

Assessment of drought and soil moisture relationship: A case study in Cyprus using geospatial data

E. Neofytou^{1*}, M. Eliades¹, S. P. Neophytides¹, C. Papoutsas¹, C. Kontoes³, D. G. Hadjimitsis²

¹ Eratosthenes Centre of Excellence, Franklin Roosevelt 82, 3012, Limassol, Cyprus

² Department of Civil Engineering and Geomatics, Cyprus University of Technology, Limassol, Cyprus

³ National Observatory of Athens, Athens, Greece

*Corresponding author: eleni.neofytou@eratosthenes.org.cy

ABSTRACT

Limited precipitation events may result in soil moisture depletion and to an overall water scarcity over a catchment areas. Forest productivity and functioning are severely influenced by drought conditions, which in some cases can even result in tree mortality. Thus, monitoring drought conditions in forested areas is essential given their critical environmental importance. The aim of this research is to identify drought events occurred in forested areas in the semi-arid island of Cyprus and its relationship with soil moisture at different depths using geospatial data. The current study used the 3-month period Standardized Precipitation Evapotranspiration index (SPEI) data for drought monitoring and GLDAS datasets, for soil moisture depths of 0-10cm, 10-40cm, 40-100cm and 100-200cm. A correlation analysis was performed to observe the relationship of SPEI with the different soil moisture depths. Pearson correlation analysis showed moderate to strong positive (0.325-0.549) linear relationship between SPEI and soil moisture at different depths with the correlation becoming stronger at deeper soil profiles. Spearman correlation analysis showed a weak to moderate positive monotonic relationship (0.294-0.439) with the correlation becoming stronger at deeper soil profiles.

Keywords: Drought, Soil Moisture, Climate Crisis, Water Resources Management, Remote Sensing

1. INTRODUCTION

The Eastern Mediterranean region is often exposed to severe drought events. Limited precipitation events, rainfall pattern alteration and rise in temperature reduced the soil moisture availability in the region. These unfavorable conditions are expected to become more severe in future decades (Payab and Türker, 2023). Extreme drought has the potential to significantly reduce forest growth on a regional and continental scale (Liu et al., 2022).

Different drought indicators have been developed over time for drought monitoring purposes. Physical variables that show the consequences of drought with variations from normal conditions include precipitation, temperature, flow, groundwater level, reservoir levels, soil moisture levels, and snowfall. Using one or more physical indices, the term "drought index" refers to numerical representations that can be used to determine the extent and severity of drought (Alahacoon and Edirisinghe, 2022).

Standardized Precipitation Evapotranspiration Index (SPEI) has been increasingly used in hydrological and climatological studies since it can assess drought conditions (Pei et al., 2024). The principle of SPEI

is based on the difference between precipitation and potential evapotranspiration (PET) and it comes in different time windows which affects the interpretation of the results based on the research questions and objectives (Abbasi et al., 2019). There are other methods also used in literature for drought monitoring such as Standardized Precipitation Index (SPI) and Palmer drought severity index (PDSI) (Gumus, 2023). Several studies focused on comparing these three indices concluding that SPEI, which is the advanced version of SPI and SPI are performing better than PDSI for drought monitoring (Vicente-Serrano et al., 2012; Wang et al., 2017). The estimation of PET from global SPEI database is based on the FAO-56 Penman-Monteith estimation since it is considered a better and more reliable way for PET estimation.

Large-scale information of soil moisture (SM) dynamics requires long-term observational records. However, there is a lack of in situ observational data to give large-scale spatial and temporal scale SM measurements, especially in dry regions. Alternatively, reanalysis and remotely sensed (RS) gridded SM products can be used to overcome this constraint (Hu et al., 2021; Yu et al., 2023). SM content and availability monitoring are essential, especially in regions that suffer from severe drought events that lead to water scarcity. To provide accurate data for SM research, the Global Land Data Assimilation System (GLDAS) integrates data from satellite and surface-based meteorological observations giving the opportunity to gain an insight in SM status at different depths (Fatolazadeh et al., 2020; Rodell et al., 2004). By combining satellite and ground-based observational data and employing sophisticated land surface modelling and data assimilation techniques, GLDAS seeks to generate high quality fields of land surface states (such as soil moisture, temperature), and fluxes (such as evapotranspiration, runoff) (Sun et al., 2022). Numerous scientific and practical applications, such as weather prediction, agricultural forecasting, drought and flood risk assessments, and enhancing knowledge of land-atmosphere interactions and the effects of climate change, depend on the accurate characterization of spatial and temporal variations in water and energy states. To create fields of water and energy levels and fluxes that are physically consistent and geographically and temporally continuous, GLDAS combine data from various ground-based and space-based monitoring systems using complex numerical models of physical processes (Moghim, 2020).

The aim of the current paper is the analysis of SPEI and GLDAS for drought monitoring in the forested areas of the Cyprus island. The main objectives are a) to monitor drought events occurring in the forested areas of southwest, southern coast and northwest sites of the island of Cyprus using the SPEI-base dataset, b) observe SM at different depths behavior during drought periods and c) examine correlation between SPEI and SM at different depths.

2. METHODOLOGY

2.1 Data acquisition

On a global scale, Standardized Precipitation Evapotranspiration Index (SPEI) (Beguería et al., 2024) database provides long time information for drought conditions. SPEI is based on the difference between precipitation and potential evapotranspiration (PET) as shown in Eq.1 (Vicente-Serrano et al., 2010). For the current study SPEI-03 months used for seasonal drought trends monitoring. The FAO-56 Penman-Monteith assessment of potential evapotranspiration serves as the foundation for the SPEI database.

$$D_i = P_i - PET_i \quad (1),$$

The Global Land Data Assimilation System (GLDAS 2.1) used for the retrieval of soil moisture at different depths (Rodell et al., 2004). The depths selected for the current study are 0-10cm, 10-40 cm, 40-100cm and 100-200cm.

Dynamic World V1 dataset is used for the current study since it provides class probabilities and information regarding land cover (Brown et al., 2022). The data set consists of nine classes where for this study trees are selected as land cover. The data collection from SPEI and GLDAS concerns the period of 2015-2023 and were retrieved from Google Earth Engine (GEE) software.

2.2 Correlation analysis

Pearson (Eq. 2) and Spearman (Eq. 3) methods were used for the current study to investigate the correlation coefficients between the SPEI-03 and SM at different depths. In statistics the correlation coefficient used to assess the linear correlation between two sets of data is the Pearson correlation coefficient (PCC). With a value that consistently falls between -1 and 1, it functions as a normalized measurement of covariance. It is defined as the ratio between the covariance of two variables and the product of their standard deviations. Pearson correlation coefficient formula is determined as follows:

$$r = \frac{\Sigma (x_i - \bar{x}) (y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2 \Sigma(y_i - \bar{y})^2}} \quad (2),$$

where the Pearson correlation coefficient is the r in the equation, x_i are the values of x-variable in a sample, the mean values of x-variable is the \bar{x} in the equation, y_i is the value of y-variable in the sample and \bar{y} is the mean value of the y-variable.

The Spearman rank correlation coefficient is a nonparametric measure of rank correlation that captures the statistical dependence between the ranking of two variables. The formula is as follows:

$$\rho = 1 - \frac{6 \Sigma d_i^2}{n(n^2 - 1)} \quad (3)$$

Where Spearman's rank correlation coefficient is the ρ in the equation, the d_i is the observation differences between the two ranks and the n is the observation numbers.

The linear relationship of the variables is measured by Pearson correlation. More specifically, the values that determine the linearity and whether this is positive or negative are from -1 to +1. When the value is close to +1 there is a strong positive linear relationship between the variables while a strong negative linear relationship is indicated when the value number is close to -1. When the value is 0 indicates that there is a little to no linear relationship.

On the other hand, Spearman correlation measures the monotonic relationships of the variables. Spearman correlation is statistical methodology that does not rely on constant linear relationship, rather is assess whether a consistent directional trend exists between the variables. A positive monotonic trend is indicated when the value number is close to +1 while negative monotonic trend is indicated when the number is close to -1. A little to no monotonic relationship is suggested when the value number is near 0. In order to determine the drought severity for our case study classification analysis performed. Based on literature SPEI value threshold selected for the determination of drought severity (Table 1) (Burić et al., 2024), (Elair et al., 2025). The correlation methods and classification performed in python.

Table 1. SPEI classification

SPEI VALUE THRESHOLD	CLASSIFICATION
≤ -2.0	Extreme Drought
-2.0 to -1.5	Severe Drought
-1.5 to -1.0	Moderate Drought
-1.0 to 0	Mild Drought
0 to 1.0	Near Normal
> 1.0	No Drought

2.3 Study area

This study focuses on the southwest, southern coast and northwest forested sites, of the island of Cyprus. The island of Cyprus is characterized as a semi-arid region with long dry and hot summer and mild winters with low precipitation. Cyprus experiences yearly mean temperatures that range from 16.1°C to 19.7°C, with an average of 17.5°C ([Cyprus - Climatology | Climate Change Knowledge Portal](#), visited 01/05/2025). From the area of interest, the data collected concerns only the trees as land cover (Figure 1).

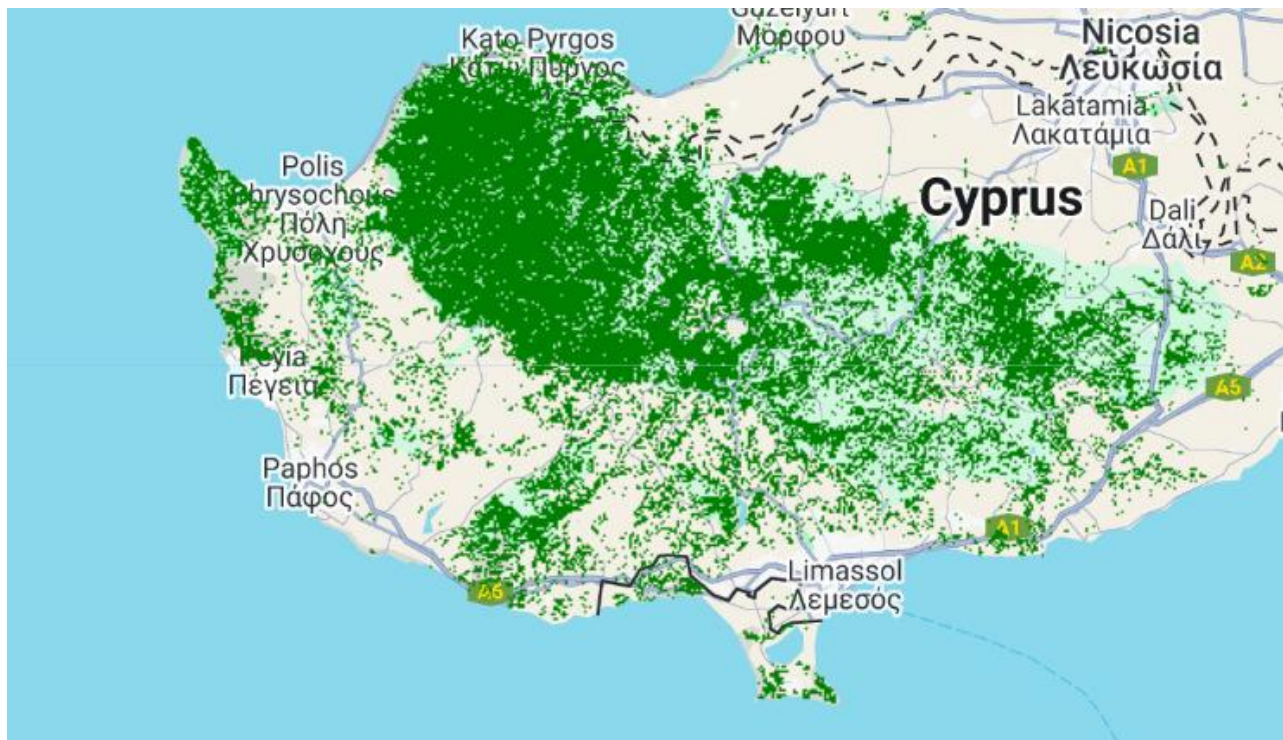


Figure 1. Study area of Cyprus where the green color illustrates trees

3. RESULTS

SPEI classification provided information regarding the severity of drought occurring in the area of interest. The results reveal that the case study land covered for trees experiencing mostly moderate to near normal drought conditions between the years of 2015-2023. No drought conditions during this 8-year period only occurred for two consecutive years (2019 and 2020). However, in October 2020 an extreme drought occurred, and since then there is mostly moderate to near normal drought conditions in the area. The plot illustrated in Figure 2 provides the information that even though there are not many severe to extreme drought conditions in the area of interest of this study there are mostly moderate, mild and near normal drought conditions which this makes the area studied vulnerable.

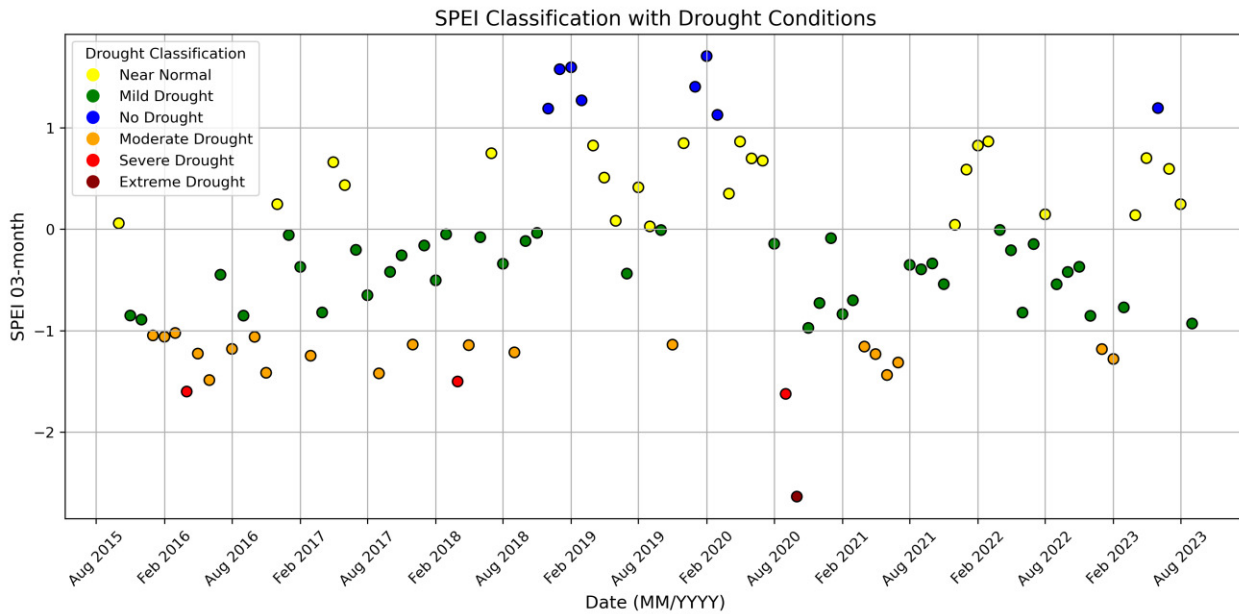


Figure 2. SPEI classification plot for drought severity determination

On this study, further analysis performed to show how soil moisture at different depths behaves during drought periods. The SM values derived from GLDAS are calculated in kg/m^3 . A chart was created to observe the behavior of SM and SPEI. Figure 3 illustrates that as SPEI increases SM does too with special influence on deeper SM layers. During the extreme drought event that occurred in October 2020 all SM depth impacted especially the deeper layers (40-100cm and 100-200cm). The chart also shows that there is no recovery from the extreme drought event occurred, especially in the SM depth of 100-200cm.

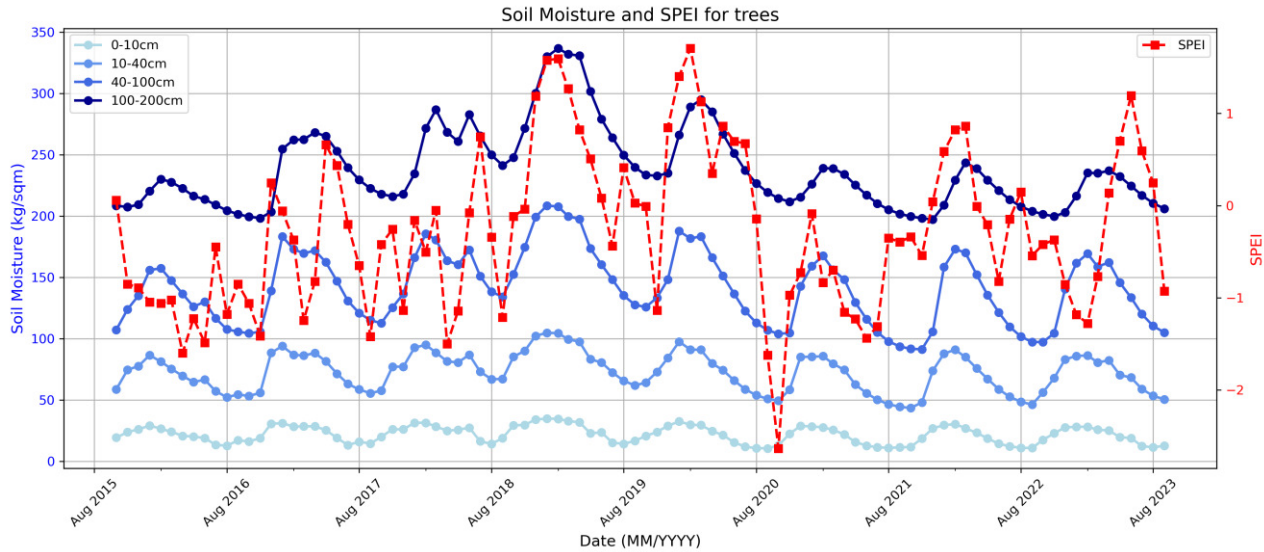


Figure 3. SM values at different depths and SPEI

Table 2 illustrates the results of the correlation analysis. Pearson correlation method adopted to obtain the correlation between SPEI and SM at different depths. The results suggest that there is a positive linear relationship between SPEI and SM at 0-10cm, 10-40cm, 40-100cm and 100-200cm. There is a weak positive linear relationship observed for SPEI and SM 0-10cm while in SPEI-SM 10-40cm and 40-100cm there is a moderate positive linear relationship. However, SPEI-SM 100-200m there is a strong positive linear relationship. The results suggest that when the soil profile depth gets deeper there is a stronger correlation between the two variables. Moreover, the results suggest that the correlation of the variables is statistically significant.

Pearson correlation adopted to observe if the one variable increase so does the other. The results suggest that there is a tendency when the one variable increase as does the other especially in deeper soil profile layer. In addition, the results suggest that even if there is a weak to strong relationship between the two variables other environmental factors such as biochemical, soil type and local hydrological conditions influence the variability of soil moisture.

Table 2. Pearson correlation between SPEI and SM at different depths

Pearson correlation analysis between SPEI and Soil Moisture

<u>SPEI-SM 0-10cm</u>		<u>SPEI-SM 10-40cm</u>		<u>SPEI-SM 40-100cm</u>		<u>SPEI-SM 100-200cm</u>	
Pearson	p-value	Pearson	p-value	Pearson	p-value	Pearson	p-value
0.325	0.001	0.429	1,25E+10	0.468	1,45E+08	0.549	6,85E+07

In addition to Pearson correlation, Spearman correlation was also used to assess the relationship of SPEI and SM at different depths. Table 3 illustrates the relationships between the variables obtained from Spearman correlations and their corresponding p-value. All the results showed that the correlation between SPEI and SM at different depths are statistically significant. Weak positive monotonic relationship observed between the SPEI and SM 0-10cm and SPEI-SM 10-40cm with a correlation

coefficient to be 0.294 and 0.379 respectively. A weak to moderate positive monotonic relationship observed between the SPEI- SM 40-100cm with correlation coefficient 0.396. As happened in Pearson correlation as the soil profile becomes deeper the correlation becomes stronger. In the case of Spearman correlation, the SPEI-SM100-200cm is 0.439 which is classified as moderate positive monotonic relationship.

Table 3. Spearman correlation between SPEI and SM at different depths

Spearman correlation analysis between SPEI and Soil Moisture

<u>SPEI-SM 0-10cm</u>		<u>SPEI-SM 10-40cm</u>		<u>SPEI-SM 40-100cm</u>		<u>SPEI-SM 100-200cm</u>	
Spearman	p-value	Spearman	p-value	Spearman	p-value	Spearman	p-value
0.294	0.003	0.379	0.0001	0.396	6,40E+10	0.439	7,36E+09

Several studies focused on the use of geospatial data and RS-derived indices and their correlation with drought index such as SPEI and SPI for the effective monitoring and assessment of drought events. Ma et al., (2023) used several indices such as solar-induced chlorophyll fluorescence (SIF), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), canopy fluorescence yield (SIFyield), fraction of absorbed photosynthetically active radiation (fPAR) and Leaf Area Index (LAI) with the use of SPEI as a drought condition benchmark. The key findings of this study suggest the effectiveness of SIFyield derived from RS in drought stress monitoring having the highest correlation with SPEI than the other variables (Ma et al., 2023). Another study performed by Amini et al., (2023) investigates the drought from SPI and SM at different depths using GLDAS data to observe variations. The key findings of their study are that SM and SPI are interrelated, GLDAS based on statistical indicators can be effectively used for SM estimation in locations with either no ground-based data or limited data, and drought events have a direct impact on SM in deeper soil profiles (Amini et al., 2023).

4. CONCLUSION

Most of the relationships between SPEI and SM at different depths are not strong, implying that other environmental factors, such as soil properties, vegetation, and hydrological processes, influence soil moisture variability. In addition, no drought periods are on its minimum in the forested areas of Cyprus make these regions vulnerable. According to Pearson and Spearman, high soil moisture in deeper soil layers increases the drought resilience, especially in soil layer of 100-200cm. The relationship of SPEI to soil moisture at different depths is always positive during the period 2015-2023. The main limitations of this study are that more input data are required for the results to be more robust such as elevation since forested areas are located in different elevations. Moreover, in most cases forested areas are not reaching 200cm soil layer. However, even deeper layers may still contribute as a reserve for moisture in drought periods or rainfall scarcity. In addition to that some vegetations such as deep-rooted trees can access moisture in deeper soil profiles for support during dry periods. In future, further analysis of the current study will take place for the results to be more robust such as the input of elevation and addition of vegetation indices to observe the impact of drought on vegetation and how SM behaves.

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