The use of remote sensing for the assessment of soil inorganic carbon in the Judean Desert (Israel)

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ABSTRACT

A method for spectral detection of carbonate content was generated based on statistical analysis. It allows the prediction of soil inorganic carbon content with a cross-validated $r^2$ above 0.95. The established model was then modified to allow its application to Landsat images. Since C.I.E. color coordinates were found to be well suitable parameters for predicting the inorganic carbon content of soils under laboratory conditions, the reflectance values of the Landsat-TM bands were transformed into C.I.E. color coordinates. Subsequently, the C.I.E. based model approach was adopted to a Landsat image with low vegetation cover from July 1998 to predict spatial distribution of the soils inorganic carbon content.

The transfer of the regression model to the satellite image allowed for prediction of the inorganic carbon content. Concentrations obtained from the satellite image are in accordance with the concentration range of the chemical analysis. The predicted soil inorganic carbon concentrations reflect the geographic conditions and show a dependence on the annual rainfall amount. A general trend to increasing concentrations of inorganic carbon can be stated with increasing aridity. Furthermore, local conditions are well reflected by the predicted concentrations.

Keywords: Inorganic carbon, soil properties, reflectance spectra, soil color, spatial analysis, Landsat image.

1 INTRODUCTION

Drylands cover almost one third of the earth's surface. Especially the semi-arid ecosystems provide important land resources for adapted land use and livestock farming. But the pressure on arid and semi-arid areas resulting from climatic variability, climate change, demands of increasing stocking rates and population development was probably never as high as nowadays [1]. Since these regions are often considered as risk areas in the context of global climate change and desertification dynamics, a broad monitoring of the status of these areas is of enormous importance. In this context the soils of these ecosystems are of outstanding relevance.

Soil loss resulting from a combination of physiographic and human factors is an important sign of degradation processes. The inorganic carbon content in soils developed on carbonatic parent material in semi-arid and arid environments is one major indicator of soil development. High inorganic carbon contents indicate weakly developed or degraded soils. Since the spatial detection of inorganic carbon has a great importance in the context of monitoring land degradation and sub-recent morphodynamics, it is necessary to develop a remote sensing based approach for spectral determination of inorganic carbon content.

Therefore, the aim of this study is the spatial assessment of the inorganic carbon content of soils. In order to fulfill this objective, an analysis of the relationship between laboratory spectral measurements and inorganic carbon content is accomplished with respect to the characteristic absorption features of carbonate. Based on statistical analysis, a method for spectral detection of inorganic carbon content is generated.

Even with laboratory spectroscopy a spatial detection of soil properties exclusively based on terrestrial inquiry for broader and inaccessible areas is rarely feasible. Operational EOS are in particular suitable for the environmental monitoring of these sensitive ecosystems [2], but they usually only endure a relatively limited number of spectral channels with a comparatively small spectral resolution. Hence, an assessment of soil properties and soil development is only feasible using these few spectral bands or parameters derived from them [3, 4, 5].

The established model for detection of inorganic carbon content based on laboratory reflectance measurements will be modified to allow spatial analysis of the inorganic carbon content of soils based on Landsat images. Subsequently, an up-scaling of the model approach will be adopted to a Landsat image in order to predict spatial distribution of the soils inorganic carbon content for the investigated region.
2 THE STUDY SITE

Research was conducted along a transect following a hypsometric rainfall gradient from east of Jerusalem to the Dead Sea covering Mediterranean, semi-arid and mildly-arid climate zones and extending to the east towards the arid area near the Dead Sea (figure 1). The transect shows a strong decrease in elevation, ranging from 650 m a.s.l. in the Judea-Samaria mountains, in the west, to 60 m below sea level in the Judean Desert. Mean annual rainfall decreases on a distance of only 33 km from 620 mm in the west to about 120 mm in the east [6, 7]. According to the amount of rainfall, the soils vary from terra rossa (Mediterranean area) through brown and pale rendzinas (semi-arid and mildly-arid areas) to desert lithosols and bare rocks (arid area). All test sites are located on limestone parent material and soils vary according to the amount of rainfall.

Figure 1. Location of the study site and mean annual rainfall in Israel (modified after [8]).

3 MATERIAL AND METHODS

3.1 Field sampling and chemical analysis

Climatic conditions are modified by physiogeographic factors at meso- microscale level. In this context the relief is of special importance. In dependence of slope and aspect, irradiation is changing both in total and in daily and seasonal distribution. South-oriented slopes show higher irradiation amounts with stronger variations. Water supply is varying due to surface flow between middle slope and top or valley bottom. These different physiogeographic conditions show effects on soil development.

Figure 2. Varying physiogeographic conditions along a sampling transect in the semi-arid part of the study site (left: top of hill; middle: upper slope; right: lower slope).

Within the study site sampling of the soil surface (upper 2 cm) material was conducted along eleven topographical transects covering north- and south- facing slopes and valley bottoms to consider the different physiogeographic conditions. In total 53 samples were collected at the different climatic regions.

The soil samples were air-dried and gently crushed in order to pass a 2mm-sieve. Subsamples were carefully homogenized for an enhancement of spectral features and to allow better reaction with the chemical reagents. For
all samples organic and inorganic carbon content were analyzed by an infrared cell in a high-frequency induction oven (LECO). The content of inorganic carbon varies between 1.57 and 9.24 % with a mean of 5.22 % and a standard deviation of 1.96.

3.2 Laboratory spectral reflectance measurements

The spectral reflectance of soils is affected by the inherent spectral characteristics of varying combinations of mineral components, organic matter and the soil moisture [9]. The relations of spectral reflectance and soil properties, like grain size distribution, soil moisture, iron oxides, carbonate content and organic matter, have been outlined in many studies [5, 10, 11, 12]. Relationships between soil reflectance and carbonate content have been established using statistical methods such as multiple regression analysis [13, 14].

Spectral reflectance measurements of homogenized soil samples were acquired in the laboratory with an ASD FieldSpec II spectroradiometer in 1 nm steps between 350 nm and 2500 nm using a reflectance standard of known reflectivity. The optical head of the spectroradiometer was mounted on a tripod in nadir position with a distance of 10 cm to the sample. A 1000 W quartz-halogen lamp set in a distance of approx. 30 cm and an illumination angle of 30 degrees was used to illuminate reference panel and samples.

Carbonates show diagnostic vibrational absorption bands in the Near Infrared at 2.30 - 2.35 µm and at 2.50 - 2.55 µm. Three weaker bands occur at 1.85 - 1.87 µm, 2.12 - 2.16 µm and at 1.97 - 2.00 µm. The band positions vary with the composition of different carbonates [15, 16]. With increasing content of Mg-carbonate the wavelength position of maximum absorption is shifted to the shorter wavelength [17]. Individual absorption features for the absorption band at 2.30 - 2.35 µm were calculated by continuum removal (figure 3). Derived parameters for this absorption feature are band position, maximum absorption depth, absorption width and area integrals.

Inorganic carbon shows a strong influence to the visible domain of the spectra. Often an increase of reflectance with rising contents of inorganic carbon can be seen (figure 3). Therefore, it was decided to include color information into the further spectral analysis. For the calculation of color parameters, the reflectance measurements were converted into trichromatic specifications, and then expressed in terms of the „Commission Internationale de l’Eclairage [C.I.E.]“ color notation (Y, x, y) from 1931. In this color system the color intensity is characterized by the tristimulus value “Y” (luminance) which represents the brightness of color while “x” and “y” are the chromaticity coordinates [18]. The C.I.E. color coordinates were already found to contain substantial information for spectroradiometric detection of soil properties [10, 12].

Modeling of inorganic carbon content was conducted by multiple regression. Validating of the model results were carried out by cross-validation. Cross-validated statistics were calculated based on estimates derived according to the ‘leave-one-out-method’ which means that each sample is estimated by means of an empirical-statistical model which was calibrated using the remaining (n-1) samples. To assess the cross-validated prediction accuracy of the approach the coefficient of determination (r²) and the root mean square error (RMSEcv) were calculated.

Figure 3. Reflectance spectra (left) and continuum removal normalized reflectance spectra (right) of soil samples with different inorganic carbon content.
3.3 Satellite image pre-processing

One major objective of this study is the spatial analysis of inorganic carbon content in the Judean Desert. The used Landsat-TM 5 image from 27th July 1998 was selected considering available meteorological data. A pronounced dry period prior to image acquisition was mandatory to guarantee optimized conditions for the detection of inorganic carbon. Long dry periods insure minimum vegetation cover in semi-arid and arid regions. Additionally, the influence of varying soil moisture contents on the reflectance signal can be rated as very low.

The satellite image has been geometrically corrected to the New Israeli Grid coordinate system based on the topographic map of the region at scale 1:50,000. The image was corrected for atmospheric effects by applying a radiative transfer model which also accounts for terrain-induced illumination effects [19].

This study is focusing on spatial detection of inorganic carbon. Vegetation cover seriously influences the spectral reflectance signature, by modifying the signal of the litho- and pedological components. Since these components show a different spectral behavior than vegetation, an estimation and elimination of the spectral component of vegetation at the reflectance signal is well feasible by spectral mixture analysis (SMA). Based on SMA, areas with vegetation cover of more than 20 percentage were excluded from further analysis.

4 RESULTS AND DISCUSSION

4.1 Estimation of inorganic carbon from laboratory reflectance spectra

Modeling inorganic carbon content of soil samples requires comparable lithological conditions for soil development, to guarantee that spectral characteristics resulting for carbonate occur due to varying concentrations instead of different chemical composition of the bedrock material. The study site is characterized by relatively homogeneous cretaceous bedrock and the developed soils show a similar soil texture (mostly silt and loam) [15].

To insure that no influence of different carbonates is given the absorption position was determined. Gaffey [16] documented the absorption positions for Calcite (2.333-2.340 μm) and Dolomite (2.312-2.322 μm). The observed absorption position of the investigated soil samples stated that the carbonate exists as calcium carbonate (Calcite) [12]. Since the carbonate absorption is detectable, a relationship between carbonate content and the absorption feature is assumed.

Increasing inorganic carbon contents lead to an increase of the intensity of the carbonate absorption. A strong relationship is observed between the inorganic carbon content and the normalized absorption depth. While this relationship seems to be linear for lower concentrations, it is non-linear when considering all soil samples (figure 4). A similar non-linear relationship is documented for the absorption area of the carbonate absorption feature.

![Figure 4](image-url)

Figure 4. Inorganic carbon vs. normalized absorption depth (left) and vs. C.I.E. chromaticity value x (right).
In a first attempt the inorganic carbon contents in the soil samples were predicted based on derived absorption features. The best result was obtained using the “normalized absorption depth”. This approach allowed to estimate inorganic carbon with a cross-validated accuracy of $r^2_{cv} = 0.876$ (RMSE$_{cv} = 0.674$). This accuracy already shows the potential of spectral determination of inorganic carbon.

The relative amount of carbonate in soils influences soil brightness substantially. Increasing inorganic carbon concentrations result in exponentially higher C.I.E. luminance values $Y$. Additionally, strong linear relationships were found for the C.I.E. chromaticity values $x$ and $y$ which substantially decrease with higher inorganic carbon concentrations (figure 4).

These findings lead to the integration of C.I.E. color coordinates into the modeling. It was expected that the integration of the luminance “$Y$” representing the soil brightness would improve the modeling result substantially. However, it was found that the integration of the luminance “$Y$” did not have a positive effect on the modeling results while the integration of the C.I.E. chromaticity value “$x$” yielded a significantly higher fit. The final model is based on the variables “normalized absorption depth” and “C.I.E. chromaticity value $x$” and results in a $r^2_{cv}$ of 0.957 with a RMSE$_{cv}$ of 0.405 for the cross validation:

$$C_{\text{inorg}} = 0.591 \cdot \log(\text{absorption depth}) - 0.446 \cdot C.I.E.-x$$

(1)

The result of the cross-validation is shown in figure 5. The regression for the cross-validation is very close to the 1:1-line with a gain of almost one and an offset that can be neglected. This supplies evidence for the high accuracy of the model approach.

In table 1 the different predicting results for inorganic carbon from laboratory reflectance measurements are listed. As mentioned above best modeling results were obtained by the combination of absorption features and C.I.E. color information ($r^2_{cv} = 0.957$; RMSE$_{cv} = 0.405$). It is remarkable that based only on the C.I.E. color coordinates a high predicting accuracy with a $r^2_{cv}$ of 0.851 (RMSE$_{cv} = 0.749$) is achieved. This is especially important in the context of modeling the spatial distribution of inorganic carbon concentrations using a satellite image, because the C.I.E. color coordinates can be calculated from Landsat-TM channels as described in the following section.

### 4.2 Mapping the spatial distribution of inorganic carbon from satellite data

The limited spectral resolution of the Landsat image does not allow the exploitation of the carbonate absorption feature at 2.30 - 2.35 µm. Since an estimation of inorganic carbon based on C.I.E. color coordinates showed sound results (see section 4.1), these color coordinates form a suitable alternative for the spatial modeling of inorganic carbon. But to transform the satellite data into the C.I.E. color system some intermediate steps are necessary.

The reflectance values in the Landsat-TM channels TM1, TM2 and TM3 do not correspond to the C.I.E. tristimulus values B, G and R and need to be transformed by empirical relationships. These relationships are depending on the surveyed soils and application to other data sets is limited. While the calculation of C.I.E. color coordinates is done based on the color matching functions, the color information of Landsat-TM is determined by the sensitivity of the detectors (figure 6).
The needed empirical equations for transforming the satellite data into C.I.E. color coordinates were determined based on the laboratory spectra. For this the reflectance values of the three Landsat channels were calculated from the continuous reflectance measurements.

Based on this approach the C.I.E. tristimulus values X, Y and Z can be calculated from the satellite data using the following equations [20]:

\[
X = 2.7659R + 1.7519G + 1.1302B \quad (2)
\]

\[
Y = R + 4.5909G + 0.06012B \quad (3)
\]

\[
Z = 0.0565G + 5.5944B \quad , \quad (4)
\]

which allows the calculation of the C.I.E. chromaticity values

\[
x = \frac{X}{X+Y+Z} \quad (5)
\]

and y accordingly.

Using the derived C.I.E. color coordinates a model for predicting inorganic carbon concentration from the Landsat-TM image was established:

\[
C_{\text{inorg}} \ [%] = -0.509 \times \text{C.I.E.-x} + 0.444 \times \log(\text{C.I.E.-Y}) \quad (6)
\]

The integration of the logarithm of the C.I.E. luminance Y instead of the original value takes into consideration the non-linearity of its relationship with the inorganic carbon concentration. Based on equation 6 the inorganic carbon concentration for the study site was predicted (figure 7).
The model allows good estimates of inorganic carbon concentrations from the satellite image and represents the spatial dynamics of the study site. The concentration ranges estimated from the image data are in accordance with the concentration range of the chemical analysis (see section 3.1).

The weathering of limestone and the corresponding removal of carbonate is mainly influenced by the available amount of water. This process is accelerated by carbonic acid and organic acids as well as high temperatures. This explains the general trend of increasing inorganic carbon content with decreasing rainfall amount in the study site. This is shown in figure 8, but it has also to be considered that in the eastern part of the study site are quaternary sediments (alluvials, Lisan marls) that are bedrock material. In this region (light blue) concentrations of above ten percentages are due to the different bedrock material. A totally different situation is given for the area under agricultural use (south of Jericho and the Jordan valley) where predicted inorganic carbon contents with three to six percentages are relatively low.

Highest concentrations occur apart from the west-east-gradient in new build-up areas where the soil has been removed and the bare bedrock appears at the surface. Such high concentrations are given for the industrial area of Mishor Adummim and the extending settlement of Ma’ale Adummim. In the case of Ma’ale Adummim the newly set up street system is clearly visible (figure 8, left). In these areas in the maximum concentrations between ten and eleven are predicted which are comparable to the inorganic carbon concentrations of pure bedrock samples of around eleven percentages.

In the western part of the study site lower to medium concentrations prevail with lowest estimates occurring in the Wadis, sometimes even below 3%. The reason is the better water supply and the resulting higher soil moisture compared to the slopes, which allows a substantially better soil development in the valleys (figure 8, right).

**5 CONCLUSIONS**

Inorganic carbon concentrations were predicted with high accuracy from laboratory reflectance measurements ($r^2_{cv}>0.95$) by combining the normalized absorption depth of the carbonate absorption feature at 2.33 µm and the C.I.E. chromaticity value $x$. It was found that the adaptation of the regression model to C.I.E. color values only also allows sound estimates of inorganic carbon contents ($r^2_{cv}>0.85$). The adaptation of the model made an up-scaling to satellite data possible and reflects the spatial pattern in the study site very well. Furthermore, the regression model allows sound estimates of the spatial distribution of inorganic carbon concentrations in the study site. Finally it is
assumed that the introduced approach can also be used for other soil parameters and is applicable to other semi-arid and arid regions with similar physiogeographic conditions.

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