Informativeness of teleconnections in local and regional frequency analysis of rainfall extremes

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Abstract. We propose an effective and reproducible framework to assess the informative content of teleconnections (or climate indices) for representing and modeling the frequency regime of rainfall extremes at regional scale. Our dataset consists of 680 annual maximum series of rainfall depth, with 1 and 24 hours durations, located in northern Northern Italy. We compute at-site time series of L-moments (i.e., the mean and the L-coefficient of variation) through sliding time windows; then we discretize the study region into tiles, where L-moments time series are averaged. We observe that the compute the 30-years sliding mean for six teleconnections: North Atlantic Oscillation, Pacific Decadal Oscillation, East Atlantic – West Russia pattern (EA-WR), El Niño Southern Oscillation, Mediterranean Oscillation Index, and Western Mediterranean Oscillation index Index (WeMOI)shows strong spatial correlation patterns with . Then, we calculate L-moments-teleconnection Spearman correlations for single sites and for tiles with several resolutions, and retain correlations with p-values≤0.05. We observe spatial patterns of strong correlation between several teleconnections and gridded L-moments. Finally, in These spatial patterns are clearly visible at various tiles' resolutions, and may be used for setting up regional prediction models. The strongest influence is detected for the sliding mean on the WeMOI and EA-WR. Finally, we show a preliminary application of climate-informed regional frequency analysis, through a hierarchical framework, where the L-moments are modelled as functions of WeMOIteleconnections. We observe high variability of WeMOI-driven rainfall percentilespredictionsteleconnection-driven predictions of rainfall percentiles, and an increase in overall goodness-of-fit of the regional model relative to the stationary frameworkclimate-informed regional models relative to stationary models. Overall, our research suggests promising pathways for climate-informed local and regional frequency analysis of rainfall extremes, and describes general methodsa general method, that can be adapted to different geographical and climatic contexts, as well as environmental variables.

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1 Introduction

There is strong evidence that large-scale climate oscillations, also called climate indices or teleconnections, have a significant influence on a region's climate (e.g., Bardossy and Plate, 1992; Bonsal and Shabbar, 2008; Rasouli et al., 2020). Several au-

thors have investigated the link between teleconnections and the seasonal regime of precipitation, and found strong influence for monthly (e.g., Das et al., 2020; Romano et al., 2022) or 3-month (i.e., seasonal, e.g., Belkhiri and Krakauer, 2023; González-

25 Pérez et al., 2022) cumulate rainfall and number of wet days (e.g., Ouachani et al., 2013; Ríos-Cornejo et al., 2015). Other authors focused on rainfall extremes, and showed how to exploit teleconnections to model the non-stationarity of the frequency regime of annual maxima (Cheng and AghaKouchak, 2014; Fauer and Rust, 2023; Ouarda et al., 2019; Ragno et al., 2018)(e.g., Cheng and . Not only the parameters of the frequency distribution can be represented as a function of teleconnections (e.g., El Adlouni and Ouarda, 200 (e.g., Johnson et al., 2025; El Adlouni and Ouarda, 2009), but also the distribution itself may change (Ouarda et al., 2019). In-

30 vestigations on the balance between increased complexity and better reliability from non-stationary frequency analysis of rainfall extremes point out that the improvement is can be worth the effort (Ouarda et al., 2020). Overall, the last findings appear to suggest the need for non-stationary frequency analysis of rainfall extremes, depending on teleconnections (see Nerantzaki and Papalexiou, 2022)(e.g., Volpi et al., 2024; Nerantzaki and Papalexiou, 2022). Most of the studies about on this topic show applications with a limited number of stations, where observations are abundant enough for fitting non-

35 stationary local frequency analysis models. However, the dependence of the extreme rainfall regime on teleconnections may have regional patterns, instead of being specific for some isolated sites. In case this dependence could be described as a function of space, this would lead to non-stationary models for regional frequency analysis, similarly as in to the case of local frequency analysis.

The presence of regional structures in the dependence between teleconnections and rainfall has been investigated by several

40 authors, focusing on monthly/seasonal or annual totals (Caroletti et al., 2021; Das et al., 2020; Ríos-Cornejo et al., 2015) or droughts (Romano et al., 2022). Differently, this field remains highly unexplored for rainfall extremes. This is a complex problem, as rainfall extremes have higher statistical and spatial complexity than seasonal/monthly rainfall totals or number of wet days. Thus, the correlation between teleconnections and extreme rainfall can vary significantly in sign, strength and significance within space across a region (see e.g., Jayaweera et al., 2023). In fact, climate may have strong local variations due

45 to orography (Marra et al., 2021), which makes it difficult to understand which teleconnections are more relevant to a specific region. Moreover, the length and quality of the observed timeseries play an important role in the reliability of the obtained results (Martins and Stedinger, 2000; Nerantzaki and Papalexiou, 2022; Ouarda et al., 2020).

In this study, we propose a framework for assessing the informativeness of teleconnections in frequency analysis of hourly and daily rainfall extremes. In particular, we want to investigate (1) whether it is possible to delineate robust regional zonation

50 of the correlation with dependence on teleconnections, and (2) what is the effect and suitability of non-stationary frequency analysisin significantly correlated areas. teleconnection-informed regional frequency analysis. Accordingly, the study and proposed framework are structured in two parts, a : correlation analysis and a regional frequency analysis, respectively. Our study area is northern-central North-Central Italy, where 680 timeseries with at least 30 years of records are available. We focus on annual maxima of precipitation with duration of 1 and 24 hours. In the first part of the research, we consider six teleconnection

55 patterns with proven influence on the rainfall regime in the study area (Caroletti et al., 2021; Criado-Aldeanueva and Soto-Navarro, 2020; Krichak et al., 2014): North Atlantic Oscillation (NAO), Pacific Decadal Oscillation (PDO), East Atlantic – West Russia pattern (EA-WR), El Niño Southern Oscillation (ENSO), Mediterranean Oscillation Index (MOI), and Western

Mediterranean Oscillation Index (WeMOI).

Differently from other studies, we do not perform our correlation analysis on the raw timeseries of the teleconnections and annual maxima. Here, two strategies are simultaneously adopted, to conveniently that is to aggregate the data temporally and spatially. First, we consider sliding time windows, which allows us to (a) account only for long-term variability components, and (b) consider the variation of the timeseries' statistics during the recorded period. In particular, we consider two linear moments (or L-moments, see Hosking and Wallis, 1997): the mean and L-coefficient of variation (L-CV) for each station. Second, we divide the study region into tiles: within each tile, we average the at-site estimation of the sample L-moments, in order to obtain timeseries of robust regional L-momentsestimates. Finally, we compute tile-wise the correlation between the timeseries of the L-moments and the rolling mean of the teleconnections and we define raster maps of the correlation with dependence of the mean and L-CV. Significance testing specifically addresses autocorrelation issues due to the use of sliding windows (Lun et al., 2023).

In the second part, we focus on areas (tiles) where significant correlations are present, and we fit a tile-wise polynomial relationship fit polynomial relationships between the L-moments and the most influent teleconnectionteleconnections. By using a hierarchical approach (see e.g. Gabriele and Arnell, 1991; Castellarin et al., 2001), we define regional Generalized Extreme Value distributions (GEV, see Jenkinson, 1955) in a stationary and non-stationary framework. "doubly-stochastic" framework. The authors use the terminology "doubly-stochastic" for frequency models where the parameters depend on stochastic variables, as teleconnections (see Serinaldi and Kilsby, 2018). We test hypothesis that the GEV parameters of rainfall extremes depend on teleconnections (i.e., doubly-stochastic model) through ad-hoc Monte Carlo experiments that take spatial correlation into account (see e.g., Castellarin et al., 2024). Finally, the research is enriched by a critical discussion on the generality and reproducibility of the proposed methodology. It is showed shown that beside the choice of the study area, our methods are innovative and universally applicable.

2   Methodological framework

We propose an innovative and structured methodological framework for assessing the effectiveness of teleconnections-informed frequency analysis of rainfall extremes. The general methodology is structured into two phases. Some elements of the procedure, which include numerical parameters and specific functions, need to be adjusted according to the specific study case; for the sake of brevity, all of these elements will be referred to as "parameters". The general methodology is represented in Figure 1 and described in this Section, while the parametrization adopted for this study is detailed in Section 3.1.

2.1   Phase 1: correlation analysis

The first part aims at (1) evaluating the possible relation between teleconnection indexes indices and the local climate indexes indices (i.e., the statistics of the rainfall regimeextreme rainfall statistics), (2) investigating the spatial structure of the correlation, and (3) producing maps of the correlation structure over the study area. These objectives are obtained through three fundamental steps which we describe below. The first step is the definition of two sliding time windows (STWs). One STW
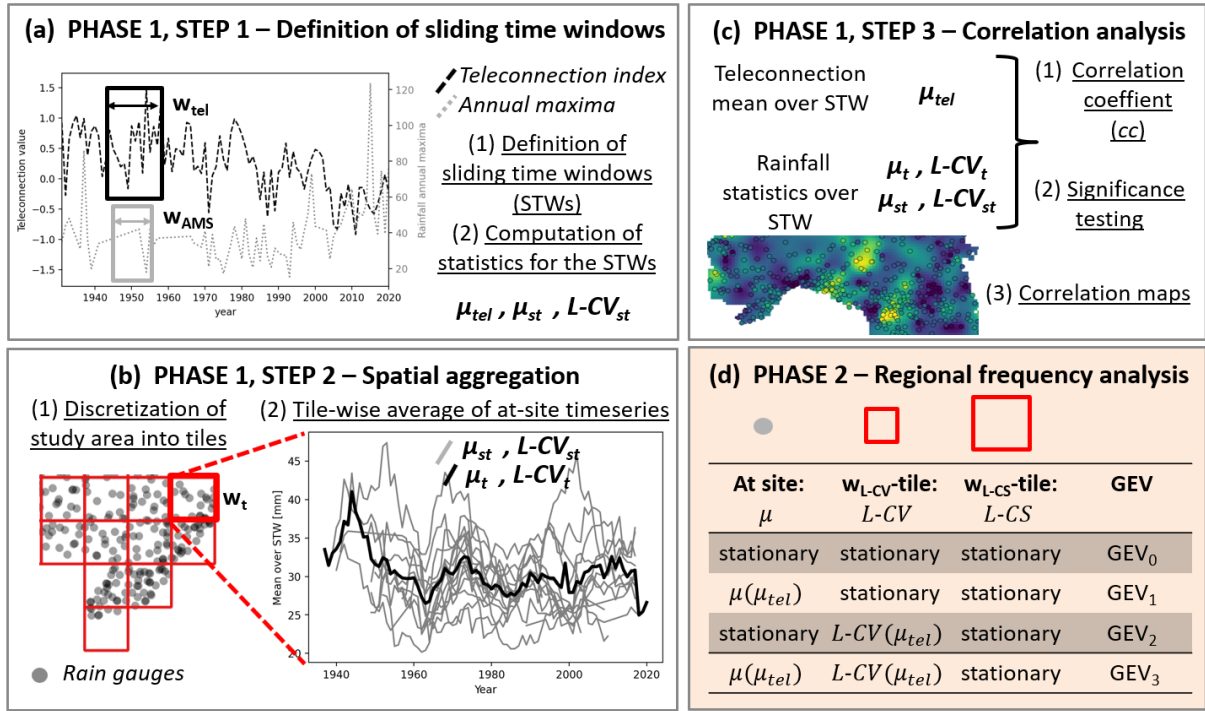
Figure 1. General methodological Methodological frameworkof the present study: first phase (white background, panels (a), (b) and (c)) and second phase (coloured background, panel (d)). Vectors (i.e., time series) are highlighted with bold, italic font, substeps are numbered and underlined.

90 is used for the teleconnections, with width w_{tel} years. Over this STW, the mean of the teleconnection μ_{tel} is computed. Another STW is used for the Annual Maximum Series (AMS), with width of w_{AMS} years. Over this STW, the at-site mean (μ) and L-coefficient of variation (L-CV, see Hosking and Wallis, 1997) of the AMS of rainfall depths are computed (see Figure 1.a). Thus, for each gauging station (st) the time series of the mean ($\boldsymbol{\mu_{st}}$) and L-CV ($\boldsymbol{L\text{-}CV_{st}}$) are obtained; these have length $n - w_{AMS} + 1$, where n is the number of years of observations for the considered site:

95 $$\boldsymbol{\mu_{st}} = \left\{ \mu_{1,st}, \mu_{2,st}, ..., \mu_{n-w_{AMS}+1,st} \right\} \tag{1}$$

$$\boldsymbol{L\text{-}CV_{st}} = \left\{ L-CV_{1,st}, L-CV_{2,st}, ...L-CV_{n-w_{AMS}+1,st} \right\} \tag{2}$$

where $\mu_{1,st}$, $\mu_{2,st}$ and $\mu_{n-w_{AMS}+1,st}$ represent the mean computed over the first, second and last time-steps defined by the STW at site st; the same notation is used for the L-CV. Notably, at each time-step of the STW, the computed The value (i.e., mean or L-CV) is attributed computed at each time-step of the STW is conventionally assigned to the last year included in

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that interval. Thus, each year is represented by a statistical moment (or L-moment) that describes the w_{AMS} previous years, including itself.of the interval.

The second step is the discretization of the spatial domain into single tiles (or cells, or pixels) that do not overlap with each other. The spatial resolution is w_t. For each single tile (t), the timeseries $\boldsymbol{\mu}_{st}$ and $\boldsymbol{L\text{-}CV}_{st}$ of the gauged sites within the tile are averaged yearly (see Figure 1.b). Thus, regional timeseries ($\boldsymbol{\mu}_t$ and $\boldsymbol{L\text{-}CV}_t$) for each tile are obtained:

$$\boldsymbol{\mu}_{\mathbf{t}} = \left\{ \frac{\sum_{i=1}^{n_1} \mu_{1,i}}{n_1}, \frac{\sum_{i=1}^{n_2} \mu_{2,i}}{n_2}, ..., \frac{\sum_{i=1}^{n_{n-w_{AMS}+1}} \mu_{n-w_{AMS}+1,i}}{n_{n-w_{AMS}+1}} \right\} \tag{3}$$

$$\boldsymbol{L\text{-}CV}_{\mathbf{t}} = \left\{ \frac{\sum_{i=1}^{n_1} L-CV_{1,i}}{n_1}, \frac{\sum_{i=1}^{n_2} L-CV_{2,i}}{n_2}, ..., \frac{\sum_{i=1}^{n_{n-w_{AMS}+1}} L-CV_{n-w_{AMS}+1,i}}{n_{n-w_{AMS}+1}} \right\} \tag{4}$$

where $n_1, n_2, ...n-w_{AMS}+1$, are the numbers of stations with available rainfall statistics at steps 1,2, ..., $n - w_{AMS} + 1$ of the STW.

The third step is the correlation analysis (see Figure 1.c). The correlation coefficient (cc) is computed for each tile between the averaged timeseries ($\boldsymbol{\mu}_t$ and $\boldsymbol{L\text{-}CV}_t$) and the rolling mean of the considered teleconnection ($\boldsymbol{\mu}_{tel}$), and the significance of the resulting correlation is tested (with significance 5%). We propose to . We adopt the Spearman coefficient , as it accounts also for non-linear correlations, yet preliminary experiments showed very similar results with the Pearson correlation coefficient. The significance of cc is tested according to the methodology described in Lun et al. (2023), which takes into account the possible presence of spurious correlations, resulting from the use of sliding time windows. Only stations with p-value≤ 0.05 are considered as significantly correlated . Only the teleconnections showing high numbers of significantly correlated pixels are considered for the further steps.(i.e., significance at 5%).

Finally, an additional analysis of the correlation coefficients is needed to delineate eventual spatial structures. Since Finally, we estimate the robustness, or reliability, of the detected correlation signals with an ad-hoc approach. This is an important step, since the definition of the parameters described above (i.e., w_{tel}, w_{AMS}, w_t) is necessarily affected by subjectivity and uncertainty, the robustness, or reliability, of the detected correlation should be assessed: the method adopted for this assessment . Then, the possible presence of spatial patterns of the correlation fields is investigated through the definition of correlation maps. The methodology adopted for correlation reliability assessment and correlation maps production is detailed in Section 3.1. Then, a map of the correlation field over the study area can be created.

2.2 Phase 2: regional frequency analysis

The second part of the present study aims at assessing (1) the possible effect of teleconnections on frequency analysis the frequency of extreme rainfall events, and (2) the benefit potential of considering teleconnections as covariates for non-stationary frequency analysisin doubly-stochastic frequency models.

For the sake of generality, the Generalized Extreme Value distribution (GEV, see Jenkinson, 1955) is considered, given its flexibility and representativeness of the frequency regime of hydrological extremes (e.g., Papalexiou and Koutsoyiannis, 2013;

130 Salinas et al., 2014). Nevertheless, the proposed framework is not limited to the selection of a given frequency case of the GEV distribution; on the contrary, it could be easily extended and adapted to the case in which alternative theoretical frequency distributions are considered and tested against each other. The cumulate probability distribution cumulative distribution function of the GEV, $F_{GEV}(x)$, depending on the location, scale and shape parameters (ξ,α,k), is defined as follows:

$$F_{GEV}(x) = e^{-e^{-y}} \text{ , where } y = \begin{cases} -k^{-1}log_e[1 - k(x - \xi)/\alpha], & k \neq 0 \\ (x - \xi)/\alpha, & k = 0 \end{cases} \qquad (5)$$

135   The hierarchical method for regional frequency analysis is adopted (see Gabriele and Arnell, 1991)(see e.g. Gabriele and Arnell, 1991) . Accordingly, for a given gauged site, the mean is computed from the at-site records, the L-CV exploits all the time series within a tile with resolution w_{L-CV} where the target site is included, and the L-CS exploits all the time series within a tile with resolution w_{L-CS} (where $w_{L-CV} \leq w_{L-CS}$). The values adopted in the present study for w_{L-CV} and w_{L-CS} are detailed in Section 3.1.

140 First, a stationary GEV is fit (GEV_0), where the mean over the whole time series is computed at-site, and the regional L-CV and L-CS are obtained as described in Hosking and Wallis (1997) as a weighted average over their respective tiles by referring to the complete sequences of annual maxima (see Figure 1).

Second, three types of non-stationary GEV GEV distributions whose parameters depend on teleconnections are set up. Following the suggestion by Serinaldi and Kilsby (2018), we term these distributions as doubly-stochastic (DS) models, even if we ac-

145 knowledge that the most common definition in the literature is "non-stationary" models (e.g., Volpi et al., 2024, and references therein) . We consider three types of doubly-stochastic models. The first type, GEV_1, adopts the same L-CV and L-CS as the GEV_0, whereas the mean varies as a function of the best teleconnection index (selected in phase 1). This function is fitted at-site, according to the hierarchical regionalization framework. The choice for its shape, $f(x)$, is detailed in Section 3.1. The second typeGEV, GEV_2, adopts the same mean and L-CS as the GEV_0, while the L-CV varies as a function $f(x)$ of the best

150 index. This is fitted on the w_{L-CV}-averaged timeseries (**L-CV$_t$**), according to the hierarchical regionalization framework. The third typeGEV, GEV_3, adopts the same L-CS as the GEV_0, while the mean and L-CV are obtained with the same methods as for the GEV_0 GEV_1 and GEV_2, respectively. Finally, the four models are compared by means of three commonly used metrics: the ratio of maximized models' likelihood (RML), the Anderson-Darling statistic (AD), and the modified Shapiro-Wilk statistic (TN. SW). These three metrics, or discrimination statistics, as they are frequently defined , are selected based

155 on the results of other authors. Ashkar and Aucoin (2012) and Ashkar and Ba (2017) found that the discrimination power of these three metrics is higher than other metrics after multiple and extensive testing. In particular, Laio et al. (2009) found that the Anderson-Darling statistic had better discrimination power than other considered metrics when the parent distribution is a GEV. The RML is . This metric is usually defined as "ratio of maximum likelihood", and is very commonly used for this purpose (e.g., Ashkar and Aucoin, 2012; Ashkar and Ba, 2017). It is defined as in Ashkar and Ba (2017):

160 $$RML = log_e\left(\frac{LH_{non-stationary}}{LH_{GEV_0}} \frac{LH_{GEV_{DS}}}{LH_{GEV_0}}\right) \qquad (6)$$

The AD statistic is defined as in Laio et al. (2009) and Laio (2004). For an ordered series of annual maxima, $x = \{x_1 < x_2 < ... < x_i < ... < x_n\}$, the AD depends on the originally version proposed by Anderson and Darling (1952):

$$AD_{1952} = -n - \frac{1}{n}\sum_{i=1}^{n}[(2i-1)\cdot log_e(F(x_i)) + (2(n-i)+1)\cdot log_e(1-F(x_i))]$$

$$AD = \begin{cases} 0.0403 + 0.116\left(\frac{AD_{1952}-\xi}{\beta}^{\eta/0.861}\right), & 1.2\xi \leq AD_{1952} \\ \left[0.0403 + 0.116\left(\frac{0.2\xi}{\beta}^{\eta/0.861}\right)\right]\cdot\frac{AD_{1952}-0.2\xi}{\beta}, & 1.2\xi > AD_{1952} \end{cases}$$

where $F(x)$ is the cumulative density function of the probability distribution under exam, AD_{1952} is the orginal Anderson-Darling statistic (see also Das, 2022), and ξ, β and η are distribution-dependent coefficients that are tabled by Laio (2004) (Tables 3 and 5)Where LH_{GEV_0} and $LH_{GEV_{DS}}$ are the likelihood of the observed timeseries computed with the stationary and doubly-stochastic models, respectively.

The TN.SW statistic, generated by the modified Shapiro-Wilk test (see the original test by Shapiro and Wilk (1965)), is performed as in Ashkar and Ba (2017). First, the series of annual maxima is transformed into a standard normal sample by applying the cumulative density function of the distribution under exam, $F(x)$, and the percentile function of Since RML is asymptotically distributed as half of a Chi-squared variable with degrees of freedom equal to the difference of the number of parameters of the two models (e.g., see Bhattacharya and Burman, 2016; Coles, 2001), a lower threshold th_{RML} should be considered to conclude that GEV_{DS} is a better fit to the data. Given that significance is tested at 5%, the standard normal distribution, $\Phi^{-1}(x)$:

$$z_i = \Phi^{-1}(F(x_i))$$

Then, the TN. SW is computed:

$$TN.SW = \left(\sum_{i=1}^{n} v_i z_i\right)^2 \Big/ \sum_{i=1}^{n}(z_i - \mu_z)^2$$

where the coefficients v_i are computed as in the approximation described by Royston (1992), and μ_z is the mean of the standardized vector z. theoretical significance threshold equals half of the 95th percentile of the corrispondent Chi-squared distribution. In the present study, th_{RML} values are evaluated with reference to the total number of parameters of the models, consisting of those of the frequency distribution and those of $f(x)$. Furthermore, since in our opinion these two sets of parameters do not have the same weight (see also what observed by Laio et al., 2009), we have also determined th_{RML} values experimentally, through a set of Monte Carlo (MC) experiments that are described in Appendix A. The thresholds obtained with the two methods, which depend on the choice of $f(x)$ are shown in Section 3.1.

These three metrics are computed for the four types of GEV at all the locations where the correlation is significant (i.e., p-value≤5%) and strong (i. e., Spearman coefficient≤-0.5 or ≥0.5) . While the RML represents the comparison between the LH of two distribution probabilities, Finally, we test field significance of possible doubly-stochastic spatial signals in presence of

cross-correlation. In fact, the number of sites with doubly-stochastic rainfall regime could be inflated by the presence of inter-site dependence (see also Castellarin, 2007; Vogel et al., 2001). For this reason, we define a significance test ad-hoc, based on the comparison of n_{DS}, the AD and TN.SW measure the goodness-of-fit of a single distribution to the data (i.e., larger values represent better fit). In order to compare the stationary with the non-stationary distributions, we consider the differences $\Delta_{AD} = AD_{non-stationary} - AD_{GEV_0}$ and $\Delta_{TN.SW} = TN.SW_{non-stationary} - TN.SW_{GEV_0}$ (Ashkar and Ba, 2017; Das, 2022). Thus, either for RML, Δ_{DA} and $\Delta_{TN.SW}$, positive values indicate that the considered non-stationary model provides a higher goodness-of-fit to the observed annual maxima relative to the stationary model. global number of sites where a given doubly-stochastic model outperforms the stationary model, with lower thresholds $th_{n_{DS}}$. These thresholds are estimated through MC experiments that are described in Appendix B.

3 DatasetStudy region and parameterization of the procedure

3.1 Study region and data

The study area includes most of northern Northern and part of central Central Italy, a region characterized by great climate variability (see Figure 2.a). Two main mountain ranges are present: the Alps in the northNorth, with a maximum elevation of about 4000 m a.s.l., and the Apennines, crossing all along continental Italy, with a maximum elevation of ∼2100 m a.s.l. in the study area. The largest Italian plain, the Po plain, is located at the southern border of the Alps, following the course of the Po River from the northwest to the northeastNorthwest to the Northeast, where low coasts are located.

We select 680 gauged stations (Figure 2.a) from the I2-RED dataset (Mazzoglio et al., 2020) , filtering by with a minimum of 30 years of data. Thus, all the selected timeseries should be long enough sufficiently long to show variations of the statistical regime during timefrequency regime of rainfall extremes, if these are present (see also Renard et al., 2008; Ouarda et al., 2019). For each station, we consider time series of annual maximum cumulative rainfall over 1 and 24 consecutive hours, which represent distinct events: mainly convective the former, and mainly synoptic , respectivelythe latter. Data have been recorded between 1928 1921 and 2020.

In the study, six teleconnections are considered; a detailed description of their nature is not reported here, since an interested reader can refer to the extensive literature cited in the text. Namely, these are the North Atlantic Oscillation (NAO, see Jones et al., 1997), the East Atlantic-West Russia (EA-WR) pattern (see Barnston and Livezey, 1987), the Pacific Decadal Oscillation (PDO, see Zhang et al., 1997), El Nino Southern Oscillation (ENSO, see Chen et al., 2019), Mediterranean Oscillation Index (MOI, see Conte et al., 1991), and Western Mediterranean Oscillation Index (WeMOI, see Martin-Vide and Lopez-Bustins, 2006). All these climate indexes indices have significant influences on local climate at several locations in Europe and the Mediterranean (e.g., Caroletti et al., 2021; Krichak et al., 2014, 2002; Krichak and Alpert, 2005). The NAO, EA-WR, PDO and ENSO are freely accessible from the NOAA Physical Sciences Laboratory data base available at https://psl.noaa.gov/data/climateindices/list/. The MOI and WeMOI can be retrieved from the University of East Anglia's Climate Research Unit (CRU; https://crudata.uea.ac.uk/cru/data/moi/).
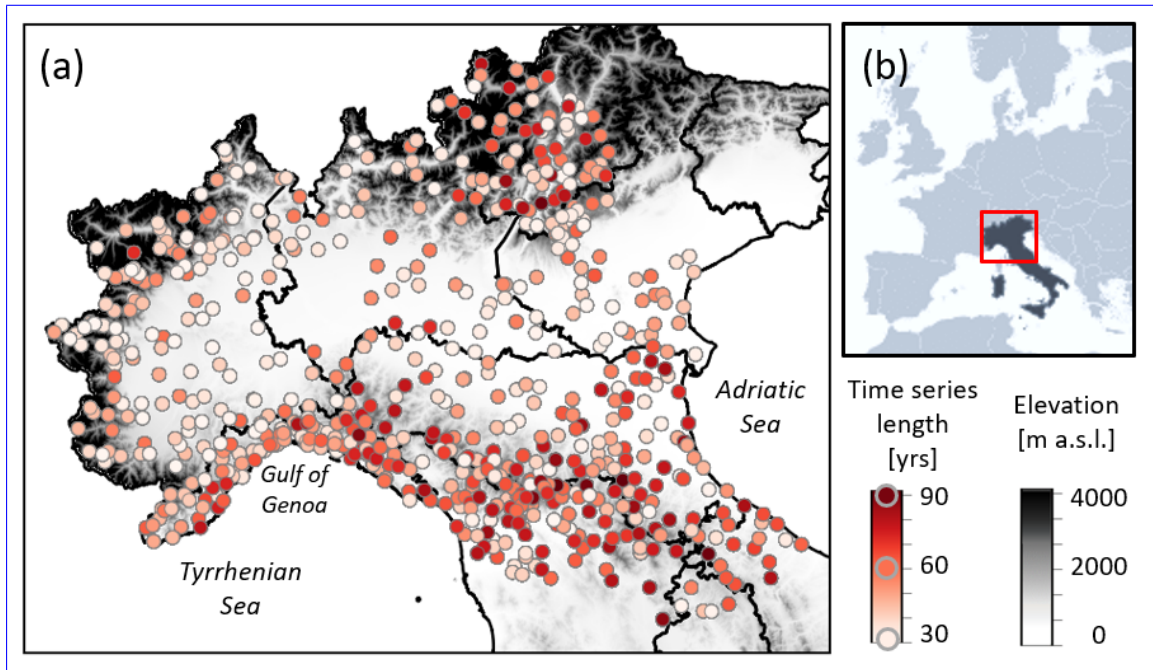
Figure 2. Elevation (a, in grey color scale) and location (b) of the study area. Length of the timeseries of sub-daily annual maximum rainfall depths (a, red color scale). In blackBlack lines: Italian administrative regions.

4 Results

3.1 Parametrization of the procedure for the study area

Based on several preliminary experiments conducted, the parametrization of the general methodology to The parameterization of the methodology for the study area is the followingpresented below results from several preliminary experiments.

The implementation of the first part of the study requires the definition of w_{tel}, w_{AMS}, w_t, and the methodology approach for the robustness analysis . (i.e., the evaluation of the reliability of the correlation coefficients computed with w_{tel}, w_{AMS} and w_t; see Section 2.1). First, w_{tel} is assumed as set to 30 years. Preliminary experiments with smaller w_{tel} provided similar results, yet not exactly the same. The final choice accounts to 30 years in order to smooth generally smooth out short interannual oscillations, considering instead a pluridecadal climate window. Shorter while preserving the pluridecadal climate variability. Also, shorter oscillations (i.e., <30 years) would not be of interest for the design of hydraulic structures, while longer ones (i.e., >30 years) would be highly uncertain to detect, due to limited length of the timeseries.

Second, the w_{AMS} parameter is assumed as is set to 10yrs. This choice is also due to a balance a trade off between a minimum width for the computation of the L-CV and a minimum length of the timeseries of the rainfall statistics (i.e., μ_{st} and $\textbf{\textit{L-CV}}_{st}$). In fact, on the one hand w_{AMS} <10 years would lead to unacceptable inaccuracy for the definition of the large sampling variability of local L-CV values. On the other hand, the μ_{st} and $\textbf{\textit{L-CV}}_{st}$ timeseries originated from an n-long annual maxima

timeseries have length of $n - (w_{AMS} - 1)$. This means that the longer w_{AMS} would lead to shorter $\boldsymbol{\mu_{st}}$ and $\boldsymbol{L\text{-}CV_{st}}$, which in turn would lead to a smaller number of stations where the correlation between teleconnections and rainfall statistics can be reliable.Indeed, to the aim of defining a zonation of the teleconnection-statistics correlation field, as in the present study, the number of sufficiently long timeseries needs to be as high as possible.

240   According to the adopted parametrization, equations 1 to 4 become the following:

$$\boldsymbol{\mu_{st}} = \left\{ \mu_{1,st}, \mu_{2,st}, ..., \mu_{n-10+1,st} \right\}$$

$$\boldsymbol{L\text{-}CV_{st}} = \left\{ L - CV_{1,st}, L - CV_{2,st}, ..., L - CV_{n-10+1,st} \right\}$$

$$\boldsymbol{\mu_t} = \left\{ \frac{\sum_{i=1}^{n_1} \mu_{1,i}}{n_1}, \frac{\sum_{i=1}^{n_2} \mu_{2,i}}{n_2}, ..., \frac{\sum_{i=1}^{n_{n-10+1}} \mu_{n-10+1,i}}{n_{n-10+1}} \right\}$$

$$\boldsymbol{L\text{-}CV_t} = \left\{ \frac{\sum_{i=1}^{n_1} L - CV_{1,i}}{n_1}, \frac{\sum_{i=1}^{n_2} L - CV_{2,i}}{n_2}, ..., \frac{\sum_{i=1}^{n_{n-10+1}} L - CV_{n-10+1,i}}{n_{n-10+1}} \right\}$$

245   For the Concerning the spatial resolution of the tile size, w_t, we adopt consider four values: 0km (i.e., considering the single gauged stations, with no spatial discretization), 15km, 30km and 50km. This multiple choice comes from a balance. On the one hand, L-CV computed over a 10yrs STW time window may have low robustnessaccuracy, which can be addressed by averaging L-CVs from several stations within large tiles . (i.e., regional prediction). On the other hand, larger tiles may be less statistically homogeneous. Moreover, averaging L-statistics over large tiles may smooth the variability of the rainfall regime, 250 hiding local patterns where the morphology is complex. Since there is no universal rule for solving this balanceguideline for finding the right trade off, we decide to consider four different values for w_t. The suitability of these values is tested by means of the heterogeneity test described by Hosking and Wallis (1997) for the heterogeneity measure for L-CV. The results show that most of the tiles are homogenous for all the resolutions. These analyses are of the test (not reported here for the sake of brevity) detected "definitely heterogeneous" tiles in a very limited number of cases for all the resolutions, confirming the viability of 255 the homogeneity hypothesis.

Regarding We assess the robustness of the correlation signal is defined at each station st through a reliability index. At each station st, it is defined as, ri_{st}, defined as:

$$ri_{st} = sign(cc_{0km,st}) + sign(cc_{15km,st}) + sign(cc_{30km,st}) + sign(cc_{50km,st}) \tag{7}$$

    Where $cc_{0km,st}$ is the correlation computed at station st, while $cc_{15km,st}$, $cc_{30km,st}$ and $cc_{50km,st}$ are the correlation coef- 260 ficients relative to the tiles (with w_t 15km, 30km and 50km) where st is inserted. Non-significant correlations are considered

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as 0. This is considered to be a measure of the spatial coherence of the correlation signal, which varies between -4 and 4. The absolute value is the coherence of the correlations at different tiles. The sign represents the sign of the prevailing correlation. For instance, considering a gauged station where the absolute value of with ri is 4 , the correlation is significant and with the same sign both indicates a significant and positive correlation when calculated at-site, and when it derives from a as well as for 15km aggregation, and at , 30km, and at 50km aggregation. On the opposite, 0 represents areas with no significant correlation or where positive and negative correlations compensate with each other (e.g. positive correlation at-site and at a 15km tile resolution, and negative correlation at 30km and 50km). In general, the resolutions). Finally, ri can be rescaled between -1 and 1, in order be more similar to a correlation coefficient. In this study, the original scale is kept, as it is more easily interpretable. Finally, the reliability index is is interpolated by ordinary kriging (Hengl, 2007) to produce a robust map (Hengl, 2007) to produce reliable maps of the correlation field of the mean and L-CV for 1h and 24h.

Regarding the second part of the study, three parameters need to be adjusted: w_{L-CV}, w_{L-CS} and $f(x)$ need to be set. The selected resolution w_{L-CV} is 30km, as it is a good balance between robustness trade off between accuracy of the prediction (i.e., aggregating at least two L-CV at-site L-CV timeseries) and representing an adequate representation of regional patterns and local variability. The selected resolution We set w_{L-CS} is to 100km, based on low spatial variability of the skewness parameter (e.g., Gabriele and Arnell, Claps et al 2022) and improved robustness (see above)(e.g., Gabriele and Arnell, 1991; Claps et al., 2022) and improved accuracy.

The function $f(x)$ between teleconnections and L-statistics is shaped as a second-order polynomial function. This form has been selected because of its simplicity (i.e., only two three parameters are needed) and yet adaptability to the data, while the dependence observed empirical data, given that the observed dependence of extreme rainfall statistics on teleconnections is clearly often non-linear. Other choices are clearly possible. However, it should be underlined that Even though other choices are possible, the aims of the present study are mainly demonstrative of the potential of the proposed approach. Thus, the nature and selection of the best function is not discussed in detail. part of the main focus of our analyses.

The lower thresholds th_{RML} considered for RML significance test at 5% (see Section 2.2) are reported in Table 1. Interestingly, our Monte Carlo experiments (see details in Appendix A) suggest that RML's diagnostic power is not affected by the duration and teleconnection considered. Also, the resulting empirical th_{RML} values are much lower than the theoretical ones, and less affected by the number of parameters of $f(x)$ (compare th_{RML} for GEV_3 with GEV_1 and GEV_2). While important for the general field of model evaluation, a detailed discussion of these results is beyond the scope of the present study. However, they present an interesting topic for further research.

	Number of parameters	Empirical th_{RML}	Theoretical th_{RML}
GEV_1	2+3	1.5	3
GEV_2	2+3	1.5	3
GEV_3	1+3+3	1.6	4.7

Table 1. RML significance thresholds, th_{RML}, at 5%

4 Results

4.1 ~~Results of phase~~ Phase 1: correlation analysis

~~First, it is observed that the WeMOI shows a remarkably higher~~ Table 2 reports the number of gauges (at-site), or tiles (resolutions from 15km to 30km), showing statistically significant correlations at 5% for each teleconnection and the two statistical moments considered here (i.e., the mean, μ, and the L-coefficient of variation, L-CV) for durations of 1 and 24 hours.

	1h				24h			
	at-site	15km	30km	50km	at-site	15km	30km	50km
NAO - μ	118	61	25	7	**110**	55	19	9
EA-WR - μ	**131**	**97**	**53**	**32**	106	**58**	**30**	10
PDO - μ	**123**	62	28	**12**	101	**53**	22	**5**
ENSO - μ	8	7	2	0	3	2	1	0
WeMOI - μ	**139**	**87**	**30**	**16**	<u>**133**</u>	**78**	**35**	<u>**14**</u>
MOI - μ	102	55	25	8	102	51	17	7
NAO - L-CV	96	48	21	10	**101**	49	**27**	10
EA-WR - L-CV	86	55	**22**	7	94	52	**22**	8
PDO - L-CV	**101**	**57**	20	**11**	**102**	**61**	24	**9**
ENSO - L-CV	8	4	3	2	4	3	2	0
WeMOI - L-CV	82	47	**25**	5	**98**	48	**17**	7
MOI - L-CV	**107**	**59**	**22**	**11**	98	**55**	**25**	**11**

Table 2. Number of significant correlations for all the considered teleconnections and tiles' resolutions. The numbers stand for stations in columns "at-site" and for tiles in the other columns. For each case (i.e., each semi-column), the highest number is marked with underlined bold font, while the second highest has bold font.

The most correlated indices are WeMOI and the EA-WR for μ, and PDO and MOI for L-CV. ENSO shows the weakest
influence on both statistics, and therefore is excluded from further analysis. The overall number of significant correlations in the study area than any other teleconnection considered in the study. When considering single stations, we found 387 significant correlationsfor hourly rainfall for WeMOI , while for the other indexes they range from 0 (ENSO)to 78 (PDO). Due to this huge difference, only the is not sufficient to fully understand the dependence relationships of μ-teleconnection or L-CV-teleconnection, nor to compare the influence of various teleconnections. Instead, we main objective is the description of the
spatial correlation field, that is the spatial patterns of significant correlations, and their robustness to varying the resolution of the spatial aggregation (i.e., tiles' size). This is represented through the interpolated reliability index, ri, in Figure 3. As defined in Sections 2.1 and 3.1, areas where $ri \geq 3$ or $ri \leq -3$ indicate "consistent" correlation. Focusing on μ, it is confirmed that WeMOI and EA-WR have a strong influence, particularly concentrated in two major patterns of consistent negative correlation in the Gulf of Genoa and in the North-Eastern Alps (panels b, d, g and i of Figure 3). These patterns are evident in the case

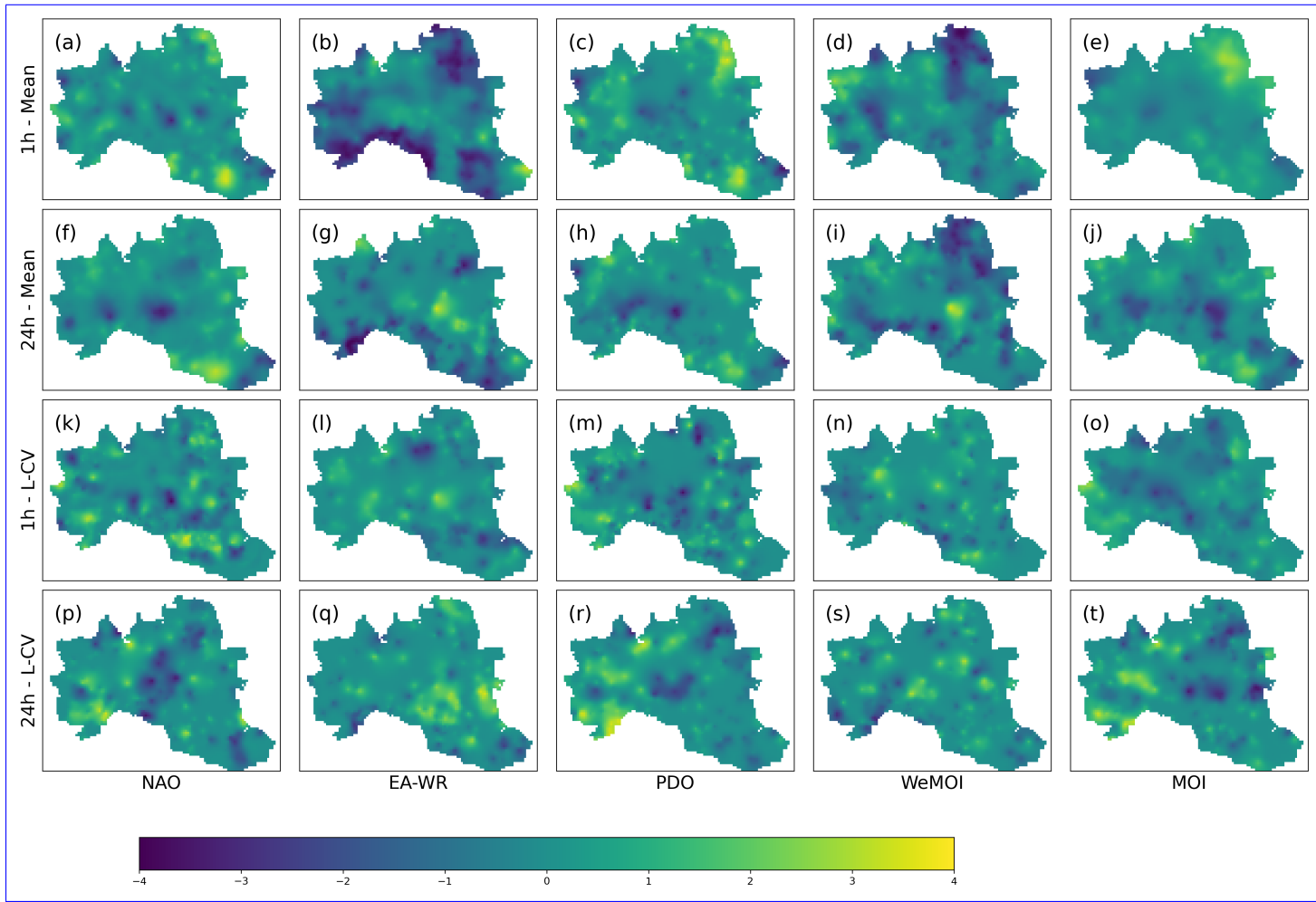**Figure 3.** Raster maps of reliability index (ri) of the correlation between teleconnections and mean (panels a-j), or L-CV (panels k-t) of AMS of rainfall depths with duration of 1h (panels a-e and k-o) and 24h (panels f-j and p-t)

of 1h duration, where the North-East shows consistent correlation with all the indices (panels a-e of Figure 3). For the 24h duration the two patterns for WeMOI and EA-WR are more fragmented and less extended, even tough still present, while the other indices show only small areas with strong influence on μ.

Focusing on L-CV, consistent correlation patterns for 1h are highly heterogeneous, suggesting that regional GEV_2 models could be ineffective (panels k-o of Figure 3). More extended, yet still restrained, patterns can be observed for 24h, in particular in the western portion of the Gulf of Genoa and in the central region of the study area (see panels p-t in Figure 3). It is difficult to establish which index is the most influent, but PDO and MOI show high similarities and promising homogeneous patterns, in agreement with Table 2.

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The results obtained for WeMOI are presented below.Figure 2 reports in detail in Figure 4, which reports statistically significant Spearman correlation coefficients with WeMOI at different resolutions for spatial aggregation for the mean (panels (a) -(h)) at different spatial resolutions for μ (panels a-h) and L-CV (panels (i)-(p))i-p), respectively. Several stations present statistically significant correlation values with this indexWeMOI, with signs and amplitude changing depending on the site considered (panels (a) and (e) for mean, (i) and (m) a and e for μ, i and m for L-CV, Figure 4). Aggregating stations into tiles reduces spatial heterogeneity , and and decreases the extension of significantly correlated areas, which allows to describe the geographical pattern of the correlation field (see other panels). Both for the mean and L-CVBoth for 1h and 24h duration, the correlation fields of extreme rainfall with 1h duration present complex μ present consistent spatial patterns, with small extended areas characterized by homogeneous values . (panels a-h). On the contrary, the correlation field of L-CV is more sensitive to the change of tiles' resolution and presents smaller isolated hotspots (panels i-p). Similar results are observed also for the other teleconnections, but they are not reported for the sake of brevity.

The reliability index (ri, see Equation 7) is showed for the mean and L-CV in Figure **??**. As observed above, stable geographical structures in the correlation are larger (1) for the 24h duration than for the 1h (compare panels (a) and (b) with panels (c)and (d) in Figure **??**),

4.2 Phase 2: Frequency analysis

Following the adopted framework (see Sections 2.2 and 3.1), polynomial relations are fitted at-site (i.e., μ-teleconnection) and at 30km-tiles (i.e., L-CV-teleconnection) to obtain the parameters for GEV_1 and (b)for the mean than for L-CV (compare panels (a)and (c) with panels (b) and (d) in Figure **??**)GEV_2 distributions, respectively, and jointly for GEV_3. Then, the goodness-of-fit is compared with the stationary framework (i.e., GEV_0) with RML (equation 6). For the sake of brevity, the gauged sites where RML is higher than a given RML threshold (Table 1) will be hereinafter referred to as "doubly-stochastic sites". The number of doubly-stochastic sites in each case, n_{DS}, is reported in Table 3, while Figure 5 represents their location.

	n_{DS}, RML $\geq$ empirical th_{RML}					n_{DS}, RML $\geq$ theoretical th_{RML}				
	NAO	EA-WR	PDO	WeMOI	MOI	NAO	EA-WR	PDO	WeMOI	MOI
1h - GEV_1	101	105	113	**171**	85	31	45	33	**61**	22
24h - GEV_1	67	98	72	**141**	86	19	43	17	**53**	16
1h - GEV_2	58	51	60	**85**	46	12	16	12	**16**	10
24h - GEV_2	65	70	60	**93**	59	17	18	**22**	21	18
1h - GEV_3	152	173	169	**248**	149	22	36	26	**50**	18
24h - GEV_3	125	170	138	**213**	119	16	29	18	**43**	13

Table 3. Number of doubly-stochastic sites (n_{DS}). I.e., stations where RML $\geq th_{RML}$. The highest number is marked with bold font in each line, corresponding to a specific duration and doubly stochastic framework. Emprical and theoretical threshold are reported in Table 1

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Regarding GEV_1, WeMOI has the highest number of doubly-stochastic sites for 1h, followed by EA-WR and PDO, depending on the threshold for RML (3 or 1.5, respectively, see Table 3). For 24h, WeMOI and EA-WR are confirmed as the most influent indices. Figure 5 is quite in agreement with Figure 3, confirming that in the two regions of the Gulf of Genoa and North-East GEV_1 fits the AMS better than GEV_0. These two regions show non-stationarity signals with all the indices (see panels a-j), but particularly with the most influent ones (panels b, d, g, i).

Concerning the mean of Regarding GEV_2, WeMOI has the highest number of doubly-stochastic sites both for 1h and 24h, followed closely by the other indices (see Table 3). In this case, detecting clear geographical patterns is difficult, but it is possible to spot some sub-regions where the signal is strong for multiple indices. Some examples are the AMS series, two major patterns of robust negative correlation are present in the Western coast of the Tyrrhenian Sea (North-East for 1h (see panels k-o of Figure 5), and the western portion of the Gulf of Genoa (in agreement with Figure 3) and the south-central portion of the Adriatic coast (see panels p-t of Figure 5).

Considering the theoretical threshold (i.e., 4.7) doubly-stochastic sites for GEV_3 have a very similar spatial configuration relative to GEV_1 or GEV_2, according to the case (see panels u-d1 of Figure 5). Hence, the numbers of GEV_3 doubly-stochastic sites in Table 3 are close to the maximum value within GEV_1 and in the north-eastern Alps. Less intense but significant positive correlation values are present along the northern flank of the northern Apennines.For the L-CV, the pattern in the Gulf of Genoa is still present, but less evident and less extended, while some positively correlated hotspots are present, mostly located in the Southern portion of the GEV_2 for each index and duration. Differently, when the empirical threshold is considered (i.e., 1.6), the results suggest that GEV_3 doubly-stochastic sites are much more than GEV_1 and GEV_2, and located over the whole study area.

Raster maps of reliability index (ri) of the correlation between WeMOI and mean/L-CV of AMS of rainfall depths with duration of 1h (a/b) and 24h (c/d)

4.3 Results of phase 2: Frequency analysis

Following the adopted framework (see Section 3.2), regional frequency analysis is applied to all the locations where significant correlation is observed (

As mentioned in Section 2.2, the field significance of non-stationary (i.e., doubly-stochastic in this context) signals in presence of intersite dependence is tested by means of lower thresholds th_{nDS} to the number of doubly-stochastic sites n_{DS} (see details of the test in Appendix B). While WeMOI and EA-WR are clearly very effective for GEV_1 and GEV_3 distributions, it is hard to unequivocally establish the best teleconnections for GEV_2. For coherence, the test in the present study is performed for WeMOI and EA-WR for all of the three models, and the results are reported in Table 4. Regarding GEV_1, the number of doubly-stochastic sites is not significant when considering 1.5 as th_{RML} (with the exception of WeMOI for 1h), while the null hypothesis (i.e., p-value≤5%) . Figure ?? illustrates the results obtained for a station (see panel (a) for its location) where the three non-stationary GEV can be fitted the distribution is stationary) is always rejected with a threshold of 3. Differently, for GEV_2 and GEV_3 the null hypothesis is rejected with all the thresholds.

	Empirical th_{RML}		Theoretical th_{RML}	
	n_{DS}, RML $\geq$1.5	th_{nDS}, RML $\geq$1.5	n_{DS}, RML $\geq$3	th_{nDS}, RML $\geq$3
EA-WR, 1h - GEV_1	105	**117**	**45**	30
WeMOI, 1h - GEV_1	**171**	139	**61**	41
EA-WR, 24h - GEV_1	98	**126**	**43**	34
WeMOI, 24h - GEV_1	141	**148**	**53**	47
EA-WR, 1h - GEV_2	**56**	19	**11**	6
WeMOI, 1h - GEV_2	**85**	24	**16**	8
EA-WR, 24h - GEV_2	**70**	28	**18**	9
WeMOI, 24h - GEV_2	**93**	31	**36**	11
	n_{DS}, RML $\geq$1.6	th_{nDS}, RML $\geq$1.6	n_{DS}, RML $\geq$4.7	th_{nDS}, RML $\geq$4.7
EA-WR, 1h - GEV_3	**173**	120	**36**	11
WeMOI, 1h - GEV_3	**248**	150	**50**	17
EA-WR, 24h - GEV_3	**170**	139	**29**	16
WeMOI, 24h - GEV_3	**213**	168	**43**	23

Table 4. Number of doubly-stochastic sites (i.e., sites where RML$\geq th_{RML}$) in the original dataset (n_{DS}), and significance thresholds against spatial dependence (i.e., empirical and theoretical th_{nDS}). For each case, corresponding to a given duration and doubly-stochastic framework, the highest number between n_{DS} and th_{nDS} is marked with bold font.

Figure 6 illustrates for a specific location an example of doubly-stochastic modeling. Panels d-f show frequency curves corresponding to single "realizations" of the teleconnection of interest (i.e. , GEV_1 in panel (c), GEV_2 in panel (d), and GEV_3, in panel (e))WeMOI in the example, colorscale from yellow to purple). Indeed, frequency curves are not theoretically consistent with the non-stationary framework. Nevertheless, the representation is very useful to visualize the degree of variability of design rainfall depth associated with alterations of the driving teleconnection.

It is evident from the example provided As clearly illustrated in Figure 6that the variation of the expected percentiles due to the dependence of the GEV parameters on the teleconnections , the variability of predicted rainfall percentiles associated with changes in the teleconnection may be very significant. It is worth noting that WeMOI changes in the example span across observed values, no extrapolation is performed. The prediction of the 100-year 24-hour rainfall depth in the selected location is equal to 370mm 240mm according to the stationary model (GEV_0), but may vary between 340 and 375 200 and 240 if the empirical relationship between WeMOI and L-CV is explicitly modelled (GEV_2), between 300 and 460 200 and 300 if the mean 24-hour annual maximum rainfall depth becomes a function of WeMOI (GEV_1), and may be as low as 275 170 and as high as 470 300 if both mean and L-CV are expressed as functions of WeMOI (GEV_3).

Figure **??** represents the RML, Δ_{AD}, and $\Delta_{TN.SW}$ (panels (a), (b) and (c), in this order). These measure the increase in goodness-of-fit due to the non-stationary regional GEV models with respect to the stationary ones. They are computed for all locations in which statistically significant correlation between AMS statistics and WeMOI was detected (see Sections 2.1 and

2.2). Values of RML (Figure **??**.a) and Δ_{AD} are mainly positive for GEV_1 and GEV_3 (i.e., non-stationary models show a better representation relative to the stationary one), where negative values are present in less than 25% of the cases. For GEV_2, in nearly half of the stations examined the precipitation regime is better represented by a stationary framework. Differently, values of $\Delta_{TN.SW}$ are almost equally divided into positive and negative for both the 1h and 24h durations and all the non-stationary models. Overall, the GEV_2 model shows the lowest number number of cases (which is still above 50%) where it should be preferred to the stationary regime. For all the three metrics, light differences are observed between the results for 1h and 24h.

Evaluation metrics for stationary and non-stationary RFA framework for locations where at-site strong and significant correlation $_{\text{WeMOI}}$-st is present (GEV_1), 30km strong and significant correlation $_{\text{WeMOI}}$-L-CV_t is present (GEV_2), and both correlations $_{\text{WeMOI}}$-st and $_{\text{WeMOI}}$-L-CV_t are strong and significant (GEV_3). In particular, RML (a), Δ_{AD} (b), and $\Delta_{TN.SW}$ (c). For all the metrics, results larger than zero represent better performances of non-stationary over stationary framework.

5   Discussion

5.1   Zonation of the correlation

The stronger influence of the WeMOI compared to the other teleconnections was expected.

5.1   Spatial correlation fields

The results in Section 4.1 clearly show that WeMOI and EA-WR have a very strong influence on the mean of extreme precipitation over the study area. This was expected, as it is in line with the observations of Caroletti et al. (2021) for Southern Italy, and Romano et al. (2022) for Central Italy. In fact, the WeMOI consists of the normalized difference in atmospheric pressure between Cadiz, in the South of Spain, and Padua, in northern Northern Italy, and thus, it describes the formation of precipitation systems over the Tyrrhenian Sea (Lopez-Bustins et al. , 2020; Redolat et al. , 2019). Strong significant correlations with the WeMOI were also found in other studies, as for Central Italy by Romano et al., 2021 and for Southern Italy by Caroletti et al. , 2021. (Lopez-Bustins et al., 2020; Redolat et al., 2019). Nevertheless, EA-WR pattern consists of four atmospheric anomalies extending from North Atlantic to Western Russia (Barnston and Livezey, 1987). Negative phases, which correspond to low-pressure anomalies over Europe and Northern China and high-pressure anomalies over the Central North Atlantic and North of the Caspian Sea, have been found to drive wetter conditions across Europe and the Mediterranean (e.g., Krichak and Alpert, 2005). Moreover, EA-WR is highly correlated with WeMOI, and hence is reasonable that the two teleconnections have similar influence.

In particular, the presence of significant intense negative correlation values in the Gulf of Genoa and the North-East for the mean-WeMOI correlation (Figure **??**.a and **??**.cmean with WeMOI (panels b and g of Figure 3) and EA-WR (panels d and i of Figure 3) is consistent with the known patterns of precipitation regimes over north-central North-Central Italy. In fact, intense daily precipitation values are expected over the Tyrrhenian Coast and north-eastern North-Eastern Alps in the presence

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of intense southwesterly flows from the Mediterranean, typical during the autumn season and favored by large scale circulation anomalies associated with negative value of the WeMOI . On the other hand, in the presence of positive values of the index, precipitation is expected to be linked to cut-off flows mostly affecting the Adriatic section of the Apennines. WeMOI and EA-WR. In the remaining portion of the study area, precipitation systems are more complex, as influenced by the passage of

420 cut-of flow lows favoring precipitation over the southern and eastern Southern and Eastern portion of the Apennines area. In this case, correlation patterns with the WeMOI WeMOI and EA-WR are expected to be more fragmented(Figure **??**. c). .

For It is very interesting to notice that although the 1h rainfall maxima , are mostly linked to convective phenomena, which are often characterized by a very limited spatial scale, the correlation with WeMOI presents more complex geographical patterns , even if still present (Figure **??**.a). and EA-WR presents more extended geographical patterns than in the daily case (compare

425 Figure 3.b and 3.d with 3.g 3.i).

A physical interpretation of the L-CV-WeMOI dependence is more complex. It is evident that some hotspots of correlation are present (Regarding the L-CV, the absence of evident correlation patterns for hourly annual maxima confirms our knowledge about spatial variability of convective phenomena (Figure 4.k-l for and 4.o-p): negative correlations are mostly located in the North-West, which partially confirms the results for the mean (compare Figure 4.f-g with 4.n-o). Elsewhere, small 3.k-o). Small

430 and fragmented, mainly positive patterns are visible . Considering the ri, the robustness of patterns to for daily rainfall (Figure 3.p-t), but a physical interpretation of the L-CV-teleconnection dependence is more complex. In general, the consistency of patterns with spatial aggregation is lower than for the mean, which may be partly due to higher uncertainty in at-site computation of L-CV within a 10-year time window. For this reason, we believe that for L-CV, a spatial aggregation at 30km should be preferred for RFA.

435 Based on the An important element to consider when commenting Figure 3 is that only correlations with p-value ≤ 0.05 were considered in the computation of ri (eq. 7). Even though this threshold value is the most commonly adopted in the literature, it is still subjective, and it could lead to discard some significant correlations. This is evident when looking at the correlations with p-value within 0.1 and 0.05 in Figure 4 (i.e., tiles without red outlines). An additional source of subjectivity is the interpolation of ri with kriging, that depends on the choice of kriging type and semivariance function.

440 Nevertheless, based on the results described in Section 4, the methods adopted generally allowed a reliable zonation lead to a useful characterization of the teleconnection-extreme rainfall correlation . This is due to two elements: the field, which can be used to drive frequency analyses. In fact, sub-regions with homogeneous rainfall-teleconnection dependence may be defined, in order to set specific doubly-stochastic RFA models. This option requires to define an objective grouping criterium, possibly based on a set of morphoclimatic characteristics (see e.g., the morphoclimatic characteristics adopted in Magnini et al., 2024);

445 due its complexity, this problem deserves specific studies, and is not further investigated in the present study.

We estimate spatial correlation fields based on two major elements: temporal and spatial aggregation of the data. First, the temporal aggregation through sliding time windows allow allows to consider the statistics of the extreme rainfall during time, instead of the rainfall depth themselves. In this way, it is possible to filter out inter-annual variability of the seasonality and magnitude of the annual maxima and focus on the decadal precipitation statistics. Second, the spatial aggregation into tiles

450 allows to obtain more reliable values of the rainfall statistics. This produces a smoothing local effect, that could be due to data

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fragmentation and noise and enhance geographical pattern recognition (see Figure 4). The choice of w_t for spatial aggregation should be carefully conducted, as it mainly depends on the morphology of the study area, and the density and location of the rain gauges. Generally, considering a number of different values for w_t is useful to analyze the reliability of the detected correlation patterns.

455 A different approach for spatial aggregation could be the one described in Castellarin et al. (2024), where overlapping tiles are used. However, including each gauged site in multiple tiles could result in eccessive smoothing effect of the orographic effect over the correlation field, and strenghtening of spatial dependence. Thus, this solution should be preferred only in case of scarce density of gauges network.

A key aspect of the proposed approach is its high adaptability. In fact, the same methodology with an appropriate parametriza-
460 tion could be used to study the influence of teleconnections on several environmental variables, such as AMS of floods or temperature or wind. Moreover, raster maps of the correlation field (as the ones in Figure ??3) could be used as descriptors of the drivers of an environmental variable, and adopted as input of predictive raster-based models (e.g., for prediction of flood susceptibility, as in Magnini et al., 2023).

5.2   Non-stationary Doubly-stochastic regional frequency analysis

465 Looking at the results of the second phase of our study(Figure 6), two main points are of general interest. First, the range of variability of the expected percentiles with doubly-stochastic models (i.e., non-stationary models depending on teleconnectionsis very significant) is very wide, confirming what observed locally by other authors (Figure 6). Second, the regional dependency of rainfall statistics on teleconnections can be successfully exploited locally for frequency analysis (see Table 3 and Figure 5). This is a useful improvement over present literature, as it allows to obtain the extreme rainfall statistics (i.e., μ_{st} and $L-CV_{st}$)
470 even where observations are not locally available. Moreover, the observed variability of the expected maximum rainfall with given return periods could be used as teleconnection-informed uncertainty range for the design of hydraulic structures.

The results in Figure ?? show that an incontrovertible evaluation of which model is the most accurate is impossible. In fact, each metric, or test, evaluates differently the goodness-of-fit and may provide wrong indication of the best model (e.g., see Laio et al., 2009; Ashkar and Aucoin, 2012; Ashkar and Ba, 2017). In general, it is positive that two metrics out of three (i.e., RML and Δ_{AD}) indicate that the non-stationary framework fits the data better for most of the stations analyzed.
475 Nevertheless, it is not surprising that one of the metrics ($\Delta_{TN,SW}$) suggests to select the stationary approach in half of the cases. In fact, the framework The framework we adopted for non-stationary doubly-stochastic RFA is based on the strong assumption that the same type of function (i.e., a polynomial function) can represent the teleconnection-statistic relationships within all the study area. Indeed, this approximation is sufficiently accurate in some stations, while being not adatp in others.
480 This is probably also the reason why the GEV_1 models perform generally better than the outperform GEV_0 globally more often than GEV_2 onesmodels (Table 3). In fact, the polynomial approximation may fit the data better when these are collected locally (as for the μ_{tel}-μ_{st} case) than when they result from tile-wise averaging (as for the μ_{tel}-L-$CV_{st\ t}$ case). Nevertheless, it is encouraging that a significant number of sites with RML$\geq$3 is detected for GEV_1 and GEV_2 (see Table 4), despite the low-complexity of the function adopted for modelling the dependence on teleconnections. Accordingly, the GEV_3 models

485 derive their goodness or badness from the sum of the GEV_1 and GEV_2 contributes. This , which leads them to be the best modelsfor some stations, and the worst for others (see the extension of most adaptable models. Therefore, a high number of doubly-stochastic sites is observed when 1.6 is considered as RML significance threshold, corresponding to a small penalty for the additional parameters of $f(x)$ (compare 1.6 and 4.7 thresholds for GEV_3 boxplots in Figure **??**. a and **??**.c) , depending on the goodness of the polynomial approximation for μ and L-CV.in Table 3).

490 To summarize, the metrics showed in Figure **??** can be considered as encouraging, as they detect better It is very interesting that the comparison of ri (essentially based on Spearman correlation) and RML highlights differences in the most influent indices (i.e., compare Table 2 with Table 3) and doubly-stochastic patterns (e.g., compare panels k-t of Figures 3 and 5). A partial difference between the two metrics is expected and natural, mainly due to three reasons. First, ri takes into account both the significance of the correlation and its sign, while RML represents the goodness-of-fitof non-stationary RFA models

495 than the stationary ones, despite the low-complexity of , and hence it does not describe the nature of the teleconnection-rainfall dependence (i.e., increasing/decreasing). Thus, RML may lead to group sites whose dependence on the teleconnection has different sign. Second, RML is probably more similar to a single correlation (i.e., at-site in the function adopted for modelling the dependence on teleconnections.GEV_1 case, and at 30km-tiles in the GEV_2 case), while ri depends on correlations at several spatial aggregations, which may disagree. Third, also correlations that are not considered significant could lead to

500 good doubly-stochastic models. Furthermore, some studies (e.g., Sugihara et al., 2012; Cappelli and Grimaldi, 2023) suggest that correlation may fail in describing the causality of two variables, and that an approach based on a model's performance can be more accurate. However, we believe that in our case both the metrics are very useful, as they can help to delineate sub-regions with homogeneous teleconnection-rainfall dependence function (see also Section 5.1). As perfectly exemplified in our results, sometimes the presence of such regions is evident (e.g., the Gulf of Genoa and North-East for GEV_1, see Figure

505 5), while in other cases it is hard to distinguish between small homogeneous regions and effects of spatial dependence (e.g., Adriatic coast and western Gulf of Genoa for GEV_2, see Figure 5).

It is important to underline that the aim of the present research is to investigate the potential of teleconnections as independent variables in RFA models, and not to propose a specific method for RFA. Indeed, the RFA results depend on a number of parameters, that are including the widths of STWs sliding time windows for temporal aggregation of the teleconnection indexes

510 indices (w_{tel}) and AMS (w_{AMS}), and the resolution for spatial aggregation (w_t). The choice of these parameters can be done by These can be set after a careful sensitivity analysis for defining the spatial field of the teleconnection-statistic correlation (see Sections 2 and 4.1). The case of setting a framework for RFA is very different and much more complex, as it requires the formalization of a function formalizing a function $f(x)$ of extreme rainfall statistics depending on teleconnection indexes. In this caseteleconnections is very different and much more complex. In fact, one should decide not only the shape of this func-

515 tion, but also the way its parameters vary in space and should be estimated, which may require the delineation of sub-regions (see considerations above). In our study, we adopted a simple framework, as this function has a limited number of parameters and the same shape (i.e., polynomial) in all the spatial domain. We showed a hierarchical RFA approach where the parameters of the polynomial functions are fitted at-site for the μ and at 30km-tiles for the L-CV. Our analyses overall suggest that even with a simple RFA framework, the use of teleconnections as dependent variables to describe the extreme rainfall regime may

520 increase the accuracy in frequency modelling.

However, different Different approaches are indeed possible. First, the best resolution for spatial aggregation and the shape of the teleconnection-statistic function should be carefully evaluated for each specific case. Second, a more complex teleconnection-statistics function could be defined. A possible approach is the one proposed by Magnini et al. (2024), which leverages neural networks' capabilities to obtain functions whose parameters depend on the location of the considered site and other morpho-

525 climatic descriptors, or the one adopted by Machado et al. (2015), which exploits generalized additive models. Indeed, the implementation and discussion of more sophisticated RFA methods to exploit teleconnections' informative content is complex, and should be addressed by future studies.

6 Conclusions

530 A growing number of recent studies show how large scale climatic indexes indices (or teleconnections) can be used as covariates to increase reliability of local frequency analysis of rainfall extremes across diverse geographical regions worldwide (e.g., Fauer and Rust, 2023; Ouarda et al., 2020; Ragno et al., 2018). It is theoretically possible to extend these methods to regional frequency analysis (RFA), but the teleconnection-extreme rainfall dependency at a regional scale should be first investigated. Beside its usefulness for correct estimation of the design rainfall for engineering applications, this topic is still not well ad-

535 dressed in the literature.

In the present study, we propose a framework to assess the link between teleconnections and the frequency regime of rainfall extremes at a regional scale, in order to perform climate-informed regional frequency analysis. RFA. The approach is tested for a large and climatically diverse region in northern Northern Italy. Our dataset consists of 680 annual maximum series (AMS) of hourly and daily (i.e., 1 and 24 hours durations) rainfall depth, recorded between 1921 and 2022. We select six global climate

540 indexesclimate indices, known to have significant correlation with local climate variability over the study area (Caroletti et al., 2021; Criado-Aldeanueva and Soto-Navarro, 2020; Romano et al., 2022): the North Atlantic Oscillation, Pacific Decadal Oscillation (PDO), East Atlantic – West Russia pattern, El Niño Southern Oscillation, Mediterranean Oscillation Index(MOI), and Western Mediterranean Oscillation Index (WeMOI).

The main steps of the proposed framework can be summarized as follows. First, we define sliding time windows in order to

545 obtain time series of pluridecadal averaged teleconnections and statistics of annual maxima(i. e. L-moments of . The latter consist of the sliding mean and L-coefficient of variation (L-CV) of AMS, which in our case were used characterized are used to characterize the distribution of sub-daily rainfall extremes). Second, we discretize the study area into tiles where the L-moments are averaged into regional predictions. Then, we evaluate the correlation of teleconnections with time series of spatially gridded L-moments. Finally, we show a preliminary application of climate-informed regional frequency analysis RFA

550 of rainfall extremes, where the L-moments are modelled as functions of WeMOI. We selected WeMOI as it shows a notably the teleconnections singularly. These models are compared with the corresponding stationary models by means of goodness-of-fit metrics.

Our results show that the sliding mean of annual maxima (both hourly and daily) has a higher number of significant correlations with the statistics of sub-daily rainfall maxima than the other teleconnection indexes. Application to different regions and hydroclimatic contexts may result in a higher relevance of other teleconnections. WeMOI and EA-WR than with the other indices. Moreover, the relationship between WeMOI and L-moments these indices and sliding mean of extreme rainfall shows clear spatial patterns across the study area, whose robustness is confirmed by their limited sensitivity to the chosen grid resolution and the partial agreement with previous studies (Caroletti et al., 2021; Romano et al., 2022). Similar patterns are found when considering the areas where the goodness-of-fit of the climate-informed regional models (where the mean depends on the WeMOI and EA-WR) outperforms the stationary approach. As well, this is coherent with the known spatial variability of precipitation regimes over the region.

The relationship between the sliding L-CV and the teleconnections is more complex, since the number of significant correlations is lower, and dependence patterns are less extended and more heterogeneous. Nevertheless, the regional models where L-CV depends on the teleconnections outperforms the stationary approach in a significant number of stations.

The proposed approach is simple and easily reproducible, yet it is new with respect to the existing literature. In fact, while most authors investigated the correlation between the teleconnections and the raw AMS, we consider the L-moments. This, in combination with spatial discretization of the domain, allows us to focus on the relationship between the teleconnections and the extreme rainfall regime, instead of the extreme values themselves, whose seasonality and interannual variability can affect the correlation analysis. Beside the preliminary nature of the our RFA application, three commonly used metrics (e.g., Ashkar and Ba, 2017) detect overall an increase in goodness-of-fit with respect to a stationary approach, in line with previous studies (Nerantzaki and Papalexiou, 2022), (Nerantzaki and Papalexiou, 2022). This shows that teleconnections may be useful covariates in a regional a framework.

Overall, our research suggests promising pathways for climate-informed local and regional frequency analysis of rainfall extremes, and our methodology is highly adaptable to different environmental variables, such as floods and temperature.

Appendix A: Statistical significance of empirical RML values: Monte Carlo simulations

The present Appendix describes the methodology adopted to empirically assess the statistical significance of RML values obtained in the study (i.e., ratio of models' likelihood, see Section 2.2). In particular, the statistical test consists of comparing RML with lower threshold values (th_{RML}) associated with a 5% significance level (see Section 2.2). We determine these threshold values by means of Monte Carlo (MC) simulations that are designed to empirically identify the RML value associated with a p-value of 95% when comparing the likelihood of a doubly stochastic GEV (i.e., GEV_{DS} with DS=1, 2, 3, see also

Section 2.2) with that of a stationary distribution (i.e., GEV_0) when the parent distribution of the generated annual sequences is GEV_0. Specifically, our simulations generate stationary synthetic annual sequences (AMS), but we do not fit new frequency distributions on the synthetic AMS. Instead, the original frequency models are used to compute the likelihood of the synthetic timeseries. The procedure to define values of th_{RML} can be described as follows:

1. For each station, the GEV_0 model (i.e., the stationary distribution fitted to the at-site mean, and regional L-CV and L-CS) is used to generate 1000 annual maxima time series with the same length of the original AMS.

2. For each simulation, RML is computed with reference to the GEV_0 model and, in turn, one of the considered doubly-stochastic models GEV_{DS} (i.e., GEV_1, GEV_2, and GEV_3). As stated above, we consider only the frequency models fitted to the original data, but RML refers to the synthetic time series. Since the parent distribution is GEV_0, RML is expected to be low (i.e., GEV_0 should provide the best fit in the majority of cases).

3. For each station (st) in the study region and each doubly stochastic GEV model, we identify the 95th percentile from the series of simulated RML. This step produces 680 percentiles for each doubly stochastic model, meaning that each station has its own percentiles ($th_{RML,st}$).

4. The values of th_{RML} for each doubly-stochastic GEV model for the entire region are defined as 95th percentiles of the 680 at-site values $th_{RML,st}$ from the previous step. Thus, we obtain a single RML threshold for a specific GEV_{DS} model that is valid for the whole study region.

We repeat this procedure for both durations, 1h and 24h, and all of the teleconnections considered for the test, namely NAO, EA-WR, PDO, WeMOI and MOI (see Section 4.1). We therefore obtain several values of th_{RML}, each one corresponding to a specific duration, teleconnection and GEV type.

The procedure described above preserves, or reproduces, all the main elements of our specific application case that may impact RML's diagnostic power: the study area morphoclimatic variability is considered by applying the MC experiments to the entire dataset; synthetic time series preserve the original length at each site (step 1). Furthermore, considering the original frequency distributions (step 2) is a key point, as it allows us to test the predictive power of RML in the real case, avoiding us to make additional assumptions on synthetic distributions.

Having the MC reference threshold values of RML, we can test the doubly-stochastic hypothesis; if the RML value we obtain for a specific case in our study region (i.e., for a given site duration, teleconnection and GEV model) is greater than the corresponding simulated th_{RML}, then the frequency regime of rainfall extremes for that site can be considered doubly-stochastic at 5% significance level.

Appendix B: Field significance of doubly-stochasticity signals: spatial bootstrap resampling

This Appendix describes the bootstrap experiments adopted to test the field significance of doubly-stochasticicty spatial signals in presence of cross-correlation, or intersite spatial dependence (see Sections 2.2 and 3.1 and 4.2). In particular, we test the

615 statistical significance of the number of doubly stochastic regimes that is observed in a specific region (n_{DS}), that is the number of sites where, according to the RML analysis, a given GEV_{DS} for a specific teleconnection provides a better fit to the data relative to GEV_0. The test adopts a threshold number of stations, th_{nDS}, that represents the 95th percentile of 1000 n_{DS} realizations for 1000 stationary (i.e. non doubly-stochastic) synthetic regions, which are generated from the original regional sample of annual maxima through spatial bootstrap resampling (see also Castellarin et al., 2024; Vogel et al., 2001).

620 The bootstrap procedure to define values of th_{nDS} is the following:

1. We generate 1000 synthetic regions by randomly reshuffling year-wise 1000 times the dataset of 680 AMS of rainfall depths with duration 1h (or 24h) year-wise. Each reshuffling produces a synthetic AMS dataset that is distinct from the original one, while preserving the distribution of observations among all AMS in any given year. Since the reshuffling is random, the 1000 synthetic datasets are realizations of a stationary world.

625 2. For each synthethic reshuffled dataset, we repeat the same hierarchical regional frequency analysis (RFA) adopted for the original dataset (see Sections 2.2 and 3.1). First, the stationary model, GEV_0, is fitted to the syntehtic data. Second, the synthetic time series of at-site μ and 30km tile L-CV are computed. Third, the polynomial functions are fitted to the synthetic μ and L-CV timeseries and the original (i.e. non-reshuffled) teleconnection timeseries; it is worth underlining here that any correlation, or relationship, between the original teleconnection and the synthetic μ and L-CV timeseries 630 is spurious, as, by construction, these synthetic μ and L-CV timeseries are obtained from stationary realizations. Fourth, the parameters of GEV_1, GEV_2 and GEV_3 are obtained for each synthetic time series.

3. For each synthethic reshuffled dataset, RML values (ratio of models' likelihood, see Section 2.2) are computed for GEV_1, GEV_2 and GEV_3

4. For each synthethic reshuffled dataset, n_{DS} is computed for GEV_1, GEV_2 and GEV_3 (see also Appendix A and Section 635 3.1)

5. The values of th_{nDS} are then obtained as the 95th percentiles of 1000 synthetic n_{DS} obtained for each considered case, that is given duration (i.e., 1h or 24h), teleconnection (i.e., EA-WR and WeMOI, see Section 4.2), doubly stochastic model GEV_{DS} (i.e., GEV_1, GEV_2 or GEV_3), and RML threshold (i.e., the theoretical one, and the empirical obtained using the procedure illustrated in Appendix A).

640 The field significance of the doubly-stochasticity signals can then be assessed at the 5% significance level by testing whether the empirical n_{DS} values obtained for the original dataset are larger than the empirical th_{nDS} obtained as described above.

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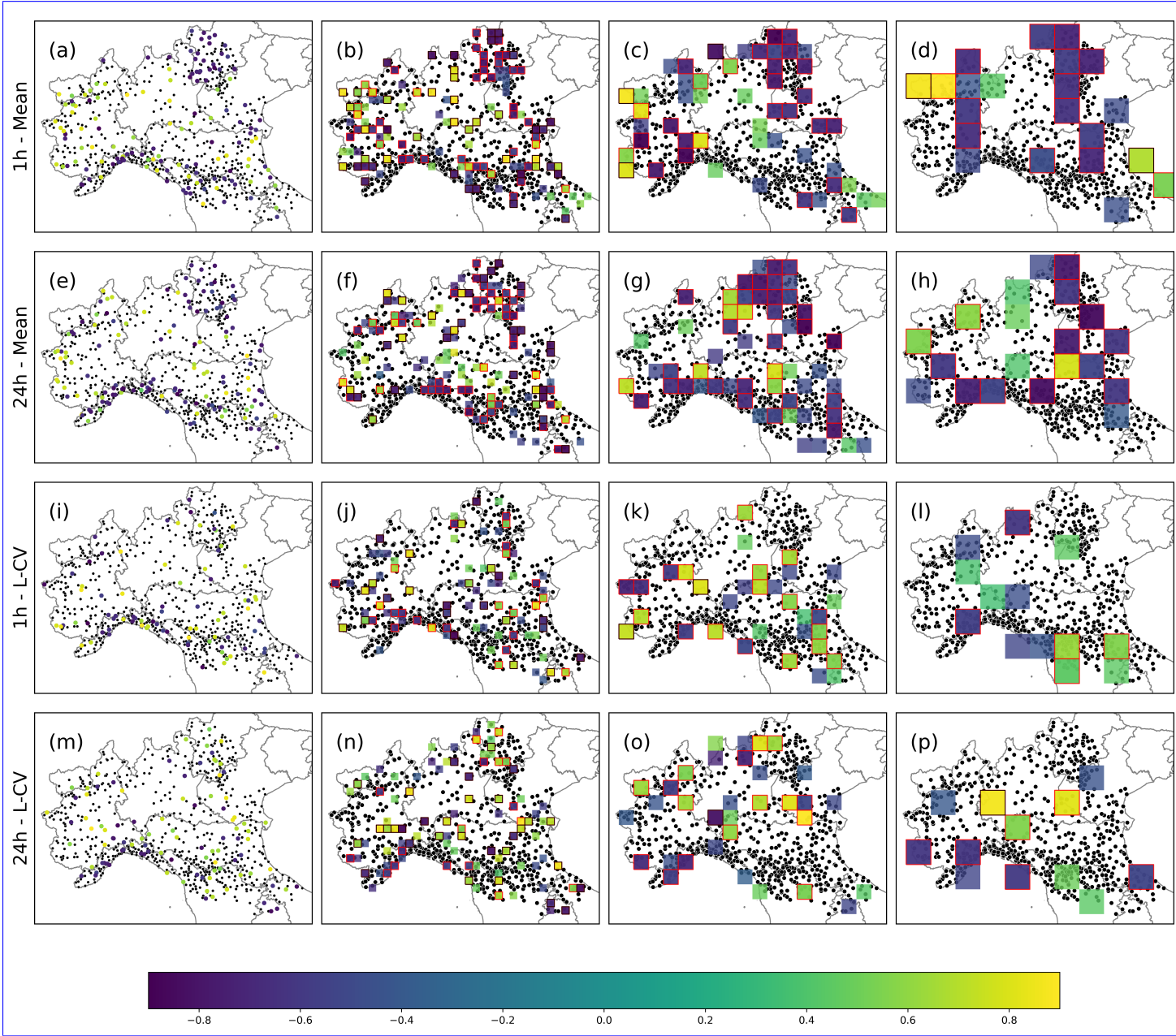
Figure 4. Correlation Spearman correlation coefficient for between WeMOI and the mean [L-CV] for AMS of rainfall depths with duration of 1h and 24h: at-site ((a)/([i]] and (e)/([m])) and for tiles of size 15km ((b)/([j]] and (f)/([n])), 30km ((c)/([k]] and (g)/([o])), and 50km ((d)/([l]] and (h)/([p])). Only statistically Statistically significant (at 510%) correlation coefficients are illustrated using a purple-green-yellow color scale. Red outlines highlight correlation significant at 5% (i.e., the ones considered for the ri). Black outlines highlight tiles where only one station is present. In panels a and i, gray circles represent non-significantly correlated stations
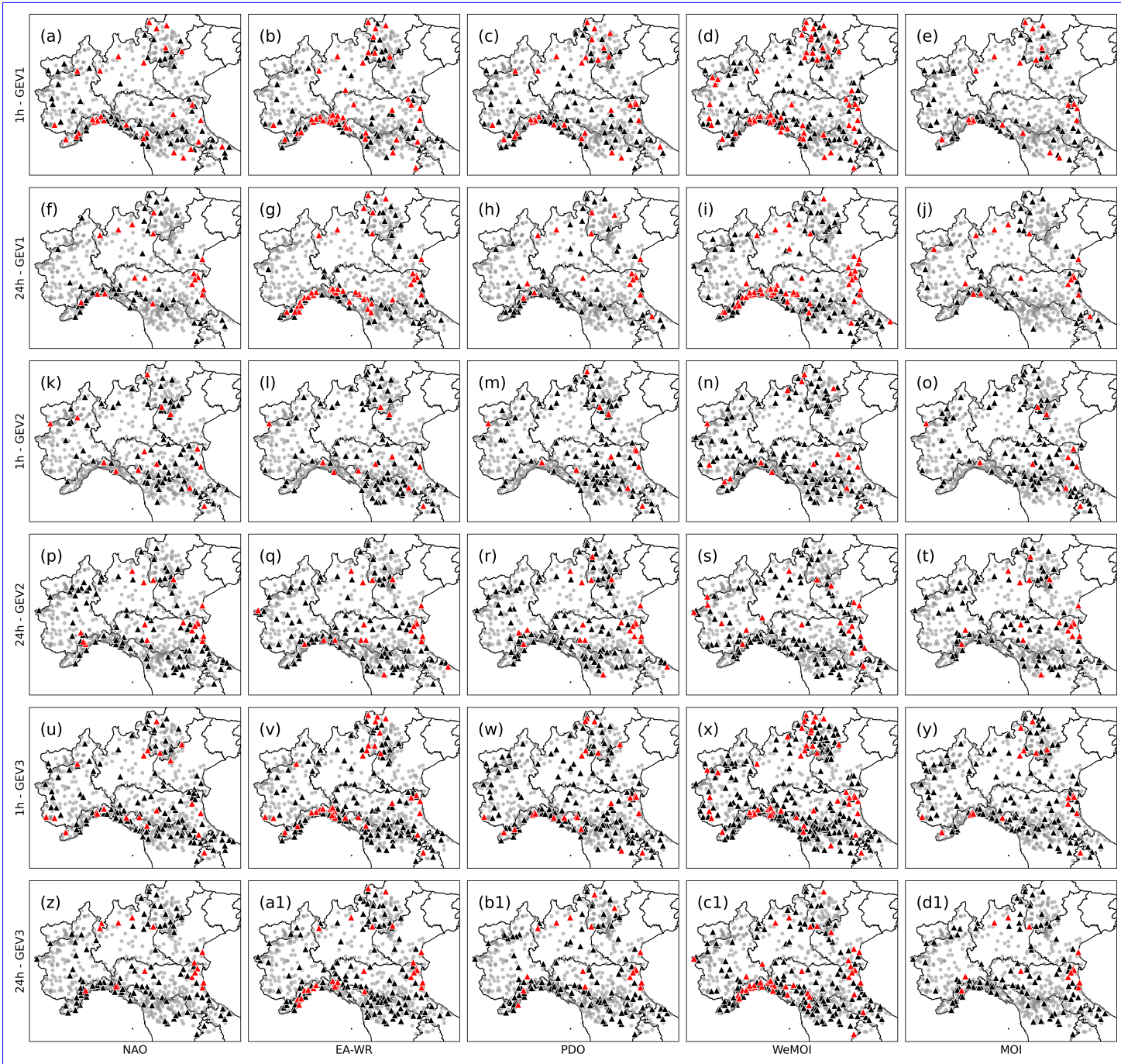
Figure 5. Doubly-stochastic sites observed for GEV_1 (panels a-i), GEV_2 (panels l-o) and GEV_3 (panels u-(d1)). Black triangles represent sites where theoretical th_{RML} >RML≥empirical th_{RML}. In red triangles, RML≥ theoretical th_{RML}. Stations where RML< empirical th_{RML} (i.e., stationary sites) are represented with grey dots.
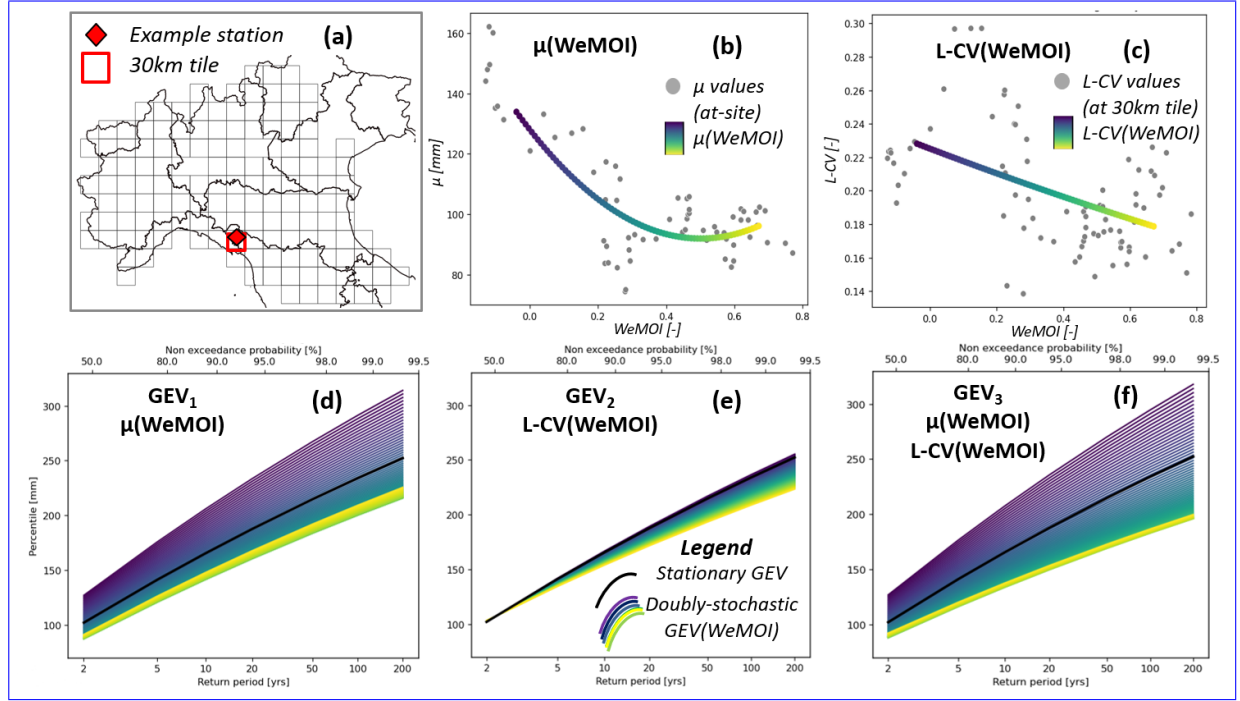
Figure 6. Example hierarchical frequency analyses of 24h rainfall annual maximum series at a given location where regional frequency analysis for 24h duration is performedthe hypothesis of doubly-stochasticity in the mean (μ) and L-CV resulted to be significal at 5% level. Upper panels: location of example considered station (a), polynomial function of mean (μ (b) and L-CV depending on WeMOI (bc). Lower panels: expected percentiles with given return periods in stationary (black line) and non-stationary doubly-stochastic framework (colored scale lines)when only , under the assumption that the mean depends on the WeMOI (cGEV_1, panel d), only the L-CV depends on the WeMOI (dGEV_2, panel e), or both mean and L-CV depend on the WeMOI (eGEV_3, panel f).