Measuring and Modelling Parameters from Hyperspectral Sensors for Site-Specific Crop Protection

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Abstract
This thesis sought to optimise systems for plant protection in precision agriculture through developing a field method for estimating crop status parameters from hyperspectral sensors, and an empirical model for estimating the required herbicide dose in different parts of the field.

The hyperspectral reflectance measurements in the open field took the form of instantaneous spectra recording using an existing method called feature vector based analysis (FVBA), which was applied on disease severity. A new method called iterative normalisation based analysis (INBA) was developed and evaluated on disease severity and plant biomass. The methods revealed two different spectral signatures in both disease severity and plant density data. By concentrating the analysis on a 12% random subset of the hyperspectral field data, the unknown part of the data could be estimated with 94-97% coefficient of determination.

The empirical model for site-specific weed control combined a model for weed competition and a dose response model. Comparisons of site-specific and conventional uniform spraying using model simulations showed that site-specific spraying with the uniform recommended dose resulted in 64% herbicide saving. Comparison with a uniform dose with equal weed control effect resulted in 36% herbicide saving.

The methods developed in this thesis can be used to improve systems for site-specific plant protection in precision agriculture and to evaluate site-specific plant protection systems in relation to uniform spraying. Overall, this could be beneficial both for farm finances and for the environment.

Keywords: hyperspectral reflectance, site-specific, plant protection, simulation model

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Dedication

Till Victor, Josef och Ella

If you can not measure it, you can not improve it.
Lord Kelvin

Contents

List of Publications

This thesis is based on the following papers, which are referred to in the text by their Roman numerals:

I. Larsolle, A. (2003). Instantaneous measurement of reflectance spectra in the open field using diode array spectrometers. *Biosystems Engineering* 86, 1-8.

II. Hamid Muhammed, H. and Larsolle, A. (2003). Feature vector based analysis of hyperspectral crop reflectance data for discrimination and quantification of fungal disease severity in wheat. *Biosystems Engineering* 86, 125-134.

III. Larsolle, A. and Hamid Muhammed, H. (2007). Measuring crop status using multivariate analysis of hyperspectral field reflectance with application to disease severity and plant density. *Precision Agriculture* 8, 37-47.

IV. Larsolle, A. (2010). A model for site-specific herbicide weed control. *Submitted Manuscript*.

Papers I-III are reproduced with the permission of the publishers. The contribution of Anders Larsolle to Paper II and III was: planning and management of the field trials; collecting the dataset from the field trials, including samples on disease severity and plant mass, and the measurements of hyperspectral reflectance; Writing the papers in co-operation with Hamed Hamid Muhammed, each with a 50% contribution.

Introduction

Background

The protection of a growing crop against weeds and diseases is an important task in today's agriculture in order to achieve efficiency in production with respect to production costs and yield and to minimise the environmental impact. Weeds in the crop compete for resources such as water, plant nutrients and light, and plant pathogens feed on and destroy crop biomass. The most common plant protection method in a growing arable crop is spraying plant protection products, for example herbicides against weeds, fungicides against fungal pathogens and insecticides against insects. In a historical perspective, the use of plant protection products was one of the main factors in the rationalisation of agriculture after the Second World War, which allowed the productivity to be increased to such an extent that in 2009 1.2% of the economically active population produced the entire agricultural output of Sweden (Statistics Sweden, 2010).

There are concerns both in the general public and in the research community about using artificial chemical agents in the production of food. This has led to initiatives to devise agricultural production forms where chemical plant protection products in principle are prohibited, or where there is safe, effective and integrated use of pesticides in conventional agriculture.

The work in this thesis examines the use of plant protection products in agricultural arable production. The most common plant protection products used in Sweden are chemical pesticides, *i.e.* containing a synthetically produced active ingredient. Statistics on the quantities of synthetic active substances sold in Sweden show the annual use of pesticides to be 1 million hectare doses (Swedish Chemicals Agency, 2009). Sweden has about 2.6

million hectares of arable land, of which 1.25 million hectares are used to grow the major annual crops: cereals, leguminous plants, oilseed crops, potatoes and sugar beet (Statistics Sweden, 2010).

Alternatives to synthetically produced chemical pesticides include biological plant protection products (Copping, 2004) or physically acting plant protection products, *e.g.* soap or acetic acid (Hall & Barry, 1995). Available figures on the amounts of biological plant protection products sold in Sweden (Swedish Chemicals Agency, 2009) show an annual use much less than 1% in relation to the total usage of plant protection products.

The work in this thesis can be applied to the use of plant protection products in general, irrespective of whether the active ingredient is a chemical agent, a biological organism or a physically acting substance. The only part of this thesis that involves a choice of a specific plant protection product is the field trial in Paper IV, where a synthetic herbicide was used.

Work on decreasing the risks involved with the use of pesticides has been intense during recent decades. One important part is the work carried out by the Swedish Chemicals Agency (*Kemikalieinspektionen*) on minimising use and assessing the environmental risk of the chemical agents allowed for use in areal production in Sweden. In the 1980s, the use of chemical products in agriculture emerged on the political agenda and an intention was expressed to decrease the amount of chemical plant protection products (Bernson & Ekström, 1991). Since then, the total amount of active ingredients sold in relation to the 1983-1985 mean value has been monitored. A few years in to the programme, the quantities sold decreased rapidly but the amount of active ingredients sold from 1991 until 2008 has remained fairly steady, at a mean value of around 1600 tons per year (Swedish Chemicals Agency, 2009).

Despite the fact that the use of pesticides has not decreased during the past few decades, farmers have a number of reasons to minimise their use of pesticides. The cost of spraying a field involves not only the cost of the pesticides, but also the labour, machine and timeliness costs, *i.e.* the cost of delaying other operations in the field while occupying labour and machines for plant protection. Minimising the consumption of plant protection products per unit area is also desirable, in order to minimise transport and refilling time.

When using conventional spraying techniques, an obvious priority is to target any unnecessary and careless use of pesticides, *i.e.* spraying where the actual need for plant protection is very low or the use of excessive doses. Experienced farmers with great knowledge about the control of diseases and weeds know that if their sprayer equipment is maintained and used correctly and spraying is carried out under optimal conditions, the dose can often be reduced considerably in relation to general recommendations. For those highly competent farmers who take great care in optimising their arable production, there may not be much margin left to decrease doses or number of sprayings without jeopardising the economic outcome of their business. For this category an important limiting factor is the technology available for applying pesticides in the field.

One technological advance that has the potential to further reduce pesticide usage is to apply pesticides site-specifically instead of uniformly, or in other words, applying precision agriculture to plant protection. For example in the case of weed control, the herbicide dose would then be adjusted according to differences in the total competitiveness of the weed flora relative to the crop as expressed by the yield.

Precision agriculture, in the sense of varying actions and means of input according to site-specific variations in requirement within fields in order to further optimise arable production through more efficient use of resources, has been developing since the introduction of the first satellite-based global navigation system (GNS) in the late 1980s. In the early development of methodology for Site-Specific Agriculture (SSA), which in this case might be a more proper term to use, most attention was focused on the site-specific application of mineral fertiliser using historical maps of yield and soil properties to estimate the variations in potential yield increase with respect to nitrogen application rate.

In the case of plant protection, yield potential indicators such as historical yield maps or soil properties might not be equally suitable for use for estimating variations in *e.g.* weed density or fungal infection within a field. There are seasonal variations in the presence and distribution within fields of weeds and fungal pathogens, depending on weather, preceding crop, cultivation, time of drilling, *etc.* Systems for site-specific plant protection would preferably include estimations of the need for plant protection based on measurements in the crop at, or just prior to, the time of the actual plant protection operation.

An approach suitable for this is measuring reflected light from the crop in the open field. This can be carried out either with spectral sensors, where radiometric measurements are made with the focus on high spectral quality and resolution, or with imaging sensors, allowing analysis of geometry. There are of course advanced measuring systems where the two principles are combined, but these generally come at a high cost for development and use in conventional arable production. Measuring reflected light has several advantages: The measurements can be made relatively rapidly, covering large areas, and the sampling is non-destructive. The sensors that can be used have generally been developed in sectors other than agriculture, and instrumentation is often available at a relatively low cost.

In order to use optical sensing technology as a measuring method in precision crop protection, appropriate agronomic variables such as weed density and fungi disease severity have to be estimated from basic sensor readings, which in this case is the measured light intensity.

The choice of site-specific input for a plant protection operation, for example the site-specific dose within the field, is basically an optimisation problem where the most effective input is to be made on each location with regard to the cost of the operation and the yield income across the field. Looking at the concept of site-specific plant protection *per se*, as opposed to the conventional uniform plant husbandry where a constant input intensity is used across the whole field, it is also important for the farmer to know whether site-specific plant protection would result in an economic benefit in the first instance. Conversion to site-specific farming requires investment in equipment and machinery in order to apply a variable rate of input in the field and obtain and handle information about the status of the crop in fields on the farm. This additional investment cost has to be covered by increased income from the conversion from uniform to site-specific plant protection. Evaluating site-specific plant protection from practical experiments covering entire fields is expensive and difficult. Another method is to compare site-specific and uniform cropping systems using a simulation model. If a field and the yield depending on the crop protection operation can be modelled, the result from site-specific and uniform strategies can be compared under exactly the same field and weather conditions and any site-specific and uniform strategy can be simulated.

The two areas described above, the development of empirical methods for measuring site-specific crop protection and the simulation of site-specific plant protection strategies, have been identified as important research needs for the development of site-specific plant protection in Sweden and they were the main focus of the work in this thesis.

Literature review

Optical sensors in plant protection

Using measurements of reflected light as a method to investigate crop status in agricultural fields has advantages associated with its non-destructive nature and the fact it is possible to record reflected light quickly and cheaply.

Techniques for recording reflected light have been available for more than a century using the photographic camera. For example, Brenchley (1968) and Wallen *et al.* (1975) used a photographic camera to track the occurrence and spread of potato late blight disease in areal images.

Remote sensing, where large areas can be included in a single image, has the potential to be used for tasks such as field crop inventory, crop monitoring and yield forecasting. Numerous scientific reports on the subject of remote sensing have been published since the 1970s as a result of the launch of earth observation satellites with the ability to record multispectral images of the earth's surface, beginning with Landsat 1 in 1972 (Morain, 1998).

From an agricultural point of view, the disadvantages with satellite remote sensing are that the time and frequency of the remotely sensed image data are limited to the satellite's predefined time of overpass. The timing of crop protection operations in agricultural fields is often a matter of days and the cost of delayed spraying of pesticides can be significant. The possibility to record image data in visible and near infrared wavelength bands is also restricted by atmospheric conditions such as the presence of clouds. An alternative would be to use aerial image data from conventional airplanes or helicopters, but the timing of the image data would still be dependent on availability of the aircraft and weather conditions. In economic terms, the cost of using satellite or aerial image data for site-specific application of pesticides, at least for single agricultural fields, would be relatively high compared with the potential profit.

For plant protection actions such as conventional spraying of pesticides to control weeds, fungal diseases or insects, viewed as a system, ground- or vehicle-based sensor technology has several advantages, compared with aerial or satellite remote sensing:

- The current status of the crop at the time of the actual plant protection input can be determined by measuring the crop status prior to the crop protection action or even by using sensors on the sprayer controlling the dosage in real time without being dependent on the availability of equipment, time of overpass for remote sensing platforms or atmospheric conditions.
- The sensors can be optimised specifically for the crop protection action, both with respect to cost and efficiency.
- Using close range sensing, at about 1-2 m above the ground, it is possible to use image analysis, *i.e.* imaging sensors (cameras) and analysis of geometric properties to enable, for example, the detection of weeds.

Typical systems where sensors are intended for use include weed and fungi control by site-specific application of plant protection products.

Spectral vegetation index sensors

Using spectral sensors to detect the presence of any vegetation in the field, as opposed to bare soil or dead plant residues, can be useful in a situation where all remaining plants are regarded as weeds to be controlled, for example after harvest in the autumn or before seedbed preparation in a set-aside field. The detection of vegetation is a fairly easy task. The spectral reflectance profile of vegetation has distinct characteristics, with generally low reflectance in visible wavelengths, where an absorption peak can be found in the red (R), and high reflectance in the near infrared (NIR) region from about 750 nm to 1300. Bare soil, on the other hand, has a rather featureless spectral characteristic in the visible NIR region, which can be described as a flat, constant increase in reflectance through the visible up to the near infrared wavelength regions (Guyot, 1990). This can be seen in Figure 7 in this thesis, where bare soil and vegetation spectral features are found at 0% and 100% plant biomass densities, respectively.

A common way to quantify vegetation using spectral characteristics is to calculate a spectral vegetation index using ratios between reflectance in bands in the visible region, often in the red (R) and near infrared (NIR), such as the ratio vegetation index: RVI = NIR/R (Jordan, 1969) or the normalised difference vegetation index: NDVI = (NIR-R)/(NIR+R) (Rouse *et al.*, 1973). The intention with using RVI and NDVI was originally to cancel out variations due to sun angle or atmospheric conditions (Jordan, 1969; Rouse *et al.*, 1973). Tucker (1979) evaluated red and NIR reflectance together with several forms of vegetation indices (RVI, NDVI, NIR and red difference and sum). He also included the corresponding indices using the green and red reflectance instead of the NIR and red band. Overall, the NIR and red reflectance combinations had the highest correlation to green leaf area and green leaf biomass. The index showing the highest significance was NDVI, followed by RVI.

Spectral vegetation sensors where these spectral vegetation indices are produced can be constructed using optical filters and electronic light detectors. Such an optical construction is a fairly straightforward level of technology and components were developed and gradually became readily available at decreased cost from the 1970s onward.

Hooper *et al.* (1976) constructed such a sensor which illuminated the ground and registered the response in two spectral bands in the near infrared and the visible wavelength range. Using electronic circuitry, a simple ratio spectral vegetation index was calculated. The intended use of the sensor was to detect occurrences of plants in row crops in order to implement automatic thinning of the crop. The sensor was mounted on a tractor, above the crop row in a field, and the signal was used for thinning operations in lettuce, cabbage and sugar beet.

Haggar *et al.* (1983) used the same concept of a simpler and cost-effective design for a spectral sensor that measured outdoor natural light spectral vegetation reflectance ratio. In that study the sensor was mounted adjacent to the nozzle on a knapsack sprayer, and an electronic control unit switched on the flow to the spray nozzle when the spectral vegetation index exceeded a threshold value. In this way spraying was targeted to patches of vegetation, as opposed to bare soil. Further research by Haggar *et al.* (1984) showed that the sensor reading was highly correlated to green leaf biomass, showing variations in seedling density or development stage in the field, while measurements in different plant species showed small differences. Shropshire *et al.* (1991) evaluated an RVI sensor for quantifying and detecting weeds between field soybean rows. The results were promising, but the sensitivity to weed density and robustness was inadequate for use of the device as a targeting sensor for weed spraying.

The sensors used by Haggar *et al.* (1983), Hooper *et al.* (1976) and Shropshire *et al.* (1991) only recorded radiance from the ground. The method of using the ratio between a red and an NIR spectral band, instead of the absolute responses from the individual spectral bands, was said to decrease the influence of variations in sun elevation or the presence of clouds on the sensor response. However, investigations have shown that ambient conditions do affect the measured ratio vegetation index (see review by Tucker, 1980).

In the search for spectral ratio vegetation sensors for estimating and detecting green vegetation density in the field, Mayhew *et al.* (1984) developed a cost-effective design using the latest advances in optoelectronics. Tests with this sensor showed that variations in ambient conditions, including cloud cover, were the greatest source of error for the technique. They concluded that it was necessary to make reference measurements on standardised 'white' plates in order to correct the sensor reading for variations in ambient conditions.

Felton *et al.* (1991) took the concept of controlling herbicide spraying to aggregated weed patches using a spectral vegetation sensor together with a conventional agricultural sprayer, by mounting a spectral sensor in front of each nozzle on the boom. The sensor system measured both radiance from the ground at each sprayer nozzle and incident light from the sky in the 630 to 670 nm band (R) and in the 835 to 870 nm (NIR). In this manner, the reflectance with respect to the ratio between radiance from the crop and irradiance from the sky could be determined. Using a threshold on the spectral sensor's output, calculated as the ratio vegetation index (RVI), each nozzle was turned on when a weed patch was detected. In this way, spraying was eliminated in field areas with no or very sparse weed incidence.

The system described by Felton *et al.* (1991) underwent further research and was developed into the commercial system Detect Spray for weed control on set-aside land or from harvest up to emergence of the crop (Duff, 1993; Felton, 1995; Blackshaw *et al.*, 1998).

Using the sun as an external light source in sensor systems for plant protection (*e.g.* Felton *et al.*, 1991) enabled a relatively simple and cost effective design. The disadvantage with these so-called passive systems was that the use was limited to the presence of daylight. Sensor systems for plant protection at night-time require active sensors that use an internal light source.

Wartenberg and Dammer (2000) constructed such a weed sensor for crop-free situations, which used an internal light source and a line sensor for scanning a transverse line on the ground with relatively high resolution. The WeedSeeker™ and the GreenSeeker™, from NTech Industries Inc. USA, are commercialised sensor systems for spot or patch spraying weeds (Barrett,

1996) and for detection of crop nitrogen stress (Inman *et al.*, 2005) that use technologies with an internal source of modulated light, *i.e.* emitting light pulses with high frequency and measuring the reflection in the same frequency. Another system that also registers spectral vegetation ratio index using a system for internal modulated light is the CropCircle™ from Holland Scientific (Holland *et al.*, 2004; Lamb *et al.*, 2009).

Merritt *et al.* (1994) also evaluated a system for controlling spraying of weed patches in the field which, like that of Felton *et al.* (1991), had R and NIR band spectral sensors mounted in front of each nozzle on a boom sprayer. However, this sensor calculated the normalised difference vegetation index (NDVI) instead of the simple ratio vegetation index (RVI). In an evaluation of reflectance vegetation indices by Nitsch *et al.* (1991), the normalised difference index (NDVI) was determined to be more suitable for estimating green vegetation cover in the field in comparison with using the RVI index. Each sensor developed by Merritt *et al.* (1994) also consisted of five individual 'sub sensors' arranged in an array along the boom. This enabled the weed detection to be carried out with a resolution of 5 pixels instead of one unary area in front of each nozzle. The advantage was that the detection threshold was lower than in *e.g.* the system devised by Felton *et al.* (1991). This could be important in weed control because, at least for the case of foliar-acting herbicides, the objective would be to prevent the growth of any small weed seedlings that would otherwise continue to grow and cause significant yield loss.

Another technique to improve the ability to detect small weeds is to scan the ground in transverse lines rather than an area like the system described by Wartenberg and Dammer (2000) and Barrett (1996).

Field multispectral sensors

Taking the development of crop sensors a step further from using one-dimensional spectral vegetation indices, research has been done on designing sensors using several spectral bands. Such sensors, with up to 10 spectral bands, are generally referred to as multispectral sensors. Much of the scientific work has focused on the proper choice of spectral bands and on enabling the device to transform the spectral readings to usable biological properties, such as weed density or the level of fungal infection.

Brown *et al.* (1994) measured hyperspectral reflectance within the range 400 to 900 nm, with 2.5 nm c-c spectral bands, in field stands of seven weed species. Using these weed species classes, statistical analysis showed best separability for the green reflectance band, centred at 550 nm, and within the near infrared region. In a choice between available optical filters, Brown *et al.* (1994) selected four spectral bands at 440, 530, 650 nm and above 760 nm. They then used the optical filters to acquire multispectral images from a video camera at about 10 m above the ground using a ground-based platform and at 500-750 m altitude using an aircraft. Weed patches in the digital images could be separated using supervised classification.

Vrindts and de Baerdemaeker (1997) measured reflectance spectra within the 200-2000 nm wavelength range from leaves of potato, beet and maize crops and from several weed species. They selected up to four spectral bands in the spectral range and showed high correlation using linear band combinations.

Broge and Leblanc (2000) compared and evaluated a number of previously reported spectral vegetation indices for estimation of leaf area index and chlorophyll content. Reviews of earlier reports on spectral vegetation indices can be found in Baret and Guyot (1991) and Bannari *et al.* (1995).

Wang *et al.* (2001) investigated the choice of spectral band reflectance in a data sample of five crops and 30 weed species in a laboratory setup. Through statistical analysis between classes of crop, weed and soil, they selected five spectral wavelengths bands to be used in a weed sensor design. From these spectral bands four normalised difference indices were calculated, basically equivalent to NDVI, using the two spectral band combinations at {614;546}, {676;546}, {676;496} nm and {752;676} nm. Using a training dataset, the discrimination levels in a validation dataset between classes of weed, crop and soil were shown to be generally high.

Field hyperspectral spectral sensors

As developments in electronics and optics progressed, the instrumentation for measuring reflectance with increased spectral resolution became successively more portable and affordable. The term hyperspectral is used here for sensors and data with more than 10 spectral bands.

Munakata and Shibayama (1985) constructed a spectroradiometer system for field measurements using a monochromator, a rotating prism, which could measure the wavelength region from 400 to 2500 nm at a speed of 100 nm per minutes. This experimental measuring system was quite heavy and it had to be mounted on substantial machinery or a crane. Using double light inputs, both reflected light and incident natural light reflected on a white standard plate could be measured for each wavelength. Measurements at 50 nm intervals of one spectrum from 500 nm to 2200 nm in a rice crop took 25 minutes (Shibayama and Munakata, 1986a). Shibayama and Munakata (1986b) used the spectrometer to make measurements at 20 nm wavelength intervals. Shibayama *et al.* (1986) developed a more portable spectrometer, with a monochromator sensor system, with improved field usability. The spectral range of measurement was 400 to 1200 nm in 10 nm steps. The time consumption for one spectra measurement was 50-60 s.

Later, more portable and cheaper instrumentation became available where hyperspectral reflectance could be measured using technology that allowed faster spectral scanning without moving mechanical parts (see for example Müller *et al.*, 2008).

One common hyperspectral analysis method is to search hyperspectral data for narrowband spectral vegetation indices (SVI) where a single or two or three band combinations, using ratios or linear combinations, are analysed and compared with regard to high correlation to field experimental data.

Such analysis carried out by Müller *et al.* (2008) in oilseed rape identified the ratio of bands 740 to 750 nm and 740 to 780 nm for use to describe biomass and development-related variables. Shwetank *et al.* (2010) reviewed hyperspectral SVI methods used for analysing rice biomass and discriminating rice cultivars. Zhang *et al.* (2009) followed crop development in a cotton and soybean field using hyperspectral vegetation indices, while Thenkabail *et al.* (2000) used hyperspectral indices to predict biomass, leaf area index, plant height and yield in cotton, potato, soybeans, corn and sunflower.

Hyperspectral SVI studies have also been carried out on plant disease severity. Apan *et al.* (2003) tested numerous published and new spectral vegetation indices, mostly normalised difference ratios using two or three spectral bands against a sugarcane fungi disease. Laudien *et al.* (2004) used hyperspectral remote sensing data to detect fungal disease in sugar beet, while Delalieux *et al.* (2009) showed a correlation between hyperspectral index and apple scab infection.

Similar studies using narrowband indices on other symptoms showing nitrogen and water status have been reported by Strachan *et al.* (2002) and Yao *et al.* (2010).

Analysis based on the selection of significant bands from a hyperspectral reflectance dataset does not utilise the whole spectral range of the data. A method for analysing the entire spectral range of hyperspectral crop reflectance is 'spectral unmixing'. This method has been used for the analysis of stress in wheat (Lelong *et al.*, 1998) and cotton (Fitzgerald *et al.*, 2004).

Evaluation of site-specific plant protection

Evaluation in terms of efficiency and resource usage of systems for site-specific plant protection systems versus conventional uniform field operations can be done in two principally different ways: either by evaluating the performance of an actual executed site-specific field operation; or by using a model to estimate or simulate site-specific plant protection. Most studies on the evaluation of site-specific plant protection have been done on weed control.

Regarding the use of spectral vegetation index sensors developed for controlling spraying to weeds in a situation where all green vegetation can be regarded as the object of control (for example between crop rows, before emergence of the crop, on set-aside land, or after harvest of an arable crop) such as those reported by Hooper *et al.* (1976), Haggar *et al.* (1983) and Felton *et al.* (1991), the evaluation of herbicide use and weed control efficiency is a relatively straightforward task. Applications of spectral vegetation index weed sensors can result in significant herbicide reductions: Biller (1998), using the DetectSpray system (see above), reported 48% average herbicide reduction for weed control on 30-70% of a conventionally tilled field, while Felton (1995) reported herbicide reductions of up to 90%.

Dammer and Wartenberg (2007) evaluated the use of the weed sensor reported by Wartenberg and Dammer (2000) over a four year period. The sensor was actually used to control the herbicide dose in cereal and pea crops by directing it at the crop-free tramlines, and assuming the same weed density in the neighbouring crop. An average herbicide reduction of 24% was found for a minimum dose representing 50% of the standard rate.

The detection or quantification of the in-field variation in weeds is an important part of a system for site-specific weed control, but not the only one. For the case of conventional agriculture, the actual parameter to decide before spraying is the herbicide dose. In the case of weed spraying in a crop-free situation as described above, a straight-forward method is to use a threshold on the weed sensor signal to turn the spraying on or off. At least for the decision of the site-specific herbicide dose when spraying in a growing crop, a more appropriate way would be to estimate the effect of the dose on the final yield.

Christensen *et al.* (2003) developed and tested a model for site-specific dose estimation based on weed species composition and weed density using a competition model, a dose response model and a model for economic optimisation. In field trials, they did not find any significant yield reduction on reducing the herbicide dose from 34 to 55%.

Lamastus-Stanford and Shaw (2004) used a decision support model to compare uniform and site-specific weed control and found that the latter resulted in an increased net return.

Kim *et al.* (2002) used a dose response model together with a weed crop competition model in order to estimate recommendations on uniform herbicide dose.

Concluding remarks

One area not entirely covered in previously published studies is the estimation of crop status in site-specific systems for plant protection using hyperspectral reflectance. This includes in particular objective analysis of hyperspectral reflectance data in a way that takes the whole spectra into account instead of selecting a few spectral bands in a high spectral resolution dataset.

Another topic where there is a need for additional research is the development and use of models for site-specific plant protection. One task would be to estimate the required site-specific dose within a field. Another important use of a simulation model is the objective and unrestricted evaluation of site-specific plant protection in order to estimate the potential profitability of site-specific plant protection in comparison with conventional uniform application of plant protection products. This is important to know in order to motivate investments in machinery and information when converting to site-specific application of plant protection products.

Objectives

The overall objective of this thesis was to increase knowledge on how to optimise site-specific plant protection in arable production with respect to minimised use of inputs, while maintaining a high yield level. The approach involved developing methods for measuring crop status parameters and modelling a system for site-specific plant protection.

The scope of this thesis is limited to developing methodology for estimating the site-specific minimum need for plant protection products based on optical measurements in the field.

Specific objectives

Specific objectives of this work were to:

- Develop a method for instantaneous measurement of hyperspectral reflectance, using two diode array spectrometers to simultaneously measure solar irradiance from the sky and the radiance reflected from the crop (Paper I).
- Use and evaluate a multispectral analysis method called Feature Vector Based Analysis (FVBA) to quantify the fungal disease severity in a wheat crop (Paper II).
- Present and evaluate a multivariate method based on an iterative normalisation procedure, further developed from FVBA, for objective hyperspectral analysis in the examination of how different parts of the reflectance spectrum are affected by crop parameters such as disease severity and aboveground plant density (Paper III).
- Present a model with which the differences between site-specific and uniform application of plant protection products can be estimated in such a way that the potential profitability of using site-

The underlying motives for this work were to improve the economic outcome for the farmer and to minimise the negative impact on surrounding ecosystems and the environment through reducing the use of artificial pesticides and energy.

The definition of plant protection in this study is conventional agricultural production using plant protection products to control weeds and fungal infection. Although most plant protection products used in conventional agriculture are based on synthetic chemical agents (pesticides), the results presented in this thesis are applicable to plant protection products based on other types of active ingredients: biological organisms and natural or physically acting substances.

The work on quantifying the optimal input and evaluating uniform and site-specific strategies for plant protection were specifically intended for conventional farming using pesticides. However, the definition of plant protection system in this work could also be extended to other weed control measures such as mechanical or thermal weeding, as long as these involve direct field operations in the crop.

Structure of the work

The work in this thesis deals with different parts of the site-specific plant protection system. Site-specific plant protection is defined here as a system where crop status is measured, whereupon the required dose is estimated and then applied in the field. In this work a spectral sensor was used to measure the site-specific crop status. This involved recording hyperspectral reflectance in the field, combined with hyperspectral analysis in order to estimate crop status, *e.g.* degree of plant disease severity. Using the estimated crop status and a model on how the competitive effect on the crop depends on the plant protection dose, the site-specific dose within the field can be decided. The next stage is to apply this dose in the field. Methods for applying doses site-specifically in the field were not examined in this thesis.

Looking at these components of the site-specific plant protection system, estimation of site-specific crop status and decision-making on the site-specific dose were identified as essential parts of the system.

Knowing what dose to apply on each spot in the field is fundamental for the whole concept. The technology to apply a varying dose across a field already exists, and developing technology to estimate the required dose within the field would give more incentives to develop technologies and methodologies for applying plant protection products at varying rates in the field. Papers I-III deal with site-specific measurements in the crop. Paper I deals with instantaneous measurement of hyperspectral reflectance in the open field, while Papers II and III cover the hyperspectral analysis to estimate crop status from the measured hyperspectral reflectance values. Paper IV deals with decision-making regarding the site-specific dose based on measured crop status using a model developed for site-specific plant protection across the field (Figure 1).

Converting from conventional farming, where plant protection products are applied uniformly across the field, to site-specific application of pesticides would require investments in machinery and technology and increase the cost of advisory and information services. These costs are assumed to be outweighed by increased income or decreased production costs. Having a tool to evaluate site-specific plant protection in comparison with conventional uniform application of pesticides would be a valuable tool for farmers and the advisory services. Paper IV presents a method, based on the model developed here for site-specific plant protection, for objective comparisons between site-specific and uniform plant protection.

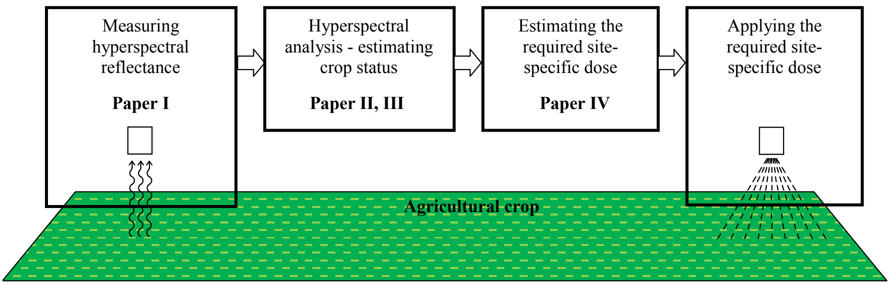


Figure 1. Subject area of Papers I-IV in the system for site-specific plant protection.

Materials and methods

The general approach was to develop measurement and analysis methods that can be used in decision-making and evaluation of rational and efficient site-specific use of plant protection products in agricultural arable production.

The work in this thesis consisted of developing:

- A method for instantaneous crop reflectance measurements
- Multispectral analysis methods for the estimation of fungal infection
- A model for deciding the dose of the plant protection product and for evaluation of site-specific weed control

One of the defined situations of end use of the work in this thesis is the direct measurement of hyperspectral reflectance in a growing crop within a relatively limited period prior to the time of the plant protection input. This influenced the choice of methodology in each part of the thesis to those that enable fast and automatic implementation. The expected time frame from reflectance measurement to application of the plant protection product is from one week up to a real time with fraction-of-a-second implementation of the system from reflectance measurement to the application of the plant protection product.

The final part of this thesis was to develop an objective method for comparing site-specific and uniform application of plant protection products. This affected the choice of methods used, especially for comparing the weed control effect of the two approaches.

A method for reflectance measurement in the open field

Using a sensor to record reflected light, which in this thesis is defined as electromagnetic radiation in the wavelength range 360-900 nm, has obvious advantages compared with alternative sampling methods such as physical sampling or estimations through visual assessment. Compared with other objective sampling methods, the reflectance sensing method is non-destructive and it is possible to construct cheap and fast measuring systems.

The hyperspectral reflectance measuring sensor system constructed in this thesis (Paper I) allows instantaneous crop reflectance measurements in the open field. Its main electro-optical components consist of products readily available on the market.

The measuring system for hyperspectral reflectance consists of both instrumentation and signal processing methodology. The system was developed here to fulfil the following requirements to enable automatic and instantaneous reflectance spectra recordings to be used to estimate crop biophysical and stress status:

- A spectral range covering the visible and adjacent infrared wavelength range (Aparicio *et al.*, 2000; Kumar *et al.*, 2002)
- Instantaneous recording of spectral data
- Correction for variations in irradiation intensity
- Full utilisation of the radiometric range of measurement

Instrumentation

In order to measure the radiated spectra in a sufficiently fast manner, in the order of fractions of a second, the main components of the instrument were two rapid spectra-scanning diode array spectrometer modules. The spectral range for the spectrometer modules was 360-900 nm, which covered the wavelength region of visible continuing into the near infrared region, covering many of the significant wavebands regions as reported in the literature review. These off-the-shelf spectrometer modules had a fibre cable light input and an electronic signal interface where radiometric spectra could be acquired and output. The internal optoelectronics consisted of a grating which projected light onto a diode array enabling the recording of radiometric spectra without any moving mechanical parts. The time consumption for each spectral recording was mainly limited by the integration time, *i.e.* the time of light exposure (around 70 ms in clear daylight for the complete sensor developed here). The time consumption for analogue to digital conversion, data transfer, signal processing and reflectance calculation depends on the choice of hardware and data transfer procedure, but in this case was of less significance.

The method developed for crop reflectance measurements was based on passive measurements, *i.e.* measurements were made with no other light source apart from prevailing ambient light. In order to measure the reflectance in an instantaneous procedure, radiance from the ground and irradiance from the sky were recorded simultaneously using one upwards directed spectrometer module (upsensor) to record global hemispherical irradiance, together with another downwards directed spectrometer module (downsensor) to record radiance from the crop in the field.

A sensor (see Figure 2A) was constructed which included the described upsensor and downsensor and circuitry (Figure 2E) for spectrometer module control, signal processing, analogue to digital conversion and communication interface.

To measure the global hemispherical irradiance, the upsensor collimator consisted of an opal glass mounted at the light input of the fibre cable (Figure 2C). The downsensor collimator consisted of a lens which projected the radiance from the ground on the light input of the other spectrometer module fibre cable, restricting the field of view (FOV) to about 20° (Figure 2D).

For the control of the spectrometer modules, the analogue to digital conversion and the communication to and data transfer from the spectrometer sensor system, a software program was written for a personal computer (PC) platform (see Figure 2F), which was connected to the communications interface of the sensor.

The measurement of reflectance spectra from crops received some attention, because of the varying radiometric response in the spectral range from 360 nm, at the start of the visible waveband range, to 900 nm in the near infrared. A typical vegetation reflectance spectra is normally around 5% in the visible range, because of photosynthetic activity, while the reflectance in the near infrared can reach 60% (Guyot, 1990). Because of these radiometric differences in measured spectra, the radiometric resolution will affect the measurement uncertainty more where the reflectance is low, *i.e.* in photosynthetically active bands. The maximum level of radiometric resolution, on the other hand, is defined from the maximum radiometric value in the spectra, which in the case of vegetation spectra are found in the near infrared. To minimise the risk of insufficient utilisation of the range of measurement when using unary integration time, especially in the low reflecting visible spectral bands, the spectral bands with the highest radiometric response should utilise as much of the whole radiometric range of measurement as possible. In this case, a procedure programmed in the digital control software connected to the sensor with the spectrometer modules automatically changed the integration time if necessary to maintain utilisation of the range of measurement between a defined percentage, normally between 90% and 100%.

Reflectance calculation

Using simultaneous measurements of irradiance and radiance, the reflectance R is defined by:

$$R = \frac{I^{Rad}}{I^{Irr}} \qquad [1]$$

where I^{Irr} is the irradiance from the sky, in this case recorded by the upsensor, and I^{Rad} is the radiance from the ground, recorded by the downsensor. The reflectance R is a vector $\{R_1, ..., R_i, ..., R_n\}$ where i is the spectral band.

In order to calculate the reflectance from the spectral raw data in the first place, the upsensor and downsensor have to be calibrated to each other. Otherwise Equation [1], using the ratio downsensor and upsensor readings, would not be valid. The calibration procedure included measurements of a constant light source with both the upsensor and downsensor in a manner that made measurements from the upsensor and downsensor independent of the choice of integration time. This procedure is described in detail in Paper I.

The centre wavelength λ^d_i of the spectral channel i for the downsensor is not equal to the corresponding central wavelength λ^u_i of the upsensor channel. In order to calculate the reflectance in channel i of the downsensor, it is therefore necessary to interpolate irradiance readings between two upsensor spectral bands, in order to estimate the irradiance for the corresponding central wavelength (λ^d_i) of the downsensor. Therefore calculating the reflectance from downsensor and upsensor readings is not as straightforward as indicated in Equation [1].

To calculate the reflectance from spectral downsensor and upsensor readings, Equation [2] was used:

$$R\left(\lambda^d{}_i\right) = \frac{\left[t^{-1}\left(d_i - d^0{}_i\right) - k^l{}_i\right]\left[\left(q_i+1\right)\left(p^h{}_n - p^l{}_n\right) - q_i\left(p^h{}_{n+1} - p^l{}_{n+1}\right)\right]}{\left[k^h{}_i - k^l{}_i\right]\left[\left(q_i+1\right)\left(t^{-1}\left[u_n - u^0{}_n\right] - p^l{}_n\right) - q_i\left(t^{-1}\left[u_{n+1} - u^0{}_{n+1}\right] - p^l{}_{n+1}\right)\right]} \qquad [2]$$

where λ^d_i is the central wavelength in the downsensor channel i, u_i and d_i are radiometric raw data from the corresponding upsensor and downsensor, and t is the integration time. The other parameters in Equation [2] are constants; $\{\boldsymbol{u^0}, \boldsymbol{p^h}, \boldsymbol{p^l}, \boldsymbol{d^0}, \boldsymbol{k^h}, \boldsymbol{k^l}\}$ are derived from the calibration procedure and $\boldsymbol{q}$ is calculated as:

$$q_i = \frac{\lambda^d{}_i - \lambda^u{}_n}{\lambda^u{}_{n+1} - \lambda^u{}_n} \quad [3]$$

where $\lambda^u{}_n$ and $\lambda^u{}_{n+1}$ are the closest central wavelengths under and over that of the downsensor $\lambda^d{}_i$.

Thus, to calculate the reflectance $R(\lambda^d{}_i)$ in Equation [2], the only variables that need to be recorded at the time and location of the reflectance sampling are $\boldsymbol{u}$, $\boldsymbol{d}$ and t. The derivation of Equation [2] is explained in further detail in Paper I.

Field experimental dataset

In order to show and validate the functionality of the spectrometer sensor system, measurements of hyperspectral reflectance in the open field were made in spring wheat (*Tríticum aestívum* L.) on 24 July in Uppsala, Sweden. The sensor was held at about 2 m height above the ground, at nadir position, which gave a circular target area on the ground of about 0.25 m² (with a diameter of about 70 cm). Reflectance measurements were made within a couple of hours before and after noon. The reflectance measurements, using the procedure and instrumentation described above, resulted in 164 spectral bands ranging from 360 to 900 nm.

The development stage of the spring wheat crop according to scale developed by Zadoks *et al.* (1974) was defined as early dough, decimal code 83. In a 1.5 m by 1.5 m plot, the crop was manually thinned to produce different plant density levels. Randomly selected shoots in the plot were cut at ground level, removed from the canopy and weighed between reflectance measurements.

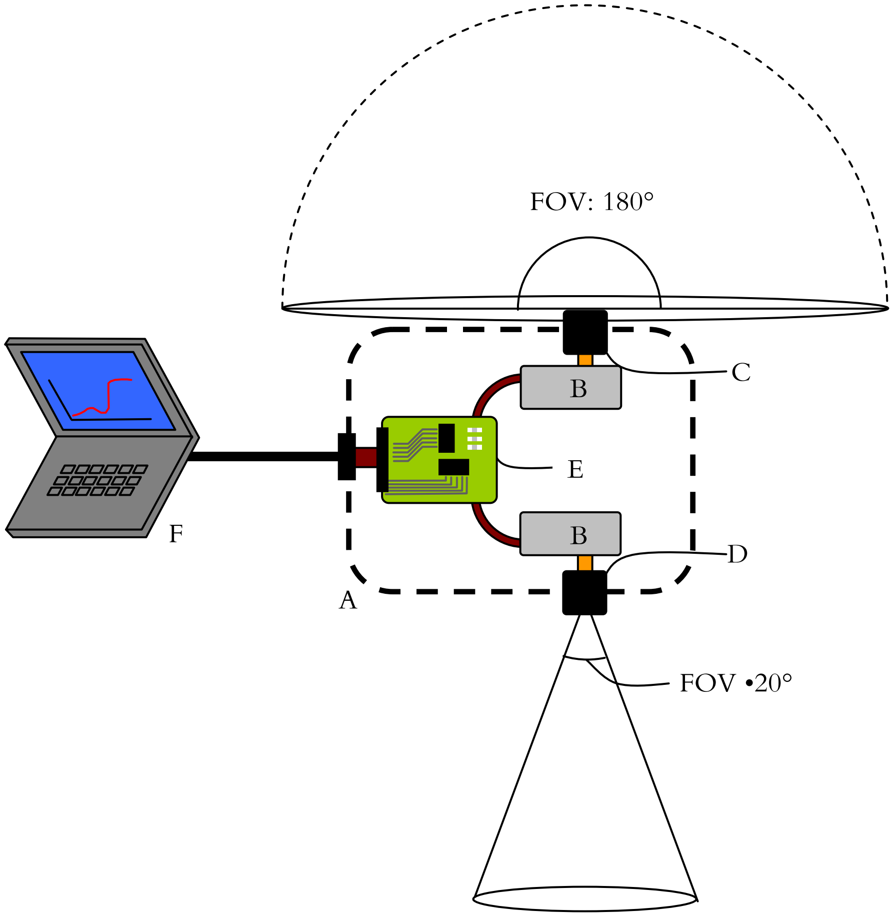


Figure 2. The spectroradiometer sensor system. The external sensor (A) comprises the spectrometer modules (B) with fibre optic inputs connecting the upwards directed sky irradiance collimator (C) and the downwards directed crop radiance lens system (D), both with defined field of view (FOV). The signals from the spectrometer modules were connected to an electronic board (E) for signal processing and communication with a personal computer (F).

Estimation of fungal infection using multispectral analysis

Although a spectrometer sensor system such as that described in the previous section produces an online measurement within a fraction of a second, it measures reflected light while the desired quantity would be the least required pesticide dose. One of the most important parameters for a sensing system estimating the site-specific need for a pesticide dose is the ability to estimate the presence of the object of control, *i.e.* weed frequency or the level of fungal disease severity in the crop. The economic value of a plant protection field operation is ultimately very much dependent on the effect on crop yield. A valid strategy would be to use estimated economic threshold, measured *e.g.* as weeds per m^2 or the severity of symptoms on leaves from fungal infection, as in the conventional uniform spray/not spray decision, but on a site-specific scale.

Field experiments were conducted in which data on hyperspectral reflectance (using the spectrometer method described in the previous section), leaf area of fungal infection and plant mass were collected. This work is described in Papers II and III.

Field experiments

The field experimental data used in the development of the multispectral analysis method originated from two field trials, both near Uppsala, Sweden (59°53'N, 17°38'E), one in spring wheat (*Tríticum aestívum*) in 1998 and one in barley (*Hordeum dístichon*) in 2003.

Hyperspectral crop reflectance in the field experiments was measured using the sensor and method described in the former section, in 164 bands in the spectral range 360–900 nm. Reflectance measurements were made within three hours before and after noon.

The spring wheat trial consisted of an area in the field of 100 m ×50 m where 0.25 m^2 circular test areas were randomly selected for spectral measurements and assessments of disease severity on 17, 27 and 30 July and 10 and 17 August. In total, 120 observations were made. In the disease severity sample, 30 fully developed shoots per observation were randomly selected in the 0.25 m^2 test areas and visual assessments were made of the percentage necrosis of the three top leaves. The mean value was calculated for these three leaves on all shoots. The field was naturally infected and the predominant fungal pathogen was *Drechslera tritici-repenti*, which causes tan spot disease.

In the barley trial, reflectance measurements were made and aboveground plant mass (fresh weight) collected on 23, 25 and 26 June. A thinning procedure was used where about half the standing shoots were evenly selected and cut at ground level within a 0.88 m^2 area between reflectance measurements. The number of sample areas on each date was 10 to 15. In the last cut, all remaining shoots were removed from the sampling area. Hyperspectral reflectance and corresponding plant mass from each sample spot were recorded for four levels ranging from 100% plant coverage to 100% bare soil exposure. Each spot was measured several times at each plant density level. The total number of reflectance measurements was 820.

The crop was at stem elongation development stage (before booting stage). Spectral measurements were made during both sunlit and overcast sky conditions. In about 29% of all reflectance measurements, the sun was more or less covered by clouds.

Hyperspectral analysis method

The hyperspectral analysis method consisted of two phases, a training and a classification phase. In the training phase a random subset of the hyperspectral field data was used to create a classification model. In the classification phase, the classification model was used on new hyperspectral reflectance measurements to estimate disease severity.

Two hyperspectral analysis methods were included in this thesis: Feature Vector Based Analysis (FVBA) and Iterative Normalisation Based Analysis (INBA). FVBA was used on the data from the wheat trial and INBA on the wheat data and the barley data. The FVBA method was first developed by Hamid Muhammed (2001) and Hamid Muhammed *et al.* (2001). FVBA had not been applied on field hyperspectral measurements prior to Paper II in this thesis.

Hamid Muhammed (2005) describes the use of a slightly different FVBA method on the same disease severity dataset used in Paper II in this thesis. The normalisation procedure in Hamid Muhammed (2005) comprised three consecutive normalisations instead of two. INBA was a new method for hyperspectral analysis presented in Paper III.

Training phase

Feature vector based analysis (FVBA) was used to analyse disease severity in the wheat dataset. The FVBA analysis training procedure consisted of a procedure with:

- ➢ Pre-processing of the hyperspectral data using a normalisation procedure, *i.e.* transformation to zero mean and unit variance
- ➢ Extraction of the spectral linear component that best describes the influence of disease severity on the normalised hyperspectral reflectance using PCA and ICA.

The normalisation procedure in the pre-processing step, also called whitening, enabled optimal functionality in the following extraction of ICA and PCA components. The variance in measured crop reflectance in spectral bands can differ significantly between different wavelength regions. The normalisation procedure takes the measured differences in all spectral bands of the same magnitude in the analysis. In principle the normalisation can be done in two ways, spectral or band-wise. The spectral normalisation subtracts each measured spectra from its mean value, and divides the result by the corresponding standard deviation. The band-wise normalisation does the same procedure, but within each spectral band. For the FVBA analysis, two combinations of normalisation were used: spectral followed by band-wise, or *vice versa*.

Principal component analysis (PCA) and independent component analysis (ICA) were used to extract linear components from the normalised hyperspectral dataset. The PCA and ICA analysis extracts the directions and magnitude of the vectors that describe the main variability in the dataset. In the case of PCA, all the components are perpendicular. ICA is a similar linear transformation analysis, also called blind source separation, where the components do not have the restriction of perpendicularity. The implementation of ICA used in this analysis was Fast ICA.

A genetic optimisation algorithm was used to find optimal linear combinations of the PCA and ICA components. This algorithm simply tries a number of linear combinations chosen according to a mechanism that imitates biological genetic evolution (see Goldberg (1989) for details about genetic algorithms). The resulting spectral component acted like a signature of the spectral characteristics of the stress effects caused by the disease.

The principal steps in the two FVBA analysis methods are shown in Figures 3 and 4, where procedures are identical with the exception of having the input dataset arranged with measured spectra in rows for the spectral normalisation and spectral bands in rows for the band-wise normalisation approach.

In the iterative normalisation based analysis (INBA), the pre-processing procedure was a normalisation procedure where the hyperspectral data were transformed to zero mean and unit variance, as in the pre-processing step for FVBA described above. However, the normalisation procedure in the INBA case consisted of a sequence of altering spectral and band-wise normalisations. This was simply performed by transposing and re-normalising the hyperspectral dataset a number of times, until a stationary result was obtained (Figure 5). The last step in the training phase for INBA consisted solely of the creation of a reference dataset using the iterative normalisation procedure on the training dataset. To visualise the spectral signature, corresponding to the FVBA case, a first order linear transformation model between the hyperspectral reference dataset and the disease severity in the training dataset was estimated.

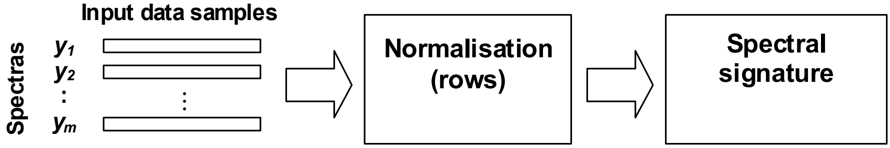


Figure 3. FVBA on input data of spectra y_1 , y_2 ... y_m using the spectral normalisation approach

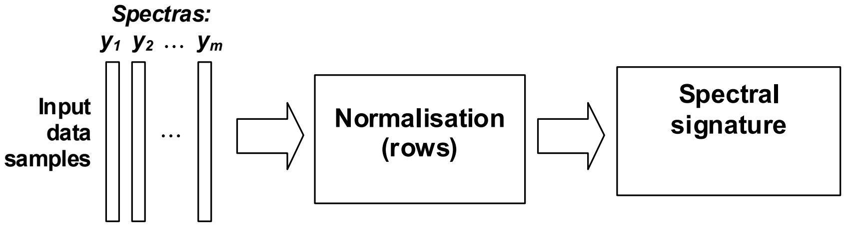


Figure 4. FVBA on input data of spectra y_1 , y_2 ... y_m using the band-wise normalisation approach.

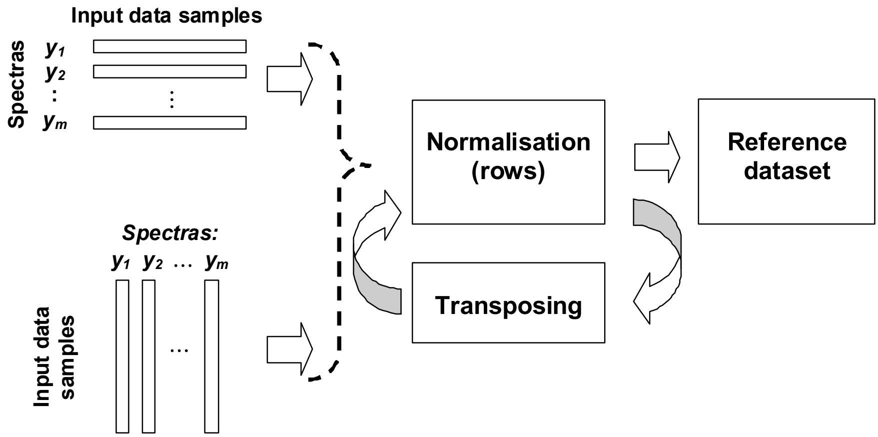


Figure 5. INBA on hyperspectral dataset using an iterative normalisation procedure with altering spectral and band-wise normalisations of the hyperspectral dataset

Classification

To classify new hyperspectral measurements, using either FVBA or INBA, the first step was to apply the corresponding normalisation procedure in exactly the same way as in the training phase for the corresponding analysis method. This involves using the same coefficients derived when performing the normalisation on the training data.

In FVBA, the correlation between normalised unknown hyperspectral data and the spectral signature component was used to estimate disease severity from new hyperspectral reflectance measurements.

To estimate the disease severity and plant biomass density in the INBA case, a classification procedure using nearest neighbour analysis of unknown hyperspectral measurements in relation to the reference dataset was used. In the nearest neighbour classifier, where each hyperspectral measurement in the reference dataset was compared with the unknown data vectors, the correlation coefficient (COR) and the sum of squared differences (SSD) were used as distance measures. Nearest neighbours were those with maximum COR or with minimum SSD.

A model for site-specific weed control

Given that yield loss inducing organisms in the crop, such as weeds or fungi, can be measured, the optimal site-specific pesticide dose becomes an optimisation problem where the outcome of the cost of pesticide application and the income from the harvested crop is maximised.

In order to make objective evaluations of site-specific weed control with respect to total herbicide usage in comparison with uniform herbicide spraying, an empirical model for site-specific weed control was developed to estimate the competitive effect of the weed population on the crop for three weed species (Paper IV).

Field experiment

The field experiment was carried out in spring barley at a location just outside Uppsala, Sweden. In order to study the weed competition behaviour in a dose response perspective, four different plots were sprayed using the herbicide Ariane S (40 g L^{-1} Fluroxypyr, 20 g L^{-1} Clopyralid, 200 g L^{-1} MCPA; DowElanco) at four different uniform doses. The doses were chosen relative to the recommended dose in Sweden (1.75 L ha^{-1}), in order to include both a range around 20-40%, where most of the transition from zero to maximum effect was expected to take place, and a dose between 90 and 100%, where the weed control effect should have been practically maximum.

The plots in which the herbicide doses were sprayed were 100 m long and 4 m wide. Each plot received a constant uniform herbicide dose according to the plan, and each treatment was repeated in four plots. The herbicide spraying was carried out when the crop had 3-4 leaves unfolded.

The experimental sprayer had a 4 m boom equipped with eight conventional flat fan nozzles with 110° top angle and 50 cm spacing.

The weed population was sampled at 50 predefined positions every 2 m along the plots, both one day prior to spraying and 30 days after spraying. On the first occasion, just prior to spraying the field trial, weed plant density was recorded by visual inspection in each of the 600 weed sampling subplots in the field experiment.

The second weed population sampling was performed 30 days after spraying in the same weed sampling subplots used in the sampling procedure just prior to spraying. This time, weeds were cut at ground level and fresh weed biomass for each weed species was recorded.

The model for simulating site-specific weed control

The weed biomass 30 days after spraying was used as an estimation of the weed population's competitive effect on the crop. In order to estimate the weed competitive effect depending on the initial weed density and the herbicide dose, a simulation model was constructed using a weed competition model and a dose response model.

Based on a hyperbolic weed competition model by Swinton *et al.* (1994), the following model was used for estimating the weed competitive effect defined as the total weed biomass:

$$w = \sum_i w_i = \frac{\sum_i I_i f_i}{1 + \frac{1}{A} \sum_j I_j f_j} \qquad [\mathrm{g\ m^{-2}}] \qquad [4]$$

where w is the total sum of weed biomass [g m^{-2}], w_i is the biomass for each weed species (i) [g m^{-2}] and f_i is the initial weed density at the time of spraying [m^{-2}]. The parameters I_i [g] and A [g m^{-2}] describe the weed biomass growth depending on its initial weed density f_i. At low weed densities towards zero, the weed biomass for an individual weed species i increase linearly with weed density: $w_i = I_i \cdot f_i$. At high frequencies towards infinity, the weed density approaches an asymptotic limit which in the single weed species case would be equal to parameter A.

An increased herbicide dose would decrease the values of the parameters I and A in Equation [4]. To describe the relationship between herbicide dose d and the response R on the weed population, a dose response function (Seefeldt, et al., 1995) was used:

$$R = R_1 + \frac{R_0 - R_1}{1 + \left(\frac{d}{a}\right)^b} \qquad [5]$$

where R_0 and R_1 are the values of R when d=0 and $d \to \infty$ respectively, and a and b describes the shape of the dose response function with respect to the position and the "sharpness" of the transition in effect from level R_0 to R_1 along the dose axis.

Using Equation [5], replacing R with the parameters A and I in Equation [4], a function for the total weed biomass w 30 days after spraying can be expressed:

$$w = \sum_i w_i =$$

$$\frac{\sum_i \left\{ f_i \left(I_{1i} + \frac{I_{0i} - I_{1i}}{1 + \left(d/a_{Ii}\right)^{b_{Ii}}} \right) \right\}}{1 + \left(A_1 + \frac{A_0 - A_1}{1 + \left(d/a_A\right)^{b_A}} \right)^{-1} \sum_j \left\{ f_j \left(I_{1j} + \frac{I_{0j} - I_{1j}}{1 + \left(d/a_{Ij}\right)^{b_{Ij}}} \right) \right\}} \quad [\mathrm{g\ m^{-2}}] \qquad [6]$$

The corresponding dose response parameters in Equation [5], $\{R_0, R_1, a, b\}$, for each of the parameters A and I_i was estimated numerically by minimising the square error between the estimated weed biomass w in Equation [6] and actual samples of weed biomass from the field experiment.

Thus having all parameters: $\{I_{0i}, I_{1i}, a_{Ii}, b_{Ii}, A_0, A_1, a_A, b_A\}$ (i = 1, 2, 3) defined, Equation [6] can be used to estimate the weed competitive effect, in terms of weed biomass growth after spraying, from the herbicide dose and an arbitrary mixture of weed population densities at the time of spraying.

In this study, Equation [6] was used as a model to simulate site-specific weed control using the weed density dataset sampled at the time of spraying in the 0.7 ha field trial. Using this simulation model, uniform and site-specific herbicide spraying could then be compared under exactly the same conditions.

Comparison between site-specific and uniform weed control

Using the simulation model described above based on Equation [6] and the weed frequency at the time of spraying, the resulting weed competitiveness from site-specific and uniform herbicide application was simulated. The site-specific dose used in this comparison was based on a predefined minimum weed control effect defined as the resulting total weed biomass 30 days after spraying. Assuming a maximum weed biomass, the least required site-specific dose over a field area was calculated using the simulation model, *i.e.* Equation [6], and data on the weed density at the time of spraying. Site-specific and uniform weed control, *i.e.* applying herbicides either minimised to the least required dose at each location in the field area or applied uniformly over the whole field area, were then compared in terms of the herbicide saving.

The comparison between site-specific and uniform spraying depended on the value of the uniform dose. Two strategies for choosing the uniform dose were evaluated: 1) the recommended dose; and 2) the dose that resulted in the same weed biomass as in the site-specific case. The latter alternative with equal weed control effect required some attention, as it is not obvious how to compare the resulting weed biomass after site-specific spraying on one hand and uniform spraying on the other. Uniform spraying will result in both under- and over-dosage, which will induce a high degree of variation in weed biomass.

One alternative would be to calculate the average weed biomass for uniform spraying. However, one could argue that the simple averaging of the weed control effect from uniform weed control would not be appropriate for use in the comparison with site-specific weed control, because the relationship between herbicide dose and crop yield loss is generally not linear, *i.e.* the crop yield loss does not decrease continually with increased dose.

Instead, the dose response relationship of yield loss might be better described as a sigmoid curve, where most of the transition between the unsprayed crop yield loss and zero crop yield loss takes place within a limited dose interval. This dose response function, as mentioned earlier, can be described by Equation [5]. Figure 6 illustrates a fictive dose response relationship for crop yield loss. Full details of how this yield loss dose response relationship was obtained are given in Paper IV.

On the dose response curve in Figure 6, a uniform dose was defined where most of the yield loss had been reduced. At this dose, it can be seen that there is a higher risk of crop yield losses from under-dosage on the 'high weed density' areas in relation to the potential crop yield increase from over-dosage on the 'low weed density' areas (Figure 6). Over-dosage from this relatively low level of crop yield loss does not result in any greater crop yield increase. The weed density cannot be decreased much further if the level is already near zero. In the case of under-dosage, there are no such technical limits on increased weed density.

Instead of using the average weed effect from uniform herbicide dose, it would be more appropriate to calculate the uniform dose where a target weed biomass has been reached on the majority of the field.

Thus, the comparison between site-specific and uniform herbicide weed control in this study was based on both a maximum weed biomass growth, representing a minimum weed competitive effect, and a proportion of the field area in the uniform application case, where the defined weed biomass threshold must be achieved.

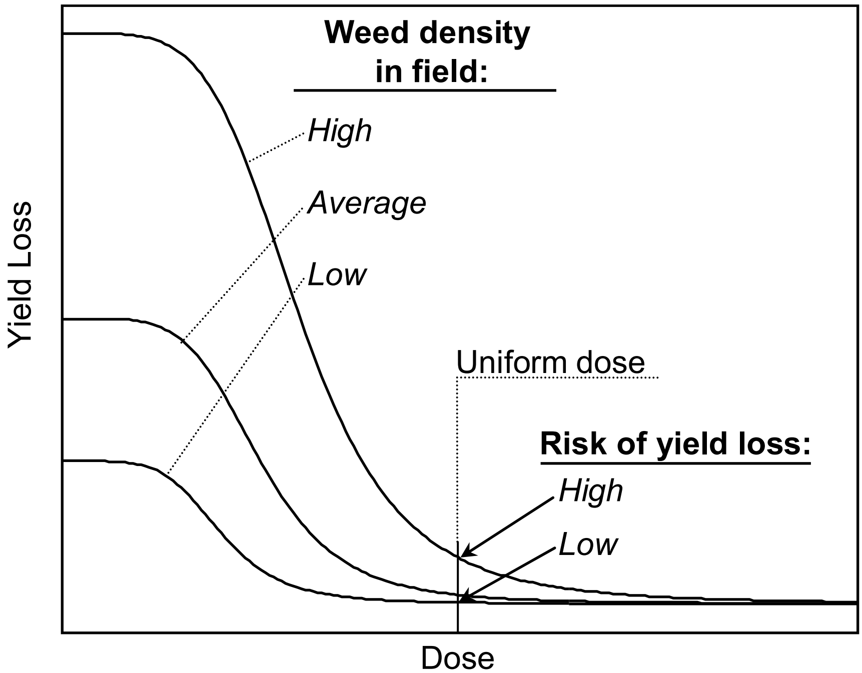


Figure 6. Influence of variations in weed population density on yield loss.

Results

Instantaneous measurement of field reflectance

Using the portable spectroradiometer instrumentation system developed, configured as shown in Figure 2, spectral measurements were made in spring wheat with different plant densities. The time span of the spectral sampling was between 10:00 and 14:00 hours, during cloud-free sunlit conditions.

The programmed procedure for integration time adjustment resulted in 90–100% utilisation of the digital radiometric range of measurement, irrespective of sky irradiance and ground radiance conditions. During spectral measurements in cloud-free conditions at noon in June, the integration was automatically adjusted to about 70 ms. During stable weather conditions, few or no integration time adjustment iterations were made for subsequent reflectance measurements over field surfaces with similar crop characteristics, once the maximal radiometric output from the upsensor and downsensor was set within the desired range of utilisation. The time consumption for each spectral measurement was mainly limited by the integration time, and each scan was done in a fraction of a second.

The calibration procedure, using the sun as a constant light standard, was performed once. Using Equation [2] the reflectance could then be calculated from instantaneous measurements of raw data $\{u, d, t\}$ from the sensor.

Figure 7 shows eight reflectance spectra for biomass densities ranging from the original unthinned crop, set to 100%, down to bare soil, 0%. The shape and behaviour of the reflectance spectra are in accordance with earlier studies (*e.g.* Deering, 1989). As the plant density decreases, the reflectance in the near infrared plateau, about 750 nm and higher, decreases and the reflectance under 700 nm, which covers the visible domain 400-700 nm where leaf absorption occurs, increases (Guyot, 1990).

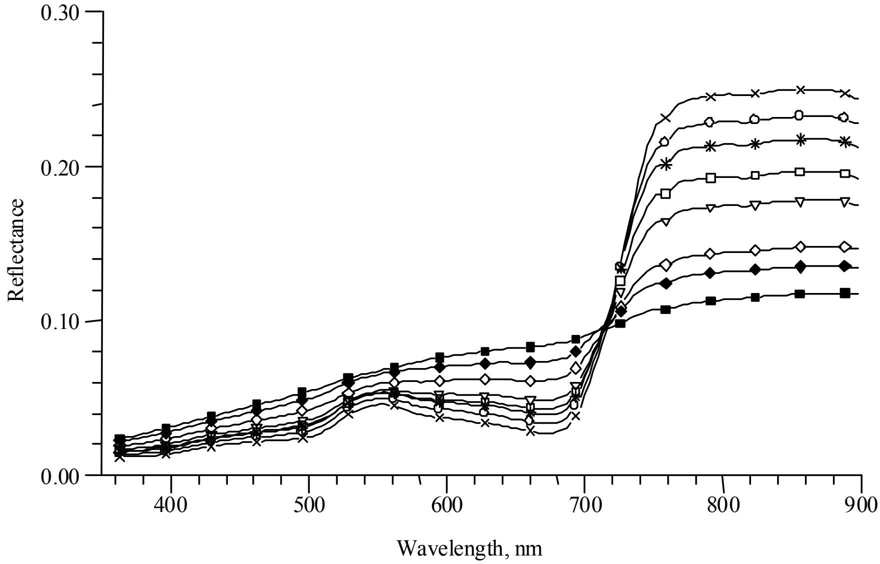


Figure 7. Reflectance spectra for a spring wheat crop, manually thinned to produce different plant density levels; —×—, unthinned 100%; —○—, 77.9%; —*—, 57.8%; —□—, 45.4%; —▽—, 31.9; —◇—, 18.1%; —◆—, 7.9%; —■—, 0%

Estimation of fungal infection using multispectral analysis

The two datasets consisted of 120 and 823 hyperspectral crop reflectance data vectors of 164 spectral bands, with the corresponding measurements of disease severity and plant density, respectively. Only 12% of each of the datasets was randomly chosen to run the hyperspectral analysis procedure and build a reference dataset, to be used to classify the remaining data vectors. Figure 8 shows four hyperspectral data samples from the disease severity dataset, from about 0.6% up to about 76.1% leaf area necrosis, and five hyperspectral data samples from the plant density dataset.

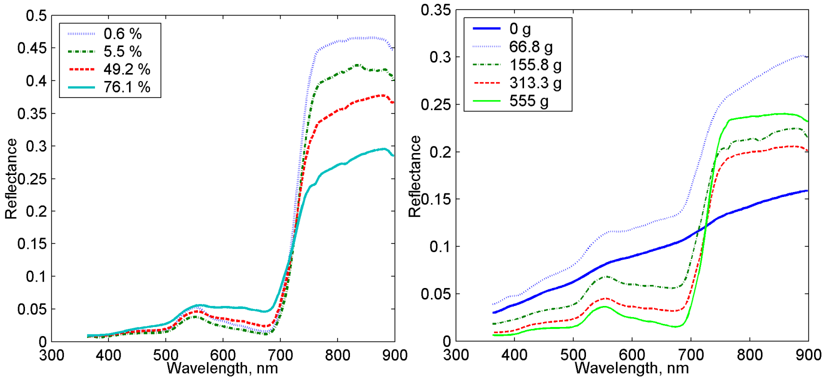


Figure 8. Original hyperspectral data samples from the disease severity (left) and the plant density (right) dataset.

FVBA

In the FVBA training phase, the randomly selected hyperspectral training dataset was first normalised, either using the 'spectral + band-wise' approach or the 'band-wise + spectral'. Then PCA or ICA was applied, followed by the extraction of optimal combinations of the linear components.

Figure 9 shows the resulting spectral signatures from the linear transformation model in the training phase, for the 'spectral + band-wise' approach and the 'band-wise + spectral' approach, when applying ICA to the hyperspectral data. Using these spectral signatures in the classification of new hyperspectral data gave the results shown in Figure 10, where the data are sorted with respect to disease severity. ICA and PCA gave approximately the same results.

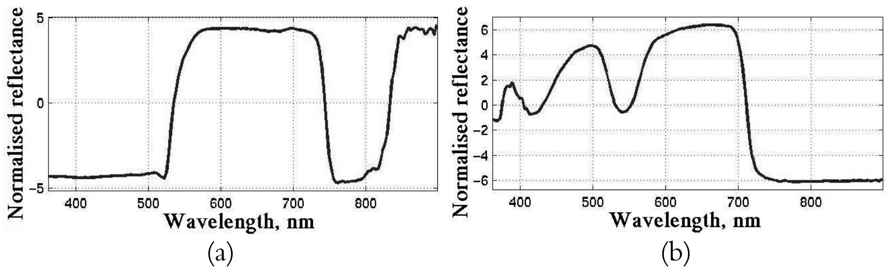
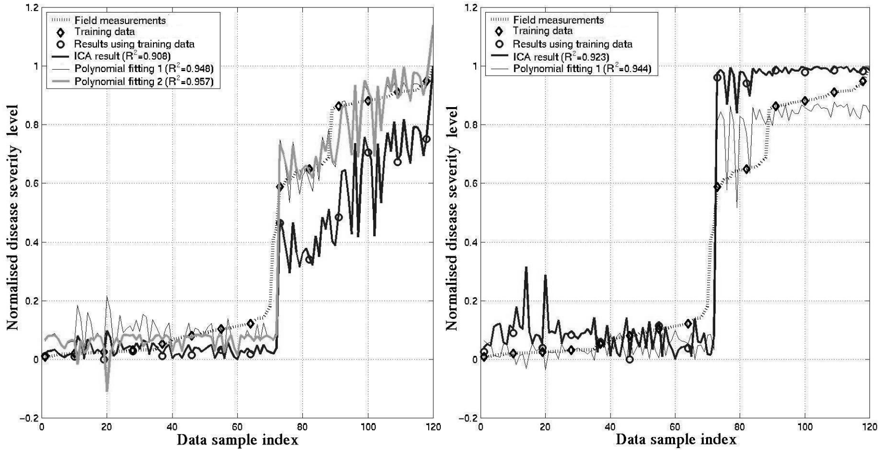


Figure 9. Spectral signatures resulting from the training phase: (a) the 'spectral + band-wise' approach; (b) the 'band-wise + spectral' approach.



(a) (b)

Figure 10. Measured and estimated relative disease severity values: (a) the 'spectral + band-wise' approach; (b) the 'band-wise + spectral' approach; ▪▪▪▪▪▪, field measurements; ◊, training data; o, results using training data; ▬ (thick black), results using independent component analysis (ICA); — (thin black), results of polynomial fitting using one second order polynomial (polynomial fitting 1); ▬ (grey), results of polynomial fitting using two second order polynomials (polynomial fitting 2).

Figure 10 also shows the results of polynomial fitting of the ICA-based FVBA estimates to the corresponding field measurements of disease severity, using one second order polynomial (Figure 10: Polynomial fitting 1), and using two second order polynomials (Figure 10: Polynomial fitting 2); one polynomial for disease severity values which are less than 0.20 and another one for values greater than 0.20. In other words, the estimates are 'corrected' by mapping them using certain polynomials. These polynomials are determined using only the training dataset by fitting the correlation results, between the resulting spectral signature from the training phase and the hyperspectral training data vectors, to the corresponding field measurements of disease severity.

Figure 10 indicates that the 'band-wise + spectral' approach results in a more binary-shaped response than the 'spectral + band-wise' approach. In comparison, the results using the 'spectral + band-wise' approach, which are sorted in ascending order with respect to the corresponding field measurements, seem to form the same main curve shape as the field measurements (Figure 10).

A comparison of the correlation coefficients, R^2, when comparing the results of the various approaches using ICA or PCA with the corresponding field measurements, is presented in Table 1. Note that the same results are obtained when using ICA and PCA. The results improved on using one polynomial fitting and normalising (*i.e.* whitening) the hyperspectral reflectance vectors, both spectral and band-wise, as can be seen from Table 1. The highest correlation coefficient, 95.7%, was obtained using the 'spectral + band-wise' approach and then mapping the results using two second order polynomials, one for values less than 0.20 and another for values greater than 0.20. However, the improvement resulting from using two-polynomial fitting seems to be caused just by increasing the degrees of freedom, since 100% fit can be achieved by simply using more polynomials.

Table 1. *Coefficients of determination R^2 when comparing the results of FVBA classification to the corresponding disease severity. The results are presented for the one, two and no polynomial fitting cases*

Approach	Number of polynomials		
	Nil	One	Two
Spectral + band-wise	90.8	94.8	95.7
Band-wise + spectral	92.3	94.4	94.4*
Band-wise	88.6	88.6	93.5
Spectral	88.2	88.4	88.4*

*: no additional improvement

If a threshold of 0.20 is used in Figure 10 to distinguish between healthy and diseased crops, only two misclassifications are obtained for the 'band-wise + spectral' approach, *i.e.* the misclassification rate is less than 2%. Only one misclassification is obtained when using a threshold of 0.20 for the results of the 'spectral + band-wise' approach followed by 1-polynomial fitting. No misclassifications are obtained in the other cases in Figure 10. Moreover, in Figure 10a, despite the fluctuations in the results when compared with the corresponding field measurements, it seems possible to determine the relative values of disease severity. To discriminate between higher or lower relative disease severity, the 'band-wise + spectral' approach followed by correction using 2-polynomials fitting was used. Ignoring relatively small fluctuations, which have little influence on the general shape of the resulting curve, 80% accuracy was achieved. Note that in only about 8% of the observations, there is a deviation of about 0.15 from the corresponding field measurements. The deviation for the rest of the observations is less than 0.05, *i.e.* relatively small, and can therefore be considered negligible.

INBA

Following the iterative normalisation described in the training phase, the resulting normalised spectral dataset converges towards a certain final result, which depends on whether the first normalisation was band-wise or spectral. This means that as in the FVBA case, there are two different final normalisation results.

Figure 11 shows the best classification outcome for the disease severity case study, while Figure 12 shows the best classification outcome for the plant density case study. The results indicate that the same performance is achieved when using COR or SSD if the last normalisation used is spectral. The results are sorted in ascending order with respect to the corresponding field measurements in order to facilitate comparison and evaluation. The best results are obtained when using the 'spectral + band-wise + ... + spectral' approach ('SBS…BS'), with a coefficient of determination (R^2) of 96.9% and 94.3% for the plant disease and the plant density case study, respectively. The results of the second 'band-wise + spectral + ... + spectral' approach ('BSB…BS') have corresponding coefficients of determination (R^2) of 91.9% and 93.6%. Table 2 presents these results, which are the mean values of 50 different classification tasks using different reference datasets, as well as the percentage of the classification results with certain minimum absolute errors (when comparing the results with the corresponding field measurements for each of the case studies).

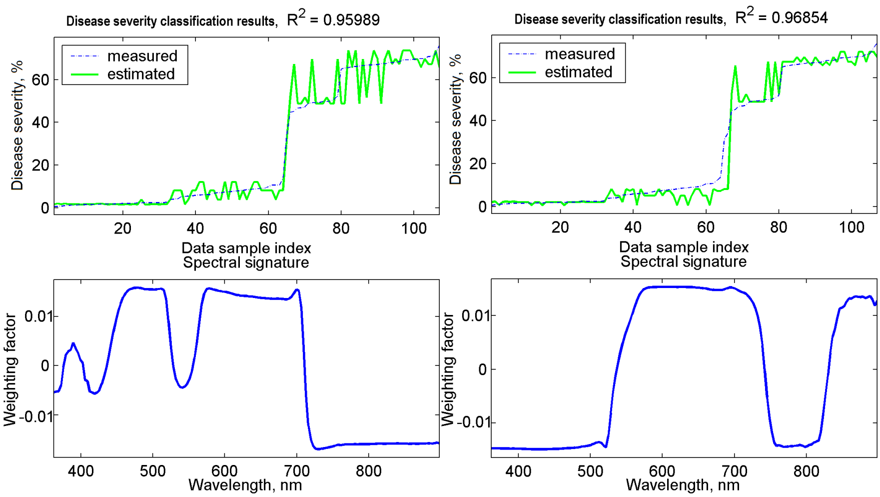


Figure 11. Best results of the disease severity case study (only one classification task) when starting with band-wise (left) and spectral (right) normalisation in the pre-processing step.

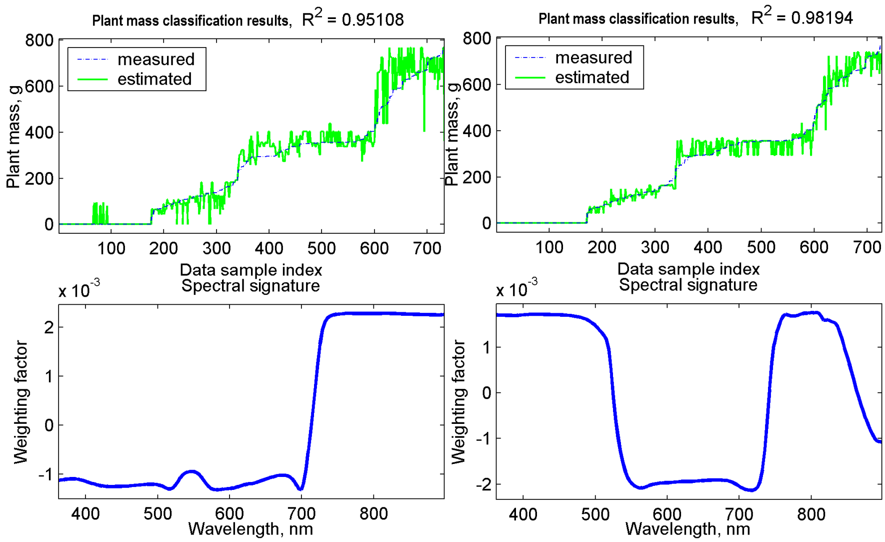


Figure 12. Best results of the plant density case study (only one classification task) when starting with band-wise (left) and spectral (right) normalisation in the pre-processing step.

Table 2. *Coefficients of determination (R^2,%), and percentage (%) of the results with certain minimum absolute errors (error, %), when comparing the results with the corresponding field measurements. The values shown are the mean values of 50 different classification tasks using different reference datasets*

Approach		R^2,%	Percentage results with		
			error ≥ 5%	error ≥ 10%	error ≥ 20%
Disease severity case study	'SBS…BS'	94.3	24.1	13.5	10.7
	'BSB…BS'	93.6	28	15.1	12
Plant density case study	'SBS…BS'	96.9	22.5	4.5	0.9
	'BSB…BS'	91.9	28.3	12.8	4.1

Figures 11 and 12 show different plant density and disease severity specific signatures obtained using linear transformation. Note that for a particular normalisation approach, similar signatures are obtained when using COR or SSD in the nearest neighbour classifier. Depending on the pre-processing normalisation procedure used, a unique signature is obtained. In the disease severity case study this describes some of the effects of increased fungal infection on the spectral properties of the investigated crop, while in the plant density case study it describes some of the effects of increased plant density on the spectral properties of the crop.

The field trial was sprayed on 11 June with the uniform doses at 19%, 38% and 94% relative to the recommended dose in treatments B, C and D respectively, leaving treatment A unsprayed.

The three main weed species in the weed biomass sample taken 30 days after spraying the field trial were *Sinapis arvensis, Galeopsis* spp. and *Chenopodium album*, which together represented 77% of the total weed biomass at that time. The weed density of these weed species within the field trial area at the time of spraying is shown in Figure 13.

The weed density (g m^{-2}) in the plots, as a measure of the weed population status at the time of herbicide application, was sampled on 4-6 June. The weed population biomass was sampled again 30 days later by cutting all weeds at ground level inside a circular frame with a diameter of 54 cm.

From the field experimental dataset it could be seen that the herbicide was relatively efficient, which motivated the assumption of zero weed biomass growth 30 days after spraying for infinitely high doses. The value of the infinite dose response parameter R_1 in Equation [5] for the I_i and A parameters in the competition function in Equation [4] was therefore set to zero.

An iterative procedure was then used to estimate the remaining model parameters in Equation [6] $\{I_{0i}, a_{Ii}, b_{Ii}, A_0, a_A, b_A\}$ (i = 1, 2, 3) by minimising the square error between $\{w_1, w_2, w_3\}$ from Equation [6] and the weed biomass for each weed species sampled in the field experiment. This implied a relatively large number of parameters to be estimated simultaneously. It was important to choose proper start values and to estimate the optimal iteration step carefully. This procedure is further described in Paper IV.

The dose response curves for parameters A and I are shown in Figures 14 and 15, respectively. The parameter values in these dose response functions made it possible to estimate the weed biomass for the three selected weed species for any herbicide dose and any initial weed population using Equation [6]

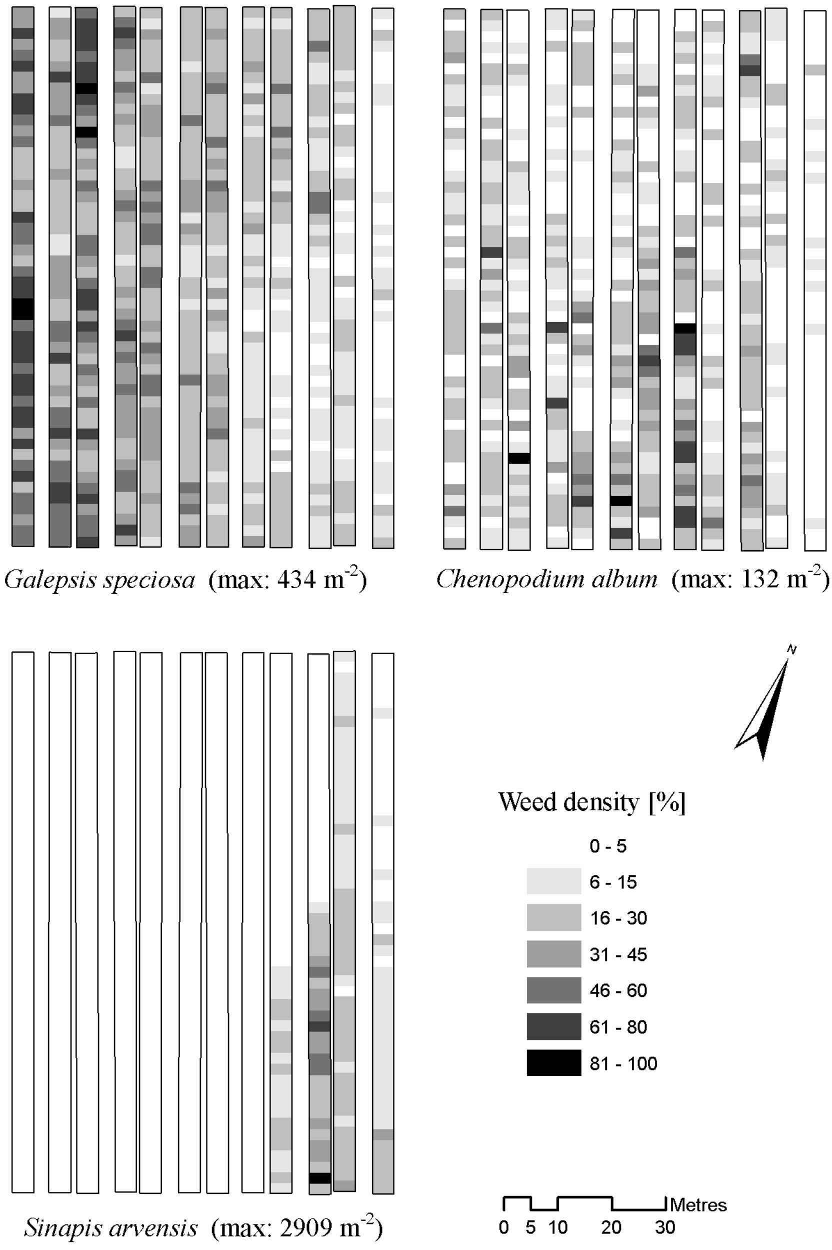


Figure 13. Weed density at the time of spraying for the three main weed species.

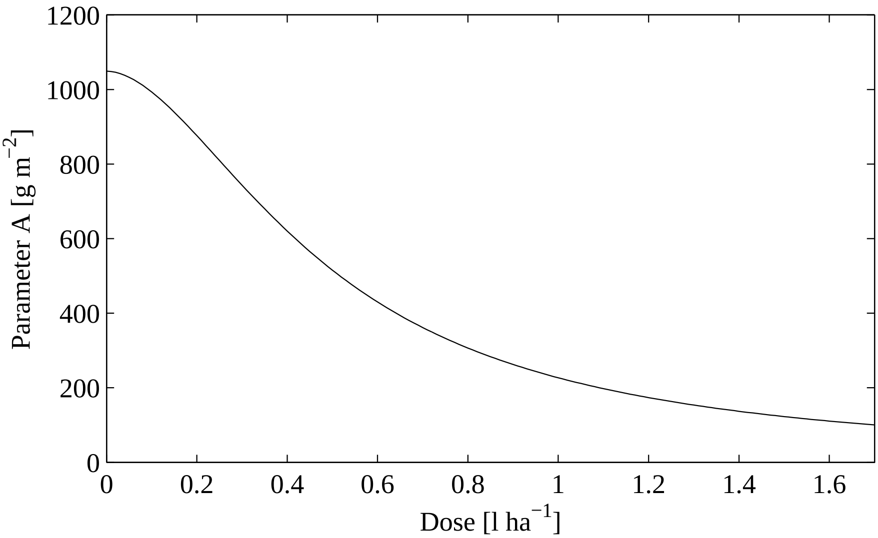


Figure 14. Estimated parameter *A* in the model as a function of herbicide dose.

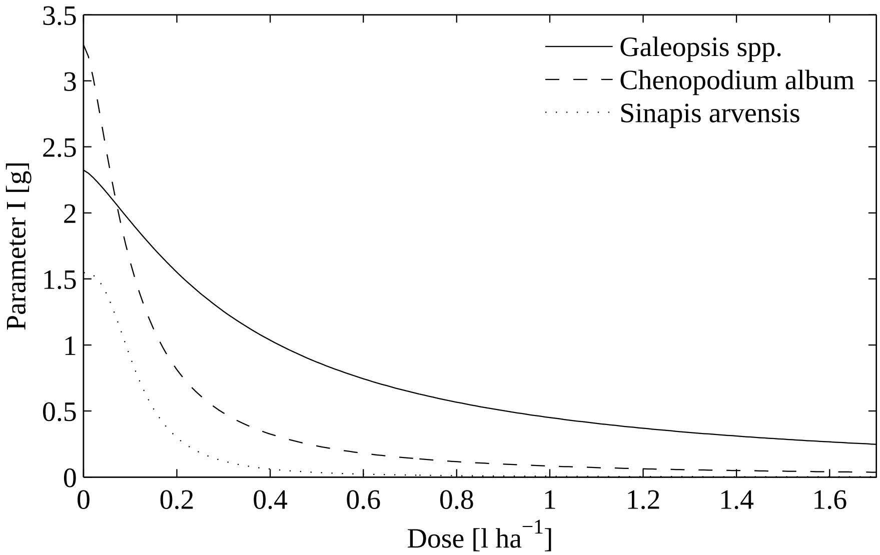


Figure 15. Estimated parameter *I* in the model as a function of herbicide dose for the three main weed species tested.

Using the model based on Equation [6] and the weed density data across the field area, it was possible to calculate the optimal site-specific dose within the field with respect to a weed biomass threshold, *i.e.* so that the actual weed biomass within the field 30 days after spraying did not exceed a certain threshold level. This can be seen in the solid line in Figure 16. Uniform spraying of the same average dose as in the site-specific case is plotted with respect to the mean resulting weed biomass in the dashed line in Figure 16. However this line coincides more or less with the site-specific case.

As mentioned earlier, using a uniform dose involves both under-dosage and over-dosage because of varying weed frequencies in the initial weed population within the field. Here it was assumed that it would be desirable to avoid under-dosage due to the risk of yield losses. As a result, the choice of uniform dose then involved both the definition of a weed biomass threshold together with the proportion of the field where the weed biomass (30 days after spraying) had to be equal to, or less than, the defined weed biomass threshold. This uniform dose spraying strategy can be seen as the dotted lines in Figure 16. Several lines are shown with percentages representing different proportions of the field on which the weed threshold have been achieved. Note that the 50% field area proportion coincides with the case of site-specific weed control and the uniform spraying of the site-specific average dose. However, when the proportion of the field area where the resulting weed biomass is less than the threshold increases, the required dose increases over the entire scale of the weed biomass threshold.

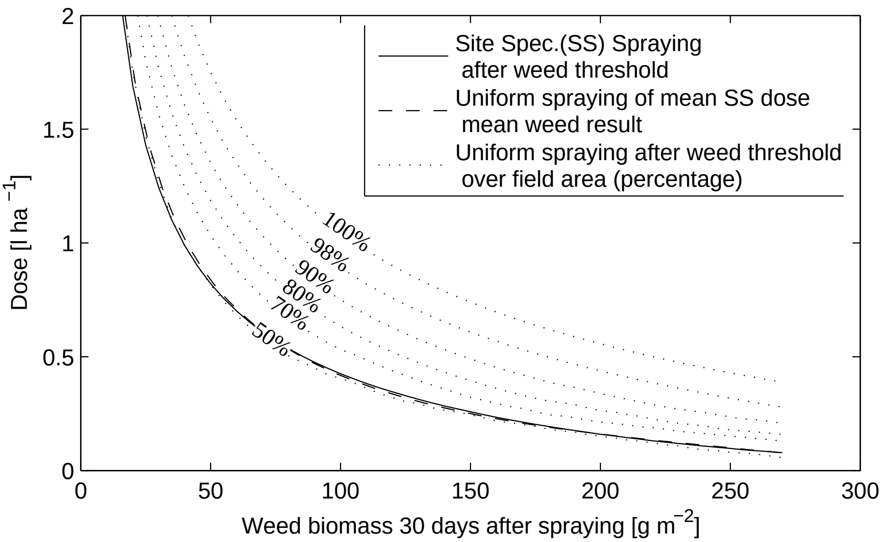


Figure 16. Simulations of the required dose within the field with respect to weed competitiveness, measured as weed biomass, for optimum site-specific spraying, uniform spraying with the site-specific total dose and uniform spraying with the weed biomass achieved on different proportions of the field.

Examining the resulting weed biomass 30 days after spraying for the two highest dose levels (treatments C and D) supported the use of 50 and 100 g m^{-2} as limits of a representative range of weed biomass thresholds. The herbicide savings in this threshold range for the site-specific dose in relation to the recommended dose of 1.75 L ha^{-1} were 53 and 76%. The corresponding savings in relation to the uniform dose with the field area proportion of 80% were 31 and 33%, while for the field area proportion of 90% they were 39 and 43% respectively.

Discussion

Measuring crop status from hyperspectral reflectance

The method for hyperspectral reflectance measurements developed and presented in Paper I was used to measure hyperspectral data in Paper II and III. This hyperspectral reflectance measuring method was also intended for use in systems for precision agriculture. In the scope of this thesis, this use was defined as the estimation of crop status in systems for site-specific plant protection.

Instantaneous recordings of hyperspectral field reflectance measurements will be required in systems for site-specific plant protection. Hyperspectral data can be recorded in the field in a separate operation prior to application of the plant protection product. Even if the time frame is a couple of days, the collection of hyperspectral field data must be reasonably efficient. In a real-time implementation with spectral sensors on the sprayer, the time frame will be fractions of a second.

The configuration of the system for hyperspectral reflectance measurements using two spectrometer sensors made it possible to record all the necessary raw data for reflectance calculation instantaneously. One ‘upsensor’ measured irradiance from the sky and one ‘downsensor’ measured radiance from the crop. Duff (1993), Felton (1995) and Blackshaw *et al.* (1998) used similar configurations with simultaneous measurements of radiance and irradiance. In contrast to the sensor developed here, they did not measure hyperspectral reflectance and only a few spectral bands were used. Similar instrumentation introduced on the market in recent years (Müller *et al.*, 2008) has the same type of spectrometer module configuration as in the measuring method presented here. However, no information is provided on whether the instrumentation used by Müller *et al.* (2008) has any functions regarding automatic adjustment of the range of measurement or on how the raw data are processed.

Once the calibration constants have been determined, Equation [2] can be used to calculate hyperspectral reflectance from the radiometric raw data. Using the high quality spectrometer modules in the hyperspectral sensor presented, the experience from practical use is that no more than one or two calibrations are needed each year.

Equation [2] is a relatively complex formula compared with the basic definition of reflectance in Equation [1]. The main reason for this is that the spectral bands of the downsensor do not have the same wavelength centres as the upsensor. This band shift originates from differences in the manufacturing of spectrometer modules. The upsensor readings were interpolated in Equation [2] in order to get radiance and irradiance values within the same spectral band. This interpolation would not be necessary if the spectral bands in the irradiance and radiance raw data were exactly the same. As a rule, the type of spectrometer modules used in this sensor will have shifts in spectral bands. On the other hand, implementing Equation [2] in the software in the measurement system takes care of this problem automatically.

The recorded irradiance will vary to some degree owing to variations in sun elevation and in the possible presence of clouds. This can lead to problems relating to utilisation of the range of measurements in the analogue to digital conversion. Spectral bands where the upper limit in the range of measurement has been reached lose all useful information and poor utilisation of the range of measurement can lead to increased measurement uncertainty. To overcome these problems, a method for automatic adjustment of the range of measurement was introduced in the system. The range of measurement can be changed by the software in the measurement system adjusting the integration time t. The reflectance from Equation [2] is independent of the absolute value of the integration time.

Having obtained the hyperspectral reflectance data, the next step in the system of site-specific plant protection is to estimate crop status. This part is covered in Paper II, which presents the Feature Vector Based Analysis (FVBA) method, and in Paper III, which presents the Iterative Normalisation Based Analysis (INBA) method. The concept of the multispectral analysis method in this thesis is the objective analysis of the entire spectral range of measurement. The FVBA method has been presented prior to Paper II (Hamid Muhammed, 2001; Hamid Muhammed *et al.*, 2001), but these reports do not include any implementation of FVBA on hyperspectral reflectance in areal crops. The modified FVBA method reported by Hamid Muhammed (2005) used up to three normalisations in the pre-processing phase. The INBA method performed the number of normalisations required to obtain a stationary result.

The use of a few wavelengths bands, for example to calculate NIR/Red ratios, has been shown to produce a relatively high correlation to various plant biophysical variables (see literature review). It is also the case that single or two band vegetation indices would involve technical simplifications when constructing spectral sensors. However, developing measuring methods with the practical use in view would require a more unrestricted analysis. In this perspective, selecting one or two spectral bands and discarding other high resolution spectral data can be considered unsound.

The analysis procedures in this thesis were unrestricted and objective. The whole spectral range in the data was used in the analysis. The hyperspectral signatures of the crop status were determined solely from the field data. In the case of unmixing analysis, as reported by Lelong *et al.* (1998) and Fitzgerald *et al.* (2004), the hyperspectral reflectance of the end-members must be known. In the case of FVBA and INBA no such information is needed.

The resulting spectral signatures from FVBA and INBA show the influence of disease severity and plant biomass density in hyperspectral reflectance in an educational way. For example, it can be seen how increased disease severity affects the hyperspectral reflectance over the whole spectral range.

FVBA and INBA appear to reveal and enhance significant changes in the hyperspectral reflectance. How the analysis does so is not intuitively easy to understand. In the so-called pre-processing procedure the hyperspectral data are normalised in order to transform the data to zero mean and unit variance. Normalisation is often preferred when using PCA or ICA. However, in this case the normalisation was carried out in both the band-wise and spectral direction. This makes all of the normalised data dependent on all initial data.

Despite this complexity, the results from the hyperspectral analysis can be explained to some degree. Two different spectral signatures are produced. The final signature depends on whether the first normalisation was performed in band-wise or spectral way. Using an initial band-wise normalisation produces a spectral signature much like the typical reflectance of a healthy dense crop. The initial band-wise signatures in Figures 9b and 11a are similar to the 100% crop biomass density reflectance in Figure 7. Disease severity will produce a reversed vegetation signature. In this case, the basic relationship between crop status and reflectance seems to be preserved. An initial spectral normalisation results in a different spectral signature. Normalising along each hyperspectral observation will reorder the reflectance data within each spectral band. This will shift the focus of the analysis to alternative modes of change. For example, the initial spectral normalisation analysis is sensitive to the slope in the near infrared region rather than the absolute level (Figures 9a and 11b).

A desired quality of the hyperspectral analysis methods would be to produce different spectral signatures for different objects in the crop. This has not been demonstrated in this thesis. The INBA analysis was performed on both the disease severity and the plant biomass dataset. The two different spectral signatures can be seen in both datasets.

In the FVBA method, the normalisation procedure consisted of two consecutive normalisations followed by extraction of the spectral signatures using PCA or ICA. Optimal linear combinations of the PCA or ICA components were finally selected. The INBA method was mainly based on a procedure where normalisations were iteratively performed in altering directions until a stationary result was obtained. No extraction of linear components was made in the INBA case. The normalisation procedure in the analysis methods is clearly significant for the performance of the analysis methods.

The FVBA and INBA method were used on a random training dataset. The rest of the unknown hyperspectral data were then classified. The classification resulted in coefficients of determination from 94% to 97% using only 12% of the total hyperspectral dataset. This can be considered to be a relatively good result. However, a proper test of the method would be a field-scale evaluation where crop status is estimated over a whole field.

It is fairly straightforward to implement an analysis model like this in a fully automatic on-vehicle system that is trained on a reference dataset, for example on crop disease. New hyperspectral crop reflectance data can then be acquired and the site-specific disease severity can be estimated. Furthermore, the actual effects of the investigated disease on the crop reflectance do not have to be exactly known or examined.

A model for site-specific weed control

Papers I, II and III deal with measuring crop status. The next step in the process is to estimate the required dose of the plant protection product. In Paper IV, a method to estimate the required herbicide dose was implemented in a model for site-specific weed control. The weed control effect, defined as weed biomass growth, was estimated using a weed competition model and a dose response model. The required herbicide dose could then be calculated from the weed control effect and the weed density at the time of spraying.

The simulation model in this thesis was used to evaluate systems for site-specific weed control in relation to conventional uniform spraying. This would reflect a situation where the farmer is considering investing in machinery for site-specific weed control. The choice of field machinery can have a significant influence on farm finances. An important question is whether the investment will be repaid by the increased income. Using a simulation model, systems for site-specific weed control can be evaluated objectively and site-specific and conventional weed control can be compared under exactly the same conditions.

The site-specific required dose within the field with respect to the weed control effect (Figure 16) is the theoretical optimal site-specific dose. It was assumed here that any dose can be applied across the field but in practice there would be limitations, *e.g.* in maximum and minimum dose levels.

Having the site-specific dose defined, the comparison will depend on the choice of uniform dose. One way is to use recommended dose in this comparison, in which case the result will depend on the expected weed control effect. The required dose increases when the expected remaining weed biomass deceases. Consequently, the herbicide savings will decrease. Examining the field trial data, a practical level of weed biomass after spraying was 50 to 100 [g m^{-2}]. This resulted in 53 and 76% herbicide savings. This can be seen as a considerable reduction in the total herbicide dose.

Assuming that the farmer knows how to minimise the herbicide dose, *e.g.* from experience and field inspections, then by using a conventional sprayer applying the herbicides uniformly, the herbicide dose can still be reduced. A lower uniform dose in the evaluation of site-specific weed control will result in less herbicide saving. The result of the comparison between site-specific and uniform weed control will depend on the choice of uniform dose. The theoretical limit for reduced dose would be the uniform dose with the same weed control effect. The corresponding herbicide saving in this case is lower, 31-43%. However, if the variations or patchiness of the weeds are higher than in Figure 13, the herbicide saving for site-specific spraying would be higher.

Work on weed competition models usually focuses on yield loss (see Paper IV for details), but in this case weed biomass was used. The reason was that the yield is dependent on factors other than weed control, for example available N in soil and weather conditions. In this work, site-specific weed control was evaluated in relation to uniform spraying. In this case the absolute value of the weed control effect in terms of yield loss is not important. Even if the yield had been modelled instead of weed biomass, the remaining weed population could be an important factor. Modelling weed biomass provides the additional option of reducing weed biomass under maximum allowable levels.

The dose and the weed control effect in the model developed for site-specific weed control are defined on a continuous scale. The HADSS model in the study by Lamastus-Stanford and Shaw (2004) made a spray or no spray decision. This resulted in a no spray decision for a uniform field treatment, while the corresponding site-specific decision resulted in spraying 51% of the field.

The DAPS model (Christensen *et al.*, 2003) applied a dose response model between weed competitiveness and grain yield. The model reported in this thesis included the dependence of herbicide dose in the weed competition function variables.

The model for estimating weed control effect presented by Kim *et al.* (2002) is similar to the model reported here, but their objective was to calculate the uniform conventional required dose. The present work used the model to compare site-specific and uniform conventional herbicide weed control, including a method to compare these two approaches to weed control based on equal effect.

Conclusions

The work presented in this thesis provides further knowledge on optimisation of systems for site-specific plant protection. Methodology for the estimation of crop status from reflected light in the open field was developed and a method was devised to estimate the required dose of a plant protection product from crop status data.

The knowledge obtained in this work can potentially lead to a defined system for site-specific plant protection. The specific parts in this process are:

- Measuring crop reflectance
- Estimating crop status
- Estimating dose of plant protection product.

The data presented in this thesis can also assist in making objective evaluations of site-specific plant protection systems. For example, before investing in field machinery for site-specific plant protection, it is fundamental to estimate the expected increase in income. Using the simulation model in this thesis, site-specific plant protection can be compared with uniform conventional plant protection under exactly the same conditions.

The results presented can also increase the possibilities to use resources more efficiently in arable production. The farmer would be able optimise production by minimising the use of plant protection products. This would lead to decreased discharge of hazardous chemical substances into the surrounding ecosystems.

Specific conclusions

The studies on hyperspectral reflectance measuring and analysis methods produced a number of findings that are beneficial for site-specific plant protection systems. These include:

- Fast and optimal measurement of hyperspectral reflectance in the open field
- Accurate, objective and conceptually simple hyperspectral analysis of the entire spectra
- Potential to separate different causes of measured spectral differences from two separate modes of influence on the reflectance spectra.

The model for site-specific plant protection presented here:

- Was constructed from mathematical functions allowing both weed competitive effect for several weed species and the influence of the herbicide dose to be simulated
- Has a relatively limited number of variables and low complexity, allowing fast and potential real-time execution
- Can evaluate site-specific weed control based on herbicide saving both with regard to recommended uniform dose and uniform dose with equal weed control effect.

Overall, these findings could be beneficial for both farm finances and the environment.

Future research

Possible areas for future research include:

- The further development and evaluation of hyperspectral analysis methods
- The development of simulation models for site-specific plant protection

The next step for the hyperspectral analysis based sensor technology is to make field-scale experiments and estimate site-specific crop stress induced by plant pathogens, and spray *e.g.* fungicides site-specifically after sensor readings.

The model for site-specific weed control presented here should be further developed to include the actual yield, the economic output from a farmer's field production. Furthermore, it would be of interest to develop a similar model for site-specific fungi control.

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