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Determining soil moisture with Sentinel-1 image

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Abstract: *Soil moisture is vital for agricultural practices, climate change, erosion, and water management issues. Thus, monitoring and spatial distribution of soil moisture is also important. Nowadays, the usage of remote sensing, apart from traditional methods, for estimating soil moisture is rapidly increasing. In this context, Synthetic Aperture Radar images constitute one of the remote sensing tools. In this study, soil moisture was estimated using Sentinel-1 imaging in a 25-decar field. In situ measurements were carried out with a soil moisture meter in synchronization with the Sentinel-1 transition. As a result of the study, soil moisture was estimated with an empirical approach, using a model derived from in situ soil moisture measurement and Sentinel-1 backscatter data.*

Keywords: Soil moisture, Sentinel-1, Surface soil moisture index, SAR

Sentinel-1 görüntüsü ile toprak neminin belirlenmesi

Öz: *Toprak nemi, tarımsal uygulamalar, iklim değişikliği, erozyon ve su yönetimi konuları için hayati önem taşımaktadır. Bu nedenle, toprak neminin izlenmesi ve mekansal dağılımı da önemlidir. Günümüzde, toprak neminin belirlenmesinde geleneksel yöntemlerin yanı sıra uzaktan algılamanın kullanımı hızla artmaktadır. Bu bağlamda, Sentetik Açıklıklı Radar görüntüleri uzaktan algılama araçlarından birini oluşturmaktadır. Bu çalışmada, 25 dekarlık bir alanda Sentinel-1 görüntülemesi kullanılarak toprak nemi belirlenmiştir. Sentinel-1 geçişi ile senkronize olarak bir toprak nem ölçer ile yerinde ölçümler gerçekleştirilmiştir. Çalışma sonucunda, yerinde yapılan toprak nemi ölçümleri ve Sentinel-1 geri saçılımından türetilen bir model kullanılarak ampirik bir yaklaşımla toprak nemi hesaplanmıştır.*

Anahtar Sözcükler: Toprak nemi, Sentinel-1, Yüzey toprak nemi indeksi, SAR

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1. Introduction

Soil moisture refers to the amount of water in a certain volume of soil. Monitoring soil moisture is significant in many aspects. Soil moisture is substantial in water management, plant growth and development in agricultural and irrigation practices. Determining the spatial distribution of soil moisture is also essential in these respects. Monitoring the spatial distribution of soil moisture has become vital today for the implementation of sustainable agriculture and irrigation policies. In addition, soil moisture is also significant for non-agricultural lands. Monitoring the spatial distribution of soil moisture in such lands helps to take early measures and combat challenges such as climate change and soil erosion (Bajgiran et al., 2013).

There are many methods to estimate soil moisture. Traditional in situ measurements are the most used. In the gravimetric method, soil moisture is calculated by drying the soil samples taken from the field in ovens and measuring their weight. Tensiometers, moisture meters, and soil-embedded moisture sensors are other methods for determining soil moisture. In these methods, unlike the gravimetric method, soil moisture can be obtained instantly. Although these methods give soil moisture with high accuracy, soil moisture can be determined point by point. Therefore, using these methods on large land areas is costly in terms of time and labor (Yetik & Asik, 2021).

Nowadays, the use of remote sensing techniques to estimate the spatial distribution of soil moisture is quite common. Soil moisture can be estimated with the help of optical satellite images, thermal images, or Synthetic Aperture Radar (SAR) images. Since soil moisture is sensitive to changes in surface temperature, soil moisture can be estimated with the help of thermal images (Li et al., 2022). Vegetation indices are used to estimate soil moisture from optical satellite images (Wyatt et al., 2021). Methods using optical satellite images and thermal images can estimate soil moisture for the soil surface. On the other hand, SAR images can penetrate the soil at various depths depending on the wavelength (El Hajj et al., 2019). In addition, SAR images have advantages such as not being affected by adverse weather conditions, higher resolution compared to optical images, and the ability to work day and night.

Soil moisture estimation from SAR images can be carried out by empirical models, semi-empirical models, change detection models, SAR data fusion, or combinations of these and machine learning methods (Bormudoi et al., 2023; Esch et al., 2018; Mirsoleimani et al., 2019; Rawat et al., 2019; Song et al., 2021). These methods have advantages and disadvantages compared to each other. Empirical models are easy to implement. However, their accuracy decreases in roughness and vegetation conditions (Gorrab et al., 2014). In semi-empirical models, physical principles are combined with SAR features. Their use and accuracy vary depending on the size of the angle of incidence and the vegetation condition (Parida et al., 2022). In the change detection method, it is assumed that the soil roughness does not change and the vegetation changes little. In this case, the time difference between the two images should not be too much (Esch et al., 2018). SAR data fusion can be carried out with optical or thermal images. These aim to increase spatial resolution and therefore working accuracy (Moran et al., 2004). Although accuracy increases in machine learning methods, the disadvantages of these methods are that they require high hardware and the training data collection process (Mirsoleimani et al., 2019).

Although many studies in the literature use SAR images, these are generally studies carried out on large areas of land. Few studies were conducted with SAR images at a small field scale. In this study, soil moisture was estimated at a field scale from Sentinel-1 images using a new empirical approach.

2. Study Area

The study area consists of 25 decare land located between the borders of the Ulaş district of Sivas province in Türkiye (Figure 1). There are no agricultural yields or vegetation in the study area.

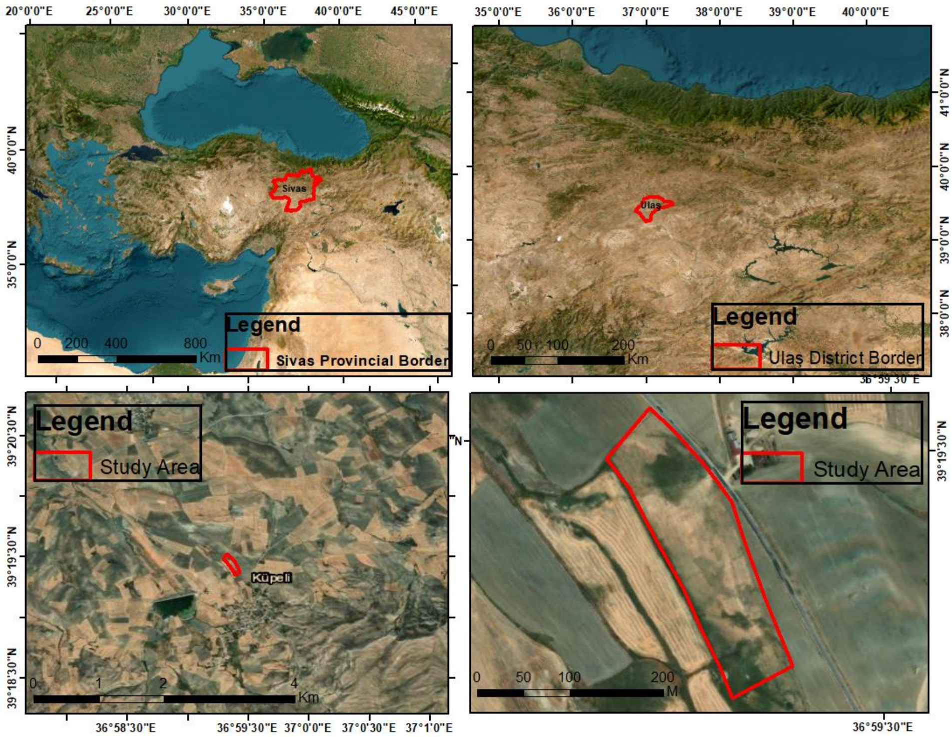

Figure 1: *Study area*

3. Material

The Sentinel-1 image, provided free of charge by European Space Agency (ESA), was used to determine the spatial distribution of soil moisture. Sentinel-1 is a c-band SAR satellite with a temporal resolution of 12 days (Geudtner et al., 2014). To control the soil moisture estimated by Sentinel-1, Honde brand soil moisture meter device capable of measuring with an accuracy of ± 2% was used.

4. Method

First, in-situ measurements were carried out with the soil moisture sensor on 03.08.2023, synchronized with the Sentinel-1 satellite transit time (Figure 2). The coordinates of the 64 points measured with the soil moisture meter were also taken with Global Navigation Satellite Systems (GNSS). Afterward, soil samples were collected from various points in the field, and the soil structure and content were analyzed in the laboratory. In laboratory analyses, it was determined that the soil at the sampling points had various characteristics such as calcareous, slightly alkaline, clay loam structure, salt-free and low organic matter content (Table 1).

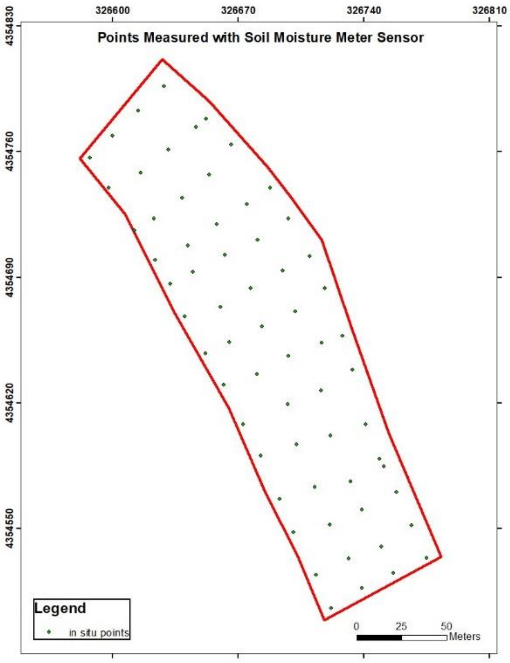

Figure 2: *In situ points*

Table 1: *Soil analysis*

Sample Number	Texture	pH (1:1 H_2O)	Salt (Ms/cm)	Organic Matter (%)	Lime (%)
1	Clayey	7.95	0.55	2.87	45.0
2	Clayey	8.14	0.79	0.58	48.8
3	Clayey	8.09	0.62	2.92	44.8
4	Clayey - Loamy	8.05	0.74	1.45	47.4
5	Clayey - Loamy	8.06	0.56	1.56	39.6
6	Clayey	7.78	0.33	0.30	44.5
7	Clayey - Loamy	8.18	0.52	1.91	49.5

After the fieldwork phase, the pre-processing process of the Sentinel-1 image was carried out. In this context, first, the "*apply orbit file*" process was carried out. In this way, location and velocity information is provided. Afterward, thermal noise removal was applied to eliminate thermal noise. Then, pixel values were converted to SAR backscatter. After the speckle removal process was applied, terrain correction was carried out. In this way, the image is defined by the coordinate system. Finally, backscatter coefficients were converted to decibel units by logarithmic transformation.

A new empirical approach to soil moisture estimation has been adopted with Sentinel-1. The method is derived from the classical soil moisture index I_{ssm} (Surface Soil Moisture Index). The classical soil moisture index is defined as follows (Zribi et al., 2020).

$$I_{ssm} = (\sigma_{VV} - \sigma_{VVmin}) / (\sigma_{VVmax} - \sigma_{VVmin}) \tag{1}$$

Here, the backscatter coefficients in the VV polarization of the Sentinel-1 image are used. Afterward, the following equation was used to convert I_{ssm} to volumetric moisture (Surface Soil Moisture, SSM).

$$SSM = I_{ssm} \text{ x } (in\ situ_{max} - in\ situ_{min}) + in\ situ_{min} \tag{2}$$

In the Eq. (2), the expressions $in\ situ_{max}$ and $in\ situ_{min}$ refer to the highest and lowest soil moisture values measured in the field. While I_{ssm} uses radar backscatter parameters, SSM uses I_{ssm} results with in situ maximum and minimum measurement values.

The following equation is defined to calibrate the SSM value.

$$SM = a \times SSM + b \tag{3}$$

According to Eq. (3), a linear regression model was defined between soil moisture values and measured soil moisture values. In Eq. (3), the value a represents the slope and the value b represents the intersection point. Measured soil moisture values refer to measurements made with a soil moisture sensor in the field.

5. Results and Discussion

Backscatter coefficients of the image whose pre-processing step was completed were obtained. Linear regression between backscatter coefficients and measured soil moisture was examined. Accordingly, it has been understood that the backscatter coefficients in VV polarization have a better relationship with measured soil moisture than those in VH polarization (Figure 3).

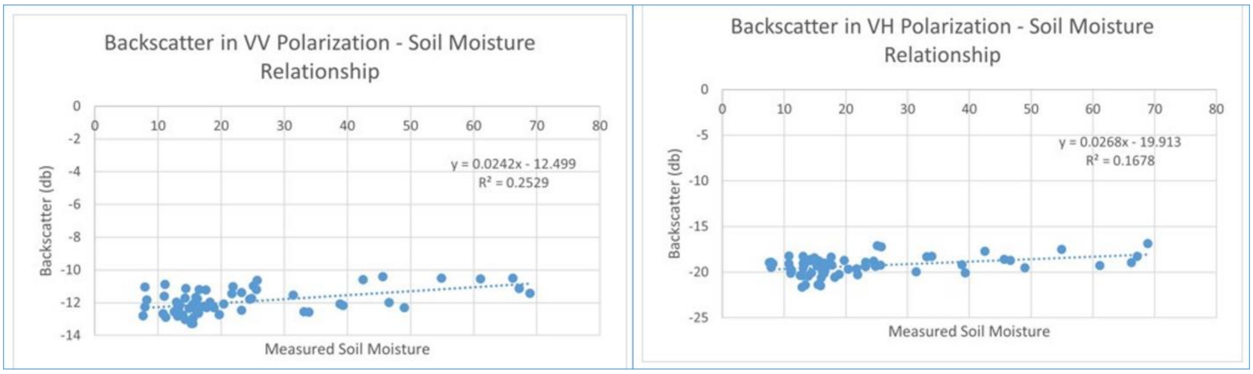

Figure 3: *Backscatter coefficients – Measured soil moisture relationship*

An empirical approach was developed, and the spatial distribution of soil moisture and the soil moisture map were obtained from the Sentinel-1 image (Figure 4). Figure 4 shows soil moisture values as percentages. The results showed that soil moisture values varied between 5% and 45%. In addition, the R^2 coefficient was 0.25 in the linear correlation between measured soil moisture values and soil moisture values estimated from Sentinel-1 (Figure 5).

The results showed that soil moisture values tended to increase volumetrically towards the south of the study area. In estimating soil moisture using empirical models from SAR images, it has been observed that correlation values are higher in fields where soil moisture changes little. In addition, these studies were carried out on larger areas of the field. This also alleviated the disadvantage of limited spatial resolution of the SAR image (Filion et al., 2014). In another study conducted with Sentinel-1, it was observed that accuracy increases in a field where soil moisture is homogeneous. It has also been observed that whether the soil is wet or dry affects performance (Bazzi et al., 2024). Another study used Radarsat 2 imagery to estimate soil moisture. It has been observed that using high-resolution images gives better results in the correlation between backscatter coefficients and soil moisture (Özerdem & Acar, 2017). As can be seen from the studies, empirical models have many advantages, such as being easy and applicable, rapid analysis, and satisfactory performance under different field conditions. These models have been successfully applied in different data types and fields.

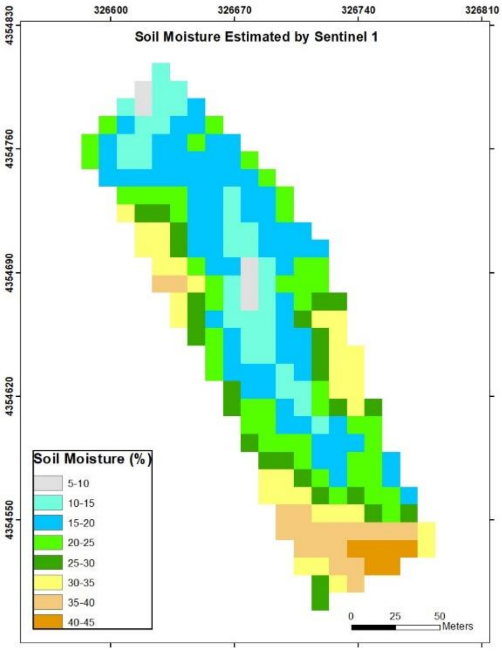

Figure 4: *Soil moisture estimated by Sentinel-1*

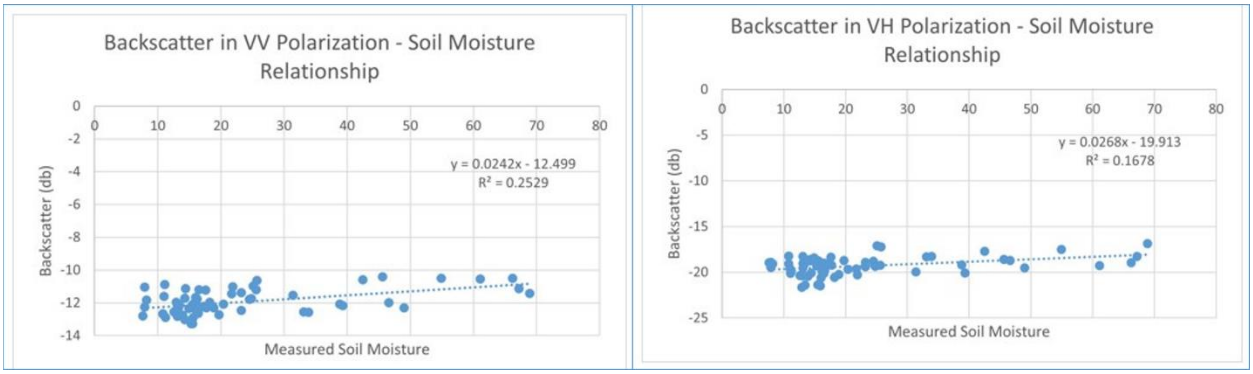

Figure 5: *Relationship between soil moisture estimated by Sentinel 1 – Measured soil moisture*

According to the in-situ measurements, it was determined that the spatial distribution of soil moisture varies significantly in percentage for short-distance intervals. After the pre-processing steps of the Sentinel-1 image are completed, the spatial resolution becomes 10 m. In this context, one pixel of the Sentinel-1 image in the study area represents an area of 100 square meters. Therefore, when the Sentinel-1 image was compared to in situ measurements, which change highly at frequent intervals, the correlation was obtained as 0.25. Spatial resolution has been the limiting factor. Nevertheless, the spatial distribution pattern of soil moisture at the field scale was understood using this method.

6. Conclusion

In this study, the spatial distribution of soil moisture was understood with a new empirical approach at the field scale using Sentinel-1 imaging, and a soil moisture map was produced. In the literature, studies implemented with SAR images were generally carried out in large areas. In this study, soil moisture was estimated from the Sentinel-1 image at field scale. Additionally, this study noted that soil moisture varies highly over short-distance intervals. This negatively affected the accuracy of the study. Using a higher spatial resolution image will increase the accuracy of the study. Consequently, soil moisture was estimated within the scope of this study with a practical and easy method using SAR images.

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Author Contribution

Rutkay Atun: Methodology, Data processing, Writing. **Onder Gursoy:** Methodology, Data processing, Writing.

Declaration of Competing Interests

The authors declare that they have no known relevant competing financial or non-financial interests that could have appeared to influence the work reported in this paper.

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