# QUANTITATIVE DERIVATION OF KEY SOIL PARAMETERS ON THE BASIS OF HYPERSPECTRAL REMOTE SENSING DATA

## - A study to detect and monitor degradation in the Subtropical Thicket Biome, South Africa -

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**ABSTRACT**

The Subtropical Thicket Biome (Eastern Cape, South Africa) with its dense shrub vegetation in pristine conditions stores unusually large amounts of carbon for a semi-arid region. Therefore it is a region of extraordinary importance [7]. Currently the region undergoes fundamental changes caused by heavy grazing of goats which is accompanied by a serious depletion of carbon stocks above and below ground.

The key soil parameters clay, iron and organic carbon can be used to assess land degradation. In this context these parameters are quantified using hyperspectral remote sensing data and multiple linear regression techniques. First, the correlation of spectral features with measured soil contents is modelled using unsupervised partial-least-squares regression analysis and second a feature-based approach is tested.

## 1. INTRODUCTION

### 1.1. Hyperspectral remote sensing of soil parameters

The possibility of using significant spectral signals of visible to shortwave InfraRed spectra for quantitative analysis of soil properties of the upper soil layer is well known. Many proposals exist where laboratory, field and airborne hyperspectral data and different modelling approaches are used to describe soil clay, iron and organic carbon content, e.g. [3, 4, 8]. Mainly PLSR and continuum removal techniques are used. A summary of key studies using imaging spectroscopy to study soil properties can be found in [2].

### 1.2. Land degradation in the Subtropical Thicket Biome, South Africa

With 16,942 km$^2$, Thicket shrub vegetation covers approximately 10% of the land area of the Eastern Cape. According to [6], 46% has been heavily and 36% moderately impacted by goat grazing. Thicket shrub vegetation is especially built up by the endemic succulent shrub *Portulaclaria afra* which stores unusually large amounts of carbon for a plant growing in a semi-arid environment. The effects of goat pastoralism are able to transform the originally dense closed-canopy shrubland to an open Savannah-like system within decades (Fig. 1). These obvious changes of vegetation coverage and species occurrence are accompanied by a serious depletion of the soil fertility. In transformed Thicket, approximately 35% less soil carbon in the upper soil layer (up to 10 cm) and approximately 75% less biomass carbon than in intact Thicket could be detected by [5].

Local partners like the *PRESENCE* network (a *LivingLands* initiative) working on restoration of the Biome are interested in quantifying recent carbon accumulators above and below ground and upgrade both of them. For example plantings of *Portulaclaria a.* which is easy to grow from cuttings are provided in separated farm sections. The efforts were established and supported with respect to future carbon credit markets.

*Figure 1. Highly degraded on one side and on the other only slightly influenced, nearly pristine Thicket shrub vegetation. Those high contrasts are typical for fence lines between pasture and game farms (Eastern Cape, South Africa).*

### 1.3. Application area

The research area in the Eastern Cape, South Africa, covers about 225 km$^2$ (Fig. 2). It was chosen as the area with the highest variance of Subtropical Thicket vegetation classes. This step makes sure that the models

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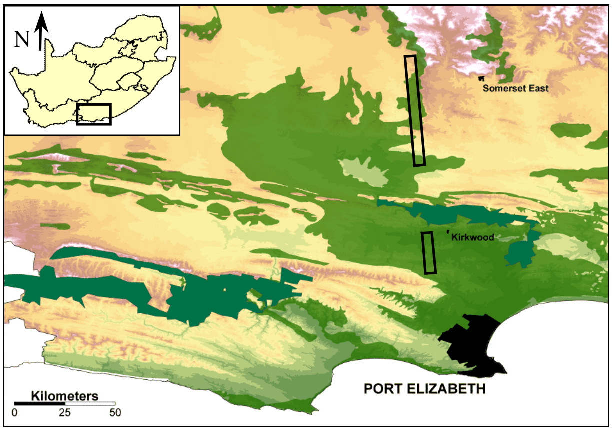


*Figure 2. Spreading of Thicket Vegetation classes and location of the research area in the Eastern Cape, South Africa (GIS data source: PRESENCE network).*

- *Research area*
- *Spreading of Subtropical Thicket Vegetation*
- *Nature Reserves*

developed based on the working area can be transferred to other regions within the Thicket Biome.

## 2. BASE DATA

Hyperspectral remote sensing data obtained from the airborne HyMap sensor were recorded in October 2009. Together with extensive ground reference data collected in two field campaigns in 2009, they serve as the data source for the research. At each of the 164 visited plots, field spectra, soil samples and information about the vegetation coverage and surface conditions were taken. A special focus was on soil crusts and stone coverage. The soils were chemically analysed (done by University of Stellenbosch, South Africa) and spectrally measured in the laboratory.

Fig. 3 shows an example for different surface conditions influencing the field spectra of two soils. A significant stone coverage reduces the soil reflectance because of shadow effects. As analysed in the laboratory, soil 1 shows relatively low organic carbon, iron and clay contents while soil 2 is characterised by a high iron and clay and an average carbon content.

## 3. DATA ANALYSIS AND FIRST MODELLING RESULTS

The three soil spectral datasets (airborne, in-situ field and laboratory) are analysed for significant absorption features. The methodical approach assumes that the concentration of the investigated soil constituent is proportional to the linear combination of properties of the absorption features present [3]. Using the measured contents in the soils as reference, a quasi-linear

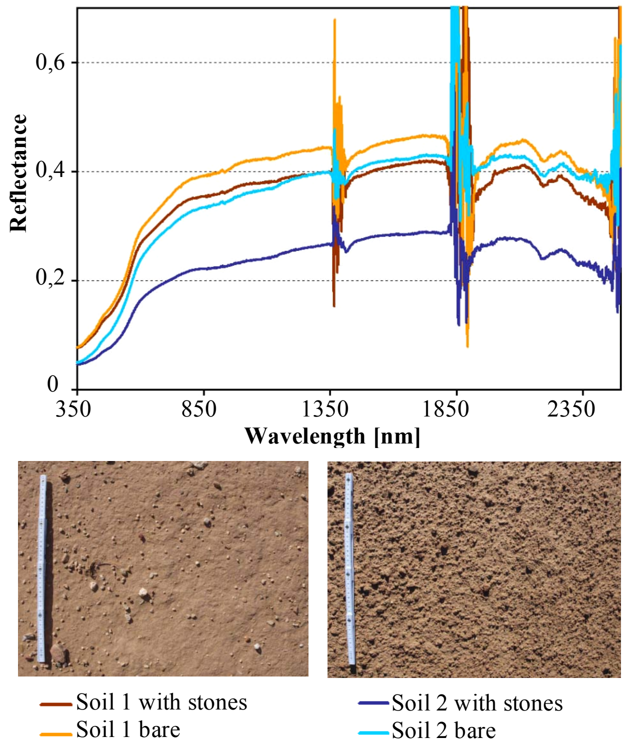


*Figure 3. Sample field spectra of two South African soils with different stone coverages measured with an ASD Field Spec Pro Spectrometer.*

relationship is established. It links spectral features to chemical contents and is modelled using multiple linear regression techniques. Validation of developed models is performed on a subset of samples separated from the main dataset by leave-n-out.

### 3.1. Partial-least-squares regression analysis

A first analysis of the correlation of spectral features and measured soil contents is conducted using the ParLes software for chemometrics based on partial-least-squares regression [9]. The number of factors to be included in the PLSR analysis is determined via leave-one-out cross-validation. All results provide good correlation accuracy (Tab. 1).

*Table 1. Results of PLS regression models based on the laboratory spectra of 164 South African soils (spectra Savitzky-Golay filtered).*

| | **Clay** | **Iron** | **$C_{org}$** |
|---|---|---|---|
| $R^2$ | 0,83 | 0,80 | 0,75 |
| Pretreatment | 1$^{st}$ derivative | 1$^{st}$ derivative | 1$^{st}$ derivative |
| No. of PLS factors | 12 | 8 | 6 |
| Parameter statistics | mean: 6,49 %<br>st.dev.: 5,09<br>min: 0,00 %<br>max: 23,80 % | mean: 3,07 %<br>st.dev.: 1,44<br>min: 0,90 %<br>max: 10,62 % | mean: 1,21 %<br>st.dev.: 0,89<br>min: 0,21 %<br>max: 5,85 % |

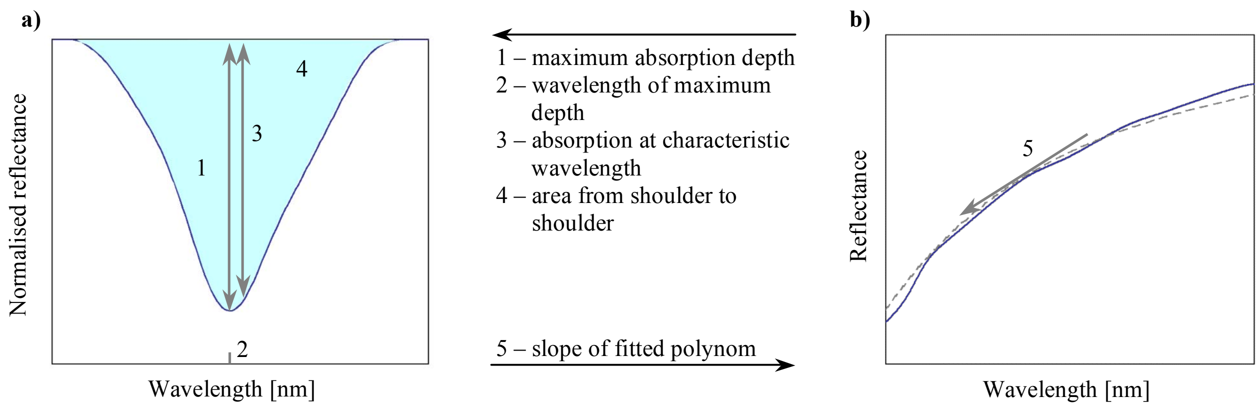


*Figure 4. Feature extraction from the soil spectral datasets is performed in two steps: a) modelling of absorption features at a characteristic wavelength and their description via four properties and b) parameterisation of the overall shape of the spectra in given ranges by properties of fitted polynoms (see $C_{org}$).*

### 3.2. Development of feature-based regression models

The second approach is based on the parameterisation of characteristic spectral features and subsequent regression analysis. For the three soil constituents (clay, iron and organic carbon), spectral features described in literature are used [3]. Table 2 shows an overview of the spectral features and pretreatments used in this first implementation of a feature-based approach. The spectral features are parameterised in two steps by the method depicted in Fig. 4. In the first step of feature extraction, continuum removal is performed in each spectral region around an absorption feature. Subsequent, the absorption features are characterised by four properties as Fig. 4 shows. The characterisation of spectral ranges is performed in a second step. For example for the determination of organic carbon, the spectral range between 500 and 900 nm is fitted by a 4th order polynom. Its slope can be used as an indicator for the soil carbon content.
A regression model is established for each soil parameter including all extracted spectral properties

*Table 2. List of spectral features used in the first development of a feature-based approach and results of subsequent regression models applied to the laboratory spectra dataset (Savitzky-Golay filtered).*
*$\lambda_{AF}$: wavelength of absorption feature to parameterise, sr = spectral range for polynom fit, $\lambda_{slope}$ = wavelength where slope of fitted polynom was calculated.*

| | |
|---|---|
| **Clay** | $R^2$ = 0,13<br>Clay 1: $\lambda_{AF}$ = 2206 nm, normalised spectra |
| **Iron** | $R^2$ = 0,50<br>Iron 1: $\lambda_{AF}$ = 870 nm, normalised spectra<br>Iron 2: $\lambda_{AF}$ = 500 nm, normalised spectra |
| **$C_{org}$** | $R^2$ = 0,54<br>Corg 1: $\lambda_{AF}$ = 2330 nm, normalised spectra<br>Corg 2: sr = 500 nm to 900 nm, no pre-treatment, fit of $4^{th}$ order polynom, $\lambda_{slope}$ = 720 nm |

related to it. Outlier samples are removed via leave-one-out cross-validation. First results of the feature-based approach show an existing correlation of spectral features with measured soil contents. As these are preliminary results, they do not reach sufficient accuracy yet (see Tab. 2). The next steps are aiming for further improvement of this approach.

## 4. FURTHER RESEARCH TOPICS

The influence of secondary characteristics like physical soil crusts or varying land coverage conditions on the spectral datasets (see also Fig. 2) will be assessed during the research and considered for model improvement. The determination of influencing features and their respective importance is another objective of the research.
A further working interest is the investigation of sensor and scaling effects and the impact on the model performance. In addition to the aerial HyMap data, Hyperion and Chris satellite sensor data as well as data simulated with the designated specifications of the future EnMap satellite sensor will be used as base data for the developed prediction model for soil parameters.

## 5. CONCLUSION AND OUTLOOK

Land degradation in the Subtropical Thicket Biome (Eastern Cape, South Africa) causes a depletion of important carbon stocks above and below ground. The three key soil parameters clay, iron and organic carbon can be taken as indicators for degradation. In this study, these parameters are quantified using hyperspectral remote sensing and multiple linear regression techniques. Using unsupervised PLS regression techniques, an accurate determination of the parameters is possible. First feature-based approaches do not reach sufficient accuracy yet and will be improved within the next iteration.

Secondary characteristics like soil crusts and the land coverage influence soil spectra and thus the model performance. They will be investigated as another objective of the research.

## 6. LITERATURE


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