



Rainfall regime and seasonality changes in semi-arid Mediterranean areas: Evidence from three regions of southern Italy (1922–2022)

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ABSTRACT

Global warming is significantly altering precipitation patterns in the Mediterranean Basin, a region already susceptible to water scarcity and extreme weather events. Changes in precipitation can exacerbate both drought conditions and soil degradation caused by increasingly erosive rainfall. Where wet season patterns mismatch peak irrigation demands, shifts in rainfall seasonality may pose a serious threat to agricultural sustainability.

This study analyses century-long (1922–2022) trends in three regions of Southern Italy representative of Mediterranean semi-arid areas (i.e., Campania, Sardinia, and Sicily), using a wide spectrum of rainfall regime indicators. A novel methodological framework is applied to an extensive database of daily rainfall time series from over 700 rain gauges, using both point-based (at gauge level) and spatially distributed analyses. This approach ensures the robust detection and localization of trends in precipitation characteristics, with a particular focus on rainfall seasonality.

Results indicate consistent temporal variations across the three regions for most indicators, including reduction in mean annual precipitation, frequency and length of dry and wet spells. Crucially, the study area exhibits reduced rainfall seasonality compared to previous historical periods, with earlier onset and longer duration of the wet season. These shifts have profound implications for water resource management, agricultural planning, and ecosystem resilience across the Mediterranean. Furthermore, spatial autocorrelation analysis highlights that some trends are highly localized, identifying priority areas for the implementation of targeted climate change adaptation strategies.

1. Introduction

Altered precipitation patterns are a clear manifestation of global warming, with pronounced regional effects. In Mediterranean areas, these changes typically produce lower annual rainfall and more intense low-frequency storm events (Ehsani et al., 2017; Kahaduwa and Rajapakse, 2022), exacerbating droughts and water shortages (Hänsel et al., 2019; Noto et al., 2023a, 2023b). Sub-hourly extremes have strengthened (Westra et al., 2014; Pumo and Noto, 2021; Sun et al., 2021), increasing rainfall induced erosivity (Piccarreta et al., 2024; Woldegebrael et al., 2025).

Shifts in intra-annual precipitation affect ecosystems and human activities (Fernandez-Illescas and Rodriguez-Iturbe, 2004; Bolan et al.,

2024). In many semi-arid Mediterranean regions, rainfall is concentrated in a wet season and it is largely absent during the dry season, which overlaps with the vegetation growth period (Gonzalez-Hidalgo et al., 2024). Winter rainfall is crucial for groundwater and reservoir recharge (Zhang et al., 2018); consequently, changes in seasonality directly affect agro-ecosystems, yields, and water availability for agriculture, domestic use and industry (Malek et al., 2018; Ingrao et al., 2023; Claro et al., 2024).

Assessing spatiotemporal variability is essential for climate change adaptation (Xoplaki et al., 2004; Nath et al., 2023). Numerous studies have investigated rainfall regimes, with contrasting findings depending on region and method (e.g. Villarini et al., 2011; De La Casa et al., 2018; Nath et al., 2023). Mediterranean rainfall seasonality has been widely analysed using various metrics (Pascale et al., 2015; Nasta et al., 2020;

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List of acronyms, symbols and abbreviations	
<i>Regions and Regional Agencies</i>	
AR	Annual Report: official hydrological yearbooks by ISPRA
ARPA	Agenzia Regionale per la Protezione dell'Ambiente
CAM	Campania
ISPRA	Istituto Superiore per la Protezione e la Ricerca Ambientale
SAR	Sardinia
SIC	Sicily
<i>Methods</i>	
GBA	Gauge-Based Approach
GBAT	Dataset for trend analysis under the GBA
SDA	Spatial Distributed Approach
PW	Pre-World Wars period (1922–1941)
CP	Central Period (1951–1986)
RP	Recent Period (1987–2022)
FP	Full period (1951–2022 for CAM, 1922–2022 for SAR and SIC)
LISA	Local Indicators of Spatial Association
MK	Mann-Kendall test
MMK	Modified Mann-Kendall test
TPM	Thiessen Polygon Method
H-H	spatial association class High-High (<i>Local Moran's Index</i>)
H-L	spatial association class High-Low (<i>Local Moran's Index</i>)
L-H	spatial association class Low-High (<i>Local Moran's Index</i>)
L-L	spatial association class Low-Low (<i>Local Moran's Index</i>)
NG	negligible trend magnitude class
LM	low-moderate trend magnitude class
MH	moderate-high trend magnitude class
<i>Symbols</i>	
C_k	centroid of the wet season at the generic k-year (DOY)
D_k	semi-duration of the wet season at the generic k-year (days)
$S_{wet,k}$	starting time of the wet season at the generic k-year (DOY)
$E_{wet,k}$	ending time of the wet season at the generic k-year (DOY)
β	Sen's slope - trend magnitude
$\Delta_{L,v}$	lower threshold for trend magnitude classification
$\Delta_{H,v}$	upper threshold for trend magnitude classification
η	parameter for the definition of $\Delta_{L,v}$
ρ	parameter for the definition of $\Delta_{H,v}$
$E[I]$	expected value of the Global Moran's Index
Δ_{CP}	relative percentage difference in an indicator between CP and RP (%)
Δ_{PW}	relative percentage difference in an indicator between PW and RP (%)
μ_t	Absolute mean magnitude of same-sign trends across GBAT stations
$\max_t$	Absolute maximum magnitude of same-sign trends across GBAT stations
MR_v	Maximum historical range for the generic variable v across the study area
<i>Symbols for rainfall regime and seasonality indicators are described in tables within the manuscript.</i>	

Luppichini et al., 2022; Senatore et al., 2025; Luppichini and Bini, 2025). For instance, Sumner et al. (2001) found increasing seasonality along Spain's eastern coast using the Seasonality Index (SI). Using the Precipitation Concentration Index (PCI), Cannarozzo et al. (2006) and Caloiero et al. (2019) detected negative trends in Sicily and Sardinia, respectively, indicating more uniform rainfall distribution within the year. The Dimensionless Seasonality Index (DSI), originally designed for the tropics (Feng et al., 2013), was later validated for the Mediterranean (Pascuale et al., 2015; Nasta et al., 2020).

This study advances prior research by examining multiple rainfall regime and seasonality indicators within Project ASAP (*Assessing and Mapping Novel Agroecosystem Vulnerability and Resilience Indicators in Southern Italy*, funded by European Union-NextGenerationEU) over a large study area in Italy of ~63,600 km², including Campania (CAM), Sardinia (SAR) and Sicily (SIC). The regions, particularly susceptible to water-related natural hazards, share common hydrological challenges shaped by climatic pressures and agricultural dependence.

Previous works illustrated region-specific dynamics (e.g., Longobardi and Villani, 2010; Longobardi and Boulariah, 2022; Capozzi et al., 2023, in CAM; Delitala et al., 2000; Boi, 2018 in SAR; Cannarozzo et al., 2006 in SIC). Avino et al. (2021) reported in CAM mostly non-significant trends over the period 1970–2018 in annual rainfall maxima across various durations; however, some localized intensification of short-duration extremes was noted. SAR rainfall was found to be more uniformly distributed throughout the year than in the past (Caloiero et al., 2019). In SIC, positive rainfall trends (decreasing with duration) were reported by Arnone et al. (2013), while Treppiedi et al. (2021) observed positive trends at high quantiles in the southeast and decreasing clusters in the west.

Two aspects distinguish this research from previous analyses in the same regions: the combined use of gauge and gridded datasets and a unified analytical framework across regions, including consistent pre-processing, dataset generation, indicators, and techniques for trend and spatial autocorrelation analyses. A major strength is the wide database

of ground-based rainfall observations from official hydrological yearbooks, produced under uniform national standards of collection and validation, ensuring homogeneity and reliability. This database provides dense coverage (~ one gauge per 90 km²) and long-term consistency, making the study area unique in the Mediterranean. The choice to first analyze rainfall at the gauge scale reflects a deliberate effort to preserve data fidelity, before moving to spatially distributed datasets, derived through simple interpolation to limit artificial smoothing. This approach valorizes historical rainfall records for robust assessment of rainfall regime evolution in semi-arid Mediterranean environments (Bayat et al., 2019).

The study covers a century long period 1922–2022, analysed as a whole and through three non-overlapping subperiods (1922–1941, 1951–1986, and 1987–2022), whose use enables a detailed characterization of long-term climatological evolution beyond standard 30-year trend analyses.

The analysis was based on a set of widely used rainfall regime metrics (capturing means, variability, and persistence at daily to annual scales) and seasonality indicators, featuring key global metrics such as SI, PCI, and DSI. Trends were assessed using a non-parametric approach widely applied in Mediterranean rainfall studies, including analyses in regions considered in this study (Arnone et al., 2013; Caloiero et al., 2019; Avino et al., 2021; Caporali et al., 2021; Treppiedi et al., 2021). A moving-window framework was implemented to better characterize the temporal evolution of the indicators over the past century. To account for autocorrelation potentially induced by overlapping windows, the Modified Mann-Kendall (MMK) test (Hamed and Ramachandra Rao, 1998) was applied. Trend magnitude were quantified using Sen's Slope Estimator (Sen, 1968). Spatial autocorrelation in the resulting trend patterns was further assessed using Moran's indices (Moran, 1950; Anselin, 1995).

The paper is organized into five sections, along with Supplementary Material (SM). Section 2 describes the study area, database, indicators and analytical framework. Section 3 presents the analyses and results,

including comparison of indicators across subperiods (Section 3.1), examination of their regional spatial distributions (Section 3.2), and the outcomes of trend analyses (Section 3.3). Sections 4 and 5 discuss the implications and provide concluding remarks.

2. Materials and methods

2.1. Characterization of the study area

The study area includes three Italian regions (Fig. 1): Campania (CAM, 13,668 km²), Sardinia (SAR, 24,106 km²), and Sicily (SIC, 25,824 km²). According to the Köppen classification (Kottek et al., 2006), all regions fall within the *warm temperate* class belonging to the *Csa - Hot-summer Mediterranean climate* group. This classification highlights the distinct seasonality of the study area, marked by dry summers and wet winters, with regional differences shaped by the local topography and proximity to the Mediterranean Sea. Winter rain is primarily driven by frontal systems, whereas summer rainfall is often convective.

CAM features coastal plains, hills, and the Apennine Mountains in the eastern part, whose inland areas experience cooler conditions and higher rainfall. Volcanic activity (Mount Vesuvius, Phlegraean Fields) has produced fertile soils, supporting intensive agriculture (e.g., vineyards, citrus fruits). SAR and SIC, the two largest islands in the Mediterranean, show stronger climate seasonality and lower annual precipitation than CAM. SAR is predominantly mountainous and hilly, with the Gennargentu Massif (1834 m a.s.l.) as its highest peak. Low precipitation levels cause arid interior areas, limited water bodies and sparse river networks, making agriculture particularly challenging and favoring pastoralism. SIC features plains, mountains, and volcanic

zones, including Mount Etna, the highest peak (3329 m a.s.l.). Very hot summers occur, with North African air masses bringing occasional hot winds. Like CAM, fertile volcanic soils in SIC sustain agricultural productivity (e.g., citrus, grapes, and olives).

All regions face water scarcity, drought, and vulnerability to rainfall extremes that trigger landslides, flooding, and erosion. CAM has larger water resources and storage capacity than the two islands, making it less exposed to droughts. However, among the three regions, it is the most prone to intense rainfall events, causing floods in plains, mudflows in volcanic areas, and landslides in the Apennines. SAR relies primarily on artificial reservoirs (e.g., Lakes Omodeo and Flumendosa). Although dry farming and drought-resistant crops are common, limited water availability and high evaporation from Mistral winds contribute to shortages and periodic rationing, while flash floods generate severe gully erosion. SIC experiences one of the most irregular rainfall regimes in the Mediterranean, with recurrent droughts leading to heavy water rationing and agricultural losses. In contrast, landslides and flash floods frequently affect hilly and mountainous areas. Water availability in artificial lakes is intermediate compared with CAM and SAR, but high irrigation demand, aging infrastructure, and water mismanagement cause major distribution losses, groundwater overexploitation, and saltwater intrusion in coastal areas.

2.2. Regional databases and data pre-processing

The official hydrological yearbooks (Annual Reports, ARs) in Italy provide over a century of ground-based hydrological observations from rain-gauge networks. While the ISPRA (*Istituto Superiore per la Protezione e la Ricerca Ambientale*) web portal provides only scanned PDF versions

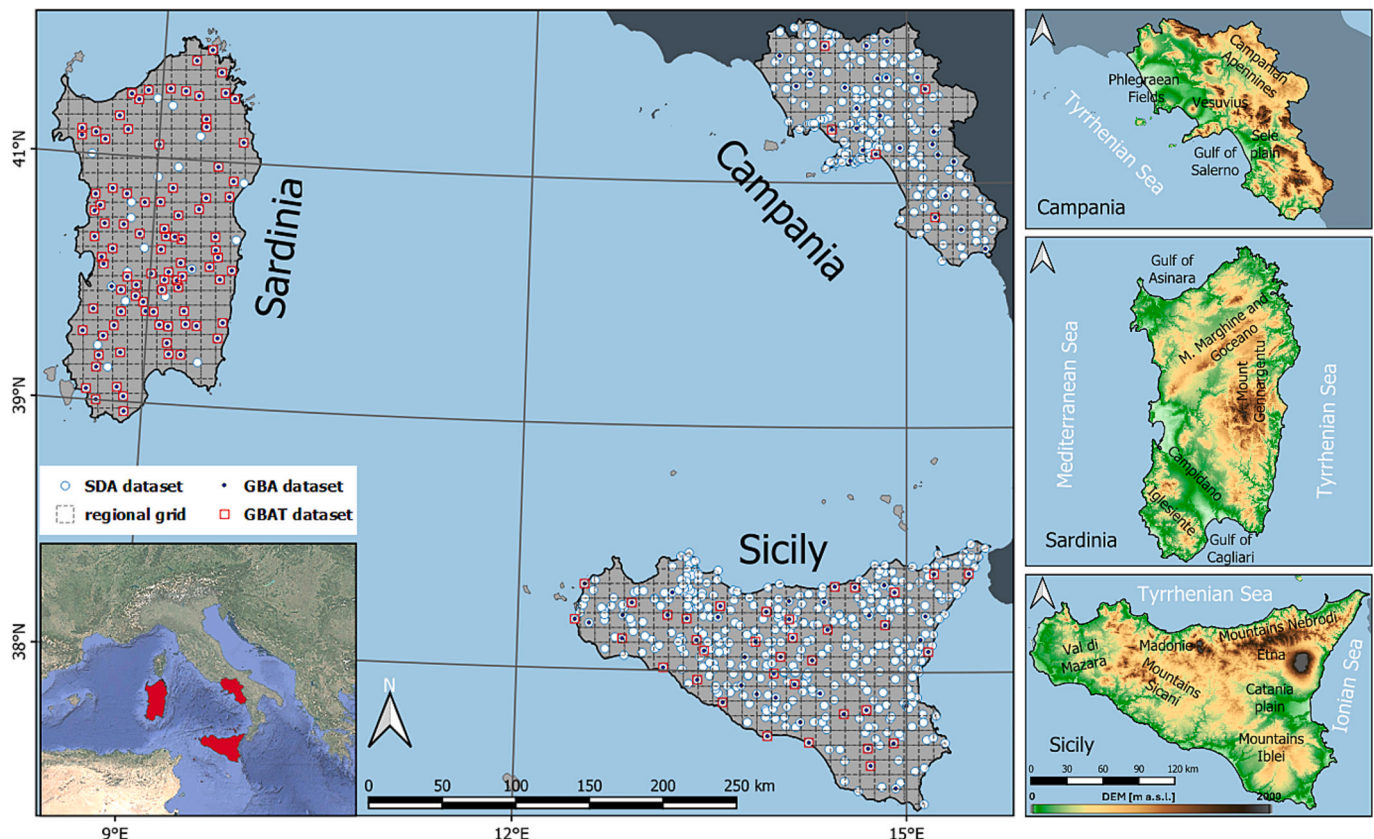


Fig. 1. Study area (CAM, SAR, and SIC), with 10 × 10 km regional grids. Cyan circles mark rain gauges used for the Spatial Distributed Approach (SDA). Stations considered for the Gauge Based Approach (GBA) are shown as black inner points. Red squares refer to stations included in the GBA dataset, specifically used for trend analysis at gauge level (Sect 2.3). Insets on the right show each region with main physiographic features and hillshade derived from a 20-m Digital Elevation Model (<http://www.pcn.minambiente.it/viewer/>). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of the original ARs (<https://www.isprambiente.gov.it/en/projects/in-land-waters-and-marine-waters/hydrological-yearbooks/>), the fully digitized daily rainfall series used in this study were obtained through formal collaboration agreements with the territorial managing agencies. Specifically, the Hydrographic and Mareographic Office of Naples (*Ufficio Idrografico e Mareografico di Napoli*) provided the CAM data, ARPA-Sardegna (*Agenzia Regionale per la Protezione dell'Ambiente della Sardegna*) provided the SAR data, and the Basin Authority of the Hydrographic District of Sicily (*Autorità di Bacino del Distretto Idrografico della Sicilia*) provided the SIC data. Despite their value, historical rainfall records contain major gaps due to World War II, which severely disrupted data collection, leading to damaged equipment, staff shortages, and lost archives especially in the period 1942–1950. In addition, the transition from manual to automatic gauges in the late 20th century caused further interruptions, station relocations, and potential changes in instrumentation. Nevertheless, the ARs remain the primary national reference for climate studies and hydraulic planning.

All series used in this study underwent standard quality control procedures by the official authorities prior to publication, including screening for measurement errors, verification of metadata, and the merging of continuous observation periods recorded at the same location. However, the present study performed additional pre-processing and metadata verification to ensure temporal and spatial consistency. First, the records from each station were formatted into a standard table and checked for physical consistency (e.g., no negative values, realistic maxima and cumulative values). Next, a cross-validation process compared records from neighbouring stations to identify and remove anomalous outliers. Station metadata, such as location and altitude, were verified. To account for potential inhomogeneities related to station relocations or instrumentation changes, all rainfall series were tested for homogeneity, using a combined Standard Normal Homogeneity Test (SNHT; Alexandersson, 1986) and Pettitt change-point test

(Pettitt, 1979) at the 5% significance level. The combined application of these complementary tests did not identify statistically significant breakpoints in recent decades, indicating that the modernization of the monitoring networks did not introduce detectable artificial discontinuities in the rainfall series used in this study (methodology and results for this analysis are reported in Sect. S1, SM).

This rigorous preprocessing and quality control phase resulted in three distinct regional databases comprising high-quality data from a total of 703 stations (189 in CAM, 110 in SAR and 404 in SIC), with the main characteristics summarized in Table 1a. A year-by-year data consistency analysis (Fig. 2) identified common periods of analysis, homogeneous in terms of data coverage across regions. Since rainfall records begin at different times in the regions, to preserve consistency, 1922 was chosen as common starting year for subsequent analyses. Between 1922 and 1941, SAR (Fig. 2b) and SIC (Fig. 2c) exhibit substantial data availability (on average, >100 operational stations per year), whereas CAM (Fig. 2a) has significantly fewer stations (only six). During the period 1942–1950, SAR maintains a high level of data consistency, whereas SIC (on average 11 stations/y) and CAM (only one station/y) experience marked declines, consistent with wartime impacts observed across most Italian regions. From 1951 to 2022, all regional datasets exhibit adequate coverage (>95 stations/y) with SIC reaching an average number of operational stations per year of 176 stations/y (Table 1a). However, for all databases, a reduction in recent decades of the number of operational stations (Fig. 2) reflects the transition to automatic gauges and decommissioning of manual stations. Data availability in 2023 is significantly lower, particularly in CAM, likely due to delays in data updating and validation by the different administrative regional authorities.

Based on these results, the periods 1922–2022 in SAR and SIC, and 1951–2022 for CAM were selected as long-term reference periods (i.e., Full Period - FP) for trend analyses. Additionally, three distinct sub-

Table 1

a) Consistency of pre-processed regional databases for CAM, SAR, and SIC, including record start and end years, minimum and maximum gauge record lengths (y), and the number of active gauges (in italics, within brackets, the average number of operational stations per year) for each subperiod (PW = Pre-World war period; WP=World War period; CP = Central Period; RP = Recent Period). **b)** Derived datasets used in the analysis: GBA (number of selected gauges, #Gauges; reference period = CP and RP in CAM, and PW, CP and RP in SAR and SIC); GBAT (aggregated dataset from 131 selected gauges over the reference period = 1922–2022, with the number of gauges from each region, #Gauges); SDA (interpolated grids for the full period, FP, with the numbers of pixels per grid, #Pixels). Data for SDA in CAM are not available (n.a.) for 1922–1951.

a)		Regional databases							
		Period of records		Record Length (y)		PW	WP	CP	RP
				min	max	1922-1941	1942-1950	1951-1986	1987-2022
CAM	1919	2023	8	92	6 (6)	6 (1)	159 (122)	182 (95)	
SAR	1922	2022	78	92	110 (108)	110 (102)	110 (108)	110 (95)	
SIC	1916	2022	8	92	291 (245)	18 (11)	330 (213)	308 (176)	

b)		Datasets of analysis				
		GBA		GBAT (1922-2022)		SDA
		#Gauges		Total gauges: 131	Grid	Period
	PW	CP	RP	#Gauges	#Pixels	FP
CAM	n.a.	27		5	135	1951-2022
SAR	93			91	238	1922-2022
SIC	53			35	259	1922-2022

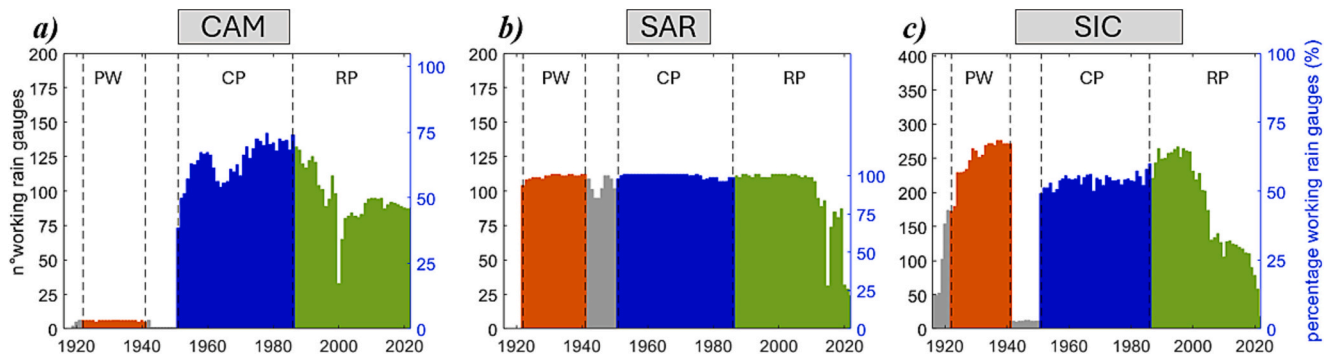


Fig. 2. Annual number of working rain gauges (bars, left y-axis) and percentage relative to the total regional network (right y-axis) for the three periods (PW, orange; CP, blue; and RP, green) in: a) CAM; b) SAR; and c) SIC. Values for all other years are shown in grey. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

periods were defined: i) Pre-World war period (PW): 1922–1941; ii) Central Period (CP): 1951–1986; iii) Recent Period (RP): 1987–2022. PW was examined only for SAR and SIC due to insufficient data coverage in CAM, while CP and RP provide two post-war intervals of equal length and comparable data consistency across all regions (Table 1a and Fig. 2). These sub-periods are used to characterize the rainfall regime and to enable a comparative assessment of its temporal evolution.

2.3. Derived datasets for the GBA and the SDA approaches

Different operational datasets were generated under the Spatial Distributed Approach (SDA) and the Gauge-Based Approach (GBA) for each region, while an aggregated database (GBAT, Gauge-Based Approach for Trend) was produced for trend analysis at the gauge level over the entire study area.

For the SDA, the regional databases (Table 1a) were fully utilized to develop spatially interpolated daily rainfall datasets over the FP of each region. Interpolation was performed on a regular grid using an automatic algorithm based on the Thiessen Polygon Method, TPM (Thiessen, 1911), implemented in GIS. TPM requires only gauge locations and records and is computationally efficient compared to more complex methods, such as Kriging or Inverse Distance Weighting (Wagner et al., 2012; Liu et al., 2022), which may introduce artificial smoothing or estimation errors. More complex geostatistical approaches, in fact, rely on assumptions about spatial covariance structures that may vary across regions and over long observation periods, potentially altering the magnitude and spatial structure of precipitation fields (Goovaerts, 2000; Ly et al., 2013), influencing rainfall regime indicators. Simpler interpolation approaches, such as TPM, are therefore often preferred when the objective is to preserve the fidelity of gauge observations, although they do not explicitly account for orographic effects and may therefore introduce spatial biases in areas with strong elevation gradients. In this study, however, such effects are expected to be limited, as the analysis does not rely on sub-daily rainfall metrics, where interpolation-induced distortions are typically more pronounced.

A dynamic generation of Thiessen Polygons (Voronoi Diagram) was implemented, based on daily updates of active rain gauges. Daily rainfall is assigned from the nearest station to Voronoi polygons, then rasterized into a 10×10 km grid. The adopted spatial resolution adequately reflects the effective spatial density of the observation network across the study area. A daily filtering criterion was also applied: interpolation was carried out only when the number of working stations exceeded one per 1000 km^2 ; otherwise, NaN (Not a Number) was assigned to all grid cells, indicating insufficient data availability.

A gauge selection process was applied to generate additional datasets (referred to as GBA datasets, Table 1b) for analyses at individual stations, aimed at characterizing and comparing rainfall regimes across subperiods (PW, CP, RP) within each region. Selection criteria were:

- data gaps must not significantly impact the assessment of annual rainfall characteristics;
- gauge time series must ensure adequate data coverage across all periods and show no major interruptions.

For criterion (i), time series were screened on yearly basis for missing data. Years with $>20\%$ gaps were set to NaN and excluded. Conversely, when gaps were $<20\%$, missing values were reconstructed using the same spatial interpolation method as in the SDA. Thus, each gauge record consists only of years with complete data (up to 20% reconstructed) or no data at all. For criterion (ii), gauges were removed if any sub-periods (PW, CP and RP) had $<70\%$ data coverage and/or if gaps exceeded four consecutive years. The selected gauges (Table 1b) ensure homogeneous, uninterrupted and balanced coverage across all sub-periods, namely ≥ 15 years during PW for SAR and SIC and ≥ 25 years during CP and RP for all regions, resulting in at least 65 years of data for SAR and SIC and 50 years for CAM over the FP.

A further dataset was created for a point-based (i.e., at gauge level) trend analysis for the entire study area over the FP (1922–2022), adopting the same criteria as GBA and referred to as Gauge-Based Approach for Trend (GBAT dataset, Table 1b). Specifically, GBAT was derived as a subset of the three aggregated regional GBA datasets, also including data from 1942 to 1950 where available. Trend detection was performed on overlapping 35-year windows sliding over the FP. Only gauges with ≥ 25 years of data in all 35-year moving windows were retained (corresponding to $>70\%$ coverage) for the GBAT dataset. As shown in Table 1b, this additional requirement led to a notable reduction of gauges in SIC and, to a higher degree, in CAM.

It should be noted that the relatively small number of stations from CAM included in the GBA and GBAT datasets reflects the stringent temporal continuity criteria adopted for station-level analyses. In contrast, the SDA for the same region relies on a substantially larger observational network, with many gauges having long-term records (e.g. 102 stations have more than 40 years of records). This ensures spatial and temporal coverage across the region under the SDA comparable to that of the other two regions.

The gauges considered for the SDA and the regional grids are shown in Fig. 1, highlighting with different colours those included in the GBA and GBAT datasets. An appreciable and uniform spatial density (~ 1 gauge per 100 km^2) and distribution of gauges within the study area and across the three regions can be noticed from the figure.

2.4. Characterization of rainfall regime and seasonality

Computation of rainfall regime indicators require sufficiently long observation periods to limit the influence of short-term fluctuations. The World Meteorological Organization (WMO, 2017) recommends at least 30 years, though shorter periods (~ 20 years) also appear in the

literature (e.g. Guo et al., 2022; Capozzi et al., 2023). In this study, the selected indicators were evaluated for each subperiod at each gauge for the GBA and for every pixel of the SDA dataset. The current rainfall regime, based on the most recent 36-year period (RP), was compared with those of the two previous periods (i.e., the 36-year CP and the 20-year PW, the latter used only for SAR and SIC). For trends analysis, indicators were assessed over all 35-year moving windows.

2.4.1. Indicators of rainfall regime

A first set of indicators, referred to as rainfall regime indicators (Table 2), was computed from daily rainfall time series at their original resolution and aggregated to monthly and annual scales to assess rainfall totals, interannual variability, and persistence characteristics. For each time series and period, the Annual Precipitation (AP) was used to compute the Mean Annual Precipitation (MAP in mm y^{-1}) and the Coefficient of Variation of Annual Precipitation (CV_{AP} in %). Monthly rainfall (mm mo^{-1}) was used to assess lower (Q1), median (Q2) and upper (Q3) quartiles, which provide valuable insights into intra-annual variability.

Daily records were also screened to derive, for each year and then averaged over the analysis period, the annual maxima (P_{max} , mm d^{-1}), the mean depth (α , mm d^{-1}) and frequency (λ , d^{-1}) of rainy days. A threshold of 1 mm d^{-1} was applied to define rainy days.

Shifts in rainfall patterns were analysed through exceedance probabilities of daily rainfall, referring to the classification provided by Alpert et al. (2002) for the Mediterranean area. Specifically, the mean annual percentage of daily rainfall was computed for three classes:

1. Light-Rainfall (F_{LR} , %) corresponding to the “Light Rainfall” class of Alpert et al. (2002), encompassing rainfall below 4 mm d^{-1} ;
2. Moderate-Rainfall (F_{MR} , %) including rainfall between 4 and 36 mm d^{-1} and, thus, bridging the “Light Moderate Rainfall” and “Moderate Heavy Rainfall” classes from Alpert et al. (2002);
3. Heavy-Rainfall (F_{HR} , %) including rainfall with depth exceeding 36 mm d^{-1} , thus, accounting for all the remaining classes defined in Alpert et al. (2002) as “Heavy”, “Heavy-Torrential” and “Torrential Rainfall”.

Persistence was evaluated via dry and wet spells, defined as periods of two or more consecutive dry or rainy days (i.e., $>1 \text{ mm d}^{-1}$), respectively (WMO, 1992). Indicators, also in this case first computed annually and then averaged over the full period of analysis, include: the mean annual number of dry (NDS) and wet spells (NWS), their mean (MDSD and MWSD) and maximum (DSD_{max} and WSD_{max}) durations (in days). Given the strong linkage between prolonged dry spells and drought occurrences, the coefficient of variation of the mean annual dry

spell durations (CV_{DSD} in %) was also computed to assess interannual variability.

2.4.2. Indicators of rainfall seasonality

Rainfall seasonality, particularly relevant for the study area, was examined through a dedicated set of indicators (Table 3). A refined version of the approach proposed by Feng et al. (2013), detailed in SM (Sect. S2), was used to separate dynamically the hydrological year into wet and dry seasons. The method estimates, annually, the centroid (C_k , expressed by the $\text{DOY} = \text{Day Of the Year}$) and semi-duration (D_k in d) of the wet (rainy) season, originally computed from monthly data but here derived from daily rainfall. These two variables allow identifying the starting ($S_{\text{wet},k} = C_k - D_k$) and ending ($E_{\text{wet},k} = C_k + D_k$) days of the wet season in a generic k -year, with the dry seasons defined as the remaining parts between subsequent wet seasons. For both seasons, the following rainfall characteristics were computed annually and then averaged over the full period of analysis: the mean seasonal precipitation P_{wet} (P_{dry}) in mm for the wet (dry) seasons, the mean depth α_{wet} (α_{dry}) and frequency λ_{wet} (λ_{dry}) of rainy days (i.e. $> 1 \text{ mm d}^{-1}$) for the wet (dry) seasons, the mean wet season contribution to annual rainfall (PP_{wet} , %), computed from the ratio P_{wet}/AP . Using circular statistics, the annual values of $S_{\text{wet},k}$ and $E_{\text{wet},k}$ were averaged over the full period of analysis to obtain the mean first (S_{wet} in DOY) and last (E_{wet} in DOY) wet season days and the resulting mean duration (D_{wet}).

Three specific dimensionless global metrics of rainfall seasonality were also evaluated: i) Seasonality Index (SI, Walsh and Lawler, 1981); ii) Dimensionless Seasonality Index (DSI, Feng et al., 2013); iii) Precipitation Concentration Index (PCI, Oliver, 1980). A synthetic overview of their computation methodologies is provided in the SM (Sect. S3), while interested readers can refer to the original papers for a more

Table 3

Set of indicators of rainfall seasonality, with symbols, units and descriptions.

Symbol	Unit	Description
S_{wet}	DOY	mean starting day of wet season
D_{wet}	days	mean duration of wet season
P_{wet}	mm	mean seasonal precipitation for the wet season
α_{wet}	mm d^{-1}	mean rainfall depth of rainy days during the wet season
λ_{wet}	d^{-1}	mean frequency of rainy days during the wet season
PP_{wet}	%	mean percent contribution of P_{wet} to the annual rainfall
P_{dry}	mm	mean seasonal precipitation for the dry season
α_{dry}	mm d^{-1}	mean rainfall depth of rainy days during the dry season
λ_{dry}	d^{-1}	mean frequency of rainy days during the dry season
SI	–	Seasonality Index
DSI	–	Dimensionless Seasonality Index
PCI	–	Precipitation Concentration Index

Table 2

Set of rainfall regime indicators, with symbols, units and descriptions.

Symbol	Unit	Description
MAP	mm y^{-1}	mean annual precipitation
CV_{AP}	%	coefficient of variation of annual precipitation
Q1	mm mo^{-1}	lower quartile in monthly rainfall time series
Q2	mm mo^{-1}	median quartile in monthly rainfall time series
Q3	mm mo^{-1}	higher quartile in monthly rainfall time series
P_{max}	mm d^{-1}	mean of annual maxima of daily precipitation
α	mm d^{-1}	mean rainfall depth of rainy days
λ	d^{-1}	mean frequency of rainy days
F_{LR}	%	mean annual percentage of Light-Rainfall ($<4 \text{ mm d}^{-1}$)
F_{MR}	%	mean annual percentage of Moderate-Rainfall (from 4 to 36 mm d^{-1})
F_{HR}	%	mean annual percentage of Heavy-Rainfall ($>36 \text{ mm d}^{-1}$)
NDS	y^{-1}	mean annual number of dry spells
MDSD	d	mean dry spell duration
CV_{DSD}	%	coefficient of variation of mean annual dry spell durations
DSD_{max}	d	mean annual maximum dry spell duration
NWS	y^{-1}	mean annual number of wet spells
MWSD	d	mean wet spell duration
WSD_{max}	d	mean annual maximum wet spell duration

detailed description. SI approaches zero under minimal seasonality and exceeds one when rainfall seasonality is strong (Walsh and Lawler, 1981). DSI is a long-term seasonality index (Feng et al., 2013), theoretically ranging from zero (uniform rainfall throughout the year) and 3.585 (annual rainfall concentrated in one month). PCI is a metric widely applied in Mediterranean climates (Cannarozzo et al., 2006; Longobardi et al., 2016; Caloiero et al., 2019; Longobardi and Boulariah, 2022); $PCI < 10$ indicates an approximately uniform rainfall, values from 11 to 20 can be interpreted as indicative of moderate to high rainfall concentration in specific months, while $PCI > 20$ denotes very strong seasonality.

2.5. Method for the statistical analysis of trend and spatial autocorrelation

A statistical trend analysis was conducted for all indicators in Tables 2 and 3 using two complementary approaches. For the GBA, indicators from 131 gauges forming the GBA dataset (referring to the whole study area, Table 1b) were individually tested for trends over 1922–2022. For the SDA, regional trends were derived from pixel-based SDA datasets (Table 1b and Fig. 2), over the FP (i.e., 72 years in CAM and 101 years in SAR and SIC).

In both cases, indicators were computed on overlapping 35-year moving window with 5-year lag. This combination balanced the need for >20–30 years for robust rainfall regime estimation and the need to retain an adequate number of available subperiods. Data gaps during the World War period (1942–1950), especially in SIC, posed challenges for spatial interpolation (Section 2.3). To address this, the same criterion used in GBA gauges selection was applied, imposing a minimum of 25 years of data availability per each time window; indicators were set to NaN for windows not meeting such threshold. The adopted combination of time-window length and time-lag minimized unclassifiable time windows due to insufficient data.

The use of overlapping windows may induce autocorrelation effects and inflate Type I errors (i.e., false detection of trends). To mitigate this issue, trends were assessed using the Modified Mann-Kendall test (MMK, Hamed and Ramachandra Rao, 1998) at a 0.05 significance level (methodology in SM, Sect. S4). Trend magnitude was estimated with Sen's slope, β (Sen, 1968), a non-parametric estimator widely applied in hydroclimatology (Gocic and Trajkovic, 2013; Markos et al., 2023; Bedada, 2024), expressed in units of the variable per year (Jiqin et al., 2023). To compare magnitudes across variables and regions, a standardized classification was developed. The maximum historical range (MR_v) across all stations in the study area was preliminarily determined for each variable, v . Two variable-specific thresholds for the absolute value of β ($|\beta|$) were then defined: a lower threshold, $\Delta_{L,v} = MR_v / \eta$, below which the trend is considered negligible (NG, $|\beta| < \Delta_{L,v}$), and a higher threshold, $\Delta_{H,v} = \Delta_{L,v} \cdot \rho$, marking the transition from low-moderate (LM, $\Delta_{L,v} \leq |\beta| \leq \Delta_{H,v}$) to moderate-high (MH, $|\beta| > \Delta_{H,v}$) trends. These thresholds reflect the observed variability across the study area and period, ensuring comparability across indicators with different units and ranges. The values of η and ρ were selected after a sensitivity analysis detailed in the SM (Sect. S4 and Fig. S1), resulting in $\eta = 1000$ (explored range: 10–3000) and $\rho = 10$ (explored range: 1–50). Soft labels (LM and MH) were intentionally used to indicate that the classification is qualitative and illustrative, supporting comparative visualization.

Spatial structure in trends was evaluated via *Global Moran's Index* (Moran, 1950) and *Local Moran's Index* (Anselin, 1995). These indices, detailed in the SM (Sect. S4) and implemented in GeoDa (Anselin et al., 2006; documentation at <https://geodacenter.github.io/documentation.html>), quantify the degree of similarity in neighbouring observations. Spatial autocorrelation describes whether trend magnitude values cluster or disperse across space; positive spatial autocorrelation occurs when neighbouring observations have similar values, while negative spatial autocorrelation is observed when adjacent observations differ

significantly in value (Haining, 2001). The *Global Moran's I* statistic (Moran, 1950) ranges from -1 (dispersed) to 1 (clustered), with null hypothesis of spatial randomness (expected value $E[I]$). *Moran's I* higher than $E[I]$ indicates clustered pattern, *Moran's I* lower than $E[I]$ suggest dispersion, while value close to $E[I]$ implies randomness, with no discernible pattern.

The *Local Moran's index*, a Local Indicator of Spatial Association (LISA) introduced by Anselin (1995), was used to identify local trend patterns. According to *Moran's* scatterplot, each spatial unit is plotted against the spatial lag (mean of neighbours), resulting in four spatial association classes (corresponding to the four quadrants of the scatterplot): H-H (High-High), H-L (High-Low), L-L (Low-Low) and L-H (Low-High). H-H and L-L indicate positive spatial autocorrelation (high/low values surrounded by high/low values), revealing local clusters (i.e., coherent regions with similar characteristics). H-L and L-H, indicate negative spatial autocorrelation and identify spatial outliers.

3. Results

3.1. Rainfall regime in the study area and comparison with the past

3.1.1. Analysis of rainfall regime indicators

For each region, Table 4 reports mean rainfall-regime indicators (μ) for the Recent Period (RP) from the GBA dataset. Relative percentage differences with respect to the Central (CP) and Pre-World War (PW) periods are also provided (Δ_{CP} and Δ_{PW} , with Δ_{PW} only for SAR and SIC) for descriptive comparison. Positive values denote increases in RP with respect to the past. Regional mean and standard deviation for all periods, using both GBA and SDA, are provided in the SM (Tables S1–S3).

Mean Annual Precipitation (MAP) confirms higher meteorological water supply in CAM compared to SAR and SIC, with similar interannual variability ($CV_{AP} \approx 25$ –29%) reflecting Mediterranean rainfall irregularity, particularly in insular contexts. From CP to RP, MAP declined in CAM and SAR and remained nearly stable in SIC, while both islands show decreases from PW to RP.

Monthly quartiles indicate widespread reductions in Q2 and Q3, especially in SAR, suggesting weaker monthly precipitation. SIC shows modest increases from CP to RP. Q1 was nearly stable from CP to RP in CAM, but raised in both islands (notably SIC, $\Delta_{CP} = 15\%$). The Inter-quartile Range ($IQR = Q3 - Q1$), decreased in all regions from CP to RP, suggesting more uniform rainfall distribution during RP.

Daily indicators (Table 4) confirm more frequent rainy days (λ) in CAM, though λ decreased everywhere. A concurrent marked decline in mean daily rainfall depth (α) explains MAP reductions. Annual maxima (P_{max}) are comparable across regions, with mostly negative variations over time.

Rainfall class indicators reveal consistent patterns across the study area. In RP, most rainy days are moderate (μ of F_{MR} from 54% to 61%), with limited heavy rain (F_{HR} , on average, from 3% to 6%). From CP to RP, CAM and SAR shift toward lighter rain, with increased F_{LR} at the expense of F_{MR} and F_{HR} . SIC shows slightly higher F_{HR} and stable F_{LR} . Compared with PW, however, SIC aligns with CAM and SAR, with reduced F_{MR} and F_{HR} and increased F_{LR} . Fig. 3 illustrates shifts in the distribution of rainy-day classes across regions and periods. Dashed bars refer to indicators from the GBA, while solid bars to those from the SDA. The figure clearly shows that increasing in F_{LR} , observed for all regions regardless of the adopted approach, was mainly balanced by decreasing F_{MR} , with F_{HR} nearly unaltered. Comparison of GBA and SDA results (see also Tables S1–S3, SM) shows minor differences ($< 5\%$) in mean values (μ) of F_{LR} , F_{MR} and F_{HR} across regions and periods, reflecting the wider spatial coverage of the SDA dataset and confirming that the interpolation preserved the statistical distributions.

Persistence indicators (Table 4) show similar μ in RP for SAR and SIC, whereas CAM has more frequent dry-wet spells alternations (higher NDS and NWS). Overall, SAR and SIC are more prone than CAM to long dry periods and drought, as also indicated by the very high (~ 2 mo) and

Table 4

Analysis of the GBA datasets: rainfall regime indicators for RP (1987–2022), with mean (μ) values across all stations in each region. Percentage changes relative to the CP (1951–1986), Δ_{CP} (%), and the PW (1922–1941), Δ_{PW} (%), are also reported.

		CAM		SAR			SIC		
		μ	Δ_{CP} (%)	μ	Δ_{PW} (%)	Δ_{CP} (%)	μ	Δ_{PW} (%)	Δ_{CP} (%)
MAP	mm y ⁻¹	1088	-9	665	-17	-15	717	-7	2
CV _{AP}	%	25	-5	29	10	9	28	17	-3
Q1	mm mo ⁻¹	35.6	-1	13.9	-7.5	5.7	14.2	5	15
Q2	mm mo ⁻¹	76.4	-4	41.4	-19.7	-12	44.2	-5	5
Q3	mm mo ⁻¹	132.2	-7	80.6	-19	-15	87.3	-5	2
P _{max}	mm d ⁻¹	70.2	-3	59.6	-1.5	-7	68.0	-6	1
α	mm d ⁻¹	11.8	-6	9.2	-18	-17	9.6	-12	3
λ	d ⁻¹	0.25	-4	0.19	-3	-1	0.20	0.36	-2
F _{LR}	%	33	11.7	42	25	20.6	42	15	0.5
F _{MR}	%	61	-6	55	-18	-14	54	-11	-1.1
F _{HR}	%	6	-9	3	18	-32	4	-19	9.9
NDS	y ⁻¹	40.1	-4.8	33.1	-11	-8	32.6	-13	-11.4
MDSD	d	11.1	-1.6	13.9	-3	-7.2	14.0	-5	-3.5
CV _{DSD}	%	22.1	24	15.1	-10	-6	14.2	-9	3
DSD _{max}	d	35.9	-5.2	58.1	-16	-18	62.1	-20	-13
NWS	y ⁻¹	20.2	-3	15.4	-9	-7	15.0	-10	-12
MWSD	d	4.5	-1	3.9	-7	-7	3.9	-1	-2
WSD _{max}	d	7.6	-2	6.1	-13	-11	6.3	-3	-4

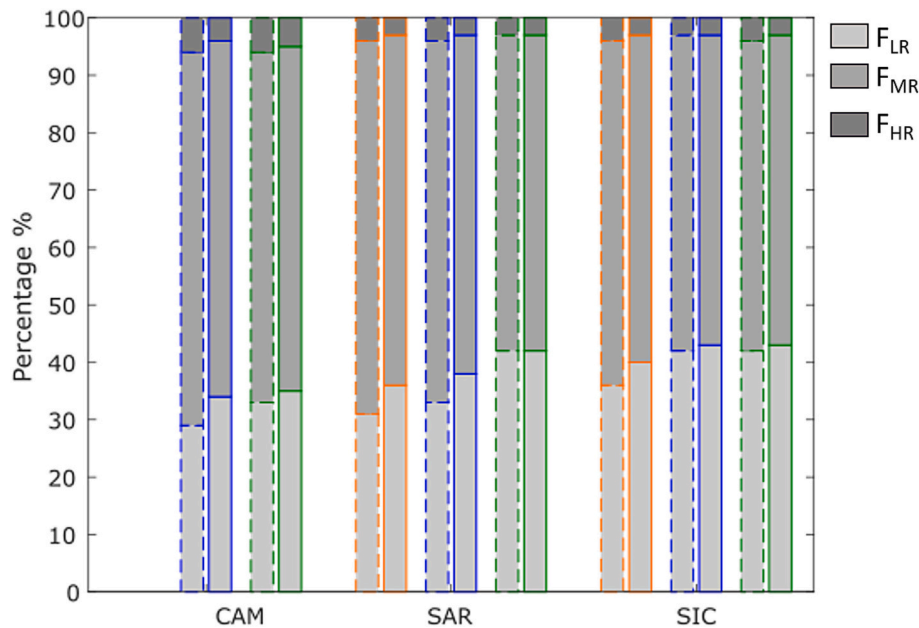


Fig. 3. Fraction of rainy days in three precipitation classes (Light, F_{LR} ; Moderate, F_{MR} ; Heavy, F_{HR}) for CAM, SAR, and SIC. Colours denote periods: PW (orange), CP (blue), and RP (green). Bars with dashed outlines refer to GBA indicators, and solid outlines to SDA. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

almost doubled mean regional value of the mean annual maximum dry spell duration (DSD_{max}). Furthermore, CV_{DSD} indicates lower interannual variability in dry spells mean duration for the islands compared to CAM. Over time, all regions experienced reductions in number and duration of both dry and wet spells (negative Δ_{CP} and Δ_{PW} for NWS, NDS, MWSD and MDSD), consistent with more frequent alternations and more uniform rainfall distribution in the RP.

Fig. 4 displays boxplots for a selection of indicators representative of water availability and drought occurrences. In particular, the values of MAP, Q2, WSD_{max} , and DSD_{max} observed in all stations and computed under the GBA (boxplots with dashed outlines) and SDA (solid outlines) over each examined period are reported. MAP (Fig. 4a) declined in SIC similarly to CAM and SAR, confirming widespread Mediterranean reductions (Noto et al., 2023a, 2023b). Q2 (Fig. 4b) also decreases across regions, indicating potentially reduced water availability caused by reduced rainfall volumes. Fig. 4c and d highlight that, in all regions,

WSD_{max} and DSD_{max} are lower in RP compared to previous periods, particularly DSD_{max} . Agreement between GBA and SDA results in Fig. 4 is high, except for a slight SDA overestimation of WSD_{max} with respect to GBA (~2 days; Tables S1 and S2, SM).

3.1.2. Analysis of indicators of rainfall seasonality

Table 5, similarly to Table 4, reports mean regional values (μ) for rainfall seasonality indicators (Table 3) in the RP, and their percentage changes relative to CP (Δ_{CP} , %) and PW (Δ_{PW} , %). Full results for all periods and for both GBA and SDA are given in the SM (Tables S1–S3).

Results for RP confirm the typical behaviour of warm temperate climate, as expected by Köppen classification (Section 2.1), with about two-thirds of annual rainfall occurring in the wet season (PP_{wet}). SAR and SIC show high climatic similarity, with nearly identical values for all indicators, including global metrics (SI, DSI and PCI). These findings indicate stronger seasonality in the islands compared to CAM, where the

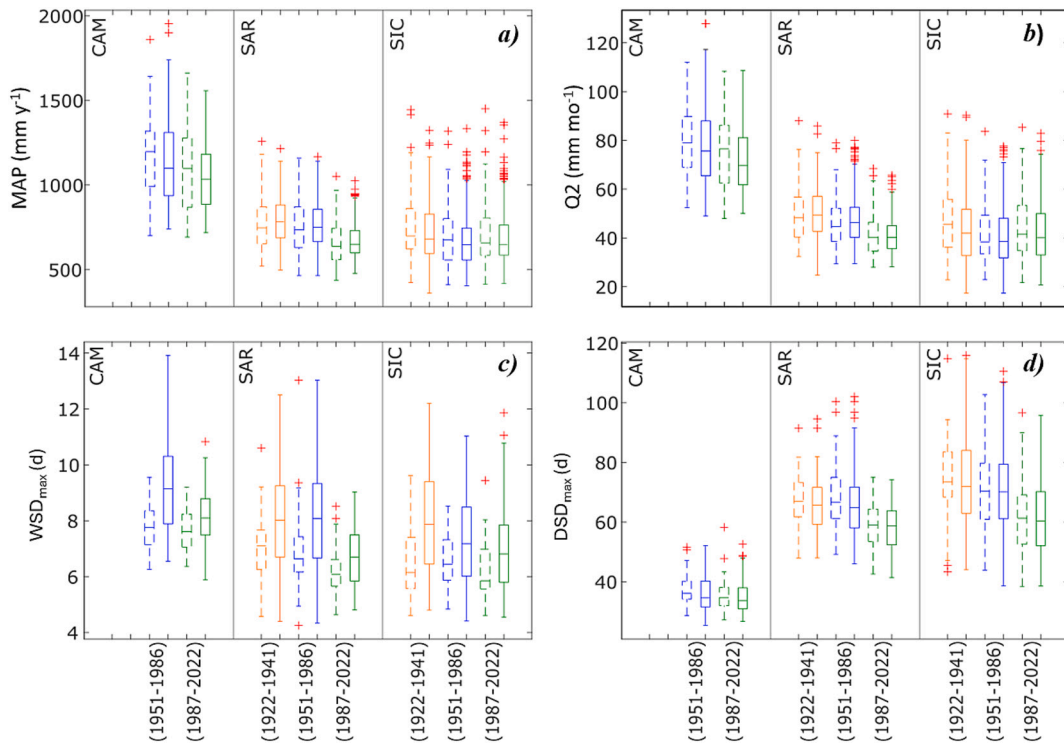


Fig. 4. Boxplots of four rainfall regime indicators computed for CAM, SAR and SIC over the PW (orange), CP (blue) and RP (green): MAP (a); Q2 (b); WSD_{max} (c); and DSD_{max} (d). Dashed and solid outlines refer to GBA and SDA, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5

Analysis of the GBA datasets: rainfall seasonality indicators for the RP (1987–2022), with mean (μ) values across all stations in each region. The percentage changes relative to the CP (1951–1986), Δ_{CP} (%), and the PW (1922–1941), Δ_{PW} (%) are also shown.

		CAM		SAR			SIC		
		μ	Δ_{CP} (%)	μ	Δ_{PW} (%)	Δ_{CP} (%)	μ	Δ_{PW} (%)	Δ_{CP} (%)
S _{wet}	DOY	283.7	−3	295.3	−3	−2	291.3	−4	−2
D _{wet}	d	170.2	4	154.9	5	5	146.1	5	3
P _{wet}	mm	704.6	−10	422.9	−21	−18	466.5	−9	1
α_{wet}	mm	13.2	−7	10.33	−19	−17	10.8	−10	3
λ_{wet}	d ^{−1}	0.14	−4	0.11	−4	−2	0.12	−4	−2
PP _{wet}	%	65	−0.2	64	−3	−2	65	−2	−0.2
P _{dry}	mm	384.2	−8	241.9	−11	−10	250.3	−3	2
α_{dry}	mm	10.9	−6	9.0	−16	−19	9.2	−15	1
λ_{dry}	d ^{−1}	0.10	−4	0.07	0.32	4	0.07	6	−0.3
SI	–	0.60	−2	0.73	−1.4	−4	0.73	−4	−5
DSI	–	0.17	−9	0.16	−49	−23	0.17	−37	−11
PCI	–	13.66	1	15.73	−2	−3	15.45	−5	−5

wet season, on average, begins ~10 days earlier and is ~20 days longer. All regions showed negative Δ_{CP} and Δ_{PW} for the mean starting day of wet season (S_{wet}), suggesting an earlier (~8 days) onset in RP compared to previous periods. Conversely, values of duration of the wet season (D_{wet}) display positive Δ_{CP} in all regions, indicating a prolongation of the rainy season from CP to RP (~1 week).

Fig. 5 illustrates these shifts in seasonality; the circular plots depict the average span of the wet (blue) and dry (red) seasons, with results from both the gauge-based (GBA, dashed lines) and spatial (SDA, solid lines) analyses in high agreement. SAR and SIC historically had shorter (~5 mo) wet season, making them more drought-prone than CAM. Comparison between present (RP, outer circles) and past (PW, inner circles) periods reveals an earlier onset and longer duration of the wet season in the islands, with the end date largely unchanged (Figs. 5b-c). Wet season's centroid advance in all regions, confirming the shift in seasonal central timing.

Seasonal rainfall totals (P_{wet} and P_{dry}) in Table 5, reflect unbalanced contributions to annual totals, mainly due to a higher wet season frequency of rainy days (λ_{wet} ~ 60% higher than λ_{dry}), while mean rainfall depth in the wet season (α_{wet}) is only slightly higher than α_{dry} . The values of Δ_{CP} and Δ_{PW} for P_{wet} and P_{dry} (Table 5), mirror MAP changes (Table 4), showing reduced winter supply in the study area (more relevant in percent terms in SAR), while SIC remained nearly unchanged from CP to RP. All regions show reduced λ_{wet} in RP compared to CP and PW (Table 5). Also the Δ_{CP} values for λ_{dry} were negative in all regions except in SAR, while Δ_{PW} showed a positive variation in both SAR and SIC. Seasonal values of α exhibited a decrease in time for both seasons in all regions, with the only exception of SIC that showed a slight increase from CP to RP, especially in α_{wet} (Δ_{CP} = 3%), offsetting the reduction in λ_{wet} and explaining its stable MAP. The contribution of the wet season to the total annual precipitation (PP_{wet}) slightly decreased, remaining almost unaltered in CAM and SIC from CP to RP.

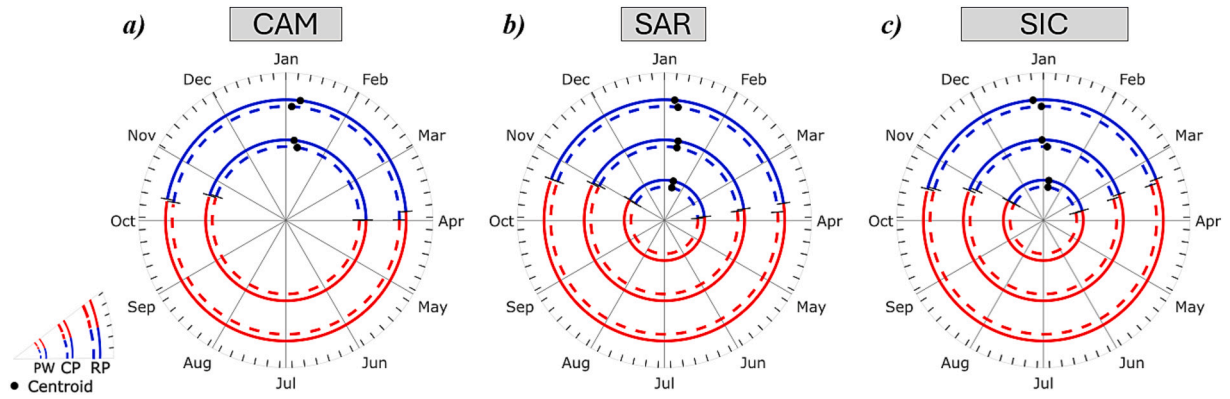


Fig. 5. Average temporal distribution of wet (blue) and dry (red) seasons for CAM **a)**, SAR **b)** and SIC **c)**. Solid lines represent SDA results, while dashed lines GBA results. Black dots mark wet season centroids, and black connectors between red and blue lines seasonal transitions. Inner, middle and outer circles refer to the PW, CP, and RP, respectively. Black ticks along the external circumference mark 5-day intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

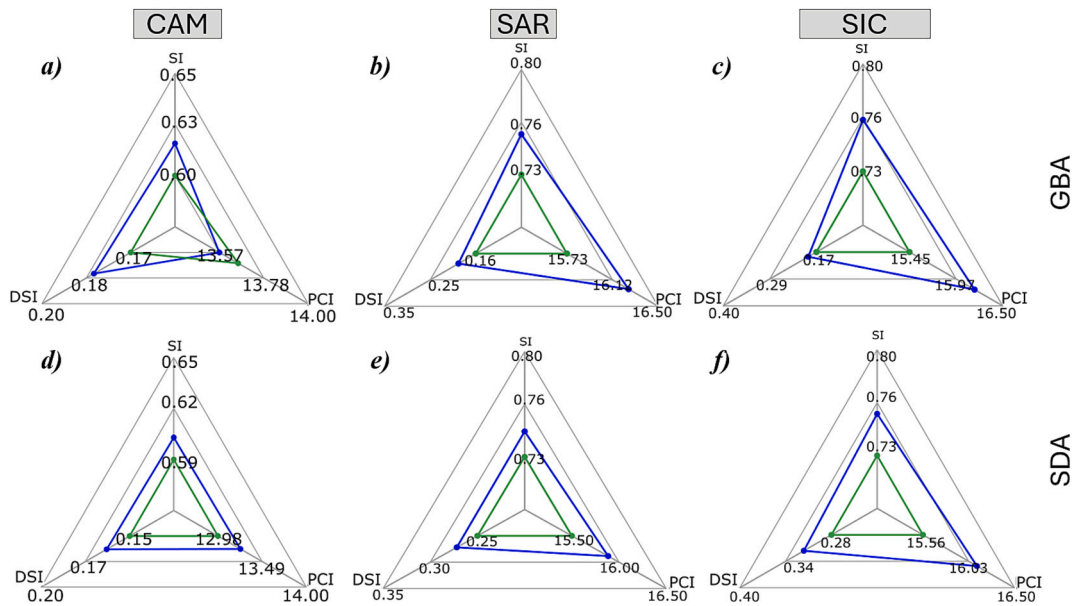


Fig. 6. Global seasonality metrics (SI, DSI, PCI) for CAM **(a, d)** SAR **(b, e)** and SIC **(c, f)**, computed for CP (blue) and RP (green) using GBA (top panels, **a-c**) and SDA (bottom panels, **d-f**). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 6 compares global seasonality metrics (SI, DSI and PCI) between CP (blue) and RP (green), using GBA (top panels, **Figs. 6a-c**) and SDA (bottom panels, **Figs. 6d-f**). Consistently with the definitions of such metrics (**Section 2.4.2** and **S3** of **SM**), all indicators confirm a moderate seasonality. CAM (**Fig. 6a**) shows weaker seasonality (lower SI and PCI), despite similar DSI. SAR (**Fig. 6b** and **e**) and SIC (**Fig. 6c** and **f**) display very similar values across periods. All global metrics decrease from CP to RP (green triangles within blue in **Fig. 6**), for both GBA and SDA. The only exception is PCI in CAM under GBA (**Fig. 6a**), which showed opposite variation in sign ($\Delta_{CP} = 1\%$, **Table 5**), likely due to the small number of stations in CAM for the GBA dataset (almost half of those in SIC and one third of those in SAR, **Table 1b**) that could affect the representativeness of the mean regional value computed at gauge level. From **Fig. 6d**, in fact, SDA results for CAM show a temporal evolution in PCI consistent with the islands, highlighting SDA advantage for regional analysis. Overall, **Table 5** and **Fig. 6** reveal a coherent shift toward reduced rainfall seasonality, with all global seasonality metrics decreasing over time.

3.2. Spatial analysis of the indicators

This section examines the spatial distribution of selected rainfall regime (**Section 3.2.1**) and seasonality (**Sections 3.2.2** and **3.2.3**) indicators computed by the SDA across all regions and periods. Temporal changes in these spatial patterns were also assessed, again using percent differences between RP and CP (Δ_{CP} , %) and between RP and PW (Δ_{PW} , %). Additional results for other indicators are provided in the **SM** (**Figs. S2-S8**).

3.2.1. Spatial distribution of rainfall regime indicators

Top panels of **Fig. 7** (**Figs. 7a-c**) present the regional spatial distribution of MAP during the RP. The centre (**Figs. 7d-f**) and bottom panels (**Figs. 7g-h**) show the associated Δ_{CP} and Δ_{PW} , respectively, with the latter limited to SAR and SIC. Spatial patterns of MAP for CP and PW are provided in **SM** (**Fig. S2**).

Figs. 7a-c show typical Mediterranean features, with maxima in mountainous areas (i.e., Apennine in CAM, $\sim 1700 \text{ mm y}^{-1}$; Genargentu in SAR, $\sim 1050 \text{ mm y}^{-1}$; and Nebrodi in SIC, $\sim 1400 \text{ mm y}^{-1}$) reflecting orographic effects on rainfall. The lowest MAP values occur on

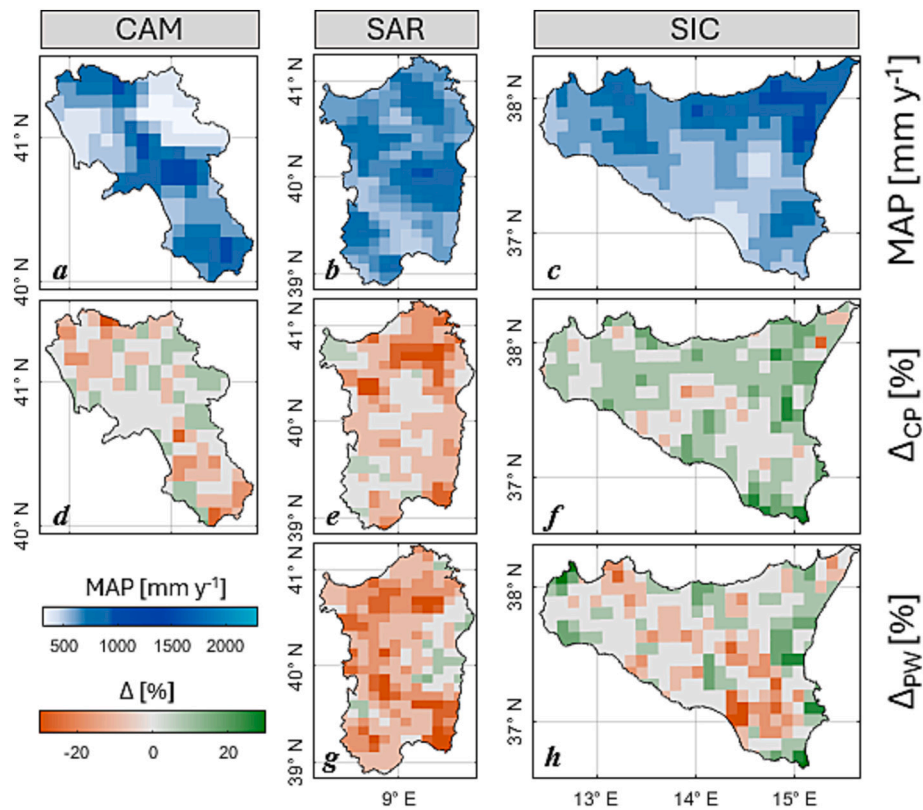


Fig. 7. Spatial distribution of Mean Annual Precipitation (MAP) over the RP (top panels, a-c); percentage MAP differences from CP to RP, Δ_{CP} (central panels, d-f) and from PW to RP, Δ_{PW} (bottom panels, only for SAR, g, and SIC, h). Results are shown for CAM (a, d), SAR (b, e, g), SIC (c, f, h).

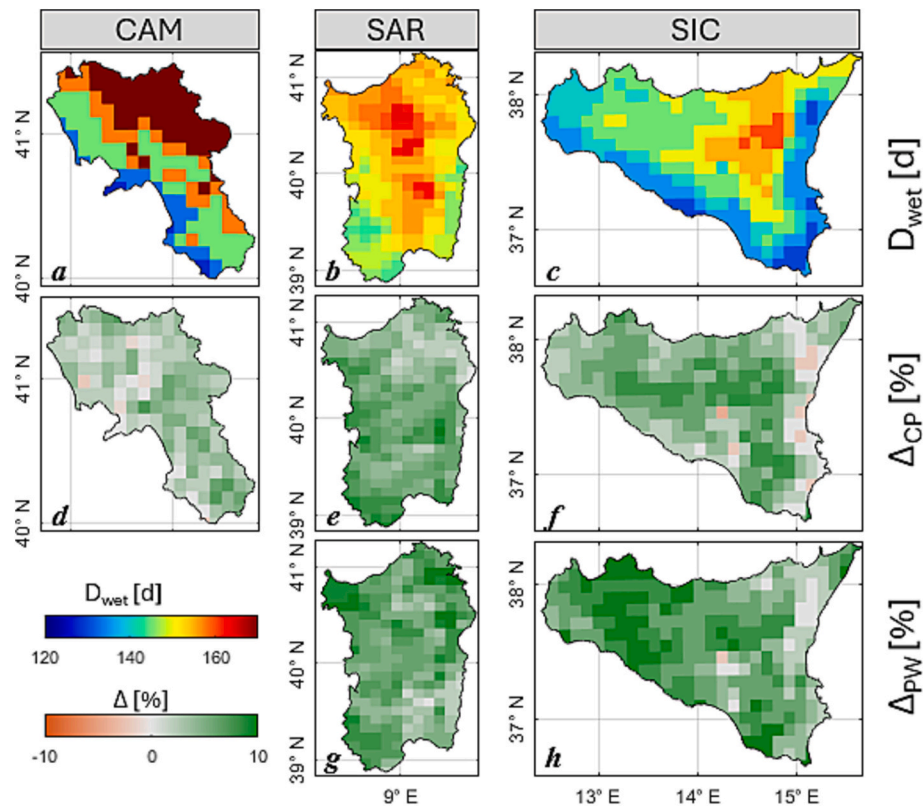


Fig. 8. Spatial distribution of the mean duration of the wet season (D_{wet}) over the RP (top panels, a-c); percentage differences in D_{wet} between CP and RP, Δ_{CP} (central panels, d-f), and between PW and RP, Δ_{PW} (bottom panels, only for SAR, g, and SIC, h). Values are displayed separately for the three regions: CAM (a, d), SAR (b, e, g), SIC (c, f, h).

the northern Tyrrhenian coast of CAM, the south-western coast of SAR and the south-eastern coast of SIC.

Δ_{CP} maps (Figs. 7d-e) reveal an overall MAP decrease from CP to RP in CAM and, to a higher degree, in SAR, denoted by dominant negative (red) pixels. SIC (Fig. 7f) shows more positive values (green coloured pixels), denoting a slightly prevalent MAP increase across the region. This increase is mainly in the northern and coastal zones, while the central inland zone shows weaker changes (Δ_{CP} close to zero). This pattern suggests that precipitation has intensified over time in the wettest areas of the region, exacerbating spatial differences in MAP. From PW to RP, SIC (Fig. 7h) shows significant differences relative to the Δ_{CP} map (Fig. 7f), with Δ_{PW} generally lower than Δ_{CP} across most pixels and a greater proportion of pixels showing negative variations, indicating a more pronounced decline during the early period.

Although SDA results for SAR and SIC show similar mean regional MAP values and comparable reductions with respect to previous periods (Tables S1 and S3, SM), spatial patterns of both Δ_{PW} and Δ_{CP} differ markedly between the two regions. SAR shows a more homogeneous and progressive MAP decline, while SIC exhibits localized decreases, affecting only limited areas and prevalently concentrated in the early period from PW to RP (Tables S1-S3, Fig. S2, SM).

Other rainfall-regime indicators also show significant spatial changes over time. For instance, maps of the mean frequency of rainy days (λ) for the various subperiods (Fig. S3, SM) display substantial differences at pixel level but confirm regional mean declines in all regions (Tables S1-S3, SM), also observed from GBA results (Table 4). Spatial distributions of the mean annual number of wet/dry spells (NWS and NDS) confirmed the overall reduction over time within the study area but largely preserved regional spatial patterns (Figs. S4 and S5, SM) and intraregional differences.

3.2.2. Spatial distribution of rainfall seasonality indicators

Analogously to Fig. 7, Figs. 8 and 9 (top panels, a-c) display the spatial patterns of wet season duration (D_{wet}) and the mean wet season contribution to the annual rainfall (PP_{wet}), for the RP, with corresponding changes relative to earlier periods (Δ_{CP} and Δ_{PW} maps) in the central (d-f) and bottom (g-h) panels. In CAM (Fig. 8a), D_{wet} exhibits marked spatial variability, from ~ 190 days in the northeast inland to ~ 130 days along the coast. SAR (Fig. 8b) shows a similar but smoother gradient, with a ~ 20 -day spread between inland and southern coastal areas, where the shortest durations (~ 150 days) are located again. SIC presents an intermediate case (spread ~ 40 days), with shorter wet seasons (and thus longer dry seasons) on the southeastern coast and longer ones inland at higher elevations. The prevalence of positive Δ values in Figs. 8d-f (for Δ_{CP}) and 8 g-h (for Δ_{PW}), indicates a progressive, spatially consistent lengthening of the wet season, aligned with GBA results (Fig. 5).

Fig. 9 displays the spatial distribution of PP_{wet} in the RP and its temporal changes (Δ_{CP} and Δ_{PW} maps), reflecting combined shifts in MAP, D_{wet} and seasonal rainfall totals. In CAM (Fig. 9a), a clear influence of latitude on the PP_{wet} map emerges, with PP_{wet} increasing southward, southern zones reaching 68% and northern areas $\sim 6\%$ lower. More clustered patterns appear in the islands: in SAR (Fig. 9b), higher PP_{wet} lies along the eastern coast, while in SIC (Fig. 9c) at higher elevations and in dry eastern coastal sectors. In particular, the south-eastern coastal area, the driest area in terms of MAP and P_{dry} , is highly dependent on winter precipitation.

Comparison with earlier periods (Figs. 9d-f and Figs. 9g-h) reveal a general PP_{wet} decrease (up to -5%) in CAM, SAR, and some localized areas of SIC, indicating a declining wet-season contribution to annual rainfall. Nonetheless, in SIC large areas display stable or even increasing PP_{wet} values (green pixels in Fig. 9f and h, with Δ_{CP} and Δ_{PW} up to 5%),

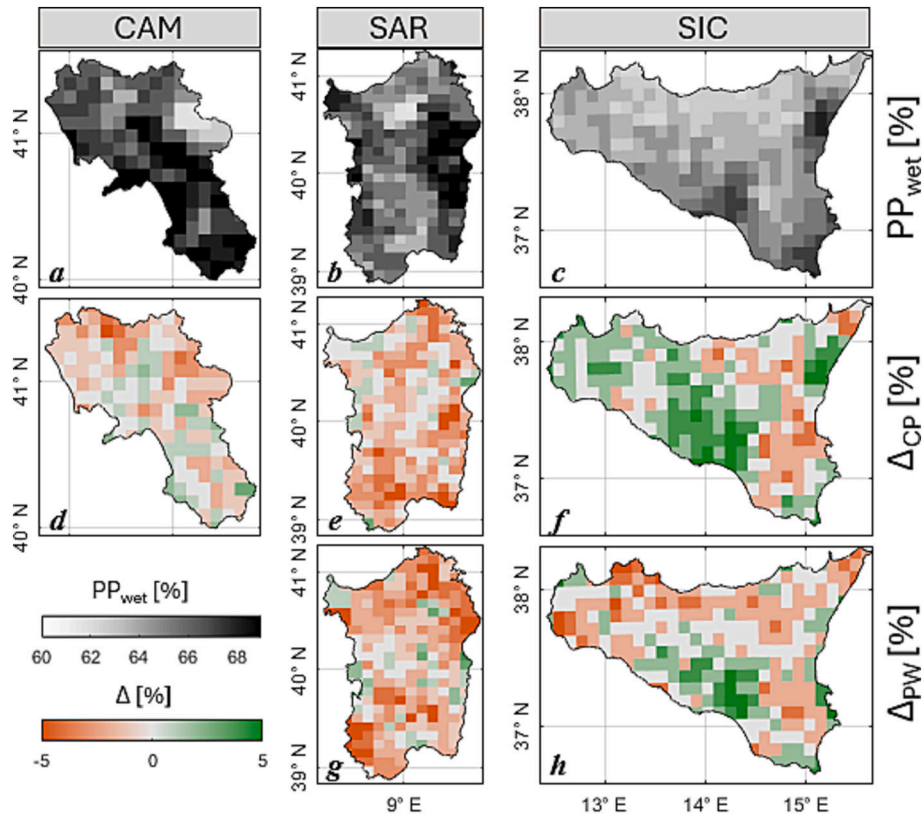


Fig. 9. Spatial distribution of the mean percent wet season contribution to the annual rainfall (PP_{wet}) over the RP (top panels, a-c); percentage differences between CP and RP, Δ_{CP} (central panels, d-f) and between PW and RP, Δ_{PW} (bottom panels, only for SAR, g, and SIC, h). Results are shown for CAM (a, d), SAR (b, e, g), SIC (c, f, h).

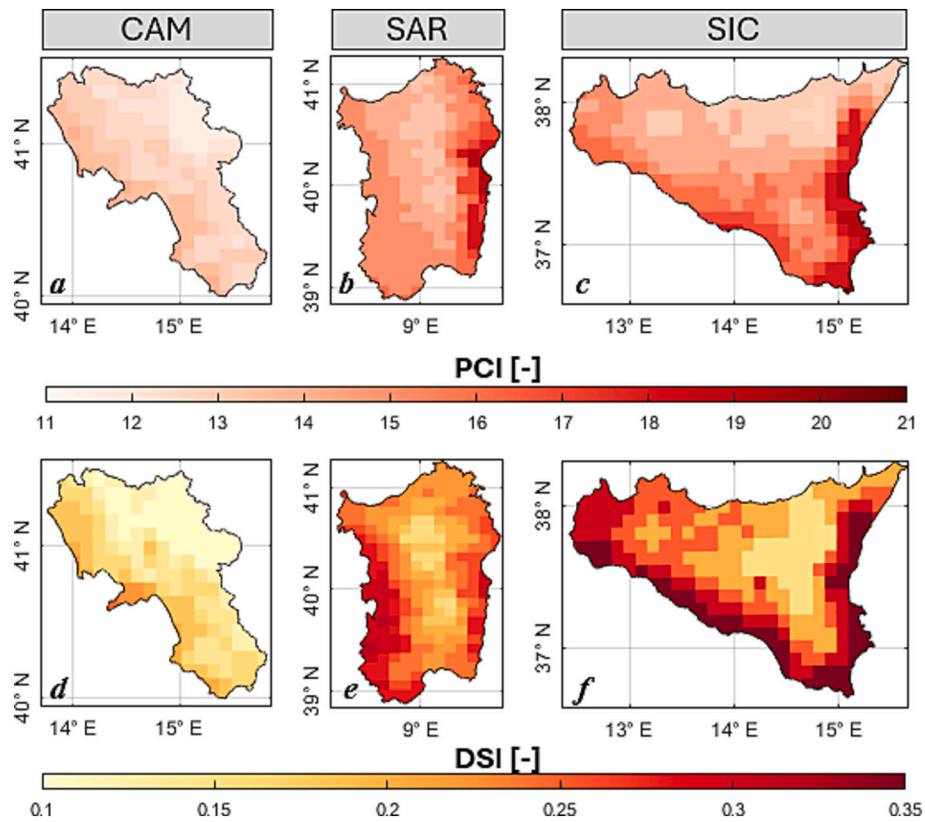


Fig. 10. Spatial distribution of PCI (top panels), and DSI (bottom panels) over the RP for CAM (a, d), SAR (b, e), and SIC (c, f).

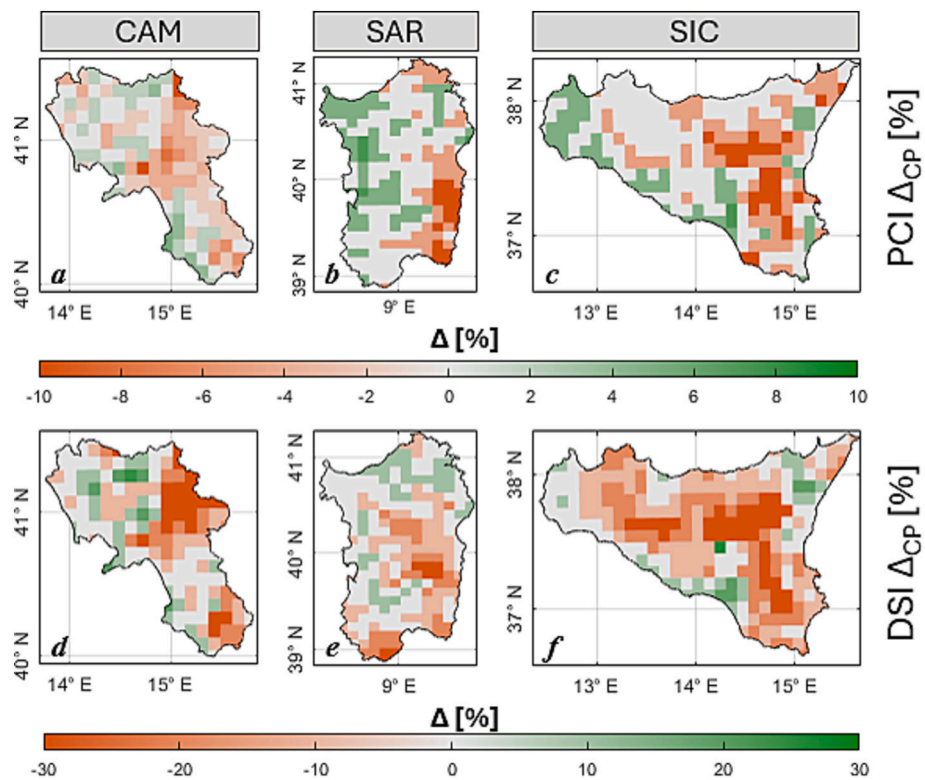


Fig. 11. Spatial distribution of the percent differences in PCI (top panels) and DSI (bottom panels) from the CP to the RP (Δ_{CP} , %) for CAM (a, d), SAR (b, e), and SIC (c, f).

reinforcing contrasts in areas already characterized by high PP_{wet} in the RP.

3.2.3. Focus on the spatial patterns of global metrics of rainfall seasonality

Fig. 10 shows the spatial distribution of the Precipitation Concentration Index (PCI) and Dimensionless Seasonality Index (DSI) for RP. PCI (Figs. 10 a-c) indicates moderate to high rainfall seasonality across the study area (values ranged from 11 to 21), with lower (mean = 12.9) and less dispersed values in CAM and higher and comparable values in SAR and SIC (means = 15.50 and 15.56, respectively). DSI maps (Figs. 10 d-f) closely mirror PCI, confirming overall moderate seasonality, with mean regional values over the RP of 0.15 in CAM and ~ 0.25 in SAR and SIC (Table S3, SM) and lower regional variability in CAM as for the PCI. Unlike PCI, DSI shows notable discrepancies between SDA and the GBA results for the two islands (Table S3, SM), indicating a greater sensitivity to the methodological approach. Both indicators exhibit clear spatial structures, similar to PP_{wet} (Figs. 9a-c). In SAR, a strong seasonality on the eastern coast is coherently suggested by the high values of both PCI and DSI (Figs. 10b and e), while on the western and southwestern coasts only the DSI indicator (Fig. 10e) shows high seasonality. In CAM and SIC (Fig. 10a, c, d and f), both indicators consistently show stronger seasonality in coastal sectors, except part of SIC's northern coast.

Fig. 11 illustrates temporal changes from CP to RP for PCI (top panels, a-c) and DSI (bottom panels, d-f) indicators. Both indicators produced highly coherent results, generally indicating declining seasonality (dominant negative Δ values), with localized increases (positive Δ values). In CAM (Fig. 11a and d), reductions in inland areas and increases along the coast suggest weaker spatial contrasts in the past (CP) compared to the present (RP). A similar pattern appears in SIC, where areas with the lowest indicators in RP (Fig. 10c and f) coincide with those showing the strongest reductions (lowest Δ in Fig. 11c and f). In SAR, the sharpest reductions in both indicators occur along the eastern coast (Fig. 11b and e), indicating that this area, currently characterized by strong seasonality (Fig. 10b and e), were even more seasonal during CP. Spatial maps of all global metrics of rainfall seasonality (including SI, here omitted for sake of simplicity) for PW can be found in the SM (Figs. S6-S8), and confirm trends consistent with variations from CP to RP (Fig. 10) in the islands.

Notably, comparing the maps of Figs. 8d-8f with Figs. 11d-11f, a

spatial correspondence emerges between areas with increasing wet season duration (positive Δ_{CP} for D_{wet}) and those with decreasing seasonality (negative Δ_{CP} for both PCI and DSI), indicating that the primary evidence of the observed reduction in rainfall seasonality over time is the lengthening of the wet season.

3.3. Statistical analysis of trends

This section distinguishes between trend analysis conducted using GBA dataset (Section 3.3.1), at individual gauge level over the period 1922–2022, and that conducted using the SDA dataset (Section 3.3.2), at pixel level for the regional grids, over the FP of each region (Table 1b). The spatial distribution of trends is analysed separately in Section 3.3.3.

3.3.1. Trend analysis under the gauge-based approach

The GBA dataset is used to assess long-term changes in rainfall regime across the full study area over the past century. However, the composition of the aggregated GBA dataset is highly unbalanced: SAR and SIC account for 97% of the records, while CAM is represented by only five stations (Table 1b), potentially limiting the spatial representativeness. In contrast, trend detection is highly robust, as GBA dataset relies on raw, non-interpolated data, unlike the SDA.

The percentage of stations with statistically significant positive, null and negative trends is reported in Table 6 for all indicators, along with absolute values of the mean (μ_t) and maximum (max_t) trend magnitudes (slope, unit of the considered indicator per year) over gauges showing positive/negative trend. A consistent percentage of stations shows negative trends in: 1) MAP and PP_{wet} ; 2) the upper quartile of monthly rainfall (Q3); 3) the mean rain depth of rainy days, both over the year (α) and at seasonal level (α_{dry} and α_{wet}); 4) the fraction of moderate rainy days (F_{MR}); and 5) the mean duration of dry and wet spells (MDSD and MWSD). For most of these indicators, μ_t and max_t magnitudes fall within the moderate-high class, MH (values in italic bold in Table 6, see also trend magnitude classification in Section 2.5.1). A very relevant percentage (> 76%) of stations exhibits significant negative trends in the maximum duration of dry and wet spells, DSD_{max} and WSD_{max} , in all global seasonality metrics (SI, DSI and PCI), and in P_{wet} . Interestingly, no station shows a positive trend in DSI, while 85% show negative MH trend values, indicating a clear long-term decline in rainfall seasonality.

The mean annual number of dry spells (NDS) is the only indicator

Table 6

Trends in rainfall regime (a) and seasonality (b) indicators from the GBA dataset over the period 1922–2022 for the entire study area. Percentage (%) of stations with significant positive (+) or negative (–) trends, or no trend. Absolute values of the mean (μ_t) and maximum (max_t) trend magnitudes (unit of the considered indicator per year) across stations showing significant positive/negative trends. Trend magnitudes are classified as negligible (NG, italic), low-moderate (LM, regular font), and moderate-high (MH, bold italic) according to Section 2.5.

a)							b)						
	NO TREND		(–) TREND		(+) TREND			NO TREND		(–) TREND		(+) TREND	
	%	%	μ_t	max_t	%	μ_t	max_t		%	%	μ_t	max_t	%
MAP	28	68	11.92	33.72	4	5.89	12.64	S_{wet}	40	58	0.78	1.90	2
CV_{AP}	40	21	0.01	0.03	39	0.01	0.01	D_{wet}	24	–	–	–	76
Q1	40	15	0.28	0.57	45	0.39	1.54	P_{wet}	22	76	8.79	22.53	2
Q2	48	39	0.66	1.70	13	0.36	1.13	α_{wet}	33	60	0.25	0.71	8
Q3	29	66	1.50	4.61	5	0.66	0.91	λ_{wet}	44	37	0.002	0.003	18
P_{max}	43	45	1.21	4.16	12	0.69	1.56	PP_{wet}	29	67	0.26	0.57	4
α	29	63	0.22	0.87	8	0.08	0.19	P_{dry}	40	51	3.87	12.48	8
λ	40	37	0.002	0.005	23	0.003	0.01	α_{dry}	27	65	0.22	1.04	8
F_{LR}	32	7	0.003	0.005	61	0.01	0.03	λ_{dry}	40	21	0.001	0.001	40
F_{MR}	32	61	0.01	0.03	7	0.003	0.005	SI	20	79	0.01	0.01	2
F_{HR}	36	51	0.002	0.01	13	0.001	0.002	DSI	15	85	0.01	0.02	–
NDS	53	11	0.41	0.74	37	0.63	1.35	PCI	21	77	0.19	0.78	2
MDSD	27	68	0.13	0.39	5	0.07	0.12						
CV_{DSD}	45	50	0.12	0.39	5	0.10	0.16						
DSD_{max}	19	79	1.27	2.98	2	0.77	0.91						
NWS	37	16	0.22	0.58	47	0.32	0.79						
MWSD	27	68	0.13	0.14	5	0.07	0.12						
WSD_{max}	19	79	1.27	0.41	2	0.77	0.91						

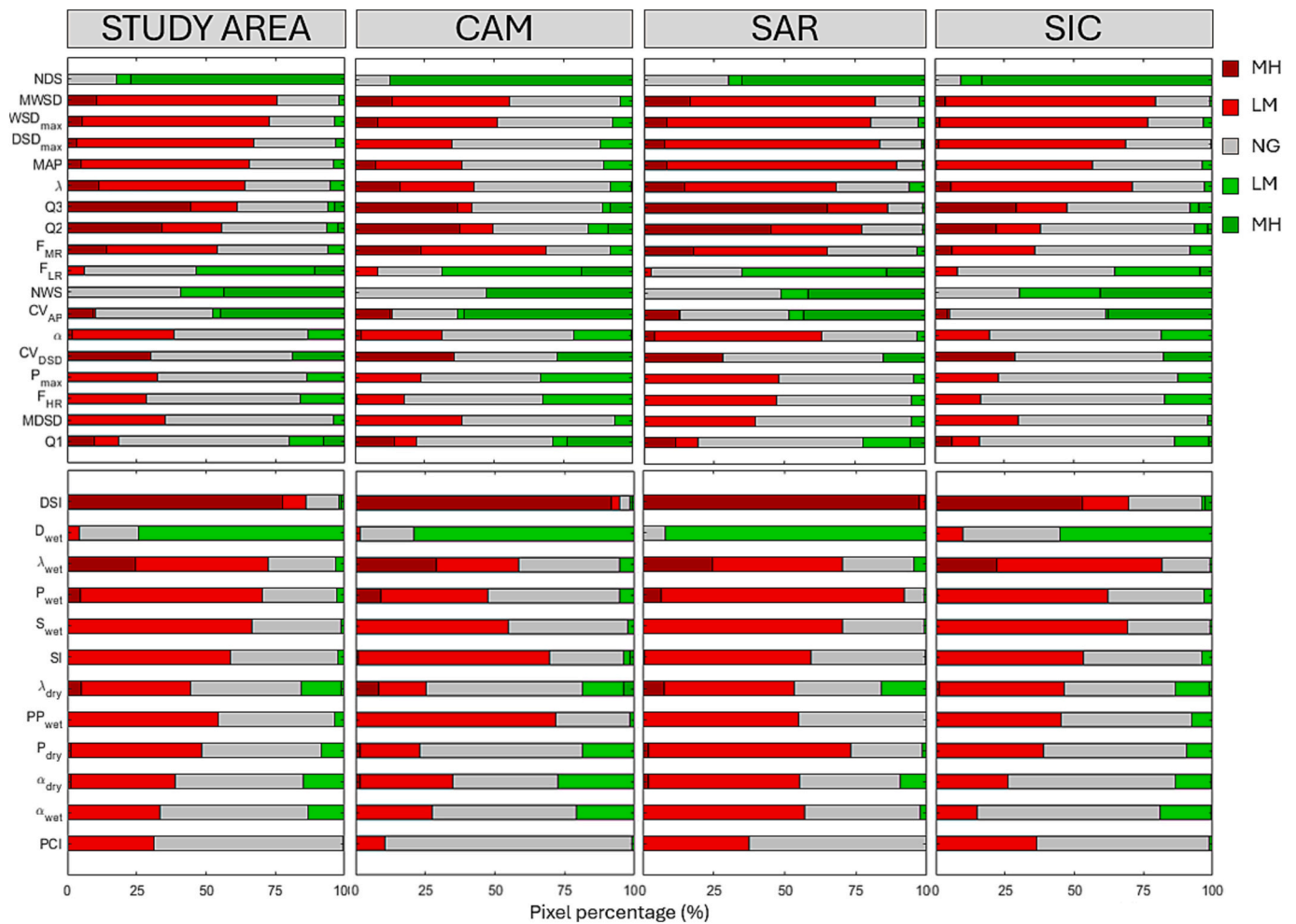


Fig. 12. Percentage of pixels in various trend magnitude classes (classification in Section 2.5.1): MH and LM negative trends (red colour); no trend, including NG negative/positive trends (grey colour); LM and MH positive trends (green colour). Top panels refer to rainfall regime indicators (Table 2), bottom panels to indicators of rainfall seasonality (Table 3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with predominant no trend (51% of stations), although a large percentage of stations (37%) showed increases (positive trends). Moderate shares of stations (from 34% to 45%) exhibit positive trends in Q1, CV_{AP}, NDS, NWS, and λ_{dry} , although partially balanced by a not negligible fraction of stations (>11%) showing significant (and sometimes strong, i.e. MH) negative trends. Only F_{LR} and D_{wet} display a clear dominance of positive trends, reflecting more frequent light rain (consistently with Table 4 and Fig. 3) and a lengthening wet season. Combined with widespread negative trends in DSI and S_{wet}, this points to reduced seasonality driven by an earlier and longer wet season. Despite this, 67% of stations show a statistically significant decrease in the wet season contribution to the annual rainfall (PP_{wet}).

CV_{AP} exhibits the greatest uncertainty, with both high (i.e., μ_t classified as MH) positive and negative trends, plus many stations with no trend, suggesting complex, locally driven variability tied to orography and distance from the sea. Overall, the trends indicate an evident long-term shift toward more arid conditions, with reduced annual rainfall totals, driven mainly by declining wet-season accumulation, despite the overall extension of the wet season. These findings statistically reinforce outcomes from the previous comparison between RP and CP (Table 4).

3.3.2. Trend analysis under the spatial distributed approach

Fig. 12 summarizes trend in rainfall regime (top panels) and seasonality (bottom panels) indicators from the SDA, expressed as the percentage of pixels with negative/positive or no trend, for the full study

area (left panels) and each region. Trends of negligible magnitude (NG) are here treated as “no trend”, while positive and negative trends are classified as low-moderate (LM) or moderate-high (MH) according to Section 2.5. Indicators are ordered by the percentage of pixels with no trend across the full study area. CAM covers 72 out of 101 years (Table 1b), so aggregated full-area results mainly serve as a reference for comparison with GBAT-based trends (Table 6).

Overall, Fig. 12 (top panels) shows results consistent with the GBAT-based findings (Table 6). For instance, NDS and NWS are the only indicators without negative trends; NDS shows predominantly positive trends (75% of pixels), often with MH magnitude, indicating more frequent dry spells, and NWS behaves similarly, but over a smaller area. Conversely, MWSD exhibits the strongest prevalence of negative trends, indicating shorter wet spells, especially in SAR and SIC, and weaker in CAM (~45% of the region). The upper quartile of monthly rainfall (Q3) exhibits the highest percentage of MH negative trends, particularly in SAR, consistently with the GBAT results (Table 6a). By contrast, Q1 showed the highest fraction of pixels without significant trends (~60% of pixels), the rest showing a balanced mix of positive and negative trends, evenly distributed across the four classes. These results highlight an overall reduction in monthly precipitation (also reflected in MAP), accompanied by a redistribution over the year, formerly concentrated in fewer months. This decline in meteorological water availability is further supported by positive trends in F_{LR}, consistently with the outcomes from the GBAT dataset trend analysis (Table 6a).

Seasonality indicators (Fig. 12, bottom panels) reveal shifts from highly seasonal to more evenly distributed rainfall, in agreement with Fig. 6. DSI shows the clearest signal, with $\sim 82\%$ (75% MH) of the study area exhibiting negative trends, consistent with GBAT-based results (i.e., 70% of stations with MH negative trends, Table 6b). In SAR, all pixels show significant negative DSI trends (95% MH) and similar values resulted in CAM. In SIC, 65% of the pixels showed negative trends (50% MH) and 5% positive trends. SI also shows mainly negative, weaker (LM) and less widespread trends than DSI. PCI exhibits the lowest percentage of pixels with negative trends ($\sim 30\%$ of the study area, all LM), with no trend in nearly all the remaining pixels.

The mean duration of wet season (D_{wet}) shows the highest percentage of positive trends ($\sim 76\%$ with LM trends), reflecting a longer wet season (Fig. 5). Indicators related to the dry season (λ_{dry} , P_{dry} , α_{dry}), showed contrasting results, with slight prevalence of no or negative trends but some positive presence. In contrast, wet season indicators (i.e., λ_{wet} , and P_{wet} , except α_{wet}) mostly show negative trends ($\sim 70\%$), indicating that MAP declines are mainly driven by a reduction of rainfall frequency during the wet season, mirrored in PP_{wet} trends (on average across the study area: 50% negative and 45% no trends).

3.3.3. Spatial analysis of trends

The spatial autocorrelation analysis using *Global Moran's I* explores the regional clustering of trends for all indicators. The obtained values of I are presented in Table 7a and 7b for rainfall regime and seasonality indicators, respectively, with regional expected values under spatial randomness, $E[I]$ (Eq. S13, SM), of -0.0075 , -0.0042 , and -0.0039 for CAM, SAR, and SIC, respectively. The regional trend distribution for all indicators shows $I > E[I]$, denoting significant spatial clustering. Focusing on Table 7a, the strongest autocorrelation occurs for NWS in CAM, NWS and NDS in SAR, and MAP in SIC. In contrast, trend distributions for CV_{DSD} , P_{max} , CV_{AP} , and Q1 show low I values, suggesting no dominant regional behaviour and reflecting the large fraction of pixels without trends ($>50\%$ in most cases) and balanced negative/positive trends in the remainder (Fig. 12).

Regional distributions of trends for seasonality indicators (Table 7b) revealed high I values in all regions associated to PCI (highest in SAR and SIC) and λ_{wet} (highest in CAM). In SAR, other indicators, including P_{wet} , PP_{wet} and DSI, show high I (>0.80). Lowest I values occur for DSI in CAM, D_{wet} in SAR, and α_{dry} in SIC. Except for α_{dry} , these indicators tend to exhibit a dominant trend type (mostly negative for DSI and positive for D_{wet}), as shown in Fig. 12.

Local Moran's index assigns a specific index for each individual

spatial unit, allowing the identification of local clusters, where neighbouring units exhibit similar trend magnitudes for a given indicator (i.e., positive spatial autocorrelation with spatial association classes H-H or L-L in the Moran scatterplot), and spatial outliers, where a unit significantly differs from its surroundings (i.e., negative spatial autocorrelation with spatial association classes HL or LH in the Moran scatterplot). In this study, the analysis is applied separately to positive and negative trend magnitudes to avoid mixing opposite behaviours, and thus, when analysing positive trends, negative magnitudes are treated as null, and vice versa.

Temporal reductions in PP_{wet} (clearly evident from Fig. 9 and particularly important for the study area), are illustrated in Fig. 13: top panels (a-c) show spatial patterns of positive (green), negative (red) and no trends (grey, including pixels with NG positive/negative magnitudes), while central and bottom panels map local association classes, based on *Local Moran's index* (see Section 2.5.2), for negative (Figs. 13d-f) and positive (Figs. 13g-i) trends, reporting only meaningful (at 0.05 significance level) cluster/outlier types from the Moran's scatterplot. Across all regions, negative PP_{wet} trends (Figs. 13a-c) dominate (only 10% of pixels exhibit positive trend in SIC, and 2% in CAM), aligning with Figs. 9d-f and spatial autocorrelation results. For instance, in SIC, small central areas with increased PP_{wet} (highlighted in green in Fig. 9h) match the local clusters of positive trends in Fig. 13c, whereas red areas in Fig. 9f are in good correspondence with negative clusters in Fig. 13c. CAM (Fig. 13a) shows more scattered negative trends (Fig. 13d), consistent with low *Global Moran's I* (Table 7b). Positive trend clusters are rare in CAM (Fig. 13g) and absent in SAR (Fig. 13h), in accordance with Fig. 9d and Fig. 9e, while negative trends are highly clustered in SAR (Fig. 13e) and SIC (Fig. 13f).

Analogous analyses of trend distributions for all global metrics of seasonality were performed, with full results provided in SM (Figs. S9-S11). These results highlight high clustered areas within each region, experiencing more pronounced changes in rainfall seasonality than others. Trend maps of the different indicators revealed strong spatial consistency, especially between SI and PCI (Fig. S12, SM).

4. Discussion

This study provides the first integrated assessment of long-term precipitation dynamics in southern Italy, combining extensive temporal depth, spatial coverage, and a multi-method approach (GBA, GBAT, SDA). This framework ensures robustness, comparability with existing literature, and offers a transferable reference for other Mediterranean areas. The wide spectrum of indicators used was proved essential in characterizing rainfall regime and seasonality, with each group of indicators contributing complementary insights. Mean precipitation analysis highlighted changes in water availability, persistence indices captured drought dynamics, and seasonality indicators, including global metrics, described temporal rainfall distribution.

Updated MAP values for 1987–2022, derived through GBA (Table 4) align with recent estimates, which reported $\sim 1200 \text{ mm y}^{-1}$ in CAM (Longobardi and Villani, 2010), and 700 mm y^{-1} in SAR and SIC (Di Piazza et al., 2011; Caloiero et al., 2019). Spatial MAP patterns (Figs. 7a-c) agree with regional evidences (Liuzzo et al., 2016; Caloiero et al., 2019; Longobardi and Boulariah, 2022). Compared to earlier periods (PW and CP), RP shows marked MAP reduction, particularly in CAM and SAR, consistent with GBAT- and SDA-based trends. Over 68% of stations show negative MAP trends (Table 6), corroborating earlier observations in CAM (Avino et al., 2021), SAR (Caloiero et al., 2019), and SIC (Bonaccorso et al., 2005; Arnone et al., 2013), and broader Mediterranean findings (Luppichini et al., 2022; Senatore et al., 2025).

Daily rainfall exceedance analysis under the GBA (Fig. 3 and Table 4) reveals a shift from CP to RP toward higher frequency of light rain (F_{LR}) and lower frequency of moderate rain (F_{MR}), with frequency of heavy rain (F_{HR}) nearly unchanged. These changes, confirmed by trend analyses (via both GBAT and SDA), are most pronounced in SAR, where the

Table 7

Global Moran's I for trends in rainfall regime a) and seasonality b) indicators. Italic font indicates the lowest values of I among the various indicators for each region, while bold font refers to the highest.

a)	b)				b)		
	CAM	SAR	SIC		CAM	SAR	SIC
MAP	0.63	0.77	0.69	S_{wet}	0.57	0.64	0.64
CV_{AP}	<i>0.48</i>	0.65	0.51	D_{wet}	0.56	<i>0.61</i>	0.64
Q1	0.50	0.63	0.48	P_{wet}	0.64	0.81	0.67
Q2	0.59	0.76	0.61	α_{wet}	0.56	0.78	0.57
Q3	0.59	0.73	0.62	λ_{wet}	0.79	0.75	0.67
P_{max}	<i>0.48</i>	0.73	0.48	PP_{wet}	0.48	0.80	0.63
α	0.57	0.79	0.64	P_{dry}	0.63	0.78	0.72
λ	0.64	0.79	0.67	α_{dry}	0.62	0.72	<i>0.51</i>
F_{MR}	0.53	0.66	0.44	λ_{dry}	0.63	0.74	0.65
F_{HR}	0.54	0.72	0.67	SI	0.53	0.79	0.65
NDS	0.61	0.81	0.64	PCI	0.71	0.86	0.74
MDSD	0.57	0.66	0.66	DSI	0.29	0.80	0.72
CV_{DSD}	0.53	<i>0.42</i>	<i>0.42</i>				
$MDSD_{\text{max}}$	0.63	0.53	0.65				
NWS	0.76	0.81	0.65				
MWSD	0.65	0.68	0.62				
$MWSD_{\text{max}}$	0.64	0.68	0.58				

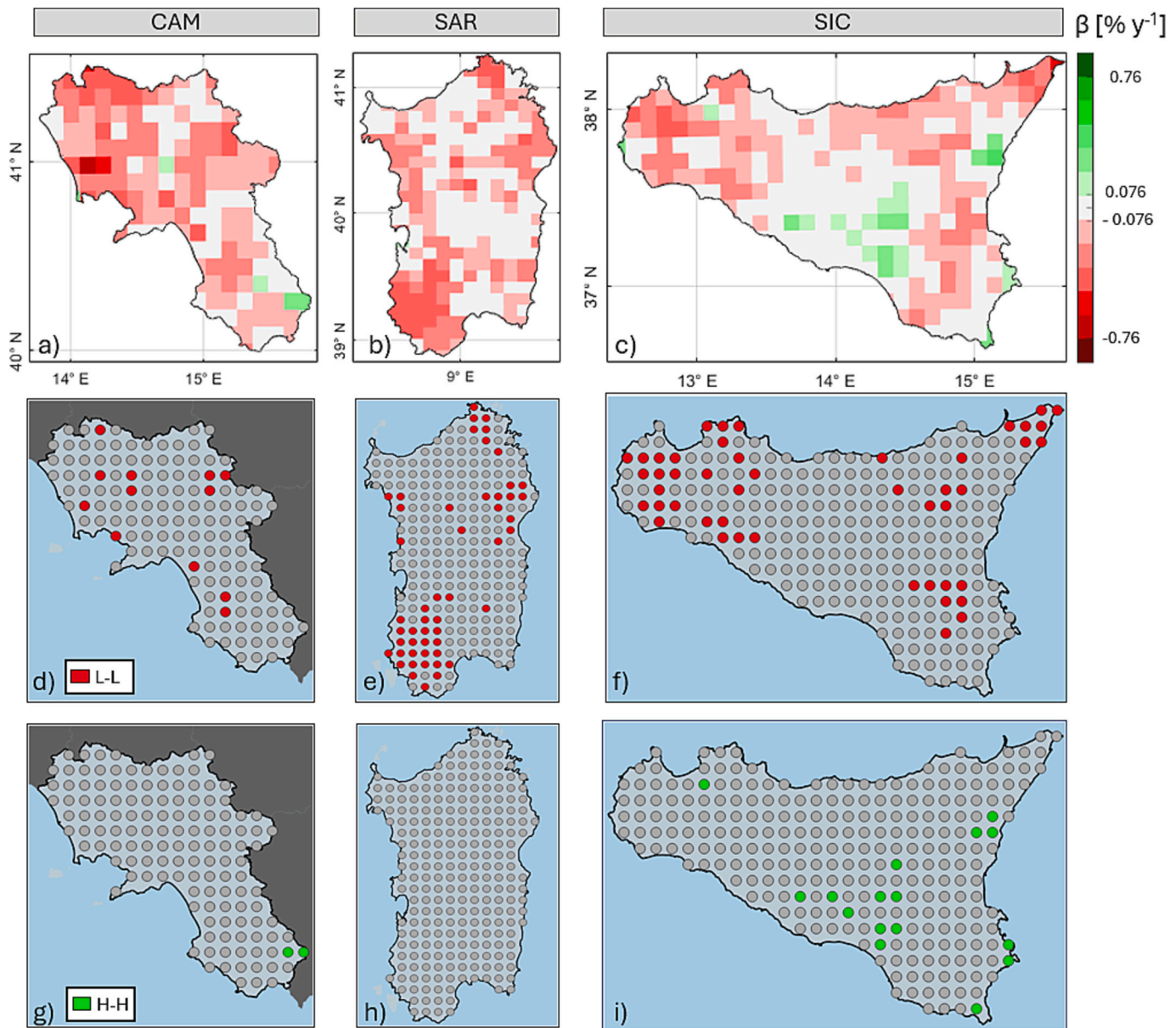


Fig. 13. Spatial distribution of trend magnitudes of the mean wet season contribution to the annual rainfall PP_{wet} (top panels, a–c); the colorbar indicates low-moderate (LM) trends in light red (negative)/green (positive) and moderate-high (MH) trends in dark red (negative)/green (positive), while grey denotes no trends (including negligible, NG, positive/negative trends, with magnitude thresholds reported along the bar). Central (d–f) and bottom (g–i) panels show the distribution of the spatial association classes based on the *Local Moran's* index for negative and positive trends, respectively. Red circles refer to the class L-L (low-value cluster: low trend surrounded by pixels with low trends) while green to the class H-H (high-value cluster: high trend surrounded by pixels with high trends). Left panels refer to CAM (a, d, g), central panels to SAR (b, e, h) and right panels to SIC (c, f, i). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

increase in light events may reduce effective water supply due to interception and limited runoff contributions; this suggests that similar analyses could anticipate water scarcity scenarios under evolving regimes.

Persistence indicators (Fig. 4) indicate that SAR and SIC experience longer dry spells than CAM (e.g., for RP, +20 days in the maximum duration of dry spells for the two islands compared to CAM). Negative trends in the mean duration of both wet and dry spells (MWSD and MDSD, Table 6a and Fig. 12) align with observations in CAM and SIC by Caloiero et al. (2018). Similar values reported for Calabria (located between CAM and SIC) for 1951–2006 (Caloiero and Coscarelli, 2020), highlight a wider susceptibility of southern Italy to drought conditions. Extending this approach to other Mediterranean basins would provide a basis for benchmarking drought intensification across different climatic

gradients.

Seasonality metrics, following Feng et al. (2013), detected changes in the onset and duration of wet and dry seasons. The average duration of the wet season, D_{wet} , in RP (Fig. 5a) agrees with Nasta et al. (2020), who reported 5.4 mo at Gioi Cilento (CAM, 1920–2018). RP shows a slight increase in D_{wet} relative to PW and CP (Table 5 and Fig. 5), especially in the islands, coupled with an earlier wet season onset. The MMK test (Table 6b and Fig. 12) confirms upward trends. In SIC, Pecorino et al. (2024) observed rising summer rain contributions over the last decade; our findings, support this, highlighting shorter dry seasons and negative trends in PP_{wet} .

Global metrics (SI, DSI, and PCI) show a progressive decline in rainfall seasonality for the study area (Table 6b, Figs. 6 and 12), consistent with previous studies (e.g., Nasta et al., 2020 in CAM for SI

and DSI). Sumner et al. (2001), using 410 stations over the period 1964–1994, reported SI values in eastern Spain comparable to those obtained here, underscoring the broader relevance of these indicators across the Mediterranean basins.

The spatial distribution of PCI (Figs. 10a–c and Fig. S5, SM) is consistent with previous studies in CAM (Longobardi et al., 2016; Longobardi and Boulariah, 2022), SAR (Caloiero et al., 2019), and SIC (Cannarozzo et al., 2006; Liuzzo et al., 2016), reflecting orographic and coastal controls (Figs. 10a–c). Temporal PCI patterns (Figs. 11a–c) show declines on SIC's eastern coast, southeastern SAR, and inland CAM. Comparable results were reported by Longobardi et al. (2016) in CAM (1917–2006), where most gauges showed no trend, while Caloiero et al. (2019) found negative PCI trends across SAR (1922–2011), particularly in the south, consistent with our results (Table 6b, Fig. S9 of SM). Cannarozzo et al. (2006) observed negative PCI trends in SIC (1921–2000), especially in western and southwestern areas, in agreement with our longer-period analysis (1922–2022), where 77% of gauges showed significant negative PCI trends. Pascale et al. (2015) provided DSI values of 0.2–0.3 across Italy, coherent with our results, supporting cross-regional comparability.

Overall, this study demonstrates a widespread MAP decline, a shift toward lighter rainfall, prolonged dry spells, and reduced rainfall seasonality across southern Italy and its islands. These patterns mirror signals detected across the Mediterranean and provide a replicable framework for regional-scale assessments. Variations in the teleconnection patterns may have contributed to the observed seasonal shifts in precipitation, including the changes in the onset and duration of the wet season. Large-scale atmospheric circulation models, such as the North Atlantic Oscillation (NAO) and the East Atlantic pattern (EA), influence precipitation across the Mediterranean region and Italy (Mariotti and Dell'Aquila, 2012). For instance, the relationship between rainfall and teleconnection indices was explicitly investigated in Caloiero et al. (2011), and significant correlations were found with large scale circulation patterns, particularly in winter and along the Tyrrhenian side of Southern Italy. Although a detailed attribution analysis is beyond the scope of this study, these circulation patterns likely represent an important driver of the observed rainfall regime variability.

5. Conclusions

A detailed characterization of rainfall regimes and their spatiotemporal variability is essential to understand the impact of global warming on water resource and related hazards, as well as to inform adaptation strategies. However, such analyses are often constrained by incomplete historical records (Prein and Gobiet, 2017; Volpi et al., 2024), while alternative sources as reanalysis products (e.g., MERRA-2, ERA-Interim, etc.) may introduce processing-related biases (Amjad et al., 2020; Jiao et al., 2021; Longo-Minnolo et al., 2022; Xu et al., 2022).

This study addresses these challenges by assembling a unique dataset of over 100 years of daily rainfall from more than 700 gauges across southern Italy, covering Campania (CAM), Sardinia (SAR), and Sicily (SIC), representative of diverse Mediterranean climates. Under the Gauge-Based Approach (GBA), data interpolation was minimized to preserve observational fidelity, selecting the longest continuous time series. In parallel, another generated dataset, Gauge Based Approach Trend (GBAT), aggregated century-long records from 131 gauges, extending trend analyses well beyond the ~50-year window typical of past studies that have separately (for each region) investigated the study area. This allowed exploration of both established and less-studied indicators, including global seasonality metrics. Nonetheless, GBAT data were less representative of CAM, not allowing for regional-scale interpretations. To complement this, subperiods with balanced regional data coverage (PW, CP, RP) were analysed via GBA, and Spatially Distributed Analyses (SDA) confirmed the robustness of results. The good agreement between GBA and SDA also confirmed the limited interpolation effects.

Key findings reveal coherent yet regionally distinctive hydrological signatures, with a persistent decline in mean annual precipitation within the study area, accompanied by greater temporal fragmentation of rainfall, especially in SAR and SIC. Both dry and wet spells became shorter and more frequent. Different global metrics of rainfall seasonality consistently revealed a weakening of rainfall seasonality over time, reflecting a reduced contribution of the wet season to annual totals despite its slight prolongation. Rainy days analysis showed increasing light rain ($< 4 \text{ mm d}^{-1}$) occurrence, balanced by a comparable decline in moderate rainfall ($4\text{--}36 \text{ mm d}^{-1}$) frequency, while relative frequency of heavy rain events remained broadly stable.

These changes point to shared challenges across the study regions, likely extendible to other semi-arid Mediterranean areas, including decreasing water availability and increased drought risk, driven by more fragmented wet and dry spells. At the same time, spatial analyses highlighted localized vulnerabilities, especially in SAR and SIC, where geographic and orographic factors modulate regional variability more strongly than in CAM. Overall, these findings provide a robust reference for sustainable water resource management and territorial planning, underscoring the need for region-specific adaptation strategies that account for both long-term trends and localized climate variability.

Some limitations should be acknowledged. The lack of sub-daily data constrains the assessment of extreme events, which are known to be intensifying across the Mediterranean, and the analysis is based solely on historical observations. In addition, although the Thiessen Polygon Method preserves the fidelity of gauge observations, it does not explicitly account for orographic effects and may therefore introduce spatial biases in areas characterized by strong elevation gradients. No direct comparison with alternative interpolation approaches, such as Kriging, Inverse Distance Weighting, or elevation-adjusted methods, was performed in the present study. Future research should integrate climate projections, hydrological modelling, higher-resolution datasets, and comparative assessments of different interpolation techniques to further strengthen the robustness of spatial precipitation analyses and support decision-making.

CRedit authorship contribution statement

Matteo Ippolito: Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing, Writing – original draft. **Paolo Nasta:** Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization, Writing – review & editing. **Andreas Langousis:** Methodology, Investigation, Conceptualization, Writing – review & editing. **Marcella Cannarozzo:** Methodology, Investigation, Conceptualization, Writing – review & editing. **Nunzio Romano:** Validation, Supervision, Methodology, Investigation, Conceptualization, Writing – review & editing. **Roberto Deidda:** Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization, Writing – review & editing. **Dario Pumo:** Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization, Writing – review & editing, Writing – original draft.

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Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.atmosres.2026.109157>.

Data availability

Most of the original yearbooks are publicly accessible in scanned PDF format at: <https://www.isprambiente.gov.it/en/projects/inland-waters-and-marine-waters/hydrological-yearbooks/>. The fully digitized daily rainfall datasets used in this study were transferred under formal agreements to the research units involved in this study by the respective managing agencies (as detailed in the manuscript). Researchers interested in accessing these datasets are encouraged to contact the agencies directly. Additional data generated in the context of this study will also be made available upon request.

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