

1 *Proceeding Paper*

2 **Selection of bias correction methods to assess the** 3 **impact of climate change on flood frequency curves**

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5 Received: date; Accepted: date; Published: date

6 Academic Editor: name

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10 **Abstract:**

11 Annual maximum daily rainfalls will change in the future because of climate change, according to
12 climate projections provided by EURO-CORDEX. This study aims at understanding how the
13 expected changes in precipitation extremes will affect the flood behavior in the future. Hydrological
14 modelling is required to characterize the rainfall-runoff process adequately in a changing climate to
15 estimate flood changes. Precipitation and temperature projections given by climate models in the
16 control period usually do not fit exactly the observations in the same period from a statistical point
17 of view. To correct such errors, bias correction methods are used. This paper aims at finding the
18 most adequate bias correction method for both temperature and precipitation projections,
19 minimising the errors between observed and simulated precipitation and flood frequency curves.
20 Four catchments located in central western Spain have been selected as case studies. The HBV
21 hydrological model has been calibrated, using the observed precipitation, temperature and
22 streamflow data available at a daily scale. Expected changes in precipitation extremes are usually
23 smoothed by the reduction of soil moisture content due to expected increases in temperatures and
24 decreases in mean annual precipitation. Consequently, rainfall is the most significant input to the
25 model and polynomial quantile mapping is the best bias correction method.

26 **Keywords:** Bias Correction; Quantile Mapping; Climate Change; Floods; CORDEX

27 **PACS:** J0101

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29 **1. Introduction**

30 Climate change is a reality and affects the most dangerous natural hazard in Europe, floods.
31 Because of that, several studies and models have been developed to try to prevent their damages. In
32 Spain, there are two sources of climate projections under climate change supplied by AEMET
33 ('Agencia Estatal de Meteorología', in Spanish) and CORDEX. [1] found that AEMET projections do
34 not characterise adequately extreme events. Consequently, in this study climate projections supplied
35 by EURO-CORDEX are used. These climate projections denote that annual maximum daily rainfall
36 quantiles will increase in some parts of Spain. Temperature and precipitation time series are the input
37 data of the HBV model, calibrated with the methodology proposed [2].

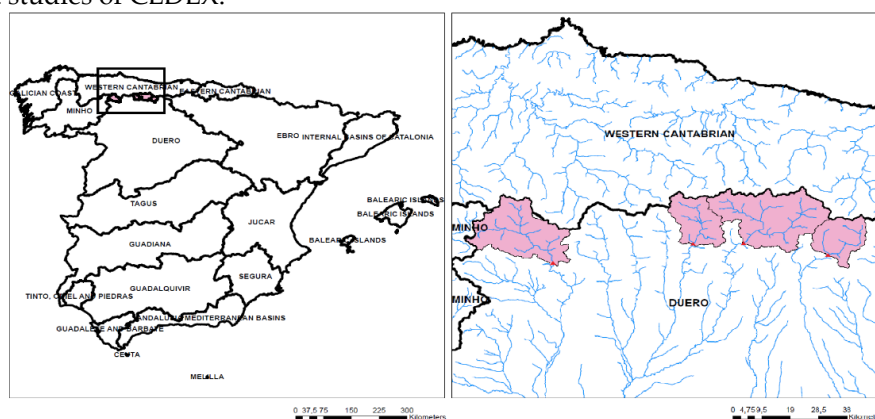
38 GCM have limited capacity to capture climatic variations at catchment scale. Therefore, the
39 mismatch between general and regional climate models needs to be corrected [3]. In addition, inputs
40 to obtain simulated floods used to design spillways need to be the most similar to observations, in
41 order to obtain accurate predictions in the future. Consequently, bias correction methods will be
42 applied to both temperature and precipitation time series.

43 2. Methods

44 The methodology consists of the following steps: (i) calibration of the HBV model to adequately
 45 characterize the rainfall-runoff processes in a changing climate; (ii) selection of the best bias correction
 46 method for precipitation and temperature time series, and (iii) assess the expected changes in flood
 47 quantiles in the future caused by climate change. A GEV distribution has been used to obtain flood
 48 quantiles for a set of return periods.

49 2.1. Study area and data

50 Four catchments have been selected as case studies. They are located in the Douro river basin, in the
 51 northwest part of Spain (Figure 1). A dam is located at the outlet of each catchment. Consequently,
 52 observed data of inflow discharges are not recorded directly, but they can be estimated from
 53 observations of mean daily reservoir water levels and dam releases, collected by the Centre for
 54 Hydrographic studies of CEDEX.



55
 56 **Figure 1.** (a) Location of the case studies in Spain; (b) Catchments of the four case studies.

57 Time series of daily observations of rainfall and temperature were supplied by the AEMET. Gaps
 58 in time series were filled by using observations at nearby gauging stations.

59 Climate change projections provided by 12 regional climate models of the EURO-CORDEX
 60 programme have been used (Table 1). Such projections are composed of daily rainfall and
 61 temperature time series with a spatial distribution through a grid with cells of 0.11°. The same control
 62 period (1971-2004, hydrological years) and future period under climate change (2011-2094,
 63 hydrological years) have been considered for all the climate models. The two representative
 64 concentration pathways (RCP) considered by the models, RCP 4.5 and 8.5, have been used.

65 **Table 1.** Regional Climate Models used

Acronym	CGM	RCM
ICH-CCL	ICHEC-EC-EARTH	CCLM4-8-17
MPI-CCL	MPI-ESM-LR	CCLM4-8-17
MOH-RAC	MOHC-HadGEM2-ES	RACMO22E
CNR-CCL	CNRM-CMS	CCLM4-8-17
ICH-RAC	ICHEC-EC-EARTH	RACMO22E
MOH-CCL	MOHC-HadGEM2-ES	CCLM4-8-17
IPS-WRF	IPSL-CMSA-MR	WRF331F
IPS-RCA	IPSL-CM5A-MR	RCA4
MOH-RCA	MOHC-HadGEM2-ES	RCA4
ICH-RCA	ICHEC-EC-EARTH	RCA4
CNR-RCA	CNRM-CM5	RCA4
MPI-RCA	MPI-ESM-LR	RCA4

66 2.2. HBV model and calibration

67 The hydrological response in the four catchments has been simulated with the HBV rainfall-
68 runoff model [4]. Specifically, the HVB-light-GUI 4.0.0.7 version has been used. The model
69 parameters have been calibrated using Monte Carlo simulations and GAP optimization. Both tools
70 are integrated in the HBV software.

71 Model parameters have been calibrated using the goodness of fit function 'Reff' integrated in
72 the HBV software, which compares the prediction supplied by the model with the simplest possible
73 prediction, a constant value equal to the mean value of observations over the entire period. (Eq. 1).

$$R_{eff} = 1 - \frac{\sum(Q_{sim}(t) - Q_{obs}(t))^2}{\sum(Q_{obs}(t) - \bar{Q}_{obs})^2} \quad (1)$$

74 where $Q_{sim}(t)$ is the simulated discharge at time step t , $Q_{obs}(t)$ is the observed discharge at time
75 step t and \bar{Q}_{obs} is the mean value of discharge observations.

76 A sensitivity analysis with 1,000,000 Monte Carlo simulations has been done as has identified the
77 most important parameters in the four catchments: FC, PERC, K0 and K1. FC is the maximum soil
78 moisture storage. PERC, K0 and K1 are associated with soil infiltration represented by the model with
79 three boxes. As expected, the snow routine is not important in the case studies.

80 Flood quantiles have been calculated by fitting a Generalized Extreme Value (GEV) distribution
81 to the annual maximum flows simulated by the model. Flood quantiles obtained by simulation have
82 been compared with flood quantiles obtained from observed data, for a set of return periods. An
83 iteration process has been used, prioritizing the similarity in the simulation of extreme values,
84 because the results of the study will be applied to dam design.

85 2.3. Bias Correction

86 Precipitation and temperature projections supplied by climate models in the control period
87 usually do not fit exactly the observations in the same period from a statistical point of view. Such
88 errors could affect simulated flows in the future period. First, temperature and precipitation have
89 been corrected separately. Second, temperature and precipitation correction techniques are combined
90 to identify the best bias correction methodology. Quantile mapping techniques have been
91 used: QM linear transformation and QM power transformation [5,6] for precipitation series and
92 simple seasonal bias correction for temperature series [6].

93 3. Results and Discussion

94 The best bias correction method has been identified for: (i) temperature projections, in terms of
95 monthly averages; (ii) extreme precipitation in climate projections, in terms of frequency curves for
96 annual maximum series; and (iii) extreme simulated discharges.

97 3.1. Temperature Correction

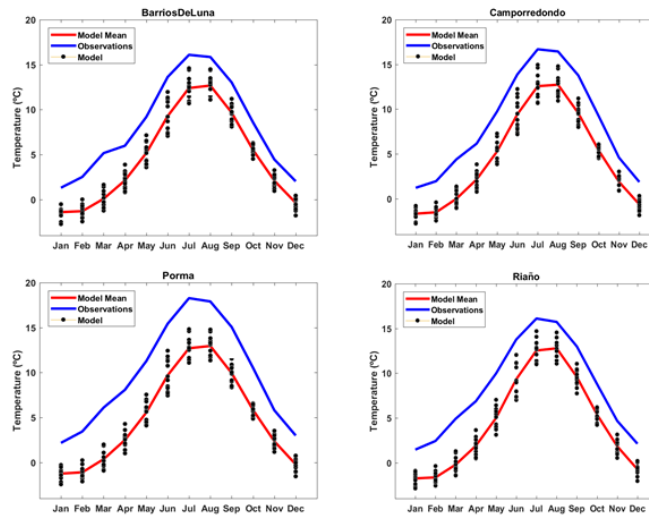
98 In the four catchments, monthly mean temperatures supplied by climate models are significantly
99 lower than observations. The difference between monthly temperatures supplied by each climate
100 model and observations has been added to the temperature time series in each month to correct the
101 bias. [6] (Figure 2).

102 3.2. Precipitation Correction

103 Climate models supply differing precipitation magnitudes in the control period compared to
104 observations. In the Barrios de Luna catchment, climate models supply larger extreme precipitations
105 than observations. However, in the other three catchments, climate models supply lower
106 precipitations.

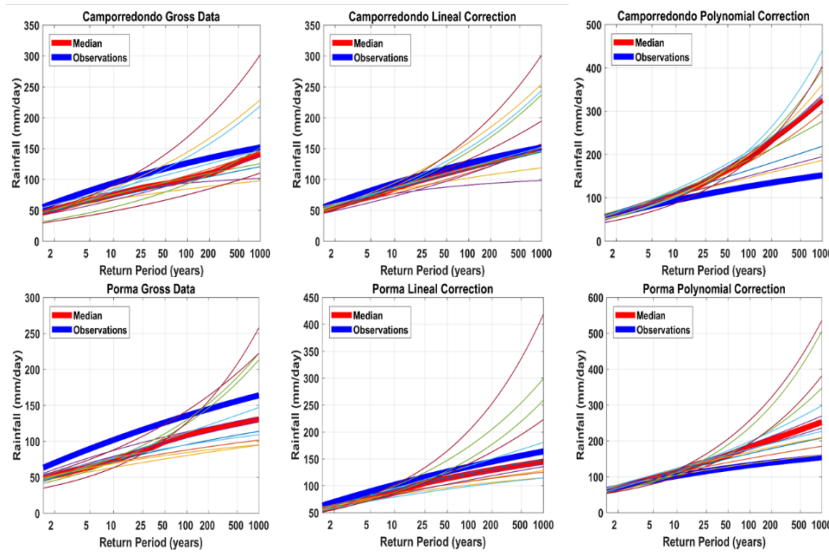
107 A set of methods have been considered to correct the errors [6]. In this paper, the Quantile
108 mapping technique has been used, consisting of fitting a function to the comparison between data

109 supplied by the models and observations. Linear and polynomial functions have been considered.
 110 The fitted function is used to correct both the control and future data.



111
 112 **Figure 2.** Comparison between monthly mean temperatures supplied by climate models and
 113 observations in the control period. Blue lines are observations. Red lines represent the median of the
 114 12 climate models considered.

115 Results obtained after correcting bias by the lineal and polynomial techniques show smaller
 116 errors than in the case of raw precipitation data. For precipitation frequency curves, the linear
 117 correction is the best bias corection method.



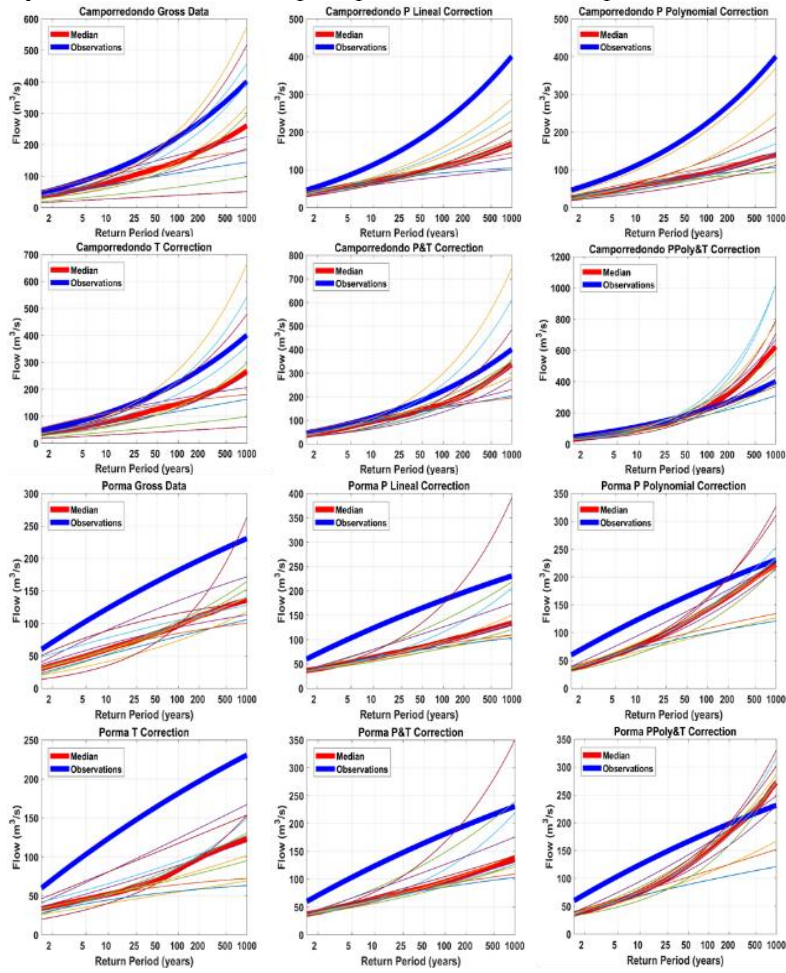
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 120
 121 **Figure 3.** Frecuency curves of annual maximum daily precipitation in two catchments
 122 (Camporredondo and Porma). Blue lines are observations. Red lines represent the median of the 12
 123 climate models considered. The first column shows raw precipitation supplied by climate models.
 124 The second column, lineal bias correction. The third, polynomial bias correction. Each row shows a
 125 case study.

126 **3.3. Flood frequency curves in the control period**

127 Simulations of the HBV model have been conducted with a set of combinations of raw and bias
 128 corrected temperature and precipitation time series as input data, in order to compare the bias
 129 correction techniques. The best bias correction technique is identified in terms of the smallest errors
 130 with the flood frequency curve estimated with observations. The higher return periods have been
 131 considered due to its importance in dam design. In general, the smallest errors are obtained with the

132 polynomial bias correction technique. In particular, the methodologies with the smallest absolute
 133 error for higher return periods are: raw temperature and precipitation supplied by climate models in
 134 Barrios de Luna; lineal correction for precipitation and mean monthly temperature correction in
 135 Camporredondo; polynomial correction for precipitation and mean monthly temperature correction
 136 in Porma; and polynomial correction for precipitation and raw temperature in Riaño.

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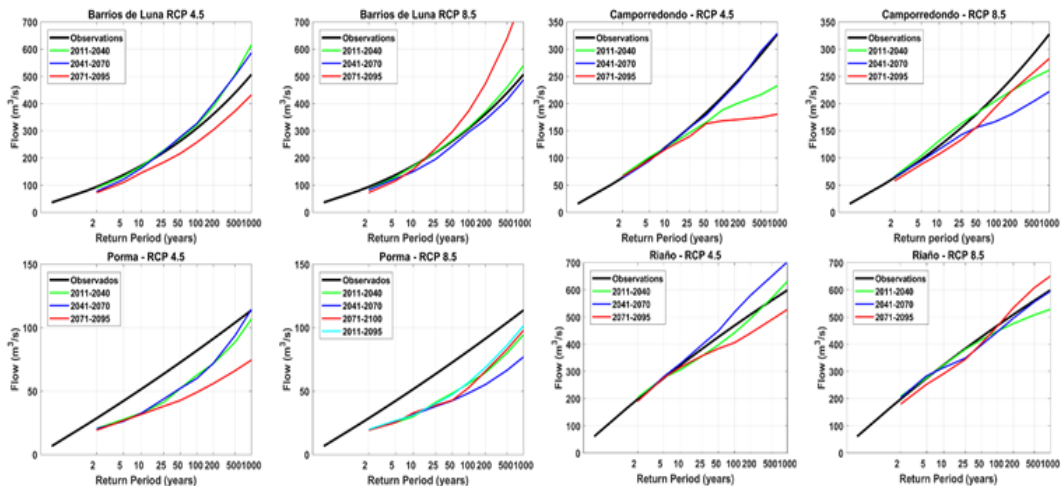


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139 **Figure 4.** Comparison between flood frequency curves with observations and HBV simulations using a set of
 140 combinations of bias correction techniques in two catchments (Camporredondo and Porma). Blue lines are
 141 observations. Red lines represent the median of the 12 climate models considered.

142

3.2. Flood frequency curves in the future period



143

144 **Figure 5.** Flood frequency curves in the future period (2011-2095) with the best bias correction
 145 techniques referred to in the previous section.

146 Finally, precipitation and temperature projections in the future (2011-2095) have been obtained
147 in each catchment with the best bias correction techniques identified in the previous step, Simulations
148 with the HBV model show that, in general, flood frequency curves decrease in the future, though an
149 increase can be seen in some cases.

150 4. Conclusions

151 Temperature time series supplied by climate models in the control period are significantly lower
152 than observed data. In addition, bias correction of precipitation time series is more important than
153 temperature correction, affecting flow results.

154 It has been found that the best bias correction method for precipitation projections, in terms of
155 precipitation frequency curves, differs from the best method in terms of flood frequency curves.
156 Simulations with the HBV model in the future period under climate change assumptions show a
157 general reduction in flood quantiles, smoothing the increases identified in precipitation quantiles. In
158 the control period, when precipitation quantiles are larger than observations, flood quantiles are
159 similar to observations. In general, the period 2071-2095 presents the smallest reductions and, in some
160 cases, the larger increases.

161 In terms of high return periods in flood frequency curves, the best bias correction techniques are
162 the polynomial correction for precipitation and the monthly mean correction for temperature, in the
163 four case studies.

164 **Acknowledgments:** The authors acknowledge funding from the Fundación Carlos González Cruz.

165 Abbreviations

166 AEMET: Agencia Española de Meteorología
167 CORDEX: Coordinated Regional Climate Downscaling Experiment
168 GCM: General Climate Model
169 GEV: Generalized extreme value
170 HBV: Hydrologiska Byråns Vattenbalansavdelning
171 QM: Quantile Mapping

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