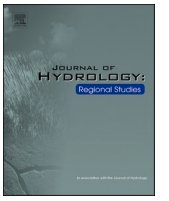
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Testing trends in gridded rainfall datasets at relevant hydrological scales: A comparative study with regional ground observations in Southern Italy

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ABSTRACT

Study region: In this study, we compared the spatiotemporal evolution of rainfall trends in E-OBS and ERA5 to those detected using historical rainfall series recorded by ground-based networks in Southern Italy. In particular, the study is applied to the Campania, Basilicata, Apulia, Calabria and Sicily regions (84,000 km^2 in total) on seasonal and annual scales.
Study focus: Meteorological gridded datasets at large spatial scales are widely used in many hydroclimatic applications as they provide long and spatially homogeneous records. Regional trend analyses based on these data need to be treated with caution due to some potential limitations at relevant hydrological scales, such as the coarse spatial resolution and the spatio-temporal inhomogeneity of the underlying data. Gradual trends and abrupt change points were studied on rainfall data from 1979 to 2019.
New hydrological insights for the region: Both gridded datasets capture the major trends in observed rainfall, with a predominance of positive values driven by changes in September-November. Overall, ERA5 returns flatter results compared to E-OBS, with the former comparing well with observations in Sicily and Apulia, while the latter is performing well in Campania and partially in Calabria and Basilicata. Most statistically significant trends are associated with discontinuities in the early 2000s, and this is well captured by both ground and gridded datasets. The general behavior in inter-annual variability trends in Southern Italy is captured by both datasets, with ERA5 also detecting regional patterns.

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1. Introduction

Understanding past and current rainfall patterns provides valuable insights into historical climate variations and helps supporting predictions of future climate scenarios (Pappenberger et al., 2009; Fantini al., 2016; Bandhauer et al., 2022). This knowledge is crucial for assessing the potential impacts of climate change on water availability, agriculture, and ecosystems, as well as for developing effective strategies for sustainable and climate-resilient growths. Moreover, reliable rainfall data support informed decision-making in sectors such as water infrastructure planning and design and preparedness for water-related extreme events, such as floods, droughts, and landslides.

Large-scale gridded datasets, such as those derived from satellite observations or the assimilation of multi-parameter and multi-platform observations and forecasts in a numerical weather prediction system (denoted as reanalysis), or created by interpolating weather station observations onto a regularly spaced grid, provide long-term continuous estimates of climate variables on a grid covering either the globe or a region (Hu and Franzke, 2020).

These gridded data products have found widespread application in atmospheric and climate sciences, as well as hydrological studies. For instance, they have been used as benchmark datasets to investigate climate variability and change, evaluate climate model simulations, and investigate extreme weather and climate events (e.g., King et al., 2013; Alfieri et al., 2022). Albeit designed for large-scale applications (from continental to global scale), these datasets have also been frequently used in regional studies (e.g., Santos et al., 2023; Varlas et al., 2022). A relevant temporal scale for such applications is the monthly scale, as demonstrated by several water balance and drought studies (e.g., Di Giovanni et al., 2023; Rossi et al., 2023; Salvati et al., 2008).

Among the gridded datasets available at the Pan-European level, the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) includes two of the most widely used, namely the E-OBS daily gridded observational dataset (Cornes et al., 2018), and the ERA5 (Hersbach et al., 2020) reanalysis dataset. Another commonly used dataset derived from ERA5 is the ERA5-Land (Munoz-Sabater et al., 2021) product. Due to the strong connection between ERA5 and ERA5-Land in the meteorological variables (Muñoz-Sabater et al., 2021), only the former is considered in this study, as it is the original data source (without downscaling) with a spatial resolution consistent with E-OBS. Other gridded precipitation datasets covering the region, such as CRU (Harris et al., 2020) and GPCC (Schneider et al., 2017) are characterized by lower spatial resolution (0.5 degrees) in their near-real time product, hence were not considered in this study.

Despite the increasing availability and applicability of these products in hydroclimatic studies, they are still subject to considerable uncertainties at the local scale. For instance, E-OBS accuracy is proven to strongly depend on data density (Bandhauer et al., 2022), hence, its reliability may suffer from sparse spatial coverage in some regions, particularly over mountainous or remote areas. Time series of the stations used as inputs for interpolation in E-OBS are usually not corrected for inhomogeneities (except for E-OBSv19.0eHOM), and station density is not constant either through time or space.

Accuracy of ERA5 precipitation has been proven to be generally better in the extratropical regions compared to the tropic, but estimates may still exhibit biases locally due to model uncertainties or deficiencies in representing certain physical processes (Lavers et al., 2022). Spatio-temporal inhomogeneity in underlying data is also a drawback for ERA5 and ERA5-Land products during the assimilation process.

It follows that analyses based on the E-OBS and ERA5 datasets should be treated with caution when conclusions at the local scale are drawn, and a careful evaluation, although challenging, is essential for studying climate dynamics and informing decision-making processes, especially when the data are used at regional or higher spatial scale.

One crucial aspect of evaluating these datasets is their skill to accurately represent the target region's climate variability and trends. In fact, one of the main limitations of large-scale gridded datasets is the relatively coarse spatial resolution (never less than 10 km) and the corresponding spatial smoothing effect, which hinders applications at relevant hydrological scales. In this regard, the Mediterranean region, due to its complex topography and sea-land interactions, is particularly challenging, but at the same time very interesting given the relevance of this region as a hot-spot of climate change (Cos et al., 2022). Within the Mediterranean region, southern Italy is a highly populated region where most of the typical Mediterranean conditions can be found, making this area an interesting test bed for gridded precipitation products.

Evaluation of rainfall gridded products usually involves comparing the datasets with high-resolution observed records from meteorological stations across the region of interest, considering the dataset's spatial and temporal resolution, biases, and uncertainties. Comparisons by using statistical metrics (e.g., bias, root mean square error, correlation coefficient, Kling-Gupta efficiency, among others) have been carried out in various regions worldwide, such as Ethiopia (Reda et al., 2021), Iran (Saemian et al., 2021), Southwest United States (Ehsani et al., 2022) and high-latitude Asia (Lan et al., 2023).

With reference to the Mediterranean region, a poor capability of the E-OBS gridded dataset to satisfactorily reproduce precipitation data has been found both at large (Kostopoulou et al., 2012), and small spatial scale (Turco et al., 2013; Dumitrescu and Birsan, 2015; Curci et al., 2021). A recent study by My et al. (2022) revealed that the E-OBS and CRU gridded datasets allow for only general indications of the spatial and temporal behavior of climatic variables over a southern Italy region (Apulia) in the period 1956–2019, especially in regard to precipitation data. On the other hand, the E-OBS dataset at 0.10° resolution was utilized as ground truth in a study aimed at improving the prediction of extreme rainfall events using ERA5 reanalysis in another southern Italy region (Calabria), given the noticeable input received from the local rain gauges network (Mastrantonas et al., 2022).

In the present study, we perform a comprehensive trend analysis of seasonal and annual precipitation from 1979 onwards in Southern Italy. The study period is selected as the most recent climatological baseline (WMO, 2017), often used as a reference to characterize current climate conditions. The study area is of particular interest as it exhibits a complex climate influenced by various factors such as Mediterranean Sea dynamics, topography (ranging from coastal areas to mountainous regions), and proximity to North

African weather systems. Specifically, the study area encompasses five administrative regions (Campania, Basilicata, Apulia, Calabria and Sicily), each covered by a dedicated monitoring network, requiring the merging and homogenizing of the observed data. This dataset can be used as a valid benchmark due to the data completeness, consistency and high spatial density.

The study focuses on the quantities characterizing the climatology, including average values and inter-annual fluctuations (via the coefficient of variation), which are analyzed through a combination of some consolidated techniques, such as the nonparametric Mann–Kendall test (Mann, 1945; Kendall, 1975) to identify the presence of significant trends in the long-term mean of the time series, and the Theil–Sen approach (Sen, 1968) to quantify the trend magnitude, the modified Mann-Kendall (Yue and Wang, 2004) to detect trends in the presence of serial correlation, and the Pettitt test (Pettitt, 1979) to detect jumps or discontinuities in the series.

After a description of the case study area and the data in Section 2, we introduce the methodology in Section 3. The results are presented and discussed in Sections 4 and 5. Finally, conclusions are drawn in Section 6.

2. Study area and rainfall datasets

2.1. Description of the study area

The precipitation pattern in Italy is complex due to the intricate topography, geographical positioning, and elongated shape of the peninsula, covering an approximate span of 10 degrees of latitude (between 36°N and 46°N). Additionally, the peninsula exhibits a pronounced west-to-east inclination as it extends into the Mediterranean Sea.

The study domain (Fig. 1) covers a significant portion (28 %) of the Italian territory, including the regions of Apulia (with a surface of 19,500 km^2), Basilicata (10,000 km^2), Calabria (15,000 km^2), Campania (13,500 km^2), and Sicily (26,000 km^2), with a population of about 17.3 million inhabitants (about 30 % of the whole Italian population). Located within the Mediterranean basin, the continental area is encircled by the Adriatic Sea to the east, the Ionian Sea to the southeast and the south, and the Tyrrhenian Sea to the west. This geographic location and the proximity to the sea result in distinctive precipitation gradients, leading to high spatial variability with notable local effects. As other areas in the Western Mediterranean, the Mediterranean Sea is the main moisture source for the region, with an average input to precipitation of almost 35 %. The North Atlantic is the second most important source, with an average percentage of 25 % (Insua-Costa et al., 2022). Spatial differences are further enhanced by a complex orography due to the north-to-south Apennine chain in the peninsula, acting as a physical barrier for precipitation events. Sicily, instead, is the largest island in the Mediterranean Sea. It is a predominantly hilly region (62 % of its territory), while 24 % is mountainous. In particular, while in eastern Sicily the Siculo Apennines can be recognized as the ideal extension of the continental Apennines, central and western areas are

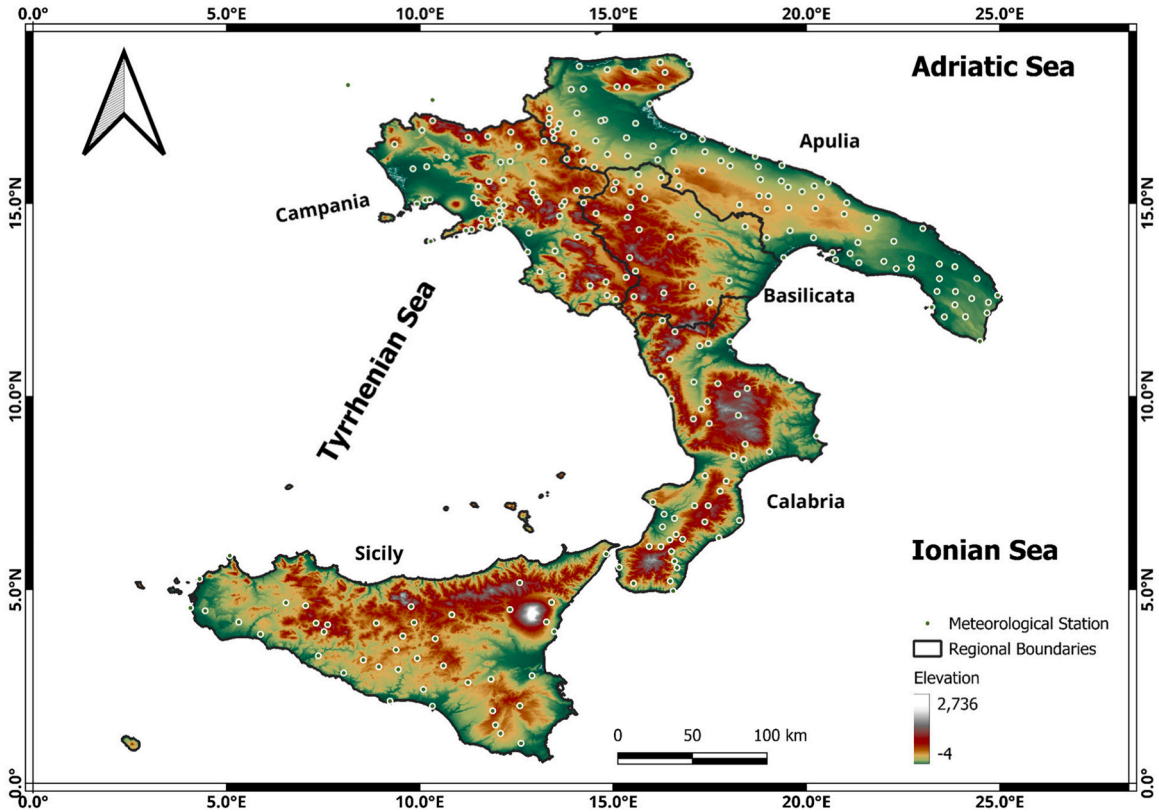


Fig. 1. Spatial distribution of the gauging stations used in this study.

characterized by isolated massifs.

The climatic conditions in this area demonstrate notable variability, predominantly influenced by the intricate orography. The climate can be broadly classified as Mediterranean, characterized by mild, rainy winters and hot, dry summers. However, this description primarily pertains to the coastal areas. In contrast, both precipitation patterns and temperature regimes can undergo substantial alterations moving towards inland areas and mountainous regions. Furthermore, the south-facing coastlines, especially in Sicily, can experience torrid summers due to hot winds blowing from the Northern African coast.

2.2. Rainfall databases

The analyses are performed on monthly precipitation data acquired from ground-based monitoring networks and gridded datasets covering the period 1979–2019. The time frame is selected as the one commonly used to characterize the most recent climatological period (see WMO, 2017), and it represents a good compromise between maximizing data availability and consistency among datasets. While rainfall records were available before 1979 (or after 2019) over some of the selected stations, the adopted study period allows maximizing the spatial coverage without compromising data consistency. Although the data were recorded at least on a daily scale, nonetheless, many daily records are missing during the period when measurements were recorded manually (i.e., before 2000–2002). For example, in some cases, daily data from consecutive days were expressed as total values. On the other hand, recorded monthly data are more continuous, require only limited reconstruction of missing data, and are suitable for a range of applications related to water balance and drought studies. Further details on the characteristics of each dataset are reported in the following sections.

2.2.1. Observed data

The dataset consists of monthly rainfall time series collected in a total of 264 stations distributed across the five regions of the study area (Table 1). The rain gauge networks in the studied regions were managed by the *Servizio Idrografico e Mareografico Nazionale* (SIMN) from 1918 to 1999 and, subsequently, the management was delegated to regional authorities. In many regions, the regional Civil Protection departments are responsible for rainfall data collection, but this is not always the case. As an example, in Sicily, the monitoring activities are supervised by the River Basin Authority of the Sicilian Hydrographic District (formerly "*Osservatorio delle Acque*"), and in Calabria by the Regional Environmental Protection Agency.

During the transfer of services between different authorities, most of the SIMN rain gauges were removed and relocated and/or replaced with new-generation instruments, resulting in discontinuous rainfall time series over time (Avino et al., 2024). Henceforth, the stations boasting the highest quantity of accessible data were chosen. Minor missing observations were reconstructed using the Inverse Distance Weighting (IDW) interpolation method (ASCE, 1996). IDW is a deterministic spatial interpolation approach that estimates missing data by calculating a weighted average of nearby measurements, where the weights decrease as the distance from the observation points increases. It is widely used in environmental data applications for its simplicity, computational efficiency, and reproducibility, making it ideal for spatial estimation (Bartier and Keller, 1996; Li and Heap, 2008). The effectiveness of IDW in reconstructing precipitation fields is well-documented in the literature (e.g., Caloiero et al., 2021). Studies such as Crespi et al. (2021) and Avino et al. (2021) demonstrated its utility in Italian conditions by interpolating precipitation data in the Trentino-South Tyrol and Campania region of Italy. Table 1 provides a detailed description of gauge observations and the corresponding missing/reconstructed data (see "Missing and Reconstructed observations'' column). The percentage of reconstructed monthly data was relatively low in Apulia, Calabria and Sicily, varying from 2 % to 6 %. In Basilicata and Campania, the percentage of reconstructed data was higher due to frequent changes in the gauging network, including relocations, equipment updates, and shifts in managing agencies. The full dataset of ground observations is available in the supplementary materials.

2.2.2. ERA5 and E-OBS datasets

Over Europe, several gridded datasets are available based on rain gauge networks alone or merged with information provided by models. Amongst them, ERA5 and E-OBS are known as the two most recent and widely used pan-European gridded datasets (Bandhauer et al., 2022). Due to their widespread usage in climatic and hydrological studies, the analysis is focused on these two datasets.

ERA5, the fifth-generation reanalysis of the European Centre for Medium-Range Weather Forecasting (ECMWF) over the past eight decades, utilizes a modern numerical weather prediction model (the Integrated Forecasting System Cycle 41r2, IFS, version from 2016) by means of a 4D-Var data assimilation system to integrate observations from different platforms (in-situ, radiosondes, satellite) (Hersbach et al., 2020). This dataset is made available from 1940 onwards. In the present study, ERA5 data was achieved on a regular longitude-latitude grid with a spacing of 0.25° and at a monthly resolution for the period of January 1979 to December 2019. Even if

Table 1
Summary of the characteristics of rain gauge-based monthly rainfall datasets used in the analysis.

Region	Period	Number of stations	Gauged observations	Missing and Reconstructed observations	Missing and Reconstructed observations (%)	Total observations
Apulia	1979–2021	105	53,284	896	1.6	54,180
Basilicata	1979–2021	12	4961	1231	19.9	6192
Calabria	1979–2019	49	22,729	1379	5.7	24,108
Campania	1979–2021	56	23,512	5384	18.6	28,896
Sicily	1979–2019	42	19,716	948	4.6	20,660

the ERA5 dataset has been successively extended back to 1940, a limited number of satellite data for assimilation were available before 1979.

E-OBS, produced by KNMI (the Dutch weather service), is a gridded surface dataset of climate variables based on extensive archive observations from weather stations. This dataset is freely available from the C3S CDS (Buontempo et al., 2020), which makes it particularly appealing for climate and environmental-related studies over Europe (in the Scopus database, E-OBS dataset is retrieved in the article title, abstract or keywords of indexed papers almost 300 times in the last two decades - accessed on 10th July 2024). Monthly precipitation data are obtained on a 0.25° grid using cubic spline interpolation. Then, deterministic daily analyses are expected to derive via a generalized additive model (GAM) with square-root transformed observations and the introduction of the previously calculated monthly field as a covariate (Cornes et al., 2018). The dataset of stations used for the interpolation is regularly updated to ensure the best possible estimate for any given date. However, these continuous updates can also be the source of temporal inconsistencies and heterogeneity in the spatio-temporal coverage. Similarly to ERA5, gridded daily precipitation data from the E-OBS v28.0e platform were extracted for the period December 1979 - December 2019 and cumulated to monthly scale.

The maps in Fig. 2 show the spatial distribution of the average total annual precipitation for the period 1979–2019 according to the two gridded datasets (panels a-b) and the rain gauges (panel c). These maps highlight the large range of variability in rainfall within the study region, with lower values in all datasets in Sicily and Apulia and higher values (up to more than 1000 mm) along the Apennines. Fig. 2 (panel c) clearly shows that the wettest areas are those located along the Tyrrhenian side of the peninsula. This behavior is influenced by the interaction between the westwards moist currents and local orography dominated by the Apennines, and it is captured by ERA5 and partially by E-OBS. A cluster analysis performed using the Principal Component Analysis (PCA) highlights that southern Italy can be divided into four main regions concerning average total annual precipitation: a Tyrrhenian one, an Adriatic-Ionian one, an Apennine one and a Sicilian one (Fig. S1, supplementary material). Significant correlations of the precipitation patterns in each of these zones to different exogenous variables can be detected (Table S1, supplementary material). The same analysis performed on the gridded datasets led to similar results, especially for ERA5.

3. Methodology

With the aim of detecting potential trends and change points in the rainfall climatic characteristics (average and inter-annual fluctuations) of the last 40 years, non-parametric trend tests, such as conventional and modified Mann-Kendell tests, and Pettit's test were applied to analyze precipitation time series. Such analyses were performed on annual and seasonal total values derived from the monthly records. Four conventional seasons were considered: December-February (DJF), March-May (MAM), June-August (JJA), and September-November (SON). In addition, changes in the rainfall inter-annual variability were investigated using the coefficient of variation (CV, the ratio between standard deviation and mean) computed over a 10-year moving window. Nicholls and Wong (1990) first introduced the concept of using CV as a metric to quantify the inter-annual variability of rainfall, and the approach has also been applied in Longobardi and Boulariah (2022) over the Campania region.

3.1. Non-parametric trend test

3.1.1. Mann-Kendall test

The Mann-Kendall test was originally proposed by Mann (1945) as a non-parametric method for trend detection, while Kendall (1975) provided the distribution of the test statistic for assessing non-linear trends and identifying turning points. In this test, each data point is compared to all subsequent data points, utilizing the ordered data samples. The Mann-Kendall statistic (S) is calculated as follows:

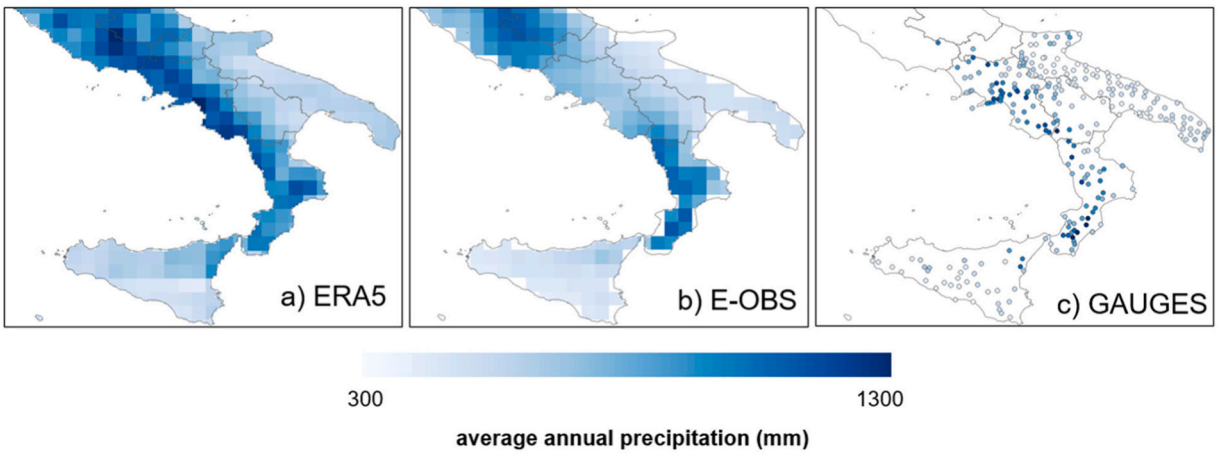


Fig. 2. Spatial distribution of the 1979–2019 average total annual precipitation (mm) according to: a) ERA5, b) E-OBS, and c) rain gauges.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} A_{ij} \tag{1}$$

$$\begin{array}{l} A_{ij} = sign(x_j - x_i) = +1 \\ \quad if\ (x_j - x_i) > 0, 0 \\ if\ (x_j - x_i) = 0, -1 \\ if\ (x_j - x_i) < 0 \end{array} \tag{2}$$

where x_i and x_j are the sequential data, n is the total number of data in the time series.

A positive (negative) S value indicates an increasing (decreasing) trend. Under the null hypothesis that x is independent and randomly distributed, for $n \geq 8$, the statistic S follows an approximate normal distribution, characterized by zero mean and variance as:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i-1)(2t_i+5)}{18} \tag{3}$$

where m is the number of tied groups (set of sample data having the same value) and t_i denotes the length of the *i-th* group.

The probability associated with the Mann-Kendall statistic S and the sample size n is then computed to statistically quantify the significance of the trend using the normalized test statistic Z as follows:

$$Z = \begin{cases} (S-1)/\sqrt{Var(S)} & S > 0 \\ 0 & S = 0 \\ (S+1)/\sqrt{Var(S)} & S < 0 \end{cases} \tag{4}$$

A positive or negative value of Z indicates an upward or downward trend. The p-value associated to each trend test is given by:

$$p = 2[1 - \varphi|Z|] \tag{5}$$

where $\varphi|Z|$ represents the cumulative distribution function of a standard normal variable Z. If the p-value falls below the pre-assigned significance level α (i.e., 0.05), we can reject the null hypothesis. This test is here used to analyze the trend in annual and seasonal rainfall records.

3.1.2. Modified Mann-Kendall test

Serial correlation, a prevalent concern in time series data, can significantly impact trend analysis. To address this issue, the modified Mann-Kendall test is employed to detect trends in hydrological and climatic data showing signs of serial correlation. This method incorporates a variance correction approach proposed by Yue and Wang (2004) to mitigate the effects of serial correlation, enhancing the reliability of trend detection in such datasets.

Yue and Wang (2004) proposed the modified variance of S statistics $Var^*(S)$ as follows:

$$Var^*(S) = Var(S) \times CF \tag{6}$$

and

$$CF = 1 + 2\sum_{k=1}^{n-1}(1 - k/n)r_k \tag{7}$$

where CF is a correction factor, and $r_k$is the k-lag serial correlation coefficient of data and ranks of data. Using Eqs. (3), (6) and (7), the modified test statistic can be obtained. This test is here used on the CV annual and seasonal records to account for the presence of autocorrelation in the datasets derived from the moving window approach.

3.1.3. Sen's slope

Using the method proposed by Sen (1968), the magnitude of the slope of the trend is estimated as follows:

$$M_s = Median\left[\frac{(x_j - x_i)}{(j - i)}\right] \quad \forall \quad i < j \tag{8}$$

If there are n values in the time series, as many as $N = n(n-1)/2$ slope estimates can be obtained. The median of these N values, denoted as M_s is used as the estimate of the trend slope. This approach leverages the median to provide a robust estimation of the trend slope, particularly effective in handling outliers or skewed data distributions.

3.2. Change point Pettitt's test

The approach proposed by Pettitt (1979) is frequently employed for the detection of a single change point in hydrological or climate series characterized by continuous data. This approach tests the null hypothesis that the variable follows one or more distributions with the same location parameter (indicating no change), against the alternative hypothesis that a change point exists. The non-parametric statistic employed in this method is defined as follows:

$$U_{t,n} = \sum_{j=1}^{t} \sum_{i=t+1}^{n} A_{ij} \tag{9}$$

The test statistic $U_{t,n}$ depends on A_{ij} and is computed for all time points from 1 to n; subsequently, the most significant change point is identified where the absolute value of $U_{t,n}$ is maximum:

$$K_n = \max_{1 \le t < n} \left| U_{t,n} \right| \tag{10}$$

A change point is deemed to occur at time t when the statistic K_n deviates significantly from zero at a specified level of significance. The approximate significance level of the test is determined by:

$$Pp = 2 \cdot \exp\left(\frac{-6k_T^2}{T^2 + T^3} \right) \tag{11}$$

Once p_p falls below the pre-assigned significance level α (i.e., 0.05), we can reject the null hypothesis.

4. Results

The main results of the statistical tests introduced in Section 3 are reported in this section for the rain gauge and the gridded datasets, separately.

4.1. Rain gauge datasets

The spatial distribution of the Sen's slope (M_s) and Pettitt's change point (T) values obtained from the total annual precipitation record in each station is depicted in Fig. 3 (panels a and b, respectively).

The results in Fig. 3a highlight mostly positive trends in all the sites, with only a few locations with negative trends scattered across the domain (see also histogram in Fig. 3a). Statistically significant ($p < 0.05$) trend values (demarcated by thick borders in both panels of Fig. 3) are observed in all regions, with clusters in northern Apulia and Campania.

Changing points are mostly located between 2000 and 2005 (about 55 % of the stations, see insert in Fig. 3b), with the spatial distribution of statistically significant results strongly resembling the one observed for the linear trend. A large cluster of changing points in the early 90 s can be observed in southern Apulia, mostly, however, corresponding to non-significant values.

Data in Table 2 summarize the results of the two tests for the different seasons on the rain gauge observations, highlighting how an overall smaller percentage of sites has statistically significant values. Most of the positive and significant trends are observed in SON, which is the rainiest season in the regions, and the same can be observed also for Pettitt's test. Statistically significant negative trends are practically absent in all the regions and seasons for the analyzed rain gauge stations.

Trends in CV (Fig. 4) show an almost equal split between positive and negative values, with the former mostly clustered on the western side of the study area, in an area encompassing most of Campania region, western Basilicata and Calabria and northern Sicily. On the other hand, negative values gather in the eastern side, including the whole of Apulia, eastern Basilicata and Calabria and south-eastern Sicily. Furthermore, a cluster of stations with opposite values compared to the rest of the region can be observed in the northern coastal area of Campania, with statistically significant negative values lower than 0.5 % y^{-1}. As for the other tests, statistically significant values are not predominant, even though their frequency is not negligible (up to 45 % in Sicily).

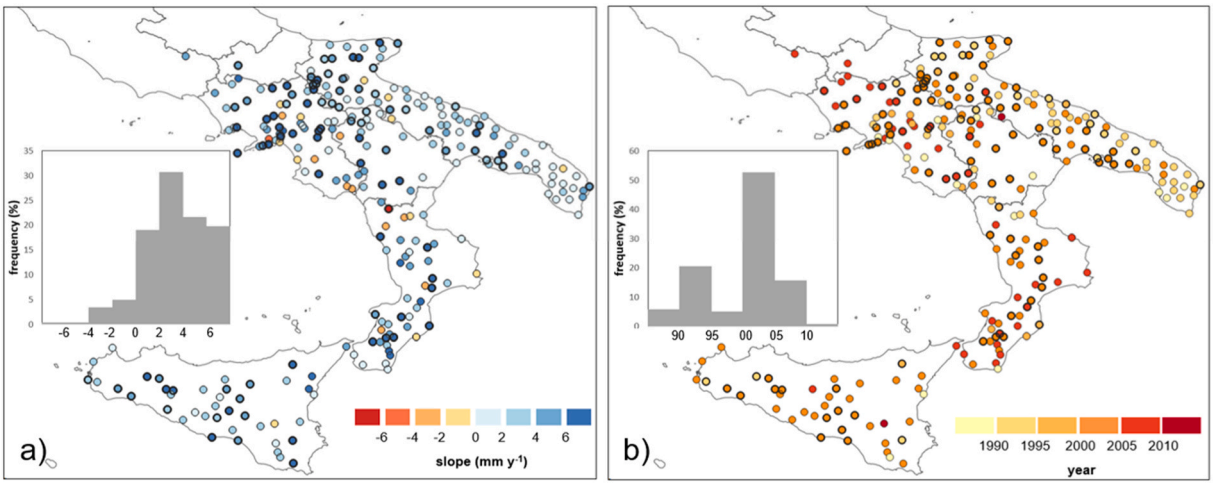


Fig. 3. Spatial distribution of Sen's slope (panel a) and Pettitt's change point (panel b) derived from total annual precipitation recorded by rain gauges in 1979–2019. Circles with thick borders highlight sites with statistically significant ($p < 0.05$) results. Inserts show the frequency distribution of the mapped values.

Table 2
Summary statistics for the Sen's slope (M_s), Mann-Kendall's (p) and Pettitt's (p_p) tests on seasonal (DJF: December-February, MAM: March-May, JJA: June-August, SON: September-November) and annual (YYY) precipitation. Values represent the percentage (%) of rain gauges in the region.

Period	Region	$M_s > 0$	$M_s > 0$ & $p < 0.05$	$M_s < 0$	$M_s < 0$ & $p < 0.05$	$p_p < 0.05$
DJF	Apulia	65	0	35	0	2
	Basilicata	50	0	50	0	8
	Calabria	61	4	39	2	6
	Campania	77	11	23	0	11
	Sicily	98	19	2	0	7
	South Italy	71	6	29	0	6
MAM	Apulia	93	17	7	0	11
	Basilicata	100	25	0	0	25
	Calabria	51	0	49	2	2
	Campania	79	11	21	0	14
	Sicily	83	7	17	0	10
	South Italy	81	11	19	0	11
JJA	Apulia	76	1	24	0	1
	Basilicata	100	33	0	0	25
	Calabria	94	8	6	0	4
	Campania	77	5	23	0	4
	Sicily	95	10	5	0	7
	South Italy	84	6	16	0	4
SON	Apulia	99	37	1	0	34
	Basilicata	100	25	0	0	33
	Calabria	96	31	4	0	20
	Campania	70	13	30	0	9
	Sicily	95	31	5	0	10
	South Italy	92	29	8	0	22
YYY	Apulia	95	35	5	0	47
	Basilicata	100	33	0	0	50
	Calabria	82	20	18	2	33
	Campania	82	38	18	0	46
	Sicily	98	45	2	0	38
	South Italy	91	34	9	0	43

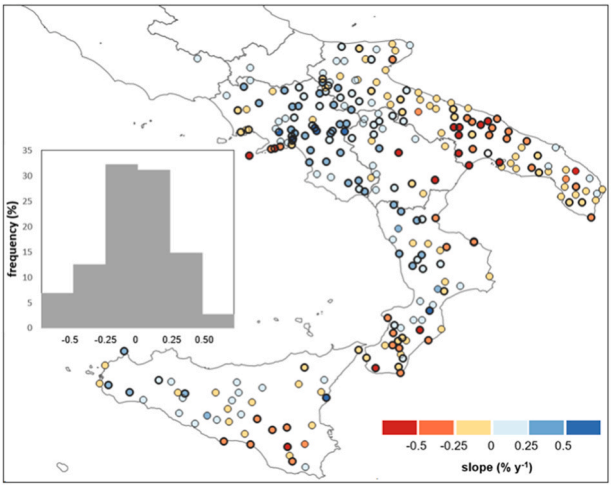


Fig. 4. Spatial distribution of the Sen's slope computed on 10-year moving-window CV derived from rain gauge annual precipitation between 1979 and 2019. Circles with thick borders highlight sites with statistically significant ($p < 0.05$) results. Insert shows the frequency distribution of the mapped values.

4.2. Gridded datasets

The Sen's slope values obtained from the gridded datasets on total annual precipitation are reported in Fig. 5 for ERA5 (Fig. 5a) and E-OBS (Fig. 5b), respectively. In both cases, trends are almost exclusively positive, with statistically significant values according to the Mann-Kendall test ($p < 0.05$) over most of the domain (hatched areas in Fig. 5). The only notable area with non-significant trends is Calabria region for E-OBS (Fig. 5b), where a mix of slightly positive (< 2 mm y^{-1}) and negative (> -2 mm y^{-1}) values are observed. Overall, trends seem to be more marked in E-OBS compared to ERA5, with slopes greater than 6 mm y^{-1} in western Sicily, northern

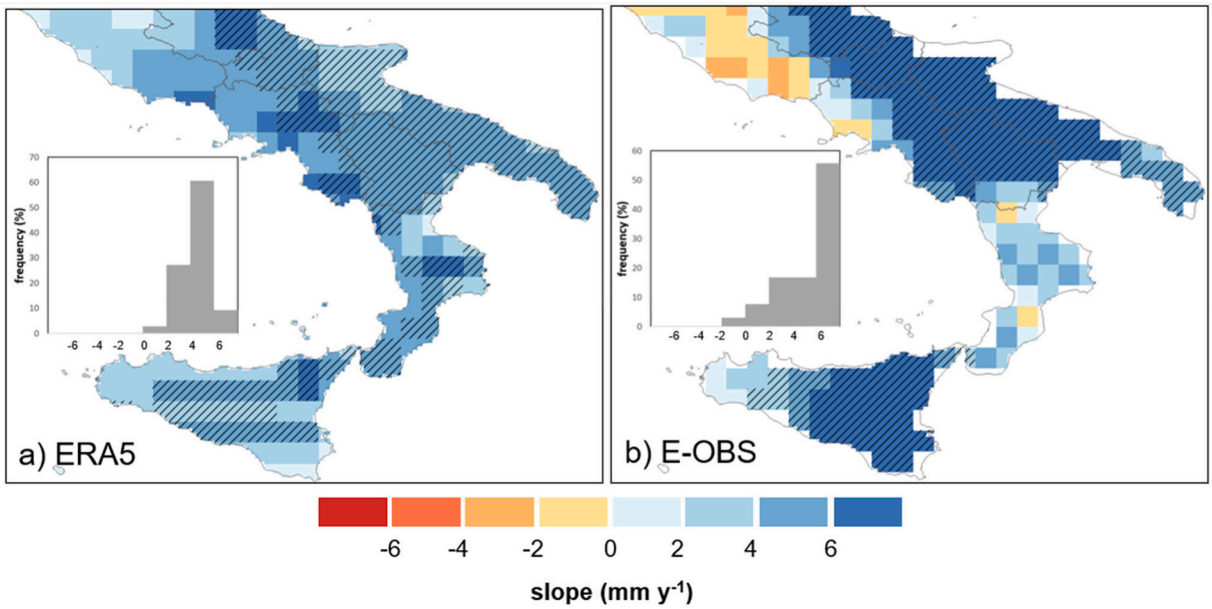


Fig. 5. Spatial distribution of the slope of the linear trend according to Sen's method for ERA5 (panel a) and E-OBS (panel b) total annual precipitation between 1979 and 2019. Hatched areas demark statistically significant ($p < 0.05$) values. Inserts show the frequency of the values in the study regions.

Apulia, Basilicata, and southern Campania.

To integrate the results on the linear trend, the presence of potential change points is analyzed as summarized by the maps in Fig. 6 for both ERA5 (Fig. 6a) and E-OBS (Fig. 6b), with statistically significant values ($p < 0.05$) according to the Pettitt's test hatched. Also in this case, the two gridded datasets return similar results, with most of the statistically significant changing points located between 2000 and 2005 (96 % and 70 % for ERA5 and E-OBS, respectively; see inserts in Fig. 6).

Results for both tests applied to seasonal data are reported in Table 3 for ERA5 and E-OBS, summarizing the outcomes for each study region. Most of the data reported in Table 3 display strong similarities. In particular, positive trends are largely observed in all the

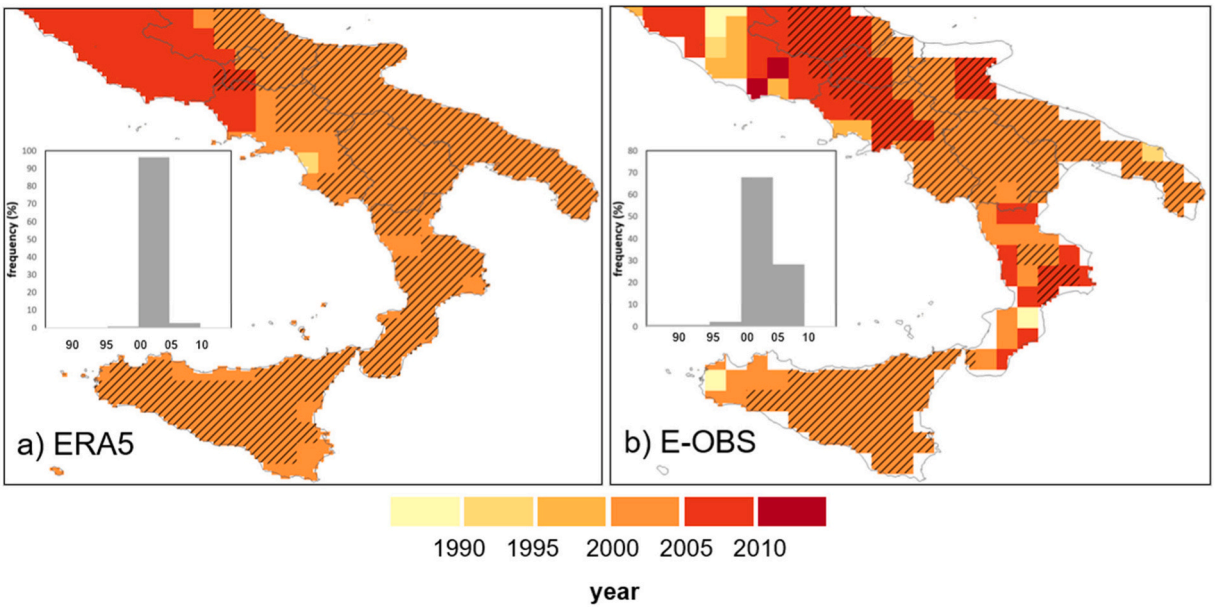


Fig. 6. Spatial distribution of the changing point location according to the Pettitt's test for ERA5 (panel a) and E-OBS (panel b) total annual precipitation between 1979 and 2019. Hatched areas identify statistically significant ($p < 0.05$) values. Inserts show the frequency of the values in the study regions.

Table 3
Summary statistics for the Sen's slope (M_s), Mann-Kendall's (p) and Pettitt's (p_p) tests on ERA5 and E-OBS seasonal (DJF: December-February, MAM: March-May, JJA: June-August, SON: September-November) and annual (YYY) precipitation. Values represent the percentage (%) of grid cells in the region.

Period	Region	$M_s > 0$		$M_s > 0$ & $p < 0.05$		$M_s < 0$		$M_s < 0$ & $p < 0.05$		$p_p < 0.05$	
		ERA5	E-OBS	ERA5	E-OBS	ERA5	E-OBS	ERA5	E-OBS	ERA5	E-OBS
DJF	Apulia	100	96	0	63	0	4	0	0	0	70
	Basilicata	100	82	0	53	0	18	0	0	0	65
	Calabria	96	57	0	0	4	43	0	0	0	0
	Campania	100	100	0	17	0	0	0	0	0	42
	Sicily	95	100	0	57	5	0	0	0	0	36
	South Italy	98	89	0	41	2	11	0	0	0	42
MAM	Apulia	100	100	10	81	0	0	0	0	17	74
	Basilicata	100	100	28	82	0	0	0	0	22	82
	Calabria	96	61	0	4	4	39	0	0	0	4
	Campania	100	100	17	58	0	0	0	0	8	75
	Sicily	98	90	0	43	2	10	0	0	2	38
	South Italy	99	90	8	52	1	10	0	0	9	51
JJA	Apulia	93	85	0	4	7	15	0	0	0	0
	Basilicata	100	100	0	0	0	0	0	0	0	0
	Calabria	100	100	4	9	0	0	0	0	0	13
	Campania	83	88	0	0	17	13	0	0	0	0
	Sicily	100	100	11	85	0	0	0	0	0	53
	South Italy	96	95	4	28	4	5	0	0	0	18
SON	Apulia	100	100	100	89	0	0	0	0	86	81
	Basilicata	100	100	78	88	0	0	0	0	50	82
	Calabria	100	100	80	48	0	0	0	0	64	26
	Campania	100	75	17	33	0	25	0	0	13	58
	Sicily	100	100	39	73	0	0	0	0	11	50
	South Italy	100	96	61	67	0	4	0	0	43	58
YYY	Apulia	100	100	100	96	0	0	0	0	100	96
	Basilicata	100	100	100	82	0	0	0	0	100	94
	Calabria	100	91	60	4	0	9	0	0	88	26
	Campania	100	92	50	58	0	8	0	0	46	79
	Sicily	100	100	55	85	0	0	0	0	80	83
	South Italy	100	97	71	68	0	3	0	0	83	76

regions and seasons, with the only notable exception being Calabria in DJF and MAM (for E-OBS). Trends are not significant during summer months (JJA) in both datasets and all regions (except Sicily for E-OBS), likely due to the low precipitation values observed during these months (corresponding to the dry period).

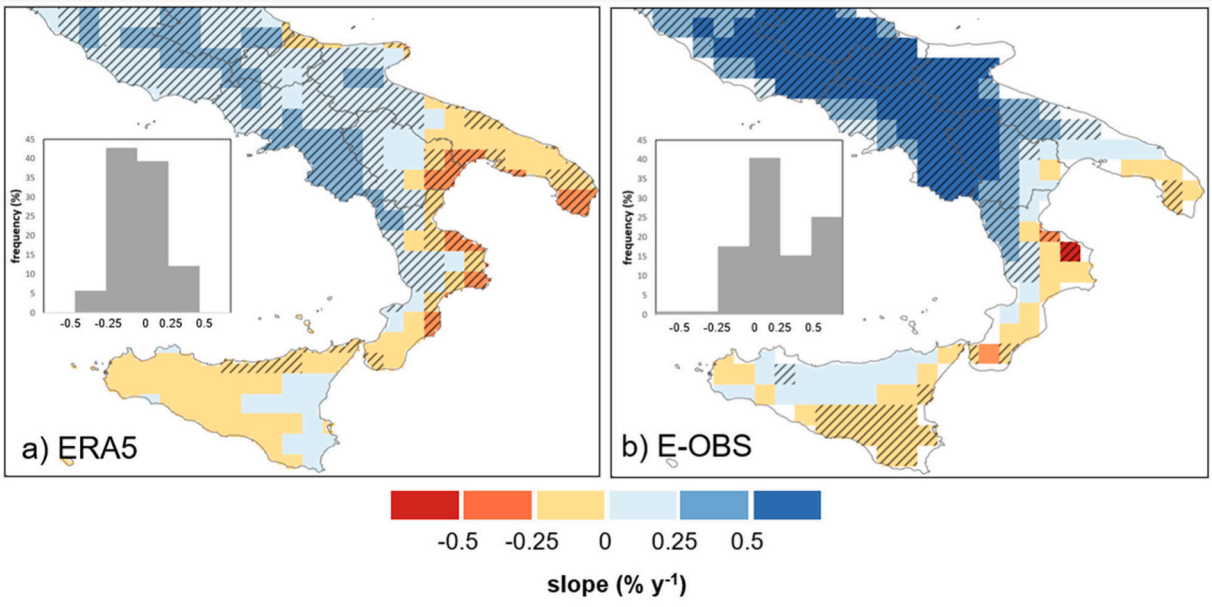


Fig. 7. Spatial distribution of the Sen's slope computed on 10-year moving-window CV for ERA5 (panel a) and E-OBS (panel b) between 1979 and 2019. Hatched areas demark statistically significant ($p < 0.05$) values. Inserts show the frequency of the values in the study regions.

Similarly, changing points are not significant in most of the regions during JJA (again, apart from Sicily in E-OBS), with a small percentage of statistically significant values in Calabria during all the seasons. Overall, the season with the most marked trends and changes is SON, which represents the period where a high fraction of the annual rainfall is concentrated.

The outcomes of Sen's slope analysis and Mann-Kendall's test on the CV are summarized in Fig. 7 for the annual rainfall data. Also in this case, the maps show consistent patterns in the trends in the two gridded datasets, with negative values mostly located in the eastern and southern areas facing the Adriatic and Ionian seas and positive trends elsewhere. Trends are more marked in E-OBS compared to ERA5, especially for the positive values (greater than 0.5 % y^{-1} in most of Campania and northern Basilicata and Apulia).

5. Discussion

The climatology of a region is often defined by the average and standard deviation of its meteorological variables in a given reference period. The trend analysis on the mean and CV rainfall values reported in this study aims at contrasting how the behavior of these two quantities is reproduced by gridded datasets compared to station observations in the most recent 40 years.

The mean temporal dynamic of annual rainfall is overall in good agreement for all three datasets, with a clear predominance of positive trends, which is particularly true when only statistically significant values are considered. Positive trends at the annual scale are mostly driven by analogous trends observed during the SON season, as consistently observed in all three datasets. This result is not particularly surprising, as a large fraction of the annual precipitation is concentrated in most of the analyzed regions during this season (Fratianni and Acquaotta, 2017).

These positive trends may seem in contrast with several previous studies in the Mediterranean region highlighting a tendency toward a reduction in precipitation (Brunetti et al., 2011; Caloiero et al., 2021; Chiaravallotti et al., 2023; Polemio et al., 2004). However, it is worth pointing out how most long-term trend studies only barely overlap with our study period, and they are often based on longer past series. In this context, our results represent a complementary outcome to studies performed over longer time frames, highlighting how contrasting behavior can be observed if different sub-periods are analyzed.

A more in-depth explanation of the observed positive trends can be given by investigating the results of the change point analysis, which highlights how significant discontinuities can be observed over large areas in both the gridded datasets and the local stations. Overall, there is a striking resemblance between the areas with significant trends and changing points, suggesting that the significance of the trend is likely mostly driven by the presence of a discontinuity rather than a continuous trend. Change points are mostly located in the early 2000s (between 2000 and 2005) in both ERA5 and E-OBS, underlining a certain consistency in this outcome. The presence of statistically significant change points around that period is confirmed in several ground stations as well.

On the one hand, in the early 2000s, many ground stations were refurbished over most of the Italian territory as part of a renovation of the instrumentation. This can explain possible discontinuities in in-situ records, but also in the E-OBS dataset (as it is based on ground data interpolation). However, as ERA5 does not directly assimilate rain gauge data, it should not be affected by this factor. On the other hand, a multi-year drought period from the early 1990s to early 2000s (Mendicino and Versace, 2007; Mendicino et al., 2008; Spinoni et al., 2012) may also be the source of the detected discontinuities, which would be observed in all three datasets. As already mentioned, the fact that some previous trend studies investigating data up to the late 1990s show mostly negative trends may be ascribed to the same reason (Brunetti et al., 2000; Piervitali et al., 1998). In this case, the positive trends observed in this study can be seen as a return to the conditions pre-1990s rather than an actual increasing tendency in total precipitation.

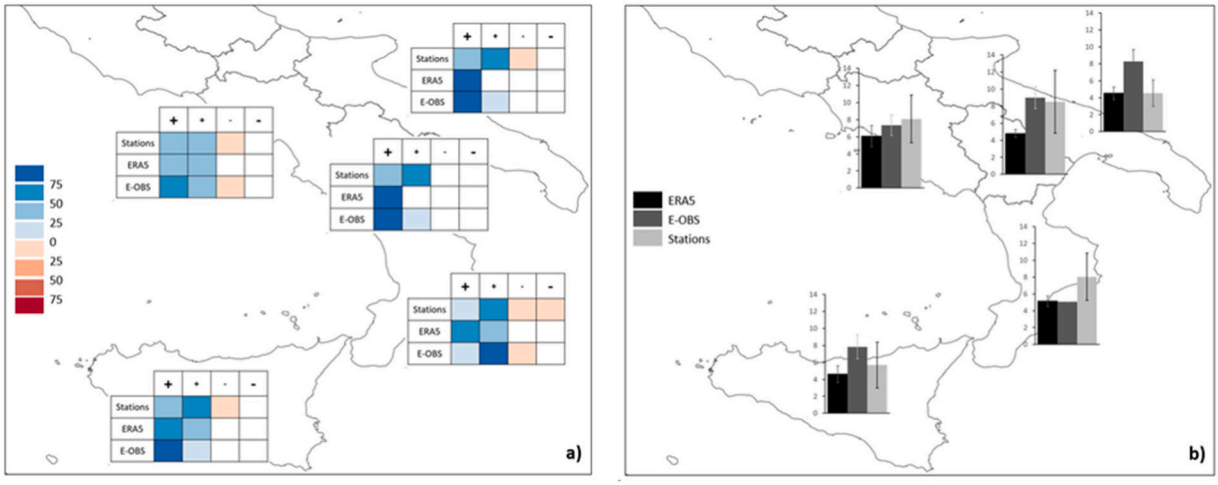


Fig. 8. Summary of the results of the trend analysis on annual total precipitation for the three datasets. Panel a) shows the percentage of each region with positive and significant (large +), positive and nonsignificant (small +), negative and non-significant (small -), and negative and significant (large -) trends. Panel b) shows the mean (and standard deviation in error bars) slope value (mm y-1) for each region, including only statistically significant values ($p < 0.05$).

Beyond the overall agreement on the predominance of positive values, results of the trend analysis at the regional scale, summarized in the maps in Fig. 8 and reporting both the percentage of the region with a certain sign in the trend (panel a) and the average (and standard deviation) slope values computed considering only the statistically significant values (panel b), provide additional insight on the behavior of the two gridded datasets at smaller spatial scale. Some differences can be observed when the data are analyzed at the regional scale, with E-OBS better in agreement with the observations over Calabria and Campania compared to ERA5. Both datasets seem to overestimate the percentage of positive and significant trends in Apulia, Basilicata and Sicily. A tendency of E-OBS to overestimate trends over Apulia was observed by My et al. (2022), whereas a tendency to underestimate was observed for the CRU dataset. Here, ERA5 seems to perform similarly to E-OBS in terms of tendency, even if the ERA5 modeled slope values are closer to the observed ones in this region (see Fig. 8b).

Generally, ERA5 trends seem flatter, on average, over the entire Southern Italy area, with mean regional values of about $+4$ mm y^{-1} in all regions (see also insert in Fig. 5a). While E-OBS shows more spatial dynamics, it reproduces the observed slope values only in Campania and Basilicata, but it overestimates the slopes in Apulia and Sicily. Flatness in ERA5 data may be related to the global scale data used to represent the terrain, which is one of the effects improved by the downscaling performed by ERA5-Land. In general, however, both gridded datasets underestimate some significantly high slopes emerging locally over Campania and Calabria, which are related to specific local climate conditions which cannot be captured at the scales used by both datasets. The large range of behaviors observed in E-OBS trend results can be ascribed to the considerable variability in space and time of the ground data used for performing the spatial interpolations. Since monitoring network management and consequent data delivery in Italy is handled at the regional level, the spatial density of observed data in southern Italy included in E-OBS is extremely heterogeneous, varying from 116 stations in Calabria (which were recently included in the dataset through the INDECIS project; Coll et al., 2019) to 38 in Campania, 8 in Sicily, 6 in Apulia and only 2 in Basilicata (see Fig. 9). Also, while most of the Calabrian stations provide data for more than 80 % of the study period, data availability from stations in Apulia, Basilicata and Sicily generally ranges from 60 % to 80 % of the study period, and for Campania drops to less than 20 % (stations from Campania were included only from version v28.e). This issue can represent a general limitation of the dataset, as highlighted by Bandhauer et al. (2022), which can hinder its use also in other geographical areas and larger spatial extensions than those analyzed here. Indeed, the two-stage process adopted to produce the daily fields relies on ground observations to capture long-range spatial trends in the data and modulate these trends locally (Cornes et al., 2018). Therefore, areas characterized by low station densities can provide contradictory or wrong information if the stations included in the dataset are not sufficiently representative of such areas. A possible high level of interpolation uncertainty in the gridded fields led to an ensemble approach for recent versions of E-OBS datasets (the term "e" in the version numbering stands for "ensemble"). In the version of the E-OBS database used in this study (i.e., v28.0e), a very high spatial density can be seen in the areas of Central Europe, whereas the Balkan area, the Iberian and Anatolian peninsulas and much of Eastern Europe are characterized by a very sparse distribution of measuring stations (KNMI, 2024). Concerning southern Italy, Fig. 9 clearly shows how each region in the area has a different spatial density of the stations.

When we focus on the trends in the inter-annual variability, as captured by the CV, we can observe, again, an overall good consistency between gridded datasets and station measurements. The results at the regional scale (Fig. 10) show a predominance of positive trends over Campania in all three datasets (Fig. 10a), as well as an increase in the percentage of negative trends in the southern regions (Sicily and Calabria). Only a few previous studies focused on the trend in inter-annual variability, despite representing a key characteristic of climate. In Campania, such results were obtained by Longobardi and Boulariah (2022). They investigated the inter-annual variability for 30 stations in the period 1918–2015, showing a large percentage of stations (about 60 %) presenting an increasing trend with an average slope of 0.035 %. By focusing on the slope values, a good agreement between ERA5 and ground data can be observed at the regional scale, whereas E-OBS tends to overestimate the slope in a few regions (e.g., Campania, Apulia, and Basilicata). Campania is the only region with a mean positive trend in CV for the observed dataset (0.2 % y^{-1}), while negative trends are observed in Calabria and Sicily (of about -0.2 % y^{-1}), as also confirmed by ERA5. An increasing trend in CV may be particularly concerning, as it translates into a larger inter-annual fluctuation in total precipitation that can cause increasing challenges in water resource management, even in the absence of significant changes in the total resource available on average.

Finally, some similarities can be observed between the spatial patterns in the trends and the ones observed in the average annual precipitation in gridded datasets and observations (discussed in Section 2.2). In particular, the subdivision of the results in four macro clusters (see supplementary material) is also partially noticeable in both CV and total precipitation patterns. This behavior may be worth of further investigations in future research studies.

6. Summary and conclusions

Two gridded precipitation datasets, ERA5 and E-OBS, were compared against ground observations over southern Italy from 1979 to 2019. This roughly 40-year stretch is commonly used to characterize the current climate, so it is important to establish how reliable those gridded datasets are as a reference for future climate change analyses.

Overall, both gridded datasets capture the major trends observed in ground-based data, with a vast majority of positive trends localized during the Autumn season (September to November). Considering that those datasets are designed for large-scale applications, this result can be considered encouraging for capturing the general trend over this key portion of the Mediterranean region. However, while ERA5 and E-OBS well capture the general behavior over Southern Italy, substantial differences can be observed when analyzed at a smaller scale (e.g., administrative region). Overall, ERA5 seems to return flatter results compared to the observed data, with good agreement with observations at the regional spatial scale over Sicily and Apulia. E-OBS is characterized by a larger range of variability, likely ascribed to poor station coverage in many areas, therefore it compares well with observations only over some of the

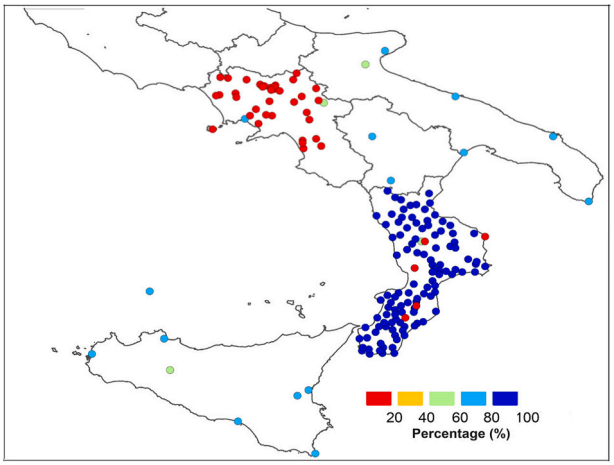


Fig. 9. Spatial distribution of E-OBS stations in southern Italy, with relative time availability in percentage terms over the study period (1979–2019).

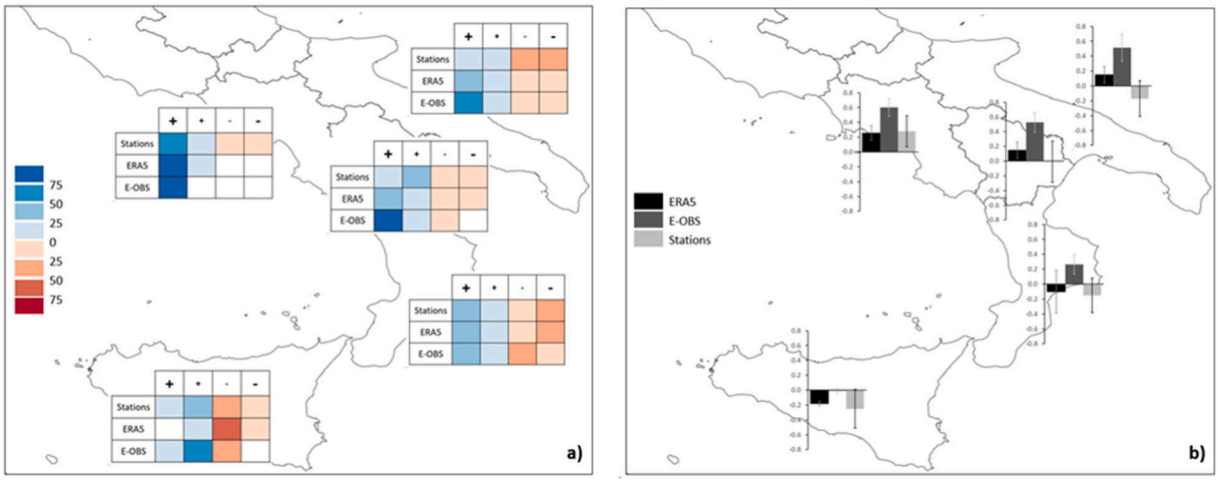


Fig. 10. Summary of the results of the trend analysis on CV for the three datasets. Panel a) shows the percentage of each region with positive and significant (large +), positive and non-significant (small +), negative and non-significant (small -), and negative and significant (large -) trends. Panel b) shows the mean (and standard deviation in error bars) slope value (% y^{-1}) for each region, including only statistically significant values ($p < 0.05$).

regions (Campania, and partially Calabria and Basilicata). This result suggests that large-scale evaluation studies on the reliability of the datasets should not be used as an assessment of the local accuracy, which may vary significantly at the local scale. The scale of interest of the study should be then accurately evaluated before using these datasets. In particular, using E-OBS, the associated station coverage should be carefully checked.

The presence of statically significant change points in all three datasets in the early 2000s suggests that the observed trends may be driven by a discontinuity rather than an actual continuous trend, with a return to precipitation levels similar to the 1980s after a relatively dry period in the 1990s. Following this result, it is clear how the conditions assumed to represent the current climate may change based on the adopted time window, and that a combination of different tools (trends, change points, etc.) should be used to evaluate the suitability of a particular period as a reference.

In addition to the average behavior, we analyzed trends in the inter-annual fluctuations, quantified by CV values computed on a 10-year moving window. This analysis shows good consistency between gridded datasets and in situ observations, with contrasting trends in some of the regions (positive for Campania and negative for Calabria and Sicily). While both ERA5 and E-OBS are in good agreement with the observations in terms of spatial patterns, ERA5 seems to better capture the magnitude of the observed trends in CV. Analysis of the inter-annual fluctuations is particularly relevant for drought studies, and the obtained results encourage the use of ERA5 gridded data for such analyses over the region.

The results of this study show how the two gridded datasets represent the dynamics in both mean and CV precipitation conditions

over southern Italy reasonably well, returning a suitable depiction of the general patterns in the two quantities. In this regard, water balance and drought studies relying on these gridded datasets should return reliable outcomes when analyzed over the entire area. Further investigations on climate extreme indices, also related to temperature, could be an extension of the analysis reported in this study.

The use of these gridded datasets at the local scale (i.e., region or finer) should be carefully evaluated, as significant discrepancies with local observations can be detected. Hydrological models forced with such large-scale gridded datasets may not be suitable for local scale applications, and the use of station data may still be preferable at regional or sub-regional scales. However, as in the most recent years mechanical stations were replaced (not only in Italy) with automatic stations, integrated analysis between local and gridded datasets can provide cross insights on data reliability.

CRediT authorship contribution statement

Salvatore Manfreda: Writing – review & editing, Supervision, Methodology, Funding acquisition. **Giuseppe Mendicino:** Writing – review & editing, Supervision, Funding acquisition. **Alfonso Senatore:** Writing – review & editing, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Brunella Bonaccorso:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Carmelo Cammalleri:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Awais Naeem Sarwar:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Angelo Avino:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Gholamreza Nikravesh:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

data are provided as supplementary material

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ejrh.2024.101950.

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