Institute of Crop Production and Grassland Research (340)
University of Hohenheim
Prof. Dr. W. Claupein

Use of sensor technologies to estimate and assess the effects of various plant diseases on crop growth and development

Dissertation
In fulfilment of the requirements for the degree
“Doktor der Agrarwissenschaften”
(Dr. sc. agr. /Ph.D. in Agricultural Sciences)

Submitted to the
Faculty of Agricultural Science of
the University of Hohenheim

by
Kerstin Gröll
born in Bietigheim-Bissingen

2008

This thesis was accepted as a doctoral dissertation in fulfilment of the requirements fort the degree “Doktor der Agrarwissenschaften” (Dr. sc. agr. / Ph. D. in Agricultural Science) by the Faculty of Agricultural Sciences of the University of Hohenheim on 13.06.2008.

Date of oral examination: 09.07.2008

Examination Committee

Dean and Head of the Committee:	Prof. Dr. W. Bessei
1. Supervisor and Reviewer:	Prof. Dr. W. Claupein
2. Co-reviewer:	Prof. Dr. R. Gerhards
3. Co-examiner:	Prof. Dr. R. Doluschitz

„Man muss das Unmögliche versuchen,

um das Mögliche zu erreichen.“

Hermann Hesse

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Acronyms

CERES	Crop Environment Resource Synthesis
cm^2	Square Centimetre
m^2	Square Meter
ha	Hectar
DSS	Decision Support Systems
DSSAT	Decision Support System Agrotechnology Transfer
Dai	Days after inoculation
GIS	Geographic Information Systems
GPS	Global Positioning System
HR	Hypersensitive response
KAS	Kalkammonsalpeter
M	Meter
N	Nitrogen
nm	Nanometre
N_{min}	Soil available mineral nitrogen
PA	Precision agriculture
r^2	Coefficient of determination
VRT	Variable Rate Technology
µm	Micron Meter

1. General Introduction

1.1. Precision agriculture

Agriculture dominates the world’s land use decision. The urgent need for doubling farm production over the next 25 years on less land with less water through further intensification would inevitably involve substantial social, economic, and environmental costs. Identification of tools to minimize such costs through enhanced productivity and economic profits while simultaneously conserving the environment is, therefore, crucial. Precision agriculture (PA) is one of such tools catching worldwide attention since the early 1990s. Precision agriculture can be defined as a holistic and environmentally friendly strategy in which farmers can vary input use and cultivation methods – including application of seeds, fertilizers, pesticides, and water, variety selection, planting, tillage, harvesting – to match varying soil and crop conditions across the field. It has been long recognized that crops and soil within a field and/or region are both spatially and temporally variable. Growers tried to manage such variability to a limited extent mainly by intuition. As early as the 1620s, colonists observed site-specific practices of Indian farmers, who placed fish directly at the roots of each crop plant (National Research Council, 1997) to optimize nutrient supply. Development in geo-spatial information and communication technologies especially in the late twentieth century have made it possible, to manage such variability much more precisely than before. Precision agriculture, therefore, differs from conventional farming as it involves determining variation more precisely and linking spatial relationships to management actions, thereby allowing farmers to look at their farms, crops and practices from an entirely new perspective, finally leading to:

1. reduction in costs,
2. optimization of yields and quality in relation to the productive capacity of each site,
3. better management of the resource base, and
4. protection of the environment (Srinivasan, 2006).

Precision agriculture promises to revolutionize farming as it offers a variety of benefits in profitability, productivity, sustainability, crop quality, environmental protection, on-farm quality of life, food safety, and rural economic development (National Research Council, 1997). In the short term, the diagnostic and databasebuilding benefits are considerable. Growers can predict and correct problems such as water and nutrient stresses, diseases, and pests more efficiently.

Man has been monitoring plants for thousands of years, especially since he started to cultivate several species. Ever since these early beginnings, the aim has been to ensure and increase the yield to guarantee the basic food supply. The development of crop rotation in the 1st century A.D. and later on the application of organic fertilizers are examples for the progressive knowledge about plants and their dependents on environmental factors such as soil, temperature, water availability or nutrition (Oppelt, 2002). Nowadays, in many countries agriculture is a highly commercialized branch, which is characterized by the calculated use of fertilizer, herbicides, fungicides and machines for attaining maximum yield and to protect the environment. The development of cost-effective techniques to discern such problems, to develop site-specific or field-specific recommendations and data analyzing tools, and to determine the appropriate scale of analysis and measurement are, therefore, prerequisites for PA. Global Positioning Systems (GPS), geographic information systems (GIS), remote and proximal sensing, variable rate technology (VRT) and decision support systems (DSS) are employed to meet these needs. In addition, new devices (e.g. GIS-enabled personal digital assistants, GPS-equipped yield and quality monitors), communication (e.g. Internet) and data compression technologies are useful for efficient collection and delivery of data, services, and products. The essential technologies for precision agriculture, as illustrated in figure 1, are sensing and monitoring systems, and control, data transfer and precision application systems (Srinivasan, 2006).

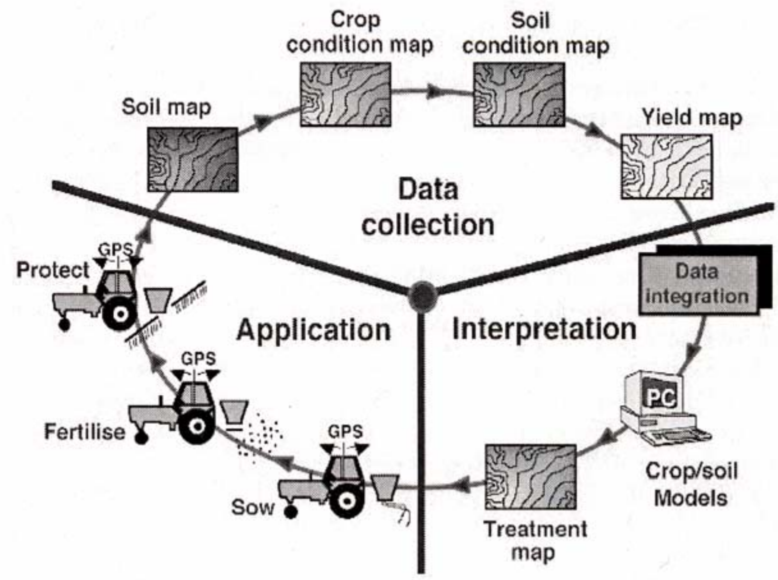

Figure 1 The precision agriculture cycle (Srinivasan, 2006)

The development of spectrometers enabled not only the investigation of the vegetation cover but also the derivation of individual constituents and furthermore the condition of plants. Ground-based spectrometers are used to deviate plant parameters such as leaf area, water content, pigment content and biomass as well as the influence of stress or disease at leaf scale (Oppelt, 2002). With the existence of airborne spectrometers, investigations and existing approaches at leaf scale were continued at canopy level.

Precision agriculture is information-intense; a lot of position tagged, sensed data, i.e. mapped data, are required to generate treatment maps. The ideal to attain is real-time, robust, low-cost mapping systems for soil, crop, and environment variables. However, the only commercial systems available to date are yield mapping, crop reflectance measurements to detect nutrient and water stress, and soil conductivity mapping systems. Satellite remote–sensed images are available but, in general, are not processed into useable forms, are too expensive, or are not timely. Soil ore crop information, such as soil moisture and acidity, crop vigor and disease presence can be obtained, but only by laborious and costly manual sampling and analysis or by visual surveying (Srinivasan, 2006).

The most widely used PA technologies are yield mapping and the sensing of nitrogen. Yield mapping is used to determine the spatial yield variability within a field (Jaynes, 1997; Lamp et al., 1997) and to delineate areas with different yield potentials over the time (Blackmore, 2000). Yield mapping systems record the relative spatial distribution of yield while the crop is being harvested. These systems collect georeferenced data on crop yield and characteristics such as moisture content. The maps can illustrate areas of yield variability resulting from either natural processes or agricultural practices. However, a yield map does not provide information about the underlying factor leading to yield variability (Link, 2005).

For the side-specific application of nitrogen, the company Agri Con (Jana, Germany) provides the N-Sensor, which measures the reflectance of light from the crop canopy. The reflectance of a crop indicates among other things the chlorophyll content, which is related to the nitrogen content in a plant and thus gives information about the current nitrogen demand of the crop. Using this sensor, the nitrogen application rate can be adapted to the nitrogen demand of the plant and the yield expectations (Liebler, 2003).

For the site-specific application of pesticides several sensor technologies are currently tested and some of those are now available on the market.

The Crop-meter (real-time sensor to measure crop biomass density) for example, measures the crop biomass density and has been designed and developed to meet the demands for practical use in site-specific farming (Ehlert and Dammer, 2006). The sensor signal of the Crop-meter is correlated with the Leaf Area Index, a measurement characterizing the plant surface (Dammer and Ehlert, 2006). The application rate of fungicides is therefore dimensioned according to plant height and plant density. The sensor is based on the pendulum principle. The suitability and measuring stability of the Crop-meter has been confirmed under field conditions in different regions of Germany. The mean goodness of fit for the correlations between crop fresh mass density and pendulum angle measurements were $R^2 = 0.89$ for all investigated pendulum parameter combinations. To perform site-specific application of fungicides in real time, the Crop-meter was combined with a tractor and a sprayer. The principle of this system is to reduce drastically the application rate of fungicides in parts of fields with sparse vegetation.

Another system has been developed by Gerhards et al. (1997) for site-specific weed control in arable crops. The system includes on-line weed detection using digital image analysis, computer-based decision making and Global Positioning System-controlled patch spraying (Gerhards and Oebel, 2006). Gerhards et al. (1998), Chapron et al. (1999) and Sökefeld et al. (2000) used digital image analysis systems to identify plant species based on characteristic shape-, color- and texture-features for each individual object in the image. For the automatic weed detection, three digital bi-spectral cameras were mounted in the front of the sprayer (Gerhards et al., 2002). After the detection of weeds, application maps were created based on interpolated maps of weed distribution and control thresholds for classes of weed species. Three different application maps were realized at the same time using a multiple sprayer with three separated hydraulic circuits. This allows the herbicide mixture to be varied during application. Each of the three sprayer circuits had a boom width of 21 m, divided into seventh sections of 3 m. Each sprayer circuit and each section were separately turned on and off by a control unit (Gerhards and Oebel, 2006). By this approach herbicide use could be reduced in winter cereals by 6-81 % for herbicides against broad leaves weeds and 20-79 % for grass weed herbicides.

1.2. Plant diseases and reflectance measurements

Plant diseases are damages on crops caused by nutritional disturbance (e.g. lack or overage of certain mineral salts or water), by influences of the weather, smoke, emissions, and by insects, fungi and virus infections. Since the beginning of agriculture plant diseases are one of the main reasons for loss in yield and quality. Approximately 30 % of the world harvest is lost on an annual basis due to biotic stress factors (Habermeyer et al., 2000). To react against plant diseases resistant varieties could be grown, different cropping systems could be done to get healthier and robust crops as well as biotic pest defense methods. But the most widely used practice in pest control in arable crops is still to spray pesticides uniformly over fields at different times during the cultivation cycle. However, most disease infestations are not evenly distributed across a field, but occur in patches. During the early stage of epidemics large areas of a field often are free of disease. Spickermann (2005) stated in his work that the investigation of the dispersion pattern of plant diseases with GIS showed that symptoms spread heterogeneously throughout a winter wheat field. This means that diseases are not distributed randomly, but instead arise preferentially in clusters or nests, where the infection begins. At the same time a preferential spreading of some plant diseases in a certain direction was detected.

This work concentrated on diseases caused by different fungi as fungi besides weeds, have with 18 % the highest damage potential in cereals (Oerke, 2000).

Roots and shoots of all plants come into intimate contact with plant pathogens. Each pathogen has evolved a specific way to invade plants. Some species directly penetrate surface layers by using mechanical pressure or enzymatic attack. Others pass through natural openings (e.g., stomata or lenticels). A third group invades only tissue that has been previously wounded. Once inside the plant, one of three main attack strategies is deployed o utilize the host plant as a substrate: *necrotroph*, in which the plant cells are killed; *biotroph*, in which the plant cells remain alive; and *hemibiothroph*, in which the pathogen initially keeps cells alive but kills them at later stages of the infection (Hammond-Kosack and Jones, 2000). In this study, biotroph and necrotroph plant diseases were selected for the investigation by sensor technologies.

Biotrophic parasites cannot survive in a dead host and therefore keep their hosts alive. Generally biotrophs complete their reproductive cycle on a living host. In biotrophic fungi, nutrient transfer from host to fungus often occurs via haustoria. The fungus obtain carbon and energy nutrient from the host plant (Lewis, 1976). Infection by biotrophic pathogens results in many changes in the metabolic processes of plant tissue including shifts in respiration, photosynthesis and transpiration (Lucas, 1998). All these changes are interrelated some occur simultaneously, others from a sequence of alterations reflecting different stages in disease development. Water loss from infected leaf areas can increase due to destruction of the leaf cuticle (Bassanezi et al., 2002), increased permeability of leaf cell membranes (Chaerle et al., 2001), or inhibition of stomatal closure (Felle et al., 2004). Reduction of transpiration may result from stomatal closure (Chaerle et al., 2001), obstruction of xylem elements and stomata, and defoliation. To defend the fungal attack the plant reduces chlorophyll around the pustules to make the fungus die. Because of the reduction in chlorophyll reflectance changes are expected in the visible wavelength range.

Necrotrophs are parasites that use another organism's tissue for their own nutritional benefit until the host dies from loss of needed tissues or nutrients. Because of the structural damage caused by a necrotroph disease reflectance changes are expected in the infrared wavelength range.

Green area of a plant canopy is considered to be at its maximum just before yield formation starts. Disease management aims to maintain green area during the yield-forming period and thus ensures that crop growth is not slowed or stopped prematurely. Therefore, the main aim of fungicides is to protect the top three leaves, as up to 80 % of the yield in wheat is derived from these leaves.

Most microbes attack only a specific part of the plant and produce characteristic disease symptoms, such as a mosaic, necrosis, spotting, wilting, or enlarged roots (Hammond-Kosack and Jones, 2000). Figure 2 shows the appearance of plant diseases on different organs of the plant. Plant diseases can attack the spike, the leaves, the stripe and the roots. The plant diseases analyzed in this work attack the plant at the leaves (septoria leaf blotch, powdery mildew) and at the stripe near the spear basis.

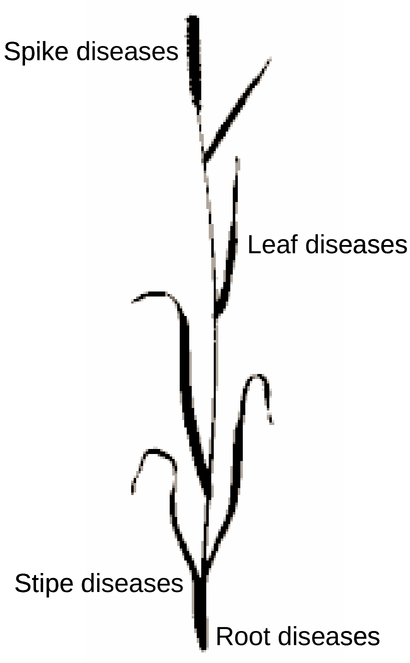

Figure 2 Appearance of plant diseases on different organs of the plant.

Foliar diseases, such as septoria leaf blotch and powdery mildew can rapidly reduce green area after maximum green area index has been reached.

Johnson et al. (1979) evaluated the effect of powdery mildew (*Erysiphe graminis)* (Figure 3) on soft wheat quality by the use of near-isogenic lines of Chancellor wheat and found that severe powdery mildew infection lowered flour protein, but did not significantly affect particle size index, flour yield or flour ash content and had only a minor effect on baking quality. The dispersion of *Erysiphe graminis* is optimal at a temperature range of 15-22 °C, whereas no defined level of humidity is necessary. The disease is passed with the wind from infested harvest residues, infested grain residues or infested fields in the neighborhood. Densely crops and high nitrogen fertilization encourage the dispersion of powdery mildew. Last (1963) detected that powdery mildew pustules are visible three days after the infection of a barley leaf. If the temperature is reduced from 18-25 °C to 15 °C the infection period is extended up to one week. Powdery mildew produces white to grey, cottony fungal growth mostly on the upper leaf surface, although some pustules may develop on the underside of the leaf (Daamen, 1989; Wiese, 1987). Pustules begin as small white circular patches of fungal mycelium often surrounded by chlorosis, most visible on the underside of the leaf. 'Green islands' appear near infected areas as the plant transports nutrients to non-diseased cells (Schafer, 1987). Within a few days after they appear, the white powdery pustules produce large quantities of small asexually produced conidia in long chains, which are easily dislodged by wind or rain. These spores are single-celled, oval (8 to 35 µm) and colorless.

Figure 3 Powdery mildew in the field (left) and on a single leaf (right).

Leaf blotch (*Septoria tritici*) (Figure 4) caused by the fungus *Mycosphaerella graminicola* (Fuckel) Schroeter, is a major necrotic leaf disease of wheat (*Triticum aestivum* L.). Where environmental conditions are favorable for disease development, yield losses ranging from 20 to 43 % have been reported (Cooke and Jones, 1971, Caldwell, 1976). Leaf blotch can reduce the economic value of wheat by decreasing both grain yield and quality. Test weight, a function of both kernel density and random kernel packing volume (Yamazaki and Briggle, 1969), and an initial indicator of grain quality, can be significantly affected by this disease. Reported reductions under natural infection reached 1680 kg (Caldwell and Narvaez, 1960). Yield loss is related to the leaf area killed by the pathogen (Brown and Paddick, 1980). *Septoria tritici,* also known as necrotic blotch or speckled leaf blotch, is characterized by necrotic blotches that contain black or dark brown pycnidia. The disease has been reported worldwide, but is most severe in wheat production areas that have cool, wet growing seasons (Eyal et al., 1987, Holmes and Colhoun, 1975, Van Ginkel and Scharen, 1988). *Septoria tritici* pycnidiospores germinate on a suitable substrate when the plants are wet. Spores begin to germinate within 12 hours, and leaf penetration occurs after 24 hours. Moisture is required for all stages of infection: germination, penetration, development of the mycelium within the plant tissue and subsequent pycnidium formation (Browning, 1979; Hooker, 1957). The usual vertical progress of the disease from lower to upper leaves is affected by the distance between consecutive leaves. As a result, pycnidia often appear earlier on upper plant parts of dwarf cultivars than they do on leaves of taller cultivars (Eyal et al., 1987). The pathogen survives on wheat stubble (Shipton et al. 1971)

Figure 4. Septoria leaf blotch in the field (left) and on a single leaf (right).

Root and stem-based diseases, like wheat eyespot, can affect plant establishment, leading to reduced canopy size before grain filling begins. Root and stem-based diseases can also cause loss of green area and premature senescent. Wheat eyespot is usually the main stem-base disease, with severe infections causing losses up to 30 %.

Wheat eyespot (Figure 5), caused by the fungi *Oculimacula acuformis* (R type) and *O. yallundae* (W type), is the most important stem base disease of wheat in humid and cold regions. The frequency of its occurrence and the disease severity is closely related to the cropping system which is characterized by narrow crop rotations with a high proportion of cereals, reduced tilling and direct and earlier sowing dates in autumn. Yield losses of 10 to 40 % were estimated usually combined with a reduction of seed quality (www.bmvel-forschung.de). Wheat eyespot reduces yield and quality by restricting water and nutrient uptake. Severe eyespot can cause lodging from weakened stems. In early sown crops lesions can appear in the autumn 10 to 20 cm above the ground. Symptoms may disappear during early spring growth as leaf sheaths die off, but can re-appear later again. The spots are elongated, oval, dark brown on the edges, with a diffuse margin, sometimes as large as the sheath itself. Grey marks (stromas) are visible on the under face of the sheath or the second sheath. The lesions can cause lodging at the end of the life cycle. Even when lodging does not occur, the disease leads to more or less severe shrivelling of the grains. The fungus survives in the haulms of previous crops. Primary infection is promoted by the conidia which spread from autumn to may-June. After the first sheath has been infected, the fungus progresses through all the successive sheaths before attacking the stem. Eyespot sporulation requires high relative humidity (RH) close to saturation and 2 - 15 °C temperature (7 °C optimum). The disseminationof conidia is airborne. Over 85% RH for at least 15 hours is necessary for the conidia to germinate on the sheaths. Contamination can occur from late autumn on. The progress through the sheaths stops if temperature rises above 25 °C (http://www.inra.fr).

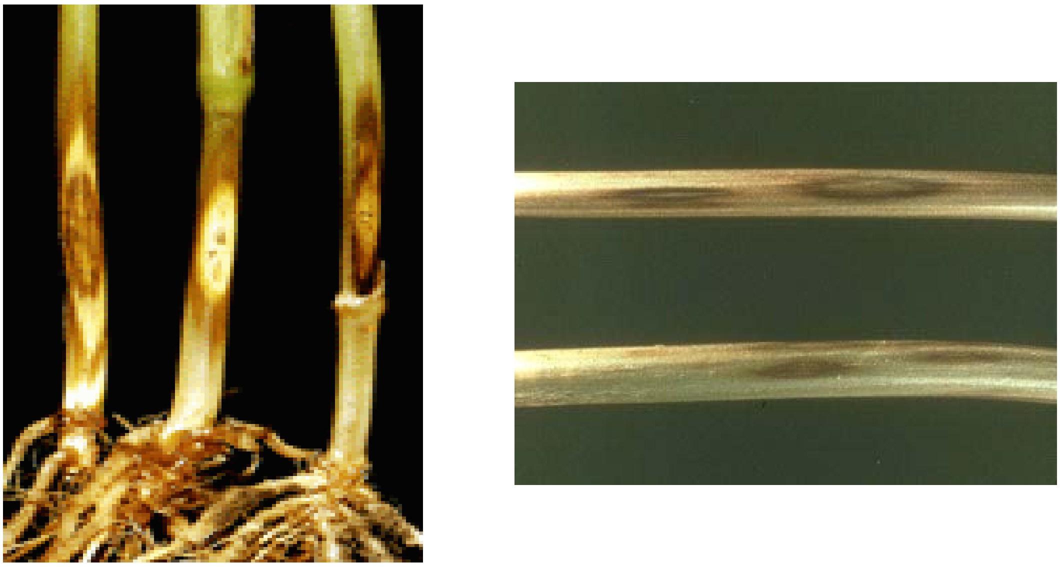

Figure 5 Wheat eyespot.

Reflectance of agricultural crops in the visible and near infrared wavelength domains has been studied by numerous researchers in order to estimate different crop parameters, such as plant species, productivity, harvest, plant nutrient and plant pathological status (Deering, 1989; Kumar et al., 2001). Spectral reflectance characteristics of leaves have been shown to be highly correlated with their chemical composition (Moshou et al., 2005). Carter et al. (2001) indicated in his studies the importance of chlorophyll concentration on the spectral signature of leaves. The spectral reflectance around 700 nm was found to be highly correlated with total leaf chlorophyll content. The optical response to stress near 700 nm, as well as corresponding changes in reflectance that occur in the green-yellow spectrum, were explained by the general tendency of stress to reduce leaf chlorophyll concentration. The reflectance of incident radiation from within the leaf interior of stressed plants increased, and as a result the stressed plants appeared brighter in the visible region of the spectrum than healthy plants (Cibula et al., 1992). Boochs et al. (1990) suggested that high-resolution reflectance spectra, especially in the red edge area (reflectance between 680 and 760 nm), would be useful for the identification of small differences in the chemical and morphological status of the plants in the field. Using methods based on measurements of reflectance of field crops to estimate crop status, the in-field variability can be recorded and can be used as a basis for the decision-making of site-specific actions of e.g. application of plant nutrients or pesticide dose. With spectral sensing, sampling of reflectance spectra of growing crops can be done relatively fast and the signal from a spectral sensor can be used to control site-specific means of inputs either indirectly by mapping the in-field variability or in real time mode using a vehicle mounted spectral sensor (Larsolle and Mohammed, 2005).

The basis for a site-specific application of fungicides is however the spatial identification of the pathogens. At this time there are no sensor systems commercially available to identify and quantify the disease pressure vehicle based. Commercially available optical sensor systems like the Yara-N-Sensor (Yara, Germany) or multi spectral cameras can be used for the detection of plant stresses like for example nutrient- or water deficiency, but they are yet not suitable to detect plant diseases. Also the Crop Meter in not able to detect plant diseases directly. The Crop Meter measures only the plant density but not the real infection level. Although this approach is simplistic it is currently one of a few systems that is already practical and useable by farmers. In terms of sustainable land cultivation it is necessary to develop sensor systems that can identify and quantify plant diseases on a spatial scale and on this basis enable a spatial regulation of the pesticide application.

1.3. Objectives of the Dissertation

This Ph.D. thesis was originated in the context of subproject 12 “Use of sensor technologies to estimate and assess the effects of various plant diseases on crop growth and development” of the *Preagro II* project. The Preagro II project has the overall title: Information guided plant production with Precision Farming as central regards content and technical assumption for a sustainable development of the agricultural land use. The project consists of 23 subprojects from public research and development institutions as well as on the part of KMUs. The duration of the project was 3 years from January 2005 till December 2007. The German Federal Ministry of Education and Research financed this project through their programs on precision agriculture. In the context of the subproject 12 a sensor technology for the identification and quantification of plant diseases was tested. Considering the complexity of various pathogens, the influence of *Erysiphe graminis* (powdery mildew), *Septoria tritici* (blotch disease) and *Pseudocercosporella herpotrichoides* (wheat eyespot) on the reflectance of wheat plants was investigated using a digital imager.

The specific objectives of the Ph.D. thesis were to:

- develop and test reflectance measurements as a possible technology to identify reflectance signatures of various plant diseases;
- develop suitable sets of calibrations that can be used for the identification and quantification of plant diseases;
- test different sensor systems at different spatial resolutions for their ability to identify plant diseases;
- develop a strategy to use plant disease information grained from sensor measurements as input dataset for the simulation of wheat growth in CERES-Wheat.

1.4. Formal structure and introduction to the chapter

This dissertation is a compilation of chapters describing basic information associated with the topic of this study, and chapters containing journal manuscripts submitted to refereed scientific journals. The manuscripts address specific objectives that were related to this study.

In the second chapter field experiments done at the experimental station "Ihinger Hof" of the University of Hohenheim were described. The third chapter describes the used sensor systems in this work and gives an overview of different sensor techniques. In the fourth chapter different crop models are introduced. Chapter six describes the results of the experiments about the identification of wheat eyespot.

This thesis consists also of four papers submitted to international high standard referenced journals. Aspects not mentioned in the articles were included in this thesis as intermediate chapters. The articles are all connected by the overall goal to identify plant diseases using reflectance measurements.

The first article (chapter 5) entitled "Spectral identification of powdery mildew (*Erysiphe graminis)* in wheat using digital image analysis." by the authors Kerstin Gröll, Simone Graeff and Wilhelm Claupein was submitted to the Journal Phytopathology. The aim of this study was to develop i) the basics for a sensor supported identification of plant diseases, and ii) to identify wavelength ranges that enable a clear identification and quantification of plant pathogens. Therefore greenhouse studies were conducted at the University of Hohenheim and the influence of powdery mildew was studied using a digital camera with a spatial resolution of 0.5 cm^2. The results of this article show that powdery mildew could be identified and quantified in the wavelength ranges 516-540 nm and 540-600 nm.

The second article (chapter 7) entitled "Use of different vegetation indices to detect various plant diseases in winter wheat (*Triticum aestivum* L.)." by the authors Kerstin Gröll, Simone Graeff and Wilhelm Claupein was submitted to the Journal Remote Sensing of Environment. In this article a range of common vegetation indices was tested for their ability to detect plant diseases in the field. Therefore a field experiment was conducted at the experimental station "Ihinger Hof" of the University of Hohenheim. The reflectance under the diseases powdery mildew and septoria leaf blotch was measured with a spectroradiometer with a spatial resolution of 0.5 m^2. The results showed that the vegetation indices REIP and RVSI were able to detect powdery mildew at an infection level of 7 % and septoria leaf blotch at an infection level of 13.7 %. In order to detect an earlier stage of septoria leaf blotch infection, a new vegetation index was developed. The developed and tested "Disease Infection Index" (DII) was able to detect septoria leaf blotch at an infection level of 4 %. Canopy reflectance measurements were able to detect powdery mildew at an infection level of about 4 % and septoria leaf blotch at an infection level of about 3 % and can be used as an alternative to vegetation indices to identify plant diseases.

The third article (chapter 8) entitled "Sensor-based identification of plant diseases: requirements of spatial resolution" by the authors Kerstin Gröll, Simone Graeff and Wilhelm Claupein was submitted to the journal Precision Agriculture. The article describes the suitability of different sensor systems with different spatial resolutions to identify septoria leaf blotch in the field. Therefore a field experiment was conducted at the experimental station "Ihinger Hof" of the University of Hohenheim. The trials were treated with three different fungicide doses. Plant reflectance was measured weekly from EC 51 with a digital camera (LEICA S1 PRO, LEICA Kamera AG, Solms, Germany) at leaf scale (0.5 cm^2) and with the spectroradiometer Field Spec® Hand Held (ASD, Inc. Boulder, CO, USA) (0.5 m^2) and the Yara N-Sensor in the field-scan modus (12 m^2) 2 m above the canopy. With the digital camera LEICA S1 PRO an identification and quantification of septoria leaf blotch was possible at an early stage of infection in the wavelength ranges 490-510 nm and 490-510 IR. With the Field Spec® Hand Held an identification of septoria leaf blotch was also possible at an early stage of infection especially in the infrared wavelength range. Because of the information loss due to the spatial resolution a quantification was not possible. The N-Sensor could not detect and quantify changes in the reflectance under septoria leaf blotch because of the low spatial resolution and the mixed signal of healthy and diseased plants.

The forth article (chapter 9) entitled “A Strategy for Incorporating Plant Diseases Coupled with Leaf Sensor Measurements into CERES-Wheat” by the authors Kerstin Gröll, Simone Graeff and Wilhelm Claupein is printed in the Proceeding of the 6th Biennial Conference of European Federation of IT in Agriculture, 2nd – 5th July 2007, Glasgow, UK. The study aims to develop a new module to simulate potential disease development in wheat and its impact on yield with and without fungicide applications. Up to date, there seems to be no practical site-specific disease models available, which include forecasting and control decisions on the basis of meteorological, soil, and management data as well as cropping factors. The article shows theoretically how plant diseases coupled with leaf sensor measurements could be implemented into crop growth models.

2. Field experiments

To measure reflectance changes under leaf blotch, powdery mildew and wheat eyespot, a series of field experiments was conducted over the growing periods 2005-2007 at the Experimental Station “Ihinger Hof” (48°44´ N, 8°56´E) of the University of Hohenheim, Stuttgart, Germany. The “Ihinger Hof” is located between Weil der Stadt and Magstadt in the district Böblingen and belongs to the region Heckengäu. The soils in this region of Baden-Württemberg emerged typically from shell limestone and Keuper with a partly floated loess cover. The experimental station exhibits mostly heavy Keuper soils with a high content of clay. The predominant soils are para-brown earth and para-brown earth-planosols. The climatic site conditions result from the longtime middle rainfall of 693 mm and the longtime middle temperature of 8.1 °C. The experimental station is located 460-520 m above see level.

2.1. Location

Figure 6 shows the site map of the experimental station “Ihinger Hof” and the location of the experiments in the year 2005 , 2006 and 2007 . The experiments inoculated with powdery mildew and septoria leaf blotch were located in the year 2005 in the field “Kirrlay II” and the experiment inoculated with wheat eyespot in the field “Inneres Täle”. In the year 2006 the experiments inoculated with powdery mildew and septoria leaf blotch were located in the field “Kirrlay Wald” and the experiment inoculated with wheat eyespot in the field “Bei den Eichen”. In 2007, the experiments inoculated with powdery mildew and septoria leaf blotch were located in the field “Kirrlay Wald” and the experiment inoculated with wheat eyespot in the field “Äußeres Täle”.

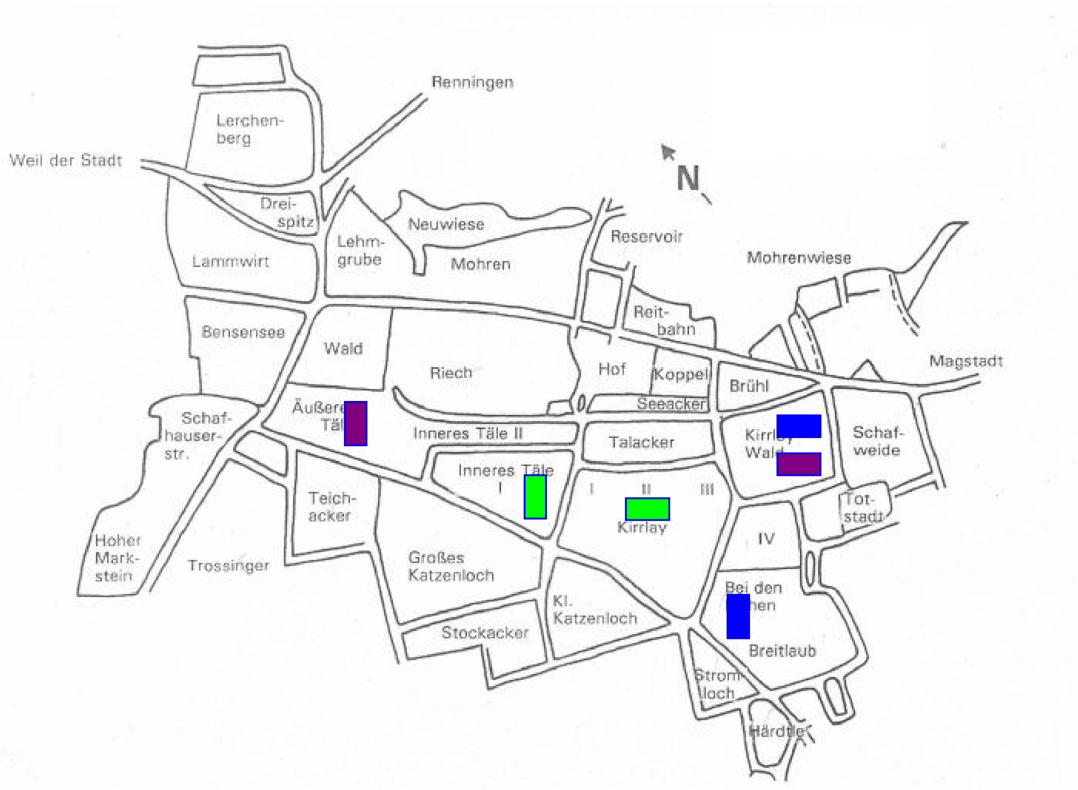

Figure 6 Site map of the experimental station Ihinger Hof and the location of the experiments in the year 2005 2006 and 2007 .

2.2. Soil

Figure 7 shows the soil map for the experimental station "Ihinger Hof" resulting of the State Soil Evaluation in 1973 (Geologisches Landesamt Baden-Württemberg), indicating different soil types including the experiments in the year 2005, 2006 and 2007 .

The major soil type of the fields was delineated by the State Soil Evaluation as a loam till heavy loam. The status level lay between 3 and 4 and the type of origin is considered to be weathered loess. The soil value varies between 53 and 58 and the field value between 47 and 64.

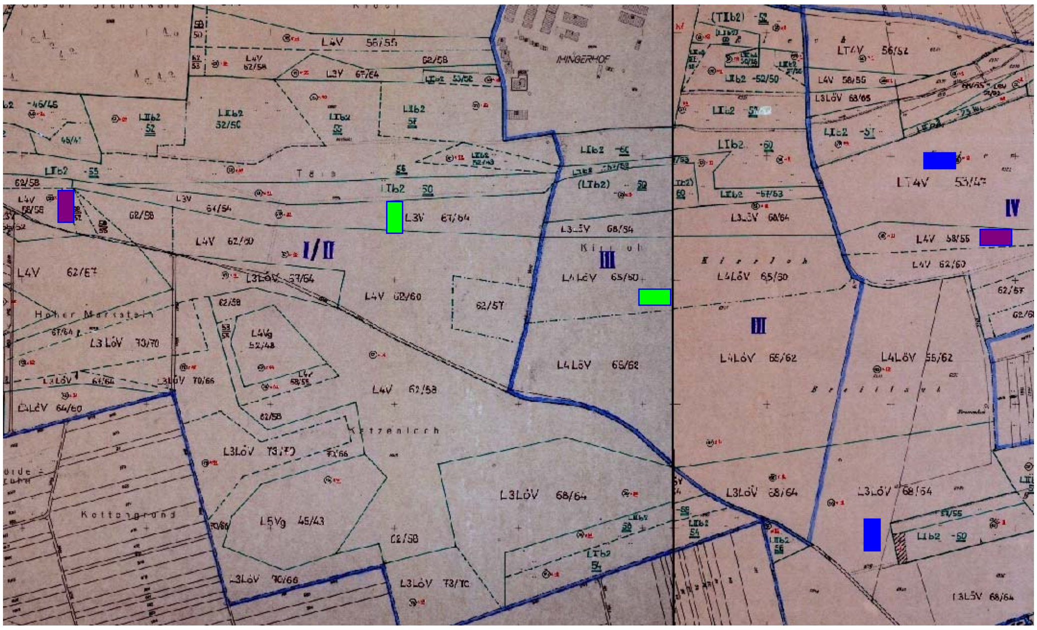

Figure 7 Soil map for the experimental station “Ihinger Hof” during the State Soil Evaluation in 1937 (Geologisches Landesamt Baden-Württemberg), indicating different soil types including the experiments in the year 2005 , 2006 and 2007 .

2.3. Climate

Figure 8 shows the monthly temperature and rainfall for the vegetation period of winter wheat in 2004/2005 on the experimental station “Ihinger Hof”. In this vegetation period the mean temperature in the growing period of winter wheat from September 2004 till August 2005 was 8.8 °C and the average precipitation was 707.2 mm. In the period of sowing and the emerging enough rain was available. In the period of growing from March till August also enough rain was available except in June where rainfall was lower than the 30 year average. In the growing period between April and August the mean temperature was 14.6 °C and the average precipitation was 340.7 mm.

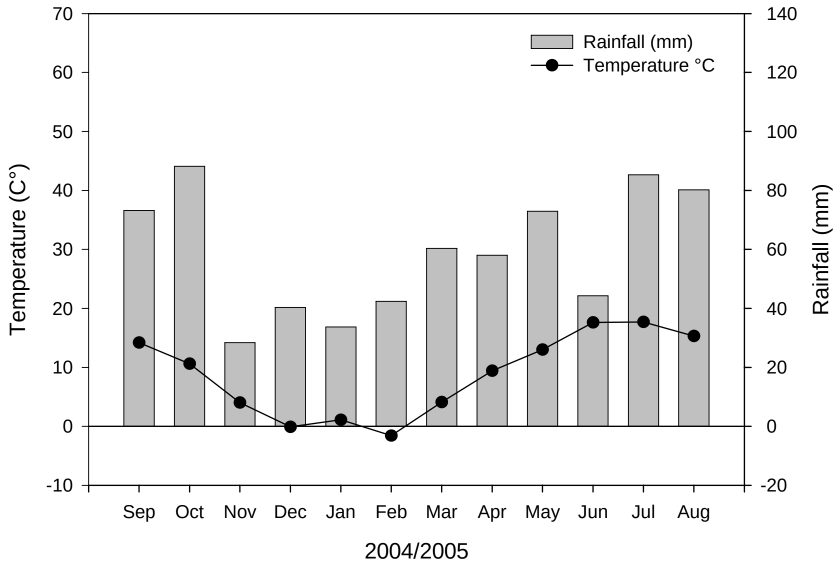

Figure 8 Monthly temperature and rainfall for the vegetation period 2004/2005 on the experimental station “Ihinger Hof”.

Figure 9 shows the monthly temperature and rainfall for the vegetation period 2005/2006 on the experimental station “Ihinger Hof”. In this vegetation period the mean temperature from September 2005 till August 2006 was 8.7 °C and the average precipitation was 583.8 mm. In the period of sowing only 31.5 mm rain was available which was under the rainfall in the year before and after. In this vegetation period the average precipitation was at 113.4 mm lower than in the year before and at 84.9 mm in the year after. From September 2005 till February 2006 and in June the rainfall was below 41 mm which is very low compared to other years. In the vegetation period from April till August the mean temperature was 15 °C and the average precipitation was 358.9 mm. In the growing period enough rain was available for the plants.

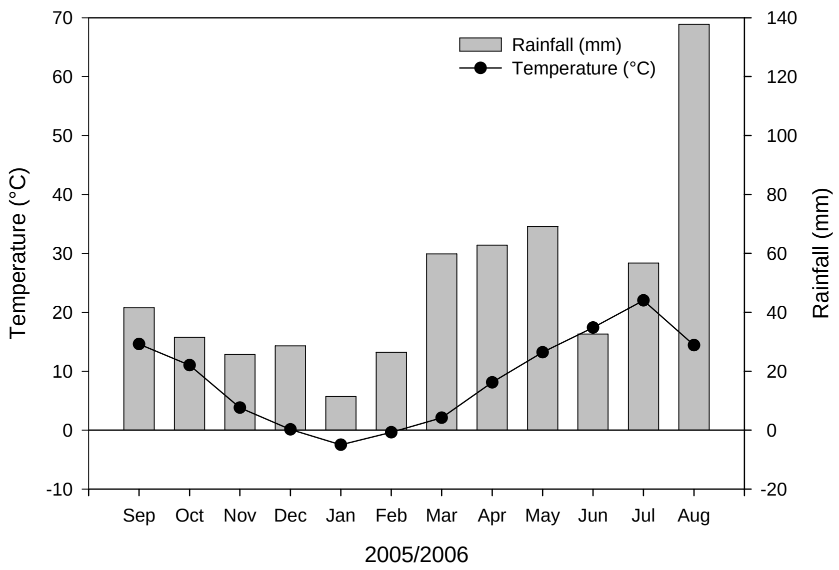

Figure 9 Monthly temperature and rainfall for the vegetation period 2005/2006 on the experimental station "Ihinger Hof".

Figure 10 shows the monthly temperature and rainfall for the vegetation period 2006/2007 on the experimental station "Ihinger Hof". In this vegetation period the mean temperature from September 2006 till August 2007 was 10.8 °C and the average precipitation was 678.7 mm. In this vegetation period the mean temperature was higher as in the years before, especially the winter months were mild. In the period of sowing and emerging the precipitation was with 50 mm iin September and 74 mm in October enough for winter wheat. In the growing period from March till August high rainfall in May and June with 103.5 and 107.2 mm and almost no rainfall in April was obtained. The precipitation in March, July and August was also high enough. In the vegetation period from April till August the mean temperature was 15.3 °C and the average precipitation was 344.3 mm.

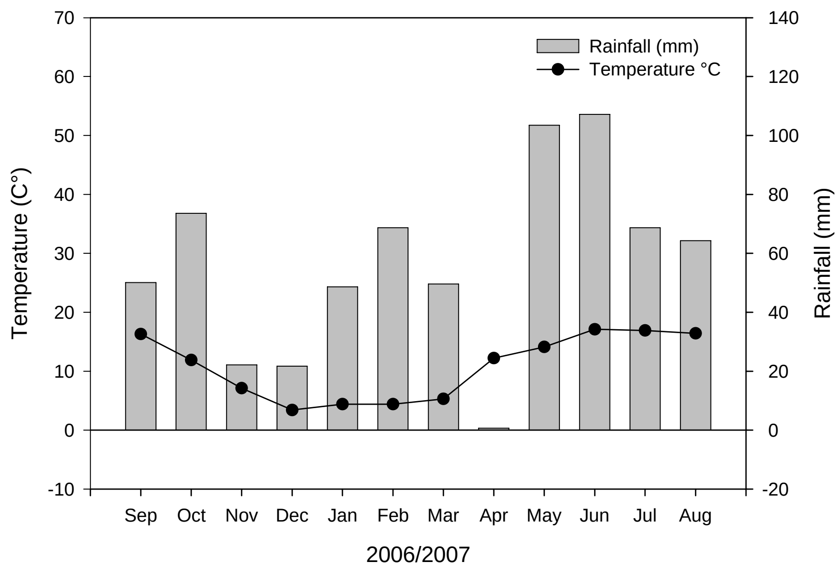

Figure 10 Monthly temperature and rainfall for the vegetation period 2006/2007 on the experimental station “Ihinger Hof”.

2.4. Management and experimental design

Field studies were conducted during the growing period of 2004/2005, 2005/2006 and 2006/2007 at the experimental station “Ihinger Hof” of the University of Hohenheim, Stuttgart, Germany. Winter wheat cv. Monopol and Empire were planted on October 23rd 2004, on September 22nd 2005 and on September 29th 2006 at a rate of 350 seeds per m². Each year the fields were ploughed followed by a seedbed preparation before sowing. The total amount of nitrogen, depending on N_{min} in the ground, was split in three rates and broadcast as KAS (13.5 % NH_4-N, 13.5 % NO_3-N, 12 % CaO). Timing of N application was set to start of vegetation, Zadoks 32 and Zadoks 49 (Zadoks et al., 1974). Herbicides and insecticides were broadcast as needed to control pests. The variety ‘Empire’ is classified as a high resistant variety, whereas ‘Monopol’ has a very low resistance against diseases in general (Bundessortenamt, 2005). The experiments were inoculated with the diseases septoria leaf blotch, powdery mildew and wheat eyespot in the inoculum steps I1 = no inoculum = control, I2 = 50 % inoculum and I3 = 100 % inoculum. The trials were set up as randomized block design with three replications.

The plots had a size of 4 x 8 m. A protection zone of 6 m was implemented between plots of different varieties and similar inoculum steps. Between different inoculum steps a 10 m protection zone to avoid cross-inoculation was implemented. Septoria leaf blotch was inoculated in spring at GS 32 (Zadoks et al., 1974) by strewing infected wheat grains into the plots (CBS 292.69, Germany). Measurements started right after the inoculation at GS 32 and were repeated every week until beginning of July. Powdery mildew was inoculated in spring at GS 30 and 32 by putting different amounts of infected pots of infected plants (50 % three pots; 100 % six pots) between the wheat plants. The inoculum of powdery mildew (*Erysiphe graminis* 150, powdery mildew resistant gene Pm1, 2, 3a, 3c, 3d, 4a, 4b, 5, 6, 7, 8 and 17) was obtained from the Federal Biological Research Centre for Agriculture and Forestry, Kleinmachnow, Germany, as infected wheat plants in 10 cm pots. Measurements started right after the inoculation at GS 30 and were repeated every week until end of June. Wheat eyespot was inoculated at GS 12, GS 15 and GS 18 by strewing infected wheat grains into the plots (CBS 118.47, UK). Measurements started at GS 39 and were repeated every week until beginning of July.

Table 1 Management data for the experiments inoculated with septoria leaf blotch, powdery mildew and wheat eyespot.

experiment	year	Sowing	Seeds/m^2	1. N rate/ha	2. N rate/ha	3. N rate/ha
Septoria leaf blotch	2005	23.10.04	350	100 kg/N	80 kg/N	40 kg/N
	2006	22.09.05	350	110 kg/N	80 kg/N	40 kg/N
	2007	29.09.06	350	80 kg/N	70 kg/N	50 kg/N
Powdery mildew	2005	23.10.04	350	100 kg/N	80 kg/N	40 kg/N
	2006	22.09.05	350	110 kg/N	80 kg/N	40 kg/N
	2007	29.09.06	350	80 kg/N	70 kg/N	50 kg/N
Wheat eyespot	2005	23.10.04	350	90 kg/N	70 kg/N	60 kg/N
	2006	22.09.05	350	100 kg/N	80 kg/N	40 kg/N
	2007	29.09.06	350	80 kg/N	70 kg/N	50 kg/N

Each plot was harvested separately with a special harvester and the yield (dt ha^{-1}), the grain-straw-ratio was measured.

Before harvesting yield parameters such as number of plants ha^{-1}, number of ears per ha^{-1}, number of kernels per ear, and thousand-kernel weight (TKW) were measured for each plot by hand harvesting an area of 1 m^2. To determine dry matter yields of each plot, one part of the plant samples was dried at 105 °C in a forced-air oven. The other part of each plant sample was dried at 40 °C and analyzed for nutrient concentration in the plant and in the kernels.

3. Sensor systems

Up to now, a lot of different crop and soil sensor systems are commercially available. These sensor systems are able to detect various parameters like soil properties, crop stress, growth conditions and yield. They have been developed to collect information about the site-specific variability of a field, but each individual system is seldom able to make decisions for variable rate application. Sensor systems can still not differ between different stress factors like nutrient stress, water stress and plant diseases. Especially in the case of disease identification, no adequate sensor system is available to detect various diseases on plants. In this context, thermography, fluorescence imaging and reflectance detection are currently the most studied sensor techniques.
In the following part different methods to detect plant diseases are described including the used sensor systems in this Ph.D thesis.

3.1. Thermography

Thermal imaging is a straightforward choice for visualizing stress-induced changes in leaf transpiration, given controlled environmental conditions (Jones, 1999). Thermography allows the visualization of differences in surface temperature by detecting emitted infrared radiation [long-wave infrared (8-14 μm)]. Computer software transforms these radiation data into thermal images in which temperature levels are indicated by a false-color gradient. Thermal imaging is well known for its ability to sense crop vitality as the temperature of plant leaves is determined by environmental factors and transpirational cooling (Nobel, 1991). Changes in plants mainly results from alterations of transpiration in response to particular stresses. Thermography can be used to detect dose stresses and to study freezing processes and local leaf water content. Modifications in the water status of a plant caused by adverse conditions lead to changes in leave transpiration as a result of active regulation of stomatal aperture (Nilsson, 1995). The associated changes in patterns of leaf cooling can be monitored instantly and remotely by thermographic imaging. Studies also show that the thermal effect provides a preview of the final extension of necrosis. In a study on tobacco and *Arabidopsis* cell death mutants that spontaneously form lesions resembling a pathogen-induced hypersensitive response (HR), a thermal effect was detected before visual damages became apparent because of the evaporation of leaking cell contents and concomitant cooling (Chaerle et al., 2000). In conclusion, active thermography permits non-destructive determination of local leaf water content, whereas passive thermography measurements can be used to estimate stress-related changes in the amount of water transpired. Although passive thermography can be used to locate emerging disease outbreaks, as shown by its current use in aerial remote sensing at the field scale, it does not characterize the stressor. When developing thermography at field scale, its sensitivity to changing environmental conditions should be taken into account (Nilsson, 1995).

3.2. Fluorescence

Visible light energy absorbed by plant leaves is either used for photochemical reactions ore dissipated as heat and fluorescence (Lichtenthaler and Miehé, 1997). Although the proportion of these three different processes changes as part of the normal function of the leaf, stress also has profound effects. An increase in blue and green fluorescence is an early indicator of biotic and abiotic stress that is correlated with the accumulation of phenolic secondary metabolites in the epidermal cell layers (Buschmann und Lichtenthaler, 1998). The combined blue and green fluorescence emission can also be used as an internal standard to quantify the variation of chlorophyll fluorescence during short-term heat stresses or herbicide treatments. Chlorophyll fluorescence was also successful in monitoring fungal infections, which are by far the most yield-limiting biotic stresses in cereal production. Biothrophic pathogens, such as rust and mildews, generally induce a decrease in photosynthesis (Scholes, 1992). Incipient lesions at the loci of fungal rust infection of *Phaseolus* bean were visualized by an increase in chlorophyll fluorescence emission (Peterson and Aylor, 1995). However, this phenomenon was limited to the initial stages of the fluorescence transient. Importantly, infected leaves are extremely heterogeneous: they consist of invaded tissue, affected but invaded tissue and unaffected tissue.

Chlorophyll imaging systems can achieve high resolution, which is necessary to study the spatial heterogeneity of leaves. However, the area that can be analyzed is generally restricted to a few square centimeters. Most of the in the literature described fluorescence imaging approaches are laboratory-based. For rapid screening of plant populations, non-imaging point measurements using portable fluorometers are currently the appropriate tool (Strasser et al., 2000). As is the case for thermography, using fluorescence imaging on the field scale can only provide a non-specific indication of stress. Additional in-field tests will thus be necessary in order to identify the stress factor.

3.3. Reflectance

In addition to influencing stomatal resistance, infections, toxic compounds and adverse growth conditions can also induce changes in surface and internal leaf structure, cause the accumulation of secondary metabolites or lead to the breakdown of photosynthetic pigments (Nilsson, 1995; Penuelas and Filella, 1998). Structural alterations modify the reflectance of light from plant leaves or canopies. These changes can be visualized by reflectance imaging, ether in the visible spectrum or in near-infrared respectively infrared wavelength ranges undetectable to the human eye. Many studies show that it is possible to differ between healthy and diseased plants at an early stage of infection by reflectance measurements (Polischuk et al., 1997; Lorenzen and Jensen, 1989; Sasaki et al., 1998; Franke et al., 2005). Also spatial variability in soil type, crop nutrient stress, water stress and yield can be detected with reflectance imaging (GopalaPillai and Tian, 1999). Obtaining an overview of spatial in-field variability would be a prerequisite for site-specific disease management. This will be important in the context of precision agriculture, where different imaging technologies could be combined into a multispectral visualization approach. Hyperspectral reflectance imaging detected herbicide-induced stress in pine several days before the first visible signs of damage (Carter et al, 1996). By contrast, thermography could not detect any presymptomatic change in temperature, which was attributed to rapidly varying environmental conditions. In summery, reflectance imaging is a promising way to detect specific signatures for a particular stress and given plant species (Penuelas and Filella, 1998).

As reflectance measurements haven shown in the past the ability to detect plant diseases as they cover a broad wavelength spectra and further offer the potential to differ between different stress factors, this technique was considered as a starting technology for the development of a site-specific sensor technology for disease detection. Three different passive sensor technologies measuring leaf and canopy reflectance at different spatial scales were implemented.

3.3.1. LEICA S1 Pro Camera

The LEICA S1 Pro Camera (Figure 11) has a spatial resolution of 0.5 cm^2 and measures the reflectance at leaf level. Reflectance spectra were taken without removing the leaf from the plant. The leaf to be measured was laid on a black aluminum plate mounted 15-20 cm away from the optics (1.28/60 mm, Leica, Germany) of the imager. The scanned surface area constituted for every measurement 1.9 x 1.1 cm. To exclude the effects of solar light as well as of stray background light the imager, light source and sample were surrounded by a black aluminum box. The imager was used in conjunction with a constant light source (Reporter 21 D MicroSun, 21 W, Sachtler, Germany). The chosen light source was equipped with a 21 W daylight discharge bulb (Sachtler, Germany; color temperature 5500 – 6000 K), with produced more light than normal 50 W tungsten luminaries. By the use of different long-pass filters (Maier Photonics, Manchester, VT, USA) each leaf was measured in the visible wavelength ranges 380-780 nm, 490-780 nm, 510-780 nm, 516-780 nm, 540-780 nm and 600-780 nm. Also each leaf was scanned in the infrared wavelength ranges of 490-1300 nm, 510-1300 nm, 516-1300 nm, 540-1300 nm and 600-1300 nm by using a daylight filter. The long-pass filters had the following general specifications: 3 mm thickness, hard-oxide coating surface, quality 80/50 per MIL-O-13810A, coating quality 60/40 per MIL-O-13830A, and temperature limits – 50 to 100 °C.

Leaf scans were analyzed with the Software ADOPE® Photoshop 7.0 in the L*a*b-color system (CIE, 1986) (Figure 12), as defined in the software. In contrast to the definition of CIE (1986), the L*a*b*-color system of Photoshop 7.0 is defined from 0-256 for a* and b*-parameters. The L*a*b*-color system is a three-dimensional system (Figure 2). The x-axis represents the parameter a* which describes the green/red percentage of a color. The y-axis represents the parameter b* which describes the blue/yellow percentage of a color. L* stands for the lightness of a color and is represented on the z-axis. Plant diseases were identified by splitting the scans into a* and b* parameters in different wavelength ranges.

Figure 11 LEICA S1 Pro Camera.

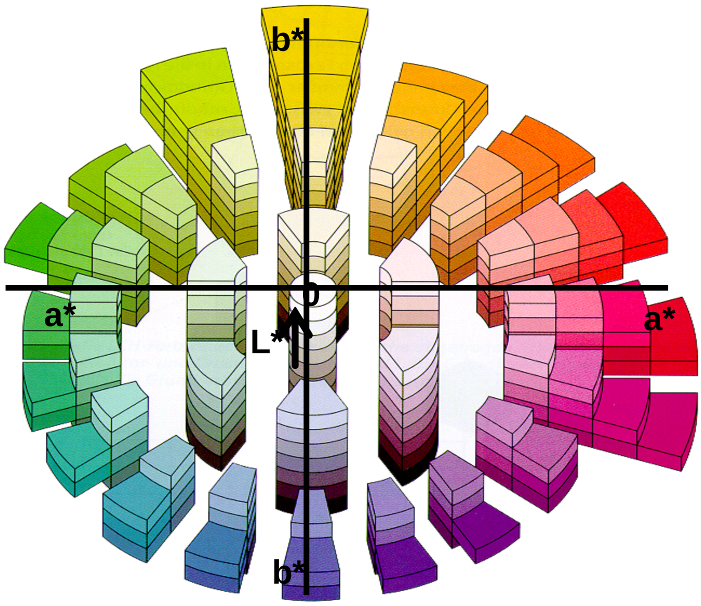

Figure 12 The L*a*b-color system.

3.3.2. Field Spec® Hand Held

The Field Spec® Hand Held (Figure 13) has a spatial resolution of 0.5 m^2 and measures reflectance on canopy level. The spectroradiometer Field Spec® Hand Held (ASD, Inc. Boulder, CO, USA) measured the reflectance 2 m above the canopy in the wavelength ranges 325 nm to 1075 nm with an interval of 1.6 nm and a viewing angle of 25 degrees. The measuring viewing angle (*a*) of 25 degrees causes a field of view

(A) of 62 cm^2 with a field of view radius ’(R) of 44 cm (equations 1 and 2) (Laudien et al., 2003).

$$R = h * \tan((\alpha/2) * \pi/180) \qquad (1)$$

$$A = \pi * r^2 \qquad (2)$$

As the spectroradiometer Field Spec® Hand Held has no own light source providing constant light conditions during the measurements, the incoming radiation was determined with a lux-meter (MAVOLUX 5032C/B USB, Gossen, Nürnberg, Germany). If light conditions changed, a white calibration of the measurement device was carried out with a barium sulfate disc. To compare healthy and diseased wheat plants, six spectroradiometer measurements were made in each plot. These measurements were averaged over field replications to one spectral curve for each fungicide treatment.

Figure 13 Field Spec® Hand Held.

3.3.3. N-Sensor

The N-Sensor (Figure 14) has a spatial resolution of 12 m^2 and measure the reflectance also on canopy level. The Yara N-Sensor (Yara, Germany) is a tractor mounted multi-spectral real time scanner sensor. The sensor is located 2 m above the canopy and measures the canopy reflectance in an array of 12 m. Four sensors detect light reflectance from the canopy and a fifth sensor detects incoming radiation from the sky. This arrangement allows changes in the reflected spectrum due to sun angle and clouds to be taken into account. The N-Sensor is based on relationships between chlorophyll content, crop N status and resulting N requirement (Link et al., 2002).

The position of the red edge (720-740 nm) is used as an indicator of chlorophyll, to make estimates of the chlorophyll content and biomass of a crop and relate this to the nitrogen demand of the crop to establish a fertilization strategy (Reusch, 1997). Under stress, like the diseases septoria leaf blotch, chlorophyll is reduced. On the basis of this consideration the N-Sensor could be suitable to establish also a fungicide application strategy. Measurements with the Yara N-Sensor were carried out in the Field Scan Modus in the wavelength ranges 450, 500, 510, 520, 550, 600, 640, 660, 680, 700, 720, 730, 740, 750, 760, 780, 800, and 850 nm.

Figure 14 Yara N-Sensor.

The identification of diseases site-specific within a field can be done by the described sensor systems. But for the farmer it is also very important to get some decision rules about what to do when. This can be done by crop growth models including sensor measurements in their forecasting. The following chapter will be about different crop growth models and the modelling of plant diseases.

4. Crop Models

Efficient use of agro-chemicals is beneficial for farmers as well as for the environment. Spatial and temporal optimization of farm management will increase productivity and/or reduce the amount of agro-chemicals. This type of management is referred to as Precision Agriculture. Traditional management implicitly considers any field to be a homogeneous unit for management: fertilization, tillage and crop protection measures, for example, are not varied within a single field. The question for management is *what* to do *when*. Because of the variability within the field, a homogeneous management often implies inefficient use of resources. Precision agriculture defines different management practices to be applied within single, variable fields, potentially reducing costs and limiting adverse environmental side effects. The question is not only *what* and *when* but also *where*.

The question *where* can be answered by using sensor systems to detect stress factors or a given heterogeneity site-specifically within a field (see chapter 3). But the questions *what* and *when* are often difficult for the farmer to answer. A lot of factors, affecting yield like weather, soil conditions, management factors, plant diseases etc. have to be factored into making management decisions. Also the information of the sensor systems have to be implemented into this decision. Crop growth models can help the farmer to combine all information and to predict crop performance under varying crop management conditions, and help to define applied research and demonstration strategies for improving crop production. With models, the many yield influencing factors that can be measured and set by soil, management or weather factors can be reduced to a few model terms, making it much easier to find an appropriate management decision.

There are many ways of defining and classifying models, depending on the perspective and the type of research one is conducting (Madden et al., 2007). Edminster (1978) defined a model as a simplification of reality. Models can be used to organize and bring together knowledge of a specific topic, in order to display interactions among many factors (Hanks and Ritchie, 1991). The yield of a plant is a complex interaction between genetic, management, soil, pests, and weather, which could change spatially and temporally over a field, during one season and from year to year. Crop models integrate next to weather and management data all relevant parameters for plant growth at one location, compute possible interactions and show possible solutions to optimize production processes and to minimize environmental damages (Ritchie, 1987; Jones et al., 2003).

Models might be categorized into empirical and process-oriented model types.

An empirical model is one type of simplified representation of a real system. It describes what happens, without telling how it happens using mathematical principles in the form of an equation or a set of equation (Teh, 2006). An empirical model only sets two parameters in relation to each other.

At the beginning of the 19th century, Carl Sprengel published several works about the role of essential resources on plant growth. He affirmed that ‘‘[...] when a plant needs 12 substances to develop, it will not grow if any one of these is not available in a sufficiently large amount as required by the nature of plants’’ (Sprengel, 1828). Some years later, Justus Von Liebig re-elaborated Sprengel’s pioneering ideas and articulated the ‘‘law of the minimum’’ (Liebig, 1855). The law of the minimum states that plant growth is limited by a single resource at any one time. Only after the availability of that resource increases to the point of sufficiency can another resource enhance plant growth. Mitscherlich (1909) enriched these theories by formulating the law of diminishing yield increments, which considers the limits of plant growth in the absence of resource limitations. According to this law, the yield response curves for a particular resource have a precise upper limit and are asymptotic. Liebig’s law and the Mitscherlich model have been widely accepted in modern agriculture (Cerrato and Blackmer, 1990). The Mitcherlich model is an example for an empirical model.

Process-orientated models are built from our knowledge of the physical, chemical or biological underlying process that governs the phenomenon under study. Thus, these model are sometimes known as explanatory models because they represent the cause-and-effect relationship among the variables (Teh, 2006). Process-orientated models can set many factors in relationship to each other. In contrast, an empirical model describes the relationships among the variables, but offers little or no insight to the underlying, cause-and-effect process of the phenomenon. In other words, an empirical model sets out principally to describe relationships, whereas a process-orientated model provides description with understanding (France and Thornley, 1984). But empirical models are often much easier to develop compared to process-orientated models because their development does not require any understanding of the underlying mechanism that explains the phenomenon. Empirical models by themselves cannot be used to imply causality among the variables or system components. Recall that empirical models merely provide description about relationships; that is, they tell us how the variables are related to each other, but not whether one variable affects another or not.

Based on these fundamental differences, a process-orientated model was used in this study as plant diseases are correlated to many factors, like e.g. weather, plant density, nutrition etc.

In the past different models have been used to decide whether to spray or not to spray. A very simple method is the use of thresholds. Zadoks and Schein (1979) defined disease management as “the total of all actions, intentional or not, that serve to regulate disease levels so that they remain below the economic threshold level…”. The idea behind the economic threshold (Stern 1973) is, in essence, to facilitate identification of the circumstances in which it is economically advantageous to adopt certain crop protection measures. In its most widely used form, the economic threshold is a discrete choice threshold: the only options open to the grower are to apply crop protection measures or to withhold them (Madden et al., 2007).

Another widely used method to forecast plant diseases is to link weather with the outbreak of diseases. The relationship between weather and disease is the basis for meteopathological forecasting, which to date has concerned itself mainly with the influence of weather conditions during the growing season of crops on the onset and development of disease caused by airborne pathogens. Such predictions are designed to warn growers of expected significant developments in the plant disease picture. They give, so to speak, advance intelligence of the movements of the enemy and, if sufficiently accurate, permit efficient and competent countermeasures to be planned. In particular, short-range disease forecasts issued at intervals during the growing of crops give guidance on the best seasonal tactics, e.g., on whether or not chemical control measures are called foe, on the optimum dates to apply such treatments, and on similar day-to-day decisions in the fight against disease. The normal result of adopting a plan of weather-indicated control measures is to reduce the number of anti-disease treatments to a well-timed few. This method is widely used by the plant production departments.

But all of these methods cannot exactly predict plant disease infection and above all they do not show the real infection level and also cannot show it on a site-specific level. The mentioned models are a simple method to give tendency in disease development, but to predict yield losses due to plant diseases more precisely more complex models are necessary.

4.1. DSSAT

The **D**ecision **S**upport **S**ystem for **A**grotechnology **T**ransfer (DSSAT) has been in use for the last 15 years and is one of the most widely used modeling system across the world (Hoogenboom, 2003). The model was initially developed under the auspices of the International Benchmark Sites Network for Agrotechnology Transfer (Hoogenboom, 2003). By using the DSSAT model, decision-makers can reduce the time and human resources required for analyzing complex alternative decisions (Tsuji et al., 1998). 16 generic simulation models are included in the DSSAT model like the cereal model CERES for wheat, corn, barley, sorghum, millet and rice (Ritchie et al., 1998), the grain legume model CROPGRO for soybean, peanut, dry bean, and chickpea (Boote et al., 1998), the SUBSTOR model for potato, the CROPSIM model for cassava, the OILCROP for sunflower and CANERO for sugarcane (Hoogenboom, 2003). These different models are process-oriented which means that they incorporate simplified approaches to describe more complex processes (Hoogenboom, 2003). Process-oriented models like DSSAT analyze interactions between weather, soil, genetic parameters, production systems and yield. The model needs as input parameter general management data like cultivar, row distance , plant density, fertilization, irrigation etc. as well as biotic and abiotic site parameters like soil type, precipitation, minimum and maximum temperature, radiation etc.. Based on this data, biomass and yield production is calculated as a function of photosynthesis, light interception, stage of development, water and/or nitrogen deficiency. Soil humidity models and nitrogen models are used to compute water- and nitrogen-balance. Weather models consider daily changes of plant growth under the influence of precipitation, minimum and maximum temperature, radiance, and CO_2 concentration. The models are designed to have global applications and work independent of location, season, crop cultivar, and management systems. The models simulate the effects of water, soil water, genotype, and soil and crop N dynamics on crop growth and yield (Jones et al., 2003).

Recent developments in crop growth modelling provide a physiologically based approach to simulate the damage effects of single or multiple pests. Pest or damage levels from field scouting reports can be entered and damage is applied to appropriate physiological coupling points within the crop growth model including leaf area index, stand density, intercepted light, photosynthesis, assimilate amount and translocation rate, growth of different plant organs and leaf senescence. Equations and algorithms were developed to describe competition among multiple pests and to link the computed total damage to the corresponding variables of the crop models (Pinnschmidt et al. 1995). This approach is mechanistic and generic and is incorporated into crop growth models like CERES-rice, SOYGRO, PNUTGRO (Batchelor et al., 1993) and other CERES models.

The crop growth models were used in the past only to simulate plant growth and yield in the whole field (Irmak et al., 2001). Nowadays crop growth models are especially used in the field of Precision Agriculture (Dobermann et al., 2004), but their complexity has often hampered decisions on input use for spatial management (Angus et al., 1993). However recent development in modelling made it possible to determine and understand spatial variability within a field. The additional information provided by the model could than be used to simulate scenarios for Precision Agriculture (Paz et al., 1999, Booltink et al., 2001, Paz et al., 2003). In a first attempt Batchelor et al., (2004) have developed the model **A**pplication of **P**recisi**o**n Agricu**l**ture for Fie**l**d Management **O**ptimization (APOLLO), which is designed to determine spatial yield variability and which assists researchers and producers in site-specific management decisions.

4.2. APOLLO

The prototype system APOLLO was developed and tested by the Crop Modeling Laboratory at the Iowa State University. Included in the DSSAT shell APOLLO assists researchers in using the CROPGRO-Soybean and CERES-Maize models to analyze Precision agriculture datasets for soybean and corn (Batchelor et al., 2004). The underlying algorithm is based on the CROPGRO-Soybean and CERES-Maize models, respectively.

APOLLO has modules that allow the user to: 1) calibrate the models to simulate historic spatial yield variability, 2) validate the models for seasons not used for calibration, and 3) estimate the yield response and environmental impact of nitrogen and plant population prescriptions. The calibration module allows users to use an optimizer to adjust up to 10 soil properties in zones defined in the field to minimize the root mean square error between simulated and observed yield. Once a field is calibrated, the validation module allows the user to test the performance of the calibration for seasons not used in the calibration. Finally, the users can run the crop growth models for numerous combinations of plant population and nitrogen rates to generate yield and nitrogen loss information that can be used to compute the economic and environmental effects of different prescriptions" (Batchelor et al., 2004). The tools allow a user to establish a management zone grid over a field area, clip digital soil surveys and yield monitor data according to the management zone grid, and print soil and yield information for each management zone in the proper format for interpretation by the crop model. The software effectively reduces the amount of time necessary to generate crop model input files for simulations on the sub-field-level scale.

Epidemics are population processes that occur in time and space. Plant diseases generally do spread in space as they increase in time, and an understanding of plant disease epidemics would be incomplete without consideration of this aspect of disease development (Madden et al., 2007). Disease spread is the result of inoculum dispersal. Dispersal is the movement of infectious units (e.g. spores) of a pathogen from one place to another ore the movement of infectious units from the place they were formed to other locations (Campbell and Madden, 1990). Out of this and to reduce the use of pesticides it is imperative to identify and also to model plant disease infection site-specific, wherefore the model APOLLO would be well suited.

Spectral identification of powdery mildew (*Erysiphe graminis)* in wheat using digital image analysis

Kerstin Gröll, Simone Graeff, Wilhelm Claupein
Institute of Crop Production and Grassland Research (340)
University of Hohenheim
D-70599 Stuttgart, Germany
groell@uni-hohenheim.de
graeff@uni-hohenheim.de
claupein@uni-hohenheim.de

Abstract

Plant disease detection and site-specific spraying of pesticides plays an important role in precision farming systems. To identify plant diseases within a field, optical sensor systems are needed. The aim of this study was to identify and quantify the plant disease powdery mildew using digital image analysis. Wheat plants (*Triticum aestivum*) where inoculated in greenhouse experiments with powdery mildew. Leaf reflectance was measured with a digital imager (Leica S1 Pro, Leica, Germany) under controlled light conditions in various wavelength ranges (380-1300 nm). The results of this study indicated that disease detection and quantification using digital image analysis may be possible in the wavelength ranges 516-540 nm and 540-600 nm. The results represent a first step of using image analysis techniques to evaluate the infection of wheat plants with powdery mildew. Digital image analysis proved to be an effective means of determining disease infection, producing both accurate and reproducible data. Further experiments to create different data sets, especially under field conditions, to develop and evaluate a regression model for the optical detection and quantification of plant diseases are necessary.

Keywords: plant diseases, digital image analysis, histograms, powdery mildew

1. Introduction

Plant diseases are a huge problem in today's crop production. Due to the occurrence of plant diseases and their impact on yield, crop yields can decrease to about 30 % [1]. In an early stage of an epidemic, large areas of a field can be free of diseases and may not have to be sprayed. Up to now most farmers still spray their field uniformly due to differences in the infection level and due to the unknown distribution of diseases.

Reflectance of agricultural crops in the visible and near infrared wavelength domains has been studied by numerous researchers in order to estimate different crop parameters, such as plant species, productivity, harvest, plant nutrient and plant pathological status [2, 3]. In-field variability can be recorded using methods based on measurements of reflectance of field crops to estimate crop status. This can then be used as a basis for site-specific operations such as application of nutrients or pesticides [4]. With spectral sensing, sampling of reflectance spectra of a growing crop can be done relatively fast and the signal from a spectral sensor can be used to control site-specific inputs either indirectly by mapping the in-field variability or in real time using a vehicle mounted spectral sensor. Plant diseases are currently very difficult to detect and locate with senor technologies as pathogens have the tendency to move within a field from year to year, thus causing troubles in the development of spatial maps and management systems. The potential of site-specific differentiated applications of fungicides is still untouched due to the lack of sensors that are able to sense either crop parameters influencing growth of fungi, or the fungi on/ or in the plants directly. At the forefront of site-specific disease research the main goal is to offer farmers the ability to spot-treat only those areas of a field needing fungicide control and to manage a healthier crop by adjusting needed inputs at the site-specific, rather than at the field level. However, site-specific disease management is a very new area, where little research and almost no practical experience exist.

The detection of stressed and thus also of diseased plants using spectral measurements is based on the premise that reflectivity of stressed plants is qualitatively and quantitatively different from that of a healthy and vigorously growing plant. The responsiveness of leaf reflectivity in the visible spectral region to stress conditions is caused by the sensitivity of chlorophyll to metabolic disturbances. As it deteriorates and absorbs less efficiently, the visible reflectance increases. Bravo et al. [5] described in their work the fact that the reflectance of leaves decreases under plant diseases. They measured the reflectance of winter wheat under yellow rust and were able to discriminate between disease infestation and nutrient stress under field conditions using spectral reflectance information between 450 and 900 nm.

Nicolas [6] promoted the potential of remote sensing as a tool to optimize the date of a fungicide application. The results of his study indicated significant differences in reflectance of winter wheat infected with s*eptoria tritici* in the visible and infrared spectral range. Safir et al. [7] were able to detect plant diseases on corn leaves. They showed that corn leaves have greater reflectance and transmittance after inoculation with *Helminthosporium maydis* than healthy leaves. These differences are more pronounced in the chlorophyll (500-700 nm) and water absorption (1450-1950 nm) regions of the spectrum, and are probably caused in part by loss of chlorophyll and water in diseased tissue. They detected increases in reflectance of diseased over healthy tissue first when disease lesions became macroscopically visible. Malthus and Madeira [8] measured spectral leaf reflectance properties of field bean (*vicia faba*) infected by the fungus *Botrytis fabae* over the wavelength range 400-1100 nm. They found four spectral bands in which leaf reflectance was significantly affected by changes in the degree of infection. In the visible region, reflectance in the blue (470-500nm) and red (590-700 nm) areas were positively correlated with lesion area, indicating increased reflectance with increased infection. In contrast, the green reflectance (around 550 nm) was significantly but negatively correlated with percentage of infection, indicating decreasing reflectance as infection progressed. Further they found the highest correlation of reflectance with percentage infection in the near-infrared region (>720 nm) of the spectrum. Reflectance decreased significantly with increasing percentage of infection.

Hence, the aim of this study was to develop i) the basics for a sensor supported identification of plant diseases, and ii) to identify wavelength ranges that enable a clear identification and quantification of plant pathogens.

2. Material and Method

2.1 Experimental design

Greenhouse studies were conducted at the Institute of Crop Production and Grassland Research, University of Hohenheim, Germany, with winter wheat cv. Monopol during the growing period of July–October 05.

Wheat seeds were sown in Mitcherlich pots containing 6 kg of soil. The soil type was a sandy loam with a pH of 7.4 and a total water holding capacity of 63 %. The soil was sterilized at 120 °C in a dry oven prior to seeding. The soil was fertilized with 250 mg N [NH_4NO_3], 125 mg P [NaH_2PO_4], 125 mg K [K_2SO_4], 120 mg Mg [$MgSO_4$], 130 mg Ca [$CaCl_2$], 10 mg Mn [$MnSO_4$], 1.5 mg Zn [$ZnSO_4$], 1.0 mg Cu [$CuSO_4$], 0.3 mg B [H_3BO_3] and 0.02 mg Mo [Na_2MoO_4] prior to seeding. About 15 grains of winter wheat were planted into the Mitcherlich pots. After 3-4 w, wheat plants were vernalized at a temperature of 4 °C and 8 h light for 4 weeks. Pots were thinned to 9 wheat plants per pot after that period and transferred to the greenhouse for further cultivation. The average temperature in the greenhouse was set to 20 °C ± 5 °C with a minimum of 18 °C and a maximum of 30 °C. Humidity in the greenhouse was kept at 70 %.

Inoculum of powdery mildew (*Erysiphe graminis* 150, powdery mildew resistant gene Pm1, 2, 3a, 3c, 3d, 4a, 4b, 5, 6, 7, 8 and 17) was obtained from the Federal Biological Research Centre for Agriculture and Forestry, Kleinmachnow, Germany, as infected wheat plants in 10 cm pots. Wheat plants were inoculated in three different inoculum steps (0 % = control, 50 % and 100 %) with powdery mildew in the growth stage GS 14 [9].The inoculum step 0 % was repeated three times and the inoculum steps 50 % and 100 % were repeated six times. For inoculation different amounts of infected pots of infected plants (50 % three pots; 100 % six pots) were placed between the Mitcherlich plots and were left there for one week. About 10 days after the inoculation, first symptoms were visible.

Image acquisition

Reflectance measurements started about 10 days after the inoculation and were carried out every second day over a period of 21 days. Each time the major fully developed leaf was measured. Measurements were carried out in the growing stages GS 26 - GS 32 [9]. Reflectance spectra were taken without removing the leaf from the plant. The leaf to be measured was laid on a black aluminum plate mounted 15-20 cm away from the optics (1.28/60 mm, Leica, Germany) of the imager. The scanned surface area constituted for every measurement 1.9 x 1.1 cm. To exclude the effects of solar light as well as of stray background light the imager, light source and sample were surrounded by a black aluminum box. Leaf scans were taken with a digital, light-sensitive (ISO 200-2400; spectral sensitivity of 250-1300 nm), high-spatial resolution (5140*5140 pixel) imager (LEICA S1 Pro, LEICA Kamera AG, Solms, Germany). The imager was used in conjunction with a constant light source (Reporter 21 D MicroSun, 21 W, Sachtler, Germany). The chosen light source was equipped with a 21 W daylight discharge bulb (Sachtler, Germany; color temperature 5500 – 6000 K), with produced more light than normal 50 W tungsten luminaries. By the use of different long-pass filters (Maier Photonics, Manchester, VT, USA) each leaf was measured in the visible wavelength ranges 380-780 nm, 490-780 nm, 510-780 nm, 516-780 nm, 540-780 nm and 600-780 nm. Also each leaf was scanned in the infrared wavelength ranges of 490-1300 nm, 510-1300 nm, 516-1300 nm, 540-1300 nm and 600-1300 nm. The long-pass filters had the following general specifications: 3 mm thickness, hard-oxide coating surface, quality 80/50 per MIL-O-13810A, coating quality 60/40 per MIL-O-13830A, and temperature limits – 50 to 100 °C.

Image analysis

By the use of a light conducting cable the picture of the leaf surface was transmitted immediately to a laptop and was processed with the camera software Leica Silverfast (Version 3.1 Lasersoft Imaging, Kiel, Germany). Using the Software Adobe Photoshop 5.0 ® (Adobe Incorporated, San José, California, USA) the scans were analyzed in the L*a*b*- color system [10] in where a color is characterized by the parameters L*, a* and b* which are plotted using a Cartesian coordinate system. Value L* represents lightness; value a* represents red/green axis; and value b* represents the yellow/blue axis. Equal distances in the space approximately represent equal color differences. The spectra of the 11 filter classes revealed that, at certain wavelengths, the contrasts between major object categories were maximized.

2.2 Harvest and analyses

After scanning, the number of powdery mildew pustules was counted on the measured leaves. For this purpose the measured leaf was held green on petri dishes with benzimidazolagar (5 g agar and 30 mg benzimidazol/l water) and kept at constant temperature and humidity conditions in a growth chamber. After 5 days visible pustules were counted. Total leaf area was measured with a leaf area meter (LI-COR, Model 3100 AREA METER, inc. Lincoln, Nebraska, USA) in order to estimate the infection grade as pustules per leaf area. The leaves and shoots of the measured plants were harvested and the fresh weight was determined at once. Plant samples were dried at 60 °C and total dry matter was determined. The remaining leaf tissue was ground, dry-ashed and analyzed for total N according to Dumas [11].

2.3 Statistical analyses

The arithmetic mean and as dispersion the standard error was calculated as location parameter from the leaf scans with the help of the statistic program Sigma.Stat. 3.1 (Jandel Scientific, USA). The experiments were analyzed with a one- respectively a two-factorial ANOVA with a following multiple comparison by means of Tukey (α = 0.05).

3. Results

First visible signs of the infection with powdery mildew in the greenhouse experiments were recognized 10 days after the infection. From the first to the last measurement date the infection with powdery mildew could be identified by reflectance measurements (Figure 1). The b*-parameter indicated in an early stage of infection significant changes between healthy and diseased leaves, while no changes of the a*-parameter could be identified in an early stage of infection (results not shown). The b* parameter increased with increasing infection level when compared to the control. Figure 1 shows the reflectance changes in the wavelength range 516-540 nm (a) and 540 -600 nm (b) over time for the control and the inoculum steps 50 % and 100 % under the infection of powdery mildew. The reflectance parameter b* changed significantly 10 days after the inoculation in the treatments 50 % and 100 %. Further, the visible wavelength rage was more distinctive to detect an early stage of infection than the near-infrared wavelength range (results not shown). Over all investigated wavelength ranges, the wavelength rages 516-540 nm and 540-600 nm were most suitable to detect an infection with powdery mildew in an early stage.

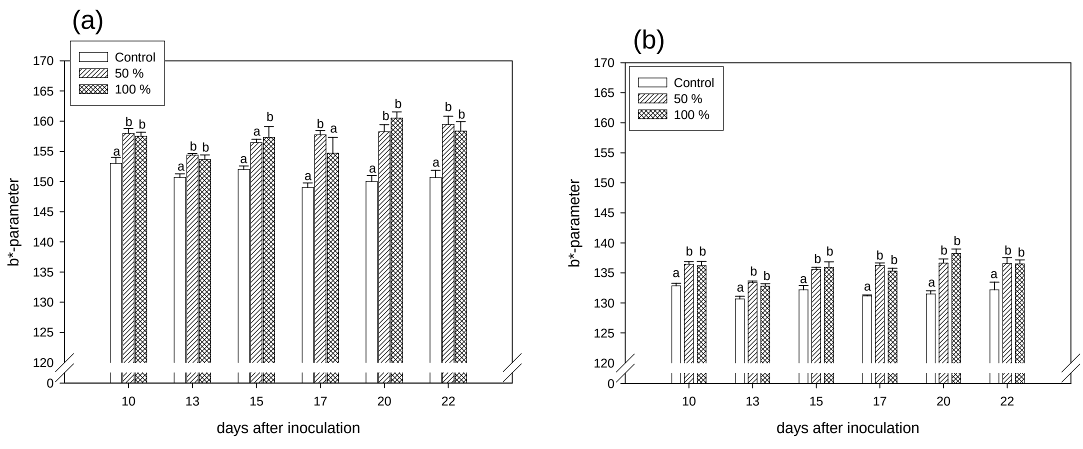

Figure 1 Change of reflectance parameter b* in the wavelength ranges 516-540 nm (a) and 540-600 nm (b) due to powdery mildew infection. Significant changes at $\alpha = 0.05$ are indicated.

Figure 2 shows the temporal development of powdery mildew pustules/cm^2 on the measured leaves. At all measurement dates the control was disease free. The inoculum step 50 % showed a steady increase of powdery mildew pustules until 20 days after inoculation. At the last measurement date, the treatment 50 % indicated a decline of powdery mildew pustules/cm^2. The inoculum step 100 % showed a steady linear increase of powdery mildew pustules/cm^2 until day 15 after the inoculation. For all measurement dates except 10 days after inoculation the inoculum step 100 % indicated higher amounts of powdery mildew pustulesc/cm^2 than the inoculum step 50 %. In general, the infection level was very low at the beginning with 0.5 powdery mildew pustules/cm^2 and increased to 9 powdery mildew pustules/cm^2 20 days after inoculation.

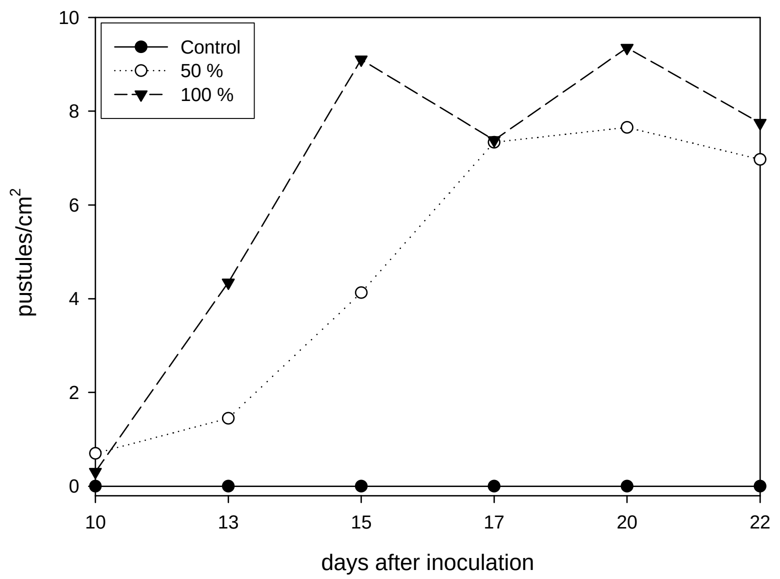

Figure 2 Temporal development of powdery mildew pustules/cm^2 on the measured leaves.

To relate leaf reflectance response to the infection level with powdery mildew, reflectance changes were correlated with the infection level (%). Based on this data, a polynomial quadratic correlation between infection level and reflectance changes was found. This relationship enabled the quantification of powdery mildew infection.

Figure 3 a/b shows the relationship between the infection level and the changes of the b*-parameter for the wavelength ranges 516-540 nm and 540-600 nm. For these wavelength ranges an $r^2 = 0.87$ (516-540 nm) and $r^2 = 0.82$ (540-600 nm) was achieved. Thus, the determined changes in the b* parameter could be related to the infection level. However, it was not possible to discriminate between the tested infection levels of 50 % and 100 %, as the parameter b* did not increase over time like the powdery mildew pustules/cm^2.

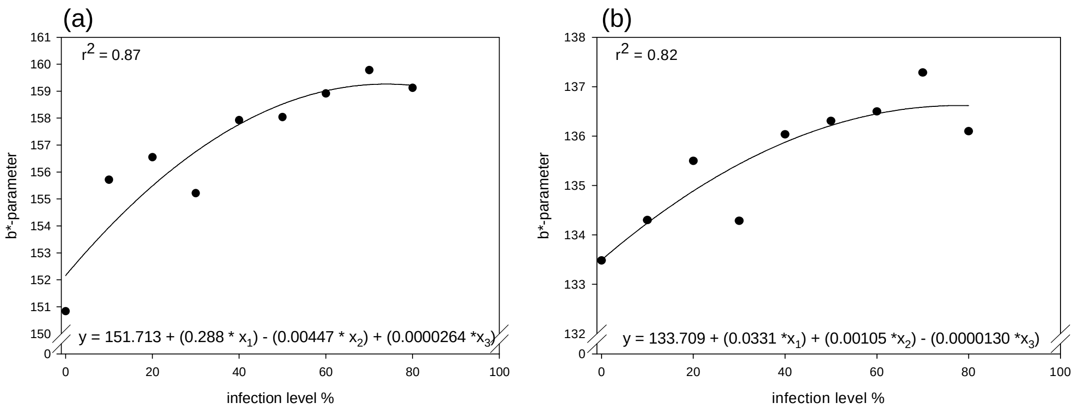

Figure 3a/b Correlation between infection level and the changes of the b*-parameter for the wavelength 516-540 nm (a) and 540-600 nm (b).

4. Discussion

In today's crop production fungicides are still sprayed uniformly although plant diseases are seldom uniformly distributed in a field. Modern practices of remote sensing and application techniques in the context of precision farming can make a contribution to reduce the application rate of fungicides. However, to identify disease patches within a field suitable sensor systems are necessary.

The results of this study indicated, that powdery mildew could be detected in the visible wavelength ranges using leaf reflectance measurements. Muhammed [12] characterized and estimated fungal disease severity in a spring wheat crop. He used a reference data set consisting of hyperspectral crop reflectance data vectors and the corresponding disease severity field assessment. The results showed a general decrease in reflectance in the NIR region especially at the wavelengths ranges above 720 nm, together with a gradually general reflectance increase in the visible region starting at about 390 nm until 720 nm. Polischuk et al. [13] used spectral reflectance measurements to detect different stages of tomato mosaic tobamovirus infection in *Nicatiana debneyi* plants. 10 days after inoculation reduction in chlorophyll content in the leaves could be detected by reflectance measurements even though significant visible differences between the control and the infected plants were not noted until after 3 weeks. Lorenzen and Jensen [14] investigated the changes in leaf spectral properties produced by powdery mildew in several varieties of spring barley. They found significant increases in reflectance in visible wavebands (422-712 nm) 6 days after inoculation, which corresponded to degradation of chlorophylls induced by the disease. The differences in the near infrared region between control and infected plants observed were small and occurred several days later than changes in the visible region. Sasaki et al. [15] tried to distinguish at an early infection stage, diseased cucumber leaves from healthy leaves based upon the spectral reflectance of the leaves in the wavebands 500, 600 and 650 nm. They found out that the ratio of red wavelength centered at 660 nm to violet wavelength centered at 400 nm gave the best results in the visible wavelength range to differ between healthy and diseased leaves. Bravo et al [16] detected successfully yellow-rust infestation in the field on winter wheat by means of a visual spectrograph in ambient illumination conditions. Carter and Miller [17] concluded that early detection of vegetation stress by remote sensing depends largely on identifying the spectral regions in which vegetation reflectance is most responsive to unfavorable growth conditions.

For individual leaves, increased reflectance at visible wavelengths (400-700 nm) is generally the most consistent response to stress within the 400-2500 nm range [18]. The reflectance spectra of most green leaves are remarkably alike due to similarities in chemical composition and leave structure [19, 20]. Plant pigments, such as chlorophyll and carotenoids, have major effects upon the reflectance properties of green leaves in the visible wavelengths, whereas reflectance properties in the near-infrared wavelengths are due to primarily to differences in leaf structure [19, 21]. Riedel and Blackmer [22] investigated the effects of sucking insects on leaf reflectance, by infesting wheat seedlings with aphids (*Diuraphis noxia Mordvilko*) or green bugs (*Schizaphis graminum Rondani*). Compared with healthy plants, the leaves from infested plants had lower chlorophyll concentrations and displayed significant changes in reflectance spectra at certain wavelengths (notably 500-525, 625-635 and 680-695 nm).

The results of this study showed that the visible wavelength range, especially the ranges 516-540 nm and 540-600 nm, were suitable to detect powdery mildew on winter wheat leaves. The suitability of the identified wavelength ranges are corresponding to the wavelength ranges found in the literature. Powdery mildew changes primarily the amount of chlorophyll and not the structure of the leaf. In the visible range reflectance is considered to be influenced by leaf pigments such as chlorophyll whereas reflectance in the near-infrared range reflectance is affected by changes in the anatomical structure of leaves [23, 24]. Occurring pigmental changes probably led to the fact, that reflectance changes due to powdery mildew infection were most pronounced in the visible spectra.

Fungi causing powdery mildew are obligate parasites and cannot be cultured on artificial nutrient media. They produce mycelium that grows only on the surface of plant tissues but does not invade the tissues themselves.

They obtain nutrients from the plant by sending haustoria (feeding organs) into the epidermal cells of the plant organs [25]. Plants produce a diverse array of secondary metabolites, many of which have antifungal activity. Some of these compounds are constitutive, existing in healthy plants in their biologically active forms. Others, such as cyanogenic glycosides and glucosinulates, occur as inactive precursors and are activated in response to tissue damage or pathogen attack. This activation often involves plant enzymes, which are released as a result of breakdown in cell integrity. There is a tendency for these compounds to be concentrated in the outer cell layers of plant organs, suggesting that they may indeed act as deterrents to pathogen and pests [26].
Because of the fact, that powdery mildew does not lead in the beginning of an infection to structural damages but to reduction of chlorophyll and a change of secondary metabolites in the leaves reflectance changes are expected to appear in the visible wavelength range. These theories confirm the results shown in this article. Further, it is assumed that the content of secondary metabolites to defend fungal attack in the leaf did not increase in the same way the powdery mildew pustules/cm^2 did in the first three weeks. However, to support sensor-based detection of the occurrence of infection for the generation of fungicide application maps, only a binary decision whether crops are infected or not, is required. To decide whether the plant is healthy or infected the correlation between the infection level and the changes of the b*-parameter showed good results. However, obtained wavelength ranges still have to be tested under field conditions, in order to explore the full potential of the proposed method to detect plant diseases.

5. Conclusion

Changes in the leaf reflectance for monitoring plant diseases could, potentially, allow the detection of infection before symptoms are visible to the human eye if subtle changes in the visible region can be solved. The experiments in the greenhouse showed that it was possible to detect powdery mildew in defined wavelength ranges. It was also possible to correlate the infection level and the changes of the b*-parameter. Further investigations with the purpose of obtaining data under different environmental conditions, especially under field conditions, to test and validate the developed method are necessary.

6. Acknowledgements

The German Federal Ministry of Education and Research financed this project through their program on precision agriculture No. 0330661. The responsibility for the content of the paper is with the author.

References

[1] J. Habermeyer and M. Gerhard: ”Pilzkrankheiten”. “Fungal infections”. BASF Landwirtschaft (2000).

[2] D.W. Deering: “Field measurements of bidirectional reflectance “Theory and applications of optical remote sensing”, ed. Asrar, G. John Wiley&Sons, New York, (1989), pp. 14-65.

[3] L. Kumar, K.S. Schmidt, S. Dury and A.K. Skidmore: “Review of hyperspectral Remote Sensing and Vegetation Science”, Imaging spectrometry: basic principles and prospective applications, eds. F.D. Van der Meer & S.M. De Jong, S.M. Kluwer Academic Press, Dordrecht, The Netherlands, (2001), pp. 111-155.

[4] A. Larsolle and H. Hamid Muhammed: “Measuring crop status using multivariate analysis of hyperspectral field reflectance with application to disease severity and plant density”, Precision Agric., Vol.8, (2007), pp. 37-47.

[5] C. Bravo, D. Moshou, J. W and A. McCartney: “In field disease and nutrient stress detection by imaging spectrography at canopy level”, AgEng, Budapest, Hungary, (2002), pp. 142 and 143.

[6] H. Nicolas: “Using remote sensing to determine of the date of a fungicide application on winter wheat”, Crop Protection, Vol. 23, (2004), pp. 853-863.

[7] G.R. Safir, G.H. Svitis and A.H. Elligboe: “Spectral reflectance and transmittance of corn leaves infected with *Helminthosporium maydis*”, Phytopathology, Vol. 62, (1972), pp. 1210-1213.

[8] T.J. Malthus and A.C. Madeira: “High resolution

spectroradiometry: spectral reflectance of field beans infected by *Botrytis fabae*", Rem. Sens. environ., Vol. 45, (1993), pp. 107-116.

[9] P.D. Lancashire, H. Bleiholder, T. van den Boom, P. Langelüddeke, R. Strauss, E. Weber and A. Witzenberg: "A uniform decimal code for growth stages of crops and weeds", Ann. Appl. Biol., Vol. 119, (1991), pp. 561-601.

[10] CIE: "Colometry". 2nd ed. Publication CIE No.Vienna: Commision Internationale de l'Eclaiage, (1986).

[11] A. Dumas: "Stickstoffbestimmung nach Dumas", Die Praxis des organischen Chemikers, (1962), Vol. 41: 45-51.

[12] H.H. Muhammed: "Hyperspectral crop reflectance data for characterizing and estimating fungal disease severity in wheat", Biosystem Engineering, Vol. 91, (2005), pp.9-20.

[13] V.P. Polischuk, T.M. Schadchina, T.I. Kompanetz, I.G. Budzanivskaya and A.L. Sozinov: "Changes in reflectance spectrum characteristic of *Nicotiana debneyi* plant under the influence of viral infection", Arch. Phytopathol. Plant Prot., Vol. 31, (1997), pp. 115-119.

[14] B. Lorenzen and A. Jensen: "Changes in spectral properties induced in barley by cereal powdery mildew", Rem. Sens. Environ., Vol. 27, (1989), pp. 201-209.

[15] Y. Sasaki, T. Okamoto, K. Imou and T. Torii: "Automatic diagnosis of plant disease: spectral reflectance of healthy and diseases leaves", Proceedings AgEng'98 Conference, Oslo, (1998), pp. 6.

[16] C. Bravo, D. Moshou, J. West, A. McCartney and H. Ramon: "Early disease detection in wheat fields using spectral reflectance", Biosystems Engineering, Vol. 84, (2003), pp. 137-145.

[17] G.A. Carter and R.L. Miller: "Early detection of plant stress by digital imaging within narrow stress-sensitive wavebands", Remote Sens. Environment, Vol. 50, (1994), pp. 295-302.

[18] G.A. Carter: “Response of leaf spectral reflectance to plant stress”, Am. J. Bot., Vol. 80, (1993), pp. 239-243.

[19] D.M. Gates, H.J. Keegan, J.C. Schleter and V.R. Weidner: “Spectral properties of plants”, Applied Optics, Vol. 4, (1965), pp. 11-20.

[20] E.B. Knipling: “Physical and Physiological Basis for the reflectance of visible and near-infrared radiation from vegetation”, Rem. Sens. Environment, (1970), pp.155-159.

[21] M.R. Slaton, E.R.Jr. Hunt and W.K. Smith: “Estimating near-infrared leaf reflectance from leaf structural characteristics”, American Journal of Botany, Vol. 88, (2001), pp. 278-284.

[22] W.E. Riedel and T.M. Blackmer: “Leaf reflectance spectra of cereal aphid-damaged wheat”, Crop Science, Vol. 39, (1999), pp. 1835-1840.

[23] G. Guyot: ”Optical properties of vegetation canopies”, In: M.D. Steven and J.A. Clark (Eds.): *Applications of Remote Sensing in Agriculture*, Butterworths, London, 1990, pp, 19-43.

[24] L. Grant: ”Diffuse and specular characteristics of leaf reflectance”, Rem. Sens. Environ., Vol. 22, (1987), pp. 309-322.

[25] G.N. Agrios: “Plant pathology”, Elsevier Academic Press, Burlington, USA, (2005).

[26] A.E. Osbourn: “Preformed antimicrobial compounds and plant defense against fungal attack”, The Plant Cell, Vol. 8, (1996), pp. 1821-1831

In the first article a sensor system was tested for the identification of a leaf disease. Therefore, a sensor system with a spatial resolution of 0.5 cm^2 was used that measured reflectance at leaf level. A greenhouse experiment was carried out with winter wheat and the disease powdery mildew.

The results of this study showed that it was possible to identify powdery mildew using reflectance measurements. Especially in the visible wavelength range differences between healthy and diseased plants could be detected. Out of these results the question was raised if not only leaf diseases but also stem diseases, that cannot directly be detected by a sensor system, could be identified using reflectance measurements.

6. Identification of wheat eyespot

6.1. Introduction

The goal of every farmer is the production of crops in a cost-effective manner. But when the objective is no longer just maximizing production, farming will become an increasingly activity. European Community police makers are becoming increasingly conscious that environmental considerations should play a role in agricultural policy (Reyniers, 2003). An increasing legislation concerning pesticide and fertilization use has become reality, because of the increasing awareness of environmental pollution, along with worries about pesticide residues in food. The aim of modern agricultural production systems will be to maximize output and reduce target inputs (increase production efficiency), whilst causing little harm to the surrounding environment. Being in regulatory compliance, verification of compliance, as well as yield levels and management practices, more time for family and recreation, and enriching the resource and information legacy that is passed on to the next generation will be other goals of farmers (Reetz and Fixen, 1999). Disease control for example could be more efficient, if the patches within fields could be identified and fungicides applied only to the infected areas. This need for improved efficiency has resulted in renewed interest in the spatial variability of crop growth not only between fields but also, particularly on large arable farms, within fields (Blakeman et al., 2000).

Doerge (1999) identified inside a field naturally occurring and management induced sources of yield variation, which can be temporal and spatial. Weather, soil-water relationships, soil physical and chemical properties, slope and aspects of a site and crop pest infestations are naturally occurring sources of yield variation. Crop inputs or condition, field history and cultural practices and/or errors are management-induced sources of yield variation.

Cropping systems, which improve agricultural efficiency while meeting environmental goals, need to be developed. Recent developments in optical sensor technologies have the potential to enable the direct detection of foliar diseases under field conditions (West et al. 2003). Also developments in controller technology, in computers and positioning systems now bring new opportunities for farm management (Goddard et al., 1995).

Eyespot on wheat, caused by the fungi *Oculimacula acuformis* (R type) and *O. yallundae* (W type), is the most important stem base disease of wheat in humid and cold regions. Eyespot is expressed by brown till black discolorations on the steam base and the destruction of nutrient and water lines. For further information see chapter 1.
The aim of these experiments was to look, if a disease that is away from the actual measurement place can be indirectly detected by a camera systems.

6.2. Material and Methods

To measure reflectance changes under wheat eyespot, a field experiment was conducted during the growing period of 2005 and 2006 at the Experimental Station “Ihinger Hof” (48°44´ N, 8°56´E) of the University of Hohenheim, Stuttgart, Germany. The “Ihinger Hof” lays between Weil der Stadt and Magstadt in the district Böblingen and belongs to the region Keckengäu. The soils in this region of Baden-Württemberg emerged typically from shell limestone and Keuper with a partly floated loess cover. The experimental station exhibits mostly heavy Keuper soils with a high content of clay. The predominant soils are para-brown earth and para-brown earth-planosols. The mainly climatic site conditions result from the longtime middle rainfall of 693 mm and the longtime middle temperature of 8.1 °C. The experimental station is located 460-520 m above see level.
Field studies were conducted during the growing period of 2004/2005, 2005/2006 and 2006/2007. Winter wheat cv. Monopol and Empire were planted on October 23rd 2004, on September 22nd 2005 and on September 29th 2006 at a rate of 350 seeds per m². The trial was inoculated with wheat eyespot at GS 12, GS 15 and GS 18 by strewing infected wheat grains into the plots (CBS 118.47, UK). Measurements started at GS 39 and were repeated every week until beginning of July. For further information see chapter 2.
Leaf scans were taken with the digital LEICA S1 Pro camera and the canopy reflectance was collected with the hyperspectral spectroradiometer “FieldSpec HandHeld”. The two sensor systems are described detailed in chapter 3.
The arithmetic mean and as dispersion the standard error were calculated as location parameter from the leaf scans with the help of the statistic program Sigma.Stat. 3.1 (Jandel Scientific, USA). The experiments were analyzed with a one- and two-

factorial ANOVA with a following multiple comparison by means of Tukey (α = 0.05).

6.3. Results

Figure 1 shows % with wheat eyespot infected plants for the treatments control, 50 % and 100 % and the cultivar Monopol and Empire. For both cultivars no significant differences between the control and the treatment 50 % and 100 % could be measured. The cultivar Monopol had an infection for the control of 8 %, the treatment 50 % of 13 % and the treatment 100 % also of 13 %. The cultivar Empire had an infection level for the control of 3 %, for the treatment 50 % of 9 % and for the treatment 100 % of 14 %.

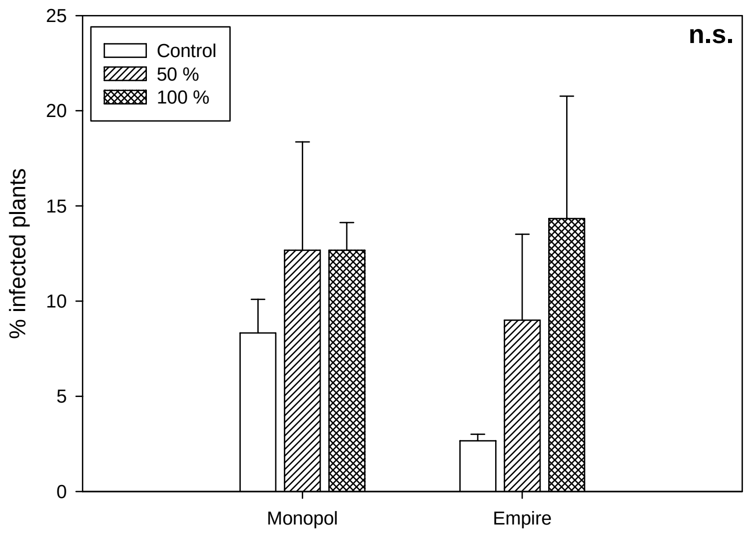

Figure 1. Percentage of wheat eyespot infected plants for the treatments control, 50 % fungicide and 100 % fungicide and the cultivars Monopol and Empire (significant changes at α = 0.05 are indicated, mean values with the same letter are not significantly different).

Figure 2 shows the obtained yield (dt ha^{-1}) for the varieties Monopol and Empire and the treatments Control, 50 % fungicide and 100 % fungicide. No significant differences between the control and the treatments 50 % and 100 % could be obtained. For the variety Monopol the control reached a yield of 50.6 dt h^{-1}, the treatment 50 % of 51.5 dt h^{-1} and the treatment 100 % of 47.9 dt h^{-1}. For the variety Empire the control obtained the yield of 60.4 dt h^{-1} the treatment 50 % of 57.7 dt h^{-1}

and the treatment 100 % of 58.8 dt h^{-1}. The resistant variety Empire obtained higher yields than the susceptible variety Monopol.

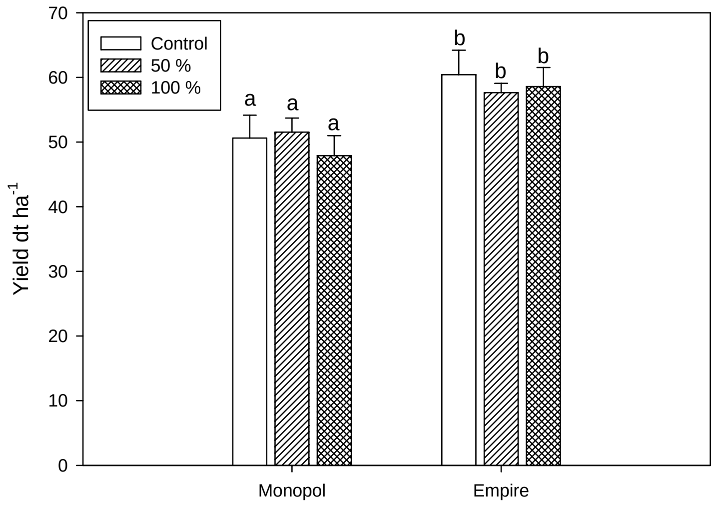

Figure 2. Obtained yield (dt ha^{-1}) for the varieties Monopol and Empire and the treatments Control, 50 % fungicide and 100 % fungicide (significant changes at α = 0.05 are indicated, mean values with the same letter are not significantly different).

Figure 3 shows the N-concentration (%) in the plant for the cultivar Monopol (a) and Empire (b) and the treatments control, 50 % and 100 % 37, 40 and 41 weeks after inoculation. For both cultivars and all measurement dates no significant differences among the different treatments could be measured. The N-concentration was at 4 % on average.

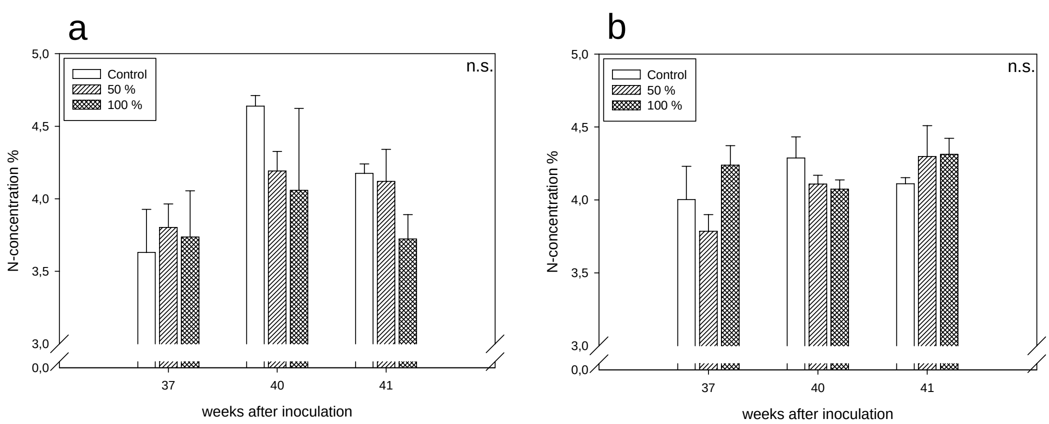

Figure 3 N-concentration (%) in the plant for the cultivar Monopol (a) and Empire (b) and the treatments control, 50 % and 100 % 37, 40 and 41 weeks after inoculation (significant changes at α = 0.05 are indicated, mean values with the same letter are not significantly different).

Figure 4 shows the dry matter (%) content of the cultivar Monopol (a) and Empire (b) and the treatments control, 50 % and 100 % 37, 40 and 41 weeks after inoculation. For both cultivars and all measurement dates no significant differences between the different treatments could be measured. The cultivar Empire indicated a lower dry matter content and therefore higher water content. The dry matter rose over time from about 21 % to 31 % for the cultivar Monopol and from about 20 % to 28 % for the cultivar Empire.

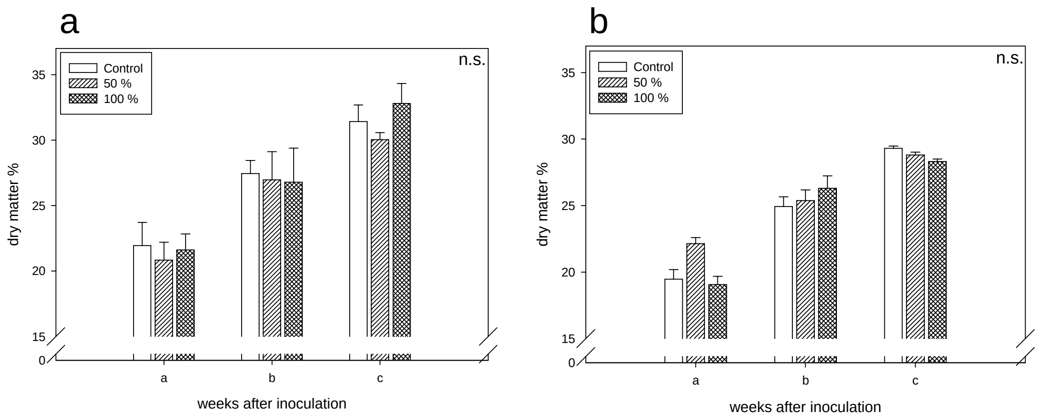

Figure 4 Dry matter (%) of the cultivar Monopol (a) and Empire (b) in the treatments control, 50 % and 100 % 37, 40 and 41 weeks after inoculation (significant changes at $\alpha = 0.05$ are indicated, mean values with the same letter are not significantly different).

With the digital camera no significant differences between the treatments 100 %, 50 % and 0 % could be obtained whether in the visible as well as in the infrared wavelength range for both cultivars.

With the spectroradiometer no significant differences between the treatments 100 %, 50 % and 0 % could be obtained at all times and for both cultivars.

Figure 6 shows canopy reflectance under wheat eyespot for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the cultivar Monopol 37 weeks (a), 40 weeks (b) and 41 weeks (c) after inoculation. At no measurement date significant differences between the control and the inoculum steps 50 % and 100 % could be measured. But it was evident that at the beginning the inoculated treatments showed a higher reflectance and after that a lower reflectance compared to the control. The experiments showed next to the infection with wheat eyespot also an infection with powdery mildew and septoria leaf blotch.

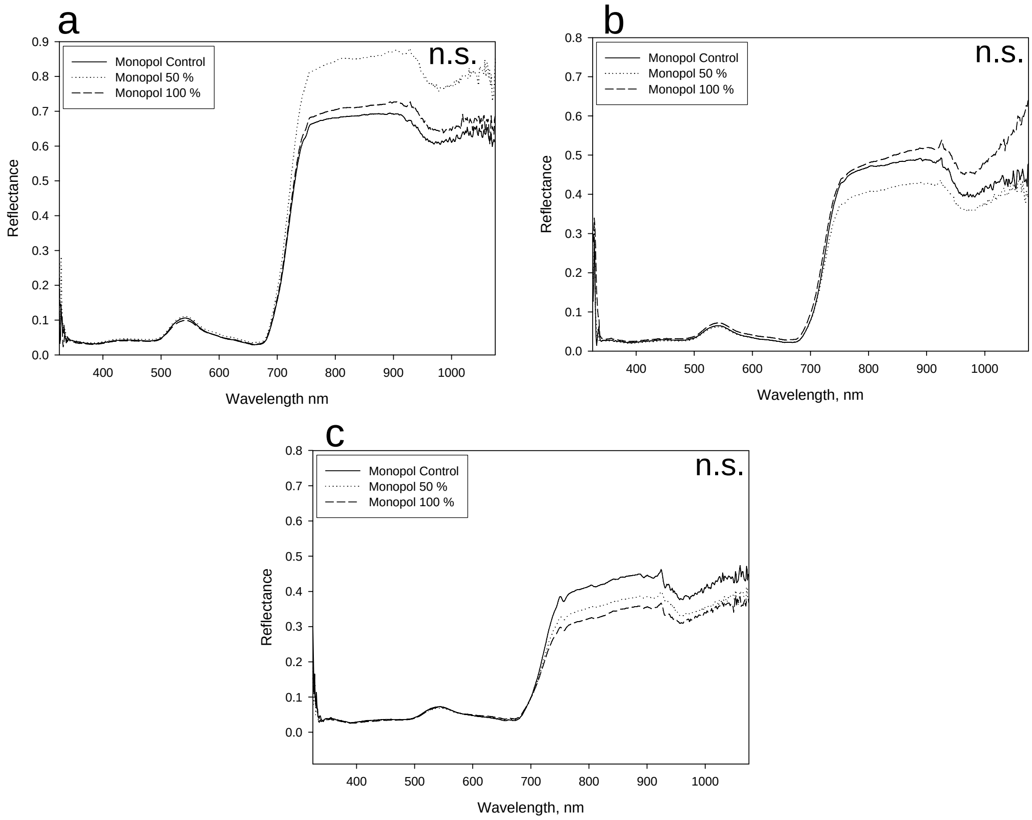

Figure 6 Canopy reflectance under wheat eyespot for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the cultivar Monopol 37 weeks (a), 40 weeks (b) and 41 weeks (c) after inoculation. (significant changes at α = 0.05 are indicated, mean values with the same letter are not significantly different)

Figure 7 shows the canopy reflectance under wheat eyespot for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the cultivar Empire 37 weeks (a), 40 weeks (b) and 41 weeks (c) after inoculation. At every measurement date differences between the control and the inoculated treatments could be measured, but the differences were not significant. Also here a mixture of wheat eyespot, powdery mildew and septoria leaf blotch was found.

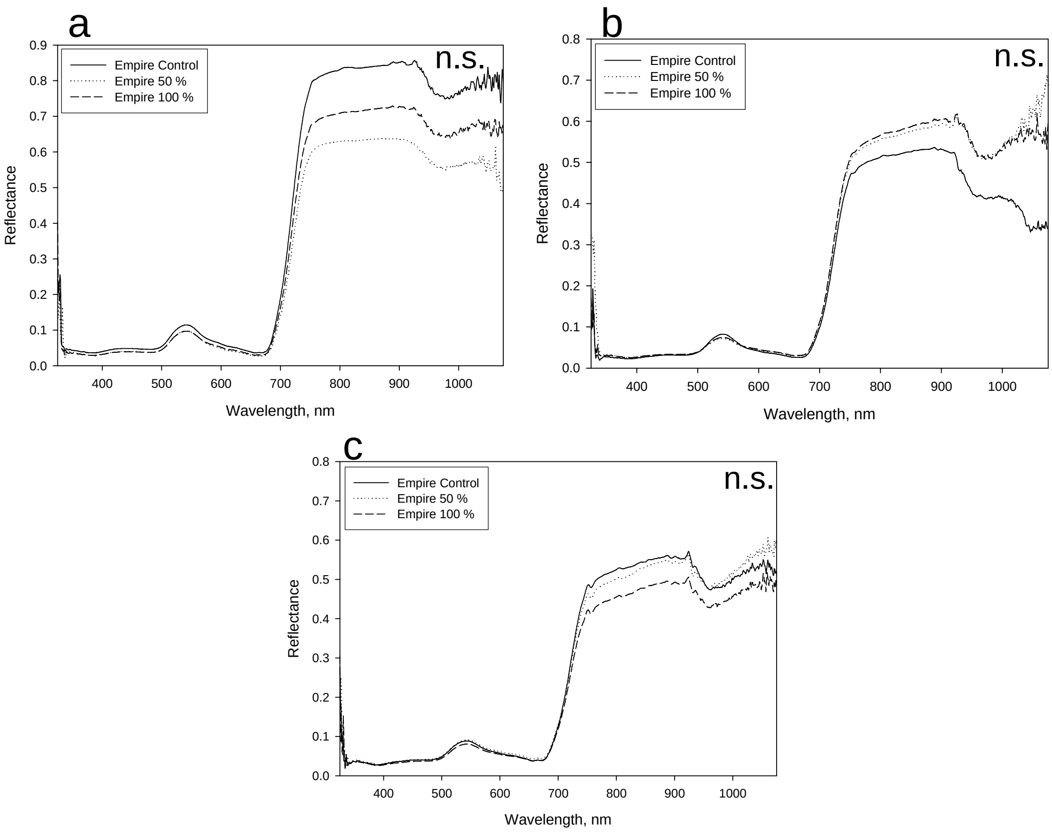

Figure 7 Canopy reflectance under wheat eyespot for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the cultivar Empire 37 weeks (a), 40 weeks (b) and 41 weeks (c) after inoculation. (significant changes at $\alpha = 0.05$ are indicated, mean values with the same letter are not significantly different)

6.4. Discussion

The effects of disease in agricultural crops are of major economic importance, in terms of both reduced final yield and the cost of remedial measures (Waggoner and Berger, 1987). Remote sensing has already proved to be a valuable tool in the detection of diseases in crops, using aerial photography and satellite sensor data (Hart and Myers, 1968; Jackson, 1986). The use of such remote sensing techniques, based on measurements of reflectance, potentially allows for the early detection of disease outbreaks. In addition, large areas can be surveyed quickly and plant diseases could be treated site-specifically.

The results of this study indicated that wheat eyespot could not be detected by reflectance measurements at any time of infection. One reason for the lack of identification may be the general low infection level of 10 % on average. Wheat eyespot is a stem base disease of wheat in humid and cold regions. Wheat eyespot reduces yield and quality by restricting water and nutrient uptake. The steam is being destroyed and therefore the conduction ways for the transportation of water and nutrient from the roots to the plants are being disturbed. Consequently an infection with wheat eyespot can only be identified over secondary changes in the plant surface.

As the results indicated that the N-concentration and water content in the plant were not affected by wheat eyespot due to the probably low infection level, a significant identification of wheat eyespot by reflectance measurement may not be possible.

Nilsson (1985) identified sclerotinia stem rot on oil seed rape by remote sensing. He used a hand-held Exotech-100AX radiometer including the wavelength bands 500-600 nm, 600-700 nm, 700-800 nm and 800-1100 nm on two occasions after flowering. He identified significant differences between healthy and diseased plants especially in the wavelength ranges 700-800 nm and 800-1100 nm. The findings were lead back to the diseased induced water stress. Similar finding were made by Nilsson (1984) in with *Pyrenophora graminea* infected barley plants.

Greaff et al. (2006), identified take-all disease in winter wheat with the digital camera LEICA S1 PRO, described in this study, in greenhouse experiments. The wavelength range 510-780 nm showed the best suitability for the identification of take-all disease. In this study take all disease could be identified over a secondary water stress caused by the fungus.

Cibula and Carter (1992) measured the spectral reflectances for the canopies of Pinus elliottii seedlings that were inoculated with the ecomycorrhizal fungus *Pisolithus tinctorius*. *Pisolithus tinctorius* leads to deficiency in plant nutrition and water uptake in slash pine. Differences between healthy and diseased plants were especially found in the wavelength range near 700 nm.

Another reason for the lack of identification of wheat eyespot could be the place of infection. Wheat eyespot appears on the stem of wheat plants and cannot be detected directly with reflectance measurements. Only secondary symptoms like nutrient ore water stress could be detected and be referred to the disease. In some cases secondary symptoms might appear at a late infection level and thus the plant disease could be detected to late. At which infection level wheat eyespot could be detected needs to be investigated in further experiments.

6.5. Conclusion

Because of a low infection level and the distance of wheat eyespot from the measuring place the disease could not be identified clearly based on reflectance measurements in this study. But it seams that differences between healthy and infected plants appear especially in the near infrared wavelength range. Further studies are necessary to detect at which infection level wheat eyespot could be detected.

6.6. References

Blakeman, R.H., Bryson, R. and Dampney, P. 2000. Assessing crop condition in real time using high resolution satellite imagery. Remote sensing in agriculture. Association of Applied Biologists, pp. 163-172.

Cibula, W.G. and Carter, G.A. 1992. Identification of a far-red reflectance response to ectomycorrhizae in slash pine. International Journal of Remote Sensing, Vol. 13, pp. 925-932.

Doerge, T.A. 1999. Variable rate nitrogen management for corn production – Success proves elusive. Site-specific Management Guidelines (SSMG) 36.

Goddard, T.W., Lachapelle, G., Cannon, M.E., Penney, D.C. and McKenzie, R.C. 1995. The potential of GPS and GIS in precision agriculture. Proc. Geomatique V: "La Route De L'Innovation". November 9-10, Montreal, P.Q., Canada.

Hart, W.G. and Myers, V.I. 1968. Infrared aerial colour photography for detection of populations of brown soft scale in citrus groves. Journal of Economic Entomology, Vol. 61, pp. 617-624.

Jackson, R.D. 1986. Remote sensing of biotic and abiotic plant stress. Annual Review of Phytopathology, Vol. 24, pp. 265-287.

Nilsson, H.E. 1984. Fjärranalys av växtsjukdomar I fältförsök. Växtskyddsrapporter, Jordbruk, 28, pp. 45-63.

Nilsson, H.E. 1985. Remote sensing of oil seed rape infected by sclerotinia stem rot and verticillium wilt. Växtskyddsrapporter, Jordbruk 33, pp. 1-33.

Reetz, Jr H.R. and Fixen, P.E. 1999. Strategic approach to site-specific system. In: Site Specific Management Guidelines, SSMG-28.Norcross, GA.

Reyniers, M. 2003. Precision farming techniques to support grain crop production. Dissertation, Catholic University of Leuven.

West, J.S., Bravo, C., Oberti, R., Lemaire, D., Moshou, D., McCartney, H.A. (2003): The potential of optical canopy measurement for targeted control of field crop diseases. Annual Review of Phytopathology, Vol. 41, S. 593-614

Waggoner, P.E. and Berger, W.D. 1987. Defoliation, disease and growth. Phytopathology, Vol. 77, pp. 393-398.

www.bmvel-forschung.de/index.cfm?STICHWORT=halmbruchkrankheit&nav=dis-play&uuid=00067D0EDACC1ED4AF

www.inra.fr/internet/Produits/HYP3/patho-gene/6pseher.htm).

Zadoks J.C., Chang T.T., Konzak C.F. 1974. A decimal code for the grown stage of cereals. Weed Research, Vol. 14, pp. 415-421.

The aim of the second article was the identification of a disease that cannot directly be detected by a sensor system. Therefore, a field experiment was conducted and the influence of wheat eyespot on winter wheat was studied. For reflectance measurements two different sensor systems with a spatial resolution of 0.5 cm^2 and 0.5 m^2 were used. One sensor system measured the reflection at leaf scale and one at canopy level.

The results showed that the used sensor systems could not detect wheat eyespot in the field. Reasons for the missing identification could be seen in the low infection level or in the infected organ.

In the literature vegetation indices are often used to analyze reflectance measurements. Out of this the question was raised if common vegetation indices could be used to detect plant diseases using reflectance measurements.

Use of different vegetation indices to detect various plant diseases in winter wheat (*Triticum aestivum* L.)

Kerstin Gröll, Simone Graeff, Wilhelm Claupein
Institute of Crop Production and Grassland Research (340)
University of Hohenheim
D-70599 Stuttgart, Germany
groell@uni-hohenheim.de

Abstract

Plant diseases are a big problem in today's agriculture as they highly influence yield and quality of agricultural plants. Annually, about 30 % of the word harvest is lost due to plant diseases. Farmers can control plant diseases by using pesticides, but there is an increasing pressure from the government and the consumers to reduce the use of pesticides and therewith the residues of pesticides in foods and the environment. One possibility to reduce pesticides is to treat plants with pesticides on a site–specific scale because plant diseases are not uniformly distributed over the field. However, this would necessitate a sensor technology to detect plant diseases site-specifically within a field. A field study was conducted to assess changes in leaf spectral reflectance of winter wheat plants due to an infection with powdery mildew and septoria leaf blotch. Leaf reflectance measurements and vegetation indices were evaluated as a tool to identify and quantify the various diseases. Plants were inoculated with the diseases in different intensities and leaf reflectance was measured once or twice a week depending on the development of the disease. Reflectance was measured with the spectroradiometer Field Spec® Hand Held (ASD, Inc. Boulder, CO, USA) in the range of 325-1075 nm in 1 nm intervals 2 m above the canopy level. A range of common vegetation indices was tested for their ability to detect plant diseases The results showed that the vegetation indices REIP and RVSI were able to detect powdery mildew at an infection level of 7 % and septoria leaf blotch at an infection level of 13.7 %. In order to detect an earlier stage of septoria leaf blotch infection, a new vegetation index was developed. The developed and tested "Disease Infection Index" (DII) was able to detect septoria leaf blotch at an infection level of 4 %. Canopy reflectance measurements were able to detect powdery mildew at an infection level of about 4 % and septoria leaf blotch at an infection level of about 3 % and can be used as an alternative to vegetation indices to identify plant diseases.

Keywords: plant diseases, reflectance measurements, vegetation indices

1. Introduction

Problematical economical surrounding conditions and environmental editions of the government make plant production very difficult at an increasing degree (Ludowicy et al., 2002). It is therefore necessary to improve the terms of plant production with regard to economic efficiency and environmental protection.

Powdery mildew, caused by *Erysiphe* (*Blumeria*) *graminis* f. sp. *tritici*, is one of the most important wheat diseases in many regions of the world. Yield losses caused by cereal powdery mildew can be attributed to the smaller and less efficient photosynthetic systems of infected plants (Last, 1953). Disease severity depends on many factors, including cultural practices, variation in weather conditions, level of variety susceptibility, regional and in-field location. The pathogen and its spread is benefited by warm and humidity places, vulnerable varieties (e.g. Monopol), early sowings of winter wheat and late sowings of summer wheat, high stand density as well as excessive nitrogen fertilization. Powdery mildrew may attack cereal plants at all stages of their growth, from emergence to ripening of the ear, and leaves that are heavily mildewed yellow prematurely. The dispersion takes place by wind-borne conidia. Favorable terms are given at a temperature of 15-20 °C and no heavy precipitations.

Septoria leaf blotch, caused by the fungus *Mycosphaerella graminicola* (Fuckel) Schroeter (anamorph: *Septoria tritici* Roberge in Desmaz) is a major necrotic leaf disease in wheat (*Triticum aestivum* L. em. Thell) (Wiese, 1987). Where environmental conditions are favorable for disease development, yield losses ranging from 20 to 43 % have been reported (Cooke and Jones, 1971; Caldwell, 1976). Septoria leaf blotch can reduce the economic value of wheat by decreasing both grain yield and quality. Yield loss is related to the leaf area killed by the pathogen (Brown and Paddick, 1982). Yield loss is less in wheat with greater resistance to the disease (Murray, 1982). Septoria leaf blotch is characterized by necrotic blotches that contain black or dark brown pycnidia. Wind-borne ascospores released from wetted stubble from autumn to winter are the primary inoculum of the disease (Brown et al, 1978). Secondary spread is by rain-splashed pycnidia (Wiese, 1987). The disease is favored by mild, wet conditions (Hess and Shaner, 1987a, 1987b). Severity has been associated with the number of rainy days in spring and with reduced number of nights with minimum temperatures below 7 °C (Shaner and Finney, 1976; Coakley et al, 1985), while rain splash is important for the rapid development of the disease on upper leaves (Royle et al., 1986) The pathogen survives between wheat crops on wheat stubble (Shipton et al., 1971). Both diseases occur in patches within a field in the early stages of infection and spread over the whole field with progressive infection.

There is an emerging body of literature indicating that precision agriculture can have positive impacts on the environment as it enables farmers to effectively use crop inputs including fertilizers, pesticides, and irrigation water. However, questions remain about cost-effectiveness and the most effective ways to use the available technological tools, but the concept of "doing the right thing in the right place at the right time" has a strong intuitive appeal. Overall, precision agriculture provides an enabling set of technologies to help reduce potential environmental problems from pest management. Up to now, these specific technologies include especially field maps of weed distribution throughout the year, detection methods for weeds within a field, application methods to apply an herbicide only on selected areas, and indications of the effects of weed populations on crop yields with data from yield monitors on combines. In principle, insects and diseases can be treated similarly to weeds using the same principles (Dammer, 1999; Fleischer et al., 1999). However, up to now suitable sensor technologies for the detection of insects or diseases are missing and still have to be developed.

The challenge for the development of suitable sensor technologies is in general to detect the occurring stress as early as possible. In this case management practices can be implemented to minimize the effect of stress factors on harvestable yield of the crops. In contrast to weeds, which may be detected and identified macroscopically as individuals using camera systems (Gerhards and Christensen, 2003), microbial plant pathogens – fungi, bacteria or viruses – which sometimes cause high crop losses (Oerke et al, 1994) have to be detected by symptoms or the reaction of plants to the pathogens. For multiple decades, the most widespread method for disease detection has been visual survey. The limitations of these methods are that few people have either the experience or the insight to detect early signs of disease infection and fields are generally too large to be adequately surveyed by eye. Hence, these assessments are time-consuming and can be inaccurate (Parker et al., 1995). Furthermore, by the time visual and tactile signs are evident, yield-limiting damage may already have occurred.

Remote sensing techniques are capable of measuring radiation and offer the possibility to quantitatively assess plant stresses caused by biotic and abiotic factors. Remote sensing generally focuses on the relation of plant pigment changes, especially chlorophylls, and biomass (Hall et al. 2002). Much evidence for the success of this method has been shown in the literature (e.g. Knippling 1970; Thomas and Gausman, 1977; Buschmann and Nagel, 1993; Filella and Peñuelas, 1994; Blackmer et al., 1996; Lorenzen and Jensen 1989; West et al., 2003; Moshou et al., 2004) The use of remote sensing techniques and spectral indices appropriate for on-ground or canopy sensors would offer several advantages compared to conventional visual methodologies. This includes the use of wavebands beyond the limit of human sensitivity, the ability to detect symptoms early (if pre-visual symptoms exist), and most importantly, the ability to co-analyze complex relationships between several properties.

Multiple studies have investigated the link between chlorophyll-related wavebands and crop plant diseases. Using (hyper-)spectral reflectance images Lorenzen and Jensen (1989) Sasaki et al. (1998), Oliver et al. (2003) and Moshou et al. (2004) were able to identify powdery mildew of barley, diseased cumber leaves, take-all and yellow rust of wheat respectively. Hansen (1991) used multi-spectral radiometry to quantify yellow rust in wheat and Adams et al. (1999) introduced a yellowness index (YI) as a measure of chlorosis in leaves of stressed plants. Sasaki et al. (1999) were able to distinguish diseased cucumber leaves from healthy leaves at an early stage of infection, based upon the spectral reflectance of the leaves in the 500, 600, and 650 nm wavebands. These studies clearly describe the potential of spectral reflectance measurements for the identification of plant diseases.A couple of studies has derived vegetation indices out of these spectral measurements. The indices can be easily used to predict e.g. LAI, biomass accumulation, light interception and yield (Rouse et al., 1973, Daughtry et al. (2000) as they stand in close correlation with pigmental changes. The modified chlorophyll absorption reflectance index (MCARI) for example has been used for the prediction of leaf chlorophyll concentration (Daughtry et al., 2000). The normalized total pigment chlorophyll a ratio index (NPCI) is highly correlated with carotenoids and chlorophyll a (Penuelas et al., 1994). The index values of the hyperspectral vegetation index (HVI) are significantly correlated to the vitality of the detected plants (Laudien et al., 2004). However, none of these studies has evaluated the application of known spectral indices for disease detection, nor have specific indices been developed for the identification of diseases.

The objective of this study was to test and compare different known vegetation indices for their ability to predict plant diseases within a field and therefore to assess the possibilities for non-destructive, site-specific sensor technologies to identify plant diseases. A field study was conducted with powdery mildew and septoria leaf blotch in the years 2005 and 2006. For the analysis of plant reflectance different vegetation indices from the literature were evaluated and compared for their ability to identify significant spectral changes between healthy and diseased plants. The study also investigated the chance to detect diseases before the symptoms are readily visible. If none of the tested vegetation indices out of the literature are able to detect an early stage of infection a new index based on the results of the field study will be investigated.

2. Experimental procedures

2.1 Experimental design

Field studies were conducted during the growing period of 2004/2005 and 2005/2006 at the experimental station “Ihinger Hof” (48°44´ N, 8°56´E; 687 mm, 7.9 °C) of the University of Hohenheim, Stuttgart, Germany. Winter wheat cv. Monopol and Empire were planted on October 23rd, 2004 and September 22nd 2005 at a rate of 350 seeds per m². Each year the fields were ploughed followed by a seedbed preparation before sowing. The total amount of nitrogen, depending on N_{min} in the ground, was split in three rates and broadcast as KAS (13.5 % NH_4-N, 13.5 % NO_3-N, 12 % CaO). Timing of N application was set to start of vegetation, Zadoks 32 and Zadoks 49 (Zadoks et al. 1974). Herbicides and insecticides were broadcast as needed to control pests. The variety ‘Empire’ is classified as a high resistant variety, whereas ‘Monopol’ has a very low resistance against diseases in general (Bundessortenamt, 2005). The experiments were inoculated with the diseases powdery mildew and septoria leaf blotch in the inoculum steps I1 = no inoculum = control, I2 = 50 % inoculum and I3 = 100 % inoculum. The trial was set up as randomized block design with three replications.

The plots had a size of 4 x 8 m. A protection zone of 6 m was implemented between plots of different varieties and similar inoculum steps. Between different inoculum steps a 10 m protection zone to avoid cross-inoculation was implemented. One trial was inoculated with septoria leaf blotch in spring at GS 32 (Zadoks et al., 1974) by strewing infected wheat grains into the plots (CBS 292.69, Germany). Measurements started right after the inoculation at GS 32 and were repeated every week until beginning of July. The second trial was inoculated with powdery mildew in spring at GS 30 and 32 by putting different amounts of infected pots of infected plants (50 % three pots; 100 % six pots) between the wheat plants. The inoculum of powdery mildew (*Erysiphe graminis* 150, powdery mildew resistant gene Pm1, 2, 3a, 3c, 3d, 4a, 4b, 5, 6, 7, 8 and 17) was obtained from the Federal Biological Research Centre for Agriculture and Forestry, Kleinmachnow, Germany, as infected wheat plants in 10 cm pots. Measurements started right after the inoculation at GS 30 and were repeated every week until end of June.

2.2 Image acquisition

To detect spectral differences between healthy and diseased wheat leaves, the hyperspectral spectroradiometer “FieldSpec HandHeld” by ASD (Analytical Spectral Devices Inc., Boulder, USA) was used to collect canopy reflectance data. The FieldSpec Hand Held 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. The spectroradiometer was located two meters above the canopy. The measuring viewing angle (*a*) of 25 degrees causes a field of view (*A*) of 62 cm^2 with a field of view radius ’(R) of 44 cm (equations 1 and 2) (Laudien et al., 2003).

$$R = h * \tan((\alpha/2) * \pi/180) \quad (1)$$

$$A = \pi * r^2 \quad (2)$$

To compare healthy and diseased wheat plants, six spectroradiometer measurements were made in each plot. These measurements were averaged to one spectral curve for each inoculum step and each variety. The intermediated results were used to appoint and evaluate appropriate vegetation indices.

2.3. Vegetation indices

For the analysis of the FieldSpec measurements, thirteen vegetation indices derived from the literature were used in this study. The indices were chosen because of their combination of wavelength ranges in which reflectance changes under plant diseases were expected.

The first index, which was used, was the often used "Normalized Difference Vegetation Index" (NDVI) (Rouse et al., 1973). This index enables the quantification of the green biomass. The NDVI is diverting from the infrared to red index. The NDVI is given in equation 3.

$$NDVI = R_{780} - R_{680}/R_{780} + R_{680} \quad (3)$$

where

R780	reflectance at 780 nm [%]
R680	reflectance at 680 nm [%]

The second index was the "Hyperspectral Normalized Difference Vegetation Index" (HNDVI). For hyperspectral analyses the HNDVI can be different from the NDVI (Oppelt, 2002). The HNDVI is shown in equation 4.

$$HNDVI = R_{827} - R_{668}/R_{827} + R_{668} \quad (4)$$

where

R827	reflectance at 827 nm [%]
R668	reflectance at 668 nm [%]

The third index was the "Modified Chlorophyll Absorption in Reflectance Index" (MCARI). The index combines the near-infrared and the green as well as the red reflectance. The index is responsive to both leaf chlorophyll concentration and background reflection (Daughtry et al., 2000). The MCARI is shown in equation 5.

$$MCARI = [(R_{700} - R_{670}) - 0.2*(R_{700} - R_{550})]*(R_{700}/R_{670}) \quad (5)$$

where

R700	reflectance at 700 nm [%]
R670	reflectance at 670 nm [%]
R550	reflectance at 550 nm [%]

The fourth index was the "Transformed Chlorophyll Absorption in Reflectance Index" (TCARI). The ratio (R_{700}/R_{550}) differences are closely linked to the variations of reflectance characteristics of background materials (soil and nonphotosynthetic components). To compensate for these effects, the ratio (R_{700}/R_{670}) is used to counteract the background influence only on the difference ($R_{700} - R_{550}$) (Haboudane et al., 2002). The TCARI is shown in equation 6.

$$TCARI = 3*[(R_{700} - R_{670}) - 0.2*(R_{700} - R_{550})(R_{700}/R_{670})] \quad (6)$$

where

R700	reflectance at 700 nm [%]
R670	reflectance at 670 nm [%]
R550	reflectance at 550 nm [%]

The fifth index was the "Optimized Soil-Adjusted Vegetation Index" (OSAWI). The OSAWI belongs to the soil-adjusted vegetation index family (Huete, 1988) and is given in equation 7.

$$OSAVI = (1 + 0.16)(R_{800} - R_{670})/(R_{800} + R_{670} + 0.16) \quad (7)$$

where

R800 reflectance at 800 nm [%]

R670 reflectance at 670 nm [%]

The sixth index was the "Normalized total Pigment Chlorophyll a ratio Index" (NPCI). The "Normalized Difference Pigment Index" is highly correlated with the ratio between total carotenoids and chlorophyll a (Penuelas et al., 1994) and is shown in equation 8.

$$NPCI= (R_{680} – R_{430})/(R_{680} + R_{430}) \quad (8)$$

where

R680 reflectance at 680 nm [%]

R430 reflectance at 430 nm [%]

The seventh index was the "Red Edge Inflection Point" (REIP). The increase in vegetative chlorophyll a concentration during the growth cycle has been shown to cause a red-shift of the infection point. At the onset of senescence, the mesophyll structures in the plant tissue (effective near-infrared reflectors) begin to collapse. Meanwhile, leaf chlorophyll decreases causing red reflectance to increase. These combined effects cause a blue-shift of REIP (Guyot et al., 1988). The REIP is shown in equation 9.

$$REIP = 700 + 40[((R_{670} + R_{780})/2 – R_{700})/(R_{740} – R_{700})] \quad (9)$$

where

R670 reflectance at 670 nm [%]

R780 reflectance at 780 nm [%]

R700 reflectance at 700 nm [%]

R740 reflectance at 740 nm [%]

The eighth index was the "Soil-Adjusted Vegetation Index" (SAVI). To account for changes in the soil optical properties, soil-adjusted indices minimizing the background influence have been developed. The leading index in such improvement is the SAVI (Huete, 1988), which includes a canopy background adjustment factor L. and is shown in equation 10.

$$SAVI= (1 + L)(R_{800} – R_{670})/(R_{800} + R_{670} + L) \quad (10)$$

where

R800 reflectance at 800 nm [%]

R670 reflectance at 670 nm [%]

The ninth index was the "Hyperspectral Vegetation Index" (HVI). The index values are significantly correlated to the vitality of the detected plants (Laudien et al., 2004). The HVI is shown in equation 11.

$HVI = R_{750}/R_{700}$ (11)

where

R750 reflectance at 750 nm [%]

R700 reflectance at 700 nm [%]

The tenth index was the "Red-edge Vegetation Stress Index" (RVSI). The RVSI was developed by Merton (1998), to identify inter- and intra-community trends based on spectral changes in upper red-edge geometry. The RVSI derives measurements of spectral concavity as a displacement in reflectance of two bisecting points; the red-edge brake point and the data mid-point value. The difference between the two modeled and data mid point values can then be expressed as positive or negative values. The RVSI is shown in equation 12.

$RVSI = [(R_{714} + R_{752})/2] - R_{733}$ (12)

where

R714 reflectance at 714 nm [%]

R752 reflectance at 752 nm [%]

R733 reflectance at 733 nm [%]

The eleventh index was the "Plant Vigor Ratio" (PPR). This index should exhibit high values for photosynthetically active canopies, that is, with strong absorption of energy in the red band and reflection in the green band; and low for weakly active vegetation, due to factors such as nutrient deficiency, stress or onset of senescence (Metternicht, 2003). The PPR is shown in equation 14.

$PVR = (R_{550} – R_{650})/(R_{550} + R_{650})$ (14)

where

R550 reflectance at 550 nm [%]

R650 reflectance at 650 nm [%]

The twelfth index was the "green Normalized Difference Vegetation Index" (NDVIg). This index is reported as a good indicator of chlorophyll contents in yellowish-green to dark-green vegetation. The reflection near 700 nm and in the range from 530 to 630 nm is highly sensitive to chlorophyll variations (Metternicht, 2003). The NDVIg is shown in equation 15.

$NDVIg = (R_{750} – R_{550})/(R_{750} + R_{550})$ (15)

where

R750 reflectance at 750 nm [%]

R550 reflectance at 550 nm [%]

2.4 Harvest and analyses

The leaves and shoots of one plant per plot were harvested and the fresh weight was determined at once at each measurement date. Plant samples were dried at 60 °C and total dry matter was determined. The remaining leaf tissue was ground, dry-ashed and analyzed for total N according to Dumas (1962).

To detect the infection level of the plants with powdery mildew and septoria leaf blotch, visual ratings were done every week. Therefore, the upper three leaves were consulted and the percentage of infected leaf area was estimated.

2.5 Statistical analysis

The arithmetic mean and as dispersion the standard error was calculated as location parameter from the measurements with the help of the statistic program Sigma.Stat. 3.1 (Jandel Scientific, USA). The experiments were analyzed with a one- and two-factorial ANOVA with a following multiple comparison by means of Tukey ($\alpha = 0.05$).

3. Results

3.1 Visual assessment of disease infection

3.1.1 Powdery mildew

Figure 1 shows the development of powdery mildew (a) and septoria leaf blotch (b) over 94 days for the winter wheat variety Monopol. The results indicated significant differences between the inoculated and non inoculated plots whereas first significant differences were obtained 22 days after inoculation. The infection with powdery mildew rose from the first measurement date till 76 days after inoculation and decreased at the last two measurement dates for the treatment 100 % and at the last three measurement dates for the treatment 50 %. 22 days after inoculation the treatment 100 % showed an infection level of 1.4 %. The highest infection level of the treatment was obtained 76 days after inoculation with 11.3 % infected leaf area. The treatment 50 % started with an infection level of 1 % and rose to an infection level of 8.7 % 71 days after inoculation. 71 days after the inoculation the experiments showed also an infection with septoria leaf blotch. The infection began with an infection level of 2 % for the control, 6.3 % for the treatment 50 % and 9.7 % for the treatment 100 %. The infection level rose to 21.3 % infected leaf area for the control, 34.7 % for the treatment 50 % and 20.3 % for the treatment 100 %. 71, 76 and 83 days after inoculation the differences between the control and the treatments 50 % and 100 % were significant.

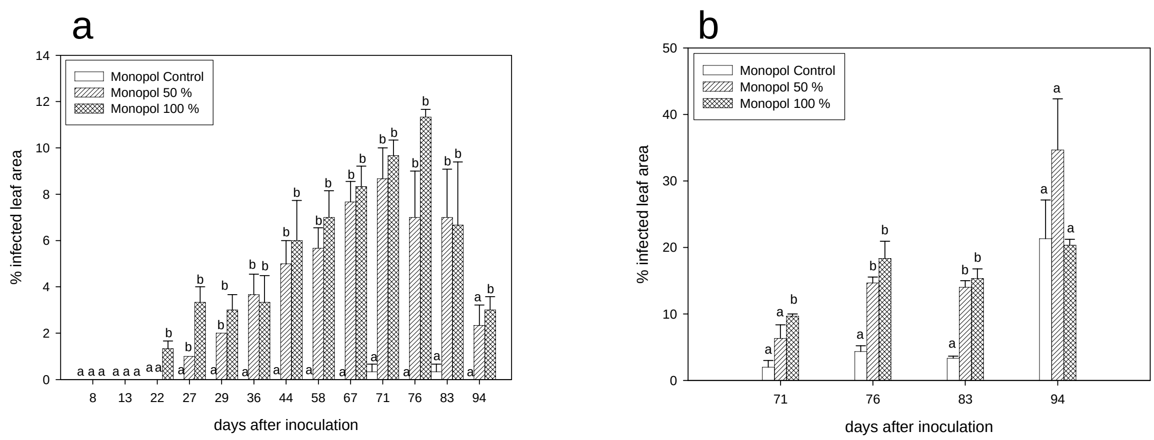

Figure 1. Percentage of infected leaf area with (a) powdery mildew and (b) septoria leaf blotch for the variety Monopol for different inoculation levels (significant changes are indicated at $\alpha = 0.05$, mean values with the same letter are not significantly different).

Figure 2 shows the development of powdery mildew (a) and septoria leaf blotch (b) over 94 days for the winter wheat variety Empire for the powdery mildew experiment. 13 days after the inoculation first symptoms of powdery mildew were visible. At this time the treatment 100 % showed an infection level of 0.3 %. The infection rose for the treatment 100 % to 3.7 % 71 days after inoculation. At the last three measurement dates the infection level declined to 1 % infected leaf area. The infection for the treatment 50 % started 22 days after the inoculation with 0.7 % infected leaf area and rose to 3.7 % 76 days after inoculation. The infection level declined at the last two measurement dates to 1 % infected leaf area. The highest infection level of the control was obtained 71 days after the inoculation with 0.7 % infected leaf area. 13 days after inoculation the differences between the control and the treatments 50 % and 100 % were significant. 71 days after the inoculation the experiments showed also an infection with septoria leaf blotch. The infection level was at the beginning at 2 % for the control, 5.3 % for the treatment 50 % and 100 %. The infection rose to 27.7 % for the control, 31.7 % for the treatment 50 % and 36.7 % for the treatment 100 %. 71, 76 and 83 days after the inoculation the differences between the control and the inoculated treatments were significant.

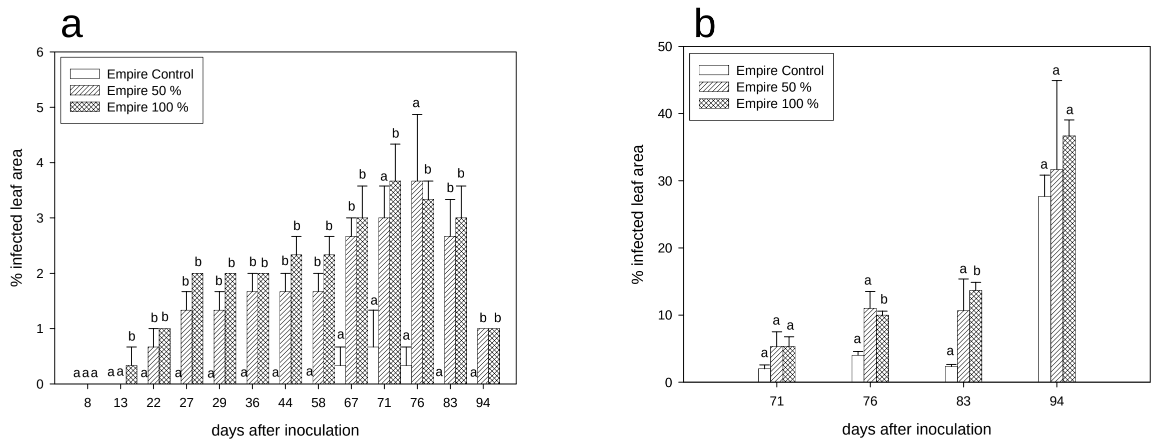

Figure 2. Percentage of infected leaf area with (a) powdery mildew and (b) septoria leaf blotch for the variety Empire for different inoculation levels (significant changes at $\alpha = 0.05$ are indicated, mean values with the same letter are not significantly different).

The comparison of the winter wheat varieties Monopol and Empire indicated significant differences between the overall infection levels. Especially the infection level of powdery mildew was lower for the resistant variety Empire than for the susceptible variety Monopol. The differences averaged out at 7 %. For septoria leaf blotch the differences were about 4 % whereas the variety Monopol had higher infection levels than the variety Empire.

3.1.2 Septoria leaf blotch

Figure 3 shows the development of septoria leaf blotch over 59 days for the winter wheat variety Monopol. One day after the inoculation first symptoms of septoria leaf blotch were visible. At this time the control showed an infection of 0 %, the treatment 50 % of 0.3 and the treatment 100 % of 0.6 %. The infection level rose over time to 35.3 % infected leaf area for the control, 36.3 % for the treatment 50 % and 32.7 % for the treatment 100 %. In general, the infection level of the treatments 50 % and 100 % were not significantly higher than the infection level of the control.

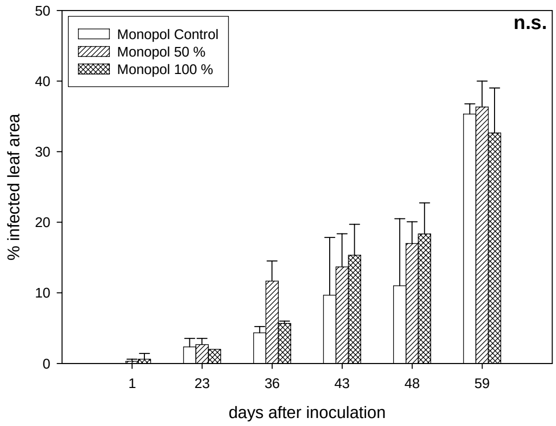

Figure 3. Percentage of infected leaf area with septoria leaf blotch for the variety Monopol and different inoculation levels.

Figure 4 shows the development of septoria leaf blotch over 59 days for the winter wheat variety Empire. Empire showed 1 day after the inoculation an infection level of 0 % for the control, 0.4 % for the treatment 50 % and 0.6 for the treatment 100 %. Over time the infection level rose to 27.3 % for the control, 37.3 % for the treatment 50 % and 39.7 for the treatment 100 % 59 days after inoculation. The differences between the control and the treatments 50 % and 100 % were at all days not significant.

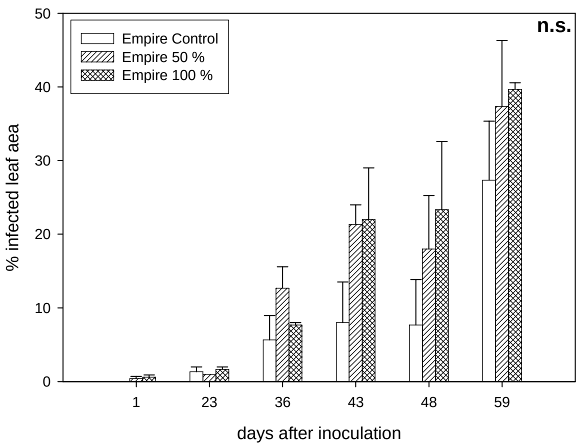

Figure 4. Percentage of infected leaf area with septoria leaf blotch for the variety Empire and different inoculation levels.

The comparison of the infection levels of the variety Monopol with the infection levels of the variety Empire indicated a lower infection level for the control but higher infection levels for the treatments 50 % and 100 %. However, the differences were not significant.

3.2 Obtained yield

3.2.1 Powdery mildew

Figure 5 shows the obtained yields in the powdery mildew experiment for the varieties Monopol and Empire. It was obvious that grain yield was reduced due to the infection with powdery mildew and septoria leaf blotch especially for the treatments 50 % and 100 % compared to the control. For the variety Monopol the control obtained 54.6 dt ha^{-1}, the treatment 50 % 48.7 dt ha^{-1} and the treatment 100 % 44.6 dt ha^{-1}. For the variety Empire the control obtained a yield of 64.8 dt ha^{-1}, the treatment 50 % of 57.3 dt ha^{-1} and the treatment 100 % of 58.4 dt ha^{-1}. The yield of the treatment 50 % was significantly lower compared to the control and the treatment 100 %. The resistant variety Empire obtained higher yields than the susceptible variety Monopol. The differences between the three treatments were significant.

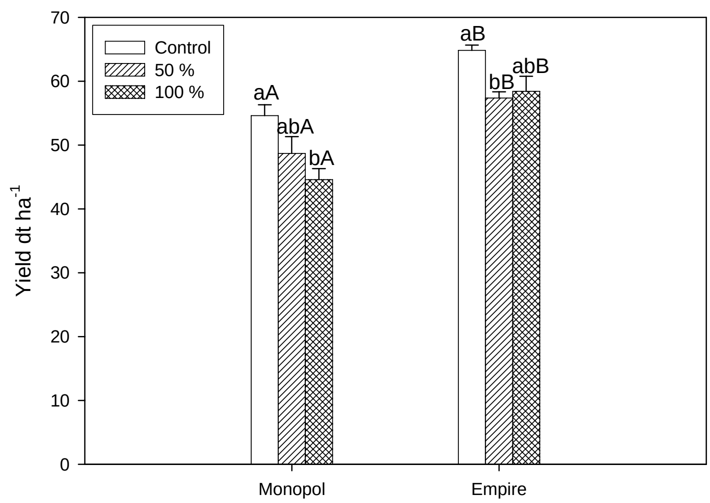

Figure 5. Obtained yield (dt ha^{-1}) for the varieties Monopol and Empire and the treatments Control, 50 % and 100 % (significant changes at $\alpha = 0.05$ are indicated, mean values with the same letter are not significantly different. Small letters describe significant changes between treatments of one variety and capitalized letters between the two varieties).

3.2.2 Septoria leaf blotch

Figure 6 shows the obtained yield for the varieties Monopol and Empire and the treatments control, 50 % and 100 % in the field trial inoculated with septoria leaf blotch. Grain yield of the treatments 50 % and 100 % was significantly reduced under the infection of septoria leaf blotch compared to the control. Yield of cv. Monopol was reduced from 51.1 dt ha^{-1} for the control to 45.7dt ha^{-1} for the treatment 50 % and 46 dt ha^{-1} for the treatment 100 %. For the variety Empire the yield was reduced from 60.8 dt ha^{-1} for the control to 54.1 dt ha^{-1} for the treatment 50 % and 53.3 dt ha^{-1} for the treatment 100 %. The differences between the control and the treatment 100 % of the variety Empire were significant. The comparison of grain yield of the two varieties Monopol and Empire indicated in general significantly higher yields for Empire than for Monopol

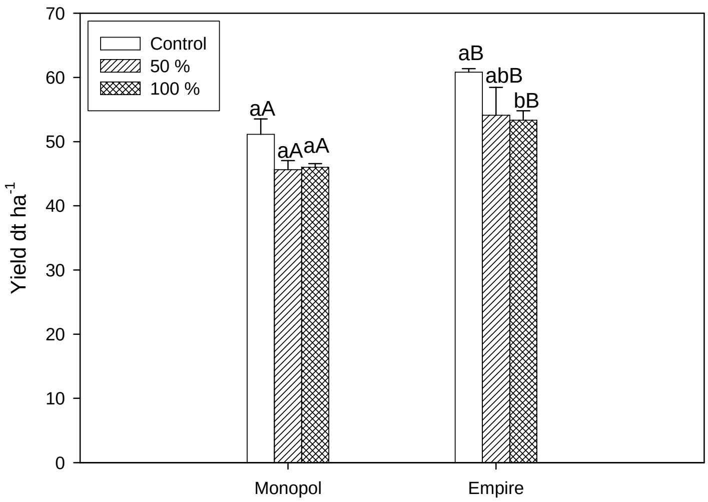

Figure 6. Obtained yield (dt ha^{-1}) for the varieties Monopol and Empire and the treatments Control, 50 % and 100 %. (Significant changes at $\alpha = 0.05$ are indicated, mean values with the same letter are not significantly different. Small letters describe significant changes between treatments of one variety and capitalized letters between the two varieties).

3.3 Vegetation indices

3.3.1 Powdery mildew

Table 1 shows the results for the tested vegetation indices 64, 76 and 84 days after inoculation for the varieties Monopol and Empire and the treatments control, 50 % and 100 % inoculated with powdery mildew. For the variety Monopol the vegetation index REIP was able to detect significant changes between the treatments control and 50 % 64 days after the inoculation at an infection level of 7.7 %. 76 days after the inoculation REIP, NDVI, HNDVI, NPCI and HVI could detect changes between the control and the treatment 50 % at an infection level of 7 %. OSAWI, REIP, NDVI, SAVI, HNDVI, NPCI, PVR, NDVIg and HVI detected significant differences at an infection level of 7 % between the control and 50 % 84 days after inoculation. Differences in canopy reflectance between the control and the treatment 100 % were identified 64 days after the inoculation by TCARI, REIP and HVI at an infection level of 8.3 %. 76 days after inoculation changes were identified by REIP, NDVI, HNDVI, NPCI and HVI at an infection level of 11.3 %. The vegetation indices OSAWI, REIP, NDVI, SAVI, HNDVI, RVSI, NPCI, PVR, NDVIg and HVI detected 84 days after inoculation significant changes at an infection level of 6.7 %. Only the vegetation index REIP was able to detect 64 days after inoculation significant changes between the control and the treatment 50 % as well as between the control and 100 %. 64 days after inoculation the vegetation indices TCARI and HVI detected significant differences between the control and the treatment 100 %. NDVI, HNDVI and NPCI were able to detect 76 and 84 days after inoculation significant changes between the control and the treatments 50 % and 100 %. All other tested indices were not able to detect changes between the treatments or to identify significant changes at a certain date or infection level. The vegetation index MCARI was not able to detect differences at all.

For the variety Empire no vegetation index was able to detect significant changes between the control and the treatments 50 % and 100 % 64 days after inoculation. At this time the treatment 50 % had an infection level of 2.7 % and the treatment 100 % of 3 %. 76 days after inoculation the vegetation indices REIP, NDVI, HNDVI and HVI were able to detect significant changes between the control and 50 % at an infection level of 3.7 %. The vegetation indices OSAWI, REIP, NDVI, SAVI, HNDVI, PVR, NDVIg and HVI could identify significant changes between the control and the treatment 50 % 84 days after inoculation at an infection level of 2.7 %. 76 days after inoculation changes between the control and the treatment 100 % were detected by REIP, NDVI and HVI at an infection level of 3.3 %. 84 days after inoculation the treatment 100 % had an infection level of 3 % and was identified by MCARI, TCARI, REIP, NDVI, PVR, NDVIg and HVI. Only the vegetation indices REIP, NDVI and HVI were able to detect 76 and 84 days after inoculation significant changes between the control and the treatments 50 % and 100 %. The other vegetation indices detected only single changes or the infection rather late. The comparison of the varieties Monopol and Empire indicated that a disease infection of Monopol could be detected earlier, which was directly related to the higher infection level at an early stage when compared to Empire. In general the vegetation index REIP was the most suitable index for disease detection for both varieties and all treatments. Also the indices NDVI and HVI were suitable but they were not able to detect changes as early as the index REIP.

Further, the REIP was able to detect changes before visible infection symptoms appeared.

3.3.2 Septoria leaf blotch

Table 2 shows the results for the tested vegetation indices 28, 40 and 48 days after inoculation for the varieties Monopol and Empire and the treatments control, 50 % and 100 %. 28 days after inoculation the vegetation index NPCI could detect significant changes between the control and the treatment 50 % for the variety Monopol at an infection level of 2.3 % for the control and 2.7 % for the treatment 50 %. The indices TCARI and RVSI could detect significant changes between the control and 50 % 40 days after inoculation at an infection level of 13.7 % at which the control had an infection level of 9.7 %. 48 days after inoculation and an infection level of 11 % for the control and 17 % for the treatment 50 % the vegetation RVSI was able to identify significant changes. Changes between the control and the treatment 100 % could only be detected 48 days after inoculation and an infection level of 11 % for the control and 18.3 % for the treatment 100 % by the vegetation indices TCARI, REIP and HVI. The vegetation indices MCARI, OSAWI, NDVI, SAVI, HNDVI PVR and HNDVIg were not able to detect changes between the treatments at all. The other vegetation indices could only detect single significant changes.

For the variety Empire no vegetation indices were able to detect significant changes between the treatments 28 days after inoculation. Here the infection level was at 1.3 % for the control, 1 % for the treatment 50 % and 1.7 % for the treatment 100 %. 40 days after inoculation the REIP index was able to detect changes between the control and the treatment 50 %. At this date the control had an infection level of 8 % and the treatment 50 % of 21.3 %. Changes between the control and the treatment 100 % could be detected by the indices MCARI, OSAWI, REIP, NDVI, SAVI, HNDVI, RVSI and HVI 48 days after inoculation at an infection level of 7.7 % (control) respectively 18 % (treatment 100 %). The comparison of the two varieties indicated that the vegetation index RVSI was the most suitable.

For the disease septoria leaf blotch and the varieties Monopol and Empire the vegetation index RVSI was most suitable. The RVSI detected changes at an infection level of 13.7 % septoria leaf blotch for the variety Monopol and at an infection level of 18 % for Empire. The other indices were not able to detect an early infection with septoria leaf blotch.

Overall, the vegetation index RVSI was most suitable to detect septoria leaf blotch.

Table 1. Used refectance indices 64, 76 and 84 days after inoculation for the varieties Monopol and Empire inoculated with powdery mildew. Significances are indicated between vegetation indices using different letters (explanation of indices see material and method).

	MCARI			TCARI			OSAWI			REIP			NDVI			SAVI		
dai *	64	76	84	64	76	84	64	76	84	64	76	84	64	76	84	64	76	84
Monopol Control	0.32 a	0.23 a	0.24 a	0.11 a	0.17 a	0.18 a	0.86 a	0.82 a	0.78 a	721.31 a	721.58 a	719.99 a	0.91 a	0.88 a	0.83 a	0.75 a	0.71 a	0.66 a
Monopol 50 %	0.35 a	0.21 a	0.18 a	0.11 a	0.16 a	0.16 a	0.84 a	0.75 a	0.68 **b**	720.42 **b**	719.78 **b**	717.88 **b**	0.91 a	0.84 **b**	0.75 **b**	0.72 a	0.61 a	0.53 **b**
Monopol 100 %	0.38 a	0.20 a	0.17 a	0.13 **b**	0.16 a	0.17 a	0.86 a	0.73 a	0.66 **b**	720.22 **b**	719.39 **b**	717.56 **b**	0.91 a	0.83 **b**	0.72 **b**	0.75 a	0.60 a	0.51 **b**
Empire Control	0.37 a	0.24 a	0.24 a	0.15 a	0.17 a	0.17 a	0.86 a	0.78 a	0.78 a	720.48 a	720.58 a	719.95 a	0.90 a	0.87 a	0.83 a	0.77 a	0.65 a	0.65 a
Empire 50 %	0.41 a	0.27 a	0.21 a	0.15 a	0.20 a	0.17 a	0.86 a	0.78 a	0.72 **b**	720.21 a	719.39 **b**	718.60 **b**	0.90 a	0.84 **b**	0.79 **b**	0.77 a	0.66 a	0.57 **b**
Empire 100 %	0.42 a	0.25 a	0.22 **b**	0.14 a	0.19 a	0.17 **b**	0.86 a	0.78 a	0.74 a	719.77 a	719.79 **b**	718.93 **b**	0.91 a	0.85 **b**	0.81 **b**	0.76 a	0.65 a	0.59 a

* days after inoculation

Table 1: continued

	HNDVI			RVSI			NPCI			PVR			NDVIg			HVI		
dai*	64	76	84	64	76	84	64	76	84	64	76	84	64	76	84	64	76	84
Monopol Control	0.94 a	0.91 a	0.89 a	-0.038 a	-0.035 a	-0.029 a	0.02 a	0.02 a	0.05 a	0.45 a	0.45 a	0.32 a	0.82 a	0.74 a	0.71 a	5.60 a	5.19 a	3.89 a
Monopol 50 %	0.93 a	0.87 **b**	0.80 **b**	-0.039 a	-0.033 a	-0.021 b	-0.03 a	0.07 **b**	0.18 **b**	0.50 a	0.40 a	0.25 **b**	0.80 a	0.69 a	0.63 **b**	5.34 a	4.16 **b**	2.95 **b**
Monopol 100 %	0.93 a	0.86 **b**	0.78 **b**	-0.044 a	-0.030 a	-0.021 **b**	0.01 a	0.10 **b**	0.19 **b**	0.48 a	0.40 a	0.23 **b**	0.79 a	0.66 a	0.61 **b**	5.14 **b**	3.88 **b**	2.77 **b**
Empire Control	0.92 a	0.89 a	0.87 a	-0.041 a	-0.032 a	-0.030 a	-0.01 a	0.05 a	0.11 a	0.47 a	0.46 a	0.34 a	0.78 a	0.71 a	0.71 a	5.04 a	4.61 a	3.94 a
Empire 50 %	0.92 a	0.87 **b**	0.83 **b**	-0.046 a	-0.034 a	-0.028 a	0.03 a	0.11 a	0.16 a	0.46 a	0.44 a	0.30 **b**	0.78 a	0.67 a	0.66 **b**	4.89 a	4.02 **b**	3.27 **b**
Empire 100 %	0.92 a	0.88 a	0.85 a	-0.044 a	-0.032 a	-0.028 a	0.03 a	0.10 a	0.13 a	0.47 a	0.46 a	0.32 **b**	0.78 a	0.67 a	0.67 **b**	4.82 a	4.19 **b**	3.48 **b**

* days after inoculation

Table 2. Used reflectance indices 28, 40 and 48 days after inoculation for the varieties Monopol and Empire inoculated with septoria leaf blotch. Significances are indicated between vegetation indices using different letters (explanation of indices see material and method).

	MCARI			TCARI			OSAWI			REIP			NDVI			SAVI		
dai *	28	40	48	28	40	48	28	40	48	28	40	48	28	40	48	28	40	48
Monopol Control	0.31 a	0.40 a	0.18 a	0.10 a	0.29 a	0.19 a	0.85 a	0.84 a	0.69 a	721.65 a	719.42 a	718.90 a	0.92 a	0.83 a	0.75 a	0.74 a	0.81 a	0.55 a
Monopol 50 %	0.34 a	0.18 a	0.14 a	0.10 a	0.16 **b**	0.17 a	0.85 a	0.74 a	0.60 a	721.38 a	719.65 a	717.48 a	0.92 a	0.80 a	0.65 a	0.75 a	0.62 a	0.46 a
Monopol 100 %	0.34 a	0.23 a	0.15 a	0.19 a	0.16 a	0.18 **b**	0.86 a	0.77 a	0.63 a	721.56 a	719.71 a	717.99 **b**	0.92 a	0.81 a	0.68 a	0.76 a	0.68 a	0.50 a
Empire Control	0.39 a	0.32 a	0.20 a	0.13 a	0.28 a	0.20 a	0.87 a	0.78 a	0.73 a	720.78 a	718.45 a	719.35 a	0.91 a	0.79 a	0.77 a	0.77 a	0.69 a	0.60 a
Empire 50 %	0.37 a	0.22 a	0.12 **b**	0.11 a	0.19 a	0.15 a	0.84 a	0.75 a	0.55 **b**	720.32 a	716.26 **b**	718.60 **b**	0.91 a	0.79 a	0.66 **b**	0.72 a	0.64 a	0.40 **b**
Empire 100 %	0.37 a	0.29 a	0.14 **b**	0.11 a	0.20 a	0.17 **b**	0.85 a	0.80 a	0.61 **b**	720.45 a	719.55 a	717.93 **b**	0.91 a	0.83 a	0.70 **b**	0.73 a	0.72 a	0.47 **b**

* days after inoculation

Table 2: continued

	HNDVI			RVSI			NPCI			PVR			NDVIg			HVI		
dai *	28	40	48	28	40	48	28	40	48	28	40	48	28	40	48	28	40	48
Monopol Control	0.94 a	0.85 a	0.79 a	-0.037 a	-0.063 a	-0.023 a	0.036 a	0.076 a	0.226 a	0.46 a	0.32 a	0.33 a	0.83 a	0.71 a	0.59 a	5.87 a	3.93 a	3.14 a
Monopol 50 %	0.94 a	0.83 a	0.70 a	-0.040 a	-0.036 **b**	-0.017 **b**	0.025 **b**	0.104 a	0.300 a	0.45 a	0.27 a	0.21 a	0.82 a	0.70 a	0.54 a	5.71 a	3.84 a	2.51 a
Monopol 100 %	0.94 a	0.84 a	0.73 a	-0.040 a	-0.042 a	-0.020 a	0.031 a	0.084 a	0.285 a	0.46 a	0.28 a	0.23 a	0.82 a	0.71 a	0.56 a	5.76 a	3.86 a	2.62 **b**
Empire Control	0.93 a	0.83 a	0.82 a	-0.044 a	-0.043 a	-0.025 a	0.042 a	0.100 a	0.224 a	0.46 a	0.37 a	0.32 a	0.80 a	0.64 a	0.63 a	5.19 a	3.69 a	3.36 a
Empire 50 %	0.93 a	0.82 a	0.70 **b**	-0.040 a	-0.037 a	-0.017 **b**	0.061 a	0.161 a	0.238 a	0.47 a	0.27 a	0.24 a	0.80 a	0.69 a	0.50 a	5.08 a	3.57 a	2.41 **b**
Empire 100 %	0.93 a	0.86 a	0.74 **b**	-0.040 a	-0.046 a	-0.018 **b**	0.048 a	0.131 a	0.280 a	0.46 a	0.32 a	0.31 a	0.80 a	0.72 a	0.52 **b**	5.13 a	3.92 a	2.71 **b**

* days after inoculation

3.4 Reflectance changes

3.4.1 Powdery mildew

Figure 7 shows the canopy reflectance of cv. Monopol under powdery mildew for the treatments control (….), 50 % (----) and 100 % (- -) 4 days (a) and 58 days (b) after inoculation. At the beginning of the infection no significant changes in canopy reflectance existed between the control and the treatments 50 % and 100 %, while at the same time the infection level was below 1 %. 58 days after inoculation significant changes between the control and the treatment 50 % could be obtained in the visible and near infrared wavelength rage. At this time the control had an infection level of 0 % powdery mildew, the treatment 50 % of 5.7 % and the treatment 100 % of 7 % powdery mildew.

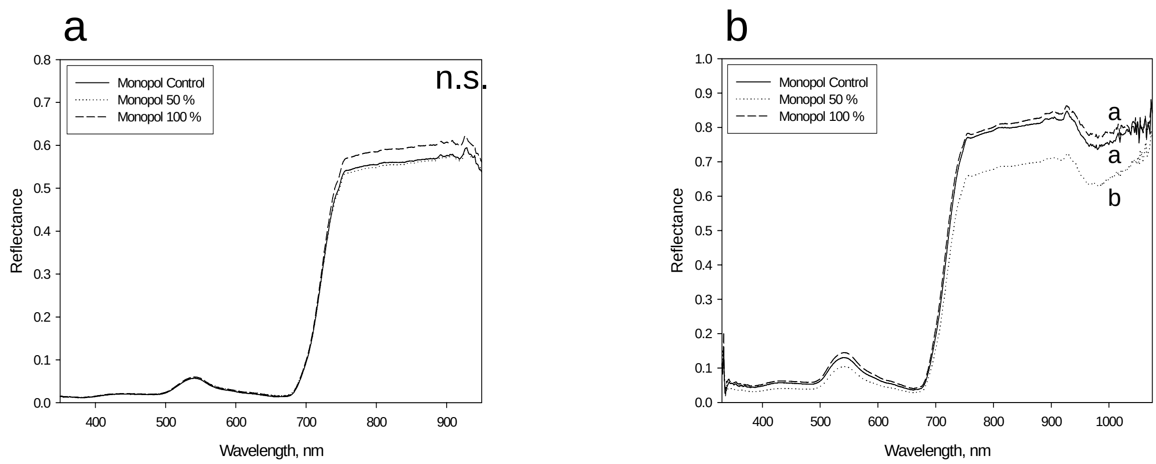

Figure 7. Canopy reflectance under powdery mildew for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Monopol (a) 4 days and (b) 58 days after inoculation for different inoculation levels (Differences between treatments are indicated by different letters).

Figure 8 shows the canopy reflectance under powdery mildew for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Empire four days (a) and 58 days (b) after inoculation. Four days after the inoculation no significant changes between the control and the treatments 50 % and 100 % could be detected. At this time there was no infection with powdery mildew visible. Also 58 days after inoculation no differences between healthy and diseased plants could be obtained. At this time the control had an infection level of 0 % powdery mildew, the treatment 50 % of 1.7 % and the treatment 100 % of 2.3 % powdery mildew.

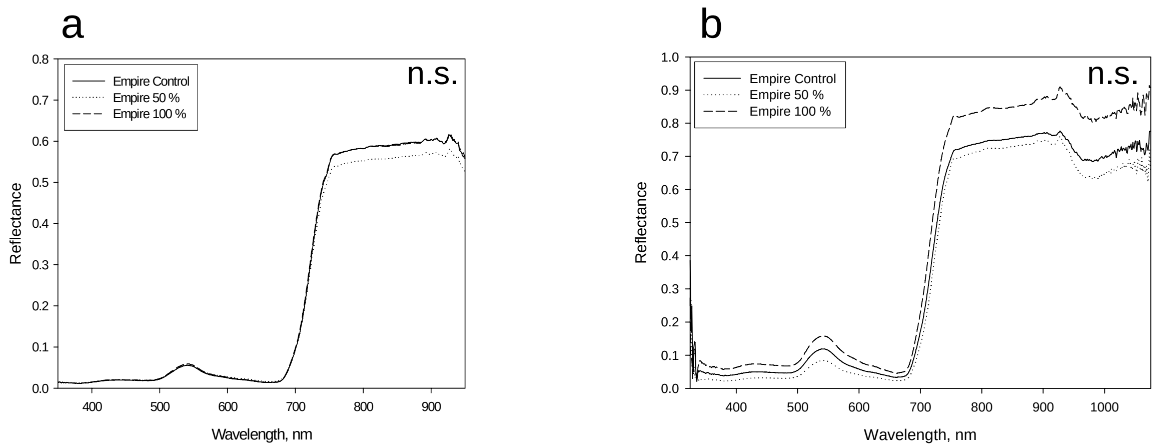

Figure 8. Canopy reflectance under powdery mildew for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Empire (a) 4 days and (b) 58 days after inoculation for different inoculation levels (Differences in the reflectance are marked with different letters).

In general, the susceptible variety Monopol showed significant differences between the control and the treatments 50 % and 100 % especially in the wavelength range 750-950 nm. Reflectance of diseased plants decreased under powdery mildew infection. The higher the infection level, the more the reflectance decreased. The variety Empire did not show any significant changes due to a very low infection level of 3.7 %.

3.4.2 Septoria leaf blotch

Figure 9 shows the canopy reflectance under septoria leaf blotch for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Monopol 4 days (a), 22 days (b) and 48 days (c) after inoculation. At an infection level of 2.3 % for the control, 2.7 % for the treatment 50 % and 2 % for the treatment 100 % the reflectance of the treatments 50 % and 100 % laid clearly beyond the reflectance of the control and significant changes could be detected. The differences between the reflectance curve of the control and the treatments 50 % and 100 % were about 0.4 in the wavelength range round 550 nm and 750-1075 nm. On the other two measurement dates no significant changes could be obtained between the treatments.

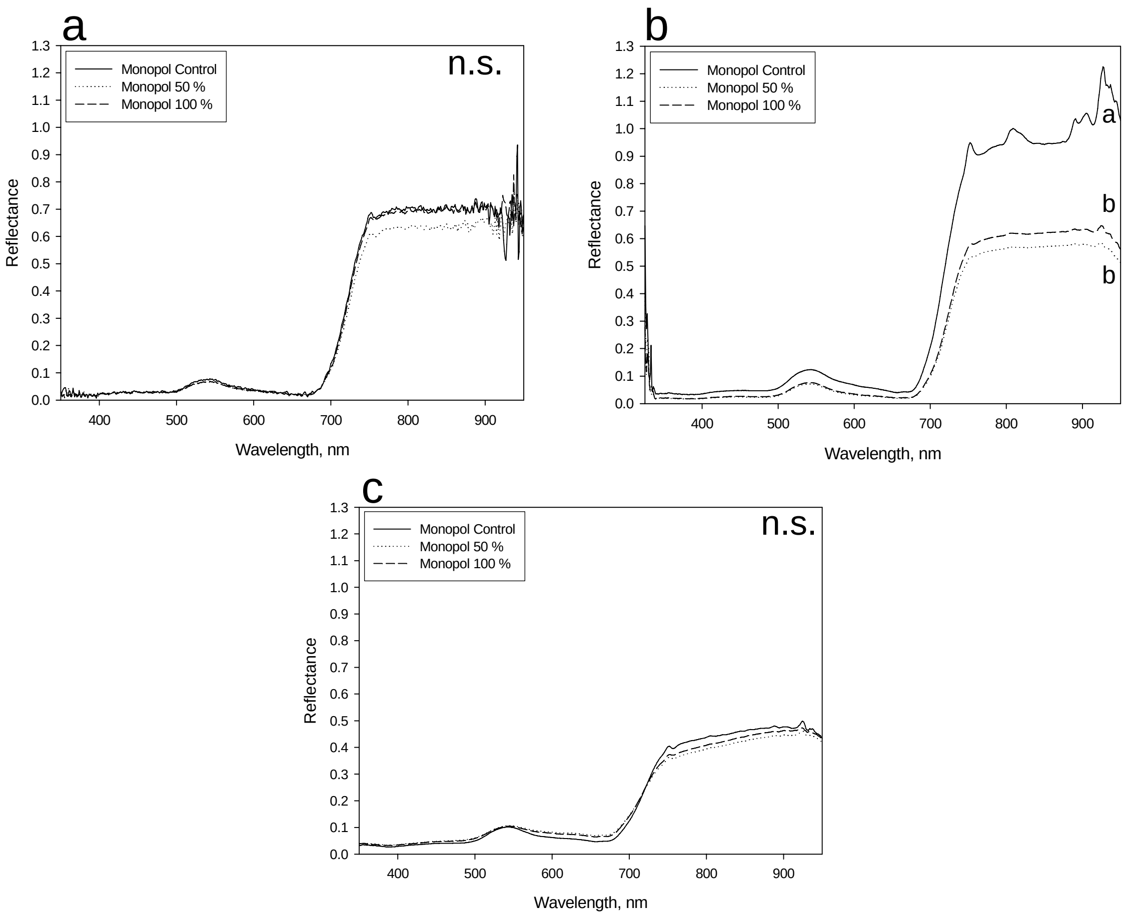

Figure 9. Canopy reflectance under septoria leaf blotch for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Monopol (a) 4 days, (b) 22 days and (c) 48 days after inoculation for different inoculation levels (Differences in the reflectance are marked with different letters)

Figure 10 shows the canopy reflectance under septoria leaf blotch for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Empire 4 days (a), 22 days (b) and 48 days (c) after inoculation. At all measurement dates the reflectance of the treatments 50 % and 100 % was lower than the reflectance of the control especially in the infrared wavelength range. At all measurement dates no significant changes could be detected between the reflectance of the control and the treatments 50 % and 100 % because the infection level was too low for the resistant variety Empire. The infection level rose only to 7.7 % septoria leaf blotch for the control, 18 % for the treatment 50 % and 23.3 % for the treatment 100 %.

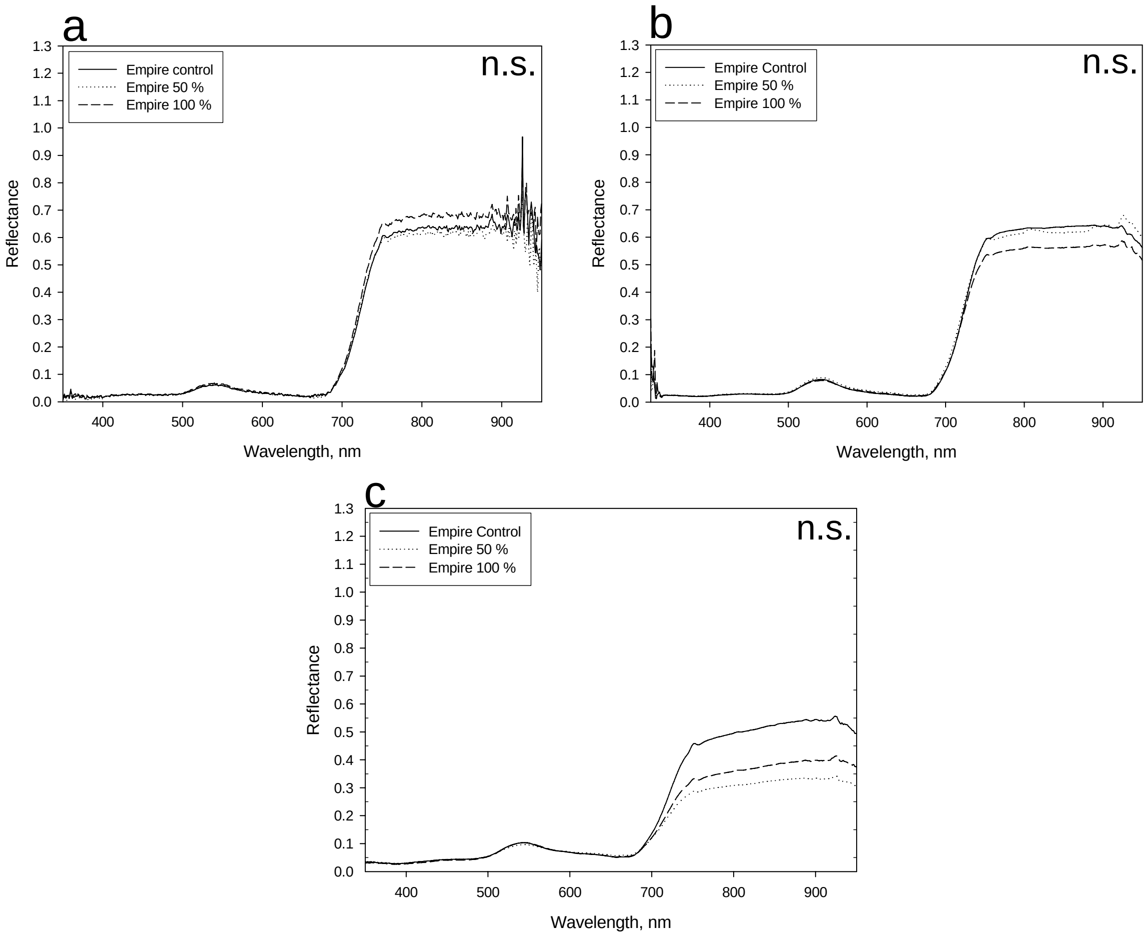

Figure 10. Canopy reflectance under septoria leaf blotch for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Empire (a) 4 days, (b) 22 days and (c) 48 days after inoculation for different inoculation levels (Differences in the reflectance are marked with different letters).

Comparing the results of the variety Monopol with the results of the variety Empire it was evident that significant changes could only be obtained for the variety Monopol 22 days after inoculation. In general the reflectance decreased under disease infection.

3.4.3 Mixed infection

Figure 11 shows the canopy reflectance under powdery mildew and septoria leaf blotch for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Monopol 76 days (a) and 84 days (b) after inoculation.76 days after inoculation significant changes between the control and the two treatments could be detected. The reflectance of the treatments 50 % and 100 % was about 0.1 lower than the reflectance of the control especially in the wavelength range 750-950 nm. 76 days after inoculation the control had an infection level of 0 % powdery mildew and 4.3 % septoria leaf blotch, the treatment 50 % of 7 % powdery mildew and 14.7 % septoria leaf blotch and the treatment 100 % of 11.3 % powdery mildew and 18.3 % septoria leaf blotch. 84 days after inoculation there were significant changes between the control and the treatment 50 % and 100 %. The control had an infection level of 0.3 % powdery mildew and 3.3 % septoria leaf blotch, the treatment 50 % of 7 % powdery mildew and 14 % septoria leaf blotch and the treatment 100 % of 6.7 % powdery mildew and 15.3 % septoria leaf blotch. Reflectance changes occurred especially in the wavelength range 750-950 nm.

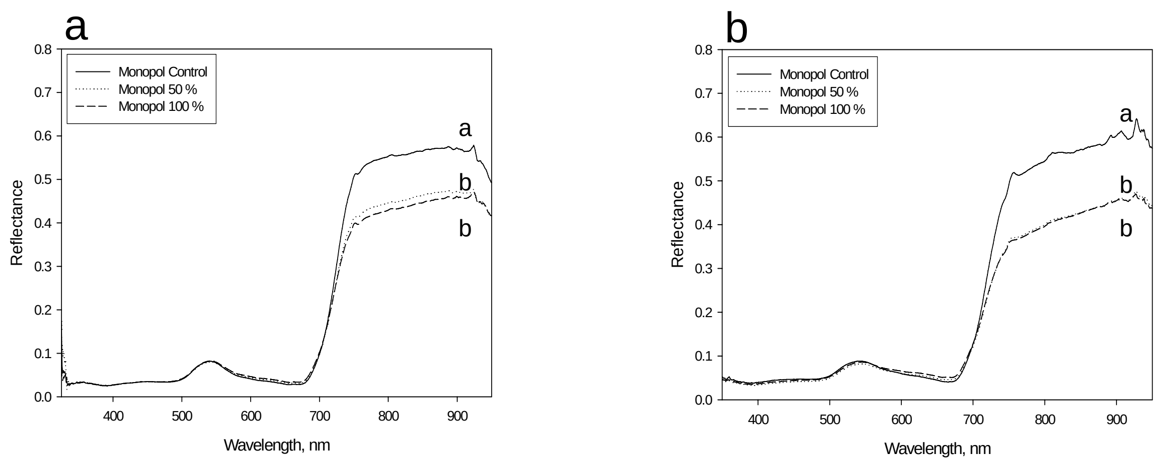

Figure 11. Canopy reflectance under powdery mildew and septoria leaf blotch for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Monopol (a) 76 days and (b) 84 days after inoculation for different inoculation levels (Differences in the reflectance are marked with different letters).

Figure 12 shows the canopy reflectance under powdery mildew and septoria leaf blotch for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Empire 76 days (a) and 84 days (b) after inoculation. 76 and 84 days after inoculation no significant changes could be detected between the reflectance of the control and the treatments 50 % and 100 % because the infection level was too low for the resistant variety Empire. The infection level rose only to 3.7 % powdery mildew and 11 % septoria leaf blotch for the treatment 50 % and 3.3 % powdery mildew and 13.7 % septoria leaf blotch for the treatment 100 %.

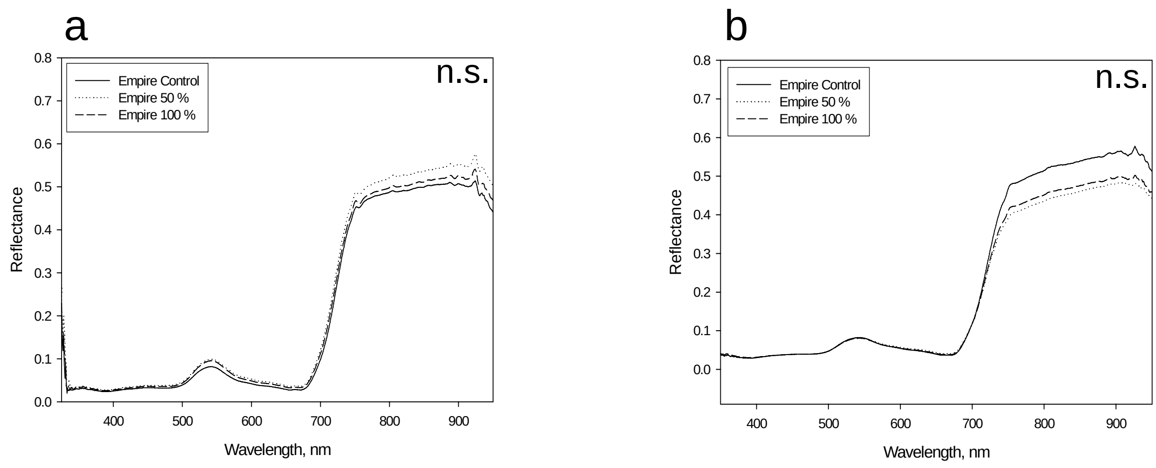

Figure 12. Canopy reflectance under powdery mildew and septoria leaf blotch for the treatments control (….), 50 % (----) and 100 % (- -) measured with the spectroradiometer for the variety Empire (a) 76 days and (b) 84 days after inoculation for different inoculation levels (Differences in the reflectance are marked with different letters).

Comparing the results of the vegetation indices with the reflectance measurements for powdery mildew the vegetation index REIP was able to detect an early infection with powdery mildew at an infection level of 7% for the variety Monopol. Also the vegetation indices NDVI and HVI were able to detect an infection of 7.7 % powdery mildew. Reflectance changes for the variety Monopol could be obtained at an infection level of 5.7 %. For the variety Empire the vegetation index REIP was the best index to detect changes between the healthy and infected plants. REIP was able to detect an infection with powdery mildew at an infection level of 3.7 %. The reflectance measurements showed no significant differences at this infection level.

For septoria leaf blotch the vegetation index RVSI detected significant changes between healthy and diseased plants at an infection level of 13.7 % for the variety Monopol and 18 % for the variety Empire. The reflectance measurements only indicated significant differences at the second measurement date at an infection level of 2.7 % septoria leaf blotch.

For the mixed infection the vegetation indices REIP, NDVI, HNDVI and HVI were able to detect differences at an infection level of 7 % powdery mildew and 14.7 % septoria leaf blotch for the variety Monopol and of 7 % powdery mildew and 14 % septoria leaf blotch for the variety Empire. At this infection level also the reflectance measurements indicated significant changes between the control and the treatments 50 % and 100 %.

As the tested vegetation indices were not able to detect an early infection of septoria leaf blotch a further aim of this study was to develop a vegetation index which is able to detect an early infection with septoria leaf blotch. The results of reflectance changes measured with the fieldspectrometer clearly indicated reflectance changes especially in the wavelength range 750-950 nm (near infrared). None of the tested vegetation index included the near-infrared part of the spectra. Hence a new vegetation index was developed for disease infection including the wavelength ranges 750-950 nm. Table 3 shows the results of the developed and tested "Disease Infection Index" (DII):

$DII = R_{750}/R_{850}$

where

R750 reflectance at 750 nm [%]

R850 reflectance at 850 nm [%]

Table 3 shows the "Disease Infection Index" (DII) 28, 40 and 48 days after inoculation for the varieties Monopol and Empire inoculated with septoria leaf blotch. Compared to the results in Table 2 the new vegetation index identified significant changes for the variety Monopol between the control and the treatment 50 % and 100 % 28 days after inoculation which is earlier than with any other vegetation index tested in this article. 28 days after inoculation the control had an infection level of 3 %, the treatment 50 % of 6.5 % and the treatment 100 % of 4 % septoria leaf blotch.

For the variety Empire no significant changes could be detected with the new index DII because of the low infection level of the resistant variety Empire.

The developed index can not be applied to powdery mildew infection, as reflectance changes occur under powdery mildew infection especially in the visible wavelength range due to pigmental changes. The developed 'Disease Infection Index' however includes only the infrared wavelength range due to structural changes under septoria leaf blotch.

Table 3. "Disease Infection Index" (DII) 28, 40 and 48 days after inoculation for the varieties Monopol and Empire inoculated with septoria leaf blotch. Significances are indicated between vegetation indices with different letters.

	DIII		
dai *	28	40	48
Monopol Control	0.91 a	0.91 a	0.85 a
Monopol 50 %	0.90 **b**	0.87 **b**	0.84 **b**
Monopol 100 %	0.89 **b**	0.88 **b**	0.84 **b**
Empire Control	0.91 a	0.91 a	0.86 a
Empire 50 %	0.92 a	0.89 a	0.88 a
Empire 100 %	0.92 a	0.89 a	0.85 a

4. Discussion

Currently inputs (fertilizer, pesticides, fungicides) are still applied uniformly over the field despite numerous variations in the soil type, crop density, or disease pressure. Recent developments made it possible to spatially apply farm applications (Secher, 1997) using remote sensing technologies. Up to now, little research has been carried out investigating, reflectance changes of plants due to plant diseases. In this study the potential of reflectance measurements and the use of vegetation indices as a tool for identifying, quantifying and discriminating different plant diseases have been assessed.

The results of this study showed that the reflectance of diseased plants was significantly reduced in the visible and near-infrared spectra when compared to healthy plants. Reflectance changes occurred at an infection level of > 6 % under powdery mildew infection in the wavelength range 750-950 nm. Septoria leaf blotch could be detected at an infection level > 4 % in the wavelength ranges round 550 nm and 750-950 nm.

Studies of (Sasaki et al., 1998) also indicated reflectance changes in the violet-blue and NIR wavebands (380-450 nm and 750-1200 nm) of cucumber leaves due to an infection with the fungus *Colletotrichum orbiculare*. Polischuk et al. (1997) also made an early diagnosis of tomato mosaic tobamovirus infection in *Nicotiana debneyi* plants using spectral reflectance. Reduced chlorophyll in the leaves was detected within 10 days of inoculation, but it took three weeks for visible changes to be observed. Lorenzen and Jensen (1989) obtained similar results on barley leaves infected by cereal powdery mildew. They found out that six days after inoculation, susceptible lines showed significantly higher reflectance in the visible (422-712 nm) wavelength region when compared to control plants. They also analyzed a relationship between the increasing reflectance and the decreasing chlorophyll contend and the increasing dry matter ratio of inoculated plants. They found out that the differences in reflectance of blue and red wavebands between control and inoculated plants were highly correlated to the chlorophyll content of infected plants. Significant changes in spectral reflectance of single leaves infected with mildew occur earlier in the visible region of the spectrum (400-706) than in the near infrared part of the spectrum. Also Franke et al. (2005) detected leaf rust on wheat plants five days after inoculation with a hyperspectral sensor in the visible wavelength range. Moshou et al. (2005) showed that optical techniques have the potential to discriminate between diseased and healthy plants. In general healthy plants typically exhibit low reflectance in the visible range of the spectra due to strong absorption by photoactive pigments (chlorophyll, anthocyanins, carotenoids) and high reflectance in the NIR due to multiple scattering at the air-cell interfaces in the leaf internal tissue. Conversely biomass reduction linked to senescence reduced growth and defoliation decreases the canopy reflectance in the NIR band. This fact can particularly be fount for septoria leaf blotch. Because of the fact, that powdery mildew does not lead in the beginning of an infection to structural damages but to reduction of chlorophyll and a change of secondary metabolites in the leaves reflectance changes are expected to appear in the visible wavelength range.

Under powdery mildew changes in the reflectance can especially be found in the region round 550 nm (Groell et al., 2007) and in the wavelength range 750-1075 nm. Also Lorenzen and Jensen (1989) showed that changes between healthy and with powdery mildew infected barley plants could especially be detected in the chlorophyll absorption wavelength ranges round 498 and 664. In a study of metabolic regulation in mildewed barley leaves, Scott and Smillie (1966) observed that, 48 h after inoculation with mildew, photosynthetic rate and chlorophyll content began to decline and the respiratory rate started to increase. When the fungus starts to sporulate, the host tissue may become chlorotic. Subsequently infected cells or cells close to infected ones begin senescence. That’s why we obtained reflectance changes not only in the visible but also in the near infrared wavelength range.

Malthus and Madeira (1993) showed in a greenhouse experiment 1989 in Nottingham with leaves of field beans cv. Tricol infected with the necrotroph fungus *Botrytis fabae*, like septoria leaf blotch, that reflectance changes appear first in the wavelength range 800 nm in connection with visible symptoms. The reduction of the reflectance in the infrared wavelength range is explained with the destruction of the leaf structure while the fungus developed. Thus it came to a reduction of the radiation dispersion within the leaf tissue and an increase of the transmission in this area (Knipling, 1970). Symptomatic for septoria leaf blotch are necrosis in the form of yellow leaf blotches which turn in the course of disease brown in the centre and get black pycnidia. If the infection is very high it may come to a drop of the leaves. At infection with septoria leaf blotch it comes to a proceeding colonization of the host tissue, cell damage and accumulation of pycnidia (Eyal, 1987, King et al., 1983). According to Gates et al., 1965, is the reflectance in the infrared wavelength range mainly influenced by structural changes in the leaves. Also Malthus and Madeira, 1993, show in their study of with *Botrytis fabae* infected field beans that the reflectance of diseased plants declined in the infrared wavelength range. The highest differences could be obtained in the wavelength range round 800 nm. They traced the results back to damages of the leaf tissue with increasing fungus infection.

As the primary effects of different diseases vary by chlorophyll, water, leaf and cell structure ore temperature effects, different wavebands are suitable for detection of different diseases (Dudka et al, 1998). Out of this fact and the results each disease need its own vegetation index including the wavelength ranges in witch reflectance changes appear. The results of this study showed that for the disease powdery mildew the vegetation index REIP was the best index for both varieties and all treatments. Also the indices NDVI and HVI were suitable but they were not able to detect changes as early as the index REIP. These indices were able to detect significant differences between healthy and with powdery mildew infected plants, because they combine the visible and the near-infrared wavelength range. But these indices weren't able to detect septoria leaf blotch so another index for septoria leaf blotch is needed.

Septoria leaf blotch couldn't be identified as early as powdery mildew with the "old" indices because the vegetation indices include the visible and the near-infrared region of the reflectance whereas reflectance changes under Septoria leaf blotch especially appear in the wavelength range 750-1075 nm. Thus to include the visible wavelength range falsified the results of the vegetation indices. That's why the index RVSI was the best index to identify Septoria leaf blotch because it includes the wavelength ranges 714, 733 and 752. But out of the results shown in this article we created a new vegetation index that includes the wavelength 750 and 850 nm to detect septoria leaf blotch in an early stage of infection. As it is shown before, under septoria leaf blotch especially the structure of the cells and the tissue is being damaged by the fungus and therefore reflectance changes appear in the infrared wavelength range especially in the range 750-950 nm as it is shown in the results. Our "new" vegetation index DII showed good results for the Variety Monopol and was able to detect septoria leaf blotch at an infection level of 4 % as the index combined only the wavelength ranges in which significant changes would be expected.

5. Conclusion

The results of this study indicated that under plant diseases the reflectance of diseased plants were lower than the reflectance of healthy plants. Further, it was possible to identify significant differences at an infection level of 7 % powdery mildew and 4 % septoria leaf blotch. The vegetation index REIP was able to detect an early infection with powdery mildew at an infection level of 7 %. Also the indices NDVI and HVI were suitable to detect powdery mildew but they were not able to detect changes as early as the index REIP. The vegetation index RVSI was able to detect septoria leaf blotch at an infection level of 13.7 %. The developed new vegetation index DII of this study was able to identify septoria leaf blotch at an infection level of 4 % with was earlier than with the "old" vegetation indices. The presented basic work show the potential of sensing site-specific disease infestation and for side-specific fungicide spraying coupled with precision farming systems.

6. Acknowledgements

The German Federal Ministry of Education and Research financed this project through their program on precision agriculture No. 0330661. The responsibility for the content of the paper is with the author.

References

Adams M.L., Philpot W.D., Norvell W.A., "Yellowness index: an application of spectral second derivatives to estimate chlorosis of leaves in stressed vegetation", Int. J. Rem. Sens., 1999, 20, 3663-3675.

Blackmer, T.M., Schepers, J.S., Varvel, G.E., Meyer, G.E., "Analysis of aerial photography for nitrogen stress within corn fields", Agronomy Journal, 1996, 88, 729-733

Brown J.S., Kellbock A.W., Paddick R.G., "Distribution and dissemination of *Mycosphaerella graminicola* (Fuckel) Schroeter in relation to the epidemiology of speckled leaf blotch of wheat", Aust. J. Agric. Res., 1978, 29, 1139-1145.

Brown J.S., Paddick R.G., "Surveys of speckled leaf blotch and other foliar diseases of wheat in Victoria, 1974-1978", Aus. J. Exp. Acric. Anim. Husb., 1982, 20, 94-96.

Bundessortenamt, Beschreibende Sortenliste. Landbuch Verlagsgesellschaft mbH, Hannover, Germany, 2005.

Buschmann C., Nagel E., "In vivo spectroscopy and internal optics of leaves as basis for remote sensing of vegetation", Int. J. Remote Sensing, 1993, 14(4), 711-722.

Caldwell R.M., "Development of the wheat *Septoria* blight problem in the USA over the period 1922 to 1975", Proc. Septoria Diseases of Wheat Workshop. B.M. Cunfer and L.R. Nelson, eds. Georgia Agric. Exp. Sta. Spec., 1976, 4, 3-6.

Coakley S.M., McDaniel L.R., Shaner G., "Model for predicting severity of Septoria tritici blotch and winter wheat", Phytopath., 1985, 75, 1245-1251.

Cook B.M., Jones D.G., "Epidemiology of *Septoria tritici* and *S. nodorum*_I. The reaction of spring and winter wheat varieties to infection by *Septoria tritici* and *Septoria nodorum*", Trans. Br. Mycol. Soc., 1971, 56, 121-125.

Dammer K.H., "Analyse und Darstellung der Dispersion von Schaderregern sowie Möglichkeiten der Stickprobennahme bei aggregiertem Auftreten (Analysis and Dispersion maps of pests and sampling design under their aggregated pattern)", Habil. Kropstädt, Germany, 1999.

Daughtry C.S.T., Walthall C.L., Kim M.S., Brown de Colstoun E., Mc Murtrey III J.E., "Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance", Rem. Sens. Environ., 2000, 74, 229-239.

Dudka M., Langton S.J., Schuler R.T., Kurle J., Grau C.R., "Use of digital imagery to evaluate disease incidence and yield loss caused by Sclerotinia Stem Rot of Soybeans", Proc. Int. Precision Agric. Conf., St. Paul, 1998.

Dumas A., "Stickstoffbestimmung nach Dumas". Die Praxis des organischen Chemikers, 1962, 41, 45-51.

Eyal Z., Scharen A.L., Prescott J.M., Ginkel M. Van, "The Septoria diseases of wheat", Concepts and methods of disease management. CIMMYT. 1987, Mexico.

Filella, I., Penuelas, J., "The red edge position and shape as indicators of plant chlorophyll content, biomass and hydric status", International Journal of Remote Sensing, 1994, 15(7), 1459-1470.

Fleischer S.J., Blom P.E., Weisz R., "Sampling in precision IPM: When the objective is a map", Phytopath., 1999, 75, 538-542.

Franke J., Menz G., Oerke E.-C., Rascher U., "Comparison of multi- and hyperspectral imaging data of leaf rust infected wheat plants", Proceedings of the SPIE, 2005, 5976, 349-359.

Gates D.M., Keegan H.J., Schleter J.C., Weidner V.R., "Spectral properties of plants", Appl. Opt., 1965, 4, 11-20.

Gerhards R., Christensen S., "Real time weed detection, decision making and patch spraying in maize (Zea mays L.), sugar beet (Beta vulgaris L.), winter wheat (Triticum aestivum L.) and winter barley (Hordeum vulgare L.)", Weed Research, 2003, 43, 1-8.

Groell K., Graeff S., Claupein W., Spectral identification of powdery mildew (Erysiphe graminis) in wheat using digital image analysis, Phytopathology, submitted.

Guyot G., Baret F., Major D.J., "High spectral resolution: Determination of spectral shifts between the red and the near infrared", International Archives of Photogrammetry and Remote Sensing, 1988, 11, 750-760.

Haboudane D., Miller J.R., Tremblay N., Zarco-Tejada P.J., Dextraze L., "Integration of hyperspectral vegetation indices for prediction of crop chlorophyll content for application to precision agriculture" Rem. Sens. Environ., 2002, 81, 416-426.

Hansen J.G., "Use of multispectral radiometry in wheat yellow rust experiments", Bulletin EPPO, 1991, 21, 651-658.

Hess D.E., Shaner G., "Effect of moisture and temperature on development of Septoria tritici blotch in wheat", Phytopath., 1987a, 77, 215-219.

Hess D.E., Shaner G., "Effect of moisture on Septoria tritici blotch development on wheat in the field", Phytopath., 1987b, 77, 220-226.

Huete A.R., "A soil-adjusted vegetation index (SAVI", Rem. Sens. Environ., 1988, 25, 295-309.

King, J.E. Cook J. R., Melville S. C., "A review of Septoria diseases of wheat and barley", Ann Appl. Biol., 1983, 103, 345-373.

Knippling E. B., "Physical and physiological basis for the reflectance of visible and near- infrared radiation vegetation", Remote Sensing of Environment, 1970, 1, 155- 159.

Larsolle A., Muhammed H. Hamid, "Measuring crop status using multivariate analysis of hyperspectral field reflectance with application to disease severity and plant density", Precision Agriculture, 2005, 217-225.

Last F.T., "Some effects of temperature and nitrogen supply on Wheat Powdery mildew", Ann. Appl. Biol., 1953, 40, 312-322.

Laudien R., Bareth G., Doluschitz R., "Analysis of hyperspectral field data for detection of sugar beet diseases", EFITA 2003 Conference Debrecen, Hungary, 2003, 375-381.

Laudien R., Bareth G., Doluschitz R., "Comparison of remote sensing based analysis of crop diseases by using high resolution multispectral and hyperspectral data –case study: Rhizoctonia solani in sugar beet-", Geoinformatics 2004, University of Gävle, Sweden, 2004, 270-276.

Lorenzen B., Jensen A., "Changes in spectral properties induced in barley by cereal powdery mildew", Rem. Sens. Environ., 1989, 27, 201-209.

Ludowicy C., Schwaibinger R., Leithold P., "Precision Farming – Handbuch für die Praxis. DLG Verlags GmbH, Frankfurt am Main, 2002.

Malthus T. J., Madeira A.C., "High resolution spectroradiometry: spectral reflectance of field bean leaves Infected by Botrytis fabae", Remote Sens. Environ., 1993, 45, 107- 116.

Merton R., "Monitoring community hysteresis using spectral shift analysis and the red-edge vegetation stress index", Proceedings of the Seventh Annual JPL Airborne Earth Science Workshop, NASA, California, USA, 1998.

Metternicht G., "Vegetation indices derived from high-resolution airborne videography for precision crop management", Int. J. Rem. Sens., 2003, 24, 2855-2877.

Moshou D., Bravo C., West J., Wahlen S., McCartney A., Ramon H., "Automatic detection of 'yellow rust' in wheat using reflectance measurements and neutral networks", Computers and Electronics in Agriculture, 2004, 44, 173-188.

Moshou D., Bravo C., Oberti R., West J., Bodria L., McCartney A., Ramon H., "Plant disease detection based on data fusion of hyper-spectral and multi-spectral fluorescence imaging using Kohonen maps", Real Time imaging, 2005, 11, 75-83.

Murray G.M., "Yield losses in wheat associated with different levels of resistance to speckled leaf blotch (*Mycosphaerella graminicola*)", Acron. Aust., 1982, 242.

Oerke E.-C., Dehne H.-W., Schönbeck F., Weber A., "Crop production and crop protection – estimated losses in major food and cash crops", Elsevier Science, Amsterdam, The Netherlands, 1994, 808.

Oliver M.A., Heming S.D., Gibson G., Adams N., "Exploring the spatial variation of take-all (*Gaeumannomyces graminis* var. *tritici*) for site-specific management", Precision Agriculture, Proceedings of the 4th European Conference on Precision Agriculture, J. Stafford, A. Werner (eds.) Wageningen Academic Publishers, Wageningen, The Netherlands, 2003, 481-486.

Oppelt N., "Monitoring of plant chlorophyll a nitrogen status using the airborne imaging spectrometer AVIS", Ludwig-Maximilians-Universität, Dissertation, 2002.

Penuelas J., Gamon J.A., Fredeen A.L., Merino J., Field C.B., "Reflectance indices associated with physiological chances in nitrogen- and water-limited sunflower leafs", Rem. Sens. Environ., 1994, 48, 135-146.

Plank J.E. van der, "Plant disease: Epidemics and control", Academic Press London, UK, 1963.

Polischuk V.P., Schadchina T.M., Kompanetz T.I., Budzanivskaya I.G., Sozinov A.L., "Changes in reflectance spectrum characteristic of *Nicotiana debneyi* plant under the influence of viral infection", Arch. Phytopathol. Plant Prot., 1997, 31, 115-119.

Rouse J.W., Haas R.H., Schell J.A., Deering D.W., "Monitoring vegetation systems in the great plains with ERTS", Third ERTS Symposium, NASA SP-351, NASA, Washington, DC, 1973, 1, 309-317.

Royle J.D., Shaw M.W., Cook R.J., "Patterns of development of *Septoria nodorum* and *Septoria tritici* in some winter wheat crops in Western Europe, 1981-83", Plant Pathol., 1986, 35, 466-476.

Sasaki Y., Okamoto T., Imo K., Torii T., "Automatic diagnosis of plant disease: spectral reflectance of healthy and diseases leaves", Proceedings AgEng'98 Conference, Oslo, 1998, 6.

Sasaki Y., Okamoto T., Imo K., Torii T., "Automatic Diagnosis of Plant Disease. Recognition between Healthy and Diseased Leaf", Journal of the Japanese Society of Agricultural Machinery, 1999, 61/2, 119-126.

Scott K.J., Smillie R.M., "Metabolic regulations in diseased leaves. The respiratory rise in barley leaves infected with powdery mildew", Plant Physiol., 1966, 41, 289- 297.

Secher B.J.M., "Side specific control of disease in winter wheat", Aspects App. Biol., 1997, 48, 57-64.

Shaner G., Finney R.E., "Weather and epidemics of Septoria leaf blotch of wheat", Phytopath., 1976, 66, 781-785.

Shipton W.A., Boyd W.R.J., Rosielle A.A., Shearer B.I., "The common Septoria diseases of wheat", Bot. Rev., 1971, 37, 231-162.

Thomas, J.R., Gausman, H.W., "Leaf reflectance vs. leaf chlorophyll and carotenoids concentrations for eight (vegetable and field) crops", Agronomy Journal, 1977, 69 (5), 799-802.

West J.S., Oberti C., Lemaire R., Moshou D., McCartney H.A., “The potential of optical canopy measurement for targeted control of field crop diseases”, Annu. Rev. Phytopath., 2003, 41, 593-614

Wiese M.V., “Compendium of Wheat Diseases”, 2nd Edn., APS Press, St. Paul, Minn., 1987.

Zadoks J.C., Chang T.T., Konzak C.F., “A decimal code for the grown stage of cereals”, Weed Research, 1974, 14, 415-421.

The aim of the third article was to test different common vegetation indices for the detection of the diseases powdery mildew and septoria leaf blotch. Therefore field experiments were carried out in winter wheat and the reflectance changes due to the two diseases were measured with a spectroradiometer.

The results indicated that the common vegetation index REIP was able to detect powdery mildew at an infection level of 7 %. For the identification of septoria leaf blotch no common vegetation index could be found to detect an early infection. Out of this the new vegetation index DII was developed, able to detect septoria leaf blotch at an infection level of 4 %.

In the course of this work we noticed that not only the right wavelength range and the measuring place but also the spatial resolution is important for the identification of plant diseases. According to this the aim of the forth article was to analyze which spatial resolution is necessary to detect plant diseases within the field.

Sensor-based identification of plant diseases: requirements of spatial resolution

Kerstin Gröll[1], Simone Graeff[1], Wilhelm Claupein[1]

[1] Institute of Crop Production and Grassland Research (340), University of Hohenheim

Fruwirthstr.23, 70599 Stuttgart, Germany

e-mail: groell@uni-hohenheim.de

Abstract

Today's agriculture is not only confronted with the production of food and animal food, but also with aspects of environmental protection and therefore with the reduction of pesticides. Disease control might be more efficient if disease patches within fields can be identified and fungicides applied only to infected areas. Recent developments in optical sensor technologies indicate the potential to enable direct detection of foliar diseases under field conditions, but no sensor system is put into practice yet. The aim of this study was to test different sensor systems at different scales from leaf level to canopy level for their ability to identify septoria leaf blotch (*Septoria tritici*) in an early stage of infection in winter wheat. A field experiment was conducted during the growing periods of 2006 and 2007 at the experimental station "Ihinger Hof" (48°44´ N, 8°56´E; 693 mm, 8.1 °C) of the University of Hohenheim, Stuttgart, Germany. The trials were treated with three different fungicide doses. Plant reflectance was measured weekly from EC 51 with a digital camera (LEICA S1 PRO, LEICA Kamera AG, Solms, Germany) at leaf scale (0.5 cm²) and with the spectroradiometer Field Spec® Hand Held (ASD, Inc. Boulder, CO, USA) (0.5 m²) and the Yara N-Sensor in the field-scan modus (12 m²) 2 m above the canopy. With the digital camera LEICA S1 PRO an identification and quantification of septoria leaf blotch was possible at an early stage of infection in the wavelength ranges 490-510 nm and 490-510 IR. With the Field Spec® Hand Held an identification of septoria leaf blotch was also possible at an early stage of infection especially in the infrared wavelength range. Because of the information lost due to the spatial resolution a quantification was not possible. The N-Sensor couldn't detect and quantify changes in the reflectance under septoria leaf blotch because of the low spatial resolution. Thus sensor systems with a high spatial resolution are able to detect and quantify plant diseases side specific.

Keywords: plant diseases, spatial distribution, remote sensing, wheat

1. Introduction

The maximum yield of plants, determined by their genetic potential, is seldom achieved. Factors such as insufficient water or nutrients, adverse climatic conditions, plant diseases, and insect damage limit growth and final yield at some stage. Especially plant diseases are one of the main reasons for yield loss. Approximately 30 % of the world harvest is lost on an annual basis due to biotic stress factors (Habermeyer et al., 2000). The most widely used method in pest and disease control in arable crops is still to spray pesticides uniformly over fields at different times during the cultivation cycle, as up suitable sensor technologies for the detection of plant diseases are widely missing. Further, most disease infestations are not evenly distributed across the field and occur in patches. Pesticides should be targeted only on those places in the field where they are needed.

Beside the identification of pathogens, spatial dispersion and distribution pattern play a decisive role for pesticide application. Different studies show that plant diseases like septoria leaf blotch show a spatial stability and that there is a well-defined connection between site-related factors and the appearance of plant diseases (Campbell and Noe, 1985; Spickermann, 2005). Factors like surface moisture, surface temperature, leaf wetness duration, which are strongly correlated with differences in soil, leaf area index, micro climate and the supply of the plant with nitrogen, might play a major role in the spatial occurrence of these patterns. Information about the spatial pattern of diseases is important, because it may help to explain the complex dynamics of pathosystems, and may help to design site-specific management strategies for fungicide application.

Remote sensing data and techniques have already proven to be relevant to many requirements of crop inventory and monitoring. Nowadays, there is an increased interest in precision farming and the development of smart systems for agricultural resources management. These relatively new approaches aim to increase the productivity, to optimize the profitability, and to protect the environment. More specifically, farmers and agricultural managers are interested in measuring and assessing soil and crop status at specific critical times: first, in earlier growth stages in order to supply adequate fertilizers quantities for a normal growth of the crop, and second, during an advanced development stage for health monitoring and the prediction of yield. For this purpose, remote sensing can play a valuable role in providing time-specific and time-critical information for precision farming, due to the capabilities in measuring biophysical parameters and detecting their spatial variability (Haboudane et al., 2002).

The initial point for a site-specific application of pesticides is the consideration that plant diseases are not uniformly dispersed over a field. The basis for a site-specific application of pesticides is however the spatial registration of the pathogens. Currently, there are no sensor systems available to identify and quantify the disease pressure on-the-go. At the market available optical sensor systems like the Yara-N-Sensor or multi-spectral cameras can be used for the detection of plant stress factors like for example nutrient- or water deficiency, but they are currently not suitable for the detection of plant diseases. In terms of sustainable land cultivation it is necessary to develop sensor systems that can identify and quantify plant diseases and on this basis to enable a spatial regulation of the pesticide application.

Leaf blotch (*Septoria tritici*) caused by the fungus *Mycosphaerella graminicola* (Fuckel) Schroeter, is a major necrotic leaf disease of wheat (*Triticum aestivum* L.). Where environmental conditions are favorable for disease development, yield losses ranging from 20 to 43 % have been reported (Cooke and Jones, 1971, Caldwell, 1976). Leaf blotch can reduce the economic value of wheat by decreasing both grain yield and quality. Test weight, a function of both kernel density and random kernel packing volume (Yamazaki and Briggle, 1969), and an initial indicator of grain quality, can be significantly affected by this disease. Reported reductions under natural infection reached 1680 kg (Caldwell and Narvaez, 1960). Yield loss is related to the leaf area killed by the pathogen (Brown et al., 1978). *Septoria tritici,* also known as necrotic blotch or speckled leaf blotch, is characterized by necrotic blotches that contain black or dark brown pycnidia. The disease has been reported worldwide, but is most severe in wheat production areas that have cool, wet growing seasons (Eyal et al., 1987, Holmes and Colhoun, 1975, Van Ginkel and Scharen, 1988). *Septoria tritici* pycnidiospores germinate on a suitable substrate when the plants are wet. Spores begin to germinate within 12 hours, and leaf penetration occurs after 24 hours. Moisture is required for all stages of infection: germination, penetration, development of the mycelium within the plant tissue and subsequent pycnidium formation (Browning, 1979; Hooker, 1957). The usual vertical progress of the disease from lower to upper leaves is affected by the distance between consecutive leaves. As a result, pycnidia often appear earlier on upper plant parts of dwarf cultivars than they do on leaves of taller cultivars (Eyal et al., 1987). The pathogen survives on wheat stubble (Shipton et al. 1971).

The aim of this study was to test and evaluate a) if septoria leaf blotch can be identified in an early infection stage by different passive sensor systems, b) if the infection can be quantified by the sensor systems in order to develop fungicide spraying decisions, c) which visible and infrared wavelength ranges are suitable to detect an infection and d) at which spatial scale (leaf, canopy,) and spatial resolution an identification of septoria leaf blotch may be possible.

Materials and Methods

Field experiment

The field experiment was carried out at the experimental station “Ihinger Hof” (48°44´ N, 8°56´E;) of the University of Hohenheim, Stuttgart, Germany. The mean annual temperature is 8.1 °C with 693 mm rainfall and 1845 sun hours per year. Winter wheat cv. Campari was planted on October 13th 2006 with a planting density of 300 kernels per m^2. The chosen soil type was a grey brown podzolic soil and the preceding crop was sugar-beet.

The plots were divided into three different fungicide application steps (0 %, 50 %, 100 %), in order to ensure a certain range in infection severity. The plots were treated at growth stage 32 with Opus Top® (Epoxiconazol + Fenpropimorph). The treatment 100 % was treated with 1.5 l ha^{-1} Opus Top® dissolved in 300 l water and the treatment 50 % was treatetd with 0.75 l ha^{-1} Opus Top® dissolved in 300 l water. The treatment 0 % did not receive a fungicide application. Disease infection was based on natural outbreak of diseases.

The trial was set up as randomized block design with four replications. The total trial had a size of 2000 m^2 and was divided into 12 plots with a size of 60 m x 12 m.

Sensor systems

Three different sensor systems were implemented to test their ability to identify septoria leaf blotch in an early infection stage. The tested sensor systems differed in scale and spatial resolution. Plant and leaf reflectance of diseased plants was taken in relevant growth stages from flag leaf stage until end of June. Measurements were taken with a digital camera (LEICA S1 PRO, LEICA Kamera AG, Solms, Germany) at leaf scale (0.5 cm^2) and with the spectroradiometer Field Spec® Hand Held (ASD, Inc. Boulder, CO, USA) (0.5 m^2) and the Yara N-Sensor (Yara, Germany) (12 m^2) 2 m above the plant surface.

Leaf scans were taken with a digital, light-sensitive (ISO 200-2400; spectral sensitivity of 250-1300 nm), high-spatial resolution (5140*5140 pixel) imager (LEICA S1 Pro, LEICA Kamera AG, Solms, Germany) (sensor 1). Reflectance spectra were taken without removing the leaf from the plant. The leaf to be measured was laid on a black aluminum plate mounted 15-20 cm away from the optics (1.28/60 mm, Leica, Germany) of the imager. The scanned surface area constituted for every measurement 1.9 x 1.1 cm. To exclude the effects of solar light as well as of stray background light the imager, light source and sample were surrounded by a black aluminum box.). The imager was used in conjunction with a constant light source (Reporter 21 D MicroSun, 21 W, Sachtler, Germany). The chosen light source was equipped with a 21 W daylight discharge bulb (Sachtler, Germany; color temperature 5500 – 6000 K), with produced more light than normal 50 W tungsten luminaries. By the use of different long-pass filters (Maier Photonics, Manchester, VT, USA) each leaf was measured in the visible wavelength ranges 380-780 nm, 490-780 nm, 510-780 nm, 516-780 nm, 540-780 nm and 600-780 nm. Also each leaf was scanned in the infrared wavelength ranges of 490-1300 nm, 510-1300 nm, 516-1300 nm, 540-1300 nm and 600-1300 nm. The long-pass filters had the following general specifications: 3 mm thickness, hard-oxide coating surface, quality 80/50 per MIL-O-13810A, coating quality 60/40 per MIL-O-13830A, and temperature limits – 50 to 100 °C.

The spectroradiometer Field Spec® Hand Held (ASD, Inc. Boulder, CO, USA) (sensor 2) measured the reflectance 2 m above the canopy. The FieldSpec Hand Held spectroradiometer measures the reflectance of a plant in the wavelength ranges 325 nm to 1075 nm with an interval of 1.6 nm and a viewing angle of 25 degrees. The measuring viewing angle (*a*) of 25 degrees causes a field of view (*A*) of 62 cm^2 with a field of view radius '(R) of 44 cm (equations 1 and 2) (Laudien et al., 2003).

$$R = h * \tan((\alpha/2) * \pi/180) \qquad (1)$$

$$A = \pi * r^2 \qquad (2)$$

As the spectroradiometer Field Spec® Hand Held has no own light source providing constant light conditions during the measurements, the incoming radiation was determined with a lux-meter (MAVOLUX 5032C/B USB, Gossen, Nürnberg, Germany). If light conditions changed, a white calibration of the measurement device was carried out with a barium sulfate disc. To compare healthy and diseased wheat plants, six spectroradiometer measurements were made in each plot. These measurements were averaged over field replications to one spectral curve for each fungicide treatment.

The Yara N-Sensor (Yara, Germany) (sensor 3) is a tractor mounted multi-spectral real time scanner sensor. The sensor is located 2 m above the canopy and measures the field reflectance in an array of 12 m. Four sensors detect light reflectance from the canopy and a fifth sensor detects incoming radiation from the sky. This arrangement allows changes in the reflected spectrum due to sun angle and clouds to be taken into account. The N-Sensor is based on relationships between chlorophyll content, crop N status and resulting N requirement (Link et al., 2002). The position of the red edge (720-740 nm) is used as an indicator of chlorophyll, to make estimates of the chlorophyll content and biomass of a crop and relate his to nitrogen demand of the crop to establish a fertilization strategy (Reusch, 1997). Under stress, like the plant diseases septoria leaf blotch, chlorophyll is reduced. On the basis of this consideration the N-Sensor could be suitable. Measurements with the Yara N-Sensor were carried out in the Field Scan Modus in the wavelength ranges 450, 500, 510, 520, 550, 600, 640, 660, 680, 700, 720, 730, 740, 750, 760, 780, 800, and 850 nm.

Harvest and analyses

After each measurement the leaves and shoots of the measured plants were harvested and the fresh weight was determined at once. Plant samples were dried at 60 °C and total dry matter was determined. The remaining leaf tissue was ground, dry-ashed and analyzed for total N according to Dumas, 1962. Also two biomass cuts were done at growing stage GS 49 (Zadoks et al. 1974) and GS 69-73 in each fungicide treatment to analyze fresh weight, total N and dry ash substance.

To detect the infection level of the plants with septoria leaf blotch visual ratings were done every week. Therefore the upper three leaves were consulted and percentage infected leaf area was estimated.

Statistics

Statistical analyses were performed with Sigma Stat 3.5 (Jandel Scientific Corp, San Rafael, CA). Differences between experimental groups were tested for by fully factorial analysis of variance (ANOVA). Tukey tests (α = 0.05) were carried out for comparison of means. Least squares regressions (α = 0.05) between reflectance values and visually assessed disease infection level were obtained.

Results

Visual rating of septoria infection

Disease infection was determined by visible rating of disease symptoms at every measurement date. The degree of infection was specified as percentage infected leaf area. Disease infection levels increased over time. In GS 65 with an infection level of 2 % was determined for all treatments. Infection with *Septoria tritici* raised to 18.75 % in the treatment 100 %, 28.75 % in the treatment 50 % and to 85 % in the treatment 0 % in GS 85 (Figure3). Significant differences between the treatments could be obtained at GS 75 and GS 85. In GS 75 and 85 the treatment 0 % indicated a significant higher disease infection level when compared with the treatment 100 %.

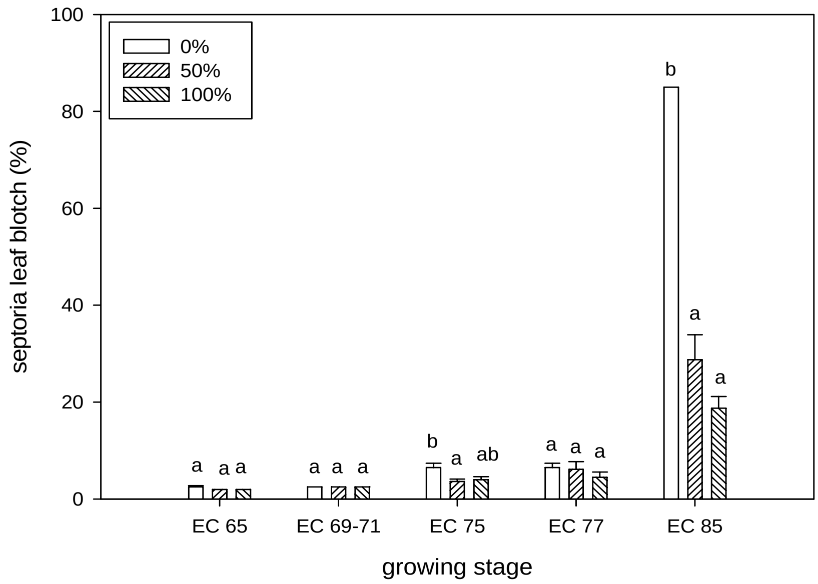

Figure 3. Visual rating for *Septoria tritici* infection over the growing stages 65-85 for all treatments (significant changes are indicated at α = 0.05, mean values with the same letter are not significantly different).

Reflectance measurements at leaf level

With sensor 1 significant differences between the treatments 100 %, 50 % and 0 % could be obtained in the visible and infrared wavelength range for the a* and b*-parameters.

Figure 4 shows the a*-parameter of the treatments 100 %, 50 % and 0 % in the visible wavelength range 490-510 nm at GS 69-85. In this wavelength range, significant differences between the treatment 100 % and 0 % could be obtained in an early disease infection stage of wheat plants (GS 69-71). At this growing stage the treatment 100 % had an a*-value of 120.75 and the treatment 0 % of 120. If we survey the results it is visible that the a*-parameter of the treatment 50 % and 0 % tend to be higher than the a*-parameter of the treatment 100 %.

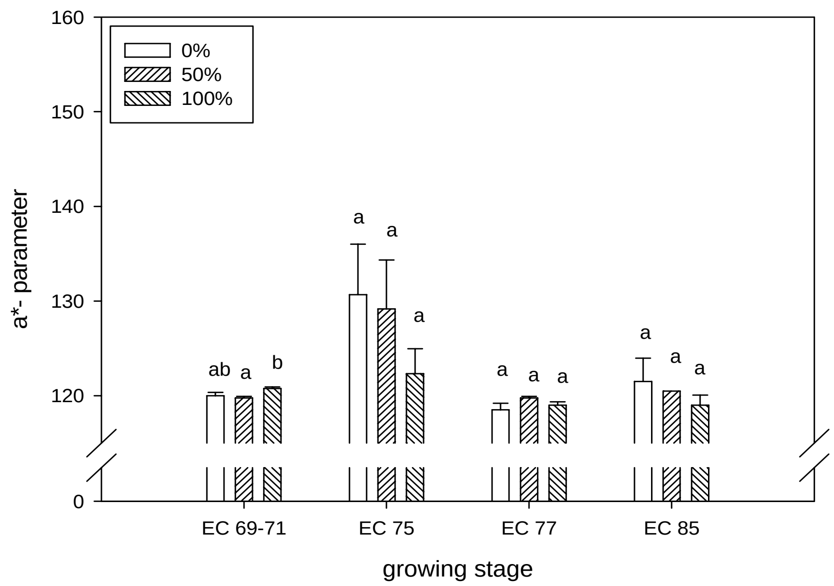

Figure 4. A*-parameter of the treatments 100 %, 50 % and 0 % for the wavelength range 490-510 nm over the growing stages 69-85 measured at leaf level (Significant changes at α = 0.05 are indicated, mean values with the same letter are not significantly different).

Figure 5 shows the b*-parameter for the treatments 100 %, 50 % and 0 % in the visible wavelength range 490-510 nm at GS 69-85. Significant differences between the treatments 100 %, 50 % and 0 % could be identified at GS 69-71 and 85. The b*-parameter of the treatment 0 % was significantly higher than the b*-parameter of the treatments 100 % and 50 %. In GS 85 the b*-parameter of the treatment 0 % rose to 162, the b*-parameter of the treatment 50 % increased to 155 due to higher disease infection while the b*-parameter of the treatment 100 % stayed at 150. At this growing stage significant differences between the treatments 100 % and 0 % could be identified.

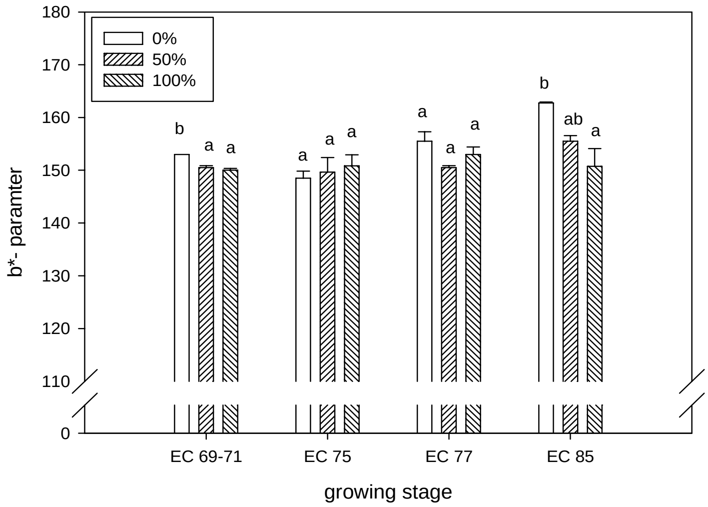

Figure 5. B*-parameter of the treatments 100 %, 50 % and 0 % for the wavelength range 490-510 nm over the growing stages 69-85 measured at leaf level (Significant changes at $\alpha = 0.05$ are indicated, mean values with the same letter are not significantly different).

In the infrared wavelength range significant differences could be identified especially in the wavelength range 490-510 IR for both the a*- and b*-parameter. Figure 6 shows the a*-parameter for the treatments 100 %, 50 % and 0 % in the infrared wavelength range 490-510 IR at GS 69-85. Significant differences between the treatments were determined at GS 69-71, 77 and 85. At GS 69-71 significant differences between the treatments 100 % and 0 % could be identified. Hereby the treatment 100 % had an a*-parameter of 170.5 and the treatment 0 % of 169. At GS 77 differences between the treatments 50 % and 0 % could be between the treatments 50 % and the treatment 0 %. At GS 85 the treatment 100 % had an a*-value of 167.5, the treatment 50 % of 178.5, and the treatment 0 % of 166. Hereby, the treatment 50 % had a significantly higher a*-value than the treatments 100 % and 0 %. In general, diseased plants indicated lower a*-values than healthy plants.

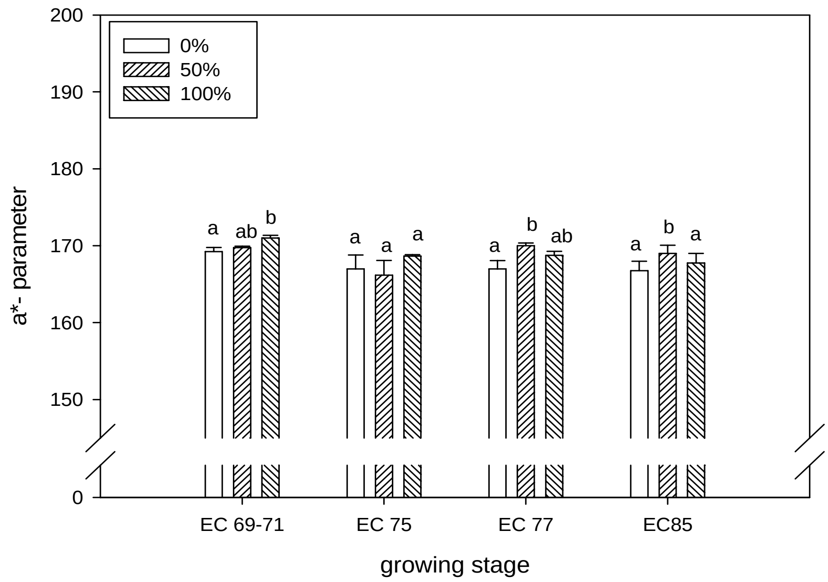

Figure 6. A*-parameter of the treatments 100 %, 50 % and 0 % for the wavelength range 490-510 IR over the growing stages 69-85 measured at leaf level (Significant changes are indicated at α = 0.05, mean values with the same letter are not significantly different).

Figure 7 shows the b*-parameter for the treatments 100 %, 50 % and 0 % in the infrared wavelength range 490-510 IR at GS 69-85. In this wavelength range significant changes between the treatments were obtained for the b*-parameter at GS 69-71 and 85. At GS 69-71 the treatment 100 % had a b*-parameter of 148, the treatment 50 % of 151.5 and the treatment 0 % of 151. The treatments 50 % and 0 % differed significantly from the treatment 100 %. At GS 85 the treatment 100 % had a b*-parameter of 154.5, the treatment 50 % of 152 and the treatment 0 % of 158. The treatment 0 % differed significantly from the treatment 50 % at this growing stage.

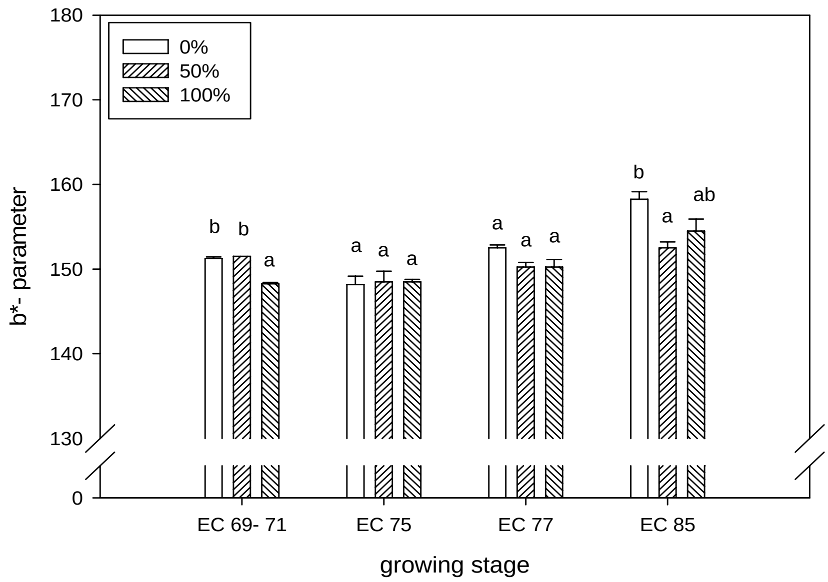

Figure 7. b*-parameter of the treatments 100 %, 50 % and 0 % for the wavelength range 490-510 IR over the growing stages 69-85 measured at leaf level (significant changes are indicated at α = 0.05, mean values with the same letter are not significantly different).

Reflectance at canopy level – sensor 2

With sensor 2 significant changes between all treatments could be identified at GS 69-71, 75 and 77. At the other measurement dates no significant changes could be obtained among the treatments.

Figure 8 shows the reflectance at GS 69-71 for the treatments 100 %, 50 % and 0 % in the wavelength range 325-1075 nm. The figure shows that the reflectance of the treatments 50 % and 0 % was significantly higher than the reflectance of the treatment 100 %. Especially in the wavelength range 750-1075 nm significant differences could be obtained between the treatments. The differences between the treatment 100 % and the treatments 50 % and 0 % averaged around 0.08.

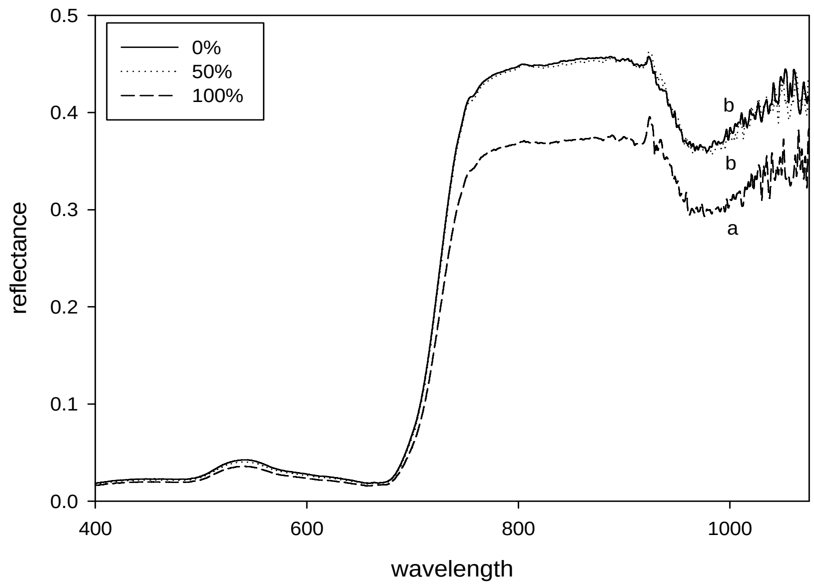

Figure 8. Reflectance of the treatments 100 %, 50 % and 0 % measured with sensor 2 at GS 69-71 (significant changes are indicated at $\alpha = 0.05$, mean values with the same letter are not significantly different).

Figure 9 shows the reflectance at GS 75 for the treatments 100 %, 50 % and 0 % in the wavelength range 325-1075 nm. At this growing stage the reflectance of the treatment 0 % laid significant beyond the reflectance of the treatment 50 % and 100 % almost over the whole wavelength range. The differences averaged round 0.04.

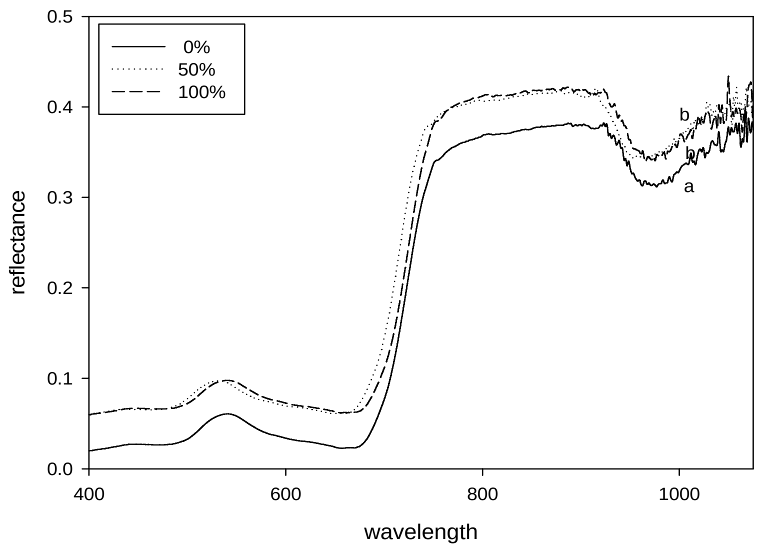

Figure 9. Reflectance of the treatments 100 %, 50 % and 0 % measured with sensor 2 at GS 75 (Significant changes at $\alpha = 0.05$ are indicated, mean values with the same letter are not significantly different).

Figure 10 shows the reflectance for the treatments 100 %, 50 % and 0 % at growing stage 77 measured with the sensor 2 for the wavelength range 325-1075 nm. Significant changes between the treatment 100 % and 50 % and the treatment 0 % were visible in the near infrared wavelength range of 750-900 nm. In the near-infrared wavelength range, the reflectance of the treatments 50 % and 0 % was significantly lower than the reflectance of the treatment 100 %. However, the differences were not as distinctive as in GS 75.

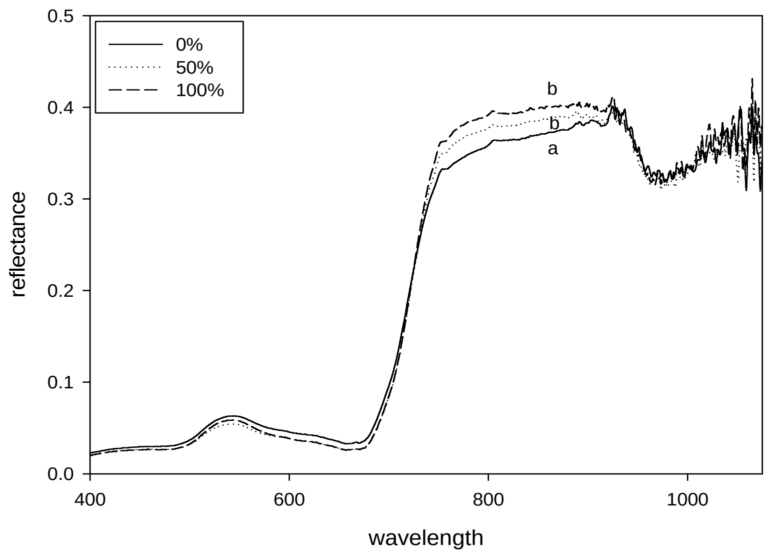

Figure 10. Reflectance of the treatments 100 %, 50 % and 0 % measured with sensor 2 at GS 77 (significant changes are indicated at $\alpha = 0.05$, mean values with the same letter are not significantly different).

Note, that the identified wavelength ranges 490-510 nm at leaf level were also distinctive at canopy level.

Figure 11 shows the reflectance measured with sensor 2 for the wavelength range 490-510 nm for the treatments 100 %, 50 % and 0 % at GS 69-71. The reflectance of the treatments 50 % and 0 % was significantly higher than the reflectance of the treatment 100 % in this wavelength range. These results are similar to the results obtained with sensor 1.

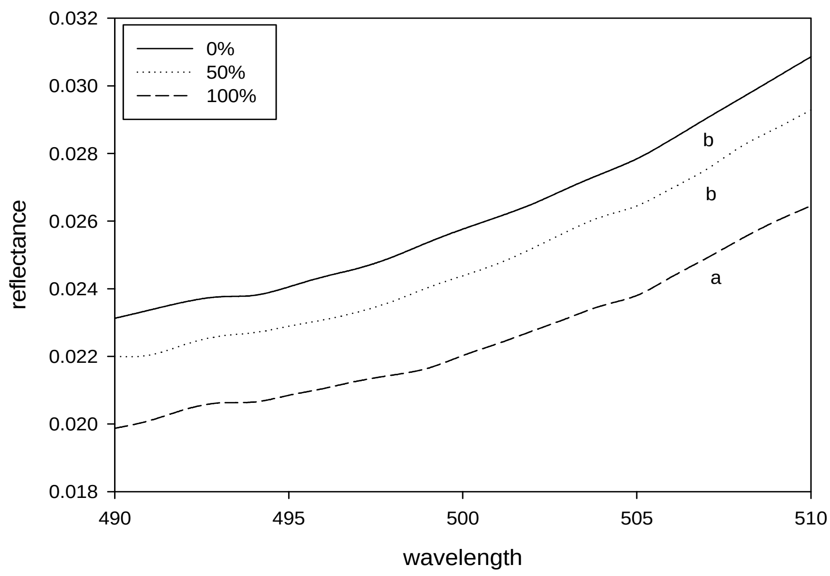

Figure 11. Reflectance of the treatments 100 %, 50 % and 0 % measured with sensor 2 in the wavelength range 490-510 nm at growing stage 69-71 (significant changes are indicated at $\alpha = 0.05$, mean values with the same letter are not significantly different).

Results from sensor 3

Measurements with sensor 3 were conducted using the Field Scan Modus in the previous selected wavelength ranges 450, 500, 510, 520, 550, 600, 640, 660, 680, 700, 720, 730, 740, 750, 760, 780, 800, and 850 nm. At all measurement dates and for all wavelength ranges no significant differences between the treatments 100 %, 50 % and 0 % could be identified with sensor 3. The reflectance of the treatment 0 % tended to be lower at the last measurement date (GS 85) than the reflectance of the treatments 100 % and 50 % (Figure 12). However, as plants were already senescent at this stage, obtained reflectance changes can also be an effect of senescence.

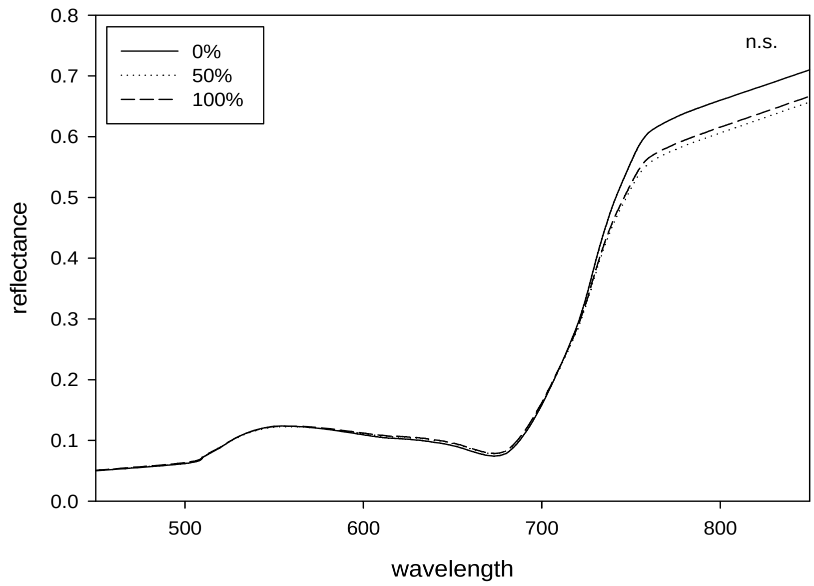

Figure 12. Reflectance of the treatments 100 %, 50 % and 0 % measured with sensor 3 in the wavelength range 450-850 nm at growing stage 85 (significant changes are indicated at α = 0.05, mean values with the same letter are not significantly different).

Quantification of the results

Quantifications were done to test if it is possible to define the infection level by means of reflectance measurements and if it is possible to dose fungicide due to the reflectance measurements. Correlations were done between the results of the reflectance measurements for all tested sensor systems at all growing stages and all wavelength ranges and the results of the visual rating of septoria leaf blotch. A good correlation (r^2 = 0.58) was obtained at leaf level between the b*-parameter and septoria infection in the wavelength range 490-510 IR. (Figure 13).

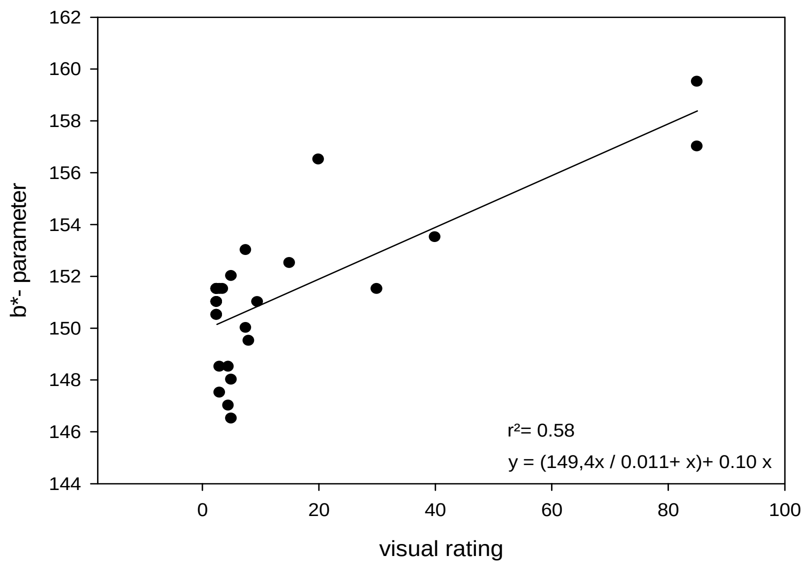

Figure 13. Correlation between the b*-parameter measured with sensor 3 in the wavelength range 490-510 IR and the results of the visual rating.

The correlation between sensor 2 and the visible rating of septoria tritici was very week. Only a correlation coefficient of 0.2 could be obtained for the wavelength range 700-900 nm.

The best correlation coefficient for sensor 3 and the visible rating of septoria tritici was obtained with r^2 = 0.4 in the wavelength range round 850 nm. But also this correlation was too weak to calculate the spraying dose due to reflectance measurements.

Discussion

The results of this study indicate that the identification and quantification of plant diseases depends strongly on the spatial resolution of the used sensor systems. With sensor 1 and a spatial resolution of 0.5 cm^2 it was possible to identify septoria leaf blotch at an infection level of 2.5 % and to quantify the results. With sensor 2 and a spatial resolution of 0.5 m^2 it was possible to identify septoria leaf blotch also at an infection level of 2.5 % but a quantification was not possible. With sensor 3 and a spatial resolution of 12 m^2 it was not possible to detect diseased plants at all and no quantification could be done.

Also Jacobi, 2005, describes in his studies that a precise detection of stress symptoms induced by nitrogen deficiency and fungal diseases is possible based on an optical very high resolution satellite sensor.

Moshou et al., 2006 write in their work that current commercial satellite

sensing might not be suitable for early disease detection (even if the wavelength at which data are collected were suitable) because of limitations in spatial resolution of only a few meters.
With sensor 1 and sensor 2 significant changes between healthy and diseased plants could be detected in the wavelength ranges 490-510 nm and 490-510 IR at an early stage of infection.
Moshou et al., 2004, showed in field experiments with the winter wheat cultivar Madrigal in Rothamsted 2000/2001 that it is possible to differ between healthy and diseased plants in an early stage of infection with reflectance measurements. In this study differences in reflectance between with yellow rust (*Puccinia striiformis*) infected plants were studied using a spectrograph. The reflectance of diseased plants raised especially in the wavelength range 543 nm and declined in the wavelength ranges 750 and 861 nm which was put down to structural damages because of the disease. For the measurement they used a sensor system with a high spatial resolution. They also noticed that a high resolution is necessary to detect early changes in disease development.
Malthus and Madeira, 1993, showed in a greenhouse experiment 1989 in Nottingham with leaves of field beans cv. Tricol infected with the necrotroph fungus *Botrytis fabae* that reflectance changes appear depending on the infection level of 0 % to 85 %. In the visible wavelength range reflectance changes at 470-500 nm were positive correlated to the appearance of necrosis. Parallel thereto significant reductions of the content of carotenoids in general and the photosynthesis rate at infestation values under 10 % were detected. Reflectance changes were first measured in the wavelength range 800 nm in connection with visible symptoms. The reduction of the reflectance in the infrared wavelength range is explained with the destruction of the leaf structure while the fungus developed. Thus it came to a reduction of the radiation dispersion within the leaf tissue and an increase of the transmission in this area (Knipling, 1970). They also used a high spectral resolution technique to investigate changes in reflectance between healthy and diseased plants.
Septoria leaf blotch is a necrotroph fungus (Robert et al., 2004) which is caused by the pathogen Mycosphaerella graminicola (Fuckel)

Schröder (Cornish et al., 1990). Symptomatic for septoria leaf blotch are necrosis in the form of yellow leaf blotches which turn in the course of disease brown in the centre and get black pycnidia. If the infection is very high it may come to a drop of the leaves. According to Eyal, 1999, the pycnidia development takes 14-21 days. The incubation rate averages about 3-5 weeks. For an infection the leaves have to be wet at least 48 h and the infestation appears after 3-4 weeks (Pflanzliche Erzeugung, 2006). Because of the fact that strong disease symptoms first appear on 27.06.07 the infection of the crops have to be theoretical at the end of May till the beginning of June. There have been 22 days between the growing stage 69-71 and 85 so an early infection at growing stage 69-71 could be probably.

According to Kema et al. (1996) with the growth of the mycelium it comes to a destruction of the chloroplast integrity (concerning size and form) and their compartmentalization inside the leaf tissue. The mycelium grows into the intercellular spaces between epidemic cells and mesophyll cells.

The change of the a*- and b*-parameter in our study for the treatment 0 % at growing stage 69-71 appear in an very early infection stage where the infection rate laid at 2.5 % septoria leaf blotch and showed hence that an early detection of disease is possible with sensor systems. Also sensor 2 showed in the wavelength range 490-510 nm at the growing stage 69-71 significant differences between the treatments 100 % and 50 % and the treatment 0 %. It is possible that this effect could depend on an early stress-related change of the pigment amount and a reduced photosynthesis rate respectively because of the infection with septoria leaf blotch like at the results of Malthus and Madeira, 1993.

Polischuk et al., 1997, could also detect in greenhouse experiments stress induced changes in the reflectance in the visible wavelength range on tobacco leaves without the appearance of visible disease symptoms. Therefore they inoculated tobacco leaves in the greenhouse with tobacco mosaic virus. Already 10 days after inoculation a reduction of chlorophyll content could be detected analytically and with reflectance measurements, whereas visible symptoms couldn't be detected until 3 weeks after inoculation. Knipling, 1970, traced back early changes in reflectance in the visible wavelength range to the sensitivity of chlorophyll to metabolic disturbance.

In the infrared wavelength range significant differences in the rage 490-510 IR for the a*- and b*-parameter could be identified with sensor 1 at growing stage 69-71 between the treatments 100 % and 0 %. Clearly changes in the infrared wavelength range showed the reflectance curves of sensor 2 from growing stage 69-71 to 77 where the treatment 0 % differ more and more from the treatment 100 %. In the growing stage 69-71 the treatment 0 % showed a significant higher reflectance than the treatment 100 % from growing stage 75 the reflectance was significantly lower for the treatment 0 %.

Lorenzen und Jensen, 1989, detected in their studies with powdery mildew infected barley plants an increase in reflectance at an early stage of disease development and a drop of the reflectance in the infrared region for the further progression of the disease. They explained the results with the increase of senescent leaf tissue.

In our study we also detected at first an increase of the reflectance and than a decrease of diseased plants. At infection with septoria leaf blotch it comes to a proceeding colonization of the host tissue, cell damage and accumulation of pycnidia (Eyal, 1987, King et al., 1983). According to Gates et al., 1965, is the reflectance in the infrared wavelength range mainly influenced by structural changes in the leaves. Also Malthus and Madeira, 1993, show in their study of with *Botrytis fabae* infected field beans that the reflectance of diseased plants declined in the infrared wavelength range. The highest differences could be obtained in the wavelength range round 800 nm. They traced the results back to damages of the leaf tissue with increasing fungus infection.

Sensor 3 showed at no time significant changes between the treatments 100 %, 50 % and 0 %. A possible reason for this could be the time of measurement. The producer of sensor 3 give a application recommendation till growing stage 59 which was clearly exceed in this work.

Because of the fact that plant diseases are not distributed uniformly over the field but appear in patches, the application of fungicides only on those patches could be very effective for disease treatment (Oerke et al., 1994, Oerke et al., 2005). For a spatial accurate application of fungicides with the help of sensor technologies, the sensors have to have a high resolution for the detection of stress symptoms (Franke et al., 2007).

The sensors used in this work differ in their spatial resolution. Sensor 1 measured the reflectance on the leaf scale under constant light conditions most accurate and was able to detect disease infection at an early stage. By the correlation of the a*- and b*-parameters with infection intensity a quantification of the infection intensity would be possible and hence a specific dosage of fungicides would be possible.

Sensor 2 measured plant reflectance 2 m above the canopy and interpolate the reflectance over a taking area of 0.5-1 m^2. The spectroradiometer detect not only the reflectance of one plant but of about 350 plants. Thus it came to a mixture of the reflectance of healthy and diseased plants and the obtained reflectance value was only an average. Because of this fact we have a lost of information with sensor 2 compared to sensor 1. Sensor 2 could detect the reflectance changes of diseased plants but a quantification was not possible.

Sensor 3 was not able to detect any reflectance changes at any time. This sensor system measure the reflectance 2 m above the canopy and interpolate the reflectance over a working width of 12 m. Therewith sensor 3 measure clearly more plants like sensor 2. Also here it came to a mixture of the reflectance of healthy and diseased plants and a reflectance change was not measurable. The information lost because of the low spatial resolution lead to the fact that an identification and quantification of septoria leaf blotch was not possible.

Furthermore the question comes up if it is necessary to quantify the infection level by the mean of reflectance measurements. To defend plant diseases and yield loses due to it the optimal date for fungicide treatment in respect of their effectiveness is a crucial and restrictive factor, because fungicides may be limited to crop growth stages and infection stages. It is also crucial to treat diseases in an early infection stage to prevent further spread. The used practice in agriculture is to apply fungicides at infection beginning and therefore it would be sufficient only to make the decision weather the plant is infected ore healthy. Also Franke and Menz, 2007, differed in their study about the multi-temporal wheat disease detection by multi-spectral remote sensing between healthy and infected plants and show that it is sufficient for the treatment of plant diseases.

Concluding this we can say that for the identification and quantification of diseased plants we need a camera system with a high spatial resolution.

Conclusion

For the detection of plant diseases within a field a high resolution sensor technique is necessary. The study indicated that with a resolution of 0.5 cm^2 an identification and quantification of septoria leaf blotch was possible at an early stage of infection in the wavelength ranges 490-510 nm and 490-510 IR. With a spatial resolution of 0.5 m^2 an identification of septoria leaf blotch was also possible at an early stage of infection in the especially in the infrared wavelength range. Because of the information lost due to the spatial resolution a quantification was not possible. At a spatial resolution of 12 m^2 no detection and quantification of septoria leaf blotch was possible because of the low spatial resolution and the resulting mixture of healthy and diseased plants. In this field of study further experiments are necessary especially with camera systems with a high spatial resolution.

Acknowledgements

The German Federal Ministry of Education and Research financed this project through their program on precision agriculture No. 0330661. The responsibility for the content of the paper is with the author.

References

Brown, J.S., Kellock, A.W. and Paddick, R.G. 1978. Distribution and dissemination of Mycosphaerella graminicola (Fuckel) Schroeter in relation to the epidemiology of speckled leaf blotch of wheat. Australian Journal of Acric. Res. 29, p. 1139-1145.

Browning, J.A. 1979. Genetic protective mechanism of plant pathogen populations: their coevolution and use in breeding for resistance. In M.K. Harris, ed. Biology and breeding for resistance. Texas Publ. MP-1451, p. 52-57. Texas, USA, Texas A&M University Press, College Station. 605 pp.

Caldwell, R.M. and Narvaez, I. 1960. Losses to winter wheat from infection by Septoria tritici. Phytopathology 50, p. 630.

Caldwell, R.M. 1976. Development of the wheat Septoria blight problem in the USA over the period 1922 to 1975. Proc. Septoria Diseases of Wheat Workshop. B. M. Cunfer and L. R. Neson eds. Georgia Agric. Exp. Sta. Spec. Publ. 4, p. 3-6.

Campbell, C.L and Noe, J.P. 1985. The spatial analysis of soilborne pathogens and root diseases. Ann. Rev. Phytopathol. 23, p. 129-148.

Cooke, B.M. and Jones, D.G. 1971. Epidermiology of Septoria tritici and S. nodorum I. Th reaction of spring and winter wheat varieties to infection by Septoria tritici and Septoria nodorum. Trans. Br. Mycol. Soc. 56, p. 121-125.

Cornish, P.S., Baker, G. R., Murray, G. M., 1990. Physiological responses of wheat (Triticum aestivum) to infection with Mycosphaerella graminicola causing Septoria tritici blotch. Aust. J. Agric. Res. 41, p. 317-327.

Dumas, A. 1962. Stickstoffbestimmung nach Dumas. Die Praxis des organischen Chemikers, 41, p. 45-51.

Eyal, Z., Scharen, A.L., Prescott, J.M. and Van Ginkel, M. 1987. The Septoria diseases of wheat: Concepts and method of disease management. CIMMYT. Mexico. D.F.

Eyal, Z. 1999. The septoria tritici and stagonospora nodorum blotch diseases of wheat. European Journal of Plant Pathology 105, p. 629- 641.

Franke, J., Menz, G., 2007. Multi-temporal wheat disease detection by multi-spectral remote sensing. Precision Agric. Online

Gates, D.M., Keegan, H.J., Schleter, J.C. and Weidner, .V.R. 1965. Spectral properties of plants. Applied Optics 4, p. 11-20.

Habermeyer, J. and Gerhard, M. 2000. Pilzkrankheiten. BASF Landwirtschaft.

Haboudane, D., Miller, J.R., Tremblay, N., Zarco-Tejada, P.J. and L. Dextraze L. 2002. Integration of hyperspectral vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sensing of Environment 81, p. 416-426.

Holmes, S.J.I. and Colhoun, J. 1975. Strawborne inoculum of Septoria nodurum and Septoria tritici in relation to incidence of disease on wheat plants. Plants Pathology 24, p. 63-66.

Hooker, A.L. 1957. Methods of inoculation and determining varietal reactions in the Septoria disease of oats. Plant Dis. Rep.Vol. 41, p. 592-597.

Jacobi, J. 2005. Teilflächige Diagnose von Pilzbefall und Stickstoffmangel an Weizen mit Hilfe der optischen Fernerkundung. Rheinische Friedrich-Wilhelm-Universität zu Bonn, Dissertation.

Kema, G. H. J.; Yu, D. , Rijkenberg, F. H. J.; Shaw, M. W. and Baayen, R. P. 1996. Histology of the pathogenesis of Mycosphaerella graminicola in wheat. Phytopathology 86, p. 777-786.

King, J.E., Cook, J. R., Melville, S. C., 1983. A review of Septoria diseases of wheat and barley. Ann Appl. Biol. 103, p. 345-373.

Knipling, E. B., 1970. Physical and physiological basis for the reflectance of visible and near- infrared radiation vegetation. Remote Sensing of Environment 1, p.155- 159.

Laudien, R. Bareth, G. and Doluschitz, R. 2003. Analysis of hyperspectral field data for detection of sugar beet diseases. Proceedings of the EFITA Conference 2003, Debrecen, Hungary, pp. 375-381.

Link, A., Panitzki, M. and Reusch, S. 2002. HYDRO-N-Sensor: Tractor-mounted remote sensing for variable nitrogen fertilization. Proceedings of the 6th international Conference on Precision Agriculture and Other Precision Resources Management. Robert, P.C. (ed.), July 14-17, Minneapolis, MN, USA. Published as CD-ROM.

Lorenzen, B., Jensen, A., 1989. Changes in leaf spectral properties induced in barley by cereal powdery mildew. Remote Sensing Environment 27, p. 201-209.

Malthus, T. J., Madeira, A.C., 1993. High resolution spectroradiometry: spectral reflectance of field bean leaves Infected by Botrytis fabae. Remote Sens. Environ. 45, p. 107-116.

Moshou, D., Bravo, C.,West, J.,Wahlen,S.,McCartney, A., Ramon, H., 2004. Automatic detection of “yellow rust” in wheat using reflectance measurements and neural networks. Computers and Electronics in Agriculture 44, p. 173- 188.

Moshou, D., Bravo, C., Wahlen, S., West, J., McCartney, A., De Baerdemaeker, J. and Ramon, H. 2006. Simultaneous identification of plant stresses and diseases an arable crops using proximal optical sensing and self-organising maps. Percision. Agriculture 7, p. 149-164.

Oerke, E-C, Dehne, H-W., Schönbeck, F., Weber, A., 1994. Crop production and crop protection- estimated losses un major food and cash crops. Elsevier science, 808 pp.

Oerke, E-C,, lindenthal M., Fröhling, P., Steiner, U., 2005. Digital infrared thermography fort he assessment of leaf pathogens. In: Proceedings of the 5th European Conference on Precision Agriculture, edited by J. V. Stafford

(Wageningen Academic Publishers, Netherlands), p. 73-80.

Pflanzliche Erzeugung, 2006, 12. Auflage, BLV Buchverlag, München.

Polischuk, V. P., Shadchina, T.M., Kompanetz, T. I., Budzanivskaya, I. G., Boyko, A. L., Sozinov, A. A., 1997. Changes in reflectance spectrum characteristic of Nicotiana debneyi plant under the Influence of viral infection. Arch. Phytopath. Pflanz. 31, p. 115- 119.

Reusch, S. 1997. Entwicklung eines reflexionsoptischen Sensors zur Erfassung der Stickstoffversorgung landwirtschaftlicher Kulturpflanzen. Institut für Landwirtschaftliche Verfahrenstechnik der Christian-Albrechts-Universität zu Kiel, Ph.D. Thesis, 157p.

Robert, C., Bancal, M. O., Nicolas, P., Lannou,C., Ney, B., 2004. Analysis and modelling of effects of leaf rust and Septoria tritici blotch on wheat growth. Journal of experimental Botany, 55(399), p. 1079-1094.

Shipton, W.A., Boyd, W.R.J., Rosielle, A.A. and Shearer, B.I. 1971. The common Septoria disease of wheat. Botanical Review 37, p. 231-262.

Spieckermann, G. 2005. GIS-basierte Erfassung und Prognose der räumlichen Verteilung von Pflanzenkrankheiten. Hohe Landwirtschaftliche Fakultät, Rheinische Friedrich-Wilhelms-Universität zu Bonn, Ph.D. Thesis.

Van Ginkel, M. and Scharen, A. L. 1988. Host–pathogen relationships of wheat and Septoria tritici. Phytopathology 78, p. 762-766.

Yamazaki, W.T. and Briggle, L.W. 1969. Components of test weight in soft wheat. Crop Science 9, p.457-459.

Zadoks, J.C. and van den Bosch, F. 1974. On the spread of plant disease: A Theory on Foci. Annu. Rev. Phytopathol. 32, p. 503-521.

The aim of the forth article was to test sensor systems with different spatial resolutions for the identification of septoria leaf blotch within the field. Therefore, a field experiment with winter wheat was conducted using sensor systems with the spatial resolution of 0.5 cm^2, 0.5 m^2 and 12 m^2.

The results showed that with a spatial resolution of 0.5 cm^2 an identification and quantification especially in the infrared wavelength range was possible. With a spatial resolution of 0.5 m^2 an identification, but no quantification was possible and with a spatial resolution of 12 m^2 no identification and quantification was possible. The problems of a low spatial resolution could be the combination of healthy and diseased plants and the overlapping signal of the healthy plants at an early infection level.

For the farmer not only the identification of diseased plants within the field but also a decision support system that decides whether to spray or not to spray on the basis of different factors is important. Out of this the aim of the fifth article was to develop a strategy to use plant disease information gained from sensor measurements as input dataset for the simulation of wheat growth in CERES-Wheat. Such a system could be used to identify plant diseases within fields and to calculate the necessity of fungicide applications. Using such a decision support system, fields could be treated site-specifically, fungicides could be saved and by this production costs and the environmental impact could be reduced.

A Strategy for Incorporating Plant Diseases Coupled with Leaf Sensor Measurements into CERES-Wheat

K. Gröll [a], S. Graeff [a] and W. Claupein [a]

a University of Hohenheim, Institute for Crop Production and Grassland Research (340), 70599 Stuttgart, groell@uni-hohenheim.de

Abstract

Along with the crowing concentration of cereal crops, the occurrence of septoria leaf blotch (*Septoria tritici*) has become an ever more serious problem. Some 20 % of the potential crop yield may get lost due to crop infections with that fungal disease. To encounter such losses, crops are treated with fungicides. There is increasing pressure to reduce the use of pesticides in modern crop production to decrease the environmental impact of current practice and to lower production costs. It is therefore imperative that pesticides are only applied when and where needed. As plant diseases often occur in patches in fields, fungicides may be applied unnecessarily to disease-free areas under current non-site-specific management practices. Disease control could be more efficient if the patches within fields could be identified and fungicides applied only to the infected areas. However, the challenge consists in making control decisions in line with the objective necessity. Control algorithms must make allowance for all knowledge of the multifarious interactions of weather conditions, measures of agronomy, course of epidemic and yield losses. Up to date, there seem to be no practical site-specific disease models available, wich include forecasting and control decisions on the basis of meteorological, soil, and management data as well as cropping factors. A field experiment was conducted during the growing periods of 2004 and 2005 at the Experimental Station “Ihinger Hof” (48°44´ N, 8°56´E; 687 mm, 7.9 °C) of the University of Hohenheim, Stuttgart, Germany for the development, calibration and validation of a possible disease algorithm in CERES-Wheat. The study aims to develop a new module to simulate potential disease development in wheat and its impact on yield with and without fungicide applications.

Key words: Plant diseases, winter wheat, modelling, CERES-Wheat, remote sensing.

1 Introduction

The maximum yield of plants, determined by their genetic potential, is seldom achieved because factors such as insufficient water or nutrients, adverse climatic conditions, insect damage and especially plant diseases will limit growth at some stage. Plants subjected to these biotic and abiotic constrains are said to be stressed. As a result of stress, physiological and anatomical changes take place within plants (Jackson, 1986). Approximately 30 % of the world harvest is lost on an annual basis due to biotic stress factors. The development of pesticides has improved the possibility to reduce pests, but in today’s crop production there is an increasing pressure to reduce the use of pesticides, to decrease the environmental impact and to lower potential production costs. Traditionally, farmers have used pesticides to spray the whole field. Because of the fact that plant diseases are not uniformly distributed within a field, it is imperative that pesticides are only applied when and where needed. The advent of direct injection sprayers and computer based information systems allow farmers now to site-specifically treat patches of weeds or diseases. The quantification of these risk elements would be a vital practical step in rationalising pesticide use. The basis for a site-specific application of pesticides is however the spatial detection of the pathogens and the development of agronomic decision rules and production functions to support fungicide spray decisions.

Computer models can be used to simulate crop production, allowing the farmer to compare model outputs with field information (Baandrup and Ballegaard, 1989). Recently, there has been an increased interest in the use of crop simulation models in association with spatial variability and precision farming (Sadler et al., 2000; Paz et al., 2001). The application of crop models to optimize in-season management for spatially variable fields in particular provides farmers with options to reduce inputs and increase net returns (Booltink et al., 2001). However, these applications require accurate crop models able to simulate occurring crop stresses like plant diseases. Furthermore, if crop models would be able to predict final yield with reasonable accuracy within a growing season depending on disease outbreak and disease development, it might justify the use of suitable sensor technologies and the reduction of fungicides on a site-specific scale.

CERES-Wheat is a crop simulation model which simulates the impacts of the main environmental factors, such as weather, soil type, and major soil characteristics, and crop management on wheat growth, development, and yield (Ritchie et al., 1998). Input requirements for CERES-Wheat include weather and soil conditions, plant characteristics, and crop management (Hunt et al., 2001). Soil inputs include drainage and runoff coefficients, first-stage evaporation and soil albedo, water-holding characteristics for each individual soil layer, and rooting preference coefficients at several depth increments. The model also requires saturated soil water content and initial soil water content for the first day of simulation. Required crop genetic inputs are coefficients related to photoperiod sensitivity, duration of grain filling, conversion of mass to grain number, grain-filling rates, vernalization requirements, stem size, and cold hardiness (Hunt et al., 1993). Management input information includes plant population, planting depth, and date of planting. The model simulates phenological development, biomass accumulation and partitioning, leaf area index (LAI), root, stem, leaf, and grain growth, and the soil and plant water and N balance from planting until harvest maturity based on daily time steps (Godwin and Singh, 1998;; Ritchie et al., 1998). The current version of CERES-Wheat does not account for the impact of plant diseases on final yield which is found to be crucial to obtain satisfactory simulation results at sites under the impact of plant diseases.

Reflectance of agricultural crops in the visible and near infrared wavelength domains has been studied by numerous researchers in order to estimate different crop parameters, such as plant species, productivity, harvest, plant nutrient and plant pathological status (Deering, 1989; Kumar et al., 2001). Spectral reflectance characteristics of leaves have been shown to be highly correlated with their chemical composition (Moshou et al., 2005). Carter et al. (2001) indicated in his studies the importance of chlorophyll concentration on the spectral signature of leaves. Using methods based on measurements of reflectance of field crops to estimate crop status, the in-field variability can be recorded which can be used as a basis in the decision of side specific actions of e.g. application of plant nutrition or pest dose. With spectral sensing, sampling of reflectance spectra of a growing crop can be done relatively fast and the signal from a spectral sensor can be used to control site specific means of inputs either indirectly by mapping the in-field variability or in real time mode using a vehicle mounted spectral sensor. Though airborne diseases tend to spread rapidly, targeting of pesticides based on disease mapping is a reasonable approach if it is combined with epidemic modelling to predict disease patch expansion (West et al, 2003). The use of epidemic modelling takes into account environmental conditions for making a decision regarding the treatment of a field with pesticides. Disease occurring in large, relatively static patches are most likely to benefit from spatially variable spraying, while disease prevalence (% area affected) must be very low if patches are small or likely to expand rapidly. This sensor data's to detect plant diseases in an early stage could then be provided as a basis for the model as update of the state variables.

The aim of the current study was to integrate a disease algorithm into CERES-Wheat using site-specific sensor measurements of disease severity as major input information.

2 Acquisition of Data

Data are needed to construct models, to test their truthfulness and usefulness and eventually to operate them. Therefore a field experiment was conducted during the growing periods of 2004 and 2005 at the Experimental Station "Ihinger Hof" (48°44´ N, 8°56´E; 687 mm, 7.9 °C) of the University of Hohenheim, Stuttgart, Germany for the development, calibration and validation of a possible disease algorithm in CERES-Wheat. Winter wheat cv. Monopol and Empire were planted on October 23rd, 2004. The variety Empire is classified as a high resistant variety, whereas Monopol has a very low resistance against diseases in general (Bundessortenamt, 2005). The trials were inoculated with the disease *Septoria tritici* with the inoculum steps I1 = no inoculum = control, I2 = 50 % inoculum, I3 = 100 % inoculum. The trial was set up as randomized block design with three replications. In the course of the vegetation period measurements with different sensor systems were made which give information about disease development and disease intension. Furthermore the impact on yield was measured.

Model theory and development

There is increasing use of mathematical models applied to improve understanding of plant disease epidemics. Linear regression analysis is one of the most commonly used methods of simulating damage due to multiple diseases. A very general yield loss model (Zhang et al., 2007) can be written as:

$$L = Y_0 - Y = b_0 + b_1X_1 + \ldots + c_1Z_1 + \ldots d_1X_1Z_1 + \ldots \qquad [1]$$

in which: yield loss can be determined in field experiments as the difference between the yield of a given plot (Y) and the yield of a disease free (control) plot (Y_0: attainable yield); X represents the disease intensity (e.g. incidence or severity), or change in disease intensity at several times or can represent the disease intensity at a particular time for different diseases; Z represents the crop characteristics or other variables (e.g. year, location). The b's, c's and d's are parameters estimated from data. However, the parameterization and evaluation of this model is complex, and require large amounts of quantitative data on the mechanism of disease damage.

Some generic deterministic models for plant disease epidemics have been proposed in the literature where most parameters can be related to those of the logistic function, the most widely used growth function for describing epidemics (66, 67, 115). Howver, the parameterization and evaluation of these models are complex and require large amounts of quantitative data on the mechanisms of disease damage. Zhang et al., (2007) estimated that the absolute yield loss due to diseases considered (difference between the mean yields of treated plots and that of untreated plots) may increase with the attainable yield (main yield of treated plots). They used the relative yield loss (RYL) of each cultivar in each trial of their study as the output variable of the model. RYL can be expressed as a percentage, as follows:

RYL = 100 * ("treated" yield – "untreated" yield)/("treated" yield) [2]

with "treated" yield = mean yield of treated plots; "untreated" yield = mean yield of untreated plots. RLY represents an output variable of the model. They built a mixed model with: (i) fixed covariate effects (potential intensities of diseases, interactions "potential disease intensity * cultivar susceptibility rating " and "potential disease intensity * trial earliness rating"), and (ii) random factorial effects (year and year * trial combination). The model can be written as:

$$\begin{aligned} RYL = {} & \alpha Mi + \beta Se + \gamma Br + \delta Yr + \alpha_1 Mi * Mis + \beta_1 SE \\ & * SeS + \gamma_1 Br * BrS + \delta_1 Yr * YrS + \alpha_2 Mi * PRE \\ & + \beta_2 Se * PRE + \gamma_2 Br * PRE + \delta_2 Yr * PRE + \sigma year \\ & + \theta[year * trial] + error \end{aligned}$$

Where Mi, Se, Br, Yr are the potential disease intensities in a trial for powdery mildew , septoria tritici blotch, brown rust and yellow rust, respectively; MiS, SeS, BrS and YrS denote cultivar susceptibility rating to these four diseases; PRE is the cultivar earliness rating. The regression coefficients for the fixed covariates are α, β, γ, and δ. Α, β, γ, δ parameters represent the main effects of disease load on yield losses: The higher the value of these parameters the more the disease contributes to yield losses. α_1, β_1, γ_1, δ_1 (α_2, β_2, γ_2, δ_2) represent the combined effects of diseases load and cultivar susceptibility (earliness) for each disease: the higher the value of these parameters, the more the interaction between disease load and cultivar susceptibility (earliness) contributes to yield losses. The model was built to be simple and parsimonious. In the case of no disease in a trial, the potential intensities of diseases are scored with 0, and so the fixed part of RYL equals 0 whatever the cultivar susceptibility. For the disease Septoria leaf blotch the model could be written as:

$$RYL = \beta Se + \beta 1SE * SeS + \beta 2Se * PRE + \sigma year + \theta[year * trial] + error$$

Batchelor et al., (1993) developed a generic framework to couple pest damage of various types into the PNUTGRO and SOYGRO models for peanut and soybean. Coupling points were identified in the models for applying damage to leaves, stems, roots, pods, seeds, whole plants, and to the supply of assimilate. The resulting models were tested by simulating crops with measured pest damage levels for peanut (foliar disease) and soybean (foliar feeding insects) and comparing observed and simulated crop growth and yield results. In these subroutines the application of damage to crop model variables can be expressed by:

$$X_{it} = X_{it}^* - \sum_{p=1}^{m} D_{ipt}$$

Where X_{it} = state (or other model) variable on day t, after damage has been applied; X_{it}^* = state (or other model) variable on day t before applying pest damage; D_{ipt} = amount of damage applied to state (or other model) variable on day t by pest type p; m = total number of pest types. In this work a specific set of crop variables have been selected for application of pest damage. These variables are referred to as coupling points.
Batchelor et al. (1993), computed different D_{ipt} for different situations. In the simple case when pest population level (N_{pt} pests m^{-2} ground area on day t) is reported for pest p, and this pest damages only one coupling point (i), then D_{ipt} can be computed by:

$$D_{ipt} = (N_{pt})(C_{ip})$$

In this equation N_{pt} would be the input (observed) pest population on day t for pest p and C_{ip} is a “pest coefficient” that represents the amount of coupling point damage per individual pest per day. To estimate the daily absolute damage that would be required to simulate the percent observed damage for leaf mass, leaf area, and stem mass coupling points In our model the daily absolute damage would be assigned from the reflection datas of the sensor measurements.
If damage is reported by the sensor assessments, D_{ipt} is computed by first writing an expression for the percent observed damage (P_{it}) in terms of absolute damage (D_{ipt}):

$$D_{ipt} = X_{it}^{*} - (1 - (P_{it}/100))(Xt_{it} - Xs_{it})$$

In this equation, P_{it} is the percent difference in the amount of coupling point in two treatments at time t (i.e., one treatment that has not been damaged and the other that has accumulated damage). The variable Xt_{it} is the cumulative amount of coupling point produced by the crop model up to time t without any damage or senescence and Xs_{it} is the cumulative senescence of coupling point I up to time t. The variable X_{it}^{*} is the value of the coupling point before damage is applied at time t. Leaf coupling points are leaf mass , leaf area index and carbohydrate assimilation. Septoria leaf blotch, caused by the fungus Mycosphaerella graminicola (Fuckel) Schroeter (anamorph: Septoria tritici Roberge in Desmaz) is a major necrotic leaf disease in wheat (Triticum aestivum L. em. Thell) worldwide (Wiese, 1987). Where environmental conditions are favorable for disease development, yield losses ranging from 20 to 43 % have been reported (Caldwell, 1976). Septoria leaf blotch can reduce the economic value of wheat by decreasing both grain yield and quality. Yield loss is related to the leaf area killed by the pathogen (Brown and Paddick, 1982), while yield loss is less in wheats with greater resistance to the disease (Murray, 1982). Septoria tritici blotch, also known as speckled leaf blotch, is characterized by necrotic blotches that contain black or dark brown pycnidia. Wind-borne ascospores released from wetted stubble from autumn to winter are the primary inoculum of the disease (Brown et al, 1978). Secondary spread is by rain-splashed pycnidia (Wiese, 1987). The disease is favored by mild, wet conditions (Hess and Shaner, 1987a, 1987b). Severity has been associated with the number of rainy days in spring and with reduced number of nights with minimum temperatures below 7°C (Shaner and Finney, 1976), while rain splash is important for the rapid development of the disease on upper leaves (Royle et al., 1986) The pathogen survives between wheat crops on wheat stubble (Shipton et al., 1971).
In the crop models, leaf area index is computed from leaf mass and specific leaf area. Thus when leaf mass damage is applied to the models using the first equation of D_{ipt}, leaf area index is subsequently reduced. Necrotic spots on leaves are a common characteristic of various plant diseases. These spots intercept light but are not capable of photosynthesis. Furthermore, a toxic effect reduces electron transport required for photosynthesis in the tissue surrounding diseased spots. Diseased leaves reduce healthy leaf area available to convert light to assimilate. The crop model use total leaf area (diseased and non-diseased) to compute light interception, however, only healthy leaf area is used to compute photosynthesis.

In order to help producers evaluate the economics of a fungicide application, the model will be run two times. In the first run, it assumes that a fungicide application is made, and simulates the resulting yield with disease control. In the second run, the model assumes that a fungicide application is not made, and simulates ongoing disease progress and subsequent yield without a fungicide application. Each run will be made using current weather data until the decision date and allowing the user to select a group of historical weather years to allow the model to run until the end of the season. This will generate a mean and standard deviation of simulated yield for the treatment and no treatment cases, which can be compared by the producer.

Conclusions

Precision agriculture has established itself as a series of techniques with the potential to contribute towards the realization of sustainable forms of land management in the future. It is important to realize that there is no such thing jet as a single tool that will solve all problems. But the detection of plant diseases with optical sensor and the integration of these data sets in a plant growth and disease model to compute the development of these diseases could be a good system to give farmers a decision tool weather to spray or not to spray.

5. References

Baandrup, M.; Ballegaard, T. 1989. Three years field experience with an advisory computer system applying factor-adjusted doses. Brighton Crop Protection Conference-Weeds v. 2: p. 555-560;
Batchelor, W.D., Jones, J.W., Boote, K.J. and Pinnschmidt, H.O., 1993. Extending the use of crop models to study pest damage. American Society of Acricultural Engineers, Vol. 36(2): 551-558.
Booltink, H.W.G., B.J. van Alphen, W.D. Batchelor, J.O. Paz, J.J. Stoorvogel, and R. Vargas. 2001. Tools for optimizing management of spatially-variable fields. Agric. Syst. 70(2–3):445–476
Bourgeois, G., 1989. Interrelationship between late leafspot disease and Florunner peanut: A modeling approach. Ph.D. diss., University of Florida, Gainesville.

Brown, J.S. Kellbock, A.W. and Paddick. R.G, 1978. Distribution and dissemination of Mycosphaerella graminicola (Fuckel) Schroeter in relation to the epidemiology of speckled leaf blotch of wheat. Aust. J. Agric. Res., Vol. 29: 1139-1145.

Brown, J.S. and Paddick, R.G, 1982. Surveys of speckled leaf blotch and other foliar diseases of wheat in Victoria, 1974-1978. Aus. J. Exp. Acric. Anim. Husb., Vol. 20: 94-96.

Caldwell, R.M., 1976. Development of the wheat Septoria blight problem in the USA over the period 1922 to 1975. Proc. Septoria Diseases of Wheat Workshop. B.M. Cunfer and L.R. Nelson, eds. Georgia Agric. Exp. Sta. Spec., Publ. 4: 3-6.

Calvero, S.B. and Teng, P.S., 1992. Validation of BLASTSIM.2 model in IRRI blast (B1) nursery and Cavinti, Laguna, Philippines. International Rice Research Newsletter, 17(5): 20-21.

Carter, C.A. and Knapp, A.K. 2001. Leaf optical properties in higher plants: linking spectral characteristics to stress and chlorophyll concentration. American Journal of Botany 88 (4): 677-684.

Deering, D.W. 1989. Field measurements of bidirectional reflectance. Theory and applications of optical remote sensing. ed Asrar, G. John Wiley & Sons, New York: 14-65.

Godwin, D.C., and U. Singh. 1998. Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. p. 41–54. In G.Y. Tsuji, G. Hoogenboom, and P.K. Thornton (ed.) Understanding options for agricultural production. Systems approaches for sustainable agricultural development. Kluwer Academic Publ., Dordrecht, the Netherlands

Hess, D.E. and Shaner, G., 1987a. Effect of moisture and temperature on development of Septoria tritici blotch in wheat. Phytopathology, Vol. 77: 215-219.

Hess, D.E. and Shaner, G., 1987b. Effect of moisture on Septoria tritici blotch development on wheat in the field. Phytopathology, Vol. 77:220-226.

Hunt, L.A., S. Pararajasingham, J.W. Jones, G. Hoogenboom, D.T. Imamura, and R.M. Ogoshi. 1993. Gencalc: Software to facilitate the use of crop models for analyzing field experiments. Agron. J. 85:1090–1094.[

Hunt, L.A., J.W. White, and G. Hoogenboom. 2001. Agronomic data: Advances in documentation and protocols for exchange and use. Agric. Syst. 70:477–492

Jackson, R.D., 1986. Remote sensing of biotic and abiotic plant stress, Annual Review of Phytopathology, 24:265-287.

Jeger MJ, van den Bosch F. 1994. Threshold criteria for model plant disease epidemics. I. Asymptotic results. Phytopathology 84:24–27

Jeger MJ, van den Bosch F. 1994. Threshold criteria for model plant disease epidemics. II. Persistence and endemicity. Phytopathology 84:28–30

Kumar, L., Schmidt, K.S., Dury, S. and Skidmore, A.K. 2001. Review of Hyperspectral Remote Sensing and Vegetation Science. Imaging spectrometry: basic principles and prospective applications, eds.

Luo, Y., Teng, P.S., Fabellar, N.G. and TeBeest, D.O., 1997. A Rice-Leaf blast combined model for simulation of epidemics and yield loss. Agricultural systems, Vol. 53: 27-39.

Moshou, D., Bravo, C., Oberti, R., West, J., Bodria, L., McCartney, A., and Ramon, H. 2005. Plant disease detection based on data fusion of hyper-spectral and multi-spectral fluorescence imaging using Kohonen maps. Real Time imaging 11: 75-83.

Murray, G.M, 1982.Yield losses in wheat associated with different levels of resistance to speckled leaf blotch (Mycosphaerella graminicola). Acron. Aust.: 242.

Paz, J.O., W.D. Batchelor, and G.L. Tylka. 2001. Method to use crop growth models to estimate potential return for variable-rate management in soybeans. Trans. ASAE 44(5):1335–1341

Pinnschmidt, H.O., 1989. Freilanduntersuchungen zur Epidemiologie von Pyricularia oryzae Cav. An Trockenreis(Fiel studies on the epidemiology of P. oryzae Cav. On upland rice). PhD Thesis, University of Giessen, Germany, pp. 268.

Rickman, R.W. and Klepper, B., 1991. Environmentally driven cereal crop growth models. Annual Review of Phytopathology, 29: 361-380.

Ritchie, J.T., U. Singh, D.C. Godwin, and W.T. Bowen. 1998. Cereal growth, development and yield. p. 79–97. In G.Y. Tsuji, G. Hoogenboom, and P.K. Thornton (ed.) Understanding options for agricultural production. Kluwer Academic Publ., Dordrecht, the Netherlands.

Royle, J.D., Shaw, M.W. and Cook, R.J., 1986. Patterns of development of Septoria nodorum and Septoria tritici in some winter wheat crops in Western Europe, 1981-83. Plant Pathology Vol. 35: 466-476.

Sadler, E.J., B.K. Gerwig, D.E. Evans, W.J. Busscher, and P.J. Bauer. 2000. Site-specific modeling of corn yield in the SE coastal plain. Agric. Syst. 64:189–207

Segarra J, Jeger MJ, van den Bosch F. 2001. Epidemic dynamics and patterns of plant diseases. Phytopathology 91:1001–1010

Shaner, G and Finney, R.E., 1976. Weather and epidemics of Septoria leaf blotch of wheat. Phytopathology, Vol. 66: 781-785.

Shipton, W.A., Boyd, W.R.J., Rosielle, A.A. and Shearer, B.I., 1971. The common Septoria diseases of wheat. Botany Revue, Vol. 37: 231-162.

Smith, P.J. and Webster, J.P.G. 1986. Behavioural aspects in the design of information systems for disease control in cereals. In: Implementation of farm management information systems: proc. 9th symposium of the EAAE, Copenhagen, November 1985, (Christensen, J. ed.) pp.133-144. Kiel: Wissenschaftsverlag Vaulk

West, J.S. ,Bravo, C., Oberti, R., Lemaire, D., Moshou, D. and McCartney, H.A. (2003): The potential of optical canopy measurement for targeted control of field crop diseases. Annual Review of Phytopathology, Vol. 41:593-614

Wiese, M.V, 1987. Compendium of Wheat Diseases. 2nd Edn., APS Press, St. Paul, Minn..

Zhang, X.Y., Loyce, C., Meynard, J.M. and Monod, H., 2007. Modelling the effect of cultivar resistence on yield losses of winter wheat in natural multiple disease conditions. European Journal of Agronomy, in press.

10. General Discussion

10.1. Site-specific agriculture

Site-specific agriculture optimizes agricultural inputs by varying application rates to match within-field requirements.
Site-specific agriculture is often divided into four tasks: collecting data, analysis and management of data, decision making, and finally carrying out the decision. The aims of site-specific agriculture are different depending on local variations, the farmers' interest, the crop under cultivation etc. (Reyniers, 2003). Although the collection of some geo-spatial data has become relatively easy, it is more difficult to know how to most effectively use that data in making crop management decisions (Sudduth et al., 1998). Data are useless without interpretation. A series of decisions must be made in the process of working towards the established goals. Management decisions in precision farming have strategic, tactical and operational dimensions (Bouma, 1997). A decision to apply precision farming instead of traditional farming, set-a-side, moving field borders etc. would be a strategic decision. Types of fertilizer use, type of tillage, crop rotation, variable rate application of inputs etc. are tactical decisions. At operational level decisions can be made about crop variety to sow and when, what and how many to till, sow, plant, fertilize and harvest. This last decision level can be divided into map based and sensor based applications. Sensor based technology means that data is collected, analyzed, and an expert system decides what to do and the decision is carried out, all in one pass. When farming according to maps, the decision is made already at the farm office from earlier collected data. The decision is transferred with a data card from the office computer to the machine controller.

Plant pathogens and diseases are associated to be distributed not uniformly within a field. Plant diseases vary along a continuum from a high degree of aggregation to randomness and from randomness to a high degree if regularity, although this last situation is probably quite rare in plant pathosystems. Spatial pattern in plant pathology may be defined as the arrangement of disease entities relative to each other and to the architecture of the host crop (Gilligan, 1982). Pattern arises owing to the direct or indirect interplay of physical, biological, and environmental factors (Taylor, 1984).

Three classifications are usually used to describe the spatial pattern of individuals in a population of pathogens or diseased plants: (a) random, (b) aggregated, contagious, or clustered, and (c) regular (Fig. 15). A random pattern is synonymous with a random or independent dispersion of individuals. An aggregated or clustered pattern is synonymous with over-dispersion or clumped dispersion of individuals. A regular pattern is synonymous with an under-dispersion, even, or uniform pattern of individuals.

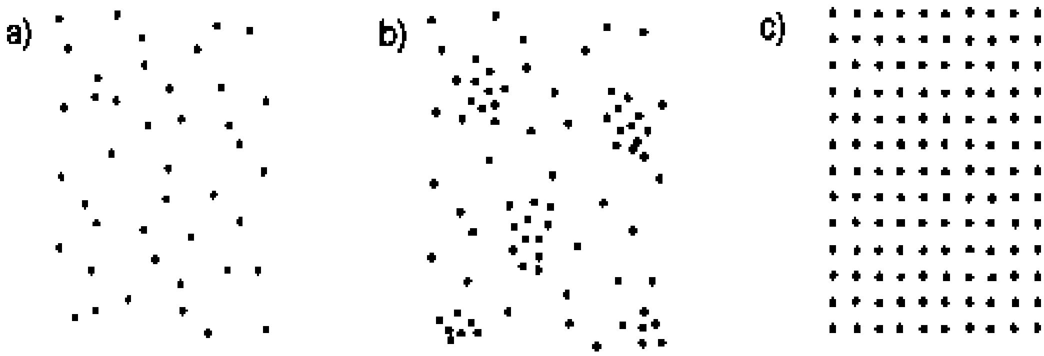

Figure15 Hypothetical spatial point patterns. Each point represents an infected plant or the propagule of a pathogen. (a) random, (b) aggregated, contagious, or clustered, and (c) regular.

Post-industrialisation farm management practices have tended towards the treatment of individual fields as spatially uniform in respect to yield controlling factors, primarily as a trade-off to economies of scale. However, increasingly critical attention is being focused by both the farming and wider communities on this notation that agriculturally productive land should be managed as a relatively homogeneous unit at the within-field scale. It may be argued that such an assumption could lead to inappropriate resource application and subsequent financial, environmental and social costs (Whelan, 1998). The significance of these imposts (such as input waste, yield reduction and soil, water and air contamination) to whole farming systems has only recently received serious consideration (e.g. Pierce and Lal, 1991).

Within-field variability in cropping system attributes is often obvious but difficult to accurately and efficiently quantify. The magnitude of the variation also changes with attribute, location and time. Importantly, variability at this scale of the soil/crop system may give rise to economic, environmental and societal problems on cropping enterprises under traditional 'uniform' management. In general, the problems arise from a decision to use 'mean-of-field' information to guide the amelioration of an area which may result in zones being under- or over-treated. Gathering data on, and extracting useful management information from within-field variability is the goal of Precision Agriculture.

The successful implementation of Precision agriculture will be dependent on the ability of individual growers to differentially manage their crops to achieve the twin goals of maximising yield or profit whilst simultaneously minimizing environmental impact. The major obstacle to this is the lack of, and uncertainty in, local information. That is information pertaining to the variation (and the component spatial and temporal variance) in crop yield and those factors which determine crop yield and resource losses from the cropping system to the environment.

The importance of such information is not a recent concept. It has been a long held and widely identified notation that field heterogeneity in influential cropping system components will affect crop yield (Harris, 1920). At the regional scale, the observable variation in crop yield can be considered the consequence of variability in the interaction between crop genetics and environmental factors (Bresler et al., 1981).

Information about local variation within the fields can be obtained using sensor systems. Remote sensing could be used to detect differences in soil parameters, water supply, nutrient supply, and plant diseases. But not only the identification of such differences within a field is necessary for site-specific agriculture but also a decision support system is necessary to process those data and to deduce the right management decisions.

10.2. Main outcomes

In this study different sensor systems with different spatial resolutions have been tested for the ability to identify plant diseases. Plant reflectance was measured with a digital camera (LEICA S1 PRO, LEICA Kamera AG, Solms, Germany) at leaf scale (0.5 cm^2) and with the spectroradiometer Field Spec® Hand Held (ASD, Inc. Boulder, CO, USA) (0.5 m^2) and the Yara N-Sensor in the field-scan modus (12 m^2) 2 m above the canopy level. The diseases powdery mildew, septoria leaf blotch and wheat eyespot have been analyzed.

To measure the reflectance of diseased plants several greenhouse and field experiments have been conducted at the University of Hohenheim and the experimental station "Ihinger Hof".

At the time of starting the work, no sensor system was on the marked to detect plant diseases in the field. On this account our first question was if it is possible at all to detect plant diseases using a sensor system. Therefore the influence of powdery mildew on the reflectance of leaves was tested in several greenhouse studies using the digital camera LEICA S1 PRO with the spatial resolution of 0.5 cm^2 (chapter 5).

The results showed, that an identification and quantification of powdery mildew was possible in the visible wavelength ranges 516-540 nm and 540-600 nm at a spatial resolution of 0.5 cm^2. For these wavelength ranges an $r^2 = 0.87$ (516-540 nm) and $r^2 = 0.82$ (540-600 nm) was achieved. The determined changes in the reflectance parameter b* could be related to the infection level. However, it was not possible to discriminate between the tested infection levels of 50 % and 100 %, as the parameter b* did not increase over time like the powdery mildew pustules/cm^2.

The results of this article are conform with the results found in the literature. Lorenzen and Jensen (1989) for example investigated the changes in leaf spectral properties produced by powdery mildew in several varieties of spring barley. They found significant increases in reflectance in visible wavebands (422-712 nm) 6 days after inoculation, which corresponded to degradation of chlorophylls induced by the disease. The differences in the near infrared region between control and infected plants observed were small and occurred several days later than changes in the visible region. Also Greaff et al. (2006) identified powdery mildew on winter wheat in greenhouse studies using reflectance measurements with a spatial resolution of also 0.5 cm^2. The results of this study showed that the visible wavelength range round 490 m led to the best results.. Powdery mildew changed primarily the amount of chlorophyll and not the structure of the leaf. In the visible range reflectance is considered to be influenced by leaf pigments such as chlorophyll whereas reflectance in the near-infrared range is affected by changes in the anatomical structure of leaves (Guyot, 1990). Occurring pigmental changes probably led to the fact, that reflectance changes due to powdery mildew infection were most pronounced in the visible spectra.

Powdery mildew is a leaf disease that means that symptoms of these diseases appear on the leaves and therefore should be detected by leaf reflectance measurements easily. Out of this a further goal of this study was to test, if diseases appearing not on the leaves directly could also be detected by reflectance measurements. Therefore field experiments were conducted on the experimental station “Ihinger Hof” of the University Hohenheim investigating the stipe disease wheat eyespot. Measurements were carried out with the digital camera LEICA S1 PRO and the spectroradiometer Field Spec® Hand Held with a spatial resolution of 0.5 cm^2 and 0.5 m^2. The results of this experiments showed that wheat eyespot could not be detected using reflectance measurements (chapter 6). Both tested sensor systems could not detect the disease at any time and in any wavelength range. One reason could be the generally low infection level of about 10 %. At this infection level no secondary changes like water and nutrient deficiency could be measured in the leaves. However different studies in the literature indicate that it may be possible to detect also stem diseases using remote sensing technologies. For example Nilsson (1985) identified sclerotinia stem rot on oil seed rape by remote sensing. He used a hand-held Exotech-100AX radiometer including the wavelength bands 500-600 nm, 600-700 nm, 700-800 nm and 800-1100 nm on two occasions after flowering. He identified significant differences between healthy and diseased plants especially in the wavelength ranges 700-800 nm and 800-1100 nm. The findings were related to the diseased induced water stress. Similar finding were made by Nilsson (1984) in with *Pyrenophora graminea* infected barley plants.

Greaff et al. (2006), identified take-all disease in winter wheat with the digital camera LEICA S1 PRO, described in this study, in greenhouse experiments. The wavelength range 510-780 nm showed the best suitability for the identification of take-all disease. In this study take all disease could be identified due to occurring water stress caused by the fungus.

The next question was if vegetation indices also could be used in this context to detect plant diseases. Therefore different vegetation indices were selected out of the literature that implicated those wavelength ranges found out to be appropriate for the detection of plant diseases (chapter 7). For the calculation of the vegetation indices the results of the field experiments with powdery mildew and septoria leaf spot measured with the spectroradiometer Field Spec® Hand Held were used.

The results of this study showed that the vegetation index REIP was most suitable for the identification of powdery mildew. The vegetation index was able to detect powdery mildew at an infection level of 7 %. Also the indices NDVI and HVI were suitable but they were not able to detect changes as early as the index REIP. For the disease septoria leaf blotch, the vegetation index RVSI was considered to be the most suitable one. The RVSI detected changes at an infection level of 13.7 % septoria leaf blotch. The other tested indices were not able to detect an early infection with septoria leaf blotch. Septoria leaf blotch could not be identified as early as powdery mildew with the indices out of the literature, because these vegetation indices combine the visible and the near-infrared region of the reflectance whereas reflectance changes under septoria leaf blotch especially appear in the wavelength range 750-1075 nm. Based on these findings, a new vegetation index that combined the wavelength ranges 750 and 850 nm was developed to detect septoria leaf blotch in an early stage of infection. The new vegetation index DII was able to detect septoria leaf blotch at an infection level of 4 %, which was much earlier than the other tested vegetation indices.

Not only the disease itself but also the spatial resolution plays an important role in identifying plant diseases. To test which spatial resolution is necessary for the detection of plant diseases a field experiment was carried out at the experimental station “Ihinger Hof”. The influence of septoria leaf blotch on the reflectance of winter wheat was measured with the digital camera LEICA S1 PRO with a spatial resolution of 0.5 cm^2, with the spectroradiometer Field Spec® Hand Held with a spatial resolution of 0.5 m^2 and with the Yara N-Sensor in the field-scan modus with a spatial resolution of 12 m^2.

The results for septoria leaf blotch (chapter 8) showed, that an identification and quantification is possible especially in the infrared wavelength range and at a spatial resolution of 0.5 cm^2. Under septoria leaf blotch infection significant differences could be identified especially in the wavelength range 490-510 IR for both the a*- and the b*-parameter and the correlation between infection level and reflectance showed good results with an r^2 of 0.58.

Summarizing the results of the measurements with the spectroradiometer at a spatial resolution of 0.5 m^2 it was evident, that an identification of septoria leaf blotch was possible especially in the infrared wavelength range. But it was also obvious, that no quantification was possible at this spatial resolution. Only a correlation coefficient of 0.2 could be obtained for the wavelength range 700-900 nm.

The results of the N-sensor with a spatial resolution of 12 m^2 showed that at all measurement dates and for all wavelength ranges no significant differences between diseased and healthy plants could be identified. The reflectance of the treatment 0 % tended to be lower at the last measurement date (GS 85) than the reflectance of the treatments 100 % and 50 % (Figure 8). However, as plants were already senescent at this stage, obtained reflectance changes my also be an effect of senescence. Correlating the results of the N-Sensor with the infection level, a low correlation of $r^2 = 0.4$ could be obtained.

These results are conform with the results out of the literature. Also Malthus and Madeira (1993) showed in their study of with *Botrytis fabae* infected field beans that the reflectance of diseased plants declined in the infrared wavelength range. The highest differences could be obtained in the wavelength range round 800 nm. They traced the results back to damages of the leaf tissue with increasing fungus infection. Xu et al. (2007) detected leaf miner damage on tomato leaf with a near-infrared spectroscopy. They found out, that the wavelength range 800-1100 nm was suitable for the detection of a necrotic disease. Nilsson (1985) identified barley stripe disease in the field using an Exotech-100-AX radiometer with different filters for the 4 Landsat-bands 500-600 nm, 600-700 nm, 700-800 nm and 800-1100 nm. The best correlation between disease incidence and reflectance factor was made in the wavelength range 700-800 nm and 800-1100 nm. Under the infection with septoria leaf blotch it comes to a proceeding colonization of the host tissue, cell damage and accumulation of pycnidia (Eyal, 1987, King et al., 1983). According to Gates et al. (1965) reflectance in the infrared wavelength range is mainly influenced by structural changes in the leaves.

The results of this study also indicated that the identification and quantification of plant diseases depends strongly on the spatial resolution of the used sensor systems. With a spatial resolution of 0.5 cm^2 it was possible to identify powdery mildew and septoria leaf blotch at an infection level of 2 % and 2.5 % and to quantify the infection. At a spatial resolution of 0.5 m^2 it was possible to identify powdery mildew and septoria leaf blotch also at an infection level of 5.7 % and 2.5 %, however a quantification was not possible. At a spatial resolution of 12 m^2 it was not possible to detect diseased plants at all and no quantification could be done.

Also in the studies of Franke and Menz (2007) it was shown that a multispectral sensor system with a high resolution is in principle able to detect plant diseases site specifically. But they also showed, that this sensor system was not able to detect an early infection with diseases precise enough for the creation of application maps. For the realization of a site-specific identification of plant diseases in practice a sensor system is necessary with a high spatial resolution to detect plant diseases at a low infection level.

Jacobi (2005) described in his studies that a precise detection of stress symptoms induced by nitrogen deficiency and fungal diseases is possible based on an optical very high resolution satellite sensors. Moshou et al. (2006) stated that current commercial satellite sensing might not be suitable for early disease detection (even if the wavelength at which data are collected were suitable) because of limitations in spatial resolution of only a few meters.

A low spatial resolution leads to the fact, that at the capture of the crop reflection not only the reflectance of the diseased but also of the healthy plants were collected and summarized over the whole area to one value. This summarizing may lead to the fact that especially at a low infection level the reflectance signature of the healthy plants overlay the reflectance signature of the diseased plants and therefore reflectance changes are not measurable. Figure 16 clarifies schematically the shown correlations. The low spatial resolution of the N-Sensor lead in this study to an information loss compared to the other two systems so that at a low infection level no identification of plant diseases was possible.

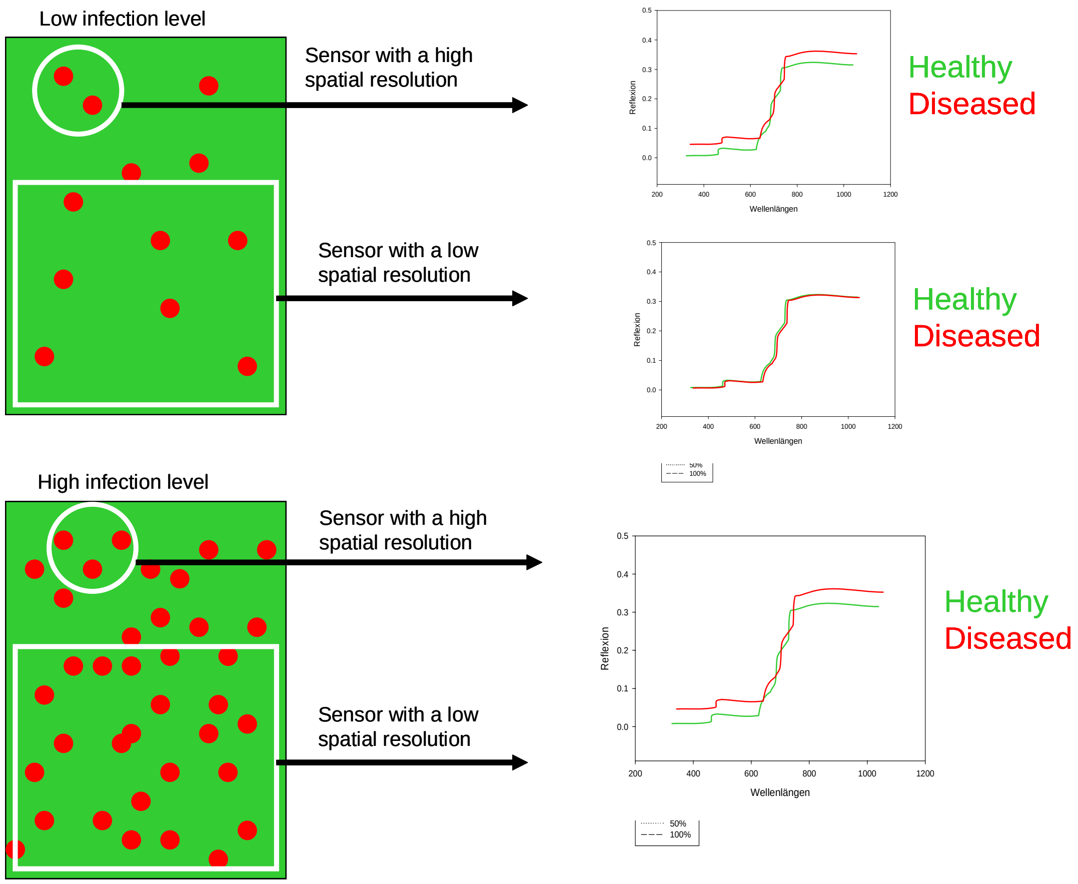

Figure 16 schematically description of the consequence of different infection levels in combination with different spatial resolution of the used sensor system on the theoretical identification of plant diseases (taken from Graeff et al., 2008).

10.3. Decision support systems

Another question in this work was if it is possible to implement data grained from reflectance measurements into a crop growth model and therefore give the farmers a decision support system when it is necessary to spray the fields subject to the infection level measured with a sensor system.

In today's crop production pesticides are sprayed uniform over the field either before symptoms of a disease are visible and therefore prophylactic or after visible symptoms appear on the plant and therefore curative. Both is a waste of pesticides because from the literature it is known that plant diseases are distributed site-specifically. Remote sensing provides an alternative method that could be used to detect plant diseases within a field site-specific and perhaps before visible symptoms appear which reduce the yield already (Nilsson, 1995).

Data grained from reflectance measurements could be implemented into a crop growth model to calculate the development of a disease. This step is a new approach in the field of decision making. Models need to be developed that use different factors and also reflectance measurements to calculate the potential yield under current conditions and disease level and show farmers the consequences of spraying or not spraying on yield.

Modern approaches and techniques for pest management increasingly rely on timely information to make strategic and tactical decisions. With rapid enhancements in microcomputer hardware and software, and their improved availability and user-friendliness, it is now possible to advance the decision making process in ways previously considered impractical (Teng et al., 1998).

Pests, whether they are insects, pathogens or weeds, occur in populations which exhibit their own dynamic and spatial characteristics. To capture these dynamics requires that techniques be available for quantifying the pest population and for modelling the dynamics. Some common measures of pest population are numbers of a specific pest per unit area (for insects and weeds), and proportion of injured tissue such as percent leaf defoliation or leaf severity (for diseases). Reflectance measurements can than be used to match the spatial characteristics of each pest population. In the context of estimating pest effects on crop yield, the growth stages at and during which infestation or infections occur is important, hence population curves are needed (Teng, 1987).

Figure 17 shows spraying decisions the farmers uses already without the use of sensor systems and decision support systems. The first method is to spray after first symptoms are visible. Using this method the farmer tries to stop the infection development. The second method which is mostly used by the farmers is to spray before an infection is visible. If needed a second application is done. But this method is often a waste of pesticides. In conjunction with a sensor technology and a crop growth model the farmer would spray after infection begins, but before visible symptoms appear (Figure 18). Using this method it is possible to spray at an early stage of infection where the yield is not reduced yet.

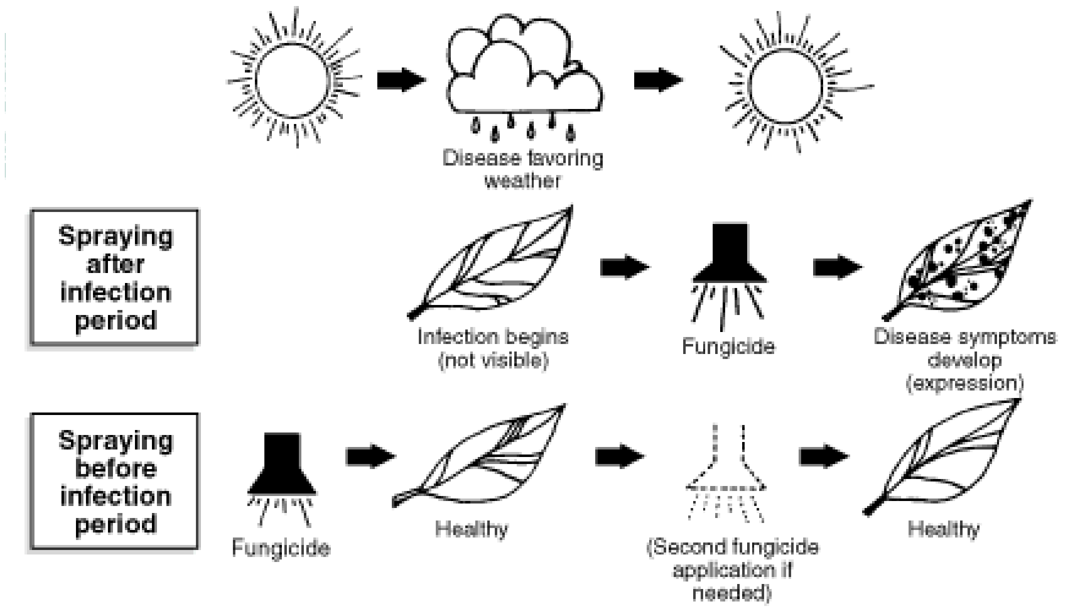

Figure 17 spraying decision without the use of sensor systems and decision support systems.

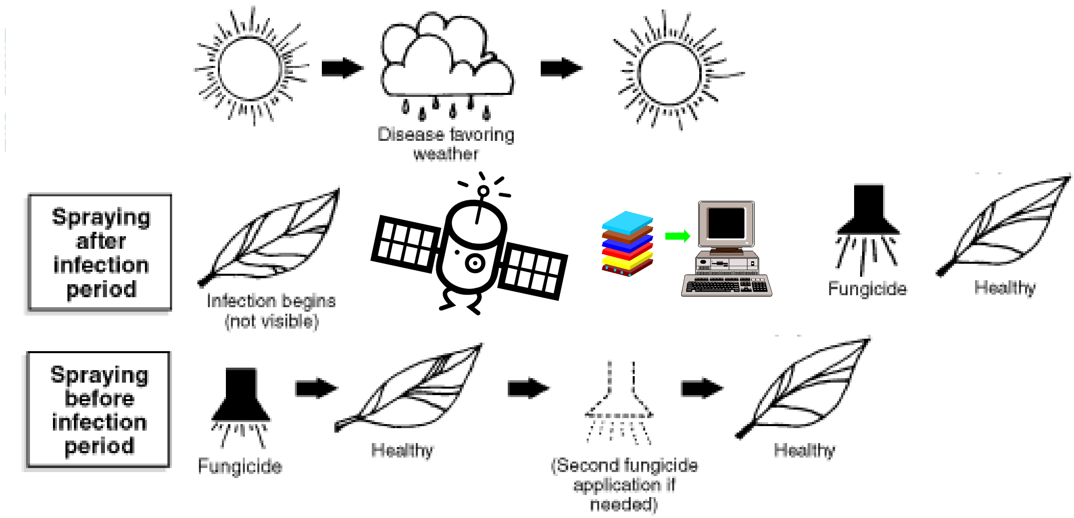

Figure 18 spraying decision with the use of sensor systems and decision support systems.

10.4. Future perspectives

There is much exiting and challenging research ahead for scientists and engineers in the field of Precision agriculture. For example the development of sensor systems to identify plant diseases site-specifically within a field is high on the list. But also the development of soil-sensing systems to replace the present requirement for manual sampling or the design of new yield sensors that do not require contact with the grain flow and can be positioned closer to the harvester front will also provide much fuel for thought (Whelan, 1998).

Precision agriculture should not be about treating a field to produce a uniform yield unless the potential is uniform. Its potential will be only realized by acknowledging diversity in yield potential and environmental conditions when formulating field management operations. By gathering and understanding the improved production information provided by Precision agriculture techniques, management will also be provided with an ideal tool for risk assessment in potentially poor growing seasons. For example, well documented areas of low yield potential may be removed from production or have their inputs reduced to minimize potential financial losses. Such assessments would from part of the decision-support system, so that management actions may be used to disperse or lower production or capital risks across a whole farm.

Site-specific agriculture represents the desire to identify and respond to large in-field variation in agricultural production processes in an optimal and timely manner. The ultimate objective should be the construction of a fully unified, real-time data acquisition-integration-decision process that, when appropriate, provides differential treatment to suit the variation in influential cropping system components. Economic optimization of resource use and the minimization of environmental impact is essential in today's agriculture.

In general the variability observed in crop yield at the within-field scale reflects interactions between influential field attributes and also between these attributes and the environment. Given the substantial temporal variability that has been shown in the literature to often dominate the spatial variation, the identification of a significantly yield limiting factor in one year may have limited bearing on the next growing season it its influence is considered singularly. Yield, soil, pest and environment variability data may need to be collected for a number of years (possibly up to 10 in highly variable environments) to adequately characterize and model this interaction. In this manner a map of yield potential for a field may be constructed and then used each year in conjunction with early season environmental indicators, reflectance measurements and crop response models to guide differential actions.

Looking at the results the question comes **up if it is really necessary to differ between different plant diseases or if it would be enough only to know that the**

reflectance has changed in the visible or infrared wavelength range and an expert system could than be used to decide which disease it could be. An expert system, also known as a knowledge based system, is a computer program that contains the knowledge and analytical skills of one or more human experts, related to a specific subject. This class of program was first developed by researchers in artificial intelligence during the 1960s and 1970s and applied commercially throughout the 1980s. An expert system is a software system that incorporates concepts derived from experts in a field and uses their knowledge to provide problem analysis to users of the software. The most common form of expert system is a computer program, with a set of rules, that analyzes information (usually supplied by the user of the system) about a specific class of problems, and recommends one or more courses of user action. The expert system may also provide mathematical analysis of the problem(s). The expert system utilizes what appears to be reasoning capabilities to reach conclusions (www.wikipedia.org). **Such an expert system could decide on the basis of weather, development stage, soil cultivation, crop rotation, etc. which plant disease could be possible at the time of measurement. Most plant diseases appear and infect the plant only at certain development stages of the plant.** Using this fact an expert system could cut all the diseases down to a few possible ones that can appear at the development stage the measurement is being done. With this reduction and the information of the reflectance measurements it would not be necessary to differ exactly between all possible diseases. Also weather plays an important role in disease development. Using this factor in an expert system a reduction of possible diseases could be done. Some diseases need a special time of humidity to develop or rainfall to spread in the field. The deposit of current weather data could exclude diseases which can not develop at this weather situation.

If it would be possible to detect plant diseases site-specifically in the field with a sensor system the question of **additional treated protection zones** around the infected zone is often raised. As the distance of disease spread could be short or long depending on the method of dispersal, this question is not easy to answer. The dispersal from plant to plant takes place by wind, water, animals or machines and therefore also over long distances. In most studies, disease gradients are measured over a few meters; thus, most disease gradients are quantified for distances less than 10 m. However in some cases, gradients are determined over greater distances over 1 km. The disease gradients have, for the most part, a characteristic shape that is determined largely by the physical process of dispersal**. Plant diseases dispersed by air need a larger protection zone than plant diseases dispersed in the soil as a greater dispersal in the air is possible. This fact has to be consided in the application maps for fungicides derived out of sensor measurements.**

Another point that needs to be discussed in that context is the **use of the application maps in the following years.** Plant diseases dispersed in the soil for example are relatively tied to a certain place, because of the restricted dispersal. For such plant diseases, maps could be integrated in the expert system and could be used to decide which plant disease could be possible at a special place within the field. For plant diseases dispersed in the air, the transfer of disease maps to the next year could be difficult because of the potential of a wide spread.

To fully answer the above mentioned questions further studies are necessary. General future work for the design of a site-specific management system should also give consideration to ***data acquisition*** like sensor systems with a high spatial resolution that are able to identify plant diseases within fields at an early infection level, ***data integration*** like suitable models for the efficient collation of variability data already available with that obtained from real-time sensors and ***management options*** like the development or adaptation of machinery and controlling software for site-specific and differentiated treatments.

Current available sensor systems that measure the reflectance of the host are not able to differ between different plant diseases. No algorithms are known for the differentiation of plant diseases by means of reflectance measurements. The sensor systems have a low spatial resolution and so there is also the problem of overlapping the reflectance of healthy and diseased plants. The next step in developing a good working sensor system would be the integration of an expert system. With the implementation of such a system it might be possible to differ between plant diseases although a sensor system with a low spatial resolution is used and no algorithms are known. The expert system could exclude at the time of measurement, due to necessary situations for the development of plant diseases (like days with a special relative humidity or minimum temperatures), diseases and so it might be possible to relate the reflectance change to a plant disease.

But the main aim of developing a sensor system in the future should be the use of a sensor system with a high spatial resolution, the identification of algorithms for plant disease identification due to reflectance changes and therefore the differentiation between plant diseases and the combination of such a sensor system with these algorithms and a crop growth model. Such a system would be able to detect plant diseases site-specific within fields, differentiate between diseases and could show different possibilities of treatments. Sensor systems with a high spatial resolution are currently tested and should be on the market soon. What currently is missing are algorithms for the differentiations of plant diseases. In this area a lot of research needs to be done in the future. Also a site-specific crop growth model is needed that integrates reflectance measurements within the calculations and decides whether it is necessary to spray or not to spray.

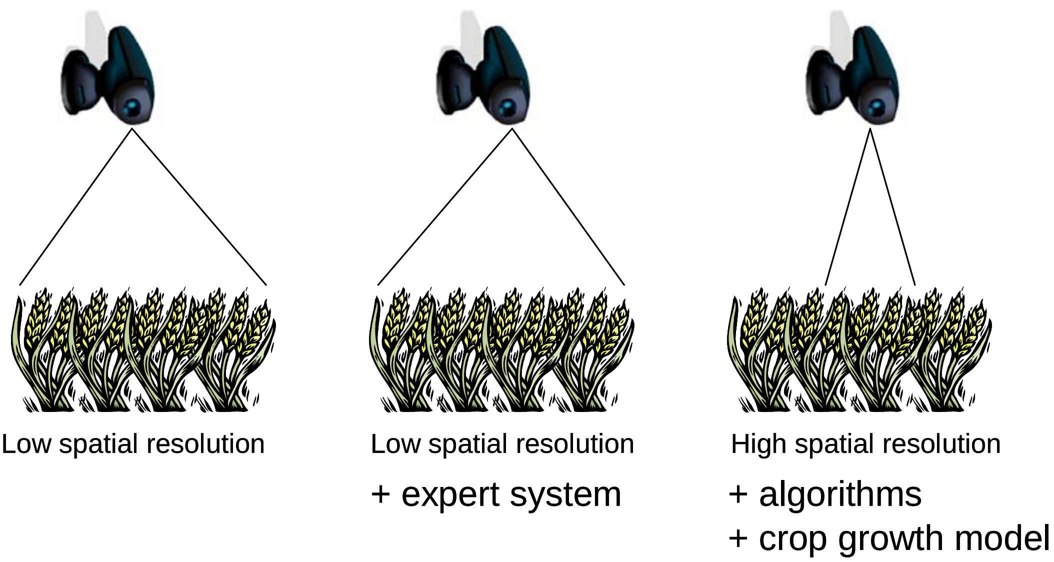

Figure 19 Possible development of a sensor system in the future.

11 Summary

The topic of this study was "Use of sensor technologies to estimate and assess the effect of various plant diseases on crop growth and development". The background of the investigation can be seen in the challenge of developing a sensor system for the site-specific identification of plant diseases.

The most widely used practice in disease control is still to spray fungicides uniformly over fields at different times during the vegetation period. However, most diseases are not distributed uniformly across a field, but occur in patches. During the early stage of epidemics large areas of the field are disease free. Excessive use of fungicides increases costs and can increase fungicides residue levels on agricultural products. As there is an increasing pressure to reduce their use by targeting fungicide spraying only on those places in the field where they are needed, the challenge is to provide farmers the the appropriate technological solutions. A simple and cost-effective optical device, based on the measurement of canopy reflectance in several wavebands, would allow disease patches to be identified and thus controlled. The implementation of these reflectance measurement data into crop growth models would allow for the development of site-specific decision rules whether to spray or not to spray.

The specific objectives of the Ph.D. thesis were to:

- develop and test reflectance measurements as a possible technology to identify reflectance signatures of various plant diseases;
- develop suitable sets of calibrations that can be used for the identification and quantification of plant diseases;
- test different sensor systems at different spatial resolutions for their ability to identify plant diseases;
- develop a strategy to use plant disease information gained from sensor measurements as input dataset for the simulation of wheat growth under disease pressure in CERES-Wheat.

In greenhouse experiments at the University of Hohenheim and in field experiments at the experimental station "Ihinger Hof" of the University of Hohenheim the influence of the diseases powdery mildew, septoria leaf blotch and wheat eyespot on the reflectance of winter wheat was analyzed. To measure the reflectance of the plants three different sensor systems were used. Plant reflectance was measured with a digital camera (LEICA S1 PRO, LEICA Kamera AG, Solms, Germany) at leaf scale

(0.5 cm²) and with the spectroradiometer Field Spec® Hand Held (ASD, Inc. Boulder, CO, USA) (0.5 m²) and the Yara N-Sensor in the field-scan modus (12 m²) 2 m above the canopy. The diseases powdery mildew, septoria leaf blotch and wheat eyespot have been analyzed.

- In a first approach it was tested if it is possible to detect plant diseases using reflectance measurements. The greenhouse studies showed that powdery mildew could be identified especially in the visible wavelength range. Also a correlation between powdery mildew pustules and reflectance changes was possible. Powdery mildew is a leaf disease and changes could directly be detected by a sensor system (Chapter 5).
- Out of this the second approach was to analyze if a stem disease that cannot directly be detected could be identified using a sensor system. The influence of wheat eyespot was investigated in a field experiment with winter wheat. The results showed that wheat eyespot could not be detected with the digital camera and the spectroradiometer. The problem was the low infection level and the distance between the measuring place and the infection place (Chapter 6).
- In a next step common vegetation indices were tested for their ability to identify plant diseases. Different vegetation indices were selected out of the literature to detect powdery mildew and septoria leaf blotch in the field using a spectroradiometer. Results indicated that the common vegetation index REIP was able to detect powdery mildew at an infection level of 7 %. With the common vegetation indices septoria leaf blotch could be detected only at a late infection level of 13.7 %. Out of this the new vegetation index DII was developed, which was able to detect septoria leaf blotch at an early infection level of 4 % (Chapter 7).
- Not only the place of infection but also the spatial resolution seems to play an important role in the identification of plant diseases. In a further approach different sensor systems with different spatial resolutions were tested in a field experiment for the identification of septoria leaf blotch. The results showed in general that septoria leaf blotch could be identified especially in the infrared wavelength range compared to powdery mildew that could especially identified in the visible wavelength range. The results showed further that the lower the spatial resolution , the more difficult it gets to identify plant

diseases site-specifically. With a spatial resolution of 0.5 cm^2 a identification and quantification was possible. With a spatial resolution of 0.5 m^2 only a identification was possible and with a spatial resolution of 12 m^2 not identification and quantification was possible. That might be because of the resulting mixture of healthy and diseased plants (Chapter 8).

- The last step of this work was then to show how reflectance measurements could be implemented into crop growth models to calculate decisions whether to spray or not to spray fungicides on a site-specific level.

Summarizing, the overall results of this study indicated that an identification of plant diseases was possible under certain conditions. An identification was possible if the infection place was also the measuring place and if a sensor system was used with a high spatial resolution. The results also showed that it was possible in a certain way to differ between biotroph and necrotroph plant diseases. For a holistic farming concept it is necessary in the future that reflectance measurements are integrated in a crop growth model to give farmers a decision tool that decides whether the infection is critical enough to spray or not.

12. Zusammenfassung

Die vorliegende Arbeit stand unter dem Titel „Use of sensor technologies to estimate and assess the effect of various plant diseases on crop growth and development”. Hintergrund der Untersuchung war die Entwicklung eines Sensor Systems für die teilflächenspezifische Identifizierung von Pflanzenkrankheiten.

Die am meist verbreiteste Technik im Bereich der Krankheitskontrolle ist immer noch die einheitliche Bearbeitung von Feldern mit Fungiziden zu verschiedenen Zeitpunkten innerhalb der Vegetationsperiode. Jedoch sind die meisten Pflanzenkrankheiten nicht einheitlich über einem Feld verbreitet, sondern treten nur auf einzelnen Teilflächen auf. Während der anfänglichen Krankheitsentwicklung sind viele Teile des Feldes noch frei von Krankheiten. Der übermäßige Gebrauch von Pflanzenschutzmitteln erhöht die Kosten und kann die Rückstände von Pflanzenschutzmitteln auf landwirtschaftlichen Produkten erhöhen. Da ein erheblicher Druck besteht, den Gebrauch von Pflanzenschutzmitteln zu reduzieren und nur noch an den Stellen im Feld einzusetzen, an denen Pflanzenkrankheiten auftreten, ist die Herausforderung, Landwirten eine geeignete technologische Lösung bereit zu stellen. Eine einfache und kostengünstige optische Erfindung, basierend auf der Messung der Bestandesreflexion in verschiedenen Wellenlängenbereiche, würde es ermöglichen, Krankheiten im Feld teilflächenspezifisch zu erkennen und zu kontrollieren. Die Einbindung dieser Reflexionsmessungen in Pflanzenwachstumsmodellen würde es ermöglichen, teilflächenspezifische Entscheidungsregeln zu entwickeln, die entscheiden, ob es notwendig ist zu behandeln oder nicht.

Die einzelnen Ziele der Arbeit waren:

- die Entwicklung und das Testen von Reflexionsmessungen als eine geeignete Technologie um Pflanzenkrankheiten anhand der Reflexion zu erkennen;
- die Entwicklung von geeigneten Kalibrierungsserie, die zur Identifizierung und Quantifizierung von Pflanzenkrankheiten verwendet werden können;
- das Testen von unterschiedlichen Sensor-Technologien mit einer unterschiedlichen räumlichen Auflösung im Hinblick auf die Erkennung von Pflanzenkrankheiten;

- die Entwicklung von Strategien um die Information über Pflanzenkrankheiten, gewonnen von den Sensormessungen, als Eingangsparameter in CERES-Wheat zu integrieren, um die Entwicklung von Weizen unter Krankheiten zu simulieren.

In Gewächshausversuchen an der Universität Hohenheim und in Feldversuchen auf der Versuchsstation „Ihinger Hof“ der Universität Hohenheim wurde der Einfluss der Krankheiten Mehltau, Blattdürre und Halmbruch auf die Reflexion von Winterweizen untersucht. Um die Reflexion der Pflanzen zu untersuchen wurden drei verschiedenen Sensoren verwendet. Die Reflexion wurde mit einer digitalen Kamera (LEICA S1 Pro, LEICA Kamera AG, Solms, Deutschland) auf der Blattebene (0,5 m^2) und mit dem Spectroradiometer Field Spec® Hand Held (ASD, Ic. Boulder, CO, USA) (0,5 m^2) und dem Yara N-Sensor im field-scan Modus (12 m^2) 2 m über dem Bestand gemessen.

- In einem ersten Ansatz wurde getestet, ob es möglich ist, Pflanzenkrankheiten mittels Reflexionsmessungen zu erkennen. Die Gewächshausversuche zeigten, dass es möglich ist, Mehltau zu erkennen, vor allem im sichtbaren Wellenlängenbereich. Auch eine Korrelation zwischen Mehltaupusteln und der Reflexionsänderung war möglich. Mehltau ist eine Blattkrankheit und kann somit direkt von den Sensoren erkannt werden (Kapitel 5).
- Daraufhin wurde in einem zweiten Ansatz untersucht ob es möglich ist ein Stängelkrankheit, die nicht direkt von Sensoren erkannt werden kann zu identifizieren. Der Einfluss von Halmbruch wurde in einem Feldversuch mit Winterweizen untersucht. Die Ergebnisse zeigten, dass Halmbruch nicht mit der digitalen Kamera und dem Spectroradiometer erkannt werden konnte. Das Problem war die geringe Infektionsrate und der Abstand zwischen Ort der Messung und Ort der Infektion (Kapitel 6).
- In einem nächsten Schritt wurden gebräuchliche Vegetationsindizes im Hinblick auf ihre Fähigkeit, Pflanzenkrankheiten zu erkennen, getestet. Verschiedenen Vegetationsindizes wurden aus der Literatur ausgewählt, um Mehltau und Blattdürre im Feld mittels des Spectroradiometers zu erkennen. Die Ergebnisse zeigten, dass der gebräuchliche Index REIP Mehltau bei einem Infektionslevel von 7 % erkennen konnte. Blattdürre konnte jedoch

mittels den gebräuchlichen Indizes erst ab einem Infektionslevel von 13.7 % erkannt werden. Aus diesem Grund wurde der neue Vegetationsindex DII entwickelt, der Blattdürre bei einem frühen Infektionslevel von 4 % erkennen konnte (Kapitel 7).

- Aber nicht nur der Ort der Infektion, sondern auch die räumliche Auflösung scheint eine wichtige Rolle bei der Erkennung von Pflanzenkrankheiten zu spielen. In einem weiteren Ansatz wurden unterschiedliche Sensorsysteme mit einer unterschiedlichen räumlichen Auflösung in Feldversuchen für die Erkennung von Blattdürre getestet. Die Ergebnisse zeigen generell, dass Blattdürre besonders im infraroten Wellenlängenbereich erkannt werden konnte verglichen mit Mehltau, der besonders im sichtbaren Wellenlängenbereich erkennbar war. Die Ergebnisse zeigen ferner, dass je geringer die räumliche Auflösung ist, desto schwieriger wird es, Pflanzenkrankheiten teilflächenspezifisch zu erkennen. Mit einer räumlichen Auflösung von 0,5 cm^2 war eine Erkennung und Quantifizierung möglich. Mit einer räumlichen Auflösung von 0,5 m^2 war nur noch eine Erkennung, aber keine Quantifizierung und mit einer räumlichen Auflösung von 12 m^2 war keine Erkennung und Quantifizierung möglich. Eine mögliche Ursache hierfür liegt in der Mischung aus gesunden und kranken Pflanzen (Kapitel 8).
- Der letzte Schritt dieser Arbeit war dann aufzuzeigen, wie Reflexionsmessungen in Pflanzenwachstumsmodellen integriert werden können, um Entscheidungen teilflächenspezifisch zu ermitteln, die entscheiden, ob es notwendig ist Fungizide auszubringen oder nicht.

Zusammenfassend zeigten die Ergebnisse, dass ein Erkennen von Pflanzenkrankheiten unter gewissen Bedingungen möglich war. Ein Erkennen war dann möglich, wenn der Messort dem Infektionsort entsprach und wenn ein Sensor mit einer hohen räumlichen Auflösung verwendet wurde. Die Ergebnisse zeigten auch, dass es möglich war, in gewisser Weise zwischen biotrophen und nekrotrophen Krankheiten zu unterscheiden. Für ein ganzheitliches Bewirtschaftungskonzept ist es in der Zukunft notwendig, dass Reflexionsmessungen in Pflanzenwachstumsmodellen integriert werden, um dem Landwirt eine Entscheidungshilfe zu geben, die ermittelt, ob die Infektion kritisch genug ist für eine Behandlung mit einem Fungizid.

General References

Adams M.L., Philpot W.D., Norvell W.A. 1999. Yellowness index: an application of spectral second derivatives to estimate chlorosis of leaves in stressed vegetation. International Journal of Remote Sensing, Vol. 20, 3663-3675.

Agrios, G.N. 2005. Plant pathology. Elsevier Academic Press, Burlington, USA.

AngusJ.F., Bowden, J.W. and Keating, B.A. 1993. Modeling nutrient responses in the field. Plant Soil, Vol. 155/156, pp. 57-66.

Baandrup, M.; Ballegaard, T. 1989. Three years field experience with an advisory computer system applying factor-adjusted doses. Brighton Crop Protection Conference-Weeds, Vol. 2, pp. 555-560.

Bassanezi, R.B., Amorim, L., Bergamin Filho, A. and Berger, R.D. 2002. Gas exchange and emission of chlorophyll fluorescence during the monocycle of rust, angular leaf spot and anthracnose on bean leaves as a function of their trophic characteristics. J. Phytopathology, Vol. 150, pp. 37-47.

Batchelor, W.D., Jones, J.W., Boote, K.J. and Pinnschmidt, H.O., 1993. Extending the use of crop models to study pest damage. American Society of Acricultural Engineers, Vol. 36(2), pp. 551-558.

Batchelor, W.D., Paz, J.O. and Thorp, K.R. 2004. Development and evaluation of a decision support system for precision farming. In: Proceedings of the 7th International Conference on Precision Agriculture. July 25-28, 2004, Minneapolis, MN. ASA, CSSA, and SSSA, Madison, WI, USA.

Batchelor, W.D., Link, E.J., Thorp, K.R., Graeff, S. and Paz, J.O. 2004. The role of crop growth models in precision farming. Workshop Precision Farming, May 13, Renningen, Germany, pp. 11-16.

Blackmer, T.M., Schepers, J.S., Varvel, G.E., Meyer, G.E. 1996. Analysis of aerial photography for nitrogen stress within corn fields. Agronomy Journal, Vol. 88, 729-733

Blackmore, B.S. 2000. The interpretation of trends from multiple yield maps. Comput. Electron. Agric., Vol. 26, pp. 37-51.

Blakeman, R.H., Bryson, R. and Dampney, P. 2000. Assesing crop condition in real time using high resolution satellite imagery. Remote sensing in agriculture. Association of Applied Biologists, pp. 163-172.

Boochs, F., Kupfer, G., Dockter, L. and Kühbauch, W. 1990. Shape of the red edge as vitality indicator for plants. International Journal of Remote Sensing, Vol. 11, pp. 1741-1753.

Booltink, H.W.G., van Alphen, B.J., Batchelor, W.D., Paz, J.O., Stoorvogel, J.J. and Vargas, R. 2001. Tools for optimizing management of spatially-variable fields. Agricultural Systems, Vol. 70, pp. 445-476.

Boote, K.J., Jones, J.W., Hoogenboom, G.J. and Pickering, N.B. 1998. The GROPGRO model for grain legumes. In: Tsuji, G.Y., Hoogenboom, G.J., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 79-88.

Bouma, J. 1997. General reflections. In: J.V. lake, G.R. Bock and J.A. Goode (Eds.). Precision agriculture: spatial and temporal variability of environmental quality. CIBA Foundation Symposium 210 on precision agriculture: spatial and temporal variability of environmental quality. Wiley, Chichester, pp. 231-241.

Bourgeois, G., 1989. Interrelationship between late leafspot disease and Florunner peanut: A modeling approach. Ph.D. diss., University of Florida, Gainesville.

Bravo, C. Moshou, D. and McCartney, A. 2002. In field disease and nutrient stress detection by imaging spectrography at canopy level. AgEng, Budapest, Hungary, pp. 142 and 143.

Bravo, C., Moshou, D., West, J., McCartney, A. and Ramon, H. 2003. Early disease detection in wheat fields using spectral reflectance. Biosystems Engineering, Vol. 84, pp. 137-145.

Bresler, E., Dasberg, S., Russo, D. and Dagan, G. 1981. Spatial variability of crop yield as a stochastic soil process. Soil Science Soc. Am. Journal, Vol.45, pp. 600-605.

Brown, J.S., Kellock, A.W. and Paddick, R.G. 1978. Distribution and dissemination of *Mycosphaerella graminicola* (Fuckel) Schroeter in relation to the epidemiology of speckled leaf blotch of wheat. Australian Journal of Acricultural Research, Vol. 29, pp. 1139- 1145.

Brown, J.S. Kellbock, A.W. and Paddick. R.G, 1978. Distribution and dissemination of Mycosphaerella graminicola (Fuckel) Schroeter in relation to the epidemiology of speckled leaf blotch of wheat. Australian Journal of Agricultural Research, Vol. 29, pp. 1139-1145.

Brown J.S., Paddick R.G. 1982. Surveys of speckled leaf blotch and other foliar diseases of wheat in Victoria, 1974-1978. Aus. J. Exp. Acric. Anim. Husb., Vol. 20, pp. 94-96.

Browning, J.A. 1979. Genetic protective mechanism of plant pathogen populations: their coevolution and use in breeding for resistance. In M.K. Harris, ed. Biology and breeding for resistance. Texas Publ. MP-1451, p. 52-57. Texas, USA, Texas A&M University Press, College Station. 605 pp.

Bundessortenamt 2005. Beschreibende Sortenliste. Landbuch Verlagsgesellschaft mbH, Hannover, Germany.

Buschmann C., Nagel E. 1993. In vivo spectroscopy and internal optics of leaves as basis for remote sensing of vegetation. International Journal of Remote Sensing, Vol. 14(4), 711-722.

Buschmann, C. and Lichtenthaler, H.K. 1998. Principles and characteristics of multi-colour fluorescence imaging of plants. J. Plant Physiol., Vol. 152, pp. 297-314.

Caldwell, R.M. 1976.Development of the wheat Septoria blight problem in the USA over the period 1922 to 1975. Proc. Septoria Diseases of Wheat Workshop. B. M. Cunfer and L. R. Neson eds. Georgia Agric. Exp. Sta. Spec. Publ. 4, pp. 3-6.

Caldwell, R.M. and Narvaez, I. 1960. Losses to winter wheat from infection by Septoria tritici. Phytopatology, Vol. 50, p. 630.

Caldwell, R.M. 1976. Development of the wheat Septoria blight problem in the USA over the period 1922 to 1975. Proc. Septoria Diseases of Wheat Workshop. B. M. Cunfer and L. R. Neson eds. Georgia Agric. Exp. Sta. Spec. Publ. 4, pp. 3-6.

Calvero, S.B. and Teng, P.S., 1992. Validation of BLASTSIM.2 model in IRRI blast (B1) nursery and Cavinti, Laguna, Philippines. International Rice Research Newsletter, Vol. 17(5), pp. 20-21.

Campbell, C.L and Noe, J.P. 1985. The spatial analysis of soilborne pathogens and root diseases. Ann. Rev. Phytopathology, Vol. 23, pp. 129-148.

Campbell, C.L. and Madden, L.V. 1990. Introduction to Plant Disease Epidemiology. John Wiley and Sons, New York.

Carter, G.A. 1993. Response of leaf spectral reflectance to plant stress. American Journal of Botany, Vol. 80, pp. 239-243.

Carter, G.A. and Miller, R.L. 1994. Early detection of plant stress by digital imaging within narrow stress-sensitive wavebands. Remote Sensing of Environment, Vol. 50, pp. 295-302.

Carter, G.A. et al. 1996. Narrow-band reflectance imagery compared with thermal imagery for early detection of plant stress. J. Plant Physiol., vol. 148, pp. 515-522.

Carter, C.A. and Knapp, A.K. 2001. Leaf optical properties in higher plants: linking spectral characteristics to stress and chlorophyll concentration. American Journal of Botany, Vol. 88 (4), pp. 677-684.

Chaerle, L., 2000. Thermographic visualization of cell death in tobacco and *Arabidopsis*. Plant Cell Environ.

Cerrato, M. and Blackmer, A. 1990. Comparison of models for describing corn yield response to nitrogen fertilizer. Agronomy Journal, Vol. 82, pp. 138–143.

Chaerle, L., de Boever, F., van Montagu, M. and van der Straeten, D. 2001. Thermographic visualization of cell death in tobacco and *Arabidopsis*. Plant Cell Environment, Vol. 24, pp. 15-25.

Chapron, M., Requena-Esteso, M. Boissard, P. and Assemat, L. 1999. A method for recognizing vegetal species from multispectral images. In: Precision Agriculture, 2nd European Conference on Precision Agriculture, Stafford, J. (ed.) Sheffield Academic Press, Sheffield, UK, pp. 239-248.

Cibula, W.G. and Carter, G.A. 1992. Identification of a far-red reflectance response to ectomycorrhizae in splash pine. International Journal of Remote Sensing, Vol. 13, pp. 925-932.

CIE 1986. Colometry. 2nd ed. Publication CIE No.Vienna: Commision Internationale de l'Eclaiage.

Coakley S.M., McDaniel L.R., Shaner G. 1985. Model for predicting severity of Septoria tritici blotch and winter wheat. Phytopathology, Vol. 75, pp. 1245-1251.

Cooke, B.M. and Jones, D.G. 1971. Epidemiology of Septoria tritici and S. nodorum I. Th reaction of spring and winter wheat varieties to infection by Septoria tritici and Septoria nodorum. Trans. Br. Mycol. Soc., Vol. 56, pp. 121-125.

Cornish, P.S., Baker, G. R., Murray, G. M., 1990. Physiological responses of wheat (Triticum aestivum) to infection with Mycosphaerella graminicola causing

Septoria tritici blotch. Australian Journal of Agricultural Ressearch, Vol. 41, pp. 317-327.

Daamen, R.A. 1989. Assessment of the profile of powdery mildew and its damage function at low disease intensities in field experiments with winter wheat. Neth. J. Pl. Pathol., Vol. 95, pp. 85-105.

Dammer K.H. 1999. Analyse und Darstellung der Dispersion von Schaderregern sowie Möglichkeiten der Stickprobennahme bei aggregiertem Auftreten (Analysis and Dispersion maps of pests and sampling design under their aggregated pattern). Habil. Kropstädt, Germany.

Daughtry C.S.T., Walthall C.L., Kim M.S., Brown de Colstoun E., Mc Murtrey III J.E. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote Sensing of Environment, Vol. 74, pp. 229-239.

Deering, D.W. 1989. Field measurements of bidirectional reflectance. Theory and applications of optical remote sensing. ed Asrar, G. John Wiley & Sons, New York, pp. 14-65.

Dobermann, A., Blackmore, S., Cook, S.E. and Adamchuck, V.I. 2004. Precision Farming: Challenges and Future Directions. In: Proceedings of the 4th International Crop Science Congress, 29 Sept – 1 Oct 2004, Brisbane, Australia.

Doerge, T.A. 1999. Variable rate nitrogen management for corn production – Success proves elusive. Site-specific Management Guidelines (SSMG) 36.

Dudka M., Langton S.J., Schuler R.T., Kurle J., Grau C.R. 1998. Use of digital imagery to evaluate disease incidence and yield loss caused by Sclerotinia Stem Rot of Soybeans. Proc. Int. Precision Agric. Conf., St. Paul.

Dumas, A. 1962. Stickstoffbestimmung nach Dumas. Die Praxis des organischen Chemikers, Vol. 41, pp. 45-51.

Edminster, T.W. 1978. Concepts for using modeling as a research tool. Technical Manual 520. U.S. Department of Agriculture, Beltsville, MD, USA.

Eyal,Z., Scharen, A.L., Prescott, J.M. and Van Ginkel, M. 1987. The Septoria diseases of wheat: Concepts and method of disease management. CIMMYT. Mexico. D.F..

Eyal, Z. 1999. The septoria tritici and stagonospora nodorum blotch diseases of wheat. European Journal of Plant Pathology, Vol. 105, pp. 629- 641.

Franke, J., Menz, G., 2007. Multi-temporal wheat disease detection by multi-spectral remote sensing. Precision Agric. Online

Felle, H.H., Herrmann, A., Hanstein, S., Hückelhoven, R., and Kogel, K. H. 2004. Apoplastic pH signaling in barley leaves attecked by the powdery mildew fungus *Blumeria graminis* f. sp. *hordei*. Mol. Plant-Microbe Interaction, Vol. 17, pp. 118-123.

Filella, I., Penuelas, J. 1994. The red edge position and shape as indicators of plant chlorophyll content, biomass and hydric status. International Journal of Remote Sensing, Vol. 15(7), pp. 1459-1470.

Fleischer S.J., Blom P.E., Weisz R. 1999. Sampling in precision IPM: When the objective is a map. Phytopathology, Vol. 75, pp. 538-542.

France, J. and Thornley, J.H.M. 1984. Mathematical models in agriculture. Butterworths, London.

Franke J., Menz G., Oerke E.-C., Rascher U. 2005. Comparison of multi- and hyperspectral imaging data of leaf rust infected wheat plants. Proceedings of the SPIE, Vol. 5976, pp. 349-359.

Franke, J., Menz, G. 2007. Multi-temporal wheat disease detection by multi-spectral remote sensing. Precision Agriculture, Vol. 8, pp. 161-172.

Fujimasa, I. 1998. Pathophysiological expression and analysis of far infrared thermal images. IEEE Eng. Med. Biol., Vol.17, pp.34-42.

Gates,D.M., Keegan, H.J., Schleter, J.C. and Weidner, V.R. 1965. Spectral properties of plants. Applied Optics, Vol. 4, pp. 11-20.

Gerhards, R. Sökefeld, M., Schulze-Lohne, K., Mortensen, D.A. and Kühbauch, W., 1997. Site specific weed control in winter wheat. Journal of Agronomy and Crop Science, Vol. 178, p. 219.

Gerhards, R., Sökefeld, M. and Kühbauch, W. 1998. Einsatz der digitalen Bildverarbeitung bei der teilschlagspezifischen Unkrautkontrolle. Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz, Sonderheft XVI, pp. 273-278.

Gerhards, R., Sökefeld, M., Timmermann, C. and Kühbauch, W. 2002. Site-specific weed control in maize, sugar beet, winter wheat, and winter barley. Precision Agriculture, Vol. 3, pp. 25-35.

Gerhards R., Christensen S. 2003. Real time weed detection, decision making and patch spraying in maize (Zea mays L.), sugar beet (Beta vulgaris L.), winter wheat (Triticum aestivum L.) and winter barley (Hordeum vulgare L.). Weed Research, Vol. 43, pp. 1-8.

Gerhards, R. and Oebel, H. 2006. Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. Weed Research, Vol. 46, pp. 185-193.

Gillian, C.A. 1982. Statistical analysis of the spatial pattern of *Botrytis fabae* on *Vicia faba*: a methodological study. Trans. Br. Mycol. Soc., Vol. 79, pp. 193-200.

Goddard, T.W., Lachapelle, G., Cannon, M.E., Penney, D.C. and McKenzie, R.C. 1995. The potential of GPS and GIS in precision agriculture. Proc. Geomatique V: "La Route De L'Innovation". November 9-10, Montreal, P.Q., Canada.

Godwin, D.C., and U. Singh. 1998. Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. p. 41–54. In G.Y. Tsuji, G. Hoogenboom, and P.K. Thornton (ed.) Understanding options for agricultural production. Systems approaches for sustainable agricultural development. Kluwer Academic Publ., Dordrecht, the Netherlands

GopalaPillai, S. and Tian, L. 1999. In-field variability detection and soatial yield modelling for corn using digital aerial imaging. Trans. ASAE, Vol. 42, pp. 1911-1920.

Graeff, S., Gröll, K., Uphaus, M. and Claupein, W. 2008. Teilflächenspezifischer Einsatz von Fungiziden – Einsatz des Yara N-Sensors® im Field-Scan-Modus. Getreidemagazin, Vol. 2-2008.

Grant, L. 1987. Diffuse and specular characteristics of leaf reflectance. Remote Sensing of Environment, Vol. 22, pp. 309-322.

Guyot G., Baret F., Major D.J. 1998. High spectral resolution: Determination of spectral shifts between the red and the near infrared. International Archives of Photogrammetry and Remote Sensing, Vol. 11, pp. 750-760.

Guyot, G. 1990. Optical properties of vegetation canopies", In: M.D. Steven and J.A. Clark (Eds.): *Applications of Remote Sensing in Agriculture*, Butterworths, London, pp, 19-43.

Habermeyer, J. and Gerhard, M. 2000. Pilzkrankheiten. BASF Landwirtschaft.

Haboudane D., Miller J.R., Tremblay N., Zarco-Tejada P.J., Dextraze L. 2002. Integration of hyperspectral vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sensing of Environment, Vol. 81, pp. 416-426.

Hammond-Kosack, K. and Jones, J. 2000. Response to plant pathogen. In: Biochemistry & Molecular Biology of Plants, B. Buchanan, W. Gruissem, R. Jones, Eds., American Society of Plant Physiologists.

Hanks, R.J. and Ritchie, J.T. 1991. Modeling plant and soil systems. Agron., Vol. 31, p 545.

Hansen J.G. 1991. Use of multispectral radiometry in wheat yellow rust experiments. Bulletin EPPO, Vol. 21, pp. 651-658.

Harris, J.A. 1920. Practical universality of field heterogeneity as a factor influencing plot yields. Journal of Agriculture Research, Vol. 19, pp. 279-314.

Hart, W.G. and Myers, V.I. 1968. Infrared aerial colour photography for detection of populations of brown soft scale in citrus groves. Journal of Economic Entomology, Vol. 61, pp. 617-624.

Hess D.E., Shaner G. 1987a. Effect of moisture and temperature on development of Septoria tritici blotch in wheat. Phytopathology, Vol. 77, pp. 215-219.

Hess D.E., Shaner G. 1987b. Effect of moisture on Septoria tritici blotch development on wheat in the field. Phytopathology, Vol. 77, pp. 220-226.

Holmes, S.J.I. and Colhoun, J. 1975. Strawborne inoculum of *Septoria nodurum* and *Septoria tritici* in relation to incidence of disease on wheat plants. Plants Pathology, Vol. 24, pp. 63-66.

Hoogenboom, G. 2003. Crop growth and development. In: Bendi, D.K., Nieder, R. (Eds.), Handbook of Processes and Modeling in the Soil-Plant System. The Haworth Press, Binghamton, New York, pp.655-691.

Hooker, A.L. 1957. Methods of inoculation and determining varietal reactions in the Septoria disease of oats. Plant Dis. Rep., Vol. 41, pp. 592-597.

Huete A.R. 1988. A soil-adjusted vegetation index SAVI. Remote Sensing of Environment, Vol. 25, pp. 295-309.

Hunt, L.A., S. Pararajasingham, J.W. Jones, G. Hoogenboom, D.T. Imamura, and R.M. Ogoshi. 1993. Gencalc: Software to facilitate the use of crop models for analyzing field experiments. Agron. J., Vol. 85, pp.1090–1094.

Hunt, L.A., J.W. White, and G. Hoogenboom. 2001. Agronomic data: Advances in documentation and protocols for exchange and use. Agric. Syst., Vol. 70, pp. 477–492

Irmak, A., Jones, J.W., Batchelor, W.D. and Paz, J.O. 2001. Estimating spatially variable soil properties for application of crop models in precision farming. Trans. ASAE, Vol. 44, pp. 1343-1353.

Jackson, R.D. 1986. Remote sensing of biotic and abiotic plant stress. Annual Review of Phytopathology, Vol. 24, pp. 265-287.

Jacobi, J. 2005. Teilflächige Diagnose von Pilzbefall und Stickstoffmangel an Weizen mit Hilfe der optischen Fernerkundung. Rheinische Friedrich-Wilhelm-Universität zu Bonn, Dissertation.

Jaynes, D.B., Colvin, T.S. 1997. Spatiotemporal Variability of Corn and Soybean Yield. Agronomy Journal, Vol. 89, pp.30-37.

Jeger MJ, van den Bosch F. 1994. Threshold criteria for model plant disease epidemics. I. Asymptotic results. Phytopathology, Vol. 84, pp. 24–27

Jeger MJ, van den Bosch F. 1994. Threshold criteria for model plant disease epidemics. II. Persistence and endemicity. Phytopathology, Vol. 84, pp. 28–30

Jones, J.W., Hoogenboom, G.J., Porter, C., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A. and Ritchie, J.T. 2003. DSSAT cropping System Model. Special Edition of European J. Agron., Vol. 18, pp. 235-265.

Jonson, J.W., Baenziger, P.S., Yamazaki, W.T. and Smith, R.T. 1979. Effects of Powdery mildew on yield and quality of isogenic lines of Chancellor wheat. Crop Science, Vol. 19, pp 349-352.

Kema, G. H. J.; Yu, D. , Rijkenberg, F. H. J.; Shaw, M. W. and Baayen, R. P. 1996. Histology of the pathogenesis of Mycosphaerella graminicola in wheat. Phytopathology, Vol. 86, pp. 777-786.

King, J.E. Cook J. R., Melville S. C. 1983. A review of Septoria diseases of wheat and barley. Annual Applied Biology, Vol. 103, pp. 345-373.

Knipling, E.B. 1970. Physical and Physiological Basis for the reflectance of visible and near-infrared radiation from vegetation. Remote Sensing of Environment, pp.155-159.

Kumar, L., Schmidt, K.S., Dury, S. and Skidmore, A.K. 2001. Review of Hyperspectral Remote Sensing and Vegetation Science. Imaging spectrometry: basic principles and prospective applications, eds.

Lamp, J.A., Dowdy, R.H., Anderson, J.L., Rehm, G.W. 1997. Spatial and temporal stability of corn grain yields. J. Prod. Agric., Vol. 10 (3), pp. 410-414.

Lancashire, P.D., Bleiholder, H., van den Boom, T., Langelüddeke, P., Strauss, R., Weber, E. and Witzenberg, A. 1991. A uniform decimal code for growth stages of crops and weeds. Annual Applied Biology, Vol. 119, pp. 561-601.

Larsolle, A. and Hamid Muhammed, H. 2005. Measuring crop status using multivariate analysis of hyperspectral field reflectance with application to disease severity and plant density. Fifth International Conference on Precision Agriculture, Uppsala, pp. 217-225.

Last F.T. 1953. Some effects of temperature and nitrogen supply on Wheat Powdery mildew. Annual Applied Biology, Vol. 40, pp. 312-322.

Last ,F.T., 1963. Metabolism of barley leafs inoculated with Erysiphe graminis merat. Annals of Botany, Vol. 27, pp. 685-690.

Laudien R., Bareth G., Doluschitz R. 2003. Analysis of hyperspectral field data for detection of sugar beet diseases. EFITA 2003 Conference Debrecen, Hungary, pp. 375-381.

Laudien R., Bareth G., Doluschitz R. 2004. Comparison of remote sensing based analysis of crop diseases by using high resolution multispectral and hyperspectral data –case study: Rhizoctonia solani in sugar beet. Geoinformatics 2004, University of Gävle, Sweden, pp. 270-276.

Lewis, D.H. 1976. In N.Sunderland, ed., Perspectives in Experimental Biology, Vol. 2, Botany, Pergamon Press, Oxford, pp. 207-219.

Lichtenthaler, H.K. and Miehé, J.A. 1997. Fluorescence imaging as a diagnostic tool for plant stress. Trends Plant Sci., Vol. 2, pp. 316-320.

Liebig, J. V. 1855. Die Grundsätze der Agricultur-Chemie mit Rücksicht auf die in England angestellten Untersuchungen. Friedrich Vieweg und Sohn, Braunschweig, Germany.

Liebler, J. 2003. Feldspektroskopische Messungen zur Ermittlung des Stickstoffstatus von Winterweizen und Mais auf heterogenen Schlägen. Herbert Utz Verlag, 192 pp.

Link, A., Panitzki, M. and Reusch, S. 2002. HYDRO-N-Sensor: Tractor-mounted remote sensing for variable nitrogen fertilization. Proceedings of the 6th international Conference on Precision Agriculture and Other Precision Resources Management. Robert, P.C. (ed.), July 14-17, Minneapolis, MN, USA. Published as CD-ROM.

Link. E.J. 2005. Investigation and modeling of the optimization potential of adapted nitrogen fertilization strategies in corn cropping systems with regard to minimize nitrogen losses. Dissertation, University of Hohenheim, Stuttgart, chapter 4.3, 6.0.

Lorenzen, B. and Jensen, A. 1989. Changes in spectral properties induced in barley by cereal powdery mildew. Remote Sensing of Environment, Vol. 27, pp. 201-209.

Lucas, J.A. 1998. Plant Pathology and Plant Pathogens. Blackwell Science, Bistrol.

Luo, Y., Teng, P.S., Fabellar, N.G. and TeBeest, D.O., 1997. A Rice-Leaf blast combined model for simulation of epidemics and yield loss. Agricultural systems, Vol. 53, pp. 27-39.

Madden, L.V., Hughes, G. and van den Bosch, F. 2007. The study of plant disease epidemics. The American Phytopathological Society, St. Paul, Minnesota, USA, APS Press, Chapter 3.

Malthus, T.J. and Madeira, A.C. 1993. High resolution spectroradiometry: spectral reflectance of field beans infected by *Botrytis fabae*. Remote Sensing of Environment, Vol. 45, pp. 107-116.

Merton R. 1998. Monitoring community hysteresis using spectral shift analysis and the red-edge vegetation stress index. Proceedings of the Seventh Annual JPL Airborne Earth Science Workshop, NASA, California, USA.

Metternicht G. 2003. Vegetation indices derived from high-resolution airborne videography for precision crop management. International Journal of Remote Sensing, Vol. 24, pp. 2855-2877.

Mitscherlich, E. A. 1909. Das Gesetz des Minimums und das Gesetz des abnehmenden Bodenertrages. Landwirtschaftliches Jahrbuch der Schweiz, Vol. 38, pp. 537–552.

Moshou D., Bravo C., West J., Wahlen S., McCartney A., Ramon H. 2004. Automatic detection of 'yellow rust' in wheat using reflectance measurements and neutral networks. Computers and Electronics in Agriculture, Vol. 44, pp. 173-188.

Moshou, D., Bravo, C., Oberti, R., West, J., Bodria, L., McCartney, A., and Ramon, H. 2005. Plant disease detection based on data fusion of hyper-spectral and multi-spectral fluorescence imaging using Kohonen maps. Real Time imaging, Vol. 11, pp. 75-83.

Moshou, D., Bravo, C., Wahlen, S., West, J., McCartney, A., De Baerdemaeker, J. and Ramon, H. 2006. Simultaneous identification of plant stresses and diseases an arable crops using proximal optical sensing and self-organising maps. Percision. Agriculture, Vol. 7, pp. 149-164.

Muhammed, H.H. 2005. Hyperspectral crop reflectance data for characterizing and estimating fungal disease severity in wheat. Biosystem Engineering, Vol. 91, pp.9-20.

Murray G.M. 1982. Yield losses in wheat associated with different levels of resistance to speckled leaf blotch (*Mycosphaerella graminicola*). Acron. Aust., p. 242.

National Research Council, Board on Agriculture, Committee on Assessing Crop Yield: Site-Specific Farming, Information Systems, and Research Opportunities. Sonka, S.T., M.E. Bauer, E.T. Cherry, J.W. Colburn Jr., R.E. Hemlich, D.A. Joseph, J.B. Leboeuf, E. Lichtenberg, D.A. Mortensen, S.W. Searcy, S.L. Ustin and S.J. Ventura. 1997. Precision agriculture in the 21st century: Geospatial and information technologies in crop management. Washington, D.C: National Academy Press.

Nicolas, H. 2004. Using remote sensing to determine of the date of a fungicide application on winter wheat. Crop Protection, Vol. 23, pp. 853-863.

Nilsson, H.E. 1984. Fjärranalys av växtsjukdomar I fältförsök. Växtskyddsrapporter, Jordbruk, 28, pp. 45-63.

Nilsson, H.E. 1985. Remote sensing of oil seed rape infected by sclerotinia stem rot and verticillium wilt. Växtskyddsrapporter, Jordbruk, 33, pp. 1-33.

Nilsson, H.E. 1985. Remote sensing of 6-row barley infected by barley stripe disease. Växtskyddsrapporter, Jordbruk, 36, pp. 1-49.

Nilsson, H-E., 1995. Remote sensing and image analysis in plant pathology. Annu. Rev. Phytopathology, Vol. 33, pp. 489-527.

Nobel, P.S. 1991. Physiochemical and Environmental Plant Physiology, Academic Press.

Oerke E.-C., Dehne H.-W., Schönbeck F., Weber A. 1994. Crop production and crop protection – estimated losses in major food and cash crops. Elsevier Science, Amsterdam, The Netherlands, p. 808.

Oerke, E.-C. 2000. Befall, Schädigung, Schaden – Eine Bewertung der Ertragsverluste durch Schadorganismen und deren Vermeidung. Habil.-Schrift, Univerität Bonn, p.313.

Oerke, E-C,, lindenthal M., Fröhling, P., Steiner, U., 2005. Digital infrared thermography fort he assessment of leaf pathogens. In: Proceedings of the 5th European Conference on Precision Agriculture, edited by J. V. Stafford (Wageningen Academic Publishers, Netherlands), pp. 73-80.

Oliver M.A., Heming S.D., Gibson G., Adams N. 2003. Exploring the spatial variation of take-all (*Gaeumannomyces graminis* var. *tritici*) for site-specific management. Precision Agriculture, Proceedings of the 4th European Conference on Precision Agriculture, J. Stafford, A. Werner (eds.) Wageningen Academic Publishers, Wageningen, The Netherlands, pp. 481-486.

Oppelt, N. 2002. Monitoring of plant chlorophyll and nitrogen status using the airborne imaging spectrometer AVIS, Dissertation. Ludwig-Maximilian-Universität, München, Kapitel 2.5, 3.3.7.3, 3.5.3.1.

Osbourn, A.E. 1996. Preformed antimicrobial compounds and plant defense against fungal attack. The Plant Cell, Vol. 8, pp. 1821-1831.

Paz, J.O., Batchelor, W.D., Babcock, B.A., Colvin, T.S., Longsdon, S.D., Kaspar, T.C. and Karlen, D.L. 1999. Model-based technique to determine variable rate N for corn. Agric. Syst., Vol.61, pp. 69-75.

Paz, J.O., W.D. Batchelor, and G.L. Tylka. 2001. Method to use crop growth models to estimate potential return for variable-rate management in soybeans. Trans. ASAE, Vol. 44(5), pp. 1335–1341

Paz, J.O., Batchelor, W.D. and Jones, J.W. 2003. Estimating potential economic return for variable soybean variety management. Trans ASAE, Vol. 46, pp. 1225-1233.

Penuelas J., Gamon J.A., Fredeen A.L., Merino J., Field C.B. 1994. Reflectance indices associated with physiological chances in nitrogen- and water-limited sunflower leafs. Remote Sensing of Environment, Vol. 48, pp. 135-146.

Penuelas, J. and Filella, I. 1998. Visible and near-infrared reflectance techniques for diagnosing plant physiological status. Trends Plant Sci., Vol. 3, pp. 151-156.

Peterson, R.B. and Aylor, D.E. 1995. Chlorophyll fluorescence induction in leaves of *Phaseolus vulgaris* infected with bean rust (*Uromyces appendiculatus*). Plant Physiol., Vol. 108, pp. 163-171.

Pinnschmidt, H.O., 1989. Freilanduntersuchungen zur Epidemiologie von Pyricularia oryzae Cav. An Trockenreis(Fiel studies on the epidemiology of P. oryzae Cav. On upland rice). PhD Thesis, University of Giessen, Germany, pp. 268.

Pinnschmidt, H.O., Batchelor, W.D. and Teng, P.S. 1995. Simulation of multiple species pest damage in rice using CERES-rice. Agricultural Systems, Vol. 48, pp. 193-222.

Pierce, F.J. and Lal, R. 1991. Soil management in the 21st century. In: R. Lal and F.J. Pierce (ed.) Soil management for sustainability. Soil Water Conservation Society, Ankeny, Iowa, pp. 175-179.

Plank J.E. van der 1963. Plant disease: Epidemics and control. Academic Press London, UK.

Polischuk, V.P., Schadchina, T.M., Kompanetz, T.I., Budzanivskaya, I.G. and Sozinov, A.L. 1997. Changes in reflectance spectrum characteristic of *Nicotiana debneyi* plant under the influence of viral infection. Arch. Phytopathol. Plant Prot., Vol. 31, pp. 115-119.

Reetz, Jr H.R. and Fixen, P.E. 1999. Strategic approach to site-specific system. In: Site Specific Management Guidelines, SSMG-28.Norcross, GA.

Reusch, S. 1997. Entwicklung eines reflexionsoptischen Sensors zur Erfassung der Stickstoffversorgung landwirtschaftlicher Kulturpflanzen. Institut für Landwirtschaftliche Verfahrenstechnik der Christian-Albrechts-Universität zu Kiel, Ph.D. Thesis, 157p.

Reyniers, M. 2003. Precision farming techniques to support grain crop production. Dissertation, Catholic University of Leuven.

Riedel, W.E. and Blackmer, T.M. 1999. Leaf reflectance spectra of cereal aphid-damaged wheat. Crop Science, Vol. 39, pp. 1835-1840.

Rickman, R.W. and Klepper, B., 1991. Environmentally driven cereal crop growth models. Annual Review of Phytopathology, Vol. 29, pp. 361-380.

Ritchie, J.T., Singh, U., Godwin, D.C. and Brown, W.T. 1998. Cereal growth, development and yield. In: Tsuji, G.Y., Hoogenboom, G.J., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 79-88.

Robert, C., Bancal, M. O., Nicolas, P., Lannou,C., Ney, B., 2004. Analysis and modelling of effects of leaf rust and Septoria tritici blotch on wheat growth. Journal of experimental Botany, Vol. 55(399), pp. 1079-1094.

Rouse J.W., Haas R.H., Schell J.A., Deering D.W. 1973. Monitoring vegetation systems in the great plains with ERTS. Third ERTS Symposium, NASA SP-351, NASA, Washington, DC, Vol. 1, pp. 309-317.

Royle J.D., Shaw M.W., Cook R.J. 1986. Patterns of development of *Septoria nodorum* and *Septoria tritici* in some winter wheat crops in Western Europe, 1981-83. Plant Pathology, Vol. 35, pp. 466-476.

Sadler, E.J., B.K. Gerwig, D.E. Evans, W.J. Busscher, and P.J. Bauer. 2000. Site-specific modeling of corn yield in the SE coastal plain. Agric. Syst., Vol. 64, pp.189–207

Safir, G.R., Svitis, G.H. and Elligboe, A.H. 1972. Spectral reflectance and transmittance of corn leaves infected with *Helminthosporium maydis*. Phytopathology, Vol. 62, pp. 1210-1213.

Sasaki, Y., Okamoto, T., Imou, K. and Torii, T. 1998. Automatic diagnosis of plant disease: spectral reflectance of healthy and diseases leaves. Proceedings AgEng’98 Conference, Oslo, pp. 6.

Sasaki Y., Okamoto T., Imo K., Torii T. 1999. Automatic Diagnosis of Plant Disease. Recognition between Healthy and Diseased Leaf. Journal of the Japanese Society of Agricultural Machinery, Vol. 61/2, pp. 119-126.

Schafer, J.F. 1987. Rusts, smuts, and powdery mildew. In E.G. Heyne, ed. Wheat and wheat improvement, 2nd ed., p. 542-584. Madison, WI, USA, ASA, CSSA, SSSA.

Scholes, J.D. 1992. Photosynthesis: cellular and tissue aspects in diseased leaves. Pest and Pathogens: Plant Responses to Foliar Attack (Ayres, P.G., ed.), pp. 85-106, Bios Scientific Publishers.

Scott K.J., Smillie R.M. 1966. Metabolic regulations in diseased leaves. The respiratory rise in barley leaves infected with powdery mildew. Plant Physiology, Vol. 41, pp. 289- 297.

Secher B.J.M. 1997. Side specific control of disease in winter wheat. Aspects of Applied Biology, Vol. 48, pp. 57-64.

Segarra J, Jeger MJ, van den Bosch F. 2001. Epidemic dynamics and patterns of plant diseases. Phytopathology, Vol. 91, pp. 1001–1010.

Shaner G., Finney R.E. 1976. Weather and epidemics of Septoria leaf blotch of wheat. Phytopathology, Vol. 66, pp. 781-785.

Shipton, W.A., Boyd, W.R.J., Rosielle, A.A, Shearer, B.I. 1971. The common Septoria diseases of wheat. Bot. Rev., Vol. 37, pp. 231-162.

Slaton, M.R., Hunt, E.R. Jr. and Smith, W.K. 2001. Estimating near-infrared leaf reflectance from leaf structural characteristics. American Journal of Botany, Vol. 88, pp. 278-284.

Smith, P.J. and Webster, J.P.G. 1986. Behavioural aspects in the design of information systems for disease control in cereals. In: Implementation of farm management information systems: proc. 9th symposium of the EAAE, Copenhagen, November 1985, (Christensen, J. ed.) pp.133-144. Kiel: Wissenschaftsverlag Vaulk

Sökefeld, M., Gerhards, R. and Kühbauch, W. 2000. Teilschlagspezifische Unkrautkontrolle – von der Unkrauterfassung bis zur Herbizidapplikation. Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz XVII, p. 227.

Spieckermann, G. 2005. GIS-basierte Erfassung und Prognose der räumlichen Verteilung von Pflanzenkrankheiten. Dissertation, Rheinische Friedrich-Wilhelm-Universität, Bonn, Kapitel 1.

Sprengel, C. 1828. Von den Substanzen der Ackerkrume und des Untergrundes. Journal für Technische und Ökonomische Chemie 2, pp. 423–474; 3: 42–99, 313–352, and 397–421.

Srinivasan, A. 2006. Handbook of precision agriculture: principles and application. Food Products Press®, an imprint of the Haworth Press, Inc., Bringhamton, NY.

Strasser, R.J. et al., 2000. The fluorescence transient as a tool to characterize and screen photosynthetic samples. Probing Photosynthesis: Mechanisms, Regulation and Adaption (Yunus, M et al., eds), pp. 445-483, Taylor&Francis.

Sudduth, K.A., Fraisse, C.W., Drummond, S.T. and Kitchen, N.R. 1997. Integrating spatial data collection, modelling and analysis for precision agriculture. In Proceedings of the 1st International Conference on Geospatial Information in Agriculture and Forestry, Vol. II, Ann Arbor, Mich.:ERIM International, pp. 166-173.

Taylor, L.R. 1984. Assessing and interpreting the spatial distribution of insect population. Annual Review of Entomology, Vol. 29, pp. 321-377.

Teh, C.B.S. 2006. Introduction to mathematical modeling of crop growth. BrownWalker Press, Boca Raton.

Teng, P.S. 1987. Crop loss assessment and pest management. American Phytopathology Society, St. Paul, Minnesota, USA, p. 270.

Teng, P.S., Batchelor, W.D., Pinnschmidt, H.O. and Wilkerson, G.G. 1998. Simulation of pest effects on crops using coupled pest-crop models: the potential for decision support. In. Understanding Options for Agricultural Production by G.Y. Tsuji et al (eds), Kluver Academic Publishers, Great Britain, pp. 221-266.

Thomas, J.R., Gausman, H.W. 1997. Leaf reflectance vs. leaf chlorophyll and carotenoids concentrations for eight (vegetable and field) crops. Agronomy Journal, Vol. 69 (5), pp. 799-802.

Tsuji, G.Y., Hoogenboom, G.J. and Thornton, P.K. (Eds.) 1998. Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands, p. 400.

Van Ginkel, M. and Scharen, A. L. 1988. Host –pathogen relationships of wheat and *Septoria tritici*. Phytopathology, Vol. 78, pp. 762-766.

Waggoner, P.E. and Berger, W.D. 1987. Defoliation, disease and growth. Phytopathology, Vol. 77, pp. 393-398.

West, J.S., Bravo, C., Oberti, R., Lemaire, D., Moshou, D., McCartney, H.A. 2003. The potential of optical canopy measurement for targeted control of field crop diseases. Annual Review of Phytopathology, Vol. 41, pp. 593-614.

Whelan, B.M., 1998. Reconciling continuous soil variation and crop yield. Dissertation, University of Sydney, Australia.

Wiese, M.V., ed. 1987. *Compendium of wheat diseases*, 2nd ed. St Paul, MN, USA, APS Press.

www.bmvel-forschung.de/index.cfm?STICHWORT=halmbruchkrankheit&nav=display&uuid=00067D0EDACC1ED4AF

www.inra.fr/internet/Produits/HYP3/patho-gene/6pseher.htm).

www.wikipedia.org/wiki/Expert_system

Xu, H.R., Ying, Y.B., Fu, X.P. and Zhu, S.P. 2007. Near-infrared spectroscopy in detecting leaf miner damage on tomato leaf. Biosystems Engineering, Vol. 96, pp. 447-454.

Yamazaki, W.T. and Briggle, L.W. 1969. Components of test weight in soft wheat. Crop Science, Vol. 9, pp. 457-459.

Zadoks J.C., Chang T.T., Konzak C.F. 1974. A decimal code for the grown stage of cereals. Weed Research, Vol. 14, pp. 415-421.

Zadoks, J.C. and Schein, R.D. 1979. Epidemiology and Plant Disease Management. Oxford University Press, Oxford.

Zhang, X.Y., Loyce, C., Meynard, J.M. and Monod, H., 2007. Modelling the effect of cultivar resistence on yield losses of winter wheat in natural multiple disease conditions. European Journal of Agronomy, in press.

“Everything should be made as simple as possible,

but not simpler.”

Albert Einstein

Danksagungen

Herrn Prof. Dr. W. Claupein gilt mein Dank für die Überlassung dieses Themas, die wissenschaftliche und persönliche Betreuung während der Anfertigung dieser Arbeit und die Begutachtung.

Bei Herrn Prof. Dr. R. Gerhards bedanke ich mich für die engagierte Übernahme des Zweitgutachtens.

Ein herzliches Dankeschön gilt all den Mitarbeitern des Institutes für Pflanzenbau und Grünlandlehre, sowie allen Mitarbeitern der Versuchstation „Ihinger Hof“ die mich stets wissenschaftlich sowie persönlich unterstützt haben. Besonders danken möchte ich an dieser Stelle Birgit Beierl, ohne die ich die viele Arbeit im Labor, im Gewächshaus und auf dem Feld nicht geschafft hätte.

Einen ganz besonderen Dank möchte ich Simone Graeff aussprechen, die mir stets den Rücken gestärkt hat, meine Arbeiten Korrektur gelesen hat und immer ein offenes Ohr für Fragen aller Art hatte.

Meinen Eltern Marion und Roland Gröll möchte ich dafür danken, dass sie mir das Studium und die Anfertigung dieser Doktorarbeit durch ihre immer währende Unterstützung ermöglicht haben. Meinen Großeltern Doris und Kurt möchte ich danken für die liebe Betreuung meines Sohnes. Auch möchte ich meinem Sohn Niklas für seine Liebe danken, die mir immer wieder Kraft gab.

Auch möchte ich all meinen Freunden, besonders Daniela Rottner, für die moralische Unterstützung danken, ohne die ich sicherlich nicht so weit gekommen wäre.

KERSTIN GRÖLL

PERSÖNLICHE DATEN

Geburtsdatum:	22. November 1980 in Bietigheim-Bissingen
Familienstand:	ledig, ein Kind
Staatsangehörigkeit:	deutsch
Studienabschluss:	Bachelor of Science Master of Agribusiness

BERUFLICHER WERDEGANG

Seit Januar 2008 Gebietsleiterin bei der Düngemittelfirma TIMAC GmbH

Apr. 2005 – Dez. 2007 Doktorandin am Institut für Pflanzenbau und Grünland Universität Hohenheim, Stuttgart
Thema: Einsatz von Nahsensorikmethoden zur Erfassung von Bestandeszuständen unter dem Einfluss von Pflanzenkrankheiten

Jan. 2003 – Dez. 2007 Probenehmer beim Landesverband für Leistungsprüfungen in der Tierzucht E.V., Baden-Württemberg

STUDIUM

Okt. 2000 – Sep. 2003 Studium der Agrarwissenschaften an der Universität Hohenheim, Stuttgart
Abschluss: Bachelor of Science
Gesamtnote: 2,2
Bachelorarbeit. „Strukturelle Änderungen als mögliche Ursache von Reflexionsänderungen bei P- und N-Mangel von Mais (*Zea mays* L.)“

Okt. 2003 – April 2005 Studium der Agrarwissenschaften an der Universität Hohenheim, Stuttgart
Abschluss: Master of Agribusiness
Gesamtnote: 2,2
Masterarbeit: „Einsatz von Pflanzenwachstumsmodellen zur Ertragsprognose und Bestimmung des Erntezeitpunktes von Silomais in Landessortenversuchen am Beispiel von DSSAT 4.0“

SCHULE

Sep. 1987 – Juli 1991	Grundschule Erligheim-Hofen
Sep. 1991- Juli 1996	Alfred - Amann - Progymnasium Bönnigheim
Sep. 1996 - Juli 2000	Gymnasien im Ellental Bietigheim – Bissingen Abschluss: Abitur (3,1) Leistungskurse: Erdkunde und Mathematik

PRAKTIKA

Aug. 2001 – Okt. 2001	Praktikum bei der Firma Agrostat, Gesellschaft für landwirtschaftliches Versuchswesen m.b.H., Herrentierbach
März 2002 – Mai 2002	Praktikum beim Tierarzt Norbert Geiping, Herbern
März 2003 – April 2003	Praktikum bei der WLZ (Baywa), Heimerdingen