

DROUGHT MONITORING IN CYPRUS VIA THE INTEGRATION OF HYDROLOGICAL, METEOROLOGICAL AND SATELLITE DATA

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ABSTRACT

The prolonged drought in Cyprus has several impacted agricultural productivity, leading to water shortages and increased economic stress on local communities. The study investigates the underlying drivers of drought using hydrological, meteorological, and satellite data derived from field measurements and online database. Primary drought indicators, particularly precipitation, temperature, evapotranspiration, dam water storage, and the Normalized Difference Vegetation Index (NDVI), were analyzed from 2000 to 2024 according to seasonal and annual time periods. Pearson correlation coefficient was used to identify linear relationships among the drought indicators, whereas long-term mean averages and anomalies (deviations from the long-term means) were estimated to identify temporal patterns and trends. Annual analyses revealed the presence of significant positive correlations between air temperature and NDVI, as well as between temperature and evapotranspiration, whereas all factors showed increasing temporal trends in recent years—indicating an increase in atmospheric moisture demand and vegetation activity. Conversely, a negative correlation is observed between air temperature and dam water storage, highlighting the stress on water availability at a national scale. A moderate positive correlation is observed between precipitation and water storage, including temporal delays due to infiltration and surface runoff. Seasonal analyses reveal a distinct reduction of precipitation rates, especially during the wet period, combined with increasing air temperatures. Temporal anomalies are identified across multiple variables, indicating the presence of extreme drought periods, such as 2008, where precipitation rates were significantly below the long-term mean values, and 2019, which exhibited anomalies increase in precipitation. The findings of this study highlight the importance of combining remote sensing and ground truth data to improve drought monitoring and water management in semi-arid regions.

Keywords: drought monitoring, meteorological drivers, hydrological drivers, hydrological drought, combined drought indicator, satellite data, time series analysis, temperature

1. INTRODUCTION

Drought is a significant natural hazard which is associated with water scarcity, driven by both climatic and human-induced factors [1,2]. It's a complex, multifaceted phenomenon that is challenging to assess accurately due to the interplay among several factors, such as spatiotemporal climatic variations, water consumption patterns, vegetation dynamic, land use development, and hydrometeorological conditions. The slow onset, uncertain duration, and delayed identification and quantification of this phenomenon often results in long-term environmental and socio-economic adverse consequences [3]. Droughts are typically classified into four interrelated types: meteorological drought, caused by a deficiency in precipitation, hydrological drought, marked by reduced streamflow and water levels in rivers and reservoirs; agriculture drought, linked to soil moisture deficits affecting crop production; and socio-economic drought, which it reflects the broader consequences on industry, food production, and public health [3,4]. The adverse consequences of droughts are extensive including reductions in agriculture productivity, energy production, tourism, and water management, as well as increases in food prices and public health issues, such as vector-borne diseases and water scarcity [4,5]. At a global scale,

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the frequency and intensity of droughts have increased during the last decades, particularly in regions like Africa, southern Europe, and eastern Australia [6].

In Cyprus, drought monitoring is carried out by the Water Development Department and the Meteorological Department through the estimation of various hydrometeorological indicators, such as the Standardized Precipitation Index (SPI), the Wet Period Runoff Index, and the Reservoir Storage Index, among others [11]. Additionally, radar reflectivity systems (CAPPI 2000) are installed in Larnaka and Papho for measuring precipitation rates, supplemented by data collected from other data sources, such as satellite repositories, ocean buoys and floats, as well as radar and lidar systems. Technologically advanced countries like Germany, France, and Russia contribute to these efforts by providing regional data and analysis in these repositories [13]. However, the Cypriot authorities still rely heavily on ground-based rainfall measurements, which inevitably suffer from different sources of uncertainties (e.g. small number of installed stations, low spatial resolution), failing to fully integrate satellite-based data for drought identification. In many countries, the monitoring network of climate variables consists of insitu measurements, outputs of physical models, and earth observation repositories (e.g., Copernicus, Google Earth Engine)[8]. The use of vegetation indices like NDVI (Normalized Difference Vegetation Index), VCI (Vegetation Condition Index), and VHI (Vegetation Health Index), along with tools such as Palmer Drought Severity Index (PDSI) and soil Moisture Deficit Index (SMDI), has significantly improved real time drought detection [1,10,12]. For example, in the Horn of Africa, satellite-based data from MODIS and Sentinel-2, combined with vegetation indices like NDVI, VCI and PDSI, has enhanced the ability to detect and monitor drought conditions. The European Space Agency’s (ESA), Copernicus program has helped regional organizations to monitor vegetation health and soil moistures levels, leading to more timely interventions such as water resource management and aid distribution. In addition, the integration of remote sensing with empirical and data-driven prediction models has further enhanced forecast capabilities, enabling more accurate and timely drought prediction [1]. This study aims to assess drought conditions in Cyprus by integrating field measurements (e.g., dam water levels, precipitation, air temperature) with satellite datasets, such as Sentinel-2 imagery, and information collected from local agencies, by covering the period 2014-2024. By combining statistical metrics, such as Pearson correlation Coefficient, this study seeks to identify patterns of drought, seasonal anomalies and prone drought regions. The goal is to propose a robust and adaptable methodology for more effective drought monitoring in Cyprus.

2. METHODOLOGY

The study area encloses nineteen major dams of Cyprus, particularly Kouris, Kalavassos, Lefkara, Evretou, Germasoglia, Dhipotamos, Arminou, Polemidia, Asprokremos, Kannaviou, Mavrokolimpos, Vizakia, Xiliatos, Argaka, Pomos, Kalopanagiotis, Agia Marina, and Achna (Figure 1). Among them, Germasoglia Dam was selected for detailed visual drought analysis due to its hydrological importance in supplying Limassol, the availability of consistent long-term records on dam levels and climate variables and its critical role in supporting both Urban and agriculture water needs.

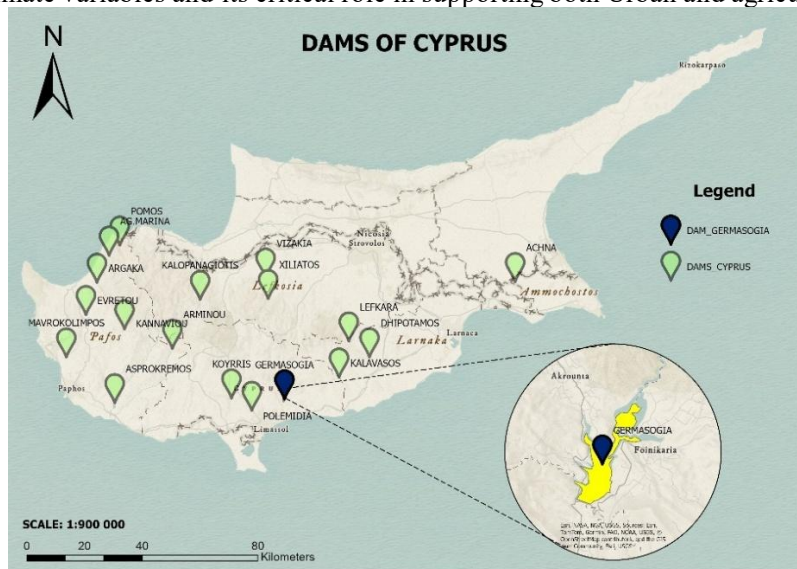


Figure 1: Geographical contribution of Cyprus Dams

Table 1 provides information regarding the data which is used in this study, along with the data sources and spatiotemporal specifications.

Table 1: Data from multiple sources.

Data sources	Time period	Temporal Resolution	Spatial resolution	References
Sentinel 2-Images for Germasogia DAM	2014-2024	Summer Months	10km	Copernicus [17]
CDI Indicator European	2014-2024	Summer Months	5 km	European Drought Observatory (EDO) [18]
Precipitation	2000-2024	Monthly	Meteorological stations	Department of meteorology [13]
Temperature	2000-2024	Mean monthly	Meteorological stations	Department of meteorology [13]
Evapotranspiration	2000-2024	Daily	19200 m	TerraClimate dataset [19]
Water storage	2000-2024	15 days	Water development department	Water development department [9]
NDVI	2000-2024	monthly/yearly	Case study	Christos Theocharides case study [20]
Climate Engine org	2000-2024	Yearly, Daily	4km	Google Earth Engine [21]

2.2 Methodology

Figure 2 provides an overview of the current methodology, which begins with the collection of datasets, comprising hydrological and climatic variables and satellite data for dams across Cyprus, obtained from national authorities and other relevant sources, as detailed in Table 1.

Given the multisource nature of the datasets, time series harmonization was carried out for all variables to an annual and seasonal temporal resolution. Hourly and daily data were aggregated into seasonal and annual resolutions by using Microsoft Excel. Subsequently, linear graphs at an annual temporal resolution were employed to identify trends, while seasonal temporal resolution was used to pinpoint the most critical months for drought-prone conditions in Cyprus.

Pearson correlation coefficient is employed to statistically assess the linear relationships between the different variables. It ranges from -1 (indicating a perfect negative correlation) to $+1$ (indicating a perfect positive correlation), with 0 representing no linear correlation. This indicator measures the strength and direction of the linear association between two continuous variables via the following equation:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}, \quad (1)$$

where x_i and y_i denote the value of x and y variables at the i -th location, respectively, \bar{x} and \bar{y} denote the average values, and n is the total number of observations. Equation (1) was applied to all pairs of variables for both annual and seasonal analyses.

While correlation analysis is used to explore linear relationship among variables, anomaly detection focuses on identifying irregularities (i.e., large deviations from the expected outputs) in the data. Statistical trends and anomalies may appear alongside or following climatic events, often associated with temporal lags in the correlation patterns.

For example, temperature-related anomalies may appear during extreme precipitation events (i.e., zero-lag), while vegetation responses, expressed via NDVI, often exhibit delayed temporal changes with respect to the precipitation events. Anomalies can be identified visually via graphs or via the use of statistical criteria as mean deviation [14,15,16].

The deviation from the long-term mean (equation 2) is a simple method for identifying anomaly of A ,

$$A = X(t) - m, \tag{2}$$

where $X(t)$ denotes the value of the variable X at time t , and m denotes the long-term mean value within the entire time period. Positive values indicate years with higher-than-average value, while negative values represent years with temperature below the mean value.

Germasogia dam was selected for visualizing the drought dynamics for period 2016-2024 from Sentinel 2 satellite. The Combined Drought Indicator (CDI) was employed to whole Cyprus from 2012 to 2024 to identify the prone drought areas potentially affected during these crucial months. Particularly, correlation analysis was conducted between CDI values and satellite-derived factors to compare the surface water in the dams and the CDI indicator to find out how both satellites ways can be correlated and be cooperated for future results. The proposed methodology integrates hydrological, meteorological, and satellite data to enhance the identification and early detection of drought-prone areas (Figure 2).

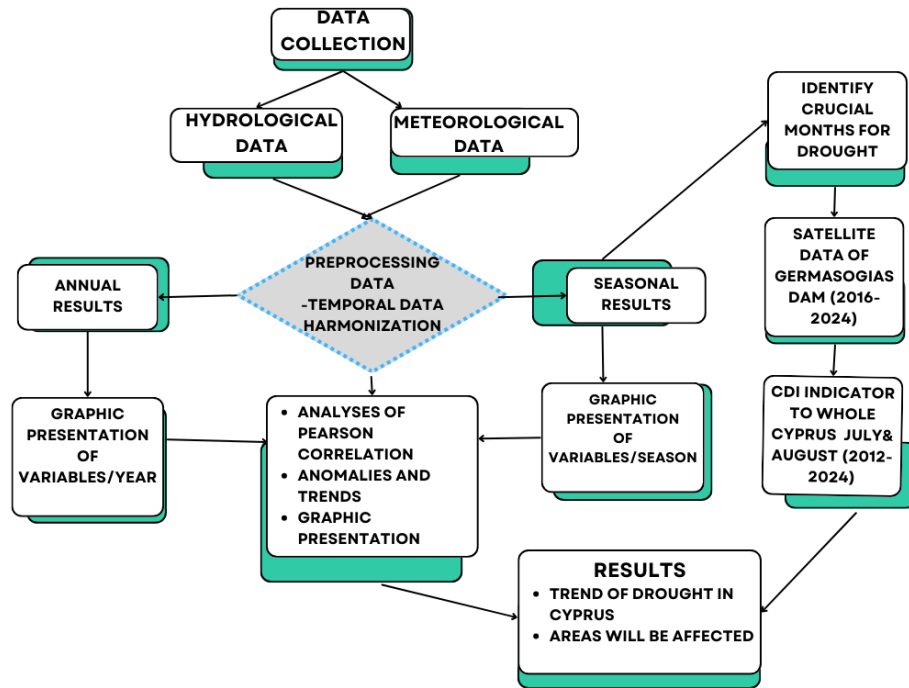


Figure 2: Overview of the current methodology.

3. RESULTS

3.1 Results from Annual scale

Figure 3 illustrates temporal trends and patterns in environmental and hydrological variables. It derives time series analyses period from 2000 to 2024, highlighting anomalies that reflect interconnected changes in climate, vegetation dynamics, and water resource availability across the entire study area. The variables dataset includes storage water area (SWA), precipitation (P), temperature (T), and Hargreaves potential evapotranspiration (based on CFSR data) across major dams (see Fig. 1), along with the Normalized vegetation index for Paphos forest primarily covered by *Pinus Brutia*. For instance, NDVI, demonstrates a clearly upward increase (mean average) trend, particularly across the forested areas of Paphos. This trend may be attributed to factors such as reforestation or other influences that have positively affected the condition of the forests.

At the same time, air temperature shows a steady increase in mean trendline (Fig.3c), NDVI and air temperature show a moderately strong positive correlation for the period 2000-2023, with both increasing and showing similar anomalies. Furthermore, NDVI and temperature mostly show positively correlated anomalies, with both rising in years like 2009, 2015, and 2023. However, divergent patterns appear in 2010 and 2016, where high temperatures coincided with NDVI

drops, likely due to heat of drought stress. These anomalies suggest that while moderate warming supports vegetation growth, extreme conditions may suppress it.

Furthermore, positive anomalies are observed in the time series analysis between 2000 and 2003 for precipitation (Fig. 3e) and water storage in dams (Fig. 3b), indicating a positive correlation between the two variables. Additionally, anomalies are evident in the relationship between temperature and water storage. For example, during the period 2008–2009, a negative anomaly in water storage was observed alongside elevated temperature levels (positive anomaly). A similar pattern appears in 2019, where low water storage (negative anomaly) coincides with high temperature levels (positive anomaly). These observations suggest a negative correlation between temperature and water storage, as supported by the mean statistical analysis. Moreover, a positive correlation is observed between evapotranspiration and temperature; as temperature increases, evapotranspiration also shows an upward trend during the same time period.

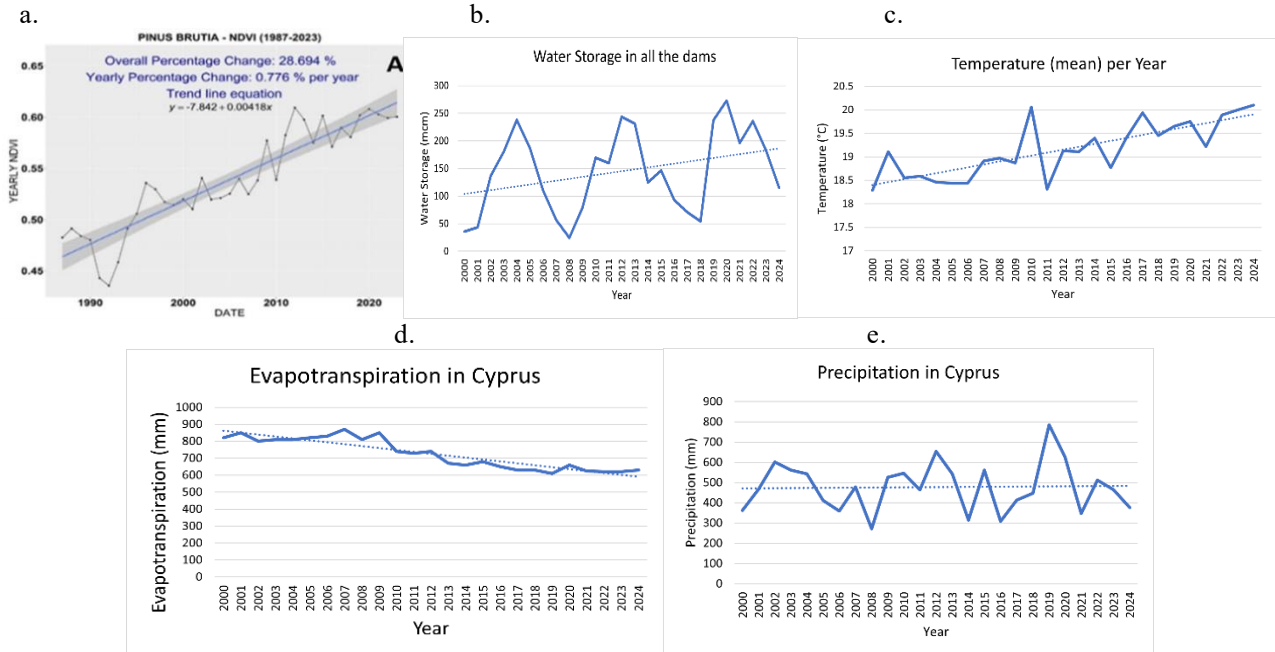


Figure 3: The time series variables are aggregated at annual scale to all Cyprus Dams for the period 2000-2024 and at Paphos forest (Pinus Brutia in NDVI) for the period 1987-2024.

As the anomalies were calculated for all variables according to Equation 2, the results presented in Figure 4 reflect the temporal deviations from the long-term mean, highlighting critical drought events and inter-variable relationships. According to figure 4, Precipitation anomalies in Cyprus ranges from -226.04 mm in 2008, indicating extreme drought, to +286.96 mm in 2019, reflecting surplus rainfall. Temperature anomalies generally showed negative deviations, with the coldest anomaly in 2000 (-1.66 °C) and a slight warming trend in 2024 (+0.15 °C). Water storage anomalies reveal years of both water deficit, such as in 2008 with -126.45 units, and surplus as seen in 2020 with +121.71 units. Evapotranspiration anomalies transitioned from positive to strongly negative values over time, with a notable drop to -146.88 mm by 2019, suggesting shifts in atmospheric demand and water availability. These anomalies highlighting the impact of climate variability and change on Cyprus’s hydrological cycle.

Additionally, lag effects were observed, as seen with peak precipitation years like 2019, which were followed by delayed increases in water storage and vegetation indicators, such as NDVI, pointing to indirect and time shifted environmental impacts.

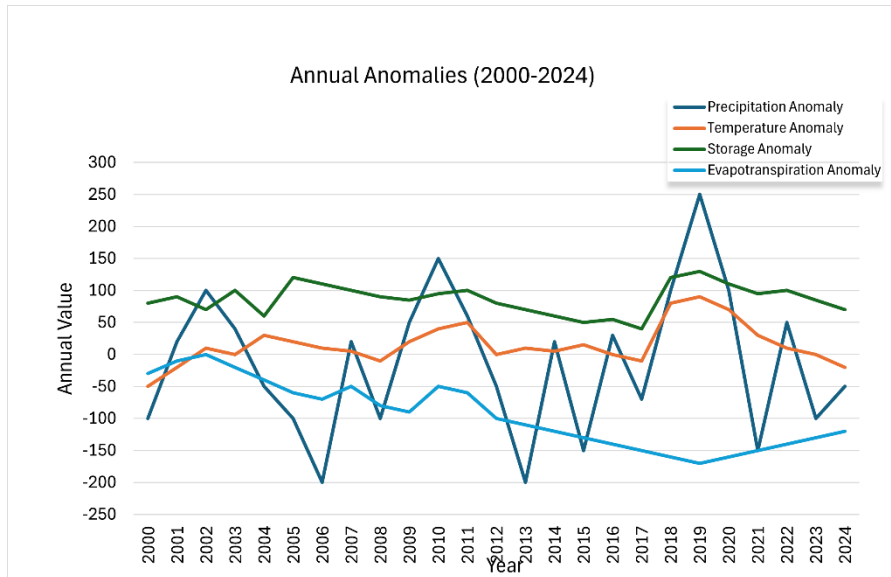


Figure 4: Annual Anomalies per Variable (Precipitation, Temperature, Water Storage, Evapotranspiration)

According to Equation 1, the Pearson correlation coefficient was calculated for all variable pairs across Cyprus's major dams, via using time series data from 2000 to 2024, to assess the strength of their correlations and potential interdependencies. The results are presented in Table 2. According to results there is a very weak positive correlation between precipitation and temperature ($r = 0.07$). A moderate positive correlation exists between precipitation and water storage ($r = 0.62$), while temperature and water storage display a weak positive correlation ($r = 0.14$). In contrast, evapotranspiration and temperature exhibit a strong negative correlation ($r = -0.72$), indicating that higher temperatures are associated with reduced evapotranspiration. Additionally, there is a moderate negative correlation between evapotranspiration and water storage ($r = -0.36$), suggesting that storage levels tend to decline as evapotranspiration increases. Finally, evapotranspiration and precipitation demonstrate a very weak negative correlation ($r = -0.06$).

Furthermore, based on the aforementioned results, an increasing trend in temperature has been observed across all years. From 2020 onward, there has been a noticeable decline in both precipitation and water storage in the dams. Since 2010, a decreasing trend in evapotranspiration has also been observed, likely due to limited water availability. Collectively, these findings indicate a clear trend toward drought conditions in Cyprus over the past five years.

Table 2: Correlation analysis.

	Precipitation	Temperature	Water storage	Evapotranspiration
Precipitation	1	0.07	0.62	-0.06
Temperature	0.07	1	0.14	-0.72
Water storage	0.62	0.14	1	-0.36
Evapotranspiration	-0.06	-0.72	-0.36	1

3.2 Results from Seasonal analysis

During winter, although precipitation peaked up, a clear decline in the mean value is observed over time, as shown by the trendline in Figure 5a. Concurrently, temperatures show a general decline compared to the mean trendline, while NDVI demonstrates an increasing mean trend, suggesting potential changes in vegetation response despite reduced rainfall and cooler conditions. Although fluctuations above and below the NDVI mean are observed in Figure 5d. further investigation is needed. A more detailed study focusing specifically on NDVI and its relationship with other variables is recommended for future research. During the spring season from 2000 to 2024, precipitation shows a downward trend, remaining below the mean trendline, while temperature exhibits an upward trend, staying above the seasonal mean. This season also records the highest levels of water storage compared to other seasons.

During the summer months, precipitation reaches its lowest level compared to other seasons (Fig.5a), while temperatures peak (Fig.5c)—particularly in August, when an anomaly of 35 °C was recorded alongside only 1 mm of rainfall.

In autumn, precipitation shows an upward trend, while temperatures decline. Notably, water storage is highest in spring and lowest in autumn, likely due to increased water consumption during the summer, which leads to reduced dam levels in the following season. Although precipitation reaches its highest level in winter, water storage typically peaks in spring due to time lags caused by infiltration and runoff delays, catchment response times, vegetation water use, and human management of reservoirs. Overall, based on the mean trendline for the years 2000–2024, a downward trend in precipitation, an upward trend in temperature, and a decline in water storage are observed, indicating a general trend toward drought conditions.

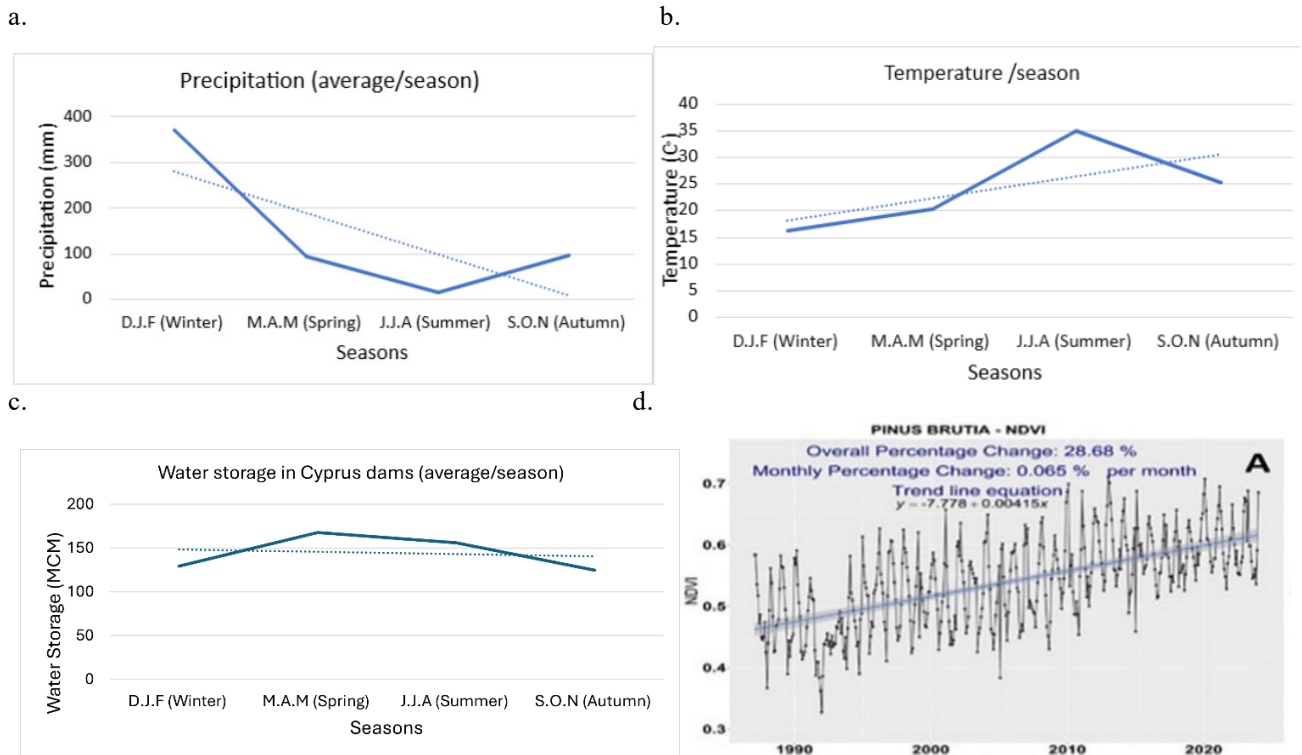


Figure 5: Seasonal Analyses of Variables- Precipitation, Temperature, Water storage in the dams, NDVI.

Anomalies calculated by using the mean anomaly formula (Equation 2), and the results are presented in Figure 6. In Winter presents a strong negative anomaly in temperature (-7.93 °C) and moderate negative anomaly in water storage (-15.07 units), despite a significant positive anomaly in precipitation (+225.75 mm). This result indicates that although winter is wet, it's immediate impact on water storage is limited, due to time lags—it takes time for precipitation to infiltrate, generate runoff, and reach reservoirs. In Spring temperatures remain slightly below-average (-3.93 °C), with a strong positive anomaly in water storage (+23.45 units), and reduced precipitation (-49.25 mm). This reflects the delay effect of heavy winter rainfall, water storage peaks in spring, as the accumulated winter precipitation gradually contributes to reservoirs levels even though spring itself is relatively dry.

The Summer records present the highest positive temperature anomaly (+10.78 °C), slight water storage increase (+11.50 units), and the most significant rainfall deficit (-128.25 mm). The high temperatures increase water demand and evaporation, while the lack of rainfall limits its replenishment. However, the water storage remains relatively stable during this season, again illustrating the lagging effect of previous accumulation.

In Autumn temperatures are slightly above average (+1.08), but water storage declines significantly (-19.88 units), accompanied by continued low precipitation (-48.25). The combined effect of the prolonged summer drought and the high-

water demand causes water storage levels to drop sharply in the dams. Autumn, rainfall proves insufficient to reverse the declining trend before the onset of Winter.

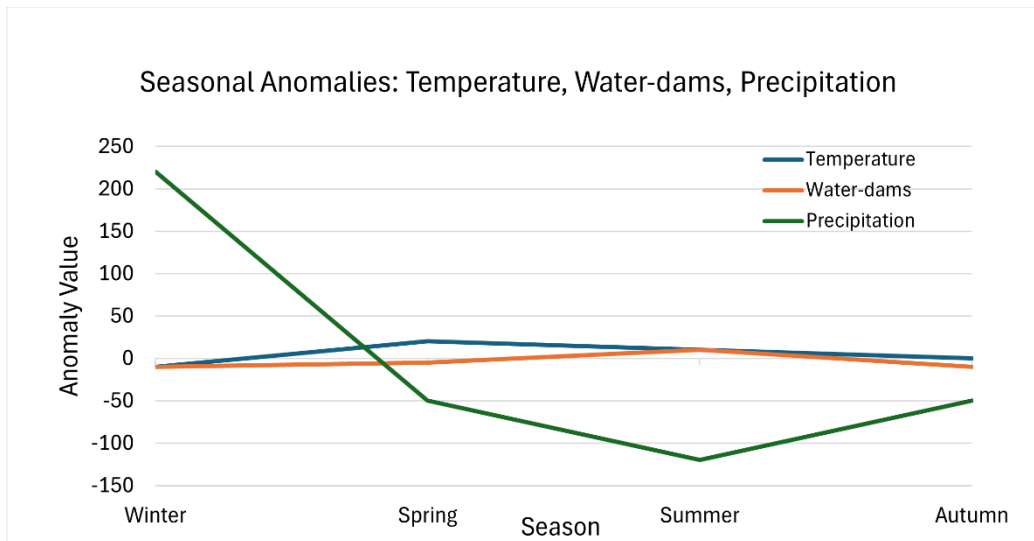


Figure 6: Seasonal Anomalies for Temperature Water Storage (dams), Precipitation

According to table 3 and the seasonal analyses of Pearson, the correlation coefficient of -0.81 between precipitation and temperature on a seasonal scale indicates a strong negative linear relationship, meaning that as temperature increases, precipitation tends to decrease, and vice versa. This suggests that warmer seasons are generally drier, while cooler seasons experience more precipitation, which could reflect typical climate patterns or emerging seasonal shifts.

A Pearson correlation coefficient of -0.52 between mean precipitation and mean water storage on a seasonal scale indicated a moderate negative relationship, meaning that as precipitation increases, storage levels tend to decrease somewhat, and vice versa. While not as strong as higher correlations, this still suggests a noticeable inverse seasonal pattern-possible due to factors like increased runoff, limited infiltration, or water management practices that reduce storage during wetter periods. This moderate negative correlation could highlight important dynamics in hydrological systems, especially when assessing seasonal water availability or reservoir behavior. A Pearson correlation coefficient of 0.26 between temperature and water storage on a seasonal scale indicates a weak positive relationship, suggesting that as temperature increases, water storage tends to increase slightly, but the connection is not strong. This could reflect indirect or complex interactions such as snowmelt contributing to storage during warmer periods, or temperature driven demand and usage patterns. Overall, the weak correlation implies that temperature alone is not a strong predictor of water storage changes seasonally, but it may still play a role in combination with other factors like precipitation, evapotranspiration or human use.

Table 3: Correlation Analyses of Pearson (season)

	Precipitation	Temperature	Water storage
Precipitation	1	-0.81	-0.52
Temperature	-0.81	1	0.26
Water storage	-0.52	0.26	1

3.3 Satellite data at Germasogia Dam in Critical Months (July-August)

The water surface of the Germasogia Dam during critical months over the years is illustrated in Figure 7 by using Sentinel 2 Satellite imagery. This visual approach enables the identification of water level fluctuations in the dam, which can be further quantified using data provided by the Water Development Department.

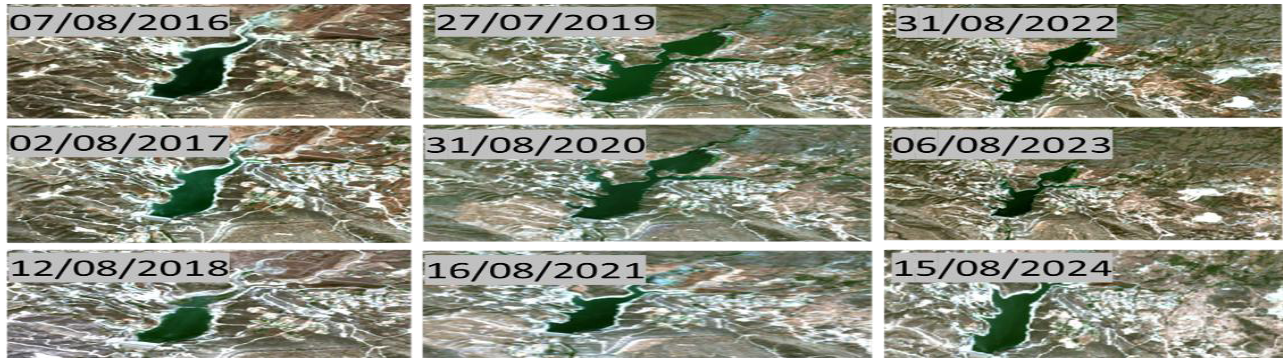


Figure 7: Satellite images from Sentinel 2, showing water distribution in Germasogia Dam from 2016-2024.

3.4 CDI Indicator

The Combined drought indicator is used for the identification the drought-prone areas in Cyprus via a time series analyses from 2012 to 2024. In Figure 8, each image displays three color codes: Yellow (-1) indicates a "Watch" status, where precipitation is below normal; Orange (-2) represents a "Warning," signaling a soil moisture deficit; and Red (-3) indicates an "Alert," suggesting more severe conditions.

According to Figure 8, the past 10 years show a clear trend toward increasing drought conditions in specific areas, particularly near Paphos forests. Additionally, a comparison between satellite images of the Germasogia Dam (Figure 7) and CDI maps (Figure 8), reveals that in years such as August 2019, 2020, and 2023—when rainfall was high and dam levels were full, Cyprus did not exhibit drought-prone areas. This is evidenced by a CDI value of approximately -1 across the island during those periods.

On the other hand, during years when the dam water storage was low, such as 2016, 2017, 2018, 2021, 2022 and 2024, the CDI indicator displayed more orange coloration (CD= -2: Warning) on the Cyprus images. This suggests that the main driver of drought in Cyprus the water levels in the damas. When the water in the dams and surrounding areas is sufficient, there is no evident trend toward drought. However, when water levels are low, drought conditions become a serious issue for the affected areas.



Figure 8: Geographical distribution of the CDI Indicator.

4. CONCLUSIONS AND FUTURE WORKS

This study proposes a methodology for the identification of drought patterns in Cyprus via the integration of hydrological, meteorological, and satellite data (CDI), offering a useful approach for detecting drought-prone areas.

By integrating field measurement from ground stations with satellite data enhances environmental monitoring through broader spatial coverage, more frequent observations and increased accuracy. Ground based data validate and calibrate satellite estimates, while satellite data fill spatial and temporal gaps. This integration enables multi-scale analysis, improves model performance, and provides a cost-effective solution for monitoring and managing natural resources and climate impacts. Furthermore, the use of this integrated methodology supports better decision-making in water resource management, improves drought prediction, and promotes proactive and sustainable drought mitigation strategies. Its adaptability also offers valuable insights for other regions facing similar challenges, contributing to global efforts in drought monitoring and climate resilience.

Future research should focus on enhancing drought monitoring by integrating satellite data with detailed field measurements for better accuracy and broader spatial coverage. Expanding the use of remote sensing indicators like NDVI, soil moisture and evapotranspiration, alongside ground-truth data, will improve early drought detection. Additionally, adopting best practices for data collection and analysis, as well as conducting comparative studies with other drought-prone regions, will help refine mitigation strategies. Prioritizing the study of climate change impacts on regional drought trends will aid in better environmental planning.

Moreover, the incorporation of more advanced statistical tools, such as machine learning, geostatistical [22,23,24] enhanced with additional sampling campaigns for measuring water quality both in surface and subsurface systems, can assist to the compilation of more holistic approaches, which can be combined with water-scarcity solutions towards the design of efficient drought management plans [25,26,27].

ACKNOWLEDGEMENTS

The authors acknowledge the ‘EXCELSIOR’: ERATOSTHENES: Excellence Research Centre for Earth Surveillance and Space-Based Monitoring of the Environment H2020 Widespread Teaming project (www.excelsior2020.eu). The ‘EXCELSIOR’ project has received funding from the European Union’s Horizon 2020 research and innovation program under Grant Agreement No 857510, from the Government of the Republic of Cyprus through the Directorate General for the European Programs, Coordination and Development and the Cyprus University of Technology.

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