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Exploring Spatial and Temporal Dynamics of Soil Moisture Using SMAP, Khorasan Razavi, Iran

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ABSTRACT: Surface soil moisture serves as a vital factor affecting soil evaporation, transpiration, hydrology, ecology, and agriculture; so accurate quantification of soil moisture is crucial. However, achieving high temporal resolution in monitoring and interpreting soil moisture patterns is challenging, especially in developing nations like Iran. To bridge the data gap, remote sensing techniques offer continuous soil moisture monitoring at moderate temporal resolution and lower cost. Multiple operational microwave satellites contribute to global surface soil moisture mapping, with Soil Moisture Active Passive (SMAP) recognized for its accuracy. This study employs SMAP satellite data to analyze the temporal and spatial dynamics of soil moisture in Khorasan Razavi province, located in Iran, providing insights into 2015-2022 trends. Findings reveal monthly average soil moisture ranging from 0.0712 m^3m^{-3} in August to 0.1625 m^3m^{-3} in March, with an annual average of 0.1150 m^3m^{-3}, lower than the country's annual average. Seasonal volumetric water content ranges from 0.1343 m^3m^{-3} in summer to 0.0751 m^3m^{-3} in winter. Variations are attributed to diverse climates, topography, and land use affecting precipitation and soil moisture. The paper also concludes that while results aid water and soil management in Khorasan Razavi, comprehensive soil moisture studies should encompass all Iranian provinces. Furthermore, recent soil moisture monitoring techniques can also be used to capture high spatial resolution soil moisture datasets.

Keywords – Google Earth Engine, Iran, Khorasan Razavi, Soil Moisture, Soil Moisture Active Passive (SMAP) satellite

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1. Introduction

Surface soil moisture is a crucial environmental factor affecting soil evaporation and transpiration [1] and is also linked to the risk of wildfire [2,3]. This variable also plays a vital role in hydrology by influencing rainfall-runoff processes, in ecology as it regulates net ecosystem exchange, and in agriculture, as it stands as a limiting factor for food security [4]. Therefore, accurate quantification of soil moisture is critical [5]. However, monitoring and interpreting soil moisture patterns at a high temporal resolution is challenging due to the expenses associated with setting up, operating, and maintaining a dense soil moisture network across a region. This challenge becomes particularly pronounced in developing nations, where financial constraints make this endeavor unfeasible due to resource competition [6,7].

As a developing country, Iran lacks a national soil moisture network. The current measurements are confined to Agricultural meteorological stations, distributed unevenly nationwide. This unequal distribution has led to certain provinces facing an absence of monitoring stations or being equipped with an inadequate number to effectively capture soil moisture dynamics. Furthermore, the available soil moisture data from these stations is often limited in duration, with few offering continuous time series data [8]. A prime illustration of this data gap is Khorasan Razavi province, located in the east of Iran, where approximately 70 percent of the region experiences arid and semi-arid climates [9] highlights the significance of consistent soil moisture monitoring [7]. The significance is heightened when considering that this province is home to Iran's second-largest city and a considerable population [10]. As a result, food security is gaining more prominence [11], underscoring the essential need for this data.

To address the deficiency of in-situ data, remote sensing techniques offer a valuable opportunity for continuous soil moisture monitoring, providing estimates at moderate temporal resolution and lower cost [6]. Recent progress in earth observation technology has turned remote sensing into a big data technology, capable of applying various data-driven approaches, comparing their efficiency, and swiftly mapping and monitoring the data in dynamics areas, which is the object of the current research [12].

Currently, multiple microwave satellites are operational for global surface soil moisture mapping, with the Soil Moisture Ocean Salinity (SMOS) and Soil Moisture Active Passive (SMAP) satellites standing out for their accuracy [13]. SMAP has been utilized in monitoring soil moisture in Iran in various studies, with results consistently highlighting robust correlations between remotely sensed data and in-situ observations [14, 15, 16]. However, less research has focused specifically on the Khorasan Razavi province.

Only one research covers this geographical scope, focusing on the temporal and spatial dynamics of soil moisture across the country [8]. However, the applicability of these findings to the current study area is debatable. This uncertainty arises due to the diverse climatic conditions, spanning from very humid to hyper-arid, characterized by considerable spatial variations in precipitation and temperature [17], the diversity of topography conditions (plain to mountainous areas, and the diversity of landcover types (built-up, bare land, grassland, waterbody, etc.) [18]. Given this diversity which affects soil moisture across various regions [19, 20, 21], while the previous research's findings provide valuable insights on a national scale, they might not accurately represent conditions at a more localized level.

To fill this gap, this research aims to explore the spatial and temporal dynamics of soil moisture within Khorasan Razavi province using SMAP to provide a good understanding of the changes in soil moisture within this region from 2015 to 2022.

2. Study Area

Khorasan Razavi province is situated in northeastern Iran and spans around 7% of the country`s total area [22]. Its geographical coordinates are between the longitude 56° 19 ´ to 61° 16 ´ E and the latitude 33 52 ´ to 37° 42 ´ N. The province shares borders with two countries, Turkmenistan, and Afghanistan, to the northeast and east. In contrast, it borders South Khorasan, North Khorasan, and Semnan provinces to the south, north, and west, respectively [23].

As the second most populated province in the nation, it accommodates an approximate population of 6 million, including the city of Mashhad, the country's second-largest city with around 3 million inhabitants [24]. Sharing the impact of climate change with the rest of Iran [25], Khorasan Razavi experiences a prevailing arid and semi-arid climate. This is characterized by an average annual temperature of 17 °C and an average annual rainfall ranging from 75 mm in the southern regions to 390 mm in the northern zones. The northern part of the province is characterized by mountainous ranges interspersed with fertile plains due to favorable rainfall and accessible groundwater resources. In contrast, the southern region is predominantly arid due to limited rainfall, and its proximity to the arid areas of southeast Iran, leading to a sparse vegetation cover and limited agricultural land [24].

Figure1. Location of the Study Area.

3. Materials and Methods

The Soil Moisture Active Passive (SMAP) mission is one of the initial earth observation satellites developed by NASA [26]. Launched in January 2015, this satellite was designed to offer global mapping of soil moisture and freeze-thaw state every two to three days, employing an L-band radar operating in an active mode, along with an L-band radiometer operating in a passive mode. Following an irreversible hardware failure of the radar on July 7, 2015, the radiometer-only soil moisture product remained the sole operational soil moisture product for SMAP [27]. This product has a grid size of 9-km and a nominal spatial resolution of 33 km [28].

This study utilized the SMAP Level-4 (L4) Soil Moisture product. This product offers surface soil moisture data for the top 5 cm of the soil and includes a series of 3-hourly time-averaged geophysical data fields from the assimilation system [29]. This dataset can be accessed through Google Earth Engine (GEE) catalogue web page (https://developers.google.com/earth-engine/datasets/). GEE is an online computational platform capable of processing satellite images, and spatial and geographical data at a petabyte scale. This web-based system facilitates high-speed access to satellite data, cloud computing, and big data processing algorithms, effectively overcoming limitations related to downscaling, data storage, and processing that can be encountered with other techniques. Consequently, many researchers have turned to GEE for their recent studies [12], including this research.

The study period is from 2015 to 2022. Despite its limited duration for climate studies, the research outcomes will be reliable due to the demonstration of low and high thresholds over extended periods, attributed to the presence of intense pluvial conditions from 2018 to 2019 and severe drought throughout 2020 to 2021 [8]. Over eight years, thousands of images encompassed the study area. Initially, these images were aggregated into monthly composites for each year. Subsequently, they were spatially averaged over the study area and temporally averaged over the study period. This process yielded 12 maps, each representing the monthly average soil moisture for the study area during the research period.

Monthly minimum and maximum maps were generated, extracting the lowest and highest soil moisture values for each month throughout the time frame. This operation resulted in 12 maps for minimum values and 12 for maximum values, one for each month. Moreover, the seasonal and annual average soil moisture values for the entire study area were calculated over the 8-year study period. These comprehensive analyses were executed using the GEE platform. Furthermore, the study also includes a plot depicting the average daily changes in soil moisture for each year.

4. Results

4.1. Average monthly soil moisture

Fig 2 displays the spatial and temporal distribution of average monthly soil moisture, captured by SMAP satellite images from 2015 to 2022. The findings illustrate that the lowest average monthly soil moisture levels appeared in July, August, and September, with values of 0.0753, 0.0712, and 0.0739, respectively. Conversely, March and April show the highest average monthly soil moisture values, reaching 0.1625 and 0.1556, respectively.

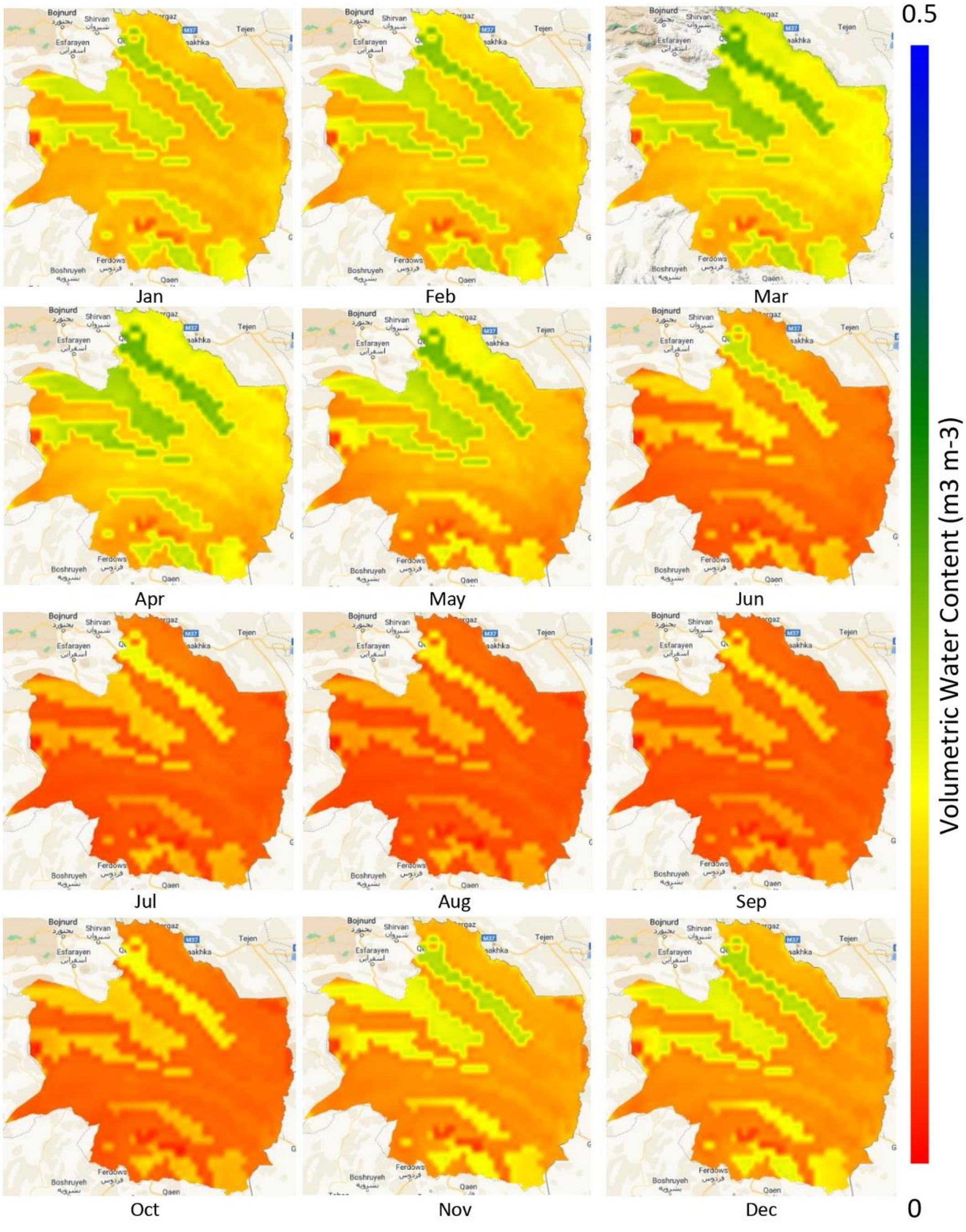

Figure 2. The spatial and temporal distribution of average monthly soil moisture at 5-cm depth, captured by SMAP over 2015-2022.

The analysis of the spatial distribution of soil moisture in the province indicates that over these years, the plains of Mashhad, Neyshabour and Joveyn in the northern region have consistently exhibited the highest soil moisture values. Conversely, the southern areas of the province display the lowest soil moisture values.

Presented in Table 1 are the average, minimum and maximum monthly values observed over the study period. The average monthly values range between 0.0712 in August, representing the minimum, and 0.1625 in March, indicating the maximum soil moisture value. Additionally, the minimum monthly soil moisture values fluctuate between 0.0019 and 0.0086. Meanwhile, the maximum monthly values vary from 0.3030 to 0.5045.

Table 1. Average, minimum and maximum monthly soil moisture values at 5-cm depth, captured by SMAP over 2015-2022.

Month	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
MIN	0.0027	0.0025	0.0024	0.0023	0.0020	0.0019	0.0022	0.0039	0.0053	0.0086	0.0048	0.0029
MEAN	0.1391	0.1463	0.1625	0.1556	0.1352	0.0943	0.0783	0.0712	0.0739	0.0849	0.1186	0.1206
MAX	0.4063	0.4271	0.4728	0.5045	0.4333	0.4172	0.3077	0.3030	0.3583	0.3748	0.4527	0.4545

Fig 3 illustrates the spatial and temporal distribution of minimum monthly soil moisture. Notably, the lowest value is evident in June, with a value of 0.0019. Conversely, the highest values are observed in October, marked as 0.0086. Furthermore, Fig 4 depicts maximum monthly soil moisture's spatial and temporal distribution. In this representation, the lowest value occurs in August and July, while the highest values are observed in April. These trends align with the average monthly soil moisture pattern illustrated in Fig 2.

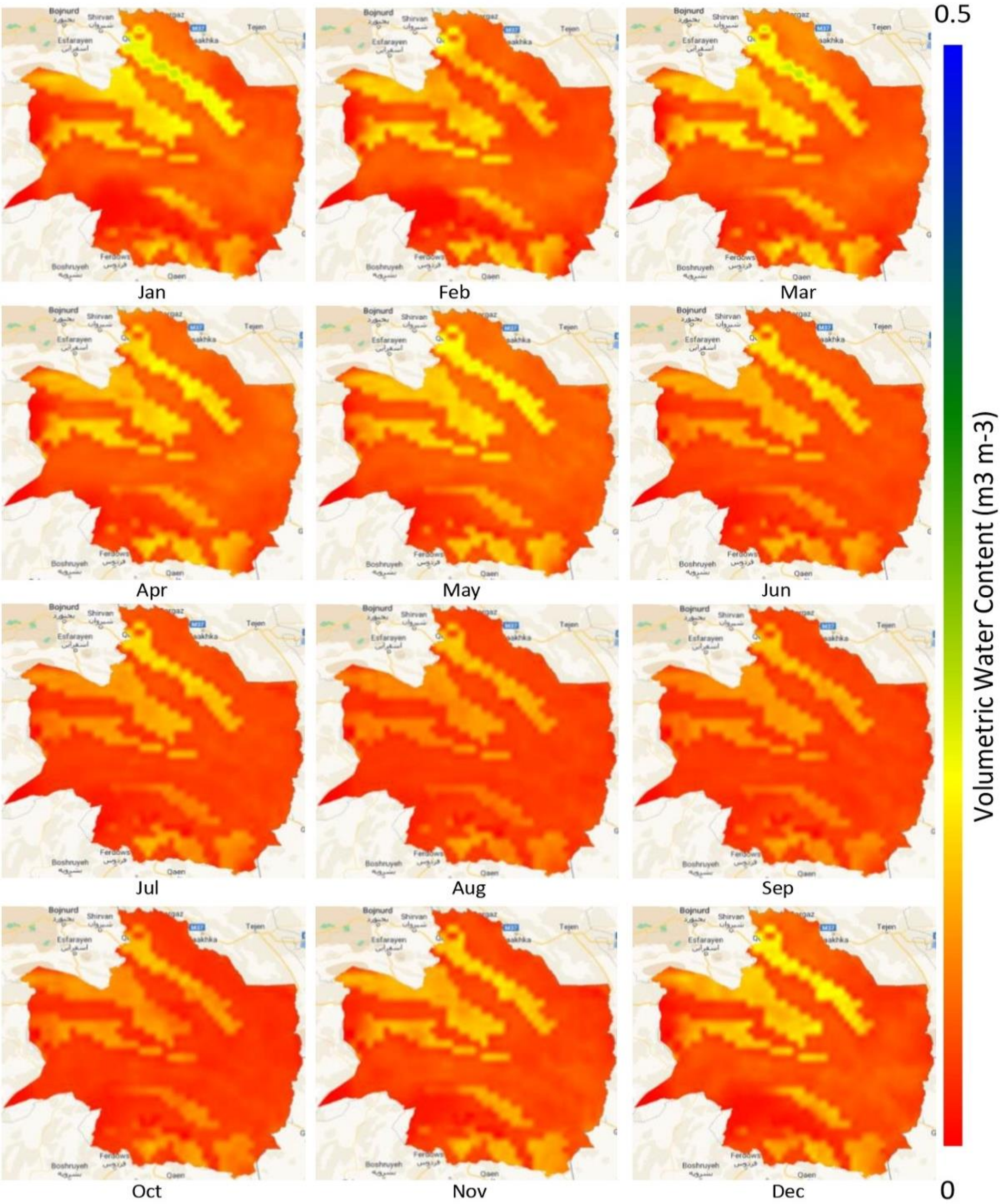

Figure 3. The spatial and temporal distribution of minimum monthly soil moisture at 5-cm depth, captured by SMAP over 2015-2022.

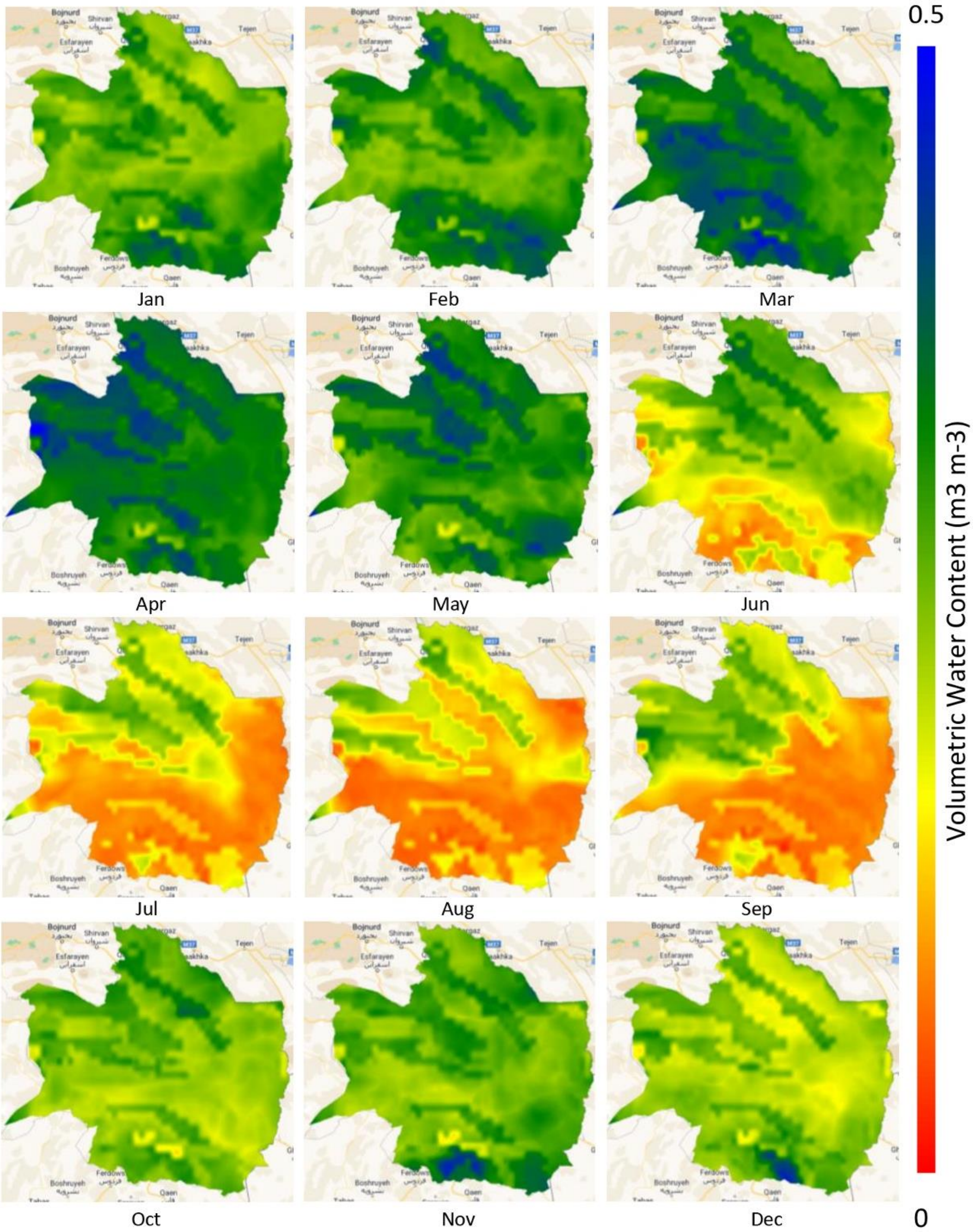

Figure 4. The spatial and temporal distribution of maximum monthly soil moisture at 5-cm depth, captured by SMAP over 2015-2022

Fig 5 presents the time series of monthly minimum, average, and maximum volumetric water content at a 5-cm depth, as measured by SMAP. The findings indicate a decrease in values from March and April, followed by an increase as the rainy season commences, in September. It's worth noting that the trends in both maximum and average monthly values display a similar pattern. However, the minimum monthly values show comparatively less fluctuation.

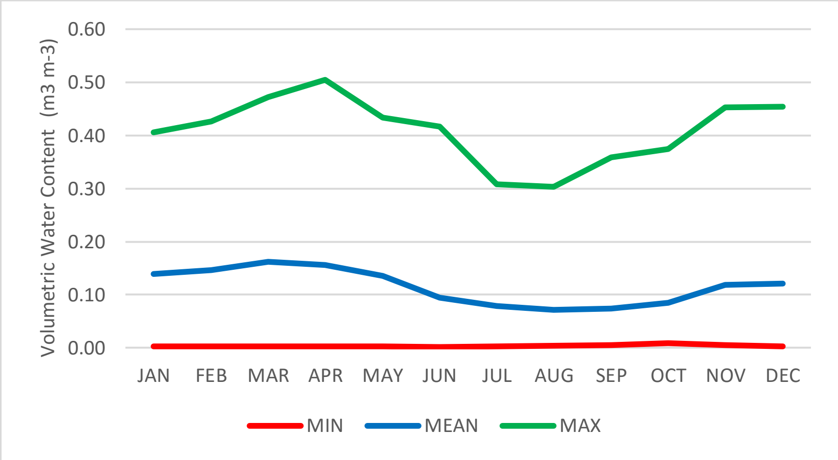

Figure 5. The time series of monthly minimum, average, and maximum volumetric water content at a 5-cm depth, captured by SMAP over 2015-2022.

Fig 6 displays the daily time series of volumetric water content at a 5-cm depth soil for each year spanning from 2015 to 2022. The data illustrates that the peak values were recorded in 2019 at the start of the year, whereas the lowest values were observed in 2021. In the middle phase of this period, minimal fluctuations are noted, with values consistently within a similar range. Towards the end of the timeframe, 2015 and 2018 show the highest volumetric water content, while 2017 and 2022 indicate the lowest values. Moreover, the most significant shifts in soil moisture values throughout the study duration are evident during the spring and summer seasons, while the autumn and winter periods display comparatively minor changes over these years.

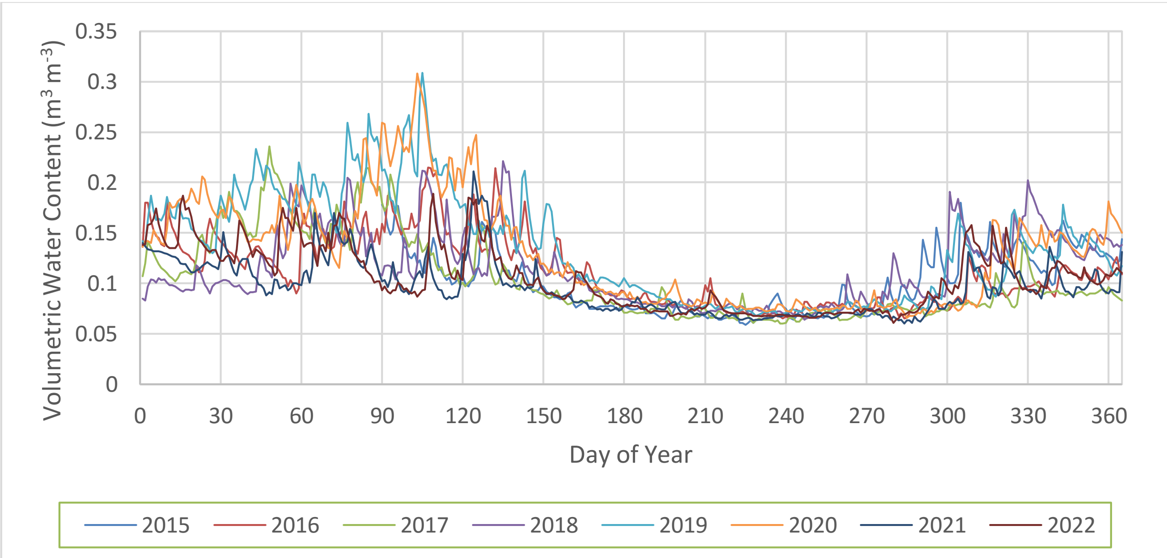

Figure 6. The daily time series of volumetric water content at 5-cm depth, captured by SMAP, in 2015-2022.

In 2016 and 2017, there was an initial rise followed by a decline in soil moisture levels from the beginning to the end of the period, relative to the year 2015. In 2018, this pattern reversed, with a decline in soil moisture during the initial months of the year, followed by an increase by the end of the year. For 2019 and 2020, soil moisture displayed a similar trend of ascending at the beginning and descending by the end of each year. The year 2021 marked a distinct deviation, as it showed a continuous reduction in soil moisture throughout the entire period compared to the previous years. In 2022, although there was an increase in soil moisture values compared to 2021, it remained notably lower compared to other years.

4.2. Average Seasonal and Annual Soil Moisture

Table 2 presents the average volumetric water content for each season and the overall annual mean. According to this data, the average soil moisture in spring, summer, autumn, and winter are 0.1343, 0.0751, 0.1100, and 0.1300, respectively. This data highlights the maximum and minimum soil moisture levels aligning with the spring and summer seasons, respectively. Moreover, during spring, the peak values are observed in 2019 and 2020, while the lowest value occurs in 2021 and 2022. In the summer, the highest value corresponds to 2019 and 2020, while 2017 is the lowest. Furthermore, the annual averages range from 0.3149 in 2015 to 0.5471 in 2019, resulting in an overall average of 0.4494.

Table 2. Average seasonal and annual soil moisture values at 5-cm depth, captured by SMAP over 2015-2022.

Years	Winter	Spring	Summer	Autumn	Annual
2015	0.0000	0.1206	0.0712	0.1231	0.3149
2016	0.1383	0.1542	0.0775	0.0951	0.4650
2017	0.1588	0.1188	0.0696	0.0859	0.4331
2018	0.1264	0.1406	0.0768	0.1318	0.4755
2019	0.1869	0.1644	0.0781	0.1177	0.5471
2020	0.1684	0.1641	0.0798	0.1205	0.5328
2021	0.1208	0.1026	0.0733	0.0985	0.3952
2022	0.1403	0.1093	0.0744	0.1076	0.4317
mean	0.1300	0.1343	0.0751	0.1100	0.4494

5. Conclusions

The lack of comprehensive soil moisture data in most regions of the country has consistently posed a significant challenge for hydrological modeling, weather forecasting, and water resource planning. This challenge stems from the limited number of soil moisture measurement stations and their uneven distribution, resulting in statistical gaps within the dataset. To tackle this issue, satellite imagery is a valuable tool to capture and provide soil moisture data [8]. So, this research aims to show the spatial and temporal pattern of soil moisture in Khorasan Razavi province, located in northeast Iran, using SMAP satellite data from 2015 to 2022.

The results show that over the study period, 2015 and 2021 were the driest years, while 2019 and 2020 experienced the highest volumetric water content. These results align with the overall pattern observed in the country [8]. However, the result revealed that the monthly average soil moisture values of the region range from 0.0712 in August to 0.1625 in March, with an annual average of 0.1150 m^3m^{-3}; while the monthly average soil moisture value in the country ranges from 0.0005 to 0.538, with an average annual value of 0.137 m^3m^{-3}, being higher that of in Khorasan Razavi [8]. Additionally, the comparison of the seasonal volumetric water content in Iran and Khorasan Razavi province shows that while in Iran, the seasonal values range between 0.082 m^3m^{-3} in summer and 0.188 m^3m^{-3} in winter [8], in this province, both the highest and the lowest value of the range are lower than the country's average, with the value of 0.1343 m^3m^{-3} in spring and 0.0751 m^3m^{-3} in summer, respectively.

This result can be attributed to several factors, one of which is precipitation. While precipitation directly impacts soil moisture by increasing its content, soil moisture also reciprocally affects precipitation by supplying water through evaporation. This interaction has led researchers to investigate soil moisture-precipitation feedback in recent decades [19]. Additionally, it is proved precipitation itself is under the effect of topography and climate conditions, and this is the reason why these factors are used in a Generalized Regression neural network model for the accuracy improvement of precipitation products [18].

Another contributing factor is land cover and topography. A study has deduced how land use and the topographic aspect of a region can impact the fractal dimension of soil particle size distribution and soil erodibility factors [20]. Additionally, the soil texture itself plays a role in soil moisture [21,30], because the size of soil particles dictates the amount of space between them, thereby influencing water movement through the soil and its capacity to retain water [31]. So, given Iran's diverse topography, climate conditions and landcover, it is reasonable to anticipate varying levels of precipitation across different regions of the country [18], leading to a wide range of volumetric water content.

So, while this research offers valuable insights for water and soil management in Khorasan Razavi, it is recommended that future studies consider conducting soil moisture data for other provinces of Iran, each characterized by distinct climatic conditions and topography. Additionally, given the relatively coarse spatial resolution of the SMAP satellite, it is also advisable to explore the utilization of alternative remote sensing techniques to map soil moisture at a higher spatial resolution.

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