Photogrammetrie • Fernerkundung • Geoinformation 3/2006, S. 217–227, 5 figs., 1 tab.

Multitemporal Hyperspectral Data Analysis for Regional Detection of Plant Diseases by using a Tractor- and an Airborne-based Spectrometer

– Case Study: Sugar beet disease Rhizoctonia solani –

RAINER LAUDIEN & GEORG BARETH, Köln

Keywords: remote sensing, sugar beet, hyperspectral remote sensing, GIS, vegetation indices, multitemporal classification

Summary: Every year sugar beet diseases cause lower sugar beet yields and qualities compared to the average. To detect and regionalize this matter of fact, high resolution field, tractor and airborne hyperspectral data were used to recognize a fungal sugar beet disease (*Rhizoctonia solani* var. *betae*) as an example.

For the airborne part of the study, multitemporal 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, Germany). Additionally, tractor based multitemporal hyperspectral reflection data provided by the *Ground-operated Visible/Near Infrared Imaging Spectrometer* (GVIS) was used to validate the AVIS data and to compare the classification results.

To indicate the difference between healthy and unhealthy plants a supervised knowledge-based classification approach was used. Beside the usage of multitemporal field based spectroradiometer data, which was collected with the *FieldSpec Handheld* (ASD) and which was used for the supervised knowledge based classification of the tractor- and airborne based datasets, this approach included the elaboration of the reflection results with hyperspectral vegetation indices to detect the sugar beet disease. Therefore, the two multitemporal tractor- and airborne based datasets were analysed by calculating the *Optimized Soil-Adjusted Vegetation* Index (OSAVI), which is a hyperspectral vegetation index. Finally, the results were classified into nine vitality classes.

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

Zusammenfassung: *Multitemporale Analyse hyperspektraler Daten zur regionalen Verortung von Pflanzenkrankheiten unter Verwendung eines traktor- und flugzeuggestützten Spektroradiometers. Fallbeispiel: Zuckerrübenkrankheit Rhizoctonia Solani.* Im Vergleich zu unbefallenen Zuckerrübenschlägen verursachen Krankheiten auf den Feldern jedes Jahr erhebliche Ernteschäden und führen so zu geringen Erträgen. Um kranke Bereiche der betroffenen Schläge zu verorten und zu regionalisieren, wurden im Rahmen der hier vorgestellten Studie hoch auflösende hyperspektrale Feld-, Traktor- und Flugzeugdaten genutzt. Die Ausführungen dieses Beitrags beschränken sich auf die Zuckerrübenpilzkrankheit Rhizoctonia solani var. betae.

Die multitemporalen hyperspektralen Flugzeugdaten wurden durch das *Airborne Visible/Near Infrared Imaging Spectrometer* (AVIS) erhoben, das von dem Ground Truth Center Oberbayern (gtco, Germany) betrieben wird. Zusätzlich dazu sind multitemporale hyperspektrale, traktorgestützte Reflexionen durch das *Ground-operated Visible/Near Infrared Imaging Spectrometer* (GVIS) gemessen worden, um die AVIS Daten zu validieren und um die Klassifikationsergebnisse zu vergleichen.

Für die Analyse der Unterschiede zwischen gesunden und infizierten Zuckerrüben wurde ein überwachter wissensbasierter Klassifikationsansatz gewählt. Neben der Verwendung von multitemporalen hyperspektralen Felddaten, die mit Hilfe des *FieldSpec Handheld* (ASD) Spektroradiometers erhoben und für die Klassifikationen der beiden traktor- und flugzeuggestützten Daten verwendet wurden, beinhaltet dieser methodische Ansatz auch die Darstellung der Reflexionen unter Verwendung von hyperspektralen Vegeta-

1432-8364/06/2006/0217 $ 2.75

tionsindizes, um die Zuckerrübenkrankheit räumlich zu verorten. Dafür wurden die Datensätze aufbereitet und der hyperspektrale *Optimized Soil-Adjusted Vegetation Index* (OSAVI) berechnet. In einem letzten Analyseschritt wurden die Ergebnisse in neun Vitalitätsklassen klassifiziert.

Dieser Beitrag zeigt die Auswertung der erzeugten multitemporalen Klassifikationen und diskutiert die Möglichkeit der räumlichen Verortung und Regionalisierung von Zuckerrübenkrankheiten unter Verwendung hyperspektraler Systeme und Methoden.

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 & Doluschitz 2004, Laudien et al. 2004a; 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. 2003, Laudien et al. 2004b, c, e). 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 & Steck 1995). *Rhizoctonia solani* attacks the beet in the middle of its vegetation period. Büttner et al. (2002) estimate the affected area of Germany with 10,000 hectares already in 2001. Studies of German sugar beet seed companies, published via internet (Syngenta 2000), strengthen the statement of Büttner and his colleagues. They re-evaluated the disease 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, and integrated image analysis can help to recognize, detect and regionalize growth anomalies of large areas (Lillesand et al. 2004).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. Thereby, a knowledge based, multitemporal, hyperspectral approach was used to calculate a sensitive vegetation index.

2 Material

For agricultural applications, the analysis of airborne, field- and satellite-based hyperspectral reflectance data is of increasing importance (Clevers & Jongschaap 2001). Consequently, in this study three 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 datasets offers more opportunities compared to multispectral ones. The used three sensors measured 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 were able to detect different crop vitalities very detailed.

2.1 *Field survey with DGPS*

Differential GPS-data, containing the diseased polygon boundaries with at least 25 percent infected area, were collected at selected fields of the study area to validate the multitemporal hyperspectral classification. For this purpose a "Trimble *Ag*GPS® 132" twelve channel receiver was connected to a SOLO CE device to store the incoming data. OmniSTAR differential GPS service was used to correct the data online.

The infected areas of the chosen fields were surveyed during a field campaign in early September 2003. In 2003, the fields of the whole study area showed single plant infection because of very dry weather conditions. As the regular symptoms of *Rhizoctonia solani* are characterized by circular infection concerning several sugar beet plants, it was almost impossible to collect polygon data via GPS. Therefore, polygons were only stored with at least 25 percent infection.

2.2 *Spectral reference measurements with ASD-FieldSpec*

To detect the spectral differences between healthy and diseased sugar beets, the hyperspectral spectroradiometer *FieldSpec HandHeld* by ASD (Analytical Spectral Devices) was used to collect field data at an artificial inoculation trial (Laudien et al. 2004c, Laudien et al. 2005d). This reflectance data was archived in a web based spectral library (Laudien et al. 2006).

The ASD handheld spectroradiometer has a wavelength range of 325 nm to 1075 nm with an interval of 1.6 nm and a viewing angle of 25 degrees. For further FieldSpec details see: http://www.asdi.com

To archive a useful spatial ground resolution, an additional technical device was developed and constructed in cooperation with the technical department of the Univer-

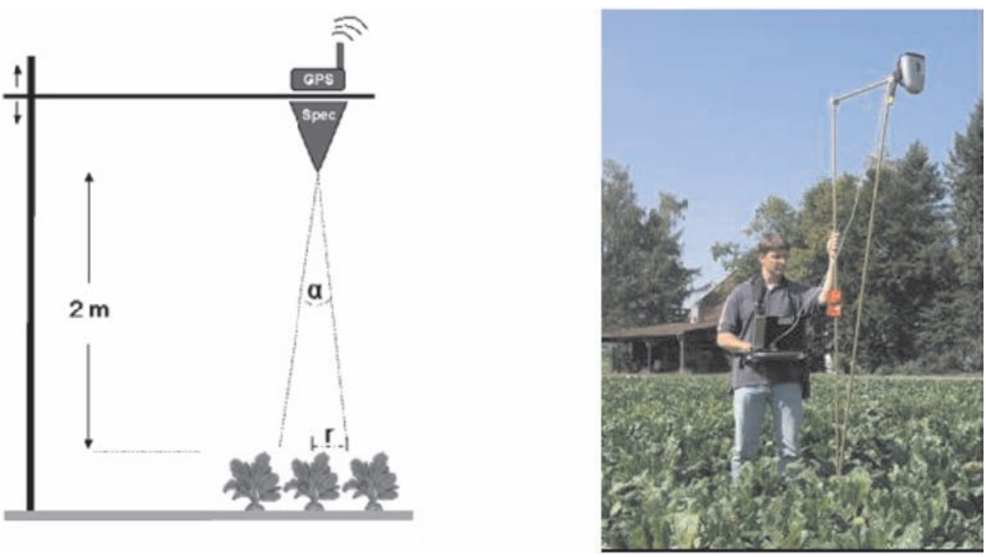

Fig. 1: Designed measurement device for collecting hyperspectral field data.

sity of Hohenheim. Fig. 1 shows the design of the measurement device and a picture of the field campaign with the equipment. Three tent-poles, which were combined with moveable joins, formed the frame of the device. The construction was designed to put the measurement equipment to the desired height above ground. A mounted spirit-level guaranteed vertical nadir measurements.

The spectroradiometer was located two metres above the foliage. The measuring viewing angle (α) of 25 degrees caused a Field of View (A) of 0.62 m^2 with a Field of View radius (r) of 44 cm (see equations 1 and 2).

$$r = h * \tan\left(\left(\frac{\alpha}{2}\right) * \frac{\Pi}{180}\right) \tag{1}$$

$$A = \Pi * r^2 \tag{2}$$

To compare healthy and infected sugar beets of the selected fields with the ones of the artificial inoculation trial, spectroradiometer measurements were made every 40 cm per row and were averaged for each treatment plot. The spots were located with a low cost GPS solution (Garmin III Plus) coupled to Software from ESRI (ArcPad, installed on a Compaq iPAQ CE computer) (LAUDIEN et al. 2003, LAUDIEN et al. 2004c).

2.3 *Airborne Visible/Near Infrared Imaging Spectrometer (AVIS)*

Beside the field measurements provided by the *FieldSpec Handheld Pro*, monthly airborne hyperspectral measurements were taken in the period of June 2003 to 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 with a spectral interval of 9 nm. At a spatial resolution of 4 meters, the AVIS sensor is able to detect crop vitalities very detailed (MAUSER & OPPELT 2000).

2.4 *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. GVIS is mounted 2 m above the foliage and each of the 16 lenses has a viewing angle of 25° (= IFOV of 0,9 m per lens). A custom recording fiber-optic system which consists 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 infrared 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 (LILLESAND et al. 2004). DOCKTER et al. (1988) and LICHTI et al. (1997) showed in their hyperspectral studies the 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 et al. 2004). 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) was modified and applied to analyse the multitemporal AVIS and GVIS datasets (see equation 3–5). The index was chosen to be the best indicator of the differences between healthy and unhealthy sugar beets. The equations 4 and 5 present the modified OSAVI for the AVIS/ GVIS data.

$$\text{OSAVI} = \frac{\text{R800} - \text{R670}}{\text{R800} + \text{R670} + 0.16} \quad (3)$$

where

R800 = reflectance at 800 nm [%]

R700 = reflectance at 670 nm [%]

$$\text{OSAVI}_{\text{AVIS}} = \frac{\text{AVIS\_channel55} - \text{AVIS\_channel37}}{\text{AVIS\_channel55} + \text{AVIS\_channel37} + 0.16} \quad (4)$$

where

AVIS_channel55 = reflectance at 804.62 nm [%]

AVIS_channel37 = reflectance at 673.38 nm [%]

$$\text{OSAVI}_{\text{GVIS}} = \frac{\text{GVIS\_channel67} - \text{GVIS\_channel35}}{\text{GVIS\_channel67} + \text{GVIS\_channel35} + 0.16} \quad (5)$$

where

GVIS_channel67 = reflectance at 799.69 nm [%]

GVIS_channel35 = 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®.

In a first analysis step, the above characterised index was calculated for the four input datasets which were provided by each of the two systems (GVIS and AVIS). Furthermore, the OSAVI of infected sugar beets was identified by using the *FieldSpec* data of June 25th, July 30th, August 27th and September 19th (see Tab. 1).

The flow chart of Fig. 1 shows the developed and used knowledge based approach. In a first analysis step, the OSAVI (which is described in equation 3) was calculated for each monthly GVIS and AVIS scene. The result of that procedure was an "OSAVI image". After that, the given *FieldSpec* OSAVI values of the inoculation trial were used as an input threshold for the analysis to mask most of the abiotic growth-anomalies.

Tab. 1: Index minima (OSAVI) of the artificial inoculation trial (collected with the *FieldSpec)* at the four GVIS/ AVIS collecting dates.

GVIS/AVIS collecting date	Minimum value (OSAVI)
06/25/2003	0.600
0730/2003	0.520
08/27/2003	0.405
09/19/2003	0.430

This enabled the generation of four quasi binary images ("OSAVI Clips"). The "OSAVI Clip" image only consisted of two values: 1 and "no Data" ("no Data" = no pixel value). Pixels, which show higher values than the threshold (see Tab. 1) received value 1, all others got the value "no Data". The clipping procedure calculated the "OSAVI biotic" image by multiplying the four "OSAVI images" by the four "OSAVI Clips". With this procedure, the results contained only the pixels, which showed higher values than the index minima. Additionally, the majority of unwanted field border effects were reduced by assigning the value "no Data".

Considering the hypothesis that the *FieldSpec* threshold indicated the minimum reflectance of infected sugar beet leaves at a specific collecting date, four raster images could be generated (OSAVI biotic) which did not contain most of the abiotic parameters anymore. After creating these four "OSAVI biotic" images they were combined by using the "add" tool of the ArcGIS™ Raster Calculator. This algorithm only allocated OSAVI values to these pixels which did not contain the value "no Data" in one or more of the four "OSAVI biotic" images. The pixels which showed the value "no Data" in one or more of the "OSAVI biotic" images received the value "no Data". The result of this procedure was a multitemporal HVI image (OSAVI multi).

In the last step the "OSAVI multi" image was classified into nine vitality classes by using the "Quantile Classification Method" of

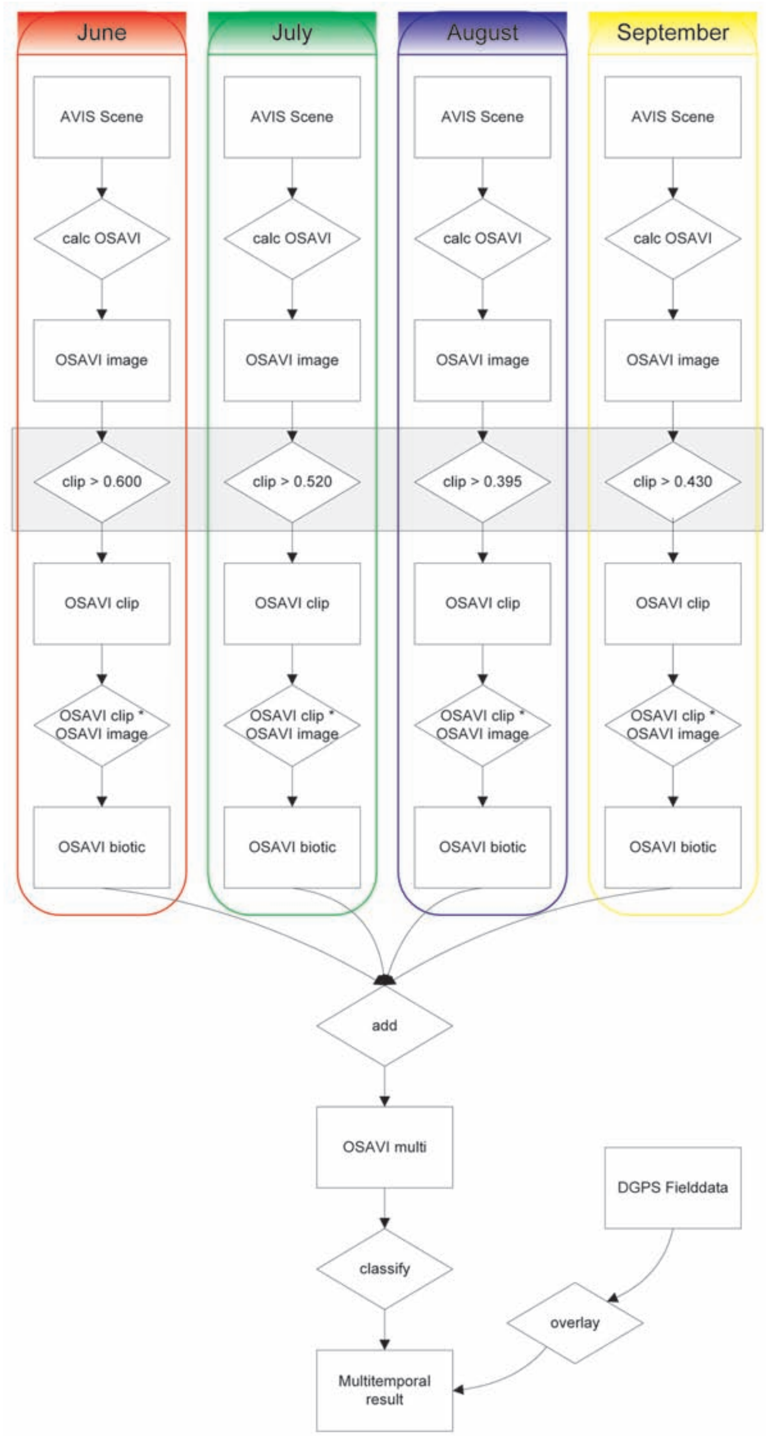

Fig. 2: Knowledge based multitemporal analysis method (note: the threshold values of the clip procedures are choosen out of Tab. 1, figure = exemplarily for the AVIS data) (LAUDIEN et al. 2004c).

ArcGIS™ Spatial Analyst. Additionally, the GPS polygons of the field campaign were added to the ArcGIS™ 8.3 project as an overlay layer, to validate and compare the multitemporal classification.

4 Results

Fig. 2 shows the above described knowledge based hyperspectral analysis method considering the scene of June as an example. After calculating the OSAVI for all pixels, a binary image was produced. This clipped image included all pixels with higher values than the specific threshold of the collecting date. The OSAVI biotic image of June was calculated by multiplying the "Clip" by the "OSAVI June" image.

Figs. 3 and 4 present the multitemporal classification results 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. The multitemporal images were classified into nine vitality classes. Low index values (healthy plants) are displayed in cold colours (blue, green). High index values (unhealphy plants) were associated with warm colours (yellow, orange, red). Significant differences concerning plant vitalities within the fields can be identified. By using the above described knowledge based 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. The stored polygons including at least 25 percent infected sugar beets do not match the spatial distribution of the remotely sensed uninfected plants very detailed.

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 assigned "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 small areas (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.

Fig. 3 presents that advantage of the GVIS system. Compared to the AVIS classification the one of GVIS shows more abiotic field border effects. That results in much lower classification accuracy. Imprecise calibrations of the two systems by gtco (AVIS, GVIS) caused different reflection value ranges and caused these hardly comparable classification results. Nevertheless, the advantages of the used two hyperspectral devices are obvious.

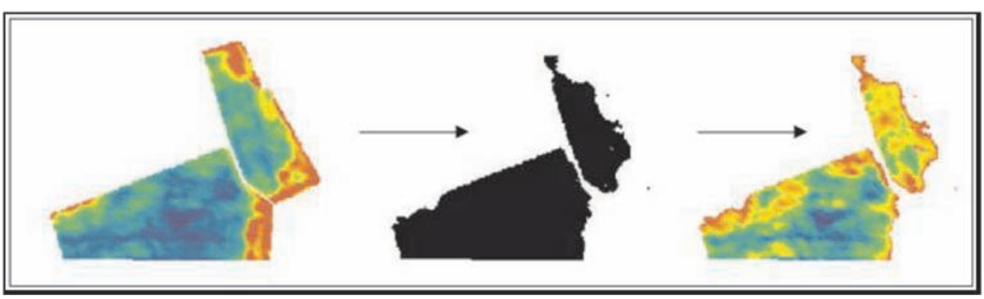

Fig. 3: Knowledge based approach considering the image of June as an example.

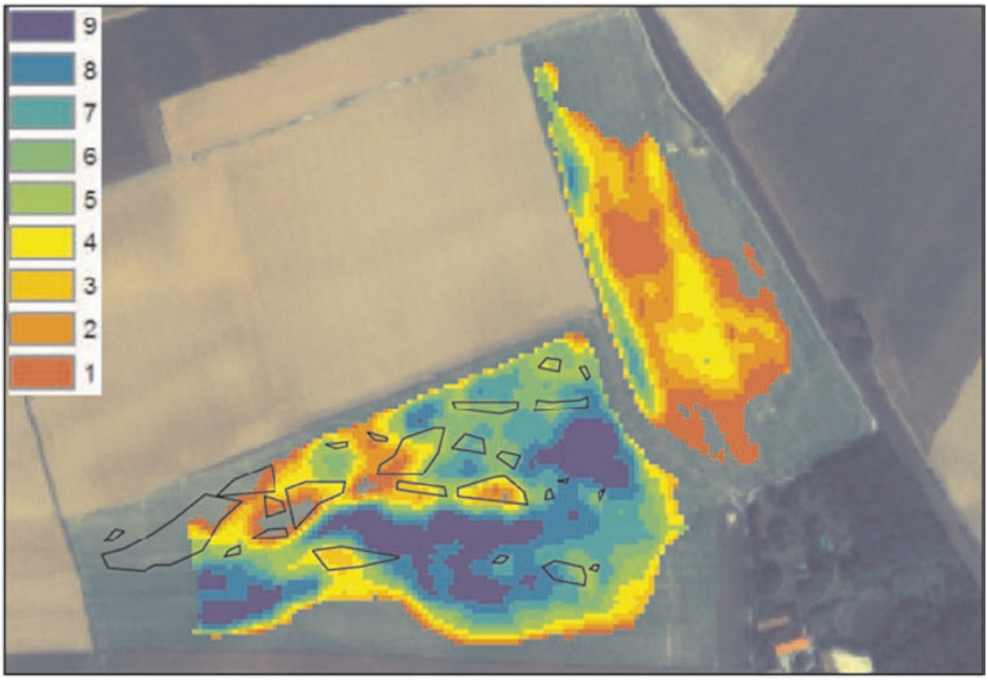

Fig. 4: Multitemporal AVIS classification result and GPS-polygon overlay with at least 25 % infected area (note: GPS measurements were only taken at one field).

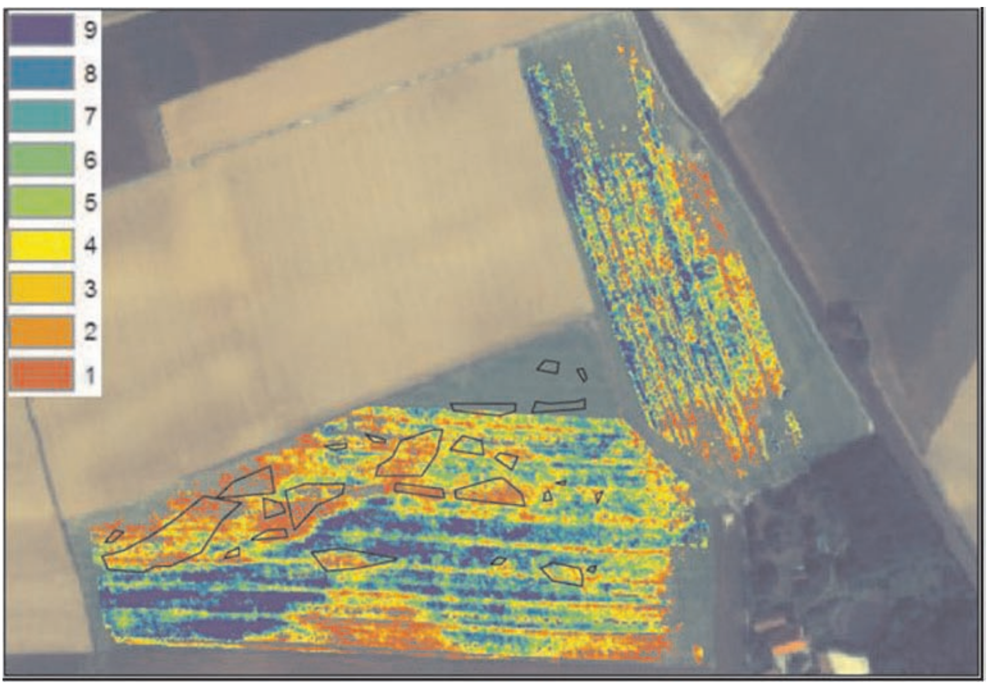

Fig. 5: Multitemporal GVIS classification result and GPS-polygon overlay with at least 25 % infected area (note: GPS measurements were only taken at one field).

Both multitemporal classifications (see Figs. 2 and 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.

Discussion

In this study, an airborne multitemporal hyperspectral remote sensing dataset was 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 and a tractor and an airborne hyperspectral sensor were used to detect sugar beet reflectance. Compared to satellite based systems, tractor and airborne platforms are more flexible concerning collecting date, repetition rate and weather conditions.

In general, the immense advantage of a hyperspectral device is its 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 GVIS and AVIS data analysis for this study, the calculation and interpretation of several HVI resulted 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 infected and healthy sugar beets.

Beside the data analysis of the tractor and airborne sensor, a hyperspectral library was generated by using weekly field based reflectance data of the artificial inoculation trail which were collected with the FieldSpec Handheld (Laudien et al. 2005d). This web based spectral library 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 reason was reasonable for the above described low significance. Furthermore, "mixed pixel phenomena's" within the GVIS and AVIS scenes covered the unusual situation of 2003, too.

Conclusions

Monitoring plant diseases during the circle of field production is one main objective within the food supply chain. Therefore, modern computer based Decision Support Systems (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 disease detection and regionalisation approach is part of a developed GIS-field based Sugar Beet Management Information System (SuMIS) (Laudien et al. 2004a, Laudien & 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.

Acknowledgements

This study as well as the development of SuMIS were enabled by a cooperation between the sugar company Südzucker AG and the University of Hohenheim (Stuttgart), Germany and founded by the "Kuratorium für Versuchswesen und Beratung im Zuckerrübenbau", Germany.

References

APAN, A., HELD, A., PHINN, S. & MARKLEY, J., 2003: Formulation and Assessment of Narrow-Band Vegetation Indices from EO-1 Hyperion Imagery for Discriminating Sugarcane Disease. – Proceedings of the Spatial Sciences Conference, Sep. 22nd–27th, 2003, Canberra: 1–13.

BÜTTNER, G., ITHURRAT, M.E.F. & BUDDEMEYER, J., 2002: Späte Rübenfäule Rhizoctonia solani – Verbreitung, wirtschaftliche Bedeutung und integrierte Bekämpfungskonzepte. – Zuckerindustrie, **127**: 856–866.

CLEVERS, J.P.G.W. & JONGSCHAAP, R., 2001: Imaging spectrometry for Agricultural Applications. – In: VAN DER MEER, F.D. & DE JONG, S.M. (Eds.): Imaging Spectrometry: Basic Principles and Prospective Applications. – 157–199, Kluwer Academic Publishers, Dordrecht.

DOCKTER, K., KÜHBAUCH, W., BOOCHS, F., VON RÜSTEN, C., TEMPELMANN, U. & KUPFER, G., 1988: Die spektrale Reflexion von Zuckerrübenbeständen im sichtbaren und infraroten Wellenlängenbereich während des Wachstums. – Mitteilungen der Gesellschaft für Pflanzenbauwissenschaften, **1:** 55–57.

GITELSON, A., MERZLYAK, M.N. & LICHTENTHALER, K., 1996: Detection of red edge position and chlorophyll content by reflectance measurements near 700 nm. – Journal of Plant Physiology, **148:** 501–508.

KUMAR, L., SCHMIDT, K., DURY, S. & SKIDMOR, A., 2001: Imaging Spectrometry and Vegetation Science. – In: VAN DER MEER, F.D. & DE JONG (Eds.): Imaging Spectrometry: Basic Principles and Prospective Applications. – 111–155, Kluwer Academic Publishers, Dordrecht.

KLOTZ, P., BACH, H. & MAUSER, W., 2003: GVIS – Ground-operated Visible/Near-Infrared Imaging Specrometer. – In: WERNER, A, & JARFE, A. (Hrsg.): Programme book of the joint conference of ECPA – 315–321, ECPLF, Wageningen, The Netherlands, Wageningen Academic Publishers, June 2003.

LAUDIEN, R., BARETH, G. & DOLUSCHITZ, R., 2003: Analysis of hyperspectral Field Data for detection of sugar beet diseases. – In: HARNOS, Z., HERDON, M. & WIWCZAROSKI, T.B. (Eds.): Information technology for a better agri-food sector, environment and rural living. – Proceedings 4th Conference of the European Federation for Information Technology in Agriculture, Food and Environment, Vol. I, 375–381, Debrecen, Budapest, Hungary.

LAUDIEN, R., BÜRCKY, K. & DOLUSCHITZ, R., 2004a: Development of a field-based Management Information System for sugar beet companies. – Sugar Industry, **8:** 565–567.

LAUDIEN, R., BARETH, G. & DOLUSCHITZ, R., 2004b: Comparison of remote sensing based analysis of crop diseases by using high resolution multispectral and hyperspectral data – case study: Rhizoctonia solani in sugar beet. – 670–676, Proceedings of the 12th International Conference on Geoinformatics, June 7th-9th, Gävle.

LAUDIEN, R. & DOLUSCHITZ, R., 2004: Führungsinformationssystem für die Wertschöpfungskette in der Zuckerwirtschaft. – Landinfo, **3:** 56–60.

LAUDIEN, R. & DOLUSCHITZ, R., 2005a: GIS-gestützte schlagbezogene Dokumentation in der Zuckerwirtschaft und deren Nutzen: Das Sugar Beet Management Information System (SuMIS). – Zeitschrift für Agrarinformatik, **13** (3): 55–63.

LAUDIEN, R., BARETH, G. & DOLUSCHITZ, R., 2005b: Geotracking and -tracing from farm to factory – Case study: Sugar Beet Management Information System (SuMIS). – EFITA/WCCA, Vial Real, Portugal, CD-Rom.

LAUDIEN, R., BARETH, G. & DOLUSCHITZ, R. (2005c): Lückenlose, GIS-gestützte Dokumentation im Zuckerrübenanbau SuMIS und dessen WinCE-Logistikprogramm zur mobilen Datenerhebung. – GeoBIT/GIS Zeitschrift für raumbezogene Informationen und Entscheidungen, **11:** 10–15.

LAUDIEN, R., BARETH, G. & DOLUSCHITZ, R. (2005d): Multitemporal hyperspectral data analysis for regional detection of plant diseases by using an airborne- and tractor-based spectrometer – Case study: Sugar beet disease Rhizoctonia solani. – In: TANG, X., LIU, Y., ZHANG, J. & KAINZ, W. (Eds.): Proceedings of International Symposium on Spatio-temporal Modeling, Spatial Reasoning, Spatial Analysis, Data Mining and Data Fusion, Beijing/China, 27.–29. 08. 2005: 265–269.

LAUDIEN, R., BÜRCKY, K., DOLUSCHITZ, R. & BARETH, G. (2006): Aufbau einer webgestützten Spektralbibliothek zur Analyse hyperspektraler Daten von mit Rhizoctonia solani inokulierten Zuckerrüben. – Sugar Industry (eingereicht).

Lichti, C., Sticksel, E. & Maidl, F.-X., 1997: Feldspektroskopische Messungen als Hilfsmittel für eine teilschlagbezogene Bestandesführung. – Mitteilungen der Gesellschaft für Pflanzenbauwissenschaften, **10:** 271–272.

Lillesand, T.M., Kiefer, R.W. & Chipman, J.W., 2004: Remote Sensing and Image Interpretation. – 5th ed., New York, Chichester, Brisbane, Toronto, Singarpore.

Mauser, W. & Oppelt, N., 2000: AVIS – Ein neuer Sensor für Umweltmonitoring und Precision Farming. – In: Birkner, U., Amon, H., Ohmayer, G. & Reiner, L. (Eds.): Referate der 21. GIL-Jahrestagung. Proceedings 21. GIL-Jahrestagung, Freising-Weihenstephan, Deutschland, Band **13:** 274–277.

Rieckmann, W. & Steck, U., 1995: Krankheiten und Schädlinge in der Zuckerrübe. – 42–43, Verlag Th. Mann, Gelsenkirchen.

Rondeaux, G., Steven, M. & Baret, F., 1996: Optimisation of Soil-Adjusted Vegetation Indices. – Remote Sensing of Environment, **55:** 95–107.

Syngenta, 2000: URL http://syngenta.de/schadorganismen/fung/104.htm (Stand: 15.11.02)

Anschrift der Autoren:

Dr. Rainer Laudien
Prof. Dr. Georg Bareth
Universität Köln, Geographisches Institut,
Abt. GIS and Remote Sensing,
Albertus-Magnus-Platz,
D-50923 Köln
Tel.: +49-221-470-6552, Fax: +49-221-470-1638
rlaudien@uni-koeln.de, g.bareth@uni-koeln.de

Manuskript eingereicht: Januar 2006
Angenommen: Februar 2006