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RESEARCH ARTICLE

Effects of Climate Change and Air Pollution on Soil Moisture: The Case of Türkiye

İklim Değişikliği ve Hava Kirliliğinin Toprak Nemi Üzerindeki Etkileri: Türkiye Örneği

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ABSTRACT: The effect of climatic variables on soil moisture is quite high. In this study, the soil moisture status in Turkey has been analyzed by using satellite data between 2016 and 2022 for Land Surface Temperature (LST), surface pressure (PS) and precipitation variables. The effects of temperature changes, surface pressure and precipitation on soil moisture and how these interactions differ in different regions of Turkey are analyzed. Surface soil moisture (SSM) was highly correlated with rainfall (R 0.74). There was a high correlation between SSM and LST (R 0.74). Subsurface soil moisture (SUSM) was highly correlated with precipitation (R 0.73). There was a high correlation between SUSM and LST (R 0.74). Greenhouse gas emission data were taken from the Turk Stat data portal and the relationship between soil moisture was examined. A high level of correlation was observed between SSM and SUSM, f gases (R 0.97, R 0.96). This study can be considered as an important step in understanding the effects of Turkey's climatic variables on soil moisture. The findings emphasize that soil moisture is important for sustainable agriculture and environmental factors and provide an in-depth understanding of how climatic variables affect it. Such analyses can provide strategic information in areas such as agricultural planning, water resources management and environmental sustainability, and contribute to a more robust basis for future decisions.

Keywords:: Soil moisture, land surface temperature, surface pressure and precipitation.

ÖZ: İklimsel değişkenlerin toprak nemi üzerindeki etkisi oldukça yüksektir. Bu çalışmada, Türkiye'deki toprak nem durumu, 2016-2022 yılları arasında uydu verileri kullanılarak Kara Yüzey Sıcaklığı (LST), yüzey basıncı (PS) ve yağış değişkenleri için analiz edilmiştir. Sıcaklık değişimlerinin, yüzey basıncının ve yağışın toprak nemi üzerindeki etkileri ve bu etkileşimlerin Türkiye'nin farklı bölgelerinde nasıl farklılık gösterdiği analiz edilmiştir. Yüzey toprak nemi (SSM), yağışla yüksek oranda ilişkiliydi (R 0,74). SSM ve LST arasında yüksek bir korelasyon vardı (R 0,74). Yeraltı toprak nemi (SUSM) yağışla yüksek oranda ilişkiliydi (R 0,73). SUSM ve LST arasında yüksek bir korelasyon vardı (R 0,74). Sera gazı emisyon verileri TÜİK veri portalından alınmış ve toprak nemi arasındaki ilişki incelenmiştir. SSM ve SUSM, f gazları arasında yüksek düzeyde korelasyon gözlenmiştir (R 0,97, R 0,96). Bu çalışma, Türkiye'nin iklim değişkenlerinin toprak nemi üzerindeki etkilerinin anlaşılmasında önemli bir adım olarak değerlendirilebilir. Bulgular, toprak neminin sürdürülebilir tarım ve çevresel faktörler için önemli olduğunu vurgular ve iklim değişkenlerinin bunu nasıl etkilediğine dair derinlemesine bir anlayış sağlar. Bu tür analizler, tarımsal planlama, su kaynakları yönetimi ve çevresel sürdürülebilirlik gibi alanlarda stratejik bilgiler sağlayabilir ve gelecekteki kararlar için daha sağlam bir temel oluşturmaya katkıda bulunabilir.

Anahtar Kelimeler: Toprak nemi, arazi yüzey sıcaklığı, yüzey basıncı ve yağış.

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1. INTRODUCTION

Climate plays a vital role in the complexity of natural systems. The relationship between soil moisture and climatic variables has decisive effects on ecological balance. In this context, the geography of Turkey draws attention with its diverse climatic characteristics.

Soil moisture is crucial for understanding the water, energy, and carbon cycles, impacting weather forecasts and flood or drought monitoring. The SMAP mission uses L-band microwave technology to monitor soil moisture, combining radar (high spatial resolution, low sensitivity) and radiometers (low spatial resolution, high sensitivity) to overcome their individual limitations. SMAP's objectives include measuring soil moisture at 40 km resolution, improving it to 10 km by merging radar and radiometer data, and detecting freeze/thaw states at 3 km resolution. This paper presents a downscaling algorithm to enhance the SMAP 10 km soil moisture product by optimizing both radar and radiometer data [1]-[10].

Understanding surface soil moisture is vital across disciplines. It impacts ecosystems, agriculture, and the environment. In ecosystems, it affects microorganisms and nutrient cycling. In agriculture, it's crucial for crop growth. Soil moisture also influences runoff, erosion, and air quality through dust. Moreover, it's linked to disease transmission. Monitoring it is key for sustainable practices and managing environmental impacts [10]-[14].

Deeper soil moisture can serve as a more nuanced parameter for certain processes, diverging from surface soil moisture (SSM) notably under dry conditions. Yet, SSM often exhibits a strong correlation with moisture in deeper layers, indicating that focusing solely on SSM doesn’t result in substantial information loss. The duration of soil moisture retention is pivotal in forecasting extreme weather events like heatwaves, droughts, floods, and storms. This is due to the considerable memory capacity of soil moisture compared to the atmosphere. While atmospheric anomalies dissipate swiftly (within hours), anomalies in soil moisture persist for extended periods (from days to months). These lingering anomalies might influence subsequent atmospheric patterns, hinting at the potential for valuable insights in seasonal atmospheric predictions [15]-[17].

In this article, Turkey's above and below ground soil moisture, surface temperature, surface pressure and precipitation data were obtained by processing satellite images. It is aimed to contribute to the understanding of these interactions by emphasizing the effects of climate variables on soil moisture. Surface temperature, surface pressure and precipitation data are important data sources for understanding regional climatic variables as well as factors affecting surface and SSM. The analyses presented in this paper provide a comprehensive use of these data to explain the dynamics of soil moisture in different regions of Turkey.

2. MATERIALS AND METHODS

2.1 Study Area

Google Earth image of Turkey is given in Figure 1. Turkey is a very diverse country in terms of its home location and topography, as well as soil moisture. While the northern and western regions of the country were wetter, the southern and eastern regions were drier. Soil moisture is important in many aspects such as agriculture, water resources and natural ecosystems. Without adequate soil moisture, plants cannot take in water and nutrients, which can lead to reduced yields. Soil moisture also plays a role in producing water and feeding rivers. Moist soil is essential for the survival of many plants and animals. Ground connections in Turkey have many factors. The most important precipitation, temperature and soil types. Soil moisture that receives adequate rainfall is higher. Soil moisture changes more through evaporation of the hot junction. Sandy soils retain less water than clay soils. It is important to preserve and sustainably use Turkey's soil moisture. This can be done through irrigation values, afforestation efforts, their control and home farming practices. Irrigation resistant, water waste can be prevented, and soil moisture can be preserved. It helps protect trees from their soil and retain moisture. It helps in erosion control and conservation of storage water. There are techniques that will help preserve soil moisture through conscious agricultural practices. Soil moisture is an important resource for Turkey's development and future generations. Protecting and using this resource sustainably, giving critical importance to sustaining production in Turkey's management and preserving the protection of natural ecosystems.

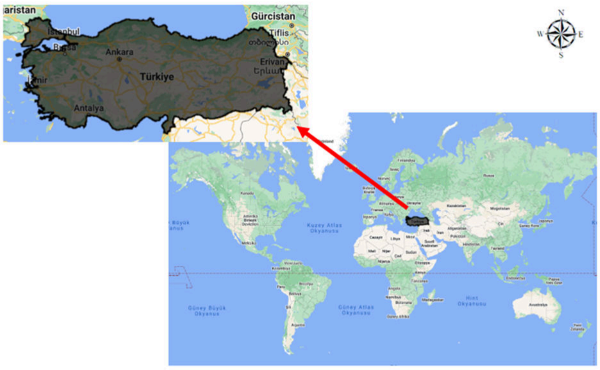


Figure 1: Google Earth image of Turkey.

2.2. Materials

The advancements in remote sensing technology in the last thirty years have significantly enhanced our capacity to regularly gather worldwide data on soil moisture levels [18]-[21]. Numerous thoroughly assessed soil moisture datasets have demonstrated their utility across diverse applications. They're instrumental in weather and climate prediction, monitoring droughts and wildfires, tracking floods and landslides, and improving agricultural output [22]-[25].

Soil moisture (θ) availability is critical for refining climate, weather, and hydrological models [26]-[28]. Satellite-based microwave sensors have the potential to globally assess θ in the topsoil layer. Yet, existing sensors like the Advanced Microwave Scanning Radiometer (AMSR-E) at C-band (7.32 GHz) face accuracy limitations in vegetated areas [29, 30]. This has led to the selection of L-band (1.4 GHz) sensors for missions like Soil Moisture and Ocean Salinity and the upcoming Soil Moisture Active and Passive (SMAP) missions [31, 32]. SMAP data were processed and used in this study.

The Modern-Era Retrospective analysis for Research and Applications (MERRA) project is a significant advancement in reanalysis products. It uses data from NASA Earth observing satellites to enhance existing reanalysis products by providing a more accurate depiction of the hydrological cycle, as highlighted in Rienecker et al.'s work from 2011. This improvement aims to offer a more realistic understanding of Earth's hydrological processes compared to previous reanalysis products [33]. Surface pressure data provided by the Merra satellite.

The precipitation data sets used were sourced from the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) database. This database is a result of collaboration between the United States Geological Survey (USGS) and the Earth Resource Observation and Science (EROS) center. CHIRPS combines satellite imagery with on-site observations from various national and regional meteorological departments. These data sets cover a wide temporal range, starting from 1981 to near the present, providing information at pentanal, decadal, and monthly intervals. The spatial resolution of this data is quite high, at 0.05°, and it offers almost global coverage, spanning from 50° S to 50° N and from 180° E to 180° W. This comprehensive coverage and resolution make CHIRPS a valuable resource for studying precipitation patterns and trends across different spatial and temporal scales [34].

The CHIRPS dataset, introduced in early 2014, is a new climate database with a particular focus on land-based precipitation, integrating three different sources of information: global climatology's, satellite forecasts and in situ observations [35]. What distinguishes CHIRPS from others is that it contains a larger amount of station data compared to other similar products. In addition, it utilizes a high-resolution background climatology, which enables more accurate forecasting of rainfall averages and fluctuations. This development leads to a better assessment of the hydrological situation [36]. In conclusion, CHIRPS is characterized by its ability to provide more refined and reliable data on precipitation patterns and contributes significantly to a better understanding of hydrological processes. Precipitation values were extracted from CHIRPS datasets.

Land Surface Temperature (LST) refers to the temperature of the Earth's land surface, and it can be determined through satellite data or direct field measurements. The impact of increasing greenhouse gases in the atmosphere is significant on LST. This temperature metric offers valuable insights into surface physical properties and climate changes on both global and regional scales. The Moderate Resolution Imaging Spectroradiometer (MODIS)–LST is a useful tool that enables the rapid acquisition of surface temperature data across large areas. Standardized processes for MODIS–LST are implemented to maintain consistency and ensure the accuracy of temperature measurements [37]-[40].

2.3. Methods

With the onset of data from ESA's Soil Moisture and Ocean Salinity (SMOS) and NASA's Soil Moisture Active and Passive (SMAP) L-band missions, a significant increase in our ability to obtain surface soil moisture using L-band satellite remote sensing is predicted over the next five years [41, 42].

These developments are important in terms of significantly increasing our capacity to monitor and understand soil moisture and enabling space-based L-band observations to be used more effectively in a variety of applications.

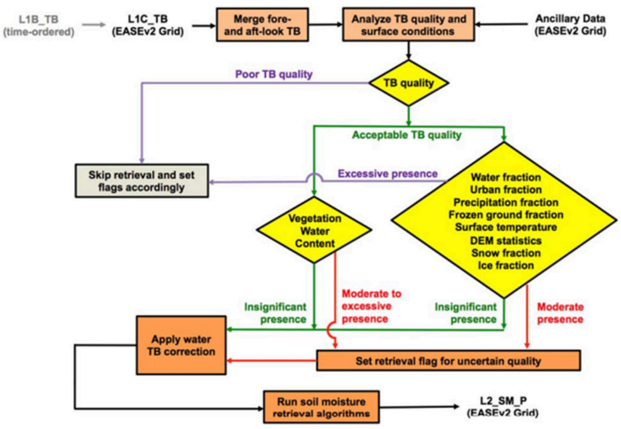


Figure 2: L2_SM_P SPS process data and soil moisture.

The L2_SM_P SPS begins with Level 1B brightness temperature observations (L1B_TB) and converts them to the Level 1C Grating Radiometer Data Product (L1C_TB) on the 36 km EASEv2 Grid in a cylindrical equidistant projection. The fore and aft view grating brightness temperature observations are then combined in the L2_SM_P SPS. The processing continues with the addition of pre-processed static and dynamic auxiliary data at finer grid resolutions. This data is used to assess the feasibility and expected quality of the retrieval. Once favorable surface conditions for soil moisture retrieval are identified in each grid cell, the retrieval process begins. Corrections for water pollution, surface roughness, effective soil temperature, and vegetation water content are applied using five pre-determined candidate soil moisture algorithms. These algorithms are then used to generate the final output. The final output contains soil moisture retrieval areas on the same 36 km EASEv2 Grid as the input L1C_TB product. In this process, corrections are applied for surface roughness, effective soil temperature, vegetation water content, and the radiometric contribution of water bodies. The basic soil moisture retrieval algorithm is then invoked with TB observations and ancillary data as input to produce L2_SM_P_E on the same 9 km EASE Grid 2.0 global projection with input L1C_TB_E [43]-[48].

Figure 3 systematically shows the process of obtaining data and preparing models for in situ measurement. In this study, the process of preparing data and models for on-site measurement in Turkey is presented. In the first step, Greenhouse gas emission statistics data were obtained from the Turkish Statistical Institute (TUIK) Data Portal. SMAP, CHIRPS, MODIS images were provided from the Google earth engine platform. (https://earthengine.google.com/platform/ last accessed January 1, 2024) Downloaded data is analyzed using the Google Earth Engine platform. Relationships and patterns between data sets are determined with data visualization, statistical analysis and machine learning techniques. These analyzes help determine the most important data sets for in situ measurements and the parameters to be used in modelling. Considering the information obtained from data analysis, regression models are developed. These models mathematically express the relationship between the dependent variable (e.g., soil moisture) and the independent variables (e.g., precipitation, temperature). Statistical Analysis linear regression model was used. The resulting measurements can be used for various purposes, such as monitoring environmental conditions in the region, estimating agricultural production and assessing the effects of climate change.

In this exercise, satellite image processing was performed using coding on the Google Earth Engine platform. Data analysis included thematic maps in ArcGIS, graphs in Excel and regression analysis in SPSS.

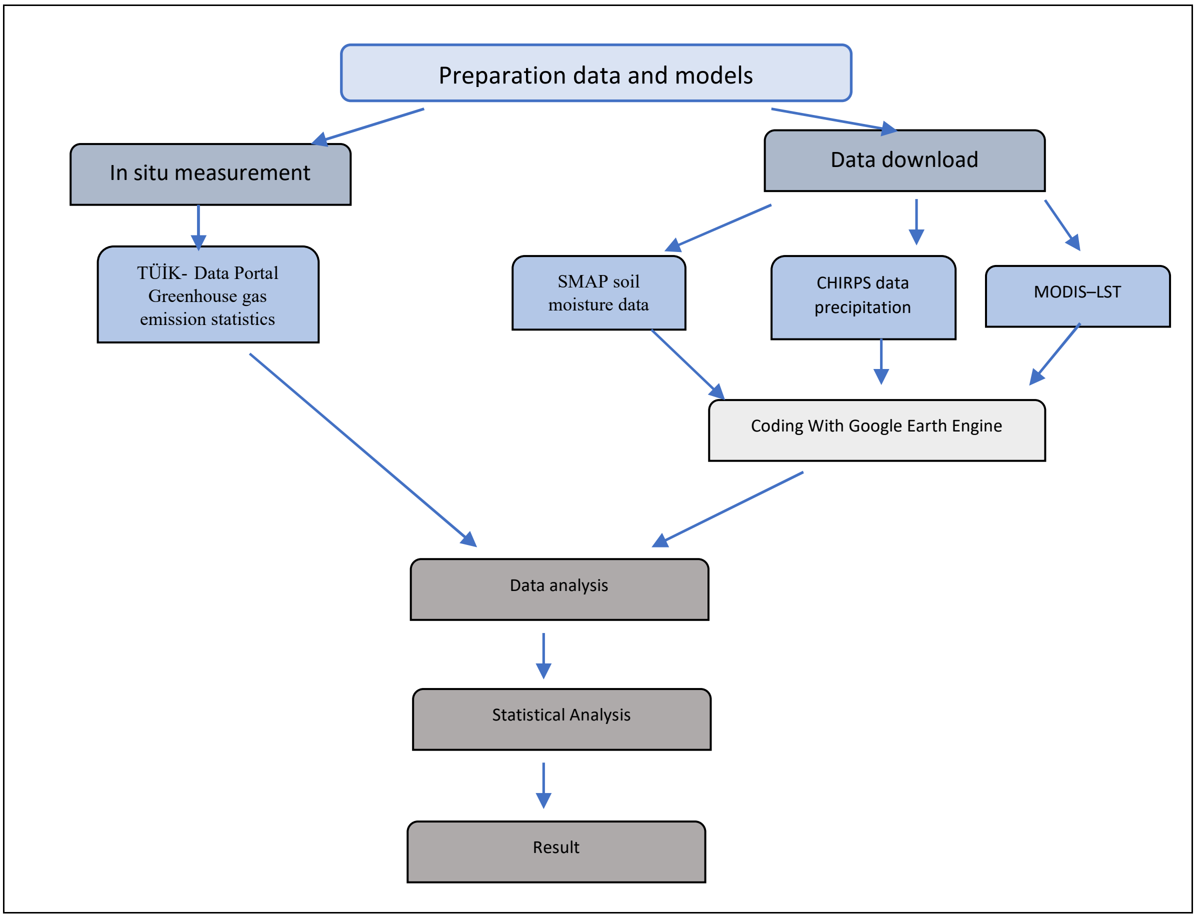


Figure 3: The chart of study design.

2.4. Statistical Analysis

Multiple regression analysis is a statistical method used to explore how a single dependent variable is influenced by multiple independent variables. Unlike simple regression, which looks at the relationship between one independent and one dependent variable, multiple regression allows for several independent variables to be considered at once. The goal is to identify how these variables together impact the dependent variable and to build a model that explains this relationship. In this analysis, the effect of each independent variable is examined while keeping the others constant, enabling a better understanding of how each contributes to changes in the dependent variable [49, 50].

In this study, a multiple regression model was used as a statistical analysis method. This method is used in many scientific and statistical analyses and helps researchers understand the effects of a set of independent variables on a dependent variable. Multiple linear regression is used to handle complexity in the dataset and model relationships between variables. This is particularly useful for understanding and predicting complex relationships. This method is used in many scientific and statistical analyzes and helps researchers understand the effects of a set of independent variables on a dependent variable. MLR is used to address complexity in the data set and model relationships between variables. This is especially useful for understanding complex relationships and making predictions.

Figure 4 shows the soil moisture maps between 2016 and 2022. It is observed that soil moisture in Turkey 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 Eastern Anatolia region.

3. RESULTS

Figure 4 shows the soil moisture maps between 2016 and 2022. It is observed that soil moisture in Turkey 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 Eastern Anatolia region.

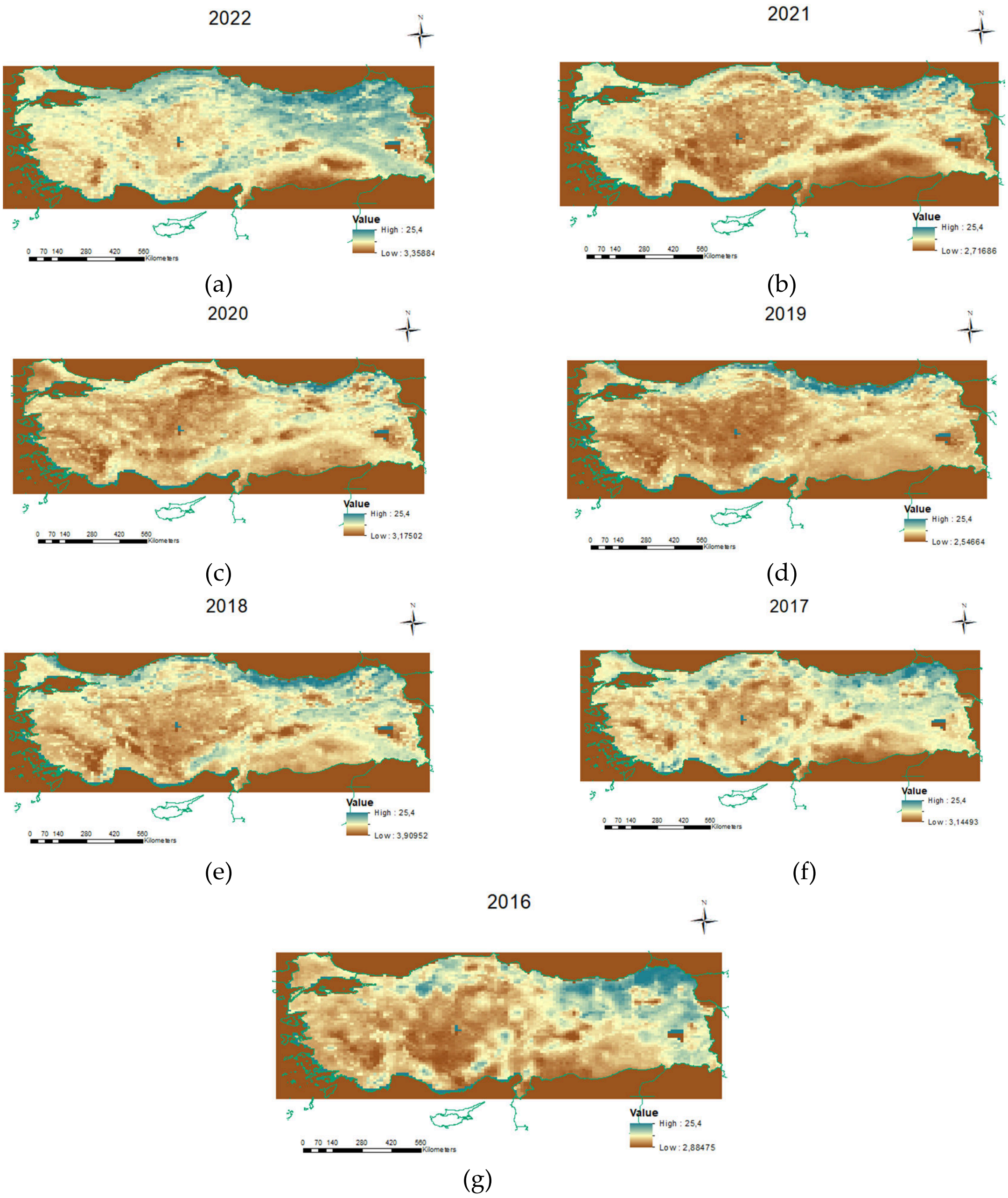
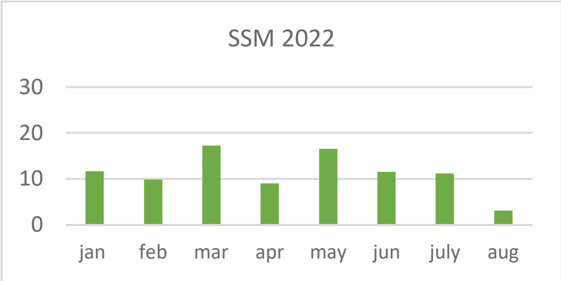


Figure 4: (a) 2022, (b) 2021, (c) 2020, (d) 2019, (e) 2018, (f) 2017, (g) 2016 soil moisture maps.



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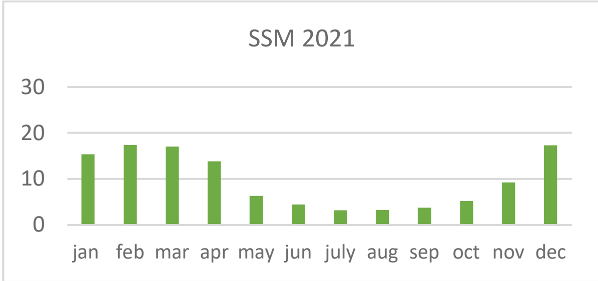

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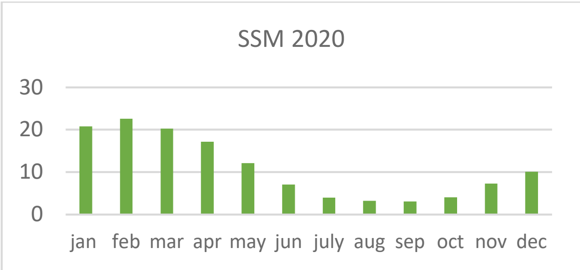

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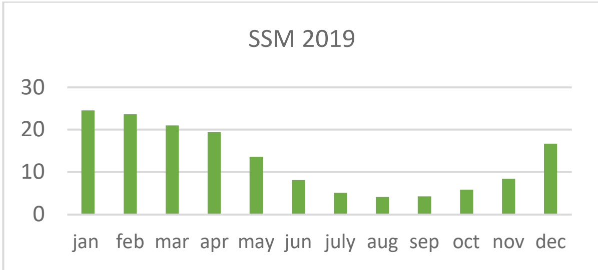

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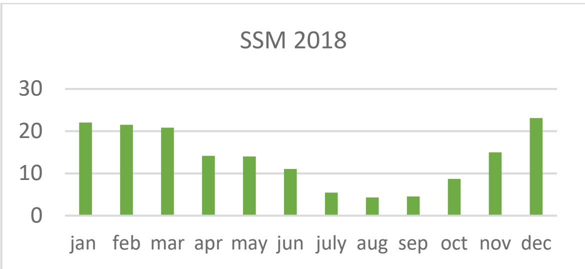

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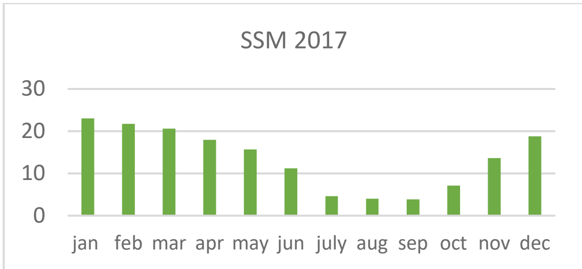

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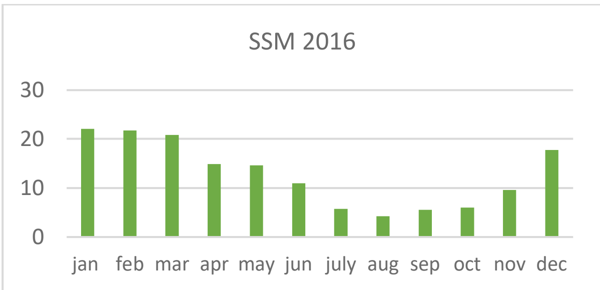

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Figure 5: (a) 2022, (b) 2021, (c) 2020, (d) 2019, (e) 2018, (f) 2017, (g) 2016 SSM graphs.

Figure 5 displays the surface soil moisture (SSM) graphs from 2016 to 2022. The highest SSM was recorded in January 2019, while the lowest occurred in August 2021. The high value in January 2019 can be attributed to winter precipitation and reduced evaporation, whereas the low value in August 2021 is likely due to increased summer temperatures and higher evaporation rates. These seasonal variations highlight the significant influence of climatic factors such as precipitation and temperature on soil moisture levels.

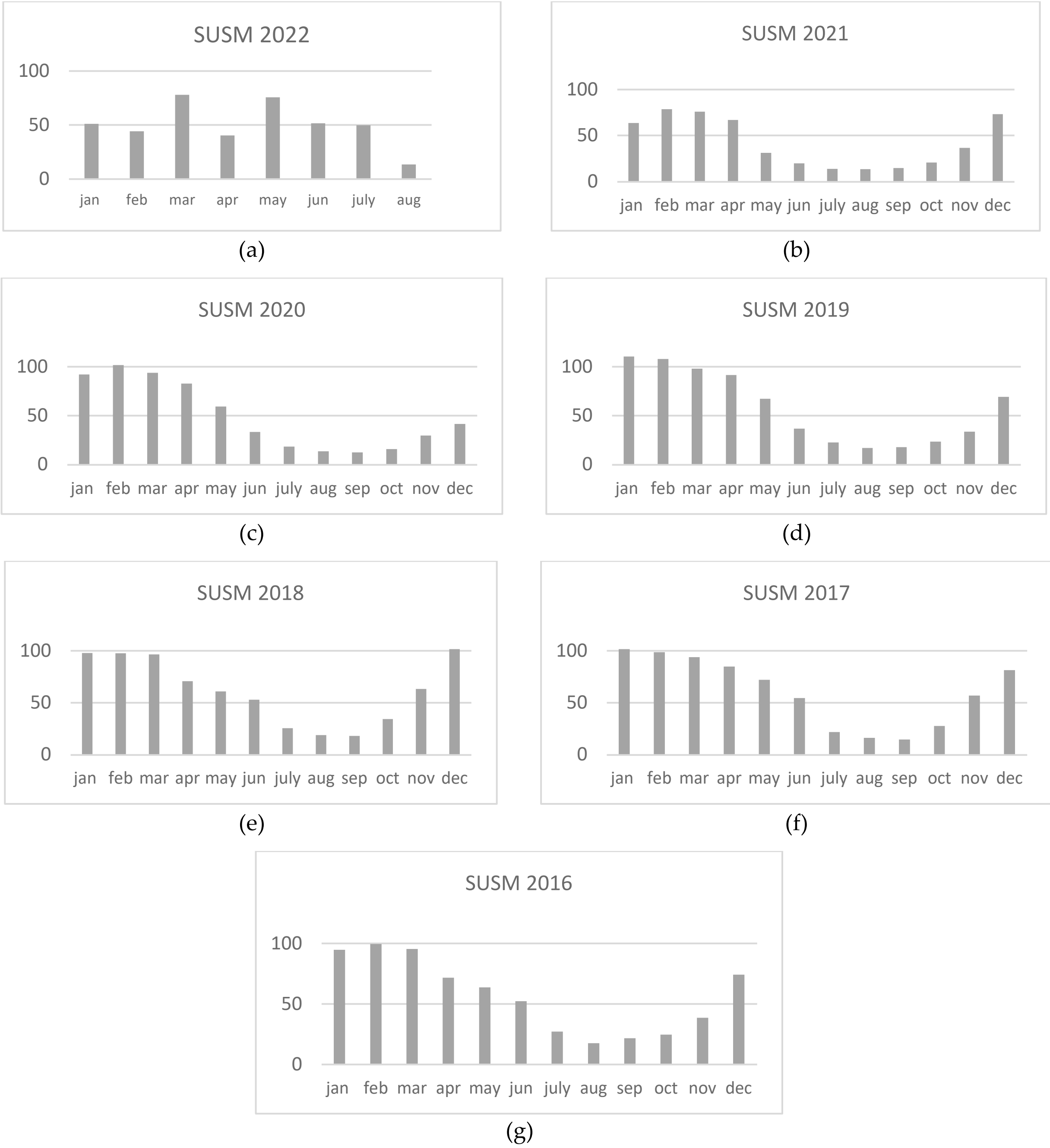

Figure 6: (a) 2022, (b) 2021, (c) 2020, (d) 2019, (e) 2018, (f) 2017, (g) 2016 SUSM graphs.

Figure 6 presents the subsurface soil moisture (SUSM) graphs from 2016 to 2022. Like surface soil moisture, the highest SUSM value was recorded in January 2019, and the lowest in August 2021. The peak in January 2019 likely reflects the accumulation of winter precipitation, while the low in August 2021 can be attributed to increased evaporation during the hot summer months. This pattern underscores the strong seasonal dependence of subsurface soil moisture on precipitation and temperature, highlighting how deeper soil layers respond to climatic changes over time.

Figure 7: Surface pressure graphs for 2022, (b) 2021, (c) 2020, (d) 2019, (e) 2018, (f) 2017, (g) 2016.

Figure 7 illustrates the surface pressure graphs from 2016 to 2022. The surface pressure values range between 88,000 and 90,000 Pa throughout the years. Notably, the highest-pressure value was recorded in November 2020, indicating stable atmospheric conditions during that period. Conversely, the lowest pressure value was observed in July 2017, which could be associated with increased weather disturbances or storm activity typical of summer months. This variation in surface pressure underscores the influence of seasonal changes and weather patterns on atmospheric dynamics over the observed years.

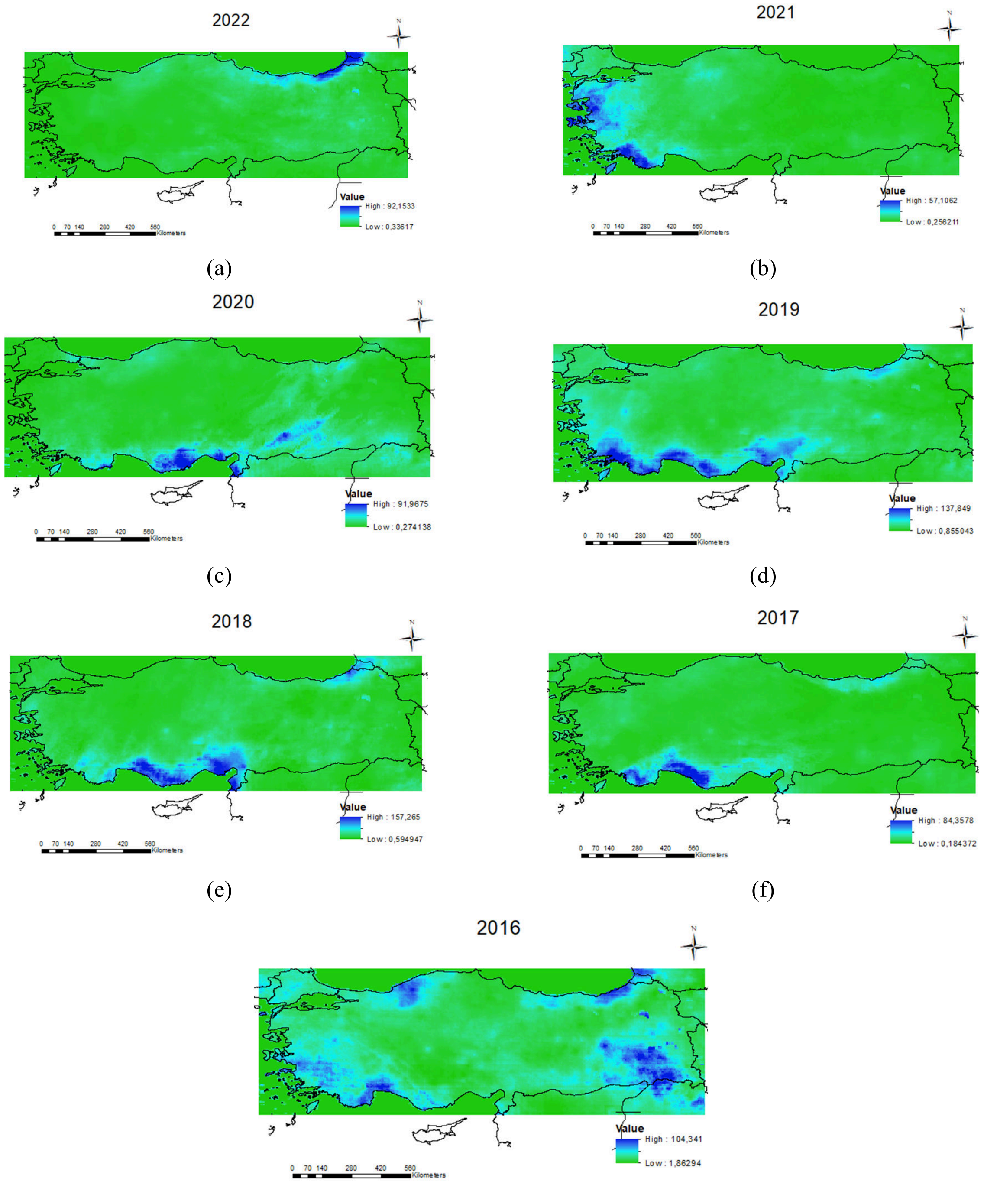

Figure 8: (a) 2022, (b) 2021, (c) 2020, (d) 2019, (e) 2018, (f) 2017, (g) 2016 precipitation thematic maps.

Figure 8 shows the thematic maps of precipitation between 2016-2022. It is observed that the amount of precipitation in Turkey is especially intense in coastal regions. The lowest value of precipitation was observed in 2017, and the highest value was observed in 2018.

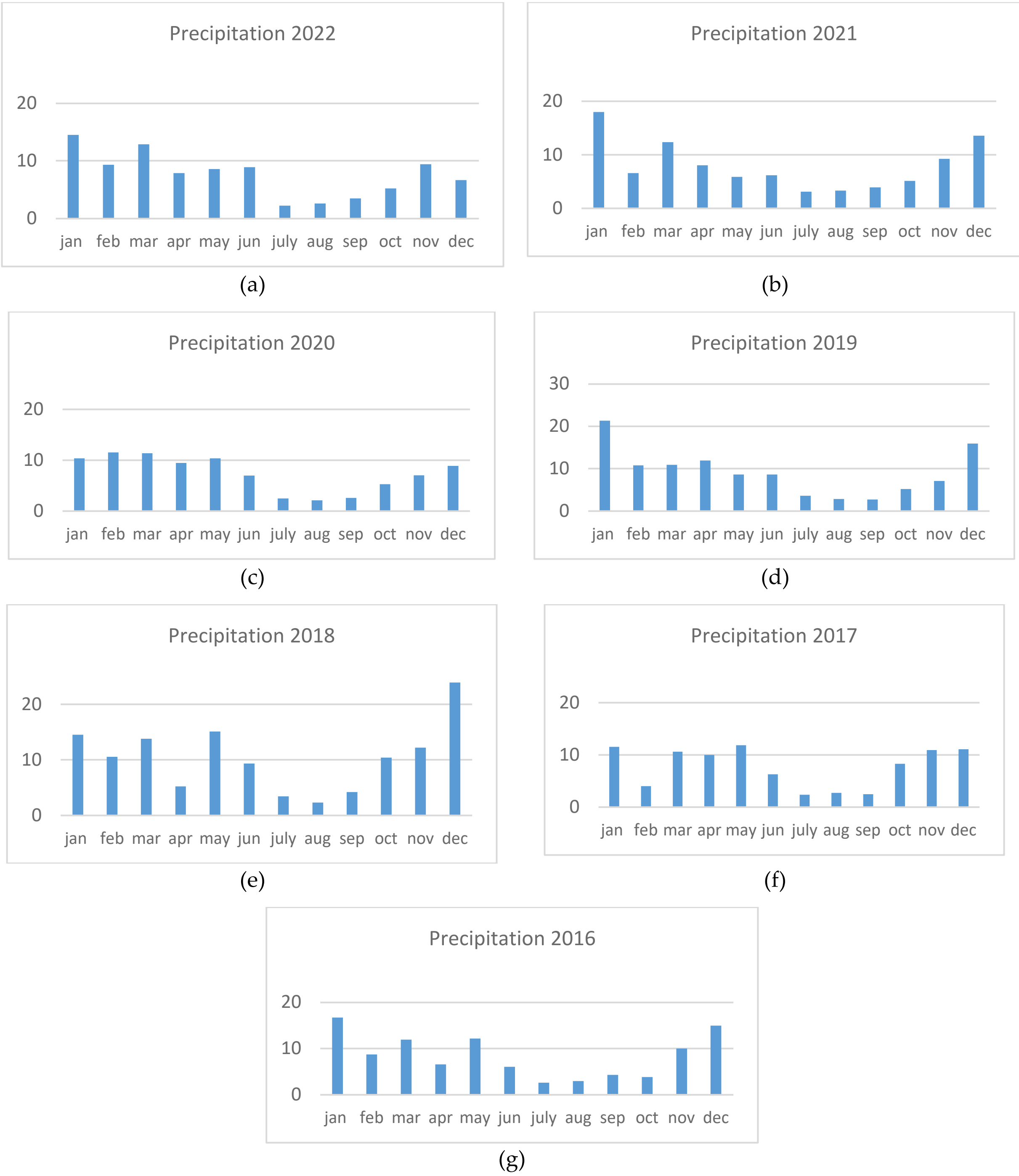

Figure 9: (a) 2022, (b) 2021, (c) 2020, (d) 2019, (e) 2018, (f) 2017, (g) 2016 precipitation graphs.

Figure 9 presents the thematic maps of precipitation across Turkey from 2016 to 2022. The maps indicate that precipitation levels are particularly high in coastal regions, reflecting the influence of maritime weather patterns. Notably, the year 2017 recorded the lowest precipitation levels, which may have implications for water availability and agricultural practices in that year. In contrast, 2018 experienced the highest precipitation, potentially contributing to increased soil moisture and improved conditions for crops. Figure 10 shows the LST thematic maps between 2016-2022. The highest LST is observed in the Southeastern Anatolia region. The lowest values were observed in the Black Sea and Eastern Anatolia regions. In 2022, it was observed that soil moisture increased in the Eastern Black Sea region and Eastern Anatolia region.

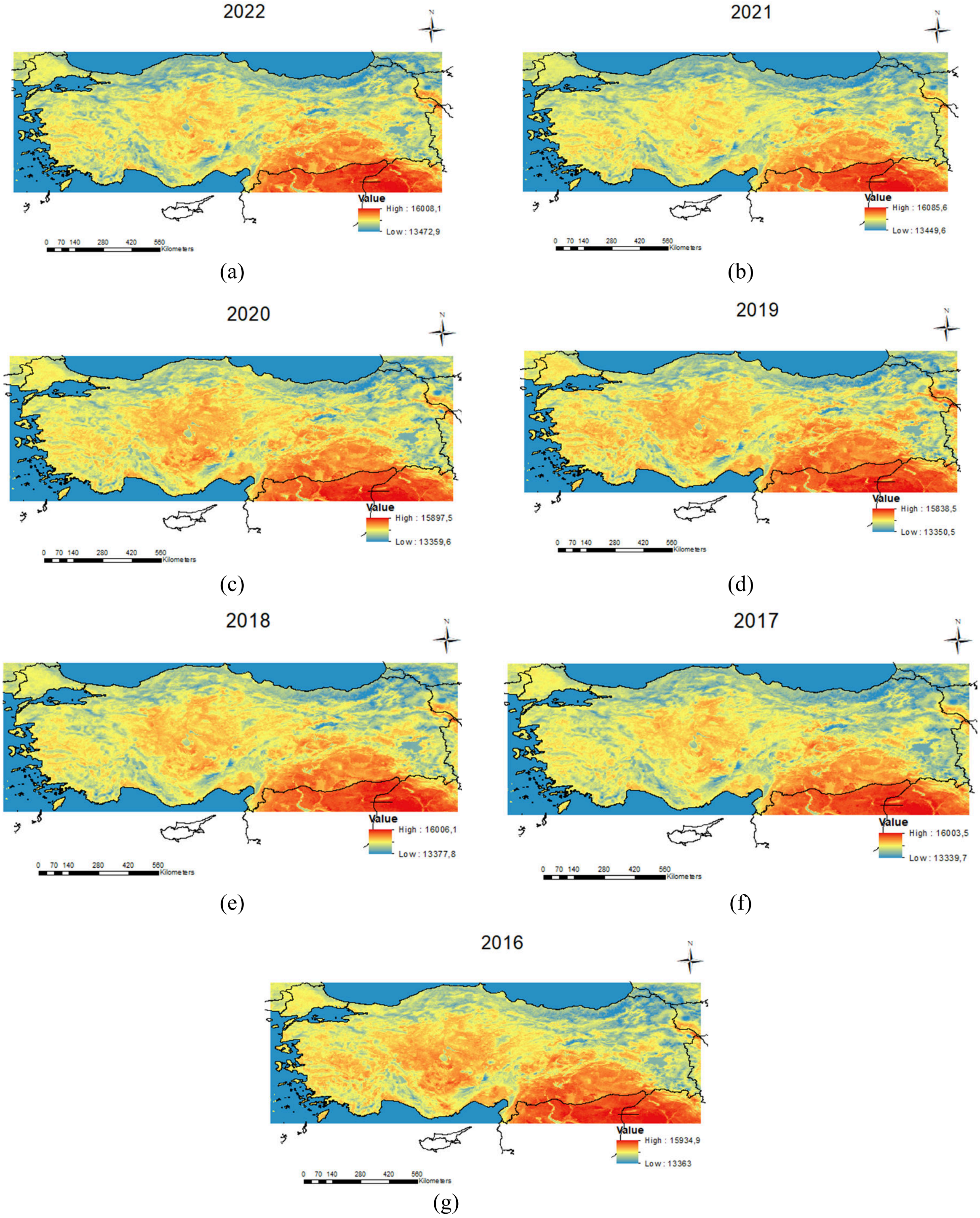

Figure 10: (a) 2022, (b) 2021, (c) 2020, (d) 2019, (e) 2018, (f) 2017, (g) 2016 LST thematic maps.

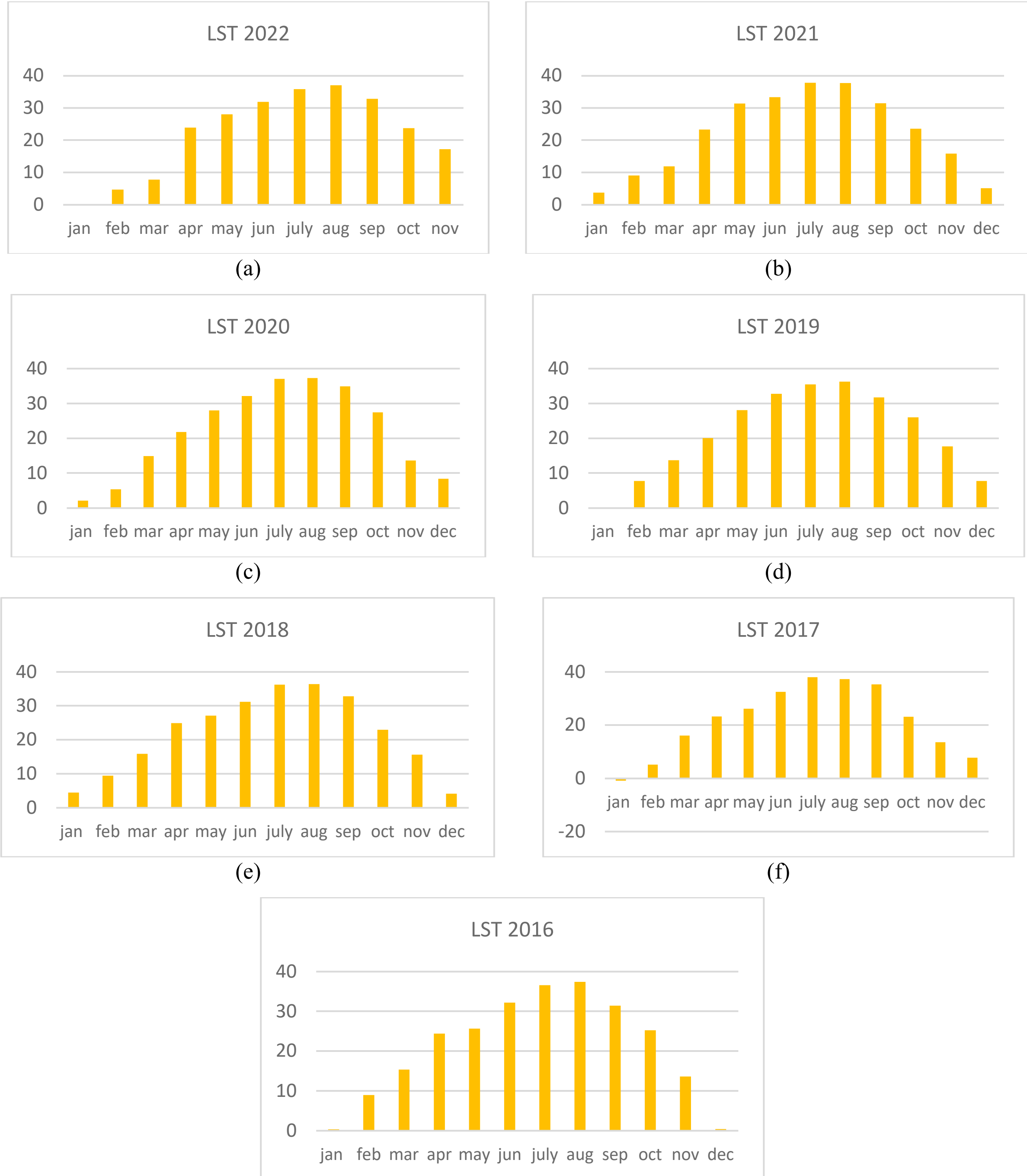

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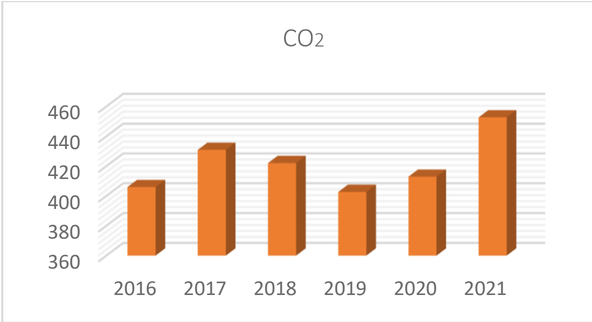
Figure 11: (a) 2022, (b) 2021, (c) 2020, (d) 2019, (e) 2018, (f) 2017, (g) 2016 LST graphs.

Figure 11 displays the surface temperature graphs for Turkey from 2016 to 2022. The data indicates that the highest surface temperatures occur predominantly in July and August, aligning with typical seasonal patterns of heat during the summer months. Conversely, the lowest surface temperatures are recorded in December, January, and February, reflecting the colder winter conditions. These seasonal fluctuations in surface temperature are crucial for understanding the climatic variations throughout the year and their potential impacts on ecological and agricultural practices.



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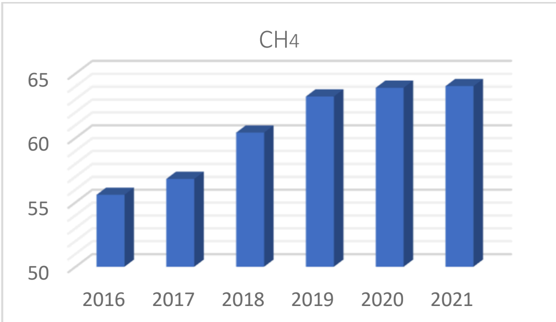

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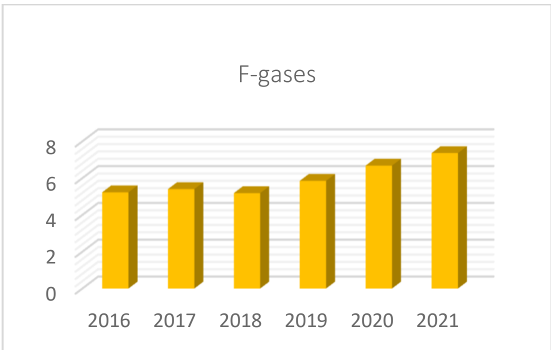

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Figure 12: Gas Emission Statistics; carbon dioxide (CO_2) (a), methane (CH_4) (b), nitrous oxide (N_2O) (c), and fluorinated gases (F-gases) (d).

Figure 12 illustrates the gas emission statistics for various greenhouse gases, including carbon dioxide (CO_2) (a), methane (CH_4) (b), nitrous oxide (N_2O) (c), and fluorinated gases (F-gases) (d). The data, sourced from the Greenhouse Gas Emission Statistics newsletter, spans the period from 2016 to 2021. It highlights emissions from key sectors such as energy, industrial processes and product use, agriculture, and waste.

4. DISCUSSION

The findings of this study shed light on the intricate relationship between climate variables and soil moisture dynamics in various regions of Turkey. The observed direct relationship between surface and subsurface soil moisture (SSM and SUSM) values with precipitation data underscores the significant influence of precipitation patterns on soil moisture content, aligning with the conventional understanding of how rainfall replenishes soil moisture, as also discussed by [51] in his analysis of large-scale meteorological drought control mechanisms. Increased precipitation contributes to higher soil moisture levels, which is crucial for maintaining ecosystem health and agricultural productivity in regions that experience seasonal fluctuations in rainfall.

Moreover, the inverse relationship between SSM, SUSM, and land surface temperature (LST) highlights the complex interplay between temperature and soil moisture. Higher temperatures result in increased evaporation rates, leading to decreased soil moisture levels. This finding aligns with [52], who emphasized the importance of considering soil moisture in climate change scenarios, especially with rising global temperatures that exacerbate soil dryness and impact vegetation-atmosphere interactions. The strong correlation observed between soil moisture and LST further supports Berg's assertion that soil moisture plays a pivotal role in understanding how climate variability influences hydrological cycles.

The notable increase in SSM, SUSM, and surface pressure (PS) values during the winter months, particularly in December and January, highlights the seasonal variability of soil moisture. Factors such as increased precipitation, reduced evaporation due to lower temperatures, and snowmelt contribute to soil moisture accumulation during this period. These seasonal changes are essential for predicting soil moisture dynamics and their implications for environmental processes such as sustainable agricultural practices and water resource management, as observed in [53]. [53]

work on the role of climate variables in air quality further corroborates the importance of studying seasonal and climatic fluctuations in understanding soil-environment interactions.

In addition to examining the relationship between soil moisture and climatic variables, this study also explored the correlation between soil moisture and greenhouse gases. A moderate relationship between SSM and methane (CH_4) (R: 0.65, $p < 0.05$) suggests that soil moisture variations can influence methane emissions, a finding that aligns with Schubert's (2016) exploration of how moisture impacts atmospheric processes. Furthermore, the high correlation between SSM and nitrous oxide (N_2O) (R: 0.89, $p < 0.05$), as well as between SSM and fluorinated gases (F-gases) (R: 0.97, $p < 0.05$), reveals a significant interaction between soil moisture and these greenhouse gases. These results are consistent with the findings of [54], who noted the influence of meteorological factors, including soil moisture, on environmental variables such as air quality and greenhouse gas emissions.

Similarly, the strong correlations between subsurface soil moisture (SUSM) and N_2O (R: 0.86, $p < 0.05$) and F-gases (R: 0.96, $p < 0.05$) suggest that deeper soil layers may also play a critical role in modulating greenhouse gas emissions. This aligns with research by Berg (2018), who emphasized the need to consider subsurface moisture conditions when examining soil-plant-atmosphere interactions under climate change. These findings underscore the potential feedback mechanisms between soil moisture and greenhouse gas emissions, highlighting the importance of integrating soil moisture data into climate models to predict future environmental changes more accurately.

The results of this study also resonate with broader global research on soil moisture dynamics, particularly in the context of climate change. As indicated by [53] and [51], understanding the relationships between soil moisture, temperature, precipitation, and atmospheric conditions is essential for managing the impacts of climate variability on agricultural systems, water resources, and carbon cycling. The strong correlations between soil moisture and greenhouse gases emphasize the importance of monitoring soil conditions, as changes in moisture levels may directly influence the release of potent gases like N_2O and F-gases, contributing to the global greenhouse effect.

In conclusion, the relationship between soil moisture and climate variables, as identified in this study, offers valuable insights for agricultural planning, water resource management, and environmental sustainability. The strong correlations between soil moisture and greenhouse gases suggest that soil conditions should be closely monitored as part of climate mitigation strategies. As noted by [52], [54], and [53], integrating climate, soil, and atmospheric data into predictive models will be critical for understanding the full range of impacts associated with soil moisture dynamics and for developing effective climate adaptation measures. This study’s contributions provide a foundation for future research and strategic decision-making in the fields of environmental sustainability and climate change adaptation.

5. CONCLUSION

Overall, the findings of this study provide valuable insights into the complex interactions between climate variables and soil moisture dynamics in various regions of Turkey. It was determined that surface temperature and precipitation are the key factors influencing changes in soil moisture, with increased precipitation leading to significant rises in soil moisture levels. The relationship between surface pressure and soil moisture, particularly in different climate zones, underscores the complexity of environmental interactions and highlights the regional and seasonal variability of these dynamics. These results are critical for both agricultural production and the preservation of natural ecosystems.

The study offers an essential resource for understanding the effects of climate change on soil moisture, which plays a crucial role in ecosystem dynamics, agriculture, and water resource management. Given the importance of soil moisture for a wide range of sectors, from agricultural output to natural habitats, such analyses hold significant value for environmental planning and resource management. The findings contribute to a better understanding of the potential impacts of climate change, laying the groundwork for more effective mitigation and adaptation strategies.

In addition, incorporating long-term data and considering future climate change impacts will further enhance our understanding of soil moisture dynamics on a broader scale. Future research could delve into the specific mechanisms driving soil moisture changes in different regions and assess their implications for ecosystems, agriculture, and water resources. This could pave the way for innovative approaches to managing soil moisture and mitigating the effects of climate variability.

In conclusion, this study contributes significantly to the understanding of environmental complexity and the influence of climate variables on soil moisture. Such research will play a critical role in informing long-term planning efforts aimed at achieving environmental sustainability.

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