Modelling of surface roughness on agriculture area using Radarsat-2 satellite

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Abstract. This research aims to model surface roughness for agricultural land using RADARSAT-2 satellite imagery. To obtain the model of surface roughness, the digital number of radar image are converted into backscattering coefficient and used as basis of surface roughness modeling. Furthermore, using the relationship between the backscattering coefficient, local incidence angle, and the wavelength was made initial models for surface roughness. The new equation that can model surface roughness on agricultural land is obtained by performing calibration between the value of the surface roughness from initial models and combinations of initial models with the value of surface roughness from field measurement that the equation resulted

\[ y = -59.1987x^5 + (9.10^{6})x^4 - (6.10^{7})x^3 + (2.10^{8})x^2 - (3.10^{8})x + (2.10^{8}) \]

with RMSE value = 0.31 cm, where y is the value of surface roughness modeled (cm) and x is the surface roughness value of the combination of initial models used during the calibration process (cm). The combination of HV, VH polarisation and local incident angle \((h_0HV + h_0VH) \times \cos \Theta\) produces a correlation value \((R^2) = 0.804\).

1. Introduction

Surface Roughness is component of surface texture that determines how an object (real object) will interact with the surrounding environment. In this research the intention of surface roughness is soil surface roughness, particularly on rice farming land. Land surface roughness will be related to soil type, rainfall, and land use, for example for agricultural land, plantations, fields, or as settlements.

Generally, measurements of ground surface roughness are carried out directly in the field using a roughness meter or laser pin [1]. The advantage of this method is that the resulting value has a high level of accuracy. Nevertheless, this method also has several disadvantages, particularly in case it is used in a large area of research by taking consider to the fact that it requires a lot of time, cost, and energy so it is less effective and efficient. The measurement method that can overcome all these things is remote sensing technology. In remote sensing technology surface roughness has a large impact on the brightness, polarization, scattering angle, and wavelength that depends on the amount of energy emitted and reflected by the object [2].

Measurement of soil surface roughness on agricultural land in Indramayu District, West Java is carried out by microwave or radar remote sensing technology and field measurements using pin meters at several points as field data samples. The field measurement data is used as validation data on the value of surface roughness that obtained from satellite imagery of RADARSAT-2.

In this research, to acquire a model of surface roughness on agricultural land from RADARSAT-2 satellite imagery by using calibrating existing models and field data. The model of surface roughness acquired is expected to be
used as one of the parameters to determine the soil moisture level. The information about soil surface moisture distribution is highly significant for a number of applications ranging from agricultural management and natural resources to the science of understanding the interactions between land-atmosphere to determine vehicle mobility [3].

The problem that will be solved in this research is how to do surface roughness modeling on agricultural land using RADARSAT-2 satellite imagery and field sample data taken with pin meters at several points in the research area located in Indramayu District, West Java.

2. Data and Methods
To reach the research objectives, a research using radar remote sensing data and field measurements covering surface roughness and soil moisture was conducted in 2014. Modified Campbell - Shepard (1996) models were applied to the radar data for estimating surface roughness.

2.1. Data
There are eight consecutive fully polarimetric C-band Radarsat-2 images were acquired in repeat pass during the growing season in 2014. All of them were acquired with the same beam mode and orbit pass, in order to build a time series in the most consistent way (Table 1). The classification analysis was performed on June 18 2014 when the paddy was in the beginning of the heading growing stage, which was proved to be optimal for paddy identification in our four-temporal data set. Their acquisition periods cover the most critical growing stage of the crop, from its sowing to its harvest, as shown in Table 1. Original Radarsat-2 images were provided in single look complex (SLC) format with pixel size of 6.89 m and 4.83 m in azimuth and ground range directions, respectively.

| Study site  | Acquisition date | Beam Mode | Orbit   | Polarization | Inc. Angel | Product type |
|-------------|------------------|-----------|---------|--------------|------------|--------------|
| Indramayu 1 | 2014-06-04       | FQ24      | Ascending | HH+VH+VH+HV | 42.95      | SLC          |
| Indramayu 2 | 2014-06-18       | FQ12      | Ascending | HH+VH+VH+HV | 31.50      | SLC          |
| Indramayu 2 | 2014-08-05       | FQ12      | Ascending | HH+VH+VH+HV | 31.50      | SLC          |
| Indramayu 1 | 2014-08-15       | FQ24      | Ascending | HH+VH+VH+HV | 42.95      | SLC          |
| Indramayu 1 | 2014-09-08       | FQ24      | Ascending | HH+VH+VH+HV | 42.95      | SLC          |
| Indramayu 2 | 2014-09-22       | FQ12      | Ascending | HH+VH+VH+HV | 31.50      | SLC          |
| Indramayu 1 | 2014-10-02       | FQ24      | Ascending | HH+VH+VH+HV | 42.95      | SLC          |
| Indramayu 2 | 2014-10-16       | FQ12      | Ascending | HH+VH+VH+HV | 31.50      | SLC          |

2.2. Study Area
The study area is located in an agricultural area located in Indramayu district (Figure 1). The location of Indramayu district which stretches along the north coast of Java Islands makes the mean daily air temperature quite high 28°C Celsius. Indramayu Regency has become a national paddy barn with paddy yields reaching 1,700,000 tons per year while regional consumption is only 250,000 tons per year, making Indramayu one of the priority areas to succeed in food sovereignty programs according to the Indramayu district regional planning data, land use patterns consist of paddy field irrigation 116.7 ha, dry land 87.3 ha, and non-irrigation 92.8 ha. In West Java (West Java), Indramayu Regency ranks second as a paddy barn. Altitude region generally ranges between 0-18 m above sea level and the low lying areas ranges between 0-6 m above sea level that consists of swamps, ponds, paddy fields, yards. This condition is susceptible to drainage, when rainy season the low areas will be puddles and when the dry season it would be severely drought.
2.3. Field Survey
Sample data of field was measured by using a pin meter and GPS (Global Positioning System) handheld device, as shown in Figure 2. This sampling of soil surface roughness data was carried out at several points in the area that were the focus of the research. To obtain the value of soil surface roughness on agricultural land, the pin meter is placed on the embankments of paddy fields. Whereas the information of point position that concerned is given in the form of coordinates acquired using a handheld GPS. Each sample point of field measurement consists of 29 ground level data.

Figure 1. Research area in Indramayu District, West Java is shown by red rectangular of radarsat-2 acquisition paths, blue triangles are points of field survey and measurements [4]

Figure 2. The Pin meter to measure surface roughness at field [5]
2.4. Methodology

The method used in this research is modeling. Modeling is carried out to acquire a model that can be used to calculate the value of surface roughness on agricultural land. The model of surface roughness is acquired by conducting a calibration between the surface roughness values of the initial model or the combination of the initial model against the value of surface roughness resulting from the field measurements. The stages of the process can be described as follows:

1. **RADARSAT-2 image:** The RADARSAT-2 image used in this process has passed through a radiometric and geometric correction process for each polarization type HH, HV, VH, and VV.

2. **Extraction of Digital Number (DN) value:** Extraction of the DN value is carried out using image processing software. Taking consideration to the fact that the radar image used is Fine Quad-Pol, extraction is carried out for each type of polarization, namely HH, HV, VH, and VV.

3. **Conversion of DN values into backscattering coefficient:** DN values on radar images represent the value of the backscattering intensity of each image pixel in each polarization. Backscattering intensity is the value of the proportion of electromagnetic waves reflected back by the object and can be received by the sensor. This value is predisposed by several factors, namely type, shape, size, direction of reflection of the target, humidity of the target area, frequency, type of radar wave polarization, and local incidence angle. DN values that represent the backscattering intensity are used to obtain a backscattering value coefficient. The equation used to calculate the backscattering coefficient value from the DN value for RADARSAT-2 images in certain types of polarization is [6]:

\[
\sigma^\circ = 10 \times \log(DN^2)
\]  

The \(\sigma^\circ\) is a symbol for backscattering coefficient in decibels (dB) for certain types of polarization (HH, HV, VH, or VV), and DN is a symbol for digital number.

4. **Preparation of initial surface roughness models:** The backscattering coefficient (\(\sigma^\circ\)) value is then converted into an initial model (\(h_0\)) using the relationship between wavelength (\(\lambda\)), backscattering coefficient HV (\(\sigma^\circ_{HV}\)), and local incidence angle (\(\Theta\)) as in the equation 2 of the following [2]:

\[
H_o (\lambda)_{HV} = \lambda \left[ - \frac{1}{60} \ln \left( 1 - \frac{\sigma^\circ_{HV}}{0.04 \cos \Theta} \right) \right]^{0.5}
\]  

The \(h_o(\lambda)\) is the value of soil surface roughness (cm), \(\lambda\) is a symbol for the wavelength used by the satellite RADARSAT-2 with a value of 5.6 cm, \(\sigma^\circ_{HV}\) is a symbol for the backscattering coefficient value of an image with the polarization type HV (dB), and \(\Theta\) are symbols for the local incidence angle (degrees).

The initial model in equation 2 only uses the HV polarization type. This point can be known from the backscattering coefficient value used, namely \(\sigma^\circ_{HV}\). Whereas the satellite imagery used in this thesis research uses four types of polarization, namely HH, HV, VH, and VV. Accordingly to determine the effect of other types of polarization, modifications to equation 2 are carried out. The alteration is carried out on the backscattering coefficient value \(\sigma^\circ_{HV}\) are altered to be the backscattering coefficient values of the polarization types HH, VH, and VV, namely \(\sigma^\circ_{HH}\), \(\sigma^\circ_{VH}\) and \(\sigma^\circ_{VV}\). The equation of the initial model is as follows:

\[
H_o (\lambda)_{HH} = \lambda \left[ - \frac{1}{60} \ln \left( 1 - \frac{\sigma^\circ_{HH}}{0.04 \cos \Theta} \right) \right]^{0.5}
\]
\[ H_0(\lambda)_{\text{HH}} = \lambda \left[ -\frac{1}{60} \ln \left( 1 - \frac{\sigma_{\text{HH}}^0}{0.04 \cos \Theta} \right) \right]^{0.5} \] (4)

\[ H_0(\lambda)_{\text{VH}} = \lambda \left[ -\frac{1}{60} \ln \left( 1 - \frac{\sigma_{\text{VH}}^0}{0.04 \cos \Theta} \right) \right]^{0.5} \] (5)

Where:

\( h_0(\lambda)_{\text{HH}} \): the surface roughness value of the polarization type HH (cm);

\( h_0(\lambda)_{\text{VH}} \): the surface roughness value of the polarization type VH (cm);

\( h_0(\lambda)_{\text{VV}} \): the surface roughness value of the polarization type VV (cm);

\( \lambda \): wavelength (5.6 cm);

\( \Theta \): local incidence angle (derajat);

\( \sigma_{\text{HH}}^0 \): backscattering coefficient value of the polarization type HH (dB);

\( \sigma_{\text{VH}}^0 \): backscattering coefficient value of the polarization type VH (dB);

\( \sigma_{\text{VV}}^0 \): backscattering coefficient value of the polarization type VV (dB).

5. **The model of initial surface roughness**: This initial model is used to acquire new equations that can describe surface roughness according to field conditions. The new equation is obtained by calibrating the initial model with field measurement data. Calibration is carried out by plotting the roughness value of the initial model against the field measurement data for the corresponding points. Furthermore, a regression is performed to acquire a calibrated equation from the initial model which is expected adequate to model surface roughness on agricultural land. The calibrated equation that chosen is the one that has the closest correlation value to 1.

This research data collection was carried out on four different dates in two months, September and October. To obtain a calibrated equation with a higher level of accuracy accordingly during the calibration process, the data used is divided into three parts. First, all existing data is used in the calibration process. Second, the data used in the calibration process is only in the same month, that is the data only in September and the data for October alone. Third, the data used in the calibration process is selected according to the date of image capture. This is not only carried out on the initial calibration model of field measurements, but also on the calibration process of the combination of initial models and the influence of the local incidence angle.

6. **Preparation of Initial Model Combinations**: Preparation of Combination Model Initial values of surface roughness results from field measurements. The initial predetermined model equation is used as the basic equation in the preparation of the initial model combination.

3. **Result and Discussion**

The basic equation used to compile the initial model is the equation found by Campbell and Shepard (1996) [2] which utilizes the relationship between the backscattering coefficient HV (\(\sigma_{\text{HV}}^0\)), local incidence angle (\(\Theta\)), and wavelength (\(\lambda\)) to calculate the roughness value ground level (\(h_0\)). Forth, a combination arrangement between initial models of different polarization types is carried out to acquire a calibrated equation with a correlation value close to 1, therefore it can be used to model surface roughness on agricultural land. Because between initial models of different types of polarization have relationships that are positively correlated with each other then a trial is conducted to combine it using mathematical operations. The mathematical operations used in this trial include the operation of the addition, subtraction, division, and multiplication of two or more initial models with different types of polarization. The local incidence angle is the magnitude of the slope angle of the satellite radar system when recording objects. To identify whether the local incidence angle influences the modeling of soil surface roughness, modifications are made to exist combinations of initial models by adding the
functions of sin, cos, and tan from the local incidence angle. The equation of the initial model combination with the influence of the local incidence angle used in the trial is given in Table 2.

The roughness value produced from the combination of initial models then calibrated with field measurement data to acquire a calibrated equation that can be used in modeling surface roughness. The trial results from the combination of initial models by adding the influence of the local incidence angle. Based on Table 3, it can be known that the correlation values of the seven data groups are higher but some are lower. The addition of the influence of angle’s local incidence on a combination of initial models had the most significant impact on the increase in correlation values. The calibration results with the highest correlation values are given by the combination of initials HV, VH, and the effect of $\cos \theta$ with a correlation value of 0.8042, calibrated of equation, and the combination of initial models for each data group can be seen in Table 3. Where $y$ is the surface roughness value (cm) and $x$ is the surface roughness value of the initial model combination (cm).

Based on the results of processing the data above, it can be seen that the calibrated equations that can model surface roughness well are those processed for data acquisition. This happens by reason of there are other influences that are not calculated in modeling, namely the influence of weather and human activities (farmers). Weather highly takes affects to the value of surface roughness on agricultural land. In case rain ensues, the surface roughness value will decrease, but if the weather is hot, this will increase the value of surface roughness. Human activities, particularly farmers who are carried out on agricultural land can also affect the value of surface roughness. Taking consideration to the fact that the agricultural land is a dynamic area and often cultivated by farmers, this will cause the value of surface roughness changes. Activities that can affect the value of surface roughness can be in the form of irrigation, paddy field hijacking, planting, harvesting, and planting periods.

| No. | Combination of Initial Models |
|-----|-----------------------------|
| 1   | $h_0_{\text{VH}} \times h_0_{\text{HV}} \times h_0_{\text{VV}} \times \sin \theta$ |
| 2   | $h_0_{\text{VH}} \times h_0_{\text{HV}} \times h_0_{\text{VV}} \times \cos \theta$ |
| 3   | $h_0_{\text{VH}} \times h_0_{\text{HV}} \times h_0_{\text{VV}} \times \tan \theta$ |
| 4   | $h_0_{\text{HV}} \times h_0_{\text{VH}} \times \sin \theta$ |
| 5   | $h_0_{\text{HV}} \times h_0_{\text{VH}} \times \cos \theta$ |
| 6   | $h_0_{\text{HV}} \times h_0_{\text{VH}} \times \tan \theta$ |
| 7   | $h_0_{\text{HH}} : h_0_{\text{VV}} \times \sin \theta$ |
| 8   | $h_0_{\text{HH}} : h_0_{\text{VV}} \times \cos \theta$ |
| 9   | $h_0_{\text{HH}} : h_0_{\text{VV}} \times \tan \theta$ |
| 10  | $h_0_{\text{VH}} : h_0_{\text{VV}} \times \sin \theta$ |
| 11  | $h_0_{\text{VH}} : h_0_{\text{VV}} \times \cos \theta$ |
| 12  | $h_0_{\text{VH}} : h_0_{\text{VV}} \times \tan \theta$ |
| 13  | $(h_0_{\text{HH}} - h_0_{\text{VV}}) \times \sin \theta$ |
| 14  | $(h_0_{\text{HH}} - h_0_{\text{VV}}) \times \cos \theta$ |
| 15  | $(h_0_{\text{HH}} - h_0_{\text{VV}}) \times \tan \theta$ |
| 16  | $(h_0_{\text{HV}} + h_0_{\text{VH}}) \times \sin \theta$ |
| 17  | $(h_0_{\text{HV}} + h_0_{\text{VH}}) \times \cos \theta$ |
| 18  | $(h_0_{\text{HV}} + h_0_{\text{VH}}) \times \tan \theta$ |
### Tabel 3. Correlation results for all data groups

| Kelompok Data | Correlation (R²) | Model Combination | Calibrated Equation |
|---------------|------------------|-------------------|---------------------|
| 1             | 0.214            | \((h_0HV+h_0VH)x \cos \Theta\) | \(y=811.89x^5 - 12165x^4 + 72747x^3 - 21705x^2 + 322934x - 191756\) |
| 2             | 0.415            | \((h_0HV+h_0VH)x \cos \Theta\) | \(y=2634.3x^5 - 39963x^4 + 242160x^3 - 732654x^2 + (10^6)x - 667773\) |
| 3             | 0.442            | \(h_0HVh_0HV\times h_0VV\) | \(y=42.61x^5 - 1387x^4 + 18024x^3 - 116884x^2 + 378225x - 488568\) |
| 4             | 0.644            | \((h_0VH+h_0VV)x \cos \Theta\) | \(y=(2.10^5)x^5 - (8.10^5)x^4 + (10^6)x^3 - (9.10^5)x^2 + (3.10^4)x - (5.10^7)\) |
| 5             | 0.804            | \((h_0HV+h_0VH)x \cos \Theta\) | \(y=-591987x^5 + (9.10^5)x^4 - (6.10^7)x^3 + (2.10^5)x^2 - (3.10^4)x + (2.10^5)\) |
| 6             | 0.648            | \((h_0HV+h_0VV)\) | \(y=7980.2x^4 - 119392x^3 + 669642x^2 - (2.10^7)x + (2.10^4)\) |
| 7             | 0.605            | \((h_0VH+h_0VV)x \cos \Theta\) | \(y=(4.10^5)x^4 - (2.10^7)x^3 + (2.10^7)x^2 - (10^7)x + (3.10^4)\) |

### 4. Analysis

Calibrated equations generated from the processing of RADARSAT-2 satellite image data and field measurement samples can be used in modeling surface roughness on agricultural land. Nevertheless, the results obtained indicate that the equations that can be used to model surface roughness are different for each data processing group as shown in Table 3. According to Table 3, it can be seen that each data group provides a calibrated equation with different correlation values, different initial models, and different levels of accuracy.

The results of processing the data are possibility influenced by several factors, namely the used of satellite imagery resolution, measurement of field data samples, modeling processes, and parameters that affect the value of surface roughness on agricultural land. The first factor sourced from the lack of satellite image resolution data with field measurements that carried out. The RADARSAT-2 satellite image used in this research has a spatial resolution of 8 m x 8 m for each image pixel. Whereas the meter pin is used to make direct measurements in a field measuring 30 cm x 30 cm. According to this, it can be known that field measurement data cannot represent the value of surface roughness in each pixel of satellite imagery. An area measuring 8 m x 8 m is less appropriate if it only represented by one field measurement using a tool measuring 30 cm x 30 cm. In addition, the measurement of surface roughness directly in the field is carried out in the embankments of rice fields. The selection of these objects is considered inappropriate taking consideration to the fact that the general area is in the form of agricultural land, with the result that sampling should be carried out on the farm.

The second factors, is highly closely related to parameters that affect the value of surface roughness. Reckon that the surface roughness is a component of dynamic, there are several factors that influence it, namely soil type, rainfall, land use, and human activity. Parameters that related to rainfall and human activities in this final project are not taken into account in making a model of surface roughness. This is because these parameters are difficult to estimate their value, particularly those related to human activities that are closely related to the activities carried out by farmers on the rice fields.
5. Conclusion
The correlation value generated by the calibration process of the combination of initial models from several different types of polarization is much higher than the calibration process of the initial model that uses only one type of polarization. This shows that quad-polarization radar imagery is better than single polarization to model surface roughness. It was also found that the combination of initial models with HV and VH polarization types generally gave the best modeling results. Local incidence angle also affects the process of modeling surface roughness using radar images. This can be seen from the increasing correlation value in several combinations of initial models after adding the influence of local incidence angle.

According to the results of data processing that has been done, it acquired the best equations that can be used to model surface roughness on rice farming land in Indramayu District, West Java. The equation is

\[ y = -591987x^5 + (9.10^6)x^4 - (6.10^7)x^3 + (2.10^8)x^2 - (3.10^8)x + (2.10^8) \]

with RMSE value = 0.31 cm, where \( y \) is the value of surface roughness modeled (cm) and \( x \) is the surface roughness value of the combination of initial models used during the calibration process (cm). The combination of Initial Model \( (h_0_{HV}+h_0_{VH})x \cos \Theta \) produces a correlation value \( (R^2) = 0.804 \).

This research can be used as supporting data for other researches that related to surface roughness or rice cropland. The method used in this research can also shorten the time, save costs, and minimize the used of amount of human resources.

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