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Surface Soil Moisture Estimation Using Synthetic Aperture Radar Data

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ABSTRACT

A study was conducted to evaluate the potential of RADARSAT data for the estimation of surface soil moisture status of Chevella watershed, Hyderabad. A regression equation was developed between RADARSAT backscatter and surface soil moisture content (%v/v) at 0-5, 5-10 and 0-10 cm depths. Validation of the model showed that for surface 0-5cm depth the root mean square error (RMSE) was 4.0%, that for 5-10 cm depth was 5.0% and that for 0-10cm depth was 4.3% respectively. Results are discussed.

Key words: RADARSAT, Backscatter, Soil moisture, regression model, Validation

Introduction

Soil moisture is a key variable for many applications pertaining to agriculture, vegetation monitoring, meteorology and weather prediction, hydrology and stream flow predictions. Soil moisture estimations help in modeling yield forecasts, scheduling irrigations and other farm management activities. It is an important link between land and the atmosphere, directly influencing the exchange of heat and moisture between these two links and as such, is an important element in the global circulation process. For hydrological and atmospheric sciences, soil moisture is particularly important for the modeling of surface processes such as soil-vegetation-atmosphere interactions, which involve water and energy exchanges. In particular, mean surface soil moisture plays an important role in evaporation and evapotranspiration, rainfall partitioning between surface runoff and infiltration and control of infiltration from surface soil reservoir to deeper reservoirs (Quesney *et al.*, 2000).

Although conventional ground based soil moisture measurement techniques such as neutron probe, time domain reflectometry (TDR), and gravimetric methods are accurate enough and permit measurements of entire soil profile; they are essentially point-based measurements at a specific time (Sano *et al.*, 1998). However soil moisture is often somewhat difficult to measure accurately in both time and space, especially over large areas. This is linked to variability of precipitation and heterogeneity of the land surface like vegetation, soil physical properties, topography etc (Owe *et al.*, 2001). Because of this variability, point measurements have limited meaning. On the other hand it is difficult to conduct ground-based measurements of soil moisture over a consistent and widespread base (Bindlish and Barros, 2000).

Remote sensing techniques with its advantage of synoptic view and high repeativity are helpful in measurement and monitoring of soil moisture status over large areas on a consistent basis. Unlike optical sensors, satellite systems with Synthetic Aperture Radar (SAR) sensors offer round the clock, year round coverage of earth's surface, independent of cloud cover and illumination conditions. Cloud cover and moderate rain do not appreciably attenuate the signals. This is advantageous in polar and tropical areas where cloud cover and rain are present for the most of the year. The measurement of soil moisture using microwave sensors is based on the large contrast between the dielectric properties of dry soil and water. As the soil gets moistened its dielectric constant varies from approximately 2.5 when dry to about 25-30 under saturated conditions (Narayanan and Hirsave, 2001). This variation leads to an increase in reflected energy by about 8 dB for wet soils compared to dry soils, making Synthetic Aperture Radar (SAR) data sensitive to soil moisture (Engman and Chauhan, 1995).

Methodology

The study area is Chevella watershed, approximately 35km away from Hyderabad. Total area of the watershed is 10,842.8 ha. Survey of India (SOI) toposheet of the area is 56K/3. The latitude of the area is $17^0 15'$ to $17^0 30'$ N and the longitude is $78^0 0'$ to $78^0 15'$E. The region comes under hot semiarid ecosystem (K6D2) and both red and black soils are present in this area. Length of growing period is 90-150 days. The watershed is rain fed and main crop of the area was maize. However in some areas rice, cotton, floricultural crops and vegetables were cultivated. There were 19 soil units in the watershed and the total number of soil unit polygons was 628. Each soil unit polygon was given a number and the last two digits of the number represent the serial number of the soil unit polygon in a particular soil unit.

Satellite data used was RADARSAT SAR data, which is operated by Canadian Remote Sensing Agency. RADARSAT provides data in C-band and HH polarization. The RADARSAT backscatter image was filtered using a median filter with a 5x5 window so as to reduce the speckle noise related to the variability of radar backscattering coefficient (Baghdadi *et al.,* 2002). Volumetric soil moisture content was determined for different locations on the date of satellite pass. Regression equation was fitted between radar backscatter and the volumetric moisture content. This equation was inverted to convert the backscatter image to a soil moisture map. Dielectric constant (ε) of soil was calculated using the equation given by Hallikainen (1985):

$$\varepsilon = (a_0+a_1S+a_2C) + (b_0+b_1S+ b_2C)\, m_v + (c_0+c_1S+c_2C)\, m_v^2 \qquad \text{—(1)}$$

Where m_v is the volumetric soil moisture content, S is percentage of sand, C is percentage of clay, and a_i, b_i, c_i are coefficients which depend on frequency. The dielectric constant thus calculated was used to derive the smooth surface Fresnel reflectivity coefficient (R_h) for C-band HH polarization data using the equation (Ulaby *et al.*, 1982):

$$R_h = \frac{\cos\theta - [\,\varepsilon\,(1 - \sin^2\theta)\,]^{1/2}}{\cos\theta + [\,\varepsilon\,(1 - \sin^2\theta)\,]^{1/2}} \qquad \text{—(2)}$$

where θ is the look angle. The Fresnel reflectivity coefficient thus calculated was converted to backscatter (dB) by taking 10 log (R_h). These values were taken as the backscatter values for smooth soil surface and it was compared with the observed backscatter values to analyze for the effect of roughness.

Results and Discussion

Soil moisture is a critical environmental parameter in rain fed agriculture. It is highly responsive to individual rainfall events and seasonal variations in precipitation and evapotranspiration. Hence accurate methods of assessment and monitoring of soil moisture is needed for better utilization of soils for crop production. In arid and semiarid areas the most important limiting factor is water availability. Agricultural development in such areas is to be done taking into account the availability of water in the region (Tansey *et al.,* 2001). Synthetic Aperture Radar that provides a remote sensing tool to estimate soil moisture in large areas like a watershed, could be utilized for proper water management in such areas.

One of the main confounding factors in determining soil moisture from SAR data is surface roughness. This is due to the fact that roughness affects the reflectivity of the surface. But in case of C-band HH polarization data, the effect of roughness on backscatter was found to be only 6%. When shorter wavelengths are used, surface roughness can be considered effectively constant through out the region, where similar agricultural practices are followed (Geng *et al.,* 1996). As long as the roughness remains more or less constant, sensitivity of soil moisture does not depend much on the absolute value of the roughness (Taconet *et al.,* 1996). Different curves representing the backscattered signal intensity versus soil moisture content, for different soil roughness values mainly differ by their offset value. An increase (decrease) of soil roughness would induce a positive (negative) translation of the curves representing backscatter versus soil moisture (Quensey *et al.,* 2000).

With these facts, the roughness in the study area (Chevella watershed) was assumed to be constant through out the region, and its effects on soil moisture retrieval was considered negligible (Geng *et al.,* 1996). The volumetric soil moisture content was determined for 0 - 5cm and 5 - 10cm depth. This was plotted against RADARSAT backscatter values and the results are given in the Figs. 1, 2 and 3.

It can be seen from the figure that that the upper 0-5 cm layer soil moisture gave a good relation with the observed backscatter than the 5-10 cm layer. For 0-5 cm depth, the R^2 value was 0.72 and the slope of the curve was 0.19. For 5-10 cm depth, the R^2 value was 0.57 and the slope of the curve was 0.17. The 0-5cm layers gave a better result, which is obvious because depth of penetration of the C-band is limited to the top thin layer of soil. The layer of soil that could be sensed

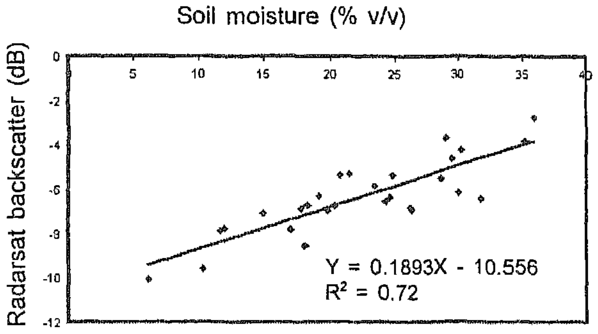

Fig. 1. Relationship between soil moisture (0-5 cm) and RADARSAT backscatter

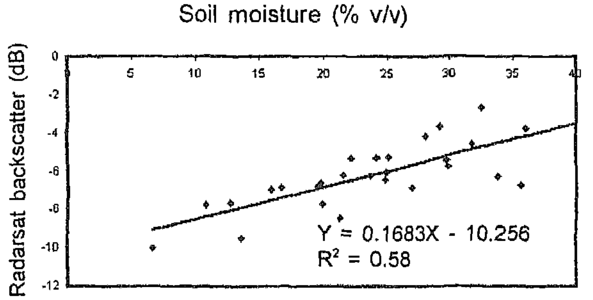

Fig. 2. Relationship between soil moisture (5-10 cm) and RADARSAT backscatter

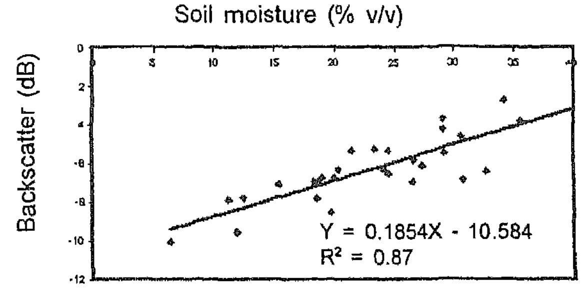

Fig. 3. Relationship between soil moisture (0-10 cm) and RADARSAT backscatter

was found to be in the order of a tenth of a wavelength or less (Wilheit, 1975). The C- band wavelength is approximately 6cm, and hence we can expect the wave to penetrate to a maximum depth of 1cm. This explains why the surface layer soil moisture gave a better relation than the 5-10cm layer soil moisture with the observed radar backscatter. However, because of the continuity of soil moisture condition to the 5-10 cm depth, still a low correlation with backscatter was observed. When the 0-10cm soil was considered as a single unit, (Fig. 3) a better relation was obtained (R^2 = 0.67 and slope = 0.18) compared to 5-10 cm depth. This improvement in the relation can be attributed to averaging effects and the relation between surface (0-5 cm) soil moisture content and the total moisture content of 0-10 cm depth.

Beaudoin *et al.*, (1990) reported that for soil moisture retrieval, a sensitivity of $0.22\text{dB}/0.01\text{cm}^3/\text{cm}^3$ at C-band HH polarization can be obtained. But in the present study it was only $0.19\text{dB}/0.01\text{cm}^3/\text{cm}^3$. This slight decrease in sensitivity may be due to the some other interfering parameters. The regression equation developed for 0-5 cm depth was inverted to derive the soil moisture map of the Chevella watershed from RADARSAT data and is given Plate 2.

The regression model obtained was validated using another set of field observed soil moisture content. But the RADARSAT data used was the same (Figs. 4, 5 and 6). The top layer (0-5 cm) gave least RMSE of 4.0%, 5-10 cm layer gave an RMSE of 5.0% and for the 0-10cm it was 4.3%. 0-5 cm layer gave the best RMSE because the regression equation for that particular depth was the best one out of the three possibilities. The same is the reason why the 0-10 cm layer gave the next best RMSE followed by 5-10 cm layer. For a soil moisture estimation study, using a linear regression equation involving L- and C- band data, Narayanan and Hirsave (2001) got RMSE of 3.58%, 3.6% and 5.1% for surface, middle and bottom layer soil moisture estimates. Their results can be attributed to the use of L-band, which have higher penetration into the soil through vegetation. Moreover the additional information from C-band could have also helped in a better performance.

To study the effect of roughness on backscatter in this particular watershed, the backscatter from smooth surface was considered. The backscatter for smooth surface was obtained by estimating the dielectric constant of the soil and incorporating it in the equation for estimating the backscatter. The dielectric constant of the soil was obtained using the Hallikainen model (1985) where in the parentage of sand, clay and volumetric soil moisture content are considered. The dielectric constants thus calculated were used to derive the smooth surface Fresnel reflectivity coefficient (R_h) for C-band HH polarization (Ulaby *et al.*, 1982). The additional input into this model was look angle. The Fresnel reflectivity coefficient thus calculated was converted to backscatter (dB) by taking 10 log (R_h). The backscatter values thus obtained represent the backscatter from a smooth surface. These were plotted against the observed soil moisture, which

Plate 1. Masked RADARSAT backscatter image of Chevella watershed

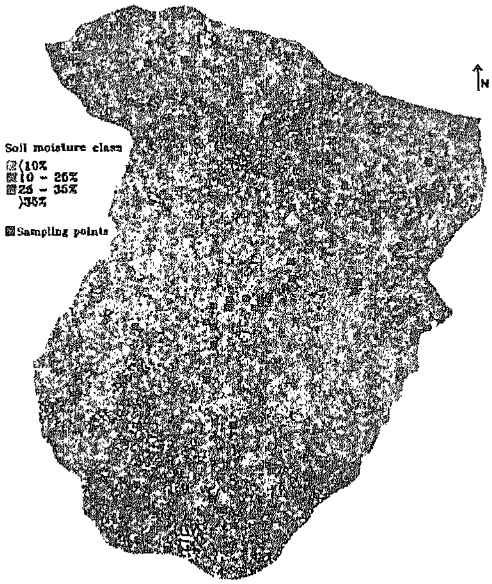

Plate 2. Surface soil moisture (% v/v) map of Chevella watershed derived from RADARSAT data

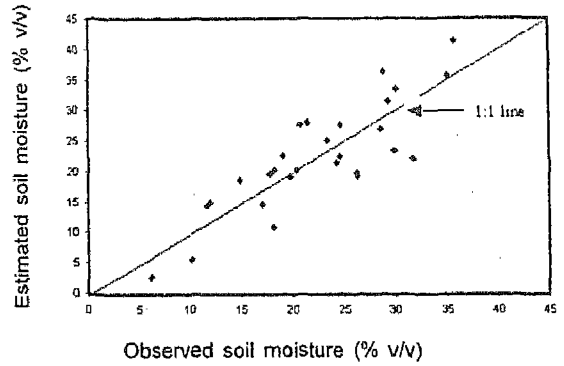

Fig. 4. Validation of soil moisture (0-5 cm) and RADARSAT backscatter relationship

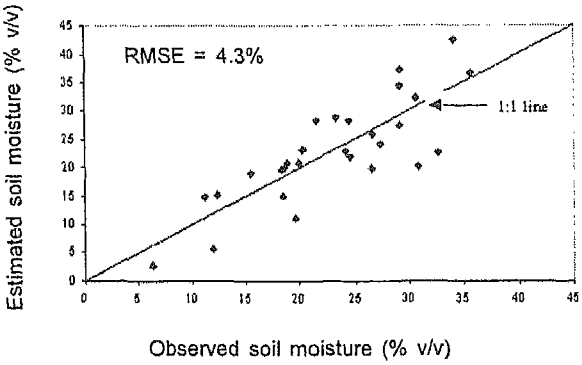

Fig. 6. Validation of soil moisutre (0-10 cm) and RADARSAT backscatter relationsip

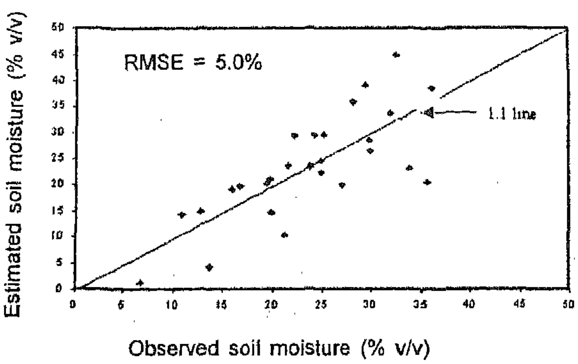

Fig. 5. Validation of soil moisutre (5-10 cm) and RADARSAT backscatter relationsip

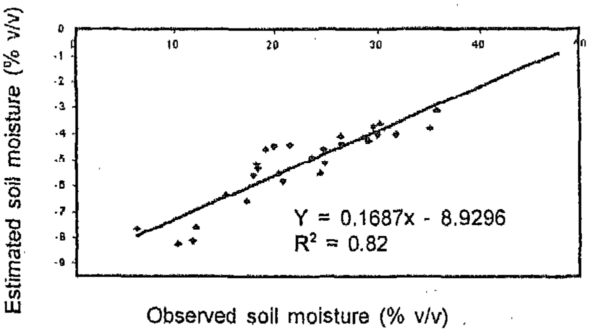

Fig. 7. Relationship between modeled backscatter (for smooth soil surface differing in texture) and soil moisture at 0-5 cm depth

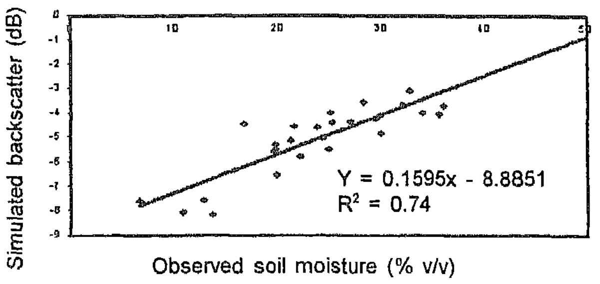

Fig. 7. Relationship between modeled backscatter (for smooth soil surface differing in texture) and soil moisture at 5-10 cm depth

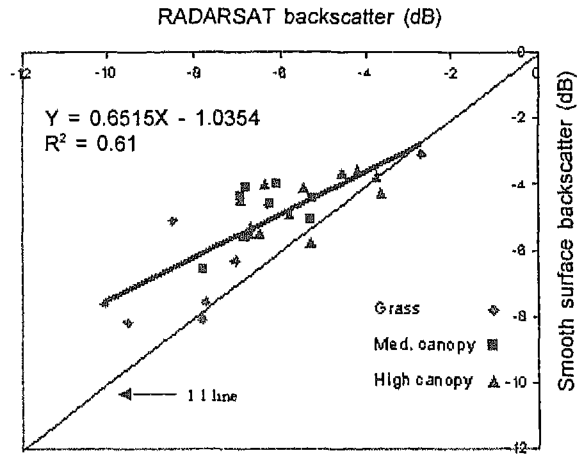

Fig. 9. RADARSAT backscatter vs. Smooth surface backscatter

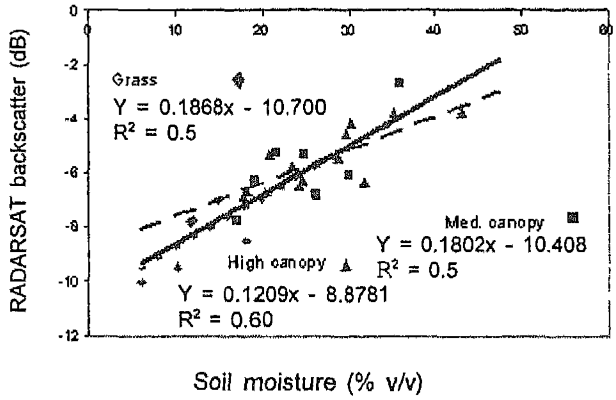

Fig. 10. RADARSAT backscatter vs. Soil moisutre (0-5 cm) under different land cover types

includes effects due to roughness and other interfering parameters (Figs. 7 and 8). The simulated backscatter values are already adjusted to the variations in texture of the soil, resulting in better relationship between soil moisture and backscatter. The R^2 value for 0-5 cm depth was 0.82 and that for 5-10 cm depth was 0.74 (R^2 values incase of RADARSAT backscatter versus soil moisture were 0.72 and 0.57 respectively). Moreover there is an increase in the intercept value in both the depths. In case of 0-5 cm depth intercept value increased from -10.56 to -8.93 and in case of 5-10 cm depth it increased from -10.26 to -8.89. Had there been any surface roughness effect, the intercept values should have reduced for regression equation developed using simulated backscatter values. So the slightly poor relation in the first set of regression equations developed using observed backscatter might have caused by the effect of vegetation and the roughness introduced by vegetation.

Vegetation decreases the sensitivity of the backscatter coefficient to soil moisture due to increased scattering and attenuation of the signal (Tansey *et al.*, 2001). Moreover, canopies contain moisture of their own that will complicate the relationship between backscatter and soil moisture. In this study it appears that the vegetation has attenuated the signal. This is the reason why a lower intercept value was obtained for regression equations using observed radar backscatter. But the effect of vegetation on observed backscatter can vary depending on the factors including dielectric constant of the vegetation, size shape and orientation of the scatterers in the canopy, and the geometry of the canopy itself (row direction and spacing, cover fraction etc.). In the case of maize, at higher viewing angles, the backscattering contribution of the canopy increases and is dominated by return from vertically aligned stalks and cobs, where as the canopy loss component is dominated by the leaves (Ulaby *et al.*, 1986). However, significant correlations are still found between radar backscatter and soil moisture for stubble and vegetated fields, which indicates that the soil surface moisture condition still dominates in governing σ^0 from the fields (Boisvert *et al.*, 1995).

To differentiate the contributions of soil moisture and vegetation to backscatter, a linear multiple regression equation was fitted taking backscatter as dependent variable and soil moisture at 0-5 cm depth and NDVI (Normalised Difference Vegetation

Index) as independent variables. Here NDVI is considered so as to characterize the vegetation. The equation developed was $Y = 0.1641*SM^2 + 0.0031*NDVI - 10.2045$. However, there was no improvement in the R^2 value ($R^2 = 0.68$ compared to 0.72 for the equation considering soil moisture alone), rather it decreased. Though it is believed that there is effect of vegetation on backscatter, this lowering of R^2 value indicate that NDVI does not characterize vegetation in terms of soil moisture radar backscatter relationship.

A 1:1 plot was done between RADARSAT backscatter and simulated backscatter values for a smooth surface derived using Fresnel equation (Ulaby *et al.*, 1982) and the result is presented in the Fig 9. It can be seen that at higher backscatter levels, the observed values are coming closer to the theoretical values. But at lower backscatter levels, model is giving higher backscatter values than the observed values. The scatter points indicate that in general, backscatter values obtained for a smooth surface overestimated the observed values (lower negative values) of the observed backscatter values.

From the ground truth information, the vegetation types were categorized into three, namely high canopy (maize), medium canopy (rice, tomato, crossandra) and grass (open land and short grass). The backscatter was plotted against each of these categories and given in the Fig. 10. It can be seen from the figure that there was no separate trends for different categories. The R^2 value for high canopy was 0.63 that for medium canopy was 0.5 and that for grass was 0.54. So there is no improvement in the relation between backscatter and moisture content after categorizing the points into different vegetation types. From the figure it can be seen that all the points have fallen into a linear trend only, disregarding the vegetation types based on height. It can be seen that all the vegetation types followed a common trend. Hence it appears that while backscatter is dominantly controlled by soil moisture, the little contribution from vegetation is not explained by canopy height and the roughness caused by vegetation.

The soil surface zone is very important in hydrological cycle because this is the place where interaction of atmospheric water with lithosphere takes place. This is the place where the complex partitioning between rainfall, infiltration, runoff, evapotranspiration and deep seepage is initiated and sustained. Information regarding the varying moisture content of soil's surface zone is of particular interest. This thin layer of soil may contain only a small amount of water, compared to the total amount of water on earth, but it is indicative of the entire interaction between the land surface and the atmosphere. Moreover, topsoil moisture affects seed germination, subsequent plant growth and ultimately the productivity of both natural and managed ecosystems (Hillel, 1998). Due to atmospheric demand, the soil surface dries during the daytime and then tries to regain moisture from deeper layer by way of sorption from the moist layers beneath. The amplitude of this fluctuation of moisture diminishes with depth and time and the phase lag increases at greater depths (Jackson *et al.*, 1973). Hence there is a need to monitor the surface moisture contents that exhibit greater variation than the moisture content of the deeper layers, which is of particular importance to agriculture. In this scenario, surface soil moisture estimation technique using SAR data attains importance, though SAR data has limited penetration.

Conclusion

SAR is a very good tool for estimating the surface soil moisture over large areas. The model developed between RADARSAT backscatter and volumetric moisture content gave an R^2 value of 0.72 with a regression coefficient of 0.19, for 0-5 cm depth. The values for 5-10 cm and 0-10 cm depth were 0.58 and 0.17 and 0.67 and 0.18 respectively. The lower R^2 values could be due to the effect of surface roughness to which microwaves are sensitive. Validation of the regression model developed showed that for surface 0-5 cm depth, the RSME was 4.0% moisture (v/v). That for 5-10 cm and 0-10 depths was 5.0% and 4.3% respectively. The smooth surface backscatter derived using the Hellikainen model and Fresnel equation gave better relationship with soil moisture content. In this case the R^2 value improved to 0.82 for 0-5 cm depth and 0.74 for 5-10 cm depth. 1:1 plot between RADARSAT backscatter and simulated backscatter values for a smooth surface derived using Hellikainen and Fresnel equations indicate that in general, backscatter values obtained for a smooth surface overestimated the observed RADARSAT backscatter values (lower negative values). From the ground truth information, the vegetation types were categorized into three classes based on the height of canopy, namely high canopy (maize), medium canopy (rice, tomato, crossandra) and grass (open land and short grass). The backscatter was plotted against each of these categories. But no specific trends for different categories depending on their canopy heights were noticed. (The R squared value for high canopy was 0.63 that for medium canopy was 0.5 and that for grass was 0.54). NDVI could not characterize the vegetation in terms of soil moisture radar backscatter relationship.

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