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Projecting future drought in Mediterranean forests: bias correction of climate models matters!

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Abstract Global and regional climate models (GCM and RCM) are generally biased and cannot be used as forcing variables in ecological impact models without some form of prior bias correction. In this study, we investigated the influence of the bias correction method on drought projections in Mediterranean forests in southern France for the end of the twenty-first century (2071–2100). We used a water balance model with two different atmospheric climate forcings built from the same RCM simulations but using two different correction methods (quantile mapping or anomaly method). Drought, defined here as periods when vegetation functioning is affected by water deficit, was described in terms of intensity, duration and timing. Our results showed that the choice of the bias correction method had little effects on temperature and global radiation projections. However, although both methods led to similar predictions of precipitation amount, they induced strong differences in their temporal distribution, especially during summer. These differences were amplified when the climatic data were used to force the water balance model. On average, the choice of bias correction leads to 45 % uncertainty in the predicted anomalies in drought intensity along with discrepancies in the spatial pattern of the predicted changes and changes in the year-to-year variability in drought characteristics. We conclude that the choice of a bias correction method might have a significant impact on the projections of forest response to climate change.

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1 Introduction

Assessing the projected response of forests to climate change in the next century has emerged as a crucial scientific challenge, due to its expected consequences on biodiversity, ecosystem services (Schröter et al. 2005), and climate change mitigation (Bonan 2008). Current estimates of future forest conditions and subsequent conservation planning rely on the projection of ecosystem models (Intergovernmental Panel on Climate Change 2007). In most of these impact studies, global and regional climate models (GCM and RCM) provide the climatic forcing data.

Consequently, part of the uncertainties in the assessment of future forest conditions originates from the uncertainties related to the outputs of climate models. On the one hand, the spatial resolution of climate models (ranging from 300 to 25 km) is generally too coarse for assessing impacts on some ecological processes (e.g. Austin and Van Niel 2011). On the other hand, several studies have shown important discrepancies between climatic simulations over historical periods and local surface observations (Déqué 2007; Anagnostopoulos et al. 2010). Thus, climate models outputs cannot be used directly as forcing entries for impact models without some form of bias corrections (Hansen et al. 2006; Christensen et al. 2008). Ecological modellers often use bias corrections methods, primarily developed for agricultural and hydrological purposes, to correct the GCMs and RCMs (see Maraun et al. 2010 for a review of these methods). Among them, the statistical output methods are easy to implement, provide suitable output data and are therefore extensively used in ecosystem impact studies (e.g. Cramer et al. 2001). These

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methods correct the outputs of circulation models by using transform functions built from the comparison between model output and climatic surface observations (Déqué 2007). Various correction methods exist, ranging from simple mean correction to more sophisticated ones, involving the comparison of cumulative distribution function (cdf). So far, impact studies have incorporated and compared different GCMs or RCMs (e.g. Thuiller 2004; Krawchuk et al. 2009; Cheaib et al. 2012), but few have taken into account the uncertainty arising from the choice of a statistical correction method.

Among the various issues investigated in global change studies, drought appears as a keystone variable to assess a number of crucial concerns such as water resources, agricultural yields and fire risk. In the Mediterranean, the summer drought is particularly critical as it controls vegetation functioning (Rambal et al. 2003). Moreover, most climate models agree that the Mediterranean area will suffer stronger and longer drought as a result of an increase in temperature and a decrease in summer rainfalls (Giorgi and Lionello 2008). In such water-limited forested ecosystems, drought is the result of dynamic, non-linear and complex interactions between weather, soil and vegetation functioning at different time scales (Rodriguez-Iturbe et al. 2001; Ruffault et al. 2013). Slight changes in the mean and distribution of climatic variables can significantly affect the characteristics of drought such as its length, intensity or timing. Consequently, the drought prediction in Mediterranean ecosystems might be particularly affected by the uncertainty in climate simulations.

In this study, we aim to assess the uncertainty in the predictions of future drought conditions in forested ecosystems arising from the choice of the RCM bias correction method. We investigate the responses of vegetation drought features to climate change in Mediterranean forested ecosystems of southern France. To capture the characteristics of drought for Mediterranean forests, we used a process-based water balance model along with specific drought indices. We simulated drought with two atmospheric climate forcings built from the same RCM simulations but using two different bias correction methods. We tested the sensitivity of the simulations of future drought features to the RCM bias correction method and aimed to quantify whether choosing one method over another causes uncertainty in drought projections. We then discuss how these uncertainties might affect the conclusions of ecological impact studies.

2 Materials and methods

2.1 Study area

The study area covers the forested zone of the administrative Languedoc-Roussillon (LR) region, located in southern France (Fig. 1). LR is delimited by the Pyrenees Mountains in the south, the Massif Central foothills in the north and the Mediterranean coastline and the Rhone River in the east. Forests are dominated by *Quercus ilex*, *Quercus pubescens*, *Pinus halepensis* and various sclerophyll shrubs. The climate is Mediterranean with hot and dry summers and hot cool and wet winters. The study area is characterized by a strong annual rainfall gradient combined with a topographic gradient of increasing altitude from the low rainfall coast (550 mm, 0 m) to the rainy Cevennes Hills (1,630 mm, 1,450 m). Within

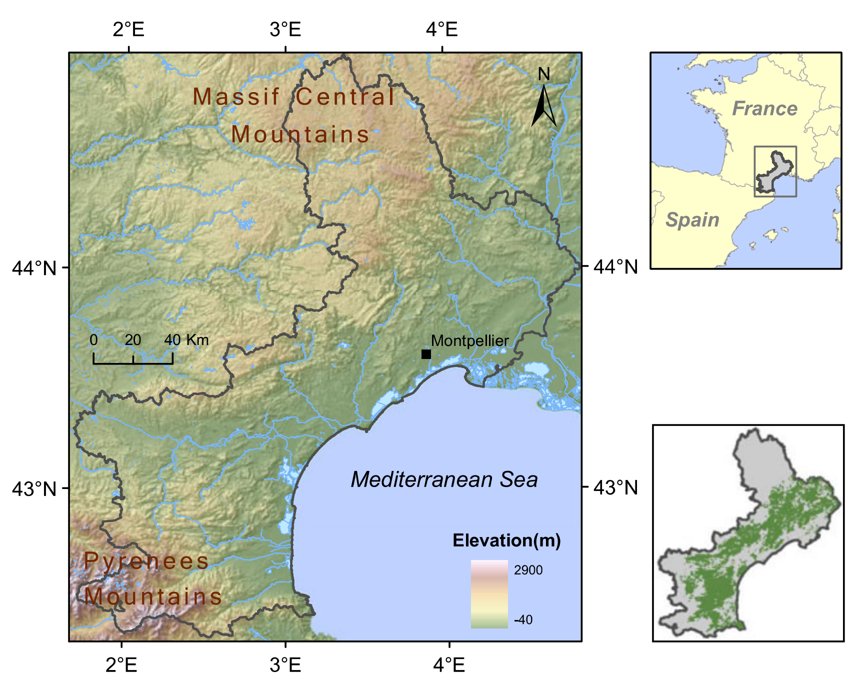

Fig. 1 Digital elevation model of the Languedoc-Roussillon (LR) Mediterranean region representing major topographical features. The *small panel at the bottom right* indicates the current geographical extent of the Mediterranean-type ecosystems considered in this study (in *green*)

this region, we restricted our study on the Mediterranean evergreen vegetation type (MET), based on the presence of *Q. ilex* forests, *P. halepensis* and shrublands, thus covering 10,990 km^2 (Fig. 1).

2.2 Climatic datasets

Two different bias correction methods were applied to the daily precipitation, temperature and global radiation simulated by one single RCM. The procedure involved three spatially explicit climate datasets: (1) the simulation of the RCM for a reference historical period (1961–1990) and (2) for the future (2071–2100) as well as (3) a gridded analysis of surface variables for the same reference period (1961–1990). The simulations of daily precipitation, temperature and global radiation data were obtained from the Météo-France atmospheric model ARPEGE-Climate Version 4. This model is a global general circulation model allowing the variation of the horizontal resolution of the grid surface (Déqué 2007). In this study, we used the output of ARPEGE run as a RCM at its maximum resolution (i.e. 50 km) over southern France. The RCM simulation for the historical atmospheric conditions (1961–1990) constituted the reference ARPEGE dataset (hereafter $\mathrm{ARPEGE_{REF}}$). A second dataset consisted in the climate projections for the 2071–2100 period (hereafter $\mathrm{ARPEGE_{FUT}}$). $\mathrm{ARPEGE_{FUT}}$ was built under the assumption that greenhouse gas and aerosol concentrations would increase up to 720 ppm by the end of the twenty-first century, according to the A1B scenario of the IPCC (Intergovernmental Panel on Climate Change 2007). Historical observations were obtained from the SAFRAN dataset (CNRM, France) (Habets et al. 2008). SAFRAN is an analysis system for surface observations spatially explicit on an 8-km resolution grid square and recently validated over France (see Quintana-Seguí et al. 2008).

2.3 Bias correction methods and downscaling

In rugged areas such as those encountered in the LR region, the effects of altitudinal gradients on temperature, rainfall and soil water retention capacity can be important. Simulations of forests' response to climate change can therefore require fine-scale resolution (e.g. Randin et al. 2009 for the Alps). Here, we chose to downscale the climatic variables at a 1-km spatial resolution, thereby striking a compromise between ecological relevance and spatial resolution of climatic and soil data available on the region. Bias correction of climate and downscaling were performed in two successive steps. We first corrected the 50-km $\mathrm{ARPEGE_{REF}}$ and $\mathrm{ARPEGE_{FUT}}$ datasets with the SAFRAN grid (8 km) using the two different techniques described below. This procedure allows both climate correction and downscaling at the 8-km SAFRAN grid. Then, to reach the 1-km resolution required for our simulations, we interpolated the climatic variables by using the thin plate spline interpolation procedure implemented in the packages "fields" and "raster" in R (R Development Core Team 2012). This method had first been compared with another hybrid-kriging method and then validated using surface observations over our study area (see Electronic Supplementary Material).

The two bias correction methods were performed as follows:

1. *Anomaly method*: The anomaly (AN) method, also named the delta method (Déqué 2007), is the simplest option to correct daily or monthly RCM outputs based on surface observations. It consists in applying a simple shift, estimated by comparing two RCM simulations for a future and a reference period, to a dataset of historical climate observations. The shift corresponds to the simulated effect of climate change between the two periods. In this study, the method was implemented for each grid cell and each input variable (temperature, precipitation and global radiation) using a two-step procedure. First, the anomalies between $\mathrm{ARPEGE_{REF}}$ and $\mathrm{ARPEGE_{FUT}}$ were computed on a daily basis. In order to account for the seasonal changes in the bias correction, this correction was applied each month. An additive shift was used for temperature and solar radiation, but a multiplicative shift was used for precipitation to preserve the sequence of zero values associated with dry days. Then, the shift between the future and present ARPEGE scenarios was applied to the daily present climate series (SAFRAN).
2. *Quantile mapping method*: The quantile mapping (QM) method consists in comparing the frequency distribution of different intensities of individual climatic events between the reference dataset and the observations (Boé et al. 2007; Déqué 2007). After the RCM simulations were downscaled on the SAFRAN grid (see above), the method was implemented for each grid cell and variable, as follows: the cumulative distribution function (cdf) of the control simulation ($\mathrm{ARPEGE_{REF}}$) was first compared to the cdf of the reference observations (SAFRAN), generating a correction value for each quantile. This correction function was then used to correct the variable from the projected climate scenario quantile by quantile. The correction was applied at a daily time step, and a correction table with the 99 percentiles of the two distributions was created. A linear interpolation was made between each quantile. The correction was applied seasonally (DJF, MAM, JJA, SON) to account for the important seasonal variations of the Mediterranean climate. As the rainfall values are bounded by zero, zero values in the cdf of the observed data may match with non-null values in the correction table (zero of positive values). Then, a value was randomly chosen in the interval where the observed cumulative frequency is less than or equal to

the probability of no precipitation. Between the last quantile and the extremes, the correction function was linearly interpolated, thus making no assumption for the extreme events (Déqué 2007).

2.4 Characterizing drought in Mediterranean forested ecosystems

Drought characterization of the vegetation was assessed using a process-based water balance model designed for MET biomes at a 1-km spatial resolution, and previously described and validated on specific sites (Ruffault et al. 2013). In this model, daily variations in soil water content is described as the difference between precipitations, rainfall interception by the canopy, soil and understory evaporation (E), transpiration (ET) and drainage. Soil is divided in three-layer bucket. Daily potential evapotranspiration (PET) is determined using the Priestley–Taylor equation. ET an E are a function of PET, leaf area index (LAI) and stomatal conductance adjusting for water stress of vegetation approximated by the soil water potential of the rooting zone. The model was parameterized according to the Mediterranean evergreen type ecosystem using functional parameters of the evergreen oak *Q. ilex* L. (see details in Ruffault et al. 2013). In order to estimate LAI of the vegetation, the water balance model was coupled with a carbon and carbon allocation model. We then used a spin-up procedure over the 1961–1990 period to compute a theoretical LAI in equilibrium with site-specific water stress according to the ecohydrology theory (see details in Ruffault et al. 2013). For all simulations, we used the LAI estimated over the 1961–1990 period; therefore, we did not consider potential changes in vegetation structure over time.

Under Mediterranean climate, vegetation usually faces a single summer drought period. In order to characterize the severity, the duration and the timing of this drought period, we computed four drought indices. We assumed that water deficit starts when the soil water potential falls below a critical value of − 0.5 MPa, matching the value beyond which a decrease of leaf conductance is observed for Mediterranean evergreen species (Sala and Tenhunen 1996; Limousin et al. 2009). Based on this threshold, we defined the drought duration (DD) as the number of consecutive days when the soil is below the critical value and the water stress integral (WSI, the yearly integral of soil water potential) as an index of drought severity (Myers 1988; Misson et al. 2010). The first and last days of this period, respectively called onset drought day (ODD) and end drought day (EDD), were also computed to characterize the timing of the drought season within a year (Ruffault et al. 2013). Additionally, we characterized the overall annual drought intensity of the forested ecosystems without introducing any threshold. In this latter case, we assumed that water stress occurs as soon as the actual transpiration (AT) is lower than the potential maximum transpiration (MT) of the ecosystem and computed the yearly sum of the daily ratio of AT/MT as an index of yearly annual drought intensity (DI).

2.5 Comparing the anomalies in climatic scenarios and model outputs

Anomalies in projected climatic variables and in the different drought indices were calculated by comparing the reference dataset (REF) to the two projected scenarios corrected with either the AN method or the QM method. Anomalies between the two future datasets (i.e. AN and QM) were also calculated in order to assess the impact of the correction method on projected climatic variables. The significance of anomalies was tested using Welch's modified t test, which assesses whether the means of non-homogeneous sample variances differ between two samples (Welch 1947). Drought indices were computed as explained above (Section 2.4), and the climatic variables were aggregated at the annual and seasonal (spring, summer, autumn) time step to capture their intra-annual variability. All variables were computed at the regional (averaged values over the region) and local (for each grid cell) scale.

3 Results

3.1 Climatic projections using two bias correction methods

Both bias-corrected climatic datasets converged towards warmer and drier conditions over the LR region for the end of the century, but with major discrepancies on the characteristics of this climatic drying (Table 1). The two corrected $\mathrm{ARPEGE_{FUT}}$ datasets predicted a strong increase in mean annual temperature (about +3.5 °C; Welch's t test, $P<0.01$), a slight increase in global radiation (about +10 %, $P<0.001$) and a decrease in summer precipitation (about −30 %, $P<0.001$) compared to $\mathrm{ARPEGE_{REF}}$. For these variables, the use of one bias correction method or another did not strongly impact the projections of seasonally averaged future climatic conditions. A maximum average difference of 0.7 °C for summer temperature ($P<0.1$), 8 % for precipitation and 4.7 % ($P<0.1$) for global radiation was observed between the two corrected datasets. Despite similar mean values, we observed a higher year-to-year variability in seasonal and annual precipitation with the QM method. By contrast, the averaged projected number of wet days significantly differed between the two bias correction methods ($P<0.001$). Using the QM method led to a steep significant decrease in the number of wet days during spring and summer seasons (with an anomaly of respectively −28 and −30 %, $P<0.001$). But the anomalies for the same climatic variables were of only −3 and −6 % when

Table 1 Past and projected climatic variables averaged over our study area obtained using two different bias correction methods: the anomaly (AN) and the quantile (QM) method. Past climatic characteristics for the end of the twentieth century ("REF.", 1961–1990) serve as a reference for projected variables for the end of the twenty-first century ("Future", 2071–2100). Annual and seasonal (except winter) statistics are reported. Standard deviations are indicated in parentheses. Significant differences between datasets were investigated using Welch's modified *t* test (*ns* not significant ($P>0.1$); $^{*}P<0.1$; $^{**}P<0.01$; $^{***}P<0.001$)

	Mean			Anomaly		
	REF.	Future AN	Future QM	Future AN	Future QM	QM-AN
Precipitation (mm)						
Year	889 (201)	857 (201)	856 (295)	−6.9 % ns	−3.7 % ns	−3.2 % ns
Spring	152 (67)	174 (56)	189 (83)	−19.0 % ns	−12.3 % ns	+6.7 % ns
Summer	141 (54)	106 (41)	98 (62)	−24.4 %**	−30.1 %**	−5.7 % ns
Fall	286 (121)	290 (124)	312 (183)	+1.3 % ns	+9.2 % ns	+7.9 % ns
Number of wet days (day)						
Year	134 (12)	132 (12)	108 (19)	−1.7 % ns	−19.6 %***	−17.9 %***
Spring	37 (7)	36 (7)	26 (6)	−3.0 % ns	−28.3 %***	−25.3 %***
Summer	29 (6)	29 (5)	20 (9)	−6.2 % ns	−30.6 %***	−24.4 %***
Fall	34 (7)	34 (7)	29 (7)	−0.1 % ns	−13.5 %***	−13.4 %**
Mean temperature (°C)						
Year	13.0 (0.5)	16.4 (0.5)	16.6 (0.6)	+3.4 °C***	+3.6 °C***	+0.2 °C ns
Spring	11.5 (0.8)	14.2 (0.8)	14.4 (0.8)	+2.7 °C***	+2.9 °C***	+0.2 °C ns
Summer	20.8 (0.9)	25.7 (0.9)	26.3 (1.4)	+4.9 °C***	+5.6 °C***	+0.7 °C*
Fall	13.5 (0.8)	16.9 (0.8)	16.8 (0.8)	+3.4 °C***	+3.3 °C***	−0.1 °C ns
Global radiation (W m^{-2})						
Year	149 (7)	162 (6)	167 (7)	+8.8 %***	+12.0 %***	+3.2 %*
Spring	170 (16)	184 (15)	189 (13)	+8.4 %***	+11.2 %***	+3.8 % ns
Summer	244 (14)	263 (14)	274 (15)	+7.8 %***	+12.5 %***	+4.7 %*
Fall	112 (9)	124 (9)	127 (9)	+11.3 %***	+13.6 %***	+2.1 % ns

using the AN method. Because we applied a multiplicative shift that maintains the number of days with no rainfall, the AN method was not expected to modify the number of rainy days. The slight decrease we observed was caused by the downscaling method that sets to zero all precipitation events below the 0.1 mm threshold (see Electronic Supplementary Material for more details).

3.2 Projections of drought features using two bias correction methods

In agreement with the increasing temperature and decreasing precipitations observed on raw climatic variables, we observed an overall drying for the end of the century but the magnitude and characteristics of this drying largely depended on the bias correction method chosen (Table 2). With both bias-corrected datasets, we projected an increase in DI ($P<0.001$), severity (WSI, $P<0.001$) and duration (DD, $P<0.001$). But drought projections indicated an anomaly of +74 % for DI and +82 % for WSI with the AN method while a much significantly greater drying was predicted when using the QM method (with an increase of 119 % for DI and 128 % for WSI, $P<0.1$). Furthermore, we also observed a higher variability in DI, WSI and DD with the QM method (±0.085 for DI) compared to the AN method (±0.054). However, both corrected climatic datasets yielded a similar significant increase in DD simulated by our model of 34 days ($P<000.1$, ±2 depending on the method) as the result of an earlier ODD (about −15.5±1.5 days, $P<0.1$) and a later EDD (about +16.5±1.5 days, $P<0.1$).

3.3 Spatial distribution of climatic and drought projections in the LR region

The spatial pattern of projected climate change was not uniform over our study area and depended on both the type of bias correction method and the type of climate variable. For summer precipitations, the two methods led to similar predictions with higher anomalies in the eastern part of the region (Fig. 2a) and there were no significant local differences

Table 2 Past and projected functional drought indices for forests averaged over our study area obtained with two different bias correction methods: the anomaly (AN) and the quantile mapping (QM) methods Past drought indices for the end of the twentieth century ("REF.", 1961–1990) serve as a reference for future values corresponding to projections for the end of the twenty-first century ("Future", 2071–2100). Standard deviations are indicated in parentheses. Significant differences between datasets were investigated using Welch's modified *t* test (*ns* not significant ($P>0.1$); *$P<0.1$; **$P<0.01$; ***$P<0.001$)

	Mean			Anomaly		
	REF.	Future AN	Future QM	Future AN	Future QM	QM-AN
Drought intensity	0.075 (0.040)	0.130 (0.052)	0.164 (0.085)	74 %***	119 %***	+45 %*
Drought duration (days)	53 (27)	85 (25)	89 (33)	61 %***	68 %***	+7 % ns
Water stress integral	68 (47)	124 (48)	154 (66)	82 %***	128 %***	+46 %*
Onset drought day (day of year)	203 (21)	189 (19)	186 (22)	−14 days*	−17 days**	−3 days ns
End drought day (day of year)	262 (24)	277 (18)	279 (20)	15 days*	18 days**	+3 days

between the two methods (Fig. 3a). For global radiation and temperature, both methods predicted a similar heterogeneous spatial pattern over the region, with anomalies increasing in magnitude towards the eastern part of the region (results not shown). As expected, the main differences between the two datasets were observed for the number of wet days (Figs. 2b and 3b). Using the QM method led to a steep reduction in the number of wet days, while the AN method yielded much smaller anomaly, thus leading to significant differences between these two methods (Fig. 3b).

Future drought projections indicated a heterogeneous pattern of anomalies over the LR region, along with discrepancies between the two bias correction methods. Thus, both methods predicted a significant increase in DI and WSI over the entire study area, with the greatest changes in the western part of the region (Figs. 2c and 3c, only shown for DI). However, the higher drought increase predicted using the QM method compared to AN method (+45 %, Table 2) was unequally distributed over the region. Thus, we observed that significant differences were mainly located in the northern part of the study area (Fig. 3c) and could reach up to 150 % (Fig. 2c). By contrast, other components of drought (i.e. drought timing and duration) did not show any particular spatial difference between the two methods (results not shown). It should also be noted that the areas where drought is predicted to increase did not necessary match those with the summer precipitations or the number of wet days are predicted to decrease (Fig. 2a, c). Moreover, the magnitude of changes was different between drought indicators, with an increase in drought intensity reaching about 250 % for a 40 % decrease of summer precipitations.

4 Discussion

Among all the sources of uncertainty in ecological impact studies related to climate change, important errors arise from input climatic data. These errors are related to the inherent hypotheses of climate scenarios as well as to the structure and parameterization of global and regional climate models (see Beaumont et al. 2008). In the present study, we show that the choice of bias correction method greatly impacts drought projections for Mediterranean-type ecosystems.

4.1 Regional climatic and drought projections: general patterns

The ARPEGE RCM used in this study projected a decrease in summer precipitation of about 30 % and an increase in mean temperature of about 3.5 °C, which is within the range of projections of most climate models used across the Mediterranean basin (Giorgi and Lionello 2008; Somot et al. 2008). Consistently, our simulations for the end of the twenty-first century converged towards a significant increase in drought proxies over the LR region, regardless of the bias correction method. Such predictions are in accordance with other studies projecting drought proxies for the end of the century at a larger spatial scale. For instance, Moriondo et al. (2006) reported an increase in the drought-driven fire weather index by 20–40 %, concomitant with an increase of +20 to +50 days in the length of the fire season, consistent with the +33 dry days that we report here. One should note that the anomalies in drought projections reported here could be balanced by the long-term drought acclimation of vegetation (e.g. leaf area index, plant allometry) (Martin-StPaul et al. 2013). However, the underlying mechanisms of such responses are still poorly understood and difficult to integrate into a process-based model (Luo et al. 2011).

When looking at the regional pattern of these changes, we observed a greater increase in DI, severity (WSI) and DD on the western and southern (mountainous) part of the LR region, regardless of the bias correction method. Those areas match not only those with a strong predicted decrease in summer rainfall but also with areas where initial drought intensities were among the lowest (see the second part of the discussion).

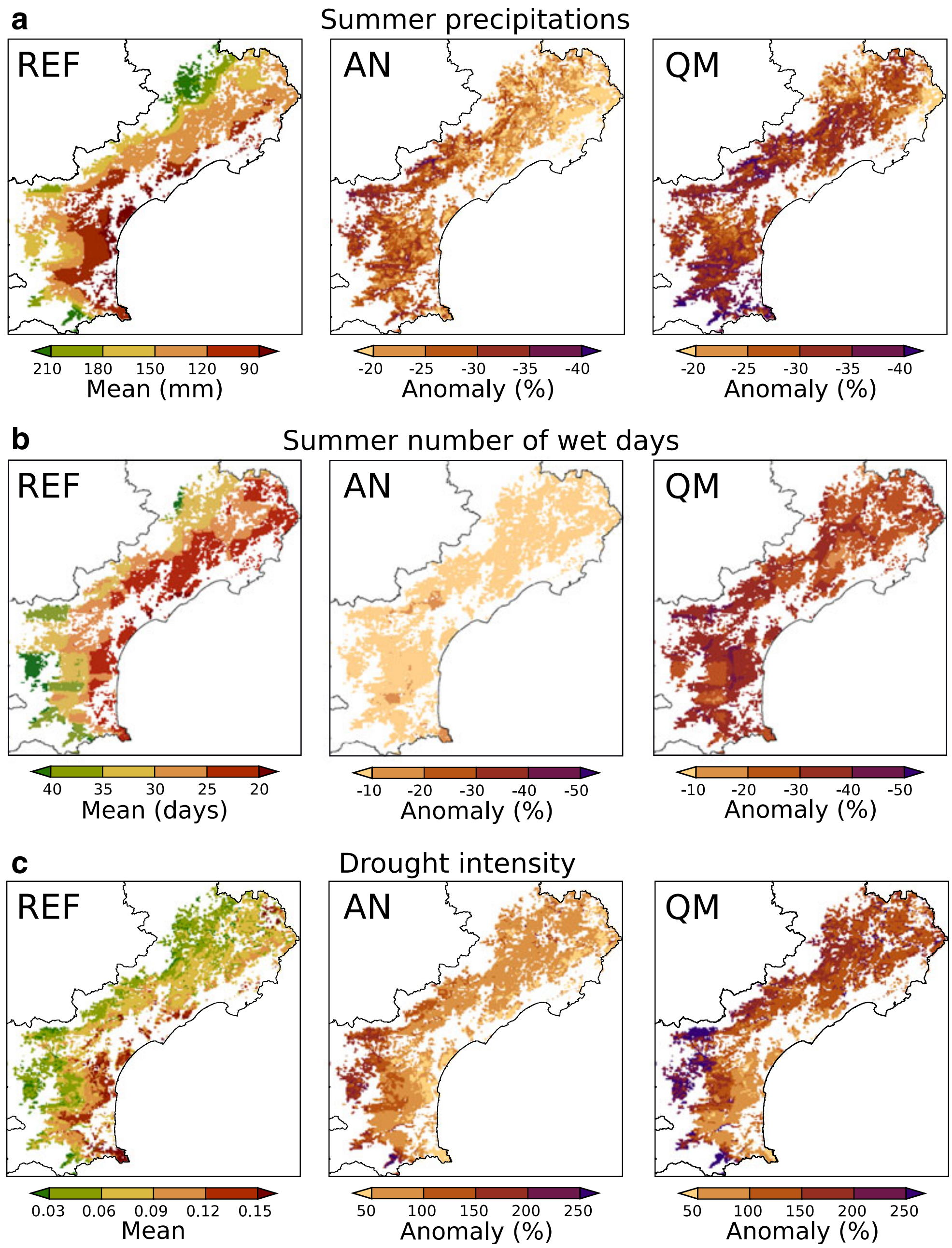

Fig. 2 Past and projected spatial distribution of mean climatic surface variables and drought indices for forested areas over the study region according to two downscaling methods: the anomaly (AN) and the quantile mapping (QM) methods. Values for the end of the twentieth century ("REF", 1961–1990) serve as a reference for future values corresponding to projections for the end of the twenty-first century (2071–2100). Only the climatic and drought variables for which important changes were found are represented: **a** summer precipitations, **b** number of wet days in summer and **c** drought intensity (see details in the main text)

One should note that the increasing drought for the end of the twenty-first century we report here is qualitatively in agreement with the trends in drought indices and climatic features reported for the last decades over the Mediterranean basin (Vicente-Serrano and Cuadrat-Prats 2007; Bartolini et al. 2012). But the shift towards an earlier drought season reported by Ruffault et al. (2013) using a historical dataset in the same LR region is not observed in our projections. This illustrates the already mentioned discrepancies between climate projections and ongoing trends in climate changes over the Mediterranean area (Barkhordarian et al. 2012; Boberg and Christensen 2012). These discrepancies might have resulted from missing local processes in the RCM (Barkhordarian et al. 2012; Boberg and Christensen 2012) such as a buffering of the rise in temperatures closer to the coast (Önol and Semazzi 2009) or an increase in temperature change with altitude (Still et al. 1999, but see Pepin and Lundquist 2008).

4.2 Drought projection uncertainties related to bias correction methods

Within this general pattern of drought increase for the end of the twenty-first century, a number of dissimilarities in drought projections arose from the use of one or the other bias correction method. In terms of climatic projections, the different statistical assumptions of the two methods mostly impacted

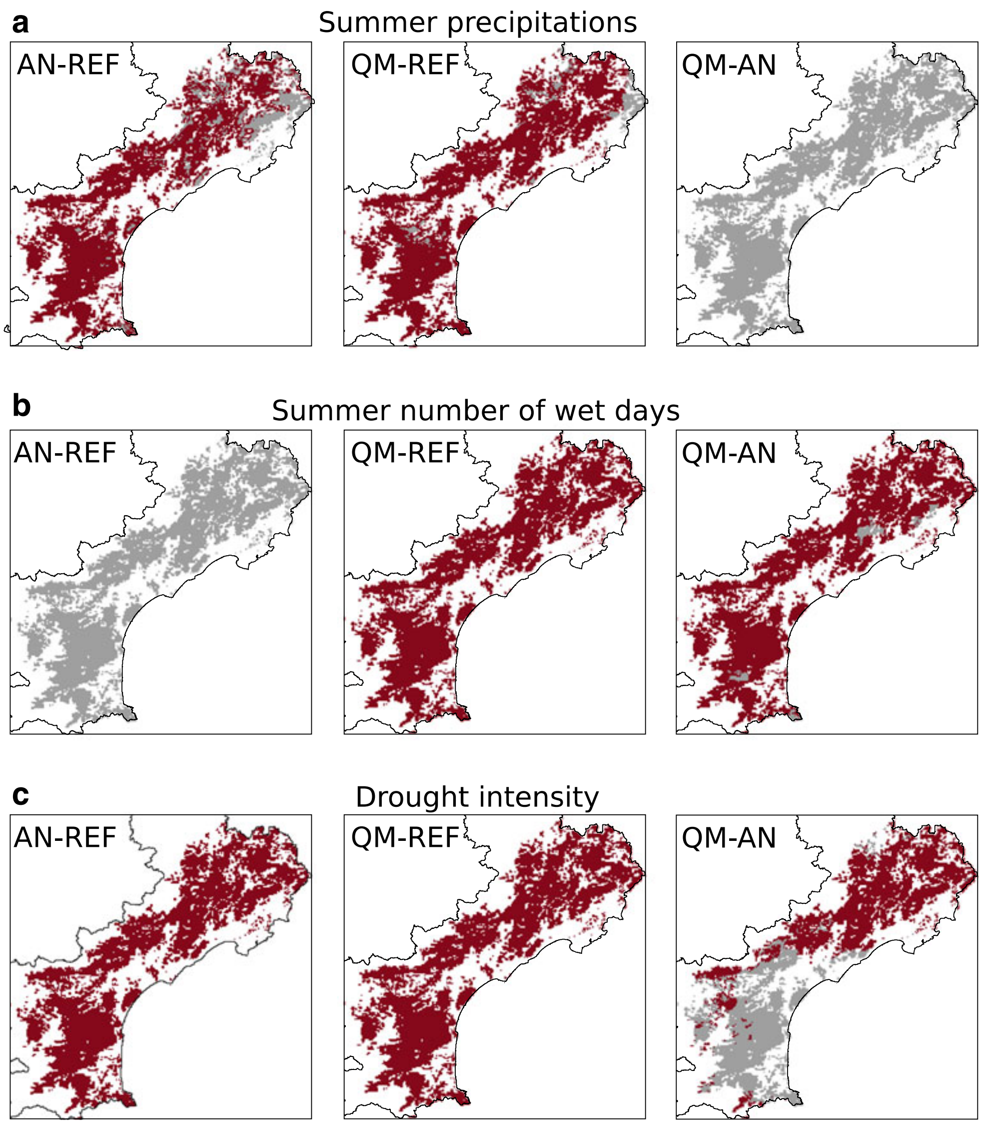

Fig. 3 Spatial distribution of significant differences between the reference dataset (REF, 1961–1990) and the two projected future datasets (2071–2100) obtained using either the anomaly (AN) or the quantile mapping (QM) correction method. Only the climatic and drought variables for which important changes were found are represented: **a** summer precipitations, **b** number of wet days in summer and **c** drought intensity (see details in the main text). Welch's modified *t* test was used to assess the significance of differences in mean value between each pair of dataset at grid-cell scale. Grid cells in which a significant difference ($P<0.1$) in mean values was observed are represented in *red*; non-significant differences are in *grey*

the projections of the number of wet days as well as the year-to-year variability in precipitations. Indeed, the AN method takes into account only modifications in monthly rainfall amount without accounting for changes in the number of wet days and therefore creates a bias in the RCM outputs compared to the QM method. The QM method allows a better consideration of this issue but introduces an additional assumption concerning the distribution of rainfall events (Déqué 2007).

Importantly, our results show that the water balance model amplified these discrepancies between the two input climate datasets. On average, using the QM method led to a significantly higher increase in WSI and DI than using the AN method (of about +45 %) along with changes in the year-to-year variability in drought characteristics. By contrast, the type of correction method weakly affected the timing and duration of drought (DD, ODD and EDD). Altogether, these results suggest that the higher anomalies observed for WSI and DI with the QM methods are not the result of a longer predicted drought period but rather of a more intense drought event due to the lower number of wet days predicted with this method. Furthermore, one should note that in some areas, a decrease of 30 % in the number of wet days generated up to 150 % differences in the predicted magnitude of change in drought intensity between the two methods. Such amplification arises from the strong non-linearities of the vegetation responses to a decrease in water availability (Hoff and Rambal 2003; Ruffault et al. 2013). Accounting for the frequency of precipitation events blurred the edges of the otherwise constrained relationship between the decrease in summer precipitations and the increase in drought intensity.

Interestingly, uncertainties related to the bias correction methods are within the same order of magnitude as those encountered between different RCM themselves. For instance, on average, bias correction methods induced 7 % difference in seasonal rainfall and 25 % differences in the number of wet days, which turned into larger differences when climate data were used to simulate drought intensity and severity (40 % on average and up 150 % locally). This uncertainty is close to the coefficient of variation of 40 % in the predicted number of consecutive dry days in Greece obtained using six different RCM simulations (Hadjinicolaou et al. 2011). Thus, as pointed out by studies on hydrological and meteorological variables in the Mediterranean areas (Vasiliades et al. 2009; Quintana Seguí et al. 2010), uncertainty assessment related to bias correction methods in ecological impact studies could have almost as much importance as the more widely considered inter-model uncertainties. These conclusions suggest that the impact of other bias correction methods (Ines and Hansen 2006; Piani et al. 2010) or other statistical downscaling approaches (see Maraun et al. 2010) on ecological studies should also be evaluated.

5 Conclusion

We have shown that the choice of correction method could generate large and significant uncertainties in the anomalies in drought intensity (40 % on average), introduce important discrepancies in the spatial pattern of projected changes and affect year-to-year variability in drought characteristics. Considering the high vulnerability of forested ecosystems to drought already observed in the context of ongoing climate change (Choat et al. 2012; Anderegg et al. 2013), uncertainties arising from the bias correction method could lead to divergent conclusions in mortality, carbon balance or species distribution simulation studies. Despite increasing accuracy in fine-scale dynamic climate modelling, bias correction and statistical downscaling are still crucial steps when assessing the projected impact of climate change on ecosystem functioning. Ecologists should be particularly aware of the uncertainty related to the choice of the bias correction method when modelling vegetation functioning.

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References

Anagnostopoulos GG, Koutsoyiannis D, Christofides A et al (2010) A comparison of local and aggregated climate model outputs with observed data. Hydrol Sci J 55(7):1094–1110. doi:10.1080/02626667.2010.513518

Anderegg LDL, Anderegg WRL, Abatzoglou J et al (2013) Drought characteristics' role in widespread aspen forest mortality across Colorado, USA. Glob Chang Biol 19(5):1526–1537. doi:10.1111/gcb.12146

Austin M, Van Niel KP (2011) Improving species distribution models for climate change studies: variable selection and scale. J Biogeogr 38:1–8. doi:10.1111/j.1365-2699.2010.02416.x

Barkhordarian A, Storch H, Bhend J (2012) The expectation of future precipitation change over the Mediterranean region is different from what we observe. Clim Dyn 40:225–244. doi:10.1007/s00382-012-1497-7

Bartolini G, Di Stefano V, Maracchi G, Orlandini S (2012) Mediterranean warming is especially due to summer season. Evidences from Tuscany (central Italy). Theor Appl Climatol 107(1–2):279–295. doi:10.1007/s00704-011-0481-1

Beaumont LJ, Hughes L, Pitman AJ (2008) Why is the choice of future climate scenarios for species distribution modelling important? Ecol Lett 11:1135–1146. doi:10.1111/j.1461-0248.2008.01231.x

Boberg F, Christensen JH (2012) Overestimation of Mediterranean summer temperature projections due to model deficiencies. Nat Clim Chang 2:433–436. doi:10.1038/nclimate1454

Boé J, Terray L, Habets F, Martin E (2007) Statistical and dynamical downscaling of the Seine basin climate for hydro-meteorological studies. Int J Climatol 27:1643–1655. doi:10.1002/joc

Bonan G (2008) Forests and climate change: forcings, feedbacks, and the climate benefits of forests. Science 320:1444–1449. doi:10.1126/science.1155121

Cheaib A, Badeau V, Boe J et al (2012) Climate change impacts on tree ranges: model intercomparison facilitates understanding and quantification of uncertainty. Ecol Lett 15:533–544. doi:10.1111/j.1461-0248.2012.01764.x

Choat B, Jansen S, Brodribb TJ et al (2012) Global convergence in the vulnerability of forests to drought. Nature 491:752–755. doi:10.1038/nature11688

Christensen JH, Boberg F, Christensen OB, Lucas-Picher P (2008) On the need for bias correction of regional climate change projections of temperature and precipitation. Geophys Res Lett 35, L20709. doi:10.1029/2008GL035694

Cramer W, Bondeau A, Woodward FI et al (2001) Global response of terrestrial ecosystem structure and function to CO_2 and climate change: results from six dynamic global vegetation models. Glob Chang Biol 7:357–373. doi:10.1046/j.1365-2486.2001.00383.x

Déqué M (2007) Frequency of precipitation and temperature extremes over France in an anthropogenic scenario: model results and statistical correction according to observed values. Glob Planet Chang 57:16–26. doi:10.1016/j.gloplacha.2006.11.030

Giorgi F, Lionello P (2008) Climate change projections for the Mediterranean region. Glob Planet Chang 63:90–104. doi:10.1016/j.gloplacha.2007.09.005

Habets F, Boone A, Champeaux JL et al (2008) The SAFRAN-ISBA-MODCOU hydrometeorological model applied over France. J Geophys Res 113, D06113. doi:10.1029/2007JD008548

Hadjinicolaou P, Giannakopoulos C, Zerefos C et al (2011) Mid-21st century climate and weather extremes in Cyprus as projected by six regional climate models. Reg Environ Chang 11:441–457. doi:10.1007/s10113-010-0153-1

Hansen JW, Challinor A, Ines A et al (2006) Translating climate forecasts into agricultural terms: advances and challenges. Clim Res 33:27–41. doi:10.3354/cr033027

Hoff C, Rambal S (2003) An examination of the interaction between climate, soil and leaf area index in a *Quercus ilex* ecosystem. Ann For Sci 60:153–161. doi:10.1051/forest:2003008

Ines AVM, Hansen JW (2006) Bias correction of daily GCM rainfall for crop simulation studies. Agric Forest Meteorol 138:44–53. doi:10.1016/j.agrformet.2006.03.009

Intergovernmental Panel on Climate Change (2007) Climate change 2007: the fourth IPCC assessment report. Cambridge University Press, Cambridge

Krawchuk MA, Moritz MA, Parisien MA et al (2009) Global pyrogeography: the current and future distribution of wildfire. PloS ONE 4(4):e5102. doi:10.1371/journal.pone.0005102

Limousin JM, Rambal S, Ourcival JM et al (2009) Long term transpiration change with rainfall decline in a Mediterranean *Quercus ilex* forest. Glob Chang Biol 15:2163–2175. doi:10.1111/j.1365-2486.2009.01852.x

Luo Y, Melillo J, Niu S et al (2011) Coordinated approaches to quantify long–term ecosystem dynamics in response to global change. Glob Chang Biol 17(2):843–854. doi:10.1111/j.1365-2486.2010.02265.x

Maraun D, Wetterhall F, Ireson AM et al (2010) Precipitation downscaling under climate change: recent developments to bridge the gap between dynamical models and the end user. Rev Geophys 48:RG3003. doi:10.1029/2009RG000314

Martin-StPaul NK, Limousin JM, Vogt-Schilb H et al (2013) The temporal response to drought in a Mediterranean evergreen tree: comparing a regional precipitation gradient and a throughfall exclusion experiment. Glob Chang Biol. doi:10.1111/gcb.12215

Misson L, Rocheteau A, Rambal S et al (2010) Functional changes in the control of carbon fluxes after 3 years of increased drought in a Mediterranean evergreen forest? Glob Chang Biol 16:2461–2475. doi:10.1111/j.1365-2486.2009.02121.x

Moriondo M, Good P, Durao R et al (2006) Potential impact of climate change on fire risk in the Mediterranean area. Clim Res 31:85–95. doi:10.3354/cr031085

Myers BJ (1988) Water stress integral: a link between short-term stress and long-term growth. Tree Physiol 4:315. doi:10.1093/treephys/4.4.315

Önol BHM, Semazzi F (2009) Regionalization of climate change simulations over the Eastern Mediterranean. J Clim 22:1944–1961. doi:10.1175/2008JCLI1807.1

Pepin NC, Lundquist JD (2008) Temperature trends at high elevations: patterns across the globe. Geophys Res Lett 35, L14701. doi:10.1029/2008GL034026

Piani C, Haerter JO, Coppola E (2010) Statistical bias correction for daily precipitation in regional climate models over Europe. Theor Appl Climatol 99:187–192. doi:10.1007/s00704-009-0134-9

Quintana Seguí P, Ribes A, Martin E et al (2010) Comparison of three downscaling methods in simulating the impact of climate change on the hydrology of Mediterranean basins. J Hydrol 383:111–124. doi:10.1016/j.jhydrol.2009.09.050

Quintana-Seguí P, Le Moigne P, Durand Y et al (2008) Analysis of near-surface atmospheric variables: validation of the SAFRAN analysis over France. J Appl Meteorol Climatol 47:92–107. doi:10.1175/2007JAMC1636.1

R Core Team (2012) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.Rproject.org/

Rambal S, Ourcival JM, Joffre R et al (2003) Drought controls over conductance and assimilation of a Mediterranean evergreen ecosystem: scaling from leaf to canopy. Glob Chang Biol 9:1813–1824. doi:10.1046/j.1529-8817.2003.00687.x

Randin CF, Engler R, Normand S et al (2009) Climate change and plant distribution: local models predict high-elevation persistence. Glob Chang Biol 15:1557–1569. doi:10.1111/j.1365-2486.2008.01766.x

Rodriguez-Iturbe I, Porporato A, Laio F, Ridolfi L (2001) Plants in water-controlled ecosystems: active role in hydrologic processes and response to water stress: I. Scope and general outline. Adv Water Resour 24:695–705. doi:10.1016/S0309-1708(01)00004-5

Ruffault J, Martin-StPaul N, Rambal S, Mouillot F (2013) Differential regional responses in drought length, intensity and timing to recent climate changes in a Mediterranean forested ecosystem. Clim Chang 117:103–117. doi:10.1007/s10584-012-0559-5

Sala A, Tenhunen JD (1996) Simulations of canopy net photosynthesis and transpiration in *Quercus ilex* L. under the influence of seasonal drought. Agric For Meteorol 78:203–222. doi:10.1038/19293

Schröter D, Cramer W, Leemans R et al (2005) Ecosystem service supply and vulnerability to global change in Europe. Science 310:1333–1337. doi:10.1126/science.1115233

Somot S, Sevault F, Déqué M, Crépon M (2008) 21st century climate change scenario for the Mediterranean using a coupled atmosphere–ocean regional climate model. Glob Planet Chang 63:112–126. doi:10.1016/j.gloplacha.2007.10.003

Still CJ, Foster PN, Schneider SH (1999) Simulating the effects of climate change on tropical montane cloud forests. Nature 398:608–610. doi:10.1038/19293

Thuiller W (2004) Patterns and uncertainties of species' range shifts under climate change. Glob Chang Biol 10:2020–2027. doi:10.1111/j.1365-2486.2004.00859.x

Vasiliades L, Loukas A, Patsonas G (2009) Evaluation of a statistical downscaling procedure for the estimation of climate change impacts on droughts. Nat Hazard Earth Syst Sci 9:879–894. doi:10.5194/nhess-9-879-2009

Vicente-Serrano SM, Cuadrat-Prats JM (2007) Trends in drought intensity and variability in the middle Ebro valley (NE of the Iberian peninsula) during the second half of the twentieth century. Theor Appl Climatol 88:247–258. doi:10.1007/s00704-006-0236-6

Welch BL (1947) The generalization of Student's problem when several different population variances are involved. Biometrika 34(1/2):28–35