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Building hazard maps of extreme daily rainy events from PDF ensemble, via REA method, on Senegal River Basin

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Abstract

The Sudano-Sahelian zone of West Africa, one of the poorest of the Earth, is characterized by high rainfall variability and rapid population growth. In this region, heavy storm events frequently cause extensive damage. Nonetheless, the projections for change in extreme rainfall values have shown a great divergence between Regional Climate Models (RCM), increasing the forecast uncertainty. Novel methodologies should be applied, taking into account both the variability provided by different RCMs, as well as the non-stationary nature of time series for the building of hazard maps of extreme rainfall events. The present work focuses in the probability density functions (PDFs)-based evaluation and a simple quantitative measure of how well each RCM considered can capture the observed annual maximum daily rainfall (AMDR) series on the Senegal River basin. Since meaningful trends have been detected in historical rainfall time series for the region, non-stationary probabilistic models were used to fit the PDF parameters to the AMDR time series. In the development of PDF ensemble by bootstrapping techniques, Reliability Ensemble Averaging (REA) maps were applied to score the RCMs. The REA factors were computed using a metric to evaluate the agreement between observed -or best estimated- PDFs, and that simulated with each RCM. The assessment of plausible regional trends associated to the return period, from the hazard maps of AMDR, showed a general rise, owing to an increase in the mean and the variability of extreme precipitation. These spatial-temporal distributions could be considered by local stakeholders in such a way as to reach a better balance between mitigation and adaptation.

1 Introduction

One of the areas hardest hit by the twentieth century climate change impacts, has been the densely populated Sahel (West Africa). Over the period 1990–2020, its population is expected to double, with projections of even higher growth for some cities in the

HESSD

8, 3817–3839, 2011

Senegal River Valley (Cour, 2001). The climatic fluctuations in the Sahel have been devastating (famines, migrations, and slow economic growth), indicating the great vulnerability of the region (Lebel et al., 2009; Paeth et al., 2009). The study of the continuous rise in greenhouse gases emission, and the associated response of the climate, has received more attention for the region in recent years. Global warming has caused changes in rainfall patterns and, consequently, changes in the frequency and magnitude of extreme events (Labat et al., 2004; Huntington, 2006; Kundzewicz et al., 2007). Huntington (2006) points out that the evidence about the current and future intensifying of the hydrologic cycle is robust, and highlights the need to improve the ability of monitoring and predicting the impacts associated with the change of hydrologic regimes. In these conditions, the presumption of hydroclimatic stationarity cannot be guaranteed, due to the interaction of various drivers (land use and climate change, and population growth, among others). In concordance with the opinion of several authors (Milly et al., 2008; Villarini et al., 2010), non-stationary probabilistic models able to reproduce the variation with time of the parameters of selected probability density functions (PDFs) should be used.

In this sense, Regional Climate Models (RCMs) have become an important tool to improve the understanding of key processes involved in the description of climate mechanisms (Sánchez et al., 2009), for the simulation of plausible climate scenarios with an appropriate resolution for impact studies at basin scale. Several authors have worked with climate models to simulate the trends in extreme rainfall patterns, especially in Europe (Kharin and Zwiers, 2005; Kharin et al., 2007; Kyselý and Beranová, 2009; Nikulin et al., 2011, among others). There are notable advances in the simulation of monsoon dynamics of West Africa using climate models (Fontaine et al., 2011; Paeth et al., 2011; Ruti et al., 2011).

However, the RCMs built for West Africa are still sensitive to physical parameterizations, spatial-temporal resolution and internal variability (Paeth et al., 2011). The RCMs exhibit differing levels of skill over different regions and hydrometeorological variables, making it difficult to identify the models with greater confidence. As a consequence, the

HESSD
8, 3817–3839, 2011

climate projections and the estimation of uncertainties associated are better based on the combination of information provided by an ensemble approach from different RCMs simulations (Giorgi and Mearns, 2002; Paeth et al., 2011). The model ensemble allows a more precise description of uncertainties and weaknesses, as well as a probabilistic approach to future climate projections (Sánchez et al., 2009). Tebaldi and Knutti (2007) conducted a review of methodologies addressing the building of model ensembles, comparing their results for regional temperature projections. However, the error obtained from combining multiple models is, sometimes, the result of error compensation. A weighting of models, based on observations, could ameliorate this problem (Sánchez et al., 2009). To assign weights to different RCMs of an ensemble, several statistics are usually compared considering observed data.

However, the use of statistics as means and standard deviations does not allow the comparison of the entire distribution of the data, even when the evidence shows those observed changes in the extreme events (tails) are different in magnitude to those observed in the mean values. In addition, the change associated with extreme values is expected to have a higher impact on biophysical systems (Perkins et al., 2007; Tapiador et al., 2009). This situation justifies questioning the ability of RCMs to simulate the distribution of observed probability of the hydrometeorological variables. There are several works about the estimation of PDFs associated with several hydrometeorological variables from climate projections (Wigley and Raper, 2001; Giorgi and Mearns, 2003; Tebaldi et al., 2005; Giorgi, 2008; Büser et al., 2009). Establishing the best skill of a climate model for simulating the observed PDF of a variable implies that estimated projections with this model will have more confidence for future (Perkins et al., 2007; Sánchez et al., 2009). However, the ability to represent the present-day climate well does not seem to be enough to asseverate the skill to simulate the future climate climate (Giorgi and Mearns, 2003).

With regard to the above, the present study focuses on the assessment of change in the PDF of the annual maximum daily rainfall (AMDR) on the Senegal River Basin (West Africa), considering the nonstationarity of time series and building at site PDF

HESSD
8, 3817–3839, 2011

using a weighted ensemble. The RCMs and observational datasets considered for the target basin are described in Sect. 2.

Section 3 describes the implementation of the Reliability Ensemble Average (REA) method proposed by Giorgi and Mearns (2002), for assessing the ability of the RCMs to reproduce the present-day climate while at the same time evaluating the convergence of different RCMs to a given forcing scenario. The score method proposed by Perkins et al. (2007), is applied to identify the skill scores of the RCMs in the PDF ensemble for each site. Previous studies in the region have considered ensemble RCMs to assess impacts on extreme rainfall events (García Galiano and Giraldo Osorio, 2011). In the work of these authors, the reliability factors were considered constant for the entire study area, and estimated only based on the bias analysis (by Smirnov-Kolmoroff test) between the observed and simulated series of AMDR (in other words, without consideration of convergence criteria between the time series to the future). In the present study, the REA factors are estimated spatially distributed.

Finally, the PDF ensembles were considered to build maps of various statistical values associated with the distribution of AMDR on the target basin, for studying the plausible trends of AMDR (Sect. 4). The PDF ensemble for each site allows to obtain a measure of the change uncertainty. The results and discussion section presents a brief analysis of the maps constructed, and the key findings of the work.

2 Target basin and datasets

The target basin of the Senegal River, shared by Guinea, Mali, Senegal, and Mauritania, presents a strong decreasing gradient of rainfall in northerly direction (Fig. 1). With less than 200 mm year^{-1} in the north (Sahel), to more than 2000 mm year^{-1} in the south (headbasin), the rainfall seasonal cycle is unimodal (Sandholt et al., 2003). The basin corresponds to three eco-regions, Sahelian savanna (north), West Sudanian savanna, and Guinean forest savanna (south).

Observed daily rainfall grids compiled by the IRD (Institut de Recherche pour le Developpement; previously ORSTOM, France), with spatial resolution of 1°, have been used. These grids were previously considered in other studies in West Africa (Diedhiou et al., 1999; Janicot and Sultan, 2001; Messager et al., 2004; García and Giraldo, 2010; Karambiri et al., 2011). Six RCMs were selected, driven by GCMs (Global Climate Models): GKSS/CLM (ECHAM5), METO-HC/HAD (HadCM3Q0), KNMI/RACMO (ECHAM5-r3), INM/RCA (HadCM3Q0), SMHI/RCA (HadCM3Q0), MPI/REMO (ECHAM5-r3), provided by the European ENSEMBLES Project (Christensen et al., 2009). The selection of RCM was based on its temporal coincidence with the IRD data (period 1970–1990), which enables the bias analysis. For the analysis, 120 sites on a regular grid of 1° × 1° were selected. However, the spatial discontinuity of the IRD data constrains the bias analysis only on 43 of these sites (Fig. 1). The AMDR series were obtained from the observed and simulated daily rainfall grids, for the sites defined.

3 Methodology

A critical need in the research of climate change impacts focuses on quantifying the uncertainty associated with future climate projections. The results of impacts studies on hydrometeorological extremes and runoff in the study region, have shown a considerable divergence (García and Giraldo, 2010; Karambiri et al., 2011), which increases the uncertainty in predicting climate change at regional level using RCMs (Giorgi and Mearns, 2002). Since it is not possible to conclude which model seems to be the most reliable, a comprehensive assessment of climate change projections needs to be based on the information provided by the RCM ensemble approach to simulate the variability of the rainfall, according to Giorgi and Mearns (2002). Based on these premises, the GAMLSS (Generalized Additive Models for Location, Scale and Shape) tool, proposed by Rigby and Stasinopoulos (2005), is applied to simulate the nonstationarity of the PDF of maximum rainfall in each site. The GAMLSS approach corresponds

HESSD
8, 3817–3839, 2011

to semi-parametric regression models (Rigby and Stasinopoulos, 2005; Stasinopoulos and Rigby, 2007). In the present work, four theoretical probability distributions of two parameters were considered: Gumbel (GU), Gamma (GA), Lognormal (LN), and Weibull (WEI). Several previous studies have applied GAMLSS for modeling nonstationary extreme hydrometeorological time series (Villarini et al., 2009; Karambiri et al., 2011), considering similar PDFs.

In the next section, the methodology for weighting the RCMs using the REA factors (Giorgi and Mearns, 2002), and the score proposed by Perkins et al. (2007) considered for assessing PDFs agreements, are introduced. Finally, the PDF ensemble methodology is explained.

3.1 Reliability Ensemble Averaging (REA) method and Perkins score

The REA method provides a measure of reliability, average and uncertainty range of simulated climate change from ensembles of different atmosphere-ocean general circulation models and RCMs (Giorgi and Mearns, 2002). Previous studies have used the REA method to evaluate the performance of climate models (Giorgi and Mearns, 2003; Bark et al., 2010; Dominguez et al., 2010; Mote and Salathé, 2010; Räisänen et al., 2010).

The method considers two criteria to estimate the model reliability factor – R in Eq. (1). The first of them consists in a model performance criterion (R_B), considering the present-day climate. The second one, model convergence criterion (R_D), evaluates the convergence of the simulated changes between the different models. For reaching high reliability for a given RCM, both criteria should be met in Eq. (1). Giorgi and Mearns (2002) define the reliability factor for model i as follows:

$$R_i = \left[\left(R_{\mathrm{B},i}\right)^m \times \left(R_{\mathrm{D},i}\right)^n\right]^{[1/(m\times n)]} \tag{1}$$

where the parameters m and n are criterion weights. In this work, we assume $m = n = 1$, giving equal weight to both criteria.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |
HESSD
8, 3817–3839, 2011

J. D. Giraldo and S. G. García Galiano

For estimation of the R_B and R_D parameters (Eq. (1)), the Perkins score method (Perkins et al., 2007) was used. The Perkins score is a simple quantitative measure of the degree of agreement between the PDFs obtained from the RCMs and that observed from the data. This metric measures the common area between the two curves of the PDFs.

The Perkins score has been applied by several authors to assign weights to different climate models of an ensemble, for the analysis of several hydrometeorological variables (Perkins and Pitman, 2009; Boberg et al., 2009, 2010; Smith and Chandler, 2010).

In the case of the estimation of model performance criterion R_B, the cumulative distribution functions (CDFs) were built from observed data and from RCMs over the 1970–1990 time period. For the assignment of a cumulative probability to each value in the ordered series, the inverse of the Weibull equation was used.

For the model convergence criterion R_D, the difficulty is that there is no AMDR PDF known for future climate. According to Giorgi and Mearns (2002), an iterative process is followed to obtain the estimated PDF and therefore to estimate R_D. The estimated PDF is built using bootstraping techniques with $N = 1000$ data, considering the simulated series for the models between 2021–2050 (30 yr). Initially, the reference PDF is built by assigning equal skill scores to all RCMs (this is, each model consists of $1000/6 \approx 167$ data, obtained from sampling with replacement from the simulated series of 30 yr). Then, the distance of each RCM to the estimated PDF is calculated and consequently the assigned weights are readjusted. This procedure converges quickly after some iterations. It should be noted that the PDF built in this way is only an estimate of the distribution of the AMDR of future climate projection. The REA average does not represent the actual climate response to the climate forcing scenarios, however the REA average represents the best estimate of this response (Giorgi and Mearns, 2002; Giorgi and Mearns, 2003).

HESSD
8, 3817–3839, 2011

The values of R_B,R_D and R are estimated in the sites where the IRD is available (Fig. 1). Then, these values are interpolated (using the method of inverse distance), and the spatial distributions of the reliability factors (Fig. 2) are obtained for the selected RCMs.

According to Giorgi and Mearns (2002, 2003), the likelihood associated with a simulated change for the RCM_i is proportional to the model reliability factor R_i. In this, the results of models with higher reliability factor are more likely to occur. The normalized reliability factors, Pm in Eq. (2), can be interpreted as this likelihood associated with each RCM. Several authors (Tebaldi et al., 2005; Tebaldi and Knutti, 2007), have shown that the normalized reliability factors are analogous to the accuracy factors defined in their ensembles built by Bayesian approaches. The likelihood Pm for each RCM is defined as follows (Giorgi and Mearns, 2003):

$$Pm_i = \frac{R_i}{\sum_1^N R_j} \tag{2}$$

From the Pm maps (Fig. 2), the PDF ensembles were built in the sites where the IRD data is not available.

3.2 Calculation of PDF ensemble

The GAMLSS adjustment to various series of AMDR in each site predicts trends that differ in magnitude and sign, depending on the RCM and site considered. As an example, the temporal variation of the AMDR PDF is represented with curves for different percentiles (5, 10, 25, 50, 75, 90, and 95%), applying GAMLSS to the six RCMs selected for site 16 (Fig. 3). The goodness of fit to the statistical model was assessed, considering the normality of the residuals, visual inspections of the qq-plots and the worm plot (not shown), according to the methodology presented by van Buuren and Fredriks (2001).

HESSD

8, 3817–3839, 2011

Therefore, for the building of the PDF ensemble in each site, greater weight was given to RCMs with high value of normalized reliability factor, using bootstrapping techniques (Efron and Tibshirani, 1993). Once the *Pm* maps were obtained, the PDF ensembles are built on each site of the study region. Random subsamples of size $N = 10\,000$ were built, considering the RCM in proportional fashion to its normalized reliability factor (e.g. on site 16, 1550 values from GKSS/CLM, 1330 from METO-HC/HAD, and so on). To obtain the evolution of the probability distribution of AMDR in each site, PDF ensembles were constructed for each ten years in the period 1970-2050, and basic statistics (mean μ and standard deviation σ) and the quantiles for 5, 10, 25, 50, 75, 90, and 95% with their respective confidence intervals (95% CI) were estimated.

From Fig. 4, for PDF ensemble in site 16, the difference in magnitude and sign of GAMLSS fit becomes more evident (e.g. the adjusted trend for the SMHI/RCA and MPI/REMO AMDR series indicates a plausible increasing, but with mean values of AMDR differences of about 30 mm, while the GKSS/CLM presents a negative trend). Another feature of adjustment is that despite having the lowest value of the model performance criterion R_{B}, the INM/RCA model presents the highest value of the model convergence criterion R_{D}. Although this situation is not presented in all the sites analyzed, Giorgi and Mearns (2002) claimed that a large individual model bias does not imply a large model divergence.

4 Results: maps of AMDR PDF statistics

Once the statistics for the PDF ensemble at each site have been obtained for the period 1970–2050, these values were interpolated to generate maps depicting the spatio-temporal evolution of the AMDR distribution. In Fig. 5, the maps constructed for the mean, standard deviation, and for 90% and 95% quantiles ($Tr = 10$ yr and $Tr = 20$ yr, respectively) for 1990 and 2050, and their percentage difference, are presented. Using the Monte Carlo method based on bootstrapping with replacement (Efron and Tibshirani, 1993; Sánchez et al., 2009), applied to AMDR populations

HESSD
8, 3817–3839, 2011

Building hazard maps of extreme daily rainy events

J. D. Giraldo and S. G. García Galiano

obtained from PDF ensemble, the sites where these differences were statistically significant for 95% bootstrap confidence intervals have been shown on difference maps with a dark grey square (Fig. 5).

The maps constructed for μ (Fig. 5a) have a spatial structure that matches the latitudinal gradient of mean annual precipitation in the region (shown in Fig. 1), nonetheless the difference between them does not preserve this structure. Significant increase in μ is expected for 2050 in the Senegal River Valley and the upper basin, while in the Sahelian zone a decrease is projected, but it is not significant. In the Valley area, the expected increase in μ will be about 10 mm, very similar to the increment for the upper basin, yet in the lower basin this represents a significant increase of over 30%. The maps of σ (Fig. 5b) retain the latitudinal gradient of rainfall maps, although less significantly than the μ maps. The difference between the two maps shows that in the lower basin a significant increase in σ is projected for 2050, which could reach 80% (25 mm), while in the upper basin the projected increase in this parameter hardly exceeds 25% (10 mm). Finally, the maps for $Tr = 10$ and $Tr = 20$ yr (Fig. 5c and d, respectively) show a clear latitudinal gradient, with a northward decrease in AMDR. A general increase in the AMDR associated with both return periods is expected for 2050, except at the northern edge of the basin and in some isolated areas of the study area within the Sudanian zone. With regard to $Tr = 10$ yr, a significant increase is foreseen in the lower basin, where a difference of more than 20–25 mm was calculated between the reference years (30–40%). On the other hand, a significant greater increase associated with $Tr = 20$ yr is estimated for the same region, where the difference is about 30–35 mm (40–50%).

Previous studies in the area with similar objectives, have been developed. The maps obtained by García and Giraldo (2011) exhibit spatial trends very similar to those presented in the Fig. 5, however, they are numerically quite different. These authors estimated increases of about 40% for μ, and up to 100% for σ, higher than calculated values in the present work, with more areas appearing with significant differences in their maps.

HESSD
8, 3817–3839, 2011

J. D. Giraldo and S. G. García Galiano

5 Discussion and conclusions

In order to distinguish the predicted changes in the severity and frequency of AMDR in the Senegal River Basin, plausible climate scenarios provided by RCMs and observed data were considered. The GAMLSS methodology and ensemble techniques allow to simulate the non-stationarity present in AMDR series for the study region.

Nevertheless, the good fit of the GAMLSS statistical model to simulated AMDR time series neither implies a proper coupling to the observed series from the IRD database, nor a proper convergence between the PDFs of AMDR future projections. In order to exploit all the information provided by the RCMs, a PDF ensemble is constructed for each site in the region based on the bias analysis, allowing the estimation of the spatio-temporal change of AMDR in the study area.

The use of weighted ensembles is justified by the fact that there are clear differences between the performance of the RCMs to simulate the present-day AMDR, where the best model may have nearly twice the skill score with respect to the worst model in some sites. However, the use of different weights affects the significance of the results. Several studies have addressed this issue, with the aim of designing more sophisticated methods for combining models. However, to know whether uncertainty in the evolution of future climate will remain at a similar level or whether it will be reduced substantially in the next decades, remains a challenge (Tebaldi and Knutti, 2007).

As key findings, from the interpolated maps various parameters of the PDF ensemble maintain the latitudinal gradient of rainfall in the area. However, in the difference maps for the reference years considered (1990 and 2050), this spatial pattern is not preserved. The percentage difference shows that in the Valley area, the increase of AMDR will be significantly higher than in the upper watershed area. In the Valley area, the increase in μ is projected to be more than 30% and the increase in σ to be close to 80%. Both increases will be reflected in the maximum precipitation amount for the 90% quantile, which will rise between 30–40% in the lower part of the basin, and for the 95% quantile, with a 40–50% increase.

HESSD
8, 3817–3839, 2011

Building hazard maps of extreme daily rainy events

J. D. Giraldo and S. G. García Galiano

Future research lines will be to highlight the deeper analysis of robust and reproducible methods of estimation of skill scores associated with each RCM in the ensemble. With the aim of its application on spatio-temporal plausible patterns of other daily rainfall features (maximum dry spell lengths, annual or seasonal number of days without rainfall, etc.), and hydrometeorological variables (evaporation, temperatures, monthly rainfall) with implications in water resources management at basin scale. Even considering their application in regions with different hydroclimatic characteristics (such as the Mediterranean area). The ensemble procedure applied in this study should be compared with other proposals for calculating the weighting, in order to verify the spatial-temporal consistency of the methodological approach.

Another issue to be taken into account is whether the improvement in resolution of the models will affect the conclusions of the studies. Wehner et al. (2010) found that at high resolutions, the climatic models can produce precipitation values of comparable magnitude to high quality observations. However, at the resolutions typical of the coupled GCM, the precipitation is underestimated.

As it was shown, the future climate change will affect the frequency and intensity of natural hazards, such as extreme rain events, on Senegal River Basin. The impact on society depends on many factors, including the sequence and intensity of events, but also depends on the ability of the people to adapt and recover from the natural hazard. The knowledge and awareness about climate change by stakeholders is important.

In conclusion, a novel PDF ensemble approach was presented, which allows the identification of plausible spatial trends from continuously changing AMDR frequency distributions. The key findings of this study could be considered by local stakeholders, for designing and implementing effective adaptation strategies to climate variability and change in the region.

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HESSD

8, 3817–3839, 2011

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HESSD
8, 3817–3839, 2011

Building hazard maps of extreme daily rainy events

J. D. Giraldo and S. G. García Galiano

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HESSD
8, 3817–3839, 2011

Building hazard maps of extreme daily rainy events

J. D. Giraldo and S. G. García Galiano

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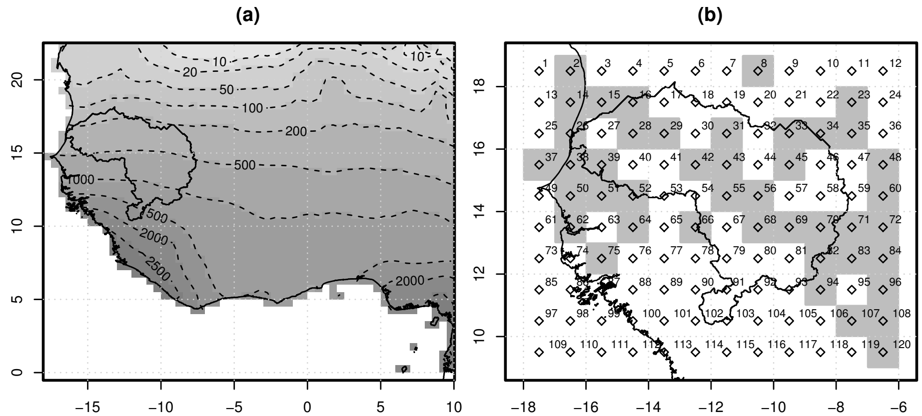

Fig. 1. Location of Senegal River Basin: **(a)** Mean annual rainfall (mm) from Climate Research Unit database (CRU, University of East Anglia, Norwich, UK), over 1961–1990 period, and **(b)** sites selected for analyses, and The IRD sites are highlighted with gray squares.

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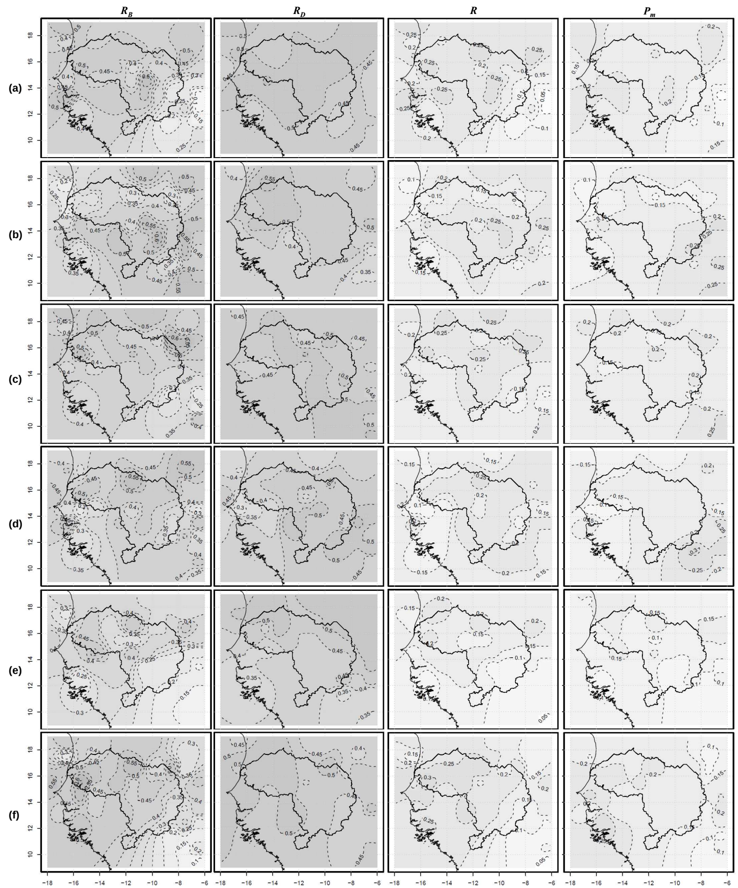

Fig. 2. Maps of RCM reliability factors R_B, R_D, R and Pm: **(a)** GKSS/CLM, **(b)** INM/RCA, **(c)** KNMI/RACMO, **(d)** METNO-HC/HAD, **(e)** MPI/REMO, and **(f)** SMHI/RCA.

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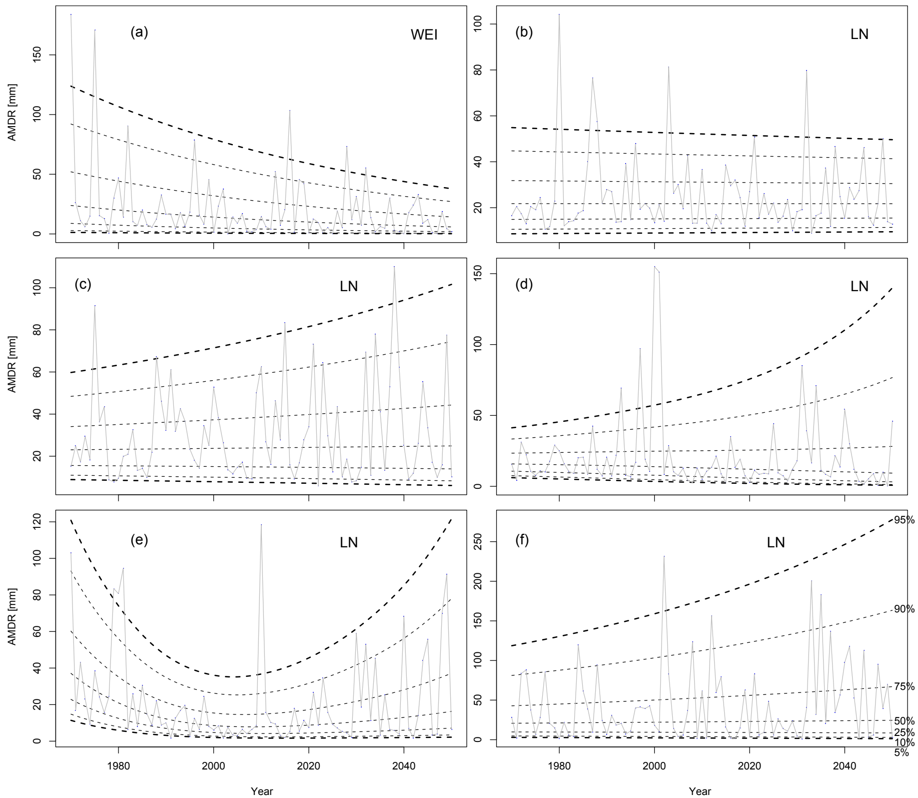

Fig. 3. GAMLSS analysis of AMDR (mm) for site 16 for several RCM: **(a)** GKSS/CLM, **(b)** METO-HC/HAD, **(c)** KNMI-RACMO, **(d)** INM-RCA, **(e)** SMHI/RCA, and **(f)** MPI-M-REMO. The centile curves (5 to 95%) are represented by dashed lines. It should be noted that the ordinate scale is automatically fixed.

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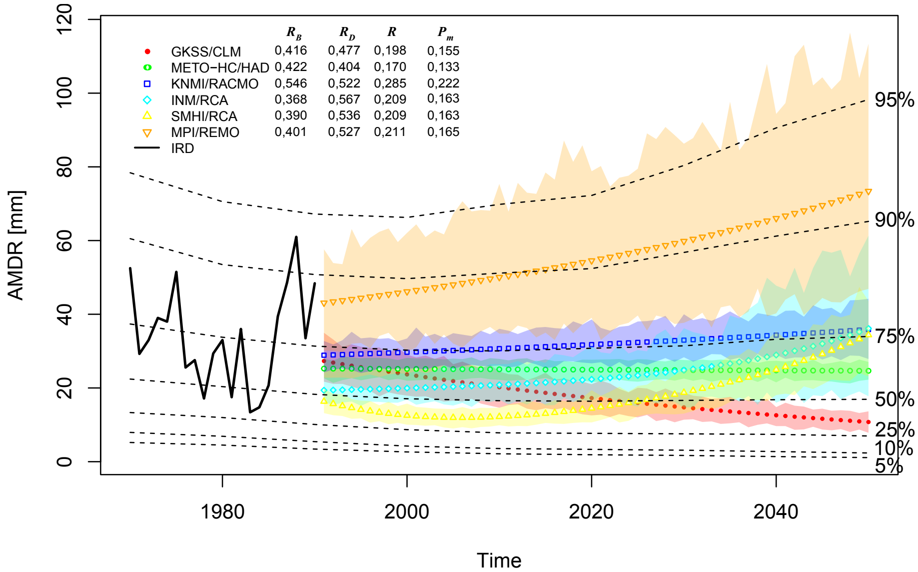

Fig. 4. PDF ensemble on site 16. The dashed lines show 5 to 95% quantiles of PDF ensemble, and markers represent the RCM mean values obtained from the fitted PDF. The polygons show the mean variability in the period 1991–2050, using the 95% CI computed with bootstrapping. The IRD AMDR series in 1970–1990 is presented as a solid line. The computed REA values (R_B, R_D, R and P_m) used to build the PDF ensemble, are presented.

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8, 3817–3839, 2011

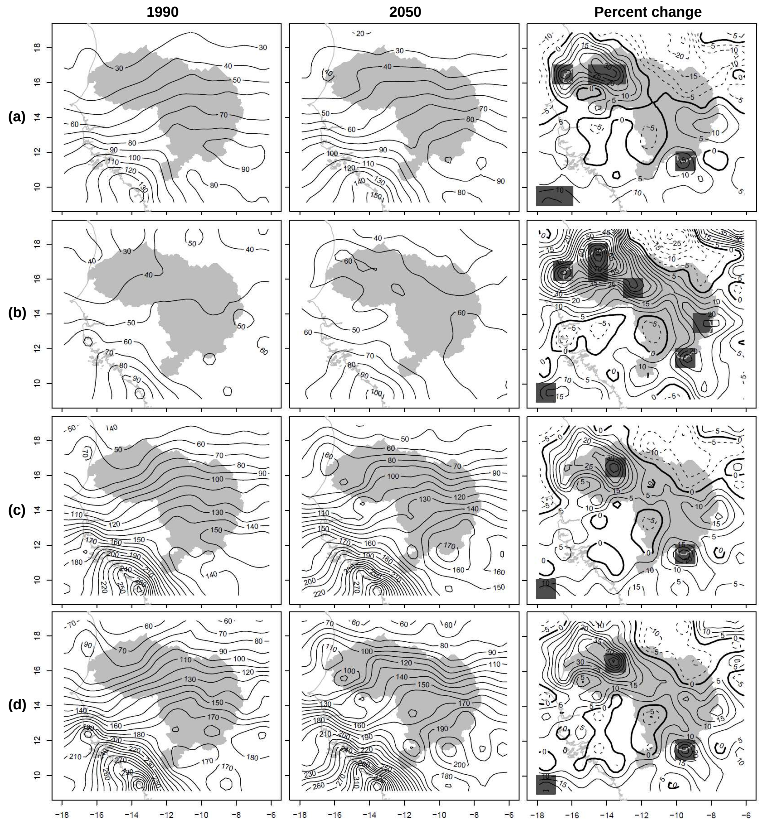

Fig. 5. Interpolated maps from the GAMLSS analysis for each site: **(a)** mean μ, **(b)** standard deviation σ; **(c)** associated with $Tr = 10$ years, and **(d)** $Tr = 20$ yr. The maps for the years 1990 and 2050, and the percentage difference between them, are presented. In the difference maps, negative values are dashed, while the 95% confidence in projected changes is highlighted with the dark gray square.