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Comparison of two physical models, IEM and fractal SPM, in surface roughness estimation using SAR images

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ABSTRACT

Radar remote sensing has been widely used to estimate moisture and surface roughness due to its sensitivity to the physical and geometrical parameters of the soil. There are different models to explain the relationship between radar backscattering, surface and sensor parameters. The most important of these models are the integral equation model (IEM) and the small perturbation model (SPM). Due to the complexity of these models, in order to estimate roughness and moisture a neural network is used for inversion of these models. In this article, the X-band of the SAR image is used to estimate the surface roughness. One of the innovations of this research is the use of fractal SPM model in surface roughness estimation. To evaluate the accuracy of roughness estimation from SAR image, digital terrain model (DTM) that prepared using lidar data is used. For calculation of field roughness, Euclidean geometry and fractal geometry have been used, and they have been compared with roughness estimated from SAR image using two fractal SPM and IEM models. The results of this research have shown that the best accuracy is related to the estimation of the surface roughness with the fractal SPM model, which is compared with the ground roughness measured by the fractal geometry method. The accuracy of this method is 22% better than the similar method with the IEM model. The results of this paper showed that the use of fractal physical model as well as fractal geometry significantly increases the accuracy of roughness estimation from SAR images.

KEYWORDS

Roughness
Moisture
Fractal SPM
IEM
Terrasar-X

1. Introduction

Radar remote sensing has been widely used for studying soil surface parameters due to its advantages, including the independence on weather conditions and the sensitivity of electromagnetic waves to geometric(roughness) and physical properties (dielectric constant) (Baghdadi & Zribi, Evaluation of radar backscatter models IEM, Oh and Dubois using experimental observations, 2006). Radar systems emit electromagnetic waves and then receive the backscattering from the surface. The backscattering of radar waves depends on various factors, including sensor parameters (wavelength, polarization and incidence angle), and surface parameters such as geometric and physical properties of the surface (Wang, Li, Han, & Jin, 2011).An important indicator of the physical property of the soil is moisture, which is expressed by dielectric constant. Another parameter that introduces the geometric characteristics of the soil is roughness, which is expressed by two statistical parameters, called standard deviation of height and correlation length (Hajnsek, 2001). The first shows the changes of height in the vertical direction and the second shows the height changes in the horizontal direction (Baghdadi, et al., 2018). Soil moisture is one of the key parameters in environmental studies including hydrology, meteorology and agriculture. Soil moisture is an important factor that plays a fundamental

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role in the interaction between the earth's surface and the atmosphere.
In addition, the soil moisture determines how much precipitation penetrates the ground and how much water flows. However, despite its importance, this parameter still does not play an essential role in hydrological and ecosystem models because of the wide spread of the surface and problems for measurement (Van Zyl & Yunjin Kim, 2010). Surface roughness is a key parameter in identifying soil surface characteristics in agricultural and hydrological applications. In agricultural areas, this parameter is an indicator of soil sensitivity to wind erosion and plays an important role in infiltration and water storage (Zobeck & Onstad, 1987) . Flooding and soil erosion are the factors of destruction of agricultural lands. Floods occur when the intensity of rainfall is greater than the infiltration of water (Beckmann & Spizzichino, 1987). Since soil roughness plays an important role in water absorption, it accelerates infiltration and reduces runoff. Soils with very low roughness have lower permeability compared to rough soils (Bissonnais, et al., 1998). Therefore, estimation of soil roughness is very important in studies related to moisture estimation, more accurate estimation of roughness will lead to more accurate estimation of moisture.
In order to express the relationship between the backscattering of radar and the sensor and surface parameters, various models including empirical, semi-empirical and physical models have been proposed (Jagdhuber, 2006; Loew., 2004). Among the physical models, the integral equation model and the SPM have been widely used due to their applicability and validity in a wide range of roughness (Fung & Chen, An update of the IEM surface backscattering model., 2004; Fung, Microwave Scattering and Emission Models and Their Applications, 1994; Chen, et al., 2003). One of the most problems of the IEM model is the inversion of this model to estimate surface roughness and moisture. Neural network is one of the most famous methods that used for inversion IEM. To measure ground roughness, in order to evaluate the accuracy of estimated roughness with physical models, two methods of Euclidean geometry and fractal geometry are used. Various studies show the superiority of fractal geometry over Euclidean geometry in estimating surface roughness. Most researches acknowledge that the fractal model is the best method to express the surface geometry (Feder, 1988; Franceschetti & Riccio, Scattering, Natural Surfaces and Fractals, 2007; Falconer, 1990; Mandelbrot, 1983). In addition, the backscattering of electromagnetic waves also has a fractal nature.
In this paper, surface roughness estimation has been done using SAR image in x-band. Roughness estimation has been done using IEM and fractal SPM model. For inversion these models, the neural network method is used. In order to evaluate the accuracy of roughness estimation, digital elevation model that prepared with the lidar data are used. Ground roughness is calculated by two methods of Euclidean and fractal geometry, and then it is compared with the output of the mentioned models and the accuracy of roughness estimation is measured.
The innovation of this paper, in addition to using fractal geometry in ground roughness estimation, is the use of fractal SPM model to estimate surface roughness on radar images.

2. Integral equation model (IEM)

IEM is one of the accurate models for determining surface parameters from SAR system. Estimation of the soil moisture and roughness is done by this model. This model was first proposed in 1992 by Fung and others (Fung, Li, & Chen, Backscattering from a randomly rough dielectric surface, 1992). Co-polarized backscattering coefficient is expressed by equation 1:

$$\sigma^0{}_{PP} = \frac{k^2}{4\pi}\exp(-2k^2s^2\cos^2(\theta))\sum_{n=1}^{+\infty}\left|I_{pp}{}^n\right|^2\frac{W^{(n)}(2k\sin(\theta,0)}{n!} \qquad (1)$$

In the equation (1):

$$I_{pp}{}^n = (2ks\cos\theta)f_{pp}exp(-k^2s^2\cos\theta^2 + (ks\cos\theta)^nF_{pp} \qquad (2)$$

In equation 2 $\sigma^0{}_{PP}$ is the copolarized backscattering coefficient (hh or vv), K is the wave number ($k=2\pi/\lambda$), λ is the wavelength, θ is the local incident angle, s is the standard deviation of the average surface and $W^{(n)}$ is the nth Fourier transform of the autocorrelation function, which is calculated from the equation (3):

$$W^{(n)}(K) = \int_{p=0}^{p=+\infty} C^n(p).p.J_0\left(K_p\right)d_p \qquad (3)$$

In the equation 2 and 3, $J_0$is the zero-order Bessel function, $f_{pp}$is a function of the incident angle and Fresnel reflection coefficient, and F_{pp} is a function of the incident angle, Fresnel reflection coefficient, dielectric constant, which are obtained from the equation 4 to 7.

$$f_{hh} = \frac{-2R_h}{\cos\theta} \qquad (4)$$

$$f_{vv} = \frac{-2R_v}{\cos\theta}, \qquad (5)$$

$$F_{hh} = 2\frac{\sin^2\theta}{\cos\theta}\left[4R_h - (1-\frac{1}{\varepsilon})(1+R_h)^2\right] \qquad (6)$$

$$F_{vv} = 2\frac{\sin^2\theta}{\cos\theta}\left[(1-\frac{\varepsilon\cos^2(\theta)}{\varepsilon-\sin^2(\theta)})(1-R_v)^2 - (1-\frac{1}{\varepsilon})(1+R_v)^2\right] \qquad (7)$$

3. Fractal SPM model

Most of the studies that has been done to improve the estimation of surface roughness parameters has been based on the fractal calculation to enter the physical models. In these studies, the fractal geometric dimension has been taken into consideration, while the backscattering model is the same as the normal physical model. In this article, in addition to the mentioned cases, SPM fractal backscattering model is used. The advantage of this method is that the fractal parameters can be extracted directly from the SAR images and as a result, the roughness parameter is calculated. Therefore, in the fractal SPM, the roughness parameter is estimated in fractal form and compared with the ground roughness samples that calculated by two methods of fractal geometry and Euclidean geometry.

The SPM model provides the simplest expression for the relationship between the backscattering coefficient and also has a suitable validity range for SAR applications (Di Martino, Riccio, & Zinno, SAR Imaging of Fractal Surfaces, 2012). The presented fractal SPM model is calculated from the equation (8) (Franceschetti & Riccio, Scattering, Natural Surfaces, and Fractals., 2006):

$$\sigma^0{}_{hh} = 4k^3\cos^4\theta|\beta_{hh}|^2\frac{S_0}{(2k\sin\theta)^{2+2H(}} \quad (8)$$

In equation 8, k is the wave number, β_{hh} is the amount of Fresnel reflection in the horizontal plane, S_0 and H are the fractal parameters of the surface and θ is the incident angle. The value of β_{hh} is obtained from equation 9:

$$\beta_{hh} = \frac{\cos\theta - \sqrt{\varepsilon - \sin^2\theta}}{\cos\theta + \sqrt{\varepsilon - \sin^2\theta}} \quad (9)$$

In equation 9, ε is the dielectric constant.

S_0 is fully related to the geometric part of the fractal SPM, which is a function of the Horst coefficient (H) and the s, that is obtained from equation 10:

$$S_0 = 2^{H+1}\Gamma^2(1+H)\sin(\pi H)\,s^2, s = T^{1-H} \quad (10)$$

the value of roughness (rms_height) can be obtained from the equation 11 (Summers, Soukup, & Gragg, 2007):

$$rms_{height} = s.L^H \quad (11)$$

4. Measurement of roughness by Euclidean geometry method

Roughness parameters in Euclidean geometry include two components of roughness changes in vertical and horizontal directions. The roughness changes in the vertical direction are expressed by rms_height and the roughness changes in the horizontal direction are related to the correlation length. The value of rms_height (σ) is obtained from the equation 12:

$$\sigma = \sqrt{\frac{1}{N}[(\sum_{i=1}^{N} z_i{}^2) - N\bar{z}^2]} \quad , \quad \bar{z} = \frac{1}{N} \quad (12)$$

In equation 12, N is the number of samples, z is the height of the measured samples, and $\bar{z}$ is the average height of all the samples. Vertical height changes are defined by the parameter k.σ, where k is the wave number and its value is equal to 2π/λ. λ is the wavelength.

5. Calculation of the roughness (rms_height) using fractal geometry

Surface roughness in fractal geometry is defined with two components, fractal dimension and topothesy. Roughness of each profile has a surface power spectral density function (PSD). To calculate the rms-height, the PSD function should be estimated. One of the most important methods for PSD calculation is the use of the Weltch method (Otis & Solomon, 1991). The relationship between the roughness parameter and PSD is obtained from the equation 13 (Di Martino, Riccio, & Zinno, SAR Imaging of Fractal Surfaces, 2012).

$$PSD = S(k) = S_0k^{-\alpha}, k = \sqrt{k_x{}^2 + k_y{}^2} \quad (13)$$

In the equation 13, k is the wavelength, α is the slope of the spectrum, and the value of S_0 is obtained from equation 14:

$$S_0 = 2^{H+1}\Gamma^2(1+H)\sin(\pi H)\,s^2 \quad (14)$$

α is equal to the slope of S(k) on a logarithmic scale. $\alpha = 2H + 1$, for profile and $\alpha = 2H + 2$ for two dimensional surfaces.

In fractal geometry, the topothesy expresses the complexity of the fractal geometry, which is obtained from the equation15 (Huang & Bradford , 1992).

$$rms - height = s.L^H, s = T^{1-H} \quad (15)$$

6. Data simulation using fractal SPM and IEM models

The SAR data used in this article are in the X band, therefore, by using the IEM model introduced in equation 1 and fractal SPM in equation 8, the simulation of the backscattering coefficient in a wide range of sensor and surface parameters, according to Tables 1 and 2 is done

Table 1- Range of sensor and surface parameters for simulating backscattering using IEM model in X band HH polarization

Parameter	Range
rms_height	rms_height=0.2:0.2:4
Incdence Angle(θ)	θ=290:20:470
Dielectric constant (ε_r)	ε_r=2:18

Table 2- Range of sensor and surface parameters for simulating backscattering using fractal SPM model in X band HH polarization

Parameter	Range
$s(m^{1-H)}$	s=0.002:0.002:0.07 mm^{1-H}
Incdence Angle(θ)	θ=14^0:2^0:55^0
Dielectric constant (ε_r)	ε_r=2:18
Hurst coefficient	H=0.1:0.1:0.9

The range of simulation parameters for the IEM model includes 20 rms_height, 10 incidence angle, and 17 dielectric constant values. Therefore, 3400 backscattering values were generated for the X band of HH polarization.

Each of these parameters was created as a vector containing 3400 values.
The parameters of fractal SPM model include 35 values for s, 21 values for incidence angle, 17 values for dielectric constant and 9 values for Horst coefficient.

6. Using neural network to inversion IEM and fractal SPM models for surface roughness estimation:

IEM and SPM physical models simulate the radar backscattering based on surface and sensor parameters. It is very difficult to invert these models based on analytical methods. Various methods have been proposed for the inversion of these models. One of the most important methods for inverting these models is the neural network method. The neural network method has been successfully used in solving inversions problems in radar remote sensing, especially in retrieving roughness and moisture parameters (Notarnicola, Angiulli, & Posa, 2008; Elshorbagy & arasuraman, 2008; Satalino, et al., 2002) . The quality of the results from the neural network depends on the quality of the training data (Baghdadi, et al., 2018).

The steps of this study's proposed method for estimating roughness using IEM and SPM models are:

1- Data simulation for a wide range of sensor parameters according to Table 1 and 2.
2- Creating neural network 1 using inputs of backscattering and incidence angle. The output of network 1 is moisture.
3- Evaluating the accuracy of moisture estimation by comparing the estimated and simulated data.
4- Creating and training neural network 2 using backscattering, incidence angle and moisture (estimated in step 2) data as inputs. In this step, the output is roughness(rms_height).

The Levenberg-Marquardt algorithm is used to train the neural network in this article. The optimal number of layers is selected based on the maximum performance and the lowest MSE (Mean Square Error value). Also, the transformation function is considered linear in all neural networks. The number of hidden layers for the neural network is two for moisture estimation and three for roughness estimation. Figure 1 shows the methodology of surface roughness estimation in this paper.

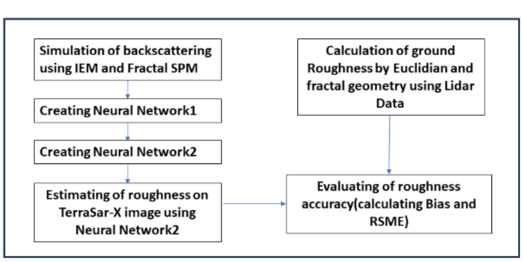

Figure 1. The methodology of estimating roughness on TerraSAR-X imge

7.Evaluating the accuracy of roughness estimation
In order to measure the roughness accuracy estimated using SAR images field data, two statistical indices are used according to equations 16and 17 (Baghdadi, Cresson, El Hajj,, & Ludwig, 2012):

$$Bias = \frac{1}{N}\sum_{i=1}^{N}(E_i - M_{i)} \quad (16)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_i - M_i)^2} \quad (17)$$

In the above equations, E_i is the estimated and M_i is the measured values of surface roughness (rms_height).
8.Real Dataset
The data used in this article include the SAR image and digital elevation model prepared using lidar data.
TerraSar-X satellite image belongs to Corvara district in Bolzano province located in Alto-Adige region in the northern of Italy. The specifications of this data are given in Table 3.
This region is a landslide area where most of its vegetation is natural grass and there are areas of bare soil that are mostly caused by landslides.

Table 3: Specifications of satellite data

Site	SAR Sensor	Incidence Angle	Acquisition Time	Spatial Resolution
Corvara	TerraSar-X	47^0	23 Nov 2016	0.67×0.47m

The digital elevation model of the area was prepared by lidar data with a resolution of 1.85 cm. This model is used to measure ground roughness.
In order to measure the ground roughness, profiles with a length of 1.36 m along and 0.95 m perpendicular to the flight line were selected. These lengths are equivalent to two pixels of the TerraSar-X image and 74 and 51 pixels of the digital elevation model, along the range and azimuth direction. Average radar backscattering coefficient was considered for each profile. Speckle noise reduction was done on radar images using multi looking technique.
9. Implementation of results on TerraSAR-X data using IEM model

Neural network 1 is used to estimate roughness (rms_height) on TerraSAR-X image. Considering that there is no field measurement of moisture, therefore, the accuracy of the proposed method is evaluated only for roughness. In the first step, the inputs of the neural network 1 are the backscattering coefficients of the TerraSAR-X image and

the incidence angle, and the moisture is estimated as a output.
Then, using neural network 2 whose inputs are backscattering coefficient, estimated moisture and incidence angle, the value of rms_height(roughness) is estimated. These roughness values are compared with the field roughness that are calculated by fractal and Euclidian geometry methods, Finally The accuracy of estimation of roughness is evaluated.
Field roughness was calculated by Euclidian and fractal method using equations 12 and15. evaluation of accuracy was done using two statistical parameters RMSE and Bias and using two equations16 and 17.
The accuracy of roughness (comparison between the rms_height estimated by the IEM model and the corresponding field roughness) calculated by the Euclidean method is RMSE=0.0056m and bias=0.0019m. While these results were obtained for fractal geometry, RMSE=0.004m and bias=0.0018. The results showed that the fractal method in this research improves the roughness estimation accuracy about 28%. Figures 2 and 3 show the comparison of estimated rms_height using IEM model and field rms_height that calculated by fractal and Euclidean geometry, respectively.

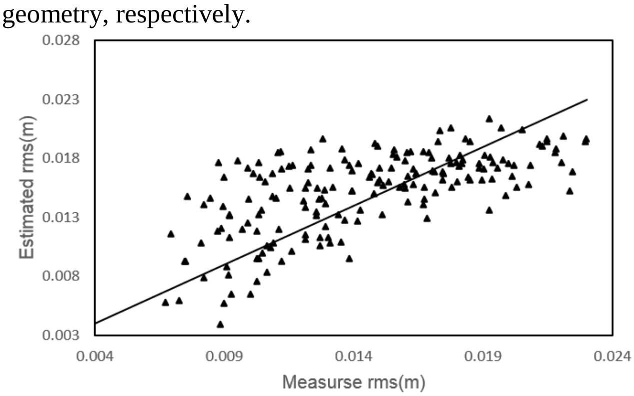

Figure 2. The comparison between the rms_height of the field, calculated by the fractal method and the corresponding estimated value by the IEM model.

In these figures, the proximity of the points to the line indicates better accuracy in roughness estimation. The Figure 2 shows that the accuracy of fractal geometry is better than Euclidean geometry.

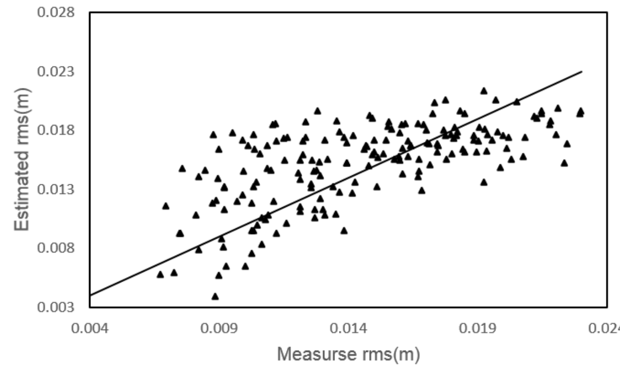

Figure 3: The comparison between the rms_height of the field, calculated by the Euclidian method and the corresponding estimated value by the IEM model.

11.Implementation of results on SAR data using fractal SPM model

In this method, surface roughness estimation is done using fractal electromagnetic model. The advantage of this method over other methods is that the rms_height value is estimated by the fractal model from the SAR image and the field roughness also is calculated by the fractal method.
One of the most important advantages of simulating with this model is its very high computational speed compared to the IEM model. In other words, this model is much less complicated than the IEM model. In some studies, this model has been used to estimate the fractal dimension on SAR images (Di Martino, Iodice , Ricc, & Ruello, 2010) . Another important advantage of this model is that by estimating the fractal dimension on SAR image, it is possible to separate the effect of roughness from the physical parameter (moisture) (Di Martino, Iodice, Riccio,, Ruello, & Zinno, 2018). One of the differences between this model and the IEM model is that the rms_height is not estimated directly, but the parameter *s* is estimated, and the rms_height is estimated using the equation 15. Therefore, in this method, the roughness of the surface is estimated and compared to the field values that calculated by fractal and Euclidean geometry.
Based on the results obtained from roughness estimation by fractal SPM, the accuracy of roughness estimation compared with Euclidean geometry, RMSE=0.0057m and bias=-0.0015m have been obtained. While comparing the roughness value estimated by this model with the ground values estimated by the fractal geometry method, RMSE=0.0031m and bias=-0.001 were obtained. Figures 4 and 5 show the comparison of the estimated rms_height by fractal SPM model and field roughness calculated by fractal and Euclidean methods. Comparing these figures shows that the accuracy of fractal geometry is better.
The comparison of all methods demonstrated that the best accuracy of roughness estimation was obtained by the fractal

SPM model and by comparing it with field roughness that calculated by the fractal geometry method. The accuracy of this method is about 22 percent better than the corresponding method in the IEM. The accuracy of roughness estimation using both models and comparing with Euclidean geometry is not much different and they are almost similar. About 47% higher accuracy is obtained from surface roughness estimation with the best method (SPM model and fractal geometry) than the worst method (fractal SPM method and Euclidean geometry). Figure 6 shows the accuracy values of all methods.

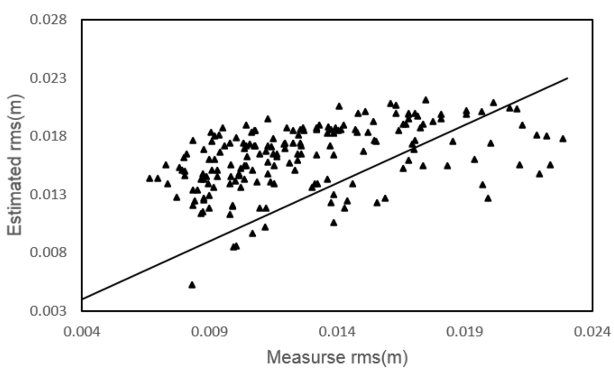

Figure 4: The comparison between the rms_height of the field calculated by the fractal method and the corresponding estimated value by the fractal SPM model

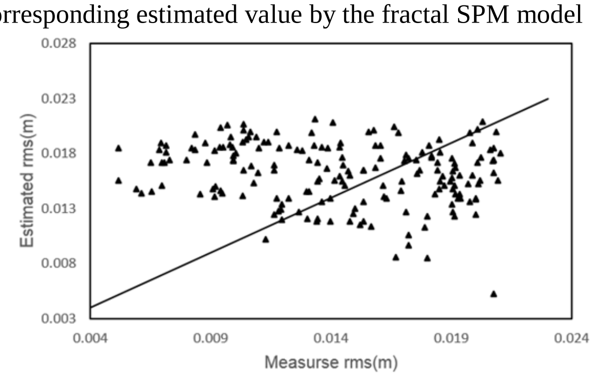

Figure 5: The comparison between the rms_height of the field calculated by the Euclidean geometry and the corresponding estimated value by the fractal SPM model.

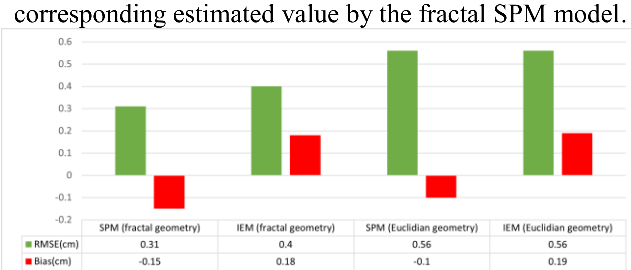

Figure 6: The diagram of RMSE and Bias values related to rms_height estimation for all methods

12.Conclusion

The main goal in this paper was to estimate the surface roughness from the X-band of SAR image using the inversion of the IEM and fractal SPM physical models. Inversion of both models was done using neural network. Roughness estimation using the fractal SPM model was less considered in previous studies. Considering the fractal nature of radar wave, it was expected that surface roughness retrieval would be done with higher accuracy. In order to evaluate the accuracy of the roughness estimated from the inversion of both models, the digital elevation model prepared by lidar data was used. Euclidean and fractal geometry methods were used to calculate field roughness.

The results showed that the accuracy of roughness estimation using the fractal SPM model is the most accurate when compared with the ground roughness calculated by the fractal method. While the worst accuracy is related to roughness estimation with the fractal SPM model when compared with ground roughness calculated with Euclidean geometry.

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