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Analysis of the Influence of Soil Roughness, Surface Crust and Soil Moisture on Spectral Reflectance

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***Abstract*.** Soil moisture is an important component of numerous systems, influencing crop development, and runoff and infiltration partitioning, among other things. However, due to its spatial and temporal variability, it is difficult to estimate soil moisture consistently using conventional techniques such as gravimetric sampling, which is point-based and time-consuming. Therefore, to overcome this drawback in soil moisture estimation and mapping, and to facilitate its measurement spatially and temporarily, remote sensing is a promising technique. Measurement of soil surface reflectance in the visible and near infrared (VIS/NIR) may be used for this purpose. However, soil reflectance within this spectral range is affected by numerous factors, including soil surface roughness and the presence of soil crust. Thus, in order to determine the utility of VIS/NIR remote sensing for surface soil moisture estimation, roughness and crusting must be considered. In this study, we quantify the effects of these three components (moisture, roughness, and degree of crusting) on soil surface reflectance within the spectral range of 450 nm to 1000 nm in order to determine the extent to which moisture can be estimated under different soil surface conditions.

Keywords. *Remote Sensing, Soil Moisture, VIS/NIR spectroscopy, soil roughness, crust*

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1. Introduction

Remote sensing is a means of collecting information about an object using sensors that are not in direct contact with the target. For this it uses the measurements of electromagnetic spectrum. Remote sensing has proven to be a useful tool to obtain data from remote areas where ground measurements are not feasible, or from large areas that would require a high cost investment for adequate monitoring. It can provide information regarding watershed or catchment characteristics like land cover, topography, vegetation etc, which can be further used in conjunction with spatial data to formulate hydrological models. Soil moisture is one of the parameters which significantly influence hydrological models as it determines governs the partitioning of precipitation into infiltration and surface runoff, and affects evapotranspiration and crop development. Therefore, it can be said that it is one of the important factors that needs to be determined accurately for a hydrological model to perform satisfactorily. It is also an important piece of information with respect to agriculture. The proper moisture condition in soil is an important factor for the proper growth and development of a crop.

2. Literature Review

While a variety of methods are available for accurate and consistent estimation of soil moisture, they may be prohibitively costly to implement with spatial and temporal density. Spectral measurement in various wavelengths (bands) can be used to measure the soil moisture accurately. Remotely sensed images based on active microwave observations are a source of data to measure soil moisture accurately at watershed scale (Filho, et al, 1996). Soil moisture retrieval algorithms based on passive microwave observations have been evaluated on coarse resolutions, large scales and diverse conditions over longer periods of time (Jackson, et al. 1999). Thus, it can be inferred that microwave remote sensing has the capability of direct measurement of soil moisture, and has the benefit of remaining largely unaffected by cloud cover and variable surface solar illumination (Njoku and Entekhabi, 1996).

However, spatial resolution of microwave sensors is generally coarser than that would be most desirable for agricultural purposes. Also, the cost is relatively high. Remote sensing in the visible and near infrared (VIS/NIR, 300nm to 1000nm) spectral region is another and more affordable method which is being widely used for other agricultural data collection. The visible and near infrared reflectance data could be used to estimate the surface (0 to 7cm) soil moisture (Kaleita et al, 2005). The relative reflectance (with in spectral range of 400nm to 2500nm) depends upon soil moisture levels. It has been found that for low and high moisture levels the relative reflectance shows a non linear relationship with soil moisture (Liu et al, 2002). Exponential models work well to describe this relationship in comparison to the linear models, which are good approximations (Muller and Decamps, 2000; Kaleita et al., 2005). Soil moisture has also been estimated using an inverted Gaussian function of near infrared (NIR) and short wave infrared (SWIR) spectra (Whiting et al., 2004)

Soil crusting and soil surface roughness are few of the factors that affect soil reflectance in VIS/NIR regions which could in turn affect the estimation of soil moisture content from spectral data. Crust development causes significant spectral differences between the crusted and non crusted soil samples (Ben-Dor et al., 2003). The spectral reflectance has been observed to be higher for the crusted samples than in non crusted soil samples (Ben-Dor et al. 2004). This higher reflectance is observed because development of crust leads to the formation of a smoother surface as a result of migration of finer soil particles due to the breakdown of structural units of soil by flowing water, raindrop impact, or through freeze-thaw action (USDA Natural Resources Conservation Service, 1996; Ben-Dor et al. 2004). On the other hand, soil surface roughness reduces reflectance by a significant amount (Escadafal et al., 1990). Matthias et al. (2000) observed that the soil albedo is highly sensitive to the roughness. A study on effect of soil roughness on radiation reflectance and soil heat flux has shown that reflectance decreases with increase in soil roughness with maximum difference being observed between the spectral range of 850nm to 1350nm and it appeared to similar with in spectral range of 400nm to 850nm. The same study also showed that the degree of reflectance increased by up to 25% for dry soil which was subjected to a 47mm rainfall 5 days before. This phenomenon was observed due to decrease in surface roughness because of the rainfall (Potter et al, 1987). The decrease in degree of reflectance due to roughness can be attributed to the scattering of incoming radiations or also due to the shadowing effect because of the presence of coarse or fine aggregates.

Some researchers have used soil reflectance data for detection of crust development and various other soil properties. Changes in both albedo and absorption enabled the crust to be detected using reflectance radiation (Goldshleger et al, 2002). Significant spectral differences occurs between crusted and the bulk soil. The spectral differences are related to texture and mineralogy of soil surface. The relationship between structural crust and soil reflectance can be used for estimating soil properties such as infiltration rate, soil runoff and erosion (Ben-Dor et al., 2003). Spectral measurements of soil surfaces done under solar illumination have suggested that crusted surfaces can be differentiated from non crusted surfaces and these measurements can assist in evaluation of degree of crust development. Also it has been observed in a study done on two California soils that crusted samples exhibited high baseline spectra as compared to non crusted samples. An absorption feature at 1400 nm suggested the presence or absence of clay in the crust, and reflectance at 1700 nm and 2300 nm provided significant correlations with infiltration rate. An inverse linear relationship was also found to exist between reflectance at many wavelengths and crust permeability during crust development stages (Eshel et al., 2004). From these studies it can be inferred that the crust development can be deduced using the spectral data. However, none of these studies have accounted for the soil moisture which would also have some effect on the reflectance data.

After analyzing the effect of roughness and crusting on the reflectance from soil surface it can be inferred that there is a need to take into account the above two factors for accurate estimation of soil moisture content. Also it can be said that spectral data can be used as a means to infer various soil properties including soil moisture and soil crusting. A spectral analysis for soil moisture content measurement and quantification of the effect of soil crusting and soil roughness on it is yet another aspect which still needs to be investigated. Therefore, the primary objective of this study is to quantify the influence of soil surface crusting and roughness on our ability to determine soil moisture with the help of reflectance data with in a spectral range of 450 nm to 1000 nm.

3. Materials and Methods

3.1 Soil Samples

Soil samples from Clarion and Webster soils, two of the common soil types in the state of Iowa were used for the analysis. Samples were taken from approximately the top 8 to 10 inches of the soil, collected from the Agricultural Engineering farms of Iowa State University. Subsamples of each were analyzed for soil textural breakdown.

Clarion loam (2 to 5 percent slopes) consists of dark colored, well drained soils that formed in glacial till. The available water capacity is high (0.16 inches per inch of soil), permeability is moderate (0.63 to 2.0 inches per hour) and content of organic matter is moderate or moderately low. The surface layer and sub soil are generally neutral (pH = 6.6-8.4). The Clarion sample was composed of 53% sand, 25% silt and 25% clay was categorized as sandy clay loam on the basis of its texture. Webster loam (0 to 2 percent slopes) is a very dark gray colored soil and consists of poorly drained, moderately permeable soils on uplands. It has been formed in loamy glacial till and glacial sediments. The Webster sample was composed of 43% sand, 28% silt and 28% clay and categorized as clay loam on the basis of its texture.

The soils were air dried and sieved through 4 mm sieve. Soils were then packed in 30 cm by 50 cm by 16 cm deep trays over a 5 cm layer of sand. The thickness of soil layer was kept to be around 8 cm.

3.2 Experimental set up

The trays were positioned at 5% slope and were subjected to simulated rainstorms of intensities equal to 40mm/hr (low intensity rainfall) and 90mm/hr (high intensity rainfall) for half an hour duration. The rainfall simulator used in this study is located in the Department of Agricultural and Biosystems Engineering at Iowa State University (ISU). It is a programmable nozzle type simulator and the velocity with which the drop is formed and released depends upon the pressure created. The simulator has 12 nozzles located in 3 rows with 4 nozzles per row. The lateral spacing between nozzles is 77 cm and the spacing between the nozzles in the same row is about 110 cm. During the rainfall simulation, nozzles sweep back and forth in a 90 degree arc with a frequency of 1 oscillation per second. The height of rainfall simulator from the soil sample is 3 meters. Although repeatable intensities are easy to obtain in this kind of simulator (by controlling the water pressure), it is difficult to get completely uniform rainfall over the area below the simulator.

Data from series of runs was collected for the analysis. All combinations of the following treatments were used to create different runs and thus imparting variability in the data.

Crust treatment: Since rainfall energy causes dispersion of soil particles, leading to the formation of crust on the soil surface, varying degrees of rainfall intensities and conditions were used to create different crusting conditions. Three main rainfall intensities used for this purpose were 0mm/hr, 40mm/hr and 90mm/hr. The 0mm/hr rainfall is equivalent to zero rainfall energy. Since it is not possible to simulate a zero-energy event using the rainfall simulator, saturation of soil using a siphon system was considered equivalent to zero intensity rainfall. The 40mm/hr and 90mm/hr rainfalls were followed by another rain event of corresponding rainfall intensity. It was expected that the degree of crusting would increase when soil was subjected to another similar intensity (Bajracharya and Lal, 1998). Thus, there were a total of five crusting conditions: 0 mm/hr rainfall, 40 mm/hr rainfall, 40 mm/hr rainfall after 40 mm/hr rainfall, 90 mm/hr rainfall, and 90 mm/hr rainfall after 90 mm/hr rainfall.

Soil crusts were categorized by their thickness or strength (USDA Natural Resources Conservation Service, 1996). It has been indicated analytically and experimentally that crust strength in rupture is proportional to the square of the crust thickness, and various field tests have indicated that crust strength in penetration is linearly related to its thickness (Upadhyaya et al. 1995). Therefore, the degree of crust induced by the rainfall treatment was determined by measuring the crust thickness using a Vernier caliper. For this measurement, a piece of crust was taken from near the side of the tray, out of the field of view of the two spectral sensors. The crust was said to develop when the top layer of the soil was dry and hard to the touch, and cracks started appearing on the. Figure 2 shows an example of a crusted soil surface.

Roughness treatment: It was also expected that degree of roughness would have some impact on crust development. This treatment had two main conditions, one with some degree of roughness and the other with no roughness on soil surface. For the no roughness condition, the surface was not disturbed. For the roughness condition, varying degrees of roughness were imparted on the soil surface using a 3 prong hand cultivator, to simulate tillage. The exact degree of roughness imparted using this method varied each time.

A 64-pin soil profilometer was used to quantify the surface roughness. Digital photographs of this profilometer were taken against a white background and were then analyzed with Image-Pro Plus software (Media Cybernetics, Silver Spring, MD). The digital photographs taken were imported into the Image Pro software and spatial calibration of each photograph was done. The height of each pin from the reference line of the profilometer was then determined using the Image-Pro "manual measurements" tool. The standard deviation of these heights was then calculated as a measure of roughness.

Roughness and crust measurements were taken at the end of each run. A drying arrangement comprised of heat and wind effect helped in development of crust. The heating effect was generated by using tungsten lamps, which were being used for illumination purposes, and wind action was generated using a table fan.

Simultaneous spectral and moisture measurements were also taken during the drying process. The moisture content of the soil was measured with a Theta probe (Delta-T Devices, Cambridge UK, marketed in the United States by Dynamax, Inc., Houston, TX) inserted in one corner of the tray outside of the field of view of the spectral sensor, discussed below. The output from the Theta probe was converted to soil moisture using equation 1:

$$\theta = 0.118\sqrt{\varepsilon} - 0.176 \tag{1}$$

where θ = moisture content after calibration

ε = dielectric constant, a function of the probe voltage measurements.

This is a laboratory calibration equation determined for Des Moines Lobe Soils (Kaleita et al, 2005). The spectral measurements were taken using Ocean Optics (Dunedin, FL) reflectance probes, USB2000 and USB4000, with in the spectral range of 300 nm to 1040 nm placed at a height of 12.5 inches. Figure 1 shows the experimental arrangement.

Figure 1. Experimental set up for drying the soil and collecting moisture and spectral data

Figure 2. Crusted soil sample

3.2.3 Preprocessing of Spectral Data

The spectral readings were converted from intensity counts to reflectance values using equation (2)

$$r = \frac{S - D}{R - D} \times RF \tag{2}$$

where r = Reflectance

S = Intensity counts from the sample

R = Intensity counts from the standard

D = Intensity counts in the dark spectra

RF = Reflection Factor of the standard

A 20% gray standard was used for the calculation of percent reflectance. The gray color standard was used instead of a white standard, which is commonly used. Use of a white standard would have necessitated a short integration time setting on the spectrometer in order to not saturate the signal from the standard. This would have meant a very low relative signal from the soil surface, which is quite dark when, wet, and could have caused difficulty in differentiating the signal noise from the actual signal. Therefore, all the percent reflectance values were multiplied by a reflection factor calculated after comparing the reflectance from the gray and white standard. This was provided by the manufacturer.

While testing the lighting condition, reflectance scans from the gray standard were recorded and the coefficient of variation (CV) of intensity count with respect to different wavelength was studied.It was observed that CV is less than 1% for wavelength range of 430nm to 1000nm. Since the spectrometer was of the range of 300nm to 1030nm such a behavior was expected. Since the variation of less than 1% is quite low so we decided to keep the data under the wavelengths ranging between 450nm to 1000nm under consideration. In other words, the data from 300nm to 450nm and 1000nm to 1030nm was eliminated due to low signal-to-noise ratio and thus, the final spectral range under consideration was from 450nm to 1000nm. The spectral resolution of the USB2000 and USB4000 was then aggregated to 6nm by averaging the wavebands so as to decrease the computational time for data analysis.

Some data, around six hours, was lost in one of the runs due to technical fault in the equipment. This run was for clarion soil and had the crust treatment of 90mm/hr of rainfall intensity with some roughness. Also, some data in a few of runs of clarion soil had a saturated signal in the spectral readings thus these scans were omitted from the analysis.

3.3 Analytical Methods

The data analysis was carried on individual treatments and also using the combined data analysis. The analysis was done by scripts developed in MATLAB (The MathWorks, Natick, MA) and Microsoft Excel. Correlation analysis, multiple linear regression (MLR), stepwise linear regression are few of the techniques that were used for the analysis of the data collected. All these techniques tried to predict soil moisture content using linear relationships.

3.3.1 Correlation Analysis

Correlation Analysis, which is a tool to describe the linear correlation between two variables, on degree of roughness, crust thickness and moisture with reflectance data was done. It was carried out so as to identify any wavelengths showing high correlation with any of the above factors.

3.3.2 Multiple Linear Regression

MLR model was constructed so as to estimate soil moisture content by including soil surface reflectance, degree of roughness and crust thickness as the predicting variables. Another MLR model with only reflectance as predicting variable was also constructed. Both these models were compared so as to observe the effect on estimation of soil moisture content if information regarding crusting and roughness is included as the variables in the model. Due to large number of reflectance variables in the MLR model there were chances of over-fitting of data therefore to avoid this and to de-correlate the data two techniques were tested and models with this de-correlated data were developed using MLR. These models were further compared with the earlier MLR model. The two techniques used were Stepwise Linear Regression and Principal Component Analysis (PCA). Stepwise linear regression model chose the significant variables to be included in a MLR model based upon the high F-statistic and low p-value.

3.3.3 Stepwise Regression Analysis

This method chooses the variables to include in a MLR model. Forward stepwise regression starts with no terms to be included in the model and with each steps includes the most significant term depending upon the high F statistic and lowest p-value. Backward stepwise regression starts with all the terms in the model and removes the least significant terms until all the remaining terms are statistically significant. It is also possible to start with a subset of all the terms and then add significant terms or remove insignificant terms (Statistical Toolbox, MATLAB). But this method might show some problems when there is collinearity between the data. Due to this problem another method known as principal component analysis was carried out to reduce the dimensionality of the data and to avoid over fitting.

3.3.4 Principal Component Analysis

The PCA is also a linear transformation to a new co-ordinate system such that projection with greatest variance lies on the first co-ordinate, the second greater one lies on the second co-ordinate and so on. It helps in reducing the dimensionality of the data and retains the most important characteristics of the dataset that contributes to maximum variance. The PCA was run over the reflectance dataset such that components showing 97 percent variance were retained. Another MLR model was constructed using the principal components (PC) alone and in conjunction with the crust and roughness values. All these MLR models were then compared and the results obtained from these have been explained in the following section.

4. Results and discussion

A correlation analysis between the reflectance data and the moisture content was carried out and a negative correlation was observed between the percent reflectance and the moisture content. The value of correlation coefficient for Clarion Loam soil varied between 0.5 and 0.69 and for Webster loam soil it varied between 0.2 and 0.55. Figure 4 shows the results from the correlation analysis for both the soils. From figure 4 it can be noticed that for both the soils the highest correlation coefficient is being observed within the spectral range of around 530nm to 890nm. This is a large spectral range and no single wavelength range can be isolated from this analysis. Though, the negative correlation further strengthens the argument that the soil reflectance decreases with the increase in moisture content.

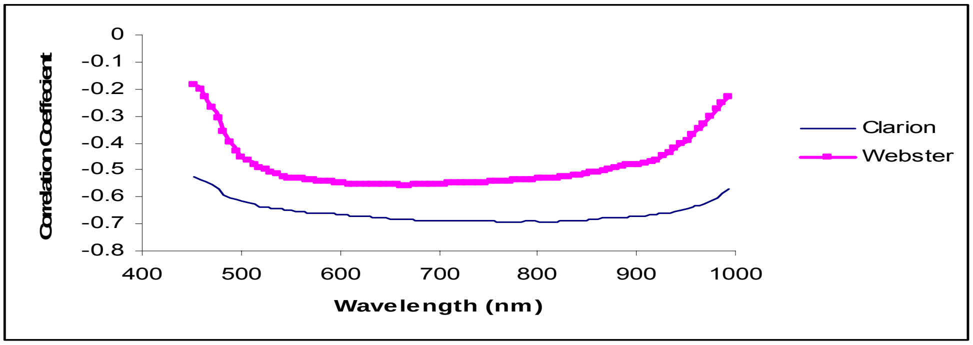

Figure 4 Correlation coefficients of reflectance with moisture for Clarion and Webster Loam soils

It was also noticed, in both the soil types, for the same moisture and roughness condition the observed reflectance was more for the crusted surface as compared to the non crusted surface (Figure5). And for same moisture and crust conditions the percent observed reflectance was less a rough surface than for a smooth surface (Figure 6). Thus it can be said that degree of reflectance of soil surface increases with the presence of crust and decreases for a rough surface.

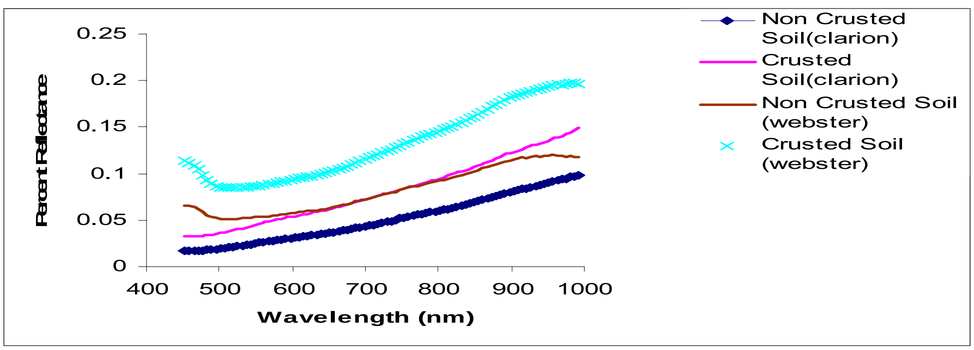

Figure 5.A sample of spectral reflectance of a crusted and a non crusted surface for same moisture and roughness conditions

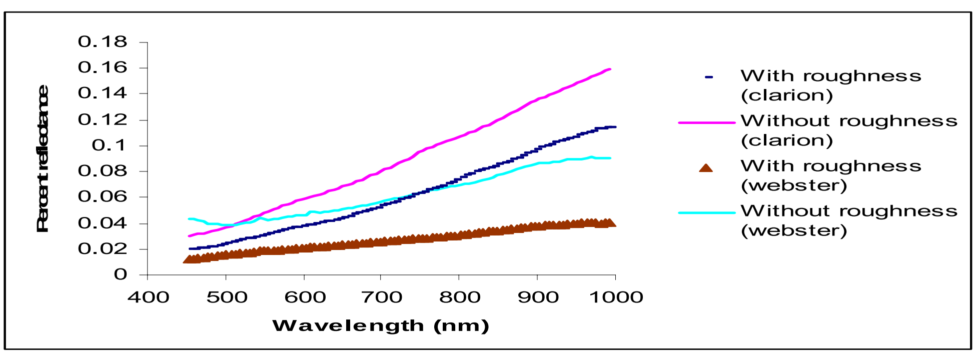

Figure 6.A sample of spectral reflectance of a surface with and without roughness for same moisture and crust conditions

Multiple linear regression (MLR) was carried out on moisture with reflectance, roughness and crusting as variables. R-square values of 0.95 and 0.74 respectively for Clarion loam and Webster loam soils were obtained. There was not much change in the R-square values when roughness and crusting variables were not included in the MLR model. Since the amount of reflectance data is more with respect to roughness and crust data there is a chance of over-fitting of reflectance data in the above two MLR models. Therefore to de-correlate and reduce the dimensionality of the reflectance data Principal Component Analysis (PCA) in MATALB environment was carried out over it. This would also help in identifying some hidden characteristics of the reflectance data. Before doing the PCA the data was normalized, so that the input values have a mean of zero and a standard deviation of 1, using an algorithm in MATLAB. The principal components (PC) showing at least 90 percent variability of the data were selected for further analysis. This 90 percent variability was shown by only one band. An R-square value of 0.44 and 0.25 for Clarion Loam and Webster Loam respectively, were obtained when a MLR was again carried out on moisture using the first PC. This value is a smaller than that we obtained from the above models, thus confirming the argument on over-fitting of data. When crusting and roughness were included as variables along with the PC the R-square value improved to 0.63 for the Clarion Loam soil but there was not much change in the R-square value for Webster Loam soil as it increased from 0.25 to 0.27. This might be due to difference in soil properties of both the soils.

Apart from MLR, a stepwise regression analysis using the complete dataset was carried out in MATLAB environment. The input dataset is scaled and normalized to have a standard deviation of 1. Default values of 0.05 and 0.1 are kept as the maximum and minimum p-values, respectively, for a predictor to be added or removed from the model. For the Webster Loam soil the R-square value increased from 0.68 t0 0.99, respectively, when the model was created with and without the roughness-crusting values. The stepwise linear model included the roughness and crusting values in the regression model to predict moisture content when the whole dataset (with roughness-crust values) was considered for analysis. The number of terms included for constructing the model was 20 when only reflectance data was considered for analysis and 30 when whole dataset was used for analysis. For Clarion Loam soil the R-square value was 0.91 and number of terms included was 18 for model with only reflectance as predictor variables. This R-square value increased to 0.94 when the whole dataset which included crusting and roughness values was used predictor variables. The number of variables included in this model was 35 and crusting and roughness were also selected to build the model. The selection of crusting and roughness as the predictor variables by the stepwise regression technique further strengths our argument that these are the important factors which need to be accounted for the estimation of moisture content.

5. Conclusion

The main objective of this study was to estimate soil moisture from reflectance within the spectral range of 300nm to 1000nm taking into account the effect of crusting and roughness on soil surface reflectance values. After carrying out various analyses it has been found that both crusting and roughness have significant effect in predicting moisture content using reflectance data using the linear regression models. But there is still a need to do further analysis and test some non linear models and other advanced models to estimate moisture content from the reflectance data and compare their results with the linear model. The results shown here are obtained under laboratory conditions but there is a need to further test these methods in real field conditions. From the above study it can be concluded that this can be considered as a good laboratory method to predict soil moisture content.

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