Article

High temporal variability not trend dominates Mediterranean precipitation

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State-of-the-art climate models project a substantial decline in precipitation for the Mediterranean region in the future[1]. Supporting this notion, several studies based on observed precipitation data spanning recent decades have suggested a decrease in Mediterranean precipitation[2–4], with some attributing a large fraction of this change to anthropogenic influences[3,5]. Conversely, certain researchers have underlined that Mediterranean precipitation exhibits considerable spatiotemporal variability driven by atmospheric circulation patterns[6,7] maintaining stationarity over the long term[8,9]. These conflicting perspectives underscore the need for a comprehensive assessment of precipitation changes in this region, given the profound social, economic and environmental implications. Here we show that Mediterranean precipitation has largely remained stationary from 1871 to 2020, albeit with significant multi-decadal and interannual variability. This conclusion is based on the most comprehensive dataset available for the region, encompassing over 23,000 stations across 27 countries. While trends can be identified for some periods and subregions, our findings attribute these trends primarily to atmospheric dynamics, which would be mostly linked to internal variability. Furthermore, our assessment reconciles the observed precipitation trends with Coupled Model Intercomparison Project Phase 6 model simulations, neither of which indicate a prevailing past precipitation trend in the region. The implications of our results extend to environmental, agricultural and water resources planning in one of the world's prominent climate change hotspots[10].

Precipitation in the Mediterranean region is characterized by its uneven distribution along the year, with a strong deficit during the warm season. The region is also known for its high spatial and temporal variability in precipitation levels[11]. The substantial year-to-year fluctuations in precipitation are of particular concern due to their significant implications for water resources, a vital asset in the region[12].

The Mediterranean region is subject to the influences of both subtropical circulation and the prevailing sub-polar-frontal low-pressure systems[11], which exhibit substantial variation in position and intensity over annual and decadal time scales[13]. Anthropogenic forcing is thought to have the potential to disrupt these circulation mechanisms, primarily due to the expansion of the Hadley circulation cell and a northwards shift of the subtropical high-pressure belts[14]. The ultimate consequence could be the prevalence of anticyclonic conditions[2], accompanied by a reduction in the occurrence of the extratropical storms that typically impact the Mediterranean region[15]. The most conspicuous outcome of these changes could be a decline in precipitation and the increased frequency and severity of meteorological droughts.

A list of affiliations appears at the end of the paper.

Indeed, a substantial body of climate change projections anticipates a predominant decrease in precipitation across the Mediterranean region through the twenty-first century[1,16]. Should this trend be confirmed, it would carry significant implications for both Mediterranean ecosystems and various human activities reliant on water resources[17]. The ramifications include reduced streamflow and water availability, heightened severity of hydrological droughts[18], elevated forest fire risks[19], increased plant mortality rates[20] and decreased crop yields[21].

Considering the conflicting findings presented by some studies on historical precipitation trends in the Mediterranean region[3,8,9], it is crucial to undertake a thorough assessment of long-term precipitation dynamics. This assessment should make use of the highest-quality and most densely distributed observational network available for scrutinizing the consistency of climate model simulations with historical observations. To address this issue, we utilized a dataset comprising over 23,000 precipitation stations, made possible through a collaborative endeavour spanning the Mediterranean region. This 2-year effort resulted in a dataset that offers a unique opportunity to accurately describe the evolution of precipitation in this region from an unprecedented historical and high-spatial-density perspective.

The dataset underwent quality control, reconstruction and homogeneity correction procedures (Methods). By employing an innovative software-sharing approach, we overcame the data-sharing restrictions imposed by some national meteorological organizations across Mediterranean countries, while making the underlying information accessible. This enabled us to discern annual and seasonal precipitation trends over the long term utilizing nonparametric statistics. We isolated the impact of atmospheric circulation on precipitation dynamics by considering the primary atmospheric indices influencing the region. Additionally, we compared historical precipitation simulations from both Coupled Model Intercomparison Project Phase 5 (CMIP5) and 6 (CMIP6) experiments with observations, enhancing the assessment of the reliability of future precipitation projections in the region.

Observed precipitation trends

Our statistical analysis underscores the substantial temporal and spatial variability in precipitation patterns throughout the Mediterranean region. Annual precipitation trends exhibit notable disparities, in terms of their sign, magnitude and statistical significance, when distinct analysis periods are considered (Fig. 1). Although some stations and periods show statistically significant trends, the overarching pattern is the prevalence of nonsignificant trends. Indeed, even during the periods marked by the most pronounced changes, such as 1951–2020, the proportion of stations exhibiting statistically significant trends remains below 15% of the total.

Heatmaps, which provide an overview of trends across different temporal windows (Supplementary Fig. 1), illustrate that significant trends tend to be concentrated within brief time frames (for example, a few decades) and are characterized by marked spatial variability. This suggests the influence of diverse drivers at sub-regional scales in governing the array of annual precipitation trends across different periods, emphasizing the multifaceted nature of the forcing factors shaping these trends[6,22].

At the seasonal level, the key findings align with those drawn from the annual analysis. The precipitation trends display considerable variability across the examined periods, with nonsignificant trends prevailing over longer time spans and notable spatial disparities (Supplementary Figs. 2–5). For instance, during the period from 1981 to 2020, the Western Mediterranean experienced a widespread decrease in precipitation, dominantly nonsignificant, while the Eastern Mediterranean had an increase in winter precipitation. Even in those cases with the highest proportion of statistically significant trends, such as summer for the period 1951–2020, there persists substantial spatial diversity in the significance of these trends. It is worth noting that the regions where summer mean precipitation is nearly zero (Supplementary Fig. 6) display the most notable decline. In such cases, the changes in absolute precipitation values are minimal, often being just a few millimetres.

Apart from a few localized regions during specific seasons, the seasonal-scale heatmaps do not reveal a prevailing pattern of significant long-term precipitation trends (Supplementary Figs. 7–10). In fact, a consistent reduction in winter precipitation is only observed in the southern regions of the Iberian Peninsula and Morocco across various sub-periods commencing after 1931, although it fails to achieve statistical significance over longer temporal frames (for example, starting from 1871 or 1901).

Aggregating data from many heterogeneous stations to form a regional average would help in capturing overarching trends. However, while some previous studies have suggested a decline in both annual[23] and seasonal[3,23] regional precipitation, this pattern is not corroborated by the extensive dataset utilized in this study. Specifically, when considering the regional average precipitation series, no significant trends are observed at an annual scale across the five analysed periods (Fig. 2). Over the entire period, from series commencing in 1871, 1901 and 1931, the observed decline in precipitation remains below 3%, with a more noticeable decrease emerging from 1951 (−5%). However, this latter trend is influenced by the relatively high precipitation levels in the early 1960s and the lower levels recorded in the 1990s. From the 1980s onwards, there is a discernible rise in precipitation (+8%), albeit without reaching statistical significance.

At the seasonal scale, the mean regional precipitation series exhibit behaviour similar to the annual pattern, except in winter. During winter, there are noticeable declining trends for the periods starting in 1931 (−10.2%) and 1951 (−13.2%). However, it is important to note that these trends do not reach statistical significance when considering the longer time series starting in 1871 (3.1%) and 1901 (−2.9%), as well as the shortest period, from 1981 (6.7%). For the other seasons, the overall pattern remains consistent, marked by high temporal variability and a prevailing long-term stationarity. These findings align with the station data available in public international databases, such as Global Historical Climatology Network (GHCN) and European Climate Assessment & Dataset (ECA&D) (Supplementary Table 1 and Supplementary Figs. 11–16). These sources indicate predominantly nonsignificant changes. However, the limited number of stations and their uneven distribution contribute to significant uncertainties and suggest a more pronounced drying trend in some periods.

Additionally, not only do annual and seasonal precipitation trends display predominantly stationary behaviour, but the characteristics of meteorological droughts, including their duration and magnitude, also exhibit a consistent stationary pattern. This contrasts with some prior studies that have suggested an increase in meteorological droughts in the region[24]. Utilizing the three-month Standardized Precipitation Index (SPI), it was found that only a small percentage of stations exhibited a significant increase in the duration and magnitude of meteorological droughts (Supplementary Fig. 17), even during the period from 1951 to 2020.

The comprehensive findings derived from the extensive dataset employed in this study indicate that annual and seasonal precipitation trends in the Mediterranean region are highly specific to particular areas and time frames, all while predominantly exhibiting stationary behaviour over the long term. This finding appears to contradict previous research that has suggested a regional decline in precipitation[2–4,23]. However, there may be several reasons for this discrepancy. First, the differing focus on time periods contributes to the inconsistency. Many previous studies commenced their analyses in the 1950s or 1960s[25,26] due to greater data availability after 1950. As demonstrated in this study, while the trends are mostly nonsignificant, there is evidence of a decrease in precipitation between 1950 and 2020, particularly during winter. Nevertheless, when examining other periods, whether longer or shorter, the precipitation trends are less pronounced and

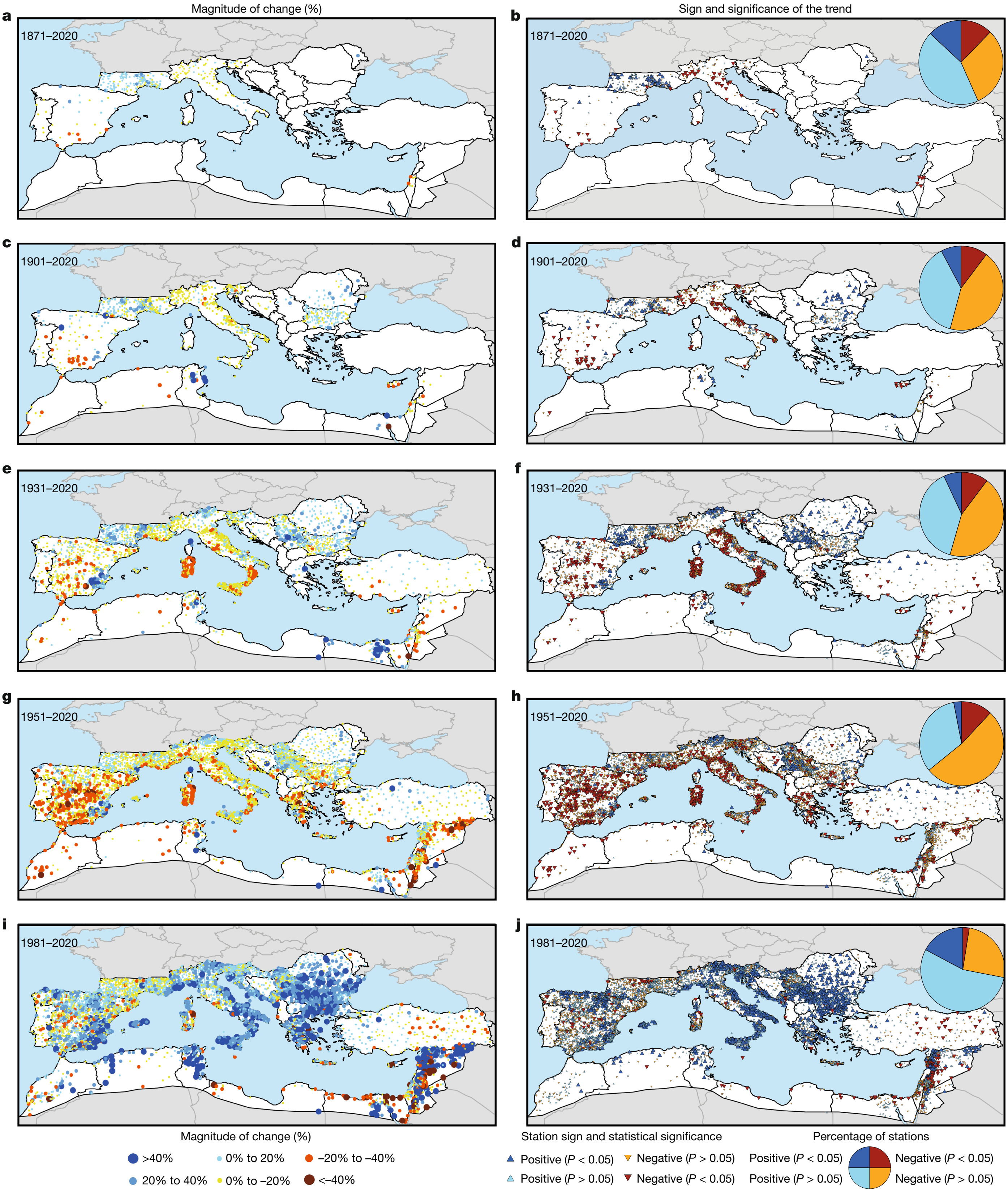

Fig. 1 | Spatial distribution of annual precipitation trend in different analysed periods. a,**c**,**e**,**g**,**i**, Magnitude of the change (in per cent) at each station. **a**, 1871–2020; **c**, 1901–2020; **e**, 1931–2020; **g**, 1951–2020; **i**, 1981–2020. **b**,**d**,**f**,**h**,**j**, Sign and statistical significance of the change at each station. **b**, 1871–2020; **d**, 1901–2020; **f**, 1931–2020; **h**, 1951–2020; **j**, 1981–2020. The circles contain the percentage of stations showing positive and negative significant (and nonsignificant) changes.

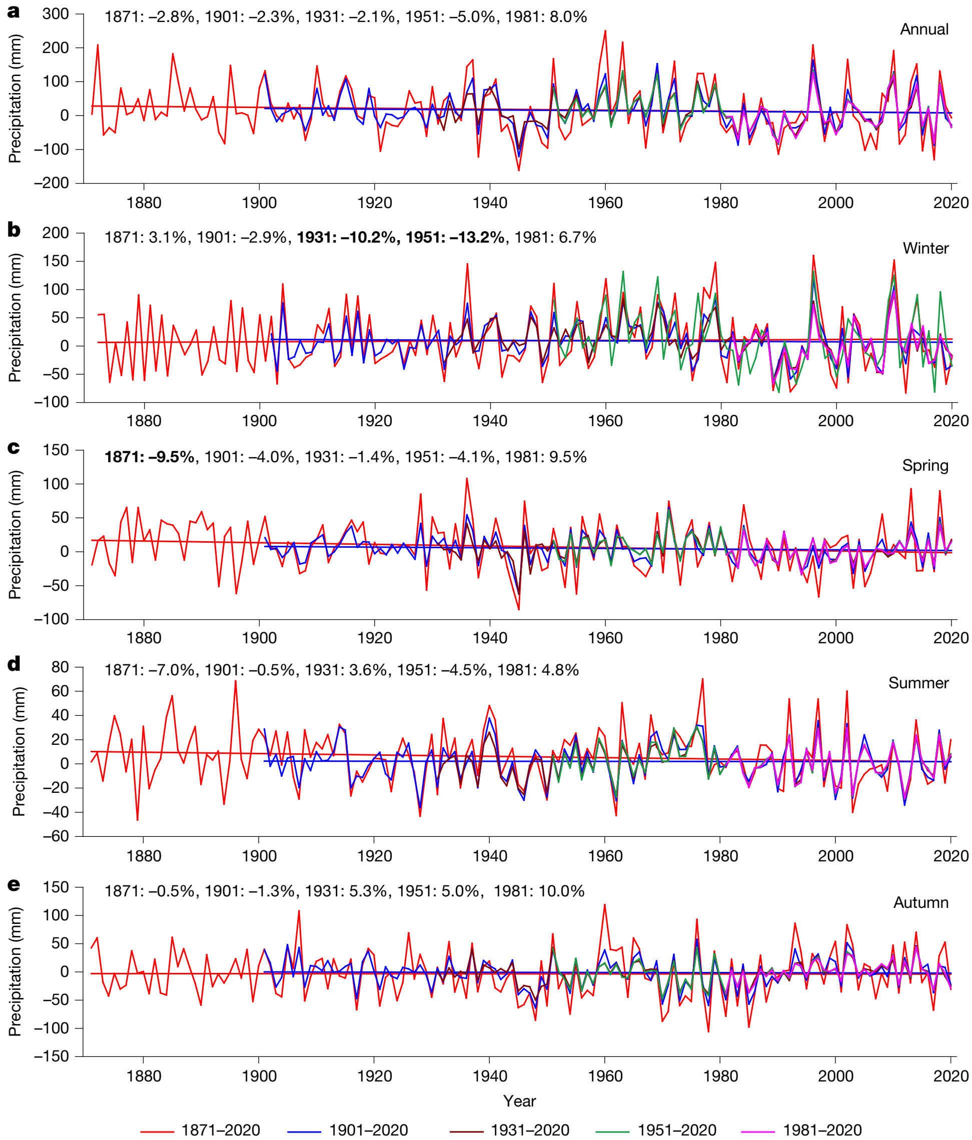

Fig. 2 | Evolution of annual and seasonal average precipitation anomalies over the Mediterranean region. a, Evolution of annual series. **b**–**e**, Evolution of seasonal series: winter (**b**), spring (**c**), summer (**d**) and autumn (**e**). The different lines represent the time series obtained from the available series for five different analysis time frames—1871–2020 (red), 1901–2020 (blue), 1931–2020 (brown), 1951–2020 (green) and 1981–2020 (pink). The anomalies were calculated using the 1981–2020 period as the reference for all cases. The percentages shown in each plot represent the magnitude of change observed for each period, starting from the given date and ending in 2020. Changes that are statistically significant ($P < 0.05$) are highlighted in bold.

less statistically significant, or even exhibit a positive sign. Second, the discrepancy can be attributed to the widespread use of global or continental gridded databases in the Mediterranean region[2,27]. In general, gridded datasets are constructed from a limited set of stations. The unavoidable reliance on spatial interpolation methods in gridded databases can lead to misleading conclusions because trends recorded at a few stations might be extended to represent larger areas with potentially different temporal dynamics. Additionally, the fluctuating number of observations over time—a characteristic of global gridded databases—has had a significant impact on trend assessments[28]. Lastly, the use of observational databases that lack rigorous quality control and homogenization can substantially affect trend evaluation[9].

Influence of atmospheric dynamics

The pronounced decadal and multi-decadal variability inherent in Mediterranean precipitation has been closely associated with large-scale atmospheric dynamics, particularly during the cold season[7,29], as well as thermodynamic processes during the summer[30]. It is plausible that the large-scale atmospheric dynamics have contributed to the observed trends over specific shorter periods[6], which is particularly relevant given that atmospheric circulation in the region is largely attributed to internal variability (Supplementary Information section 3.1).

The results of the stepwise regression models for both the long-term (1901–2020 and 1931–2020) and short-term (1951–2020 and 1981–2020) periods, using the North Atlantic Oscillation (NAO) and Mediterranean Oscillation (MO) indices as independent variables (Methods), show significant percentages of explained variance in annual precipitation variability across the Mediterranean. Specifically, the annual models using the NAO and MO explain between 32% and 39.1% of the variance, whereas models that also incorporate regional circulation mechanisms (storms, ridges and blocks) for the short-term explain over 68% (Fig. 3). Supplementary Tables 2 and 3 detail the atmospheric circulation variables included in the stepwise regression models and their relative importance across different periods. These results

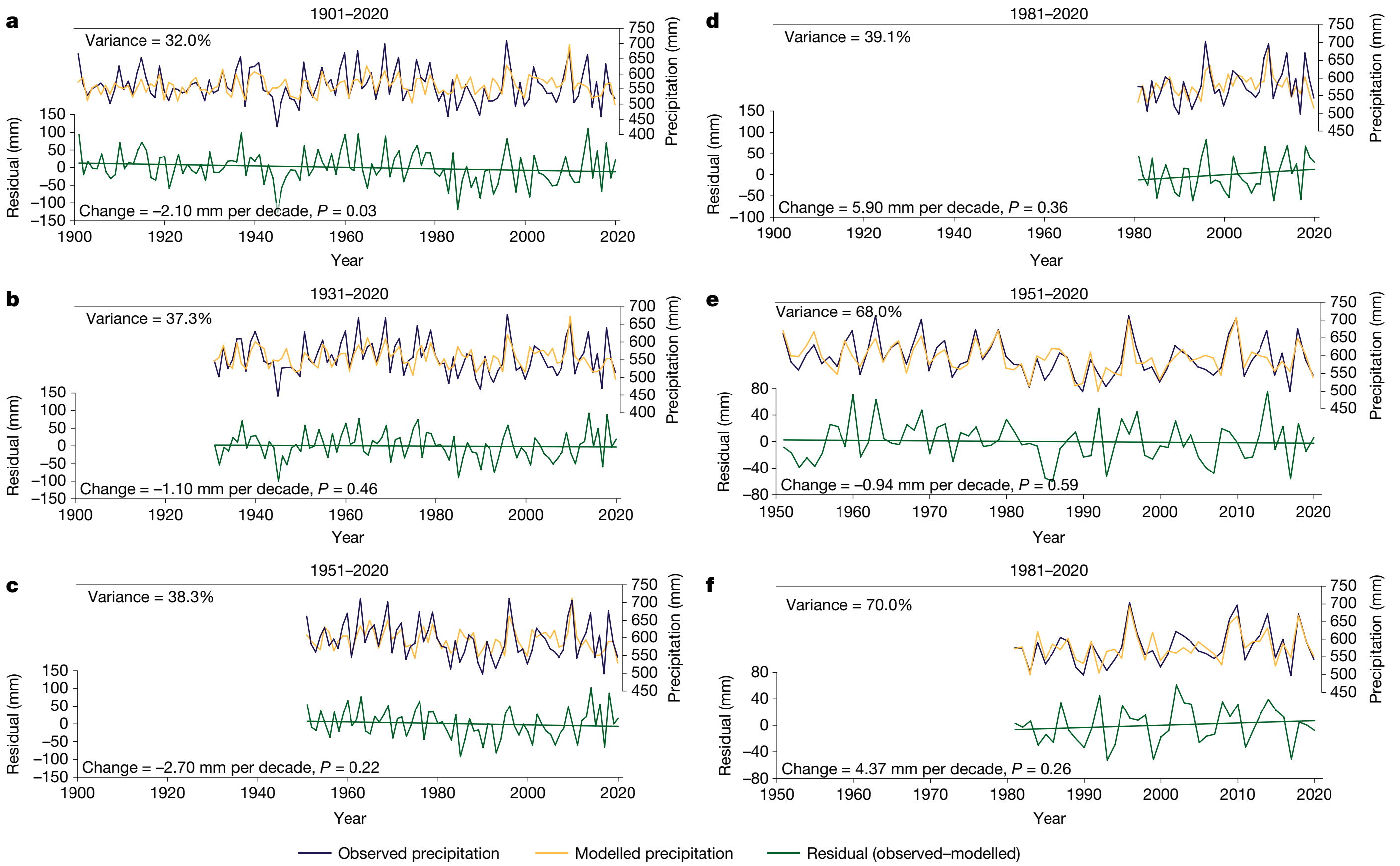

Fig. 3 | Evolution of annual average precipitation over the Mediterranean region for three analysis periods along with the modelled annual precipitation. a–f, Modelled precipitation based on the seasonal NAO and MO (**a**–**d**; **a**, 1901–2020; **b**, 1931–2020; **c**, 1951–2020; **d**, 1981–2020), and the seasonal frequency of storms and presence of ridges and blocks, in addition to the seasonal NAO and MO, exclusively for the periods 1951–2020 (**e**) and 1981–2020 (**f**). Green lines represent the evolution of the residuals for each regression model. The percentage of annual precipitation variability explained by each model is indicated, along with the magnitude and significance of the residual change. The variables and their weights in the models are provided in Supplementary Tables 1 and 2.

indicate that a significant portion of the precipitation variability in the region can be attributed to these circulation indices alone, aligning with earlier research[22,25,31]. Consequently, the identified periods of increased or decreased precipitation in the observational record align well with the statistical models employing these circulation indices as predictors. Of particular note, except for the period 1901–2020, the residuals of these models are temporally stationary throughout the same periods, showing no significant trends and minimal short-term variability. This implies that the majority of the shifts in annual Mediterranean precipitation can be satisfactorily accounted for by the variability in the atmospheric circulation influencing the region.

This pattern is even more pronounced at the seasonal level (Supplementary Figs. 18–21). While disparities are attributed to the distinct roles of the physical mechanisms of precipitation (with a greater role of dynamic mechanisms in winter)[29,32], regional atmospheric drivers (storms, ridges and blocks) generally play a larger role than broader atmospheric circulation modes (NAO and MO), except in winter. Despite these differences, the combined variance of winter precipitation explained by all circulation mechanisms exceeds 58% when using only MO and NAO across the analysed periods (Supplementary Table 2), and reaches 77% when regional circulation mechanisms are included (Supplementary Table 3). Moreover, the residuals from the regression models remain largely stationary over the long term, with low variability in the short-term, especially during the periods 1951–2020 and 1981–2020, where atmospheric dynamics can be robustly quantified using various circulation mechanisms. Indeed, the only area exhibiting a consistent and substantial reduction in winter precipitation across different periods—the Iberian Peninsula and Morocco, for periods commencing in 1931 and thereafter (Supplementary Fig. 2)—shows a prominent influence of atmospheric circulation mechanisms over the temporal patterns of winter precipitation (Supplementary Fig. 22), the observed trends being fully explained by regression models that include only the NAO and MO. In spring and autumn, the atmospheric mechanisms account for a smaller fraction of the precipitation variability, although the residuals exhibit a dominant stability in their evolution. In summer, the sensitivity of precipitation to thermodynamic processes[33] likely accounts for the small percentage of variance not explained by atmospheric dynamics and the declining trend of residuals during the periods starting in 1931 and 1951. This trend may be influenced by disparities in land–ocean warming and land–atmosphere feedbacks, linked to reductions in soil moisture[30,34]. These mechanisms, combined with the significant warming observed in the region[35], likely contribute to reduce relative humidity[36], potentially suppressing convection and associated precipitation. However, it is crucial to reiterate that this decline in summer precipitation affects only an exceedingly small portion of the total annual precipitation and might not be representative in terms of magnitude compared to the role of atmospheric dynamics in the cold season.

In light of these results, it becomes apparent that atmospheric circulation variability is the foremost explanatory factor governing precipitation trends across the Mediterranean region. This finding provides a plausible explanation for the limited number of significant precipitation trends that have been identified. Although previous research has often attributed these trends to anthropogenic forcing[3,5,24], it appears more likely that its impact is, at best, indirect and mediated through potential alterations in atmospheric circulation. However, it is important to emphasize that there is limited evidence of anthropogenic forcing influencing the atmospheric circulation mechanisms (both large-scale and regional) considered in this study (Supplementary Information section 3.1). Although short-term trends have been observed in the primary atmospheric circulation drivers affecting the Mediterranean over brief periods—such as the winter NAO between 1950 and 2000[31]—these trends should be contextualized within century- and millennium-long reconstructions of these circulation mechanisms[37]. This suggests that such trends are probably intrinsic to the natural variability of atmospheric systems, a perspective consistent with the conclusions of the most recent Intergovernmental Panel on Climate Change report[16].

Trends by general circulation models

One of the key factors contributing to the prevailing perception of declining precipitation in the Mediterranean region can be attributed to the outcomes of numerical model simulations. Since the inception of the Coupled Model Intercomparison Project (CMIP), general circulation models (GCMs) have consistently projected a substantial decrease in precipitation across the Mediterranean region over the course of the twenty-first century in both winter and summer[38], accompanied by an increased frequency and severity of meteorological droughts[39]. These trends are especially pronounced under high greenhouse gas emission scenarios[38]. Furthermore, research based on synthetic regional series and multi-model averages derived from CMIP simulations, which employ observed radiative forcing data from since the start of the industrial era, have consistently shown long-term declines in Mediterranean precipitation[2,27,40]. However, the importance of this pattern is not corroborated by the extensive dataset employed in this study.

One notable characteristic of large GCM ensemble datasets is the substantial variability in precipitation outcomes, both on annual and seasonal scales[7] (Supplementary Fig. 23). Consequently, utilizing spatial and temporal averages over a set of different models is not a suitable approach for comparison with observational data. Such averages tend to amplify the effects of external radiative forcing while masking the internal variability within model simulations, which, in fact, is the dominant source of variability.

As an alternative approach, we compared the observed changes in precipitation, based on the extensive observational dataset employed in this study, with complete grid-cell-level data extracted from a wide range of CMIP Phase 5 (CMIP5) and CMIP Phase 6 (CMIP6) model outputs. This comparison revealed that, while the model simulations tend to depict a higher proportion of grid cells with negative trends than seen in the observational data (for example, for the annual scale across the long-term periods commencing in 1871, 1901 and 1931), there are no significant disparities between either dataset (Fig. 4). In some instances, the observational records show a higher frequency of negative trends than the models (for example, annual precipitation starting in 1951 and winter precipitation for periods beginning in 1931 and 1951). Conversely, there are situations where the models do not capture the positive trends found in the observations (for example, winter precipitation starting in 1871 and 1901, autumn for most periods and, overall, all seasons for the period starting in 1981). Nevertheless, these disparities for specific periods are expected because the model simulations are not designed to replicate the observed variability. Nonetheless, it is worth noting that the range of precipitation trends among GCMs is typically narrower than the variation found in the observed data. This difference arises because point observations and gridded data inherently exhibit different characteristics, with point data often showing higher variability. Despite this, there is a convergence in the distributions of trends between point observations and gridded models, particularly in terms of similar averages between the two datasets. This underscores a substantial agreement between observed and modelled precipitation trends.

In summary, analysis of the CMIP model outputs does not point towards a widespread decline in precipitation. Instead, it reflects behaviour consistent with the variability emphasized by the observations. When comparing the trends of the Mediterranean regional precipitation series with those derived from the ensemble of models for the region (Supplementary Fig. 24), it is noteworthy that the observed trends fall within the broad spectrum of trends produced by the models, encompassing both positive and negative values. This corroborates findings from prior studies[26,38], underscoring that, due to this pronounced variability, the extent to which the GCM ensemble mean is representative of the observed precipitation trends is not clear. Notably, not only do the results derived from the observations fall within the range of the CMIP models, even when they approach the upper and lower boundaries, but the model outputs also indicate a prevalence of statistically nonsignificant historical precipitation trends in the region. In fact, the simulations from the CMIP6 experiment reveal that only a limited number of areas, seasons and time spans exhibit more than 50% of the models depicting significant negative trends (Supplementary Figs. 25–29). Additionally, the CMIP6 models outperform their CMIP5 counterparts in replicating observed trends, showing less drying over both long and short durations and a higher prevalence of nonsignificant precipitation trends—a pattern that aligns with the observed data.

These findings serve to harmonize Mediterranean precipitation trends observed in reality with those simulated by models. It is probable that earlier studies, which relied on CMIP Phase 3 and CMIP5 models[3] and used multi-model averages[2,23,27,40], may have led to a mistaken perception of a widespread drying trend in the recent history over the Mediterranean region.

Discussion

Our comprehensive analysis offers a broader understanding of precipitation trends across the Mediterranean region than any previous, scattered study. Although some research has suggested a drying trend in precipitation with a significant influence from anthropogenic forcings[3,5,24], our findings do not support this claim. The results indicate that historical precipitation trends are dependent on the time frame, exhibit strong spatial variability, and are primarily stationary over the long term, whether examined annually or seasonally. These conclusions echo the findings of multi-centennial studies based on data from limited meteorological stations in the northern part of the Mediterranean region, which are marked by their long-term stability and a predominance of pronounced multi-decadal and interannual variability[8].

The atmospheric circulation in the Mediterranean region is characterized by high complexity, and further investigation is needed to clarify the specific impact of the physical mechanisms related to anthropogenic climate change that could lead to a decline in precipitation[7,33]. Recent studies have raised questions about the extent of an amplification of the Arctic influence on mid-latitude climate, with suggestions that its effect could be relatively limited[41], generating uncertainties concerning the dynamic of the Hadley circulation. Although it has been suggested that the Hadley cell has widened in the last few decades in response to anthropogenic forcing[14], observations have suggested noticeable multi-decadal variability[42] driven by internal dynamics[43], and important regional differences, with no substantial changes over the Mediterranean region[44,45]. This circulation dynamic has implications for the presence of anticyclonic conditions and the influence of storms in the Mediterranean region[46]. Furthermore, alternative dynamic mechanisms have been proposed as primary drivers of future Mediterranean precipitation[2,29,47], but they are challenging

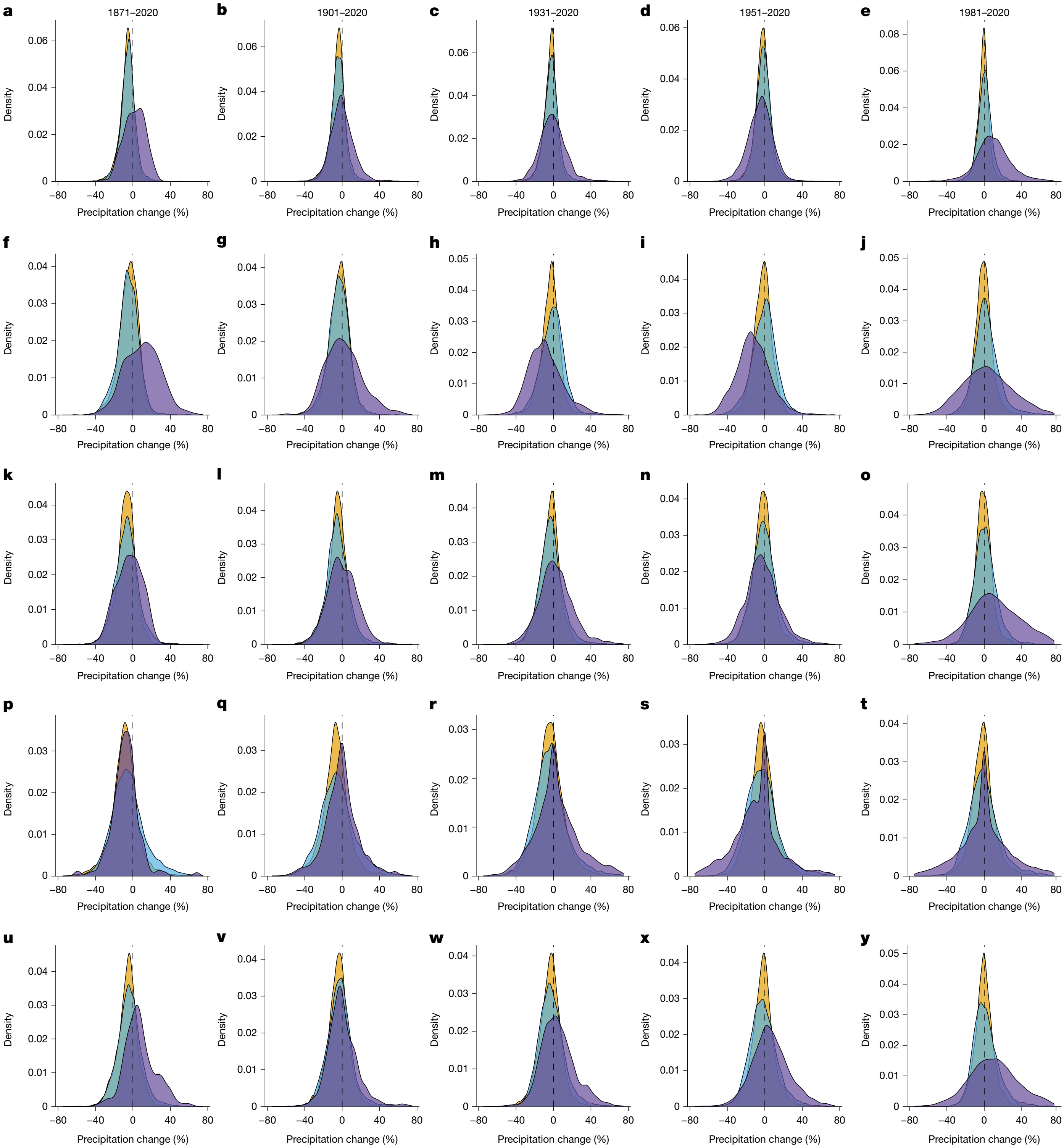

Fig. 4 | Density plots of the magnitude of change in the annual and seasonal precipitation. The density curves represent the available precipitation observatories and all the grid cells from the different CMIP5 and CMIP6 models for the different periods. **a**–**e**, Annual. **f**–**j**, Winter. **k**–**o**, Spring. **p**–**t**, Summer. **u**–**y**, Autumn. Purple: observations, teal: CMIP5, orange: CMIP6.

to assess accurately from CMIP model simulations[7,32,47]. Despite these uncertainties, the most recent round of model experiments (CMIP6) appears to better replicate the observed precipitation trends compared to earlier CMIP iterations. This enhanced model performance provides greater confidence in projecting a decline in precipitation for the Mediterranean region, especially under scenarios characterized by high greenhouse gas concentrations[1].

This study underscores the importance of harnessing the immense potential of available observational databases. It was indeed a challenging undertaking, given the international nature of the dataset used here, which necessitated overcoming different data-sharing protocols and restrictions imposed by participating countries. Our innovative code-sharing approach, however, successfully overcame the bottlenecks related to data availability, enabling us to provide the most accurate and comprehensive assessment of precipitation dynamics in the Mediterranean region to date. This initiative represents a significant step forward, setting our study apart by addressing challenges related to data policies that have constrained previous research. This effort serves as a testament to the fact that, in regions where uncertainties remain about ongoing climate change processes, a focus on existing raw observations can contribute greatly to clarifying these climate dynamics.

In an era marked by the availability of copious climate data, including various reanalysis datasets and model outputs, it is crucial to emphasize the high value of maintaining traditional meteorological station networks. Ongoing efforts in data rescue and archiving are of paramount importance because numerous unexploited data sources hold great relevance for long-term studies[48]. Furthermore, there is an urgent need for the development of regional observation databases, particularly in the countries of the Global South. These databases could help overcome the challenges of data access and facilitate the documentation of climate change in these regions.

Finally, the results of this study challenge prevailing misconceptions about the drying trend in the Mediterranean, underscoring the imperative for further scientific investigation and discussion. It is important to emphasize that, despite the negligible precipitation trends found in the observational record over the last 150 years, the Mediterranean region is indeed undergoing a process of increasing climatic aridity. This trend is primarily being driven by an increase in atmospheric evaporative demand[49], which is a consequence of the substantial observed temperature rise[17,26]. These conditions are expected to intensify in the future, according to climate projections. As a result, the region could experience more severe ecological and agricultural droughts[50]. It is crucial to note that this process of increased aridity is independent of the observed and projected precipitation dynamics. However, the projected precipitation reduction, as indicated not only by earlier CMIP models, but also by the most recent and reliable CMIP6 models for the twenty-first century, could exacerbate this issue by further diminishing water resources for ecosystems and human societies[17]. This underscores the pressing need to address the complex challenges posed by changing climate conditions in the Mediterranean region.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41586-024-08576-6.

1. Douville, H. et al. in *Climate Change 2021: The Physical Science Basis* (eds Masson-Delmotte, V. et al.) Ch. 8 (Cambridge Univ. Press, 2021).
2. Seager, R. et al. Climate variability and change of Mediterranean-type climates. *J. Clim.* **32**, 2887–2915 (2019).
3. Hoerling, M. et al. On the increased frequency of Mediterranean drought. *J. Clim.* **25**, 2146–2161 (2012).
4. Philandras, C. M. et al. Long term precipitation trends and variability within the Mediterranean region. *Nat. Hazards Earth Syst. Sci.* **11**, 3235–3250 (2011).
5. Christidis, N. & Stott, P. A. The influence of anthropogenic climate change on wet and dry summers in Europe. *Sci. Bull.* **66**, 813–823 (2021).
6. Kelley, C., Ting, M., Seager, R. & Kushnir, Y. The relative contributions of radiative forcing and internal climate variability to the late 20th century winter drying of the Mediterranean region. *Clim. Dyn.* **38**, 2001–2015 (2012).
7. Zappa, G., Hoskins, B. J. & Shepherd, T. G. The dependence of wintertime Mediterranean precipitation on the atmospheric circulation response to climate change. *Environ. Res. Lett.* **10**, 129501 (2015).
8. Camuffo, D. et al. Western Mediterranean precipitation over the last 300 years from instrumental observations. *Clim. Change* **117**, 85–101 (2013).
9. Peña-Angulo, D. et al. Long-term precipitation in southwestern Europe reveals no clear trend attributable to anthropogenic forcing. *Environ. Res. Lett.* **15**, 094070 (2020).
10. Giorgi, F. Climate change hot-spots. *Geophys. Res. Lett.* **33**, L08707 (2006).
11. Lionello, P. et al. The Mediterranean climate: an overview of the main characteristics and issues. *Dev. Earth Environ. Sci.* **4**, 1–26 (2006).
12. García-Ruiz, J. M., López-Moreno, J. I., Vicente-Serrano, S. M., Lasanta-Martínez, T. & Beguería, S. Mediterranean water resources in a global change scenario. *Earth-Sci. Rev.* **105**, 121–139 (2011).
13. Hurrell, J. W. Decadal trends in the North Atlantic Oscillation: regional temperatures and precipitation. *Science* **269**, 676–679 (1995).
14. Staten, P. W., Lu, J., Grise, K. M., Davis, S. M. & Birner, T. Re-examining tropical expansion. *Nat. Clim. Change* **8**, 768–775 (2018).
15. Priestley, M. D. K. & Catto, J. L. Future changes in the extratropical storm tracks and cyclone intensity, wind speed, and structure. *Weather Clim. Dyn.* **3**, 337–360 (2022).
16. Gulev, S. K. et al. in *Climate Change 2021: The Physical Science Basis* (eds Masson-Delmotte, V. et al.) Ch. 2 (Cambridge Univ. Press, 2021).
17. Cramer, W. et al. Climate change and interconnected risks to sustainable development in the Mediterranean. *Nat. Clim. Change* **8**, 972–980 (2018).
18. Forzieri, G. et al. Ensemble projections of future streamflow droughts in Europe. *Hydrol. Earth Syst. Sci.* **18**, 85–108 (2014).
19. Turco, M. et al. Exacerbated fires in Mediterranean Europe due to anthropogenic warming projected with non-stationary climate-fire models. *Nat. Commun.* **9**, 3821 (2018).
20. Buras, A. & Menzel, A. Projecting tree species composition changes of European forests for 2061–2090 under RCP 4.5 and RCP 8.5 scenarios. *Front. Plant Sci.* **9**, 1986 (2019).
21. Cammarano, D. et al. The impact of climate change on barley yield in the Mediterranean basin. *Eur. J. Agron.* **106**, 1–11 (2019).
22. Mariotti, A. & Dell'Aquila, A. Decadal climate variability in the Mediterranean region: roles of large-scale forcings and regional processes. *Clim. Dyn.* **38**, 1129–1145 (2012).
23. Mariotti, A., Pan, Y., Zeng, N. & Alessandri, A. Long-term climate change in the Mediterranean region in the midst of decadal variability. *Clim. Dyn.* **44**, 1437–1456 (2015).
24. Gudmundsson, L. & Seneviratne, S. I. Anthropogenic climate change affects meteorological drought risk in Europe. *Environ. Res. Lett.* **11**, 044005 (2016).
25. Xoplaki, E., González-Rouco, J. F., Luterbacher, J. & Wanner, H. Wet season Mediterranean precipitation variability: influence of large-scale dynamics and trends. *Clim. Dyn.* **23**, 63–78 (2004).
26. Cos, J. et al. The Mediterranean climate change hotspot in the CMIP5 and CMIP6 projections. *Earth Syst. Dyn.* **13**, 321–340 (2022).
27. Orlowsky, B. & Seneviratne, S. I. Elusive drought: uncertainty in observed trends and short- and long-term CMIP5 projections. *Hydrol. Earth Syst. Sci.* **17**, 1765–1781 (2013).
28. Beguería, S., Vicente-Serrano, S. M., Tomás-Burguera, M. & Maneta, M. Bias in the variance of gridded data sets leads to misleading conclusions about changes in climate variability. *Int. J. Climatol.* **36**, 3413–3422 (2016).
29. Tuel, A. & Eltahir, E. A. B. Why Is the Mediterranean a climate change hot spot? *J. Clim.* **33**, 5829–5843 (2020).
30. Tuel, A. & Eltahir, E. A. B. Mechanisms of European summer drying under climate change. *J. Clim.* **34**, 8913–8931 (2021).
31. Hurrell, J. W. & Deser, C. North Atlantic climate variability: the role of the North Atlantic Oscillation. *J. Mar. Syst.* **78**, 28–41 (2009).
32. Fereday, D., Chadwick, R., Knight, J. & Scaife, A. A. Atmospheric dynamics is the largest source of uncertainty in future winter European rainfall. *J. Clim.* **31**, 963–977 (2018).
33. Seager, R. et al. Causes of increasing aridification of the Mediterranean region in response to rising greenhouse gases. *J. Clim.* **27**, 4655–4676 (2014).
34. Liu, Y., Garcia, M., Zhang, C. & Tang, Q. Recent decrease in summer precipitation over the Iberian Peninsula closely links to reduction in local moisture recycling. *Hydrol. Earth Syst. Sci.* **26**, 1925–1936 (2022).
35. Doblas-Reyes, F. J. et al. in *Climate Change 2021: The Physical Science Basis* (eds Masson-Delmotte, V. et al.) Ch. 10 (Cambridge Univ. Press, 2021).
36. Douville, H. & Willett, K. M. A drier than expected future, supported by near-surface relative humidity observations. *Sci. Adv.* **9**, eade6253 (2023).
37. Olsen, J., Anderson, N. J. & Knudsen, M. F. Variability of the North Atlantic Oscillation over the past 5,200 years. *Nat. Geosci.* **5**, 808–812 (2012).
38. Lionello, P. & Scarascia, L. The relation between climate change in the Mediterranean region and global warming. *Reg. Environ. Change* **18**, 1481–1493 (2018).
39. Lionello, P. & Scarascia, L. The relation of climate extremes with global warming in the Mediterranean region and its north versus south contrast. *Reg. Environ. Change* **20**, 31 (2020).
40. Christidis, N. & Stott, P. A. Human influence on seasonal precipitation in Europe. *J. Clim.* **35**, 5215–5231 (2022).
41. Dai, A. & Song, M. Little influence of Arctic amplification on mid-latitude climate. *Nat. Clim. Change* **10**, 231–237 (2020).
42. Bronnimann, S. et al. Southward shift of the northern tropical belt from 1945 to 1980. *Nat. Geosci.* **8**, 969–974 (2015).
43. Grise, K. M. et al. Recent tropical expansion: natural variability or forced response? *J. Clim.* **32**, 1551–1571 (2019).
44. D'Agostino, R., Scambiati, A. L., Jungclaus, J. & Lionello, P. Poleward shift of northern subtropics in winter: time of emergence of zonal versus regional signals. *Geophys. Res. Lett.* **47**, e2020GL089325 (2020).
45. Lionello, P., D'Agostino, R., Ferreira, D., Nguyen, H. & Singh, M. S. The Hadley circulation in a changing climate. *Ann. N. Y. Acad. Sci.* **1534**, 69–93 (2024).
46. Zappa, G., Hawcroft, M. K., Shaffrey, L., Black, E. & Brayshaw, D. J. Extratropical cyclones and the projected decline of winter Mediterranean precipitation in the CMIP5 models. *Clim. Dyn.* **45**, 1727–1738 (2015).
47. Tuel, A., O'Gorman, P. A. & Eltahir, E. A. B. Elements of the dynamical response to climate change over the Mediterranean. *J. Clim.* **34**, 1135–1146 (2021).
48. Brönnimann, S. et al. Unlocking pre-1850 instrumental meteorological records a global inventory. *Bull. Am. Meteorol. Soc.* **100**, ES389–ES413 (2019).
49. Vicente-Serrano, S. M., McVicar, T. R., Miralles, D. G., Yang, Y. & Tomas-Burguera, M. Unraveling the influence of atmospheric evaporative demand on drought and its response to climate change. *Wiley Interdiscip. Rev. Clim. Change* **11**, e632 (2020).
50. Seneviratne, S. I. et al. in *Climate Change 2021: The Physical Science Basis* (eds Masson-Delmotte, V. et al.) Ch. 11 (Cambridge Univ. Press, 2021).

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Methods

Data availability

This study used an unprecedented dataset comprising monthly observed precipitation series spanning the Mediterranean region, encompassing 27 countries characterized by diverse socioeconomic and administrative profiles. The countries included in this dataset are as follows: Morocco, Algeria, Tunisia, Libya, Malta, Egypt, Jordan, Israel, Syria, Lebanon, Cyprus, Turkiye, Moldova, Romania, Bulgaria, Greece, the Republic of North Macedonia, Albania, Montenegro, Serbia, Bosnia–Herzegovina, Croatia, Slovenia, Italy, France, Spain and Portugal. The data were directly procured from national meteorological or hydrological agencies that actively contributed to this study. In some cases, data were acquired from national research centres collaborating directly with their respective country's meteorological agency. However, it is noteworthy that meteorological or scientific institutions in Malta, Cyprus and Albania did not respond to our invitations to participate in this study. To ensure coverage for these countries, available precipitation information from continental and global databases—specifically the ECA&D, the GHCN[51,52], and in a few cases the Global Surface Summary of the Day (ftp://ftp.ncdc.noaa.gov/pub/data/gsod/)—was incorporated into our dataset.

The dataset comprises a total of 10,238,736 monthly precipitation records derived from 23,609 stations. These monthly records were computed from daily observations, with the strict requirement that no data gaps were permitted in the calculation of monthly totals. Consequently, the dataset represents the aggregation of over 300 million daily precipitation observations collected by rain gauges. The dataset encompasses an extensive temporal range, from 1871 to 2020. However, it is important to note that the temporal coverage exhibits considerable variability. In 1871, a minimum of 117 stations were available, which gradually increased over time to reach a peak of 12,573 stations in 1977. Subsequently, there was a progressive decline, culminating in 6,186 stations by the year 2020 (Extended Data Fig. 1). The spatial coverage also experienced significant transformations. Initially, the stations were concentrated primarily in the north-western part of the region. However, from 1901 onwards, there was a marked expansion of station coverage in most countries, leading to a high density of stations after 1931 (Extended Data Fig. 2). These fluctuations in spatial and temporal coverage are attributed to the historical development of meteorological networks in various countries, influenced by the establishment of national meteorological services, historical and international conflicts, and divergent digitization efforts by national meteorological services.

Our investigation necessitated the use of restricted data sources to achieve our research objectives comprehensively because previous studies in this area have often been limited by datasets that are either spatially or temporally constrained. These limitations have contributed to an incomplete understanding of precipitation patterns within the region. Publicly accessible global and continental databases contain significantly fewer series compared to those held by meteorological services (Supplementary Fig. 30), failing to capture the considerable variability in precipitation characteristics of the Mediterranean region.

Our access to restricted data aimed to address these gaps, offering a more comprehensive analysis of precipitation variability and trends in the Mediterranean. All available raw data from the different Mediterranean countries were accessible for the analysis. However, its sharing and/or redistribution was subject to the specific policies of each country (Extended Data Fig. 3). Several countries, including Croatia, Egypt, France, Israel, Moldova, Portugal, Romania, Slovenia, Spain and Syria, provided all available raw precipitation data, while Greece and Italy supplied a subset from their stations. This data is available in the following repository: https://zenodo.org/records/12607467. Details regarding the data availability and sharing policies for countries that either did not provide raw data or restricted redistribution can be found in a supplementary Excel file.

We developed and distributed data processing software to national meteorological services and research institutions, with the aim of balancing respect for data privacy concerns with the need for comprehensive analysis. This approach facilitated standardized data processing and maximized the use of available data within the constraints of national data policies, representing a pragmatic solution for conducting a robust climate study in an area with restricted data access.

The developed software was used with the data from the countries that provided information for free, and was distributed to and used by participants from the countries involved in the study who could not share their data given their restricted data-sharing policies. The primary purpose was to process raw monthly precipitation series by conducting various data quality control procedures, a gap-filling process, performing a homogeneity test and rectifying data inhomogeneities. Subsequently, the software was employed to execute the statistical tests, yielding the results presented in this study. The same procedure was applied to the series available from the GHCN and ECA&D databases to replicate the analysis using the currently available data in these public databases.

These tasks were performed by the national teams that could not share their data. To enhance accessibility and replicability, the results for individual countries have been made available as separate files in a public repository (https://doi.org/10.5281/zenodo.10022617). The repository also contains regional precipitation series for the entire Mediterranean region, along with detailed information on the file contents and an example script for accessing and reading the data.

Precipitation quality control and reconstruction

During the quality control phase, precipitation series with durations of less than 10 years were excluded from the analysis. For the remaining series (18,140), each monthly observation was subjected to a comparison with corresponding values from neighbouring stations, after transforming each time series into their empirical quantiles[53]. Observations that exhibited differences in excess of 0.8 units from the average quantiles of the five closest stations within a 200-km radius were flagged as suspicious and subsequently discarded. In addition, the quality control process involved the assessment of chains of zero values. Specifically, all chains comprising more than five consecutive months with zero precipitation were eliminated from the dataset if any of the months in the chain had less than 70% of zero values. Chains of more than eight consecutive months with zero precipitation were also removed unless they encompassed the summer season, during which zero precipitation is a plausible occurrence in the region. The quality control process was applied to 9,997,914 records, resulting in the removal of 23,239 suspicious records—equivalent to 0.23% of the total data. Most of the series showed a percentage of removed records at or near 0% (Supplementary Fig. 31).

An inherent challenge in observational datasets covering extensive time periods, as was the case with the dataset developed for this study, is the fragmented nature of most precipitation series. It is a common occurrence for older observatories to cease operations while new ones are established throughout the extensive time frame under consideration[54–56]. To address this issue, a data reconstruction process was developed. Its purpose was to bridge the gaps in the dataset and generate continuous series of uniform length, free from data gaps.

To address data gaps, we adopted a procedure consisting of filling each gap with the observation from the nearest neighbouring station, after rescaling the records from the neighbouring series to align with those of the candidate series while preserving the temporal variance[57,58]. The selection of neighbouring series was guided by both correlation and distance criteria, requiring a minimum correlation coefficient of 0.7 and a maximum distance of 200 km. Also, a minimum overlapping period of 15 years between both time series was required to correct the bias between them. This approach aligns with previous studies that employed a similar methodology[54,55,57].

To mitigate potential biases and variance differences between the two series (the one undergoing reconstruction and its neighbouring counterpart), the precipitation records were subject to standardization, using data from their overlapping time periods. Notably, precipitation series do not adhere to a normal distribution[59]. Therefore, standardization involved selection from a range of skewed, positive-valued distributions, which included gamma, exponential, general extreme value, generalized logistic, generalized Pareto, generalized normal, lognormal, Pearson type III and Weibull distributions. These distributions are widely employed in the analysis of hydroclimatic data[60–64].

For each station and month of the year, the distribution was selected on the basis of the distribution that yielded the highest *P*-value of the Shapiro–Wilks normality test after standardization[63], ensuring the normality of the standardized series. It is noteworthy that, due to the unique characteristics of Mediterranean precipitation, certain monthly series could not be effectively fitted to any of the candidate distributions, particularly during the summer season in regions where the majority of records registered zero precipitation. These specific series were treated individually and reconstructed by directly utilizing the precipitation values from the neighbouring series, adjusted according to the monthly long-term ratio between the candidate series and the neighbouring region.

The standardized values from neighbouring stations were converted into cumulative probabilities, denoted as $P(X) = p(x \le X)$, and subsequently employed to fill gaps in the dataset of the target station. This iterative procedure began with the closest neighbouring station and extended to progressively more-distant ones, adhering to the previous criteria. To restore the inputted values to their original magnitudes (measured in millimetres), quantiles corresponding to their cumulative probabilities were computed using the data of the target station. As an exception to this procedure, instances where a value of zero precipitation existed in the neighbouring series led to the direct incorporation of such zero values into the dataset of the target station.

We established five distinct datasets based on the following time frames: 1871–2020, 1901–2020, 1931–2020, 1951–2020 and 1981–2020. Within each period of analysis, we exclusively retained series that had at least 75% of their original records fall within the specified time period and that showed no data gaps after reconstruction. However, a small percentage of series that did not meet the 75% threshold for some periods were retained for analysis during those particular periods. This was done because they met the 75% requirement in earlier periods and were necessary to maintain continuity in the analysis across different time frames. Consequently, the number of stations in each set varied accordingly.

As an exception, stations with data gaps accounting for less than 5% of the corresponding time frame were subjected to a secondary reconstruction process. During this process, we relaxed the conditions for auxiliary stations to possess a correlation coefficient (r) exceeding 0.5, with no distance restrictions at the country level. This relaxation allowed for the inclusion of additional series in each respective set. Series that could not be fully reconstructed were eliminated.

Finally, in the case of Libya, where it was not possible to obtain a significant number of complete series, even using the procedure described above, we permitted data gaps of up to 3 years. However, these gaps were subject to the condition that they did not occur within the first or last 5 years of the series, so as not to unduly impact trend analysis. To address these gaps, we employed a strategy of filling them with the 3-year precipitation average from the periods immediately preceding and following the gap.

Most of the series used in our study across various periods have low percentages of reconstructed data (Extended Data Fig. 4), indicating that the analysed series predominantly consist of a high percentage of original data. The number of data gaps filled in the series retained for analysis varies across different periods. However, the percentage of reconstructed data in each series was minimal. The average percentage of reconstructed data across the series for the different periods is as follows: 1871–2020, 11.07%; 1901–2020, 12.42%; 1931–2020, 12.40%; 1951–2020, 10.68%; and 1981–2020, 11.06%. Moreover, there is no significant spatial bias in the percentage of reconstructed data in the series retained for analysis in each period (Supplementary Fig. 32). In the most recent period (1981–2020), some series were used with less than 75% original data, particularly from Tunisia, Italy, Libya and Bosnia–Herzegovina. In these regions, recent conflicts or changes in the management of meteorological networks had led to interruptions in data recording or significant data gaps in the series. Despite these challenges, our conservative data reconstruction approach ensured that the resulting series remained of high quality, with the majority of the original data being preserved in the final analysis.

Our methodology not only filled gaps in the time series, but also modelled the observed precipitation records using data from neighbouring stations—that is, missing data were statistically hindcasted. This approach facilitated the evaluation of reconstruction quality through comparisons between observed and reconstructed series. Monthly reconstructions from each station exhibited a remarkably high level of agreement between the observed and reconstructed precipitation, a relationship assessed using the agreement index[65] (Extended Data Fig. 5). Comparing the available observed and reconstructed data revealed widespread agreement, with the majority of records exhibiting a near-perfect match between observed and modelled precipitation records, irrespective of the season (Extended Data Fig. 6). Importantly, this reconstruction is not influenced by data availability. Even for the 1871–1900 period, during which fewer neighbouring series were available, the reconstruction maintained a comparable level of quality (Supplementary Fig. 33). Moreover, this consistency is not impacted by seasonality.

Precipitation homogeneity

After reconstructing the series, we subjected them to a rigorous homogeneity testing process to identify any potentially suspicious temporal deviations. For each of the 12-monthly series, homogeneity testing was conducted against an independent reference series. Reference series were constructed as the average of the five neighbouring series that were best correlated with the series of the target station, after which all of them were transformed to difference series[66]. Subsequently, the standard normal homogeneity test was employed to identify potential rupture points indicative of inhomogeneities[67]. In the cases where these inhomogeneities displayed a *P* value less than 0.1, they were considered acceptable and subsequently corrected. In such instances, the affected series were split at the detected rupture point, and the oldest of the two subsets was corrected by multiplying it by the ratio between the average values of the records before and after the rupture point[68]. This procedure was repeated for each series until no more inhomogeneities were identified. The homogeneity assessment was initially performed for the series commencing in 1871, and subsequently for those starting in 1901, 1931, 1951 and 1981. Notably, once a series had been corrected for a specific period, it was not subjected to homogeneity testing in subsequent periods, thereby ensuring that a single station did not exhibit different records across the five distinct sets. The number of inhomogeneities identified and subsequently corrected varies from one country to another, contingent upon the quality of the available data. Nonetheless, with the exception of Egypt and Syria, the original data series, on the whole, displayed high temporal quality (Supplementary Table 4). Importantly, the impact of data homogenization on the assessment of precipitation trends was minor. This is evident in the very high spatial agreement between annual precipitation trends (in percent) using the series before and after the homogenization process for different periods. The homogenization process did correct a small number of series affected by problems, but it did not alter the magnitude and spatial trend pattern (Supplementary Fig. 34).

The aforementioned process allowed us to obtain a quality controlled, reconstructed and homogenized dataset, encompassing 307 series, for the period 1871–2020—912 for 1901–2020, 2,908 for 1931–2020, 5,441 for 1951–2020 and 7,151 for 1981–2020. The generated number of series significantly surpasses those derived from the precipitation data available in publicly accessible global and continental databases (Supplementary Table 5). National average series were compiled from all the available stations within each of the five selected analysis time frames. To create a comprehensive regional overview, global average time series were subsequently derived for the entire Mediterranean region. This entailed computing an area-weighted average, where each country's contribution was weighted proportionally according to its surface area. This process ensured a robust representation of regional precipitation dynamics.

Furthermore, we computed the SPI[59] at a three-month time scale for each station across the five analysis periods. These calculations aimed to assess potential changes in meteorological drought occurrence and intensity. We identified meteorological drought episodes by evaluating sequences of consecutive negative SPI values. For each of these episodes, we determined both their duration and magnitude, adhering to established protocols for drought characterization[69,70].

Statistical analysis

The analysis of precipitation changes across the available series for different time periods was conducted using the nonparametric Mann–Kendall test, which assesses both the trend signal and its statistical significance. Notably, the Mann–Kendall test is nonparametric in nature and does not rely on any specific underlying probability distribution of the data. It offers robustness against outlier data, making it a suitable choice for our analysis. As a preliminary step, we applied pre-whitening to the series before conducting the test[71,72].

To evaluate the magnitude of precipitation change, we employed the nonparametric Theil–Sen (TS) regression. The TS slope estimator provides insights into the temporal rate of change, quantifying how precipitation evolves over time (that is, precipitation change per year). Higher slope values indicate more rapid changes in precipitation. Importantly, we expressed the rate of change in terms of relative percent change per year with respect to the TS regression intercept, rather than absolute values in millimetres. This approach enhances the spatial comparability of different stations located in regions with substantially varying precipitation values.

When examining precipitation trends on a seasonal basis, we adhered to the delineation of boreal seasons, including winter (December–February, DJF), spring (March–May, MAM), summer (June–August, JJA) and autumn (September–November, SON).

To ensure a robust assessment of precipitation trends, accounting for the sensitivity of these trends to variations in the study period's length and selection[73], we conducted a systematic analysis encompassing all feasible temporal frames of 30 years or more within each of the four study periods. The results were visually summarized using heatmaps, which illustrate both the magnitude of change and its statistical significance.

Due to the substantial number of stations and time frames, summarizing the heatmaps required the application of principal component analysis in S-mode[74]. This approach enabled the identification of regions exhibiting similar patterns in temporal trends as represented by the heatmaps. In total, we obtained five components for each period starting in 1901, 1931 and 1951 on an annual scale, as well as for each of the four seasons, resulting in a total of 15 components both annually (Supplementary Fig. 1) and seasonally (Supplementary Figs. 7–10). These components were expressed in the same units as the original variables, representing the percentage change in precipitation per year. The weights assigned to each component at each station were also used to calculate the corresponding P values for each component. By mapping the component loadings, we determined the geographical areas where each heat map component was most representative.

Atmospheric circulation indices

To disentangle the influence of natural climate variability and other atmospheric forcing mechanisms from the precipitation dynamics of the entire Mediterranean region, we employed a stepwise regression approach[75]. Details about the methodological approach are provided in Supplementary Information section 3.2. We considered the annual and seasonal precipitation averaged over the Mediterranean region as dependent variables and two large-scale atmospheric circulation indices as independent variables[22,76]. These indices were the NAO[13] and the MO[77] (details in Supplementary Information section 3.3). We purposely excluded other atmospheric mechanisms, such as the Indian Ocean Dipole[78], which impacts precipitation in the Eastern Mediterranean, due to the limited availability of reliable long-term time series[16]. The two selected indices exhibit stationarity over the long term, and their recent dynamics are mostly associated with the internal climate variability (Supplementary Information section 3.1). In addition to the large-scale circulation indices, we utilized regional atmospheric circulation indices, focusing on storm frequency and the occurrence of blocks and ridges impacting the Mediterranean region. Methodological details for calculating these metrics are provided in Supplementary Information section 3.4. The NAO and MO were correlated with the dynamics of these regional drivers (Supplementary Information section 3.5), although they exhibit independent capacities to model precipitation during the cold season.

In our analysis, we focused on the four distinct periods commencing in 1901, 1931, 1951 and 1981. Following the model fitting process (Supplementary Information section 3.2), we examined the trends of the residuals, representing the disparities between the modelled and observed precipitation values. This step aimed to determine whether the observed precipitation trends could be explained by atmospheric dynamics (in which case the residuals would lack a statistically significant trend) or if they were influenced by other factors (indicated by statistically significant trends in the model residuals). We employed the t-statistic to assess the role of each circulation index in explaining precipitation variability.

Climate model simulations

We conducted a comparative analysis of the long-term precipitation trends observed across the Mediterranean region and those derived from climate model simulations over corresponding time frames. The primary objective of this assessment was to evaluate the consistency of model simulations in relation to observational data, rather than attributing trends to anthropogenic factors.

Our comparison encompassed five distinct analysis periods and involved historical simulations from both the CMIP5[79] and CMIP6[80] experiments. Despite the improvements in model physics, parametrization and spatial resolution in CMIP6, signifying potentially more reliable results in this iteration, we decided to include both the CMIP5 and CMIP6 experiments to ensure a more comprehensive evaluation.

For CMIP5, we utilized precipitation data from 47 models representing the historical experiment spanning from 1860 to 2005, as well as the Representative Concentration Pathway 8.5 experiment covering the period from 2006 to 2020. In the case of CMIP6, we employed data from 25 models for the historical experiment, ranging from 1850 to 2014, and the Shared Socioeconomic Pathway 5-8.5 experiment spanning from 2015 to 2020 (Supplementary Table 6).

The choice of Representative Concentration Pathway 8.5 (CMIP5) and Shared Socioeconomic Pathway 5-8.5 (CMIP6) scenarios was based on their alignment with observed CO_2 concentrations for the considered years. Rather than relying solely on the ensemble mean of each CMIP experiment, we incorporated the complete range of individual model simulations. This approach enabled us to account for the uncertainties inherent in a multi-model ensemble.

Supplementary Fig. 35 provides a comprehensive overview of the methodological approach employed in this study. It encompasses various aspects, including data processing and temporal analysis.

Data availability

Details regarding data availability can be found in the Supplementary Table. The files with the raw results from each of the national independent analyses are also publicly available at Zenodo (https://doi.org/10.5281/zenodo.10022618)[81]. The maps for this study were created using ArcGIS v.10.8.2, with country base maps sourced from Esri layers.

Code availability

The source code for the software is publicly accessible at https://github.com/lcsc/mediterraneancalculations, complete with a comprehensive tutorial and a working example.

51. Klok, E. J. & Tank, A. M. G. K. Updated and extended European dataset of daily climate observations. *Int. J. Climatol.* **29**, 1182–1191 (2009).
52. Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E. & Houston, T. G. An overview of the Global Historical Climatology Network-Daily database. *J. Atmospheric Ocean. Technol.* **29**, 897–910 (2012).
53. González-Rouco, J. F., Jiménez, J. L., Quesada, V. & Valero, F. Quality control and homogeneity of precipitation data in the southwest of Europe. *J. Clim.* **14**, 964–978 (2001).
54. González-Hidalgo, J. C., Brunetti, M. & de Luis, M. A new tool for monthly precipitation analysis in Spain: MOPREDAS database (monthly precipitation trends December 1945–November 2005). *Int. J. Climatol.* **31**, 715–731 (2011).
55. Álvarez-Rodríguez, J., Llasat, M. C. & Estrela, T. Analysis of geographic and orographic influence in Spanish monthly precipitation. *Int. J. Climatol.* **37**, 350–362 (2017).
56. Crespi, A., Brunetti, M., Lentini, G. & Maugeri, M. 1961–1990 high-resolution monthly precipitation climatologies for Italy. *Int. J. Climatol.* **38**, 878–895 (2018).
57. Beguería, S. et al. Gap filling of monthly temperature data and its effect on climatic variability and trends. *J. Clim.* **32**, 7797–7821 (2019).
58. Teegavarapu, R. S. V. & Nayak, A. Evaluation of long-term trends in extreme precipitation: implications of in-filled historical data use for analysis. *J. Hydrol.* **550**, 616–634 (2017).
59. McKee, T. B., Doesken, N. J. & Kleist, J. The relationship of drought frequency and duration to time scales. In *Proc. of the Eighth Conference on Applied Climatology* 179–184 (American Meteorological Society, 1993).
60. Yue, S. & Hashino, M. Probability distribution of annual, seasonal and monthly precipitation in Japan. *Hydrol. Sci. J.* **52**, 863–877 (2007).
61. Juras, J. Some common features of probability distributions for precipitation. *Theor. Appl. Climatol.* **49**, 69–76 (1994).
62. Raziei, T. Performance evaluation of different probability distribution functions for computing Standardized Precipitation Index over diverse climates of Iran. *Int. J. Climatol.* **41**, 3352–3373 (2021).
63. Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Loon, A. F. V. & Stahl, K. Candidate distributions for climatological drought indices (SPI and SPEI). *Int. J. Climatol.* **35**, 4027–4040 (2015).
64. Guttman, N. B. Accepting the Standardized Precipitation Index: a calculation algorithm. *J. Am. Water Resour. Assoc.* **35**, 311–322 (1999).
65. Willmott, C. J., Robeson, S. M. & Matsuura, K. A refined index of model performance. *Int. J. Climatol.* **32**, 2088–2094 (2012).
66. Peterson, T. C. & Easterling, D. R. Creation of homogeneous composite climatological reference series. *Int. J. Climatol.* **14**, 671–679 (1994).
67. Alexandersson, H. A homogeneity test applied to precipitation data. *J. Climatol.* **6**, 661–675 (1986).
68. Alexandersson, H. & Moberg, A. Homogenization of Swedish temperature data. Part I: Homogeneity test for linear trends. *Int. J. Climatol.* **17**, 25–34 (1997).
69. Loon, A. F. V. Hydrological drought explained. *Wiley Interdiscip. Rev. Water* **2**, 359–392 (2015).
70. Vicente-Serrano, S. M. et al. Long-term variability and trends in meteorological droughts in Western Europe (1851–2018). *Int. J. Climatol.* **41**, E690–E717 (2021).
71. Hamed, K. H. K. H. & Rao, A. R. A modified Mann–Kendall trend test for autocorrelated data. *J. Hydrol.* **204**, 182–196 (1998).
72. Yue, S. & Wang, C. Y. The Mann–Kendall test modified by effective sample size to detect trend in serially correlated hydrological series. *Water Resour. Manag.* **18**, 201–218 (2004).
73. Hannaford, J., Buys, G., Stahl, K. & Tallaksen, L. M. The influence of decadal-scale variability on trends in long European streamflow records. *Hydrol. Earth Syst. Sci.* **17**, 2717–2733 (2013).
74. Serrano, A., García, J., Mateos, V. L., Cancillo, M. L. & Garrido, J. Monthly modes of variation of precipitation over the Iberian Peninsula. *J. Clim.* **12**, 2894–2919 (1999).
75. Hair, J. F., Anderson, R. E., Tatham, R. L. & Black, W. C. *Multivariate Data Analysis* (Pearson Education, 1995).
76. Mariotti, A. Recent changes in the Mediterranean water cycle: a pathway toward long-term regional hydroclimatic change? *J. Clim.* **23**, 1513–1525 (2010).
77. Conte, M., Giuffrida, A. & Tedesco, S. The Mediterranean Oscillation: impact on precipitation and hydrology in Italy. In *Proc. of Conference on Climate and Water* 121–137 (Academy of Finland, 1989).
78. Cai, W. et al. Increased frequency of extreme Indian Ocean dipole events due to greenhouse warming. *Nature* **510**, 254–258 (2014).
79. Taylor, K. E., Stouffer, R. J. & Meehl, G. A. An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* **93**, 485–498 (2012).
80. Eyring, V. et al. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.* **9**, 1937–1958 (2016).
81. Vicente-Serrano, S. M. Precipitation trend analysis for different Mediterranean countries. *Zenodo* https://doi.org/10.5281/zenodo.10022618 (2023).

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Additional information

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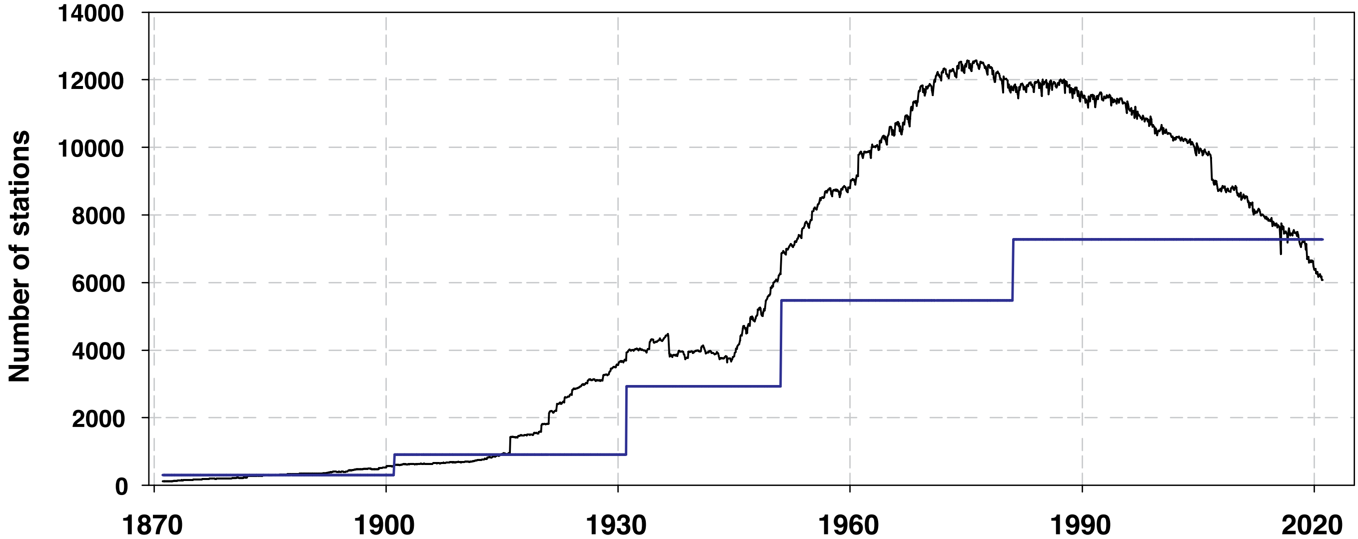
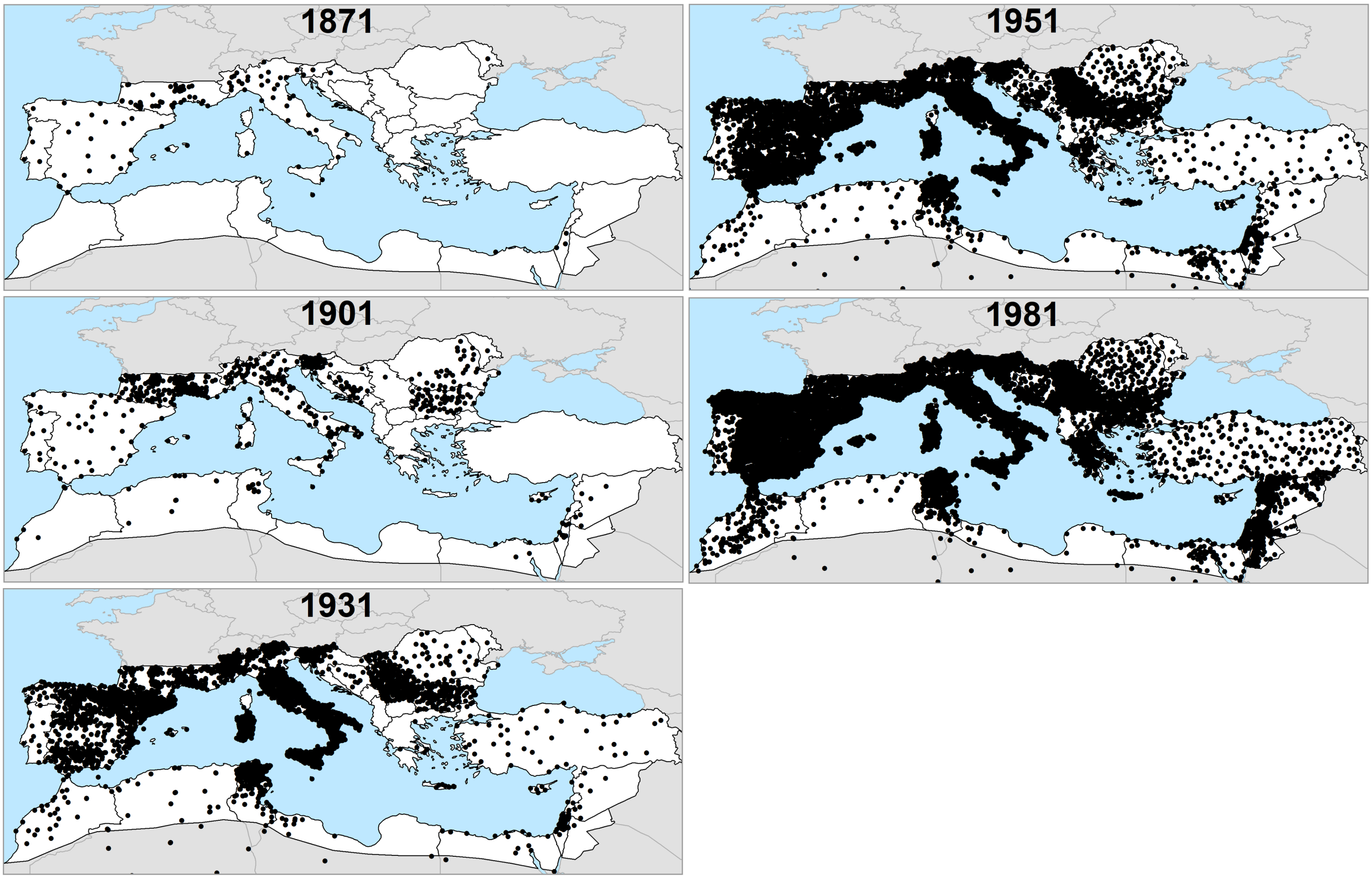
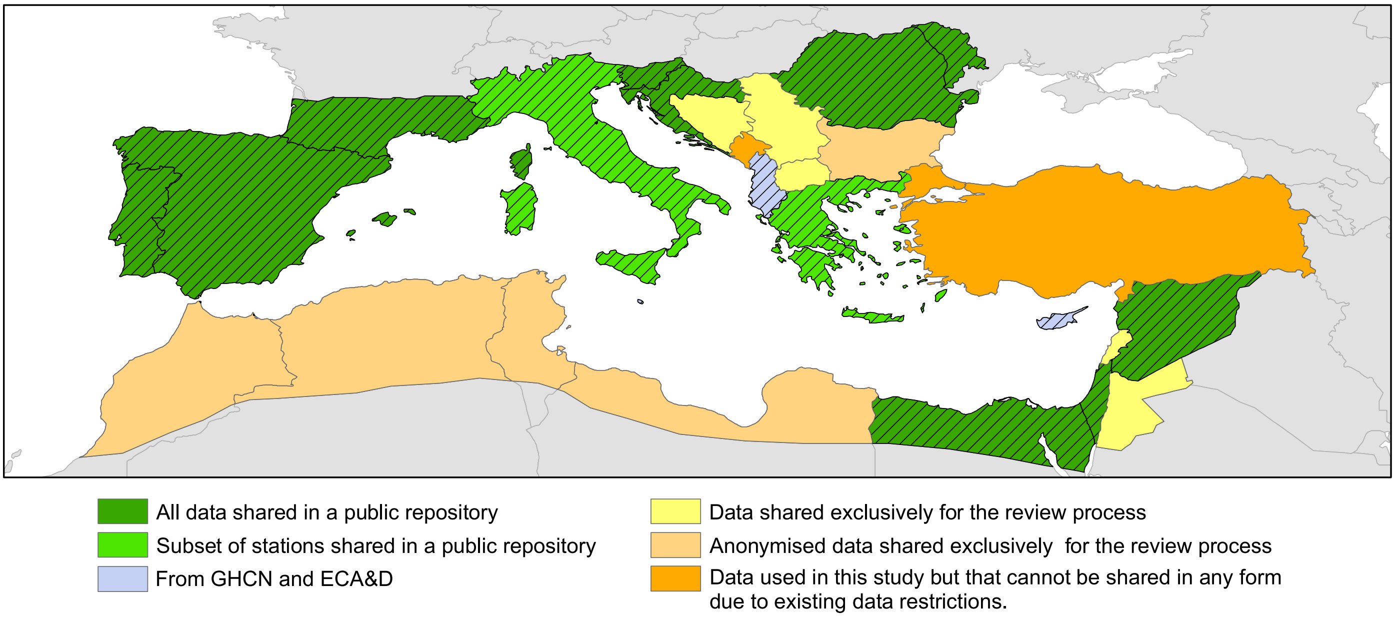


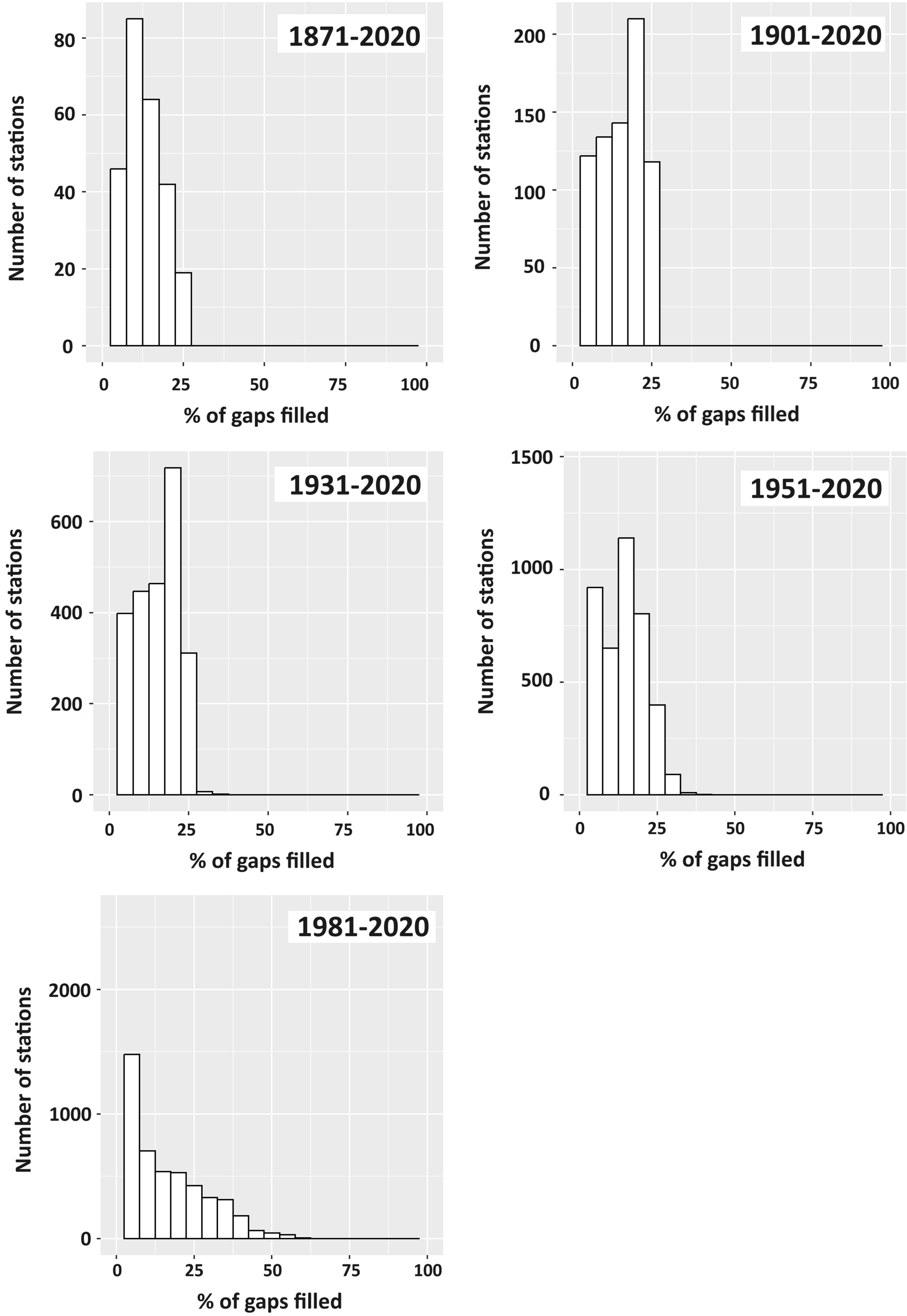
Extended Data Fig. 1 | Evolution of the number of meteorological stations used in this study. In black the number of stations with raw data. In blue the final number of stations reconstructed and homogenized used for each period.



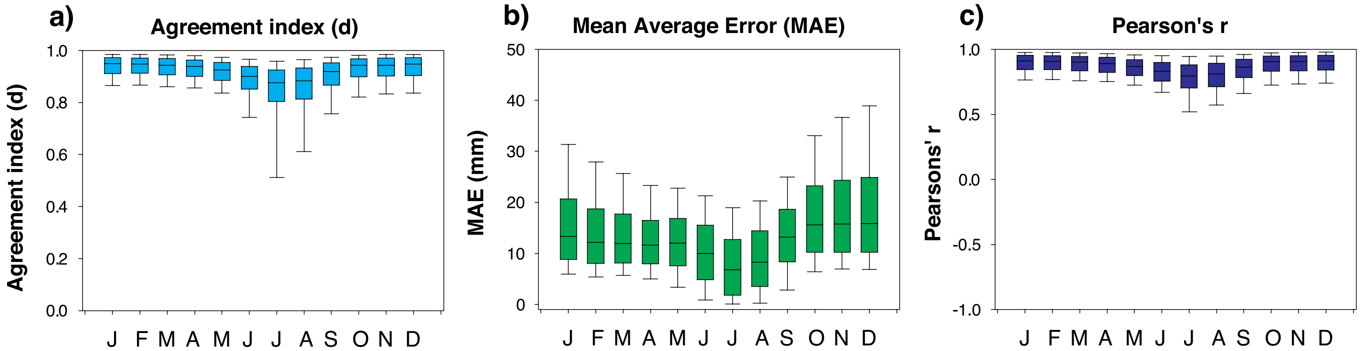
Extended Data Fig. 2 | Spatial distribution of the original available meteorological stations. The information is provided both for the overall total and for the individual periods.



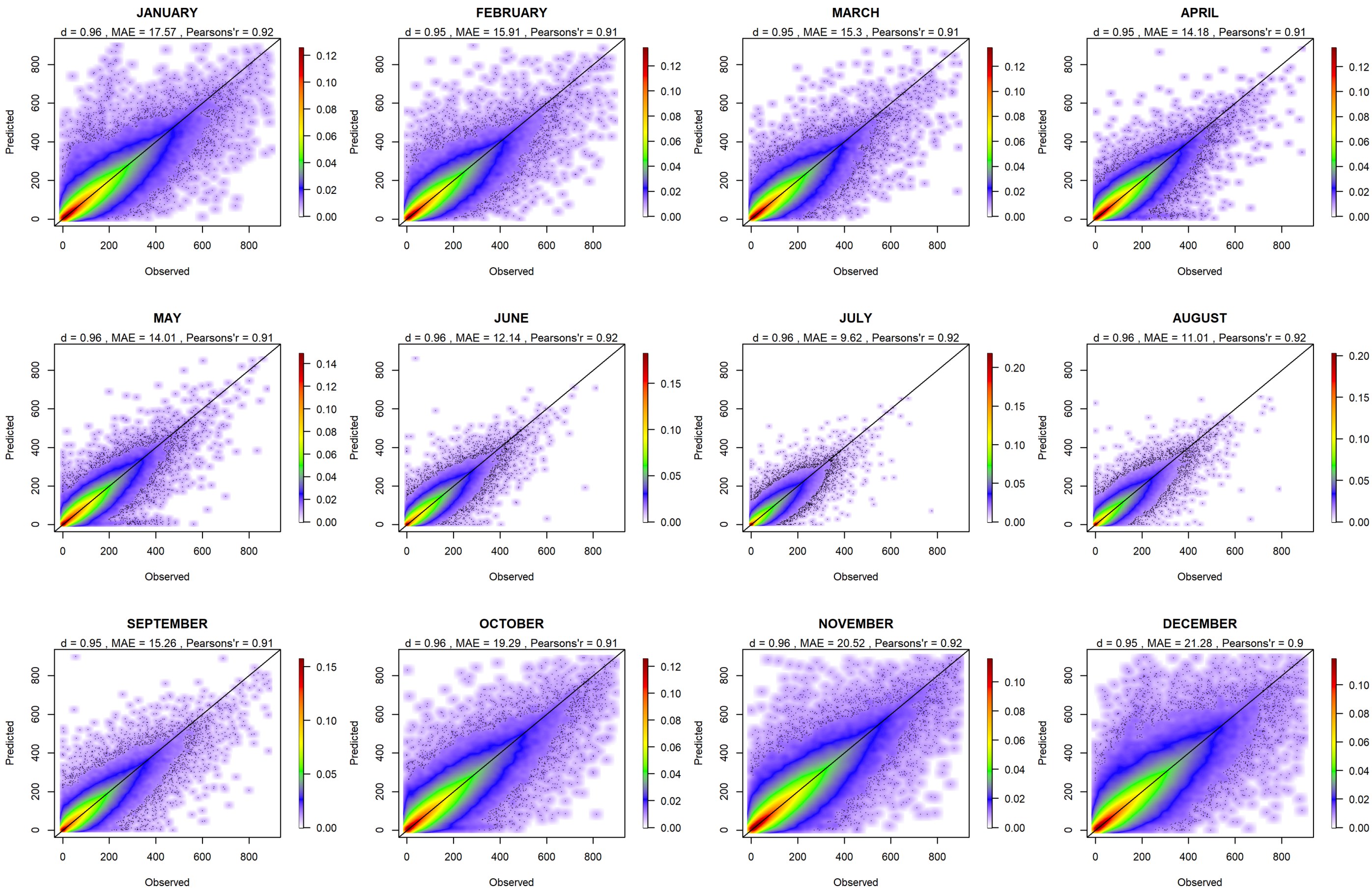
Extended Data Fig. 3 | Data availability conditions for the data used in this study across the various countries involved. Striped lines indicate countries where the data (all data or a subset of stations) are available in a public repository. Find additional details in the Supplementary Excel file.



Extended Data Fig. 4 | Number of stations used for the analysis of precipitation trends across different periods. The data are presented as a function of the percentage of gaps filled in each complete series for the corresponding period.



Extended Data Fig. 5 | Box-plots illustrating agreement and error statistics between observed and modelled precipitation data at the monthly temporal scale. These statistics encompass the agreement index (d), the mean average error (MAE), and the Pearson's r coefficient. Within each box-plot, the central horizontal line represents the median, the shaded box spans the 25th and 75th percentiles, and the whiskers extend to the 10th and 90th percentiles.



Extended Data Fig. 6 | Relationship between observed and modelled precipitation data. The analysis considers the reconstruction procedure for the entire available series spanning from 1871 to 2020. Each plot incorporates agreement and error statistics, namely, d, mean average error (MAE), and Pearson's r. The colours used in the plots represent point densities, while the black points specifically represent a sample of 1,500 points that exhibit a higher level of disagreement between observed and modelled precipitation.