

# MULTITEMPORAL HYPERSPECTRAL DATA ANALYSIS FOR REGIONAL DETECTION OF PLANT STRESS BY USING AN AIRBORNE- AND TRACTOR-BASED SPECTROMETER – CASE STUDY: SUGAR BEET DISEASE RHIZOCTONIA SOLANI –

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## ABSTRACT:

Every year sugar beet diseases cause lower sugar beet yields and qualities compared to the average. For that reason, high resolution field and airborne hyperspectral data is used to recognize a fungal sugar beet disease in a study area of south Germany. For the airborne part of the study, multitemporal hyperspectral remote sensing data is provided by an airborne Spectroradiometer (AVIS), which is operated by the Ground Truth Center Oberbayern (gtco, Germany). Additionally, tractor based multitemporal hyperspectral reflection data provided by the GVIS specrometer is used to validate the AVIS data and to compare to two classification results. To indicate the difference between healthy and unhealthy plants a supervised knowledge-based classification approach is used. To detect the sugar beet disease *Rhizoctonia solani*, the reflection results can be elaborated with hyperspectral vegetation indices. Therefore, the two multitemporal datasets are analysed by calculating the OSAVI, which is one of these vegetation indices. Finally, the resulting images are classified into several vitality classes.

This paper presents the evaluation of the generated multitemporal classification and discusses the possibility of detecting and regionalizing sugar beet diseases with hyperspectral systems and methods.

## 1. INTRODUCTION

For the majority of the European citizens, the availability of daily food with high quality standards is common. Among other things, this matter of fact attributes to the demands of the legislator and the market, who claim quality control and (geo-) traceability of all processes within the food supply chain. With respect to this background, a GIS based Management Information System for Sugar Beet Companies was developed (Sugar Beet Management Information System = SuMIS), which includes geographical, attribute and remote sensing data (Laudien et al. 2005a, b & c). Therefore, a field based approach was chosen to collect spatial and alphanumeric information of every production step. This enables SuMIS to trace and track in a field based way – from the soil sampling to the beet-delivery (“from field to factory”) – and meets the above mentioned requirements.

One objective of SuMIS is to detect sugar beet diseases by using multitemporal hyperspectral remote sensing data provided by an airborne-, tractor- and handheld spectroradiometer. (Laudien et. al, 2004a; Laudien et al., 2004b, Laudien and Doluschitz, 2004). Two different hyperspectral sensor systems were used to detect the sugar beet disease *Rhizoctonia solani* var. *betae*. This fungal disease rots the beet roots and also causes a weathering of the foliage (Rieckmann and Steck, 1995). *Rhizoctonia solani* attacks the beet in the middle of its vegetation period. Büttner et al. (2002) estimates the affected area of Germany with 10,000 hectare (nearly 25,000 acres) already in 2001. Studies of German sugar beet seed companies,

published via internet (Strube-Dieckmann, syngeta-seeds), strengthen the statement of Büttner and his colleagues. They re-evaluated the diseased area of Germany in 2002 and reached the conclusion that the number of the affected fields was nearly reduplicated (ca. 20,000 hectares).

Beside the common survey which is carried out by professionals in several field campaigns, the usage of remote sensing systems, materials, and methods can help to recognize, detect and regionalize growth anomalies of large areas (Lillesand and Kiefer, 1994). With this matter of fact, the increasing importance of detecting and locating *Rhizoctonia solani* is not unusual.

For this purpose a method has been developed to visualize diseased and healthy parts of a sugar beet field. Therefore, a knowledge based, multitemporal, hyperspectral approach was used to calculate a classified vegetation index image.

## 2. MATERIAL

For agricultural applications, the analysis of airborne, field- and satellite-based hyperspectral reflectance data is of increasing importance (Clevers and Jongschaap, 2001). Consequently, two hyperspectral devices collected reflectance data to detect the disease. In contrast to multispectral remote sensing the hyperspectral measurements acquire very narrow spectral bands throughout the visible, near infrared and mid-infrared portions of the spectrum. Therefore, the analysis of hyperspectral

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datasets offer more opportunities compared to multispectral ones. The used two sensors measure the spectral reflectance between the visible and the near infrared part of the electromagnetic spectrum by using several channels and a very narrow spectral interval. With their high spatial resolution, they are able to detect crop vitalities very detailed.

## 2.1 Airborne Visible/Near Infrared Imaging Spectrometer (AVIS)

Beside the field measurements provided by the FieldSpec Handheld Pro (Laudien et al. 2003 & 2004c), monthly airborne hyperspectral measurements were taken in the period of June 2003 until September 2003 to regionalize the ground based data. For this purpose, hyperspectral remote sensing data was provided by the “Airborne Visible/Near Infrared Imaging Spectrometer” (AVIS), which is operated by the Ground Truth Center Oberbayern (gtco). The hyperspectral AVIS sensor measures spectral reflectance between 400 and 845 nm by using 63 channels and a spectral interval of 9 nm. With a spatial resolution of 4 meters, the AVIS sensor is able to detect crop vitalities very detailed (Mauser and Oppelt, 2000).

## 2.2 Ground-operated Visible/Near Infrared Imaging Spectrometer (GVIS)

In contrast to the AVIS Sensor, the “Ground-operated Visible/Near Infrared Imaging Spectrometer” (GVIS) is a ground-based system which allows reflectance data acquisition at field sites by using a tractor as a carrier platform. Besides the flexible and cost-efficient use of GVIS another advantage of the system is the possibility to simultaneously record the reflectance of a reference panel due to a newly developed fiber-optic system. The GVIS sensor collects spectral reflectance data between 380 to 860 nm by using 63 spectral bands. As GVIS is mounted 2 m above the foliage and as each of the 16 lenses has an FOV of 25° the ground resolution is about 0.9 m per lens. A custom recording fiber-optic system consisting these 16 lenses enables the simultaneous perpendicular recording of up to 12 m across the driving direction of the tractor (Klotz et al., 2003).

## 3. METHODS

The red and near infra-red parts of the reflectance spectra are important for agricultural applications (Kumar et al., 2001). The significant difference of the reflectance at the red portions of the spectra compared to the near-infrared ones can be used to predict vegetation conditions. Dockett et al. (1988) and Lichti et al. (1997) showed that matter of fact in their hyperspectral studies to point out spectral differences in winter wheat and sugar beets.

Hyperspectral vegetation indices (HVI) are calculated, by using red and near-infrared reflectance (Apan et al., 2003; Lillesand and Kiefer, 1994). The HVI values are significantly correlated to the vitality of the detected plants. In this study, the Optimized Soil-Adjusted Vegetation Index (OSAVI) of Rondeaux et al. (1996) is modified to analyse the multitemporal AVIS and GVIS datasets (see equation 1 to 3). The index is calculated to indicate the difference between healthy and diseased sugar beets. The equations 2 and 3 present the modified OSAVI for the AVIS/ GVIS data.

$$OSAVI = \frac{R800 - R670}{R800 + R670 + 0.16} \quad (1)$$

where

$R800$  = reflectance at 800nm [%],  
 $R670$  = reflectance at 670nm [%].

$$OSAVI_{AVIS} = \frac{AVIS\_Band55 - AVIS\_Band37}{AVIS\_Band55 + AVIS\_Band37 + 0.16} \quad (2)$$

where

$AVIS\_Band55$  = reflectance at 804.62 nm [%],  
 $AVIS\_Band37$  = reflectance at 673.38 nm [%].

$$OSAVI_{GVIS} = \frac{GVIS\_Band67 - GVIS\_Band35}{GVIS\_Band67 + GVIS\_Band35 + 0.16} \quad (3)$$

where

$GVIS\_Band67$  = reflectance at 799.69 nm [%],  
 $GVIS\_Band35$  = reflectance at 670.83 nm [%].

The spatial analysis as well as the index calculation and classification were accomplished by using the GIS Software ArcGIS™ 8.3 by ESRI® (Minami, 2000).

In a first analysis step, the above characterised index is calculated for the four input datasets which are provided by each of the two systems. Furthermore, the OSAVI of infected sugar beets is identified with the FieldSpec data of June 25<sup>th</sup>, July 30<sup>th</sup>, August 27<sup>th</sup> and September 19<sup>th</sup> by interpolating the values of the collecting days from the field measurements (see Table 1) (Laudien et al., 2004c).

Table 1: Index minima (OSAVI) of the the FieldSpec measurements at the four collecting dates.

Collecting Date	Minimum value (OSAVI)
June 25 <sup>th</sup> 2003	0.600
July 30 <sup>th</sup> 2003	0.520
August 27 <sup>th</sup> 2003	0.405
September 19 <sup>th</sup> 2003	0.430

The float chart of figure 1 shows the knowledge based method. In a first analysis step, the OSAVI (which is described in equation 2) is calculated for each monthly AVIS scene. The result of that procedure is an “OSAVI image”. After that, the given FieldSpec OSAVI values of the inoculation trial are used as an input threshold for the analysis to mask most of the abiotic growth-anomalies. This enables the production of four quasi binary images (“OSAVI Clips”). The “OSAVI Clip” image only consists of two values: 1 and “no Data” (“no Data” = no pixel value). Pixels, which show higher values than the threshold (see Table 1) receive value 1, all others get value “no Data”. This matter of fact enables the clipping procedure to calculate the “OSAVI biotic” image by multiplying the four “OSAVI images” by the four “OSAVI Clips”. With this procedure, the results contain only these pixels, which show higher values than the index minima. Additionally, the majority of unwanted field border effects are reduced by assigning the value “no Data”.

Considering the hypothesis that the FieldSpec threshold indicates the minimum reflectance of infected sugar beet leaves at a specific collecting date, four raster images can be generated (OSAVI biotic) which do not contain most of the abiotic parameters anymore. After creating these four “OSAVI biotic” images they are combined by using the “add” tool of the ArcGIS™ Raster Calculator. This algorithm only allocates

OSAVI values to these pixels which do not contain the value “no Data” in one or more of the four “OSAVI biotic” images. The pixels which show the value “no Data” in one or more of the “OSAVI biotic” images get the value “no Data”. The result of this procedure is the multitemporal HVI image “OSAVI multi”.

In the last step the “OSAVI multi” image is classified into nine vitality classes by using the “Quantile Classification Method” of ArcGIS™ Spatial Analyst. Additionally, the GPS polygons of the field campaign are added to the ArcGIS™ 8.3 project as an overlay layer, to validate and compare the multitemporal classification.

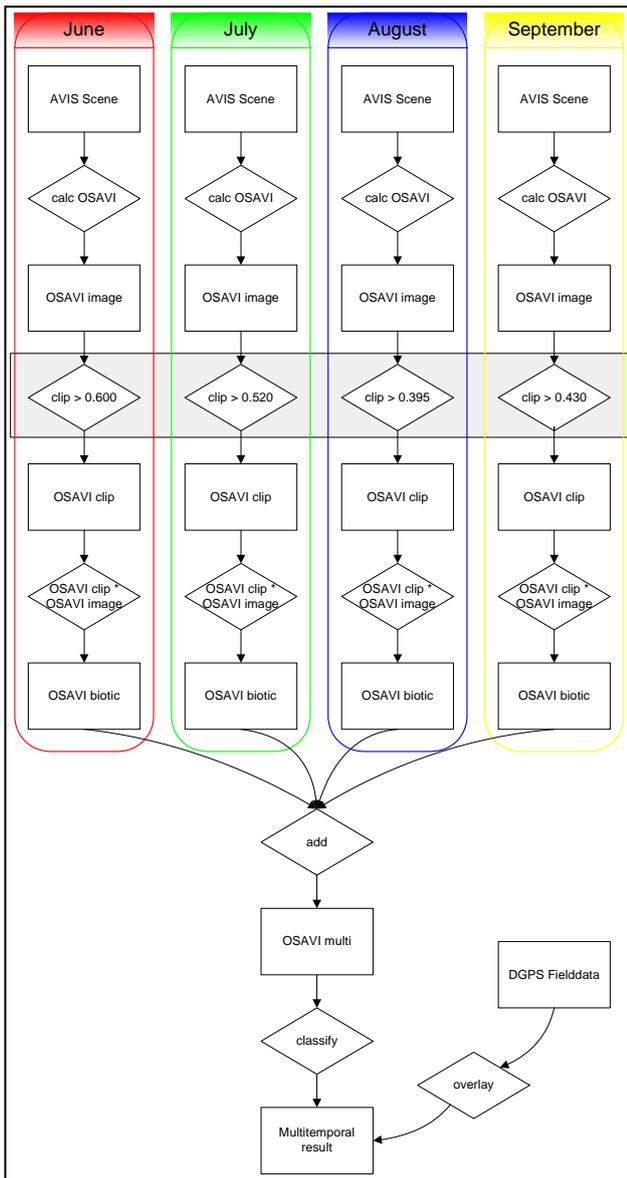


Figure 1: Knowledge based multitemporal analysis method (note: the threshold values of the clip procedures are chosen out of table 1, figure = exemplarily for the AVIS data) (Laudien et al. 2004c).

#### 4. RESULTS

Figure 2 shows the multitemporal classification result of two selected fields (see methodological approach shown in Fig. 1 for details).

According to the leaf vitality of sugar beets, the values of the calculated OSAVI were increasing with healthier and decreasing with unhealthier plant conditions.

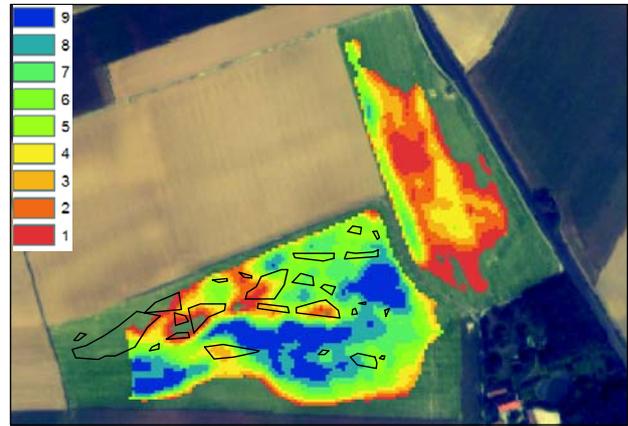


Figure 2: Multitemporal AVIS classification result and GPS-polygon overlay with at least 25% infected area (note: GPS measurements were only taken at one field).

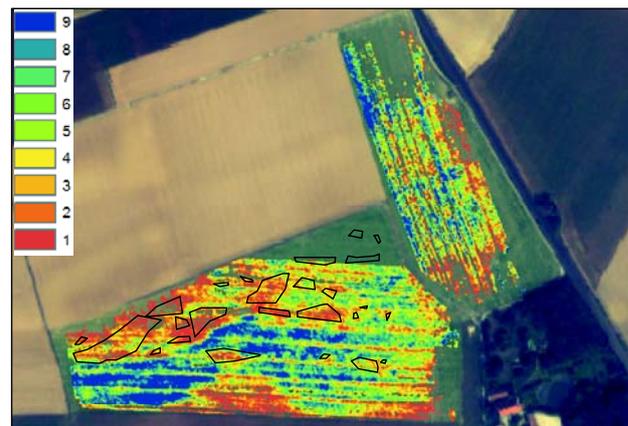


Figure 3: Multitemporal GVIS classification result and GPS-polygon overlay with at least 25% infected area (note: GPS measurements were only taken at one field).

The multitemporal images were classified into nine vitality classes. Lower classes were assigned to low index values, higher ones to high index values. Significant differences concerning plant vitalities within the fields can be identified. Red to orange areas within the two fields refer to diseased spots, green to blue ones to healthier parts of the fields. By using the above described knowledge based supervised classification approach most of the abiotic factors (field border effects, bare soil, etc.) were clipped in an early stage of the analysis. Therefore, the multitemporal results show many unclassified areas within the two fields.

The overlay of the GPS polygon layer confirms the difficulty of surveying single infected plants within a field. With the matter of fact, that the stored polygons include at least 25 percent infected sugar beets, they do not show the spatial distribution of the diseased plants very detailed. In contrast, vitality

information concerning spatial location and intensity can be derived by using remote sensing sensors (i.e. the above described AVIS or GVIS).

The area of “no Data” in the western part of the southern field (see Fig. 2) comes from the incomplete AVIS dataset of July. As there occurred sensor problems during collecting the reflectance data, the “flight-stripe” had to be cut off. Hence, the multitemporal algorithm assigns “no Data” for that region of the field. In contrast to the tractor based GVIS system a major advantage of AVIS is its very time-efficient manner of collecting reflectance data of a large area. The GVIS device can only be used to record data of a small area (field size). But as the spatial resolution of GVIS is much higher than the one of the AVIS the classification result is more detailed. Therefore, smaller infected areas can be differentiated a lot better. Figure 3 presents that advantage of the GVIS system. Compared to the AVIS classification the one GVIS shows more abiotic field border effects and results in a much lower classification accuracy. Imprecise calibrations of the two systems by *gtco* (AVIS, GVIS) cause different reflection value ranges and result in these hardly comparable classification results. Nevertheless, the advantages of the used to hyperspectral devices are obvious. Both multitemporal classifications (see Fig. 2 & 3) show significant differences in plant vitalities within the fields under investigation. In combination with the DGPS measurements and the knowledge of the disease (disease stages, dispersion, etc.) the hyperspectral results can be used to detect, differentiate and regionalize healthy and diseased sugar beets.

## 5. CONCLUSIONS

Monitoring plant diseases during the circle of field production is one main objective within the food supply chain. Therefore, modern computer based DSS should include tools to detect and regionalize such plant conditions. Furthermore, demands of the EU market and the agricultural policy concerning food quality and documentation push the development of computer based Geographical Information Systems (GIS), which meet these requirements. The presented approach is part of a developed GIS-field based Sugar Beet Management Information System (SuMIS) (Laudien et al., 2004a; Laudien and Doluschitz 2004; Laudien et al. 2005a, b & c). SuMIS contains several types of geo-data which were collected in a local pilot region to fulfil the qualifications of a functional field based GIS. It includes - beside many other important tools - the visualisation, the documentation and the detection of all processes within a cultivation year of sugar beets.

In this study, an airborne and a tractorbased multitemporal hyperspectral remote sensing dataset were classified on the basis of hyperspectral field data by using a hyperspectral vegetation index. In contrast to the conventional sugar beet disease survey, shape and structure of the infected areas within the selected fields could be spatially identified by using a multitemporal knowledge based classification approach.

Field based hyperspectral measurements, tractor- and airborne hyperspectral sensors were used to detect sugar beet reflectance. Compared to satellite based systems, airborne platforms are more flexible concerning collecting date, repetition rate and weather conditions. The immense advantage of hyperspectral devices is their very high spectral resolution. The possibility of analysing datasets by using hyperspectral vegetation indices for the detection of plant vitalities instead of common multispectral

ones - i.e. the OSAVI (which was used in this study) or the hyperspectral index of Gitelson et al. (1996) - offers more opportunities for agricultural applications (Apan et al., 2003). The mathematical possibilities of band calculations and combinations for the creation of new HVI are disproportionately enhanced. In the beginning of the AVIS data analysis for this study, the calculation and interpretation of several HVI result in using the OSAVI because of its low sensitivity concerning bare soil and other abiotic parameters. Furthermore, the OSAVI showed a high range between values of diseased and healthy sugar beets.

Beside the data analysis of the tractor and airborne sensors, a hyperspectral library was generated by using weekly field based reflectance data of the artificial inoculation trail which were collected with the FieldSpec Handheld. This dataset contains the reflectance characteristics of the sugar beet disease *Rhizoctonia solani* and could be used as a reference for the regionalization.

As the infection of the disease and its outbreak were not typical in 2003 and the spatial resolutions of the input datasets were too low for detecting single affected plants with a significant accuracy, the D-GPS polygon measurements showed not the quality of those having been collected in previous years. Circular affected areas within the selected fields did not occur in 2003. This matter of fact was reasonable for the above described low significance. Furthermore, “mixed pixel phenomena’s” within the AVIS and GVIS scenes covered the unusual situation of 2003, too.

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