environmental sciences proceedings

Proceeding Paper

Retrieval Soil Moisture Using Time Series of Radar and Optical Remote Sensing Data at 10m Resolution †

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† Presented at the 5th International Electronic Conference on Remote Sensing, 7–21 November 2023; Available online: https://ecrs2023.sciforum.net/

Abstract: Soil moisture (SM) is an important variable related to the health of terrestrial ecosystems, agriculture, continental water cycle, etc. It also provides an opportunity for drought monitoring, flood forecasting, weather forecasting, and calibration of hydrological models. This study aims to estimate surface soil moisture at high spatial resolution (10m) by combining radar and optical remote sensing data and improving spatial resolution and accuracy. Synthetic Aperture Radar (SAR) operates with the competence to acquire data in any weather condition. SAR images were acquired by C-band SAR sensors in the VV polarization boarded on Sentinel-1 satellites and optical images were obtained from a Sentinel-2 multi-spectral instrument. The main algorithm involves the retrieval of soil moisture using radar data through a change detection (CD) method that is somehow combined with the WCM model (parameters include vegetation descriptors and model coefficients) to estimate SM and reduce the effect of vegetation cover. The method is applied in 13 months of time-series satellite data from November 7, 2019, to October 20, 2020, over Salamanca (western Spain) and is validated using field data acquired at a study site with the use TDR sensor. The results showed good accuracy between retrieved and ground measurement soil moisture data (Root Mean Square Error (RMSE) of 0.053 m^3/m^3 and the obtained accuracy is promising compared to recent similar works.

Keywords: soil moisture; change detection; time-series; sentinel-1; sentinel-2; SAR; WCM

Citation: To be added by editorial staff during production.
Academic Editor: Firstname Lastname

1. Introduction

With the increase in population and excessive use of available water resources, many different parts of the world have experienced the phenomenon of water shortage and drought, which leads to dangers and adverse consequences such as the disruption of natural and human ecosystems. Due to the vitality of this issue and the discussion of water resources management, it is necessary to study soil moisture in different parts. Remote sensing technology is an effective way to understand the behavior of the world and evaluate changes on Earth, and of course, it provides a very powerful tool for describing the monitoring of soil moisture on a large scale near the Earth's surface. Soil moisture is one of the basic components of the water cycle that affects the processes of infiltration, runoff, and evaporation. In addition, it modulates energy exchange as well as carbon exchange at the surface, which is influenced by a wide range of spatial factors: climate, meteorology, and hydrology [1].

With advances in remote sensing technologies, many algorithms for scheduling surface soil moisture depending on the use of light, especially reflection and thermal diffusion, and remote sensing radar, especially synthetic aperture radar (SAR), have been introduced in previous studies. In recent years, SAR satellite data have been used to estimate soil texture, surface roughness, and soil moisture. In addition to the fact that the recoveries are only sensitive to high soil, the information provided by them can be used to assess the root-soil moisture of the area, which is an important variable for climate prediction, drought analysis, and carbon cycle modeling [2, 3]. SAR data also have limitations on surface soil moisture recovery because accurate information on surface soil moisture depends on target parameters such as surface roughness, vegetation, dielectric constant, and topography and radar characteristics such as frequency, polarization, and incidence angle (θ). Various methods have been proposed in recent years. For microwave remote sensing, models depending on the type of data (active or inactive microwave) for bare and vegetated soil surfaces are presented.

The backscattering coefficient is a function of the physical and electrical properties of the soil surface and the characteristics of the radar (wavelength, polarization, and incidence angle). In addition, in the case of the vegetation soil surface, the backscattering coefficient depends on the amount of radiation reflected from the vegetation as well as the soil layers. In the case of vegetation soils, vegetation attenuation increases with vegetation water content. Therefore, the contribution of vegetation to the rear scattering coefficient, which is measured by an active sensor in a vegetative pixel, should be considered [4]. This model is naturally quasi-experimental because the model parameters are site-dependent and require calibration [5]. Water cloud model represents the canopy as a cloud of water droplets and higher order scattering contributions are neglected. Bindlish and Barros [5] incorporated water cloud model to retrieve the soil moisture in the vegetated area. Xu et al,[6] utilized the water cloud model to remove the vegetation effect from the observed backscattering coefficient.

In this study, soil moisture was estimated by two WCM models and the changes were performed using active radar time series data of Sentinel 1 satellite, Sentinel 2 optical data, and also soil moisture data in nine different stations in the central and central part of Spain (Salamanca Province). Optical images used in this research have been used to eliminate the effect of vegetation on radar signals and the main processing has been done on radar data. Ground station data was used to validate the model outputs. The reason for choosing the WCM model in this study is to eliminate the effect of land cover vegetation and also for the model to investigate changes in reducing the effect of surface roughness on radar data.

2. Materials and Method

2.1. Case Study

According to the objectives of this study, the main part of which is estimating soil moisture in areas with agricultural use as well as simultaneous access to three types of data (radar, optical data, and ground measurement) As well as the joint coverage of these three types of data in a single image of remote sensing data, several areas was examined.

The priorities for selecting these areas are as follows:

1. The soil moisture of the stations should be measured at a depth of 5 cm;
2. A large part of the target area includes agricultural land;
3. The stations are located in different vegetation;
4. All stations are in the same image of radar and optical data.

According to surveys, a region in the province of Salamanca in the west of Spain has been selected. Salamanca is a province in western Spain, in the western part of the Autonomous Community of Castile-Leon. The provincial capital is the city of Salamanca. The area of the province is 12,058 square kilometers. Agriculture and animal husbandry are prominent in this region. The reason for choosing this area in this study is the existence of agricultural areas as well as the terrestrial data network with continuous data. The study area is located between the three cities of Salamanca, Valladolid, and Zamora, most of which include agricultural land. The dimensions of this area are 36 x 24 km.

Figure 1. Image related to the study area in the province of Salamanca, Spain.

2.2. Data Collection

According to the selected method by reviewing previous studies on soil moisture estimation, the required data include radar and optical data and ground measurements. Radar data has been used in the change detection model to estimate soil moisture using the backscatter of radar signals and optical data has been used to calculate vegetation indices to remove the effect of ground cover vegetation from radar signals. Soil moisture data measured at fixed ground stations were used to calibrate the model as well as validate the model results.

2.2.1. Radar Data

The Sentinel-1A (S-1A) and Sentinel-1B (S-1B) were launched in April 2014 and April 2016, respectively, as part of the European Space Agency's Copernicus program, which surveys and monitors the Earth's surface. Operations are designed with environmental information in mind. Artificial aperture radars (SAR) are indifferent to weather conditions and allow data to be retrieved at any time of the day or night. SAR sensors on each of these satellites, located 180 degrees apart on a simultaneous solar orbital plane, provide images at both the VV and VH polarizations in the C band.

In the present study, signals recorded at VV polarization were used to calculate soil moisture estimates. According to studies by Karjalainen [7] and Chauhan [8], VH data have only a limited potential for estimating soil moisture, especially as a result of its high sensitivity to volume dispersion, which depends a lot on the geometric alignment and vegetation characteristics.

Sentinel 1 data were collected from November 7, 2019, to October 20, 2020. Several processing steps were performed on each image to extract the backscattering coefficient. These products are available from the Copernicus website (https://scihub.copernicus.eu) These processes are developed in the SNAP software environment developed by the European Space Agency (ESA) for radiometric and geometric calibration of Sentinel satellite images.

Pre-processing performed on Sentinel-1 images includes the following:

1. Radiometric calibration;
2. Thermal noise removal;
3. Terrain correction using SRTM DEM at 30m.

2.2.2. Optical Data

Sentinel 2 is an Earth observation mission developed by the European Space Agency (ESA) and includes two multispectral imaging satellites, Sentinel-2A and Sentinel-2B. The Sentinel-2A was launched in June 2015, followed by the Sentinel-2B in March 2017. These satellites provide complete coverage of the earth's surface with repeated 5-day visits. Images are produced in 13 spectral bands that cover visible and mid-infrared wavelengths in three different spatial resolutions (10, 20, and 60 meters). The optical images used for the present study were obtained from the USGS website at the French Territorial Data Center (https://earthexplorer.usgs.gov), which makes the data available in the so-called "Level-2A" format. This data was collected between November 8, 2019, and October 18, 2020. This data is co-registered in the ENVI software environment with a quadratic polynomial compared to the first image.

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{1}$$

$$\mathrm{EVI} = \mathrm{G}.\frac{\mathrm{NIR} - \mathrm{Red}}{(\mathrm{NIR} + \mathrm{C_1} * \mathrm{Red} - \mathrm{C_2} * \mathrm{Blue}) + \mathrm{L}} \tag{2}$$

Sentinel 2 optical data were used in the calculation of NDVI and EVI indices to calibrate the WCM model to eliminate the effect of vegetation.

2.2.3. Ground Measurement

The International Soil Moisture Network is an international partnership to establish and maintain a global soil moisture database. This database is an essential tool for validating and improving global satellite products, and land, climate, and hydrological models (https://ismn.geo.tuwien.ac.at/en/).

In-situ soil moisture data in this study was used as a reference for the validation of soil moisture products recovered from satellite sources. Ground measurements in Spain were obtained free of charge through the International Soil Moisture Network (ISMN). Data from the REMEDHUS network in Spain are used to validate the humidity obtained through remote sensing data.

Since ground measurements were used to evaluate the quality of the products obtained from Sentinel 1 images, the selection of sites was done by considering being in the common area between Sentinel 1 and Sentinel 2 images in the study area. Also, measurements were made at stations at a depth of 5 cm above the soil surface. Therefore, soil moisture data were collected from nine stations.

2.3. Method

In summary, the method used and the pre-processing and processing performed in this study to estimate soil moisture can be mentioned in the following steps:

1. Perform pre-processing of radar and optical images and calculate NDVI and EVI indices
2. Calculation of coefficients A and B related to calibration of WCM model by least squares method using backscatter of Sentinel 1 radar signals, NDVI and EVI indices obtained from Sentinel 2 data, and soil moisture data measured at ground stations
3. Calculation of backscatter of radar signals from the soil surface by WCM method, using coefficients A and B obtained in step (2), backscatter of radar signal levels of Sentinel 1 and NDVI and EVI indices obtained from Sentinel 2 optical data

4. retrieval of soil moisture by change detection and using backscatter of soil surface Radar data calculated in step (3) and soil moisture data measured at ground stations
5. Validation of change detection model results using soil moisture data measured at ground stations

This method involves the retrieval of soil moisture using radar data through a change detection method that is somehow combined with the WCM model. During the process of performing soil moisture estimation processes, 8 ground stations were used and Granja G station was considered as a checkpoint. According to this method, which is compatible with the data characteristics of Sentinel 1, the backscatter of radar signals from the soil surface without vegetation and under the influence of vegetation is as follows:

$$\sigma^0_{\text{cover}} = \sigma^0_{\text{veg}} + \tau^2\sigma^0_{\text{soil}} \tag{3}$$

$$\sigma^0_{\text{veg}} = AV_1\cos(\theta)\,(1-\tau^2) \tag{4}$$

$$\tau^2 = \exp\left(-2BV_2/\cos(\theta)\right) \tag{5}$$

σ^0_{cover}: surface backscatter; σ^0_{veg}: backscatter from the plant surface; σ^0_{soil}: backscatter from soil surface; τ^2: Effect of vegetation on backscattering from soil surface (attenuation coefficient) (Due to re-crossing on the return route has a power of 2) [9]; θ: incidence angle; V_1 and V_2 are vegetation descriptors that show the scattering and attenuation characteristics of vegetation; A and B are model coefficients that depend on the vegetation descriptor and sensor configuration.

Vegetation indices such as NDVI, EVI, NDWI, LAI, or other indices are used for parameters V_1 and V_2. In this study, NDVI and EVI indices have been used for parameters V_1 and V_2.

By performing pre-processing of Sentinel 1 radar data, σ^0_{cover} is obtained. According to the pixels associated with ground stations, NDVI and EVI indices and ground surface backscatter σ^0_{cover}, with two scenarios and using least squares division, the A and B coefficients related to WCM model calibration have been obtained. These two scenarios and calibration coefficients obtained can be seen in Table 1:

Table 1. Calibration coefficients.

scenario	V_1	V_2	A	B
First	NDVI	EVI	-40.16	0.63
second	EVI	NDVI	-67.31	0.38

All processing steps related to soil moisture retrieval have been done programmatically in Matlab software environment. All processes related to the removal of vegetation effect and estimation of soil moisture have been performed according to the two scenarios mentioned.

Considering the two previous scenarios and the obtained coefficients, the backscatter of the ground surface using equations (3) to (5), the backscatter of the soil surface σ^0_{cover} is obtained. Due to the time difference between two consecutive images, the roughness effect is greatly reduced, which is one of the reasons for using the method to detect changes in this issue. According to the output obtained from the WCM method, the minimum value of σ^0 is related to the drier state specified for each pixel:

$$\Delta\sigma^{NDVI}_{(i,j)} = \sigma^0_{(i,j)}(d) - \sigma^0_{dry,(i,j)} \tag{6}$$

$\sigma^0_{(i,j)}(d)$: backscatter in pixel (i, j) on the date d obtained using sentinel 1 and sentinel 2 images. $\sigma^0_{dry,(i,j)}$: The lowest backscatter value is associated with the driest day (according to Sentinel 1 time series data).

According to several experimental studies that show a linear relationship between changes in radar signal and changes in soil moisture [10] [11]

$$\Delta\sigma^{\mathrm{NDVI}} = \alpha\,(\mathrm{NDVI})\Delta\mathrm{Mv} \quad (7)$$

ΔMv: Soil moisture changes between day d and the driest day. The α parameter is dependent on NDVI.

As NDVI increases, signal sensitivity to soil moisture is expected to decrease [12,13]. This means that the difference between the backscatter on day d and the backscattering on the driest day is reduced due to NDVI. The strongest variable in humidity is related to the difference between the wettest and driest states:

$$\Delta\mathrm{Mv_{max}} = \mathrm{Mv_{max}} - \mathrm{Mv_{min}} \quad (8)$$

According to the defined conditions of $\Delta\mathrm{Mv_{max}}$, the most changes in backscatter are as follows:

$$\Delta\sigma_{\mathrm{max}} = \alpha(\mathrm{NDVI})\Delta\mathrm{Mv_{max}} = \mathrm{f(NDVI)} \quad (9)$$

To calculate the equation f, taking into account NDVI as well as the driest backscattering difference for each pixel, and subtracting the top 1% of the data with the highest backscattering difference, one line is fitted to the points that have the most $\Delta\sigma^{NDVI}_{max}$, which can be seen in Figure 2 [14,15].

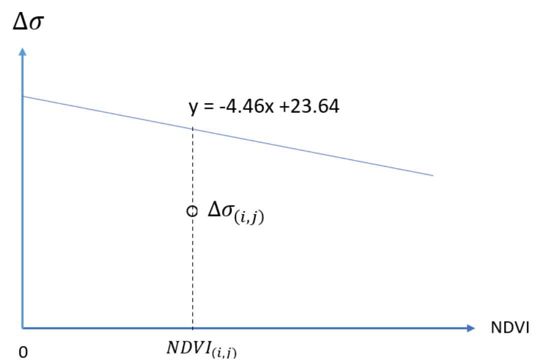


Figure 2. Relationship between NDVI and backscatter difference.

The equation of this line is calculated by considering all points in the time series of Sentinel 2 radar data. Considering the largest backscattering difference in different NDVIs, the equation f changes as follows [16]:

$$\Delta\sigma_{\mathrm{max}} = \mathrm{f(NDVI)} = \mathrm{aNDVI} + \Delta\sigma^{\mathrm{bare}}_{\mathrm{max}} \quad (10)$$

When NDVI is zero, it corresponds to the largest open-point difference relative to the driest state on the surface of vegetation-free soil, in fact $\Delta\sigma_{max} = \Delta\sigma^{bare}_{max}$.

Finally, soil moisture in each pixel is estimated using the following formula [17]:

$$\mathrm{Mv(i,j,d)} = \frac{\Delta\sigma_{(i,j)}}{\mathrm{f(NDVI)}}(\mathrm{Mv_{max}} - \mathrm{Mv_{min}}) + \mathrm{Mv_{min}(d)} \quad (11)$$

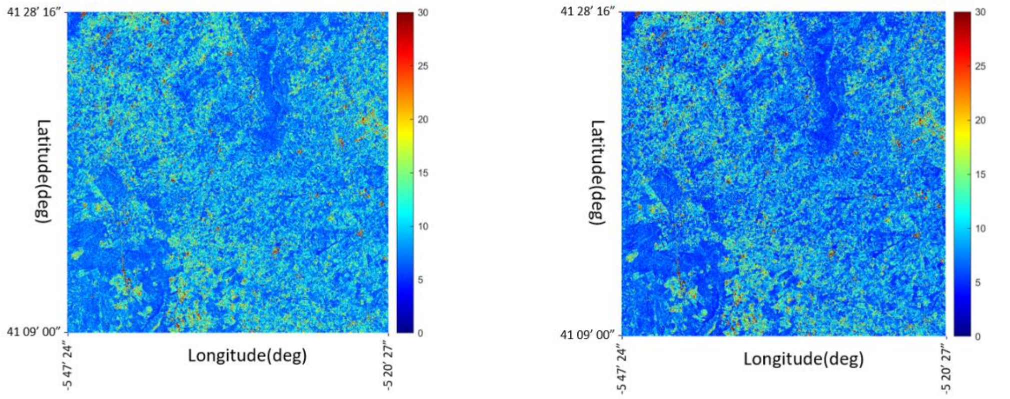
3. Experimental Results

In this part of the study, the output results of the soil moisture estimate model are presented according to the two scenarios mentioned in the previous chapter. Also, the evaluation of the results has been done according to the ground stations for measuring soil moisture, and the two scenarios for estimating soil moisture have been compared with each other and statistical indicators have been obtained.

For processing related to soil moisture estimation, two scenarios were considered in the vegetation removal section using the WCM model, and further, the process of soil moisture estimation processing based on the change detection model has been performed for both scenarios. Soil moisture is estimated based on changes in pixel-by-pixel backscatter every day compared to the driest day of the period. According to Table 2, the image taken on September 14, 2020, is the driest day during one year under review. Based on this, using 30 radar images, you have 29 outlets of soil moisture. The following is an example of the output of the model related to two scenarios and similar dates.

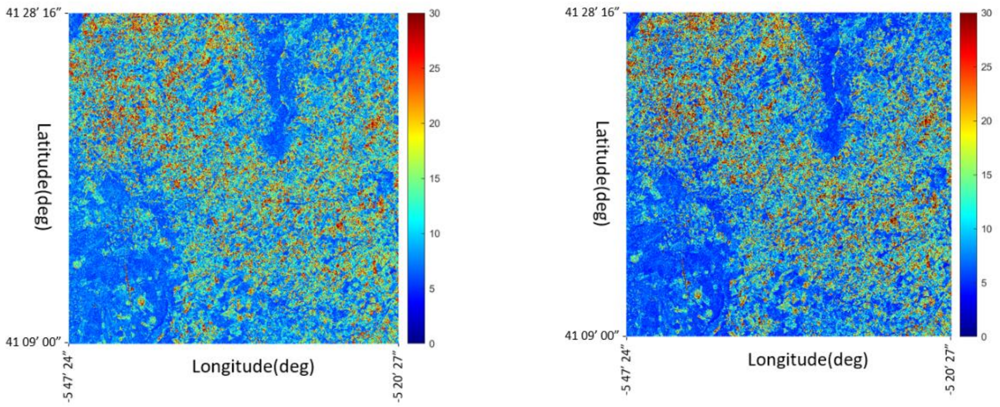
The outputs obtained from the model used to have an image size of 3600 x 2400 pixels, each pixel has a spatial resolution of 10 meters. These results have been validated using soil moisture measured by on-site soil moisture stations. The results obtained in the two scenarios show the correlation of the results with the values of soil moisture measured by ground stations. Table 2 lists the calculated values of the accuracy indicators.

One station has a very high RMSE compared to other stations and the difference between the estimated and measured values of soil moisture. According to the characteristics of this station, the vegetation on its surface is forest trees, which has a great effect on the radar signal.



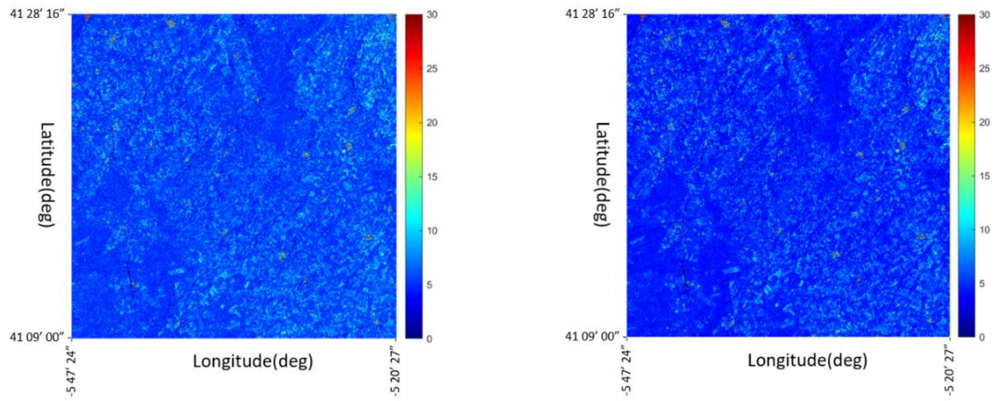
(**a**) (**b**)

Figure 3. Soil Moisture Results on May 17, 2020 : (**a**) Scenario 1 and (**b**) Scenario 2 (color bar shows soil moisture values $m^3 \ / \ m^3 * 100$)



(**a**) (**b**)

Figure 4. Soil Moisture Results on October 20, 2020: (**a**) Scenario 1 and (**b**) Scenario 2 (color bar shows soil moisture values $m^3 \,/\, m^3 * 100$)



(**a**) (**b**)

Figure 5. Soil Moisture Results on September 2, 2020: (**a**) Scenario 1 and (**b**) Scenario 2 (color bar shows soil moisture values $m^3 \,/\, m^3 * 100$)

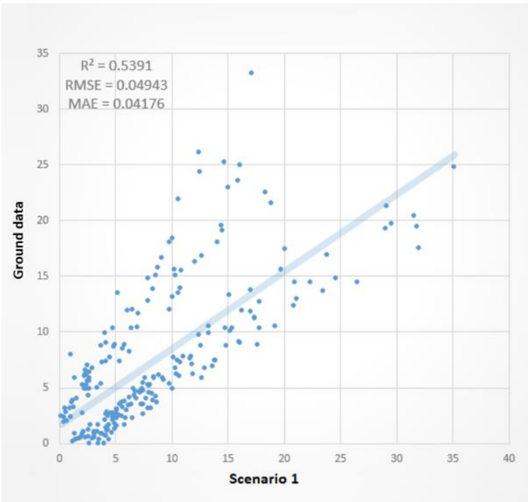
Table 2. Statistical index values calculated at each station.

Ground station	**RMSE (m^3/m^3)**		**MBE**		**Average station soil moisture (m^3/m^3)**
	1st scenario	**2nd scenario**	**1st scenario**	**2nd scenario**	
Las Arenas	0.08340	0.08123	-0.01435	-0.01474	0.181
Paredinas	0.03122	0.03800	0.01744	0.02225	0.031
Zamarron	0.05093	0.04817	0.01444	0.01438	0.094
Las Bodega	0.14884	0.14416	-0.14259	-0.13789	0.162
Carretoro	0.03447	0.03817	0.01212	0.01522	0.054
Granja G	0.03365	0.03176	0.01743	0.01629	0.032
Las Victorias	0.04290	0.03812	0.01563	0.01512	0.054
Las Brozas	0.03449	0.03291	0.01710	0.01498	0.035
El Coto	0.06062	0.05807	0.0160	-0.04470	0.111

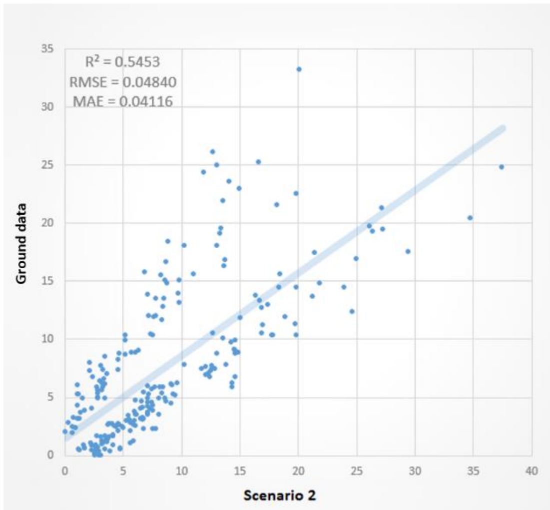
Samples of the results from retrieving soil moisture in two scenarios (Table 3) in the study area are visible in the images above. Figure 5 depicts the driest day during the period under review. In figures 3 and 4, the upper right and lower left sections exhibit denser vegetation compared to other areas, as evidenced by the estimation of soil moisture.

Granja G station, which is considered a check and according to the RMSE values calculated in this station, is close to the average RMSE of other stations. Linear regression was performed between the two scenarios concerning ground station data and the determination coefficient (R^2), RMSE and mean absolute error (MAE) were calculated.

Soil moisture values of each station during the period under review and RMSE calculated, show the close performance of the two scenarios. As discussed in the previous section, Las Bodega Station Due to the type of ground cover, there was a large difference between the values estimated by the model and the values of soil moisture measured by the station. This difference increases the amount of RMSE in the evaluation of the model used. By deleting this station in calculating statistical indicators and performing regression, significant changes are made in model evaluation. The regression results, in this case, are as follows (Figure 6):



(**a**)



(**b**)

Figure 6. Linear regression between the estimated soil moisture values of scenario 1 and the measured values at the stations (By removing Las Bodega station): (**a**) Scenario 1 and (**b**) Scenario 2. (RMSE unit: $(\mathbf{m^3/m^3})$)

Table 3 shows the statistical indices and determination coefficient for the two scenarios in the two mentioned cases, which shows an increase in the output accuracy of the model by removing the Las Bodega station. In addition to increasing the RMSE, the absolute mean error also decreases.

Table 3. Examining statistical indicators for two scenarios (*: By removing Las Bodega station)

	RMSE $(\mathbf{m^3/m^3})$	R^2	MBE	MAE
1st scenario	0.06807	0.2524	-0.00680	0.05296
2nd scenario	0.06626	0.2675	-0.00654	0.05191
1st scenario*	0.04943	0.5391	0.01018	0.04176
2nd scenario*	0.04840	0.5453	0.00988	0.04416

4. Discussion

Based on previous studies, there are various methods for estimating soil moisture under vegetation, which can be obtained by combining different remote sensing data such as radiometric, radar, thermal, and optical data. Different algorithms have been proposed and implemented. In this study, an attempt was made to improve the accuracy of estimating soil moisture in agricultural areas and also to increase the spatial accuracy of the final output of soil moisture. For this purpose, radar data of Sentinel 1 sensor as well as optical data of Sentinel 2 sensor with a spatial accuracy of 10 meters have been used.

According to the results and methods used in this study, to estimate soil moisture without the use of ground data, it is necessary to calibrate the models used to eliminate the effect of vegetation in the study area. Also, during the processing process related to the change detection section, which uses soil moisture values, the soil moisture products of radiometer sensors can be used to replace the soil moisture used during the calculation process. Because the spatial accuracy of these sensors is very low, it reduces the accuracy of soil moisture output obtained by the model.

The number of ground stations in the calibration process and calculations related to the soil moisture estimation model can be checked by performing calculations using the number of different ground stations in an area to check the number of optimal stations for estimating soil moisture. Other models such as IWCM, which is an extended model of WCM, or AIEM can also be used to eliminate the effect of vegetation and surface roughness to assess the impact on the accuracy of soil moisture assessment and the use of different vegetation indicators in the calibration of these models.

5. Conclusion

According to previous studies, the backscattering of radar signals is sensitive to changes in soil moisture, and in addition, vegetation and soil roughness also affect these signals. Because the method of change detection is used to estimate soil moisture and also changes in soil roughness during the period under study are insignificant and negligible. Due to the selected method in this study as well as studies that have been done in the past, models that use radar data have better accuracy than other models. Also, for vegetated areas, hybrid models perform better in accurately estimating soil moisture.

In this study, an effort has been made to improve the accuracy of soil moisture estimation in agricultural areas and also to increase the spatial accuracy of the final output of soil moisture. For this task, the radar data from the Sentinel 1 sensor and the optical data from the Sentinel 2 sensor, with a spatial accuracy of 10 meters, were utilized. Based on past studies, radar signal backscatter is affected by changes in soil moisture, as well as by vegetation and soil roughness. Using the WCM model, attempts have been made to mitigate the impact of vegetation on radar signals by utilizing suitable data. Because the change detection method is employed to estimate soil moisture, the alterations in soil roughness during the investigated time period are negligible and can be disregarded. The calibration of the WCM model greatly impacts the accuracy of soil moisture estimation. This is achieved using NDVI and EVI indicators obtained from optical data of the Sentinel 2 sensor, in conjunction with soil moisture values measured by fixed stations.

In a study by Gao et al. (2017), the estimation of soil moisture in the agricultural region of north-eastern Spain in the range of 20 x 20 km using two ground stations measuring soil moisture, the value of the determination coefficient (R^2) is equal to 0.099 and the value of RMSE is equal to 0.087 (m^3/m^3) with a spatial resolution of 100 meters. Also, in a study conducted by [18], which used Sentinel 1 radar data and MODIS optical data on an area similar to the study area in this dissertation, the RMSE value was obtained. Is equal to 0.055(m^3/m^3). In this study, in addition to increasing the accuracy of soil moisture estimation (RMSE) from 0.055 to 0.049(m^3/m^3), spatial accuracy also increased from 100m to 10m.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript." Please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

Funding: Please add: "This research received no external funding" or "This research was funded by NAME OF FUNDER, grant number XXX" and "The APC was funded by XXX". Check carefully that the details given are accurate and use the standard spelling of funding agency names at https://search.crossref.org/funding. Any errors may affect your future funding.

Data Availability Statement: We encourage all authors of articles published in MDPI journals to share their research data. In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Where no new data were created, or where data is unavailable due to privacy or ethical restrictions, a statement is still required. Suggested Data Availability Statements are available in section "MDPI Research Data Policies" at https://www.mdpi.com/ethics.

Conflicts of Interest: The authors declare no conflict of interest.

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