# SENSITIVITY OF SPECIES CLIMATE ENVELOPE MODELS TO BASELINE CLIMATOLOGY AND EFFECT ON RCM-BASED FUTURE PROJECTIONS

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## ABSTRACT

Climate Envelope Models (CEMs) are predictive tools widely used in ecological research to estimate the distribution of species by combining observations of their occurrence/abundance with bioclimatic indicators. In this contribution, we show that the resulting projections are highly sensitive to the quality of the baseline climate data, an aspect often overlooked in model criticism. Using distributional data of European beech in northern Spain (Cantabria region), we analyse the discrepancies in model performance and future projections using three public high-resolution climate datasets: WorldClim (WC), the University of Barcelona Atlas (UAB) and a new regional climate grid developed by Cantabria University (UC). We considered the future climate scenarios from several regional climate models (RCMs) of the EU-funded project ENSEMBLES. We demonstrate that the quality of the baseline climate used to derive the present and future bioclimatic indices has a great impact on the stability of the estimated CEMs, although commonly used performance metrics (AUC, Cohen's kappa) failed to detect this in the cross-validation experiments. WC models lead to unreliable future projections, whereas UAB models performed better but were outperformed by UC, demonstrating the paramount importance of reliable climate input data.

**Key words:** *Fagus sylvatica*, climate envelope, species distribution modelling, regional climate projection, impacts of climate change.

## 1. INTRODUCTION

Climate Envelope Models (CEMs) are popular statistical tools widely used in ecological research to estimate the distribution of species (e.g. Guisan and Thuiller, 2005). Typically, these techniques use high-resolution grids over the area of interest and combine observations of species occurrence (or abundance) with appropriate bioclimatic indicators defined at the grid-box scale. The potential applications of CEMs are manifold (see Guisan and Thuiller, 2005, and references therein) although several uncertainties and limitations of this methodology have been already pointed out in different studies (Austin, 2007; Guisan et al., 2006).. In recent years, CEMs are gaining popularity in climate change impact studies to project species distributions under future climate scenarios (Hijmans and Graham, 2006). However, to date most of studies fail to explicitly analyze the sensitivity of the results to the baseline climate data considered. This problem is of particular importance in this context, since general-purpose datasets such as the freely available Worldclim dataset (Hijmans et al., 2005) are commonly used in this type of studies due to the lack of specific high-resolution climatic data. In this contribution we show that this issue becomes critical when extrapolating CEMs into future climate conditions, an exercise that increases the degree of uncertainty (Beaumont et al., 2008), thus compromising their practical validity for planners and adaption strategists.

We present a sensitivity analysis of future projections of a tree species, the European Beech (*Fagus sylvatica* L., *Fagus* henceforth) in Northern Iberian Peninsula to three different baseline climate datasets: the WorldClim global database, the climate grid by the Universitat Autonoma de Barcelona for the Iberian Peninsula, and a regional grid developed by the authors at the University of Cantabria for Northern Spain; hereafter we will refer to them as WC, UAB and UC respectively.

## 2. AREA OF STUDY AND DATASETS

The study area is centered in the province of Cantabria (Northern Spain, 42.60ºN;-5.00ºE to 43.60ºN;-2.99ºE, Fig. 1). This window will be referred to as global domain hereafter. In the Iberian Peninsula, *Fagus* forests are mainly found in the mountain areas of northern Spain although it reaches the Iberian and Central Ranges at some locations (Costa et al., 1998).

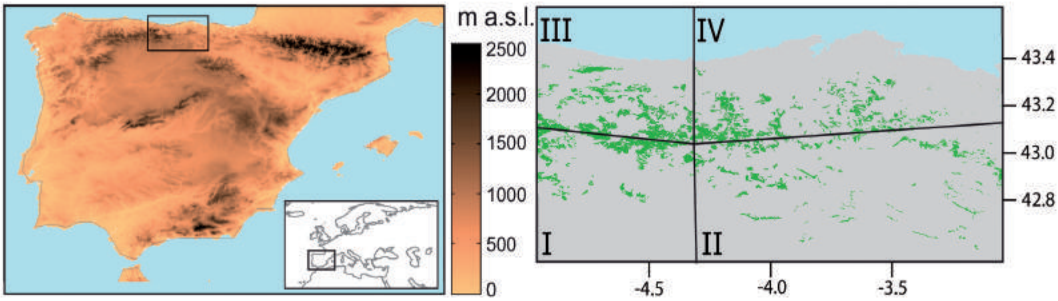


FIG. 1: *Location of the study area in the Iberian Peninsula. In the lower panel, the distribution of Fagus (green) and the administrative limit of the region of Cantabria (dark shaded) are indicated. The subdomains used for cross-validation are identified with roman figures.*

### 2.1. Species data (*Fagus*)

The information on *Fagus* distribution (Fig. 1) was obtained from the Forest Map produced by the Third National Forest Inventory (MARM, 2006). Lacking real absences, we generated background points in an equal number to the presences. We set a buffer radius of 2000 m around known presences, in order to minimize false negatives. In addition, the global domain was partitioned into four sub-domains for a 4-fold cross-validation experiment (Fig. 1).

### 2.2. Climate data

#### 2.2. a. BASELINE CLIMATE DATASETS

WorldClim (WC, Hijmans et al. 2005) is a global climate dataset with a spatial resolution of 30 arc-seconds, covering most of Earth's surface and a time interval of approximately 50 years (1950-2000). This dataset is freely available for download from internet (http://www. worldclim.org).

The University of Barcelona Atlas (UAB, Ninyerola et al. 2005) are climate surfaces calcu1ated by multiple regression and residual analysis, introducing as covariates a relatively simple set of variables: altitude, slope, different indices used to describe distance to the sea, solar radiation and terrain curvature. Temperature and precipitation data were obtained from the national network of the Spanish Meteorology Agency (AEMET), and from the literature in the case of Portugal. The UAB dataset is provided at a very high resolution (200 m) for the entire Iberian Peninsula, and is available for download from the internet (http://opengis.uab.es/wms/iberia/mms/index.htm).

The high resolution climate grid developed for Cantabria and surrounding territories by the University of Cantabria (UC, Gutiérrez et al., 2010), is based on climate data provided by the AEMET stations network. From more than 400 stations, 148 were used for precipitation and 62 for temperature, after a process of data quality control. The grid was first created to a 10 km resolution in order to calibrate the interpolation method and to analyze uncertainty. After testing the performance of thin-plate splines, angular distance weighting and kriging, the latter was chosen. In the case of the precipitation, first occurrence was interpolated using indicator kriging (Juang and Lee, 1998); then, the amount of precipitation was interpolated using ordinary kriging, assigning values of 0 to all "dry" points. The final 1 km-resolution grid was obtained by regression-kriging (Hengl et al., 2007), introducing a set of 30 covariates describing terrain characteristics used for iteratively building a regression model. The grid was subject to expert revision by meteorologists of AEMET based on the reference observations for this region (Cano, 1999), leading to final refinement by elimination of some coastal weather stations with systematic errors, not detected in the previous stage of automated data quality control (Fig. 2).

We selected the baseline period 1950-2000 for the three datasets (UC, UAB and WC) in order to obtain a common period for accurate comparison and they were interpolated to a common 1 km grid using nearest neighbors (Fig. 2). From them, we calculated a set of 19 bioclimatic variables (Table 1).

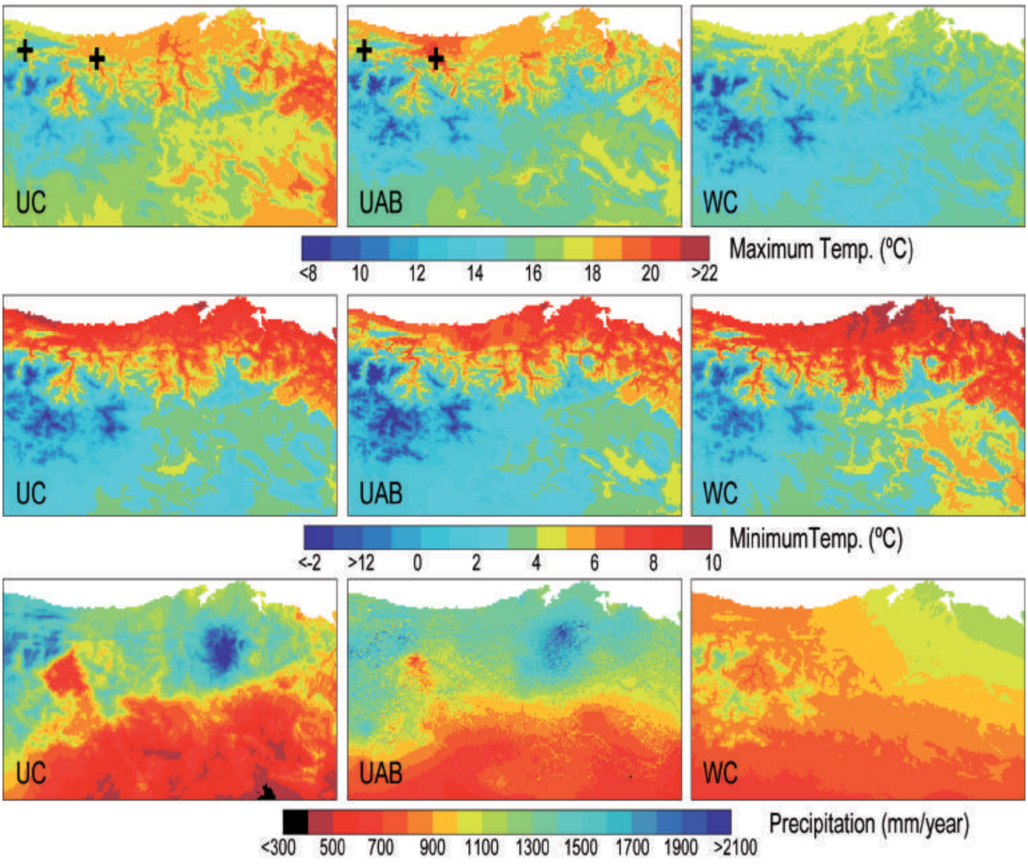


FIG. 2: *Mean maximum and mean minimum temperatures (Tx and Tn) and annual precipitation (P) in the geographical domain of this study according to UC, UAB and WC datasets for the baseline period 1950-2000 (Spatial resolution of 0.0083º, ≈ 1 km). The points indicated in UC and UAB maps of maximum temperature by black crosses are the locations of two weather stations with defective temperature data not considered for the UC surface generation.*

| Nr | Bioclimatic variable | Nr | Bioclimatic variable |
|---|---|---|---|
| **1*** | Mean annual temperature | **2*** | Mean diurnal temperature range |
| **3*** | Isothermality | **4*** | Temperature seasonality |
| **5** | Max. Temperature of warmest month | **6** | Min. Temperature of coldest month |
| **7** | Annual temperature range | **8** | Mean temperature of wettest quarter |
| **9** | Mean temperature of driest quarter | **10** | Mean temperature of warmest quarter |
| **11** | Mean temperature of coldest quarter | **12*** | Annual precipitation |
| **13** | Precipitation of wettest month | **14** | Precipitation of driest month |
| **15** | Seasonality of precipitation | **16** | Precipitation of wettest quarte |
| **17** | Precipitation of driest quarter | **18** | Precipitation of warmest quarter |
| **19** | Precipitation of coldest quarter | | |

TABLE 1: *Summary of explanatory bioclimatic variables. After checking for collinearity, we used a subset of five variables (indicated with an asterisk) as input for Fagus modelling.*

### 2.2. b. FUTURE CLIMATE PROJECTIONS

In order to project species distribution models into future climate scenarios, we considered the regional projections given by seven Regional Climate Models (RCMs) from the EU-funded ENSEMBLES project (van der Linden and Mitchell, 2009) with a spatial resolution of 25 km (see Table 2). These RCMs were run over a limited domain covering Europe, driven at the boundaries by a particular GCM simulation under the A1B emission scenario. However, it has been recently recognized that the outputs of the RCMs cannot be used directly for impact studies, since they may contain important biases resulting from different physics and parameterizations involved in the formulation of the models (Winkler et al., 1997). To alleviate this problem, we applied the so called `delta' method (see, e.g., Zahn and von Storch, 2010) and, thus, the baseline climatological values are modified at a grid-box level by a change factor, obtained as the difference/ratio of the temperature/precipitation values in a future period and in a control period. Then, the resulting modified climatological values are input into the bioclimatic model. We computed future scenarios for the periods 2011-2040, 2041-2070 and 2071-2100.

| Institution | Model | Boundary GCM | Reference |
|---|---|---|---|
| Centre National de Recherches Meteorol. | RM4.5 | CNRM-CM3 | Radu et al., 2008 |
| Danish Meteorological Institute | HIRHAM5 | CNRM-CM3 | Christensen et al., 2006 |
| Koninklijk Nederlands Meteorol. Instituut | RACMO2 | MPI-ECHAM5-r3 | Van Meijgaard et al., 2008 |
| Hadley Center/UK Met Office | HadRM3 | HadCM3-Q0 | Collins et al., 2006 |
| Abdus Salam Int. Centre for Theor. Physics | RegCM3 | HadCM3-Q0 | Pal et al., 2007 |
| Max Planck Institute for Meteorology | REMO | MPI-ECHAM5-r3 | Jacob et al., 2007 |
| Swedish Meteorol. and Hydrol Institute | RCA3.0 | BCCR-BCM2 | Kjellström et al., 2005 |

TABLE 2: *Summary of the ENSEMBLES regional climate models used in this study.*

## 3. METHODS

### 3.1. Model development

CEMs were built using multivariate adaptive regression splines (MARS, Friedman, 1991), a non-parametric method for regression which approximates the underlying function through a set of adaptive piecewise linear regressions known as basis functions. In this work, we used the implementation of MARS algorithm in the R package "earth" (v. 2.4-4). For variable importance estimation, we looked at the reductions in the Generalized Cross-Validation estimate of error (GCV) in the selection routine performed by the MARS algorithm (Kuhn, 2010). We followed the method described by Blanchet et al. (2008) in order to check for collinearity among the set of the 19 bioclimatic variables, retaining a final set of 5 non-collinear variables (marked with asterisks in Table 1).

### 3.2. Model assessment and cross-validation experiment

We constructed ROC curves for each model and calculated the corresponding areas under the curve (AUC). We also computed Cohen's kappa using prevalence as probability threshold (P = 0.5). The global model was calibrated by randomly splitting the data into an arbitrary proportion of 25% for testing and 75% for training. In addition, we evaluated the calibration of the models by inspection of the corresponding plots, which give a good qualitative overview of the goodness-of-fit of the models and enable the detection of defective predictive systems (further details are given in Bedia et al., 2011).

Additionally, we carried out a 4-fold cross-validation by considering the four subdomains shown in Fig. 1. Each of these subsets was used as the test set (and the remaining ones for training). The process was repeated four times so that all subdomains were used just once for testing. Therefore, when we refer to subdomain I, statistics correspond to a model trained using data from subdomains II, III and IV and tested using data from subdomain I, and so on.

## 4. RESULTS

### 4.1. Current climate envelope models

The global models constructed with UC, UAB and WC datasets achieved high AUC values, typically attributed to predictive systems with high discrimination ability (see Table 3). However, only UC and UAB models exhibit an adequate calibration, with a good agreement between predicted and observed probabilities, slightly better in the UC model (Fig. 3). In contrast, WC model was poorly calibrated, with a tendency to over-estimation in all probability ranges greater than 0.3. Similarly, marked differences were found in the consistency of variable importance results across the global domain and the four subdomains, as shown in Fig. 4, revealing a lack of consistency for the importance of the different variables in the WC model For the global domain (Fig. 4a), variables 2 (mean diurnal temperature range) and 12 (annual precipitation) were very important in WC model whereas they had small or marginal importance in UAB and UC models. Variables 1 (mean annual temperature) and 3 (isothermality) were the most and least influential in all cases, respectively. Finally, variable 4 (temperature seasonality) played an important role for both UC and UAB, whereas it was marginal for WC. As depicted in Fig. 2, precipitation from WC is very different to UC and UAB datasets and clearly unreliable. Similarly, variable 2 (mean diurnal temperature range) had a large weight in WC model but was not so important in UC and UAB models. Variable 1 (mean annual temperature) was the most important in all models. In the case of the four cross-validated subdomains (Fig. 4b-d), the importance of the variables is preserved across the subdomains for the UC, and partially by UAB, whereas it shows a great variability for WC models. This indicates a lack of robustness in this last case.

The above results warn about the use of certain metrics (in this case the AUC and kappa) for model assessment that could mask the deleterious effect of defective input data. AUC has become a standard metric of accuracy for probabilistic model evaluation (Fielding and Bell, 1997), in spite of its shortcomings for ecological model assessment reported by some authors (Austin, 2007; Lobo et al., 2008). The probabilistic distributions for *Fagus* from the three global models are shown in

Fig. 5. In spite of the different input baseline climatologies, the three models are quite similar to each other, with some differences more apparent in the WC model when compared against the others.

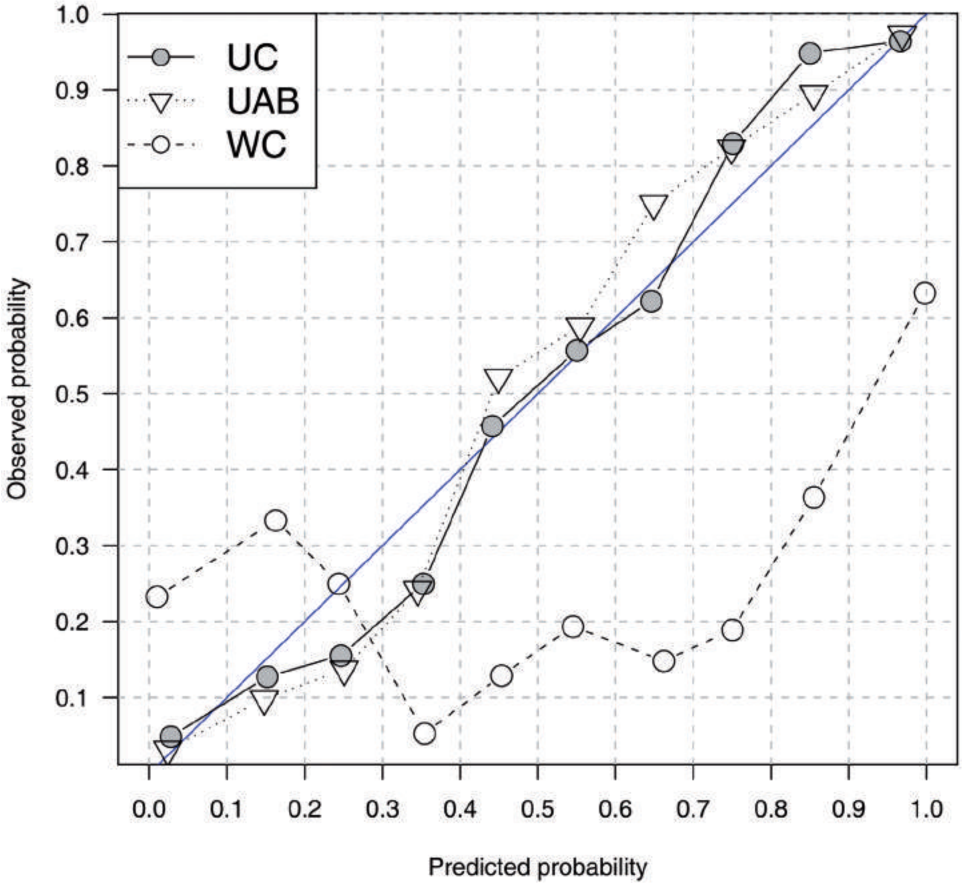


FIG. 3: *Calibration plot of the global models using the UC, UAB and WC databases.*

The same models where then constructed for each subdomain following the 4-fold cross-validation procedure described in section 3.2. AUC and kappa values where similar for the three datasets, but lower than in the global models (Table 3). This loss of discrimination ability from global to partitioned models might be due to the local variation of ecological niche among subdomains, and also as a result of the lower number of observations in the training datasets (Mateo et al., 2010b). Regarding calibration, WC models exhibited a systematic tendency to under or over-estimating *Fagus* probabilities in the different subdomains (not shown), whereas UC partial models attained in general a moderate to good calibration. UAB models had in general an intermediate calibration, performing notably better than WC but outperformed by UC models in subdomains I and III. Variable importance in UC and UAB partitioned models was consistent with that of their respective global models (Fig. 4). UC partial models were the most consistent across subdomains, since in all four partial models the variables were equally ranked, with variables 1 and 4 being the most important, and variable 3 the less influential. UAB models showed a similar behavior, but with larger variability in variable importance across partial models. In contrast, there was no agreement in variable importance among WC subdomains. Variable 12 (annual precipitation) was poorly represented by the WC dataset (see Fig. 2), but had an important weight in some WC partial models.

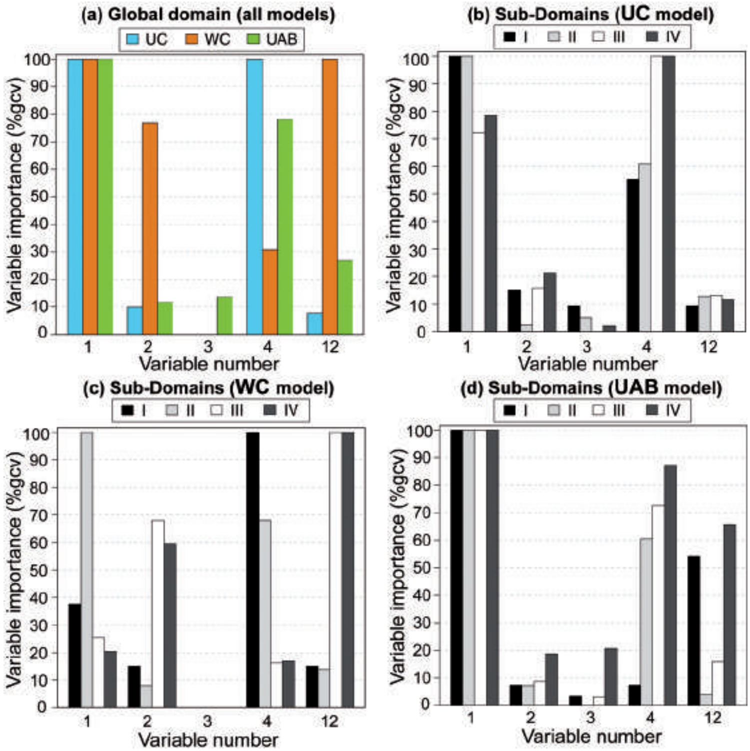


FIG. 4: *Variable importance of envelope models constructed for the global and partitioned subdomains derived from UC, UAB and WC climate datasets (variable meaning in Table 1).*

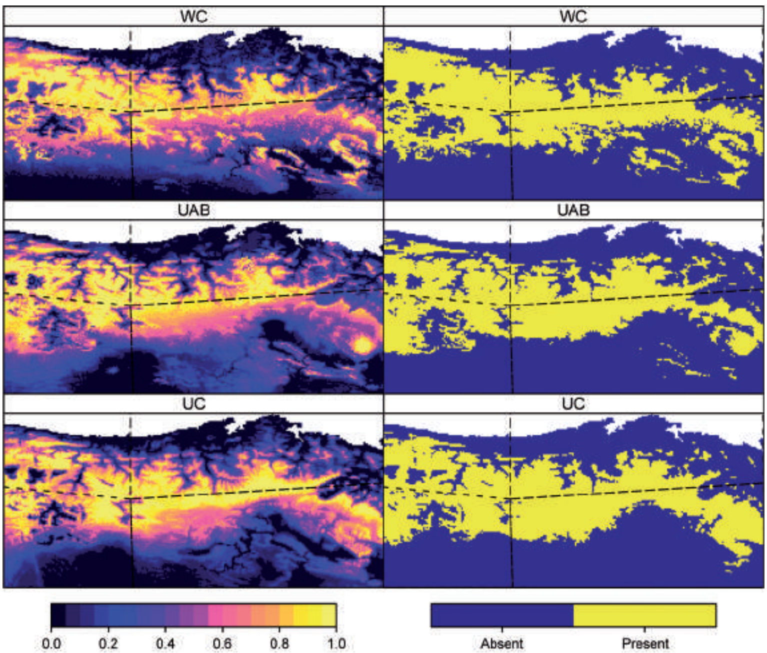


FIG. 5: *(left) Probabilistic distribution and (right) binary occurrence (obtained with a probability threshold of 0.5) for Fagus predicted under current climate conditions (baseline period 1950-2000) using the UC, UAB and WC databases considering a single model for the whole domain.*

| | UC | | UAB | | WC | |
|---|---|---|---|---|---|---|
| **Domain** | **AUC** | ***k*** | **AUC** | ***k*** | **AUC** | ***k*** |
| Global | 0.922 | 0.7 | 0.917 | 0.68 | 0.925 | 0.72 |
| I | 0.781 | 0.56 | 0.875 | 0.52 | 0.817 | 0.65 |
| II | 0.818 | 0.48 | 0.757 | 0.39 | 0.755 | 0.43 |
| III | 0.785 | 0.41 | 0.881 | 0.57 | 0.854 | 0.5 |
| IV | 0.905 | 0.62 | 0.875 | 0.58 | 0.885 | 0.57 |

TABLE 3: *AUC and Cohen's kappa for the probability threshold p = 0.5 of the models constructed for the global domain and for the four subdomains of the cross-validation experiment (indicated in Fig. 1).*

### 4.2. Future distribution forecasting

Future *Fagus* distributions were computed with the models obtained in the previous section but driven by the regional scenarios described in Sec. 2.2.b. The projected distributions corresponding to each member of the ensemble were computed individually and the mean and standard deviation of the resulting ensemble was computed as a grid box basis; thus Fig. 6 shows both the mean and the standard deviation of the ensemble. In general, future distributions using UC and UAB datasets were not very different, and represented the expected trend of *Fagus* retreat in its southern European limit of distribution, in accordance with previous studies (Felicísimo et al., 2010). However, RCM future projections in the case of UAB climatology produced a somewhat "noisy" pattern that did not occur with UC projections. In contrast, future range projections produced by WC were absolutely unrealistic considering that *Fagus* was predicted to occur with very high probabilities in areas where today is not present, even in the first period of reference (2011-2040). Furthermore, the uncertainty (i.e., the standard deviation of the ensemble) associated to WC projections was far beyond the acceptable.

## 5. CONCLUSIONS

This *Fagus* case-study justifies the need of high-quality local climate surfaces from the point of view of the ecological modeller, especially with regard to future distribution modelling. As we have seen, artifactual patterns associated to base climatology propagate into the derived CEMs, and their deleterious effect tends to be magnified when models are extrapolated to future climate scenarios.

With regard to model assessment, we have demonstrated that MARS was able to construct models of high discrimination ability although in the case of WC, it was using defective input variables. As a consequence, apart from AUC and kappa, we advocate the use of additional metrics all of which aid in the completion of a global picture of model performance.

WC models were unable to generate reliable future projections. In contrast, the future projections using the UC models are in accordance with previous studies on the impact of climate change on *Fagus* distribution. UAB models attained also an acceptable performance, although we have pointed to problems at the local scale that should be considered in model criticism. Thus, we recommend the use of UC dataset for modelling exercises in the region of our study, and we present this dataset to impact researchers, that can be freely accessed and downloaded at *http://www.meteo.unican.es/datasets/climaCantabria*. The area available will be enlarged soon in order to cover a wider domain encompassing northern Iberian Peninsula.

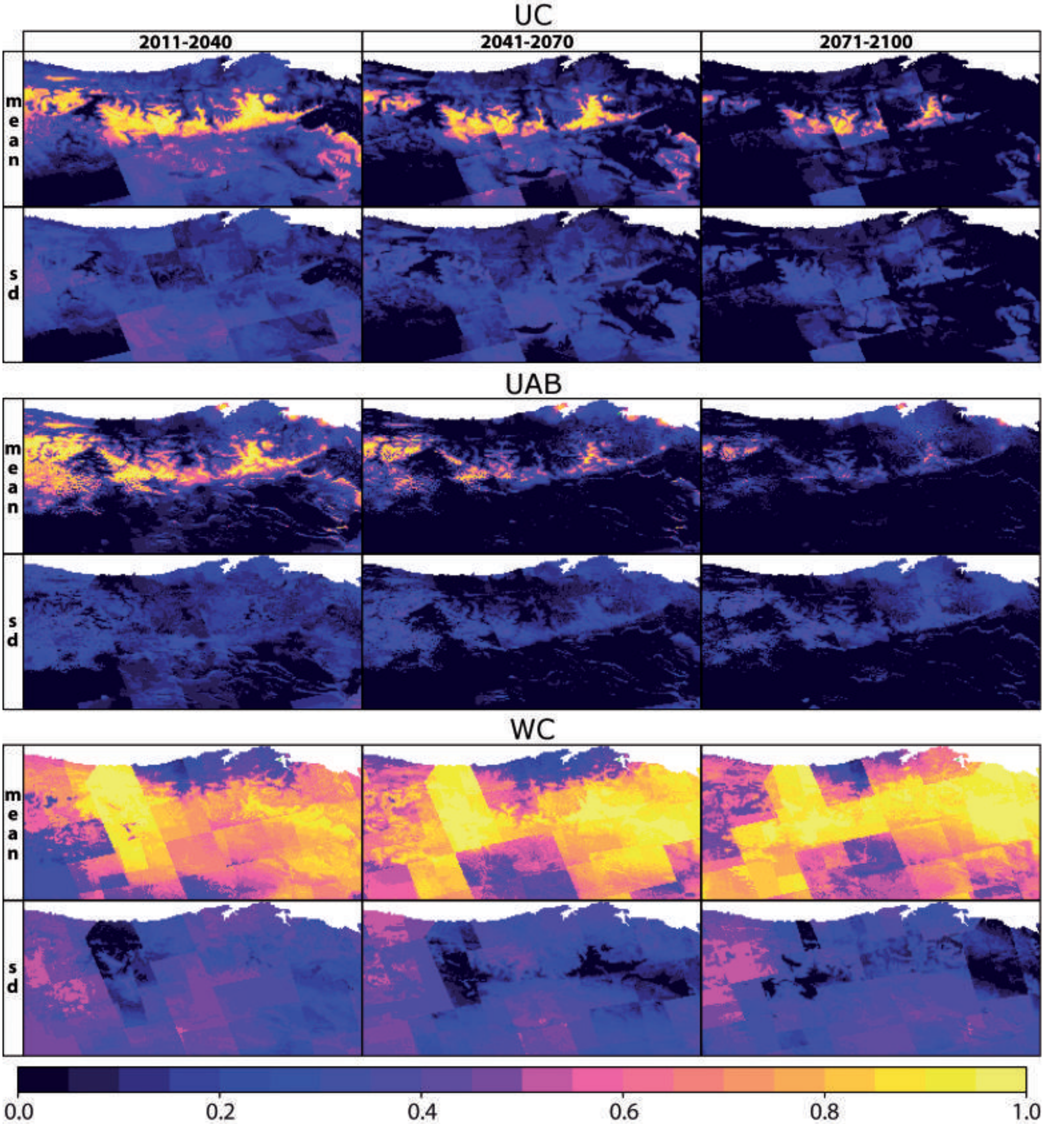


FIG. 6: *RCM projections of future Fagus distributions obtained with the UC, UAB and WC models for three different future periods: 2011-2040, 2041-2070 and 2071-2100.*

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