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## Optimization approach to retrieve soil surface parameters from single-acquisition single-configuration SAR data

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### ABSTRACT

This study suggests a novel approach to the retrieval of soil surface parameters using a single-acquisition single-configuration synthetic-aperture radar (SAR) system. Soil surface parameters such as soil moisture and surface roughness are key elements for many environmental studies, including Earth surface water cycles, energy exchange, agriculture, and geology. Remote sensing techniques, especially SAR data, are commonly used to retrieve such soil surface parameters over large areas. Several backscattering models have been proposed for soil surface parameters retrieval from SAR data. However, commonly, these backscattering models require multi configuration SAR data, including multi-polarization, multi-frequency, and multi-incidence angle. Here we propose a methodology that employs single-acquisition single-configuration SAR data for the retrieval of soil surface parameters. The originality is to use single-acquisition single-configuration SAR data to retrieve the soil surface parameters using an optimization approach by the genetic algorithm (GA); we have used the modified Dubois model (MDM) in HH polarization as the backscattering model. Three HH polarization and C band data sets from Quebec (Radarsat-1), Ontario (SIR-C), and Oklahoma (AIRSAR) were analyzed. The retrieved values of soil moisture and soil surface roughness were then compared to ground truth measurements with corresponding parameters. We employed diverse criteria, including the mean absolute error (MAE), the root mean square error (RMSE), the coefficient of performance (CP), and the correlation coefficient to investigate the performance of the proposed methodology. This analysis suggests the capability of the GA for the retrieval of soil surface parameters. Based on our findings, this method presents a viable alternative approach to the retrieval of soil surface parameters when only single-acquisition single-configuration SAR data is available.

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## 1. Introduction

Soil surface parameters such as soil moisture and soil surface roughness are key elements in many environmental studies, including earth surface water cycles, energy exchange, agriculture, and geology (Herrmann et al., 2016; Paloscia et al., 2012; Sellami et al., 2014; Zhang et al., 2015).

Moreover, these parameters can be used to investigate natural hazards, such as floods, droughts, and climate changes (Costantini, 2016). Soil moisture and soil surface roughness are especially critical parameters that well describe soil surface. Soil moisture represents the abundance of water in soil on a volumetric or gravimetric basis (Zhao and Li, 2013). Soil moisture has received much attention because it affects various processes involved in atmosphere–surface interactions and has been reported as an essential climate variable (Al-Yaari et al., 2014). Another

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main feature of the ground is its surface roughness (Baghdadi et al., 2002). In particular, the latter influences water infiltration. Therefore, obtaining information on soil moisture and soil surface roughness is critical to many applications.

Traditionally, soil moisture data has been collected by field measurements. Yet those only provide sparse point measurements. In recent decades, researchers proposed several methods to estimate the soil water content using remote sensing data in the thermal and microwave domains (Haider et al., 2004; Maltese et al., 2013a, b; Minacapilli et al., 2012; Rao et al., 2013). Synthetic-aperture radar (SAR) is increasingly becoming a vital sensor used to retrieve soil surface parameters because it overcomes the limitations of the thermal sensors by providing higher spatial resolution and weather condition data acquisition (Aubert et al., 2013; Bousbih et al., 2017; Capodici et al., 2013; Dong et al., 2013; El Hajj et al., 2017, 2018; Gao et al., 2017).

The backscattering coefficient ( $\sigma^0$ ), which is the signal returned from that SAR sensor, is affected by the soil's dielectric constant, which is linked to soil moisture and to soil surface roughness (Bertoldi et al., 2014; Kornelsen and Coulibaly, 2013). The dielectric constant is defined as the number of water dipoles per unit volume fraction (Dobson and Ulaby, 1986). In soil surface parameters retrieval from SAR data, it is common to use a backscattering model that represents the relation between the soil surface parameters and the SAR returned signal (Sahebi et al., 2002). In particular, the backscattering models may be composed of soil surface parameters and sensor configurations such as incidence angle, polarization, frequency, and backscattering coefficients. Therefore, it can be stated that the backscattering models are employed to simulate the relation between SAR backscattering coefficient ( $\sigma^0$ ) value and sensor-surface condition. Clearly sensor-surface condition refers to soil surface parameters and sensor configurations. It should be noted that sensor configurations are provided as the metadata hence the only unknown parameters are the soil surface parameters. Professionally, the backscattering coefficient is thereby determined by the sensor configurations and soil surface parameters (MirMazloumi and Sahebi, 2016). Researchers have developed various backscattering models, which can be classified into three groups: 1) theoretical models, based on electromagnetic wave scattering, such as the Integral Equation Model (IEM) (Fung et al., 1992) and the modified IEM (Baghdadi et al., 2015); 2) empirical models that have been developed based on corresponding ground soil surface parameters and SAR backscattering coefficient measurements (Attema and Ulaby, 1978; Sahebi et al., 2003); and 3) semi-empirical models that have been developed based on the relation between dielectric constant and signal behaviour as well as laboratory measurements by scatterometer (Dubois and VanZyl, 1994; Oh et al., 1992). Common backscattering models are composed of two or three surface parameters simultaneously, and therefore multi-incidence angle (Srivastava et al., 2009), multi-polarization (Baghdadi et al., 2015; Bourgeau-Chavez et al., 2013), and multi-frequency (Pierdicca et al., 2008) SAR data are required to retrieve the soil surface parameters. Another methodology has been

to use multi-temporal SAR data based on the assumption that temporal changes in surface roughness occur over a longer time than data acquisition delays (Lievens and Verhoest, 2012). Therefore, the main limitation of retrieving soil moisture and soil surface roughness simultaneously from SAR data using backscattering models is the necessity to acquire multi-configuration SAR data.

The Modified Dubois Model (MDM) is one of the SAR backscattering models for soil surface parameters retrieval from SAR data (Sahebi and Angles, 2010; Sahebi et al., 2003; Zhang et al., 2015). Since the MDM is composed of two unknown variables, including soil dielectric constant (soil moisture) and soil surface roughness, it is inevitable to use multi-configuration (Rao et al., 2014; Sahebi and Angles, 2010; Sahebi et al., 2003) or multi-temporal (Zhang et al., 2015) SAR data to retrieve soil surface parameters. Multi-frequency techniques suffer from diverse penetration depths of the different frequency SAR signals in the soil, which means that various dielectric constants affect the SAR returned signal. The main downside of multi-polarization techniques is the low sensitivity to soil surface roughness of the different polarizations (Sahebi et al., 2002). A serious criticism of multi-incidence angle methods is that they assume that soil moisture values are constant over time, since multi-incidence angle SAR data must be acquired in different days. Therefore, the goal of this study is to propose a methodology based on the genetic algorithm (GA) to retrieve both dielectric constant (soil moisture) and soil surface roughness from single-acquisition single-configuration SAR data in an optimization approach. The GA is an optimization algorithm that had been used in remote sensing for different applications (Almeida and Torres, 2017; Zhang et al., 2017).

## 2. Data

In this study, we have used two types of data: 1) ground truth data, which are field measurements of the two soil surface parameters, 2) SAR data. Three SAR datasets with corresponding ground measurements from the USA (one site) and Canada (two sites) in HH (horizontal transmit and horizontal receive) polarization and C band are used. The first dataset includes twenty field measurements with the corresponding AIRSAR C band SAR data from the Little Washita Experimental Watershed (LWREW) located in Oklahoma; it was acquired during the Soil Moisture Experiments (SMEX03) (Jackson and Cosh, 2006). Eleven and eighty-four field measurements with corresponding Radarsat-1 and SIR-C data in the C band were used from Quebec and Ontario provinces, respectively. Soil surface roughness values were calculated through digitizing of photographed grid boards and the soil moisture values were measured with impedance probe (ThetaProbes) for all three datasets. These values were measured for agricultural parcels. In particular, a different number of measurements (regarding the size of each parcel) were conducted within an agricultural parcel and then the mean value was devoted to each parcel as the ground truth measurement. The specifications of the three data sets are provided in Table 1. The soil moisture values are converted into dielectric constant and reverse (Delta-T Devices Ltd, 2017).

**Table 1**  
SAR data specification for each study area used for the proposed methodology evaluation.

Specifications	Study area		
	Oklahoma	Quebec	Ontario
Number of ground measurements	20	11	48
Incidence angle of SAR acquisition (degree)	62–69	44–46	33–44
Dielectric constant	3–11	7–17	9–22
Soil surface roughness	0.4–3 cm	2–5 cm	1–5 cm

The detailed pre-processing explanation steps and data descriptions of the Quebec, Oklahoma, and Ontario datasets are provided in [Sahebi and Angles \(2010\)](#) and [MirMazloumi and Sahebi \(2016\)](#), respectively. Hence, the pre-processing steps are only briefly provided herein. At first, we have applied a radiometric calibration on three SAR datasets to convert the DN value to the backscattering coefficient. Afterward, the SAR datasets of both Quebec and Ontario were geo-referenced using ground control points collected by GPS while the AIRSAR dataset of Oklahoma was geo-referenced using a digital ortho photo quadrangle. Finally, the mean value of the backscattering coefficient for each (same as the ground measurements) parcel was calculated for the three datasets.

### 3. Methodology

We have used the modified Dubois model (MDM) which has been used by [Sahebi and Angles \(2010\)](#) as the backscattering model in this study. We have chosen the MDM based on two reasons. In our previous investigation, we recognized that the MDM has the most precise performance to establish the relation between ground truth and modeled (using MDM and SAR data) soil surface parameters. The MDM was calibrated for HH polarization with multi-incidence angle measurements as shown in Eq. (1):

$$\sigma_{hh}^0 = 10^{-3.67} \frac{\cos^{1.5}\theta}{\sin^5\theta} 10^{0.112 \tan\theta \varepsilon} (k s \cdot \sin\theta)^{0.883} \lambda^{0.7} \quad (1)$$

where  $\sigma_{hh}^0$  is the backscattering coefficient,  $\theta$  is the incidence angle,  $\lambda$  is the SAR wavelength,  $k$  is the wave number,  $\varepsilon$  is the dielectric constant (soil moisture), and  $s$  is the soil surface roughness. Eq. (1) contains two unknown variables which are the dielectric constant (soil moisture) and soil surface roughness. Therefore, multi-configuration SAR data is required to retrieve the two unknowns from Eq. (1) as explained earlier. The previous solution ([Sahebi and Angles, 2010](#)) was to invert the MDM in order to use the multi-incidence angle inversion to solve the MDM and retrieve the dielectric constant (soil moisture) and soil surface roughness separately.

Optimization approaches can be utilized to solve an equation with two unknowns when only one observation is available. Moreover, the optimization approach does not require to invert the backscattering model. This can reduce

the complexity of retrieving soil surface parameters especially in cases that backscattering models are not invertible and requires numerically iterative solutions ([Oh et al., 1992](#)).

The GA is a subclass member of evolutionary algorithms that are inspired by the natural selection process ([Pal and Wang, 2017](#); [Sastry et al., 2014](#)). Simply, the goal of the optimization is to minimize or maximize a function by selecting the best element from different input values (soil dielectric constant and soil surface roughness in our case). In particular, this best element is the global minimum of the corresponding function. In this study, the cost function is a reformation of the MDM, as shown in Eq. (2).

$$\sigma_{hh}^0 - 10^{-3.67} \frac{\cos^{1.5}\theta}{\sin^5\theta} 10^{0.112 \tan\theta \varepsilon} (k s \cdot \sin\theta)^{0.883} \lambda^{0.7} = 0 \quad (2)$$

In an ideal situation, the difference between the first term (backscattering coefficient) and the second term (including the soil dielectric constant and soil surface roughness as unknown variables) must be zero. It is worth noting that the other variables in Eq. (2) are provided in the metadata of the satellite data.

In the first step, an initial number of random populations (initial populations), which are candidate solutions, are generated by the GA. In our case, each candidate solution is composed of a pair of soil dielectric constant and soil surface roughness values. These values are randomly selected within a pre-defined upper and lower boundary of each variable. The upper and lower boundaries are determined based on the conditions each dataset. The information regarding the conditions of the datasets are provided based on field studies and ground truth values. This will decrease the possibility for the GA to fall into local minima and also help the GA find the best solution faster.

These candidate solutions are used to minimize Eq. (2). In particular, the second term of Eq. (2) is calculated from the metadata and each pair of candidate solutions. Then the final form of Eq. (2) is calculated. A score value based on the final value of Eq. (2) is assigned to each candidate pair. It is clear that any candidate solution that leads Eq. (2) to be closer to the ideal situation will be assigned a better score. In the next step, the tournament selection (TS) procedure is applied to choose the suitable (with a high score in the previous step) candidates as parents for the crossover stage. TS is a selection mechanism for selecting candidate solutions for the further stage of the GA named crossover ([Miller and Goldberg, 1995](#)). In the crossover stage, two candidate solutions from TS are combined to produce a new solution. Also, a number of new solutions are produced based on a random change in the soil surface parameters value from the initial population, which is called mutation. The reproduced solutions in the crossover and mutation stages are evaluated (computing their score) based on Eq. (2). All the solutions from the initial population, crossover, and mutation stages are sorted based on their score and a pre-defined number of best solutions are selected. These solutions will be the population in the new iteration. The GA continues to produce new generations (set of solutions) and all operation above including TS, crossover, and mutation is applied to

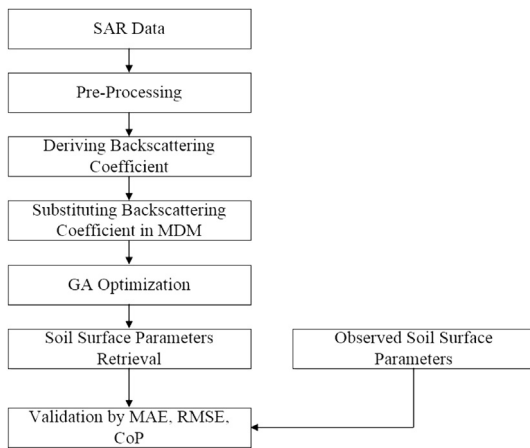


Fig. 1. Flowchart of the proposed methodology.

each solution. At last, the operation stops when the soil surface roughness and dielectric constant pair (candidate solution) validates the stopping criterion. In this study, the stopping criterion is set based on the final value of Eq. (2). In particular, if the calculated value from Eq. (2) for one solution is smaller than  $10^5$ , the GA will stop. Obviously, the final optimum solution is the corresponding solution that validates the stopping criterion. Fig. 1 represents the flowchart of the proposed methodology.

After the retrieval procedure using the GA, we have compared the retrieved values of soil surface parameters with the ground truth measurements. We have used four criteria, including correlation coefficient (CC), mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of performance (CP) (James and Burgess, 1982) to evaluate the performance of the proposed methodology. The CP is an error evaluation criterion that allows the comparison of retrieved and ground measured values of the soil surface parameters, which is shown in Eq. (3):

$$CP = \frac{\sum_{i=1}^n (R(i) - O(i))^2}{\sum_{i=1}^n (O(i) - O_{Average})^2} \quad (3)$$

where  $O(i)$ ,  $O_{Average}$ , and  $R(i)$  represent the ground measurement value, the mean value of the ground measurements, and the retrieved values, respectively. The CP approaches zero as the retrieved and ground measurement values of soil surface parameters get closer. RMSE and MAE are used to measure differences between retrieved and ground measurement values. Both RMSE and MAE have the

same behaviour as CP. However, both RMSE and MAE have comparable behaviour (Brassington, 2017); one important advantage of RMSE over MAE is that RMSE is more sensitive to outliers (Chai and Draxler, 2014; Pontius et al., 2008). CC measure the similarity of a set of retrieved and ground measurement values and approaches to one as the retrieved values get closer to ground measurements.

#### 4. Results and discussion

Table 2 represents the values of MAE, RMSE, and CP of the soil dielectric constant, soil moisture, and soil surface roughness for each dataset separately.

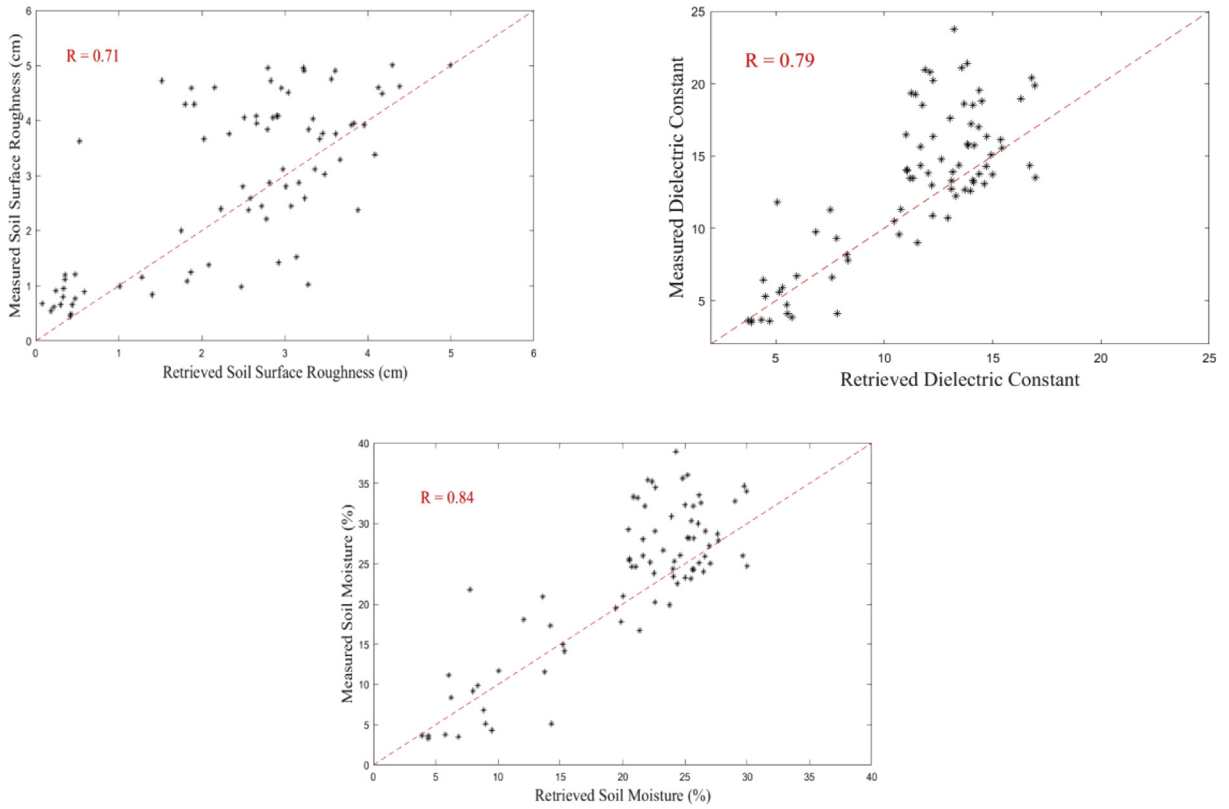
Table 2 shows that the retrieval procedure based on the GA provided promising results with only single-acquisition single-configuration SAR data. Fig. 2 shows the correlation between the retrieved values of the soil dielectric constant, soil moisture, and soil surface roughness, and the corresponding ground measurement values. Generally, it can be seen in soil dielectric constant and soil moisture scatterplots of Fig. 2 that there are two clusters of values. The reason is that soil dielectric constant and soil moisture of two datasets (out of three datasets) have nearly the same ranges, as can be seen in Table 1. In addition, these clusters are related to the physical characteristics of agricultural parcels that have been used in this study. In addition, a number of outlier points can be seen in Fig. 2. Falling into local minima can be the reason for this behavior. In particular, the best candidate solution of the GA which has satisfied the stopping criterion may have fallen into local minima. Local minima are defined as a point in which the candidate solution may result in satisfying the stopping criterion while it is not the actual (close to ground measurements) best solution. This issue shall happen if the cost function has several local minima around the global minima. Whatever it be, Fig. 2 suggests that the optimization approach for the retrieval of soil surface parameters provides promising results based on the satisfying correlation coefficients between retrieved and ground measurement values of the soil surface parameters.

Also, we have investigated the relationship between the soil surface parameters retrieval error (the difference between retrieved and ground measurement values) and the incidence angle (Fig. 3). According to this investigation, the retrieval errors of the soil dielectric constant, soil moisture, and soil surface roughness in the optimization approach do not have any dependency on the SAR incidence angle. According to Fig. 3, it can be understood that each cluster (the first cluster from 30 to 40, the second cluster from 40 to 50 and the third cluster from 60 to 70) of soil surface parameters generally experience the same range of retrieved

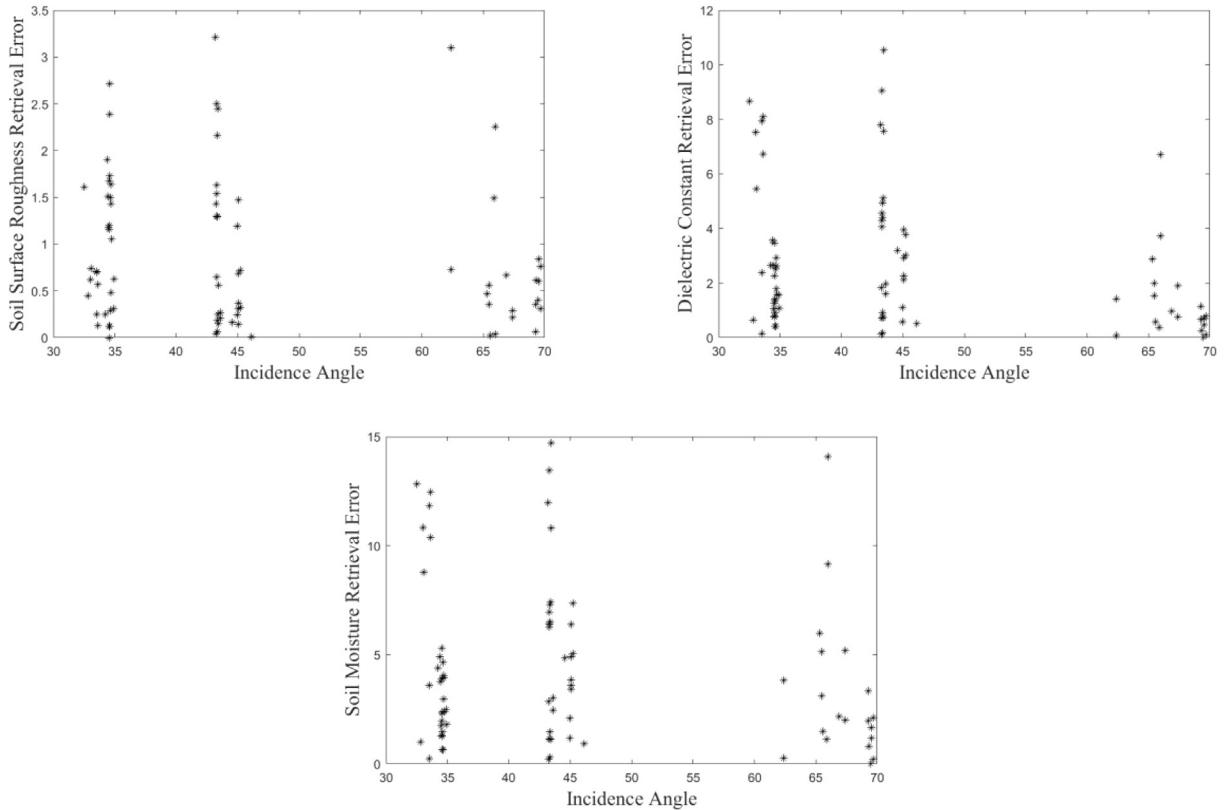
Table 2

Obtained values (MAE, RMSE, and CP) of the dielectric constant, soil moisture, and soil surface roughness with genetic optimization for three datasets.

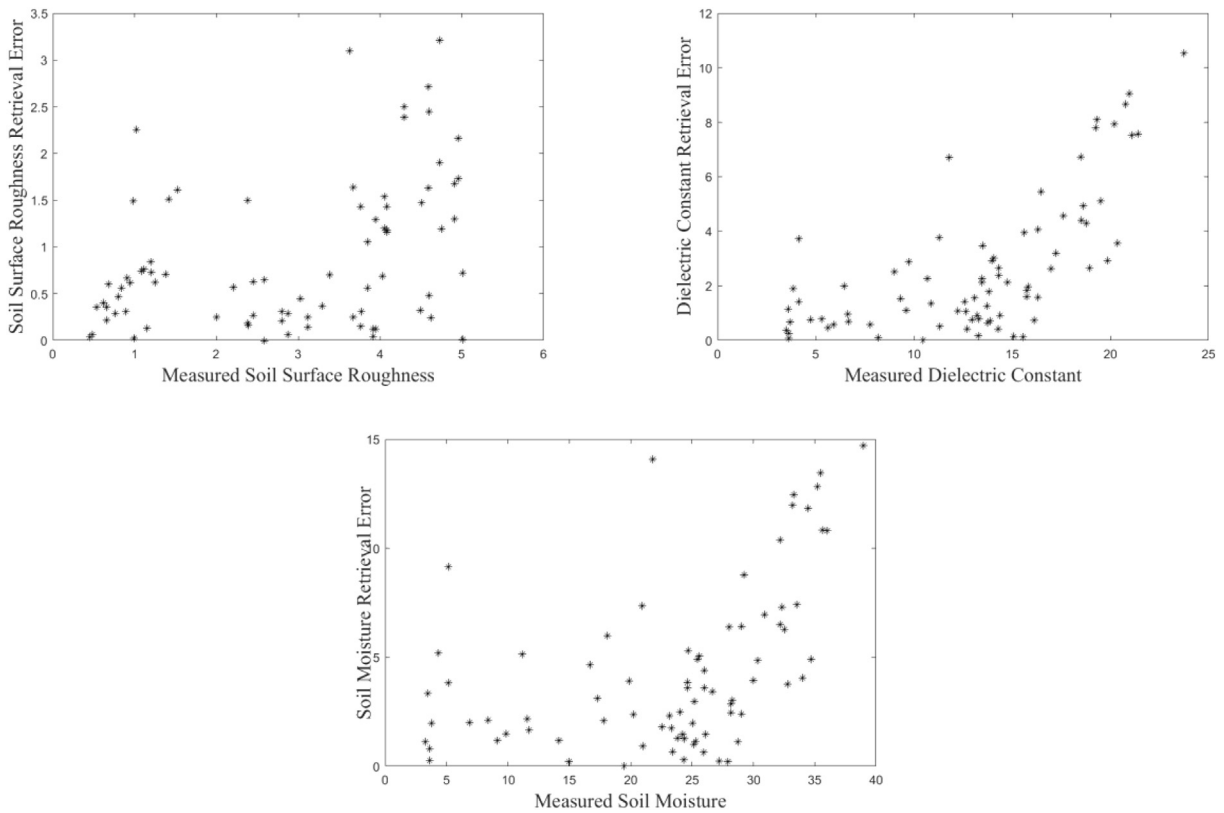
Parameters and criteria Dataset	Soil dielectric constant			Soil moisture (%)			Soil surface roughness (cm)		
	MAE	RMSE	CP	MAE	RMSE	CP	MAE	RMSE	CP
Quebec	0.51	0.71	0.68	2.32	2.71	0.98	3.97	4.63	0.96
Oklahoma	0.71	1.05	2.52	1.35	2.11	0.67	3.25	4.65	0.64
Ontario	1.02	1.3	1.34	3.23	4.27	1.69	4.89	6.37	1.69



**Fig. 2.** Comparison between measured and retrieved soil surface parameters for all three datasets (Quebec, Ontario, Oklahoma).



**Fig. 3.** Investigating the relation between the incidence angle and the retrieved soil surface parameters for all three datasets (Quebec, Ontario, and Oklahoma).



**Fig. 4.** Investigating the relation between measured values of soil surface parameters and retrieval (the GA) errors for all three datasets (Quebec, Ontario, and Oklahoma).

error. In other words, Fig. 3 illustrates that the retrieval error does not have a dependency on the incidence angle.

Fig. 4 presents the relation between the retrieved soil surface parameter errors and the ground-measured values of the soil surface parameters. It shows that the higher values of the soil dielectric constant, soil moisture, and soil surface roughness contain higher retrieval errors. This behavior can be explained through the inherent issue in the MDM. The MDM backscattering model is sensitive to high values of the soil surface parameters (Angles, 2001). In

particular, the Dubois model has been developed for moderate soil surface roughness and, therefore, it may have less accuracy in simulating the relation between high soil surface values to backscattering coefficient (Dubois and VanZyl, 1994). Also, it should be noted that each backscattering model has a validity range that shows the range in which the model performs robustly, and the confidence of the model should decrease out this range (Ulaby et al., 1982).

For a more comprehensive performance evaluation of the proposed methodology, we compared our results with

**Table 3**

Comparison of the results of the current study with data from works by other scholars carried out with alternative solutions.

Year	BM	Technique	Soil surface roughness (cm)		Dielectric constant		Soil moisture (%)		
			MAE	RMSE	MAE	RMSE	MAE	R	RMSE
Sahebi et al. (2003)	MDM	Inversion	2.49	1.39	3.5	1.25	–	–	–
Sahebi and Angles (2010)	MDM	Multi-angle	1.23	–	2.46	–	3.88	–	–
		Inversion							
Rao et al. (2014)	MDM	Multi-angle	Correlating root mean square height with polarizations	Cross	–	–	–	0.87	2.87
		Multi-polarization		Co	–	–	–	0.77	3.20
Zhang et al. (2015)	MDM	Inversion	Assuming constant soil surface roughness during the period of SAR acquisition	–	–	–	0.84	2.07	
		Multi-band		–	–	–	0.82	2.32	
		Optimization		–	–	–	0.84	2.32	
Current study	MDM	GA	0.87	1.17	2.63	3.64	4.89	0.84	5.76
		Single-configuration							



alternative available approaches that employed multi-incidence angle (Sahebi and Angles, 2010; Sahebi et al., 2003), multi-incidence angle and multi-polarization (Rao et al., 2014), and multi-frequency and multi-temporal (Zhang et al., 2017) SAR data. It is worth noting that these approaches used an inversion procedure to retrieve soil surface parameters that require multi-configuration SAR data. Table 3 provides the results when using the other approaches. The two latter approaches (Rao et al., 2014; Zhang et al., 2017) have used further assumption to eliminate soil surface roughness from their computations. Zhang et al., (2017) assumed that soil surface roughness is constant during the period of SAR data acquisition. As the result, soil surface roughness was omitted in the inversion approach and, therefore, no retrieval for this soil surface parameter was done. Rao et al., (2014) have used a cross polarization ratio (HV/HH) to retrieve soil surface roughness and then the other soil surface parameter was calculated using the inversion method.

Since the evaluation criteria have been explained earlier, it can be understood from Table 3 that the proposed methodology achieved promising results while only single-configuration SAR data were used. In particular, the proposed methodology retrieved both the dielectric constant of the soil (soil moisture) and soil surface roughness simultaneously without any further assumption (Zhang et al., 2015), or use of any auxiliary procedure (Rao et al., 2014).

## 5. Conclusion

This study presents an optimization approach using the GA to the retrieval of soil dielectric constant, soil moisture, and soil surface roughness values from single-configuration SAR data. We have used the MDM as the backscattering model for the retrieval of the soil surface parameters. The satisfying correlation coefficients between the retrieved and ground-measured values of the soil surface parameters (R-soil surface roughness = 0.71, R-dielectric constant = 0.79, and R-soil moisture = 0.84) suggest the feasibility of employing the GA. Despite the common inversion methods that require multi-frequency, multi-incidence angle, and multi-polarization SAR data, the optimization approach can be applied to single-configuration SAR data without any further assumption. Besides, the proposed methodology does not share the drawbacks associated with multi-configuration SAR data. We have obtained promising results suggesting the capability of employing the GA to retrieve soil surface parameters simultaneously from a single-configuration SAR data. We believe our approach would be well suited for use by other SAR backscattering models and different frequency SAR data. Our investigations into this area are still in progress.

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## References

- Almeida, A.E., Torres, R.D.S., 2017. Remote sensing image classification using genetic-programming-based time series similarity functions. *IEEE Geosci. Remote Sens. Lett.* 14 (9), 1499–1503.
- Al-Yaari, A., Wigneron, J.P., Ducharne, A., Kerr, Y.H., Wagner, W., De Lannoy, G., Mialon, A., 2014. Global-scale comparison of passive (SMOS) and active (ASCAT) satellite based microwave soil moisture retrievals with soil moisture simulations (MERRA-Land). *Remote Sens. Environ.* 152, 614–626.
- Angles, J., 2001. Séparation de l'humidité et de la rugosité dans le signal rétrodiffusé des images RSO selon une approche multi-angle. In: *Mémoire de maîtrise. Département de géographie et télédétection Université de Sherbrooke, QC, Canada*, 82 p.
- Attema, E.P.W., Ulaby, F.T., 1978. Vegetation modeled as a water cloud. *Radio Sci.* 13 (2), 357–364.
- Aubert, M., Baghdadi, N., Zribi, M., Ose, K., El Hajj, M., Vaudour, E., Gonzalez-Sosa, E., 2013. Toward an operational bare soil moisture mapping using TerraSAR-X data acquired over agricultural areas, *IEEE Journal of Selected Topics. In: Applied Earth Observations and Remote Sensing (JSTARS)*, vol. 6, issue 2, pp. 900–916. <https://doi.org/10.1109/JSTARS.2012.2220124>.
- Baghdadi, N., King, C., Bonnifant, L., 2002. An empirical calibration of the integral equation model based on SAR data and soil parameters measurements. In: *Geoscience and Remote Sensing Symposium, IGARSS*, vol. 02, pp. 2646–2650.
- Baghdadi, N., Zribi, M., Paloscia, S., Verhoest, N., Lievens, H., Baup, F., Mattia, F., 2015. Semi-empirical calibration of the integral equation model for co-polarized L-band backscattering. *Remote Sens.* 7, 13626–13640. <https://doi.org/10.3390/rs71013626>.
- Bertoldi, G., Chiesa, S.D., Notarnicola, C., Pasolli, L., Niedrist, G., Tappeiner, U., 2014. Estimation of soil moisture patterns in mountain grasslands by means of SAR RADARSAT2 images and hydrological modeling. *J. Hydrol.* 516, 245–257.
- Bourgeau-Chavez, L.L., Leblon, B., Charbonneau, F., Buckley, J.R., 2013. Evaluation of polarimetric Radarsat-2 SAR data for development of soil moisture retrieval algorithms over a chronosequence of black spruce boreal forests. *Remote Sens. Environ.* 132, 71–85.
- Bousbih, S., Zribi, M., Lili-Chabaane, Z., Baghdadi, N., El Hajj, M., Gao, Q., Mougenot, B., 2017. Potential of Sentinel-1 radar data for the assessment of soil and cereal cover parameters. *Sensors* 17, 2617. <https://doi.org/10.3390/s17112617>.
- Brassington, G., 2017. Mean absolute error and root mean square error: which is the better metric for assessing model performance?. In: *EGU General Assembly Conference Abstracts*, vol. 19, p. 3574.
- Capodici, F., Maltese, A., Ciraolo, G., La Loggia, G., D'Urso, G., 2013. Coupling two RADAR backscattering models to assess soil roughness and surface water content at farm scale. *Hydrol. Sci. J.* 58 (8), 1677–1689.
- Chai, T., Draxler, R.R., 2014. Root mean square error (RMSE) or mean absolute error (MAE)?—Arguments against avoiding RMSE in the literature. *Geosci. Model Dev. (GMD)* 7 (3), 1247–1250.
- Costantini, E.A., 2016. Soil indicators to assess the effectiveness of restoration strategies in dryland ecosystems. *Solid Earth* 7, 397.
- Delta-T Devices Ltd, 2017. *User Manual for the ML3 ThetaProbe*. Delta-T Devices Ltd, Cambridge, UK.
- Dobson, M.C., Ulaby, F.T., 1986. Active microwave soil moisture research. *IEEE Trans. Geosci. Remote Sens.* 24, 23–36.
- Dong, L., Baghdadi, N., Ludwig, R., 2013. Retrieving surface soil moisture using radar imagery in a semi-arid environment. *IEEE Geosci. Remote Sens. Lett.* 10 (3), 461–465.
- Dubois, P.C., VanZyl, J., 1994. An empirical soil moisture estimation algorithm using imaging radar. In: *Surface and Atmospheric Remote Sensing: Technologies, Data Analysis and Interpretation. International Symposium on Geoscience and Remote Sensing*, vol. 3, pp. 1573–1575.
- El Hajj, M., Baghdadi, N., Zribi, M., Bazzi, H., 2017. Synergic use of Sentinel-1 and Sentinel-2 images for operational soil moisture mapping at high spatial resolution over agricultural areas. *Remote Sens.* 9, 1292. <https://doi.org/10.3390/rs9121292>.
- El Hajj, M., Baghdadi, N., Zribi, M., Rodríguez-Fernández, N., Wigneron, J.P., Al-Yaari, A., Al Bitar, A., Albergel, C., Calvet, J.C., 2018. Evaluation of SMOS, SMAP, ASCAT, and Sentinel-1 soil moisture products at sites in Southwestern France. *Remote Sens.* 10 (569), 1–17. <https://doi.org/10.3390/rs10040569>.

- Fung, A.K., Li, Z., Chen, K.S., 1992. Backscattering from a randomly rough dielectric surface. *IEEE Trans. Geosci. Remote Sens.* 30 (2), 356–369.
- Gao, Q., Zribi, M., Escorihuela, M.J., Baghdadi, N., 2017. Synergetic use of Sentinel-1 and Sentinel-2 for soil moisture mapping at 100 m resolution. *Sensors* 17, 1966. <https://doi.org/10.3390/s17091966>.
- Haider, S.S., Said, S., Kothiyari, U.C., Arora, M.K., 2004. Soil moisture estimation using ERS 2 SAR data: a case study in the Solani River catchment. *Hydrol. Sci. J.* 49 (2).
- Herrmann, F., Baghdadi, N., Blaschek, M., Deidda, R., Duttman, R., La Jeunesse, I., Sellami, H., Vereecken, H., Wendland, F., 2016. Simulation of future groundwater recharge using a climate model ensemble and SAR-image based soil parameter distributions – a case study in an intensively-used Mediterranean catchment. *Sci. Total Environ.* 543 (B), 889–905.
- Jackson, T., Cosh, M., 2006. SMEX03 Soil Climate Analysis Network (SCAN): Oklahoma, Version 1. Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center.
- James, L.D., Burgess, S.J., 1982. Selection, calibration and testing of hydrologic models. In: Hann, C.T., Johnston, H.P., Brakkensiek, D.L. (Eds.), *Hydrologic Modeling of Small Watersheds*. ASAE, St. Joseph, MI, USA, pp. 437–472.
- Kornelsen, K.C., Coulibaly, P., 2013. Advances in soil moisture retrieval from synthetic-aperture radar and hydrological applications. *J. Hydrol.* 476, 460–489.
- Lievens, H., Verhoest, N.E.C., 2012. Spatial and temporal soil moisture estimation from RADARSAT-2 imagery over Flevoland, The Netherlands. *J. Hydrol.* 456–457, 44–56.
- Maltese, A., Bates, P.D., Capodici, F., Cannarozzo, M., Ciruolo, G., La Loggia, G., 2013a. Critical analysis of thermal inertia approaches for surface soil water content retrieval. *Hydrol. Sci. J.* 58 (5), 1144–1161.
- Maltese, A., Capodici, F., Ciruolo, G., La Loggia, G., 2013b. Mapping soil water content under sparse vegetation and changeable sky conditions: comparison of two thermal inertia approaches. *J. Appl. Remote Sens.* 7 (1), 073548.
- Miller, B.L., Goldberg, D.E., 1995. Genetic algorithms, tournament selection, and the effects of noise. *Complex Syst.* 9 (3), 193–212.
- Minacapilli, M., Cammalleri, C., Ciruolo, G., D'Asaro, F., Iovino, M., Maltese, A., 2012. Thermal inertia modeling for soil surface water content estimation: a laboratory experiment. *Soil Sci. Soc. Am. J.* 76 (1), 92–100.
- MirMazloumi, S.M., Sahebi, M.R., 2016. Assessment of different backscattering models for bare soil surface parameters estimation from SAR data in band C, L and P. *Eur. J. Remote Sens.* 49 (1), 261–278.
- Oh, Y., Sarabandi, K., Ulaby, F.T., 1992. An empirical model and an inversion technique for radar scattering from bare soil surfaces. *IEEE Trans. Geosci. Remote Sens.* (2), 370–381.
- Pal, S.K., Wang, P.P., 2017. *Genetic Algorithms for Pattern Recognition*. CRC press.
- Paloscia, S., Pettinato, S., Santi, E., 2012. Combining L and X band SAR data for estimating biomass and soil moisture of agricultural fields. *Eur. J. Remote Sens.* 45 (1), 99–109.
- Pierdicca, N., Castracane, P., Pulvirenti, L., 2008. Inversion of electromagnetic models for bare soil parameter estimation from multifrequency polarimetric SAR data. *Sensors* 8, 8181–8200.
- Pontius, R.G., Thontteh, O., Chen, H., 2008. Components of information for multiple resolution comparison between maps that share a real variable. *Environ. Ecol. Stat.* 15 (2), 111–142.
- Rao, S.S., Kumar, S.D., Das, S.N., 2013. Modified Dubois model for estimating soil moisture with dual polarized SAR data. *J. Indian Soc. Remote Sens.* 41, 865–872.
- Rao, S.S., Sahadevan, D.K., Wadodkar, M.R., Nagaraju, M.S.S., Chattaraj, S., Joseph, W., Rajankar, P., Sengupta, T., Venugopalan, M.V., Das, S.N., Joshi, A.K., Sharma, J.R., Amminedu, E., 2014. Soil moisture model with multi-angle and multi polarisation RISAT-1 data. In: *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume II-8, 2014, ISPRS Technical Commission VIII Symposium*, 09 – 12 December 2014. Hyderabad, India.
- Sahebi, M.R., Angles, J., 2010. An inversion method based on multi-angular approaches for estimating bare soil surface parameters from RADARSAT-1. *Hydrol. Earth Syst. Sci.* 14 (11), 2355–2366.
- Sahebi, M.R., Angles, J., Bonn, F., 2002. A comparison of multi-polarization and multi-angular approaches for estimating bare soil surface roughness from spaceborne radar data. *Can. J. Remote Sens.* 28 (5), 641–652.
- Sahebi, M.R., Bonn, F., Gwyn, Q.H.J., 2003. Estimation of the moisture content of bare soil from RADARSAT-1 SAR using simple empirical models. *Int. J. Remote Sens.* 24 (12), 2575–2582.
- Sastry, K., Goldberg, D.E., Kendall, G., 2014. Genetic algorithms. In: *Search Methodologies*. Springer, Boston, MA, USA, pp. 93–117.
- Sellami, H., La Jeunesse, I., Benabdallah, N., Baghdadi, N., Vanclooster, M., 2014. Uncertainty analysis in model parameters regionalization: a case study involving the SWAT model in Mediterranean catchments (Southern France). *Hydrol. Earth Syst. Sci.* 18, 2393–2413.
- Srivastava, H.S., Patel, P., Sharma, Y., Navalgund, R.R., 2009. Large-area soil moisture estimation using multi-incidence-angle RADARSAT-1 SAR data. *IEEE Trans. Geosci. Remote Sens.* 47, 2528–2535.
- Ulaby, F.T., Moore, R.K., Fung, A.K., 1982. *Microwave Remote Sensing: Active and Passive*. Vol. 2, Radar Remote Sensing and Surface Scattering and Emission Theory. Addison-Wesley, Reading, MA, USA.
- Zhang, X., Chen, B., Fan, H., Huang, J., Zhao, H., 2015. The potential use of multi-band SAR data for soil moisture retrieval over bare agricultural areas: Hebei, China. *Remote Sens.* 8 (1), 7.
- Zhang, Y., Yang, B., Liu, X., Wang, C., 2017. Estimation of rice grain yield from dual-polarization Radarsat-2 SAR data by integrating a rice canopy scattering model and a genetic algorithm. *Int. J. Appl. Earth Obs. Geoinf.* 57, 75–85.
- Zhao, W., Li, Z.L., 2013. Sensitivity study of soil moisture on the temporal evolution of surface temperature over bare surfaces. *Int. J. Remote Sens.* 34, 3314–3331.