A parametric approach for simultaneous bias correction and high-resolution downscaling of climate model rainfall for practical applications

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1. Introduction

Among different approaches to bias correct climate model (CM) results, distribution mapping has been identified as the most efficient one in reproducing the statistics of rainfall at a regional level, and hydrologically relevant temporal scales (e.g. daily). However:

- Non-parametric (empirical) distribution mapping is sensitive to sample length variations, the presence of outliers, and may lead to significant biases, especially in extreme rainfall estimation.
- Bias-corrected results are constrained by the nominal resolution of the RCM used (i.e. ~ 25 km), which does not suffice to accurately resolve the statistical structure of rainfall at a basin level.

Here (see also Mamalakis *et al.*, 2017) we propose a two step parametric approach that addresses the aforementioned two issues:

✓ **Fit a two-component theoretical distribution model** (i.e. Exponential (Exp.) and Generalized Pareto (GP)) to the historical and CM rainfall series ⇨ ***robustness in extreme rainfall modeling***

✓ **Interpolate the distribution parameters** over a user-defined high-resolution grid, using kriging for uncertain data (KUD) ⇨ ***Downscaling***

2. Region of study – Available Data

We compare the proposed parametric method with its non-parametric variant, in bias correcting daily rainfall products from 4 CMs (i.e. KNMI, MPI, C4I, SMHE), over Sardinia (Italy) for the period 1951-2008.

Data used:
243 stations with more than 30 years of recordings

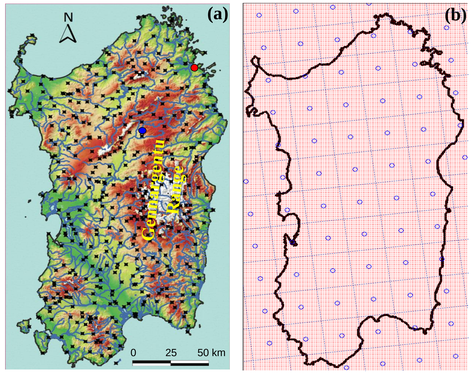


Figure 1: a) The island of Sardinia in Italy. Points indicate rainfall stations, while circles indicate the stations used in Figure 2: #110 (blue) and #288 (red). b) High-resolution grid (i.e. 1 km resolution; red dots) and CM grid (25 km resolution; blue circles).

3. Fitting the two-component distribution model

Use a **GP** model for rainfall intensities above a specified threshold u^*, and an **exponential** model for lower rainrates.

GP model
- **Distribution fitting** using the *Multiple Threshold Method* (MTM) of Deidda (2010) with probability weighted moments (PWM) ⇨ ***robust parameter estimation***
- **Standardization of distribution parameters** to zero threshold ⇨ ***prerequisite for regional frequency analysis***

Exp. model ⇨ **Distribution fitting using** *Least Squares* (LS) to account for all available information on low rainrates.

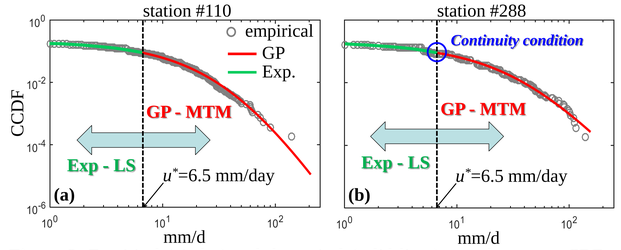


Figure 2: Empirical (circles) and theoretical (solid lines) complementary CDFs for the selected stations shown in Figure 1.a, in the control period 1951-1965.

4. Kriging of distribution parameters

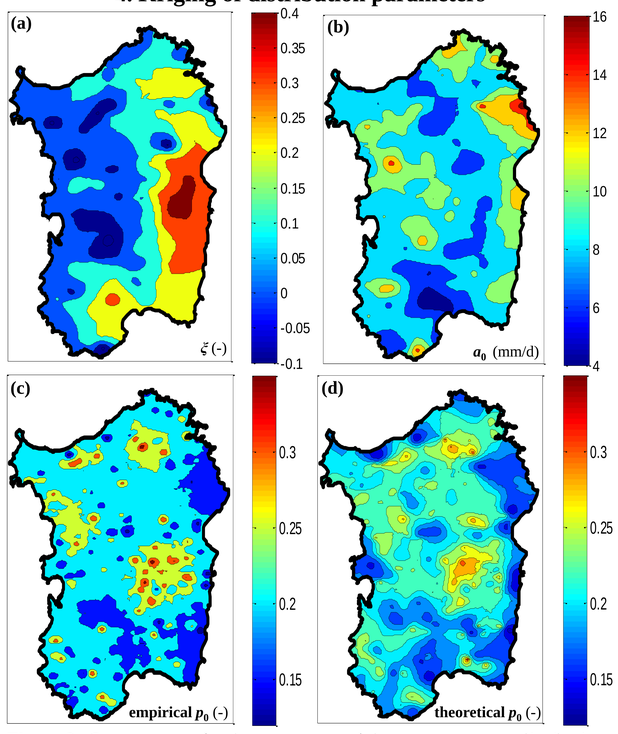


Figure 3: Contour maps for the parameters of the two-component distribution model in the control period 1951-1965, interpolated using KUD: a) GP shape parameter ξ (-), b) standardized to zero threshold scale parameter a_0 (mm/d), c) empirically estimated fraction of wet days p_0 (-), d) theoretically calculated p_0 (i.e. honoring continuity condition; see Figure 2).

5. Simultaneous bias correction and downscaling

$$x_{cor}^{(m,l)}(t)=\begin{cases} Q^{-1}_{KUD,l}\{Q_{m,k}[x_{CM}^{(m,k)}(t)]\}\ , & x_{CM}^{(m,k)}(t) > 0 \\ Q^{-1}_{KUD,l}(p_k) & , \ x_{CM}^{(m,k)}(t) \le 0 \end{cases}$$

$x_{CM}(t)$ denotes the rainfall estimate at grid cell k (blue circles in Figure 1.b) on day t from CM m; $x_{cor}(t)$ is the corresponding bias corrected and downscaled rainfall product at location l (red dots in Figure 1.b); Q is the two-component distribution model, and p_k is uniformly distributed in the interval $[0, Q_{m,k}(0)]$.

6. KNMI results (control period 1951-1965)

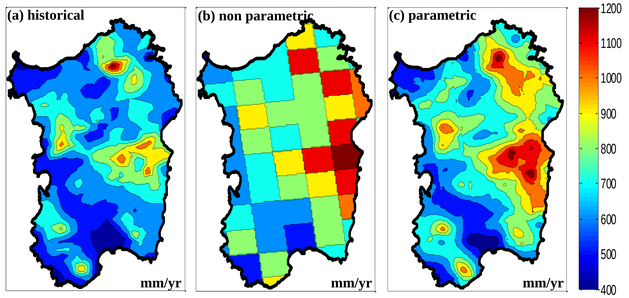


Figure 4: Estimates of the mean annual rainfall depth (mm/yr) for the 43-year validation period 1966-2008, using: a) historical rainfall observations, b) bias corrected KNMI rainfall products with non-parametric distribution mapping, and c) parametric distribution mapping, with parameters drawn from Figure 3.

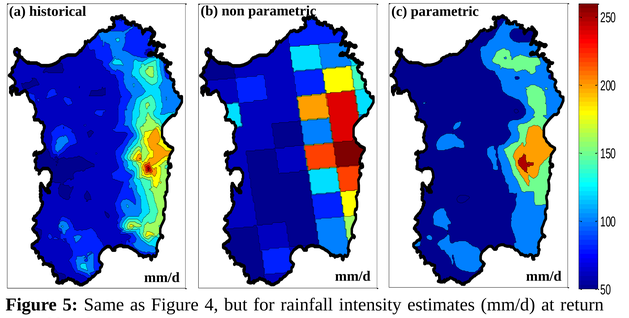


Figure 5: Same as Figure 4, but for rainfall intensity estimates (mm/d) at return period level T =10 years.

7. Sensitivity to control-validation periods and CM used

$$DRMSE = \left(\frac{1}{N} \sum_{i=1}^{N} \left(\frac{z_i' - z_i}{z_i} \right)^2 \right)^{1/2}$$

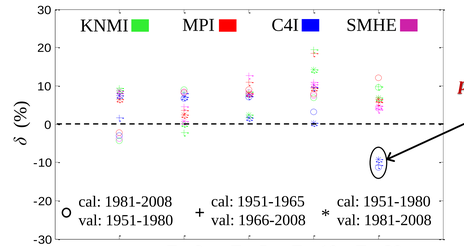
z_i and z_i' are the historical and model-based estimates of statistic Z, respectively.

Table 1: Dimensionless RMSEs (%) for different combinations of control-validation periods, based on Q-Q corrected KNMI rainfall products using non-parametric (i.e. empirical; emp.) and parametric (par.) distribution mapping; **bold** values indicate cases where the non-parametric approach performs better.

control period	validation period	mean annual depth		T = 2 years		T = 5 years		T = 10 years		T = 30 years	
		emp	par	emp	par	emp	par	emp	par	emp	par
1951-1980	1981-2008	33.19	24.46	19.14	19.02	21.36	19.00	35.45	21.30	31.90	25.02
1951-1965		39.09	30.15	**18.91**	**25.09**	27.29	24.61	44.08	26.54	36.84	28.96
1951-1957		37.63	25.98	**27.13**	**27.83**	38.44	26.21	49.22	29.83	40.84	31.17
1951-1965	1966-2008	29.37	19.96	**16.91**	**19.15**	26.02	17.64	40.97	21.49	34.79	25.03
1951-1957		29.98	20.56	23.95	22.47	37.24	21.54	46.54	24.20	37.40	28.72
1981-2008	1951-1980	**23.89**	**28.22**	25.71	16.77	28.84	21.11	30.49	23.61	37.02	27.39

Similar findings when
- ✓ upscaling the results of the parametric approach to the CM grid
- ✓ randomly eliminating half of the stations

✓ ***parametric approach performs better****, especially for extreme rainfall*



pronounced biases in C4I rainfall products; see Mamalakis et al. (2017)

Figure 6: Difference δ = DRMSE$_n$ – DRMSE$_p$ for the statistics in Table 1, obtained by applying the non-parametric bias correction approach (DRMSE$_n$) and parametric distribution mapping (DRMSE$_p$) to 4 different CMs, for 3 combinations of non-overlapping control and validation periods. Positive values of δ indicate superiority of the parametric approach.

8. Conclusions

While **parametric bias correction** of climate model results cannot eliminate the signature of pronounced biases in raw CM rainfall products:

- It demonstrates **significant skill** in modeling the effects of topography and local climatology on the magnitude, general tendencies, and high-resolution spatial structure of rainfall statistics, including rainfall extremes
- It is rather **insensitive** to the characteristics of the calibration period, including its length, and the climate model used.

References

Deidda, R. (2010) A multiple threshold method for fitting the generalized Pareto distribution to rainfall time series, *Hydrol. Earth Syst. Sci.*, **14**(12), 2559-2575.

Mamalakis, A., A. Langousis, R. Deidda, and M. Marrocu (2017) A parametric approach for simultaneous bias correction and high-resolution downscaling of climate model rainfall, *Water Resour. Res.*, **53**, doi:10.1002/2016WR019578.

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