**Hydrology and Earth System Sciences Discussions**

# Improving runoff estimates from regional climate models: a performance analysis in Spain

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## Abstract

An important aspect to assess the impact of climate change on water availability is to have monthly time series representative of the current situation. In this context, a simple methodology is presented for application in large-scale studies in regions where a
5    properly calibrated hydrologic model is not available, using the output variables simulated by regional climate models (RCMs) of the European project PRUDENCE under current climate conditions (period 1961–1990). The methodology compares different interpolation methods and alternatives to generate annual times series that minimize the bias with respect to observed values. The objective is to identify the best alter-
10    native to obtain bias-corrected, monthly runoff time series from the output of RCM simulations. This study uses information from 338 basins in Spain that cover the entire mainland territory and whose observed values of naturalised runoff have been estimated by the distributed hydrological model SIMPA. Four interpolation methods for downscaling runoff to the basin scale from 10 RCMs are compared with emphasis on
15    the ability of each method to reproduce the observed behavior of this variable. The alternatives consider the use of the direct runoff of the RCMs and the mean annual runoff calculated using five functional forms of the aridity index, defined as the ratio between potential evaporation and precipitation. In addition, the comparison with respect to the global runoff reference of the UNH/GRDC dataset is evaluated, as a contrast of the
20    "best estimator" of current runoff on a large scale. Results show that the bias is minimised using the direct original interpolation method and the best alternative for bias correction of the monthly direct runoff time series of RCMs is the UNH/GRDC dataset, although the formula proposed by Schreiber also gives good results.

## 1 Introduction

25    In recent decades, many studies have addressed the potential impact of climate change on hydrology and water resources (i.e. Arnell, 1999; Vicuna and Dracup, 2007; Buytaert et al., 2009; Elsner et al., 2010), gaining considerable attention among

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researchers. The use of regional climate models (RCMs) is an important tool for assessing water management under future climate change scenarios (Varis et al., 2004). In order to evaluate this impact in hydraulic systems, it is necessary to have monthly time series of stream flow for the period of analysis. The standard procedure to study
5   climate change impacts on water resources is to downscale climatic variables, such as temperature or precipitation, from RCMs, and use a hydrologic rainfall-runoff model to generate stream flow series for the basin of interest. However, it is very difficult to calibrate a rainfall runoff model for regional studies covering extensive areas. If a calibrated rainfall-runoff model is not available, the only source of stream flow time
10  series may be other indirect variables simulated by the RCMs, such as surface runoff, whose generation process is conceptually similar to that of hydrologic rainfall-runoff models. These variables may reproduce the basic seasonal and spatial characteristics of surface hydrology (Graham et al., 2007; Hurk et al., 2004) and could be useful to undertake water availability analyses. In addition to that, the UNH/GRDC (University of
15  New Hampshire/Global Runoff Data Center) gives high-resolution annual and monthly mean surface runoff layers that preserve the accuracy of measurements of observed flows at the main hydrologic stations around the world. Currently, this layer is the "best estimator" of surface runoff over great extensions of land (Fekete et al., 1999), and it can be used to correct bias from RCMs.
20      In light of this situation, it is essential to analyse several alternatives that will enable us to obtain simulated stream flow series and can be introduced in water resources models to estimate climate change impacts. In the present study, we consider the use of direct surface runoff series simulated using RCMs or obtained applying climate formulas (such as those based on the aridity index Arora, 2002), which give surface
25  runoff variables on an annual time scale. In this regard, it is noteworthy that numerous studies have highlighted the calculation of the mean annual surface runoff using a non-parametric focus that does not depend on a hydrologic model (i.e. Sankarasubramanian and Vogel, 2003), using climate formulas based on the aridity index to evaluate the sensitivity of surface runoff to climate changes (in 1337 basins in the United States).

In hydrologic applications, the spatial resolution of a given climate model plays a significant role in determining its impact on hydrologic systems. For this reason, in recent years, the use of RCMs has improved the spatial details of climate change projections obtained with global climate models (Déqué et al., 2005). The European PRUDENCE project (Christensen et al., 2007) provides high-resolution climate change scenarios with results that include the simulations of several RCMs for the projection of climate variables in current and future climate situations. However, despite the relatively high resolution of RCMs, hydrologic modelling generally requires information on a smaller scale than that provided by the typical RCM grid size (Hagemann and Gates, 2003). Thus one of the limiting factors regarding the use of information projected by RCMs (in hydrologic predictions) is the scale misalignment between the output of the climate models and the scale used by the hydrologic models (the river basin) (i.e. Lettenmaier et al., 1999; Bergström et al., 2001; Wood et al., 2002). Several studies have designed different downscaling techniques to overcome this deficiency, focusing their attention on temperature and precipitation variables because they are the key variables by which hydrologic models calculate surface runoff (i.e. Leung et al., 2003; Dibike and Coulibaly, 2005; Terink et al., 2010).

A broad range of downscaling techniques has been developed, including methods involving artificial neural networks (Hewitson and Crane, 1992), empirical regression methods (Von Storch et al., 1993) and methods based on linear interpolation, spatial desegregation and bias correction (Wood et al., 2004; Chen et al., 2011). For all of these, the general limitations are well documented in the existing literature (Wilby et al., 2004). However, many of these reports only evaluate the advantages and disadvantages associated with a specific method's use and do not give accurate information regarding the best method for evaluating the effects of climate change on hydrologic systems (Fowler et al., 2007). Therefore, using several methodological alternatives to downscale runoff output from RCMs in current climate conditions and comparing their results with respect to observed data may reveal the procedure that gives the best fit.

Another factor that limits the use of RCM output is its bias, which has to be eliminated before it can be used for other purposes (Christensen et al., 2008). In general, climate models' behaviour show less bias for precipitation and temperature than for surface runoff (Girorgi et al., 1994; González Zeas, 2010). Bias-correction techniques have been developed for precipitation and temperature variables used in hydrologic models (Piani et al., 2010a, b). Changes in specific statistical aspects, generally mean and variance values, of the simulated fields are used in the bias correction formulations, which are directly applied to current observations that are subsequently used to force the hydrologic models (Haerter et al., 2011). Many hydrologic models have been used to determine current surface runoff values from precipitation and temperature variables simulated by climate models (e.g. Leavesley et al., 2002; Döll et al., 2003). However, due to the limited availability of data and the lack of a correctly calibrated hydrologic model that allows surface runoff determination from basic climate variables (i.e. precipitation and temperature) when working on a large regional or continental scale, it is often difficult to generate surface runoff series that accurately represent the current conditions and, thus, can be successfully employed with water resources management models (Strzepek and Yates, 1997; Yates, 1997; Hagemann et al., 2004; Kirchner, 2006; Silberstein, 2006; Döll et al., 2008). For this reason it is important to evaluate which of the alternatives considered in this study minimise bias with respect to observed values.

The present study compares several interpolation procedures used to downscale the surface runoff variable by applying them to projections made via 10 RCM simulations from the PRUDENCE European project under current climate conditions. The capability of each method to reproduce the observed behaviour of this variable is emphasised. Conducted for 338 basins that cover the whole of mainland Spain, the study's main objective is to determine the accuracy of surface runoff output obtained from RCM simulations and to evaluate possible alternatives for generating monthly series that minimise bias with respect to the observed values. The specific objectives are as follows: (1) to determine the interpolation method that most closely approximates the

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observed values, (2) to evaluate to what extent the outputs of direct surface runoff from RCMs and climate formulas can be used for large-scale studies in the absence of correctly calibrated hydrologic models, (3) to validate the methods by comparing results to global runoff data provided by the UNH/GRDC and (4) to generate a monthly series that is representative of current conditions using a simple bias correction methodology based on the alternative that best reproduces the observed values.

## 2  Data

### 2.1  Area of study

The area of study is the mainland territory of Spain, which has an area of 504 782 km$^2$. The study considers 338 sub-basins, which are defined from points in the river network that are relevant to the management of water resources (MARM, 1998). Figure 1 shows the 338 elemental sub-basins. The basins on which this study has been performed were obtained by accumulating all the elemental sub-basins located upstream of the point being considered. Table 1 summarises the characteristics of the accumulated basins and classifies them by river basin districts (RBDs).

The basins studied are broadly variable in their size, with the largest being 84 923.85 km$^2$ (the basin of the Ebro RBD) and the smallest being 15.89 km$^2$ (in the North I RBD). The mean size of the basins is 4358.13 km$^2$, with a coefficient of variation of 1.89.

### 2.2  Observed surface runoff series

The hydrologic regimes of most rivers in Spain are strongly affected by water abstractions and flow regulations. Thus, data measured in the gauging stations cannot be directly compared to surface runoff in natural regime. Natural regime surface runoff data were obtained from the results of the Precipitation Runoff Integrated Model (SIMPA, by its Spanish acronym) (Estrela et al., 1996). This model is calibrated for the entire territory of Spain, enabling the monthly series of runoff in natural regime to be obtained

in a grid with a 1 km$^2$ resolution. Evaluation/comparisons of the climate models' results employed the monthly surface runoff series generated by the SIMPA model (labelled as observed data in this study) in each of the 338 elemental study basins for the period from 1961–1990.

## 2.3  Regional climate models

The present study utilises projections made by eight regional climate models presented in the European PRUDENCE project (Christensen et al., 2007) nested in a single global model, referred to as HadAM3H. The regional models give information relative to a large number of variables (temperature, precipitation, runoff, evaporation and solar radiation, among others) with daily, monthly and seasonal resolution for the periods from 1961–1990 (control period) and 2071–2100 (climate change scenario). The PRUDENCE project gives the values of the simulated climate variables, using the grid of each model's original coordinates (O), with a spatial resolution that varies between 25–50 km depending on the model, and in the unified coordinates CRU (Climate Research Unit) with a spatial resolution of $0.5° \times 0.5°$ (cells of approximately 50 km sides). The DMI model has 3 different simulations; thus, in total, this study has used data generated by 10 climate simulations of the PRUDENCE project.

## 3  Methodology

The methodology used herein consists of comparing the observed surface runoff series with the series downscaled from the results of the RCMs via different alternatives and analysing the results to select the most accurate procedure. Given that the SIMPA model has been specifically conceived and calibrated to generate monthly runoff series with high spatial resolution, its results should be more accurate than those produced by RCMs. The surface runoff layers generated by the UNH/GRDC, an additional global reference, are also considered because they specifically pertain to surface runoff with the same spatial resolution as generated by RCMs.

The runoff series in the basins were generated from the results of the RCMs of the PRUDENCE project using the following two procedures: (1) directly using the monthly runoff variables of the models and (2) using five climate formulas based on the aridity index. The average values of the basic variables in each basin (surface runoff, temperature, precipitation and solar radiation) were obtained using a spatial interpolation procedure in a grid with greater resolution than the simulations of the models, considering the outputs of the variables in original coordinates (O) of each model as well as the unified CRU coordinates. The following calculation procedures were used in each case: (1) direct method (D) and (2) interpolated method (I). Topologic analyses were performed on the elemental basins, and surface runoff values were obtained for the accumulated basins. The goodness of fit between the observed and generated annual runoff time series was evaluated using statistical indicators. Next, we determined and evaluated the alternative that best reproduced the observed values and that was, therefore, used to correct the bias and to generate the monthly surface runoff series at the hydrologic basin scale (which can be introduced in the water resources management models). As summarised in Fig. 2, the analysis process had the following steps: (1) interpolation of climate variables, (2) generation of surface runoff series for the basins studied, (3) generation of surface runoff series for the accumulated basins, (4) determination of the goodness of fit of the generated surface runoff series and (5) determination of the method and alternative that provided the best agreement with observed values and, thus, that was used to correct the bias of the monthly series simulated by the RCMs.

## 3.1 Interpolation methods

Four procedures were used to generate the basic series for the basins studied. The base was determined by the outputs of the 10 RCM simulations in the O coordinates of each model and in the common CRU coordinate system with a resolution of $0.5° \times 0.5°$. The behaviours of the two coordinate systems were evaluated because, although it is easier to work in the common system, the interpolation process that enables transition

to the unified CRU domain can alter the values of some variables, particularly in the coastal regions. In addition, errors introduced by the existence of different landscapes at specific points between the original grid and the regular 0.5° grid can be overlooked (Hagemann and Jacob, 2007).

In general, the spatial resolution of the cells of the RCMs is inadequate when working at the river basin scale. Given that the area of some sub-basins can be less than the area of the output grids of the RCMs, spatial disaggregation of the cells is necessary to achieve a finer scale that can take into account the smallest sub-basins. A 2.5 min size grid was used for the working scale. The outputs of the RCMs were translated to this grid with two interpolation methods: the D method and the I method. Figure 3 shows the scheme used; Fig. 3a shows the CRU grid superimposed on the elemental sub-basins of the analysis; Fig. 3b shows the application of the D method, in which the assumed value of the variable on the work grid is the nearest element of the grid RCM; Fig. 3c shows the application of the I method, in which the assumed value on the work grid is obtained from the values for the nine nearest points in the RCM grid through a weighted mean in which the weighting coefficient of each value is the inverse of the distance squared. A similar procedure is used with the output in O coordinates. Therefore, four interpolation methods are compared in this study: CRU-D, CRU-I, O-D and O-I.

## 3.2 Generated temporal surface runoff series

Using the four interpolation methods, mean annual surface runoff series were generated for the basins studied, considering the following alternatives: (1) the direct runoff of the 10 RCM simulations and (2) the mean annual surface runoff obtained via application of five functional forms based on the aridity index (Arora, 2002). In addition, the D and I procedures were applied to the surface runoff layers of the UNH/GRDC, a reference of the current global surface runoff (Fekete et al., 1999).

Arora (2002) showed that the use of functional forms based on the aridity index ($\phi$), defined as the relation between the potential evaporation (PET) and precipitation (P),

are a reasonable first-order approximation of the current evaporation (ET). Functional forms based on this index consist of formulas proposed by different authors (Schreiber, Ol'dekop, Buyko, Turc-Pike, and Zhang et al. (2001)(Table 2)) that allow calculation of the mean annual surface runoff values. These formulas determine the relation between the current evaporation (ET) and the precipitation ($P$) through the balance of water and energy.

The mean value of annual surface runoff ($R$) is obtained by the balance of water, as follows:

$$R = P - \text{ET} - \Delta S \text{ ,} \tag{1}$$

Assuming that $\Delta S$ (the change in moisture storage in soil) is very small over an annual time scale, the current evaporation (ET) can be calculated in each of the functional forms of Table 2 and substituted in Eq. (1), thereby yielding the value of the mean annual surface runoff as a function of the aridity index:

$$R = P(1 - F(\phi)) \text{ ,} \tag{2}$$

where $F(\phi)$ corresponds to each of the five functional forms used.

For calculation of the PET, the Hargreaves method is used (Hargreaves and Samani, 1982) as follows:

$$\text{PET} = 0.0023 \cdot (T_{\text{mean}} + 17.8) \cdot (T_{\text{max}} - T_{\text{min}})^{0.5} R_{\text{A}} \text{ ,} \tag{3}$$

where PET is the potential evaporation in mm, $R_{\text{A}}$ is the solar radiation in the upper part of the atmosphere in $\text{W m}^{-2}$, $T_{\text{mean}}$ is the mean temperature in °C, $T_{\text{max}}$ is the maximum temperature in °C and $T_{\text{min}}$ is the minimum temperature in °C.

Information regarding precipitation, temperature and solar radiation used for the calculation of the PET and the mean annual surface runoff is obtained from the outputs of the PRUDENCE RCM simulations. As a consequence, for each functional form of Table 2, 10 mean annual surface runoff values are generated, 1 for each simulation of the PRUDENCE project.

The UNH/GRDC dataset provides monthly climatological runoff fields, which are runoff outputs from a water balance model that is driven by observed meteorological data and then corrected with the runoff fields that are disaggregated from the observed river discharges at the main gauging stations in the world. The UNH/GRDC dataset preserves the accuracy of the observed discharge measurements and maintains the spatial and temporal distributions of the simulated surface runoff. Thus, because it provides the "best estimate" of surface runoff on a large scale (Fekete et al., 2002), the UNH/GRDC dataset has been used as a reference in the calibration and validation of different surface runoff models (e.g. SIMTOP, SIMGM) that use global and regional climate models (Wei et al., 2002; Niu et al., 2005; Sperna Weiland et al., 2012; Wisser et al., 2010). This study used the annual surface runoff layer of the UNH/GRDC dataset as a reference for the "best results" that can be obtained at the working scale of each RCM. The surface runoff layer of the UNH/GRDC dataset has the same resolution as the CRU grid.

A total of 60 mean annual surface runoff values for each interpolation method are generated as follows: 10 corresponding to the RCM simulations of the European PRU-DENCE project and 50 corresponding to the 5 climate formulas (10 for each functional form). In addition, two annual runoff series (D and I) are generated using the UNH/GRDC runoff fields. In total, 40 series of direct runoff are obtained, considering that four methods of interpolation are used, similarly 200 series are obtained for the five climatic formulas and 2 series for the UNH/GRDC dataset, since in this case only a single simulation is available and the outputs are only in CRU coordinate systems.

## 3.3 Criteria for comparison(s) of results

It is appropriate to evaluate/compare models, such as those used in this study, using quantitative indicators of goodness of fit (Legates and McCabe, 1999). Along these lines, analyses of the discrepancies between the output of the models and the observed values have been reported by several authors (Adam and Lettenmaier, 2003; Fekete and Vörösmarty, 2004). Thus, quantitative measurements were used to determine the

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agreement (goodness of fit) between the mean annual surface runoff observed and the simulated surface runoff determined by different interpolation methods, and the bias and the index of agreement proposed by Willmott (1981) were evaluated.

The bias reveals the model's tendency to overestimate or underestimate one variable and quantifies the systematic error of the model (Janssen, 1995). The bias can be determined from the mean error, which is normalised by the mean of the values observed for the group of 338 accumulated basins and for the different alternatives analysed, as follows:

$$\text{Bias} = \frac{\overline{S} - \overline{O}}{\overline{O}} , \tag{4}$$

where $\overline{S}$ and $\overline{O}$ represent the mean annual simulated and observed runoff for the group of basins studied, respectively.

In order to obtain a better measure of the relative agreement between simulations and observations, the index of agreement was also determined. The index of agreement is a measure of the mean relative error obtained by normalising the mean quadratic error with respect to the potential error, that represents the largest value that the squared difference of each pair can attain (sum of the absolute value of the difference between the predictions and the mean of the observations and the observations and the mean of the observations). As a dimensionless measure that can be used to compare models and that is broadly discussed in Willmont (1982, 1985), Hall (2001), Krause et al. (2005) and Moriasi et al. (2007), the index of agreement is expressed in the following manner:

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - \overline{O}| + |O_i - \overline{O}|)^2} , \tag{5}$$

where $S_i$ represents the simulated surface runoff in basin $i$, $O_i$ is the surface runoff observed in the basin $i$, $\overline{O}$ is the mean observed surface runoff, $n$ is the number of

basins studied and $d$ is the index of agreement (which varies between 0 (not a good adjustment) and 1 (perfect adjustment)).

## 3.4 Correction of the bias

Considering the lack of a correctly calibrated hydrologic model in large-scale studies, monthly surface runoff series are built from RCM simulations, using the alternative that best reproduces the observed values. The results are validated with information obtained from the UNH/GRDC dataset. It is well known that the output of the RCMs cannot be used directly if there is no procedure that eliminates the existing bias (Sharma et al., 2007). Studies conducted by Murphy (1999), Kidson and Thompson (1998) and Wilby et al. (2000) suggest the need to correct the bias in the outputs of the climate models to ensure accurate results in hydrology and water resources management applications. Different methodologies have been used to correct the bias. The simplest methodology uses changes in one specific statistical aspect, often the mean or the variance. This method is equivalent to correcting the observed series with a constant multiplying factor (e.g. Kleinn et al., 2005). More advanced bias-correcting methodologies, such as those developed by Schmidli et al. (2006) and Leander and Buishand (2007), correct the bias using more than one specific statistical aspect. Improvements in the simpler methods of bias correction have been obtained by fitting the probability density function to the histograms of the observed data (Piani et al., 2010a; Maraun et al., 2010). This study proposes a simple bias-correction methodology based on the determination of an annual correction factor, which is obtained using the alternative that minimises the bias and gives the surface runoff series that most closely agrees with observed values. Using the mean of the annual series as a representative statistical parameter, constant multiplying factors are determined that are then used to correct the monthly runoff time series directly simulated via RCMs. The corresponding corrected monthly runoff series are obtained as follows:

$$R_{\text{control,cor},i} = R_{\text{control},i} \cdot \left( \frac{R_{\text{alt}}}{R_{\text{control}}} \right) , \tag{6}$$

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where $R_{\text{control,cor},i}$ are the corrected monthly runoff series of the RCMs, $R_{\text{control},i}$ are the monthly runoff series of the RCMs, $R_{\text{alt}}$ is the mean annual runoff of the alternative that best approximates the observed values and $R_{\text{control}}$ is the mean annual runoff value of the RCMs.

5    In order to evaluate the performance of the results obtained for the corrected monthly surface runoff series, the Nash-Sutcliffe (NS) efficiency coefficient is used. NS is a dimensionless indicator widely used to evaluate the goodness of fit of the data (Nash and Sutcliffe, 1970). This coefficient represents the relative improvement of the simulated values with respect to the mean of the observed values and is expressed in the

10   following manner:

$$NS = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \ , \tag{7}$$

where $S_i$ and $O_i$ represent the simulated and observed values in month $i$ and $\overline{O}$ is the mean observed surface runoff. NS ranges from minus infinity (poor model) to 1 (perfect model).

15  ## 4   Results

### 4.1   Comparison of the interpolation methods

In this section, the interpolation method that generates a surface runoff series that most closely approximates the observed values is determined. Using the bias and the index of agreement, the relative errors of the mean annual runoff obtained by the

20   different alternatives was calculated for each interpolation procedure. The values of the indicators represent the behaviour of the group of the 338 basins of the study.

Figure 4 shows the cumulative probability of the bias and index of agreement of the CRU-D, CRU-I, O-D and O-I methods for 10 simulations of direct surface runoff and 5 climate formulas. In total, 60 values are presented for each interpolation method.

The cumulative probability of the bias curve, Fig. 4a, shows that the bias of the O-D method is less than those of all other methods, indicating that the O-D method tends to minimise errors with respect to observed values. Similarly, the results shown in Fig. 4b indicate that the cumulative probability of $d$ obtained with the O-D method is greater than that obtained by any other method, indicating a better adjustment.

Table 3 summarises the values of the indicators for the mean of the 10 RCM obtained for each alternative using each interpolation method. Once again, the best results are obtained with the O-D method, which outputs mean bias and $d$ values of −31 % and 0.840, respectively. However, the difference between the O-D method and other methods is not very marked; comparing the O-D method to the CRU-D, O-I and CRU-I methods, the error in the results decreases by only 2, 3 and 5 %, respectively.

Similar comparisons were made with the mean annual surface runoff values given by the UNH/GRDC dataset. For methods D and I, the results show an existing bias with respect to the observed values of −3 and −4 % and $d$ values of 0.959 and 0.957, respectively, indicating that method D gives the best results.

## 4.2 Evaluation of the annual surface runoff obtained by direct runoff from RCMs and climate formulas

In this section, the direct runoff values determined by the RCMs and the mean annual runoff obtained from five climate formulas are compared to determine if they can adequately represent the observed values of mean annual surface runoff. The results are also compared to the reference surface runoff values obtained from the UNH/GRDC dataset.

We have already determined that the O-D method is the method that minimises bias with respect to the observed values. Therefore, from this point on, we use the mean annual surface runoff results calculated with this procedure. Figure 5a,b show the fitting indicators of the direct surface runoff from RCMs, the runoff from the climate formulas of Schreiber, Ol'dekop, Budyko, Turc-Pike, Zhang et al. and the mean annual runoff in the UNH/GRDC dataset. Results are shown for all 10 RCM simulations. The fitting

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indicators show best behaviour for the UNH/GRDC dataset because the associated bias is minimum with a value of −3 % and the $d$ value is 0.959, which is greater than the $d$ values obtained with alternative approaches. The climate formulas behave better with regard to the direct runoff of the RCMs. Compared to the rest of the functional forms, Schreiber's formula performs better with regard to all RCMs simulations studied. The formula from Zhang et al. shows similar results, although they are slightly less accurate than the ones obtained with Schreiber's formula. Using the formulas of Budyko and Turc-Pike similar results are generated, and results using Ol'dekop's formula show the poorest agreement of all the functional forms. Despite demonstrating the least favourable overall results, comparisons with direct surface runoff demonstrate better agreements than Schreiber's formula for the GKSS, SMHI and UCM models. The bias obtained for the direct surface runoff is −35 % for the mean of the 10 RCMs, while that obtained for Schreiber's formula is −20 %.

Some of the 10 RCMs obviously provide better results than others. With regard to Schreiber's formula, the best performing model is DMI.3, which has a bias of −8 % and a $d$ value of 0.955. Regarding direct surface runoff, the GKSS model performs best with bias and $d$ values of 8 % and 0.940, respectively. With all alternatives investigated, the ETH model had the greatest errors when compared to the observed surface runoff in the basins of Spain.

Therefore, Schreiber's formula and the DMI.3 model produce the best fit with observed values. Compared to the UNH/GRDC dataset, the error in the results is on the order of −5 %.

## 4.3 Corrected monthly series

Considering that the monthly series determined via direct runoff from RCMs cannot be directly introduced into the management models of water resources due to their inherent bias and that Schreiber's formula gives only annual values of surface runoff in the basins studied, this section generates corrected monthly time series from simulations obtained using RCMs. These series are generated using annual correction

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factors calculated based on the methodology that most approximates the observed values. The results are compared with the monthly time series that are corrected with the annual values given by the global runoff reference of the UNH/GRDC dataset.

So as to compare the corrected monthly distributions with respect to observed and direct runoff, Fig. 6 illustrates the cumulative probability of the monthly runoff obtained by ordering from lowest to highest value of every month of the entire period of analysis (1961–1990). The results in the figure highlight the overall behaviour of the 10 RCM simulations for the entire territory of mainland Spain and its most important RBDs (Duero, Ebro, Tagus, Guadiana I and Guadalquivir). The direct runoff values are significantly lower than the observed data whereas the corrected values are much closer. As seen from this figure, some RBDs show better matches than others with respect to monthly observed runoff. However, the proposed methodology gives reasonable results and similar to the observed data.

In addition, Fig. 7 shows the mean monthly surface runoff values in Spain for each of the 10 RCM simulations utilised in this study. The observed runoff values are compared to runoff corrected by Schreiber's formula for the DMI.3 RCM simulation, the runoff corrected by UNH/GRDC dataset and direct runoff from RCMs. The monthly values in the figure represent the 30-yr mean behaviour (1961–1990). Generally, the corrected RCM series adequately represent the predominant seasonal cycle in the observed series. Nonetheless, there are certain seasonal discrepancies that vary from one model to another. The GKSS, SMHI and UCM models more adequately represent the observed seasonal cycle. The DMI.1, DMI.2, DMI.3, KNMI and MPI models tend to underestimate the observed values during autumn and winter, and the ICTP and ETH models underestimate the values in winter and spring.

Because we are interested in evaluating the extent to which the bias correction process represents the temporal behaviour of the observed series, a statistic indicator was used to inform us about the efficiency of the results. According to the monthly distribution of runoff in Spain for the mean of the 10 RCMs (see Fig. 6), the NS efficiency coefficient of the direct surface runoff is 0.43, whereas for the monthly series

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corrected by the UNH/GRDC dataset, the value of NS is 0.96 and for the monthly series corrected with Schreiber's formula, the NS value is 0.93. The efficiency indicator values show that the results significantly improve with the corrected series. The fit obtained using Schreiber's formula is lower than that obtained using the global surface
5   runoff from the UNH/GRDC dataset; however, the differences in their results are not very marked.

    Figure 8 summarises the NS efficiency coefficients obtained as a result of the comparison between the monthly distribution series (direct runoff and bias corrected runoff with UNH/GRDC dataset and Schreiber's formula) with respect to monthly distribution
10   series of the observed values (see Fig. 6) for the 14 RBDs of Spain and for all of the mainland territory. The values shown are the means of the 10 simulations of the RCMs. The negative values of NS indicate the minimal capacity of the simulations to reproduce the observed series. In all the RBDs, direct surface runoff is characterised by presenting the most unfavourable NS values. A clear improvement in the NS values
15   is observed for the corrected series; nonetheless, the efficiency in the results varies spatially and depends on the correction method used. In the case of mainland Spain and the North I, North III, Duero, Tagus, Guadiana I and Guadalquivir RBDs, the series corrected with the UNH/GRDC dataset provide the best results. On the other hand, the series corrected by Schreiber's formula give better results in the North II, Galicia
20   Coast, Ebro, Internal Basins of Catalunya, Jucar and Segura RBDs. The results show negative NS values for both the direct series and the corrected series in the South and Guadiana II RBDs.

## 5   Discussion and conclusions

This study explores different alternatives that utilise RCM simulations to generate sur-
25   face runoff time series that approximate observed values and that comprise the basis for generating a design series that, when introduced into management models, will allow us to evaluate the impacts on water availability under future scenarios of climate

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change. Considering the absence of a correctly calibrated hydrologic model when working on a large scale, this study analysed four interpolation procedures for downscaling surface runoff at the river basin scale. Different alternatives were also considered, particularly with regard to the measure to which each of them approximates the observed values.

Using fit capability indicators, the behaviour of the group of Spanish basins was evaluated using four interpolation procedures: CRU-D, CRU-I, O-D and O-I. The cumulative probability curves (for the bias and the index of agreement values) show that the O-D method minimises deviation with respect to the observed values. This result indicates that the O-D method is the best procedure to determine the runoff series for a given river basin using RCM outputs. It is easiest to determine the values of the variables in each basin based on the influence of the nearest point in the grid that corresponds to the climate model simulation. Similar results were obtained for the runoff series generated by the climate formulas and the UNH/GRDC dataset. Others studies (for example, Wood et al., 2004) have also used spatial desegregation techniques on RCM outputs. However, without an additional bias-correction step, they were determined to not be very useful for hydrologic and management purposes, in agreement with the results of the present study.

Once the O-D method was established as the best spatial disaggregation process at the river basin scale, different alternatives were compared to determine which of them gives the best approximation to the observed values of mean annual runoff. These alternative methods were evaluated by comparing the direct runoff simulated by the RCMs and the mean annual runoff calculated with climate formulas. The results were contrasted with the surface runoff given by the UNH/GRDC dataset. The statistical indicators applied show that climate formulas based on the aridity index approximate better the observed values than direct runoff obtained from RCM simulations. It was expected that climate formulas would give better results than those obtained with direct runoff because climate formulas use precipitation and temperature variables to determine mean annual surface runoff values and because the uncertainties associated with

climate-model simulations present less bias for precipitation and temperature than for surface runoff. Other studies (e.g. Sankarasubramanian and Vogel, 2002; Arora, 2002; Potter and Zhang, 2009; McMahon et al., 2011) have also satisfactorily evaluated surface runoff using the formulas proposed by Schreiber, Ol'dekop, Budyko, Turc-Pike and

⁵ Zhang et al. Of the five functional forms of the aridity index, Schreiber's formula generates mean annual surface runoff values that minimise error compared to observed data. The least favourable results were obtained with the direct surface runoff method, with the exception of the GKSS, SMHI and UCM models, whose goodness-of-fit indicators show superior behaviour compared to results obtained with Schreiber's formula. In ad-

¹⁰ dition, the UNH/GRDC values show better agreement with observed values compared to results obtained with climate formulas and direct runoff. This result confirms that, as established by Fekete et al. (2002), the combination of a water balance model and contributions of the main hydrologic stations of the world can generate mean annual runoff fields that are consistent with observed values, preserving the spatial accuracy

¹⁵ for large-scale domains. Comparison of climate formulas and direct runoff reveals that, despite the fact that they were not based on a model specifically conceived for the study of surface runoff, Schreiber's formula applied to the DMI.3 model presents results similar to those obtained with the UNH/GRDC dataset. Similarly, Vogel et al. (1999) and Sankarasubramanian and Vogel (2003) determined that, on a large scale and without

²⁰ requiring the assumption of a model or a calibration strategy, the use of non-parametric estimators, such as those based on the aridity index to determine surface runoff, give results that are comparable to those obtained with a basin model.

Monthly and annual runoff corrected variables were quantitatively similar to observed data. However, some RBD show a poor adjustment in the monthly distribution cor-

²⁵ rected by Schreiber, in spite of the fact that Schreiber formula is a highly approximate annual model of runoff. For example, the Guadalquivir RBD (see Fig. 6) may appear not to reflect true current conditions, this may be the case where seasonal rainfall distribution plays an important role in runoff formation. Evaluation of the monthly surface runoff series simulated by the RCMs and corrected with the UNH/GRDC dataset

and Schreiber's formula applied to the DMI.3 model (for the mean of 30 yr in mainland Spain) has demonstrated a greater accuracy in matching the observations using the annual correction factor based on UNH/GRDC dataset. Thus, for the control scenario, the best alternative for correcting the monthly runoff series simulated by RCMs is to use the global surface runoff information given by the UNH/GRDC dataset. However, it is also worth mentioning that the series corrected with Schreiber's formula give good values for the NS coefficient and do not differ significantly from the UNH/GRDC results obtained for mainland Spain. In some cases, the former alternative actually shows improved performance when the behaviour is evaluated at the RBD level. It is noteworthy that, when working with accumulated basins, some errors of upstream basins can be compensated for downstream basins. The NS efficiency coefficients in Fig. 8 show different behaviours for the different RBDs. Thus, the RBDs that belong to the Cantabrian, Pyrenees and Mediterranean slopes (North II, Galicia, Ebro, Internal Basins of Catalunya, Segura and Jucar) show more accurate results when the bias is corrected with Schreiber's formula. However, the RBDs that belong to the Atlantic slope (Duero, Tagus, Guadiana and Guadalquivir) show more satisfactory results when the bias is corrected with the UNH/GRDC dataset. As a consequence, both the UNH/GRDC dataset and Schreiber's formula can be used to correct the bias of the direct surface runoff simulations that utilise RCMs. The existing literature contains several studies that focus on bias correction of the temperature and precipitation variables, the results of which are then used in the hydrologic models to determine surface runoff values (e.g. Fujihara et al., 2008; Piani et al., 2010b). However, this study underscores the importance of correcting the bias of the direct surface runoff simulated by RCMs, suggesting that the accuracy of the results of the corrected monthly series may be comparable to those obtained by other studies (i.e. Hay et al., 2002, 2003).

A shortcoming of annual models such as the formulas based on the aridity index described here is the inability to track changes in soil moisture and the loss of important seasonal variability which exists in many regions. Because the corrected monthly surface runoff series are obtained from direct runoff in RCM simulations, the monthly,

seasonal and year-to-year variability in the current climate situation will depend on the characteristics of each RCM. The results depicted in Fig. 7 show a general trend toward accurate representation of the observed seasonal cycles. However, the results differ from one climate model to another. The GKSS model best represents the observed seasonal cycles for mainland Spain.

Fekete et al. (1999) showed that working with a spatial resolution of $0.5° \times 0.5°$ provides more accurate results in basins with areas greater than $25\,000\,\mathrm{km}^2$. In fact, RBDs with smaller areas, like South and Guadiana II, give less accurate results. Thus, it is important to consider the effects of the study area on the accuracy of the results. Although this particular observation was not an intended objective of this study, it will be kept in mind for future research. In addition, the results from Hagemann and Jacob (2007) indicate that the accuracy of RCM results is different in different basins.

Despite the fact that RCM-generation of surface runoff uses simple simulation methods and is not necessarily designed to calculate the stream flow values with the accuracy of a hydrologic model, results obtained by this method reflect the general trends of water balance. In addition, the errors that can exist can be directly linked to errors within the variables related to the hydrologic cycle, which are errors that cannot be eliminated even by the most sophisticated hydrologic models.

In conclusion, monthly series that are representative of the present conditions are generated using direct surface runoff outputs from RCMs calculated with the O-D interpolation method and bias-corrected with annual factors given by the alternatives most closely approximated to the observed values (UNH/GRDC dataset and Schreiber's climate formula).

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**Table 1.** Characteristics of the basins used in this study by river basin district.

| River basin district | Code | Number of basins | Maximum area (km$^2$) | Minimum area (km$^2$) | Mean area (km$^2$) | Coefficient of variation |
|---|---|---|---|---|---|---|
| North I | NorI | 15 | 16 320.85 | 15.89 | 2295.24 | 1.86 |
| North II | NorII | 20 | 13 888.75 | 31.36 | 1468.41 | 2.04 |
| North III | NorIII | 13 | 4463.18 | 31.31 | 737.24 | 1.57 |
| Galicia Coast | Gal | 20 | 8599.34 | 31.09 | 786.69 | 2.38 |
| Ebro | Ebr | 48 | 84 923.85 | 31.42 | 6186.81 | 2.56 |
| Catalunya | Cat | 16 | 12 458.64 | 32.32 | 1931.93 | 1.53 |
| South | Sou | 20 | 9973.39 | 68.70 | 980.90 | 2.22 |
| Segura | Seg | 9 | 15 752.37 | 738.34 | 5494.19 | 1.09 |
| Jucar | Juc | 17 | 35 912.64 | 50.25 | 7586.91 | 1.28 |
| Duero | Due | 33 | 75 544.62 | 63.08 | 8693.35 | 2.37 |
| Tagus | Taj | 39 | 55 758.17 | 16.25 | 6587.23 | 2.18 |
| Guadiana I | GnaI | 23 | 54 395.58 | 99.70 | 9806.86 | 1.68 |
| Guadiana II | GnaII | 9 | 63 03.90 | 101.81 | 1253.73 | 1.61 |
| Guadalquivir | Gqv | 56 | 60 939.80 | 34.19 | 7204.32 | 2.11 |
| Total | | 338 | 84 923.85 | 15.89 | 4358.13 | 1.89 |

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**Table 2.** Functional forms F($\phi$) used to calculate the evaporation ratio.

| Functional form | Evaporation ratio |
|---|---|
| Schreiber (1904) | $\dfrac{ET}{P} = 1 - e^{-\phi}$ |
| Ol'dekop (1911) | $\dfrac{ET}{P} = \phi \tanh\left(\dfrac{1}{\phi}\right)$ |
| Budyko (1948) | $\dfrac{ET}{P} = \left[\phi \tanh\left(\dfrac{1}{\phi}\right)\left(1 - e^{-\phi}\right)\right]^{1/2}$ |
| Turc (1954)-Pike (1964) | $\dfrac{ET}{P} = \dfrac{1}{\sqrt{0.9 + \left(\dfrac{1}{\phi}\right)^2}}$ |
| Zhang et al. (2001) | $\dfrac{ET}{P} = \dfrac{1 + w\phi}{1 + w\phi + \dfrac{1}{\phi}}$ |

$w$ – coefficient that depends on the kind of vegetation.

**Table 3.** Mean values of the bias and the index of agreement of the annual mean surface runoff obtained with the 10 RCMs for each interpolation method and for the different alternatives considered.

| Alternatives | Bias (%) | | | | Index of agreement ($d$) | | | |
|---|---|---|---|---|---|---|---|---|
| | CRU-D | CRU-I | O-D | O-I | CRU-D | CRU-I | O-D | O-I |
| Direct Runoff | −36 | −38 | −35 | −37 | 0.761 | 0.746 | 0.779 | 0.762 |
| Schreiber | −23 | −25 | −20 | −23 | 0.867 | 0.855 | 0.883 | 0.867 |
| Ol'dekop | −47 | −49 | −44 | −47 | 0.775 | 0.756 | 0.804 | 0.775 |
| Budyko | −34 | −37 | −32 | −35 | 0.830 | 0.815 | 0.852 | 0.830 |
| Turc-Pike | −36 | −38 | −33 | −36 | 0.823 | 0.808 | 0.846 | 0.823 |
| Zhang et al. | −25 | −27 | −22 | −25 | 0.857 | 0.845 | 0.874 | 0.857 |
| Mean | −33 | −36 | **−31** | −34 | 0.819 | 0.804 | **0.840** | 0.819 |
| UNH/GRDC | **−3** | −4 | | | **0.959** | 0.957 | | |
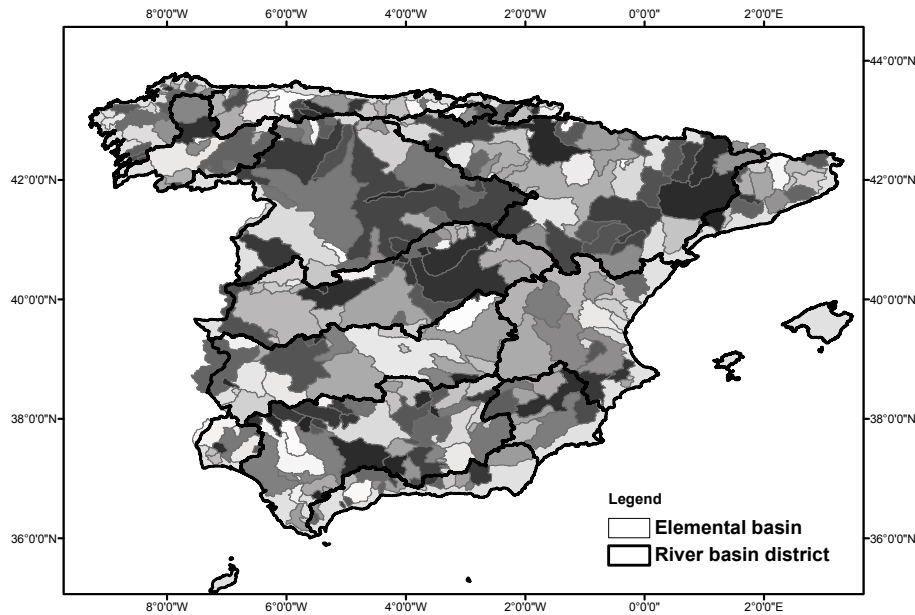
**Fig. 1.** Elemental basins of study. The methods used in this study were applied to the accumulated basins below, including all the sub-basins upstream of the point being considered.
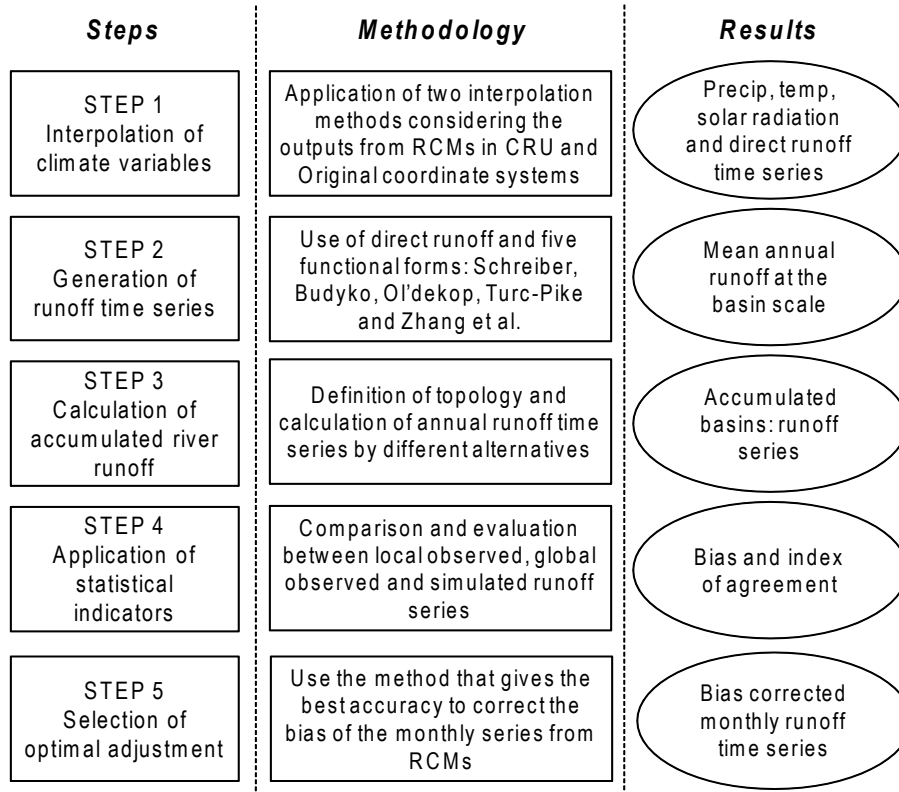
**Fig. 2.** Scheme of the analysis methodology.

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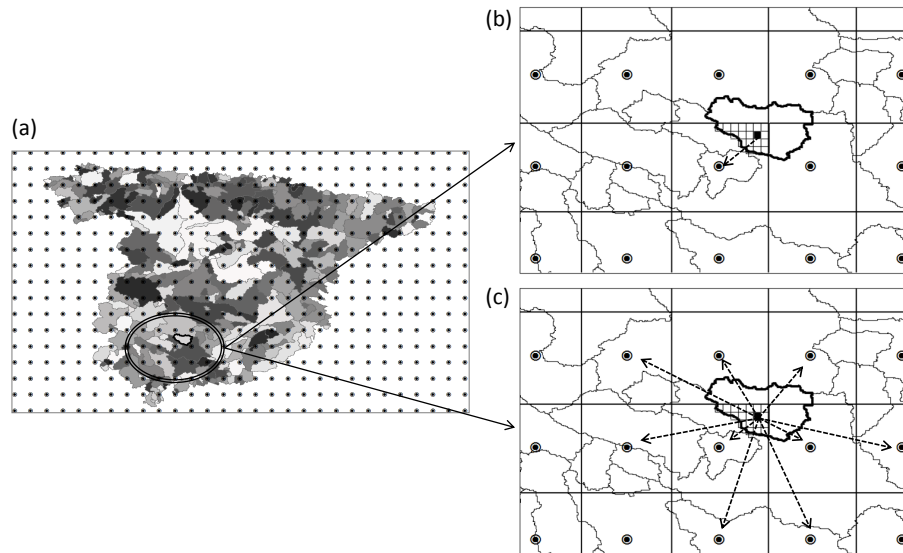
**Fig. 3.** Interpolation methods: **(a)** CRU domain of the RCMs, **(b)** direct method (D) and **(c)** interpolated method (I). A similar procedure was used with the RCM outputs in original coordinates.
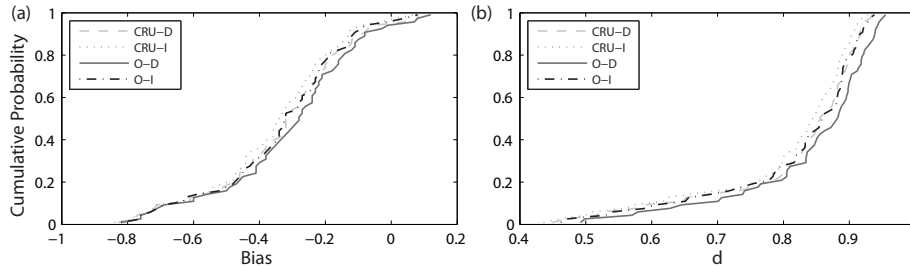
**Fig. 4.** Cumulative probability of the 60 values that correspond to all of the alternatives analysed for each interpolation method: **(a)** bias and **(b)** index of agreement.
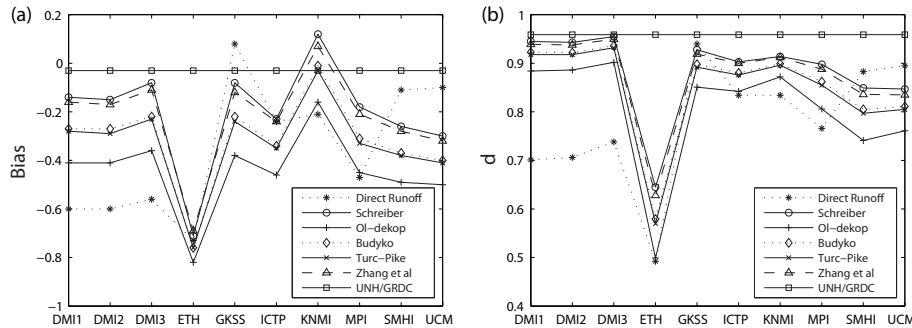
**Fig. 5.** Goodness of fit indicators obtained for the direct surface runoff, the five functional forms (Schreiber, Ol'dekop, Budyko, Turc-Pike and Zhang et al.) for the 10 RCM simulations and for the UNH/GRDC dataset: **(a)** bias, **(b)** index of agreement.
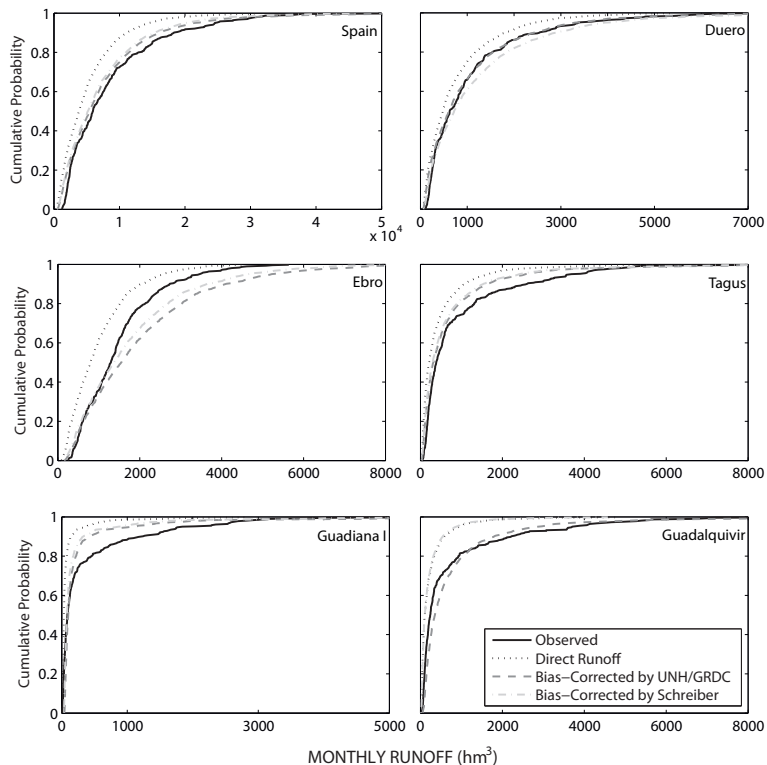
**Fig. 6.** Monthly distribution of runoff in Spain and its most important river basin districts (Duero, Ebro, Tagus, Guadiana I and Guadalquivir). The figures show the cumulative probability of the mean runoff of every month of the entire period of analysis (1961–1990). The comparison is made among the observed data, direct runoff, bias corrected runoff by UNH/GRDC dataset and bias corrected runoff by Schreiber. The monthly distributions of runoff represent the behaviour of the mean of the 10 RCM simulations.

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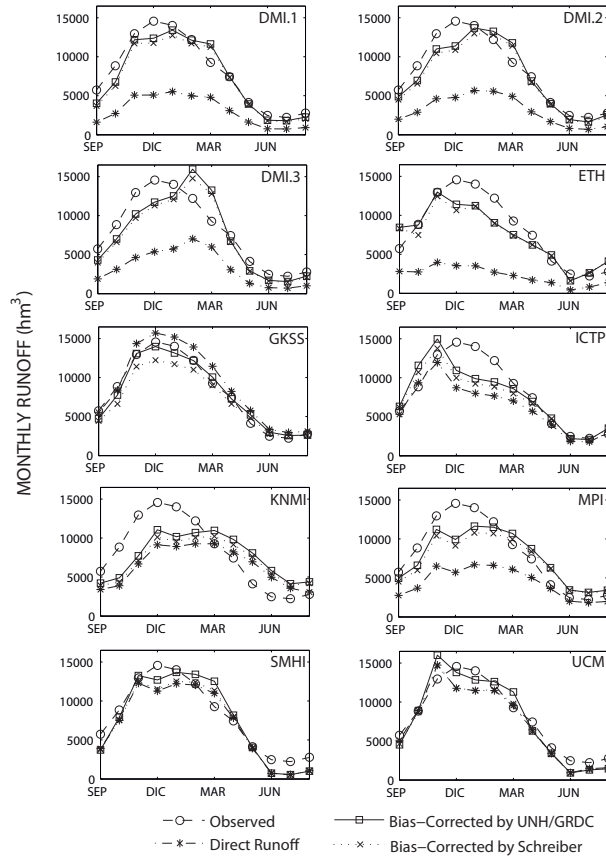Printer-friendly Version

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**Fig. 7.** Comparison of mean monthly runoff in mainland Spain for the 10 RCM simulations obtained from observed values, direct runoff, bias-corrected by UNH/GRD dataset and bias-corrected by Schreiber's formula (mean of period 1961–1990).

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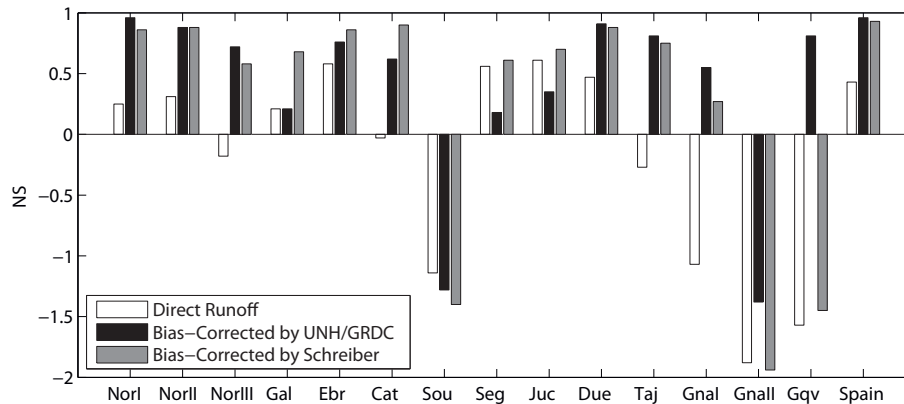Printer-friendly Version

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**Fig. 8.** Nash-Sutcliffe (NS) efficiency coefficients of the monthly series of direct and corrected surface runoff for Spain and its 14 river basin districts. The river basin district code is defined in Table 1.