# EMPIRICAL ESTIMATION OF VEGETATION PARAMETERS USING MULTISENSOR DATA FUSION

**Franz KURZ and Olaf HELLWICH**
Chair for Photogrammetry and Remote Sensing
Technische Universität München, D-80290 Munich, Germany
Phone: +49/89/289 22676, Fax: +49/89/280 9573
E-mail: franz@photo.verm.tu-muenchen.de
URL: http://www.photo.verm.tu-muenchen.de

Working Group VII/4

**KEY WORDS:** Agriculture, Data fusion, Multi-sensor, Land use/Land cover, GIS

## ABSTRACT

To estimate parameters of large-scale vegetation heterogeneity for the determination of soil heterogeneity a method based on fusion of multisensor image and pointwise ground-truth data is proposed. Regression analysis of multispectral imagery and ground-truth data is used to map soil indicative vegetation parameters for the area of a complete field. With high-resolution aerial imagery natural and disturbances in a field, like tracks, weed-stripes and turning areas of crop machines, can be detected and excluded from mapping of vegetation heterogeneity. The disturbances caused by human cultivation and external natural influences hinder the estimation of the underlying soil condition. First results show the strong influence of disturbances on multispectral imagery and poor applicability of linear regression equations for predicting soil indicative vegetation parameters.

## 1 INTRODUCTION

Regarding the relationship between soil and vegetation canopy, structure and local differences of the soil, also called soil heterogeneity, play an important role. In combination with the hydrological conditions within a field they cause certain patterns of homogeneous regions with equal properties of vegetation and underlying soil. To determine area-wide soil heterogeneity patterns, remote sensing is a useful tool due to contactless and non-destructive data acquisition. As most of the soil is hidden by vegetation, a direct estimation of soil heterogeneity cannot be established. Therefore, the vegetation canopy with its own heterogeneity acts as the interface between remote sensing and soil science. The goal of our approach is to determine the vegetation heterogeneity to indicate lateral and vertical soil heterogeneity on a local scale.

Our approach is based on the acquisition of high-resolution remote sensing data over vegetated areas for which information of the soil is mostly hidden from the sensors. Vegetation parameters are empirically estimated and used to classify the investigated area into regions with homogeneous vegetation canopy. For the estimation of vegetation parameters point-wise ground truth data are acquired and related to the multispectral data. (Wehrhan and Selige, 1997) used single-regression analysis for quantitative estimation of soil-indicative vegetation parameters. Optimal band combinations were found which correlate to parameters like biomass, grain yield and field capacity. Linear regressions are used for the area-wide mapping of these parameters within single fields. Local disturbances in high-resolution remote sensing data, like compression of soil caused by crop machines, and variation in reflectance caused by other vegetation parameters limit the applicability of such regression equations. The sources of variability in canopy reflectance in combination with disturbances have to be examined with respect to their influence regression analysis. We aim to determine the influences of such parameters and disturbances by fusing multispectral scanner with aerial imagery and point-wise ground truth data using regression equations.

## 2 DATABASE

For a $1.5\,km^2$ study site in the north of Munich, Daedalus multispectral scanner data and aerial photography was acquired. A comprehensive agricultural database was built up during the last ten years, including information on the relief, soil and landuse for a number of fields. Dry biomass and water content on representative sites were measured for grassland and winter wheat field. The wet samples were weighted, oven dried and weighted again to assess dry biomass and water content.

The Daedalus multispectral scanner operates in 11 spectral bands of the VIS, NIR, SWIR and TIR spectrum with a ground resolution of 1.2 m. The measured radiance of the Daedalus scanner was atmospherically and geometrically corrected. Thus radiometrically corrected and georeferenced canopy reflectance is available and can be correlated to ground-truth data as well as to aerial photography. Hence vegetation parameters like biomass or water content can be estimated through regression equations. The aerial photography with a infrared-colour film shows a ground resolution of 0.06 m which is ideal for detecting local disturbances. A georeferenced orthophoto of the whole scene was generated and overlaid with the multispectral data. Thereby the contour of local disturbances can be identified and located in the aerial photography and transferred to the scanner images. The geometric precision of both sensors plays an important role for assigning small local disturbances to single pixels in the scanner images. Actual deviations of up to 3 meters between georeferenced orthophoto and geometrically corrected scanner image can be improved through local transformations like rubber sheeting.

## 3 METHODOLOGY

### 3.1 Regression analysis

On a local scale the vegetation canopy consists of a variety of structures, patterns and objects caused by influences of soil properties, hydrological conditions, relief and human cultivation. The varying impact of these factors cause the vegetation canopy to appear heterogeneous within a field. The growth of vegetation and, therefore, the spectral properties depend on such influences. In our approach the focus lay on the vegetation patterns which are supposed to be partly caused by certain properties of the soil like field capacity, water-conductibility or soil density. Some vegetation parameters (e.g., biomass, grain yield and water content) reflect the conditions of the underlying soil. Together with some soil parameters like field capacity they can be estimated by linear regression analysis using ground-truth data. The ground truth data are necessary to estimate the correlation between parameters and reflectance of vegetation canopy, e.g. grey values. (Aase and Siddoway, 1981) derived regression equations between canopy spectral reflectance and total dry biomass of wheat. Their results were linear equations describing the state of the plants from the growing stage to flowering. (Tucker et al., 1981) found strong correlation between integrated normalized difference vegetation index and total above-ground biomass in grasslands. (Wehrhan and Selige, 1997) selected optimal bands for correlation in the red and in the SWIR spectrum and set up linear regression equations for winter wheat and grasslands. A strong correlation coefficient of 0.85 between Daedalus channel 5 (RED: 630 nm - 690 nm) and dry biomass in a winter wheat field was found. In our approach we use linear regression equations between red reflectance and biomass as well as water content.

### 3.2 Semantic model

A semantic model is a powerful tool for the declaration of complex relations between objects on several levels of abstraction. Knowledge representation as well as the implementation of methods can be based on semantic modelling. (Tönjes et al., 1999) and (Hellwich and Wiedemann, 2000) use semantic modelling for the automatic extraction of road networks from aerial imagery. In our approach a semantic model is applied which describes multisensor data fusion for the estimation of vegetation parameters. Figure 1 shows a semantic model for the determination of vegetation heterogeneities to support the evaluation of soil conditions. The predominant component of an agricultural field is the main crop which can be disturbed by natural and anthropogeneous influences. Examples of anthropogeneous disturbances are tracks and turning areas of crop machines, trails, terraces, and watering-places, etc.. Natural disturbances, like erosion, landslides, diseased and ancillary crops, influence the vegetation canopy and thus the spectral properties.

Ancillary crop are regions with mixed vegetation types. Examples for ancillary crop are small weed-islands within the main crop or weed-stripes on the edge of a field. Both main crop and ancillary crop can be disturbed by anthropogeneous influences. Only the regions with intact main crop are evaluated with respect to vegetation heterogeneities, because only they should be related to ground truth vegetation parameters through regression analysis. All other regions are excluded from further evaluation.

| *kind of disturbance* | *geometric properties* | *radiometric properties* |
|---|---|---|
| tracks | parallel straight wheel ruts with constant distance,<br>in the length direction of a field | dark in all bands,<br>sometimes brighter in infrared band |
| turning areas | irregularly shaped areas<br>on the short sides of a field | mostly brighter in infrared band |
| weed islands | rounded shapes with strong edges,<br>irregular distribution over the field | mostly rough texture |

Table 1: Geometric and radiometric properties of disturbances in a winter wheat field

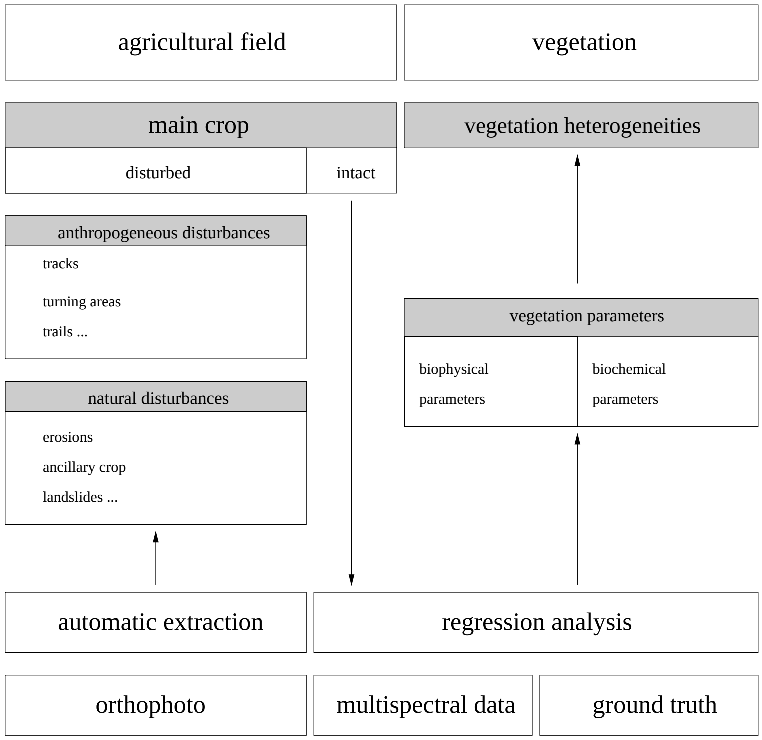


Figure 1: Sensorfusion model for the extraction of vegetation heterogeneities.

The disturbed vegetation as well as the ancillary crop has altered spectral properties which are not applicable for empirical estimation of vegetation parameters. Table 1 describes some disturbances and ancillary crops with its geometric and radiometric properties. These properties can be used to detect the disturbances with automatic extraction algorithms (e.g. edge detection, texture analysis, segmentation methods). Figure 2 shows a field with senescent winter wheat. Because of a ground-resolution of 0.06 meter in the infrared colour orthophoto, small structures in the field can be identified and located. Some disturbances and ancillary crops are marked manually. The regions with intact main crop appear as bright and mostly homogeneous regions, disturbed by lanes, weed islands and weed stripes. The heterogeneous regions of the main crop are supposed to be caused by underlying soil or hydrological conditions. These description of the relations between main crop and soil is an objective of further investigations.

## 4 RESULTS

Figure 2 shows an orthophoto with a ground resolution of 0.06 m and a Daedalus scanner image of Channel 6 (NIR: 695 nm -750 nm) with a ground resolution of 1.2 m. Whell ruts and regions of ancillary crops were extracted from the orthophoto. The Daedalus image appears heterogeneous with small bright regions and some stripes in north-south direction. These disturbances cannot be identified without ambiguities, because several structures are mixed in one pixel. This image is overlaid with the structures extracted from the orthophoto to visually judge their influences. Lanes appear as bright stripes in the scanner image, because grass is growing in the lanes which is photosynthetically more active than the senescent winter wheat. The weed islands and weed stripes show high reflectance in the infrared band, too. The remaining variabilities in the reflectance are mainly caused by varying vegetation parameters influenced by soil and hydrological conditions. Thus by using the orthophoto we are able to minimize errors in estimating vegetation parameters by exclusion of disturbed main crops.

In Figure 3 a linear regression equation was estimated to relate dry biomass to red reflectance in grasslands. Red reflectance shows the strongest correlation coefficient of -0.79 to dry biomass. The linear regression equation is used to map dry biomass area-wide within a single field. For the confidence of predicted dry biomass from red reflectance a confidence interval with a significance of 5% was calculated. The total range of dry biomass values lies between 196 and 330 $\frac{g}{m^2}$, whereas the mean width of the confidence interval amounts 130 $\frac{g}{m^2}$. In spite of the high correlation coefficient this linear regression fails to give a confident prediction of dry biomass from red reflectance because of the broad confidence interval and the small range of values.


Figure 2: Orthophoto and Daedalus Image of a winter wheat field.

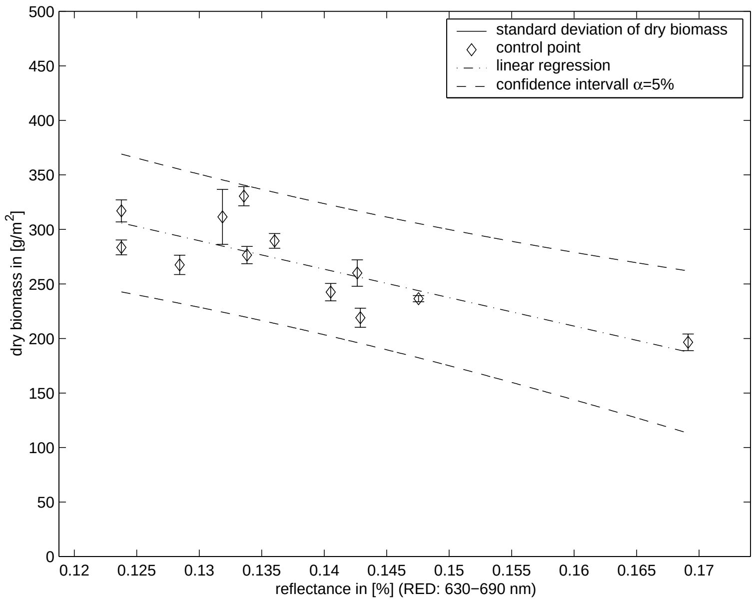


Figure 3: Regression equation for dry biomass in grassland.

## 5 OUTLOOK

Linear regression analysis between soil indicative vegetation parameters, like biomass and water content, and reflectance is unreliable for the area-wide mapping of this parameters within a single field. For better applicability of regression analysis all sources of local variability in reflectance have to be examined. (Asner, 1998) evaluates the sources of variability in canopy reflectance and shows the importance of canopy biophysical parameters (e.g. leaf and stem area, leaf and stem orientation, and foliage clumping) which are primarily responsible for the variability in canopy reflectance. Other sources of variability are biochemical parameters (e.g. lignin, water content, nitrogen and carbon), soil reflection, illumination conditions and viewing geometry. Thus, certain biochemical and biophysical parameters which have a strong influence on variability in canopy reflectance should be included in a multi-regression analysis. Our goal is a approach for high resolution and precise mapping of vegetation heterogeneities based on point-wise ground truth and multisensor data.

The next steps in our approach are:

- Automatic detection of disturbances due to their geometric and radiometric properties.
- Investigation of the influence of biochemical, biophysical, soil, viewing and illumination parameters on the variability of reflectance.
- Derivation of multi-regression equations using Bayesian Inference in order to estimate vegetation parameters more reliably.

## 6 ACKNOWLEDGMENTS

F. Kurz thanks GSF, National Research Center for Environment and Health, for the financial support of his work.

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