

Article

Identifying Persistent Drought Regions for Mediterranean Basin Using Simple Coincidence Deficit Index Approach

Gökçe Ceylan Akan ¹, Abdurrahman Ufuk Şahin ^{1,*} and Arzu Özkaya ²¹ Department of Civil Engineering, Hacettepe University, 06800 Ankara, Türkiye; gokceceylan@hacettepe.edu.tr² Department of Civil Engineering, Ankara Yıldırım Beyazıt University, 06010 Ankara, Türkiye; a.ozkaya@aybu.edu.tr

* Correspondence: ufuksahin@hacettepe.edu.tr

Abstract: This study introduces the Simple Coincidence Deficit Index (SCDI) and employs Drought Severity Analysis (DSA) to enhance drought detection and assess patterns and persistency across the Mediterranean basin. Utilizing the Global Land Data Assimilation System (GLDAS) based multi-satellite data for precipitation (P) and groundwater storage (GWS), this research applies both SCDI and DSA to visualize and interpret hydrological event time series across the region. The SCDI uniquely combines precipitation and groundwater levels to provide a comprehensive view of drought intensity. DSA tracks the persistence of water deficit and allows straightforward analysis without requiring transformation or normalization, making it easier to use with remote sensing data. The DSA determines the longest drought periods across various time windows, quantifying the number of months a hydrological deficit persists based on groundwater and precipitation data. Findings show that significant deficits are observed in specific months, which become less apparent in shorter time windows ($\Delta = 1$) due to their rarity. Conversely, in broader time windows ($\Delta = 12$), the cumulative effects of these deficits significantly impact seasonal and yearly averages, with implications extending from lower to higher latitudes. Additionally, as time windows extend, the variability in SCDI values increases across all regions, rendering long-term drought conditions more visible, particularly in North Africa. These findings form the basis of future studies focusing on understanding of drought phenomena and enhancing drought predictability using remote sensing data. The proposed DSA and SCDI methodologies represent a significant advancement over traditional indices by offering new tools for more effective drought analysis.

Keywords: coincidence index; drought; GLDAS; groundwater storage; Mediterranean basin



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1. Introduction

Drought is a complex phenomenon with definitions that may vary across disciplines and perspectives [1]. Hydrologists generally describe drought as water deficits in hydrological cycle components (precipitation, soil moisture, river flow, and groundwater) or through its impact on public water supply, irrigation, and hydropower demands [2]. This water deficit indicates the deviation from the normal conditions for a region in interest, but comprehensive understanding also involves factors like water supply, demand, and management, including human intervention [3]. Occurring in diverse climates, drought affects both high- and low-rainfall areas and exhibits a regional nature influenced by meteorological and hydrological factors. While some regions like the Great Plains, Sahel, India, and Australia are commonly associated with drought, areas typically considered water-rich

including Southeast Asia, Brazil, Western Europe, and parts of the eastern United States, may also experience drought [4]. For a broader meaning, drought can also be defined as an extended period of unexpected dry weather resulting in a serious hydrological imbalance from insufficient precipitation which reduces water availability over specific areas and periods [5,6].

Unlike floods, hurricanes, and earthquakes, drought is a natural disaster, characterized by its indistinct onset and end, with its effects developing gradually and sometimes persisting for years beyond its end. This makes droughts crucial considerations in water resource planning and management [7]. Studying drought begins with gathering information about the climate characteristics of a region, requiring both pre-event and post-event climatological data to define the probability of drought events, while indicators of drought initiation may be evident in the region's climatic behavior [4,8]. Increases in global temperature and changes in rainfall distribution are directly linked to the frequency and severity of drought events [9,10]. Consequently, precipitation is the main component of most drought indices, and other critical parameters are essential in assessing drought severity. Thus, using the longest, gap-free, and reliable records is vital for accurately visualizing current and historical conditions [11]. Various methods have been proposed to monitor droughts, combining ground-based and remote sensing approaches to address their respective limitations and strengths.

Drought monitoring is vital for effective management, supporting early warning systems and contingency planning [12,13]. Given the unique climatic conditions of Mediterranean ecosystems, various approaches and tools have been developed to accurately quantify and assess drought impacts in these regions [14,15]. Among these, commonly used indices such as the Standardized Precipitation Index (SPI) [16] and the Standardized Evapotranspiration Index (SPEI) [17] are utilized to monitor drought severity and duration, as well as to explain complex interactions with hot spot regions [18]. Additionally, the Vegetation Health Index (VHI) is widely applied for agricultural drought assessment, further enhancing the overall effectiveness of drought monitoring [19,20]. Mediterranean droughts, particularly during the dry season, reduce groundwater levels and available water in reservoirs [21], which in turn, impacts biodiversity, hinders agricultural production, and affects economic sectors, especially in rain-fed regions like North Africa and the Middle East [22]. In addition to historical data, there is a consensus that climate models consistently project an increased frequency and severity of droughts in the Mediterranean basin, driven by rising temperatures and decreasing precipitation levels [23]. Currently, water resources in the Mediterranean basin exhibit pronounced spatial disparities, with notably limited availability in the southern regions [24]. This severe meteorological drought intensifies hydrological drought due to excessive surface water development and unregulated groundwater abstraction, both of which are further exacerbated by population growth [25]. In addition, forecasting droughts in the Mediterranean basin with seasonal to annual lead times is essential for implementing proactive strategies in agricultural and water resource management [26]. Although no single index can capture all aspects of drought-related problems, the use of multiple drought indices and models significantly improves monitoring accuracy, especially in diverse contexts [11,27]. Among the indices, ground-based drought indices are more accurate but limited in coverage, while remote sensing indices offer broader coverage with lower precision. Ref. [28] demonstrated that the bias-corrected random forest (BRF) model effectively monitors drought with sparse ground observation networks, highlighting the complementary roles of both observation methods. Space observations with high spatial and temporal resolution greatly enhance drought assessment [29], enabling the monitoring of drought-related variables over larger temporal and spatial scales compared to traditional in situ measurement-based results [30,31]. Ref. [32] further

highlighted that satellite-based rainfall products, particularly Modern-Era Retrospective Analysis for Research and Applications (MERRA)-Land, offer more accurate precipitation estimates compared to ground-based observations. Similarly, the Gravity Recovery and Climate Experiment (GRACE) Drought Severity Index (GRACE-DSI) utilizes detrended total water storage (TWS) time series to eliminate the influence of non-climatic factors on TWS, thereby providing a more accurate reflection of drought conditions [33]. However, the effective use of drought indices, including GRACE-DSI, is often limited by the need for long-term climatic data [34], an understanding of statistical distributions [35], and the necessity of data transformation [36].

Given these challenges, the importance of drought research is increasing not only in the Mediterranean but also in West and Southwest Asia, as these regions confront significant vulnerabilities related to water shortages and climatic variations. With predominantly arid and semi-arid climates, the regions in Southwest Asia are intensely prone to drought-related challenges. Studies have shown that major climatic events like La Niña play a crucial role in triggering droughts, as evidenced by the severe drought periods of 1999–2001 and 2007–2008 [37,38]. In these regions that experience severe drought conditions, the duration of drought recovery tends to be extended [39] while forests exhibit the greatest levels of resistance and resilience to such events [40]. Additionally, the dynamic interplay between regional synoptic storms and the wave energy from increased tropical precipitation in the Indian Ocean has been identified as a key driver of drought conditions in Central and Southwest Asia [38]. Moreover, climate models predict deteriorating drought conditions across these regions as a consequence of global warming. For instance, ensemble forecasts from the Coupled Model Intercomparison Project Phase-6 (CMIP6) models predict that South Asia will see marked escalations in drought severity, with significant increases in their duration, frequency, and intensity [41]. Likewise, projections indicate a future where West Asia, particularly northern regions, will endure more frequent and severe droughts due to a reduction in average rainfall [42]. The historical and anticipated patterns highlight the critical need for robust drought mitigation and adaptation strategies. The ongoing aridification and the expansion of arid zones throughout the past century in dryland Asia, including parts of West Asia, underscore the immediacy of implementing both immediate and sustained interventions to counter the escalating risk of drought [43]. Furthermore, insights gained from studying moisture dynamics during extreme drought episodes, like those observed in Southwest China, are invaluable for enhancing water resource management and drought resilience in similar settings [44].

In this study, the newly developed Simple Coincidence Deficit Index (SCDI) and Drought Severity Analysis (DSA) were applied by integrating remote sensing datasets of The Global Land Data Assimilation System (GLDAS) based precipitation (P) and ground-water storage (GWS) across the Mediterranean basin. The analysis involved calculating and visualizing the joint fraction of occurrence and the number of occurrences within the specified time domain, enabling the evaluation of different regions in the basin across various time windows to capture the cumulative effects of drought. Additionally, changes in drought severity as percentages between these time windows were assessed, revealing the influence of latitude on drought dynamics. In other words, this study aims to evaluate the effectiveness of SCDI and DSA in overcoming specific challenges, such as inconsistencies in traditional index definitions and enhancing the capability to capture data coincidences and their spatiotemporal variability as required. This approach aims to improve the precision of drought monitoring in the Mediterranean basin through the application of GLDAS-based remote sensing data. To the best of the authors' knowledge, such an approach has not been previously applied for identifying spatiotemporal drought patterns with latitude-based variations in severity.

2. Study Area

2.1. Dataset Information

The NASA Goddard Earth Sciences Data and Information Services Center (GES DISC) provides Land Data Assimilation System (LDAS) datasets and the ability to give subset data both spatially and temporally. These datasets include the Global LDAS (GLDAS), North American LDAS (NLDAS), National Climate Assessment-LDAS (NCA-LDAS), and Famine Early Warning Systems Network LDAS (FLDAS). GLDAS provides high-quality, global land surface fields to enhance weather and climate prediction, water resource applications, and water cycle investigations. A massive archive of modeled and observed, global surface meteorological data and parameter maps has been obtained from the project results [45]. GLDAS is a high-resolution, global terrestrial modeling system that combines satellite and ground-based observations to generate optimal fields of land surface states and fluxes in near-real time [46]. The spatial resolution of GLDAS data is 0.25 degrees. GLDAS data can be served on several time resolutions such as daily, weekly, and monthly, for specific parameters. It is designed to produce high-quality data by integrating satellite and ground-based observational data products using land surface modeling and data assimilation techniques [45,47]. This system provides extensive runoff data, which are especially valuable for assessing water resources in areas with limited gauging stations. Additionally, GLDAS data have been used to evaluate land–atmosphere coupling through soil moisture and precipitation data, highlighting its importance in understanding hydrological processes [48]. Researchers have effectively utilized GLDAS data to monitor extreme agricultural drought events, analyze changes in groundwater storage, and evaluate soil moisture variations across diverse regions [49–51]. Overall, GLDAS is a valuable resource for researchers studying a range of environmental and hydrological phenomena, due to its comprehensive and reliable data outputs.

GLDAS offers comprehensive datasets that are invaluable for global data assimilation; however, there are some challenges related to data continuity, resolution, and potential biases that may impact its utility. Issues with data continuity were highlighted in the studies, including substantial precipitation inaccuracies in 1996 and temperature discrepancies during 2000–2005 [52]. GLDAS also fails to incorporate human modifications to hydrological processes, resulting in considerable errors in runoff predictions, notably in areas such as the Tibetan Plateau [53]. In terms of spatial resolution, while GLDAS provides extensive global coverage, its resolution may be inadequate for detailed local analysis. Instances where lower-resolution datasets like GLDAS outperform higher-resolution ones such as NLDAS suggest that resolution alone does not dictate the efficacy of these products in capturing accurate data [54]. Systematic overestimations in soil moisture and biases in arid conditions or during seasonal changes are also apparent [55], and underestimations in snow water equivalent are observed due to deficiencies in atmospheric forcing information and model resolution [56]. Despite these highlighted limitations, GLDAS operates on a global scale, integrating a vast array of satellite and ground-based observational data. This integration is crucial for modeling extreme weather processes, particularly in ungauged regions characterized by complex topography.

2.2. General Information About the Mediterranean Basin

The Mediterranean basin (Figure 1) is recognized as a hotspot for climate change due to its unique climate characteristics and vulnerability to climate change impacts. Therefore, drought is a significant concern with the potential for increased frequency and severity in the region [57]. The Mediterranean basin, located at approximately 30°–50° N latitude and 5° W–45° E longitude, is a region of profound ecological and environmental significance. Encompassing countries such as Spain, Italy, Greece, and Turkey, the Mediterranean basin is

characterized by a diverse range of livelihoods, including agriculture, tourism, and fishing. Covering an area of around 2.5 million square kilometers, the basin is known for its unique climate, featuring hot, dry summers and mild, wet winters. However, the Mediterranean basin is widely affected by human-induced environmental changes, driven by climate factors, population growth, pollution, unsustainable practices, and non-native species. These changes impact both ecosystems and human communities. As global and regional trends persist, these impacts are expected to intensify, particularly if global warming exceeds 1.5 to 2 °C above pre-industrial levels. Consequently, significantly greater efforts are required to adapt to these changes, mitigate their underlying causes, and enhance the resilience of nature [58].

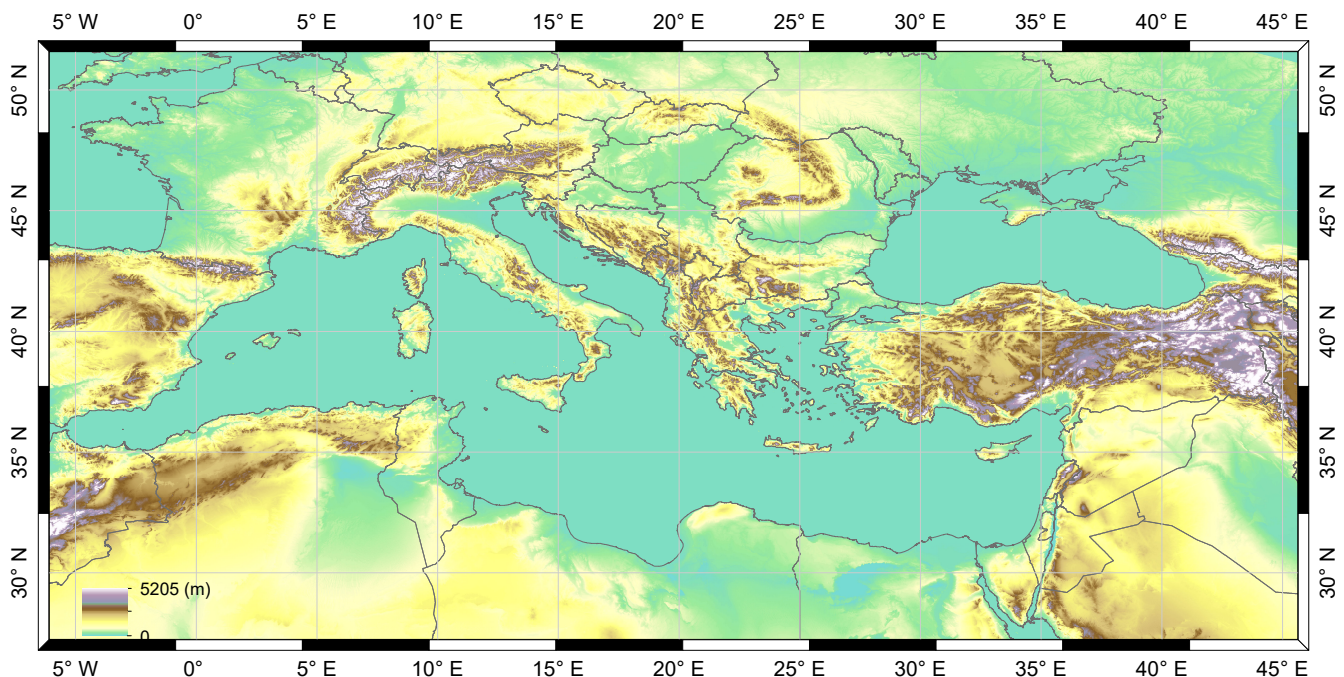


Figure 1. Mediterranean basin.

Groundwater storage and precipitation parameters are vital for the effective detection and management of drought in the Mediterranean basin. This region experiences challenges stemming from uneven seasonal distribution of precipitation, with most rainfall occurring in winter while dry summers exacerbate water management difficulties [59]. Groundwater depletion during droughts poses a threat to future water security, emphasizing the need to monitor groundwater levels and adapt management strategies [60,61]. Furthermore, the effect of climate change on precipitation patterns and evaporation rates in the Mediterranean basin underscores the necessity of effective drought monitoring and management plans to mitigate its impact on water resources [62,63]. Therefore, this paper focuses on analyzing groundwater storage and precipitation datasets for drought detection and index calculations in the Mediterranean basin.

In this study, data from GLDAS were utilized to calculate the changes in precipitation and groundwater storage for the period 2003–2023. The dataset, GLDAS Noah Land Surface Model L4 monthly $0.25^\circ \times 0.25^\circ$ v2.1 (GLDAS_NOAH025_M), was gathered from GES DISC. Since changes in groundwater storage and precipitation are typically the largest and most crucial components of terrestrial water storage variation, the datasets were analyzed in detail on a monthly and 0.25° spatial resolution. Figure 2 was generated by aggregating monthly groundwater storage and precipitation data on an annual basis, from which the mean values were computed for the Mediterranean region covering the period from 2003 to

2023. Defining a drought cycle typically requires data spanning several decades to centuries to accurately reflect observed regional and specific cyclic patterns. For instance, research has identified a 208-year drought cycle in the Yucatan Peninsula linked to solar activity [64]. In Portugal, drought cycles with periodicities of 2.4, 3.6 and 13.4 years have been observed, varying by region [65]. In Central Asia, tree-ring data analysis has revealed drought cycles ranging from 2.1 to 10.8 years, with additional longer cycles of 30–40 years also noted [66]. Utilizing a dataset spanning 20 years, it is postulated that while long-term trends may be discernible in some regions, decadal variability has been addressed across all regions. The inclusion of projected datasets for these regions in future studies may provide more definitive conclusions regarding long-term trends.

Panel (a) of Figure 2 displays the spatial distribution of annual mean GWS across the Mediterranean region. There is a significant spatial variability of GWS, with higher storage values predominantly found in northern Europe, particularly in areas such as the Alps and the surrounding regions where GWS exceeds 2000 mm. In contrast, southern regions, including parts of North Africa, experience lower GWS values often below 500 mm, emphasizing the challenges posed by groundwater depletion in these arid areas.

Panel (b) of Figure 2 represents the significant variability in annual total precipitation across the Mediterranean basin. It shows high precipitation in the northern Mediterranean regions, while the southern parts, especially in North Africa and the Arabian Peninsula, receive less rainfall. Analyzing the precipitation data, it is evident that Egypt has the minimum precipitation value of 33 mm, whereas Slovenia, Albania, Croatia, and Montenegro have maximum values exceeding 1000 mm.

As illustrated in Figure 2, there is an obvious precipitation gradient, with the highest rainfall values concentrated in the northern regions. This gradient is consistent with the subtropical high-pressure systems and the presence of the Sahara Desert in the southern Mediterranean, which leads to arid conditions and significantly reduced precipitation in countries such as Egypt, Libya, Tunisia, and parts of Algeria. The southern regions of the Mediterranean basin, particularly in North Africa, exhibit very low precipitation values, often below 250 mm annually. This is typical of the semi-arid and arid climate zones in these areas. These regions, influenced by the Saharan Desert and other surrounding arid zones, experience extremely limited rainfall, exacerbating water scarcity challenges. The Arabian Peninsula, which includes countries like Palestine, Israel, Lebanon, and Jordan, experiences relatively low precipitation values, particularly in the southern and central parts. These areas are influenced by desert climates, which contribute to the general dryness and limited rainfall. However, some coastal areas, like parts of Lebanon, receive slightly higher rainfall due to their proximity to the Mediterranean Sea, which moderates temperatures and supports more precipitation.

Table 1 presents the geographical regions for each country along with annual precipitation and groundwater values for 12,461 grid points, and statistical summaries for the selected period (2003–2023).

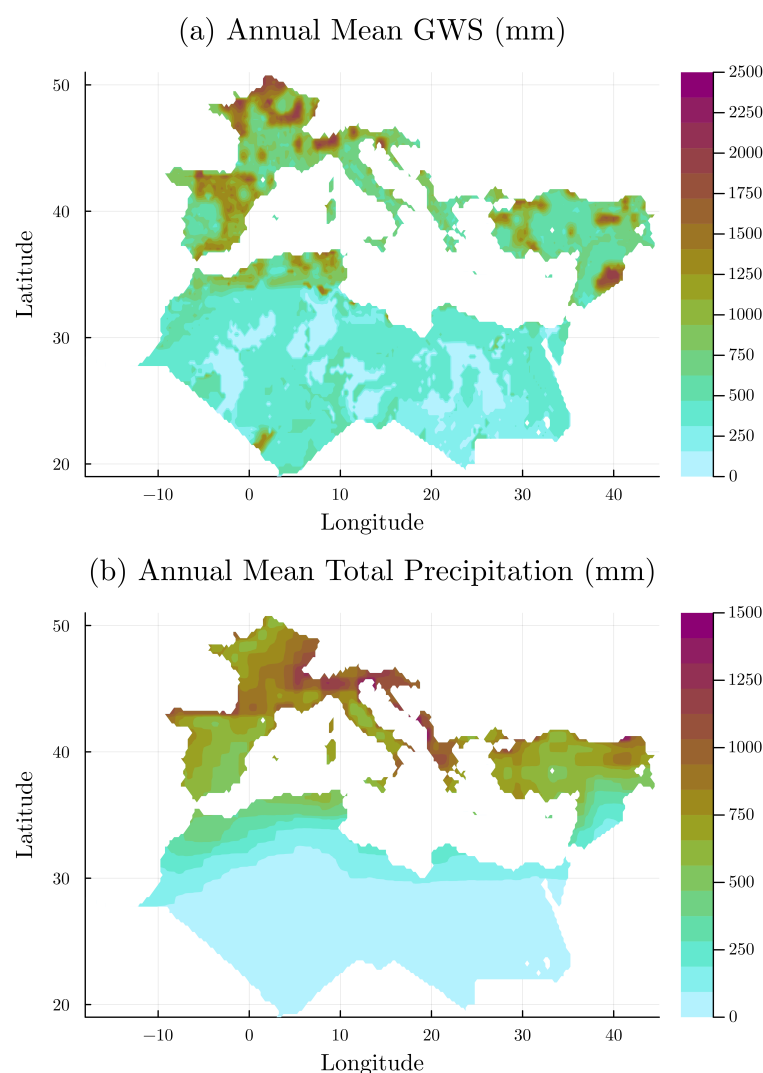


Figure 2. Annual mean GWS (a) and annual mean total precipitation (b) from GLDAS over the Mediterranean region, covering the period from 2003 to 2023.

Table 1. Statistical summary of countries based on annual mean groundwater storage and rainfall values between 2003–2023.

Country	Region	Mean	Annual Rainfall (mm)			Annual Ground Water Storage (mm)			
			Std	Min	Max	Mean	Std	Min	Max
Albania	Central and Eastern Europe	1060	159	755	1377	803	106	562	948
Algeria	Northern Africa	102	24	60	155	390	240	78	1647
Croatia	Central and Eastern Europe	1067	165	731	1438	871	294	441	1964
Cyprus	Southern Europe	459	108	282	682	569	14	554	590
Egypt	Northern Africa	33	10	23	67	297	124	78	930
France	Western Europe	841	82	697	978	1061	388	416	2050
Greece	Southern Europe	823	88	677	989	647	139	428	1210
Israel	Arabian Peninsula	190	34	116	244	602	158	405	914
Italy	Southern Europe	848	113	665	1078	865	325	515	2076
Lebanon	Arabian Peninsula	379	92	195	530	683	110	543	945
Libya	Arabian Peninsula	52	8	37	68	285	138	79	1800
Montenegro	Central and Eastern Europe	1102	175	758	1405	897	175	581	1402
Morocco	Northern Africa	272	79	177	448	512	164	123	1352
Slovenia	Central and Eastern Europe	1133	142	878	1455	989	277	622	1778
Spain	Southern Europe	655	94	495	830	971	309	268	1966
Syria	Arabian Peninsula	292	62	179	394	889	476	352	2017
Tunisia	Northern Africa	273	56	155	386	669	392	88	1713
Turkey	Central and Eastern Europe	680	72	545	839	769	268	351	1836

3. Methodology

3.1. The Simple Coincidence Deficit Index

The successive coincidence deficit index was recently proposed by [67], which focuses on identifying mutual deficit fractions over a time period for the selected hydrological events. In this study, the index was simplified to create the Simple Coincidence Deficit Index (SCDI), which arranges the hydrologic event time series using moving local averages over a user-specified time window. Let E be a hydrologic event having a total of N months of ordered data starting from January over the years where the corresponding data points are $E = e_1, e_2, \dots, e_N$. Thus, the k th entry of the event is arranged with respect to the moving local statistics function as the local mean or sum, respectively.

$$S_k = \frac{1}{\Delta} \sum_{i=k-\Delta+1}^k e_i, \quad k = \Delta, \Delta + 1, \dots, N - \Delta + 1 \quad (1)$$

or

$$S_k = \sum_{i=k-\Delta+1}^k e_i, \quad k = \Delta, \Delta + 1, \dots, N - \Delta + 1 \quad (2)$$

where S is the modified hydrologic event array, Δ is the time window, and N is the number of data points in an event. Note that Δ has similar definition in SPI, which shows the time interval. When $k < \Delta$, the first entries up to $\Delta - 1$ will be empty. Therefore, the S array will be a length of $N_c = N - \Delta + 1$. For instance, if a total of 240 months of precipitation data are available, the length of the S array will be 235 months when $\Delta = 6$. The SCDI procedure continues with the conversion of the hydrologic data in question given in time series to their binary series form. Suppose B is the binary form of this event, which is then computed as

$$B(i : 12 : N_c) = \begin{cases} 1, & S(i : 12 : N_c) < \frac{1}{n} \sum_{i=1}^{N_c} S(i : 12 : N_c) \\ 0, & \text{otherwise} \end{cases} \quad i = 1, 2, \dots, 12 \quad (3)$$

where $S(i : 12 : N_c)$ denotes the array entries of the event starting from i th entry and continues to N_c with an increment value of 12, and n is the length of the $S(i : 12 : N_c)$ array. Note that $i = 1$ implies January, but if the starting month is not January, Equation (1) is adjusted to the starting month accordingly. In the context of this analysis, which focuses on P and GWS levels, the binary values are assigned based on their comparison to the dataset's average. Specifically, a value of 1 is assigned if either P or GWS falls below the average, indicating potential drought anomalies. Conversely, a value of 0 is assigned when these levels meet or exceed the average. As a summary, Equation (3) implies that an event time series is first rearranged by Equation (1) with a specific Δ value. Then, this time series is grouped for each month. As a next step, the entries belonging to January are compared to the mean value of January. If any value in January is less than this month's mean value, it is designated as 1 (which shows deficit), and otherwise 0. This process is repeated for each month. This binarization process brings flexibility since it avoids the need for an a priori statistical distribution of the event of interest.

Let B_1 and B_2 be binary series of two different hydrologic event datasets, respectively. Then, the coincidence deficit array (CDA) between B_1 and B_2 is computed as

$$CDA = B_1 \otimes B_2 \quad (4)$$

where $\otimes$ is array-wise multiplication. Note that CDA is an array with a length of N_c and whose entries are composed of either 1 (coincidence) or 0 (not coincidence). Finally, SCDI can be found as

$$SCDI = \frac{1}{N_c} \sum_{k=1}^{N_c} CDA_k \quad (5)$$

In this study, P and GWS were used as hydrologic events. Groundwater and precipitation play crucial roles in this water budget equation. Precipitation is the primary input of the system, directly affecting the availability of surface and groundwater resources [68,69]. Conversely, groundwater serves as a vital reservoir in surface water availability, specifically during dry periods when surface runoff may be limited [70]. The interaction between precipitation and groundwater is crucial for maintaining hydrological balance, as groundwater recharge occurs from precipitation that infiltrates the soil and percolates down to the water table [71].

For illustrative purposes, a sample point in the study area was selected. With the time window, $\Delta = 3$, Equation (1) was applied to compute the moving local mean values of GWS and precipitation values rearranged using Equation (2) for that location as shown in Figure 3.

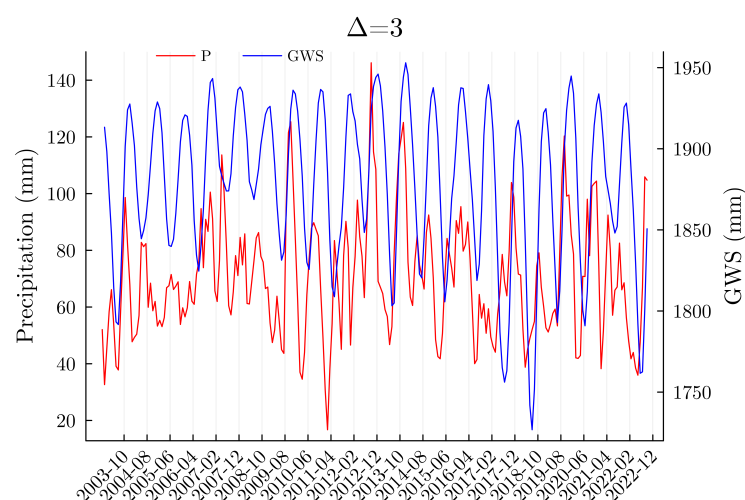


Figure 3. Time series of P and GWS time series for sample point ([Latitude, Longitude]: 50.815°, 1.87°; France).

Subsequently, Figure 4 illustrates the binarization process outlined in Equation (3).

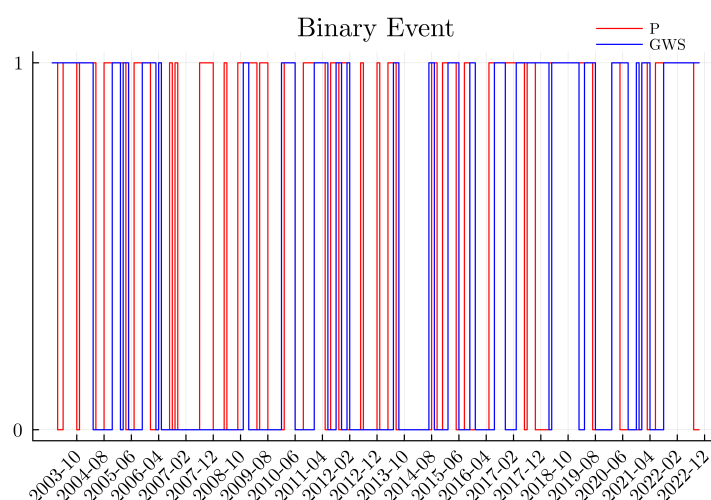


Figure 4. Binarization process of sample point in study area.

Finally, the CDA of both events can be obtained using Equation (4), as shown in Figure 5. By summing the CDA over the given time period, the SCDI value is computed as explained in Equation (5). For this sample point application, the SCDI was found to be $75/238 = 0.3151$.

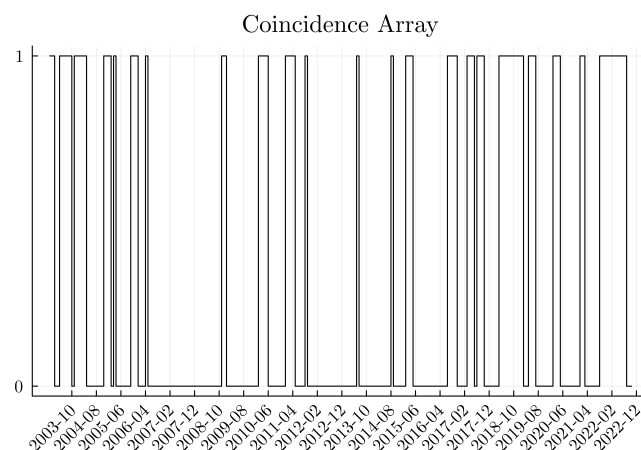


Figure 5. Coincidence array of sample point in study area.

3.2. Drought Severity Analysis (DSA)

Drought severity analysis (DSA) is also conducted by means of CDA to examine the duration of coincidence deficits. To achieve this, each coincidence deficit duration noted in the CDA is counted according to a predefined successive occurrence time. In other words, CDA is transformed into a new binary array as

$$\lambda(\theta_j) = \begin{cases} 1, & \sum_{i=k-\theta_j+1}^k CDA_i \geq \theta_j \\ 0, & \text{otherwise} \end{cases} \quad \text{for } \begin{matrix} k = \theta_j, \theta_j + 1, \dots, N_c \\ \theta_j = 1, 2, \dots, 36 \end{matrix} \quad (6)$$

and

$$DS(\theta_j) = \sum_k^{N_c} \lambda_k(\theta_j) \quad (7)$$

where DS is drought severity, λ is the number of successive months which satisfy the continuous deficit condition, and θ_j is the pre-defined successive occurrence time. DSA also provides the longest drought duration within the period of interest. In addition, mean drought duration and other statistical properties can be derived through an appropriate distribution fit for DS . The DS variation for the sample point, as outlined in Equation (6) and Equation (6), is depicted in Figure 6 from the analysis presented in the previous section. Figure 6 provides a statistical view of drought durations over successive months. The height of stairs decreases as the duration extends, indicating the rarity of prolonged droughts. The curve, representing a Poisson distribution fit, shows a steep rise and then a plateau, indicating a low probability of long-lasting droughts. For this sample example, the longest duration is observed as 11 successive months.

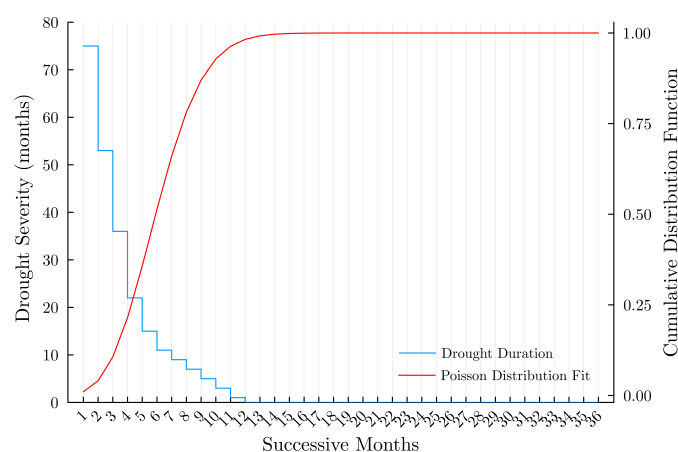


Figure 6. DS variation of sample point in study area.

In this study, a detailed assessment of SCDI and DSA was applied to investigate the behavior of persistent drought in the basin. Accordingly, the SCDI and DSA were applied across various time windows for 1-, 3-, 6-, and 12-month in order to analyze short- and long-term drought conditions. Considering both short-term and long-term drought analyses is crucial for a comprehensive understanding of drought dynamics. Short-term droughts may lead to sudden fluctuations in streamflow and soil moisture, which can significantly affect water availability and ecosystem health [21,72]. Conversely, long-term droughts create more profound and long-lasting impacts on hydrological systems, such as alterations in groundwater levels, which may not be immediately visible [73]. Therefore, analyzing both time windows facilitates a more effective drought evaluation for the selected region. The workflow of the study is shown in Figure 7 as a flowchart.

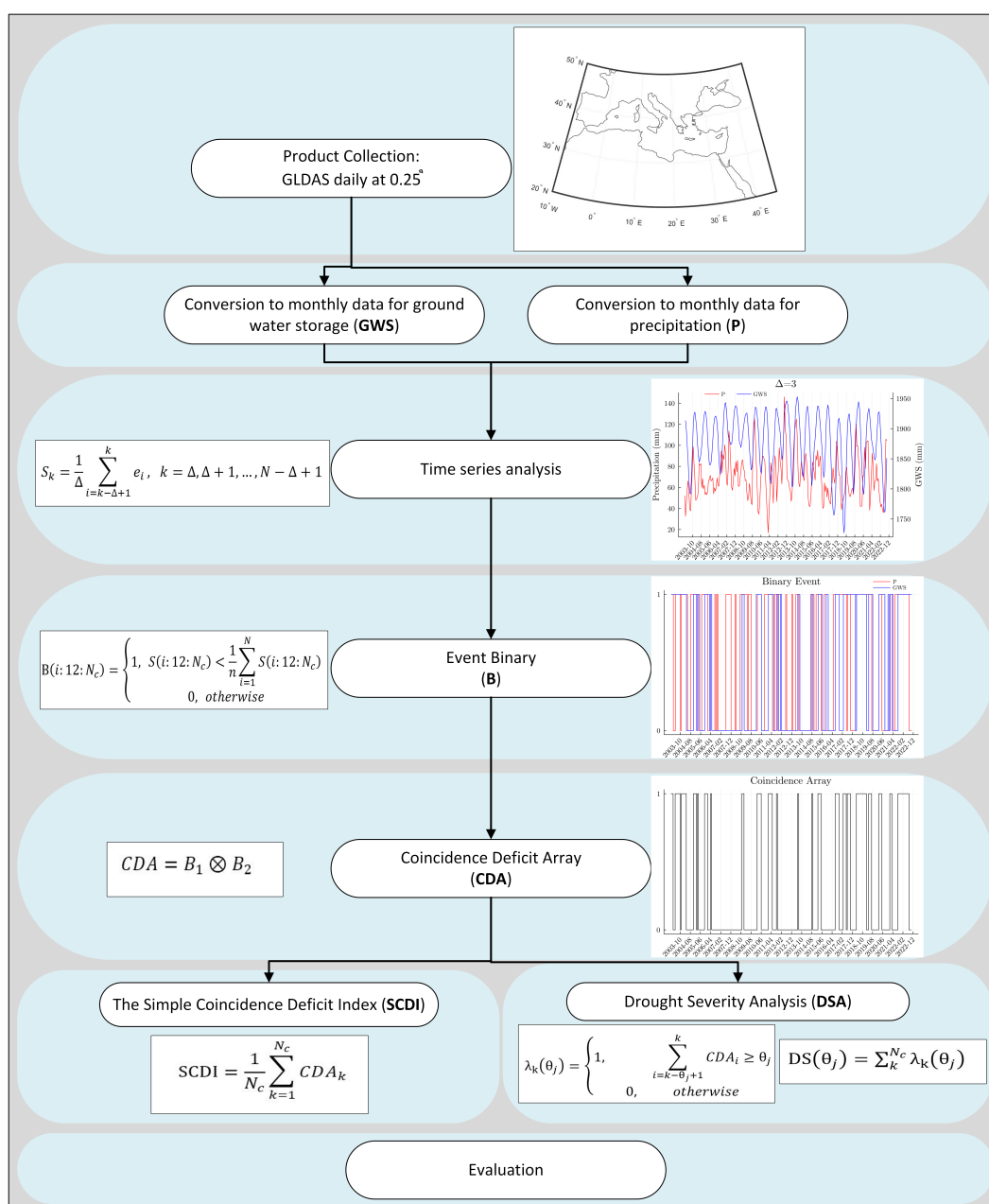


Figure 7. Workflow of our study.

4. Results

4.1. SCDI Distribution over Mediterranean Basin

The proposed SCDI, with calculation steps outlined in the previous section, is calculated for 12,461 grid points in the Mediterranean basin for several time windows including $\Delta = 1$, $\Delta = 3$, $\Delta = 6$, and $\Delta = 12$, as presented in Figure 8. Each panel (a, b, c, d) in Figure 8 represents SCDI values calculated over the respective aggregation periods.

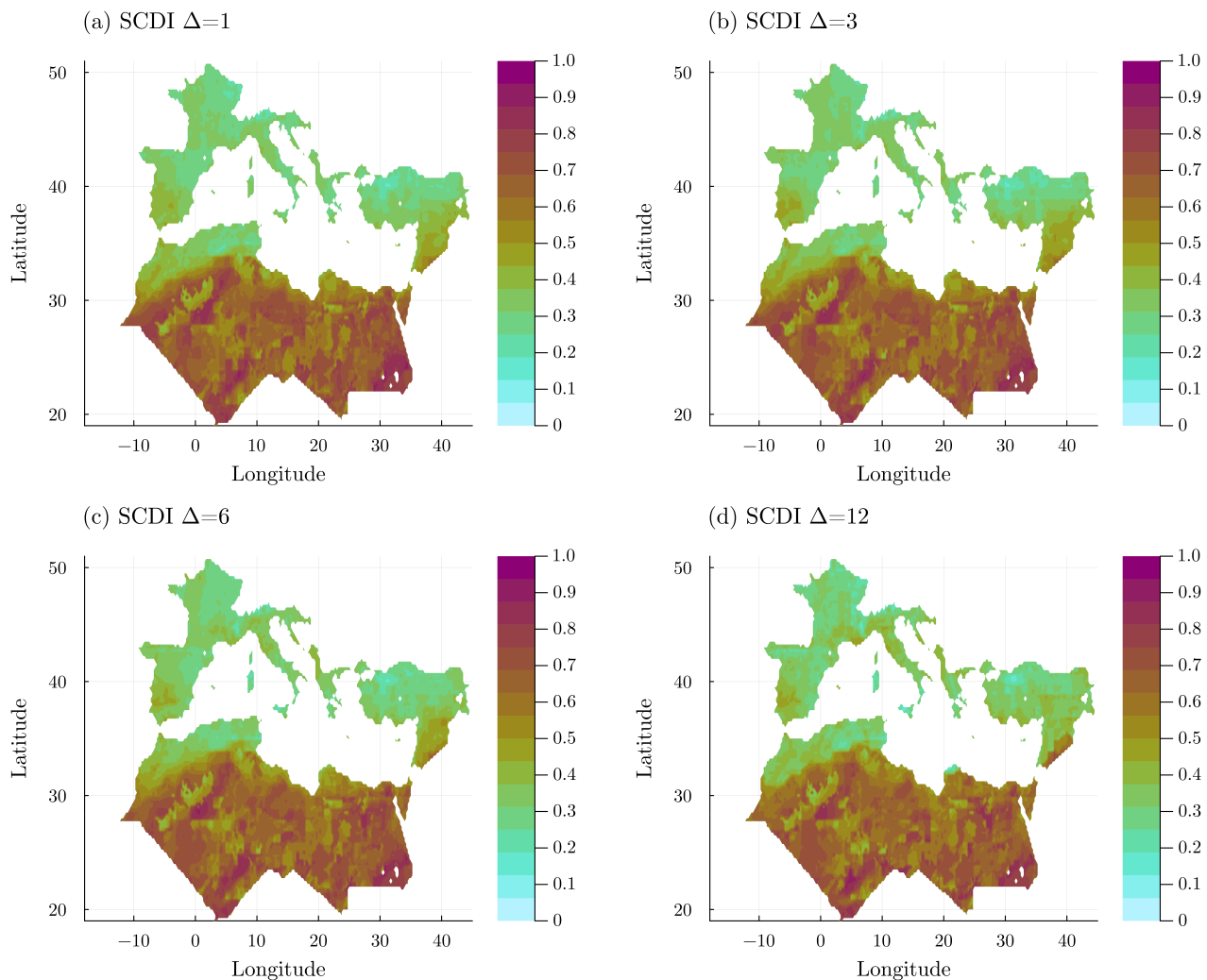


Figure 8. SCDI results of Mediterranean basin in various time windows.

Panel (a) of Figure 8 ($\Delta = 1$) shows the coincidence of deficits for P and GWS. Considering Figure 2, areas with higher GWS values do not overlap with those of P, indicating that P is not the only parameter that controls drought over the basin in a broader sense. For instance, while Balkan countries (i.e., Greece, Albania, Slovenia) exhibit higher annual mean precipitation values, their GWS values are slightly lower than the overall GWS distribution across the basin. In addition, SCDI values for the region above 36° latitude are low compared to the remaining parts of the Mediterranean region. Similarly, panel (b) of Figure 8 reflects that SCDI values computed for a time window $\Delta = 3$ show how the SCDI methodology responds to the seasonality effect of the parameters implemented in this study. The time windows ($\Delta = 1$ and $\Delta = 3$) can be interpreted as indicating short-term drought pressure on the basin, similar to the classical SPI. As observed in panels (a) and (b) of Figure 8, no significant changes can be noted

throughout the region. Panel (c) of Figure 8 shows that SCDI values increase slightly as the persistent drought intensifies, especially along the southern Mediterranean coast. Panel (d) of Figure 8 illustrates a slight increase in SCDI values compared to those in panel (c). However, the southern and eastern coasts of the Mediterranean, particularly in parts of Spain, Türkiye, Greece, Tunisia, and Libya, may suffer from long-term drought events. Furthermore, all possible percentage differences in SCDI values across varying time windows were calculated and are depicted in Figure 9.

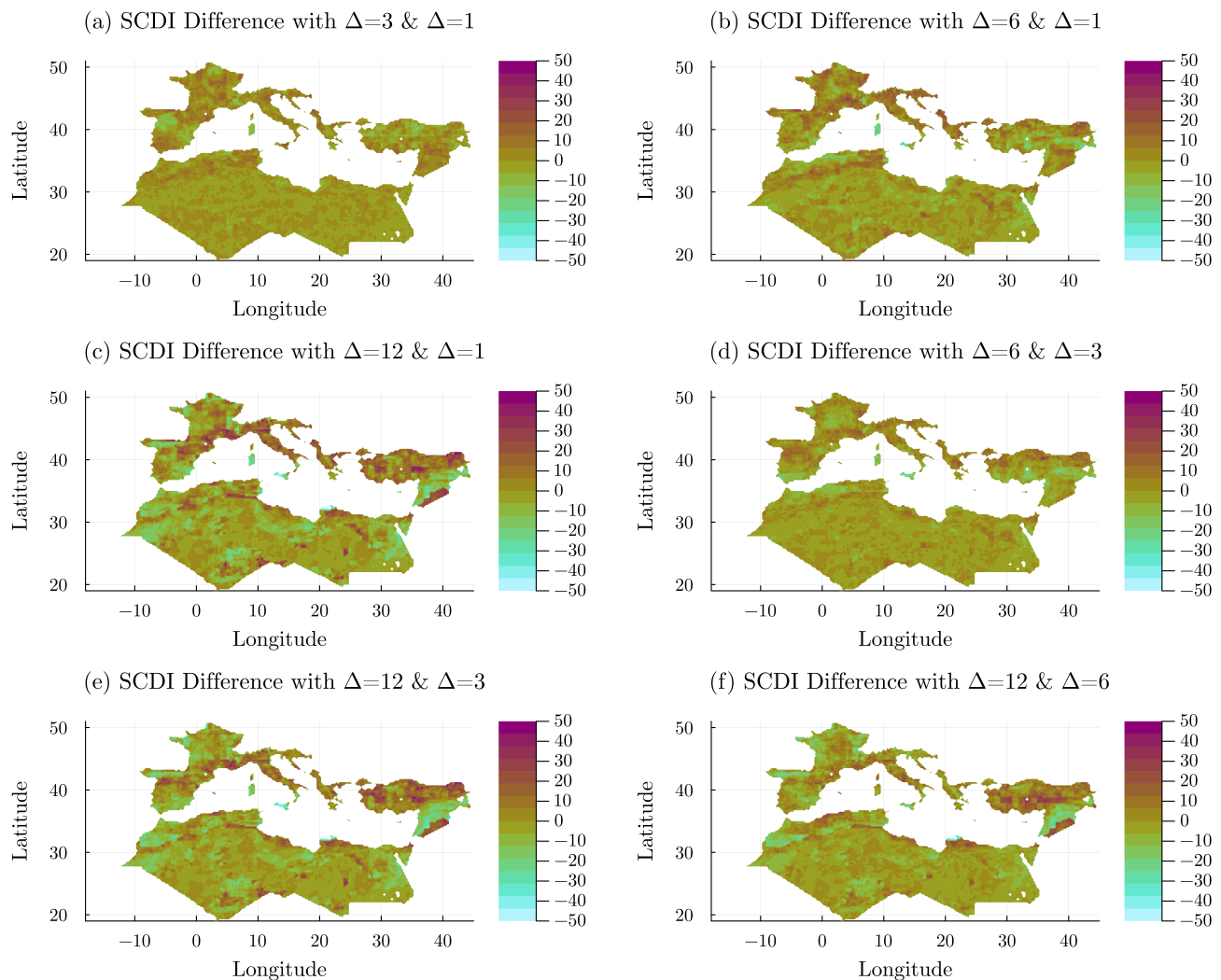


Figure 9. Percentage differences of SCDI values.

As shown in Figure 9, notable changes in SCDI values were observed when a yearly time window ($\Delta = 12$) was compared to shorter reference time windows, particularly $\Delta = 1$, as illustrated in panels a, b, and c. These percent changes reflect how longer time windows emphasize the cumulative effects of drought, making persistent drought conditions more visible. This trend is not limited to $\Delta = 1$, similar patterns can be observed in comparisons with other shorter time windows, as delineated in panels d, e, and f of Figure 9. The increase in percentage differences with longer time windows shows that annual aggregation ($\Delta = 12$) better captures drought persistence than monthly resolution ($\Delta = 1$). In addition, the spatial distribution of SCDI, as shown in Figure 8, seems to correlate with latitude. Regions above 35° latitude generally show lower SCDI values, indicating less severe drought conditions, while areas in the southern Mediterranean display higher values, reflecting greater drought intensity.

and persistence over time. In addition to climatic differences, northern regions have more consistent rainfall and lower evapotranspiration while southern areas face higher temperatures and less precipitation. Northern regions often have rivers and mountains that help retain water, whereas southern regions lack such features for effective water storage. Therefore, additional analysis was conducted to quantify the relationship between SCDI and latitude for different time windows as given in Figure 10.

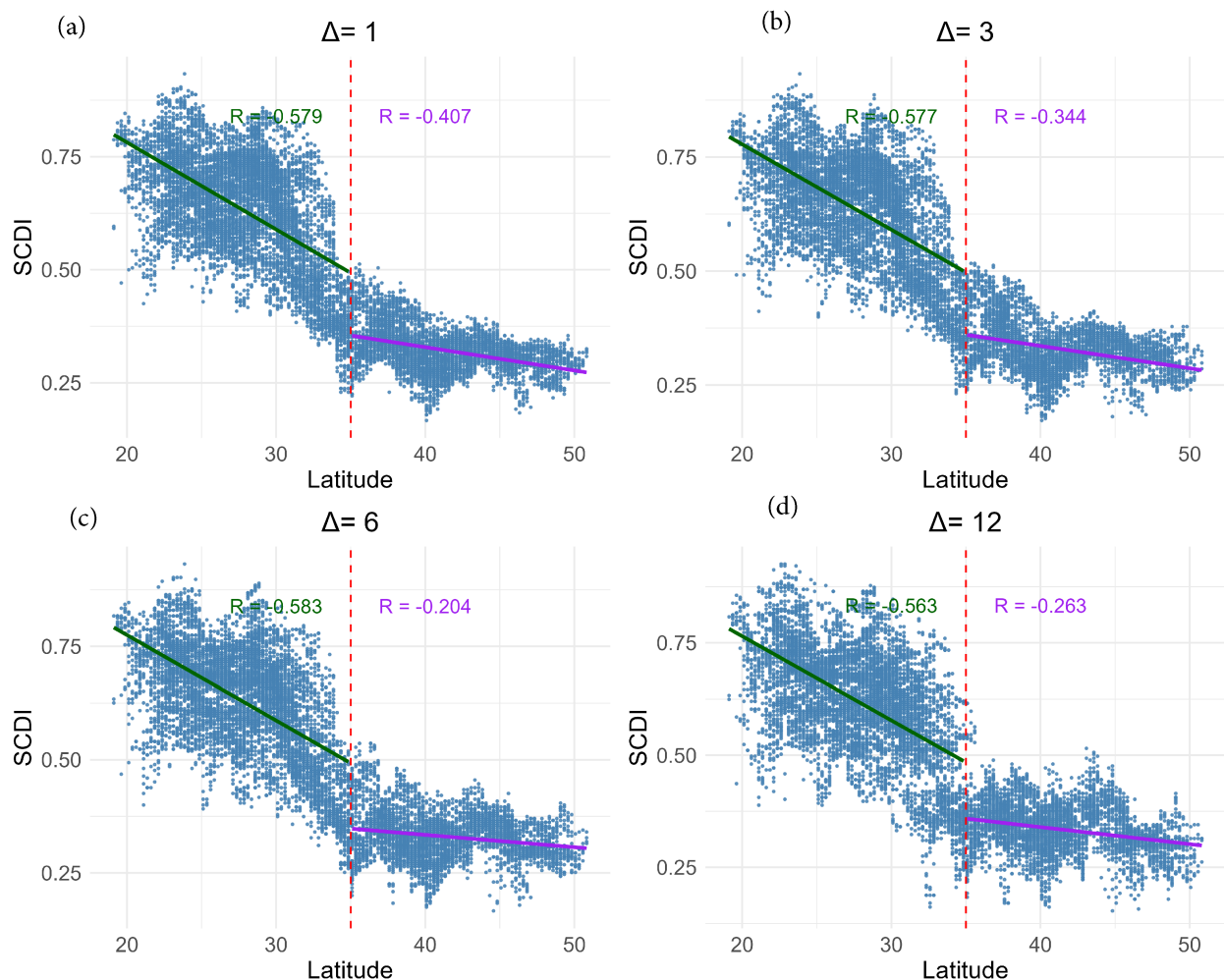


Figure 10. SCDI variation with latitude for various time windows.

Panel (a) of Figure 10 is divided in half by a red line to show the variation of SCDI values with latitude. It is assumed that the northern part of the basin lies above 35° latitude, while the southern part is below 35° latitude. The Pearson coefficient correlation, R , is calculated as -0.579 for latitude values below 35° and -0.407 for latitudes above 35° . In the southern part of the basin (below 35° latitude), SCDI values decrease significantly as latitude increases, indicating that drought conditions become less intense at higher latitudes in this region. However, in the northern part of the basin (above 35° latitude), the decrease in SCDI values with latitude is less pronounced, suggesting that drought intensity shows a weaker correlation with latitude in this area. Panel (b) of Figure 10, representing the $\Delta = 3$ -time window, shows that R is -0.577 for latitudes below 35° and -0.344 for those above 35° . The southern part of the basin shows a similar correlation as observed in panel (a), while the northern part shows a weaker correlation compared to panel (a). In panel (c) of Figure 10, where $\Delta = 6$, R is calculated as -0.583 for the southern part and -0.204 for the northern part. Similar results were obtained here as in the previous case,

with no significant change in the southern part of the basin. In panel (d) of Figure 10, which represents the $\Delta = 12$ time window, R is -0.563 for the southern part and -0.263 for the northern part. This case, representing long-term drought, shows no significant change in the southern part, consistent with the other panels. However, in the northern part, the correlation decreases significantly compared to the smaller time windows. Overall, these findings show that the correlation in the southern part of the basin remains stable across time windows, indicating consistent drought dynamics. In contrast, the northern part shows a noticeable latitude–SCDI correlation for the $\Delta = 1$ time window, but this weakens with larger time windows.

The interplay between latitudinal trends, regional climate drivers, and human activities varies by region. Subtropical highs, semi-permanent pressure zones between 20 and 40 degrees latitude, significantly influence these trends. They contribute to asymmetrical warming and vegetation growth, with the Northern Hemisphere experiencing greater effects [74]. Historical records show a latitudinal shift in the boundary separating the Mediterranean and African monsoonal climates, which has influenced the hydrology and climate dynamics of Northwest Africa [75]. Comparative analyses across regions corroborate these findings, showing that the SCDI exhibits higher values and greater variance in NA and AP. Additionally, human-induced activities are influencing global precipitation patterns by increasing rainfall amounts at high latitudes and decreasing that amount in subtropical regions in the Intertropical Convergence Zone (ICTZ) [76]. Although the study area does not encompass the ITCZ, variations in SCDI with latitude support these findings.

SCDI values were clustered to emphasize the effect of regions—the Arabian Peninsula (AP), Central and Eastern Europe (CEE), Northern Africa (NA), Southern Europe (SE), and Western Europe (WE)—over different time windows ($\Delta = 1, 3, 6, 12$). For each time window, the boxplots (Figure 11) provide insights into the variability of SCDI values across these regions, as outlined in Table 1. For $\Delta = 1$, the SCDI values exhibit distinct patterns among the regions. NA shows the highest median and interquartile range (IQR), reflecting greater variability and higher SCDI values, which highlight more intense drought conditions in this region. Compared to NA, the AP shows a relatively narrow IQR, with moderate SCDI values centered around 0.5. In contrast, CEE and WE display much narrower IQRs with lower SCDI values, indicating limited variability. SE exhibits the narrowest IQR with a median SCDI value of 0.4. For $\Delta = 3$, the general patterns of the boxplots remain constant, but there is a slight broadening of the SCDI distributions in the region of SE and the median SCDI value of NA increased to 0.68. As the time window increases to $\Delta = 6$, the range of the IQRs for AP, CEE, and WE increases, and almost all regions show an increase in the median SCDI values. This indicates that regional drought dynamics become more heterogeneous (wider IQRs) and more pronounced (higher medians) for longer time windows. For $\Delta = 12$, representing the longest time window, the range of IQRs for almost all regions reach their broadest ranges. Overall, the increasing time windows strengthen the variability in SCDI values across all regions, with long-term drought conditions becoming more apparent, particularly in NA.

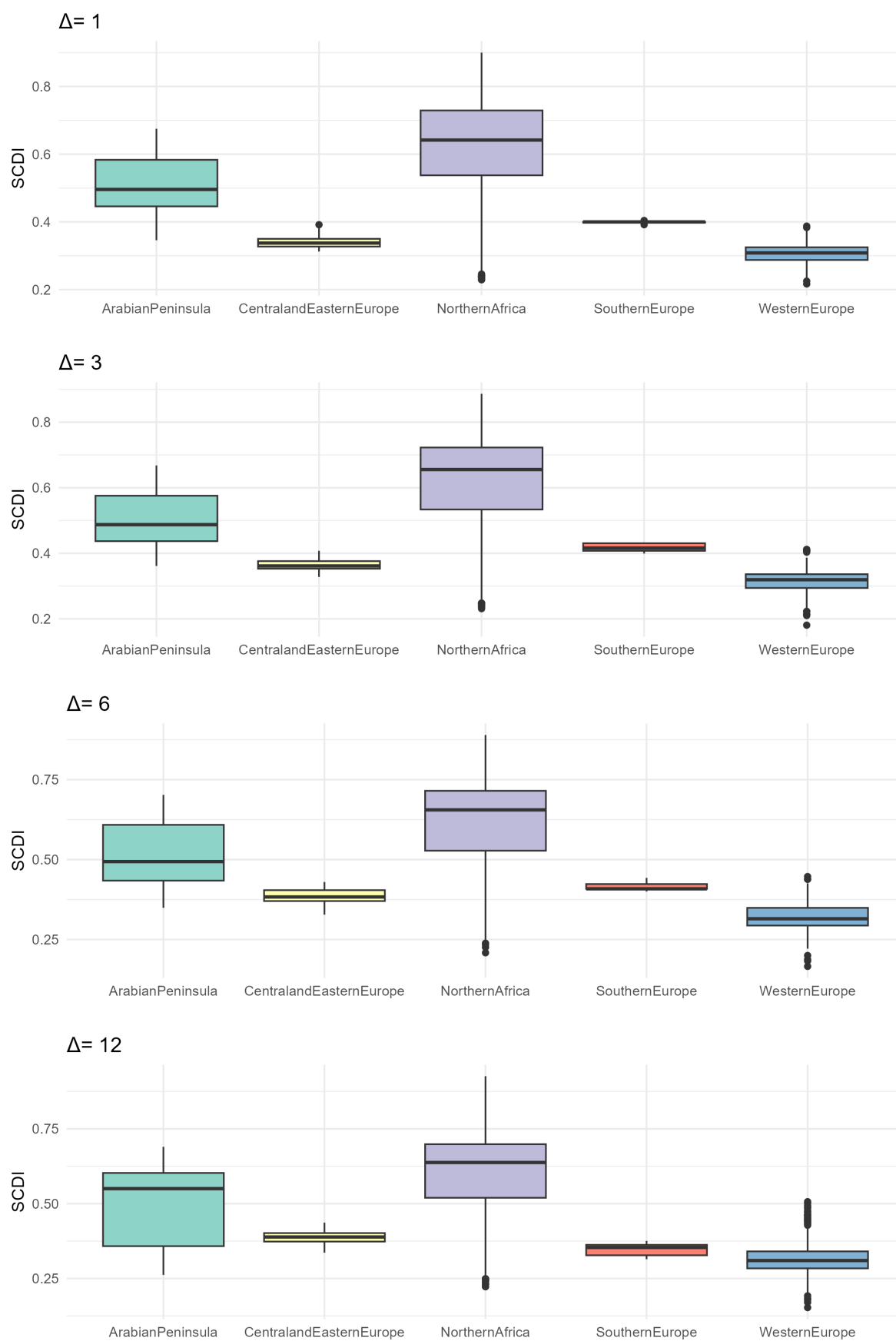


Figure 11. SCDI results based on regions.

4.2. Drought Severity Distribution

The drought severity analysis (DSA) based on SCDI detects the longest drought periods for gridded data. This analysis numerically expresses the number of months during which the mutual deficit of groundwater storage and precipitation persists. Figure 12 shows the duration of the longest drought period detected in a particular grid cell for various time windows.

Panel (a) of Figure 12 shows that the longest drought durations (>36 months) occur predominantly in the countries within the NA region, as expected. When $\Delta = 3$, a significant increase in longest drought duration is observed in Spain, France, Italy, and southern Türkiye as seen in panel (b) of Figure 12. In the $\Delta = 6$ -month period, prolonged drought durations are observed in almost all of Spain, France, and Italy, as well as in the coastal and coastal interior parts of the Balkans and Türkiye, as shown in panel (c) of Figure 12. In the southern part of the basin (latitudes lower than 30°), drought traces extend from the interior regions toward the coast. In panel (d) of Figure 12, there is a significant increase in the drought durations detected throughout the basin. As expected, the highest values for the longest drought duration are detected in the southern parts of the basin. In particular, prolonged drought durations are observed in southern Spain, southeastern Türkiye, Syria, Lebanon, and Palestine. This finding reveals that long-term drought events have increased especially in these areas. In summary, DSA based on SCDI reveals that the risk of drought is high along the southern and eastern coasts of different countries in the Mediterranean region. As the time window increases, drought conditions appear to propagate northward of the basin. The possible reason for this outcome may be the extreme effect of specific months with significant deficits, which are less noticeable in the $\Delta = 1$ time window due to their limited occurrence. However, in wider time windows like $\Delta = 12$, the aggregation of all 12 months amplifies the influence of these extreme deficits, increasing their weight in the total sum. This leads to a greater impact on seasonal and yearly averages, and this effect is observed to propagate from lower to higher latitudes.

A further analysis was conducted to relate DSA with regions as shown in Figure 13. When $\Delta = 1$, it is seen that the distributions of the calculated values for SE and AP show a more uniform pattern compared to other regions. For $\Delta = 3$ and $\Delta = 6$, most regions show higher median values compared to their previous time windows, with varying IQRs across regions. In these time windows, as the variation (IQR) in AP increases, the variation in NA shows a reduction. For $\Delta = 12$, most of the calculated long drought durations, excluding outliers, in AP and NA regions are determined as 35. While the values in CEE are more uniform, those in WE and SE regions have moderate variability. Overall, Figure 13 underscores that the aggregation of extreme months over longer time windows amplifies drought severity and variability, particularly in regions like NA and AP. This effect is less pronounced in shorter time windows ($\Delta = 1$) and higher latitudes, but as the time window lengthens, the cumulative impact of extreme months becomes more evident across the basin, including SE and WE.

NA has experienced frequent and severe droughts throughout the past century, particularly during the 1970s, 1980s, and early 2000s, with these events often linked to complex physical mechanisms such as the El Niño–Southern Oscillation (ENSO) and sea surface temperature anomalies, complicating effective drought monitoring and forecasting [77]. While some localized areas have shown trends of increasing rainfall, these instances are generally considered abnormalities (Figure 13), and the predominant long-term trend across northern Africa is shifting towards increasingly arid conditions. This shift poses significant challenges for water resource management and food security [78]. Furthermore, this escalating drought risk is intensified by socio-economic pressures, including rapid pop-

ulation growth and ongoing land degradation, which heighten the region's susceptibility to the adverse effects of drought [79].

The DSA results provide consistency across different time windows and highlight the long-term drought impact. Figure 12 shows that as the time window increases, the drought moves inland from the coasts and increases its severity. This may indicate that long-term drought is more important in the basin and should be taken into consideration. Long-term droughts may have serious impacts on agricultural production, water resources, and ecosystems. Comprehending drought is crucial due to its impacts on the ecosystem in the Mediterranean basin. Drought affects vegetation activity, and various studies have assessed its impacts on vegetation communities across the basin [80]. Beyond vegetation, drought also impacts water resources and agricultural activities in the basin. Therefore, decision-makers should take precautions and develop strategies regarding the issue. Furthermore, calculated high values of DSA indicate that groundwater resources in these regions may be under prolonged pressure, emphasizing the need for effective water resource management.

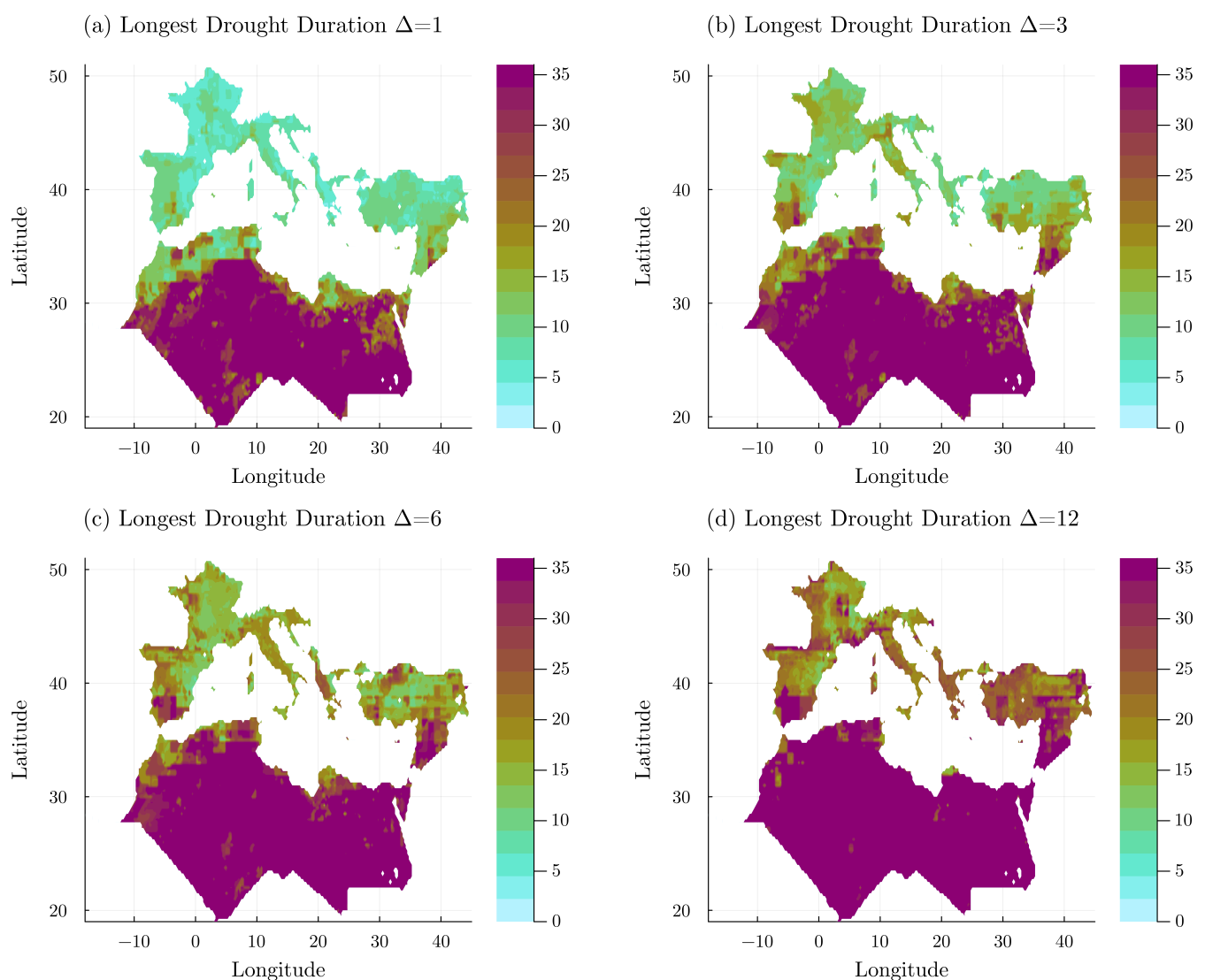


Figure 12. DSA results of Mediterranean basin in various time windows.

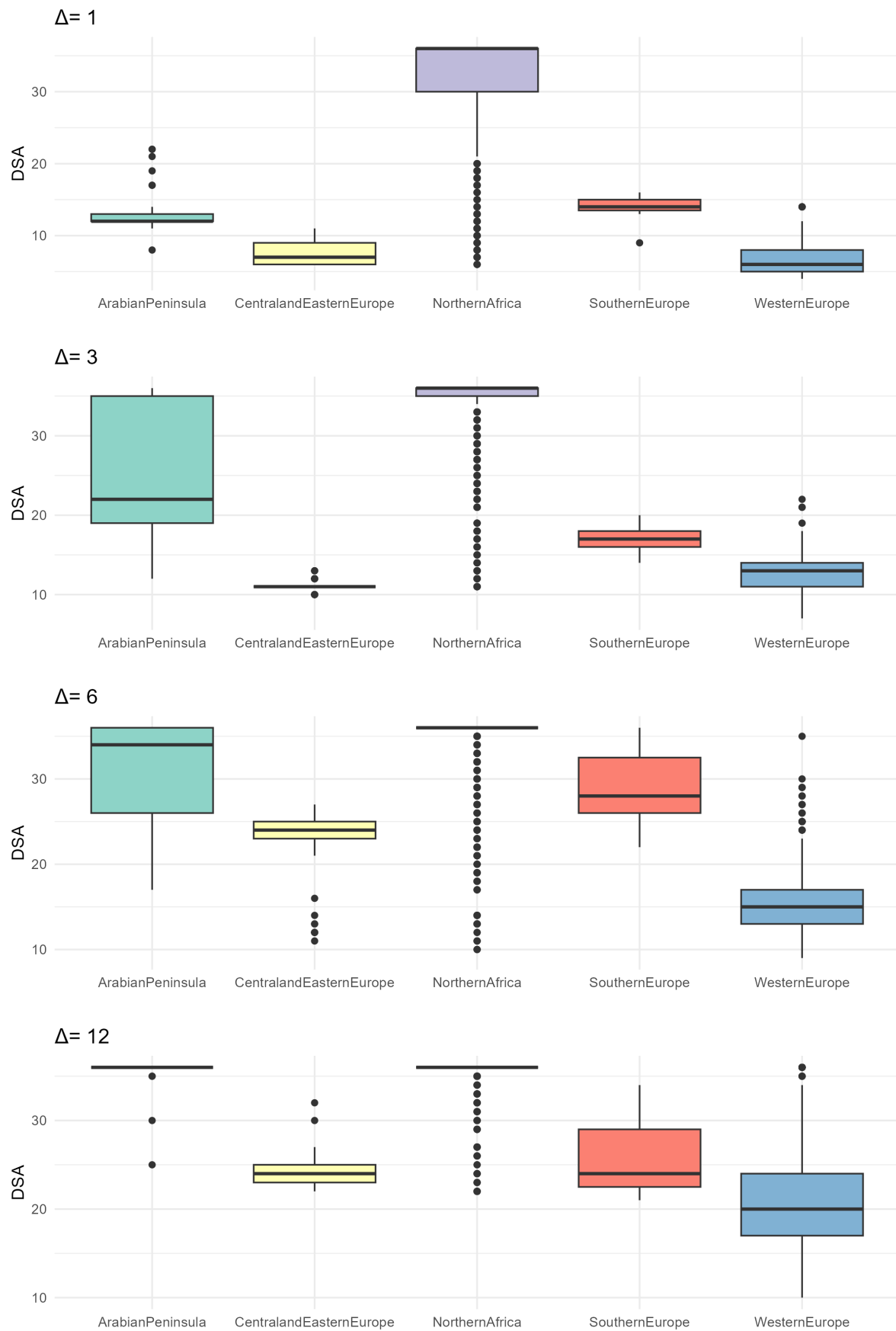


Figure 13. DSA results based on regions.

5. Discussion

The SCDI can also serve as a drought index for monitoring persistent drought across the basin of interest. Within the scope of this study, the results of the proposed new methodology were evaluated and compared with the SPI, which is widely used in the literature. National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) drought monitoring maps based on the SPI for the Europe region are presented in Figure 14 for 3-, 6-, 12- and 24-month time series.

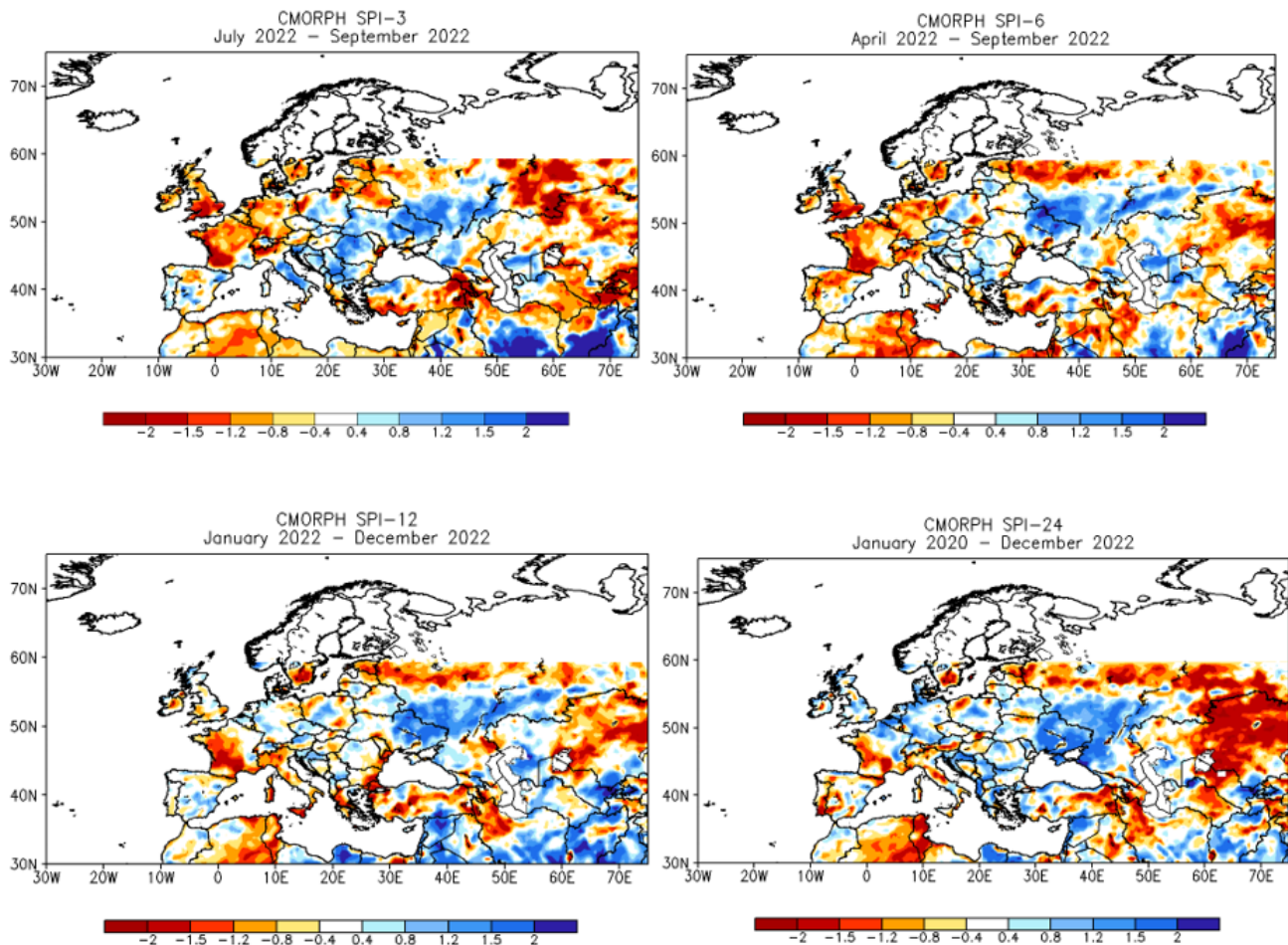


Figure 14. drought.gov data, providing GIS and web-ready formats of SPI maps (Source: National Oceanic and Atmospheric Administration, National Integrated Drought Information System (2024). Standardized Drought Indices generated from Climate Engine. <https://www.drought.gov/data-download> (accessed on 8 January 2023)).

The SPI-3 map shows that most of southern Europe (Spain, Italy), France, and eastern Türkiye show signs of drought. This period only indicates short-term drought conditions. The 6-month SPI map shows more medium-term drought signals. On this map, the drought situation, especially in France, Italy, and Spain, continues. The 12-month map of SPI indicates longer-term drought trends. Drought continues in some parts of France, Spain, and Türkiye during this period, indicating long-term drought conditions. The 24-month SPI shows long-term drought patterns in the region. Signs of severe drought continue especially in France, Spain, and eastern Türkiye, while regions of Eastern Europe appear largely wet. Because the SPI is a time-dependent index, the results can be misleading. For example, when SPI maps are examined in Figure 14, France appears quite dry, while Syria appears wet. Although it is very practical and common in use, it is only based on precipitation and does not consider soil water balance components. The SPI has been criticized for its

inability to effectively represent drought conditions in areas with complex hydrological dynamics. For example, in regions where groundwater and surface water interactions are significant, the SPI may not provide a comprehensive image of drought impacts, as it does not incorporate soil moisture or groundwater levels into its calculations [81]. The SCDI may be a better alternative to drought intensity monitoring since it considers both precipitation and groundwater [67].

The direct comparison of traditional drought indices like the Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI) often proves challenging due to their reliance on climatological factors with preset thresholds. Additionally, the datasets used in these indices generally do not adhere to a normal probability distribution. This deviation from normality requires that data be transformed to fit the standard normal distribution, which is a critical assumption in most statistical analyses. Ignoring this requirement can lead to significant errors in the results of statistical evaluations. While traditional indices like SPI and SPEI provide valuable insights, the discrepancies and limitations in these methods highlight the need for more robust methods. Conversely, the Simple Coincidence Deficit Index (SCDI) enhances computational efficiency by calculating the mutual coincidence fraction, offers greater flexibility by enabling analysis of multiple events, and facilitates a deeper understanding of the temporal relationships among these events. The SCDI and Drought Severity Analysis (DSA), as evidenced by their application in the Mediterranean, allow for more nuanced articulations of temporal and spatial drought variations and offer consistency despite their different index definitions. By incorporating both precipitation and groundwater storage data, the SCDI provides a more comprehensive drought monitoring, and DSA describes persistent drought over the study area. Thus, SCDI and DSA methodologies present a significant advancement over the traditional SPI.

Comprehending drought is substantial due to its impacts on the ecosystem in the Mediterranean basin. Furthermore, effective water resource management and planning in the Mediterranean basin depend on understanding the temporal characteristics of droughts to manage the considerable seasonal and inter-annual variability in precipitation patterns [82]. In addition, research on drought in the Mediterranean basin highlights the significance of examining adaptive responses to evolving environmental conditions. For example, the adaptive phenotypic plasticity of Mediterranean oak species in response to drought stress is vital, given the anticipated rise in inter-annual weather variability and the increased frequency of severe droughts in the region [83]. Furthermore, exploring the effects of drought on plant–soil interactions with well-studied species such as the holm oak offers valuable insights into ecosystem responses to drought in the Mediterranean basin [84]. Ref. [85] analyzed 900 years of Mediterranean drought variability using the Old-World Drought Atlas (OWDA), revealing a historical pattern of spatiotemporal drought variability in the region over the last 900 years, which indicates anthropogenic influences on regional drying. This historical variability supports future projections. The Intergovernmental Panel on Climate Change (IPCC) has warned about the intensification of droughts in the Mediterranean basin [86] with warmer and drier conditions predicted for the basin [87].

Research on drought in the Mediterranean presents varied yet consistent observations. Key climatic phenomena like the North Atlantic Oscillation (NAO) and the El Niño–Southern Oscillation (ENSO) are commonly identified as significant influences of drought patterns, impacting both their frequency and severity across different areas [20,88,89]. Historical data often point to natural climate variability as the primary cause of past droughts, but contemporary analyses indicate an escalating role of anthropogenic factors [88,89]. Common tools for evaluating drought include well-established indices such as the SPI and SPEI [86,90]. Nevertheless, there is a noted variation in the drought metrics and indices utilized, leading to inconsistencies in capturing drought du-

ration and frequency. This variation underscores the necessity for a multi-index strategy that accommodates the diverse atmospheric patterns influencing droughts in the western Mediterranean, typically associated with high-pressure systems over central Europe, and the distinct conditions in the eastern Mediterranean [20,89]. Moreover, the impact of drought on vegetation varies across the Mediterranean, with some studies noting more pronounced effects in drier regions and specific seasons. This variability emphasizes the importance of developing drought management strategies that are tailored to regional conditions [80,91]. With the proposed SCDI and DSA methodologies, temporal and spatial variations can be more easily articulated, and the differences in index definitions do not result in varying outcomes.

Building on the discussion of advancements in drought assessment methodologies, the field of climate engineering introduces further complexities to environmental management [92]. While it offers a potential avenue for mitigating some of the most severe impacts of global warming, it also raises substantial concerns regarding its possible effects on regional weather patterns, particularly the exacerbation of drought. Techniques such as modifying cirrus clouds can cool the climate and mitigate droughts in areas like the Sahel [93]. Additionally, methods that increase the reflectivity of the Earth's surface can reduce extreme heat and improve soil moisture, thereby alleviating drought conditions [94]. However, these approaches may also lead to unintended climatic consequences, including disrupted precipitation patterns that could worsen droughts in other regions [93,94]. Therefore, while promising for producing drought mitigation strategies, climate engineering demands thorough investigation and cautious application.

As a summary, drought research offers critical insights for enhancing practical water resource management, informing policy decisions, and shaping climate adaptation strategies. These studies highlight the significance of the adaptive management of water resources, which involves integrating surface and groundwater resources to tackle water scarcity. Strategies such as managed aquifer recharge and the adoption of water-efficient technologies, including advanced irrigation systems, are recognized as cost-effective methods to improve water reliability during drought conditions [95]. Moreover, integrated water management approaches like conjunctive water use play a pivotal role in alleviating the impacts of hydrological droughts by ensuring a balance between water supply and demand [96]. Drought research also drives policy-making by emphasizing the necessity for sustainable water management practices. Implementing policies that facilitate water markets, where water rights are allocated for environmental uses, can harmonize economic and environmental objectives during drought periods [97]. Additionally, findings from these studies are integral in planning climate adaptation strategies that consider environmental, social, and economic factors. Recommendations include updating reservoir operation protocols and adopting low-impact development practices to adjust to the climatic impacts on water resources [98].

6. Conclusions

In this research, an extensive analysis was implemented with the SCDI and DSA to monitor drought patterns using remote sensing, namely, GLDAS-based rainfall and groundwater storage datasets, over the Mediterranean basin. The main findings may be summarized as follows:

1. The SPI is a widely utilized metric for assessing drought conditions; however, it primarily focuses on precipitation without accounting for the soil water balance, which can lead to an incomplete understanding of drought severity. While precipitation is a strong driving force in the water cycle, hydrologic elements like groundwater and

soil moisture can act as stabilizing factors, mitigating drought impacts even during periods of limited rainfall.

2. In contrast, the SCDI incorporates both precipitation and groundwater levels, providing a more comprehensive view of drought intensity. The potential advantages of this innovative approach over traditional indices include simplified computation through mutual coincidence fraction, flexibility in analyzing multiple events simultaneously, and enhanced understanding of temporal relationships between events.
3. Unlike traditional indices that categorize drought severity, the SCDI can identify drought patterns by analyzing water deficit persistence. Its flexibility eliminates the need for data processing steps like transformation or normalization, making it easier and faster to apply. Using remote sensing data, the SCDI provides a cost-effective, straightforward approach for identifying these zones.
4. Research indicates that there is a significant correlation between the SCDI and both precipitation and groundwater storage, suggesting that while precipitation is a primary driver of drought conditions, groundwater storage also plays a vital role.
5. The DSA detects the longest drought periods across various time windows. This index numerically expresses the duration of hydrological deficits and is based on groundwater reserves and precipitation parameters.
6. The SPI requires a long-term precipitation record and the calculation consists of a transformation of one frequency distribution (e.g., gamma) to another frequency distribution (normal, or Gaussian). However, the DSA and SCDI are independent of the distribution and time interval of the data.
7. The DSA results provide consistency in various time windows and they are an important source of information to determine which region is under long-term drought pressure.
8. The DSA is also used to determine the impact of drought on groundwater reserves. High values of DSA indicate that groundwater resources in these regions may be under longer-term pressure.
9. The SCDI and DSA results reveal that the risk of drought is high on the southern (i.e. Spain, Greece and Türkiye) coasts of different countries in the Mediterranean region. Long-term droughts are especially noted in regions such as North Africa and eastern coast of Mediterranean.

In conclusion, the Mediterranean basin confronts substantial challenges related to drought, intensified by climate change. Investigating drought in this region is crucial for comprehending its effects on vegetation, water resources, and ecosystems. The proposed methodology serves as a baseline for stakeholders and policymakers to manage and monitor drought. The methodologies utilized in this research, particularly the high computational efficiency in calculating the mutual coincidence fraction and the ability to adapt multiple datasets, lay a foundational framework for future applications across extensive regions vulnerable to drought.

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Abbreviations

The following abbreviations are used in this manuscript:

DSA	Drought Severity Analysis
GES DISC	Goddard Earth Sciences Data and Information Services Center
GLDAS	The Global Land Data Assimilation System
GWS	Groundwater Storage
IPCC	The Intergovernmental Panel on Climate Change
SCDI	Simple Coincidence Deficit Index
SPI	Standardized Precipitation Index

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