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Precipitation bias correction of very high resolution regional climate models

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Abstract

Regional climate models are prone to biases in precipitation that are problematic for use in impact models such as hydrology models. A large number of methods have already been proposed aimed at correcting various moments of the rainfall distribution. They all require that the model produce the same or a higher number of rain days than the observational datasets, which are usually gridded datasets. Models have traditionally met this condition because their spatial resolution was coarser than the observational grids. But recent climate simulations use higher resolution than the gridded observational products and the models are likely to produce fewer rain days than the gridded observations.

In this study, model output from a simulation at 2 km resolution are compared with gridded and in-situ observational datasets to determine whether the new scenario calls for revised methodologies. The gridded observations are found to be inadequate to correct the high-resolution model at daily timescales. A histogram equalisation bias correction method is selected and adapted to the use of stations, alleviating the problems associated with relatively low-resolution observational grids. The method is efficient at bias correcting both seasonal and daily characteristics of precipitation, providing more accurate information that is crucial for impact assessment studies.

1 Introduction

Regional Climate Models (RCMs) are an outstanding tool to study the mechanisms of climate at scales that are not yet resolved by General Circulation Models (GCMs). RCMs higher spatial resolution and specifically designed parameterisations improve the representation of many aspects of climate (Feser et al., 2011; Giorgi, 2006), especially variables that are essentially local such as precipitation (Di Luca et al., 2011; Evans and McCabe, 2010; Tselioudis et al., 2012). Hydrological models, which are es-

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pecially sensitive to precipitation, thus benefit from high-resolution RCM outputs (Maraun et al., 2010).

However, RCMs are still prone to biases and the simulated climate is not always fully consistent with the observations, which is critical in climate change impact research (Portoghese et al., 2011). Previous authors (Christensen et al., 2008; Déqué et al., 2007) have advocated the use of bias correction to reduce model systematic deviations and provide more reliable outputs. It is arguable that bias correction should not be regarded as a definitive solution and its application is also matter of criticism (Ehret et al., 2012). Despite the fact that efforts should indeed be devoted towards the development of better models, there are no feasible alternatives to bias correction in terms of improving current simulations. Furthermore, some authors have examined the uncertainty introduced by bias correction and its impact on climate change estimates and overall recommended the use of non-linear methods to provide better projections (Chen et al., 2011; Themeßl et al., 2012).

Several methodologies have been recently proposed and evaluated, mostly focused on precipitation and temperature (Berg et al., 2012; Bordoy and Burlando, 2013; Haerter et al., 2011; Piani et al., 2010a; Terink et al., 2010). The physical characteristics of precipitation make it more difficult to correct and most studies tend to concentrate on precipitation correction. Methods of different complexity have been put forward, aimed at correcting various moments of the rainfall distribution. They range from relatively simple linear methods (Hay et al., 2000; Lenderink et al., 2007) to distribution-based algorithms, either using empirical distributions (Themeßl et al., 2011) or theoretical functions (Piani et al., 2010a). Hydrological impact studies require at least accurate daily data and hence methods that correct higher moments are preferable (Portoghese et al., 2011). Several evaluations (Lafon et al., 2013; Teutschbein and Seibert, 2012; Themeßl et al., 2011) have shown that distribution-mapping methods generally outperform others.

Bias correction is normally performed towards gridded datasets such as E-OBS (Haylock et al., 2008) or AWAP (Jones et al., 2009), because they cover the entire

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spatial domain and have complete timeseries. Both the model outputs and the gridded dataset are reduced to the same grid and the transfer functions are calculated grid-point by grid-point.

No matter which method is selected among the myriad proposed, they all impose a common limitation to provide accurate corrections: they assume that the model produces the same or a higher number of rain days, independently from how these are defined. Distribution-based methods do not strictly require an equal or larger number of events, but if the model is generating too few rain days, the method will fail to adequately correct the model outputs. If any method is to be applied to model output with fewer rain days, it is necessary to introduce additional precipitation events (e.g. through Frequency Adaptation as in Themeßl et al. (2012)) otherwise daily intensity is unrealistically corrected to match, for example, the monthly means.

So far this situation has rarely arisen and RCMs have traditionally met the aforementioned condition, partly because their spatial resolution is coarser than the observational gridded dataset to which they are compared. Models, and to a certain extent gridded observations, often display the "drizzle effect" (Argüeso et al., 2012; Gutowski Jr. et al., 2003) as a function of spatial resolution, producing more frequent but less intense precipitation than the station measurements as the resolution decreases. However, RCM simulations that exceed the spatial resolution of most gridded products have become possible due to improvements in computational resources. In this scenario, RCMs are likely to produce systematically less rain days than the gridded observations and thus the existing bias correction methodologies have to be revised.

In this paper, we analysed a RCM simulation at 2 km spatial resolution and compared it with both gridded and station based in-situ observational datasets to determine whether increasing resolution has implications in terms of the bias correction. We propose an alternative approach to the use of gridded observations for this purpose.

2 Model and observational data

2.1 Model description and setup

The Weather Research and Forecasting (WRF) model version 3.3.1 (Skamarock et al., 2009) was selected to simulate the recent climate (1990–2009) over the Sydney region (Fig. 1a). The model was configured following (Evans and McCabe, 2010, 2013; Evans and Westra, 2012), where thorough evaluations of WRF over the region are provided covering time scales from sub-daily to inter-annual. The original simulation comprised two domains at 50 and 10 km spatial resolution covering southeastern Australia. The boundary conditions were obtained from the National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) Reanalysis Project (NNRP1) and are provided every 6 h to the model.

An additional 2 km spatial resolution domain (Fig. 1) that covers the Sydney region was added to the original configuration (Argüeso et al., 2013). The convective parameterisation was switched off in this domain, while the microphysics parameterisation was changed to the more complex Thompson scheme (Thompson et al., 2006).

2.2 Observational data

The first observational reference dataset used in this study was a gridded dataset derived from observations and generated by the Australian Water Availability Project (AWAP) as described in (Jones et al., 2009). The resulting grid covers Australia at a 0.05° by 0.05° (~ 5 km by 5 km) spatial resolution and provides values for different surface variables including precipitation, which was used here. The precipitation grid was constructed by interpolating surface station measurements that amounted to between 6000 and 7000 stations for the period 1990–2009.

The second dataset to represent the Sydney region climate was obtained from the Global Historical Climatological Network (GHCN) database (Menne et al., 2012) and

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comprised 362 rain gauges distributed within the 2 km domain that had at least 10 yr of valid data over the period 1990–2009 (Fig. 1c).

3 A methodology for the new paradigm

Existing methods usually perform the bias correction grid-point by grid-point and assume that the model produces too many rain events. However, the number of days tends to decrease with resolution as evidenced by Fig. 2 and thus that assumption is unlikely to be valid for the increasingly high-resolution simulations being performed now and in the future. Indeed, the 2 km WRF simulation produces many less rain days than AWAP and therefore using the gridded dataset to correct the 2 km model outputs is problematic. As mentioned before, introducing new rain days to match the observed frequency poses a number of problems (i.e. when to introduce them, what is their intensity, how to keep spatial coherence) that encourages the proposal of alternatives.

Because the number of rain days decreases with increasing resolution the question that arises is: why is station data not used directly to correct very high-resolution model outputs? There are two major obstacles that explain why bias correction has not traditionally been carried out based on in-situ measurements: (1) spatial and temporal coverage and, (2) discrepancies in the spatial scale represented by models and stations. Spatial discrepancies are reduced with higher resolution, but it remains a burden when comparing stations and model outputs. The coverage is still an issue regardless of the model spatial resolution.

A completely new method is not necessary given the large number of bias correction methodologies that have already been proposed and proven to provide satisfactory results. Instead, we suggest here an alternative approach aimed at overcoming the two obstacles above, which consists in adapting an existing method based on histogram equalisation (Piani et al., 2010a,b) to the use of stations as observational reference. This method was chosen among a wide range of options available because it is widely adopted (Lafon et al., 2013; Piani and Haerter, 2012; Rojas et al., 2011; Schoetter

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et al., 2012), corrects high moments of the distribution and performs generally better than others (Berg et al., 2012; Teutschbein and Seibert, 2012). Here we call attention to a problem that is likely to emerge in future simulations as resolution increases, and offer a solution.

The original method proposed in Piani et al. (2010a) is a distribution-based algorithm, which assumes that the probability distribution of both the observed and the simulated daily rainfall could be approximated by a theoretical function, a gamma distribution. In particular, the algorithm calculates the cumulative probability from each of the theoretical distributions (i.e. from the model and the observations) at every grid-point. It then corrects each of the modelled events towards the observed value to match their respective cumulative probabilities (Fig. 3).

In this study, the method has been modified such that the 5 nearest stations to each model grid-point are selected to correct its precipitation instead of a gridded dataset. Therefore, for each model grid-point and each day there will be 5 possible corrections and not only one as occurs in the original method. These 5 corrected values are averaged using an inverse distance squared weighting. The obstacle of not having a unique associated station with a complete timeseries for each of the model locations is hence circumvented. Also, the stations are aggregated and the spatial scales of the observations and the model are now more comparable.

In addition, the area is divided into different regions (Fig. 1c) of climatological affinity that were identified using a multi-step regionalization (Argüeso et al., 2011). It consists of three successive steps (Principal Component Analysis, an agglomerative clustering and a non-hierarchical clustering) that are applied to daily precipitation. In this case it was applied to AWAP daily precipitation and let us identify 5 different regions with similar precipitation characteristics according to the observations. The monthly climatologies of AWAP precipitation averaged over the grid points from each of the regions are illustrated in Fig. 4 to show how different their rainfall regimes are, particularly during the first half of the year. Using the regionalisation, we are able to give larger weight to stations that belong to the same region as the model grid-point and penalise those that are likely to have different precipitation regimes. Stations belonging to a different region are penalised with a factor of 0.5 when averaging the corrected values.

The parameters of the gamma distributions are calculated using only rain days, which are usually defined as days with precipitation above a certain threshold. Observed rain days are here defined using a 0 mm day^{-1} threshold, although this is not the only possible choice and other authors have chosen slightly higher thresholds to define wet days (Argüeso et al., 2012; Berg et al., 2012; Herrera et al., 2012). Modelled rain days are defined in a more flexible way, using a calibrated precipitation threshold as proposed in Schmidli et al. (2006) to adjust the excess of wet-day frequencies.

The bias correction was originally designed to use all available values at once and generate a single gamma function for each grid point. The substantial differences in the mechanisms that drive precipitation throughout the year could result in different biases for each of the seasons, which motivated us to apply the bias correction seasonally and thus calculate the gamma parameters for each of seasons separately.

4 Results

Both the original and the bias corrected model output are compared with the gridded and the station observations to investigate the suitability of the observational datasets for bias correction purposes and to assess the performance of this particular method.

The seasonal deviations of the corrected and non-corrected model outputs with respect to both datasets are illustrated in Fig. 5. The biases of the original model outputs show that the model tends to be very sensitive to topography at this spatial resolution. As a consequence, it generates too much precipitation east of the mountains and shows a deficit of rainfall in the interior, west of the mountains.

Figure 5 also shows that the bias correction methodology is efficient at seasonal timescales since most of the systematic errors are reduced or even removed with respect to both observational datasets. Indeed, seasonal deviations are reduced to below 10 mm month^{-1} over most of the domain. Although certain areas still show slight

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biases after histogram equalisation, the improvement by the bias correction is noteworthy since the original model estimates were strongly affected by biases in these areas (e.g. inner west and mountains). For instance, in the inner west (region 5, see Fig. 1c) the bias with respect to stations is reduced on average from $-46.3\,\mathrm{mm\,month^{-1}}$ to $-13.5\,\mathrm{mm\,month^{-1}}$ in winter and from $-45.2\,\mathrm{mm\,month^{-1}}$ to $-21.1\,\mathrm{mm\,month^{-1}}$ in spring. For the rest of the regions and seasons, the improvements are even larger.

The spatial patterns of the biases with respect to both stations and AWAP are very similar, but the magnitude of the seasonal deviations differs in some areas (e.g. positive biases along the coast in JJA and SON). The agreement between seasonal precipitation from corrected and non-corrected WRF outputs indicates that both observational datasets are appropriate for bias correction of high-resolution models as far as monthly or seasonal timescales are concerned. However, the differences in the magnitudes indicate that they might not be equally adequate at shorter timescales.

Indeed, impact assessment studies strongly rely on accurate daily precipitation. The correct distribution of events according to their intensity as well as their occurrence is crucial to evaluate the risks and characterise their possible impact. The probability distribution of events is examined for AWAP, the stations and the two model outputs to assess the performance of the bias correction at daily timescale and evaluate the potential benefits of using stations to correct high-resolution climate simulations.

The contribution to total precipitation by events of different intensity is used instead of the traditional Probability Distribution Function (PDF). This alternative view of the probability distribution makes it easier to evaluate the relative importance of the errors through the entire rainfall spectrum.

Figure 6 summarises the contribution from different events in the 5 regions. This figure complements the information provided by the monthly climatologies (Fig. 4) and emphasises the differences amongst regions. Also, the comparison between distributions from observational datasets yields important differences in all regions, especially for events below $10\,\mathrm{mm\,day^{-1}}$, which are systematically overestimated by AWAP. As for more intense events, AWAP tends to underestimate their contribution to total precipita-

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tion in most regions; though, in the northeast (region 3) there is a clear overestimation. These differences are related to the difference in the spatial scales the observational products represent and suggest that AWAP, and more generally the observation-based grids, are not suitable to correct model outputs with finer resolution.

In most regions, WRF produces too much light precipitation (0–2 mm day^{-1}), underestimates moderate events (2–20 mm day^{-1}) and generates too many extreme events (> 20 mm day^{-1}), which altogether results in the positive biases shown in Fig. 5. The behaviour of the model is different in region 5, where the overall negative bias is persistent across the entire spectrum of events, except for the very light events that are also overestimated.

While the bias correction is not able to completely remove the errors, particularly in regions 4 and 5, it succeeds in providing a much better representation of the events distribution compared to the stations, which is a good indicator of the method skills. To quantify this improvement, the similarity between different PDFs was measured using the skill score (SS) proposed in Perkins et al. (2007), which calculates the common area shared by two PDFs. The SS confirms that the bias correction significantly improves the events distribution in the model over the entire domain. Ordered by regions, the non-corrected model outputs and the in-situ observations share 80.3, 70.2, 74.0, 76.1 and 54.5 % of their precipitation PDFs, whereas the bias correction increases these percentages to 97.1, 95.1, 96.7, 96.6 and 94.0 %, respectively.

In the station dataset, the events with the largest contribution occur in the range between 2–6 mm day^{-1}, whereas rain events below 2 mm day^{-1} make a smaller contribution. This feature of the rainfall distribution usually goes unnoticed in RCMs and is not captured by gridded datasets either, but it is better reproduced in the bias-corrected model outputs.

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5 Conclusions

Bias correction has traditionally relied on the assumption that models produce more rain days than the reference observations, which are usually gridded datasets due to their spatial and temporal characteristics. However, climate simulations are currently being completed at spatial resolutions that make this assumption no longer valid. A histogram equalisation method (Piani et al., 2010a) was adapted to be used with stations, which are not subjected to the drizzle effect and thus make this assumption valid again. The stations were aggregated to bypass the two major obstacles for their use in bias correction: the differences in the model and stations spatial scales, and the completeness and sparseness of the timeseries. The method has been proven to substantially reduce the seasonal biases of precipitation when compared to both gridded and station datasets. Gridded datasets are appropriate to correct high-resolution model at seasonal or even monthly time scales, but it has been shown here that they are not adequate to correct daily features of precipitation. Indeed, the major contribution of this study is the efficient bias correction of the daily precipitation probability distributions of very high-resolution models. A much better representation of the frequency of the events is achieved after bias correction for all regions, especially in those where rainfall is overestimated. The relative importance of moderate events with respect to very light ones is also better reproduced, which could have important implications for impact assessment studies.

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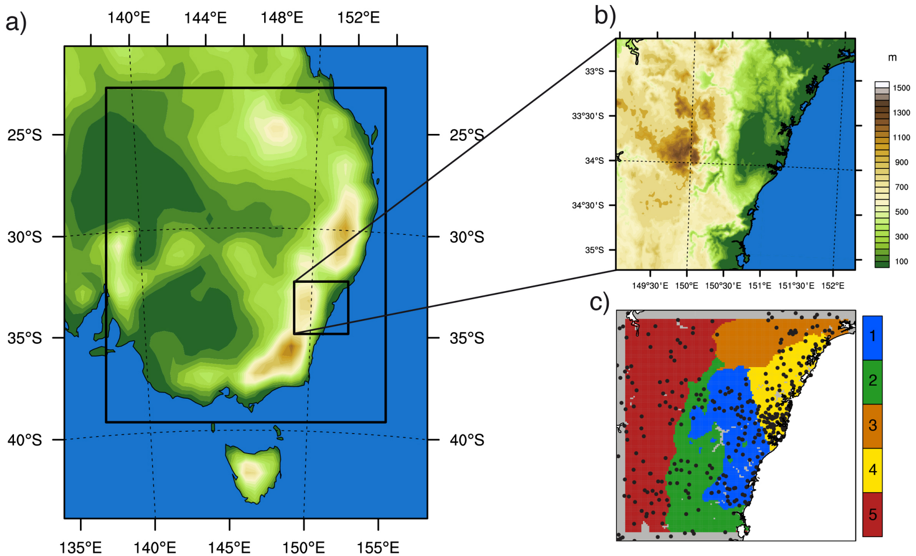

Fig. 1. (a) Topography and location of all domains of the simulation, **(b)** topography and extension of the inner domain, and **(c)** location of the stations (black dots) and the 5 different precipitation regions (colored areas) within the model domain.

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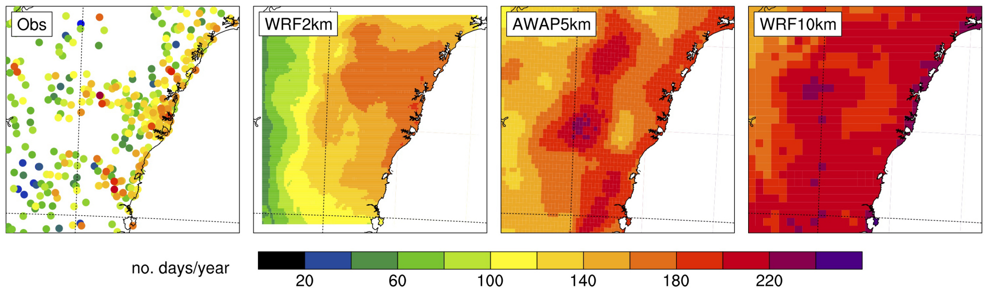

Fig. 2. Annual mean number of rain days over the period 1990–2009 for stations, the WRF simulation at 2 km resolution, the AWAP dataset and the intermediate WRF domain at 10 km resolution used to provide the boundary conditions.

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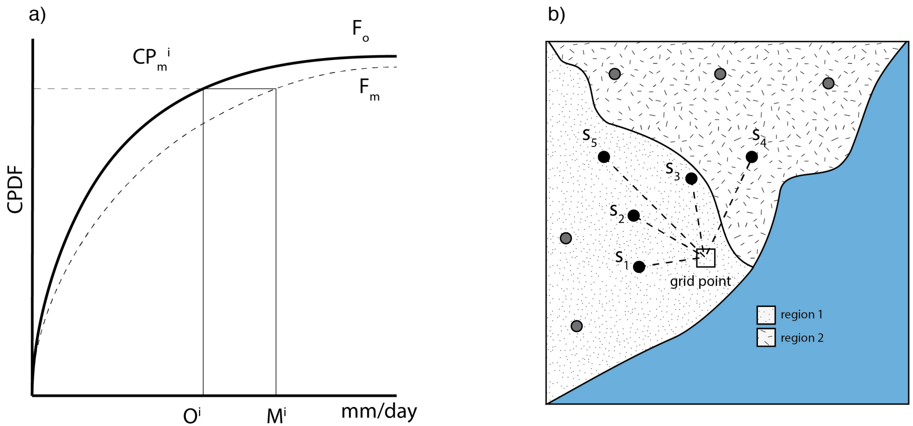

Fig. 3. (a) Schematic of the bias correction proposed by Piani et al. (2010a). Mi is the intensity of an event in the model and Oi is intensity of an observed event with the same cumulative probability (CPmi) as defined by Fm and Fo, which are the cumulative probability functions for the model and the observations. **(b)** Schematic of the adaptation of the bias-correction method using stations and regions.

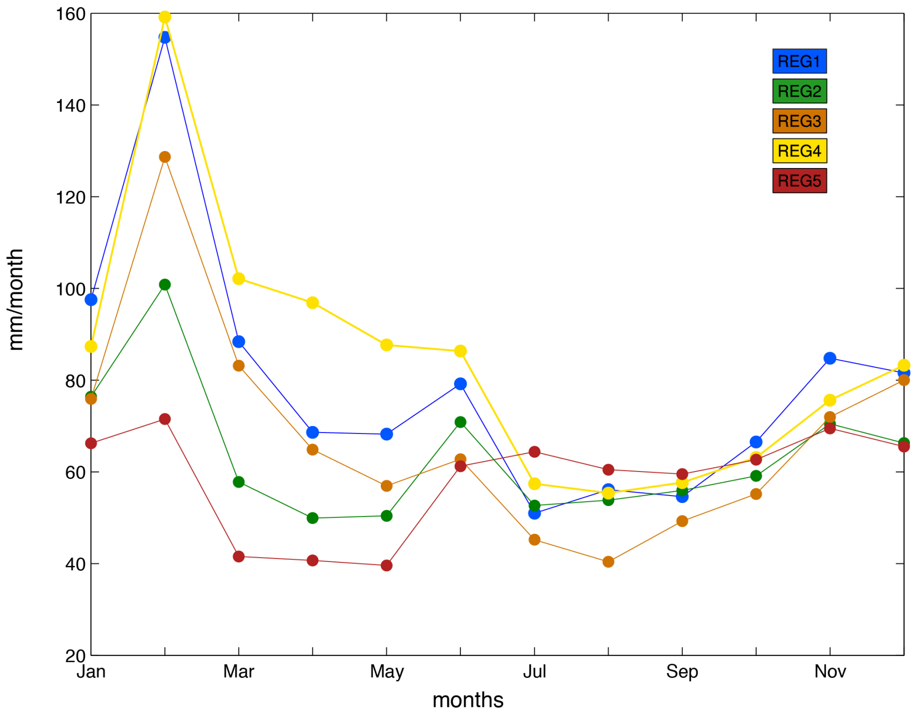

Fig. 4. Monthly climatologies of precipitation for each of the regions obtained by averaging all AWAP grid points that belong to each of the divisions.

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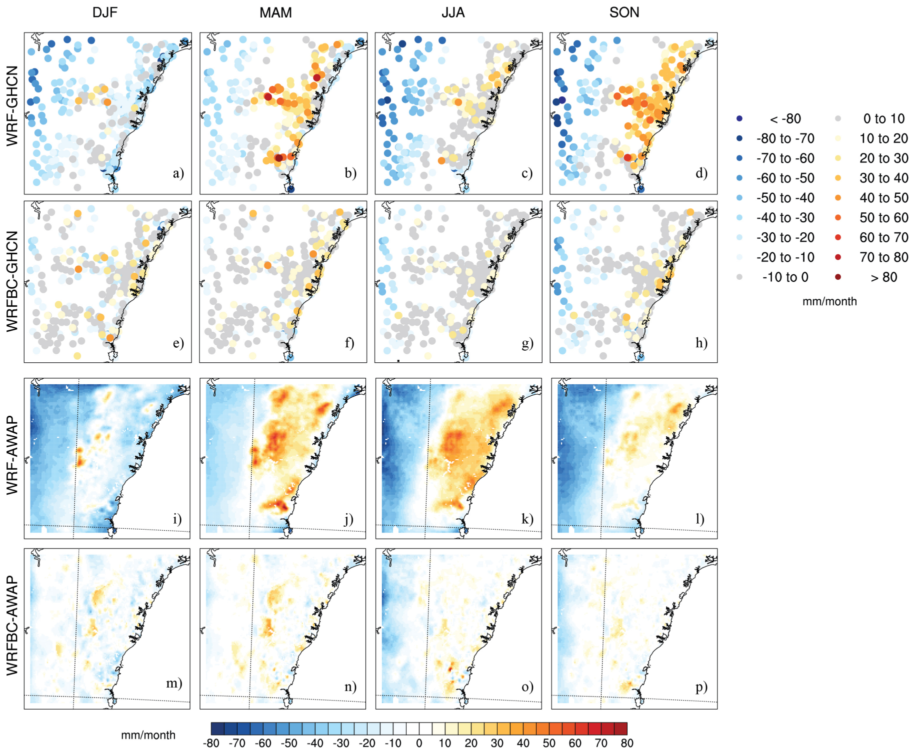

Fig. 5. Precipitation seasonal biases of non-corrected WRF with respect to the stations **(a–d)**, bias-corrected WRF with respect to the stations **(e–h)**, non-corrected WRF with respect to AWAP **(i–l)** and bias-corrected WRF with respect to AWAP **(m–p)** over the period 1990–2009.

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High-resolution RCM precipitation bias correction

D. Argüeso et al.

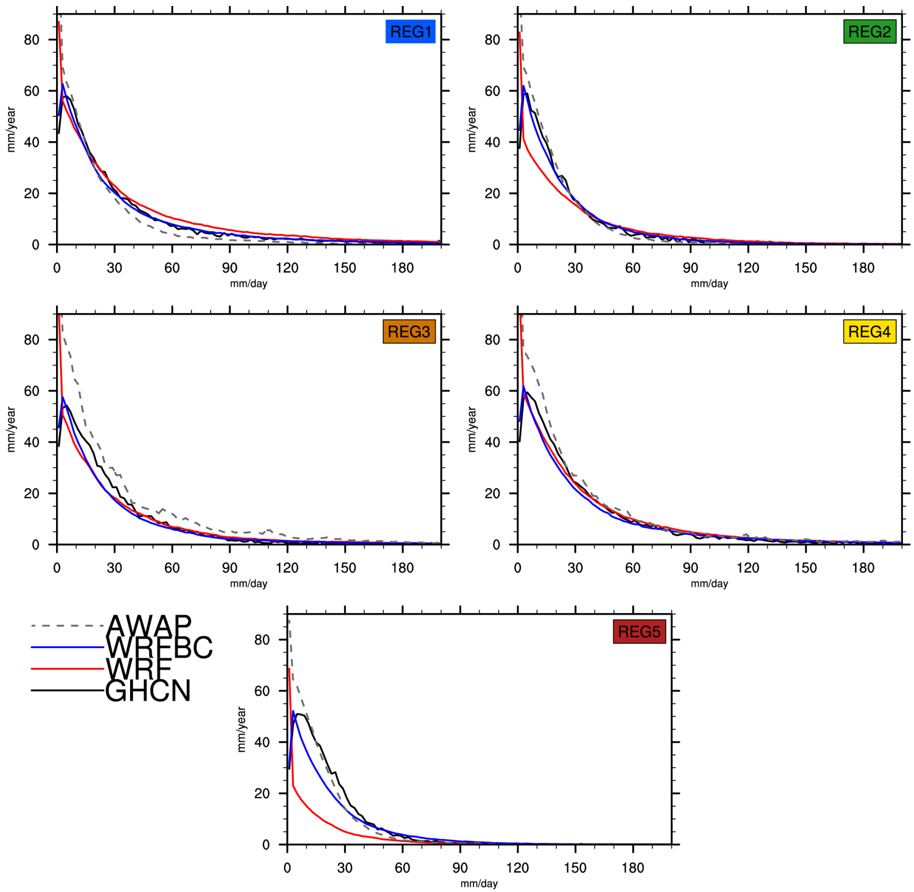

Fig. 6. Contribution to total annual precipitation by events of different intensity in the 5 precipitation regions for AWAP, bias-corrected and non-corrected WRF outputs, and GHCN stations.