THE INFLUENCE OF SLOPE IN THE QUANTIFICATION OF SOIL IRON CONTENT WITH SPECTRAL REFLECTANCE BASED IRON INDICES

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ABSTRACT:

Remote sensing has proven to be a useful tool to determine the presence of iron over large areas. However, in airborne imaging spectroscopy terrain characteristics influence the reflectance. With the PARGE/ATCOR model the bias of these characteristics is corrected, but the model does not correct for soil BRDF, which leads to different deviations for individual wavelengths. In this research the influence of slope on the prediction of soil iron content using spectral reflectance based iron indices is assessed. An experimental set-up is designed where the slope of the sample is varied, resulting in different illumination angles. From these reflectance data different iron indices are calculated; the ratio-based Redness Index and the area and standard deviation after continuum-removal for the iron absorption features located at 550 nm and 880nm. Linear regression and multiple linear regression are used to estimate the soil iron content. Moderately accurate models ($0.62<R^2<0.69$) are found with linear regression between iron and the calculated indices, but the R^2 is significantly higher when texture is included in the multiple linear regression analysis ($0.76<R^2<0.82$). From the analysis, it became clear that the ratio based Redness Index is not significantly influenced by slope. Slope has minor influence on the area and standard deviation of the continuum-removed spectrum at 550 nm. For both the area and the standard deviation of the continuum-removed spectrum at 880 nm, slope is clearly influencing the indices. The errors are significant, but can be corrected with a correction model.

1. INTRODUCTION

Iron is an important indicator in the soil science; it is an indicator for soil fertility, soil usability and it can indicate the age of the deposits [1]. Iron species are also an indicator that soil is being formed because iron is strongly correlated with the soil weathering process on the short and long term [2]. Determining the spatial distribution of different types of iron with traditional fieldwork and laboratory analyses is time-consuming and expensive. Remote sensing has proven to be a useful tool to determine the presence of iron in extended areas and various research fields [1]. Chemical and physical properties of the surface influence the soil reflectance and interfere with the iron absorption features [2, 3]. Much research has been done in the discrimination of soils based on a combination of different soil properties retrieved from spectral data [4-6]. The main reason that the influence of slope on soil reflectance is not taken into account is because of the assumption that in the processing stage the reflectance is corrected for this. This is partly true, the PARGE/ATCOR model corrects for the bias of some terrain characteristics. However, the model does not correct for soil BRDF which leads to different deviations for individual wavelenghts.

2. METHODOLOGY

Almost all soil reflectance spectra show a steep decrease in reflectance towards the blue and ultraviolet wavelengths which is due to a strong iron-oxygen charge transfer band that extends into the ultraviolet. Other absorption bands often occur near 700 nm and 880 nm due to the electronic transition of ferric iron. Electronic transitions involving ferrous iron can cause strong absorption bands near 880 nm as well. Several weaker absorption bands between 400 nm and 550 nm are present due to one or the other iron ion.

Continuously reflectance spectra are acquired in the laboratory experiment, using an ASD fieldspec ProFR spectrometer [7]. An experimental set-up is designed where the slope of the sample can be varied, resulting in different illumination angles. Measurements are taken every 5^0 ranging from a 25^0 slope facing towards the light source to a 25^0 slope facing off the light source. The soil samples are taken form the slopes of El Hacho de Álora in Southern Spain and analyzed for total iron content in the laboratory. Soil texture is determined manually by an expert according to the FAO classification system [8]. The iron extraction method, the geological and topographical settings are more extensively described in [1].

From the reflectance data three different iron indices are calculated; the ratio based Redness Index and the area and standard deviation after continuum-removal for the iron absorption features located at 550 nm and 880nm. With multiple linear regression and general statistics the relation between slope and the prediction of soil iron content is quantified. Soil texture was manually classified and has been implemented as second regression parameter. In this article, the absorption features are being referred to as; *D550* for the dip occurring between 400 and 550, *D700* for the dip around 700nm and the dip around 880nm is referred to as *D880.* The indices derived from the continuum-removed spectrum are referred to as $D880_{area}$ and $D880_{S.D.}$.

2.1 Ratio Based Redness Index

Weathering products of iron bearing minerals contain iron oxides, which will color the soil red when these become available to the soil [3]. Therefore, the ratio based Redness Index can be used as an indicator for soil iron. The Redness Index is expressed as the reflectance in the red part of the spectrum divided by the sum of visible red, green and blue reflectances (Eq. 1):

$$R = BRF_r / (BRF_r + BRF_g + BRF_b) \qquad (1)$$

Where BRF_n = the bidirectional reflectance in the corresponding part of the visible spectrum

BRF_n is calculated by (Eq. 2):

$$BRF_n = R_t / R_c \qquad (2)$$

Where BRF_n = the bidirectional reflectance in waveband n
R_t = the radiance from the target surface
R_c = the radiance from the reference panel [9]

2.2 Continuum removal

The normalization of the absorption features is based on the convex hull method, which is commonly used for normalization of soil reflectance data. For example [10] and [11] used the convex hull method successfully for the retrieval of soil properties. The mathematical theories behind the convex hull method are described by [12, 13]. After continuum removal, the area of the dip is calculated as indicator for iron. The depth and width of the absorption dips are represented with the standard deviation after continuum removal; the larger the width and depth of an absorption feature, the higher the standard deviation.

2.3 Prediction of the soil iron content.

For the calculation of the iron content, a linear regression model was established based on the samples measured from nadir (Fe_{est_0}). The calculated index is used as independent variable and iron content measured in the laboratory is the dependent variable [1], see Eq. 3.

$$Fe_{est\_0} = a + b * Index \quad (3)$$

Next, it is being examined if a multiple linear regression will improve the results. Since texture is also explaining deviations in reflectance, this variable is included as second regression parameter (Eq. 4).

$$Fe_{est\_0} = a + b * Index + c * Texture \quad (4)$$

In order to find out what the influence of slope is on the determination of the iron content, the soil iron content for sloping samples is predicted with the functions derived from a nadir position ($Fe_{pred\_slope(x)}$). The regression functions are applied on the index values for different slopes on both the calibration and the validation set. Next, the difference between the predicted iron from nadir and the predicted iron with a slope is calculated. The difference is calculated in percentages so results are normalized and a comparison can be made between different iron contents. The significance of this error is determined by means of a Paired-Samples T-test. When the 2-tailed significance is smaller than 0.05 slope has a significant influence on the determination of the iron content [14].

Finally, a slope correction model is developed. The regression function, based on the calibration data set, must predict the correction for each index and slope, with the estimated error as dependent variable. The performance of the slope correction models is assessed with the standard error of calibration (SEC), standard error of prediction (SEP), the bias and the ratio of performance to deviation (RPD) values [15, 16].

3. RESULTS AND DISCUSSION

The reflectance of bare soil varies with the slope (Fig. 1). Up to 600 nm the differences are small. At higher wavelengths the deviation in reflectance from nadir increases. Around 1000 nm differences in reflectance for a negative slope deviate up to -6% and for positive slopes up to 2%. The maximum difference can be found around 1800 nm, with a difference up to -8% for the negative facing slopes and up to 3% for the positive slopes. The specific absorption features from iron are clearly visible, from 390 to 600 nm, around 700 nm, and from 800 nm up to 1000 nm. It can be concluded that the deviation from nadir is larger for the slopes facing off the light source than for the slopes facing towards the light source.

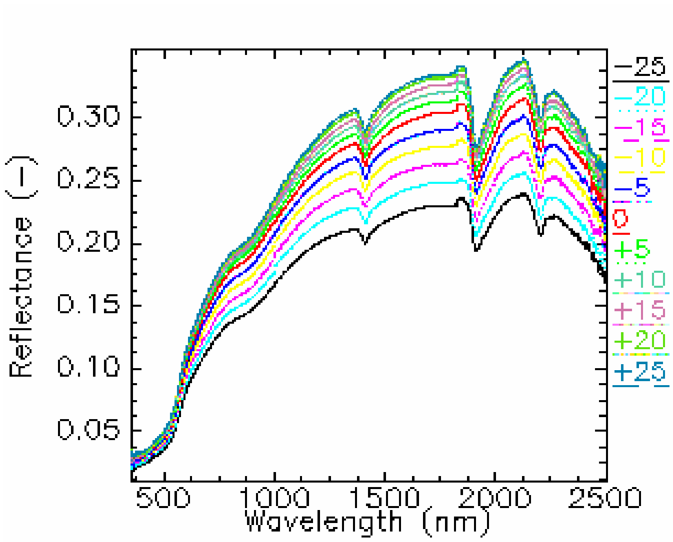

Figure 1: Reflectance of bare soil under different slopes.

In Table 2 the overall correlation (*R*) between the iron indices and the iron content of the soil samples measured in the laboratory are given. The ratio based Redness Index has an average correlation of 0.80. $D550_{area}$ has an average correlation of -0.82 and $D550_{S.D.}$ has a correlation of 0.82, which means that with decreasing iron content the area of the dip decreases as well. For *D700* the average correlations are much lower: -0.53 for $D700_{S.D.}$ and 0.51 for $D700_{area}$. The correlation for $D880_{area}$ is on average -0.84 and 0.84 for $D880_{S.D.}$. The correlation of *D700* is almost as low as a random relation. Therefore, this absorption feature will not be used for the next part of the research.

The R^2 for linear regression is significantly lower compared to multiple linear regression. For linear regression, the results vary between 0.62 up to 0.69 for the calibration set and between 0.68 up to 0.77 for the validation set.

Higher R^2 values are found for multiple linear regression when soil texture is included. Values range from 0.76 up to 0.82 for the calibration set and from 0.77 up to 0.82 for the calibration set. It can be concluded that the multiple regression functions have a better performance and that texture does improve the prediction of soil iron content, so these functions will be used to estimate soil iron content. The significance of the effect of slope on the estimation of soil iron content is tested by means of paired-samples T-Test. The pairs that are compared are the prediction values of iron content under a certain slope with the estimation values of iron content measured at nadir. Values have been tested on the 95% confidence interval for the error in iron content in mg/kg. If the 2-tailed significance is lower than 0.05 the deviation of iron content is significant. The results are given in Table 3 where the significant deviations are given in red.

Table 2: Average correlation coefficient (R) of iron and spectral reflectance based iron indices under different slopes.

	RI	$D550_{Area}$	$D550_{S.D.}$	$D700_{Area}$	$D700_{S.D.}$	$D880_{Area}$	$D880_{S.D.}$
Mean	0.798	-0.817	0.817	0.512	-0.534	-0.835	0.839
S.D.	0.002	0.005	0.004	0.067	0.058	0.005	0.002

Table 3: 2-tailed significance of the compared pairs, the significant differences are given in italic.

Slope (°)	RI	$D550_{Area}$	$D550_{S.D.}$	$D880_{Area}$	$D880_{S.D.}$
-25	0.061	*0.027*	*3.22E-11*	*1.81E-07*	*6.51E-19*
-20	0.236	*0.003*	*2.27E-08*	*4.74E-09*	*1.08E-21*
-15	0.956	*0.016*	*5.24E-09*	*2.56E-07*	*6.02E-21*
-10	0.053	0.12	*2.06E-07*	*7.40E-08*	*6.38E-21*
-5	*0.011*	0.177	*3.79E-07*	*1.07E-09*	*3.82E-24*
5	0.467	*0.022*	0.139091	0.433653	*1.26E-05*
10	0.525	0.421	*0.00029*	*0.043252*	*2.57E-10*
15	0.644	*0.03*	*2.22E-06*	*0.007264*	*6.23E-11*
20	0.872	*0*	*2.84E-06*	*0.000204*	*3.34E-14*
25	0.791	*0.001*	*5.72E-06*	*8.07E-05*	*1.25E-19*

The differences between the estimated iron content at nadir and the predicted iron content under a certain slope do not significantly differ for the Redness Index except for a slope of -5^0 (facing off the light source). The differences for $D550_{area}$ are partly significant. For slopes larger than $+15^0$ and -15^0 the deviation is significant, for smaller slopes the model is robust, except for $+5^0$. These results show that slope has significant influence on the iron prediction. For both the *area* and the *S.D.* of *D880* all values are smaller than 0.05 except for *D880* with $+5^0$. From this test it can be concluded that the Redness Index is robust and performing well under varying slopes. The continuum removed indices appear to be very sensitive to variations in slope. The differences are higher for the negative facing slopes; this might be due to the retroreflectance properties of the material [2] and the non-lambertian behavior of the surface [14]. One reason that *D880* performs better is that this adsorption dip is caused by only the mineralogical composition. The major bearing iron mineral is hematite which will give an adsorption dip around 900 nm and is directly related to texture while other features are not influencing the dip as is the case in the VIR. Since texture is only included as extra variable in the prediction model, *D880* performs best.

A slope correction model is developed for all indices but in this paper only the results are shown for $D880_{S.D.}$ because the errors are the largest for this index. The mean error has become 0 after the application of the slope correction model and the V-shape is no longer present (Fig. 4a). The performance of the model when applied on the validation set is good because the slopes do not deviate anymore and the model has corrected for the so called 'V-shape' (Fig. 4b).

The SEC values range between 1.09 and 1.15 mg/kg and the SEP values varies between 1.87 and 1.94 mg/kg. The bias values ranges between -1.78 and -1.86 mg/kg. The bias is negative which means that iron content is being underestimated when the terrain is sloping. The bias is relative small and the R^2 values are 0.76 and 0.77 which is good. The RPD values are all larger than 2, which means that this model can be classified as a class A model according to [15]. The correction model would be better if after the correction the standard deviation would become smaller. This is not the case because the regression function only corrects for the bias of the estimation. The standard deviation can only decrease if the uncorrected data can be aggregated by a third soil attribute.

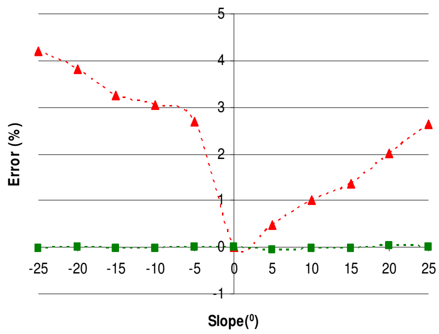

Figure 4a: Mean error of the predicted iron content for corrected and uncorrected data of the calibration set for D880$_{S.D.}$

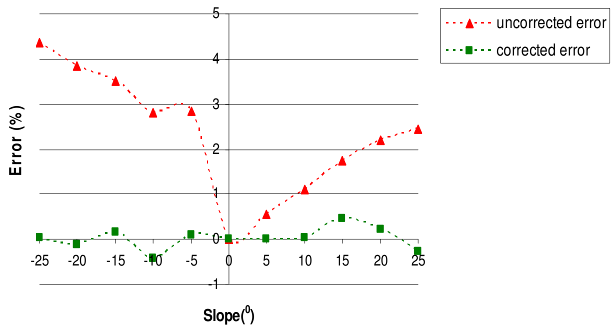

Figure 4b: Mean error of the predicted iron content for corrected and uncorrected data of the validation set for D880$_{S.D.}$

4. CONCLUSIONS

Linear regression and multiple linear regression have been used to estimate the soil iron content using spectral indices. The R^2 is significantly higher when multiple linear regression with both index and texture is used for the estimation of soil iron content. It became clear that the Redness Index is not significantly influenced by slope. Slope has minor influence if iron is estimated using the area and standard deviation of the continuum-removed spectrum at 550 nm. The error increases with increasing slope but there is no clear trend visible.

For both the area and the standard deviation of the continuum-removed spectrum at 880 nm the slope is clearly influencing the indices and errors are significantly. The effect is stronger for the slopes facing away from the light source, which might be due to the retroreflectance properties of the material and the surface roughness. A correction model, which uses slope and wavelength as input variables, is developed to minimize the estimation error caused by slope and was able to correct the disturbing effect of slope well.

REFERENCES

1. Bartholomeus, H., G. Epema, and M. Schaepman, Determining iron content in Mediterranean soils in partly vegetated areas, using spectral reflectance and imaging spectroscopy. International Journal of Applied Earth Observation and Geoinformation, 2007. 9(2): p. 194-203.
2. Ben-Dor, E., Irons, J., Epeman, G.,, Remote Sensing for the earth sciences: manual of remote sensing 3ed, ed. E. Ben-Dor. 1999, New York: John Wiley & Sons, Inc.
3. Irons, J.R., R.A. Weismiller, and G.W. Petersen, *Soil reflectance,* in Remote Sensing for the earth sciences: manual of remote sensing, E. Ben-Dor, Editor. 1999, John Wiley & Sons, Inc. : New York
4. Dematte, J.A.M., Characterization and discrimination of soils by their reflected electromagnetic energy. Pesquisa Agropecuaria Brasileira, 2002. 37(10): p. 14.
5. Nanni, M.R., Spectral reflectance methodology in comparison to traditional soil analysis. Soil Science Society of America Journal, 2006. 70(2): p. 16.
6. Farrand, W.H., Identification and mapping of ferric oxide and oxyhydroxide minerals in imaging spectrometer data of Summitville, Colorado, U.S.A., and the surrounding San Juan Mountains. International Journal of Remote Sensing, 1997. 18(7): p. 1543 - 1552.
7. Batholomeus, H., Short Manual Fieldspec Pro. 2007, Laboratory for Geo-Information Science and Remote Sensing: Wageningen.
8. FAO and ISRIC, Guidelines for soil description. 1990, FAO: Rome.
9. Bullard, J.E. and K. White, Quantifying iron oxide coatings on dune sands using

spectrometric measurements: an example from the Simpson-Strzelecki Desert. Journal of Geophysical Research, 2002. 107: p. 14.
10. Islam, K., A. McBratney, and B. Singh, Rapid estimation of soil variability from the convex hull biplot area of topsoil ultra-violet, visible and near-infrared diffuse reflectance spectra. Geoderma, 2005. 128: p. 9.
11. Withing, M.L., L. Li, and S.L. Ustin, Predicting water content using Gaussian model on soil spectra. Remote Sensing of Environment, 2003. 1: p. 18.
12. Hu, T., Non-linear control design for linear differential inclusions via convex hull of quadratics. Automatica, 2007. 43: p. 8.
13. Hu, T., R. Goebel, A.R. Teel, and Z. Lin, Conjugate Lyapunov functions for saturated linear systems. Automatica, 2005. 41: p. 8.
14. Isaaks, E.H. and R.M. Srivastava, An introduction to applied geostatistics, E.H. Isaaks, Editor. 1989, Oxford University: Oxford.
15. Chang, C., D. Laird, M.J. Mausbach, and C.R. Hurnburgh, Near-Infrared Reflectance Spectroscopy - Principle Components Regression Analyses of Soil Properties. Soil Science Society of America Journal, 2001. 65: p. 11.
16. Chang, W.H., S. Chen, and C.C. Tsai, Development of a Universal Algorithm for use of NIR in Estimation of Soluble Solids in Fruit Juices. American Society of Agricultural Engineers, 1998. 41: p. 7.