Combining the Optical and Microwave Remote Sensing Indices for Soil Moisture Assessment: An Empirical Study

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Abstract
Radar and Optical sensor integration combines traditional space-borne optical data from the visible and infrared wavelengths with the longer wavelengths of radar to improve land cover classification and the potential of land use classification. Optical data gives the details of vegetation and microwave data on the other hand provide the texture and terrain characteristics. The indicators of vegetation stress in optical include NDVI analysis and texture and Dielectric Constant of microwave. The LISS III data for optical and EnviSAT ASAR data for backscattering coefficient and dielectric constant were used. Soil Moisture plays an important role in the interactions between the land surface and the atmosphere. Soil moisture is a highly variable component in land surface hydrology and plays a critical role in agriculture and hydrometeorology and has been found not easy to map with only optical data. Therefore, a study to fit a mathematical equation to relate soil moisture condition and the micro wave parameters in a part of Cumbum valley in south west Tamil Nadu. The optical vegetation stress indicators were studied along with the micro wave parameters were analyzed to judge upon the vegetation stress. The present work is to have synergetic use of the bands from both optical and microwave data which are quite complementary in nature. The optical and microwave data are processed using separate tools. An index called Soil Moisture Index function was generated for the estimation of the wet and dry nature of the soil. The NDVI image was generated and it was cross verified with land cover of the study area. As the NDVI is a consistent parameter of vegetation stress, this image was used as the base for the soil moisture equation. The dielectric constant generated from the back scatter image was referenced with the NDVI image. From the generated back scatter and dielectric constant values, soil moisture index was estimated. Regression and correlation analysis was carried out for the prediction of the values and the error estimation of the generated empirical relation of BSC and DC with respect to the SMI. The result showed a good agreement of dielectric constant with soil moisture index yielding R^2=0.958 and for backscatter and soil moisture index yielding R^2=0.694 for the generated SMI relation. A map was generated to indicate the soil moisture across space. It is observed that an empirical relation between the dielectric constant and the soil moisture stress is possible to draw by correlation and the study has to be perfected with more critical field observed data.

1. Introduction

The field of remote sensing is a continuously growing market with applications like mapping, monitoring and assessing of various observations in and around the earth. The increase in applications is due to the invention of various satellite images from different sensors and the intense of optimal utilization of the resources. Optical data gives the details of vegetation and microwave data on the other hand provide the texture characteristics and soil information. The vegetation parameters like NDVI from optical data and the dielectric constant and texture from microwave data can be the useful tools for environmental assessment. Soil Moisture plays an important role in the interactions between the land surface and the atmosphere. Soil moisture is a highly variable component in land surface hydrology and plays a critical role in agriculture and hydrometeorology. Microwave remote sensing can provide the most feasible technique to map spatially distributed soil moisture (Li et al., 2002). Radar and Optical sensor integration in combining traditional space-borne optical data from the visible and infrared wavelengths with the longer wavelengths of radar improves land cover classification (Haack et al., 2002). It also improves the potential of land use classification (Othman et al., 2000 and Silva et al., 2007). Image integration is worth exploring to generate more details of land surface conditions (Alaparone et al, 2004). Many algorithms and methods are tried for this purpose (Wilfredo et al., 2008). Mathematical model have been used for analyzing bare earth and vegetation variation with respect to the soil moisture and the effects of vegetation cover on the estimation accuracy of soil moisture are derived from radar observations and it is also studied that the backscattering coefficient and the dielectric constants are correlated (Ulaby et al., 1982). Wang et al., in 2000 proposed use of microwave backscattering models based on soil moisture content, and surface roughness in rms height and willow ground coverage, etc. to study the effects of land cover on the estimation of soil moisture. Computation of the mean backscattering coefficient and its sensitivity to soil-moisture is compared to that predicted by a semi-empirical scattering model has also been tried (Bignami et al., 2004). X-band SAR has the ability to map small agricultural fields, assess their relative soil water content and distinguish between young and mature tree plantations (Blumberg, 2005). Backscattering from leaves with dielectric permittivity considers dry-matter fraction of leaf and permittivity saline water. Backscattering coefficient varies with variation of complex dielectric permittivity (Hsieh, 2003). Therefore, backscatter and dielectric constant combined with NDVI estimates will give value addition for soil moisture assessment. Other indices directly related to wetness and the greenness with atmospheric correction has either strong correlation with NDVI or to be improvised further (Schnieder, 2008). K. B Mao in 2008 reported that according to simulation analysis of the advanced integral equation model (AIEM), there is a good linear relationship between emissivity and soil moisture under conditions of given roughness. NDVI a consistent indicator of vegetation stress (Goetz, 1997 and Lu, 2004) combined with microwave parameters can yield a better understanding of the vegetation stresses. Therefore, the combination of optical and microwave indicators will certainly be good incremental step in the vegetation stress analysis, while it is important to understand the sensitivity of the microwave parameters to the land cover and the vegetal stress. An empirical equation for relating the vegetal stress and the backscatter and the dielectric constant is attempted here by simple regression. The relation may pertain to the backscattering values with plant biomass, height, leaf area index etc. Three representative land covers namely forested area, the croplands and barren rough soils are taken for very good to bad soil moisture conditions to test the dependability of the regression equation.

2. Study Area

Cumbum valley is a part of Theni district of Tamil Nadu constitutes hilly areas with thick vegetation and perennial stream from the hills on the western side. It is located at the latitudes of $9^0 30'$ – $9^0 45'$ N and longitudes of $77^0 15'$- $77^0 30'$ E. A range of hills runs parallel to Western Ghats. The land is quite rough in the hill slopes and the plain along the valley portion. The western slopes are lush with vegetation and the valley portion has crop lands and the eastern slopes have patches of barren soil. Three representative land covers namely water body, forested area/ the croplands and barren rough soils are taken for very good to bad soil moisture conditions to test the dependability of the regression equation.

2.1 Data Used

2.1.1 Microwave data

ENVISAT ASAR data collected in C-band (5.3GHz) having spatial resolution 30m in digital formats.

- VV-VH (IS1) Dual Polarized image-19thMay - 2006 18 UTC: 30:17:000000

Data (Raw) Product Characteristics

Product type: PRI (Precision Product)
Sensor Mode: AP (Alternate Polarization)
Image Scale: dB, *Source*: ASAR
Data format: MPH-SPH, ENVISAT
Polarization: VV, VH, HH & HV
Absolute Orbit Number: ABS_ORBIT = 15747
Orbit - Direction: DESCENDING
Swath Number: IS1, *Latitude*: $9^0 30'$ – $9^0 45'$ N
Longitude: $77^0 15'$ – $77^0 30'$ E

Optical Data

- IRS LISS III data

3. Methodology

The NDVI image was generated from the optical data and the different plots with good and bad soil moisture were selected. A principal component technique was used to merge the NDVI image and the microwave multi polarized data. This merged data was used for generating the soil moisture index. The flowchart found below explains the detailed methodology. After the preprocessing steps like image reading and the speckle removal using BEST software, the microwave image was registered with optical data with 0.56 RMS error using ENVI software. The Figure 1 below show the processed multi polarized data.

For the visual appreciation, the co-registered polarized data sets and the optical data were displayed in RGB combination as seen in Figure 2a and 2b.

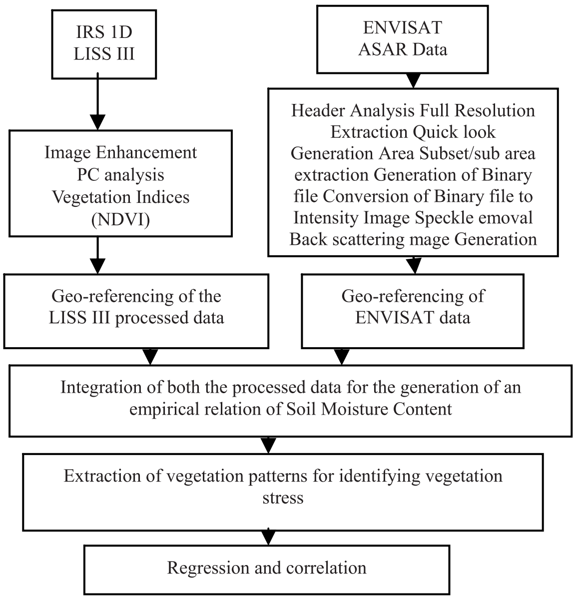

Figure 1: Methodology Flow Chart

3.1 Back Scattering Coefficient

With respect to the Incident wave, the Back Scattering Coefficient is proportional to the Reflected power per unit solid angle. From the intensity image generated by the microwave data, the Back Scattering Coefficient can be extracted for different features using the below standard formula:

$$\sigma_{dB} = 10 \log_{10} [(DN^2 / K)+A_0]+ 10 \log_{10} [\sin \theta]$$

Equation 1

Where, K – Calibration Constant, DN – Digital Number, A_0 – Automatic Gain control, θ – Incident Angle and σ_{dB} - Back scattering Coefficient. The intensity image generated from the microwave data is shown below in Figure 3a. NDVI is the most consistent vegetation stress parameter. For this study three representative soil moisture conditions namely water body for saturation, crop lands for medium and partial soil moisture condition and barren soil for the low soil moisture condition. This was to be verified on the ground and checked. Therefore, the NDVI map was generated, as shown in Figure. 3b, for the study area and test area were ascertained with respect to their general soil moisture condition.

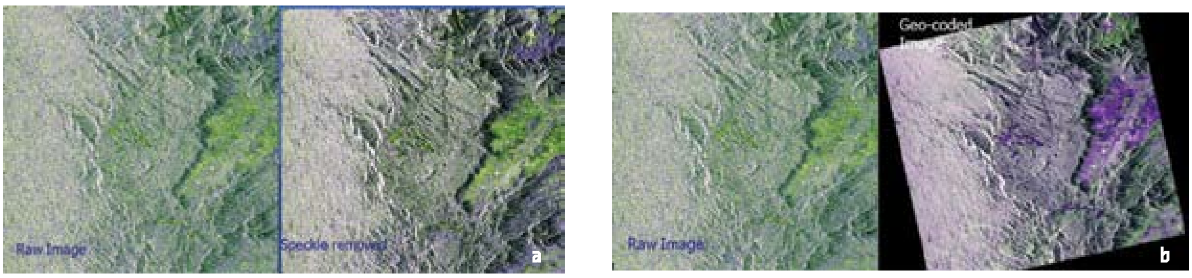

Figure 2: a) Processed and Speckle removed POLSAR image in RGB combination, b) Geo-coded and co-registered SAR and Optical data

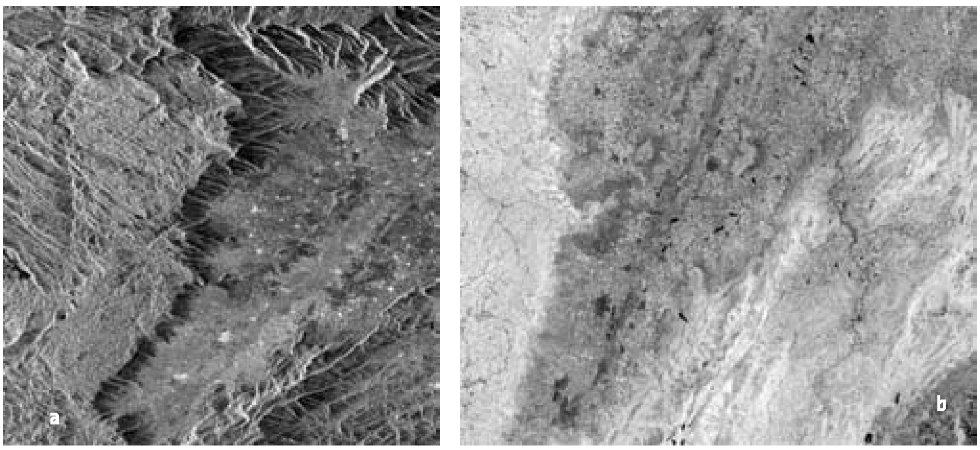

Figure 3: a) Intensity image of ENVISAT, b) NDVI image of LISS III data

Table 1: Extracted BSC values and NDVI values for the features

Feature	*Back Scattering Value(dB)*	*NDVI*
Water body	-32.5	-0.1865
Agriculture	-3.5	0.3135
Settlement	-1.041	0.0869
Dry soil	-14.1	0.1645

A comparative study of the NDVI and the back scatter values for the test areas was done and discussed below. Comparing the two graphs, the indices are related as same for all the features except the settlement. The observation shows there is possibility of relating NDVI estimate, back scatter value and the dielectric constant to soil moisture of the known land use classes, once the sensitivity of optical and microwave parameters to soil moisture is established. For this purpose, three typical soil moisture regimes namely, water body with saturation, crop land/ forest land for intermediate soil moisture condition and the barren soil for the dry condition were selected and the dependency for the remote sensing parameters were studied by simple regression. The Back scatter and dielectric constant images generated from the intensity images were so registered with the NDVI image and the plots for regression were picked up. The correlation between the NDVI and the backscatter is shown pictorially in the Figure 4.

3.2 Generation of Soil Moisture Index (SMI)

- Assuming there are 4 unknown quantities, 'A','B','C','D'
- Taking into account the feature parameters that we have observed from BSC image (Water body, Agriculture, Settlement and Dry soil) with known Back scattering image and unknown Dielectric constant
- Consider the Soil Moisture Index (SMI) as a function of back scattering Coefficient (σ) and Dielectric Constant (ε)

$$f_{SMI}(\sigma,\varepsilon)=A(\sigma^2)+B(\sigma^2)\varepsilon+C\sigma\varepsilon+D\varepsilon$$

Equation 2

- The unknown quantities can be found with the standard values of Dielectric constant and observed BSC and assumed SMI
- Calculated values are obtained and the equation modifies to:

$$f_{SMI}(\sigma,\varepsilon)=0.9(\sigma^2)-0.2(\sigma^2)\varepsilon+0.1\sigma\varepsilon+0.0112\varepsilon$$

Equation 3

Generally, the Dielectric Constant (DC) of water is 80. As the moisture content increases, dielectric constant also increases. Let us suppose assume that dry soil may have 10<DC<15. For wet soil let the value be 25<DC<50

3.3 SMI Calculated for the Observed Features

The Soil moisture Index was calculated for different combinations of Backscatter and Dielectric constant were calculated. The SMI values calculated for the typical features with comparable scale of wetness are also reported in the table 3. The graphical representation of the SMI indicated that there is a good correlation of SMI value for the wetness as in Figure 5.

4. Regression and Correlation Analysis

Linear regression analysis is carried out for Dielectric Constant and Back Scattering Coefficient with respect to Soil Moisture Index and Correlation Coefficient is obtained for the same. The over all error in the correlation of Dielectric constant, Back Scattering Coefficient with respect to Soil Moisture Index is 4.17% and 30.59% respectively. The curve fit for the both parameters with respect to SMI is obtained and the Correlation Coefficients are derived as shown in Figure 6 below.

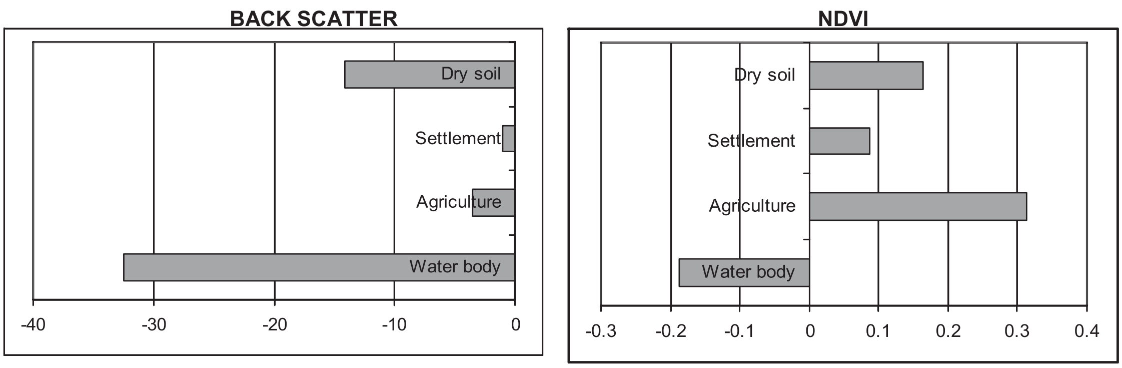

Figure 4: Graphical representation of the extracted values

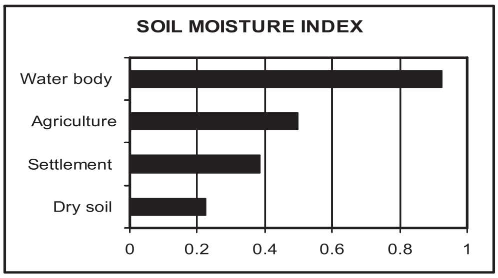

Figure 5: Soil moisture Index for the selected land use classes

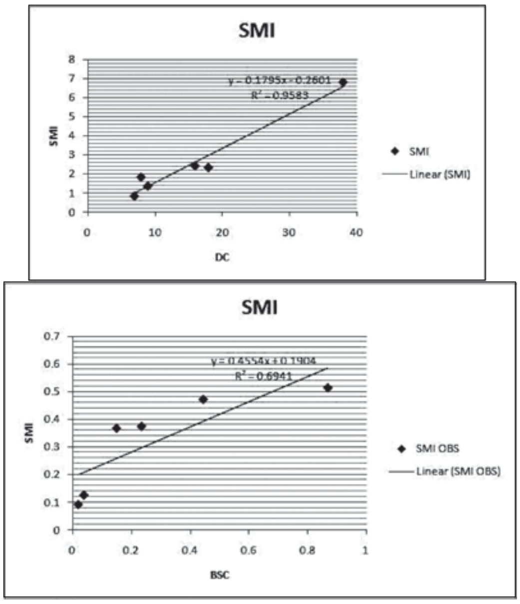

Figure 6: A regression curve fit and correlation coefficient for DC vs SMI and BSC vs SMI

Table 2: SMI for combination of BSC and DC a) for dry (left) and b) for wet (right)

BSC	DC	SMI	BSC	DC	SMI
0.0389	10	0.149235	0.4467	25	0.578632
0.0389	11	0.164023	0.4467	30	0.658441
0.0389	12	0.17881	0.4467	35	0.738251
0.0389	13	0.193598	0.4467	40	0.81806
0.0389	14	0.208385	0.4467	45	0.897869
0.0389	15	0.223172			
0.0389	16	0.23796			

Table 3: SMI for the Observed features with standard Dielectric constant

Feature	BSC	DC	SMI
Dry soil	0.0389	15	0.223172
Settlement	0.7227	4	0.38611
Agriculture	0.4467	20	0.498823
Water body	0.00063	82	0.92356

The regression coefficients were used to generate the SMI image using the map algebraic function to understand the soil moisture condition across space, with the dielectric constant, Back scatter values and NDVI values. The Model maker of ERDAS was used to generate the images with the SMI empirical relation obtained from regression. The maps of SMI would be highly helpful in monitoring the soil moisture conditions more dependably if the land use class is known. The SMI image as generated from the derived regression coefficients are shown in Figure 7.

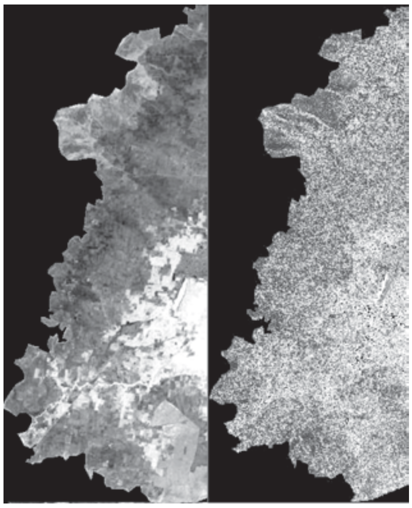

Figure 7: Dielectric constant and SMI map using regression coefficients

5. Summary and Conclusion

The microwave data was processed in POLSAR Pro to remove Speckle in SAR image as well as in BEST to obtain the calibration constant which is a parameter in the generation of Back scattered image and Coefficient. Using PCA analysis, both the LISS III and ENVISAT data were merged in ERDAS where, the features could be identified but not conducive for interpretation. The study suggests that the interpretation could be improved by merging the LISS III+PAN and ENVISAT data. From the processed raw data of SAR, binary files are generated which related to the intensity of the data. NDVI was generated from LISS III image and the values that vary for various features were identified. As the NDVI values were used identified the features of relative sweetness characters combined with filed verified truth, other indices were not necessary. Backscattering coefficient and the dielectric constant were correlated and supported by the detailed ground verification. The NDVI for the selected features verified on ground correlated very well. Maps were generated as indirect indicator of soil moisture availability with field Back scattering values were plotted for various features from the back scattered image generated from ENVISAT data. NDVI and Back scatter coefficient were compared and found that both the indices are correlated. Soil Moisture Index was generated considering the two parameters i.e., back scattering coefficient and dielectric constant and assuming the standard parameter values for wet and dry soil surface of Dielectric constant, a non-linear equation of Soil Moisture Index was generated. Using the equation, the Soil Moisture Index for the surface features was determined and the areas which are under stress were identified. The study gives a confidence that the SMI can be generated with more precise land use classification. Regression analysis and correlation coefficient were generated for DC and BSC with respect to SMI and the overall error were calculated as 4.17% and 30.59% respectively. Hence, it is possible to relate empirically the vegetation stress with respect to Dielectric Constant and Back scatter and the regression analysis proved that it is closely related to Dielectric Constant. The monitoring of the soil moisture conditions and the mapping of the same can be done for known land use classes. Further, the study can further be carried out by improving the relation of the parameters, which is possible with constant field verification.

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