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VEGETATION AND EVAPOTRANSPIRATION ANALYSES ON CLIMATE MAPS

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Abstract: This study focuses on the investigation of Evapotranspiration (ET) processes under the climatic and geographical characteristics of Türkiye. ET refers to the process by which plants transfer water vapor to the atmosphere and is an important part of the water cycle. This research analyzes ET in Türkiye using imagery data from NASA Global Land Data Assimilation System Version 2 (GLDAS-2), MODIS, TerraClimate, SMAP Level-4, and Penman-Monteith-Leuning ET V2 (PML_V2). Surface Soil Moisture (SSM) data for Türkiye between 2016 and 2022 and Land Surface Temperature (LST) data between 2000 and 2022 were obtained from MODIS images. In the study, regression analyses were performed with ET values and SSM and LST data. The best result was a moderate correlation (R 0.57) between ET produced from SMAP Level-4 data and LST. A high correlation (R 0.59) was observed with SSM. Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) 1981 and 2023 precipitation data and 1981 and 2023 Surface Pressure (PS) data were obtained from MERRA image. Regression analyses were performed between ET data and PS and precipitation values. A moderate relationship (R 0.37) was observed between ET and PS produced from MOD16A2 V105 data. A moderate relationship (R 0.50) was observed between ET and precipitation obtained from TerraClimate data. This study aims to contribute to the development of strategies to effectively manage water resources and improve agricultural sustainability by analyzing ET in various regions of Türkiye.

Keywords: ET, GLDAS-2, MODIS, TerraClimate, SSM, LST

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1. Introduction

Starting in the 1970s, remote sensing techniques have been used to determine parameters such as surface turbulent energy fluxes and soil water content. This method was initially adopted by geologists to level out mineral deposits and later by meteorologists to estimate the surface. Some geologists have used remote sensing techniques to detect ore deposits. They developed remote sensing methods to study turbulent energy flows at the surface and to determine soil water content. These studies were among the first examples where remote sensing techniques were used to determine soil properties. Later, meteorologists adopted this method and developed remote sensing techniques to measure and predict surface parameters. Researchers such as Price (1980), Soer (1980), Carlson et al. (1981), Price (1982), Wetzel et al. (1983) and, Carlson et al. (1984) used remote sensing techniques to determine important parameters such as surface turbulent energy fluxes and soil water content. Throughout the 1990s, this trend continued, and many papers were published on this topic.

ET, in conjunction with precipitation and runoff, plays a pivotal role in determining water availability and the distribution of turbulent energy fluxes across the Earth's surface (McCabe and Wood, 2006). The utilization of satellite remote sensing for observing surface fluxes and soil water content has evolved across various spatial and temporal scales, especially following the recognition of the appeal and functionality of thermal infrared remote sensing in the 1980s (Kalma et al., 2008). This evolution has led to the development of diverse modeling schemes, each with its distinct mechanisms and levels of complexity.

ET, combining both evaporation and transpiration, involves the absorption of water by plants from their root zones (Brooks et al., 2003). ET not only tracks the amount of water essential for efficient water management but also contributes to the surface energy balance (Bogawski and Bednorz, 2014; Wang et al., 2012). As water efficiency improves globally and locally, preserving water in irrigation planning becomes more challenging (Krishna, 2019). ET can be used to measure plant water stress since the rates of water uptake by vegetation cover are uniform (Islam and Karim, 2019). Decreased water resources due to inadequate allocation can negatively impact harvests and jeopardize food security. Optimizing the water management system and accurately predicting ET are crucial in this context (Reyes and Gonzalez, 2017).

Precise estimation of ET is vital to understanding uncertainties in the behavior of the hydrological cycle in response to climate change by identifying factors influencing ET and measuring it accurately. Reliable ET predictions, based on strong foundations, are essential to regulating irrigation system components, considering factors like the size and power of channels, reservoirs, and pumps, as ET plays a significant role in the water balance at all scales, from individual land plots to global land systems (Kharrou et al., 2021; Hao et al., 2022).

Studies combining remote sensing and ground methods to estimate ET over large areas, including agricultural regions, rangelands, and natural ecosystems, were applied in the review by Glenn et al. (2007). Different methods have been developed and applied to estimate evaporation from remote sensing data, ranging from SVAT models to complex methods based on the assimilation of remote sensing data in Cour et al. (2005).

Huang et al. (2024), aimed to perform analyses on a global scale using machine learning algorithms to accurately simulate ET in agricultural areas. The results constitute a valuable resource for agricultural water management and sustainable agriculture practices.

Deng et al. (2024), focused on evaluating the integration of remotely sensed ET into hydrological models in basins in CONUS. The performance of ET assimilation of various satellite data and its impact on different aspects of flow conditions were analyses and the influence of representative catchment characteristics on flow simulations was investigated in detail.

Du et al. (2024) investigated the important input factors that determine daily ET in different climate zones and the applicability of four different machine learning models, evaluated the accuracy of these models, and investigated the most appropriate model for each climate zone.

An important difference of this paper is that it utilises different satellite data in the process of determining ET. These data include factors such as LST, rainfall and pressure. Using these multiple data sources, the paper explores in detail how ET can be determined by remote sensing methods and how these determinations can be related to various environmental factors. In this way, it is aimed to obtain valuable information that will shed light on issues such as agricultural water management and sustainable development.

2. Materials and Methods

In recent decades, remote sensing technology has enabled the development of models for mapping ET and surface fluxes across large regional scales (Mu et al., 2007). These models rely on surface variables like albedo, leaf area index, and surface temperature from remote sensing products. However, achieving both high temporal and spatial resolutions remains a challenge for these products.

Different satellite products offer unique advantages. Landsat provides imagery at a high spatial resolution of 30 meters, albeit at a temporal resolution of 16 days. Meteosat Second Generation (MSG) excels in high temporal resolution (approximately every 15 minutes) but with coarse spatial resolution (Anderson et al., 2011). MODIS satellites, with a 1-kilometer spatial resolution, conduct daily scans and capture a wide spectral range, making them extensively used for regional-scale ET mapping (Huete et al., 2002).

GLDAS_NOAH025_3H_2.1 operates using the Noah land surface model v.3.6, a widely accepted Land Surface Model integrated into the Global Forecast System model by NCEP (Rodell et al., 2004; Beaudoing et al., 2020). TerraClimate merges monthly climatic water balance and climate variables from various datasets and uses a modified Thornthwaite–Mather climatic water-balance model for calculating actual ET (Abatzoglou et al., 2018).

SMAP Level-4 Soil Moisture (L4_SM) provides global 9-kilometer resolution soil moisture data using an ensemble Kalman filter technique integrating SMAP Tb observations into the NASA Catchment land surface model (Reichle et al., 2017; Reichle et al., 2019). The model incorporates observed precipitation, surface radiation, air temperature, humidity, and wind data from global weather analysis (Lucchesi, 2018).

Estimating ET is crucial for water resource planning, but direct measurement is challenging. Hence, methods rely on analyzing measurable meteorological variables over time (Granata, 2019). This study thoroughly analyzed ET patterns across Türkiye using data from GLDAS-2, MODIS, TerraClimate, SMAP Level-4, and PML_V2. Leveraging diverse datasets allowed a comprehensive examination of ET dynamics and trends in different Turkish regions. A graph for Türkiye between 2016 and 2022 was created from SSM data. Graphs were created from LST data for Türkiye between 2000 and 2022. SSM and LST data were obtained from MODIS images. In the study, regression analyses were performed with ET values and SSM and LST data. CHIRPS precipitation data between 1981 and 2023 and PS data between 1981 and 2023 were obtained from the MERRA image. Regression analyses were performed between ET data and PS and Precipitation values.

2.1. Study Area

In Figure 1, Google Earth image of Türkiye is given. The relationships between ET, precipitation, and Atmospheric Pressure (AP) play an important role in Türkiye's climate and water resource management. Türkiye's geographical location has various effects on ET, precipitation, and atmospheric pressure due to its different climatic zones. The relationship between ET and precipitation varies in different regions of Türkiye. In coastal areas, rainfall is generally higher, and this provides access to more water to meet the water needs of plants. On the other hand, the reduced amount of precipitation in inland areas creates equilibrium where ET is usually higher than precipitation.

Figure 1. Google Earth image of Türkiye.

AP generally influences the general characteristics of climate systems. High atmospheric pressure is generally associated with generally sunny and dry weather conditions, which can affect ET. Atmospheric pressure changes in different regions of Türkiye have an impact on wind patterns and air masses, which can have significant effects on precipitation and water resources. The analyses conducted in this study and the use of satellite data is important for understanding these variations and developing strategies for sustainable water resource management.

A visual of Türkiye's climate according to Aydeniz is given in Figure 2. Image was obtained from the Turkish State Meteorological Service website. Türkiye exhibits significant climatic variations due to its diverse geographical location and topographic features. Particularly, the Mediterranean climate is characterized by hot and dry summers, and mild and rainy winters. These seasonal changes influence the ET process; while the evaporation rate increases during hot and dry summer months, the water loss of plants decreases during the mild and rainy winter months. The Black Sea climate, on the other hand, remains rainy throughout all seasons, primarily due to the influence of the sea, facilitating the transfer of abundant water vapor into the atmosphere. Inland areas with semi-arid and continental climates are notable for their temperature differences, experiencing hot and dry summers, and cold winters. This diversity plays a crucial role in various sectors ranging from agricultural production to tourism potential. ET, influenced by these climatic variations, shapes the water loss and water cycle of the region.

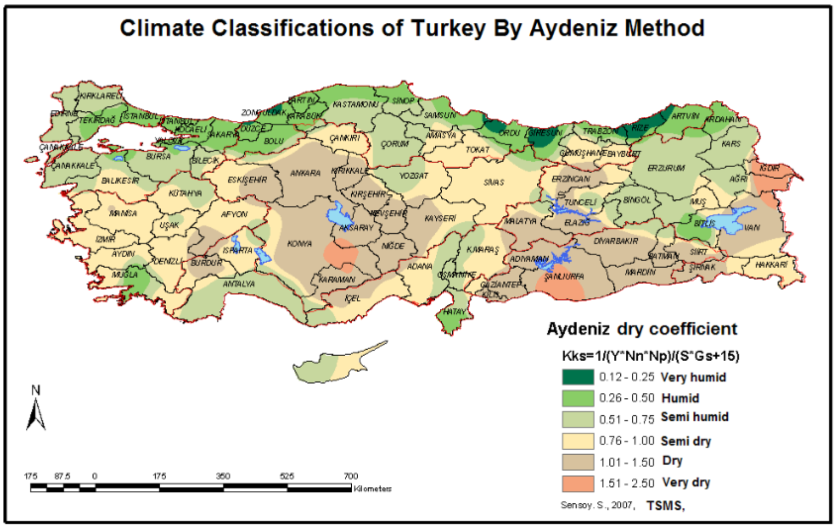


Figure 2. Climate of Türkiye according to Aydeniz. (added English version of the map)

3. Results

ET is a significant component in the global water cycle and provides a critical link between water, carbon, and surface energy on land. However, measuring and predicting ET, especially at large scales, is a challenging process. Remote sensing provides a suitable tool to overcome this challenge and is used to estimate ET at regional and global scales. Over the past thirty years, numerous studies have been conducted on remote sensing-based ET estimation (Zhang et al., 2016).

In this study, a comparison and analysis of ET data obtained from different satellite platforms were conducted. The measurement techniques, sensitivity levels, and coverage areas of different satellite systems vary. Therefore, this study aims to evaluate how these differences affect ET predictions. A comparative analysis was performed using ET data obtained from different satellite platforms. The characteristics of the data provided by each satellite platform were thoroughly examined, and the potential advantages and limitations of these data in ET predictions were identified. Additionally, methods for integrating and analyzing different satellite data were developed. These methods were designed to ensure consistent and comprehensive evaluation of ET even when data are obtained at different time intervals or resolutions. The results demonstrate how different satellite platforms may produce varying results in ET predictions under specific conditions. This study aims to establish a foundation for more effective use of satellite data and to achieve more accurate results in the remote sensing and prediction of ET.

Figure 3a shows the ET values for Türkiye between 2000 and 2023 from GLDAS-2 images. ET values between 1.2 and 1.5 were observed on average. The highest year was 2014, while the lowest year was 2000. The map of average ET values between 2000 and 2023 is given in figure 3b. It has been observed that the ET value is more intense in coastal regions.

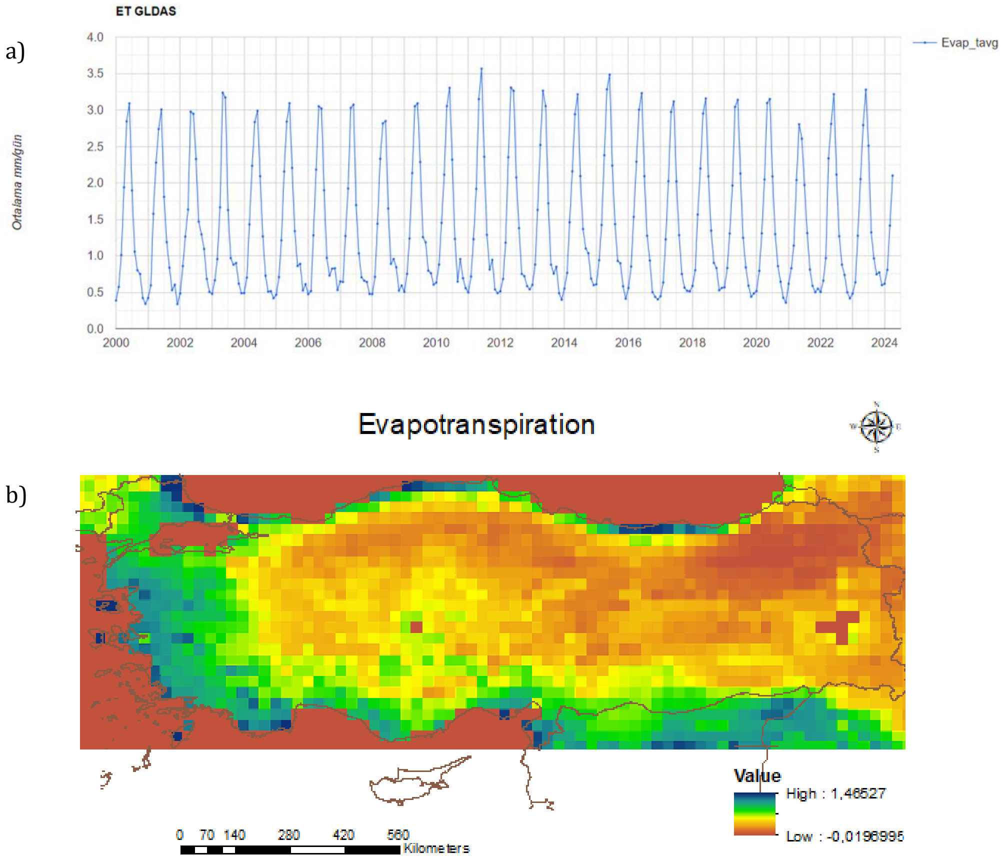


Figure 3. ET values of GLDAS-2 image during 2000 and 2023 (a), Map of average ET values in 2000 and 2023 (b).

Figure 4a shows the ET values for Türkiye from MOD16A2 product images between 2000 and 2014. Between 0.9 and 1.1 values were observed. Looking at the annual average values, 2011 was the highest and 2008 was the lowest. Figure 4b shows the map of average ET values in 2000 and 2015. It was observed that the ET value was more intense in the southeastern Anatolia region.

Figure 5a shows the ET values for Türkiye between 2001 and 2023 from MOD16A2 Version 6.1 images. In 2018, it reached the highest average value, and in 2001, it reached the lowest average value. Figure 5b shows the map of average ET values between 2001 and 2023. It was observed that the ET value was more intense in the Aegean Sea and Mediterranean coastal regions.

Figure 6a shows the ET values for Türkiye between 1958 and 2022 from TerraClimate images. It was observed that the average was between 1 and 1.5. While 2018 had the highest average, 1973 had the lowest average. Figure 6b shows the map of average ET values in 1955 and 2024. It has been observed that the ET value is more intense in coastal regions.

Figure 7a shows the ET values for Türkiye between 2015-2023 from the SMAP Level-4 images. It remained between 1.2 and 1.7. The highest average value was observed in 2015, and the lowest was observed in 2022. Figure 7b shows the map of average ET values in 2015 and 2024. It was observed that the ET value was low in the Central Anatolia and Eastern Anatolia regions.

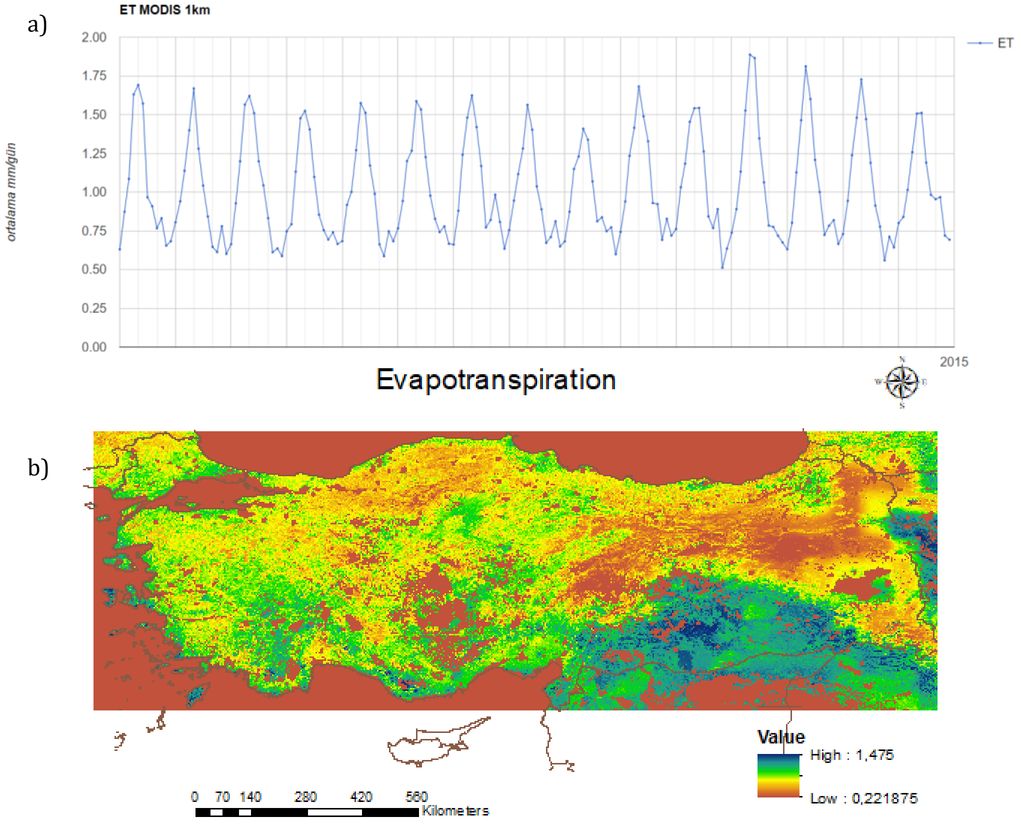


Figure 4. ET values of the MOD16A2 V105 product 2000 and 2014 (a), Map of average ET values in 2000 and 2015 (b).

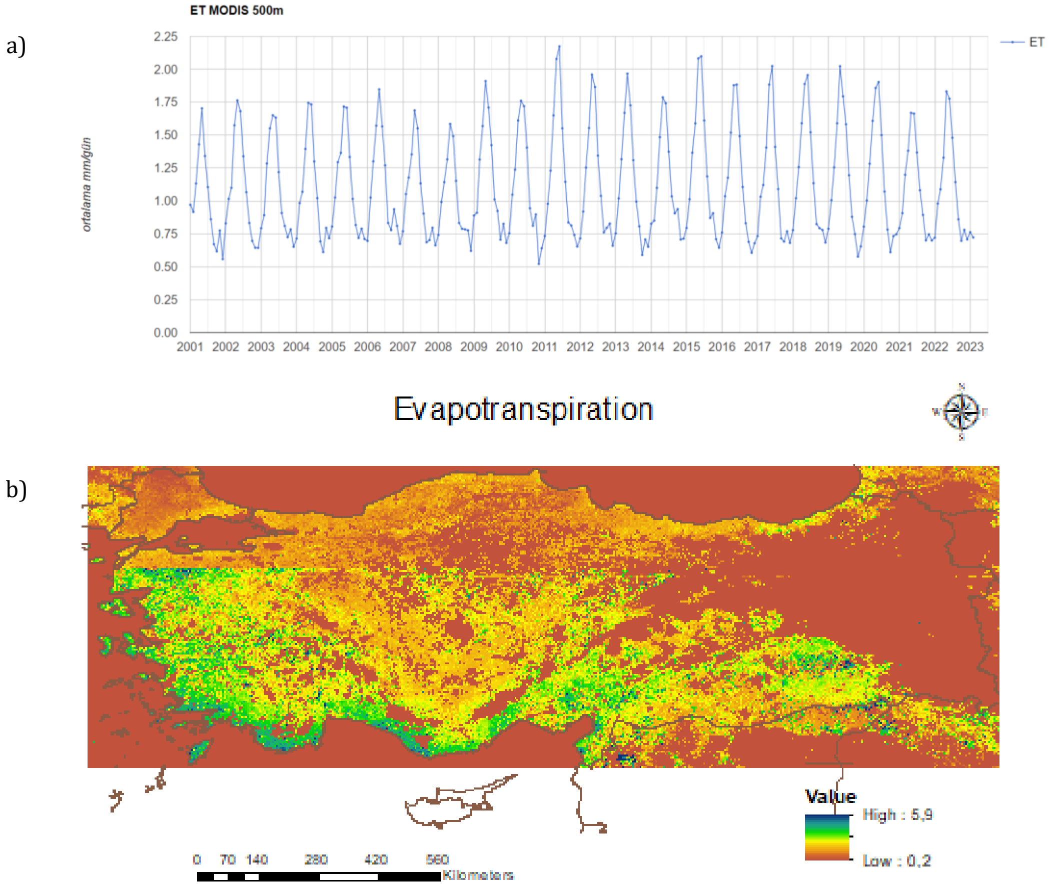


Figure 5. ET values of the MOD16A2 Version 6.1 image during 2001and 2023 (a), Map of average ET values in 2001 and 2023 (b).

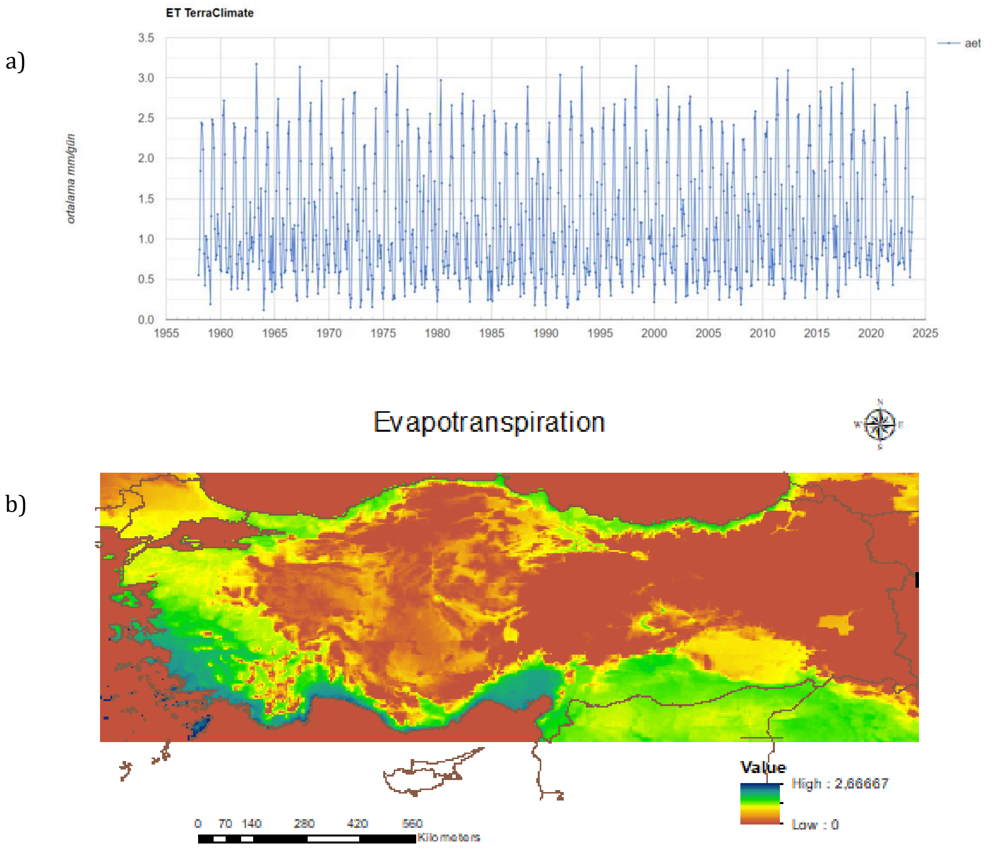


Figure 6. ET values of the TerraClimate image between 1955 and 2022 (a), Map of average ET values in 1955 and 2024 (b).

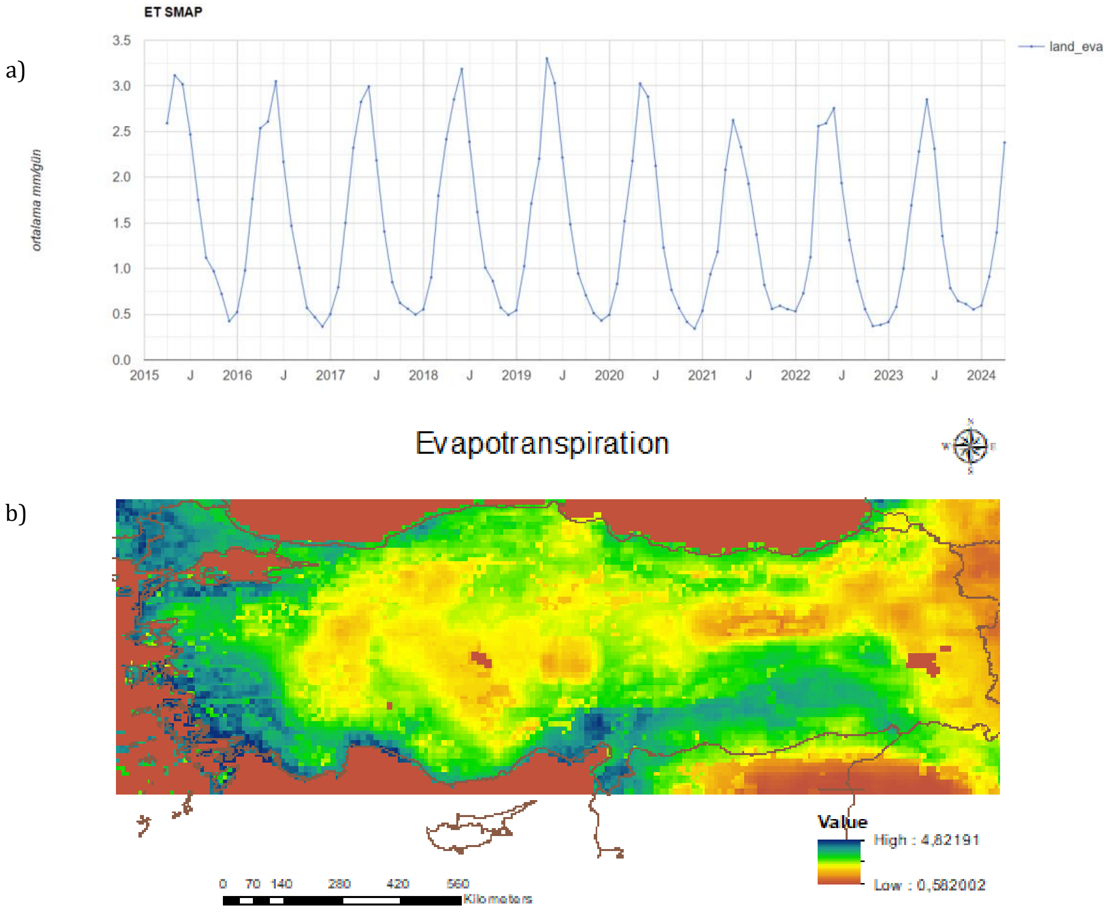


Figure 7. ET values of the SMAP Level-4 image in 2015 and 2023 (a), Map of average ET values in 2015 and 2024 (b).

Figure 8a shows the ET values for Türkiye between 2000 and 2022 from PML_V2 images. Vegetation transpiration (Ec) reached the highest value in 2020 and the lowest value in 2008. Soil evaporation (Es) reached the highest value in 2014 and the lowest value in 2019. Interception from vegetation canopy (Ei) reached the highest value in 2007 and the lowest value in 2000. Figure 8b shows the map of average ET values in 2000 and 2021. It was observed that the ET value was high in all coastal regions except the Black Sea.

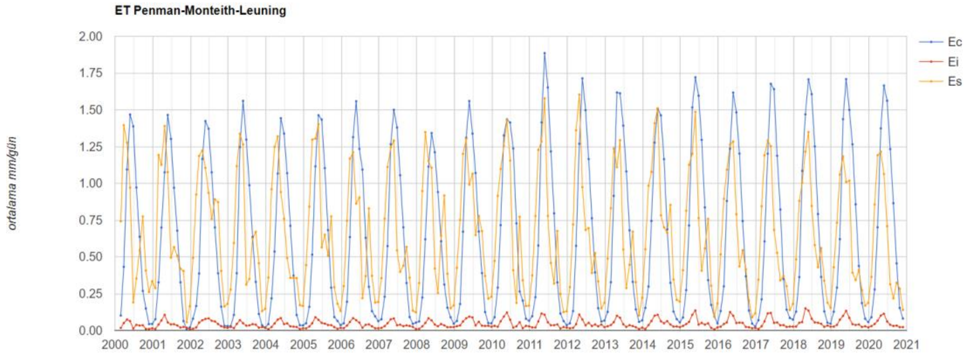
Graphs were generated utilizing SSM data for Türkiye between the years 2016 and 2022, extracted from MODIS images in Figure 9a. These graphical representations offer a detailed overview of the temporal trends and spatial distribution of soil moisture levels across various regions of Türkiye during the specified timeframe. Figure 8 shows the surface soil moisture graphs between 2016 and 2022. SSM was highest in January 2019 and lowest in August 2021. It is observed that soil moisture in Türkiye is particularly intense in the Eastern Black Sea region. The lowest value of soil moisture was observed in 2019. In 2022, it was observed that soil moisture increased in the Eastern Black Sea region and the Eastern Anatolia region. Figure 9b shows the map of average SSM values in 2016 and 2022. It was observed that the ET value was high in the Black Sea region.

Graphs were created from LST data for Türkiye between 2000 and 2022 extracted from MODIS images in Figure 10a. These visualizations provide a comprehensive depiction of the temporal patterns and spatial distribution of LST across different regions of Türkiye during the specified period. 22-year LST values are given in the figure. It was created by averaging the monthly average values. It was observed that the highest average was reached in 2000, and the lowest average was reached in 2011. A map of the average LST values in 2000 and 2022 is given in Figure 10b. It was observed that the ET value was high in the Black Sea and Eastern Anatolia regions.

CHIRPS provide high-resolution precipitation data between 1981 and 2023 in Figure 11a. This dataset offers valuable information to researchers, policymakers, and various stakeholders for analyzing long-term precipitation patterns, assessing drought conditions, and monitoring water resources. Figure 10 shows the precipitation values between 1981 and 2023. The highest precipitation value was observed in 2009, and the lowest precipitation value was observed in 1989. Figure 11b shows the map of average precipitation values in 1981 and 2023. It was observed that the ET value was high on the coasts of Antalya and Mersin provinces.

PS data between 1981 and 2023 were acquired from MERRA image, providing a comprehensive record of atmospheric pressure variations over this period. This dataset, derived from a combination of satellite observations and atmospheric models, offers valuable information for studying atmospheric dynamics, weather patterns, and climate variability. Figure 12a shows the PS values between 1981 and 2023. The highest PS value was observed in 1989, and the lowest PS value was observed in 1981. A map of the average PS values between 1981 and 2023 is shown in Figure 12b. It was observed that the ET value was high in coastal regions.

a)



b)

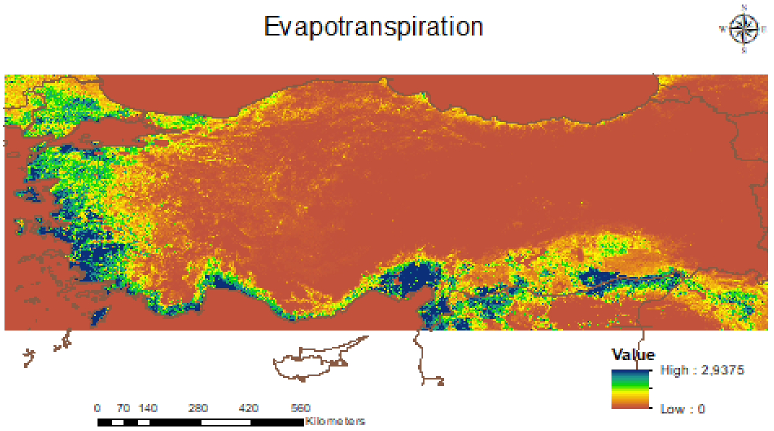


Figure 8. ET values of the PML_V2 image in 2000 and 2022 (a), Map of average ET values in 2000 and 2021 (b).

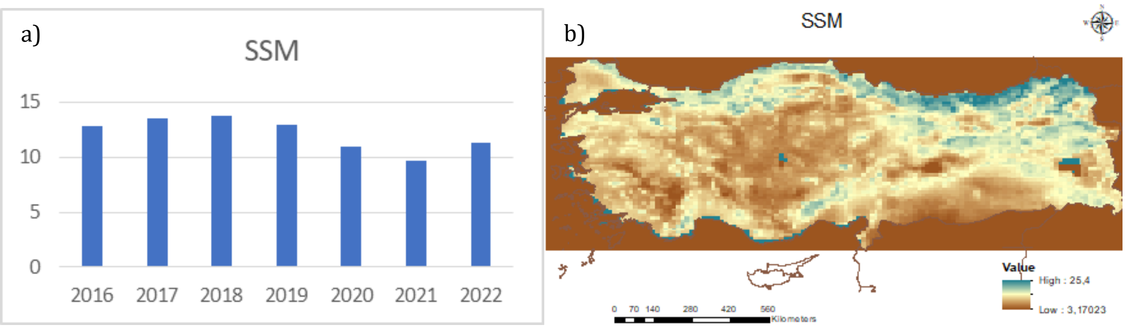


Figure 9. SSM graphs in 2022 and 2016 (a), Map of average SSM values in 2016 and 2022 (b).

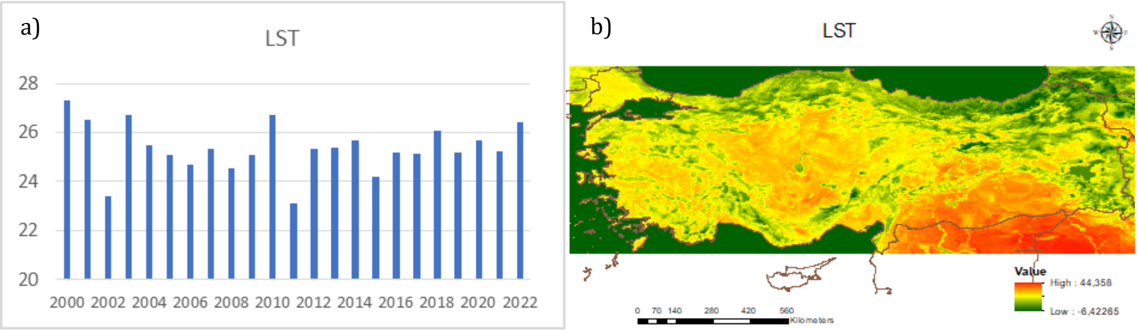


Figure 10. 22-year LST values table (a), Map of average LST values in 2000 and 2022 (b).

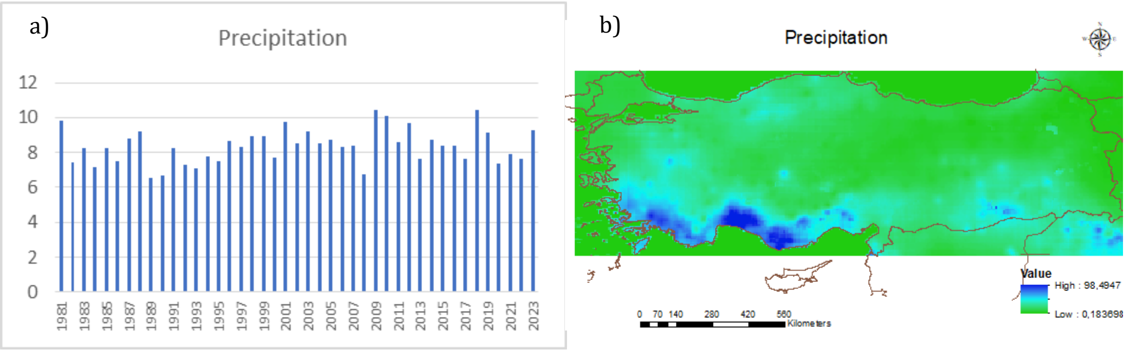


Figure 11. Precipitation values in 1981 and 2023 (a), Map of average precipitation values in 1981 and 2023 (b).

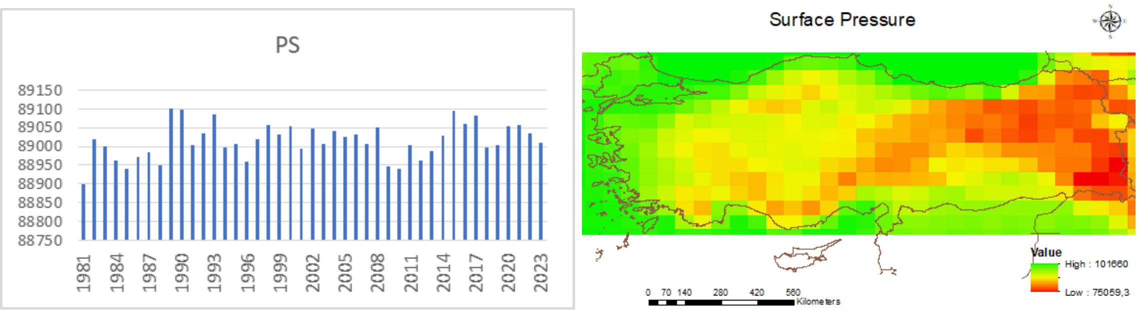


Figure 12. PS values in 1981-2023 (a), Map of average PS values in 1981 and 2023 (b).

4. Discussion

This study is based on combining major satellite data sources such as GLDAS-2, MODIS, TerraClimate, SMAP Level-4, and PML_V2 to provide a comprehensive analysis of ET patterns in various regions of Türkiye. To accurately estimate ET, different algorithms and models are used to synthesize these data sources. This synthesis was done to gain a deeper understanding of the factors affecting ET in Türkiye. These factors include climate variability, topographical differences, soil composition, and vegetation typology.

This article highlights an important difference in the use of various satellite data in the determination of ET. Using various data sources such as LST, precipitation and pressure, the paper explores in detail how ET can be determined by remote sensing methods and how these determinations relate to environmental factors. The aim of this study is to provide valuable information on issues such as agricultural water management and sustainable development. Direct ET values were calculated for products such as GLDAS-2, MODIS, TerraClimate and SMAP Level-4. On the other hand, for ET calculations in the PML_V2 product, separate analyses of plant transpiration, soil evaporation and water from vegetation were performed. The resulting average ET values are as follows: 1.4 for GLDAS-2, 1 for MOD16A2 V105, 1 for MOD16A2 Version 6.1, 1.1 for TerraClimate, and 1.4 for SMAP Level-4. PML_V2 analyses revealed average values of 0.6 for plant transpiration, 0.6 for soil evaporation, and 0.05 for water from vegetation.

Regression analysis between parameters is given in Table 1. All analyzes were made in the SSPS program by taking the average annual values of all data. A moderate correlation (R 0.42) was observed between LST and ET generated from GLDAS-2 data. A moderate correlation (R 0.45) was observed with SSM. Moderate correlation (R 0.43) between LST and ET generated from MOD16A2 V105 data. A moderate correlation (R 0.34) was observed between LST and ET generated from MOD16A2 Version 6.1 data. A moderate correlation (R 0.33) was observed between the ET created from MOD16A2 Version 6.1 data and SSM. Low correlation (R 0.21) between LST and ET generated from TerraClimate data. A moderate correlation (R 0.59) was observed with SSM. Moderate correlation (R 0.57) between LST and ET generated from SMAP Level-4 data. A moderate correlation (R 0.39) was observed with SSM. A moderate correlation (R 0.54, R 0.37) was observed between Ec and SSM generated from Ei and PML_V2 data. Statistical analyses were performed by taking the mean values of each year.

Table 1. Regression analysis between parameters

Image	Cor. with PS	Cor. with LST	Cor. with Precipitation	Cor. with SSM
GLDAS-2	0.21	0.42	0.43	0.45
MOD16A2 V105	0.37	0.43	0.33	-
MOD16A2 Version 6.1	0.06	0.34	0.17	0.33
TerraClimate	0.05	0.21	0.50	0.59
SMAP Level-4	0.07	0.57	0.52	0.39
PML_V2 (Ec)	0.06	0.11	0.04	0.54
PML_V2 (Ei)	0.07	0.19	0.36	0.37
PML_V2 (Es)	0.14	0.22	0.30	0.27

Cor= correlation, SP= surface pressure, LST= land surface temperature, SSM= surface soil moisture.

When the relationship between ET and soil moisture was analyzed by regression, which is a statistical analysis, a moderate relationship was observed. A moderate relationship means a situation where soil moisture level decreases as ET increases or, conversely, soil moisture level increases as ET decreases. This indicates that there is a balance between the absorption of water by plants and its release back to the atmosphere. These regression analyses can be used to understand the impacts of agricultural practices, water resource management, and climate change. A moderate relationship can be an important indicator for developing appropriate strategies for water resource management and plant growth.

Medium level (R 0,43) between ET and precipitation generated from GLDAS-2 data. A low-level relationship was observed with PS. Medium level (R 0,33) between ET and precipitation generated from MOD16A2 V105 data. A moderate relationship (R 0.37) was observed with PS. A low-level relationship was observed between ET and precipitation generated from MOD16A2 Version 6.1 data, and a low-level relationship was observed with PS. There was a moderate relationship (R 0.50) between ET and precipitation generated from TerraClimate data and a low relationship with PS. There is a moderate relationship (R 0.52) between ET and precipitation generated from SMAP Level-4 data. A low-level relationship was observed with PS. ET generated from PML_V2 data showed a moderate relationship between Ei and precipitation (R 0.36) and a low relationship with PS. Statistical analyzes were made by taking the average values of each year.

The relationship between ET and precipitation generally shows a moderate relationship. As the amount of precipitation increases, the amount of water in the soil and the water absorption capacity of plants increase. This means that plants evaporate more water, which leads to increased ET. This intermediate relationship represents a balance point of the plants' need for water and the return of water to the atmosphere.

On the other hand, the relationship between ET and PS is low. Surface pressure refers to the pressure exerted by the air masses in the atmosphere on the earth's surface. Increased ET usually does not directly affect the surface pressure since this process mostly involves the passage of water vapor into the atmosphere. High ET is not usually associated with low surface pressure, as these two parameters refer to different processes in the atmosphere.

5. Conclusion

As a result, the intermediate relationship between ET and precipitation forms part of the water cycle, while the low relationship between ET and surface pressure reflects the complexity of atmospheric conditions. Understanding these factors is important in understanding the variability affecting climate systems and water resources. Among the expected outcomes of this study is a better understanding of spatio-temporal ET patterns specific to Türkiye. Furthermore, combining, and comparative analysis of data from these different satellite sources aims to improve the understanding of ET dynamics and drivers. The results of this study can help formulate effective water resource management strategies and facilitate ecosystem monitoring in the Turkish context.

The predicted results of this study include a detailed understanding of ET patterns in different geographical regions of Türkiye. Furthermore, combining and analyzing data from these different satellite sources aims to provide a deeper understanding of the dynamics and influencing factors of ET. These results can make important contributions to the development of Türkiye's water resources management strategies and sustainable monitoring of ecosystems.

Author Contributions

The percentage of the author(s) contributions is presented below. The author reviewed and approved the final version of the manuscript.

	N.U.
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
CR	100
SR	100
PM	100
FA	100

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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