Spatial variability of precipitation extremes over Italy using a fine-resolution gridded product

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1 Introduction

CONTEXT and PROBLEM STATEMENT

- Analysis of extreme precipitation events is the cornerstone of statistical hydrology
- It plays a crucial role in planning and designing hydraulic structures
- Extreme value theory [1] offers a solid theoretical basis for using the Generalized Extreme Value (GEV) distribution [2] as a probabilistic model to describe precipitation annual maxima
- Sparse station networks in most regions lead to sparse point estimates that may distort the actual spatial patterns of the GEV's parameters

GOAL and CONTRIBUTION

- Offer robust estimates of extreme precipitation and create maps for different return periods
- We use a fine-resolution satellite-based gridded product to investigate the spatial variation of the GEV distribution over Italy

[1] Fisher, R.A., Tippett, L.H.C., 1928. Limiting forms of the frequency distribution of the largest or smallest member of a sample. Math. Proc. Cambridge Philos. Soc. 24, 180–190.

[2] von Mises, R., 1936. La distribution de la plus grande de n valeurs. Rev. Math. Union Interbalcanique 1, 141–160.

2 Data

- We used the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS v2.0) that is a quasi-global (50°S-50°N and all longitudes) precipitation dataset [3-4].
- The CHIRPS product provides daily precipitation at the resolution of 0.05°
- We analysed precipitation in the 1981-2019 period
- We extracted 13,247 grid cells covering the whole Italy and analyzed the corresponding time series

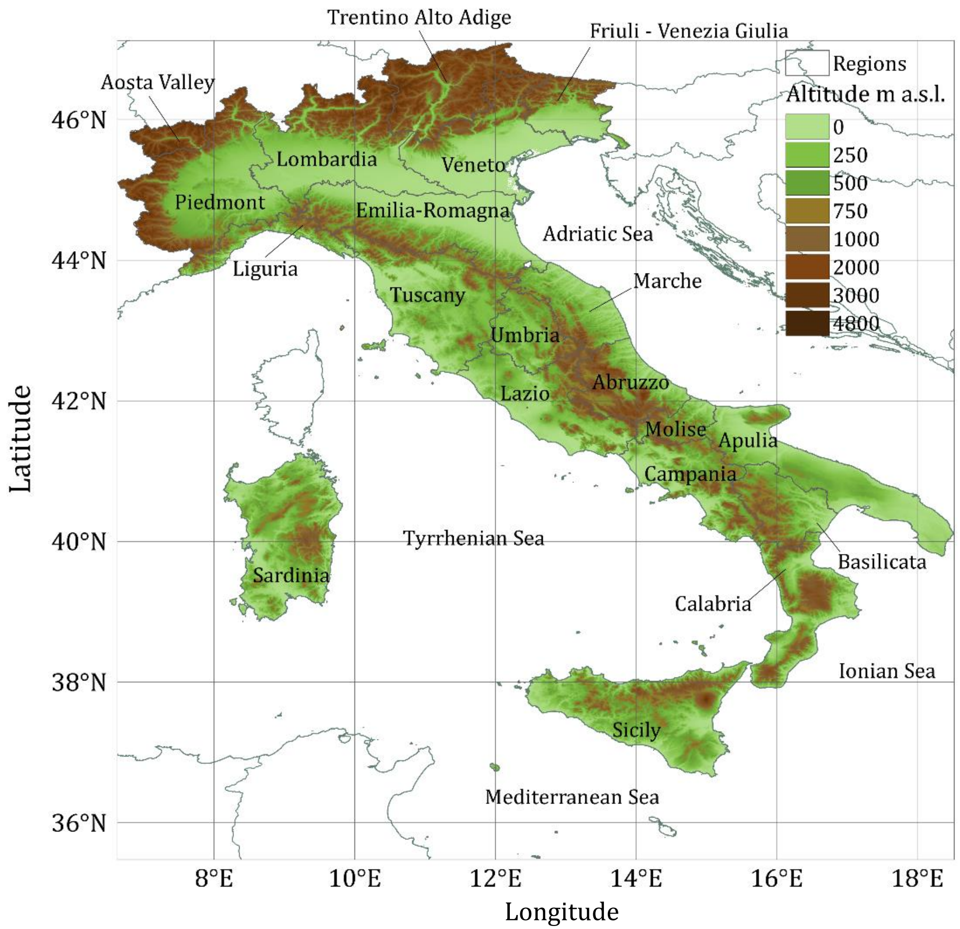

Figure 1. Elevation map of Italy

[3] Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J., 2015a. The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. Sci. Data 2, 1–21. https://doi.org/10.1038/sdata.2015.66

[4] Funk, C., Verdin, A., Michaelsen, J., Peterson, P., Pedreros, D., Husak, G., 2015b. A global satellite-assisted precipitation climatology. Earth Syst. Sci. Data 7, 275–287. https://doi.org/10.5194/essd-7-275-2015

3 Statistics of the CHIRPS product

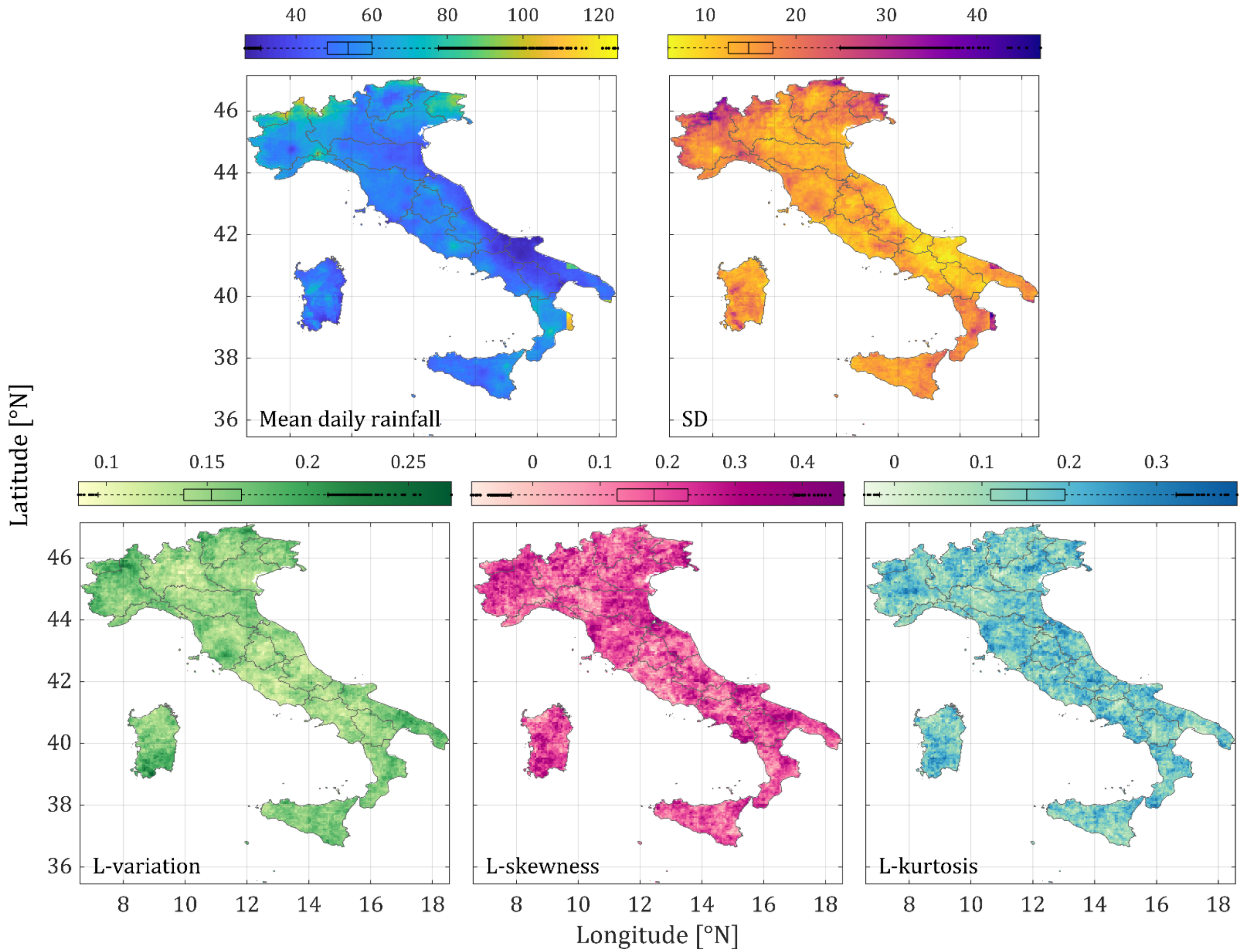

Figure 2. Spatial representation of the estimated statistics calculated for the 13,247 annual maxima samples. The boxplot in each panel represents the statistic's variability.

4 Methodology

GENERALIZED EXTEREME VALUE ($\mathcal{GEV}$) DISTRIBUTION

- We performed the analysis for the 13,247 samples of daily rainfall annual maxima (AM)
- The $\mathcal{GEV}$ distribution function is

$$F_{\mathcal{GEV}}(x) = \exp\left(-\left(1+\gamma\frac{x-\alpha}{\beta}\right)^{-\frac{1}{\gamma}}\right), \qquad 1+\gamma\frac{x-\alpha}{\beta} \geq 0$$

  where $\alpha \in \mathbb{R}$, $\beta > 0$ and $\gamma \in \mathbb{R}$ are, respectively, the location, the scale and the shape parameters.

- Depending on the value assumed by the shape parameter, the $\mathcal{GEV}$ distribution encompasses the three limiting distributions of the Extreme Value Theory (EVT): the type I or Gumbel (G), the type II or Fréchet (F), and the type III or reverse Weibull (RW).
- The use of a distribution bounded from above to describe rainfall events is physically inconsistent [5]. We avoided using bounded from above $\mathcal{GEV}$ distributions.

[5] Papalexiou, S.M., Koutsoyiannis, D., 2013. Battle of extreme value distributions: A global survey on extreme daily rainfall. Water Resour. Res. 49, 187–201. https://doi.org/10.1029/2012WR012557

5 Fitting Procedure based on the L-moments

- The shape parameter γ can be estimated by numerically solving

$$\hat{\tau}_3 = \frac{2(1-3^\gamma)}{1-2^\gamma} - 3$$

where $\hat{\tau}_3$ is the sample L-Skewness.

- The location α and scale β parameters are analytically given by:

$$\alpha = \hat{\lambda}_1 - \frac{\hat{\lambda}_2(\Gamma(1-\gamma)-1)}{(2^\gamma-1)\Gamma(1-\gamma)}$$

$$\beta = -\frac{\hat{\lambda}_2}{(2^\gamma-1)\Gamma(-\gamma)}$$

where $\Gamma(\cdot)$ is the gamma function.

6 L-moments fitting

- 44.9% of the samples indicate a negative shape parameter value (white cells in Fig. 3)
- To avoid using $\mathcal{GEV}$ distributions with upper bounds, when $\gamma_{\mathcal{GEV}} < 0$ we fitted the Gumbel distribution:

$$F_{\mathcal{Gu}}(x) = \exp\left(-\exp\left(-\frac{x-\alpha}{\beta}\right)\right), x \in \mathbb{R}$$

- The scale and the location parameters are:

$$\beta = \frac{\hat{\lambda}_2}{\ln 2}$$

$$\alpha = \hat{\lambda}_1 - \bar{\bar{\gamma}}\beta$$

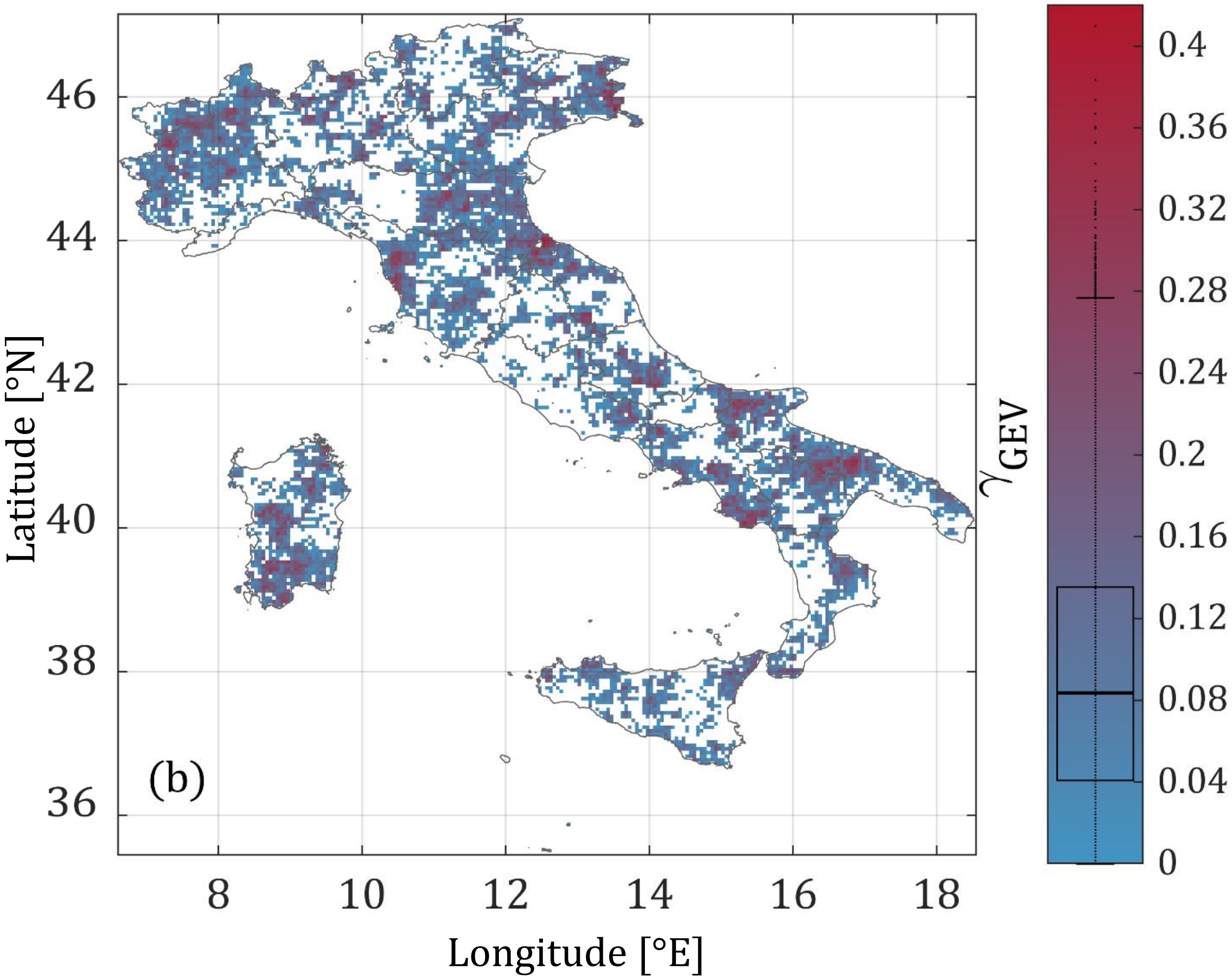

Figure 3. Spatial variability of the $\mathcal{GEV}$'s shape parameter: white cells are representative of $\gamma_{\mathcal{GEV}} < 0$, while colored cells are characterized by $\gamma_{\mathcal{GEV}} > 0$.

7 Rainfall Maps

- We used the fitted $\mathcal{GEV}$ and the Gumbel distributions to evaluate the rainfall depths for fixed return periods

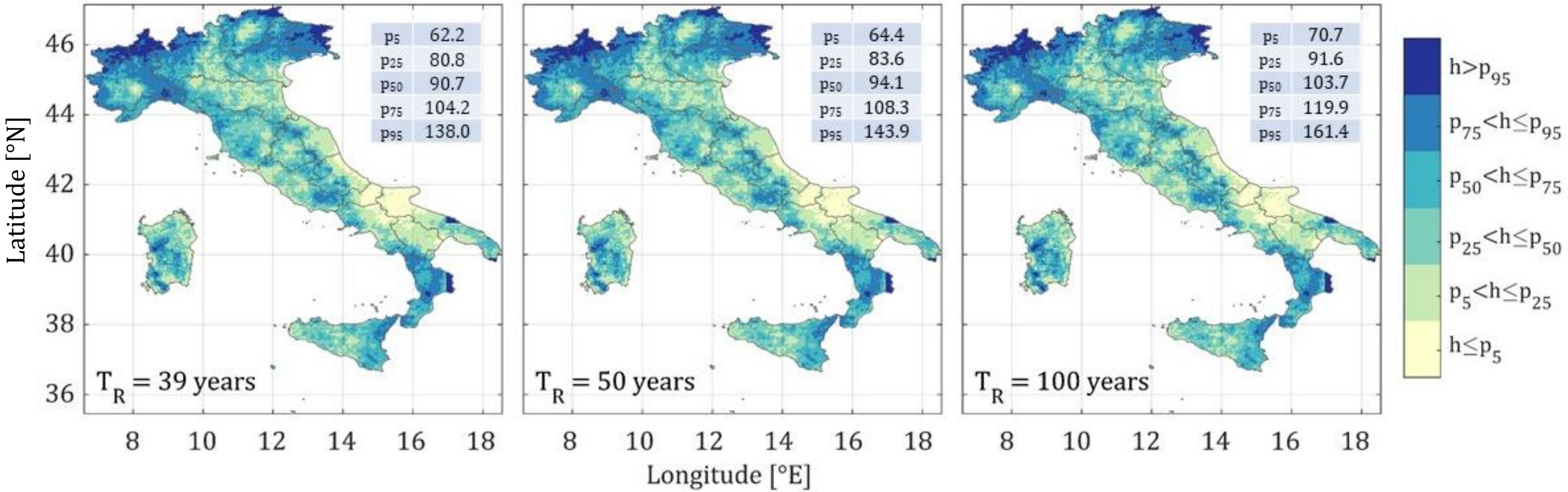

Figure 4. Spatial representation of the daily rainfall depth h (mm) for three return periods (39, 50 and 100 years) classified in percentile classes p_{th}, reported in the tables inside each panel.

8 Conclusions

- We analyzed 13,247 daily time series given by a fine-resolution gridded product: the CHIRPS v2.0. The high spatial resolution of this product allows to study rainfall data all over Italy and including locations where gauge measurements are not available.
- We fitted, using the method of L-moments, the $\mathcal{GEV}$ and the Gumbel distributions to daily annual maxima.
- Clear patterns emerged on the spatial distribution of the $\mathcal{GEV}$'s shape parameter (Fig. 3).
- We produced maps of the rainfall depths associated to different return periods. These maps may be useful to update and to integrate the estimated rainfall depths evaluated with the rain gauges network.