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Soil Moisture Content Determination by Means of the Electromagnetic Spectrum Julia I. Loshelder

Abstract

Soil moisture content provides information about the strength, permeability, and compressibility of the soil under investigation. In the research described herein, the relationship between moisture content and reflectance values obtained from spectroscopy was developed to investigate whether in-situ moisture content can be determined in a faster and more efficient way than the current methods. The soil under investigation was laboratory-compacted kaolinite clay mixed with pyranine dye. These specimens were placed beneath an ultraviolet light and a halogen illuminator where reflectance values were collected over a 24-hour period. Correlations were developed from the following methods: 1) spectral indices, 2) continuum analyses through the 1450nm, 1900nm, and 1940nm wavebands, 3) linear regressions between moisture contents and normalized reflectance (initial spectra divided by final spectra), and 4) analytical models of the time dependent moisture content at 1450nm and 1900nm. The 1450nm waveband was found to have the highest correlation between the reflectance values and the moisture contents with coefficients of determination (R²) values greater than 0.922 in all cases. Other wavebands of interest included 1900nm, 1940nm, and 2200nm; however, these bands consistently had lower correlation values. With further study of the 1450nm waveband, in-situ moisture contents can be accurately predicted in a non-intrusive way in the laboratory and in the field.

Introduction

Soil property identification is a required process for geotechnical engineers to properly assess soil that is used or built upon for construction purposes. The determination of in-situ moisture content serves an important role in identifying these properties but is a lengthy process. The time required to properly determine the moisture content and therefore other soil properties may be shortened by investigating how the soil reflects or refracts light through reflectance spectroradiometry. Reflectance spectroradiometry is a technique that is used to measure the ratio of incident and reflected light intensity to predict properties of a given material (Peddle et. al. 2001). The results of this process provide spectra of continuous, narrow, wavelength bands in the electromagnetic spectrum. When these bands are observed together minerals, rocks, and soil types that are present can be identified.

Hyperspectral imaging is the process of using the electromagnetic spectrum to identify soil properties (Plaza et. al. 2009). Reflectance spectroscopy, a field of hyperspectral imaging where the amount of light reflected is quantified, provides reflectance values for specific mineral types at specific wavelengths (Goetz 2009). Therefore, the intensity of the reflected light from a soil surface may provide insight into the strength, permeability, and compressibility properties of soil. The observed intensity of the various wavelengths may also provide understanding about the types of isotopes, the amount of moisture within the soil, and the amount of suction within the soil. The research that is described herein was conducted to investigate if the moisture content of kaolinite soil could be accurately assessed using reflectance spectroscopy techniques, leading to a faster and more efficient way of identifying moisture content in the field.

Background

The application of remote sensing for moisture content determination has been previously investigated by researchers in the geotechnical engineering and agricultural fields. In Whalley et. al. (1991), a variety of particle size distribution and clay contents of soils was investigated. The device used by Whalley et. al. (1991) recorded near infrared reflectance produced by light emitted at 1450 nm, therefore not considering moisture content features at other wavelengths within the

near infrared portion of the electromagnetic spectrum. With this Whalley et. al. (1991) device, a correlation between reflectance and moisture content was found to exist in sands. For clays, especially those containing kaolinite, the swelling behavior created inconclusive results using the 1450nm wavelength. Therefore, Whalley et. al. (1991) suggested that wavelengths greater than 1450nm are required to properly analyze clay soils, such as the soil that was chosen for the research described herein.

Weidong et. al. (2002) investigated the correlation between moisture content and reflectance values for a large range of moisture contents and discovered that longer wavelengths were more efficient for low moisture contents and that shorter wavelengths were more efficient for high moisture contents. Seven different wavebands were chosen for correlation purposes that covered the range of possible wavelength values: 450nm, 574nm, 986nm, 1400nm, 1672nm, 1998nm, and 2189nm. The reflectance at each of these wavebands was normalized to the reflectance of dry soil for further computations.

Bogreckci et. al. (2006) converted reflectance values into absorbance values to find the relationship between light absorbance and phosphorous concentration. The Moisture Determination Ratio (MDR) was computed from 340nm, 1450nm, and 1940nm as a way of comparing samples with different moisture contents. Dry soil spectra were successfully reconstructed form the existing wet soil spectra by removing the effect of moisture content (by considering the MDR).

In Wang et. al. (2009) and Fabre et. al. (2015), a correlation between moisture content and several spectral indices was compared. Wang et. al. (2009), with a purpose of identifying plant moisture content, eleven spectral indices comprised of a combination of reflectance values and physical properties of the sampled plant leaves. In addition, a continuum analysis was performed

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that centered around the 1450nm or 1940nm wavelength bands. Correlating these analysis methods with moisture content, the greatest coefficient of determination (\mathbb{R}^2) was 0.587 indicating that directly computing moisture content from these methods will not provide accurate results of the in-situ moisture content. Similarly, Fabre et. al. (2015) used existing spectral indices such as the Normalized Soil Moisture Index (NSMI) and Water Index SOIL (WISOIL), to new spectral indices derived from obtained data and linear and non-linear regressions. Using a normalized reflectance quantity and the moisture content, Fabre et. al. (2015) obtained an \mathbb{R}^2 value of 0.87. Although improved, this value still does not provide accurate correlated in-situ moisture content values.

Yuan et. al. (2019) analyzed the relationship between moisture content and reflectance by considering diffuse scattering. The moisture content could be computed directly after the absorption and scattering coefficients of the soil were determined. The R^2 values obtained from correlating the estimated and measured moisture contents tended to be greater than 0.85, depending on the type of soil under investigation.

Several researchers have worked towards obtaining analytical models that can directly compute the moisture content from acquired reflectance data. Lobell et. al. (2002), found that the best fit model that related moisture content and reflectance was an exponential model, while Whiting et. al. (2004) found that a Gaussian model provided the best results. Fabre et. al. (2015) expanded on these models and determined that a quadratic model was the best analytical solution. By inverting the derived equation, the moisture content was directly computed by identifying the moisture content that minimized the quadratic error. This method provided R² values ranging from 0.90 to 0.97 depending upon the soil type that was investigated.

Methods and Procedures

For the research described herein, soil specimens were compacted in the laboratory at standard energy in a 0.000678 cubic meter mold to achieve a variety of moisture contents that were used for testing. Kaolinite clay was mixed with a fluorescent dye (pyranine) to achieve the desired moisture contents of 15, 22, 29, and 32 percent. The pyranine dye was first concentrated from one highlighter ink cartridge and 400 grams of deionized water for a minimum of 24 hours. The dye was chosen as the liquid for the desired moisture contents to increase the visible light reflectance peaks that would be recorded from the spectroradiometer when viewed underneath an ultraviolet light with a wavelength of 320 nm.

For testing, the compacted specimens were sliced so that three or four 38.1 mm high samples could be obtained from each of the compacted specimens (Figure 1). These samples were then trimmed into 38.1 mm in diameter and 19.05 mm high consolidation rings. Each individual sample, within the consolidation ring, was placed into a Petri dish for the spectroradiometer readings. The specimen was illuminated by a 320nm ultraviolet light and a halogen illuminator (Figure 2). The ASD FieldSpec 4 spectroradiometer was used to record the reflectance values

every minute for a 24-hour period as the specimen dried. The specimen weight was also continuously recorded for the same 24-hour duration. After the 24hour period concluded, the oven dry weight of each specimen was obtained. Compacted specimen with 4 sub-samples Light Sample in ring in Petri dish

Figure 1. Schematic of soil specimens used for testing.

A variety of techniques and procedures were utilized to locate and interpret the correlations between the reflectance and moisture content values. Each recorded weight throughout the duration of the test was converted into a moisture content percentage by using the initial and final weights of the specimen. This information was then used to compare how the reflectance changed for each specimen as a function of time and moisture Additionally, content. the reflectance value at each time period was



Figure 2. Arrangement of the spectroradiometer, ultraviolet light, halogen illuminator, and scale.

normalized by dividing each reading by the final reflectance value that was measured for each corresponding specimen to allow for a complete comparison to be obtained.

The following spectral indices utilized in Wang et. al (2009) and Fabre et. al. (2015) were computed using Equations 1-5 and the obtained data are reported herein. Employing a continuum analysis through the 1450nm and/or 1940nm wavelength bands, as demonstrated by Wang et. al. (2009), the band depths as shown in Figure 3, were computed using Equations 6 and 7.

$$MSI = \frac{R_{1600}}{R_{820}}$$

Wang et. al. (2009)

Equation 1

where:

MSI = Moisture Stress Index

$R_{1600} = reflectance at 1600 nm$

 $R_{820} = reflectance at 820 nm$

$$NDWI = \frac{R_{850}-R_{1240}}{R_{860}+R_{1240}}$$
Wang et. al. (2009)Equation 2where:NDWI = Normalized Difference Water Index $R_{860} = reflectance at 860 nm$ $R_{1240} = reflectance at 1240 nm$ $WI = \frac{R_{900}}{R_{970}}$ Wang et. al. (2009) $WI = \frac{R_{900}}{R_{970}}$ Wang et. al. (2009)where: $WI = Water Index$ $R_{900} = reflectance at 900 nm$ $R_{970} = reflectance at 970 nm$ $NSMI = \frac{R_{1800} - R_{2110}}{R_{1800} + R_{2119}}$ Fabre et. al. (2015)Equation 4where:NSMI = Normalized Soil Moisture Index

 $R_{1800} = reflectance at 1800 nm$

 R_{2119} = reflectance at 2119 nm

$WISOIL = \frac{R_{1450}}{R_{1300}}$	Fabre et. al. (2015)	Equation 5
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where:

WISOIL = Water Index SOIL

 R_{1450} = reflectance at 1450 nm

 $R_{1300} = reflectance at 1300 nm$

$D_{1450} = 1 - \frac{R_{1450}}{R_{1450i}}$	Wang et. al. (2009)	Equation 6
1450 <i>l</i>		

where:

 D_{1450} = band depth of the absorption feature at 1450 nm

 R_{1450} = reflectance at 1450 nm

 R_{1450i} = reflectance of continuum line at 1450 nm

$$D_{1940} = 1 - \frac{R_{1940}}{R_{1940i}}$$
 Wang et. al. (2009) Equation 7

where:

 D_{1940} = band depth of the absorption feature at 1940 nm

 R_{1940} = reflectance at 1940 nm

 R_{1940i} = reflectance of continuum line at 1940 nm



Figure 3. Continuum analysis performed in Wang et. al. (2009).

Results

As illustrated in Figure 4, the spectral signature of each specimen was determined and then normalized (Figure 5) for use in comparisons. By normalizing the spectra between the initial time to the final time, trends in the peaks and troughs between specimens were identified (Figure 6).



Figure 4. Spectral signature of a kaolinite specimen as a function of time.



Figure 5. Normalized reflectance of a kaolinite specimen as a function of time.



Figure 6. Normalized reflectance (initial spectra divided by final spectra) for the kaolinite specimens compacted at different target moisture contents.

The coefficients of determination between the measured data at 1450nm, 1900nm, 1940nm, and 2200nm and the initial moisture content of the specimen are shown in Table 1. Additionally, coefficients of determination were obtained between the initial moisture content and combinations of 1450nm, 1900nm, and 2200nm; these results are reported in Table 2. As stated previously, several indices from previous investigations were computed for the purpose of this research. These values are recorded in Table 3. Using the continuum analysis proposed in Wang et. al (2009), the band depths presented previously in Equations 6 and 7 were computed. An example of the continuum analysis method for one specimen is presented in Figure 7. The coefficients of determination between the waveband depth and the initial moisture content are provided in Table 4.

Table 1. Coefficient of determination between normalized reflectance (initial spectra divided by final spectra) and initial moisture content at different wavelengths.

Wavelength [nm]	\mathbb{R}^2
1450	0.943
1900	0.896
1940	0.879
2200	0.910

Table 2. Coefficient of determination between combinations of normalized reflectance (initial spectra divided by final spectra) and initial moisture content.

Wavelength Combination	\mathbb{R}^2
1450nm × 1900nm	0.920
1450nm × 2200nm	0.946
1900nm × 2200nm	0.908
1450 nm \times 1900nm \times 2200nm	0.915

Table 3. Coefficient of determination between the index and the initial moisture content.

Index	\mathbb{R}^2
MSI	0.923
NDWI	0.916
WI	0.929
NSMI	0.200
WISOIL	0.897



Figure 7. Continuum analysis surrounding the 1450 nm and 1900nm waveband.

Table 4. Index correlations with initial moisture content at 1450 nm, 1900nm, and 1940 nm as computed using the continuum analysis.

Spectral Index	\mathbb{R}^2
D ₁₄₅₀	0.922
D ₁₉₀₀	0.273
D ₁₉₄₀	0.098
R _{1450i} /R _{1900i}	0.819
R_{1450i}/R_{1940i}	0.793
D_{1450}/D_{1900}	0.833
D_{1450}/D_{1940}	0.870

To understand how the moisture content changed as a function of time, the calculated moisture content measurements were aligned with the reflectance at each time increment (one minute) for each specimen for 1450nm (Figure 8) and 1900nm (Figure 9) wavelengths. As proposed in Fabre et. al. (2015), an analytical solution was determined for each moisture content

curve by fitting a polynomial to each curve. The proposed polynomial by Fabre et. al. (2015) was a second order polynomial. By changing from a second order polynomial to a fourth order polynomial, the R^2 value improved from 0.928 to 0.943 for the 1450nm waveband, and the R^2 value improved from 0.902 to 0.924 for the 1900nm waveband.



Figure 8. Normalized reflectance (R_t divided by R_f) as a function of target moisture content at the 1450nm wavelength.



Figure 9. Normalized reflectance (R_t divided by R_f) as a function of target moisture content at the 1900nm wavelength.



Figure 10. Correlation between the normalized reflectance (R_t divided by R_f) as a function of moisture content at the 1450nm wavelength.



 $R_{\rm f}$) as a function of moisture content at the 1900nm wavelength.

Discussion

In the work described herein, one soil type (kaolinite) was tested at a variety of molded gravimetric moisture contents (15, 22, 29, 32). As expected, the reflectance values increased as a function of time for each specimen, as can be seen by the spectral signature shifting upward shown previously in Figure 4. Similarly, the specimens with a higher initial moisture content had lower reflectance values, and specimens with a lower initial moisture content had higher reflectance values shown previously in Figure 6. Additionally, when comparing the time dependent normalized reflectance (R_t/R_t) as a function of time dependent gravimetric moisture content (w_t) (Figures 8 and 9), the slope of the resulting curves was steeper for the specimens with lower initial moisture contents, and the slope was shallower for the specimens with higher initial moisture contents.

When analyzing the reflectance and the initial moisture content data based on a linear regression, the 1450nm waveband provided the most accurate results with an R^2 of 0.943 compared to 1900nm ($R^2 = 0.896$), 1940nm ($R^2 = 0.879$) and 2200nm ($R^2 = 0.910$). For the subsequent analyses, 1900nm was used instead of 1940nm since 1900nm had a higher R^2 value. Although multiplying the reflectances at these wavelengths (1450nm, 1900nm, and 2200nm) together increased the coefficients of determination concerning the 1900nm and 2200nm, these values remain lower than the original value computed for the 1450nm. This leads to the conclusion that the 1450nm waveband is the most useful and reliable to predict soil moisture content when the visible and infrared spectrum is used.

As stated previously, several indices concerning different wavelength bands were computed during the analysis. Four out of five of these indices resulted in coefficients of determination around 0.9. NSMI, however, resulted in an R² value of 0.200. As this index involves the 1800nm waveband and 2119nm waveband, either of the bands or both of these bands are problematic and inconsistent across the specimens.

When using the continuum analysis, the 1450nm waveband once again proved to be a more consistent method to predict moisture content because the R^2 value of the waveband depth at 1450nm was 0.913. However, both the 1900nm and 1940nm wavebands were once again problematic with coefficients of determination of 0.273 and 0.098, respectively. By computing the ratio of the reflectances at the continuum bands and the ratio of the waveband depths, the coefficients of determination greatly increased for the ratios concerning the 1900nm and 1940nm wavebands, however, the values are still not as accurate as that obtained from the 1450nm waveband. Therefore, the 1450nm seems to be the most reliable waveband for predicting moisture content reliably.

Lastly, the moisture content at each time increment was compared to the resulting reflectance value for each specimen at the 1450nm waveband and the 1900nm waveband (Figures 5 and 6 shown previously). As in the analysis cases, the 1450nm waveband provided the most accurate prediction method for the moisture content with an R^2 value of 0.943 compared to 0.925 for the 1900nm waveband. Not surprisingly, the 1450 nm waveband provided the more accurate values being consistent with the other conducted analyses.

Conclusion

The determination of soil moisture content in the laboratory and in the field is integral to better understanding the fundamental properties of soil such as strength, permeability, and compressibility. The use of hyperspectral imaging for geotechnical applications has the potential to provide information on moisture content, mineral types, and isotopes. Using this method, engineers may be able to provide results for designers and researchers in a shorter time frame than through the current methods.

Through the research described herein, a better understanding of how to predict moisture content from reflectance spectra, as obtained from a spectroradiometer, was presented. Throughout the analysis process, the 1450nm waveband seemed to provide reliable results independent of whether that prediction came from a continuum analysis (maximum R^2 value of 0.922), a linear regression between initial moisture content and normalized reflectance (R^2 value of 0.943), or an analytical model of the time dependent moisture content (R^2 value of 0.943). Time dependent normalized reflectance ratio correlations computed for other wavebands (1900nm, 1940nm, and 2200nm) proved to be a less successful in accurately predicting the moisture content values.

Continued research will help to improve upon these predictions of the moisture content based on reflectance data. The research described herein was concerned with analyzing laboratoryprepared kaolinite specimens. Future work will consider other soil types and more target moisture contents to verify if the results found in this research prove to be reliable in all cases.

References

- An, X., Li, M., Zheng, L., Liu, Y., Zhang, Y., (2016). "Real Time Detection of Soil Moisture in Winter Jujube Orchard Based on NIR Spectroscopy." 6th Computer and Computing Technologies in Agriculture (CCTA), Zhangjiajie, China, pgs. 447-455.
- Bogreckci, I. and Lee, W.S., (2006). "Effects of Soil Moisture Content on Absorbance Spectra of Sandy Soils in Sensing Phosphorus Concentrations Using UV-VIS-NIR Spectroscopy." American Society of Agricultural and Biological Engineers, Vol. 49(4), pgs. 1175-1180.
- Chabrillat, S., Ben-Dor, E., Cierniewski, J., Gomez, C., Schmid, T., van Wesemael, B., (2019). "Imaging Spectroscopy for Soil Mapping and Monitoring." Surveys in Geophysics, Vol. 40, pgs. 361-399.
- Dallon, D., (2003). "Measurement of Water Stress: Comparison of Reflectance at 970 and 1450 nm." Water Stress, Paper 1.
- Duke, C., and Guerif, M., (1998). "Crop Reflectance Estimate Errors from the SAIL Model Due to Spatial and Temporal Variability of Canopy and Soil Characteristics." Remote Sensing of the Environment, Vol. 66, No. 3, pgs. 286-297.
- Fabre, S., Briottet, X., and Lesaignoux, A., (2015). "Estimation of Soil Moisture Content from the Spectral Reflectance of Bare Soils in the 0.4-2.5 μm Domain." Sensors (Basel), Vol. 15(2), pgs. 3262-3281.
- Goetz, A.F.H., (2009), "Three Decades of Hyperspectral Remote Sensing of the Earth: A Personal View," Remote Sensing of Environment, Vol. 113, pgs. S5-S16.
- Lesaignoux, A., Fabre, S., and Briottet, X., (2012). "Influence of Soil Moisture Content on Spectral Reflectance of Bare Soils in the 0.4 – 14 μm Domain." International Journal of Remote Sensing, Vol 34, No. 7, pgs. 2268-2285.
- Lobell, D.B., and Asner, G.P., (2002). "Moisture Effects on Soil Reflectance." Soil Science Society of America Journal, Vol. 66, No. 3, pgs. 722-727.
- Peddle, D.R., White, H.P., Soffer, R.J., Miller, J.R., LeDrew, E.F., (2001). "Reflectance Processing of Remote Sensing Spectroradioimeter Data." Computer & Geosciences, Vol. 27, No. 2, pgs. 203-213.

- Plaza, A., Benediktsson, J.A., Boardman, J.W., Brazile, J., Bruzzone, L., Camps-Valls, G., Chanussot, J., Fauvel, M., Gamba, P., Gualtieri, A., Marconcini, M., Tilton, J.C., Trianni, G., (2009), "Recent Advances in Techniques for Hyperspectral Image Processing," Remote Sensing of Environment, Vol. 113, pgs. S110-S122.
- Wang, J., Xu, R., and Yang, S., (2009). "Estimation of Plant Water Content by Spectral Absorption Features Centered at 1,450 nm and 1,940 nm Regions." Environmental Monitoring and Assessment, Vol. 157, pgs. 459-469.
- Weidong, L., Baret, F., Xingfa, G., Qingxi, T., Lanfen, Z., Bing, Z., (2002). "Relating Soil Surface Moisture to Reflectance." Remote Sensing of the Environment, Vol. 81, No. 2-3, pgs. 238-246.
- Whalley, W.R., Leeds-Harrison, P.B., and Bowman, G.E., (1991). "Estimation of Soil Moisture Status Using Near Infrared Reflectance." Hydrological Processes, Vol. 5, pgs. 321-327.
- Whiting, M.L., Li, L., and Ustin, S.L., (2004). "Predicting Water Content Using Gaussian Model on Soil Spectra." Remote Sensing of the Environment, Vol. 89, No. 4, pgs. 535-552.
- Yuan, J., Wang, X., Yan, C., Wang, S., Ju, X., Li, Y., (2019). "Soil Moisture Retrieval Model for Remote Sensing Using Reflected Hyperspectral Information." Remote Sensing, Vol. 11, No. 366, pgs. 1-17.
- Zhang, D., Zhou, G., (2016). "Estimation of Soil Moisture from Optical and Thermal Remote Sensing: A Review." Sensors, Vol. 16, No. 1308, pgs. 1-29.

Appendix



Figure A1. Correlation between the initial water content and the normalized reflectance (initial reflectance divided by final reflectance) at 1450nm.



Figure A2. Correlation between the initial water content and the normalized reflectance (initial reflectance divided by final reflectance) at 1900nm.



Figure A3. Correlation between the initial water content and the normalized reflectance (initial reflectance divided by final reflectance) at 1940nm.



Figure A4. Correlation between the initial water content and the normalized reflectance (initial reflectance divided by final reflectance) at 2200nm.



Figure A5. Correlation between the initial water content and the normalized reflectance (initial reflectance divided by final reflectance) at 1450nm multiplied by the normalized reflectance (initial reflectance divided by final reflectance) at 1900nm.



Figure A6. Correlation between the initial water content and the normalized reflectance (initial reflectance divided by final reflectance) at 1450nm multiplied by the normalized reflectance (initial reflectance divided by final reflectance) at 2200nm.



Figure A7. Correlation between the initial water content and the normalized reflectance (initial reflectance divided by final reflectance) at 1900nm multiplied by the normalized reflectance (initial reflectance divided by final reflectance) at 2200nm.



Figure A8. Correlation between the initial water content and the normalized reflectance (initial reflectance divided by final reflectance) at 1450nm multiplied by the normalized reflectance (initial reflectance divided by final reflectance) at 1900nm multiplied by the normalized reflectance (initial reflectance divided by final reflectance) at 2200nm.



Figure A9. Correlation between the initial water content and the MSI Index.



Figure A10. Correlation between the initial water content and the NDWI Index.



Figure A11. Correlation between the initial water content and the WI Index.



Figure A12. Correlation between the initial water content and the NSMI Index.



Figure A13. Correlation between the initial water content and the WISOIL Index.



Figure A14. Correlation between the initial water content and the waveband depth at the 1450nm waveband.



Figure A15. Correlation between the initial water content and the waveband depth at the 1900nm waveband.



Figure A16. Correlation between the initial water content and the waveband depth at the 1940nm waveband.



Figure A17. Correlation between the initial water content and the ratio of the reflectance of the continuum line at 1450nm to the reflectance of the continuum line at 1900nm.



Figure A18. Correlation between the initial water content and the ratio of the reflectance of the continuum line at 1450nm to the reflectance of the continuum line at 1940nm.



Figure A19. Correlation between the initial water content and the ratio of the depth of the 1450nm waveband to the depth of the 1900nm waveband.



Figure A20. Correlation between the initial water content and the ratio of the depth of the 1450nm waveband to the depth of the 1940nm waveband.