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Assessment of Water Cloud Model based on SAR and optical satellite data for surface soil moisture retrievals over agricultural area

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Abstract

Water availability to plants a significant role in agricultural areas, especially in arid and semi-arid areas. This research aimed to evaluate the potential of Water Cloud Model (WCM) for retrieving surface soil moisture, which is associated to water availability, in a semi-arid areas based on the combination between Sentinel-1B SAR (Synthetic Aperture Radar) and optical Sentinel-2B data. The performance of the applied model was assessed using ground observed soil moisture (0-5 cm). Accuracy evaluation was performed by the cross-validation method (k-fold), it showed a coefficients of determination (R^2) of 0.65 and RMSE of 1.45%. The obtained results show a good concordance between retrieved model and ground observed surface soil moisture. In addition, this model was used for the mapping spatio-temporal variation of soil moisture at high spatial resolution in the study areas. This approach could be used by environmentalists and decision-makers as a practical tool for monitoring and estimating the change of surface moisture content.

Keywords: Remote sensing, Soil moisture, Sentinel-1B, Sentinel-2B, WCM, SAR, agricultural areas.

Introduction

The agricultural area is an important socioeconomic and strategic sector, especially in arid and semi-arid regions and half of the world's food comes from rainfed areas (Seckler et al., 1999; Geerts and Raes, 2009). In Morocco, water content availability is the principal factor for crop growth and final yield. Soil moisture, which is associated to water availability, is considered one of the most important agricultural variables (Jawson and Niemann, 2007; Sun et al., 2012; Benabdelouahab et al., 2015; Khellouk et al., 2019). In arid and semi-arid dryland conditions, the soil moisture estimation provides important information for assessing water content availability for vegetation growth, crop drought and yield prediction monitoring (Zhao et al., 2014; Yang et al., 2015; Pablos et al., 2017; Whyte et al., 2018). In face of the importance of soil moisture, its spatial and temporal assessment is difficult. The conventional methods based on in-situ observations provides very accurate punctual results (Chu, 2018). However, these soil moisture measurements; it is unable to extend it and generalized it for a large area due to its high cost and the large spatial heterogeneity of soil properties, vegetation cover and topography (Benabdelouahab et al., 2015).

In contrast with the previous methods, remote sensing tools provide efficient approaches for surface soil moisture retrievals at large-scale with high temporal and spatial resolution and low cost (Entekhabi et al.,

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2010; Benabdelouahab et al., 2019). Three main remote sensing methods are employed for estimating soil moisture from spectral information: The optical, thermal infrared (TIR) and microwave (MW) ranges of the electromagnetic spectrum (Sadeghi et al., 2015). The optical methods are based on spectral indices behaviors related to soil water content changes. The application of these methods are simple, but can be easily affected by meteorological conditions (Sadeghi et al., 2015). For infrared thermal methods, they make it possible to estimate surface soil moisture basing on thermal characteristics (Verstraeten et al., 2006). However, in areas completely covered by vegetation, information on soil radiation is masked by the vegetation cover, which influences the accuracy of the soil moisture assessment. Therefore, these methods are applicable for monitoring soil moisture in bare and sparse vegetation areas in cloudless conditions (Khellouk et al., 2018). However, microwave remote sensing (SAR) at has stronger frequencies and longer wavelengths has a higher penetrating ability, which is less affected by weather conditions, and can be used to monitor various surface parameters, including surface soil moisture, over agricultural regions (Benabdelouahab et al., 2019).

Many models based on SAR remote sensing have been proposed to recover soil moisture, including the Oh model (Oh et al., 1992), IEM model (Fung and Chen, 1992), Dubois model (Dubois et al., 1995) and Baghdadi model (Baghdadi et al., 2016). These models cannot be applied directly for estimating surface soil moisture over densely vegetated areas due to the speckle effects caused by the vegetation leaves structure (Prakash et al., 2012). For this purpose, Attema and Ulaby (1978) have been developed the semi-empirical Water Cloud Model (WCM) to remove scattering effect of vegetation cover in order to estimate soil moisture content. This model has been applied in several areas for multiple SAR satellites, such as C-band ASAR and SPOT/HRV data (Zribi et al., 2014), ESA's ENVIronment SATellite (ENVISAT) platform (Kumar et al., 2012), X-band SAR data (El Hajj et al., 2016), TERRASAR-X data (Gorrab et al., 2015). Furthermore, several studies have shown that the results of soil moisture retrieval are precise when optical and microwave data were integrated rather than using separate microwave data (Notarnicola et al., 2006; Hosseini and Saradjian, 2011). In this context, the objective of this work is considerering a synergy of Sentinel-1B Synthetic Aperture Radar (SAR) and optical Sentinel-2B data to evaluate the potential of Water Cloud Model (WCM) for estimating soil moisture in the central provinces of Fkih-Ben Saleh and Khouribga (Morocco). In addition, the model was applied to mapping the surface soil moisture. The soil moisture maps analysis, accurately indicate the spatiotemporal change of soil moisture content status in the study area. The area chosen is subject to recurrent drought and rainfall irregularity, and whose results from this study can be exploited to improve land-use planning, crop choices, and soil and water management.

Material and Methods

Study area

The study zone is located in the Beni-Mellal-Khénifra region, Morocco (32°25'- 33°01'N; 7°26'- 7°15'W) covering 2157 ha (Figure 1). Their economy is mainly based on agricultural activities due to soil types (fertile soils) (Barakat et al. 2017; Ennaji et al. 2018; Oumenskou et al. 2018). At the site, the altitude varies between 440 and 882 meters above the mean sea level.

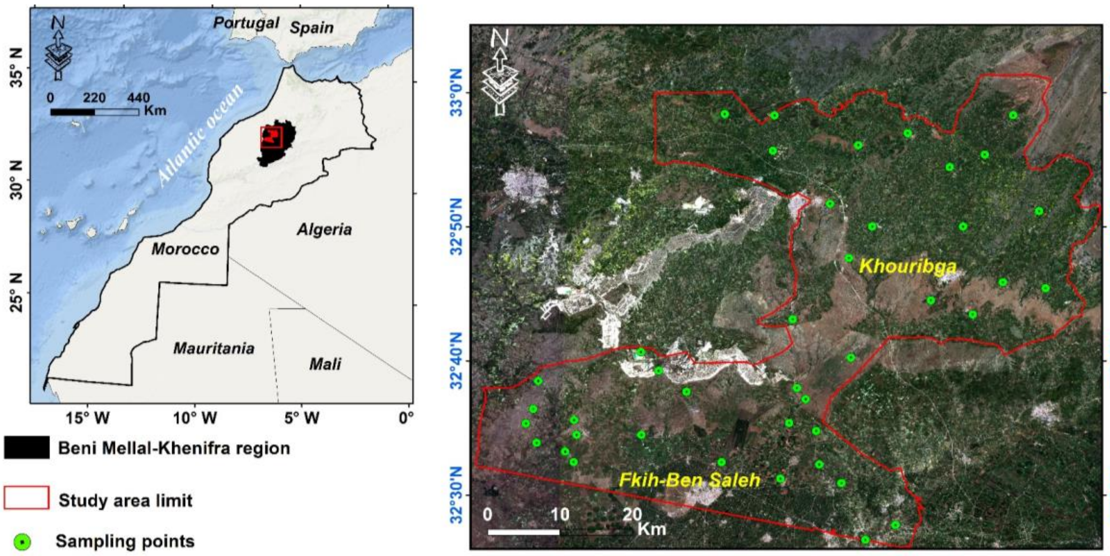

Figure 1. Localization of the study area and sampled points

In this region, cultivated land covers a total area of 70%, which is dominated by cereal crops (42.7%). The climate is semi-arid with mean annual temperature of 3.5°C in winter and 38°C in summer, the total annual rainfall is 350 mm with an annual evaporation of around 1800 mm. The rainy season starts in November and ends in March while the dry season is from April to October. The study area is dominated by dry agricultural land. So, in this area, the surface soil moisture presents is one of the essential parameters of agricultural growth and can directly affect crop productivity.

Soil moisture data

The measurement of soil moisture content covered the study site were collected randomly at the depth of 0-5 cm (Figure 1). At the sampling sites, these soil samples were georeferenced with a with a GPS receiver, packed in polyethylene bags, labelled and transported to the laboratory for preparation and analysis. Then, the soil surface moisture content of each sample taken was determined in the laboratory by the oven drying method at 105 °C for about 18 hours by comparing weights before and after drying. The percentage of soil moisture is calculated using the expression below.

$$\text{Soil moisture}\ (\%) = \frac{(\text{Weight before drying} - \text{Weight after drying})}{\text{Weight before drying}} \text{x } 100 \qquad (1)$$

The soil sampling was collected simultaneously with satellite imagery acquisition dates to obtain a good agreement between measured and predicted soil moisture from remotely sensed data. The soil moisture sampling have been converted to shapefile points, which allows to extract pixel values from each satellite image linked spatially and temporally to ground measurements.

Satellite data and processing

Sentinel-1B SAR data

Sentinel-1 (S1) satellites are an important part of the European Copernicus program (Global Monitoring for Environment and Security-GMES). The Sentinel-1 operates in a C-band SAR sensor (5.4 GHz frequency), and provides double polarization: vertical-vertical (VV) and vertical-horizontal (VH) imagery with a spatial resolution of 10 m.

In this study, five Sentinel-1 SAR images covering the studied area from 21 January to 26 June 2018 were acquired (Table 1). These satellite imageries were acquired during different periods of growing season for agricultural crops. It was freely downloaded from the Open Access Hub site (https://scihub.copernicus.eu/dhus/#/home). Then, the acquired SAR images was processed using the SNAP software (Sentinel Application Platform) (http://step.esa.int/main/toolboxes/snap). The geometric correction was applied using the Range-Doppler terrain correction algorithm. Then, the speckle filtering was applied using refined lee filter. In addition, the radiometric calibration was used to derive the backscattering coefficient data. Finally, the backscattering coefficient (in linear/Digital number format) is converted to decibels (dB) unit using SNAP software.

Sentinel-2B optical data

The Sentinel-2B optical images of the study site were acquired with atmospheric and geometric corrections from Theia Scientific Expertise Center (https://www.theia-land.fr/) (Table 1). The acquired satellite images are characterized by a high spatial resolution 10 meters and temporal resolution 5 days. For each image date, the Normalized Difference Vegetation Index (NDVI) was then calculated with the Red (Band 4) and Near-Infrared (NIR) (Band 8) using the equation 2:

$$\text{NDVI} = (\text{NIR- RED})/(\text{NIR+RED}) \qquad (2)$$

Table 1. List of satellite data acquired over study area.

Data type	Time of acquisition	Data type	Time of acquisition
Sentinel-1 B	21 January 2018 26 February 2018 22 March 2018 24 April 2018 26 June 2018	Sentinel-2 B	19 January 2018 23 February 2018 23March 2018 20 April 2018 26 June 2018

The acquisition dates of some Sentinel-2B and SAR Sentinel-1B images are different; the maximum differences between these Sentinel-2B and SAR data is four days, whose NDVI values show low variation.

Methods

The overall procedure applied in this study to estimate soil moisture is represented in Figure 2. First, in order to derive the backscattering coefficient, the acquired Sentinel 1 radar data were pre-processed. Then, for each pixel the backscattering coefficients values that corresponding spatially to each ground measurement were extracted according to the coordinates (X, Y). In addition, the NDVI index images covering the study area were calculated based on the bands 4 and 8 of acquired Sentinel-2B images. Then, the vegetation indices (NDVI) values of each sample were extracted according to the coordinates (X, Y).

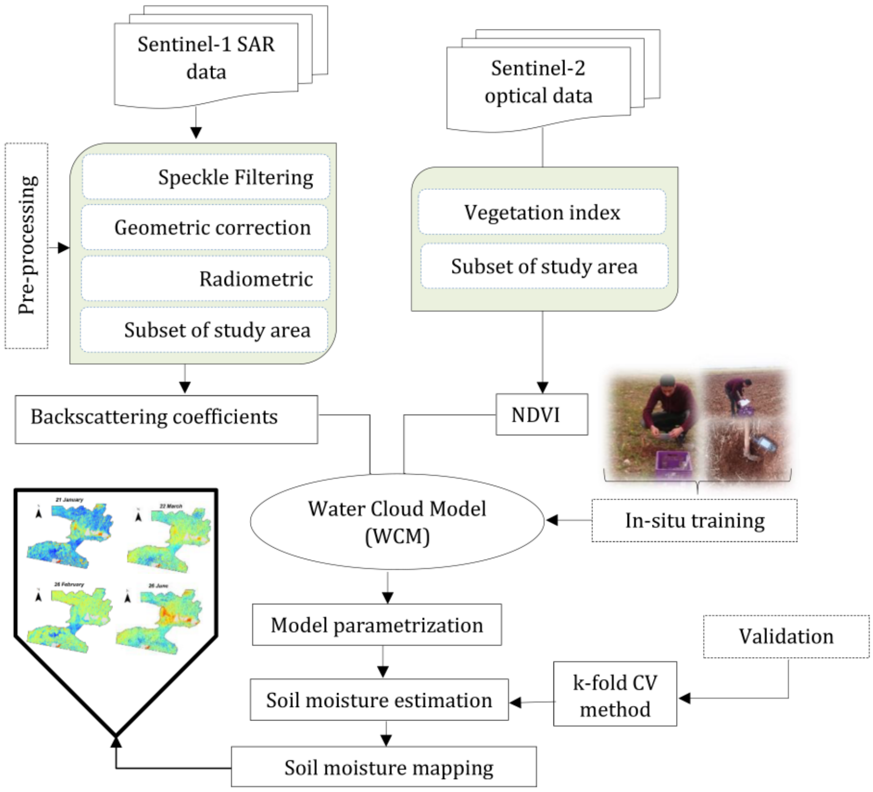

Figure 2. Flowchart of the methodology followed in this study

Afterwards, the extracted values were used for parametrization and calculate the components of the Water Cloud Model (WCM). This model links the backscattering coefficient (σ^0) to surface soil moisture (Kumar et al., 2015). It compounds the backscatter coefficients due to vegetation (σ^0_{veg}) and to the soil (σ^0_{soil}). The σ^0_{veg} of WCM depends on vegetation characteristics (Bala et al., 2015; Bousbih et al., 2017). In this model, the total backscattering coefficient (σ^0) is expressed by the following formulas:

$$\sigma^0 = \sigma^0_{veg} + T^2\,\sigma^0_{soil} \tag{3}$$

Where σ^0 is the total backscattering coefficient (dB), σ^0_{soil} represents the soil backscattering coefficient and σ^0_{veg} represents the vegetation backscattering coefficient. T^2 is a bidirectional attenuation parameter for radar waves passing through vegetation.

$$T^2 = \exp(-2BV_1 \sec(\theta)) \tag{4}$$

$$\sigma^0_{veg} = A\,V_1 \cos(\theta)\,(1- T^2) \tag{5}$$

Where V_1 is the vegetation indicator (NDVI); A and B are empirical coefficients that depends on the vegetation parameter. In this research we used that defined by (Bousbih et al., 2017) in a study area with land cover similar to our study area; θ is incident angle (°) of Sentinel-1 image, it was derived from metadata file for each acquired satellite images.

The soil contribution σ^0_{soil} is expressed by a linear regression equation as a function of the surface soil moisture:

$$\sigma^0_{soil} = C + D \times SM \tag{6}$$

C and D are the coefficients of bare soils, which are, characterizes the relationship between surface soil moisture and radar signal. These parameters were defined on the basis of simple linear correlation between the soil backscatter coefficient and the in situ measurements (soil moisture).

Substituting the parameters leads to get the formula of Water Cloud Model (WCM):

$$\sigma^0 \text{ (dB)} = \text{A NDVI} \cos(\theta) \left(1- \exp\left(-2\text{BNDVI} \sec(\theta)\right)\right) + (\text{C} + \text{D} \times \text{SM}) \tag{7}$$

The soil moisture obtained by equation 7 is expressed in dB unit. Therefore, to have the soil moisture in quantitative unit we headed the parameter (SM) of the equation 7 to get the formula of soil moisture (SM):

$$\text{SM} = \frac{\dfrac{(\sigma^0 - (\text{A V1} \cos(\theta)\,(1 - \exp(-2\text{BV1} \sec(\theta)))))}{\exp(-2\text{BV1} \sec(\theta))} - \text{C}}{\text{D}} \tag{8}$$

The model prediction results were assessed using field data of soil moisture. Then, this model was applied to map the spatio-temporal variability of surface soil moisture. These maps were generated for each date of the satellite image acquired.

Evaluation and Validation of soil moisture retrieval model

The evaluation was carried out by comparing the applied model results and observed measurements. Soil moisture data measured at 41 sampling sites were used for the model evaluation. This evaluation was carried out using two statistical parameters such as the coefficient of determination (R^2) to analyze the linear relationship between the measured soil moisture and the estimated soil moisture (equation 9) and the root mean square error (RMSE) to assess the differences between values estimated by a model and the values measured (equation 10).

$$R^2 = \left(\frac{\sum_{i=1}^{n} (x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \cdot \sum_{i=1}^{n} (y_i - \bar{y})^2}} \right)^2 \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - x_i)^2}{n}} \tag{10}$$

where: x_i and y_i representing the measured and estimated soil moisture values, respectively;
and $\bar{y}$ representing the mean of measured and estimated soil moisture values respectively;
i represents an identifier varying from 1 to n; n represents the number of measured values.

The predictive accuracy of a model was assessed using the cross validation approach (k-fold CV) (Cassel, 2007). This statistical approach is based on k replicate samples of measured data, (k-1) / k of data for model construction and the remaining 1/k for model testing. We emphasize that the random k-fold CV takes k independent samples of size N*(k-1)/k (Cassel, 2007). In this study, we used 33.3% of data for validation, the remaining 66.6% was used as training data, with N = 10 repetitions.

Results and Discussion

Water cloud model parametrization

The WCM characterized by two important components, namely : (i) the soil backscattering coefficient (σ^0_{soil}), which can be determined by using a linear regression with measurement of soil moisture, and (ii) the vegetation water content (σ^0_{veg}) that can be handled by Vegetation Index (NDVI) (Bala et al., 2015; Bousbih et al., 2017). The application of this model was parameterized based on NDVI as vegetation indicator, ground observed soil moisture (0-5 cm) and SAR data. The first component concerns the soil contribution σ^0_{soil} (equation 6) which is defined based on the correlation between the soil backscatter coefficient and the ground measurements of surface soil moisture. The results obtained is σ^0_{soil} = -0.16* SM-17.90 with D= -0.16 and C= -17.90. The second component is the vegetation backscattering coefficient (σ^0_{veg}) that is characterized by two coefficients A and B (equation 4 and 5). In this research, we used that defined by (Bousbih et al., 2018) in a study area with land cover similar to our study area [A=0.18 and B=0.25]. The NDVI retrieved by the optical data was used as a vegetation index. It is the most effective index and the most used in several studies (El Hajj et al., 2018; Rawat et al., 2019) for soil moisture estimation of based on Water cloud model. The set of results derived for each parameter were integrated in the model in order to generate the water cloud model (WCM) in (dB). Then, an inversion approach (Zhuo et al., 2019) of this model was applied to transform the WCM values into a percentage unit, as expressed by the equation 8.

Assessment of Water Cloud Model (WCM)

The relationship between observed and estimated soil moisture using the WCM is shown in the scatter plot (Figure 3). A linear correlation between the observed and estimated soil moisture was observed, which reveal that the approach discuss handle here can be effective and successfully used to retrieval of surface soil moisture in study site over agricultural area. The statistical analysis of the results showed the level of agreement of the derived soil moisture model with the observed soil moisture. The evaluation model statistical indicators obtained were 0.70 and 1.30% for R^2 and RMSE, respectively.

In order to validate the obtained results, we have compared the observed surface soil moisture values and those predicted by using the cross validation method, (Figure 4). The validation model statistical parameters obtained for predicted soil moisture in study area were 0.65 and 1.45% for R^2 and RMSE, respectively. These results are in good agreement with those reported by Bao et al. (2018) obtaining an R^2 of 0.62. Also, Rawat et al. (2019) reported similar results using the WCM for estimation of soil moisture over agricultural area using Landsat-8 and Sentinel-1 satellite data in Punjab state (India). This model gives encouraging results for an accurate estimate of soil moisture. It can be applied to monitoring the soil moisture status in regional areas.

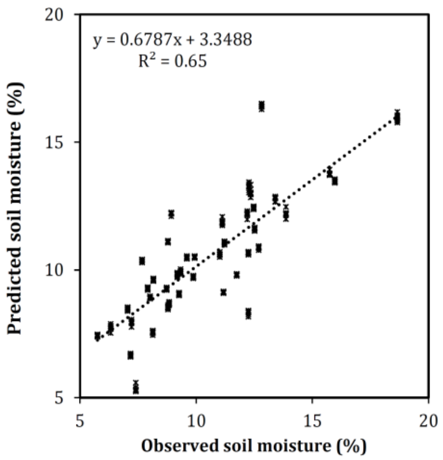

Figure 3. Linear relationship between the observed soil moisture and the soil moisture estimated by the WCM

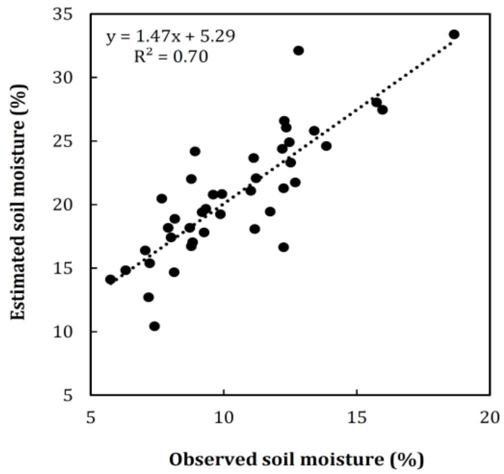

Figure 4. Comparison between observed and predicted soil moisture (%) using the k-fold cross validation

In the present work, the assessment of Water Cloud Model based on SAR and optical satellite data for surface soil moisture retrievals over agricultural area showed significant results. The main advantage of our methodology is the possibility of retrieving soil moisture using freely available SAR and optical remote sensing data. It can be offering many advantages for a number of research and environmental applications.

Soil moisture mapping

Soil moisture mapping is an important technique for analyzing the spatial variability of soil water content levels. In this study, soil moisture mapping was performed using the WCM model and Sentinel-1B and Sentinel-2B data over the study site. Figure 5 represent the soil moisture maps covering the study area during the agricultural season 2018 (from January to June). The maps obtained are clearly showed that the different classes of soil surface moisture distribution varied from 0% (red color) to> 23% (blue color).

Spatial analysis of maps has shown that areas with low soil moisture levels (0-11%) are located in the middle and south-east of the study site, they cover a large area in early January and at the end of June, this is the case on January 21, March 22, April 24 and June 26. This spatial distribution in these zones can be explained by the soil texture types (loam-clay soils, loam soils) and low rainfall levels. Contrariwise, the northern part is characterized by a significant increase in the soil moisture levels (January 21, March 22 and April 24), these levels of soil moisture are explained by the topographical parameters (high altitude :700-1000 m), the increase in mean of rainfall and the predominance of clay soil.

Precipitation is the main source of soil water content in all parts of the study area. In all derived maps, the percentage of soil moisture depends on the date of acquisition of the satellite data and the date of rainfall. More than the gap is longer more than the soil moisture rate is decreased and vice versa. For example in the map of January 21, high soil moisture was noted which is explained by the rate of rainfall before this date (12 mm). However, in 26 June, the distribution of soil moisture is lower than other dates. The distribution of soil moisture in this period (summer) can be justified by the increase in precipitation and decrease in evaporation due to the drop average in temperature (38°C).

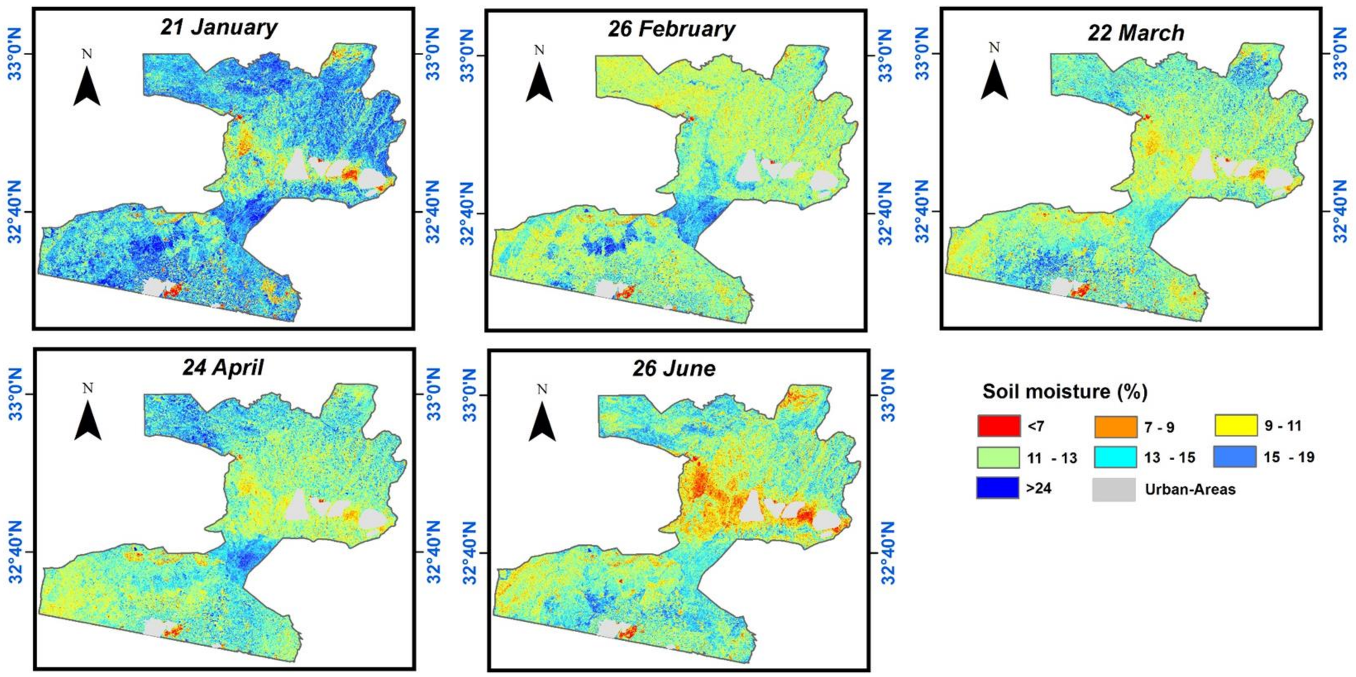

Figure 5. Spatial distribution of the surface soil moisture from 21 January to 26 June -2018 in the study area

Conclusion

In dry regions, soil moisture estimation can avoid numerous socio-economic issues by helping farmers to make informed decisions for improving their agricultural production. Thus, the aim of this research was to evaluate the potential of WCM to estimate the surface soil moisture using SAR and optical satellite data. Model accuracy of the retrieval soil moisture has tested and found good agreement with ground observed soil moisture. In addition, this model was used for the mapping spatio-temporal variation of soil moisture during the agricultural season (2018) in the study area. The mapping results showed the distribution and the different variations of surface water content over the whole study area. We concluded that the tested approach could be used as an efficient tool to estimate, monitoring and mapping the variation in surface soil moisture in dry areas. It can be applied by farmers for crop management and monitoring.

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