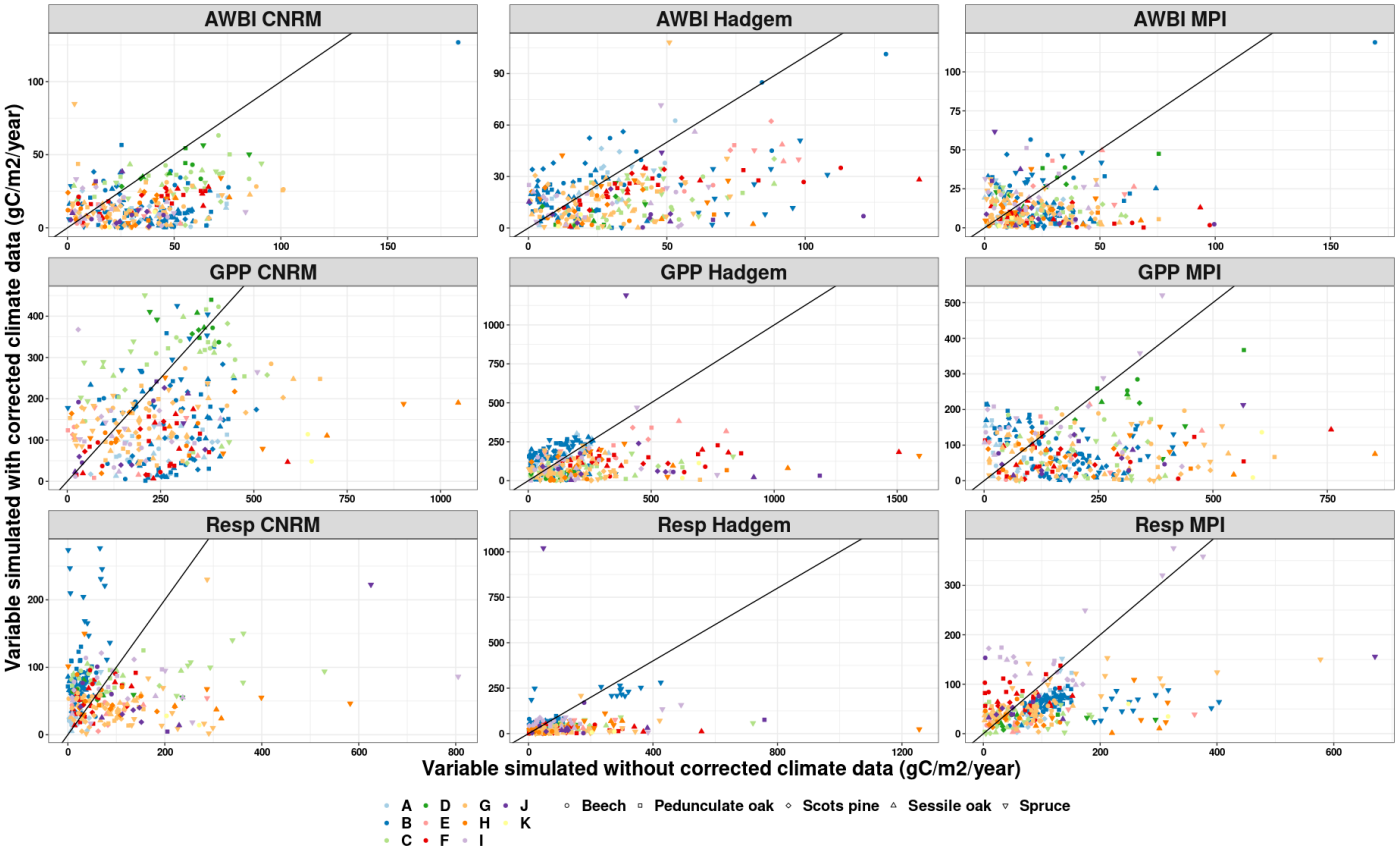


Figure 3: Bias percentages of simulations (y-axis) (i.e., percent of bias compared to process levels simulated with SAFRAN), process (column), and scale (x-axis), for all year (a) and driest years (b). Coloured points represent the mean uncertainty by species and scale: red (pedunculate oak), green (sessile oak), blue (spruce), orange (beech), pink (Scots pine). Black points represent the mean uncertainty by scale, i.e. whatever the species. The dashed line represents the 10% threshold.

3.2 Process bias in SAFRAN simulations during driest years

Bias before vs. after correction

Process biases decrease overall when the climatic data are corrected (on average 13 gC/m²/y for *AWBI*, 98 gC/m²/y for *GPP* and 34 gC/m²/y for *Resp*) and reach an error of 14% on average at the plot level. Stressful years are listed in Table A.5. The absolute value of the bias between simulation with SAFRAN and with uncorrected models is greater than that with corrected models for the MPI and Hadgem models (averages of 72% and 68% for all combinations of processes, respectively) and for the CNRM model for *GPP* and *AWBI* (75% on average), meaning that climatic corrections reduce the biais (Fig. 4). This result is more nuanced for the CNRM model for *Resp* (only 50% of SER shows a bias improvement for respiration).



401

402 *Figure 4: Comparison of process bias between simulations with uncorrected data and corrected data during*
403 *the four driest years for each process and each model. Shapes represent species, and GRECOs are indicated*
404 *by colour. The black line is the 1:1 line. Points below the line indicate a decrease in bias between uncorrected*
405 *and corrected climate data. Points above the line indicate an increase bias between uncorrected and corrected*
406 *climate data.*

407

408 **Simulation bias and the importance of scales**

409 The correction of climate model data decreases the percentage of process bias by a factor of almost
410 two for each scale and each process (Table A.7). The bias percentages of the processes simulated with
411 corrected climate model data differ among the scales (plot, SER, GRECO) and the processes studied (Fig. 3b).
412 At the plot level, the bias of the process is on average 10% for *GPP*, 8% for *Resp* and 19% for *AWBI* (Table
413 A.7) but reaches 100% (or more) for *AWBI* in monospecific stands, whatever the species. At the regional scale
414 (SER, GRECO and France), the bias percentages are on average 9% for *GPP*, 8% for *Resp* and 16% for *AWBI*
415 for SER, 10% for *GPP*, 8% for *Resp* and 17% for *AWBI* for GRECO and 9% for *GPP*, 8% for *Resp* and 16%
416 for *AWBI* for France. Standard error decreases when aggregation increases. The difference in bias percentages
417 among scales varies depending on monospecific stands, from the highest bias percentage for beech stand *AWBI*
418 (from 26% for plot scales to 18% for France scales) to the lowest bias percentage for spruce stand *Resp* (from

4% for plot and France scales). The percentage of *AWBI* bias is higher than the percentages of *GPP* and *Resp* biases at every scale.

Higher bias percentages compared to an average year

Uncertainties are higher at every scale in driest years than in average years (Fig. 3. a, b and Table A.7). The error can be twice as large for *AWBI* at the plot scale or can be only slightly larger for *GPP* and *Resp* at regional scales (SER or GRECO).

4 Discussion

4.1 Scale and drought stress intensity affect impact model outputs (biases)

Process biases decrease overall when the climatic data are corrected and reach an error of 8% on average at the plot level (instead of 16% on average). In terms of percentage, the impact model output errors after climate data correction are satisfactorily low (lower than 8%, respectively. This means that quantile-quantile and bias correction of climate data are essential and efficiently reduce biases in impact model predictions (De Cáceres et al., 2018; Ivanov & Kotlarski, 2017; Ruffault et al., 2014).

4.1.1 Assessing the effects of spatial scale

According to our results, a larger scale induces fewer extreme values (with fewer outliers) but not a systematic decrease in the average bias. Note, however, that increasing the aggregation level leads to decreases in *AWBI* bias (especially in monospecific sessile oak stands) and in *GPP* bias in monospecific beech stands. The question of the relationship between aggregation of model outputs at a larger scale and biases has already been addressed in the literature (Heuvelink & Pebesma, 1999, on soil process modelling). However, to our knowledge, no study has compared results on photosynthesis, *AWBI* and respiration.

In our work, we focused on emphasizing bias percentage differences in fluxes (*GPP*, *AWBI*, *Resp*) among several spatial scales. This point is central because forest management questions require responses at different scales (as suggested in Bellassen et al., 2011 and Bolte et al., 2009): from the plot scale (management of a few hectares of forest) to the regional scale (supplying the wood industry). Understanding prediction

443 quality at these different scales will make it possible to give answers in different ways depending on the
444 question being asked.

445 On the one hand, aggregation at the regional scale induced less dispersion in CASTANEA predictions
446 (i.e., fewer outliers) since outliers are very sensitive to large local climatic differences between SAFRAN and
447 climate model data. In fact, aggregation decreases the statistical weight of extremely biased values. On the
448 other hand, monospecific stand areas per ecological region were available for only some GRECOs (from 3 to
449 7 out of 11 GRECOs, depending on the species) and a limited number of SERs (from 4 to 10 out of 91 SERs,
450 depending on the species). However, the five species are present in almost all GRECOs: from 8 to 10 out of
451 11 GRECOs, depending on the species. The aggregation method therefore allows us to study a representative
452 part of French territory focusing on ecological regions where a forest area computed by species is available.

453 There are some limitations to the approach used in this paper. For example, the aggregation method
454 involves regional data on monospecific forest area by species, yet the standard deviation in the area can be
455 very large (Table A.8), and the information or species may also be missing (see above). If we are interested in
456 only comparisons, as is the case in this article, this is not a problem. However, we must keep in mind that
457 absolute value predictions at the larger scale (regional levels such as SER or GRECO) add de facto an
458 additional error. In this respect, overall, predictions with the least bias may not necessarily be the ones at the
459 largest scale.

460 **4.1.2 Focus on the driest years**

461 In addition, we focused on the bias generated during the driest years. Droughts are predicted to be more
462 frequent (Dubrovský et al., 2014; Giorgi & Lionello, 2008; Polade et al., 2017), and it is therefore crucial to
463 quantify model errors and to improve the prediction quality of models. Uncertainty comparisons between
464 stressful years and average years are very rare. For example, Jung et al. (2007) highlighted that the major
465 discrepancies are related to, among other things, the water stress effects in most terrestrial ecosystems.
466 According to our work, dry years have a lower prediction quality than average years at the plot level: a higher
467 error of 4 more percentage points in *GPP*, 1 in *Resp* and 8 in *AWBI*. This trend is in agreement with the results
468 of Jung et al. (2007).

We observed that the climates of the driest years based on each climate dataset (Fig. A.6) were mostly similar when *T* and *Rg* dynamics were considered but depended on the geographic area and climate model for *Prec*, *V* and *RH*. This problem is mostly present in uncorrected climate data (for *V*) and in mountainous areas (for *Prec* and *RH*). In particular, in the uncorrected data, summer *RH* is largely underestimated in the majority of GRECOs (A-G), and winter *RH* is overestimated in GRECOs H and I. The corrections decrease the differences between climate model data and SAFRAN data with regard to magnitude and seasonal variation, even if an overestimation still remains significant (p-value<0.0005 with Student's test) in mountainous ecological regions (Pyrenees and Alps). Overall, the most driest years are equivalent between the corrected climate model dataset and the SAFRAN dataset. The large differences in *V*, *RH* and *Prec* in uncorrected climate data are larger and not limited to mountainous areas. The larger bias of process predictions during stressful years may be due to large differences between meteorological modelling data and SAFRAN data.

4.1.3 Correlation between climate data and impact model output biases

We observed that the SERs with the greatest errors due to climatic data biases are essentially in the Mediterranean rim and southeast Massif Central (Fig. A.9-10-11). To assess the effect of climatic variables, we tried to evaluate whether a correlation could be found between climatic variables (*T, RH, Rg, V, Prec*) and the process biases (*GPP, Resp, AWBI*). Methods and results are developed in A.12.

The results show that the correlations between climate variables and process biases are almost all significant (Pearson test, p-value<0.05) (72/75), with an average correlation coefficient of 0.18. The correlations are mostly positive (61/75), meaning that larger biases in climate models induce larger biases in impact model outputs. The rare negative correlations (11/75) are mostly weak (average correlation coefficient of -0.15), except for Scots pine stand *AWBI* and precipitation and temperature (correlation coefficient of -0.23 and -0.21, p-value=0.05). The strongest positive correlations are between biases in Scots pine, spruce, and pedunculate and sessile oak stand respiration and mean annual temperature and between biases in spruce stand *GPP* and temperature. This can be explained by the large effect of temperature on photosynthesis and respiration (Delpierre et al., 2012; Dusenge et al., 2019).

4.2 Process-based model prediction in the context of global change

Process-based models take into account the direct effect of climate on photosynthesis and respiration, contrary to a great number of models. In the context of prediction in changing climate (like resilience study), the process-based models represent promising prospects, not fully explored, for understanding and predicting changes in forest ecosystem functioning. Studies have already tried to predict trends in forest productivity (Madani et al., 2018; Prislan et al., 2019; Tei et al., 2017), carbon storage (Gustafson et al., 2017; Lindner et al., 2014; Lo et al., 2019) and C, H2O and N dynamics (Dong et al., 2019) in the decades to come.

The quantification of biases in impact model outputs that are caused by the quality of the climate data used as input is rarely studied (Glotter et al., 2014; Palma et al., 2018; Stéfanon et al., 2015). Such studies are crucial, however, to be able to develop nuanced interpretations of predictions, especially since the conclusions are contrasting. According to Stéfanon et al. (2015), the goodness of fit of the CASTANEA-derived beech distribution can be between 70% (when using meteorological data from the Aladin climate model) and less than 10% (when using meteorological data from the WRF climate model). The results are similar for the other model used (BIOMOD, a niche model). This means that the climate model used for prediction has great importance (see also Glotter et al., 2014, for American yield). Palma et al. (2018), on the other hand, has shown with 3-PG (Landsberg & Waring, 1997; Sands & Landsberg, 2002) that datasets of simulated climate can have minimal reduction in performance (in this study RACMO and WRF). Note that Palma et al. (2018) used stock and not fluxes in their comparison, in contrast to the other cited studies.

It is also important to keep in mind that not all climate models allow the same quality of estimation. For example, in our study, the use of the CNRM climate model as input (with corrections) induced larger biases in the impact model simulations than the other climate models (almost twice as large as those of Hadgem for *GPP* and *Resp*). It is therefore important to compare impact model outputs used with climate model input data against impact model outputs used with observed climatic data over a historical period. This allows the quantification of the uncertainty associated with climatic data (see Jung et al., 2007) and is a prerequisite condition before making predictions about the future period.

More specifically, this work makes it possible to estimate the biases in CASTANEA simulations when using climate model data in French territory and to quantify simulation errors for each climate model.

As explained in the introduction, uncertainties in impact model outputs are accumulated along a cascade of uncertainty (Lindner et al., 2014; Reyer, 2013), composed of uncertainty sources at each step of the chain. According Lindner et al. (2014), there are three sources of uncertainties in models inputs, structure and parameters uncertainties. In this work, we focused on only one single step of this cascade of uncertainty: the effect of climatic input data biases on impact model output biases. In fact, for extreme climatic years (considering temperature and precipitation), the bias of climate data may be the largest source of uncertainty (Iizumi et al., 2017). However, uncertainty of the impact model itself can also have a strong influence on the outputs. For example Carbone et al. (2016) questioned the uncertainties associated with the structure of the FöBAAR model (should respiration be separated into autotrophic and heterotrophic, or not?) or Chave et al. (2004) concluded that main source of uncertainties in AGB estimation is allometric model choice. Moreover parameter uncertainties may be different within a model. For example, Levy et al. (2004) highlighted that more sensitive parameters are connected to leaf, roots and stem allocation (in three models studied). Previous studies focused on CASTANEA uncertainties due to process-based model parameters (Dufrêne et al., 2005), and magnitude of parameter uncertainty is similar to climate data uncertainties (see Table 6 and Figure 3 of Dufrêne et al 2005).

Even quantifying uncertainties is an important research topic, the effects of model structural, input and parametric uncertainty are rarely considered together (Lindner et al., 2014; Reyer, 2013). Moreover, it is important to note that all three aspects of uncertainty contain different levels of uncertainty: statistical uncertainty, scenario uncertainty and uncertainty due to ignorance (Walker et al., 2003). Statistical uncertainty refers to the measurement uncertainty, like for example sampling error, inaccuracy and imprecision. Scenario uncertainty deals with plausible changes of these scenarios, which are based on alternatives assumptions. Finally, the uncertainty due to ignorance can be divided into two categories: “known unknowns” and “unknown unknowns”. To summarize, importance of one type of uncertainty compared to another is specific to each model, via accepted assumptions and mechanisms taken into account, and difficult to generalize. It is therefore necessary for each modeller to think about uncertainty sources associated with his model and to discuss his results accordingly. That is why we proposed this study focusing on input uncertainties.

Finally, we would like to remind the reader that we used only one process-based model, CASTANEA, which limits the generalisability of our results. Contrary to others studies like Nishina et al. (2015) or Cheaib et al. (2012) with 6 models. In fact, inter-model comparison studies show that the same set of climate data could induce different answers to the same question depending on the impact model used (see Cheaib et al., 2012; Jung et al., 2007). It might be instructive to replicate our approach with other mechanistic models and more broadly with other impact models driven by climate model data.

5 Conclusion

Our work highlighted several crucial points in the development of process-based model predictions in the context of climate change. First, a simple correction of the climatic data provided a significant improvement in the predictions of the CASTANEA model (57 gC/ha/y on average, in 78% of the cases). Second, a study at different scales showed that work on a regional scale (SER, GRECO, France) reduced the bias due to the climate model but did not significantly reduce the average bias. Third, we were able to highlight that the bias in the model's predictions when using different climate models increases for the driest years compared to the average years. These results are similar regardless of the process considered. Fourth, biases (in %) for wood growth (*AWBI*) are higher than those for *GPP* and *Resp*.

Therefore, using an impact model to make predictions using climate model data as input is relevant and useful provided that the appropriate corrections are performed. This study performed on a historical period was necessary to assess the relevance of the method (Jung et al., 2007) and to prepare prediction studies on future periods (2020-2100).

Author contributions

MJ conceived the original question and simulation setup of this study. NMStP provided the climate model dataset. MJ, CF, NMStP and ED designed the research and developed the methodology; MJ processed and analysed the data; MJ, CF, ND, NMStP and ED wrote the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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Supplementary materials

Appendix 1: CASTANEA calibration results

We calibrated the carbon allocation to aboveground biomass in CASTANEA for *Fagus sylvatica*, *Picea abies*, and *Pinus sylvestris*. We used the IFN inventory, i.e., only even-aged regular monospecific stand plots. The dataset is made up of individual 5-year tree ring increment inventories between 1970 and 2017. Then, we divided the whole inventory for each species into two groups, one quarter for calibration and three quarters for validation, except *Pinus sylvestris*, for which we used one-half for calibration and one-half for validation. To perform this calibration, we compared the observed and simulated radial increments of the mean tree using the *optim* function from the *stats* package.

Species	Number of calibration plots	Number of validation plots	RMSE of calibration dataset	RMSE of validation dataset
Fagus sylvatica	1036	3109	0.16	0.2
Quercus sp.	2228	6683	0.16	0.13
Pinus sylvestris	2562	2563	0.18	0.17
Picea abies	752	2511	0.31	0.20

We computed the RMSE, slope of the linear model (simulated radial increment explained by observed radial increment) and R^2 for the calibration and validation subparts of the dataset.

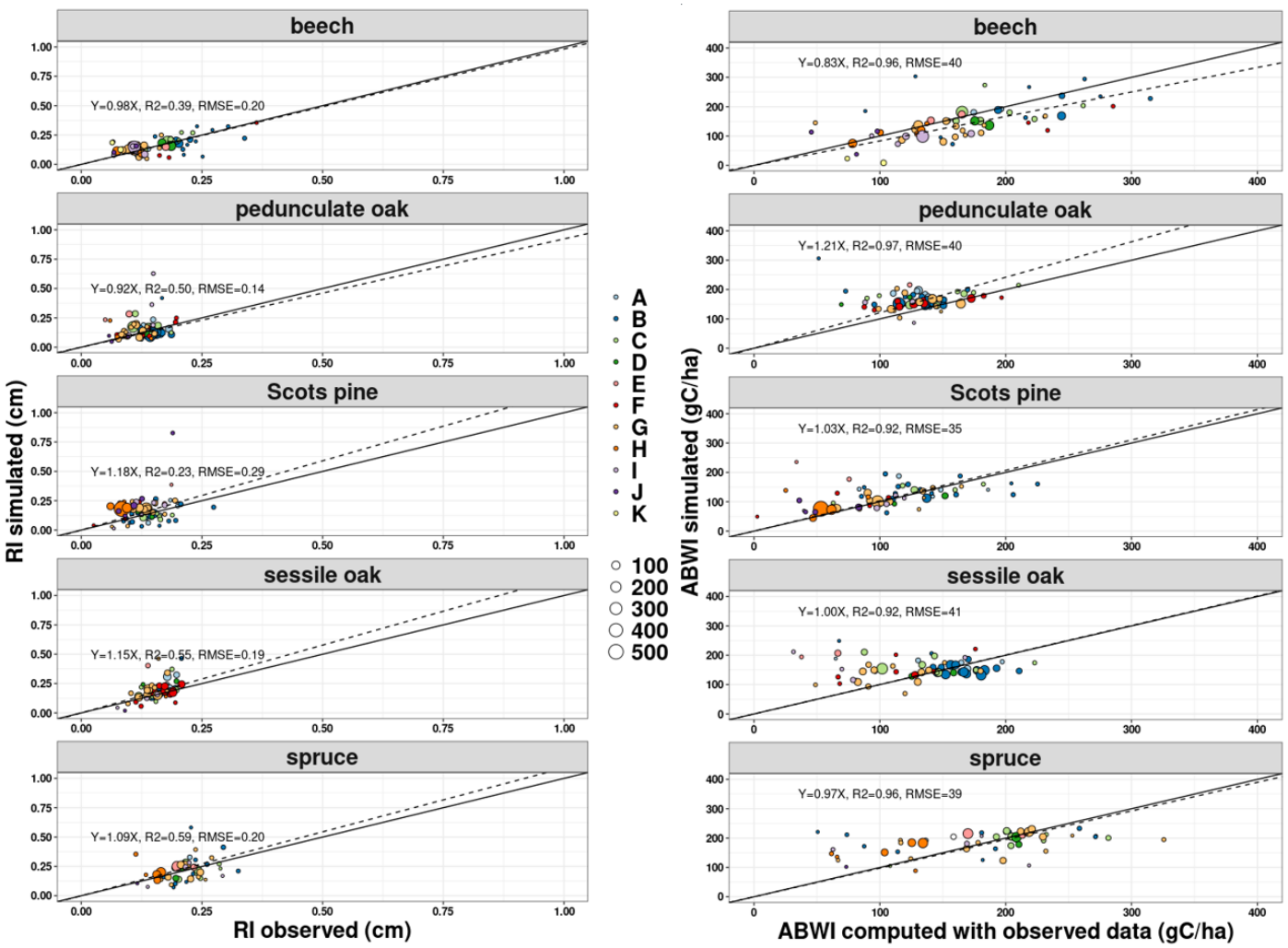
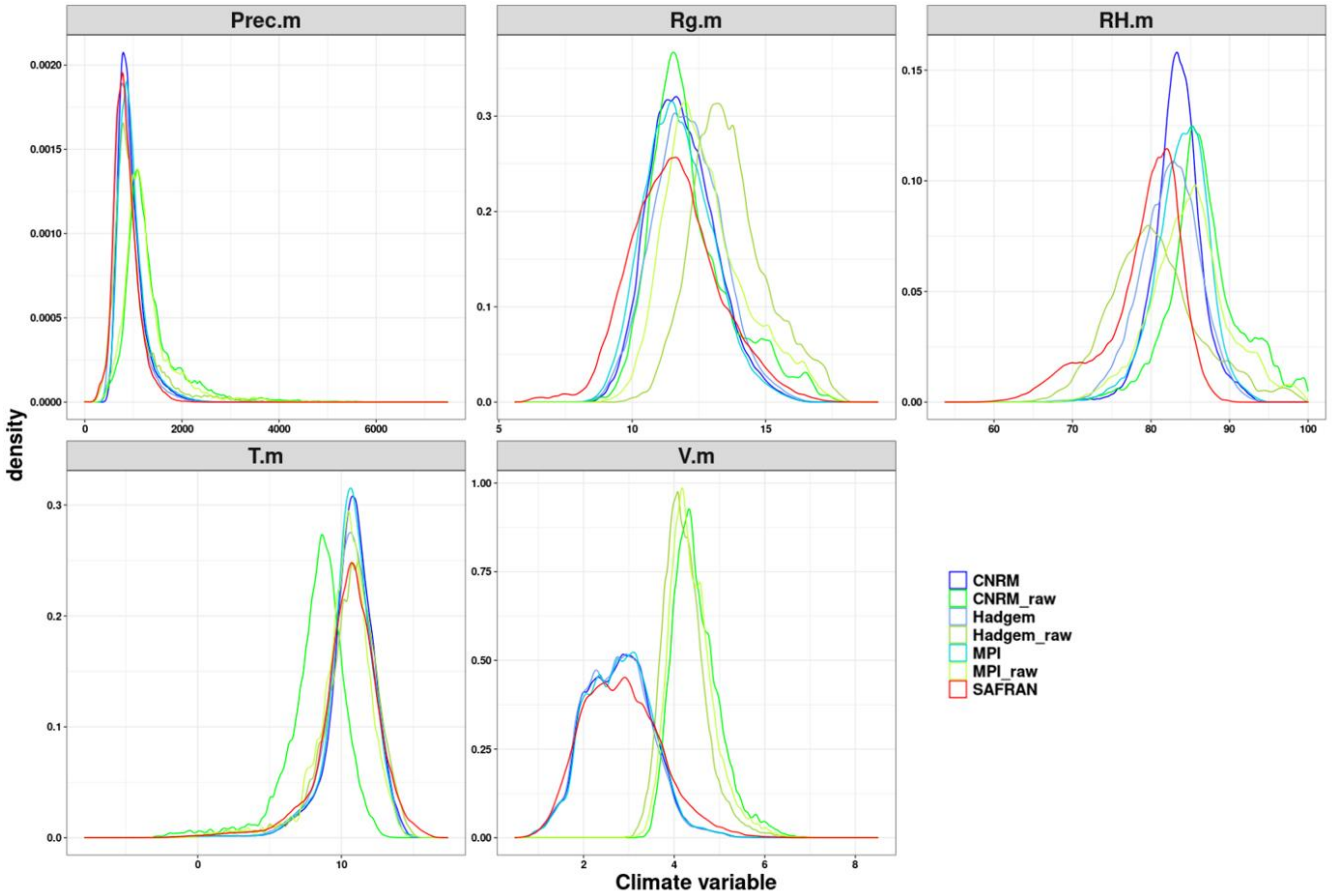


Figure 1: The graphs represent the simulated vs. observed annual radial increment in cm (left) and NPP_{wood} in gC/m² (right) by species. Each point represents the mean plot value for each SER (see Figure S1); the size represents the number of plots in the SER, and the colour indicates the GRECO. The dashed line represents the linear model $Var_{sim} \sim Var_{obs}$, and the regression equation is indicated with R-squared for each species (all coefficients are significant, p-value<0.0005). The black line is the 1:1 line.

The overall performance of the model is equivalent to what is found in the literature (see Palma et al., 2018 on stock or Forrester et al., 2017 on fluxes): the directing coefficient of the equation obtained in our study, 0.97 (±0.22), is comparable to the directing coefficient of the equation in Forrester et al. (2017), i.e. 1 (±0.17). The results vary among species. The results are different for monospecific Scots pine, where stand radial increments and annual *AWBI* are slightly overestimated by the model (with slopes of 1.14 and 1.4, respectively). This observed inaccuracy in Scots pine simulations may be explained by the fact that Scots pine carbon fluxes were calibrated with flux site data from the northern part of the distribution area (Hyytiälä, in Finland; Delpierre et al., 2012) while wood growth was calibrated with data from the southern part of the distribution area (French National Inventory, IFN). To a lesser extent, the annual radial increments and annual *AWBI* fluxes of pedunculate and sessile oaks are slightly underestimated (with slopes of 0.74 and 0.70 for annual radial increments and slopes of 0.87 and 0.79 for annual *AWBI* fluxes, respectively).

Appendix 2: Climate model and SAFRAN variable characteristics

a)



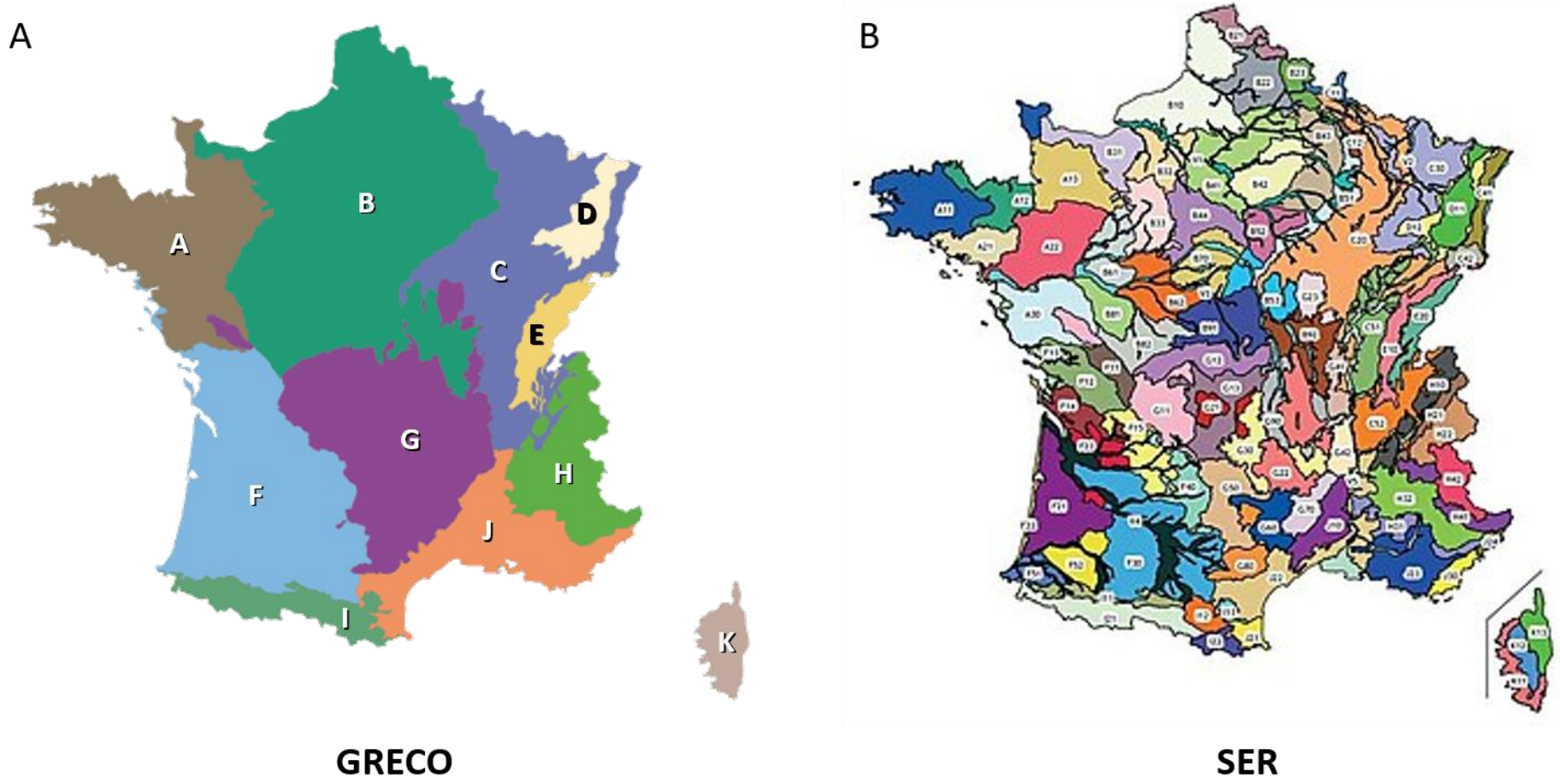
Spatial distribution of climate variables for radiation (Rg), relative humidity (RH), mean temperature (T) and precipitation (Prec)

b)

GCM	From	RCM	Projected climate changes in Europe
CNRM-CERFACS-CNRMCM5	Centre National de recherche météorologiques	RCA4	Moderate summer temperature increase, slight summer precipitation increase
MOHC-HadGEM2-ES	Met Office Hadley Centre	RCA4	Large summer temperature increase, large summer precipitation decrease
MPI-M-MPI-ESM-LR	Max Planck Institute	RCA4	Large summer temperature increase, medium summer precipitation decrease

The table shows characteristics of the selected climate models (adapted from Fargeon et al., 2020).

Appendix 3: GRECO and SER



Maps of the geographical delimitations of GRECO (Grande Region ECOlogique), macro-regional scale (A), and SER ("Sylvo-Eco-Region" or Ecological Forest Region), meso-regional scale (B), from the website (https://inventaire-forestier.ign.fr/).

Appendix 4: Computational details of equations 6 and 7

To study the scale effect on the quality of prediction (objective n°2, see above), we focused on two regional scales, SER and GRECO, to understand the aggregation effect. At the regional level, stand age distribution could have a strong effect on prediction because processes are strongly affected by stand age in CASTANEA and can interact with climate effects. For the following analyses, we considered four age classes (20-60 years, 60-120 years, 120-180 years, >180 years). We tested different age classes, and the results were similar.

We compute the proportion of bias compared to the variable level at the regional scale as in eq. 3, using the total surface of the species (S_{sp}), mean level per hectare of variable V for all plots *i* of a given age class, species, model and SER ($mean_i(V_{mod,sp,s,age})$) and proportion of that age class ($p_{sp,s,age}$):

$$\delta_{mod,v,sp,s} = V_{mod,sp,s} - V_{saf,sp,s}$$

$$= S_{sp} * \sum_{age} p_{sp,s,age} * mean_i(V_{mod,sp,s,age}) - S_{sp} * \sum_{age} p_{sp,s,age} * mean_i(V_{saf,sp,s,age})$$

$$= S_{sp} * \sum_{age} p_{sp,s,age} * \left(mean_i(V_{mod,sp,s,age}) - mean_i(V_{saf,sp,s,age})\right)$$

$$= S_{sp} * \sum_{age} p_{sp,s,age} * mean_i(V_{mod,sp,s,age} - V_{saf,sp,s,age})$$

$$= S_{sp} * \sum_{age} p_{sp,s,age} * mean_i(\delta_{mod,v,sp,s,age}) \quad \text{(a)}$$

Then,

$$p.biais_{mod,v,sp,s} = \delta_{mod,v,sp,s} / V_{saf,sp,s}$$

$$\sum_{age} \%_{sp,s,age} * mean_i\left(\delta_{mod,v,sp,s,age}\right) / \sum_{age} \%_{sp,s,age} * mean_i(V| \quad |saf, sp, s, age| \quad |\ ) \quad \text{(b)}$$

We need to assign a total monospecific area per region to each age class and each species. The monospecific stand area is not available by age class and species, only by species. We therefore decided to compute the area by age class and by species using the total specific area and proportion of monospecific stand plots for each age class and species. Then, we extracted the total surface area by *SER* and *GRECO* from the IFN data (see Appendix S8). The ratio of plot number in each age class (nb_{age}) to the total plot number

(nb_{tot}) is then determined for each type of monospecific stand by computing this proportion annually and averaging over the 10 years of inventory available (between 2006 and 2017). This gives, for each year *i*, SER *s*, age class *age* and species *sp*:

$$\%_{sp,s,age,i} = n\,b_{age,sp,s,i} / n\,b_{tot,sp,s,i} \quad \text{(c)}$$

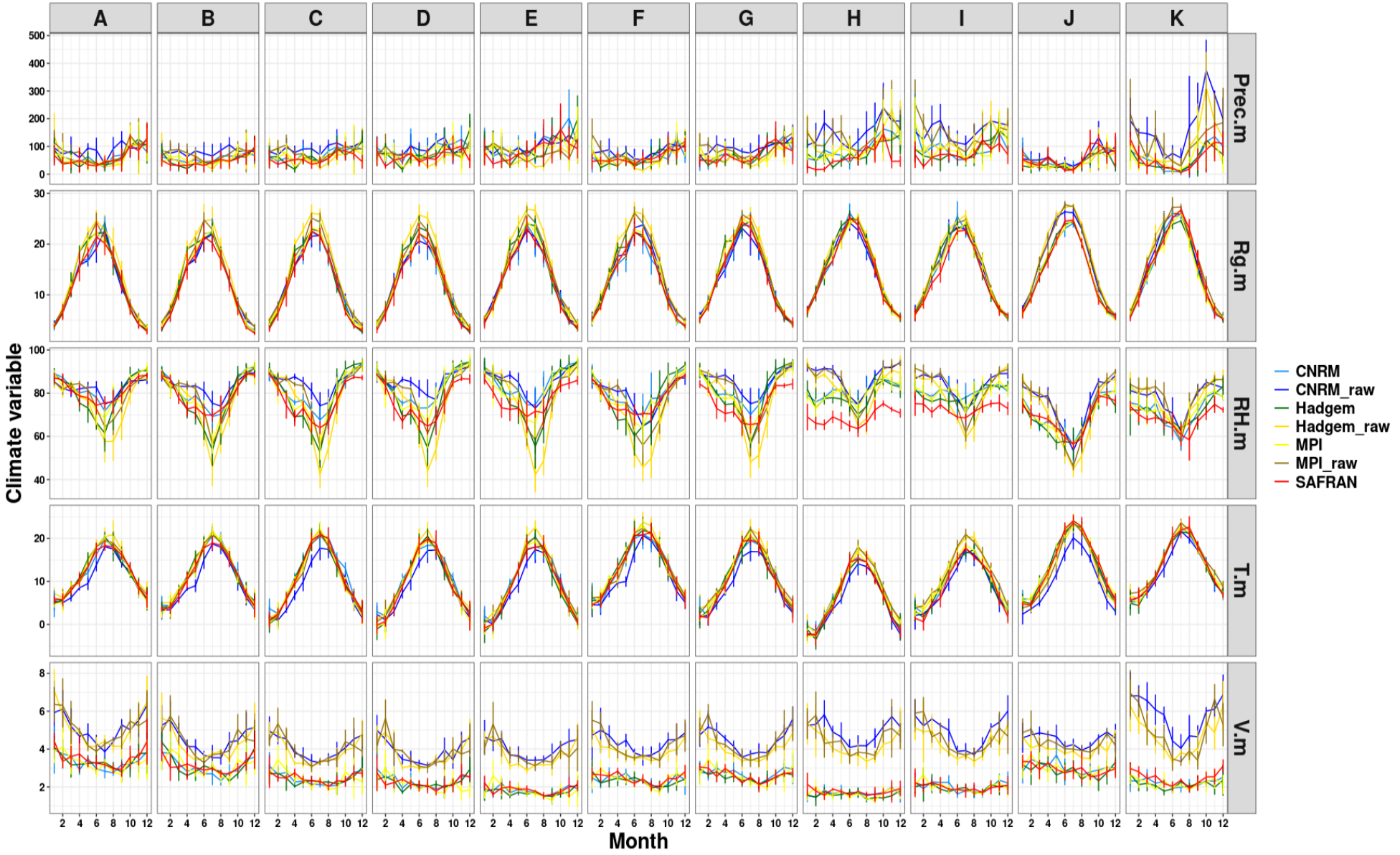
The calculations are the same for the GRECO level and France level.

Appendix 5: Most stressful years

model	A	B	C	D	E	F	G	H	I	J	K
NUM_SAF	1976	1976	1976	1976	1976	2005	1976	2003	1967	2003	1961
	2011	2011	2003	2003	2003	1976	2003	2004	2005	2005	2017
	1959	1996	2015	1964	2004	2011	2015	1976	1986	2006	2003
	2005	1959	1964	2015	2009	2003	2005	2005	2006	2004	1973
CNRM	2001	2009	2001	2001	2001	2001	2009	2001	2001	2001	1997
	1970	2001	1964	1964	2009	2009	1964	1964	1964	1985	1985
	2009	1974	2009	2009	1964	1964	1998	1972	1997	1974	1998
	1985	1970	2005	2006	2006	1981	2001	2009	1999	1998	1970
Hadgem	1975	1975	1966	2002	2002	1966	1966	1966	1987	1966	1966
	1990	1966	2002	1966	1966	1987	2002	1987	1966	1987	2001
	1967	2011	1967	1975	1967	2002	2011	1967	2006	1967	1987
	1966	1986	1975	1967	1986	2011	1995	1995	1995	1990	1984
MPI	2005	2005	2000	2000	2006	2012	2012	1973	2007	2012	2007
	1970	2000	2005	1985	1970	1970	2000	1970	1999	1973	1995
	2012	1973	1973	1970	2000	1973	2006	2012	2000	2002	1973
	2000	1963	1970	2005	2005	2000	2005	2002	2012	1964	1978
CNRM_brut	1970	2009	2009	2001	2001	2001	2009	2001	1964	2001	1997
	2001	1970	2001	2009	2009	2009	1964	1964	2001	1985	1985
	1989	2001	1964	1989	2006	1970	1974	1972	1997	1964	1998
	2009	1974	2005	1964	1964	1974	2005	2009	1985	1972	1970
Hadgem_brut	1975	1975	1966	2002	2002	1966	1966	1966	1987	1966	1966
	1990	1966	2002	1966	1966	1987	2002	1987	1966	1987	1982
	1966	2000	1975	1975	1986	2002	1987	1983	2006	2011	1987
	1987	2011	1967	1967	1967	2011	2011	2011	1995	1982	1984
MPI_brut	2005	2005	2000	2000	2006	2012	2012	1973	2000	2012	2007
	1970	1973	2005	2005	1970	2000	2000	2012	2007	1973	2012
	2012	2000	1970	1970	2000	1970	2006	1985	1999	2007	1973
	2000	1970	1973	2006	2005	1979	1973	1970	2012	2002	2000

The table shows the four driest years of 1960-2010 for each climate data source and each GRECO.

Appendix 6: Seasonal variations in climate variables during stressful years



Monthly climate variables for radiation (Rg.m), relative humidity (RH.m), mean temperature (T.m) and precipitation (Prec.m) for the climate models before and after correction and for each GRECO.

Appendix 7: Table of mean bias percentage

		Average years			Stressful years		
scale	**correction type**	**ABWI**	**GPP**	**Resp**	**ABWI**	**GPP**	**Resp**
plot	**Corrected**	8 (±8)	6 (±4)	7 (±5)	19 (±29)	10 (±8)	8 (±6)
	Non-corrected	23 (±20)	13 (±11)	12 (±11)	40 (±52)	18 (±14)	4 (±12)
SER	**Corrected**	7 (±7)	6 (±4)	7 (±4)	16 (±10)	9 (±6)	8 (±5)
	Non-corrected	22 (±11)	13 (±9)	11 (±8)	34 (±24)	17 (±12)	13 (±9)
GRECO	**Corrected**	7 (±4)	6 (±3)	7 (±3)	17 (±10)	10 (±7)	8 (±5)
	Non-corrected	22 (±10)	14 (±8)	12 (±6)	35 (±15)	18 (±9)	13 (±7)
France	**Corrected**	7 (±3)	6 (±3)	7 (±3)	16 (±5)	9 (±3)	8 (±3)
	Non-corrected	21 (±5)	13 (±2)	12 (±3)	33 (±9)	17 (±4)	13 (±3)

Table of mean bias percentage (and standard deviation) of simulations compared to process levels simulated with SAFRAN, by process (column), scale and correction type (row), for average years and the most stressful years.

Appendix 8: GRECO and SER areas by species

a)

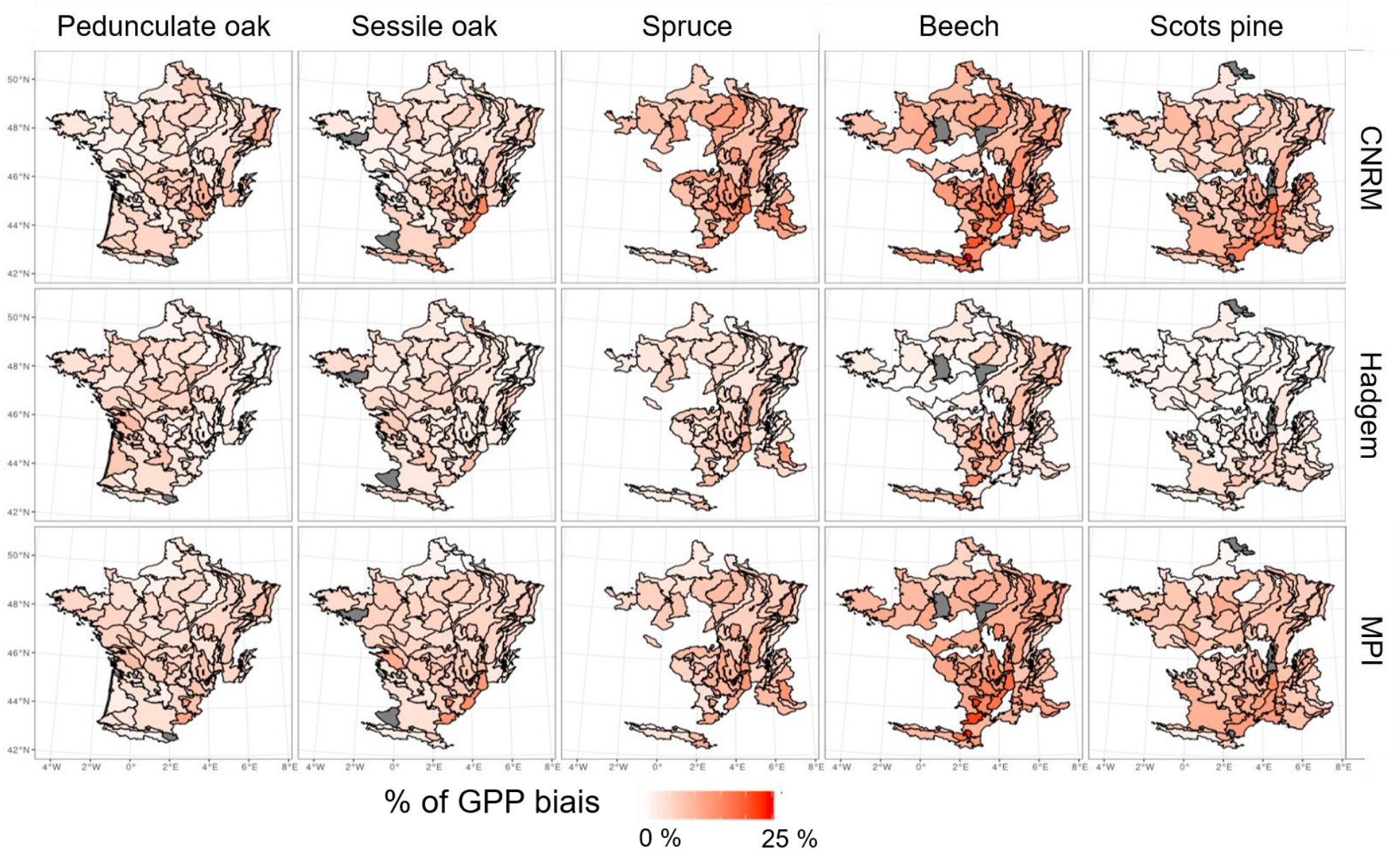
	A	B	C	D	E	F	G	H	I	Total
P. oak	81 (±13)	253 (±23)	68 (±12)	-	-	185 (±22)	134 (±18)	-	-	734 (±41)
S. oak	52 (± 10)	423 (±28)	146 (±18)	26 (±7)	-	34 (±10)	118 (±17)	-	-	814 (±41)
B	-	61 (±11)	110 (±15)	57 (±11)	33 (±9)	-	129 (±18)	66 (±15)	127 (±18)	618 (±39)
S	-	-	47 (±10)	35 (±9)	47 (±10)	-	105 (±16)	74 (±14)	-	327 (±28)
SP	-	75 (±13)	-	-	-	-	132 (±19)	220 (±27)	-	503 (±38)

b)

	A11	B10	B32	B33	B41	B52	B53	B62	B70	B91	B92	C20	C30	D11	D12	E20	F21	F30	F52	G11	G13	G22	G30	G60	H10	H30	H41	I21
P. oak	21 (±6)	-	-	-	-	-	-	-	68 (±12)	-	-	-	23 (±7)	-	-	-	38 (±11)	33 (±10)	32 (±9)	33 (±9)	32 (±8)	-	-	-	-	-	-	-
S. oak	-	-	37 (±9)	40 (±9)	32 (±8)	38 (±9)	44 (±9)	36 (±9)	35 (±8)	53 (±10)	27 (±7)	79 (±13)	32 (±8)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
B	-	28 (±8)	-	-	21 (±6)	-	-	-	-	-	-	76 (±12)	-	29 (±8)	28 (±8)	-	-	-	-	-	-	33 (±9)	30 (±8)	-	-	-	-	95 (±15)
S	-	-	-	-	-	-	-	-	-	-	-	-	-	28 (±8)	-	36 (±9)	-	-	-	-	-	35 (±9)	-	-	38 (±10)	-	-	-
SP	-	-	-	-	-	-	-	-	40 (±9)	-	-	-	-	-	-	-	-	-	-	-	-	42 (±11)	-	41 (±11)	-	157 (±23)	41 (±12)	-

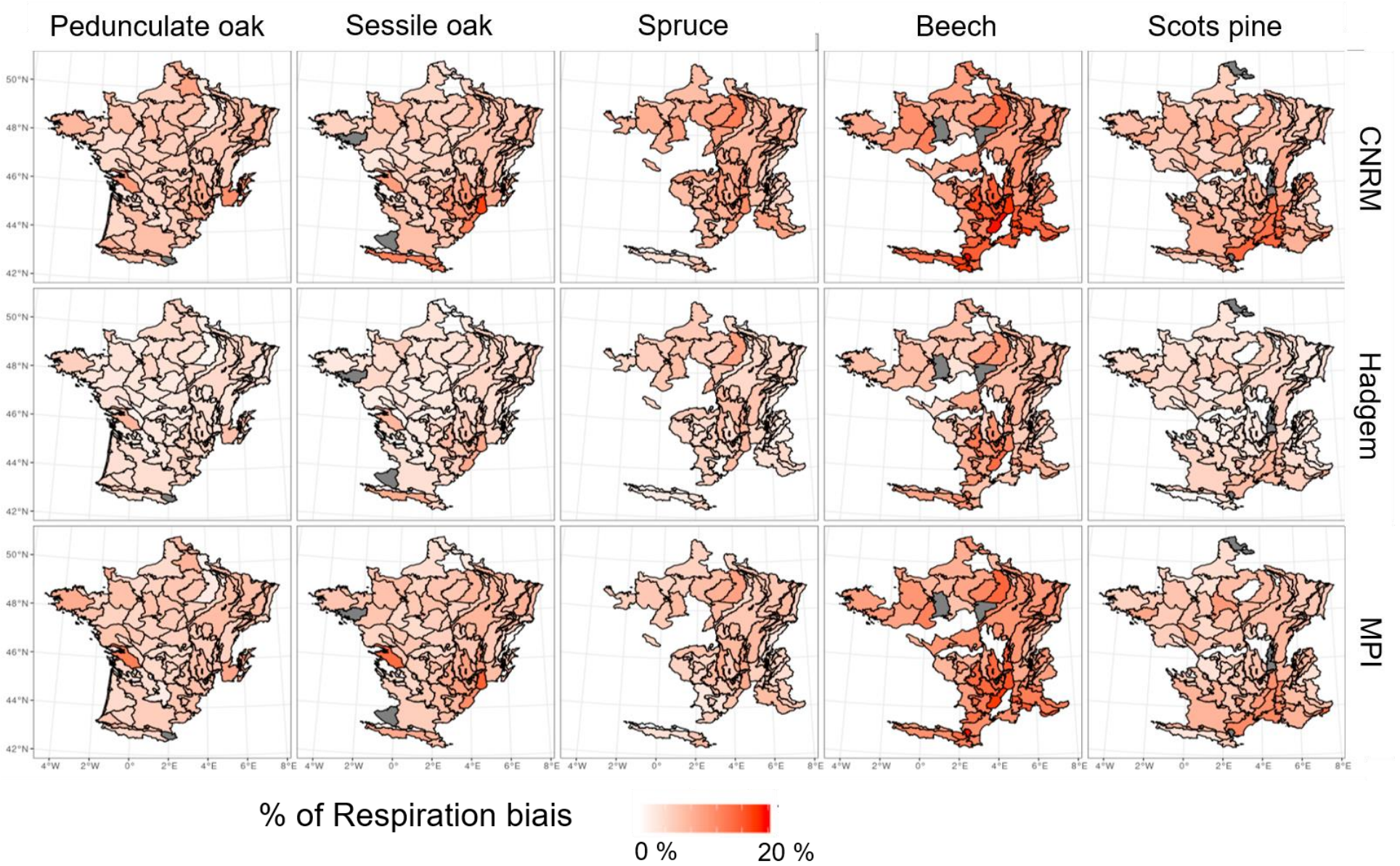
Tables show the surface area (thousand hectares) of monospecific stands in each species (rows) and region (columns) in GRECO (a) and SER (b).

Appendix 9: Maps of GPP bias



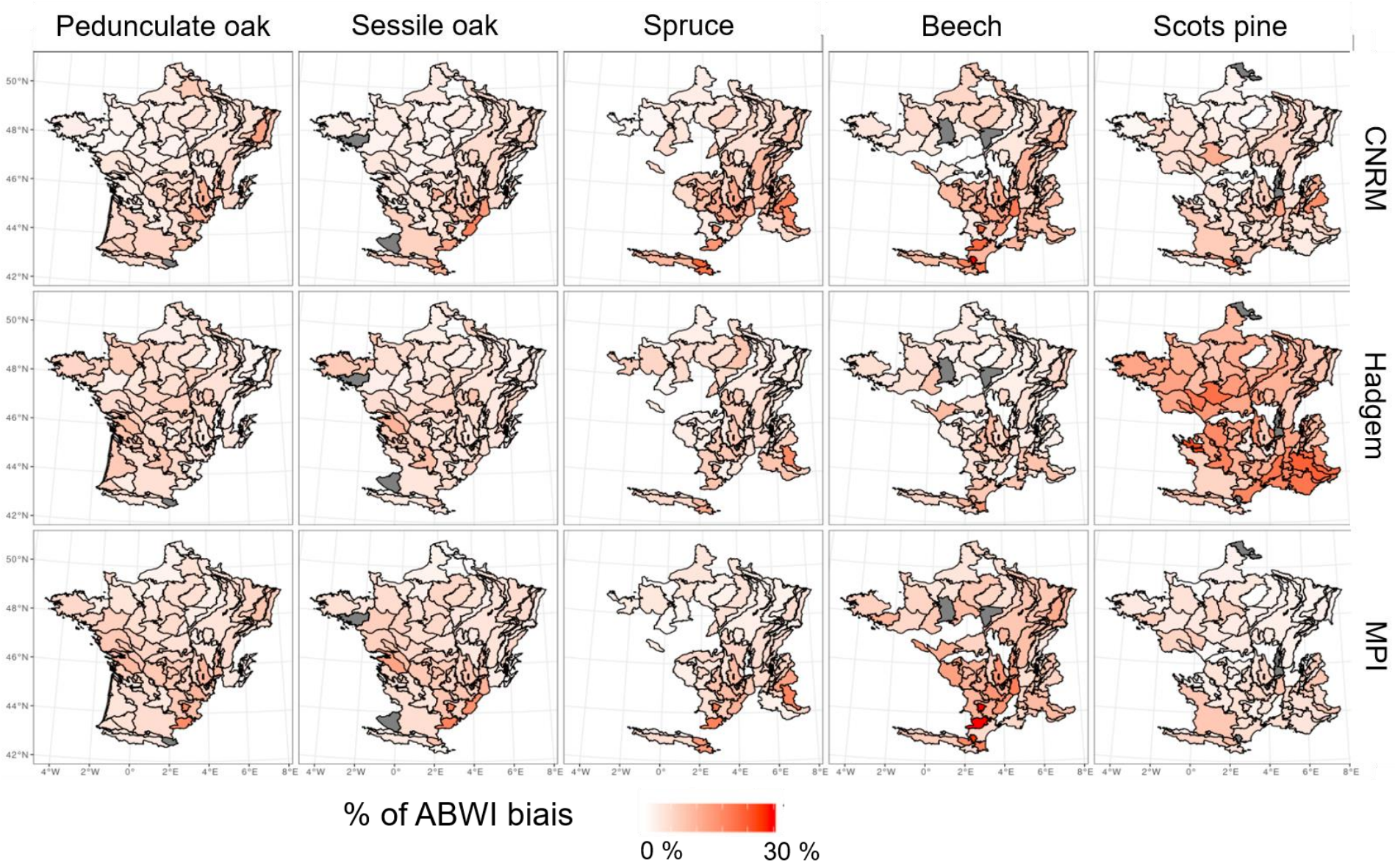
Maps of the average GPP bias percentage at the plot scale, comparing simulations with climate models and with SAFRAN data, for each model and each species. Polygons correspond to SER and colours correspond to the uncertainty level.

Appendix 10: Maps of respiration bias



Maps of the average Resp bias percentage at the plot scale, comparing simulations with climate models and with SAFRAN data, for each model and each species. Polygons correspond to SER and colours correspond to the uncertainty level.

Appendix 11: Maps of AWBI bias



Maps of the average AWBI bias percentage at the plot scale, comparing simulations with climate models and with SAFRAN data, for each model and each species. Polygons correspond to SER and colours correspond to the uncertainty level.

Appendix 12: Correlations between climate and process biases

We decided to quantify the relationship between process bias and climate bias in the SER with the highest percentage of bias (higher than 40%). First, climate variables were averaged over the period 1960-2010 by plot. Second, climate bias was computed similarly to (1) for each variable (*V*), model (*mod*), species (*sp*) and plot:

$$\delta_{mod,v,sp} = V_{mod,sp} - V_{saf,sp} \quad (1b)$$

We wanted to understand which climate variables affect the process percentage of bias (eq. 4 in the main document) as a function of climate bias (1b). Then, we decided to quantify the correlation between process bias and climate bias for each species and each process.

	Scots pine			Beech			Spruce			Pedunculate oak			Sessile oak		
	GPP	Resp	AWBI	GPP	Resp	AWBI	GPP	Resp	AWBI	GPP	Resp	AWBI	GPP	Resp	AWBI
T	0.41	**0.64**	-0.21	0.26	0.38	-	**0.62**	**0.78**	0.09	0.03	0.3	-0.14	0.09	0.35	-0.06
RH	0.23	-	-0.05	0.42	0.37	0.23	0.12	-0.19	0.44	0.15	0.18	0.18	0.31	0.37	0.29
Rg	0.21	0.23	0.2	0.27	0.26	0.11	0.31	0.28	0.03	0.1	-0.11	0.1	0.1	-	0.16
V	0.27	0.18	-0.1	0.41	0.32	0.23	0.23	0.16	0.24	0.08	0.18	0.1	0.2	0.26	0.12
Prec	0.29	0.12	-0.23	0.23	0.22	0.11	0.04	-0.16	0.22	0.11	0.39	-	0.31	0.49	0.12

The table shows the correlation between climate bias and process bias at the plot scale for each species and each process. Numbers represent every significant correlation, and bold numbers correspond to a strong positive (>0.5) or negative correlation (<-0.5).

Declaration of interests

☐The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☒The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Marion Jourdan reports financial support was provided by French Environment and Energy Management Agency.

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TO: Editorial Board of *Agricultural and Forest Meteorology*,

Paris, Septembre 2021

Dear Editor-in-Chief,

My co-authors and I would like to ask you to consider for publication in Agricultural and Forest Meteorology the attached manuscript entitled "**Reliable predictions of forest ecosystem functioning require flawless climate forcings.**".

Following the thorough and very helpful comments of the reviewers and the editor, we have substantially changed and amended the manuscript according to their suggestions. Among the modifications done, we have notably improve model description, shorten the results to be clearer and complete introduction and discussion with the perspective of the different sources of uncertainty.

We have enclosed a point-by-point response to all comments. We hope that you will now find the revised manuscript suitable for publication. This work is original and has not been submitted for publication elsewhere. The manuscript is submitted with four figures and 12 appendices as supplementary material.

Thank you for evaluating our manuscript. We look forward to hearing from you.

Yours sincerely,

Marion Jourdan

Hightlights: “Idol with feet of clay”: Reliable predictions of forest ecosystem functioning require flawless climate forcings.

- Predictions of physiological process depends on climate model, species and region
- Predictions were improved after correction for the three models considered
- Processes simulated exhibited large variability at the plot scale
- This variability faded out at larger scales, owing to an aggregation effect
- Process predictions were more variable during the driest years

Responses review for Agricultural and Forest Meteorology: Reliable predictions of forest ecosystem functioning require flawless climate forcings

Reviewer #1:

Comments on "Idol with feet of clay: Reliable predictions of forest ecosystem functioning require flawless climate forcings" submitted by M. Jourdan et al. to Agricultural and Forest Meteorology

This study assessed the influences of the quality of forcing data on simulation results by a process-based model (CASTANEA) for five tree species in France. It was found that bias-corrected meteorological forcing data allowed to reduce biases in the simulated productivity and biomass growth.

General comments

The primary research objective, specifying the source of uncertainty, is definitely important for model studies. However, I did not find new insights in this study, because this issue has been explored by other studies in a more systematic manner. For example, the Inter-Sectoral Impact Model Intercomparison Project conducted simulations with multiple climate data, atmospheric CO2 scenarios, and impact models (including process-based models). The project evaluated the contributions of the uncertainty factors among variables and revealed the spatial and temporal patterns (e.g., Nishina et al. 2015). The species-based assessment would be a merit of this study, based on elaborate works using a regional climate model and forest inventory. This study presented analyses on scale dependence and extreme years, but these findings were not presented in a comprehensive manner.

The manuscript reads lengthy and can be shortened substantially. Also, I found many awkward phrases and sentences, which can be improved. The description of CASTANEA model was too simple to understand the results. Therefore, I cannot recommend the manuscript as a candidate for publication, because thorough revisions are required.

Reply: We thank reviewer #1, which helped us to highlight innovative aspects of our work, compared to Nishina et al. (2015) work and the Inter-Sectoral Impact Model Intercomparison Project. We integrated this references in our manuscript (l.79-81, 120, 139 and 546)

We try to shorten and clarify the manuscript, improving some sentences. We added details in CASTANEA description, the description is now more comprehensive (see l.149-179)

The manuscript was edited by American Journal Expert before submission. The certificate is attached. Moreover, we will send them the final version of the article for final English edition.

We hope that these changes have substantially improved the manuscript. We give the details of minor changes in the following responses.

Specific comments

1. Title: I recommend removing "Idol with feet of clay". Also, 'flowless' may be too strong word.
Reply: We changed the title as suggested by both reviewers, removing "Idol with feet of clay".

2. Line 75-76: I don't agree with the statement, because many models such as dynamics vegetation models can take into account the influence of climate change in the processes of forest functioning.
Reply: We amended the sentence to appear less categorical: "In many studies, this type of forecasting is carried out in the contemporary period with empirical growth models (BICAFF project, Valade et al., 2018; MARGOT model, Wernsdörfer et al., 2012), without integrating climate change."(l.72-74)

3. Line 85: Zhao et al. (2012) is missing in References.
Reply: We added the missing reference. (l-87)

4. Line 118: 'different modelled climate data' is an example of awkward phrase.
Reply: We amended sentence: "We propose here to evaluate process-based model simulation over a historical period (1960-2010) to estimate error predictions, comparing results with three climate models." (l.118-120)

5. Line 181: What kind of radiation did you use? Shortwave? Photosynthetically active radiation? Please specify.
Reply: In Castanea model, we use Global Incoming Solar Radiation to compute evapotranspiration and Photosynthetically active radiation (PAR) to compute photosynthesis.

6. Line 206: Usually, ESGF stands for Earth System Grid Federation. Please check.
Reply: Reviewer #1 is right, we changed the acronym (l. 225)

7. Line 242: What are the 'evolving factors'? Please explain.
Reply: "Evolving factors" are factors which change across large period as age or biomass. To be clearer we have made our point explicit. (l. 260)

8. Line 233: I was impressed by the authors' effort for analyzing such a large number of inventory data. Just a comment.
Reply: Thank you for this comment.

9. Line 292: I recommend not using '%' for a variable symbol.
Reply: As suggested by reviewer, we changed variable symbol between lines 311 and 316.

10. Line 335: Slope for what? Please give an explanation around here.
Reply: We amended the sentence to clarify our point : "The overall performance of the model is equivalent to what is found in the literature (see Palma et al., 2018 on stock or Forrester et al., 2017 on fluxes): the directing coefficient of the equation obtained in our study, 0.97 (±0.22), is comparable to the directing coefficient of the equation in Forrester et al. (2017), i.e. 1 (±0.17). The results vary among species." (l.914-917)

11: Line 504-507: I could not understand what the authors want to say here. I am convinced that there are more than 9 process-based models in the world. Also I could not understand logical linkage between before and after 'For this reason'.
Reply: We agree with the reviewer; the wording was not adequate. We changed to: "Process-based models take into account the direct effect of climate on photosynthesis and respiration, contrary to a great number of models. In the context of prediction in changing climate (like resilience study), the process-based models represent promising prospects, not fully explored, for understanding and predicting changes in forest ecosystem functioning." (l.495-498)

References

Nishina, K. et al. Decomposing uncertainties in the future terrestrial carbon budget associated with emission scenario, climate projection, and ecosystem simulation using the ISI-MIP result. Earth System Dynamics 6, 435-445, doi:10.5194/esd-6-435-2015 (2015).
Reply: Thank you for this reference. We integrated it in our manuscript and fully detailed the differences between our work and their work (see reply to general comment).

Reviewer #2:

The paper by Jourdan et al. explores the question of how bias-correction in climate model input data improves impact of key variables from a process-based forest biogeochemical model. The approach is based on the historical period (1960-2010) and uses 3 climate models, both corrected and uncorrected, along with the observationally-based SAFRON data. The evaluation is based on comparing three key fluxes, GPP, AWBI, and resp from the CASTANEA model, over a series of spatial scales (plot, macroregional, microregional, and all of France) and extreme drought years, which differ between the models. The results show using corrected climate model data reduces biases by half, regardless of regional scale (though larger biases at plot scale), with larger errors in extreme dry years. Overall this is a worthwhile study to explore this important issue bias introduced by climate input. I suggest minor revisions (i.e. no overall change in approach or required model experiments) dependent upon the following clarifications:
Reply: We thank reviewer #2 for his/her consideration. We amended manuscript to response to every comments.

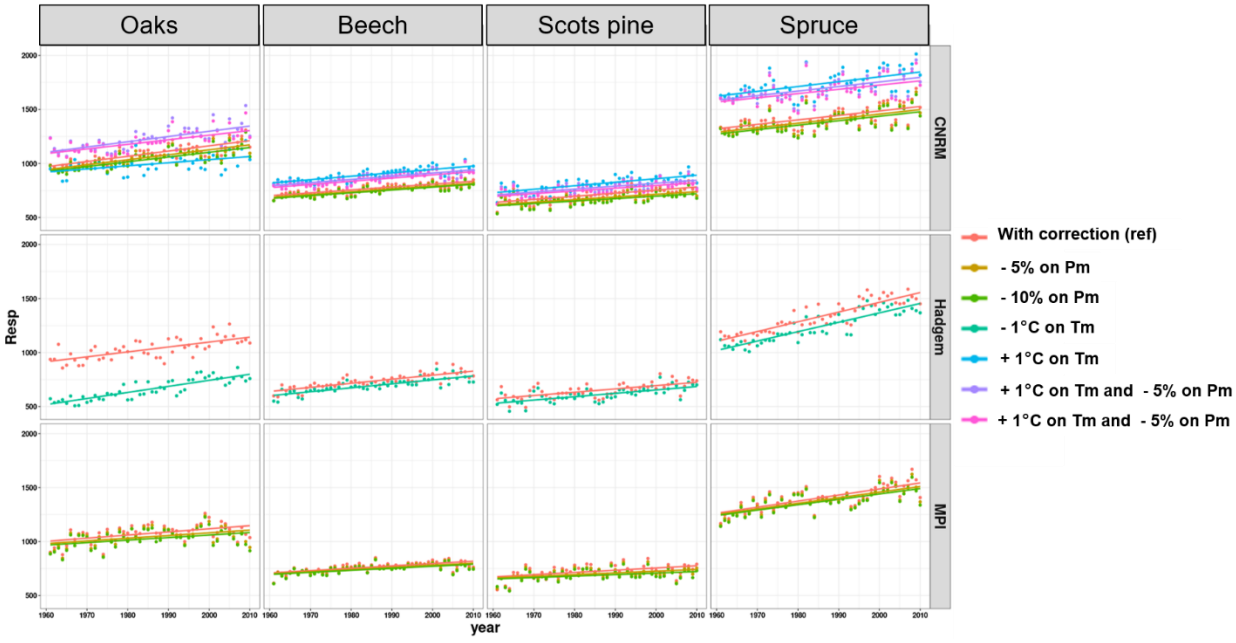
1. My reading of CASTANEA is that it is a similar to a typical large-scale model (like BIOME-BGC or CLM) widely used coupled into existing model. Please explain how CASTANEA may differ from those commonly used in GCMs in order to ascertain the applicability of this study to these types of models. The authors may want to speculate how their results might differ for a stand-level forest model, if possible.

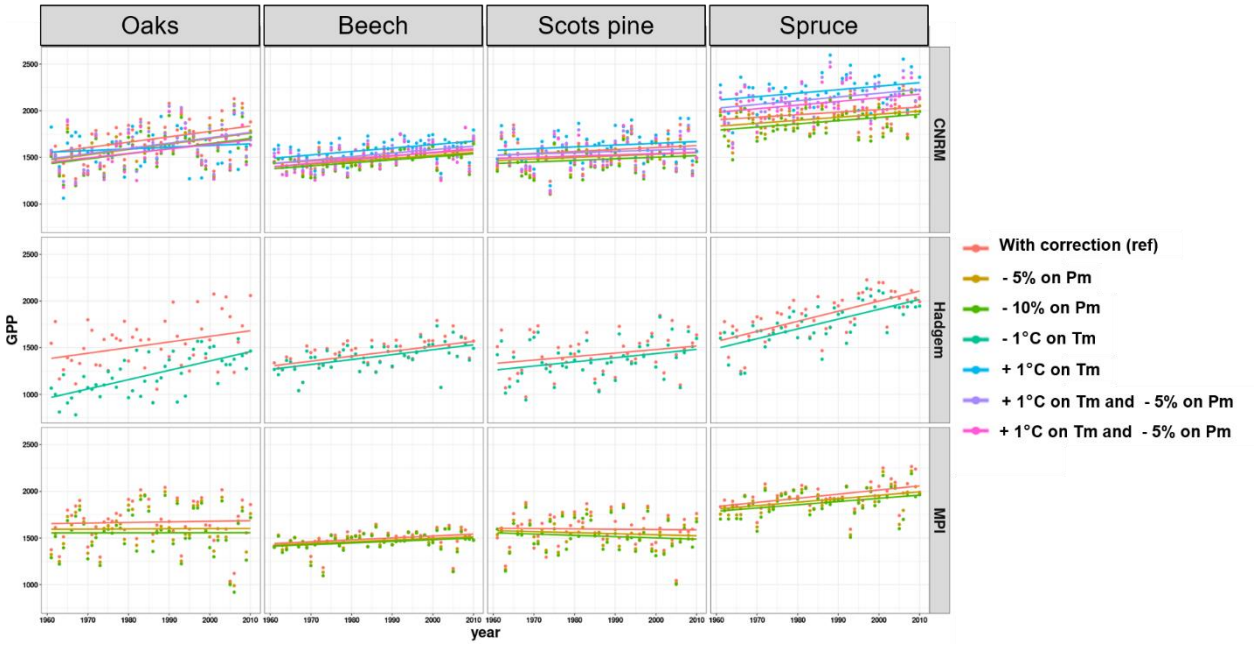
Reply: We specified differences between CASTANEA and large-scale model and focused on own feature (l.134-139): "To address this topic, we used the stand process-based model CASTANEA (Dufrêne et al., 2005), and not large-scale model (like in Palma et al. 2018 or Nishina et al. 2015,), to test the relevance of 3 different climate models (including correction or not, i.e., six climate cases) in the past period compared with historical climatic data (French mesoscale SAFRAN

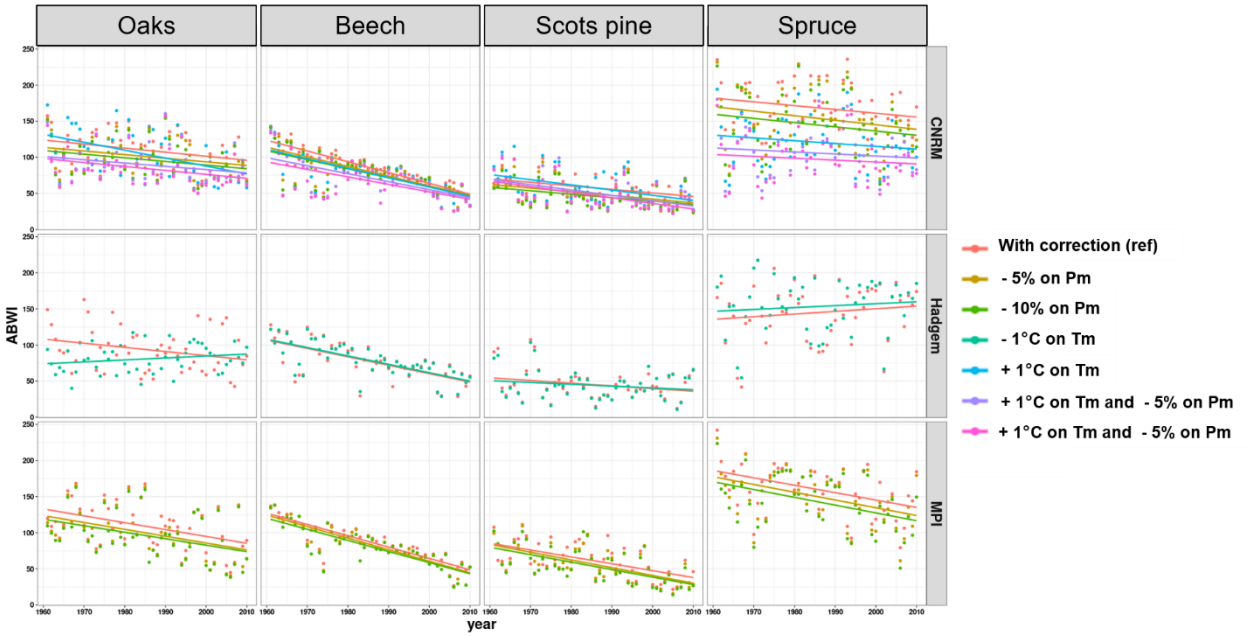
analysis system, Durand et al., 1993). By definition this type of model allows to understand and predict the functioning at forest plot level. Then, we aggregated the simulation at regional scale." (l.137-142). BIOME-BGC seems to work on PFT and not specific species, contrary to CASTANEA. That being said, there is a lot of similarities between both models and our results can be used to put in perspectives results of process-based models like BIOME-BGC. We hope that we highlight the difference and concordance with previous studies.

2. Do these results necessarily imply an improvement in using bias-correction for future scenarios? I suppose so, but is there any sense about how using corrected data improves the sensitivity to change? For example, if there is a warming trend in the data over years 1960-2010, can the authors show that the bias-corrected data improves the response of GPP, AWBI, and resp, or is the response similar regardless of the bias correction?

Reply: I am not sure I understood fully the question of reviewer #2. I will therefore rephrase it. It seems to me that the reviewer would like to know if the correction of climate bias has an impact on the sensitivity of the model to climate variation, isn't it? Theoretically, there are several cases where the sensitivity to climatic variables could change drastically in CASTANEA: (i) when relation between climatic variable and process is not linear (like the exponential relationship between temperature and respiration) and (ii) when climatic variable effect on process is associated to a threshold (as for water stress effect on growth). Dufrêne et al (2005) describes sensitivity of process response on climatic variations (as relationship between respiration and temperature). In following figures, we represent some test illustrating process sensitivity on temperature and precipitation for Respiration, GPP and ABWI. We tested for each species on one characteristic stand: with an age around 80 years (for coniferous) or 120 years (for deciduous), localised in the middle of French distribution area and with an RU around 100. Figures represents process variation during 1960-2017 period, with different change on temperature and precipitation, corresponding of mean difference between corrected climate data and un-corrected climate data (Pm= monthly precipitation and Tm = monthly temperature).







Trend of response is similar, except in one case (oaks ABWI with model Hadgem). This preliminary results show there is no gap in process response in the range created by the bias correction of climatic data (precipitation and temperature). Precisely, we are preparing another article studying sensitivity of process to climate variation ("Climate and structure forest effect on photosynthesis, respiration and wood growth of French monospecific forest").

3. In the discussion, can the authors speculate how errors in model input may compare to errors in parameter uncertainty (which may be minimal in a model that validates well, like this one – though just because something validates well does not mean it necessarily gets the correct sensitivity to change) or model physics? This would just require some additional literature review to compare to other studies that have carried out this kind of analysis on those sources of uncertainties.

Reply: This question is very interesting. CASTANEA is a model comprising many parameterizations made with various datasets. It is therefore difficult to make an exhaustive quantitative list of errors linked to parameter uncertainties. A part of them are described in Dufrêne et al 2005 : in §5.3, Table 6 and Fig 3 you can see that parameters uncertainties reach 10% on GPP and RESP, and 14% on AWBI. The order of magnitude is similar to the uncertainty of climate data correction (l 422-433).

On the other hand, we have, as advised by the reviewer, do a bibliographic review on the subject and complete the paragraph already present in the discussion: "As explained in the introduction, uncertainties in impact model outputs are accumulated along a cascade of uncertainty (Lindner et al., 2014; Reyer, 2013), composed of uncertainty sources at each step of the chain. According Lindner et al. (2014), there are three sources of uncertainties in models inputs, structure and parameters uncertainties. In this work, we focused on only one single step of this cascade of uncertainty: the effect of climatic input data biases on impact model output biases. In fact, for extreme climatic years (considering temperature and precipitation), the bias of climate data may be the largest source of uncertainty (Iizumi et al., 2017). However, uncertainty of the impact model itself can also have a strong influence on the outputs. For example Carbone et al. (2016) questioned the uncertainties associated with the structure of the FöBAAR model (should respiration be separated into autotrophic and heterotrophic, or not?) or Chave et al. (2004) concluded that main source of uncertainties in AGB estimation is allometric model choice. Moreover parameter uncertainties may be different within a model. For example, Levy et al. (2004) highlighted that more sensitive parameters are connected to leaf, roots and stem allocation (in three models studied). Previous studies focused on CASTANEA uncertainties due to process-based model parameters (Dufrêne et al., 2005), and magnitude of parameter uncertainty is similar to climate data uncertainties (see Table 6 and Figure 3 of Dufrêne et al 2005).

Even quantifying uncertainties is an important research topic, the effects of model structural, input and parametric uncertainty are rarely considered together (Lindner et al., 2014; Reyer, 2013). Moreover, it is important to note that all three aspects of uncertainty contain different levels of uncertainty: statistical uncertainty, scenario uncertainty and uncertainty due to ignorance (Walker et al., 2003). Statistical uncertainty refers to the measurement uncertainty, like for example sampling error, inaccuracy and imprecision. Scenario uncertainty deals with plausible changes of these scenarios, which are based on alternatives assumptions. Finally, the uncertainty due to ignorance can be divided into two categories: "known unknowns" and "unknown unknowns". To summarize, importance of one type of uncertainty compared to another is specific to each model, via accepted assumptions and mechanisms taken into account, and difficult to generalize. It is therefore necessary for each modeller to think about uncertainty sources associated with his model and to discuss his results accordingly. That is why we proposed this study focusing on input uncertainties." (l.521-546)

4. Model input clarification: This study uses 3 uncorrected climate models and 3 versions corrected by RCMs using EURO-CORDEX. Line 210 is confusing, because it seems to suggest

that they did their own downscaling with RCA4, but I'm pretty sure that is just referring to the EURO-CORDEX data, so that should be clarified.

Reply: We understand it was misleading. We reword the sentence to completely clarify this point: "Finally, we worked with model data from three GCMs (MPI-ESM-LR, MOHC-HadGEM2-ES, CNRM-CERFACS-CNRMCM5), downscaled with one RCM (RCA4) at 50 km (De Cáceres et al., 2018; Fargeon et al., 2020; McSweeney et al., 2015)". (l.227-229)

Sentences 217-218 refer to statistical downscaling – this seems to be a reference to other work, but, again, its placement made it seem like it was new to this study. To be clear, the regional climate modeling approach used here should be distinguished from statistical downscaling. Is there any way using these results to compare these methods to determine if the added complexity of regional climate modeling really improves upon the statistical downscaling?

Reply: We reword the sentence to completely clarify this point: "Consequently, statistical downscaling and bias corrections were performed by Fargeon et al. (2020) using the SAFRAN reanalysis as reference observational data (8 km resolution) and standard methods based on monthly mean bias or monthly quantile mapping (Bedia et al., 2014; Ruffault et al., 2014), which strongly reduced the bias in model outputs.". (l.235-238) In our study we compared in one side RCM downscaling from GCM and statistical downscaling (to have climate data at 8km scale) with in other side RCM downscaling from GCM and statistical downscaling (to have climate data at 8km scale) and bias reducing.

5. Abstract line 31: 1970 should be 1960. Also line 189 says 1961 instead of 1960.

Reply: We corrected the mistakes.

6. The Appendix data jumps all over the place and is completely out of order – please order the appendices in the order to which they are referenced.

Reply: We reordered the appendices, which appear now in the same order than in the main article.

7. Equation 6 it is not clear what all the subscripts refer to – please make sure the explanatory text corresponds to the exact subscripts used in the equations.

Reply: We added details to clarify equation 6a: "We compute the proportion of bias compared to the variable level at the regional scale as in eq. 3, using the total surface of the species (Ssp), mean level per hectare of variable V for all plots i of a given age class, species, model and SER ($mean_i(V_{mod,sp,s,age})$) and proportion of that age class ($p_{sp,s,age}$)" (l. 308-310). We added also a reference to appendix 4

8. Figure 1 is really part of the validation and not the results, so maybe it should be part of the methods where validation is discussed?

Reply: We agree with reviewer #2 and moved this part of the results in appendix 1, corresponding to calibration and validation part of methods. This reduces the main manuscript.

9. How are the error bars determined in Figure 2?

Reply: Error bars represent spatial heterogeneity. We added this explanation in the caption of the Figure 2.

10. Figure 3 caption change to “points below line indicate less bias in uncorrected”. Line 367 – change “decrease the bias in SAFRON simulations” to “reduce bias relative to SAFRON” – as there is no bias (our assumption) in SAFRON. Line 407, change “decrease the bias in SAFRON simulations” to “reduce the bias”.

Reply: We amended the different lines.

11. Figure 4: I am not sure how to interpret this figure. What do the y-axis values represent? Why are the black dots associated with the blue (spruce)?

Reply: We clarified the caption of Figure 4: “Bias percentages of simulations (y-axis) (i.e., percent of bias compared to process levels simulated with SAFRAN), process (column), and scale (x-axis), for all year (a) and stressful years (b). Coloured points represent the mean uncertainty by species and scale: red (pedunculate oak), green (sessile oak), blue (spruce), orange (beech), pink (Scots pine). Black points represent the mean uncertainty by scale, i.e. whatever the species. The dashed line represents the 10% threshold.” (l.386-390)

12. Figure 5 and elsewhere in discussing stress: To be clear, stress refers to drought stress throughout the paper. Also in caption change “in” to “increase”.

Reply: We amended the caption of the figure and specified in main manuscript that stress means drought stress.

13. I don’t understand the title “Idol with feet of clay” – I had to look this up to see what it meant. Maybe should be changed to be less colloquial (and perhaps regionally known).

Reply: According to both reviewers, we changed the title.