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Estimation of Vegetation Parameters from Multispectral Data using Physical Models and Ground Control Measurements

FRANZ KURZ, München, OLAF HELLWICH, Berlin & HEINRICH EBNER, München

Summary: We propose a general framework to estimate vegetation parameters from multispectral remote sensing data using physical radiative transfer models and a moderate amount of ground control data. This framework has been exemplarily demonstrated for different winter wheat fields imaged by a Daedalus ATM multispectral scanner in the last two years. The main focus lies on the variations of vegetation parameters within single fields, which are used to derive information about soil heterogeneities for precision farming. For the estimation of vegetation parameters we use physical radiative transfer models, e. g. SAIL and PROSPECT, combined with a linear empirical model. Results show the invertibility of the models for leaf area index, chlorophyll content, specific dry matter, and specific water content. A strategy for the use of ground control data is proposed to receive high accuracies of the estimated vegetation parameters with a minimum of necessary measurements.

Zusammenfassung: *Schätzung von Vegetationsparametern aus Multispektraldaten mit Hilfe physikalischer Modelle und Bodenkontroll-Messungen.* In dieser Arbeit wird ein Verfahren zur Schätzung von Vegetationsparametern aus multispektralen Fernerkundungsdaten mit Hilfe physikalischer Strahlungstransfer-Modelle und einer moderaten Anzahl von Bodenkontroll-Messungen vorgestellt. Dieses Verfahren wurde über einen Zeitraum von zwei Jahren exemplarisch an verschiedenen Schlägen mit Winterweizen getestet, die mit einem Daedalus ATM Multispektralscanner aufgenommen wurden. Von besonderem Interesse sind hierbei die Schwankungen der Vegetationsparameter innerhalb einzelner Schläge zur Ableitung von Informationen über Bodenheterogenitäten, die im Precision Farming eine wichtige Rolle spielen. Zur Schätzung der Vegetationsparameter verwenden wir verschiedene physikalische Strahlungstransfer-Modelle, u.a. SAIL und PROSPECT, in Kombination mit einem linearen empirischen Modell. Die Ergebnisse zeigen, dass durch Invertierung der verwendeten Modelle der Blattflächenindex, der Chlorophyllgehalt, die spezifische Trockenmasse und der spezifische Wassergehalt zuverlässig geschätzt werden können. Eine Strategie zur Verwendung von Bodenkontroll-Messungen wurde entwickelt, bei der hohe Genauigkeiten mit einem Minimum an Messaufwand erreicht werden können.

1 Introduction

Remote sensing techniques play an important role in precision farming by providing continuous and contactlessly acquired data of agricultural crops. Remote sensors image vegetation, which is growing on different soil types with different water availability, substrate, impact of cultivation, and relief. These differences influence the state of the plants and cause heterogeneous regions within single fields. Hence the heterogeneous vegetation acts as an interface between soil and remote sensing information, because vegetation parameters describing the state of the plants can be deduced from remote sensing imagery.

In this context a framework for the estimation of vegetation parameters from mul-

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tispectral imagery is proposed. The main focus of our approach lies on the variation of the vegetation parameters within single fields assuming that field borders and vegetation type are given. This framework applies both a physical and an empirical model to derive the functional relationship between vegetation parameters and measured image grey values. The physical model is used to estimate selected vegetation parameters by an inversion process, whereas the empirical model fits the physical model to local characteristics and sensor specifics.

This technique has been exemplarily tested for several sites with winter wheat imaged by a *Daedalus* ATM multispectral scanner from *DLR* (German Aerospace Center). Results show the attained accuracies for the estimated vegetation parameters with respect to the amount of ground control points.

2 Related Work

The estimation of vegetation parameters using physical models is based on the description of radiative transfer in the canopy by means of an analytical reflectance model. In the last 30 years, various models describing radiative transfer in canopy, soil and leaves have been published. These models provide the relationship between the radiation incoming from the sun and – according to the bidirectional reflectance distribution function (BRDF) – to the observer scattered radiation. Inputs of these models are the structural and spectral parameters of the vegetation/soil medium. Models describing the complete vegetation/soil medium are called *canopy transfer models*, e. g. the *SAIL* model (Verhoef 1984), the Nilson-Kuusk canopy reflectance model (Nilson & Kuusk 1989), and the *LCM2* model (Ganapol et al. 1999). In these models, the leaves are considered as the only components of the vegetation canopy characterised by their reflectance and transmittance. The spectral properties of the leaves are mainly influenced by the chemical consistency of the leaves, which can be modelled by so called *leaf optical physical models*, e. g. *PROSPECT* (Jacquemoud & Baret 1990), *LEAFMOD* (Ganapol et al. 1998), and *SLOPE* (Maier 2000).

Generally, these models were set up in the forward mode. This means output parameters are the reflectance on top of the canopy for given parameters of the vegetation/soil medium. The solution of the resulting inverse problem was subject of many investigations during the last years. Depending on the applied sensors two main methods can be distinguished, inversion with multidirectional and with multispectral data. Independent of the method the inversion of the physical model was conducted using different mathematical algorithms such as look up table (Knyazikhin et al. 1998), iterative optimisation (Jacquemoud et al. 1995), and neural networks (Buelgasim et al. 1998). These algorithms adjust the model input parameters in such a way that the model-predicted values closely match the measured values. A comparison of these methods (Pragnere et al. 1999) gives slight advantages to the neural networks technique that is most robust for different sensors and canopy types. Up to now the inversion studies are performed with simulated reflectance or field spectrometer measurements. In practical applications with airborne or space-borne sensor data, a variety of empirical tools, such as vegetation indices and spectral mixture models, are widely used to derive biophysical parameters of the vegetation. Our approach combines strict inversion of physical models with empirical elements to estimate biophysical parameters from airborne sensor data. In previous work (Kurz & Hellwich 2000), we describe our inversion method, the investigation of invertibility and the selection of relevant biophysical parameters in more detail. We chose four parameters for a partial inversion of the applied physical models: *leaf area index*, *chlorophyll content*, *specific dry matter*, and *specific water content*. The inversion was conducted using simulated annealing followed by a least squares adjustment.

3 Methodology

3.1 *Overview*

Modelling of radiative transfer is usually established in the forward direction, i. e. the model follows the way of the photons from the sun to the observer to calculate sensor grey values given some information about the surface and atmosphere. The reverse direction is also referred to as model inversion with given sensor grey values to derive information about the surface and atmosphere.

Fig. 1 shows the combination of several physical and a linear empirical model in the forward and reverse mode. The model input is divided into constant and variable parameters. The variable parameters, leaf area index, chlorophyll content, specific dry matter and specific water content, are part of the input parameters as well as the target parameters of the model inversion. These parameters are chosen because they show the highest variability within single fields, whereas the other input parameters, e. g. the soil reflectance or the leaf angle distribution, are assumed to be known and constant. Output parameters of the physical models are sensor grey values $g^{\lambda}_{\text{phys-mod}}$ that have to be fitted to grey values $g^{\lambda}_{\text{meas}}$ actually occurring at the test site. We use a linear empirical model to attain fitted model-predicted grey values $g^{\lambda}_{\text{model}}$.

During the model inversion variable parameters are calculated given the measured grey values. The model inversion is conducted by a *least-squares* adjustment in combination with *simulated annealing*.

In the following chapter a more detailed description of the applied physical and empirical models with all input parameters is given.

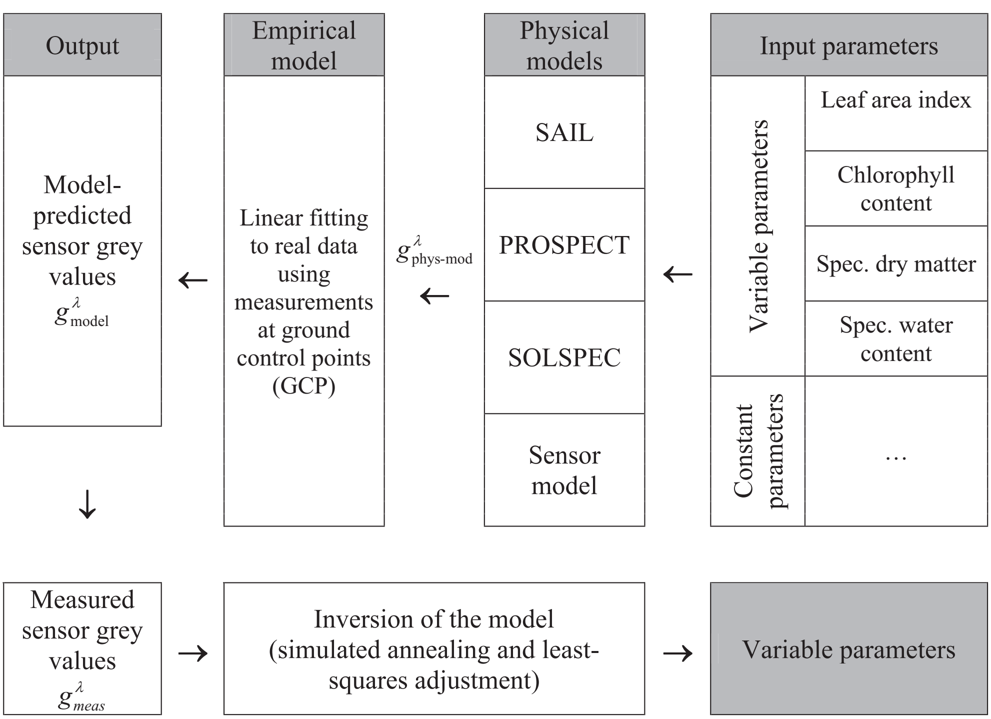

Fig. 1: Overview of the applied physical and empirical models in the forward (upper part) and reverse (lower part) direction.

3.2 *Physical and Empirical Models*

3.2.1 *The SAIL model*

The *SAIL* model (Verhoef 1984) calculates the directional reflectance on top of the canopy as a function of structural and spectral properties of the vegetation/soil medium. A functional relation between vegetation- and soil parameters and directional reflectance ρ^λ can be sketched by

$$\rho^\lambda = SAIL\ (LAI,\ LAD,\ \rho_l^\lambda,\ \tau_l^\lambda,\ \rho_s^\lambda,\ SKYL^\lambda,\ a,\ z,\ z_{sun}) \qquad (1)$$

The vegetation canopy is considered as a homogeneous layer characterised by leaf area index *LAI*, leaf angle distribution *LAD*, as well as reflectance ρ_l^λ and transmittance τ_l^λ of the leaves. Other input parameters of the *SAIL* model are soil reflectance ρ_s^λ, diffuse percentage $SKYL^\lambda$ of the incoming radiation, azimuth angle a of the observer with respect to the azimuth angle of the sun, zenith angle z of the observer, and zenith angle z_{sun} of the sun.

3.2.2 *The PROSPECT model*

The *PROSPECT* model (Jacquemoud & Baret 1990) provides hemispherical reflectance ρ_l^λ and hemispherical transmittance τ_l^λ of fresh leaves over the whole solar domain given only four parameters

$$(\rho_l^\lambda,\ \tau_l^\lambda) = PROSPECT\ (chl_{ab},\ c_m,\ c_w,\ N) \quad (2)$$

The variables are the content of chlorophyll a and b chl_{ab}, the specific dry matter c_m, the specific water content c_w, and a structure parameter N. The reflectance and transmittance of leaves calculated with the *PROSPECT* model are used as input parameters for the *SAIL* model.

3.2.3 *The SOLSPEC Model*

A simple solar spectral model is used to transform the directional reflectance on top of canopy to spectral band radiances L^λ at the sensor. The *SOLSPEC* solar spectral model (Bird 1984) calculates direct normal E^λ_{direct} and diffuse irradiances $E^\lambda_{diffuse}$ at tilted surfaces as well as the diffuse percentage $SKYL^\lambda$ of the incoming radiation, which is an input parameter of the *SAIL* model. Input to *SOLSPEC* includes date, time and position, the surface orientation, the temperature, the amount of precipitable water vapour, ozone, and the surface air pressure.

$$E^\lambda_{direct},\ E^\lambda_{diffuse},\ SKYL^\lambda) = SOLSPEC\ (date,\ time,\ \mathrm{K}) \qquad (3)$$

No further atmospheric corrections are applied. Given the total incoming radiation $E^\lambda_{direct} + E^\lambda_{diffuse}$ and the directional reflectance of the vegetation canopy ρ^λ, the spectral band radiances L^λ at the sensor can be calculated.

$$L^\lambda = \frac{(E^\lambda_{diffuse} + E^\lambda_{direct})\rho^\lambda}{\pi} \qquad (4)$$

3.2.4 *Sensor Model*

A sensor model is applied to transform the continuous spectral band radiances L^λ at the sensor into band specific grey values $g^\lambda_{\text{phys-mod}}$. First the spectral sensitivities of the sensor bands are taken into account to calculate representative spectral radiances for each band. Then with given calibration constants of the sensor and the representative spectral band radiances grey values $g^\lambda_{\text{phys-mod}}$ can be calculated.

3.2.5 *Empirical Model*

As mentioned above the grey values $g^\lambda_{\text{phys-mod}}$ have to be fitted to the grey values g^λ_{meas} actually occurring at the investigated test site using simple parameters such as offset a^λ and scale b^λ for each sensor band. These parameters are assumed to be constant for each dataset. This linear fitting is necessary due to simplifications made in the physical models and uncertainty of constant model parameters.

The model-predicted sensor grey values g^λ_{model} are calculated by linear transformation of the grey values $g^\lambda_{\text{phys-mod}}$ using

$$g^\lambda_{\text{model}} = a^\lambda + b^\lambda\, g^\lambda_{\text{phys-mod}} \qquad (5)$$

Fig. 1 illustrates the calculation of the model-predicted sensor grey values $g^{\lambda}_{\text{model}}$ from input parameters using the described physical and empirical models.

3.3 *Inversion Process*

During the inversion process an optimal set of variable input parameters is estimated from the given grey values by non-linear and linear optimisation methods for each pixel (v. Fig. 1). In our approach the inversion of the applied models was conducted by the global optimisation method *simulated annealing* (Hellwich 1999) followed by a conventional *least-squares* adjustment using a Gauss-Markov model (Mikhail 1976) with weighted observations. There is a redundancy of five for each pixel with the measured grey values $g^{\lambda}_{\text{meas}}$ in nine spectral bands as observations and four unknown vegetation parameters, LAI, chl_{ab}, c_m, and c_w. In addition the offset a^{λ} and scale b^{λ} are introduced as unknown parameters as well as observations. The introduction of pseudo observations $a^{\lambda} = 0$ and $b^{\lambda} = 1$ with low weights supports the inversion process. The pseudo observations decrease the influence of weak ground control points and reduce ambiguities.

The empirical parameters a^{λ} and b^{λ} should be estimated once for each dataset, which leads to 2×9 additional unknown parameters for a single dataset. The ground truth parameters measured on the selected ground control points are also introduced as observations being uncertain to a degree corresponding to the acquisition method. All other input parameters are assumed to be known and constant in the inversion process. Now the unknown empirical parameters and the vegetation parameters for each pixel can be estimated in a simultaneous least-squares adjustment. For this approximate values for the unknown vegetation parameters are necessary. First approximate values for the offset and scale parameters can be estimated through linear regression with the grey values $g^{\lambda}_{\text{phys-mod}}$ and measured grey values $g^{\lambda}_{\text{meas}}$ of at least two ground control points. Then approximate values for the unknown vegetation parameters are estimated using *simulated annealing*. As an alternative standard values of the unknowns may be used as approximate values.

The poor robustness of the inversion process is the main problem. The inversion fails, if vegetation parameters leave the definition range or the maximum number of iterations is reached. To improve the accuracy and robustness some enhancements have been implemented.

- Pixels not representing the main crop, e. g. tracks of agricultural machines and weed, are eliminated from the estimation process. For the extraction of these disturbances some classification methods have been suggested (Kurz et al. 2000).
- Robustness and accuracy are improved by averaging grey values of neighbouring pixels belonging to homogenous areas.
- To restrain the vegetation parameters inside the definition range a penalty technique was applied during *simulated annealing*. If vegetation parameters leave the definition range during the least squares adjustment the parameters are set back to values at the edge of the definition range. If this procedure is not successful, the corresponding point will finally be eliminated.

4 Results

4.1 *Database*

The investigations were conducted under the umbrella of the *Forschungsverbund Agrarökosysteme München* (*FAM*, Research Network Agricultural Ecological Systems Munich), which is presently using the Daedalus multispectral scanner as standard remote sensing instrument. For the 1.5 km^2 *FAM*-test sites in north of Munich, *Daedalus* multispectral scanner data and colour-infrared aerial photography were acquired. Flight dates were 28 June 2000 and 27 June 2001, when winter wheat changes to maturity. The *Daedalus* multispectral scanner operates in *11* spectral bands of the *VIS, NIR, SWIR* and *TIR* spectra. Nine of these channels are used in the inversion process. The ground pixel size amounted to *1.33 m*. The *Daedalus* image data were geocoded by matching with ortho imagery with a ground pixel size of *0.06 m*. The influences of the wide scan angle (RICHTER 1992) on the radiometry of the *Daedalus* scanner were corrected by DLR.

At several fields with winter wheat randomly distributed measurement sites were selected each year. At these sites as many as possible input parameters of the applied physical models were measured, such as total dry matter and total water content of samples, leaf area index and mean leaf angle. The wet samples corresponding to an 0.25 m^2 area were weighed, oven dried and weighed again to assess total dry matter and total water content. Leaf area index and mean leaf angle were measured with the *Licor LAI-2000* analyser. Combining leaf area index with total dry and wet matter, specific dry matter and specific water content are derived. From the mean leaf angle and a shape parameter the leaf angle distribution *LAD* is derived based on an ellipsoidal distribution. Using the *Licor LAI-2000*, ears, stems and leaves of winter wheat plants cannot be separated for the assessment of leaf area index and mean leaf angle. Thus, all measurements are made without separation of different plant components. The chlorophyll content has been estimated qualitatively considering the visual appearance of the leaves. Most measurements are repeated to assess accuracy properties.

4.2 *Estimation of vegetation parameters at the test sites*

The estimation of vegetation parameters was conducted using the described models and *Daedalus* multispectral scanner data. The measurement sites within the fields are arbitrarily divided in ground control points and validation points.

The ground truth measurements at the ground control points are an essential part of our model, whereas the measurements at

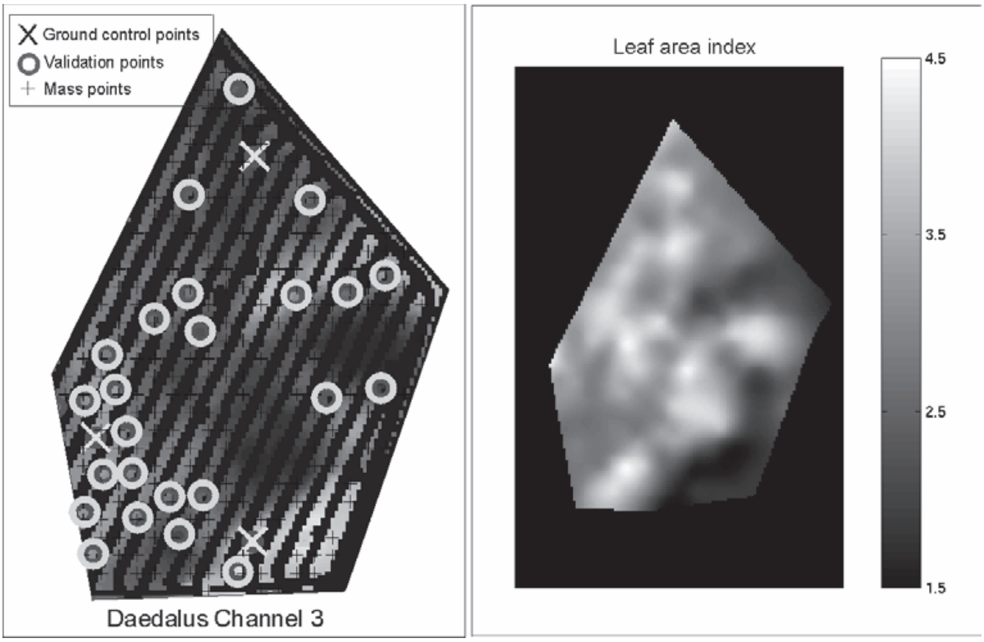

Fig. 2: Data acquisition with *Daedalus* ATM scanner and ground truth measurements on June 28th 2000. Regions with disturbed vegetation are masked out. In this example three ground control points are selected for model inversion. The estimation has been conducted at validation and mass points to create maps of vegetation parameters (for example leaf area index on the right).

the validation points are used to prove the accuracy of the inversion process. No measurements are made at mass points, which are used to estimate unknown vegetation parameters at any position within the field. To reduce computing time mass points are chosen in a grid of 10 × 10 pixels. Fig. 2 illustrates the distribution of the different types of points. In this special case three ground control points are chosen. Disturbed pixels and pixels near the wheel tracks have been eliminated. Thus, mass points lying on the eliminated pixels have been excluded from the inversion process. The *Daedalus* multispectral scanner data have been smoothed with a mean filter of mask size 5 × 5. Approximate values for the vegetation parameters at mass points are estimated using simulated annealing. After the least-squares adjustment the resulting maps of vegetation parameters are calculated by interpolating between the estimated vegetation parameters.

4.3 *Accuracies*

Our goal is to derive a strategy for the use of ground control points. From a practical view the number of necessary ground control points should be low to reduce required ground truth measurements. On the other hand the robustness of the inversion process and attained accuracies of the estimated vegetation parameters should be high. In Fig. 3 two kinds of accuracies of the estimated leaf area index for two combinations of ground control points are illustrated. The theoretical standard deviation, which is derived from the least-squares adjustment, corresponds quite well with the empirical deviation at the validation points with a tendency of higher empirical deviations for both combinations. The empirical deviation is the difference between measured and estimated vegetation parameters.

Fig. 4 shows the relation between the number of ground control points and the empirical or theoretical accuracies of the vegetation parameters. For this purpose the theoretical and empirical accuracies at the validation points are estimated for different combinations of ground control points. Using the accuracies at the validation points the *RMSE* (root mean square error) for each vegetation parameter expressed in percent of the mean value has been calculated. The results show that the *RMSE* of the vegetation parameters are more or less independent of the number of ground control points. The inversion fails completely, if no ground control points are used, i. e. most vegetation parameters leave the definition range.

Note, that the accuracies and robustness of the inversion depend on quality of the measurements at ground control points and

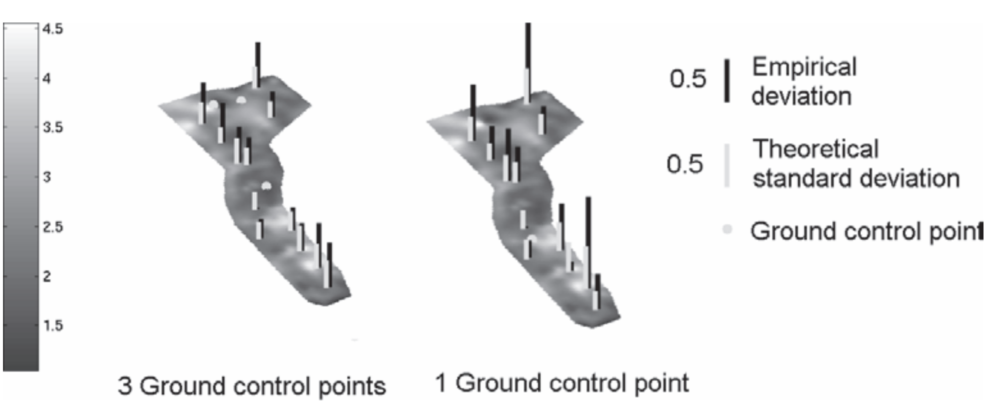

Fig. 3: Maps of leaf area index estimated with *Daedalus* scanner data of June 27th 2001. For two combinations of different ground control points the empirical deviations and the theoretical standard deviations of the leaf area index at the validation points are calculated.

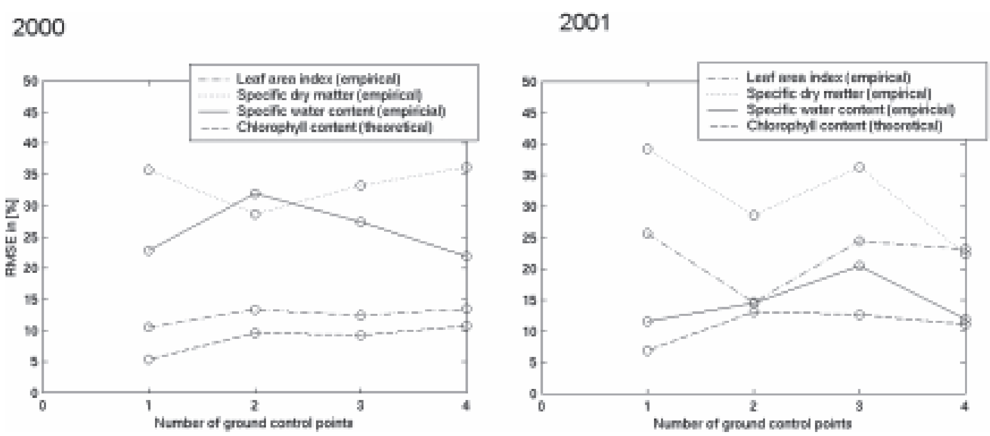

Fig. 4: Relation between the number of ground control points and the accuracies of the estimated vegetation parameters for two campaigns in the years 2000/2001.

spectral distribution of these points. For practical applications the ground control points have to be selected before or during the data acquisition and should ideally cover the whole range of grey values in each band. Unfortunately, the selection can be based only on the visual appearance of the fields unless there are multispectral data available before or during the data acquisition. Thus the selection of ground control points is based only on the visual bands independent of the grey values of these points in all other bands.

Generally spoken, the robustness of the inversion process can be increased by using more than one ground control point. In this case the ground control points should be spectrally well distributed in their visual appearance. Using only one ground control point, accuracies and robustness may be poor, if the grey values of the ground control point lie at one end of the value range in the visible bands. For acceptable accuracies the ground control point should lie near the centers of the grey value range.

4.4 *Influence of constant model parameters*

During the inversion process the constant model parameters have to be set to realistic values, which are partly difficult to determine. Uncertainties of constant model parameters influence the inversion process and can be attenuated through the empirical fitting of the physical models. Our goal is to investigate which constant parameters can be set to any values within the definition range and which should be adjusted to the actual situation. Thus, the accuracies of the vegetation parameters are computed as a function of constant parameters, which vary within their definition range. Results show that only three constant parameters influence the accuracies of the vegetation parameters and should be adjusted to the investigated vegetation type and soil: the structure parameter N, the leaf angle distribution LAD, and the soil reflectance ρ_s^λ. All other constant parameters can be set to any values, because a variation of these parameters only slightly influences the accuracies.

5 Summary

A new semi-empirical technique for the estimation of vegetation parameters from multispectral image data was proposed and tested with real data. By inverting physical radiative transfer models in combination with an empirical model agriculturally relevant vegetation parameters can be estimated given the grey value vector of the *Daedalus* scanner imagery. The inversion of models was conducted by a *least squares* adjustment in combination with *simulated annealing*. Four vegetation parameters *leaf area index*, *chlorophyll content, specific dry matter, and specific water content* have been selected for the inversion process.

Ground control points are a necessary part of our inversion process and are used for a linear fitting of model-predicted grey values to measured grey values. The goal is to use a minimum of ground control points to receive acceptable accuracies for the estimated vegetation parameters. Results show that by using at least one ground control point the accuracies are more or less independent of the number of ground control points. Using more than one point increases the robustness of the inversion process. In this case the grey values at ground control points should cover the whole range of grey values in the visible bands. If only one ground control point is used this point should lie near the center of the grey values range for acceptable accuracies and robustness.

The influence of constant input parameters of the physical models on the accuracies has been investigated. Only three input parameters influence the accuracies, the soil reflectance, the leaf angle distribution and the structure parameter. The three constant parameters should be adjusted to the actual vegetation type and soil at the investigated sites. All other constant parameters can be set to any values within the definition range.

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Addresses of the authors:
Dipl.-Ing. FRANZ KURZ, Chair for Photogrammetry and Remote Sensing,
Technische Universität München,
Arcisstraße 21, D-80333 München, Germany.
Tel.: 49-89-289 22676, Fax: 49-89-280 9573
e-mail: Franz.Kurz@bv.tum.de
URL: http://www.remotesensing-tum.de

Univ.-Prof. Dr.-Ing. OLAF HELLWICH,
Photogrammetrie und Kartographie,
Technische Universität Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany
Phone: +49 30/314 22796, Fax: +49 30/314 21104
E-mail: Hellwich@fpk.tu-berlin.de
URL: http://www.fpk.tu-berlin.de

Univ.-Prof. Dr.-Ing . HEINRICH EBNER
Chair for Photogrammetry and Remote Sensing,
Technische Universität München, Arcisstraße 21,
80333 Munich, Germany,
Phone: +49 89/289 22670, Fax: +49 89/280 9573,
E-mail: Heinrich.Ebner@bv.tum.de
URL: http://www.remotesensing-tum.de

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