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Research papers

Are rainfall extremes increasing in southern Italy?

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ABSTRACT

The growing number of extreme hydrological events observed worldwide has raised the level of attention towards the impact of climate change on the rainfall process, which is difficult to quantify given its strong spatial and temporal heterogeneity. Therefore, the impact of the climate change should be determined ranging from individual hydrological series to a regional and/or district scale. With this context, the present study aims to identify trends and dynamics in extreme sub-daily rainfall patterns in southern Italy from 1970 to 2020. A comprehensive database of annual maxima was constructed using all available rainfall data and further expanded through the implementation of the gap-filling procedure, specifically the spatially-constrained ordinary kriging method. This expanded dataset was utilized to explore regional and local trends in annual maxima, offering valuable insights into the evolving nature of rainfall patterns in recent years. While most of the observed trends did not reach statistical significance, a significant number of locations exhibited upward tendencies for shorter durations. It is noteworthy that these trends tended to disappear over longer durations.

1. Introduction

In the last decades, climate change has received growing attention from the scientific community and aroused keen interest in the political and economic spheres due to its strong negative impacts (extreme weather events, water scarcity, losses of biodiversity, and risks to food production) on communities and ecosystems worldwide (Bandh et al., 2021; Lehner et al., 2006; Tabari, 2020). As extensively discussed in the literature (the Fifth and Sixth Assessment Reports of the IPCC, 2014, 2021), the climate crisis, in terms of rising temperature and changes in precipitation, is increasingly impacting Europe, with every region of the continent recording extreme weather events (floods, droughts, devastating heatwaves, and forest fires) every year. In this context, the Mediterranean area is a 'hot spot' for global warming since the level of warming in the next few decades has been estimated to be about 20 % higher than the global average (IPCC, 2021).

Climate change could have effects on several environmental variables, such as precipitation, temperature, atmospheric composition, and average sea level. However, rainfall represents the most important hydrological variable for water resource management and hydrological hazard mitigation. Investigating the rainfall regime is crucial when dealing with the design of hydraulic systems and infrastructure for the exploitation of water resources, protection of communities, and mitigation of hydrogeological risks. Hence, the need to explore changes in rainfall patterns is one of the most important topics in climatic research of the last few decades for water resource managers and the scientific community and is still one of the main challenges nowadays.

Therefore, to understand the characteristics and entity of these phenomena, identify the areas at higher risk, analyse their impacts, and enhance the development of adaptation and mitigation strategies, long-term changes in precipitation regime need to be identified in terms of frequency and intensity. In the scientific community, there is very high confidence that the frequency and intensity of heavy rainfall events are increasing in most regions with warming, but regional or local changes are less certain and detectable (Ingram, 2006). Therefore, in the last few years, significant effort has been devoted to investigating the temporal and spatial variability of extreme rainfall and the number of studies exploring trends in extreme rainfall series at annual, seasonal, or at most daily scale has increased enormously with several contrasting and strong regional differences. These include assessments at large regional scale

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(e.g., United States (Groisman et al., 2012); South America (Skansi et al., 2013); China (Gu et al., 2017); Australia (Nicholls and Lavery, 1992); Europe (Moberg et al., 2006; Senent-Aparicio et al., 2022; van den Besselaar et al., 2012; Zolina et al., 2009)) and global scales (Alexander et al., 2006; Donat et al., 2013a, 2013b; Groisman et al., 1999; Groisman et al., 2005; Westra et al., 2013). In general, an increase in intensity and frequency of extreme daily precipitation events on a global scale is widely recognised (Fischer and Knutti, 2016; Papalexiou and Montanari, 2019; Sun et al., 2021; Westra et al., 2013), only a few studies investigate sub-daily rainfall extremes as highlighted by Westra et al. (2014) due to the limited availability of long-term sub-daily rainfall records and the uneven spatial distribution of rain gauges in different countries across the world. Therefore, the scarcity of studies focusing on sub-daily time scale does not allow direct conclusions on global or local patterns of trends to be drawn (Fowler et al., 2021; Lewis et al., 2019). Furthermore, findings from investigations at the daily scale cannot be seamlessly extrapolated to the hourly or sub-hourly time scales, given the heightened sensitivity of short-duration rainfall events to local climatic condition and orographic influences (Westra et al., 2014; Caloiero et al., 2015). The need for an in-depth analysis of hourly rainfall extremes is becoming more critical considering that sub-daily rainfall extremes may intensify more quickly than daily precipitation events (Lenderink and Van Meijgaard, 2008; Morrison et al., 2019).

In Italy, as in many other countries around the world, studies on precipitation trends have shown discordant results (Brunetti et al., 2000; Brunetti et al., 2001) due to natural variability of precipitation regime. Focusing more specifically on southern Italy, rainfall trends from daily to annual time scales have been analysed in several studies, highlighting a decrease in annual precipitation and in the number of rainy days (Brunetti et al., 2004; Brunetti et al., 2006; Buffoni et al., 1999; Caloiero et al., 2011b; Caloiero et al., 2018). Furthermore, annual and monthly negative precipitation trends were registered for several regions of southern Italy such as in the case of Apulia (Lionello et al., 2014), Basilicata (Piccarreta et al., 2004), Calabria (Brunetti et al., 2012; Caloiero et al., 2011a; Caloiero et al., 2015; Caloiero et al., 2020), Campania (Diodato, 2007; Longobardi and Villani, 2010) and Sicily (Cannarozzo et al., 2006).

However, it is worth noting that the majority of studies have primarily focused on annual, seasonal, or, at most, daily time scales, as underlined by Caporali et al. (2020) in their review of 54 published research works on rainfall trend analyses. Additionally, they confirmed the widespread awareness that studies on short-duration rainfall are still scarce in the literature due to the lack of continuous sub-daily precipitation series. In Apulia region, Polemio and Lonigro (2015) analysed rainfall series of short-duration (from 1 h to 5 days) annual maxima in the period 1921–2005 detecting a generalised decreasing trend except for a small number of stations with an increasing trend in series up to 6 h-duration. In Campania, instead, the majority of the analysed rain gauges exhibited no trend for all the durations in the period 1970–2018, even if a clear upward tendency was observed in specific small areas only for shorter durations (Avino et al., 2021). In Sicily, different works (Arnone et al., 2013; Bonaccorso et al., 2005; Bonaccorso and Aronica, 2016; Treppiedi et al., 2021) have consistently identified distinct patterns in sub-daily annual maximum rainfall series. Specifically, these investigations reveal an upward trend in precipitation for shorter durations, accompanied by an increasing number of series exhibiting decreasing tendencies for longer durations. Finally, Libertino et al. (2019) and Petrucci et al. (2012) detected a consistent decreasing trend in long-term hourly rainfall time series in Calabria region. Unfortunately, studies on short-durations precipitation events are completely lacking in Basilicata and Molise and not update in Campania and Apulia regions.

The present study provides a comprehensive investigation on how extreme events have changed in the last 50 years (1970–2020) in a data-scarce area (southern Italy). For this reason, databases of sub-daily (1, 3, 6, 12 and 24 h) rainfall annual maxima were constructed using all available records and extended using spatial interpolation methods, such as the spatially-constrained ordinary kriging proposed by Avino et al. (2021). The data reconstruction was needed to fill the existing gaps in the time series due to malfunctioning and repeated changes experienced by the monitoring network (activation and removal of rain gauges, changes in position and type of sensor). This extended database enabled the assessment of rainfall trends, thereby reducing the statistical uncertainties, and the analyses of the influence of the spatial and temporal scale on observed trends. In particular, the study: i) investigates changes in rainfall regime by applying the Mann-Kendall (MK) (Mann, 1945; Kendall, 1975), Sen's slope (Sen, 1968) and Spearman's rank correlation (Spearman, 1904) tests at site and by using the Regional Kendall (RK) (Helsel and Frans, 2006) test at the country and regional scale; ii) evaluates trends in low, medium, and high categories of rainfall maxima by applying the Innovative Trend Analysis (ITA) method (Sen, 2012).

The paper is organized as follows: Section 2 presents the study area, the structure of the monitoring network and the assembled rainfall dataset used for the analysis; Section 3 describes the procedure for the reconstruction of missing rainfall data by applying the spatially-constrained ordinary kriging method; the trend analysis, instead, is presented in Section 4 dwelling on the different methods implemented (at-site MK test, Regional Kendall test, at-site Spearman's rank correlation test and ITA method); finally, conclusions are drawn in Section 5.

2. Case study and rainfall dataset

2.1. Description of the study area

The study area comprises a substantial portion (20 %) of the Italian peninsula, encompassing the regions of Apulia (with a surface of 19500 km^2), Basilicata (10000 km^2), Calabria (15000 km^2), Campania (13500 km^2), and Molise (4437 km^2). Situated within the Mediterranean basin, it is surrounded by the Adriatic Sea to the east, the Ionian Sea to the southeast, and the Tyrrhenian Sea to the west. The area is intricately shaped by the north-to-south Apennine chain, contributing to a complex orography.

The climate in this region exhibits remarkable variability, primarily driven by the complex orography of the area. While it can generally be categorized as Mediterranean, featuring mild, rainy winters and hot, dry summers, this characterization predominantly applies to the coastal regions. However, it is essential to note that both rainfall patterns and temperature regimes can undergo substantial alterations as we move towards inland areas.

In particular, the complex orographic features of the study area serve as formidable physical barriers for meteorological phenomena, exerting a profound influence on the precipitation patterns and resulting in substantial spatial variability and distinct local effects, as highlighted by Furcolo et al. (2016). Furthermore, the region's geographic positioning and its proximity to the sea give rise to unique precipitation gradients, creating pronounced distinctions between the Tyrrhenian, Ionian, and Adriatic sides.

2.2. Structure of the rainfall monitoring network

This section aims to describe the set-up of the hydrological monitoring system in southern Italy, highlighting how the network has been working intermittently with changes in both the number and location of rain gauges. The network of rainfall stations has been managed, over the years, by different agencies: initially the National Agency for Hydro-Meteorological Monitoring (Italian Hydrographic Service, SII; National Hydrographic and Mareographic Service, SIMN) and, subsequently, the Regions through the regional Departments of Civil Protection and agrological Agencies. In particular, in 2002, because of the D.P.C.M. (i.e., ministerial decree) of July 24, in compliance with the Legislative Decree 112/1998, the monitoring activities (data collection and management tasks) carried out by the SIMN were transferred to a regional level. In the changeover process, the SIMN network was partly dismissed and partly relocated for the new civil protection activities, which are mainly aimed at early warning of extreme rainfall events.

The historical data collected by SIMN are published in the SII/SIMN Hydrological Yearbooks that are freely available (ISPRA, 2012). Instead, the most recent data are available upon formal request from the new regional agencies (detailed in Table 1). The spatial distribution of the existing and previous rainfall networks operating in the five considered regions is depicted in Fig. 1.

As can be noted in Fig. 1, two different networks are considered (the SIMN and the Civil Protection ones) in Calabria, Campania, and Molise regions because the SIMN rain gauges were removed and relocated after the administration change introduced by the Legislative Decree 112/1998. Most of the new rainfall stations managed by the Civil Protection have been installed in sites at higher elevation to obtain more representative estimates of rainfall amounts due to the abundance of orographic precipitation, thus missing the opportunity to build continuous time series. Only for the Apulia region the spatial distribution of the rain gauges was preserved because there was no need to collect orographic precipitation as most of the territory is flat. Furthermore, in Basilicata region, it was possible to collect the rainfall data recorded by the agrometeorological monitoring network of ALSIA (i.e., the Lucanian Agency for Development and Innovation in Agriculture), allowing for an increase in the spatial density of rain gauges in this region.

To sum up, the assembled database consists of 907 rain gauges, including SIMN stations that have been removed, SIMN rain gauges currently managed by the Civil Protection, the new rainfall stations officially installed and managed by the Civil Protection and the gauges of the agrometeorological monitoring networks.

2.3. Sub-daily rainfall annual maxima dataset

The analysis of rainfall frequency and trends necessitates the build-up of an updated and cohesive dataset without excessive fragmentation. To achieve this, we compiled a comprehensive database encompassing annual rainfall maxima for sub-daily durations (ranging from 1 to 24 h) spanning the period from 1970 to 2020. This effort involved leveraging data from the SIMN Hydrological Yearbooks and sourcing information from regional authorities, including the Department of Civil Protection and local Agencies for Agriculture. Merging these disparate datasets proved to be a time-consuming task due to variations in data formats (ranging from digital databases to yearly PDF files) and the utilization of different spatial reference systems. During the data consolidation process, we conducted meticulous manual quality checks by visually inspecting and verifying all the gathered data.

Table 1
Regions of Southern Italy with the related Managing Agencies for hydrological activities and information on the availability of data.

Region	Monitoring Agency	Available on
Apulia	Department of Civil Protection Puglia region	Hydrological Yearbooks – Part I: https://protezionecivile.puglia.it/annali-idrologici-parte-i-documenti-dal-1921-al-2021
Basilicata	Department of Civil Protection Basilicata region	Manfreda et al. (2015) and Hydrological Yearbooks – Part I: https://www.centrofunzionalebasilicata.it/it/annali1.php
	ALSIA – Lucanian Agency for Development and Innovation in Agriculture	available upon request
Calabria	ARPACAL – Functional Centre of Civil Protection Calabria region	Hydrological Yearbooks – Part I: https://www.cfd.calabria.it/index.php/dati-stazioni/dati-storici (password-protected website, access granted upon request)
Campania	Functional Centre of Civil Protection Campania region	Data provided by the Department for Territorial Policies – General Directorate for Public Works and Civil Protection – U.O.D. 53.08.05 Functional Centre
Molise	Functional Centre of Civil Protection Molise region	available upon request

Some features of the rainfall stations included in the assembled database are mapped in Fig. 2. In particular, the length of the time-series of each rain gauge in the period 1970–2020 is depicted in Fig. 2a, while Fig. 2b shows the number of active rainfall stations per year for the five considered regions.

It is worth noting that 44 % of the stations have less than 15 years of observations (i.e., 30 % of completeness in the period 1970–2020) and about 78 % of the series have less than 50 % of the total number of observations. Instead, only 15 % of the rain gauges included in the database have more than 35 years of observations (as later described the threshold was chosen as a compromise between the large number of missing records in the analysed temporal window and the reconstruction possibilities of the implemented methodology (see Section 3)). In detail, Table 2 shows the number and percentage of rainfall stations with a completeness of at least 70 %. However, as highlighted in Fig. 2a, level of completeness of the rainfall time series is spatially heterogeneous with the Apulia region showing the largest number of stations with time series longer than 35 years (about 62 % of the rain gauges within the administrative borders and 11 % of the total stations in the study area).

Moreover, as we can see in Fig. 2b, the number of observations per year is extremely variable across the analysed period with a relevant increase in recent years due to installation of new stations. Additionally, it can be noted a data availability decrease over the decade 1990–2000, when the rain gauges under the SIMN management were transferred to the local operational centres. In that period, most of the SIMN rain gauges were removed and relocated and/or replaced with new-generation instruments. Finally, the decreasing number of stations that emerges in recent years is due to the fact that data are not yet fully available for all stations.

To summarise, the assembled database of annual maximum rainfall data consists of 907 rain gauges for a total of 17,000 annual observations, representing 36.8 % of the total number of data that would be available if all stations had been operating continuously.

3. Extreme rainfall data reconstruction

The compiled database of sub-daily rainfall annual maxima exhibits significant fragmentation. This critical issue can be attributed to several factors contributing to gaps within the climate records. As demonstrated earlier, many of the time series of rainfall maxima suffer from missing values, primarily due to the frequent alterations in gauging network setting, including location, equipment, and managing agency. Furthermore, the persistent malfunctioning of monitoring stations results in data gaps, preventing the extraction of annual maxima.

The temporal-spatial discontinuity in rainfall data can introduce significant biases in trend detection as the extent of missing data increases (Teegavarapu and Nayak, 2017). To mitigate this issue, various reconstruction methods have been devised to fill data gaps, ensuring a complete dataset and unbiased statistical results.

Over the years, several interpolation techniques (Armanuos et al., 2020; Koutsoyiannis and Langousis, 2011; Pappas et al., 2014) have been developed for rainfall data reconstruction, including conventional methods like Thiessen polygons (Thiessen, 1911), isohyet mapping, and normal-ratio (ASCE, 1996), as well as deterministic distance-based methods like inverse distance weighting (IDW), coefficient of correlation weighting (CCW), inverse exponential weighting (IEW), and nearest neighbour distance weighting (NNDW) (Teegavarapu and Chandramouli, 2005). Additionally, complex stochastic and geostatistical methods such as kriging, cokriging, kriging with an external drift (KED), artificial neural networks (ANN), and the Kalman filter approach have been employed (Goovaerts, 2000; Teegavarapu, 2009).

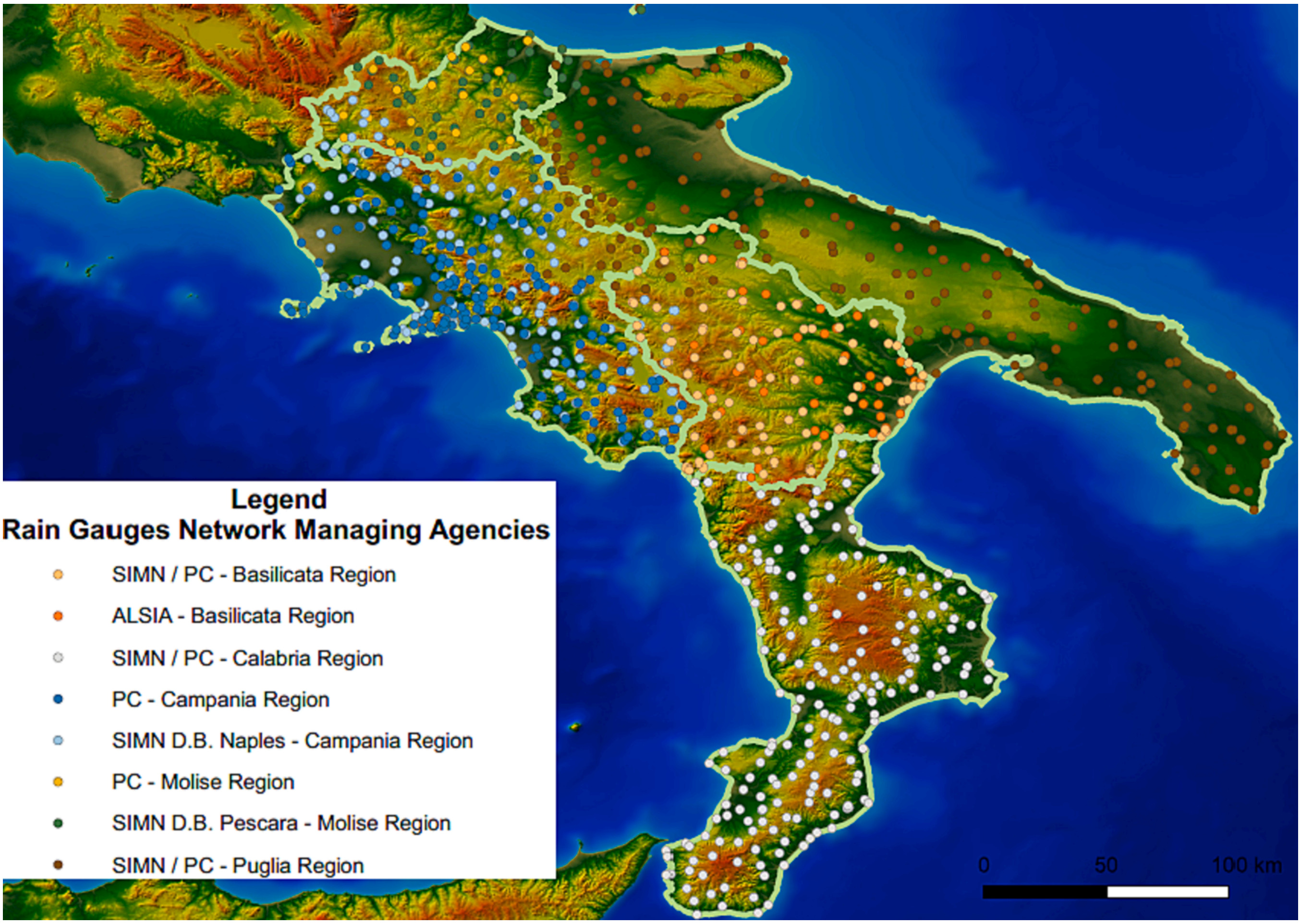

Fig. 1. Spatial distribution of the rainfall stations over the Southern Italy with references to the local Monitoring Agency involved in data collection and management tasks (SIMN stands for National Hydrographic and Mareographic Service; PC stands for Civil Protection; ALSIA is the acronym of Lucanian Agency for Development and Innovation in Agriculture). Sources DEM: TINITALY DEM (Tarquini et al., 2012).

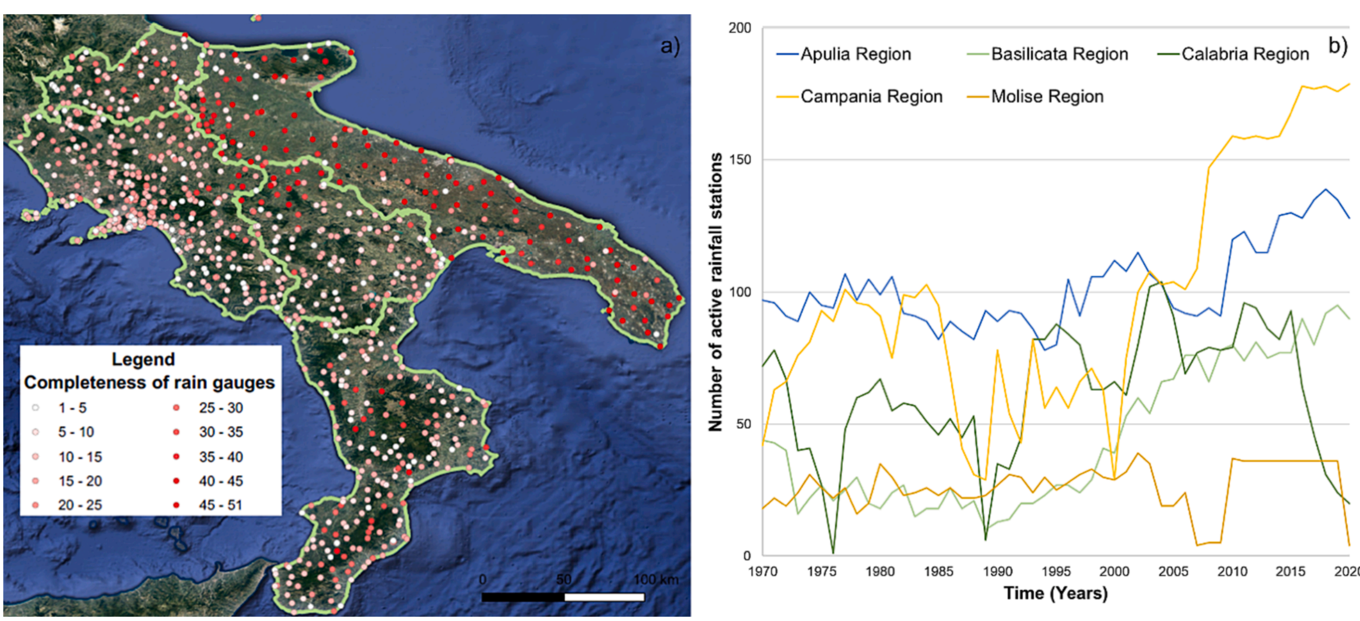

Fig. 2. a) Spatial distribution of the rain gauges over the Southern Italy. The colour refers to the length of the time series (i.e., the number of years with recorded annual maxima in the period 1970–2020); b) Number of active rainfall stations per year for the five considered regions.

Table 2
Total number of rain gauges and number and percentage of stations, within the administrative boards of each region, with at least 35 years of observations (70 % of completeness) in the period 1970–2020.

Region	Total number of stations	Number of stations with at least 70 % completeness*	Percentage of stations with at least 70 % completeness*
Apulia	159	99	62 %
Basilicata	143	12	8 %
Calabria	199	13	6 %
Campania	333	8	2 %
Molise	73	7	10 %
Southern Italy	**907**	**139**	**15 %**

* At least 35 records of observations in the period 1970–2020.

The effectiveness of these reconstruction techniques depends on various factors, including the geomorphological characteristics of the study area, the distribution and density of rain gauges, and the variance of rainfall data. Consequently, selecting the most suitable interpolation method for a specific study area can be challenging.

In this study, we utilized the spatially-constrained ordinary kriging (SC-OK) method (Avino et al., 2021). This approach combines ordinary kriging (OK) with spatial constraints determined using the inverse distance weighting (IDW) technique.

3.1. Implementation of the SC-OK method

The spatially-constrained ordinary kriging (SC-OK) method combines ordinary kriging (OK) and inverse distance weighting (IDW) techniques to optimize rainfall data interpolation. OK, lacking spatial constraints, can lead to substantial extrapolation errors in data-sparse regions, thus, SC-OK integrates the spatial limitations of IDW to restrict the reconstruction to areas with adequate neighbouring stations. This method capitalizes on OK's benefits while ensuring spatially constrained estimates. Notably, OK is a widely used geostatistical method for its consideration of spatial correlations and provision of unbiased, low-variance estimates. A key step in implementing the OK algorithm is the definition of the theoretical and experimental variogram structure. The study employed a spherical model to fit a global mean sample variogram, following the recommendation of Libertino et al. (2018).

Calibration of the IDW parameters (Brimicombie, 2003) is the first step in implementing the SC-OK procedure. The three IDW parameters (the exponent n, the radius of influence of each rainfall station or neighbourhood size (R), and the minimum number of stations or neighbours (N) within the radius R centred on the ungauged station) were calibrated using a genetic algorithm (Goldberg, 1989) with the aim of minimizing the root mean square error (RMSE) related to the reconstruction.

As suggested in Avino et al. (2021), to simplify the computational steps, we defined ρ as the minimum density of rainfall stations required to perform the reconstruction, given by:

$$\rho = \frac{N}{\pi R^2} \quad (1)$$

where N is the minimum number of rain gauges existing within the radius R centred on the given station where the annual maximum rainfall depth need to be reconstructed. As ρ varied, only the value of n and N were optimized, whereas R was calculated from Eq. (1).

In practice, a matrix, $M_{Reg,d}$, of size $n_r \times Y$ was assembled comprising the recorded annual maxima for each duration (d) and region (Reg); $n_r(Reg)$ represents the number of rainfall stations and $Y(Reg, n_r, d)$ is the number of years. For each value of ρ, the calibration of the IDW parameters was carried out with a three-step procedure: i) the 10 % of the rainfall data in the $M_{Reg,d}$ matrix was randomly removed; ii) the RMSE related to the IDW reconstruction of the deleted data was computed; iii) the three parameters (i.e., n, N, R) were selected as those that minimize the RMSE value.

Then, the missing rainfall data in $M_{Reg,d}$ matrix were estimated using the OK equation coupled with the optimized parameters and the percentage of filled data was calculated. At this step, to achieve an acceptable reconstruction in terms of series completeness, values of ρ with the number of reconstructed data less than a threshold equal to 30 % of the recorded data numerosity were discarded.

In order to evaluate the goodness of the SC-OK method and identify the optimal setting for the spatial parameters, 10 different matrices were drawn from $M_{Reg,d}$ by randomly removing 10 % of the recorded data. For the selected values of ρ, the deleted data were estimated by means of the SC-OK method and the RMSE related to reconstruction was calculated. The optimal value of ρ is that with the minimum average RMSE. A more detailed description of the SC-OK procedure, covering both calibration and implementation aspects, can be found in the Supplementary material (refer to S1 for the detailed description titled "SC-OK Interpolation Method – Calibration and Application").

The calibration procedure was applied independently to all durations and regions and the results are presented in Table 3; in particular, the optimal value of n, N and R are shown with an overview of the reconstruction errors in terms of root mean square error (RMSE) and mean absolute percentage error (MAPE).

In addition, to verify the accuracy of the estimated data, the two-sample Kolmogorov-Smirnov (K-S) homogeneity test was carried out (with 5 % significance level) on each time series by assessing whether recorded and reconstructed series are drawn from the same distribution. It was found that all the extended rainfall series pass the test, demonstrating that the SC-OK interpolation method provides reconstructed series consistent with the historical ones.

Table 3
The optimal values of R (the radius of influence centred on the rainfall station where the missing value needs to be reconstructed), N (the minimum number of rain gauges within the radius R) and n (the exponent), the average value of RMSE (root mean square error) and the average value of MAPE (mean absolute percentage error), for each considered duration (1, 3, 6, 12, and 24 h) and for each region (Apulia, Basilicata, Calabria, Campania, and Molise).

Region	Parameter	1 h	3 h	6 h	12 h	24 h
Apulia	**R [km]**	**23.36**	**28.61**	**30.16**	**30.16**	**26.97**
	N [–]	**6**	**9**	**10**	**10**	**8**
	n [–]	0.99	0.61	1.13	0.55	0.92
	RMSE [mm]	11.66	14.12	14.66	15.36	17.28
	MAPE [%]	39	37	32	28	26
Basilicata	**R [km]**	**17.84**	**33.04**	**20.13**	**20.13**	**25.23**
	N [–]	**6**	**12**	**7**	**7**	**11**
	n [–]	0.52	0.57	0.53	1.14	1.67
	RMSE [mm]	10.25	12.60	12.90	14.21	15.24
	MAPE [%]	38	34	27	25	22
Calabria	**R [km]**	**27.25**	**28.61**	**18.81**	**14.57**	**37.14**
	N [–]	**7**	**9**	**5**	**4**	**13**
	n [–]	0.58	1.38	0.77	0.54	0.94
	RMSE [mm]	10.79	16.99	21.56	25.76	32.71
	MAPE [%]	39	32	32	30	28
Campania	**R [km]**	**17.24**	**10.09**	**12.94**	**10.09**	**13.68**
	N [–]	**7**	**4**	**5**	**4**	**5**
	n [–]	0.63	0.65	0.91	0.73	1.61
	RMSE [mm]	9.19	12.02	14.20	17.50	19.86
	MAPE [%]	29	23	23	22	22
Molise	**R [km]**	**26.26**	**22.37**	**27.25**	**27.25**	**12.24**
	N [–]	**13**	**11**	**14**	**14**	**4**
	n [–]	1.91	2.54	1.49	1.64	1.61
	RMSE [mm]	6.12	8.70	9.30	10.48	13.90
	MAPE [%]	26	23	22	20	20

To summarise, in the present manuscript, the SC-OK model was applied to reconstruct missing rainfall data using an average spherical variogram and the IDW model parameters calibrated by means of a genetic algorithm.

3.2. Validation of the SC-OK method

To validate the proposed SC-OK method, we decided to test its performance in terms of reconstruction error. In particular, 10 % of randomly chosen stations in the regional database were removed one at a time and, subsequently, the data were reconstructed by using the SC-OK procedure. The reconstruction error was calculated using two error indices (i.e., RMSE and MAPE).

The regional performance statistics are shown by means of a box-plot graph for the RMSE (Fig. 3) and MAPE (Fig. 4) statistical indices.

By analysing the results of the validation analysis, we can point out that the mean value of RMSEs at the southern Italy scale ranges from 10 to 20 mm as the duration increases, while the mean MAPE passes from 23 % at 1-h to 20 % at 24-h. At the regional scale, the largest variability of error indices (in particular MAPE index) and, therefore, the greatest uncertainty in estimation occur in regions (Calabria and Molise) with the lowest density of stations and the most missing data. However, to investigate the impact of reconstruction error on the homogeneity of the series, the K-S test was carried out, providing that the extended time series are consistent with the historical ones.

3.3. Data reconstruction with the SC-OK method: characteristics of the extended dataset

Following the calibration of the optimal values for R and N pertaining to the selected time intervals, the missing rainfall data were effectively estimated through the employment of the SC-OK method in conjunction with IDW spatial parameters. This procedure demonstrated its efficacy in creating a dependable database well-suited for subsequent statistical analyses and trend identification. Table 4 offers a concise overview of the data completeness within the rainfall database, illustrating the state of data availability both before and after the reconstruction process.

As depicted in Table 4, the completeness of the rainfall records falls within the range of 40 % to 84 %, signifying an approximate 20 % improvement following the reconstruction process. To further illustrate the effects of this reconstruction, Fig. 5 offers a comprehensive visual representation. It displays the total count of annual rainfall maxima for each year, distinguishing between observed and reconstructed series for every examined region.

As shown in Table 4 and Fig. 5, the implemented procedure allows for the extension of the recorded time series, and the procedure is more effective for years with more observations in space. Although the completeness of time series has increased, we decided to discard reconstructed series with a completeness of less than 70 %, given the potential bias produced by the presence of a significant number of gaps (Teegavarapu and Nayak, 2017). This value was chosen as a compromise between the maximum completeness attained using the proposed method and the extent of the temporal window of analysis (1970–2020). The selection criteria adopted limited the total number of rainfall stations offering uneven spatial coverage over the entire study area. The results of the procedure are summarised in Table 5 providing the number of selected series for each duration and region.

The implemented SC-OK procedures allowed to overcome the time series discontinuity issue, with an increase in both the number of data and their temporal continuity. Therefore, expanding the dataset size should improve the statistical significance of the trend detection and the frequency analysis of extreme rainfall.

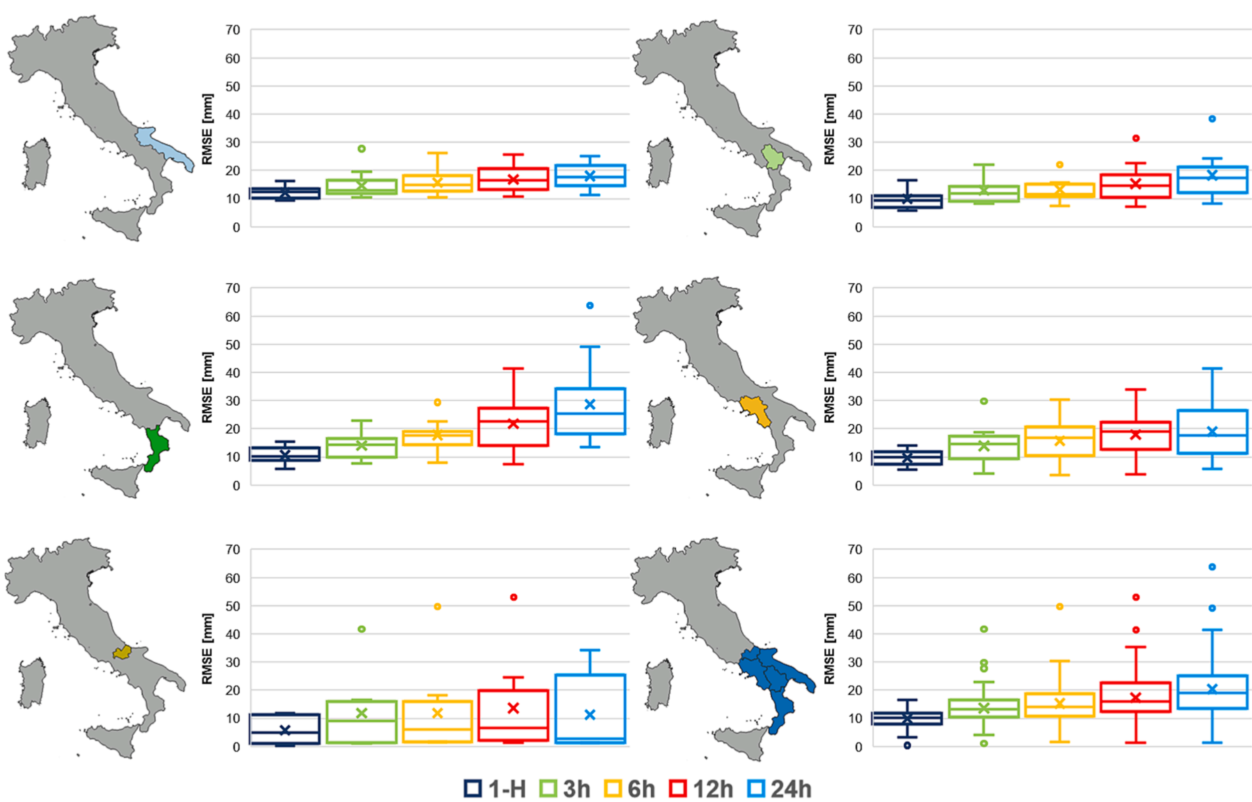

Fig. 3. Box-plot graph of the root mean square error (RMSE) values related to the reconstruction of the rainfall data of 10% of randomly chosen stations in the regional database. The box-plot provides the representation of the following statistics: maximum and minimum (whiskers), 75th percentile and 25th percentile (rectangle edges), median or 50th percentile (horizontal line in the rectangle), mean (x symbol), outliers (o symbol).

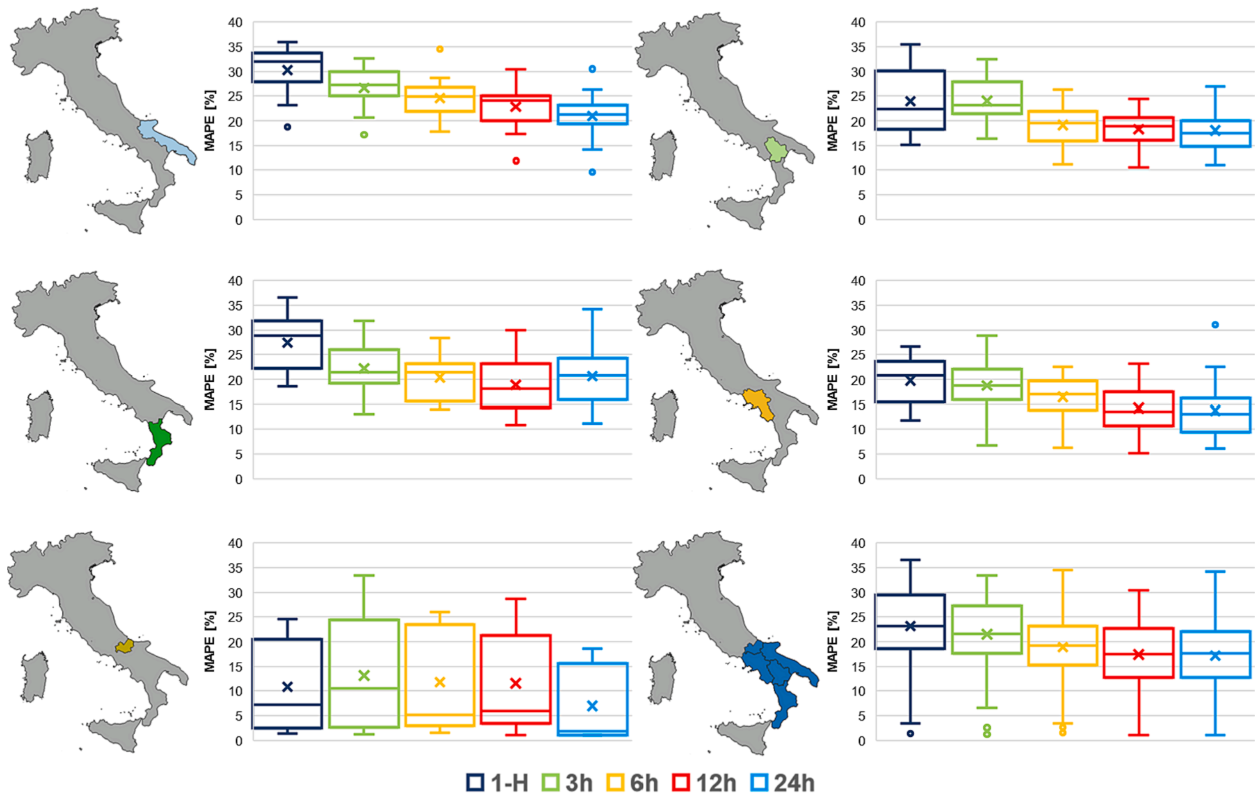

Fig. 4. Box-plot graph of the mean percentage absolute error (MAPE) related to the reconstruction of the rainfall values of 10% of randomly chosen stations in the database of each region and each duration. The box-plot provides the representation of the following statistics: maximum and minimum (whiskers), 75th percentile and 25th percentile (rectangle edges), median or 50th percentile (horizontal line in the rectangle), mean (x symbol), outliers (o symbol).

4. Rainfall trend analysis

To investigate the presence of temporal trends within the reconstructed rainfall series, three distinct methodologies were employed:

1. At-Site Mann-Kendall (MK) test: this test was utilized to detect local trends in the magnitude of rainfall intensity. Simultaneously, the Regional Kendall (RK) test was applied to identify overarching trends spanning specific regions.
2. At-Site Spearman's Rank Correlation test: this test shared the same objective as the MK test, to reveal trends in local rainfall characteristics.
3. Innovative Trend Analysis (ITA) technique: this innovative approach facilitated a graphical assessment of trends within different ranges of data values, allowing for the evaluation of trends across low, medium, and high values in the data series.

4.1. Mann-Kendall (MK) trend test

The non-parametric Mann-Kendall (MK) trend test is widely applied to detect monotonic trends in hydrological time series, without assuming its distributional properties. Given a random variable h, and a sample of sl independent data $h = (h_1, \cdots, h_{sl})$, the Kendall S_k statistic (Mann, 1945; Kendall, 1975) can be defined as follows:

$$S_k = \sum_{i=1}^{sl_k-1} \sum_{j=i+1}^{sl_k} sign(h_j - h_i) \tag{2}$$

where h represents the data values at times i and j, sl_k is the length of the kth series and

$$sign(\vartheta) = \begin{cases} 1 if \vartheta > 0 \\ 0 if \vartheta = 0 \\ -1 if \vartheta < 0 \end{cases} \tag{3}$$

Under the null hypothesis that h is independent and randomly distributed, for $sl_k \geq 8$, the result of Eq. (2) is approximately a normal variable with zero mean and variance equal to:

$$\sigma_k^2 = \frac{sl_k(sl_k-1)(2sl_k+5) - \sum_{m=1}^{N_{tg,k}} l_{m,k}\left(l_{m,k}-1\right)\left(2l_{m,k}+5\right)}{18} \tag{4}$$

where $N_{tg,k}$ is the number of tied groups, and $l_{m,k}$ is the length of the m^{th} group.

The standardized test statistic Z_k can be calculated by:

$$Z_k = \begin{cases} \frac{S_k - 1}{\sigma} if S_k > 0 \\ 0 if S_k = 0 \\ \frac{S_k + 1}{\sigma} if S_k < 0 \end{cases} \tag{5}$$

The p-value for each trend test is given by:

$$p = 2[1 - \Phi|Z_k|] \tag{6}$$

where $\Phi|*|$ represents the cumulative distribution function of a standard normal variable. Using this approach, the p-value is evaluated and then compared with a given significance level.

MK method is extensively used to analyse hydrological and climatological time-series due to its advantages, such as missing values are allowed, and the data need not to be conform to any distribution.

Application of the MK test to the extended rainfall series for different durations may indicate possible duration-dependent trend existence in the extreme precipitation events over the study area found, for example,

Table 4
The number of measurements and record completeness in the database before and after the reconstruction and the reconstruction percentage, for each duration (1, 3, 6, 12, and 24 h) and for each region (Apulia, Basilicata, Calabria, Campania, and Molise).

Region	d [h]	Number of Measurements [–]	Record Completeness [%]	Number of Measurements [–]	Record Completeness [%]	Reconstruction [%]
		Database before reconstruction		Database after reconstruction		
Apulia	1	5209	64.24	6770	83.49	19.25
	3	5255	64.80	6720	82.87	18.07
	6	5287	65.20	6741	83.13	17.93
	12	5318	65.58	6771	83.50	17.92
	24	5345	65.91	6856	84.55	18.64
Basilicata	1	2267	31.08	3127	42.88	11.8
	3	2272	31.15	4171	57.19	26.04
	6	2274	31.18	3191	43.75	12.57
	12	2274	31.18	3191	43.75	12.57
	24	2271	31.14	3208	43.99	12.85
Calabria	1	3163	31.17	6227	61.36	30.19
	3	3161	31.15	5363	52.84	21.69
	6	3162	31.16	4922	48.50	17.34
	12	3162	31.16	4253	41.91	10.75
	24	3161	31.15	5632	55.49	24.34
Campania	1	5044	29.70	8507	50.09	20.39
	3	5046	29.71	6908	40.68	10.97
	6	5049	29.73	7717	45.44	15.71
	12	5049	29.73	6915	40.72	10.99
	24	5044	29.70	8248	48.57	18.87
Molise	1	1343	36.07	2009	53.96	17.89
	3	1343	36.07	1752	47.06	10.99
	6	1343	36.07	1972	52.97	16.9
	12	1343	36.07	1973	52.99	16.92
	24	1343	36.07	1857	49.88	13.81

in another southern Italy region (Sicily) by Arnone et al. (2013). As a general result, most of the series do not display statistically significant tendencies for all the temporal intervals. However, it is not possible to compare the results in terms of the number of stations showing trends for the different durations and regions, as the number of series used to perform the analysis is quite variable. Nevertheless, some overall conclusions can be drawn by considering the percentage of stations exhibiting increasing or decreasing trends (significant or not at 5 % significance level) as shown in Fig. 6 (for the five considered regions) and 7 (for the whole southern Italy).

As shown in Fig. 6, a prevailing increasing trend was found, especially for the shorter durations. In particular, in Calabria and Molise 100 % of the considered rain gauges present an increasing trend at 1-h duration, even if only 50 % turn out to be statistically significant. The percentage of rain gauges with positive trend decreases as the duration increases, but it never falls below 70 %. Concerning the Apulia region, the ratio of stations with upward and downward trends is nearly constant (4 to 1) at all durations. Instead, Basilicata and Campania display the greatest percentage of stations showing a decreasing tendency, nearly or even more than 50 % for longer durations. Based on the above results, it can be concluded that there is a general behaviour in which the percentage of stations with positive trend decrease with the duration. In particular, for the whole study area (Fig. 7), that percentage decrease from 86 % at 1-h to 68 % at 24-h; while the percentage of negative trends increase from 14 % to 32 %. Considering this, we can state that the detected trends are typically positive for short durations and both positive and negative for the longer time intervals.

By analysing only time series with statistically significant trends under 5 % significance level, a general increasing trend is confirmed at shorter durations, which tends to disappear or become less significant for rainfall events of longer durations. In Basilicata and Campania about 20 % (21 % and 24 % respectively) of the stations show an increasing trend at 1 h, but that percentage tends to zero at 24 h. Such behaviour was also observed in Calabria and Molise where the percentage of series exhibiting an upward tendency decreases from 50 % at 1 h to 20 % at 24 h. Similar results were presented by Arnone et al. (2013) in Sicily region, showing an increasing trend for precipitation maxima at shorter durations (1-h duration), while the tendencies are mainly negative for longer durations.

Conversely, decreasing trends are only detected at longer durations (12 and 24 h), however their percentage is not very significant in all the regions, ranging from 0 % in Apulia and Basilicata to 2 % in Calabria and Campania up to 9 % in Molise at 24 h. Therefore, the correlation between percentage of the stations with significant trend and the rainfall duration is less evident than in the case of positive trend analysis, showing an almost constant behaviour with duration. Finally, since the percentage of decreasing trends is almost constant, while the one of the increasing trends decreases with the duration, it follows that the percentage of series not showing a statistically significant trend increases with the duration.

The obtained results align well with findings from Bonaccorso et al. (2005) and Arnone et al. (2013) for the Sicily region, affirming a consistent upward trend in short-duration rainfall. This positive tendency extends beyond national boundaries, as evidenced in studies conducted in the United Kingdom (Darwish et al., 2018), the French Mediterranean area (Ribes et al., 2019), and Turkey (Albayrak et al., 2022). As well as the statistical analysis of the detected trends, observing the spatial distribution of the rainfall stations with trends (Fig. 8) is an aspect of particular interest. In fact, this spatial representation allows to identify local clusters of stations characterised by an increase or decrease in extreme precipitation regime over the period 1970–2020.

Trends in extreme precipitation vary from location to location; however, some local clusters of increasing in rainfall intensities could be identified at shorter durations (1 and 3 h). It is important to consider,

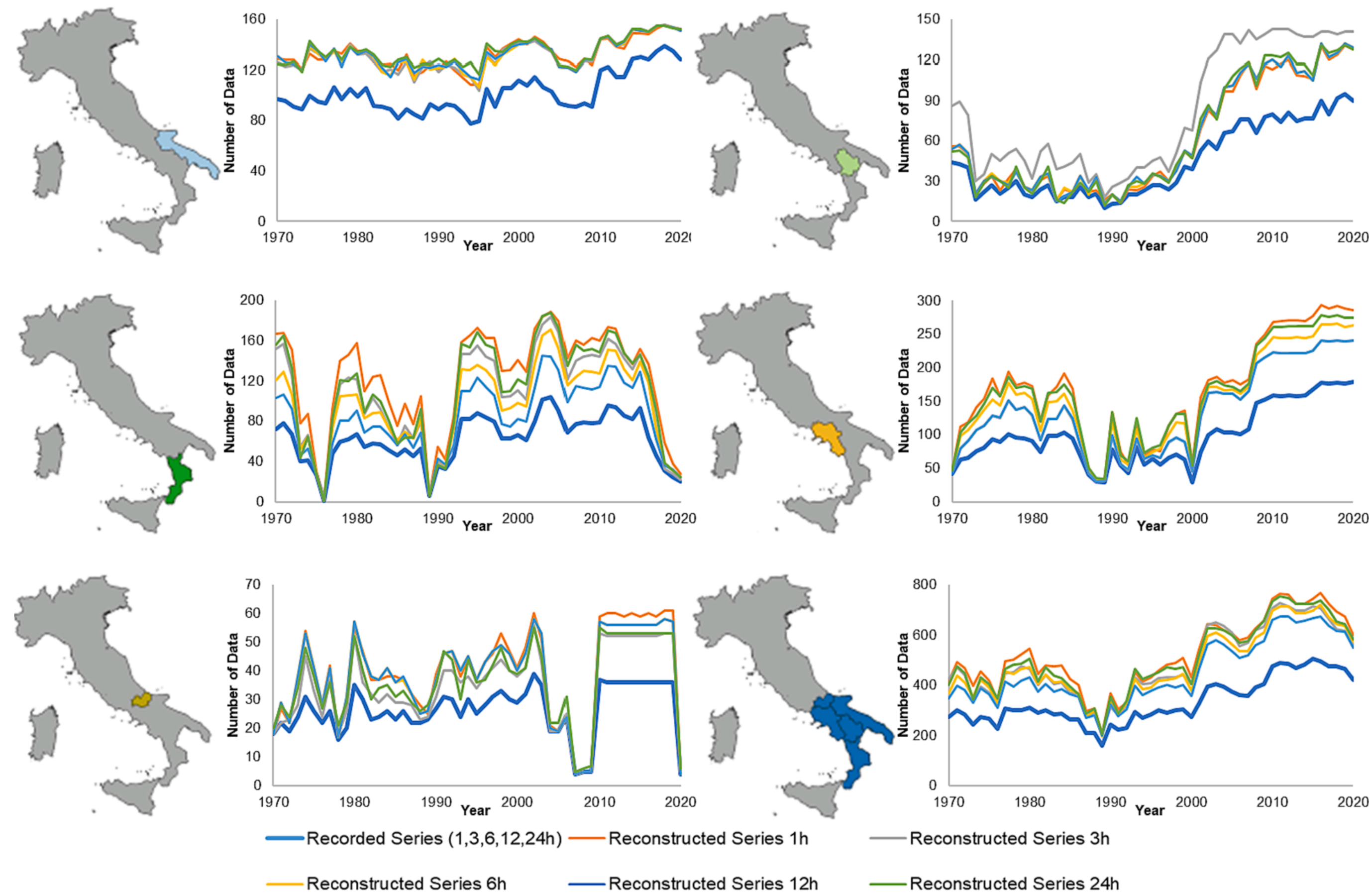

Fig. 5. Data availability per year in the observed and reconstructed databases for each considered region (Apulia, Basilicata, Calabria, Campania and Molise) and for the entire territory of Southern Italy.

Table 5
Number of rainfall series with a completeness of more than 70 % of the possible length (at least 35 years of measurements) in the period 1970–2020 for each duration (1, 3, 6, 12, and 24 h) and for each region (Apulia, Basilicata, Calabria, Campania, and Molise).

d [h]	Number of time series analysed					
	Apulia	Basilicata	Calabria	Campania	Molise	TOT. Southern Italy
1	132	19	78	71	28	**328**
3	129	36	42	33	16	**256**
6	129	20	33	49	27	**258**
12	129	20	15	33	27	**224**
24	134	20	55	62	22	**293**

though, that the sparseness of rain gauges did not allow to provide a full analysis of the investigated area. In fact, there are many areas, especially in Campania and Basilicata, where no station was selected in the previous step of data reconstruction due to the limited number of observations. By analysing the maps, we can state that, for longer durations, most of the series have no statistically significant trend in all regions. In addition, it was not possible to identify local clusters of change as the few stations with trends are widely scattered over the entire territory. Conversely, for shorter durations (1 and 3 h), three areas characterised by a well-defined increase in extreme rainfall were identified: from north to south, the central highlands of Molise and the Matese Regional Park, on the border between Campania and Molise; the Campano Apennines area on the border between Molise, Campania and Apulia; the Calabrian Apennines, from the Sila upland to Aspromonte. In Calabria, some of these local upward trends persist even at longer durations.

The noted rise in short-duration precipitation carries significant implications for the planning of urban drainage systems and the assessment of hydrological basin responses, particularly in small catchments characterized by low times of concentration. As emphasized by Adamowski et al. (2010), these observed increasing trends may result in a heightened frequency of occurrence of the design storm (for a given duration and return period), a crucial parameter in various hydrological applications such as the design of urban hydraulic systems and flood hazard mitigation. Consequently, when developing Depth-Duration-Frequency (DDF) curves by fitting theoretical distributions to rainfall annual maxima at different durations, an analysis of non-stationarity may be necessary (De Michele et al., 1998; Forestieri et al., 2018) to prevent underestimation of the critical storm.

As second step, the Regional Kendall (RK) test was applied to assess the presence of a general trend at the regional scale. The regional Kendall's statistic, S_{reg}, (Helsel and Frans, 2006) was evaluated as the sum of the S Kendall's statistics calculated for each series:

$$S_{reg} = \sum_{k=1}^{n_r} S_k \tag{7}$$

where n_r is the number of rain gauges for each duration, and S_k is the S Kendall's statistics for the k^{th} series. The test statistic, Z_{reg}, was then evaluated using Eq. (5) with $S = S_r$ and $\sigma = \sigma_r$, where:

$$\sigma_r^2 = \sum_{k=1}^{n_r} \frac{sl_k(sl_k - 1)(2sl_k + 5)}{18} \tag{8}$$

where sl_k represents the number of data in each series.

The regional Kendall trend slope was calculated as the median of all

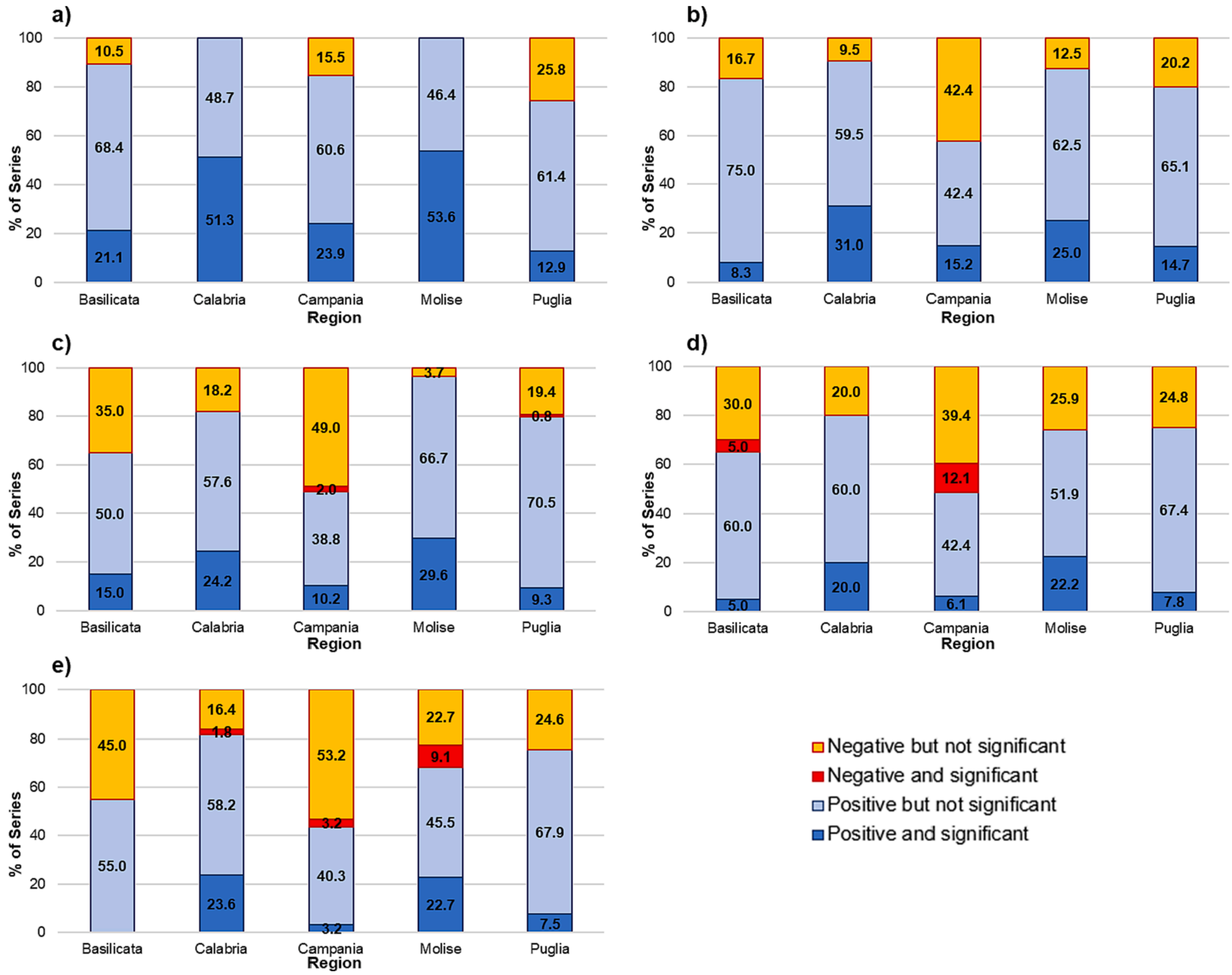

Fig. 6. Results of the application of the Mann-Kendall (MK) trend test (5 % significance level) to the reconstructed series for all regions and for the five considered durations: a) 1 h, b) 3 h, c) 6 h, d) 12 h and e) 24 h. The graphs show the percentage of rainfall series showing positive significant (dark blue), positive not significant (light blue), negative significant (red) and negative not significant (yellow) tendencies. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

slopes between data pairs. Moreover, the Van Belle and Hughes (1984) test was applied to assess the homogeneity of the trends. The failure of the test means that the stations within the considered region have different trend directions and, hence, the regional trend slope is not statistically acceptable. The results of the RK and Van Belle and Hughes tests at regional scale are reported in Table 6.

As shown in Table 6, the RK test revealed a statistically significant increasing trend in Apulia, Calabria, and Molise regions. Furthermore, the detected trend turned out to be homogeneous according to Van Belle and Hughes tests for all durations, except 1-hour in Apulia and 24-h in Molise. This non-homogeneity is likely due to the non-uniform behaviour of the rainfall station in terms of trend directions. Indeed, different stations can exhibit contrasting trends, which does not allow to consider that region as a climatically homogeneous area. In particular, about 26 % of the rainfall series in Apulia and 32 % in Molise present respectively a 1-h and 24-h decreasing tendency, even if not statistically significant (as shown in Fig. 6), contrasting the behaviour of the remaining rain gauges.

Instead, a specific attention is needed for Basilicata and Campania regions. A statistically significant and homogeneous increasing trend was only detected at shorter durations, e.g., 1-, 3- and 6-h in Basilicata and 1- and 3-h in Campania (although the 3-h tendency is not homogeneous due to the local contrasting trends as previously explained), while for longer time intervals the test revealed no trend, with the regional trend slope tending towards zero as the duration increases. This is likely explained by the absence of statistically significant trends in most of the time series, as shown in Fig. 8. However, these results need to be investigated further because they could be affected by the limited number of series selected, that provides an inadequate spatial coverage of the area under investigation and may introduce a bias into the regional-scale trend detection.

The results of the RK and Van Belle and Hughes tests at the study area scale (considering the southern Italy as a climatically homogeneous area) are reported in Table 7.

The RK test detected a statistically significant increasing trend at southern Italy scale for all the durations. However, these tendencies turned out to be non-homogeneous according to the Van Belle and Hughes' homogeneity test. Two different explanations can be given to justify this result: there might be no trend in most, or all, the time-series, or individual rain gauges of the region might show contrasting trends. Considering the morphological configuration of southern Italy and its climatic variability, we can state that this non-homogeneity is due to the

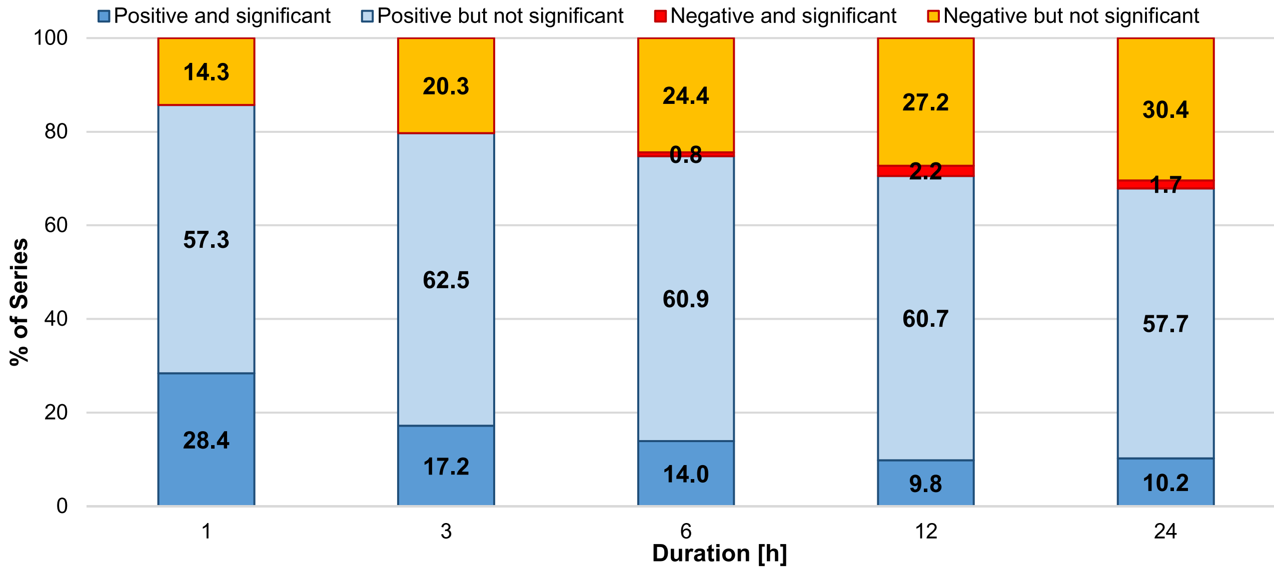

Fig. 7. Results of the application of the Mann-Kendall (MK) trend test (5% significance level) to the reconstructed series for the whole study area (Southern Italy) and for the five considered durations (1, 3, 6, 12, and 24 h). The graph reports the percentage of rainfall series showing positive significant (dark blue), positive not significant (light blue), negative significant (red) and negative not significant (yellow) tendencies. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

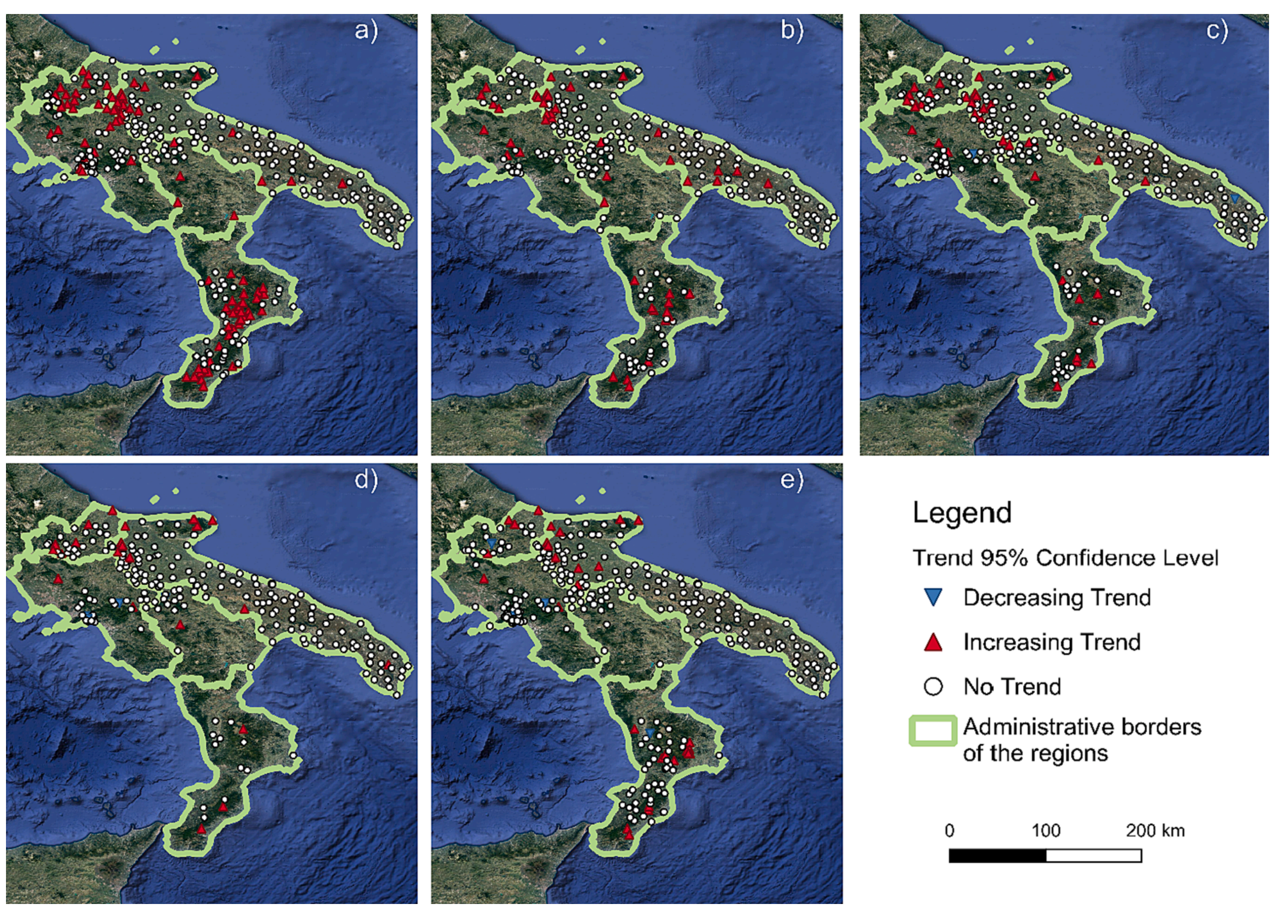

Fig. 8. Maps of the local trends for the rainfall annual maxima detected with Mann-Kendall (MK) trend test at 5 % significance level for the five durations: a) 1 h, b) 3 h, c) 6 h, d) 12 h, e) 24 h. The red triangle shows an increasing trend, the inverted blue triangle shows a decreasing trend, while the white circle represents no statistically significant trend. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6
Results of the Regional Kendall (RK) and Van Belle and Hughes tests carried out at 5% significance level. Statistically significant and homogeneous increasing trends are highlighted in green, while in orange statistically significant upward trends that are not homogeneous.

Regions	d [h]	RK test	RK test Slope	Van Belle-Hughes test
Apulia	1	Increasing Trend	0.085	Non-Homogeneous Trend
	3	**Increasing Trend**	**0.080**	**Homogeneous Trend**
	6	**Increasing Trend**	**0.100**	**Homogeneous Trend**
	12	**Increasing Trend**	**0.107**	**Homogeneous Trend**
	24	**Increasing Trend**	**0.138**	**Homogeneous Trend**
Basilicata	1	**Increasing Trend**	**0.162**	**Homogeneous Trend**
	3	**Increasing Trend**	**0.076**	**Homogeneous Trend**
	6	**Increasing Trend**	**0.054**	**Homogeneous Trend**
	12	No Trend	0.050	Homogeneous Trend
	24	No Trend	0.042	Homogeneous Trend
Calabria	1	**Increasing Trend**	**0.269**	**Homogeneous Trend**
	3	**Increasing Trend**	**0.333**	**Homogeneous Trend**
	6	**Increasing Trend**	**0.267**	**Homogeneous Trend**
	12	**Increasing Trend**	**0.281**	**Homogeneous Trend**
	24	**Increasing Trend**	**0.559**	**Homogeneous Trend**
Campania	1	**Increasing Trend**	**0.154**	**Homogeneous Trend**
	3	Increasing Trend	0.061	Non-Homogeneous Trend
	6	No Trend	-0.010	Non-Homogeneous Trend
	12	No Trend	-0.005	Non-Homogeneous Trend
	24	No Trend	-0.084	Non-Homogeneous Trend
Molise	1	**Increasing Trend**	**0.249**	**Homogeneous Trend**
	3	**Increasing Trend**	**0.245**	**Homogeneous Trend**
	6	**Increasing Trend**	**0.262**	**Homogeneous Trend**
	12	**Increasing Trend**	**0.108**	**Homogeneous Trend**
	24	Increasing Trend	0.208	Non-Homogeneous Trend

Table 7
Results of the Regional Kendall (RK) and Van Belle and Hughes tests carried out at 5% significance level. Statistically significant and homogeneous increasing trends are highlighted in green, while in orange statistically significant upward trends that are not homogeneous.

d [h]	RKT	RKT Slope	Van Belle-Hughes test
1	Increasing Trend	0.156	Non-Homogeneous Trend
3	Increasing Trend	0.115	Non-Homogeneous Trend
6	Increasing Trend	0.115	Non-Homogeneous Trend
12	Increasing Trend	0.106	Non-Homogeneous Trend
24	Increasing Trend	0.137	Non-Homogeneous Trend

contrasting trend directions exhibited by the stations. In fact, although most of the stations have an upward tendency, there is nevertheless a significant percentage of series with a decreasing trend (ranging from 14 % at 1-h to 32 % at 24-h), as shown in Fig. 7. In line with the findings presented by Libertino et al. (2019), there is no statistically homogeneous trend identifiable across southern Italy as a whole. However, discernible and statistically significant trends emerge when examining smaller domains, such as at the regional or local levels. Westra et al. (2014) also highlight similar features, demonstrating an upward trend in sub-daily rainfall events across Europe and the Mediterranean area. However, it's essential to recognize that these trends are highly contingent on factors such as region, season, and duration.

When analysing the presented results, it must be considered that most the recent observations (starting from 2001) are recorded with digital rain gauges that offer a higher precision. This may affect the results reported herein, especially at the hourly scale. In fact, mechanical stations operating typically at hourly scale may under-estimate annual maxima up to 12 %, which, in turn, may impact on the observed trend (Pelosi et al., 2022). Nevertheless, this impact tends to decrease at larger timescales (i.e., three hours or more) where we still observe a relatively large number of increasing trends.

4.2. Spearman's rank correlation test

Spearman's rank correlation test (Lehmann, 1975; Sneyers, 1990; Spearman, 1904) is a rank-based test for monotonic trend detection. As the MK test, it does not require any assumption on the data distribution. Given a random variable h, and a sample of sl independent data $h = (h_1, \cdots, h_{sl})$, the test statistics r_s is defined as:

$$r_s = 1 - \frac{6\sum_{i=1}^{sl} D_i^2}{sl(sl^2 - 1)} \quad (9)$$

where $D_i = r_i - s_i$, being r_i and s_i the rank of the first (h) and second (time interval, i.e., year) variables, respectively, and sl the length of the series.

For approximately $sl > 20$, the Student's t-distribution (with sl-2 degrees of freedom) can be used after transforming the r_s value as follows:

$$t_s = \frac{r_s}{\sqrt{\frac{1-r_s^2}{sl-2}}} \quad (10)$$

Following the definition of the t_s critical value at α significance level, $t_{(sl-2,1-\frac{\alpha}{2})}$, by means of the Student's t-distribution table, if $|t_s| > t_{(sl-2,1-\frac{\alpha}{2})}$ it means that a statistically significant trend exists in the time series. The positive values of t_s represent an increasing trend, while negative values signify a decreasing trend.

The Spearman's test was applied (at 5 % significance level) to each reconstructed time series separately for all the considered regions (Apulia, Basilicata, Calabria, Campania and Molise) in order to detect potential tendencies. The results are depicted in Fig. 9 (for each region) and in Fig. 10 (at the southern Italy scale).

The Spearman's test was applied as a comparison with the Mann-Kendall test and as expected, the outcomes are almost equivalent both at the study area and regional scales. In detail, the Spearman's test tends to overestimate the percentage of stations with a statistically significant trend by 1–2 % compared to the MK test. With regard to the spatial distribution of stations with detected trend, the test largely confirms the

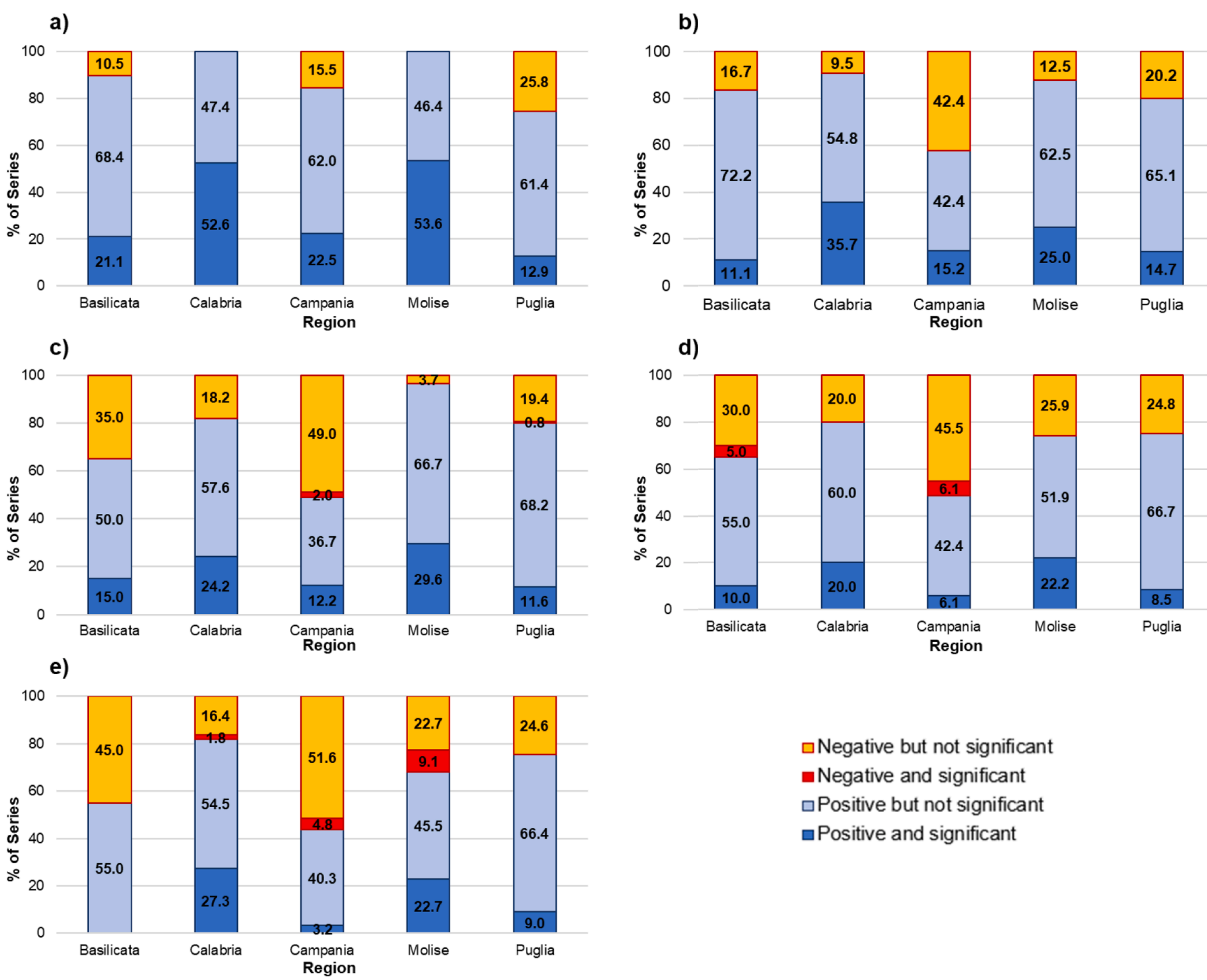

Fig. 9. Percentage of series with positive significant (dark blue), positive not significant (light blue), negative significant (red) and negative not significant (yellow) trends (detected with Spearman's rank correlation test at 5 % significance level) for each duration: a) 1 h, b) 3 h, c) 6 h, d) 12 h, and e) 24 h. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

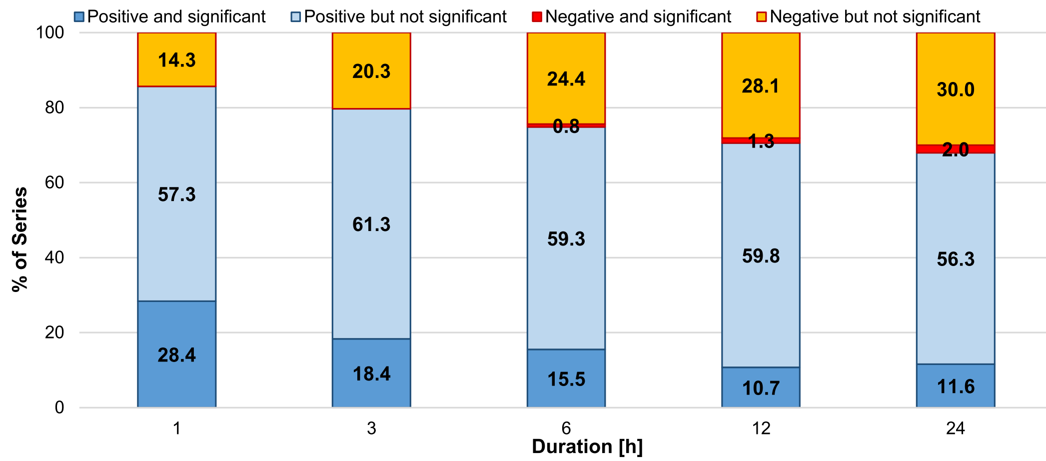

Fig. 10. Percentage of series with positive significant (dark blue), positive not significant (light blue), negative significant (red) and negative not significant (yellow) trends (detected with Spearman's rank correlation test at 5% significance level) at the southern Italy scale. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

distribution depicted in the maps in Fig. 8.

4.3. Innovative trend analysis (ITA) method

The Innovative Trend Analysis (ITA) method, introduced by Sen (2012, 2017), is a graphical trend analysis technique. Contrary to the traditional trend test, it does not require any assumptions (i.e., serial correlation, non-normality, sample number) and, for this reason, it has been widely used in recent years. In addition, the ITA technique allows for the investigation of trends in the low, medium, and high values of a time series.

In applying the ITA method, a time series (in chronological order) is divided into two equal halves, both sorted separately in ascending order. In a Cartesian diagram, the first subseries is located on the x-axis, and the second subseries on the y-axis. If the data points are clustered on a 1:1 straight line, it means that there is no trend. Data clustered above the 1:1 straight line represent an increasing monotonic trend, while points below this line indicate a decreasing monotonic trend. The data line is the parallel to the 1:1 line, with the centroid point (s_1, s_2) falling on this line, being s_1 and s_2 the arithmetic mean of the two sub-series respectively. The vertical difference between the data line and the 1:1 line is related to the slope of the existing trend. The statistic of the ITA method is:

$$S_{ITA} = \frac{2(s_1 - s_2)}{n} \tag{11}$$

where s_1 and s_2 are respectively the arithmetic averages of the two sub-series and n is the total number of data points. S_{ITA} is related to the trend slope: a positive value of S_{ITA} means that the time series has an increasing trend, while a negative value means that a decreasing trend is detected. According to the test significance proposed by Sen (2017), the slope of the series is statistically significant if it falls outside the confidence limits (CLs). The CLs of the slope, that follow a Gaussian probability density function (PDF) with zero mean and standard deviation, are:

$$CL_{(1-\alpha)} = 0 \pm s_{cri}\sigma_s \tag{12}$$

where α is the significance level, s_{cri} is the confidence limit of a standard normal PDF with zero mean and standard deviation σ, and σ_s is defined as follows:

$$\sigma_s = \frac{2\sqrt{2}}{n\sqrt{n}}\sigma\sqrt{1 - \rho_{s_1,s_2}} \tag{13}$$

where ρ_{s_1,s_2} is the correlation coefficient between the two mean values s_1 and s_2 and σ is the standard deviation of the time series.

According to the procedure proposed by Caloiero et al. (2018), the reconstructed series were converted into rainfall anomalies. In detail, for each series, the sample mean was subtracted from the observed precipitation values, and the difference was divided by the sample standard deviation. Then, an average series of rainfall anomalies was calculated for each duration and region Thereafter, the ITA method was applied by splitting the series into two sub-periods: 1970–1994 and 1995–2020, and the results are presented in Fig. 11 and in Table 8. Fig. 11 shows the change graphs of extreme rainfall anomalies obtained according to the ITA method. It is worth pointing out that the coloured points are the data points of the two sub-series of rainfall anomalies, while the solid orange line represents the no-trend (1:1) line. The black and grey dashed lines are respectively 0.5 and 0.25 confidence bounds (as indicated in Caloiero et al., 2018). In the following, results are discussed considering low, medium and high values which were identified as lower than −0.5, between −0.5 and 0.5 and higher than 0.5, respectively.

As we can see in Fig. 11 and Table 8, increasing trend is prevailing in all regions and for all the durations. However, in more detail we can point out that:

- in Apulia, an upward trend in low and high rainfall anomalies within the 0.25 bound and in medium values within the 0.5 bound was observed for shorter durations (1, 3 and 6 h). On the contrary, for longer durations (12 and 24 h) an increasing trend in low values within the 0.5 bound and in medium anomalies within the 0.25 bound was detected, while a meaningless tendency prevails in high anomaly values;
- in Basilicata, a significant increasing trend (around the 0.25 bound) in low, medium and high anomalies values was detected for 1- and 3-h durations, while the 6-h anomaly values do not show any clear tendency. No trend in low values and a downward tendency (within the 0.25 bound) in medium and high values was displayed at 12- and 24-h;
- in Calabria, the clearest result is the positive trend shown by 1-h rainfall anomalies, with most of the data outside the 0.5 bound. Instead, a meaningless trend in low values and a significant increasing trend in medium (within the 0.25 bound) and high (within the 0.5 bound) anomalies was detected for the other durations;
- in Campania, no clear evidence of general trends could be identified. However, for shorter durations there is a slight increasing trend in

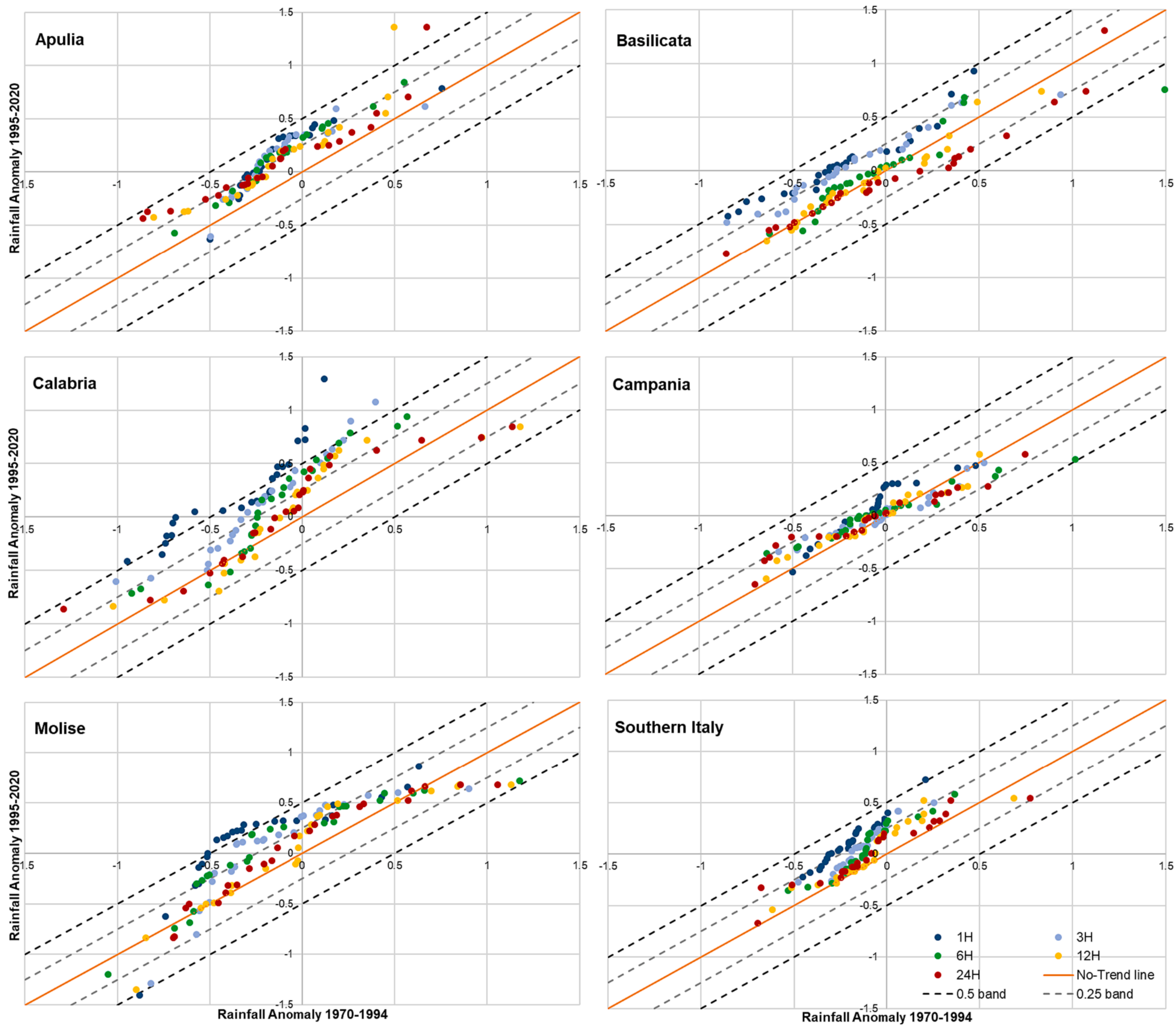

Fig. 11. Results of the ITA method for the five regions of southern Italy. Coloured points are the data points of the two sub-series of rainfall anomalies sorted in ascending order for the five durations (dark blue for 1 h, light blue for 3 h, green for 6 h, yellow for 12 h and red for 24 h). The solid orange line represents the no-trend (1:1) line, while the black and grey dashed lines are respectively 0.5 and 0.25 confidence bounds. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

low and medium anomaly values, though within the 0.25 bound, and no trend in high values. Instead, for longer durations an increasing trend in low anomalies, no trend in medium values and decreasing trend in high ones was detected;

- in Molise, a significant increasing trend is shown by 1-h rainfall anomalies, with most of the medium values outside the 0.5 bound. Moreover, 3- and 6-h anomalies are characterised by positive tendency (within the 0.5 bound) in medium values and variable behaviour in low and high ones. Instead, for longer durations there is no trend in low and medium values and a meaningless decreasing tendency in high anomalies.

Finally, in the bottom-right map of Fig. 11 the results of the ITA method for the whole study area are reported. First, it is worth noting that there is no difference between low, medium and high rainfall anomaly values. In addition, the clearest result is the significant 1-h upward trend, though within the 0.5 bound. The same tendency was detected for all the duration, even if the date line gets closer to the no-trend (1:1) line as the duration increases.

These findings are further summarised in the Table 8, where the ITA slope of the extreme rainfall anomalies trends is reported. An increasing trend was observed in anomaly series for all time intervals in Apulia and Calabria regions. In Campania and Molise there is an upward tendency for shorter durations and no significant trend for longer ones. Finally, in Basilicata an increasing trend at 1- and 3-h, no trend at 6-h and decreasing trend at 12- and 24-h was detected.

These outcomes are fairly in line with the ones obtained by means of RK trend test (Table 6 and 7). Indeed, regarding to the southern Italy both methods detected a statistically significant increasing trend for all durations. Moreover, at regional scale ITA and RK techniques revealed a statistically significant upward tendency in Apulia and Calabria for all the durations and in Basilicata, Campania and Molise at 1 and 3 h. For longer durations, some contrasting findings were achieved instead. Indeed, in Molise RK test pointed out an increasing trend at 12- and 24-h

Table 8
Results of the ITA method for the five regions of southern Italy and for the five durations. In particular, the ITA trend slope, S_{ITA}, the confidence limits, CLs (lower and upper), at 5% significance level and the detected trend are reported.

Regions	d [h]	S_{ITA}	Lower CL	Upper CL	Trend
Apulia	1	0.0107	-0.001526	0.001526	↑
	3	0.0103	-0.001566	0.001566	↑
	6	0.0101	-0.000647	0.000647	↑
	12	0.0094	-0.001550	0.001550	↑
	24	0.0096	-0.001558	0.001558	↑
Basilicata	1	0.0120	-0.001064	0.001064	↑
	3	0.0088	-0.001009	0.001009	↑
	6	0.0009	-0.001885	0.001885	-
	12	-0.0012	-0.000964	0.000964	↓
	24	-0.0040	-0.001358	0.001358	↓
Calabria	1	0.0227	-0.002083	0.002083	↑
	3	0.0138	-0.001162	0.001162	↑
	6	0.0100	-0.001558	0.001558	↑
	12	0.0044	-0.002285	0.002285	↑
	24	0.0050	-0.002025	0.002025	↑
Campania	1	0.0053	-0.000855	0.000855	↑
	3	0.0010	-0.000676	0.000676	↑
	6	0.0015	-0.000734	0.000734	↑
	12	-0.0004	-0.001439	0.001439	-
	24	-0.0003	-0.001272	0.001272	-
Molise	1	0.0144	-0.002926	0.002926	↑
	3	0.0083	-0.002496	0.002496	↑
	6	0.0066	-0.002325	0.002325	↑
	12	0.0008	-0.002208	0.002208	-
	24	0.0006	-0.002624	0.002624	-
Southern Italy	1	0.0126	-0.000443	0.000443	↑
	3	0.0083	-0.000613	0.000613	↑
	6	0.0064	-0.000825	0.000825	↑
	12	0.0039	-0.001121	0.001121	↑
	24	0.0036	-0.001066	0.001066	↑

Symbols: ↑: increasing trend; ↓: decreasing trend; -: no trend.

in contrast to the ITA method which showed no statistically significant tendencies. Similarly, in Basilicata RK test identified an increasing trend at 6-h, while ITA test identified no trend; in addition, 12- and 24-h rainfall series presented no trend according to the RK test and decreasing trend according to the ITA method. Notwithstanding these slight differences, both methods (RK and ITA) demonstrate an increase of short-duration (1 and 3 h) extreme rainfall events at regional scale.

5. Conclusion

The aim of the present manuscript was to provide the characterisation of rainfall extremes over a poorly monitored region (southern Italy). To this purpose, a statistical analysis of short-duration extreme rainfall time series was carried out to detect potential trends at different spatio-temporal scales in the period 1970–2020. A database of sub-daily rainfall annual maxima was constructed using all available records and extended by applying gap-filling techniques. Indeed, in this work we tried to advance the definition of a general framework for working in data-scarce environments in order to improve rainfall statistical analysis in gauged and ungauged locations. The proposed spatially-constrained ordinary kriging technique exploits all available information from recorded series, regardless of length, and provides annual extreme rainfall estimates at ungauged sites or points with missing data. The methodology combines the ordinary kriging approach with the same spatial constraints as the IDW method. The procedure allowed us to reconstruct the missing data in the assembled database for southern Italy with an average reconstruction error of 20 %.

The study investigated the presence of trends in hourly rainfall intensities at both local and regional scales using the Mann-Kendall and Spearman's rank correlations tests. The results of the trend analysis at individual sites revealed that, for most durations, the observed trends were not statistically significant. However, when a trend was detected, it tended to be positive for shorter durations and could be either positive or negative for longer durations.

Interestingly, upward trends were often observed for shorter durations at specific locations, but these trends tended to weaken or disappear for rainfall events of longer durations. Moreover, the analysis indicated that, in general, most of the regions under consideration showed no significant trends for longer durations. Nevertheless, certain clusters of increasing trends were identified for shorter time intervals.

Unfortunately, the sparseness of rain gauges limited the full coverage of the investigated area, making it challenging to draw definitive conclusions about trends across the entire region.

The regional test detected a statistically significant increasing trend in the rainfall intensities for all the durations. However, the trends turned out to be non-homogeneous due to the different trend directions exhibited by individual stations. These outcomes emphasise the importance of investigating hydrological trends at different spatial and temporal scales, given its strong heterogeneity. Indeed, they cannot be investigated on individual hydrological time series but must be assessed on a regional and/or district scale.

CRediT authorship contribution statement

Angelo Avino: Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, Investigation, Validation. **Luigi Cimorelli:** Data curation, Writing – review & editing. **Pierluigi Furcolo:** Writing – review & editing. **Leonardo Valerio Noto:** Data curation, Writing – review & editing. **Anna Pelosi:** Data curation, Writing – review & editing. **Domenico Pianese:** Conceptualization, Writing – review & editing, Visualization, Investigation, Supervision. **Paolo Villani:** Conceptualization, Writing – review & editing, Investigation. **Salvatore Manfreda:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Visualization, Investigation, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Salvatore Manfreda reports financial support was provided by University of Naples Federico II.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2024.130684.

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