PROJECT REPORT No. 288

SPECTRAL REFLECTANCE AS A BASIS FOR IN-FIELD SENSING OF CROP CANOPIES FOR PRECISION HUSBANDRY OF WINTER WHEAT
(The SPARTAN project)

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by

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ABSTRACT

In general, spectroradiometers measure the spectral characteristics of crop canopies – reflectance, transmittance and absorption of incoming radiation. Historically, simple vegetation indices have been derived from 2 wavebands within the visible and infra-red parts of the spectrum. This 'vegetation index' does correlate with crop parameters but it is hoped that using much larger numbers of wavebands (hyperspectral spectroradiometry) that more accurate determination of crop characteristics could be obtained. Quantification of these hyperspectral characteristics enables a 'spectral signature' of the crop to be obtained. These spectral signatures can then be related to crop canopy size. This report provides an overview of the SPARTAN project (SPectral Analysis Relating To Nitrogen and disease) which aimed to evaluate the use of in-field spectroradiometry to distinguish variation within canopies of winter wheat as an aid to crop management decisions.

Work within the SPARTAN project aimed to evaluate 1) whether crop characteristics can be discriminated with hyperspectral data; 2) whether use of hyperspectral data can improve on the use of vegetation indices such as NDVI. The main emphasis of the project was on the determination of differences in crop canopy size due to nitrogen fertiliser input. Within the SPARTAN project, hyperspectral data were obtained using an in-field, hand-held spectroradiometer measuring in the range 350 – 850 nm.

The project has demonstrated that simple reflectance measurements such as NDVI, although they can be correlated with crop characteristics, are limited in their value. Hyperspectral measurements offer greater scope for determining crop characteristics beyond the range obtainable using simple vegetation indices. The project has demonstrated that good estimates of canopy size can be obtained during the period when major decisions on nitrogen, plant growth regulators and fungicides are made. The relationship between spectral reflectance and canopy size offers the opportunity to develop automatic, routine measurement of crop canopies which can be incorporated into simple models which can be used to generate application maps. Factors such as soil background colour and type, varietal colour and architecture, which can interfere with the data acquisition, were investigated and found generally to be manageable within the range of crop growth stages required for management purposes. Investigation of factors such as the angle of view of the sensor and the effects of shading on crop spectral signatures were carried out and again, no major constraints to using the technology were found. The basis of simple models which could be incorporated into a spatially variable input system for on-farm use is described.

Spectroradiometry technology is rapidly developing and coupled with our scientific understanding of crop growth and development, offers a real opportunity to develop a routine, accurate and inexpensive crop monitoring system. The project has demonstrated that crop characteristics such as canopy size could be determined remotely. The use of spectroradiometry, either as tractor mounted, air-borne or satellite-borne sensors could thus be of real value in crop management in the near future.

SUMMARY

HGCA-funded research has shown that the requirement of many crop inputs such as nitrogen, fungicides and plant growth regulators is related to the 'state' of the crop. Crop characteristics such as plant number and the size of the canopy, measured as green area index (GAI) are important to helping optimise crop inputs such as nitrogen, fungicides and plant growth regulators. However, these crop characteristics are currently very difficult to measure and to define spatially within a field. Details of the research on which this concept is based are outlined in the following two Project Reports:

HGCA Project Report No. 151
Assessments of wheat growth to support its production and improvement
Volume I (The wheat growth digest; Methods for in-field crop assessment; Forecasting crop progress for wheat)
Volume II (How to run a reference crop)

HGCA Project Report No. 166 (pages 64 – 102)
Matching crop management to growth and yield potential.

The SPARTAN project aimed to further develop some of the key concepts described in the Project Reports, particularly that of routine remote measurement of canopy size and nitrogen content.

If crop characteristics could be measured remotely and routinely then crop managers would be able to make more rational decisions on crop input requirements, particularly where there is a large degree of within-field variability in the crop.

Spectroradiometers measure the spectral characteristics of crop canopies – usually the reflectance of incoming radiation (light). These characteristics, particularly the reflectance of light, enable a spectral signature or 'fingerprint' of the crop to be obtained. This can then be related to crop structure, size and health status. However, there are factors which may disrupt or interfere with the spectral reflectance of the crop including weather conditions (especially light levels), soil colour and texture and varietal characteristics.

1 Canopy size and crop inputs

Crop canopy size has a marked effect not only on the use of nitrogen but also on the use of plant growth regulators and fungicides. Optimising canopy size across a field not only gives a canopy size optimal for light interception, often by reducing the amount of nitrogen applied, it also reduces the risk of crop lodging and disease risk. It is important to avoid crop lodging and disease as they both reduce yield and grain quality. Thus, optimising crop nitrogen applications has many benefits, not only on crop inputs such as nitrogen, plant growth regulators and fungicides. Because, by definition, it optimises crop nitrogen use it should also reduce nitrogen leaching into the environment. Because most crops have canopy size variation within the field, the ability to measure canopy size spatially using spectral signature would allow the adjustment of many crop inputs.

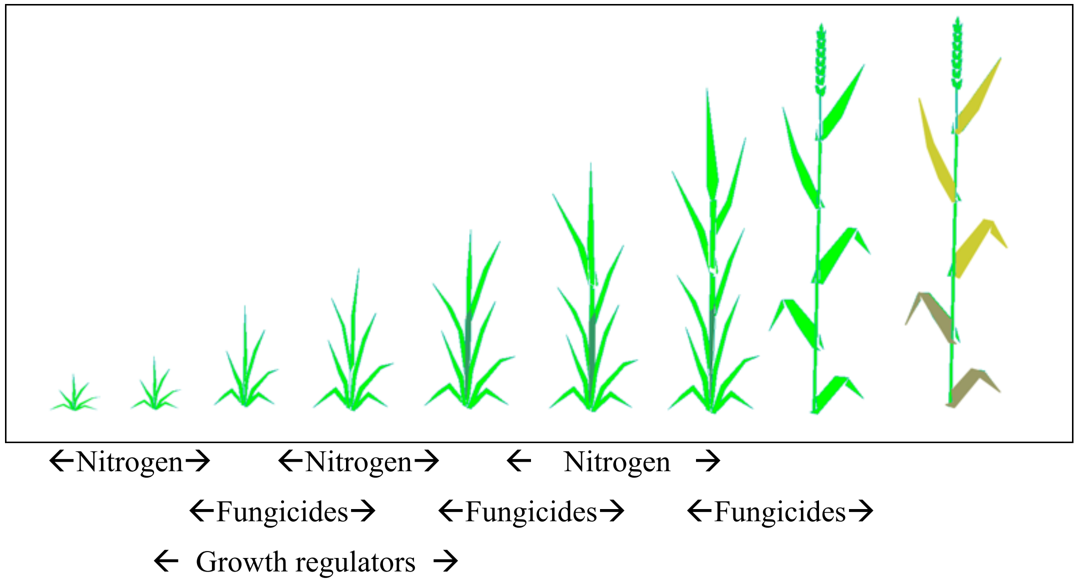

Figure 1 Typical decision making periods for inputs of nitrogen, fungicides and plant growth regulators in a wheat crop

2 Remote sensing of crops

The practice of precision agriculture involving spatially variable application of crop inputs requires the deployment of accurate and reliable crop monitoring techniques to provide information on the spatial variations in key agronomic parameters. A potentially valuable source of information on the state of the crop canopy is offered by remote sensing using air-borne and satellite-borne sensors. High resolution systems are imminent and commercial services will soon be available in the UK. Re-visit times have reduced considerably but the major limitation of optical systems is still the cloud cover which restricts image acquisition. The use of synthetic aperture radar offers some longer term hope of 24 hour coverage. Optical images can be integrated with other 'sensed' information or spatial data about crops or fields.

3 Factors interfering with hyperspectral data interpretation

Spectral measurements made in the field depend not only on the characteristics of the surface being measured, but also critically on the instrumental configuration and procedure applied in the measurement and on the illumination conditions at the time. These extraneous factors are particularly important in monitoring crops because the foliage is viewed against a contrasting soil background and the instrument configuration affects the relative impact of these two components in the measurement. The relationship between sunlit and shaded measurements has been established within the project and it has been shown that it is possible to convert between them with reasonable accuracy. With wide-angle measurements it is clear that there is a relationship with measurements made using a standard narrow field of view configuration, but that relationship has not been established with sufficient precision for application in all areas. However, this limitation is less critical to the establishment of sensing techniques in precision farming: it affects the ability to apply the findings of previous studies directly. What is important is that both wide and narrow field of view measurements exhibit similar relationships with key canopy parameters. Functional relationships established in previous studies with narrow field of view instruments can be expected to apply with wide field of view. This theoretically gives us reasonable flexibility in helping to design a tractor-mounted sensor as the angle of view of the sensor could be accounted for using these relationships.

The issue of whether hyperspectral measurements taken when the crop is in full sun or is shaded by cloud has been addressed and it appears that it is possible to account for this with reasonable accuracy. There is clearly considerable flexibility in the time window around solar noon that measurements can be taken – a serious practical issue that could affect the number of crops in which measurements could be taken during a single day.

Differences between varieties in terms of colour and plant architecture were potential confounding factors when taking spectral measurements of wheat canopies. However, with either NDVI or hyperspectral data, differences between varieties at early growth stages (GS30-32) were found to be either small or absent. As varieties developed their full canopy size, differences affecting spectral reflectance became more apparent. Thus, measurements taken later in crop growth would be confounded by varietal differences and some compensation would need to be made to adjust for such differences. However, the use of spectral reflectance to determine canopy size would be used during the very early growth stages of wheat (GS30-31) so varietal differences would not be expected to confound the spectral reflectance measurements at this stage.

4 Canopy size determination throughout the growth of the crop. The use of NDVI and hyperspectral signatures

The project has shown that there is a clear relationship between NDVI and LAI but also that the relationship changes through the growing season, particularly as the canopy size (LAI) changes. At the start of the growing season there is a linear relationship between LAI and NDVI. Later in the season, after about a LAI of 2.5 is reached, the relationship plateaus and it is no longer possible to predict LAI with NDVI alone. The linear relationship between NDVI and LAI up to a LAI of 2.5 is useful in managing nitrogen applications and some crop protection inputs. The main nitrogen applications would be applied during this period of crop growth, as would the plant growth regulator applications. The first fungicide application would also be applied during this period of crop growth and an estimate of LAI could be a useful tool in helping decision making. Principal components analysis of the hyperspectral reflectance data found five factors of importance in summarising the variation in the spectral data. A stepwise multiple regression of these factors with LAI found a highly significant relationship which is generally linear and therefore can potentially predict LAI over the range 0.5-4.0 rather than only up to 2.5 as seen by the extent of the linear part of the relationship between LAI and NDVI.

5 Farm machinery technologies and application maps

On-board computer systems such as AGCOs 'Fieldstar' have a significant role in helping to develop canopy measurement technology because they provide the farmer with the tools to measure and manage inputs. Inputs such as seed, fertiliser and crop protection products can be varied within a field and matched to canopy size. Such computer systems also allow the opportunity to farmers to automate the process of creating field records providing them with traceability information.

The ability to variably apply nitrogen and crop protection inputs relies on having a map of the treatable area showing the variability in the factor which affects the crop input. Canopy size is one key factor which affects many key inputs. The project has shown how such canopy maps could be used in simple models to help in managing crop inputs. The ability to measure and map variation in canopy size across fields would allow the generation of application maps for many crop protection inputs.

6 Applying the technology on farm

There are many practical issues that would need to be addressed before this technology could be applied in practice. These include:

a. The angle of view of the sensors. This determines the size of the 'footprint' (the area of crop 'seen' by the sensor. The decision on sensor view angle is a compromise as this would also determine the number of sensors required.

b. The mounting of the sensors. Sensors could be tractor-mounted or boom-mounted. This has great implications because boom mounted sensors could be orientated to have a vertical view of the crop. This is the conventional view of sensors on aircraft, satellites and hand held sensors used in this project. If sensors were to mounted on a tractor they would have to be non-vertical, having an oblique view of the canopy. The implications of such mounting would be significant and further work would be needed to re-test the hypotheses.

c. The minimum number of wavebands that need to be included in any sensor array.

Many farms need to invest in computer systems and software that would allow them to handle and integrate the types of spatial data that will become available in the near future.

7 Integration of data acquisition systems

In the future most benefit is likely to be gained by incorporating information sets derived from a number of sources. No single dataset is likely to meet all of the requirements of the farmer. Tractor mounted systems offer the greatest flexibility in that they will rarely be constrained by the weather. However, air-borne and satellite-borne sensors offer large scale image acquisition which offers 'directed scouting' opportunities together with whole field or whole farm maps showing large scale changes such as soil variation. CropStar is an example of a satellite mission designed specifically to meet the needs of precision agriculture. With 11 wavebands selected for the retrieval of crop biophysical parameters it should be possible to provide high-value information products to aid decision making and help in spatially applying crop inputs.

1. BACKGROUND

1.1 Use of spectroradiometry in crop management

If crop characteristics could be measured remotely and routinely then crop managers would be able to make more rational decisions on crop input requirements, particularly where there is a large degree of within-field variability in the crop. Spectroradiometers measure the spectral characteristics of crop canopies – usually the reflectance of incoming radiation (light). These characteristics, particularly the reflectance of light, enable a spectral signature or 'fingerprint' of the crop to be obtained. This can then potentially be related to crop structure, size and health status, all of which could aid crop management decisions. There are, however, many factors which may disrupt or interfere with the spectral reflectance of the crop including weather conditions (especially light levels), soil colour and texture and varietal characteristics. Many of these factors are investigated within the project.

1.2 Crop management decisions in the wheat crop

Many decisions made on the husbandry of the wheat crop are at present crude; the crop is only taken into account in a qualitative way, if at all. HGCA funded research has shown that optimal applications of fertiliser, fungicides and other pesticides are affected by the crop state (Bryson *et al*, 1995, 1997a,b; Clare *et al*, 1996; Clark & Bryson, 1997; Sylvester-Bradley *et al*, 1995). The research methods used to quantify crop state are very laborious, frequently involved destructive sampling and therefore are not realistically adoptable by farmers and advisers. Some of the crop characteristics that have been identified as particularly important are: canopy size and structure, proportion of healthy and diseased leaf area and shoot density.

Of the crop characteristics above, canopy size is probably the most important as it affects so many crop inputs. ADAS and The University of Nottingham have developed a management principle to achieve target canopy sizes to optimise crop performance. Canopy size is defined by the Green Area Index (GAI). For example, a GAI of 3 refers to a crop within one square metre of ground having the total area of all its green tissues (one side only) measuring 3 square metres.

Optimum canopy size can be achieved by first managing the plant stand, through appropriate adjustment of seed rate, then by the manipulation of the amount and timing of nitrogen applications to give the necessary number of shoots. Nitrogen management aims to control the expansion of the green canopy to achieve full light interception during the yield forming period (normally from late May to the end of July). This technique has the advantage over conventional nitrogen management as it constantly allows adjustments to be made as the canopy develops, moving towards a defined target canopy size. Conventional nitrogen management makes assumptions at the beginning of spring growth based on soil type, previous cropping and frequently the expected yield of the crop. Under the canopy management approach, compared to conventional N management, the aim is for canopy expansion to be reduced but canopy survival to be enhanced (see Fig. 1.1).

Key Points of Canopy Management:

- It is important to achieve a GAI of 3 as early in May as possible
- The aim is for the canopy to reach a maximum of GAI 6.5 by GS59.
- Application of 'late' nitrogen to maintain the canopy size throughout the grain filling period.

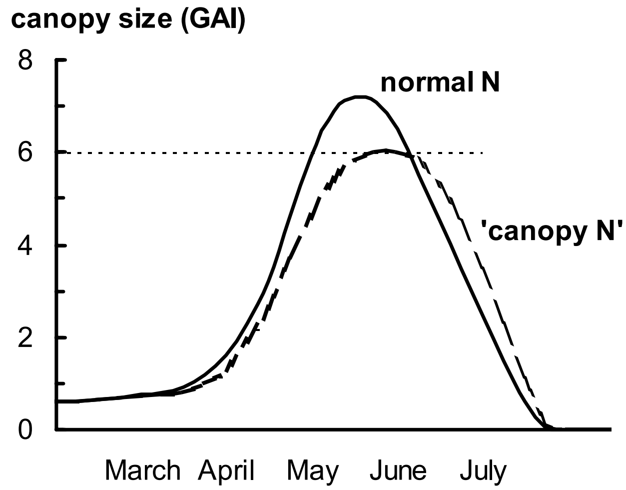

Figure 1.1 Canopy development in canopy-managed wheat (canopy N) compared with conventionally managed wheat (normal N).

In crops with smaller canopies, the lower leaves (leaf 3 and 4) contribute more to yield and therefore need better protection from disease than in thicker crops. However, the spread of foliar disease within the crop is often slower.

Crop canopy size has a marked effect not only on the use of nitrogen but also on the use of plant growth regulators and fungicides. Optimising canopy size across a field not only gives a canopy size optimal for light interception, often by reducing the amount of nitrogen applied, it also reduces the risk of crop lodging and disease risk. It is important to avoid crop lodging and disease as they both reduce yield and grain quality. Thus, optimising crop nitrogen applications has many benefits, not only on crop inputs such as nitrogen, plant growth regulators and fungicides. Because, by definition, it optimises crop nitrogen use it should also reduce nitrogen leaching into the environment. Because most crops have canopy size variation within the field, the ability to measure canopy size spatially using spectral signature would allow the adjustment of many crop inputs.

Measurement of Canopy Size

In order to apply the principles of canopy management throughout the season, canopy size must be measured. Various techniques have been developed to estimate canopy size including visual assessment from keys, tiller counting and ground cover estimate. These techniques vary in their accuracy and even if they were very accurate they still suffer from the problem that they do not take into account canopy size variation in different parts of a field. One of the key aims of this project is to enable canopy size to be mapped automatically and routinely using spectral signatures to quantify canopy size. This would allow the generation of GAI maps of fields that would then give information to apply not only nitrogen, but also plant growth regulators and fungicides.

1.3 Use of remotely sensed data in monitoring agricultural systems

The practice of precision agriculture involving spatially variable application of crop inputs requires the deployment of accurate and reliable crop monitoring techniques to provide information on the spatial variations in key agronomic parameters. A potentially valuable source of information on the state of the crop canopy is offered by remote sensing. Spectral measurements of the land surface made by earth observation satellites date back to the launch of Landsat 1 in 1972. The measurements derived from Landsat and its successors have shown the ability of remote sensing techniques to measure the status of growing vegetation at all scales, from the continental scale down to the local scales of variation within arable field. For example Steven and Millar (1997) showed that spectral indices derived from SPOT satellite data were able to account for about half of the within-field variance of yield in a variety of crops, while analysis of the spatial interdependence of the spectral and yield variations suggested that certain stress effects in crops could be distinguished from variations in plant density. With time, advances in both data sources and processing techniques are improving the level of information that can be derived by remote sensing, and hence increasing the potential value to the grower.

1.3.1 Vegetation Indices

The basis of the most well developed remote sensing techniques for monitoring arable crops is the vegetation index. This is an algebraic construction based on the contrast between the near-infrared waveband (which is strongly reflected by vegetation) and a visible band (usually red, which is strongly absorbed by plant chlorophyll). When viewing a vegetation canopy against a background of bare soil, the vegetation index provides a powerful measure of the density of the canopy, expressed as leaf area index, or better as the fractional interception of photosynthetically active radiation (Steven *et al*., 1983). This approach has been widely tested across a range of agricultural crops (e.g. Daughtry *et al*., 1992; Casanova, Epema and Goudriaan, 1998) and is sufficiently accurate to be applied operationally in the prediction of crop yield (Jaggard and Clark, 1990; De Koeijer *et al*., 2000). The ideal formulation of the vegetation index is a matter of some debate. The most widely used version is the Normalised Difference Vegetation Index (Tucker, 1979), but this index has also been widely criticised for its sensitivity to soil background. However, considerable progress has been made in revised formulations of vegetation index to correct for variations due to soil colour (Huete, 1988). Rondeaux, Steven and Baret, (1996) provides a comparative review of a range of these indices while Steven (1998) evaluated index sensitivity to a range of environmental and observational variables.

1.3.2 Advanced parameter retrieval

Although vegetation indices can indicate important variations within a crop and are often well correlated with important biophysical parameters, they are very much 'data products' (as opposed to 'information products') and require a great deal of interpretation by the grower if they are to be used for decision support. For this reason a number of academic institutions and commercial companies have been developing techniques to retrieve more meaningful crop parameters from remotely sensed data (airborne, tractor-mounted and satellite) over the last ten years, with a view to providing information with a genuine commercial value to the grower. Parameters such as Leaf Area Index (LAI), chlorophyll concentration and biomass can be estimated through modelling the interaction of incident light with specific crop canopies (insert refs esp Jacquemoud & Baret). In turn these parameters have been used in conjunction with agronomic models to produce user-friendly maps of anomalies, risk, and even input recommendations for the grower. This approach generally requires more advanced sources of data (such as 'superspectral' visible/near infrared data or high resolution polarimetric SAR data) which are not readily available from current satellite systems, so current applications are relatively small-scale and are based on airborne or tractor-mounted data sources. Commercially speaking, this type of crop monitoring is in the pre-operational or market introduction phase, and within Europe there are planned satellite missions and tractor-mounted initiatives that aim to make this more widely available over the next few years.

1.3.3. Constraints on monitoring

The ability of satellite sensors to monitor the status of arable crops is not simply defined by the ability to measure a distinct signal. Consideration must also be given to the scale or spatial resolution of observation, the detail of spectral information (spectral resolution) required of the observations and the frequency with which the observations are made (temporal resolution) through the growing season. Table 1 shows the range of current and future planned satellite missions (some of which are designed specifically for the precision agriculture market) which will significantly relieve many of the constraints imposed by current satellites if they come to fruition.

1.3.4. Spatial resolution

The size of objects that can be measured on the surface is limited by the spatial resolution of the instrument. This is formally defined as the instantaneous field of view (IFOV) of the instrument as projected onto the earth's surface: less formally it is usually identified with the pixel size, which for most (but not all) satellite observing systems is approximately the same as the IFOV. For large-scale agricultural monitoring the spatial resolution must be high enough to distinguish individual fields, so that in Western Europe a spatial resolution of about 100m would normally be sufficient. A large number of satellite instruments are available to provide this (Table 1). However for *Precision Agriculture*, the spatial scale of interest is finer, requiring a spatial resolution of about 10m or better. The study by Steven and Millar (1997) used 20m resolution data from the SPOT satellite which is usually sufficient to distinguish problem areas associated with soil physical properties, but too coarse to identify small patches (1-2m) of stressed plants, which may be associated with the early development of disease (Blakeman, 1990). Only the most recent satellites offer a capability approaching this level; for example IKONOS can image areas at a spatial resolution of 4 metres in three bands or 1m in panchromatic mode. An alternative for applications that require very high resolution imagery (and an option which currently offers better timeliness than VHR satellites) is *airborne* crop monitoring. Given a sufficient number of fields in a particular region, airborne remote sensing of arable crops can be commercially viable, and carries the advantage of being able to use advanced instruments that are not yet available on satellite platforms. Such services were introduced in France in 2001, are available from a number of providers in North America, and are being piloted in the UK in 2002.

1.3.5. Spectral resolution

The ability to measure plant characteristics by remote sensing depends critically on the specific wavebands used, and the precision with which those characteristics can be measured depends on the number and narrowness of the bands – termed the spectral resolution of the instrument. Systems like Landsat, SPOT and IKONOS have a few relatively broad wavebands (7, 4 and 3 respectively) centred on the main regions of interest for vegetation monitoring. However, greater spectral detail is potentially of importance in measuring biochemical concentrations in plant canopies (Curran, Dungan and Peterson, 2001) and for monitoring stress responses in crops (Steven *et al*., 1990). Several imaging spectrometers that would be able to deliver such data are in an advanced state of development, including Hyperion, a 220-band instrument recently launched on the EO-1 satellite (Table 1). For an operational system for growers, a compromise may be necessary in terms of spectral resolution (trade-offs with spatial and temporal resolution), such as that proposed for the CropStar system, which is described as ‘superspectral,’ having around 11 bands of intermediate bandwidth, chosen specifically for retrieving crop parameters

1.3.6. Temporal resolution

In monitoring arable crops, it is also essential to consider the frequency with which repeated observations can be made through the growing season (Steven, 1993; Moran, 2000). This factor is determined by the orbital parameters of the satellite, the angular width of the instrument and the cloudiness of the region of operation. Current satellites such as Landsat or SPOT that are designed for observation of the land surface are typically in polar orbits that overpass a given site on the earth’s surface every 15 to 30 days. The ability to acquire data can be increased to some extent by using multiple satellites or, with some systems, by pointing the satellite sensor at the target. However, even when a site can be targeted more frequently, in the UK cloud cover often restricts the practical imaging opportunities. Moran (2000) specifies a revisit requirement of one week to meet the user information requirements of agricultural management. Clearly, satellites such as SPOT, Landsat and IKONOS were not designed to meet the needs of arable crop monitoring, so their usefulness to the grower is limited to applications that are not very time-critical. Companies planning to address the precision agriculture market by remote sensing are aware of the timeliness issue, and have adopted various approaches to tackling it, including pairs of wide-swath instruments in complementary orbits, constellations of ‘small-sats,’ airborne data sources, Synthetic Aperture Radar, and tractor-mounted systems.

1.3.7. Synthetic Aperture Radar

Synthetic Aperture Radar (SAR) is able to penetrate cloud cover and operate both day and night, so has clear advantages in terms of temporal resolution over satellite systems. SAR is sensitive to different influences than optical data (crop structure/bulk and leaf/soil moisture as opposed to leaf chemistry) but recent studies have shown potential to provide valuable information for precision agriculture (Anon 2001). SAR imagery is already available from satellite platforms, but not with a spatial resolution or information content that is very useful for precision agriculture. Research is under way in Europe (the ‘ISOCrop’ project, under EC Framework V, using X and L-band polarimetric SAR data from an airborne platform) with the aim of establishing retrieval techniques for parameters such as biomass, canopy moisture and surface soil moisture, in preparation for exploiting planned SAR satellite missions (e.g. TerraSAR). The status of SAR capabilities is some years behind the optical techniques, but it is felt that SAR has an important role to play in certain parts of the world, perhaps providing the temporal reliability within an integrated optical/SAR service to growers.

1.3.8. Choice of observation systems

Increases in spatial, spectral and temporal resolution all imply an increasing demand for data. In the practical design of satellite observing systems, there is a limit to the amount of data that can be handled, which in turn implies that there is a fundamental trade-off between the spatial, spectral and temporal resolutions available from a given system (Steven, 1993). Thus, systems with high spatial resolution tend to offer only limited information in the spectral domain and are usually severely limited in terms of the frequency and timing of data acquisition. Optimal trade-offs are therefore being designed specifically for precision agriculture (e.g. Xstar). While current satellite-borne imaging spectrometers can offer a detailed spectral analysis of an extensive region of the earth, they have limitations for precision farming operations because their return time is inevitably long. This indicates that current satellite data may be useful as a strategic tool to provide information on within-field variability for future planning, but that data acquisition is not sufficiently reliable at least in Western Europe, for tactical monitoring where the information is used to guide management operations on a specific crop. Tractor-mounted sensors are well suited to fill this gap as the data acquisition is much less dependent on weather, the measurements may be made when the tractor is in the field for other purposes and the information is readily accessible to the farmer without the need to wait for processing by a third party. It may also be an advantage that the data acquired are available only to the farmer concerned and not to others. However, any application of measurements made from tractors must take into account the particular problems of this mode of measurement, such as the variable viewing angle, reliance on field soil conditions to allow travelling, variable illumination, non-specialist operation, the tendency toward a 'black-box' approach and not least, capital cost. Airborne systems are also available which provide the necessary spatial, spectral and temporal resolutions for precision agriculture. Airborne systems have their own inherent complications, not least the need to cover a large area in a given region to make the system cost-effective, but some of these systems are operated as precursors to future optical and SAR satellite-based services. The relative merits of observing systems vary by specific precision farming applications, and ultimately the choice comes down to which system can be exploited to give the widest range of cost benefits to a particular user.

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Table 1. Satellite observation systems suitable for agricultural monitoring

CURRENT MISSIONS

Platform/Sensor	**Agricultural Applications**	**No. of Bands**	**Polarisation**	**Spatial Resolution**	**Swath**	**Revisit period (days) / with selective targeting**
Landsat 7 / ETM+	Landsat was designed for general land observation purposes but has some applications to agriculture due to a reasonably well suited range of bands; - crop type distinction and mapping, vegetation health and moisture, soil moisture studies and plant heat stress measurement. However applications to precision farming are limited due to spatial resolution and effective revisit period allowing for cloud cover. Furthermore, for truly high-value information extraction there are insufficient spectral channels.	7 - 3 VIS - 1 NIR - 2 SWIR - 1 TIR (- PAN 2,3,4)	N/A	60m (TIR) 30m (MS) 10m (Pan)	185km	16
SPOT 4 / HRV	Unlike its predecessors (SPOT 1-3) SPOT 4 has a SWIR sensor specifically included for agricultural classification. However, applications to precision agriculture are limited by the spectral content and the effective revisit period of 26 days. The maximum orbit repeat period of 2-3 days comes with the cost of selective targeting at the expense of other areas, and competition with other users.	4 or Pan - 3 VIS - 1 SWIR	N/A	20m (MS) 10m (Pan)	60km	26 / 2-3
IRS / LISS -III	This sensor is designed for landcover and land-use, as part of the IRS programme to support natural resources. Although slightly more spectrally diverse in the IR region than SPOT 4, this sensor is still limited due to its lengthy revisit period.	4 or Pan - 2 VIS - 1 NIR - 1 MWIR	N/A	23m (MS) 6m (Pan)	140km	22

Platform/Sensor	Agricultural Applications	No. of Bands	Polarisation	Spatial Resolution	Swath	Revisit period (days) / with selective targeting
IKONOS	IKONOS, the first high-resolution commercial satellite was launched in 1999 and uses four bands equivalent to Landsat bands 1-4, making it potentially applicable to simple precision farming products. However, practical constraints make it very difficult to acquire timely imagery. The maximum revisit period of 1.5 days can only be achieved for a single target at 40º latitude within an 11km swath, which is totally inappropriate for studying large areas of agricultural land on a frequent basis, and data are costly.	4 or Pan - 3 VIS - 1NIR	N/A	4m (MS) 1m (Pan)	11km	142 / 1.5 at 40º latitude
QUICKBIRD	QUICKBIRD, also operating in four bands offers better still resolution than IKONOS but suffers from the same constraints, narrow swath and high costs.	4 or Pan -3 VIS - 1NIR	N/A	2.5m (MS) 0.6 (Pan)	16.5km	0.5 - 1
RADARSAT-1	RADARSAT SAR data has shown some success in basic crop mapping, rice monitoring and providing information on crop condition and within field variability. SAR data also the obvious advantage of not being limited by cloud cover. However the maximum resolution of 8m is only available with a swath of 50km, which reduces the effective revisit. The amount of agricultural information in also limited by the systems restriction to C band and HH polarisation. Furthermore, after necessary processing the effective resolution of thematic products is substantially reduced.	1 (C)	HH	8m –100m	50 – 500km	24

IMMINENT MISSIONS

Platform/Sensor	Agricultural Applications	No. of Bands	Polarisation	Spatial Resolution	Swath	Revisit period (days) / with selective targeting
ENVISAT / ASAR	Of the different instruments on board ENVISAT, launched successfully in March 2002, ASAR has the most potential for applications in agriculture at production level. The 'alternating polarisation mode' can produce to two images of the same scene in different polarisation combinations, which may prove a useful research tool in preparing for future SAR missions. However it is not expected to be a suitable data source for routine services to growers due to resolution, the restriction to C-band, and revisit period.	1 (C)	HH/VV or HH/HV or VV/VH	< 30m	100km	35
SPOT 5 /HRV	SPOT 5, to be launched in may this year, offers further improved resolution over SPOT 4, but has the same associated limitations with respect to precision agriculture. The arrival of SPOT 5 makes 3 SPOT satellites available for programming, so it may be feasible to offer some kind of immediate service for precision farming with reasonable timeliness using all three.	4 or Pan	N/A	10m (MS) 20m (SWIR) 2.5 & 5m (Pan)	60km	26 / 2-3

FUTURE MISSIONS

Platform/Sensor	Agricultural Applications	No. of Bands	Polarisation	Spatial Resolution	Swath	Revisit period (days) / with selective targeting
RADARSAT-2	RADARSAT-2 will offer polarimetric SAR imagery of unprecedented resolution when launched in 2003. The additional polarisation will enable differentiation between soil and vegetation thus providing more information on ground conditions than RADARSAT-1. Results however will still be limited, as this system will also only operate in C-band, and when operating in 'ultra-fine' resolution mode the swath will be severely limited to 20km. Final product resolution will also be reduced with processing.	1 (C)	HH, VV, HV, VH	3 – 100m	20-500km	24
TerraSAR	TerraSAR is likely to be realised through a combination of an ESA-managed implementation (L) and a German national contribution (X) by 2005/2006. The dual band and multi-polarisation capability, coupled with the high spatial resolution, is expected to hold potential for providing valuable crop parameter information. This information may be integrated into a service also using optical-based products	X & L	X – HH VV L – Quad Pol	3-6m X 5-9m L (Stripmap mode)	40km (Stripmap mode)	11 days (same look direction)
CropStar	CropStar is an example of a satellite mission designed specifically to meet the needs of precision agriculture. With 11 channels selected for the retrieval of crop biophysical parameters it should be possible to provide high-value information products. This service is already operational over limited areas of Europe, based on airborne data. Furthermore, with 2 or 3 wide-swath satellites in complementary orbits a short revisit time should be achievable.	11 (Vis/NIR)	N/A	10-20m	320km (each satellite)	2-3 days (without programming)

1.4 Project aims and scientific objectives

The main emphasis of this project is the remote determination of crop canopy size using hyperspectral reflectance data obtained using a hand-held, in-field spectroradiometer. The overall objective of the project is to identify key signatures of wheat crops indicative of canopy size, structure and composition due to nutrient input and disease. Within this overall objective, there are several constituent objectives:

1) To identify differences in winter wheat spectral signatures due to crop nitrogen status and related crop structure.
2) To carry out spectral component analysis of the spectral signatures of contrasting disease epidemics by manipulating the crop with nitrogen and by applying differential fungicide spray regimes.
3) To concentrate the study on two economically important and biologically contrasting foliar pathogens, *Septoria tritici* and yellow rust (*Puccinia striiformis).*
4) To evaluate changes in the spectral signatures of crops under stress due to drought, weed competition or pest attack.
5) To identify any practical problems in interpretation of the spectral signature. Factors such as crop size, soil type and moisture and incident radiation (bright v dull days) will be identified which may affect the spectral signature of the crop.
6) From the results of spectral component analysis key spectral signatures indicative of individual crop conditions would be identified.
7) To incorporate the spectral signatures of crop parameters into a simple model and assess the feasibility of using it to improve crop management decisions by farmers and advisers.

Investigations were carried out to meet each of the specific objectives. Field experiments concentrated on obtaining data on hyperspectral reflectance signatures of crops of a range of varieties and canopy size.

1.5 Methodology, instrumentation and data pre-processing

1.5.1 Spectral measurements

High-resolution spectral irradiance measurements were taken using a LICOR LI-1800 (Li-Cor, inc. Lincoln, Nebraska, USA) scanning spectroradiometer over visible and near-infrared wavelengths (350 to 850 nm). The measurements of both incident (sensor pointing up) and reflected (sensor pointing down) radiation were made at 1 or 2 nm intervals with a cosine corrected head held horizontally 50 cm above the target surface. In most experiments on each plot and sampling occasion reflectance from the crop was measured four times and this was preceded and followed by a measurement of incident irradiance. In the field mapping experiments only single crop reflectance measurements were made to allow a larger area to be mapped.

When possible the measurements were made under conditions of stable incoming solar radiation, ideally under clear cloud free skies. This aim was not always achieved due to changes in weather during the length of time required to complete measurements on all replicate plots. This problem and the large quantity of data involved resulted in significant time being spent in data processing to ensure that only valid reflectance calculations were made. The stability of incoming radiation was assessed from time course of total incoming radiation obtained by integrating irradiance under each of the incoming spectral response curves after applying appropriate calibrations. This allowed simple separation of periods of stable and unstable solar radiation. A further check was made using the ratio of amounts of solar radiation in ten specified wavebands to total solar radiation to aid the detection of any transient changes in irradiance. Final checks were made by comparing graphs of the replicate reflected spectra with the incoming radiation before and after the measurements on a plot. Comparison of measurements between stable and unstable periods showed the major cause of variation in reflected radiation between replicate measurements over our relatively uniform crops was variation in incoming radiation. Thus in stable periods the nearest in time incoming radiation was used for reflectance calculations. In less stable periods after removing incident measurements showing unstable spectra, remaining reflected measurements were matched to appropriate incident spectra by assuming changes occurred in parallel and the reflectances calculated. All valid reflectances for a plot were averaged at each wavelength and the mean used for further analysis.

1.5.2 Plant Canopy Analyser (PCA) measurements

In these experiments a Plant Canopy Analyser (PCA, LAI-2000, Li-Cor inc. Lincoln, Nebraska, USA) was often used to estimate green area index (GAI) of crop canopies rather than the more traditional destructive measurements. It estimates GAI from light measurements above and below the canopies at five solid angles using a hemispherical cosine corrected sensor, using calculations according to Campbell and Norman, 1988.

Reference

Campbell, G.S. 1988, The description and measurement of plant canopy structure. In: Plant Canopies: their Growth, Form and Function (G. Russell, B Marshall and P.G. Jarvis, eds.). pp. 1-19. Society for experimental Biology Seminar Series 29, Cambridge University Press.

The following five sections describe the investigations carried out to identify practical issues associated with use of hyperspectral reflectance to monitor crops: Section 2 investigates the effects of soils on sensing of crops and Section 3 the effect of spectroradiometer angle of view and illumination effects on spectral measurements. Section 4 reports the results on differences in spectral characteristics with different varieties of winter wheat. In Section 5, the relationship between spectral characteristics and canopy size is investigated and the difference between the use of hyperspectral data and vegetation indices is evaluated. Section 6 provides a discussion of the project findings, their implications for improved crop management and a discussion of the use of data from current and future satellite platforms for crop management.

2. THE EFFECT OF SOILS ON REMOTE SENSING OF CROPS

2.1 Introduction

The specific objective of this part of the project was to investigate the effect of soil in interfering with the spectral signal from the crop canopy. This work meets the specific objective of identifying practical problems in interpretation of the spectral signature. In this report section the effect of soil type and moisture are evaluated using information from experimental work and existing scientific literature.

Many of the applications of remote sensing to the land surface are associated with classification of the type of surface observed. The assumption is that the surface is a discrete entity that may be distinguished from neighbouring surfaces of different types. The remote sensing of crops differs from this kind of problem in that the surface observed represents a continuum of conditions from a few emergent seedlings to a closed green canopy, to a senescent crop. The plants and their condition are observed against a background of soil and the field of view of a remote sensor contains a mixture of both components. The problem is to extract the information about the status of the crop against this background. While this introduces difficulties associated with variability in signal associated with the brightness and colour of the background soil, it is also the factor that enables measurement of the size of the canopy. Figure 2.1 shows typical spectra of a soil and of winter wheat with a range of leaf area indices, measured in the course of this project. The dramatic contrast between the spectra of soil and foliage brings about a systematic evolution of the canopy spectrum with LAI. This change in reflectance with crop growth is particularly marked in the red and near-infrared bands and allows spectral measurements to be used to measure the density of foliage.

2.2 Soil spectra

The reflectance spectrum of soil is somewhat variable and creates problems in the interpretation of canopy reflectance spectra. Typical spectra measured in the course of this project are shown in figure 2.2. Variations in brightness and colour between soils are associated with the fractional content of organic matter, which darkens the soil and iron oxides, which give soils a reddish hue (Escadafal, 1993). Huete and Escadafal, (1991) suggested that the spectra of dry soils could be characterised by a linear mixture of four “basis” curves or eigenspectra, broadly representing overall brightness, iron oxides, organic constituents and goethite, a yellow, reduced form of iron oxide. The first of these components alone represented all but 1.87% of the spectral variation in the soils measured. An Atlas of soil reflectance values was presented by Stoner *et al*., (1980), representing several hundred soils across the USA. In general, the reflectance curves under controlled conditions for different soils are similar in shape (as indicated by the results of Huete and Escadafel, 1991) but differ in magnitude by as much as a factor of 5 or 6 (e.g. Escadafal, 1993). If soil type were the only source of variation in soil, it would be sufficient for the purposes of agricultural management to produce a similar Atlas of UK soils. However, for a particular soil type, variations in brightness are also caused by surface wetness and roughness, both of which have the effect of darkening the soil (Baret, Jacquemoud and Hanocq, 1993; Jacquemoud, Baret and Hanocq, 1993; Bausch, 1993; Rondeaux, Steven and Baret, 1996). The magnitude of the effect is about a factor of 2, depending on soil type, usually with slightly more change for wetness than for roughness. The roughness effect, which is caused by self-shading of the surface, is also a function of solar and viewing angles (Cierniewski and Courault, 1993).

2.3 Soil Adjusted Vegetation indices

The idea of a "vegetation index" was developed to express the systematic change in spectral response of vegetation canopies with leaf area. The ratio of near-infrared to red reflectance is perhaps the simplest index, but the most widely used is the "normalised difference vegetation index", defined as:

$$NDVI = (\rho_{IR} - \rho_R)/(\rho_{IR} + \rho_R)$$

where ρ_{IR} and ρ_R are measured reflectance values in the near-infrared and red bands respectively. Functionally, the NDVI is identical to the simple ratio (one can be transformed directly into the other), but has the computational advantage that its values are restricted to the range -1 to +1.

Although it primarily responds to a combination of leaf area and leaf angle, the NDVI is also sensitive to a range of other factors, particularly soil background colour. This means that its response to vegetation parameters will not be universal and quite large errors in estimation of canopy size may occur. To assess this effect, Huete, Jackson and Post (1985) performed experiments to measure the near infrared and red spectral responses of potted plants arranged to give a known fraction of ground cover, with varying soil backgrounds. Huete (1988) subsequently developed a "soil adjusted vegetation index" (SAVI), which reduces the effect of soil background to a minimum while retaining the vegetation response. The definition of SAVI is:

$$SAVI = (1+L)(\rho_{IR} - \rho_R)/(\rho_{IR} + \rho_R + L)$$

where L is an empirical constant taken by Huete to be 0.5. The basis for this approach is that the relationship between near-infrared and visible reflectance for soils is characterised by a single straight line and that the effect of the growing crop can be measured by the departure from this line, expressed either as the Euclidean distance or as an angular difference (Baret, 1995). Mathematically, SAVI is an angular index, but with the origin of the red and near-infrared axes shifted to negative values (figure 2.3). Subsequent authors have suggested several other values for the constant L, while Baret and Guyot (1991) derived a generalised formulation (TSAVI) in terms of the slope and intercept of the soil line. A comparison of soil adjusted indices was presented by Rondeaux, Steven and Baret, (1996), who tested a range of L values and found an optimum value of 0.16. There is probably no ideal value of L and the difference between L values found by different authors may in part be due to differing sets of soil data used to develop the index. In fact any of the soil-adjusted indices are a considerable improvement on NDVI. For example, Bausch (1993) found that SAVI corrected effectively for the effects of soil moisture. Steven (1998) simulated the residual sensitivity of OSAVI, (the index with L = 0.16) to factors such as sun angle, satellite viewing angle, atmospheric effects etc. The result of this analysis was that with an appropriate soil adjustment, vegetation indices can be used to estimate fractional ground cover to an error of about ±5%.

2.4 The limiting point of soil interference

If crop canopy spectra are to be used to estimate canopy variables other than size, an issue to consider is the point in time through the growing season at which soil ceases to significantly affect the signal. It can be seen from Figure 2.1 that the soil spectrum is rapidly overshadowed by the effect of the overlying vegetation and the vegetation signal "saturates", or approaches an asymptotic value at large values of LAI (Tucker, 1977). In this project, this concept has been applied explicitly in the analysis of the effects of field of view and shading (see section 3). A "pure foliage" spectrum was estimated by extrapolating the spectral values at each wavelength to an estimated value at 100% ground cover. For the purpose of estimating the limiting point of soil interference, the critical value was assumed to be the point at which 95% of the evolution from the soil spectrum to the "pure foliage" spectrum had taken place. This value, ρ_{crit}, which also takes the form of a spectrum, was calculated simply as the weighted average of the pure foliage and soil spectra (weighted in the ratio 0.95:0.05). The limiting values L_{crit} corresponding to this spectrum were calculated using the fitted curve between the measured spectral data and estimated ground cover that had been used to estimate the pure vegetation spectrum. First the value of crop cover corresponding to ρ_{crit} was calculated by inverting the equation. Then L_{crit} was calculated from the assumed relation between crop cover and L (Section 3). The values derived from the measurements made at ADAS Terrington on 23 May 2001 are shown in figure 2.4. The vegetation signal saturates at an LAI of 2-3 in the visible part of the spectrum and 5-6 in the near-infrared. The difference arises because leaves are partly transparent in the near-infrared, causing the signal to change over a greater range of values. Values of L_{crit} were derived for both the narrow and wide field of view probes used in that study: differences are minimal in the visible, but near-infrared values of L_{crit} are slightly lower for the wider field of view, because the effective leaf area seen by the instrument at the larger angles is greater than when viewing directly down. The analysis breaks down in the red-edge region (*ca*. 730-750 nm) because the vegetation and soil spectra cross and the assumption of evolution of one spectrum into another no longer holds.

An extension to this analysis is to consider the effect of varying the brightness of the soil background. For this purpose, the soil spectrum measured at ADAS Terrington (which was dry at the time) was adjusted by a factor of 2 to simulate brighter and darker soils. This conversion is reasonable and realistic because of the similarity in shape of soil curves noted above. The 2 x ADAS Terrington case can be regarded as a simulation of a much brighter soil, possibly dry chalk, while the 0.5 x ADAS Terrington case can be regarded as simulating ADAS Terrington in the wet. The values of L_{crit} were computed as before and are shown in figure 2.5. The effect of the darker soil is for L_{crit} to reach a value of about 4 across the whole spectrum. The effect of the brighter soil is for the spectrum to saturate at an L_{crit} of 2 or less in the visible region, but only at a value of about 8 in the near-infrared. The analysis breaks down in the red-edge region, as before. These results should be interpreted with caution because while the calculation of L_{crit} for these simulated soils takes account of the change in ρ_{crit}, it does not allow for changes with soil brightness in the relationship between canopy reflectance and ground cover when estimating the matching value of L. However, since the 95% point is close to the value for the pure vegetation spectrum, which should be insensitive to soil, the errors involved in this approximation should be minor.

2.5 Generalisation of the soil adjustment approach

The effects of soil on the crop reflectance spectrum affects hyperspectral data in just the same way as it affects simpler measurements made in 2 or 3 bands. It is therefore relevant to determine whether the SAVI approach can be generalised to deal with all wavelengths. The success of this approach depends (1) on the use of one spectral band to act as a reference point for another; (2) on the plot of corresponding soil reflectance values at the two wavelengths falling in a straight line and; (3) on the relationships between reflectance values at the two wavelengths with different soils for different ground covers being at least approximate straight lines that converge to a common point as in figure 2.3.

Baret, (1995) showed that the soil line concept applied to most soils in the red and near-infrared domain and with some restrictions in the middle infrared. The near-linear forms of the spectra in figure 2.2 also support this. Baret presented soil line equations for a series of paired wavelengths representing SPOT HRV and Landsat TM bands. The TSAVI approach (Baret and Guyot, 1991), in which the slopes and intercepts of these lines are used explicitly to generate the index, provides a direct means of applying the correction. Although no full hyperspectral experiment on vegetation canopies against varying soil backgrounds has been reported to date, it is reasonable to expect linearity and convergence across the spectrum as shown in figure 2.3, because the red and near-infrared wavelengths already in use represent the extremes of difference between vegetation and soil. On this basis, the concept of generalising the soil adjustment approach to hyperspectral data is promising. However, the paired wavelengths cannot be too similar. If a fixed wavelength is used across the spectrum, the soil correction will be mathematically undefined at that wavelength and will be prone to large errors at neighbouring wavelengths, or indeed at any other wavelength where the reflectance properties of vegetation and soil are similar (Baret *et al*., 1994). One approach might be to use a reference wavelength outside the specific region of interest for vegetation monitoring, but this would be limiting; an alternative would be to use separate reference wavelengths for different regions of the spectrum, the paired regions selected for contrast in the soil and vegetation reflectance properties. Further study involving both theoretical analysis and spectral measurements on carefully designed experiments is required to evaluate this concept.

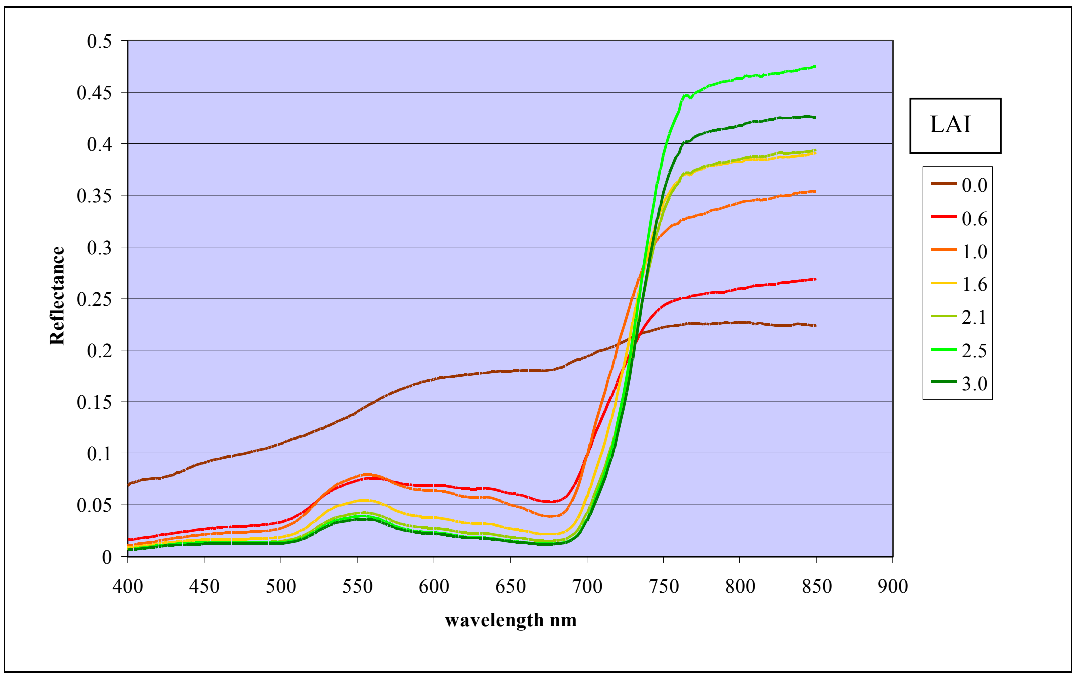

Figure 2.1: Spectral reflectance as a function of leaf area index. The measurements were made with a wide field of view sensor on a nitrogen trial in winter wheat (23/05/01).

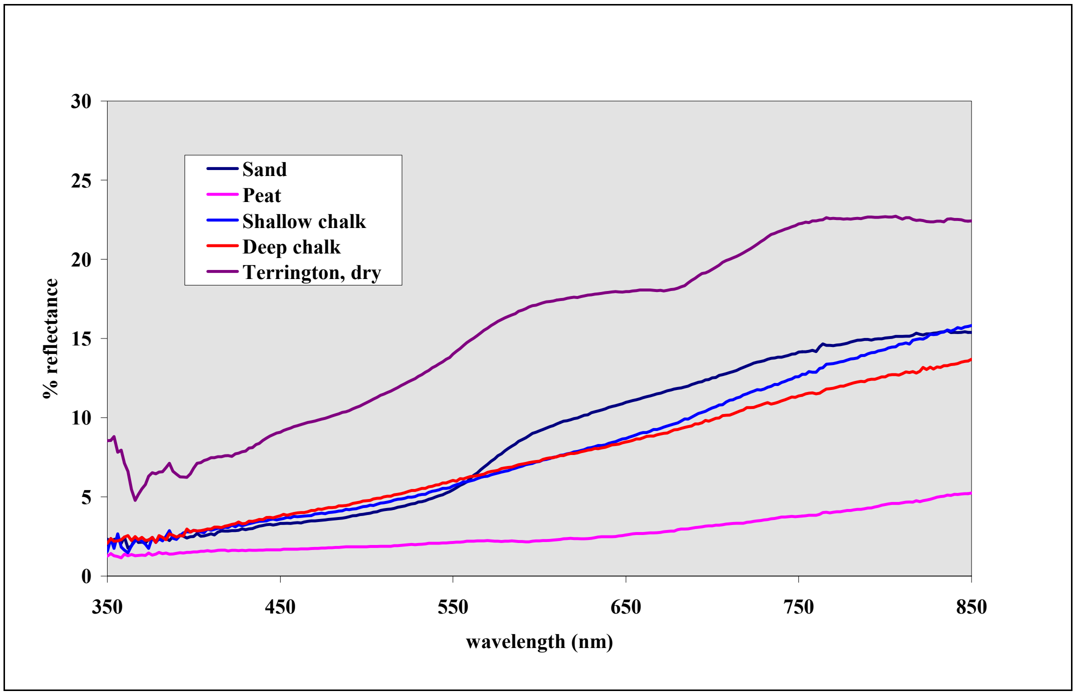

Figure 2.2: Typical soil spectra from ADAS field sites

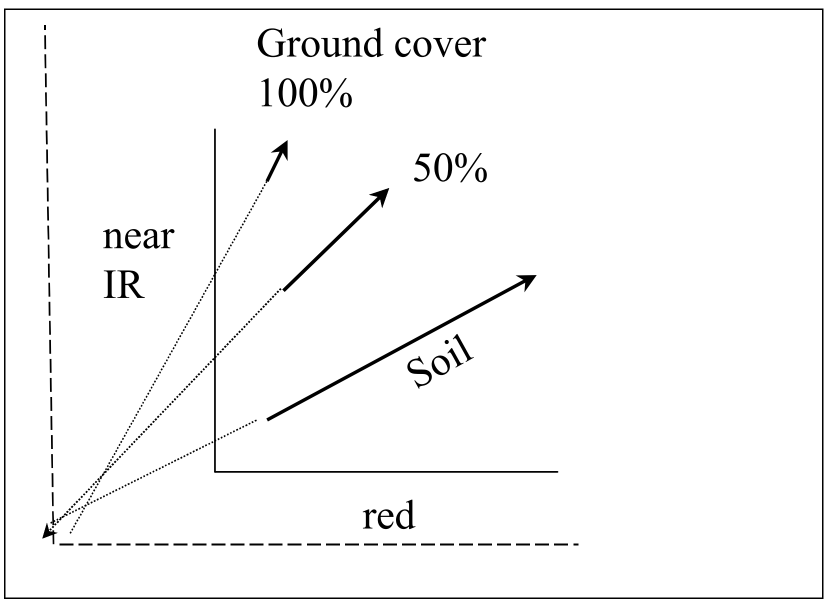

Figure 2.3 - The basis of the soil adjusted vegetation index: The relationship between near-infrared and red reflectances for given ground cover is a series of straight lines.

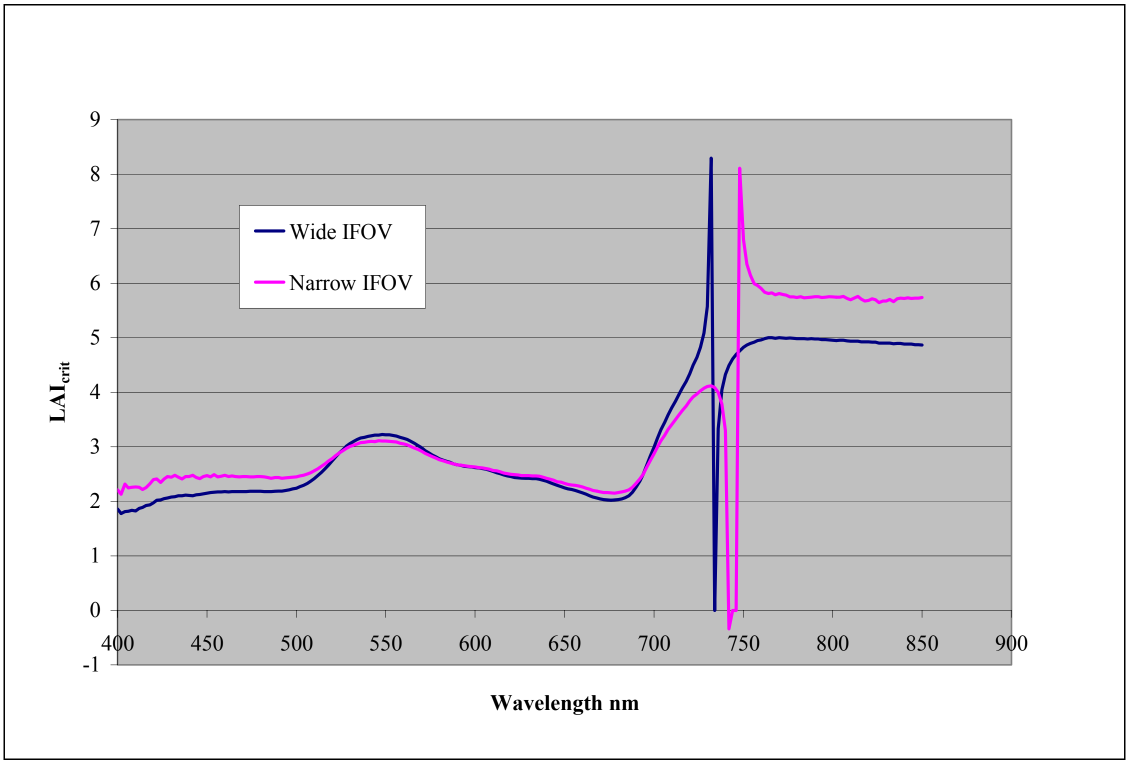

Figure 2.4 – Estimation of the critical value of leaf area index for 95% evolution of the vegetation canopy spectrum

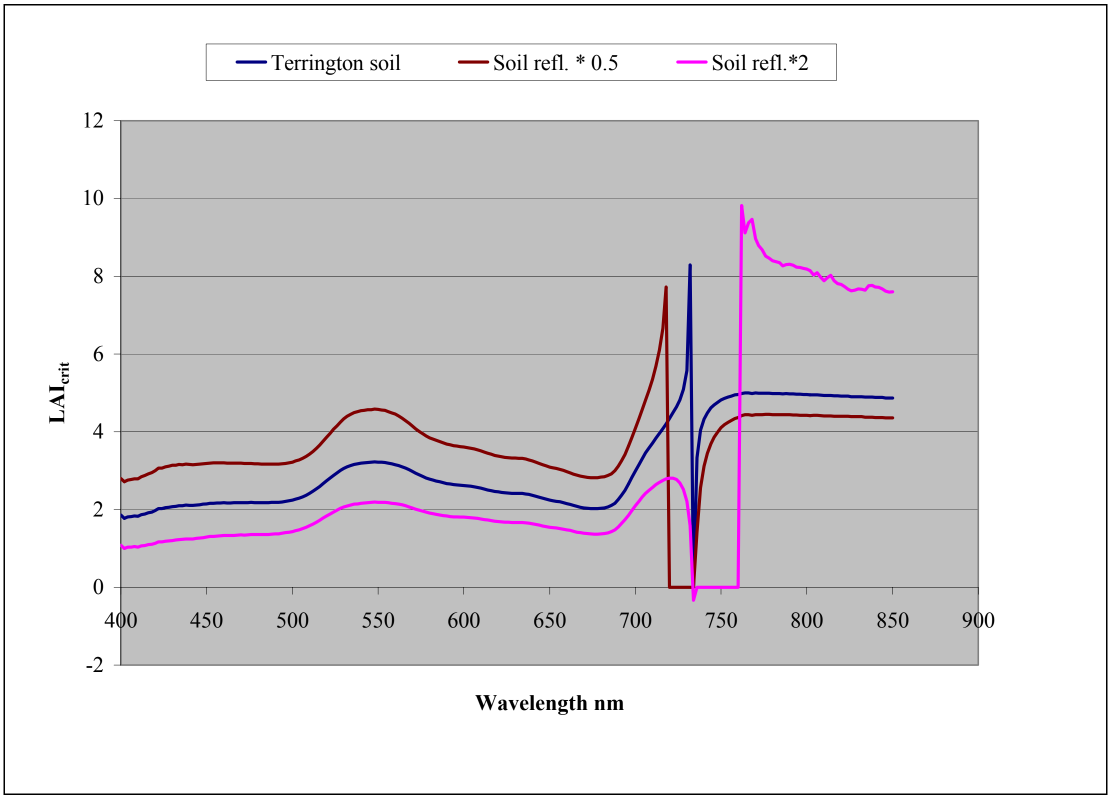

Figure 2.5 – Estimation of the critical value of leaf area index, with simulated soils of double and half the original reflectance.

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3. THE EFFECT OF ANGLE OF VIEW AND ILLUMINATION ON SPECTRAL MEASUREMENTS

3.1 Introduction

The specific objective of this part of the project was to determine the degree of interference that changes in the angle of view of a crop radiometric sensor and the illumination of the crop would have on the practical measurement of crop parameters. If there are large effects of the angle of view and illumination of the crop on spectral measurements then this would have a significant impact on both the type of equipment that could be used in practice, and on the time of day that the equipment could be used to take crop measurements.

Spectral measurements made in the field depend not only on the characteristics of the surface being measured, but also critically on the instrumental configuration and procedure applied in the measurement and on the illumination conditions at the time. These extraneous factors are particularly important in monitoring crops because the foliage is viewed against a contrasting soil background and the instrument configuration affects the relative impact of these two components in the measurement. In the context of the SPARTAN project, it is essential to be able to account for the effect of these factors on the measurements, both to allow comparison with previous work reported in the literature and to evaluate the implications for sensing under operational conditions in the field. This report describes an experimental study to investigate the effects of instrument field-of-view and shading on plot spectral measurements.

3.2 Angles of view

Conventionally, in remote sensing of vegetation from a satellite or an aircraft, reflected solar radiation is received by a scanning detector in a form that allows the reconstruction of an image of the scene. This process requires a very narrow instantaneous field of view (IFOV), for example the Landsat TM sensor has an IFOV of about 0.04 milliradians. In addition to the narrow IFOV, the data are almost invariably collected in bright sunlight, as the presence of cloud would obscure the target. Most published data on the spectral characteristics of growing canopies have been collected under bright sunlight conditions and with a relatively narrow IFOV for the purpose of understanding and validating satellite remote sensing systems.

In the SPARTAN project, spectral measurements have been made with the Licor LI-1800 equipped with a fibre optic attachment ending in a cosine-corrected receptor with a hemispherical field of view (IFOV = 2π radians). When looking up, such a configuration provides a view that encompasses the sun and the entire sky, weighted so as to give an unbiased measurement of the total incoming solar irradiance. For field measurements this configuration has the advantage that the amount of light collected is greater and therefore the signal is more stable. Reflectance is also measured directly, using an upward-looking measurement of the total solar irradiance as the reference, whereas instruments with a narrow IFOV have to be referred to a measurement on a reference surface, which requires special calibration. However, when looking down, the light reflected from the canopy has different characteristics at different viewing angles. (This phenomenon is formally described by the “bidirectional reflectance distribution function” or BRDF, which in vegetation is largely controlled by the relative fractions of soil and foliage visible in a given direction). At large incidence angles the scene will appear to be fully vegetated, even when LAI is small, whereas the nadir (vertically downward) view will show more soil. Using the cosine-corrected head gives an IFOV that mixes these different components of the BRDF and may even include some signal from neighbouring plots. To avoid these problems, field instruments used to simulate remote sensing are normally designed to restrict the field of view to 20° or less, over which range the variations in the BRDF are small. To account for variations in illumination during measurement, reference measurements are made on a calibrated surface, usually a white panel of known characteristics. The vegetation reflectance value determined by this method is known as the bi-conical reflectance and differs from the bi-hemispherical measurement in that it refers only to a single direction of view.

An operational tractor-mounted spectral sensing system could be designed with either narrow or wide IFOV. It is conceivable that a wide IFOV system might be deliberately selected in order to increase sensitivity to variations in foliage pigmentation while reducing the sensitivity to soil. However, in order to interpret the SPARTAN measurements in a way that allows them to be used to predict the responses of satellite or similar instruments, or to relate SPARTAN data to previous studies in the literature, it is necessary to compare the wide-angle and narrow-angle responses directly.

3.3 Illumination effects

Measurements made in the field may also be critically affected by the directional characteristics of the source of illumination. Under a clean, cloudless sky, the direct solar beam is generally the source of over 80% of the illumination (Monteith and Unsworth, 1990), and provided that measurements are restricted to the period 2-3 hours either side of solar noon (in summer), the angle of illumination is not a major source of variation. However, measurements made earlier or later, when the sun is lower in the sky, may exhibit considerable variations. In particular, the near-infrared, which is strongly reflected by vegetation, will tend to be exaggerated relative to other parts of the spectrum, because more of the light is intercepted by the foliage and less by the soil. Also, when the sun is obscured by cloud, the illumination is totally diffuse and emanates from all regions of the sky. Roughly half of the diffuse illumination comes from elevations greater than 45°. Vertical illumination penetrates more effectively to the soil and the spectral characteristics measured will tend to be less weighted towards the near-infrared. Conversely, the half of the diffuse illumination that comes from lower elevations will tend to emphasise the near-infrared. The differences caused by these effects depend both on the leaf area index (with a maximum in the LAI range 1-3) and on the leaf angle distribution, being greater for vertical leaves and less for horizontal leaves. The effect will also depend on the solar elevation and on the spectral characteristics of the soil relative to those of the vegetation. Empirical measurements are required to quantify the effects for particular crops.

3.4 Materials and Methods

Field studies were conducted on 3 April and 23 May 2001 with the following objectives: to measure the effects of field of view and diffuse illumination geometry on the spectral signature. The sky conditions on the first date were overcast and all data were collected with diffuse light only. On the second date, the conditions were sunny with only occasional patches of cirrus.

3.4.1. Instrumentation

All measurements were made with a Licor LI-1800 spectroradiometer. To investigate the effects of field of view, an aperture restrictor device was constructed to fit over the sensor head of the spectroradiometer. The device consisted of an aluminium block with a cylindrical hole designed to sit directly over the cosine head of the LI-1800. The hole was threaded and painted black to reduce internal reflections and the outer aperture formed by a washer of slightly smaller diameter. The length of the hole was 23mm and the orifice diameter 12.3mm, giving a 15° half-angle IFOV at the centre of the sensing surface. Taking into account the diameter of the cosine head (7.3mm) at its base, the device restricted the uptake of light to a cone of half-angle approximately 23°. The device was secured in place by a rubber band, which facilitated rapid change from hemispherical to restricted view. Due to concern about the reduction in signal with the field restrictor, a second Licor LI-1800 spectroradiometer was borrowed from the University of Nottingham School of Life and Environmental Science. The Nottingham instrument had a narrow IFOV probe (full angle approximately 5°) mounted on the end of a 2m fibre optic bundle. The two instruments were used in parallel on the first field study (3 April 2001). Spectral measurements were made from 400 to 850nm, sampled at intervals of 2nm. The spectral resolution of the LI-1800, as represented by the band width at half-power is about 6 nm, so this scanning procedure oversamples by a factor of 3. The time taken for a scan is about one minute. A PTFE panel was used as the field reference for the narrow IFOV measurements with both instruments; the PTFE panel was calibrated to Barium Sulphate in the laboratory and a standard reflectance curve for Barium Sulphate used to determine absolute reflectance. The reference measurements correct for any spectral variations in the incoming solar radiation, but do not account for the geometry of illumination.

To investigate illumination geometry, a shading device approximately 1.5 x 1.5m was made of white cotton fabric supported on two poles.

3.4.2. Experimental procedure

The SPARTAN Nitrogen trial plots were selected for this study in order to provide a wide range of canopy covers on a single date. The general protocol was for a sequence of wide-angle measurements to be made followed immediately by a sequence of field-restricted measurements and their respective reference measurements for the same field plot. Four sets of repeat measurements were made at evenly spaced locations in each plot. Two reference measurements of the appropriate type were made for each set of four target measurements. The whole sequence was conducted as rapidly as possible to minimise changes of illumination with time.

Measurements on 3 April 2001

Measurements were made with the ADAS Licor LI-1800 using both the wide angle and narrow angle probes and with the Nottingham Licor LI-1800 with its narrow angle probe. Conditions were cloudy, so it was not necessary to deploy the shading device. Poor weather restricted the number of measurements possible and only Plot 6 was measured. However, Nitrogen fertiliser had only recently been applied to the trial and no differences between plots were yet apparent.

Measurements on 23 May 2001

Comparison of the Nottingham and ADAS Licor instruments on 3 April indicated that the signal was adequate with the field restrictor on the ADAS instrument, so that the backup Nottingham instrument was unnecessary. Measurements on 23 May were made on Plots 1 to 10, with alternate series of wide-angle measurements, narrow angle measurements with the field restrictor and measurements of a shaded canopy with the field restrictor. Separate measurements of the reference panel were also made with and without the shading device.

3.5 Results

Figure 3.1 shows the comparison of spectra measured over plot 6 on 3 April 2001 when Leaf area index was 0.3. The spectra measured with narrow IFOV by both ADAS and Nottingham instruments are very similar and the difference between them is well within the margin of error (5-10% of signal) associated with varying light conditions on that day. Measurements with the wide IFOV cosine head however are substantially higher in the near-infrared and correspondingly lower in the visible. This result supports the prediction that wide-angle measurements sense a greater proportion of leaf relative to soil.

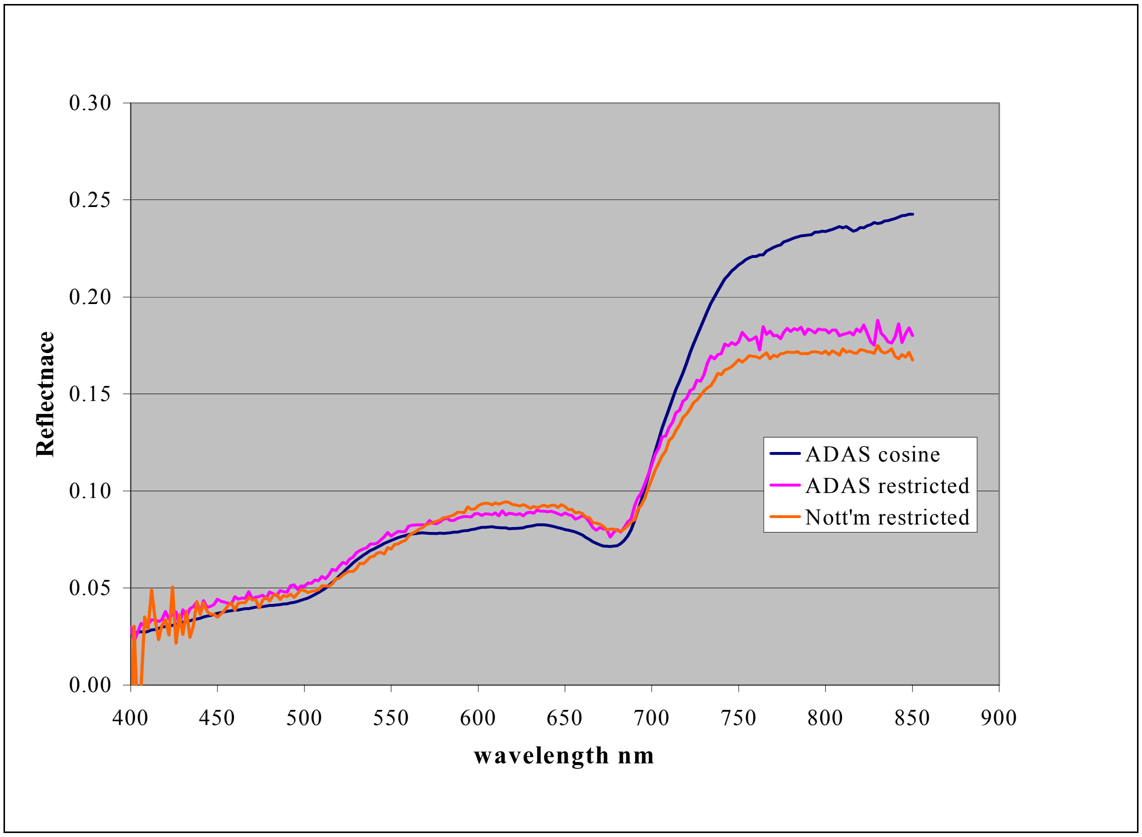


Figure 3.1: Spectral measurements on 3 April 2001 (Plot 6)

The results of 23 May indicate a similar behaviour. Table 3.1 shows the leaf area indices of the plots, together with an estimate of ground cover based on LAI and the Normalised difference vegetation index (NDVI) determined from values of spectral reflectance ρ at 800nm (IR) and 680nm (red), measured with the narrow IFOV. The formula for NDVI is as follows

$$NDVI = (\rho_{IR} - \rho_{red})/ (\rho_{IR} + \rho_{red}) \quad (1)$$

where the reflectance values were in this case averages of 30nm about the nominal wavelength. Percentage ground cover C% was estimated as

$$C\% = 100\ (1 - \exp(-0.7\ LAI)) \quad (2)$$

where 0.7 is a leaf area projection coefficient typical of cereal crops (Monteith and Unsworth, 1990). NDVI is closely correlated with ground cover with all measurement configurations (figure 3.2). The values converge at high cover density and the slope is shallower with the cosine and the shaded measurements, but there is no loss in the ability of the index to predict cover.

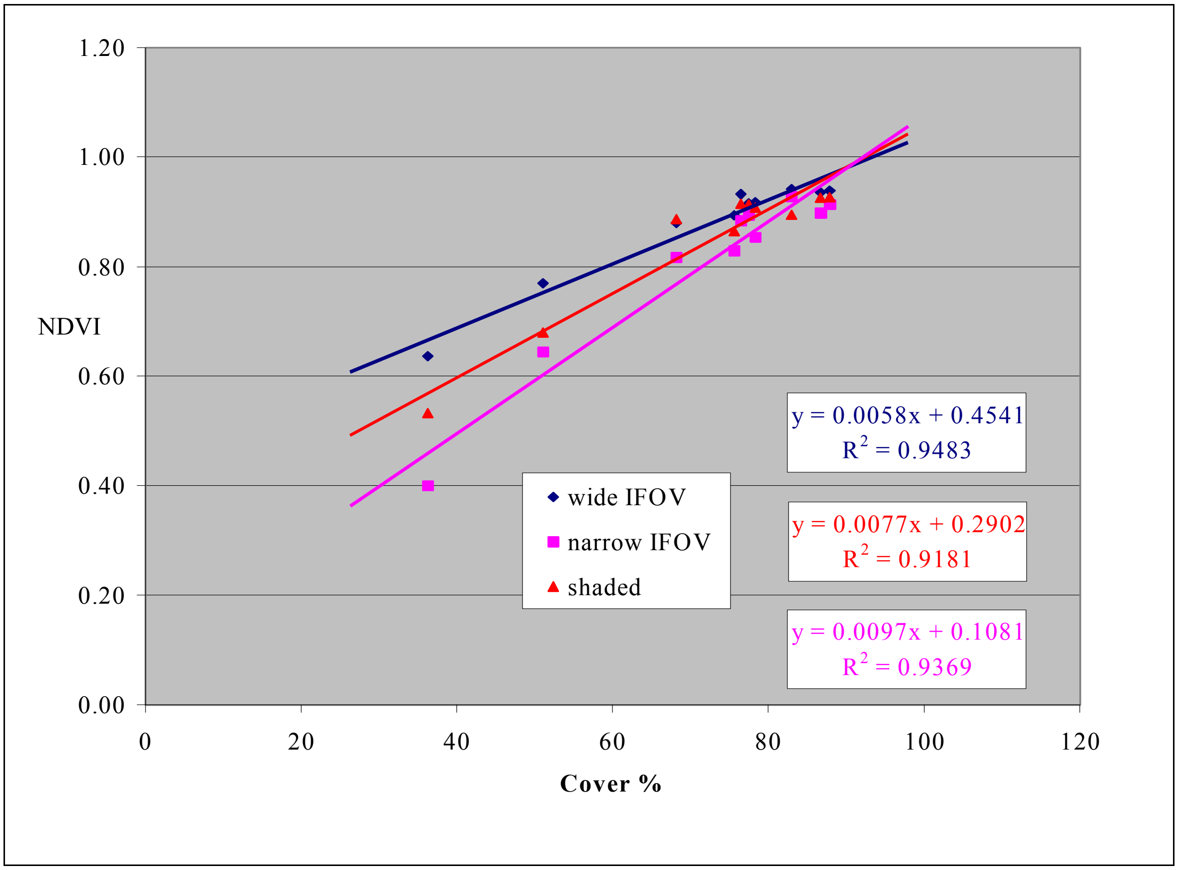


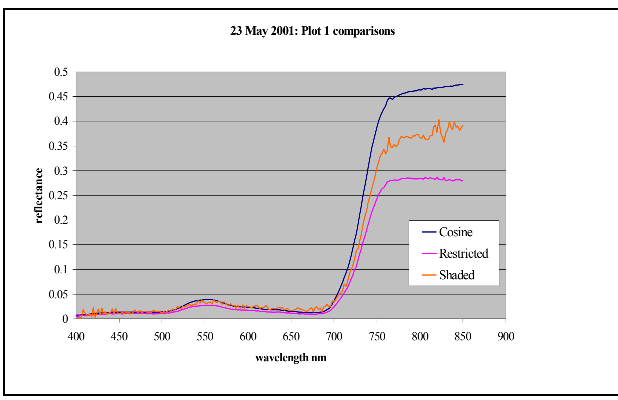
Figure 3.2: The effect of measurement configuration on NDVI as a function of crop cover

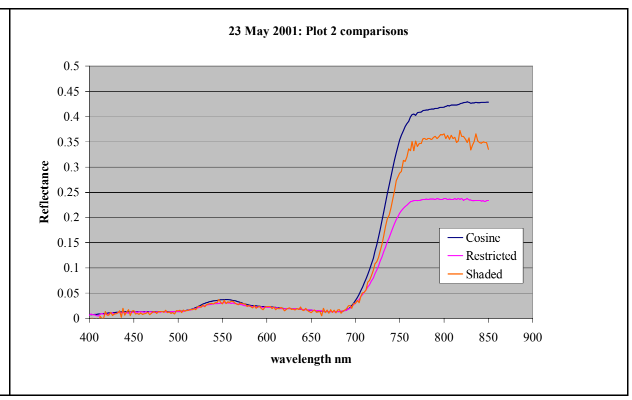
Table 3.1: Plot characteristics on 23 May 2001

Plot	LAI (Green)	LAI (Total)	% cover	NDVI
1	2.5	2.5	83	0.93
2	2.0	2.1	76	0.89
3	1.9	2.0	76	0.84
4	2.1	2.2	78	0.87
5	3.0	3.0	88	0.92
6	1.6	1.6	68	0.83
7	2.9	2.9	87	0.91
8	0.6	0.6	36	0.42
9	2.1	2.1	78	0.90
10	0.9	1.0	51	0.67

The measured spectra for the plots are shown in figure 3.3. As predicted, all the spectra show more exaggerated vegetation characteristics (higher near-infrared and lower visible reflectance) with the cosine head than with the field restrictor. The spectral response with the field restrictor with the crop shaded also shows an exaggerated vegetation response relative to the sunlit case, but to a somewhat lesser extent. The high frequency data fluctuations, particularly at the extremes of the wavelength range in the shaded spectra, are due to instrumental noise, which becomes more important when light levels are reduced by restricting the field of view or by shading.

When the shaded and cosine head measurements are normalised with respect to the measurements made with the field restrictor (figure 3.4), the spectra measured with the cosine head show the distinct spectral signature of vegetation even after normalisation, whereas the shaded measurements show little pattern in the normalised spectrum, except for a small increase in the near-infrared. When examined individually by plot, the cosine-measured spectra are clearly ranked according to leaf area. The shaded measurements appear to show a weaker form of the same behaviour, but the differences tend to be masked by noise.





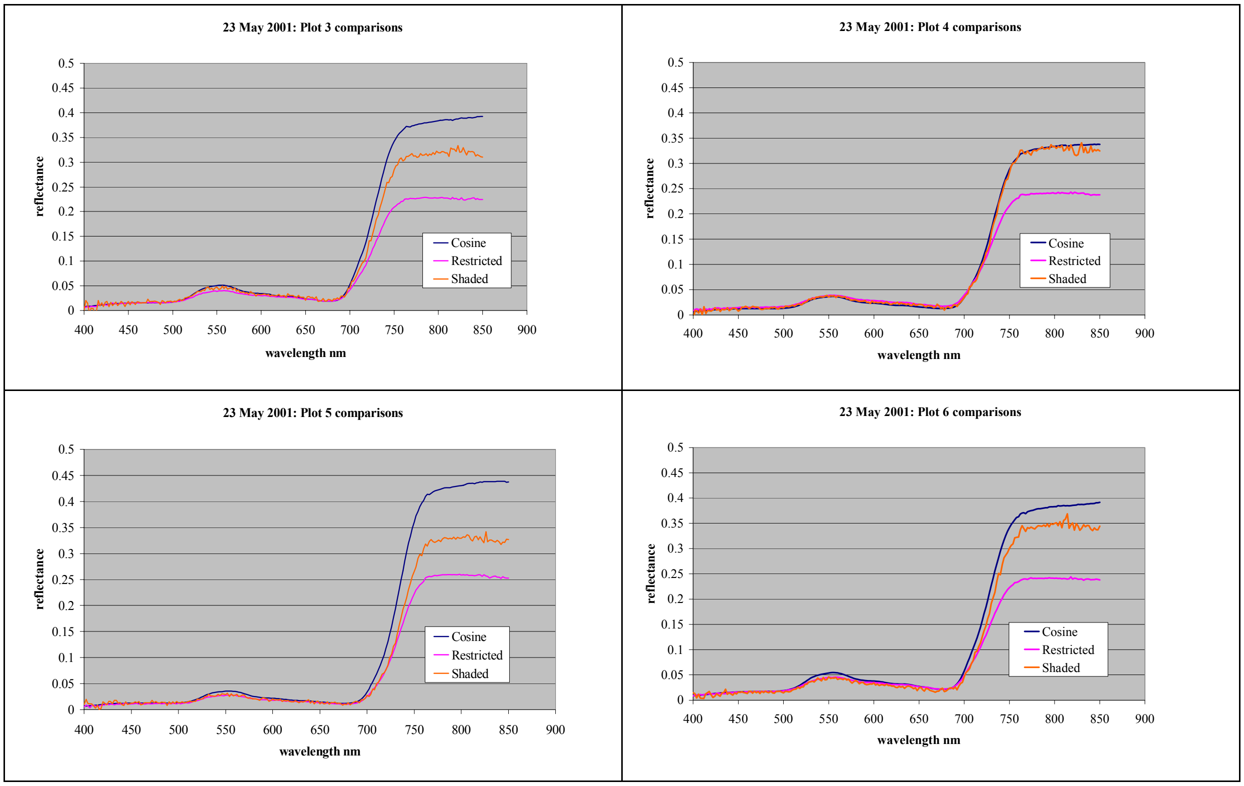


Figure 3.3: Spectral measurements of field plots using different configurations

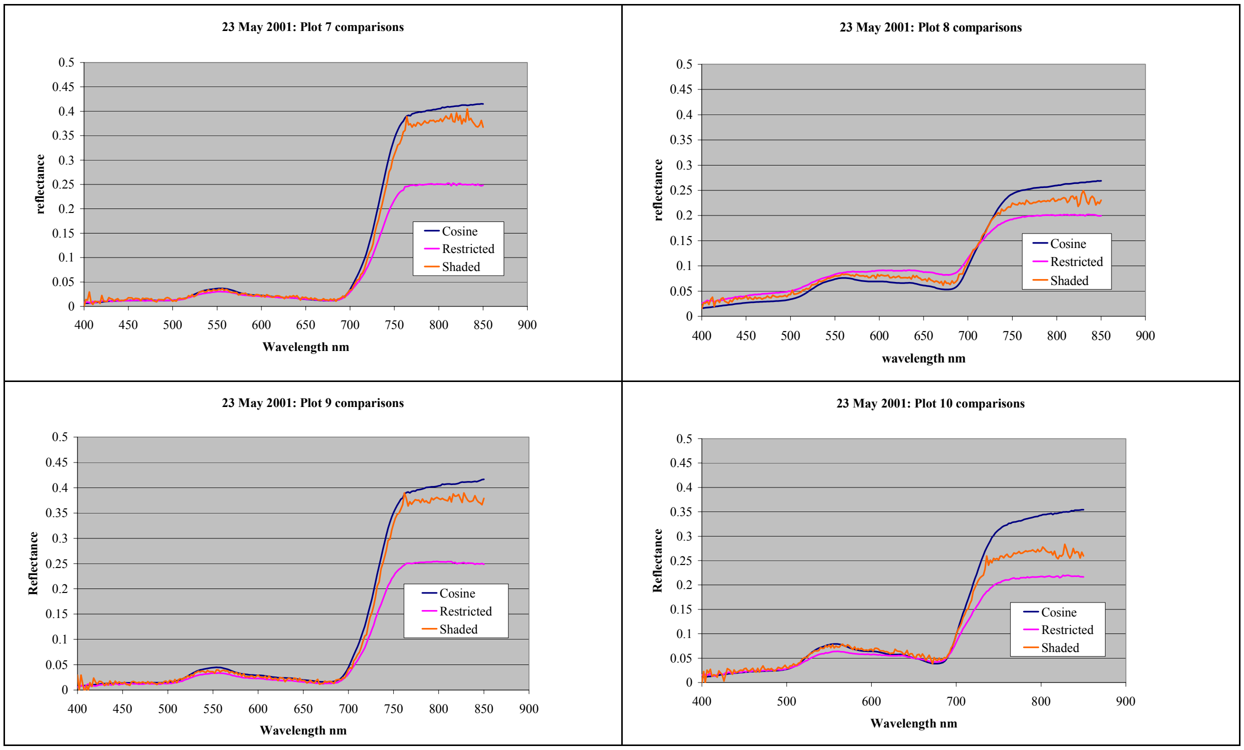


Figure 3 (cont.): Spectral measurements of field plots using different configurations

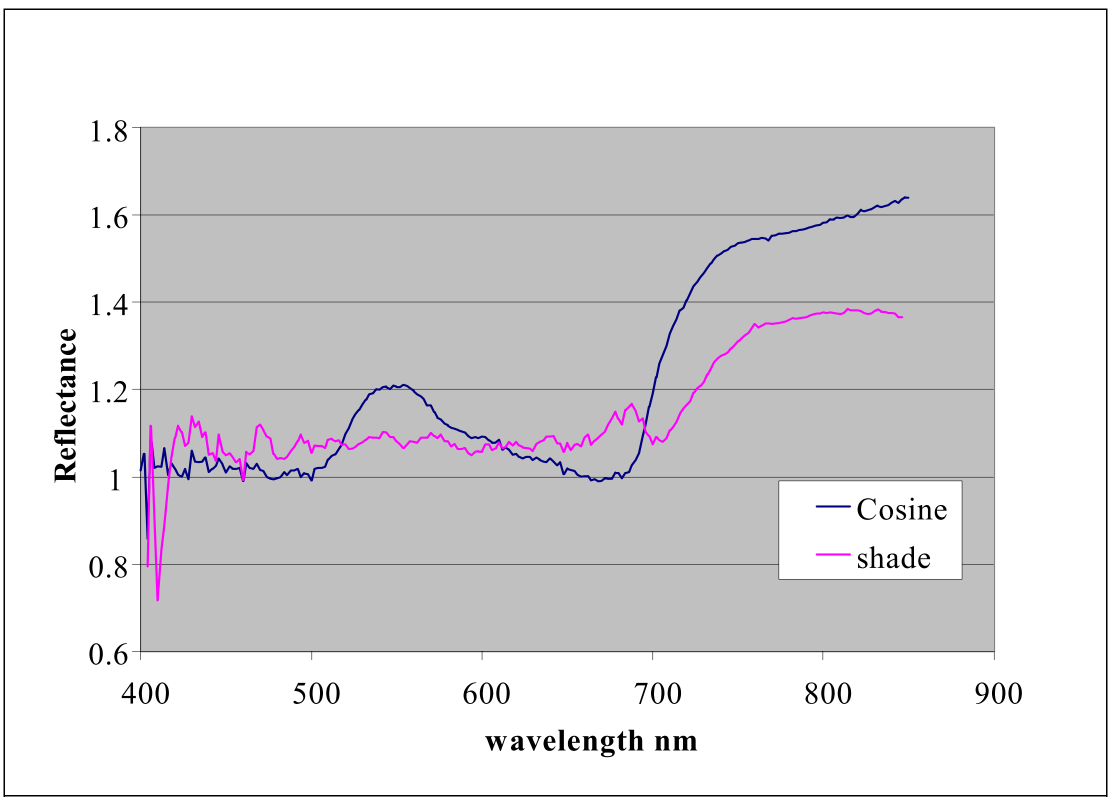


Figure 3.4: Spectral data normalised to restricted field values: average over all plots

To make a systematic assessment of the differences in spectral behaviour with measurement conditions, four representative wavelengths were selected. Values at 500, 550, 680 and 800nm were chosen, representing the main troughs and peaks in the vegetation spectrum. To reduce the effect of noise, the average across a 30nm band centred on the nominal wavelength was used. Figure 3.5 shows the functional dependence of reflectance on LAI at 800nm with the three measurement configurations. About two thirds of the variance in reflectance is explained by a linear relationship with LAI, and while the slope of the line is steeper with the cosine head, the coefficient of determination is about 4% lower. The results at the other wavelengths selected show similarly strong relationships with LAI, but the relationships are less linear, the slopes in the visible bands are negative and the curves are not so well separated.

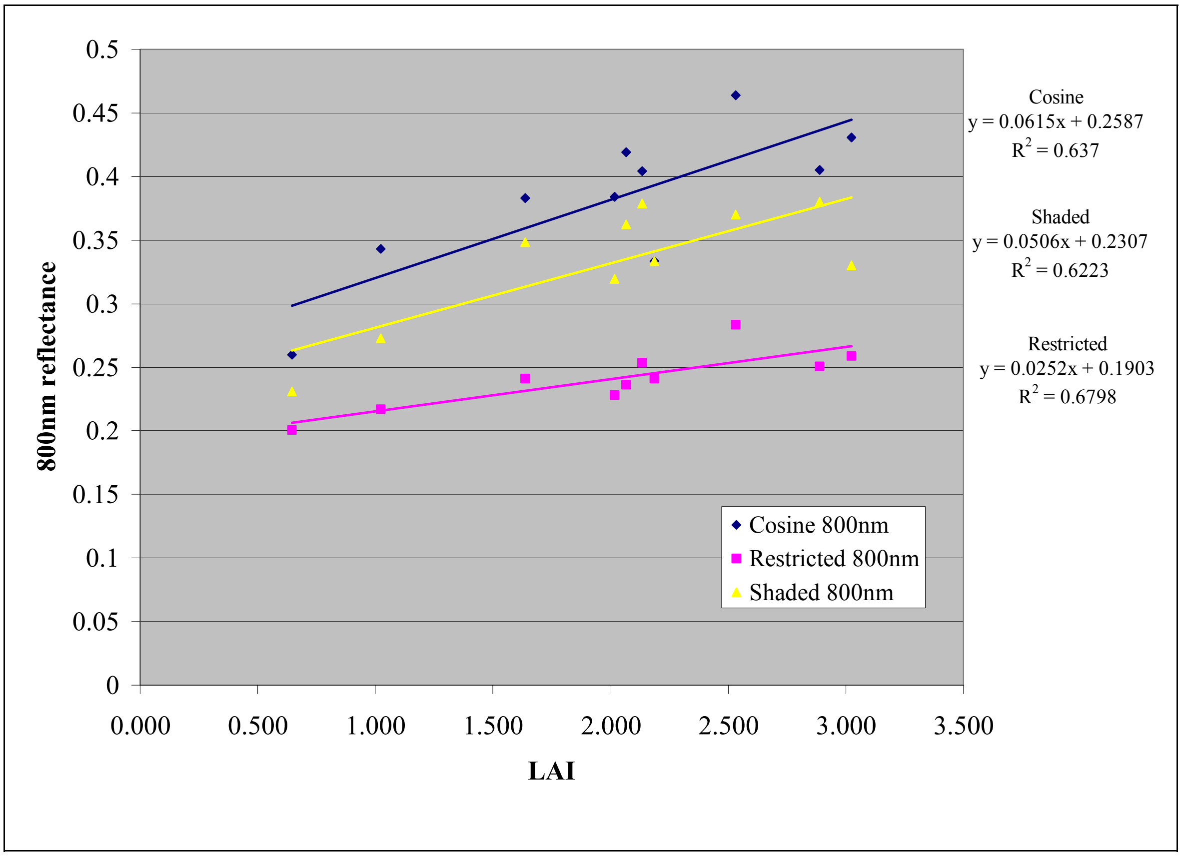


Figure 3.5: Reflectance at 800nm with leaf area, for different measurement configurations

3.6 Theoretical Analysis

The effect of instrument IFOV and shading can be modelled in terms of what the instrument "sees" with each configuration. If we assume that the surface consists of three components:

Leaf - with reflectance ρ_L, occupying a fraction f_L of the scene

Soil - with reflectance ρ_S, occupying a fraction f_S

Shade - areas (of leaf or soil) with reflectance 0, occupying a fraction f_0

where $f_L + f_S + f_0 = 1$ (3)

The conventional (narrow IFOV) measurement can then be expressed as

$$V = \rho_L f_L + \rho_S f_S \quad (4)$$

Assume that to a first approximation, ρ_L and ρ_S are independent of viewing angle. Increasing IFOV will always increase f_L relative to f_S, because larger angles decrease the chance of light penetrating through the canopy from the soil and at some angle towards the horizon, the soil ceases to be visible. Therefore, we can suppose that the wide IFOV measurement can be approximated as a weighted average of the value measured at nadir by a narrow IFOV instrument and a signal dominated entirely by foliage, i.e. ρ_L. For the wide IFOV cosine head measurement, the value measured then becomes

$$V' = \Omega(\rho_L f_L + \rho_S f_S) + (1 - \Omega)\beta\rho_L = \Omega V + (1 - \Omega)\beta\rho_L \quad (5)$$

Where Ω is a coefficient (≤ 1) that accounts for the relative weights of the nadir and the large angle component. The coefficient β (also ≤ 1) is applied to ρ_L to account for the fact that the view towards the horizon contains a component of shade, so that the signal from this region is less than would be obtained purely from foliage. β also accounts for systematic error in the value of ρ_L which is derived empirically. Equation 5 can then be expressed as

$$V'/\rho_L = \Omega V/\rho_L + (1 - \Omega)\beta \quad (6)$$

In principle, this formulation separates the wavelength dependence in V, V' and ρ_L from the angular dependence which is incorporated in the coefficients Ω and β. A plot of V'/ρ_L against V/ρ_L should give a straight line from which Ω and β can be determined from the slope and intercept.

Estimation of a pure foliage spectrum

A problem remains in that ρ_L is not precisely known. For the purposes of this study, an estimate was made by fitting the measured reflectance values as a function of percentage ground cover (c%). This was performed separately at each 2nm wavelength λ from 400 to 850nm. By trial and error it was found that the wide angle measurements yielded an estimate of ρ_L that performed better in subsequent analysis than that derived from the narrow IFOV data. The function that was fitted to the data took the following form:

$$V'(\lambda) = \alpha_\lambda \exp(\gamma_\lambda (100\text{-c\%})) \quad (7)$$

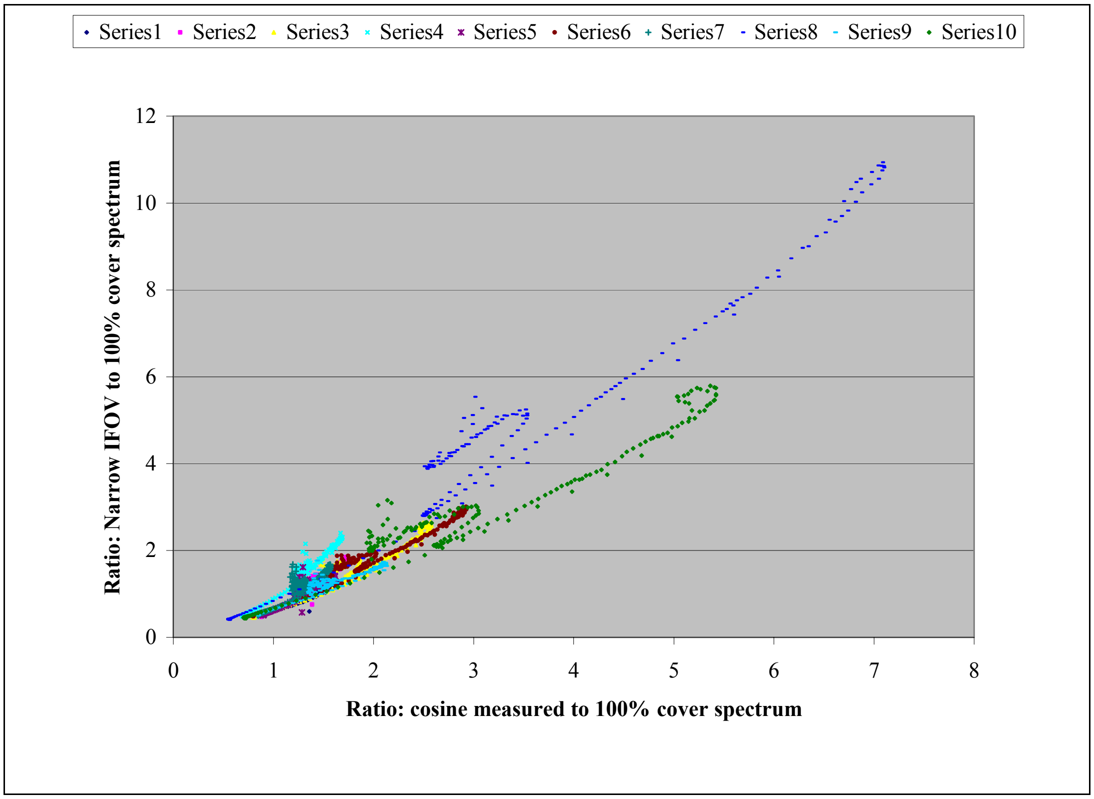


Figure 3.6: Comparison of normalised values for wide and narrow IFOV

Although linear regression also gave good statistics of fit, extrapolation to 100% cover sometimes gave negative reflectance values and the exponential form was found to be more realistic. Some experiments were also performed to test whether extrapolation to cover values beyond 100% might give a more ideal spectrum, but it was found that the spectra generated this way had unrealistically low reflectance values around 670nm and that this had a biasing effect on subsequent analysis. The fitted value of α_λ was therefore selected, corresponding to the extrapolated value at 100% estimated cover. This spectrum is listed in Appendix A.

Reconstruction of spectra

Figure 3.6 shows the effect of normalising the wide and narrow IFOV measurements to the value of ρ_L estimated by α_λ. When the values are plotted the result approaches a straight line as predicted by equation 6, although it is apparent that normalisation does not account for all of the wavelength dependence. The results are better for the analysis of shading (figure 3.7), where the graph indicates little residual spectral dependence. Regression analysis of the data from the individual plots indicated no significant dependence of slope and intercept on leaf area index, whether for the analysis of angle or shade effects. Average values of these coefficients were therefore used in the subsequent analysis.

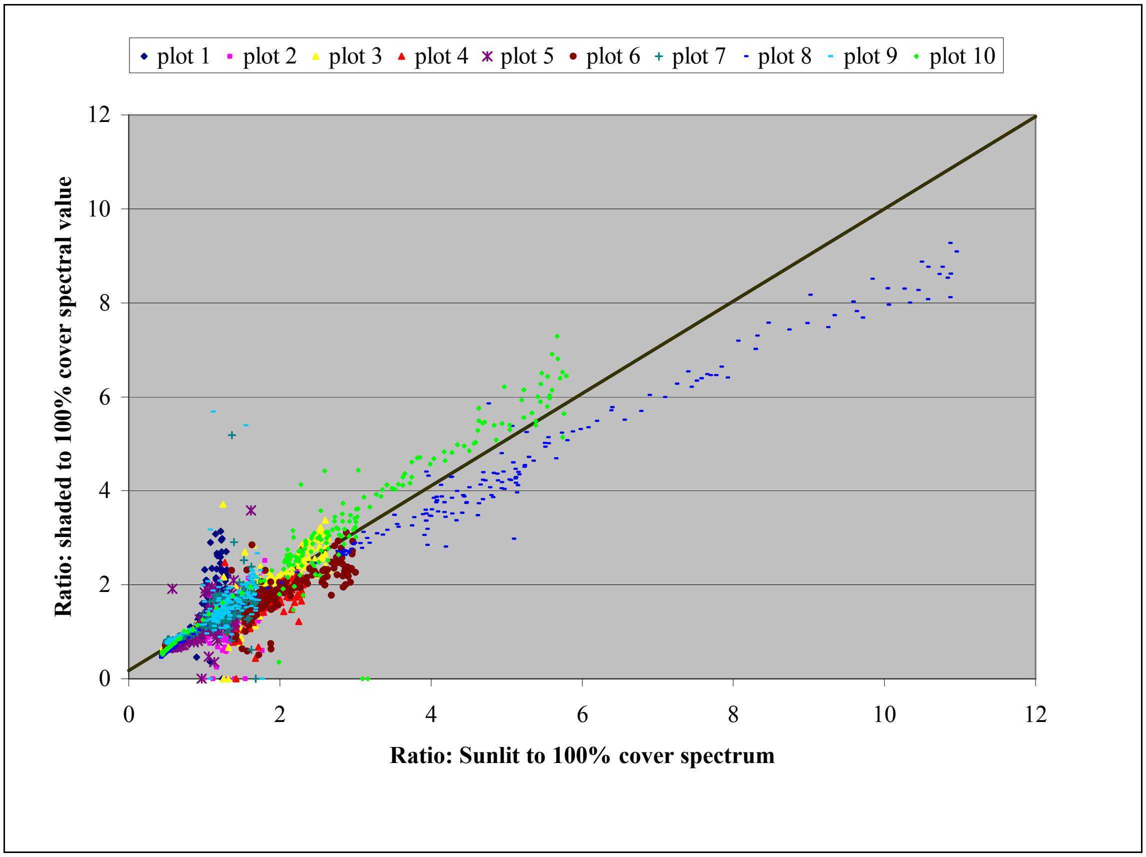


Figure 3.7: Comparison of normalised values for shaded and sunlit spectra

The test of this analysis is to use the coefficients determined from the slopes and intercepts in figures 3.6 and 3.7 to reconstruct spectra as measured in the standard configuration (narrow IFOV, sunlit) from measurements made under non-standard conditions (wide IFOV, or narrow IFOV in shade). Inversion of equation 5 gives

$V = V'/\Omega - (1 - \Omega)\beta\rho_L/\Omega$ or

$$V = V'/m - k\,\rho_L/m \qquad (8)$$

Where m and k are the mean slope and intercept respectively of these relationships (Table 3.2). The results of this analysis are shown for selected plots in figures 3.8 and 3.9.

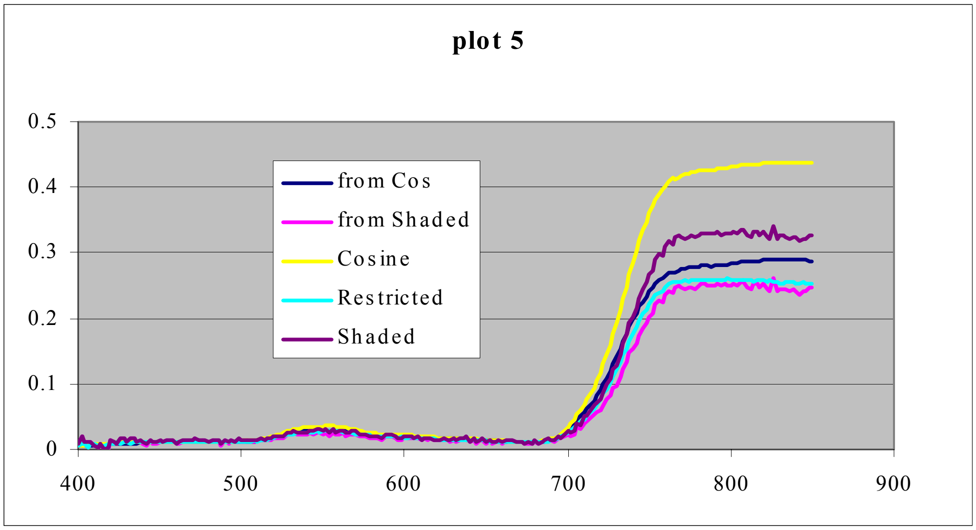


Figure 3.8: Reconstruction of standard configuration measurement for plot 5, where "from" indicates a reconstruction of the measured "restricted" spectrum.

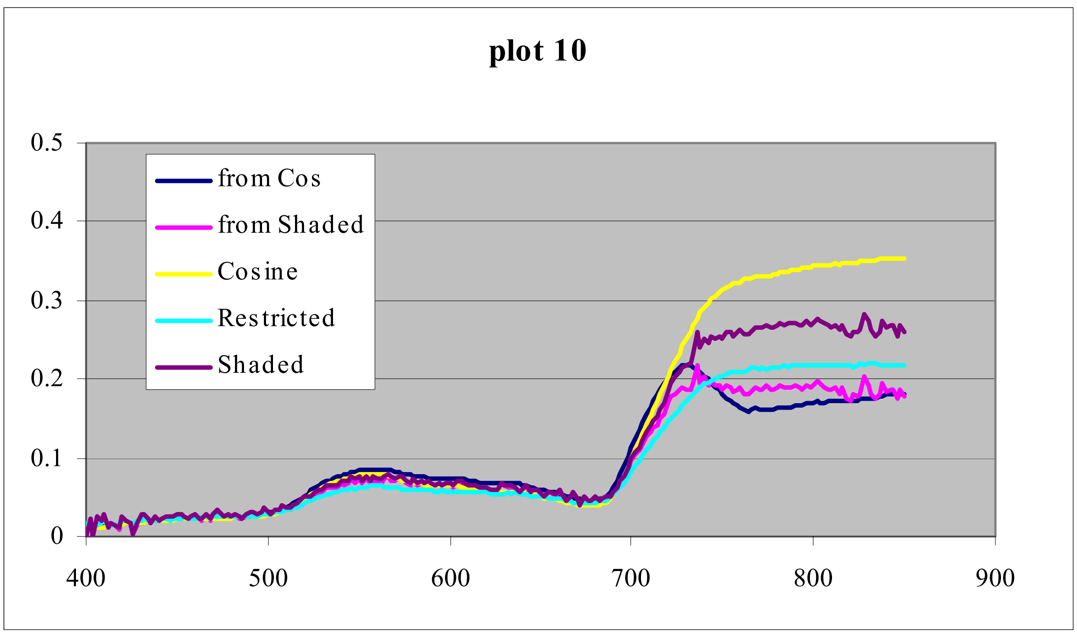


Figure 3.9: Reconstructions for plot 10 - details as figure 3.8

In general, the results show that the standard conditions can be reproduced reasonably well from the shaded measurements, but there are larger errors when attempting to convert from wide IFOV to narrow IFOV, particularly when LAI is low (plots 8 and 10 in this analysis). These errors are most apparent in the near-infrared, because the values are larger, but the relative errors are in fact broadly uniform across the spectrum (figure 3.10). The relative errors for estimating from wide IFOV are about ±20%, while estimation from shade is typically ±10-15%.

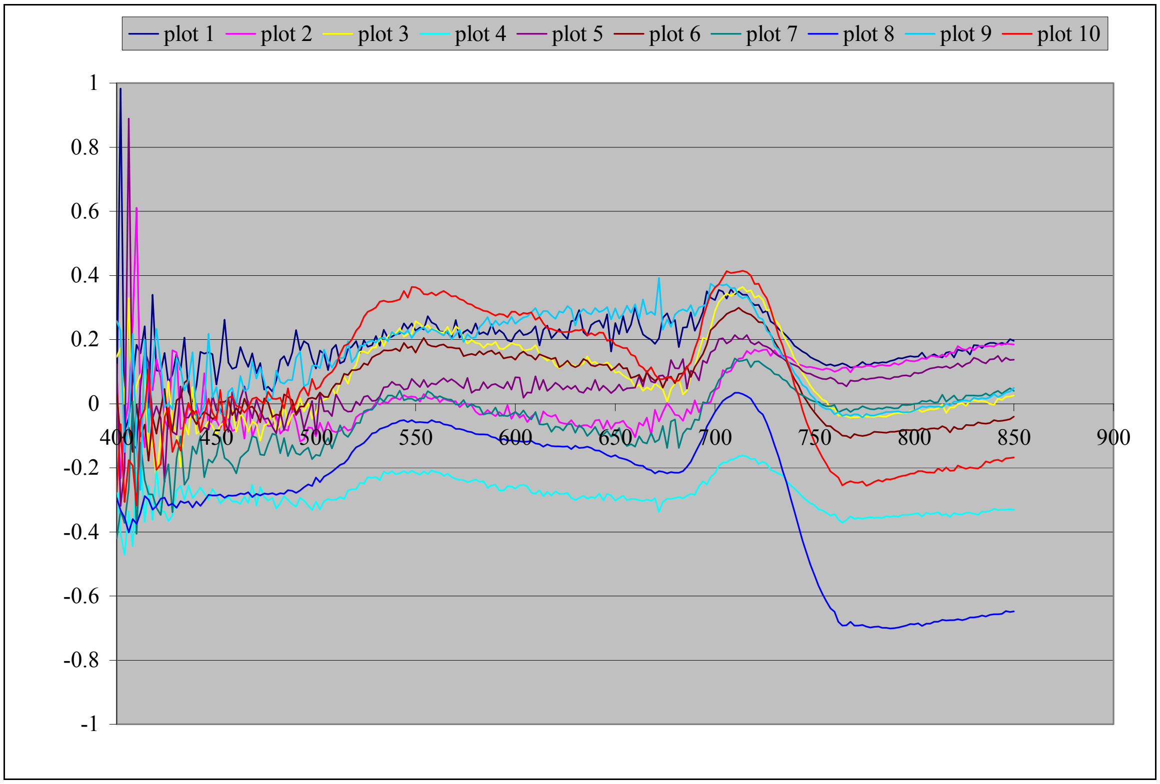


Figure 3.10 : Relative error of reconstructed narrow-IFOV data from wide angle measurements

Table 3.2: Mean values of spectral reconstruction coefficients

	m	k
From Cosine	0.775	0.440
From shade	0.983	0.173

3.7 Discussion

The theoretical analysis outlined in equations 5 to 8 above has been described in terms of the comparison of wide and narrow angle measurements and it has been implicitly assumed that the same mathematics should apply to shaded versus sunlit measurements. The justification for this is that the effect of changing from effectively a single illumination angle in sunlight, to a full hemisphere of diffuse illumination in shade is mathematically equivalent to the change from a single direction of view to a wide angle incorporating all directions. This equivalence is enshrined in the principle of reciprocity which states that the probability of a beam of light passing from A to B through some medium (the canopy in this case) is the same as the reverse probability of passing from B to A. The difference in practice here is that the single direction of view is vertical whereas the single direction of the UK summer sun is some 30-40° from the zenith; and that the diffuse illumination is not uniform in direction and its spectrum varies from that of the sun. These differences affect the coefficients, but not the fundamental geometry expressed in the equations. However, the descriptive terms applied to the coefficients should be adjusted to refer to changes in the proportions of vegetation and soil illuminated rather than the proportions in the field of view.

The results of this analysis indicate that reconstruction of standard sunlit spectra from measurements made in shade is possible and that reasonable accuracy can be achieved. This ability is essential in the context of using tractor mounted sensors for precision farming, because the crop must be measured in any weather conditions. The field of view restricting device cut the light levels to be measured by a factor of about 20 and the measurements made were quite noisy, particularly in shade. It is therefore reasonable to suppose that the intrinsic relationship is quite robust and that more precise spectral reconstruction could be achieved with a stronger signal. However, reconstruction of standard narrow IFOV measurements from wide angle measurements gives a more equivocal answer. Instrumental noise is not a major issue in these measurements, but it must be remembered that the wide angle measurements necessarily detect a much larger area than the corresponding measurements with the field restrictor so that unlike the sunlit versus shade comparisons, the areas seen are not the same. This will introduce noise in the LAI rather than the spectral domain. The plots in figure 6 show some curvature and spectrally related deviations from the general trend, which suggests either that the value of ρ_L derived by extrapolation of the data is biased in some respect, or that the theory itself is over simplistic. That the theory is partly successful is indicated by the closeness of the "from Cos" reconstruction to the "Restricted" curve in figure 3.8, but as figure 3.9 shows, the reconstruction can generate not just inaccurate, but unrealistic spectra when LAI is low.

Unfortunately, it was not possible to investigate the effect of shading on measurements made with the cosine corrected head; the wide IFOV of the sensor meant that the shading device required would be excessively large.

In conclusion, it can be stated that the relationship between sunlit and shaded measurements has been established and that it is possible to convert between them with reasonable accuracy. There is theoretically some dependence on solar elevation but although the measurements in this instance were made from 0959 to 1411 GMT, the variations were not large enough to confound the relationships. Further investigation of the sensitivity to this factor can if necessary be made using canopy models. With the wide-angle measurements it is clear that there is a relationship with measurements made using a standard narrow IFOV configuration, but that relationship has not been established with sufficient precision for application. This limitation is less critical to the establishment of sensing techniques in precision farming: it affects the ability to apply the findings of previous studies directly; but as figure 3.2 demonstrates, both wide and narrow IFOV measurements exhibit similar relationships with key canopy parameters. Functional relationships established in previous studies with narrow IFOV instruments can be expected to apply with wide IFOV, but the forms and coefficients of these relationships will have to be re-established by experiment. This theoretically gives us reasonable flexibility in helping to design a tractor-mounted sensor as the angle of view of the sensor could be accounted for using these relationships.

The development of a tractor-mounted sensor system would have to address the issues of angle of view of the sensors (and hence the sensor 'footprint') and the height of the sensors above the canopy - which would directly affect the number of sensors that would be required to give a practical area of crop that could be viewed at a point in time. The issue of whether hyperspectral measurements taken when the crop is in full sun or is shaded by cloud has been addressed and it appears that it is possible to account for this with reasonable accuracy. There is clearly considerable flexibility in the time window around solar noon that measurements can be taken. This is reassuring as, from a practical point of view, it could have seriously reduced the number of crops in which measurements could be taken during a single day.

References

J.L. Monteith and M.H. Unsworth, *Principles of Environmental Physics*. 2nd edition, Edward Arnold, London, 1990

4. THE EFFECTS OF VARIETY ON SPECTRAL SIGNATURES OF WINTER WHEAT

4.1 Introduction

The specific objective of this part of the project was to investigate the effect of variety in affecting the spectral signal from the crop canopy. Using spectral reflectance measurements to estimate canopy size relies on there being minimal interference from factors which may differ between varieties. Otherwise, variety-specific prediction tools would be required in order to predict canopy size from sensed data.

The main factors that would be expected to have significant effects on spectral reflectance are:

1. Leaf colour
2. Leaf insertion angle
3. Leaf position / architecture
4. Wax layer of leaf
5. Presence of awns

In order to test the range of variables that exist in wheat varieties, five varieties were compared to see the effect that such characteristics had on the spectral reflectance. The varieties were specifically chosen to represent the widest range of variability in the above characteristics. The varieties chosen were Avalon, Soissons, Consort, Equinox and Shamrock.

Variety	Characteristic likely to affect spectral reflectance
Avalon	Large, dark green, floppy (i.e. not erect) flag leaf
Consort	Modern variety, upright flag leaf.
Equinox	Modern wheat type, spikey upright flag leaf. Highly waxed leaf giving an apparent blue coloration.
Shamrock	Variety with very low wax cover on leaf giving the variety an apparent grass-green colour.
Soissons	Variety with small flag leaf held horizontally, awned ears.

Many of the above characteristics are not apparent throughout the growth of the crop so spectral reflectance measurements were taken at key growth stages in the life of the crop. The crop input decisions which might rely on spectral reflectance measurements for canopy characterisation are made early in the life of the crop between GS30 and GS32. Thus, it is important that crop canopy characteristics at these growth stages are known.

4.2 Materials and Methods

4.2.1. Experimental design

A fully randomised block design was used with 3 replicate plots of each of 5 varieties of winter wheat (Avalon, Soissons, Consort, Equinox and Shamrock). Conventional agronomy/management practices and same seed rates (375 seeds/m^2) were used in order to attempt to generate similar canopy sizes. Foliar disease assessments and percentage green area were carried out weekly from GS 31. Crop canopies were sampled throughout the growing season during 1999 and 2000.

4.2.2. LAI measurements

In these experiments a Plant Canopy Analyser (PCA, LAI-2000, Li-Cor inc. Lincoln, Nebraska, USA) was used to estimate green area index (GAI) of crop canopies rather than the more traditional destructive measurements. It estimates GAI from light measurements above and below the canopies at five solid angles using a hemispherical cosine corrected sensor, using calculations according to Campbell and Norman, 1988. Plant canopy measurements were taken from mid-March weekly up until GS39, and then every two weeks until leaf senescence.

4.2.3. Spectral measurements

High-resolution spectral reflectance measurements were taken at 4 points within each plot using a LICOR LI-1800 spectroradiometer. The LICOR LI-1800 is a rapid scanning instrument operating over visible and near-infrared wavelengths (350 to 850 nm at 2nm intervals). The LICOR LI-1800 was fitted with a cosine corrected optical head and was held at a height of 1m. For each plot and sampling occasion both target radiance (looking directly downwards) and incident irradiance (looking directly upwards) were monitored almost instantaneously to allow correction of reflectance for varying incident irradiance. The four replicate measurements were taken per plot and used to make a mean spectrum corrected for incident irradiance that contained 250 wavelength 'variables' that could then be used in the data analysis.

When possible the measurements were made under conditions of stable incoming solar radiation, ideally under clear, cloud-free skies. This aim was not always achieved due to changes in weather during the length of time required to complete measurements on all replicate plots. The stability of incoming radiation was assessed from examining the time-course of total incoming radiation - obtained by integrating irradiance under each of the incoming spectral response curves after applying appropriate calibrations. This allowed the identification and simple separation of periods of stable and unstable solar radiation. A further check was made using the ratio of amounts of solar radiation in ten specified wavebands to total solar radiation to aid the detection of any transient changes in irradiance. Final checks were made by comparing graphs of the replicate reflected spectra with the incoming radiation before and after the measurements on a plot. Comparison of measurements between stable and unstable periods showed the major cause of variation in reflected radiation between replicate measurements over our relatively uniform crops was variation in incoming radiation. Thus in stable periods the nearest in time incoming radiation was used for reflectance calculations. In less stable periods after removing incident measurements showing unstable spectra, remaining reflected measurements were matched to appropriate incident spectra by assuming changes occurred in parallel and the reflectances calculated. All valid reflectances for a plot were averaged at each wavelength and the mean used for further analysis.

NDVI, which is defined as: $NDVI = (\rho_{IR} - \rho_R)/(\rho_{IR} + \rho_R)$

where ρ_{IR} and ρ_R are measured reflectance values in the near-infrared and red bands respectively was calculated using the hyperspectral reflectance data. The average reflectance over 790-850nm was taken as the near-infrared reflectance and the average reflectance over 600-690nm was taken as the red reflectance.

4.2.4. Statistical Analysis

One-way ANOVA

The extent to which mean values of NDVI and LAI are significantly different for each of the variety groups was analysed one-way ANOVA.

Principal Components Analysis (PCA)

The analysis of hyperspectral data can be complex because of the simultaneous response of 250 variables to treatments and because these individual wavelengths are strongly correlated. For example, if the spectral reflectance at e.g. 650nm is high, then it is likely that the spectral reflectance at 648 and 652 nm will also be high. In statistical terms this is referred to as multicollinearity. A correlation analysis of all the variables together would show many variables are correlated with each other. This fundamental characteristic of the hyperspectral data has implications for the nature of the statistical analysis and interpretation of analysis results. First, there is considerable redundancy in the data (the variation in the data set could be explained with fewer variables). Secondly, variables may appear spuriously significant because they are correlated with other variables. In order to deal with issues such as these, multivariate statistical methods are required.

The high degree of multicollinearity present in the hyperspectral reflectance data made it necessary to reduce to data to fewer, uncorrelated variables prior to data analysis to detect any varietal differences. PCA provides a means of creating new “variables” that capture the maximum amount of variability within the existing data set. This is achieved by the creation of new axes within the existing data space, with the first positioned to capture the greatest spread within the data. The second axis is then defined orthogonally in relation to the first and the values for the second principal component for each 10 km grid square are assessed from this axis. Further axis are defined within the data space until the variation within the data set explained by an axis drops below a predefined threshold, as measured by the axis’ eigenvalue.

Principal components analysis identifies a new set of uncorrelated variables where each variable is a linear combination of the original hyperspectral reflectance wavelengths. Because principal components analysis is used where there is a large degree of multicollinearity (very high correlations between the variables), it is usually the case that a large part of the variation in the original data set can be explained with just a few principal components. The wavelength variables that were important in forming the new principal component variables is determined by the loadings – these are simple correlations between the original wavelength variables and the new principal component variables. The higher the loading the more influential the wavelength variable was in forming the principal component and so the loadings can be used to interpret the meaning of the new variables, or to determine the underlying process that they might represent.

The new variables (factors) resulting from the principal components analysis were used as input variables for further analysis of the data. The advantage of using the principal components is that the new variables are not correlated and the problem of multicollinearity is avoided.

Discriminant Analysis

Discriminant analysis was used to identify whether significant differences existed within the hyperspectral data between the 5 varieties. The output of discriminant analysis are discriminant functions which separate out the treatments (varieties in this case) in the best way possible using the hyperspectral data (factor scores from PCA). It is often the case that it is not possible to account for all of the differences among the treatment groups by a single discriminant function in which case additional discriminant functions are produced which are always uncorrelated with the first discriminant function. To display the results of the discriminant analysis, discriminant scores for each replicate are plotted to show the separation between treatments along the discriminant function 'axis'. The significance of each of the discriminant functions was determined using Wilk's Lambda. A one-way ANOVA of the discriminant function scores followed by Tukey multiple range tests was used to identify the particular varieties where significant differences occurred.

4.3. Results

Differences in NDVI

Significant differences in the NDVI were seen between varieties on all sampling occasions except the earliest sample taken in 2000 (growth stage 30). Table 4.1 shows the results of a one-way ANOVA.

Table 4.1 Results of ANOVA showing differences in NDVI between varieties at each sampling occasion

	Growth Stage	**ANOVA**	
		F	**P**
28/4/1999	GS 32- 33	65.2	<0.001
14/6/1999	GS 65 - 75	14.3	<0.001
20/3/2000	GS 30	1.5	.NS
8/5/2000	GS 33-37	25.8	<0.001
31/5/2000	GS 41-59	21.5	<0.001

The differences in NDVI between varieties are illustrated for two points in the growing season in Figures 4.1 and 4.2. Figure 4.1 shows that the NDVI calculated from the spectral reflectance data collected at GS30 is not significantly different between the five varieties. However, by GS 45-59 (Figure 4.2) the characteristics of the varieties were beginning to be more obvious and by this growth stages there were significant differences in NDVI between the varieties. The main differences were in the varieties Avalon and Soissons, which are both extreme varieties in terms of modern wheat varieties. Because Avalon has very large floppy flag leaves, the top of the canopy closes as soon as the flag leaves are fully emerged. It would be expected that this might affect spectral reflectance differently from modern varieties. Soissons, apart from having awns, also matures earlier than the other varieties and so leaf senescence might be expected to be more advanced than in other varieties. These characteristics would be expected to affect the spectral reflectance from the variety. Consort, Equinox and Shamrock are much more representative of modern commercial varieties and it is clear that even in the later growth stages, the differences in spectral reflectance between these varieties are not significant.

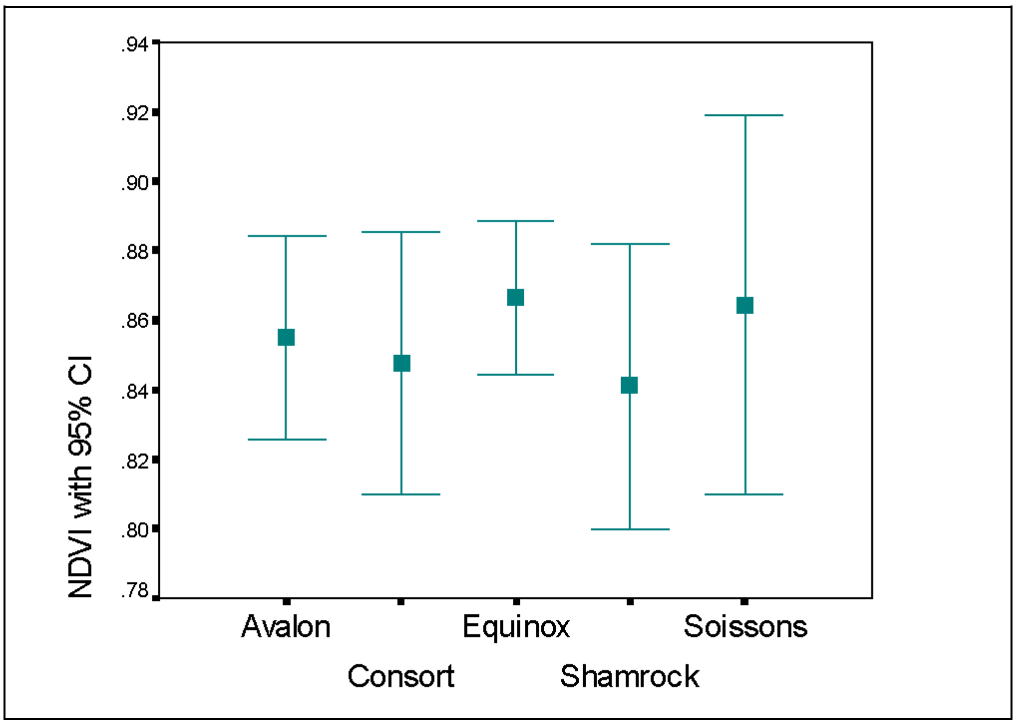


Figure 4.1 NDVI with 95% confidence limits shown for five varieties at growth stage 30. (20 March 2000).

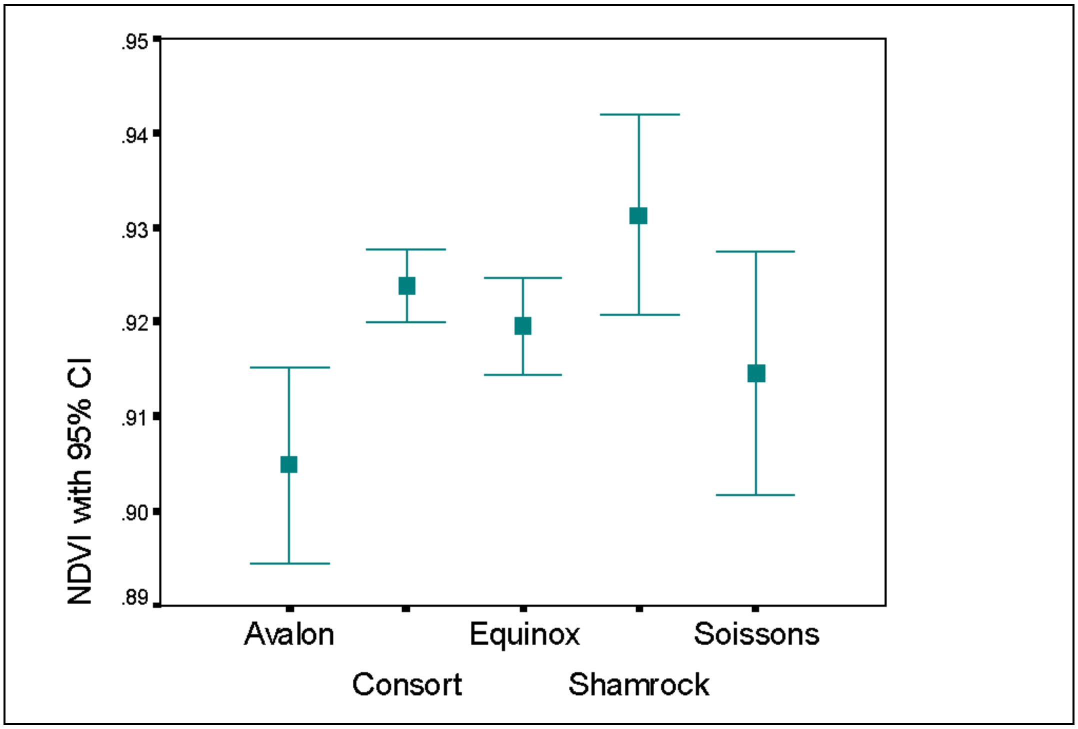


Figure 4.2 NDVI with 95% confidence limits shown for five varieties at growth stage 45-59. (31 May 2000).

ANOVA – LAI varieties differences.

It was intended that each variety plot should have a similar canopy size, because of the establishment practice of sowing by seed number and then applying uniform management to all varieties. Thus, the main differences between plots should be due to colour and architectural differences. There are, however, potential causes of differences in LAI between the varieties because of differences in average leaf size. Avalon is known to have larger average leaf size, whereas Soissons has a smaller average leaf size. However, differences in LAI between varieties, shown in table 4.2, were not significant.

Table 4.2 Results of ANOVA showing differences in LAI between varieties at each sampling occasion

	Growth Stage	**F**	P
28/4/1999	GS 32- 33	3.9	.036
14/6/1999	GS 65 - 75	1.2	.369
20/3/2000	GS 30	.9	.514
8/5/2000	GS 33-37	5.7	.012
31/5/2000	GS 41-59	2.7	.089

Discriminant Analysis

Results of the discriminant analysis are shown in Table 4.3. No significant difference in spectral characteristics between the varieties was observed early in the season (growth stage 30). Significant differences in hyperspectral signatures were seen within later in the season. These effects are the same as those observed for NDVI.

Table 4.3 Results of discriminant analysis for each sampling occasion

	Growth stage	**Wilks' Lambda**	**Chi-square**	**df**	**Sig.**
28/4/1999	GS 32- 33	.001	63.605	16	.000
14/6/1999	GS 65 - 75	.000	71.080	20	.000
20/3/2000	GS 30	.068	25.500	16	.061
8/ 5/2000	GS 33-37	.003	56.727	12	.000
31/5/2000	GS 41-59	.001	64.135	20	.000

An ANOVA of the discriminant function scores (for function 1) followed by multiple range tests was used to identify where significant differences occur between particular varieties. These results are summarised below:-

28/4/99 All varieties have distinct spectral characteristics from each other except for Shamrock and Equinox.

14/6/99 All varieties have distinct spectral characteristics except Shamrock and Soissons.

8/5/00 Avalon and Soissons both have discrete spectral characteristics compared to varieties Consort, Equinox and Shamrock which form a group with similar spectral characteristics.

31/5/00 All varieties have distinct spectral characteristics except for Consort and Shamrock which share some similar features.

The differences outlined above can be seen visually by plots of the discriminant scores for functions 1 and 2 which are shown for each of the three sampling occasions for 2000 in Figures 4.1, 4.2 and 4.3. At GS30, the differences between the varieties are again relatively small except for Shamrock which stands out as different from the other varieties (Figure 4.1). By GS 45 (Figure 4.3) the varieties are showing very different spectral characteristics, with differences being intermediate at GS37 (Figure 4.2).

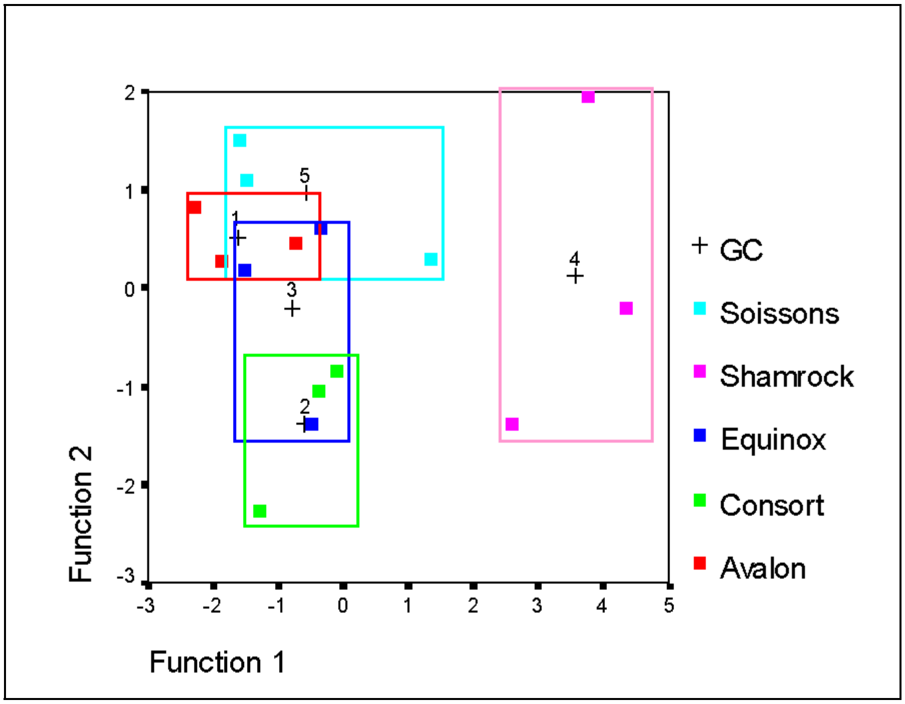


Figure 4.1 Discriminant analysis of hyperspectral data for five wheat varieties at GS 30.
(20 March 2000)

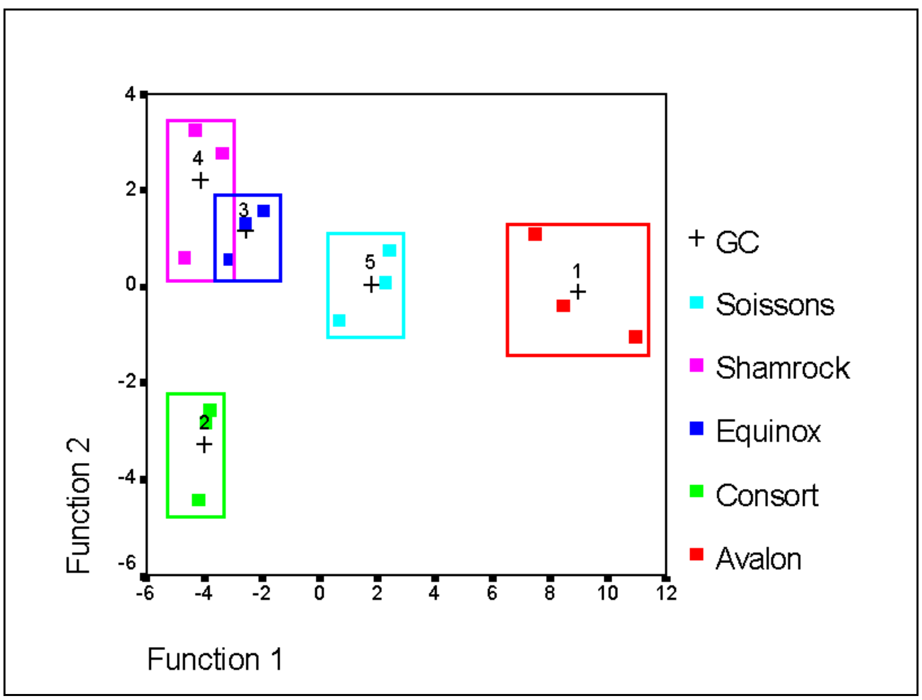


Figure 4.2 Discriminant analysis of hyperspectral data for five wheat varieties at GS 33-37.
(8 May 2000)

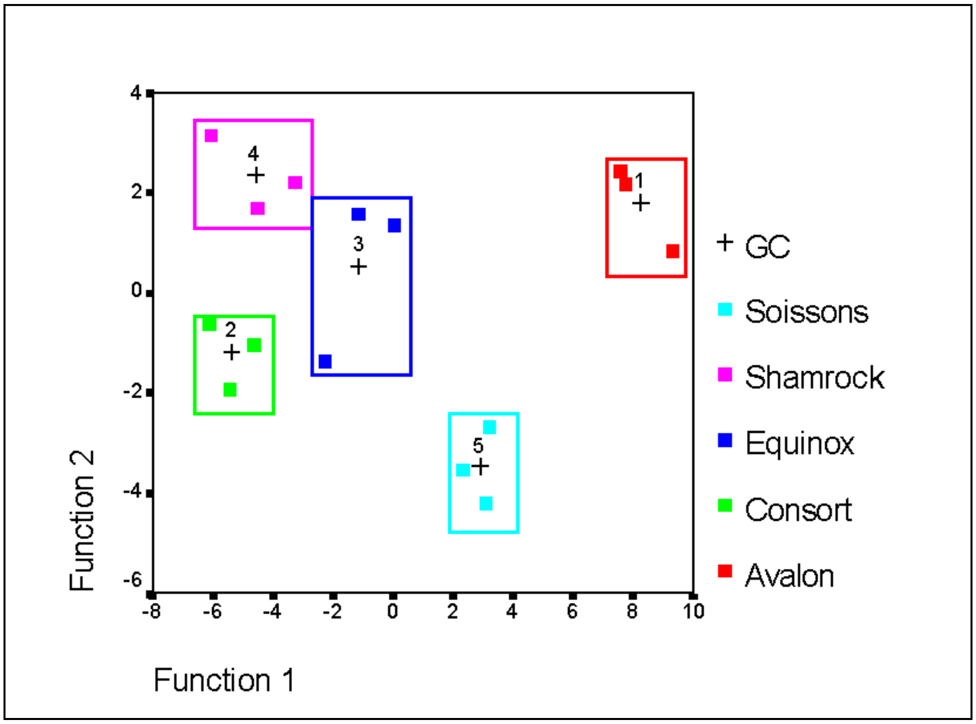


Figure 4.3 Discriminant analysis of hyperspectral data for five wheat varieties at GS 45-59. (31 May 2000)

4.4 Discussion

With either NDVI or hyperspectral data, differences between varieties at early growth stages (GS30-32) are either small or absent. As varieties develop their full canopy size, differences affecting spectral reflectance become more apparent. Thus, measurements taken later in crop growth would be confounded by varietal differences and some compensation would need to be made to adjust for such differences. The use of spectral reflectance to determine canopy size would be used during the very early growth stages of wheat (GS30-31) so varietal differences would not be expected to confound the spectral reflectance measurements at this stage. Similarly, detection of disease patches (e.g. yellow rust) would be more likely to be necessary early in crop growth (pre-GS32) so the later confounding effects of varietal characteristics would not come into play.

5. SPECTRAL SIGNATURES OF WHEAT CROPS INDICATIVE OF CANOPY SIZE

5.1 Introduction

In order to manage nitrogen inputs to a wheat crop using the principles of canopy management, estimates of canopy size must be made at key stages during the growing season so that nitrogen applications can be adjusted. The amount of nitrogen fertiliser applied at each stage is adjusted according to the canopy size at that stage, aiming to produce a final canopy size of about 6.5. This is the optimal canopy size for a wheat crop. The mean canopy size across a field can be estimated visually but where variation occurs across a field it is necessary to continuously measure and spatially locate crop areas which may need differential treatment. This cannot be done easily and lends itself to an automatic, routine remote sensing system which could both measure and then map variation across a field. The map of variability in crop parameters could then be used to create an application map for nitrogen as well as other crop protection inputs such as fungicides and plant growth regulators. The main decisions on nitrogen, fungicide and plant growth regulator application are normally made early in the growing season (March, April, May - GS 31-37). Thus it is more important to be able to measure canopy size during the early growth stages of a crop. Measurement of canopy size after flag leaf emergence (GS39, mid-May) is less important as most decisions on crop inputs have already been made.

The specific objective of this section of the project is to examine the relationships between hyperspectral reflectance and crop canopy size in order to establish relationships that could be used to measure canopy size using sensed data. Specifically, the work addresses four questions:

1. Are there significant differences in hyperspectral reflectance spectra with canopy size?
2. Can analysis with hyperspectral data improve on indices such as the NDVI? The hypothesis underlying this is that by providing greater spectral resolution, hyperspectral reflectance data might be more sensitive to differences in crop canopies and therefore have a stronger relationship with canopy size than the simple vegetation index.
3. Are there distinct wavelength regions of the hyperspectral data that can be identified as being important in predicting canopy size?
4. Can the relationships between NDVI and canopy size or hyperspectral reflectance and canopy size be used to predict crop canopy size?

5.2 Materials and Methods

5.2.1. Experimental design

A series of field experiments were set up to provide a range of canopy sizes with concomitant hyperspectral reflectance data. Experiments were set up in the growing seasons of harvest years 1999, 2000 and 2001. In each year, a fully randomised block design was used with 3 replicate plots of each of 5 nitrogen treatments and two fungicide treatments. This was designed to generate plots with and without disease. The varieties in the experiments were chosen to generate epidemics of single diseases. The winter wheat varieties chosen were Brigadier in 1999 to generate yellow rust *(Puccinia striiformis*) and Consort in 2000 and 2001 to generate *Septoria tritici*. Total nitrogen applications (as ammonium nitrate) for treatments 1 to 5 were 0, 80, 160, 240 and 320 kg N/ha respectively, applied as follows:

	early April	mid/late April	early May	total (kg/ha)
N1	0	0	0	0
N2	20	30	30	80
N3	40	60	60	160
N4	80	80	80	240
N5	100	120	100	320

The fungicide treatments were:

		GS31/32	GS39	GS59	Total
F1		…………….	Untreated	…………..	0
F2	Opus	0.67 l/ha	0.67 l/ha	0.67 l/ha	2.0 l/ha
	Patrol	0.5 l/ha	0.5 l/ha	0.5 l/ha	1.5 l/ha

Conventional agronomy/management practices were used. Crop canopies were sampled throughout the growing season during 1999 and 2000.

5.2.2. LAI measurements

A Plant Canopy Analyser (PCA, LAI-2000, Li-Cor inc. Lincoln, Nebraska, USA) was used to estimate green area index (GAI) of crop canopies. It estimates GAI from light measurements above and below the canopies at five solid angles using a hemispherical cosine corrected sensor, using calculations according to Campbell and Norman (1988).

5.2.3. Spectral measurements

High-resolution spectral reflectance measurements were taken at 4 points within each plot using a LICOR LI-1800 spectroradiometer. The LICOR LI-1800 is a rapid scanning instrument operating over visible and near-infrared wavelengths (350 to 850 nm at 2nm intervals). The LICOR LI-1800 was fitted with a cosine corrected optical head and was held at a height of 1m. For each plot and sampling occasion both target radiance (looking directly downwards) and incident irradiance (looking directly upwards) were monitored almost instantaneously to allow correction of reflectance for varying incident irradiance. The four replicate measurements were taken per plot and used to make a mean spectrum corrected for incident irradiance that contained 250 wavelength 'variables' that could then be used in the data analysis.

When possible the measurements were made under conditions of stable incoming solar radiation, ideally under clear cloud free skies. This aim was not always achieved owing to changes in weather during the length of time required to complete measurements on all replicate plots. The stability of incoming radiation was assessed from the time course of total incoming radiation obtained by integrating irradiance under each of the incoming spectral response curves after applying appropriate calibrations. This allowed simple separation of periods of stable and unstable solar radiation. A further check was made using the ratio of amounts of solar radiation in ten specified wavebands to total solar radiation to aid the detection of any transient changes in irradiance. Final checks were made by comparing graphs of the replicate reflected spectra with the incoming radiation before and after the measurements on a plot. Comparison of measurements between stable and unstable periods showed the major cause of variation in reflected radiation between replicate measurements over our relatively uniform crops was variation in incoming radiation. Thus in stable periods the nearest in time incoming radiation was used for reflectance calculations. In less stable periods after removing incident measurements showing unstable spectra, remaining reflected measurements were matched to appropriate incident spectra by assuming changes occurred in parallel and the reflectances calculated. All valid reflectances for a plot were averaged at each wavelength and the mean used for further analysis.

NDVI, which is defined as: $NDVI = (\rho_{IR} - \rho_R)/(\rho_{IR} + \rho_R)$

where ρ_{IR} and ρ_R are measured reflectance values in the near-infrared and red bands respectively was calculated using the hyperspectral reflectance data. The average reflectance over 790-850nm was taken as the near-infrared reflectance and the average reflectance over 600-690nm was taken as the red reflectance.

5.3 Statistical Analysis

The analysis of hyperspectral data can be complex because of the simultaneous response of 250 'wavelength variables' to treatments and because these individual wavelengths are strongly correlated. For example, if the spectral reflectance at e.g. 650nm is high, then it is likely that the spectral reflectance at 648 and 652 nm will also be high. In statistical terms this is referred to as multicollinearity. A correlation analysis of all the variables together would show many variables are correlated with each other. This fundamental characteristic of the hyperspectral data has implications for the nature of the statistical analysis and interpretation of analysis results. First, there is considerable redundancy in the data (the variation in the data set could be explained with fewer variables). Secondly, variables may appear spuriously significant because they are correlated with other variables. In order to deal with issues such as these, multivariate statistical methods are required (Everitt & Dunn, 1991). The high degree of multicollinearity present in the hyperspectral reflectance data made it necessary to reduce to data to fewer, uncorrelated variables prior to data analysis.

Principal components analysis (PCA) provides a means of creating new "variables", or factors that capture the maximum amount of variability within the existing data set. This is achieved by the creation of new axes within the existing data space, with the first factor positioned to capture the greatest spread within the data. The second axis is then defined orthogonally in relation to the first. Further axes, or factors, are defined within the data space until the variation within the data set explained by an axis drops below a predefined threshold, as measured by the axis' eigenvalue.

PCA therefore identifies a new set of uncorrelated variables where each variable is a linear combination of the original hyperspectral reflectance wavelengths. Because PCA is used where there is a large degree of multicollinearity, it is usually the case that a large part of the variation in the original data set can be explained with just a few principal components. The actual number of principal components to use in the analysis can be determined using a scree plot or by setting limits on the eigenvalue or cumulative percentage variance explained.

The wavelength variables that were important in forming the new principal component variables can be seen from the loadings – these are simple correlations between the original wavelength variables and the new principal component variables. The higher the loading the more influential the wavelength variable was in forming the principal component and so the loadings can be used to interpret the meaning of the new variables, or to determine the underlying process that they might represent.

The new variables resulting from the PCA can be used as input variables for further analysis of the data. The advantage of using the principal components is that the new variables are not correlated and the problem of multicollinearity is avoided. Once PCA had been conducted, the relationship between LAI and factor scores (the output from the PCA) was then analysed using stepwise multiple regression.

5.4 Results

5.4.1. Leaf Area Index

Table 5.1 Summary of datasets and LAI ranges produced across the experimental plots

Date	**Growth Stage**	**LAI mean**	**LAI range**
07/5/1999	32	2.61	2.24-3.16
15/6/1999	65	3.35	2.37- 4.73
21/3/2000	30	1.43	0.92-2.00
30/3/2000	30	1.68	0.79-2.15
5/4/2000	30	1.76	1.14-2.55
5/5/2000	32	3.34	1.64-4.69
9/5/2000	33	3.48	1.40-5.45
31/5/2000	41	2.04	4.14-5.72
16/6/2000	61	4.42	1.91-6.03
27/6/2000	69	5.05	2.29-7.34
18/7/2000	78	4.36	1.66-7.39
7/3/2001		0.26	0.15-0.46
27/4/2001	30	0.55	0.27-1.05
23/5/2001	33	2.08	0.49-3.75
4/7/2001	67	2.10	0.34-4.22

The ranges of canopy size encountered in the experiments conformed well with those that could be expected in commercial crops. Figure 5.1 shows the typical benchmark figures for growth stage and canopy size in commercial wheat crops.

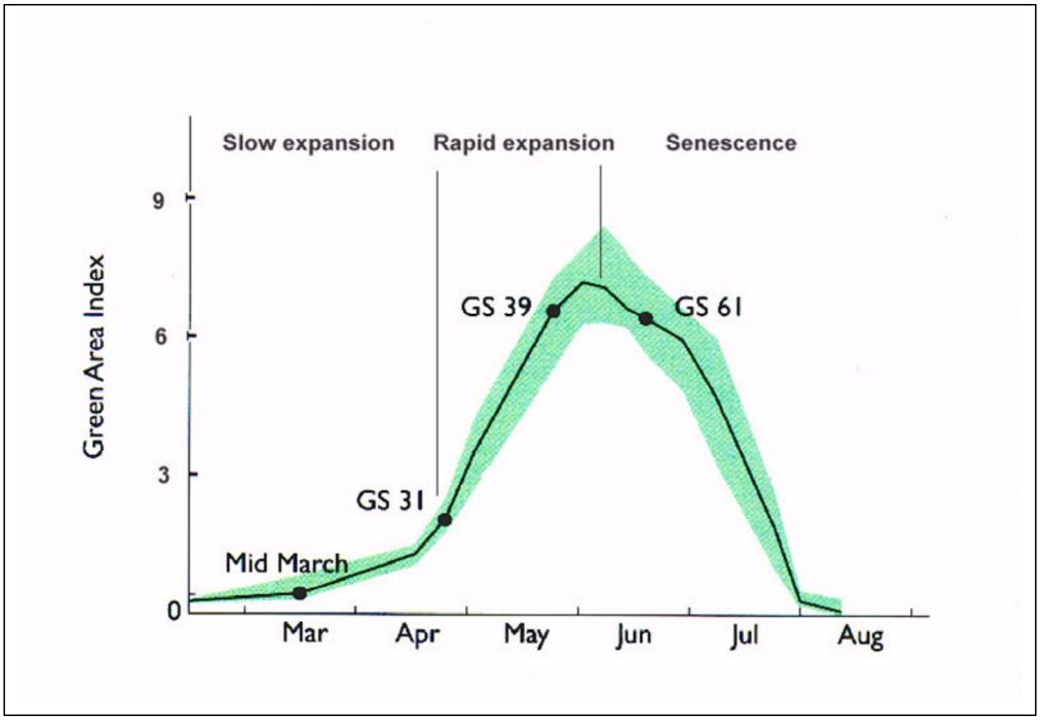


Figure 5.1 Benchmark growth stages and canopy size
(from the HGCA publication 'The Wheat Growth Guide')

5.4.2 Disease differences

The 2 varieties chosen were Brigadier in 1999 to generate yellow rust *(Puccinia striiformis*) and Consort in 2000 and 2001 to generate *Septoria tritici*. Disease assessments were carried out at weekly intervals from mid May until the end of July. There was limited scope for analysis of spectral reflectance of diseased crops as very little disease was detected, other than on the lower leaves (leaves 4 and 5, where the flag leaf is leaf 1). In 1999, no significant disease (>5% leaf area affected) was present within the experimental plots until 15 June. In 2000, no significant disease was present in the crop until the final sampling occasion, 18 July. In 2001 septoria tritici was recorded at significant levels only on leaf 3 and 4, but only after flag leaf emergence in mid May.

With the limited amount of disease present, analysis of relationship between disease effects and spectral reflectance concentrated on investigating whether early detection of disease could be identified using the spectral reflectance data. Analysis was carried out on the 2000 data, where disease was at very low levels throughout the majority of the growing season and only reached marked levels (>5%) at 18 July. Differences in NDVI were examined between plots to see whether the plots where disease was present at 18 July showed any difference earlier in the growing season at a time when decisions about fungicide spray applications would be made. The Green Leaf Area (GLA) of leaves 1, 2 and 3 within plots on 18 July was correlated with the NDVI of the same plots on 17 May and 31 May. No relationship was observed.

5.4.3. Relationship between NDVI and LAI

The relationship between NDVI and LAI was examined for each dataset. The relationships between LAI and NDVI for the 2000 and 2001 datasets are shown graphically in Figures 5.1

and 5.2. Typically, at lower LAI levels a linear relationship between NDVI and LAI was observed. At higher LAI levels often a plateau in the relationship with NDVI was observed.

Figure 5.1 (following pages) Relationship between NDVI and LAI at each sampling occasion in 2000. Treatments can be identified using the following key:-

Open circles (treatments 1 to 5) – no fungicide applied

Closed circles (treatments 6 to 10) – standard fungicide applications

Colours denote the level of nitrogen applied throughout the course of the experiment (for application dates see Methods).

Red (0 kg N/ha),

Yellow (80 kg N/ha),

Blue (160 kg N/ha),

Light green (240 kg N/ha)

Dark green (320 kg N/ha).

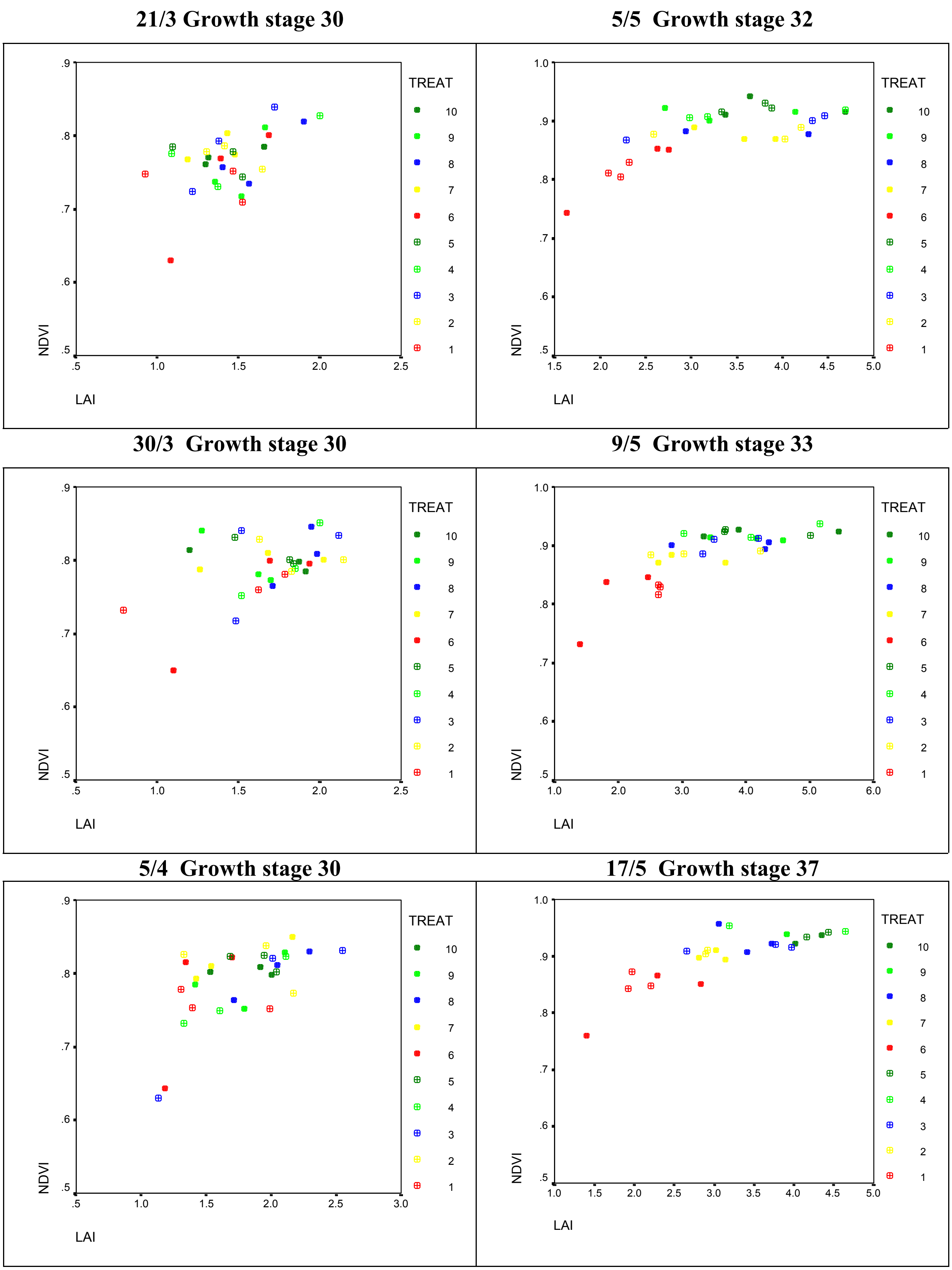


Figure 5.1 Relationship between NDVI and LAI at each sampling occasion

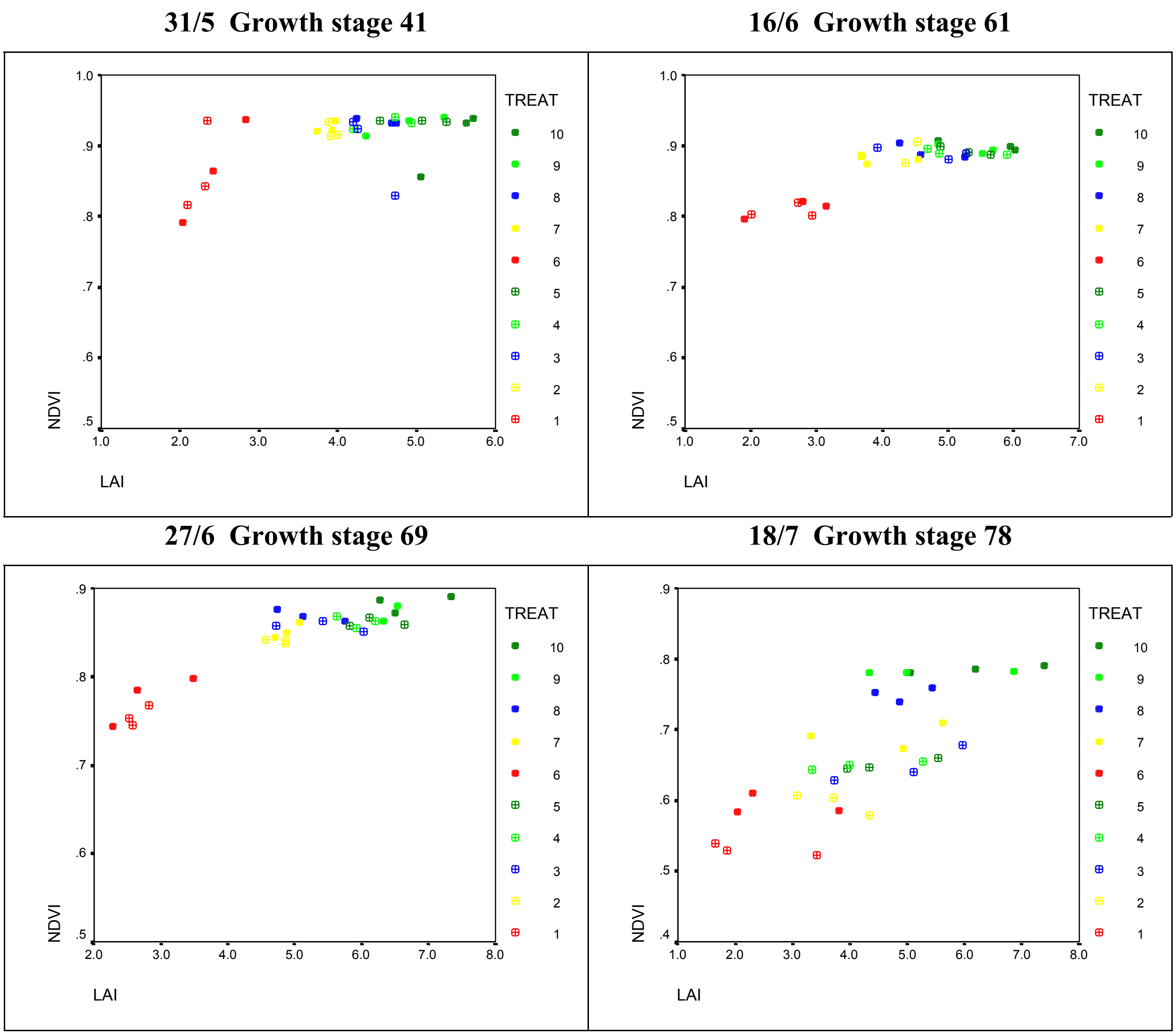


Figure 5.1 (cont) Relationship between NDVI and LAI at each sampling occasion

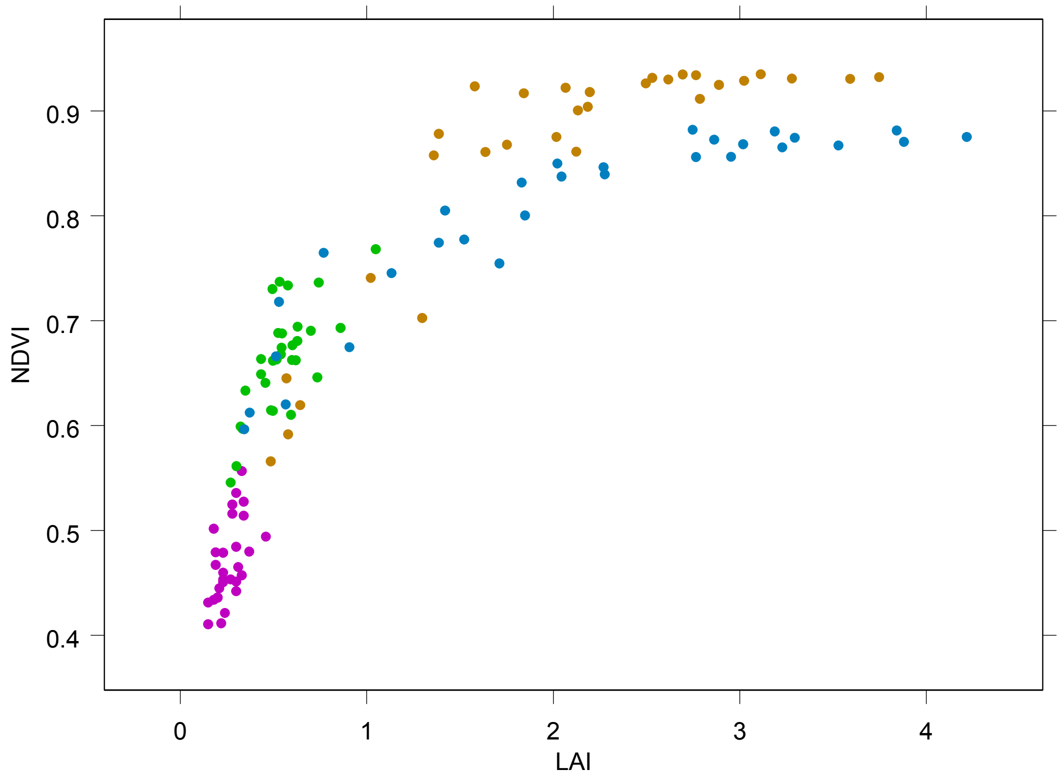


Figure 5.3 Relationship between NDVI and LAI in 2001 data where purple is sampling occasion 1 (7 March), green is sampling occasion 2 (27 April), brown is sampling occasion 3 (23 May) and blue is sampling occasion 4 (4 July).

Figure 5.3 shows clearly that there is a relationship between NDVI and LAI but that the relationship changes through the growing season, particularly as the canopy size (LAI) changes. At the start of the growing season there is a linear relationship between LAI and NDVI. Later in the season, after about a LAI of 2.0 is reached, the relationship reaches a plateau and it is no longer possible to predict LAI with NDVI alone. A key point to the analysis is therefore to determine whether the use of hyperspectral data can improve on the prediction of LAI past this point at which the plateau is seen.

5.4.4. Detailed statistical analysis with hyperspectral data

Detailed analysis of the relationship between hyperspectral reflectance and canopy size and a comparison with the relationship between NDVI and LAI was carried out on datasets from sampling occasions in 2000 and 2001. This preliminary analysis took the form of an exploratory analysis to determine a methodology for analysis of all the datasets collected within this part of the project.

2000 data sets – comparison of NDVI and hyperspectral reflectance data

The aim of the analysis is to compare the effectiveness of NDVI and hyperspectral reflectance data in predicting values of LAI. These results (Table 5.2) show that there is usually an improved potential prediction of LAI if the hyperspectral reflectance data (summarised by principal components analysis) is used over the simpler NDVI.

Table 5.2 Correlation between NDVI and hyperspectral data with leaf area index measurements throughout the 2000 growing season.

Date	**Growth stage**	**LAI range**	**Linear range (LAI value)**	**Regression with NDVI**		**Regression with Hyperspectral data**	
				R^2 %	P-value	R^2 %	P-value
21/3	30	0.92-2.00	All	23	0.005	25	0.025
30/3	30	0.79-2.15	All	18	0.011	13	N/S
5/4	30	1.14-2.55	2.25	32	0.001	37	0.002
5/5	32	**1.64-4.69**	3.5	44	<0.001	54	<0.001
9/5	33	**1.40-5.45**	3.5	55	<0.001	57	<0.001
31/5	41	**4.14-5.72**	3.5	28	0.002	90	<0.001
16/6	61	**1.91-6.03**	4.0	66	<0.001	62	<0.001
18/7	78	**1.66-7.39**	6.0	55	<0.001	51	<0.001

2001 Sampling occasion 2 – Growth Stage 30

At growth stage 30, a linear relationship was seen between NDVI and LAI (Figure 5.2) which was highly significant (R^2 0.51, $p < 0.001$). This relationship allows prediction of LAI up to 1.05.

The results of the PCA of the hyperspectral reflectance data collected on this sampling occasion showed five important, uncorrelated, factors that could summarise the variation in the hyperspectral reflectance data. The relative importance of each of these factors in describing the variation in the spectral data is shown below:-

	Percentage variance explained	Cumulative percentage variance explained
Factor 1	64.51%	-
Factor 2	32.75%	97.27%
Factor 3	2.04%	99.30%
Factor 4	0.59%	99.89%
Factor 5	0.03%	99.93%

Factors 1 and 2 accounted for the majority of the variation in the data.

A stepwise multiple regression of LAI against these five factors found Factor 1 and 2 to be best at predicting LAI and was highly significant:-

$$\mathbf{LAI = 0.55 + 0.009\ Factor\ 1 + 0.0078\ Factor\ 2}$$

$R^2 = 0.55$ $p<0.001$

The R^2 values associated with this regression equation is similar to that of the regression equation between LAI and NDVI. Thus with this dataset, little difference is observed between use of the NDVI and the hyperspectral reflectance data.

In order to detect the wavelength or wavelength regions of importance in predicting LAI, the loading of each wavelength associated with Factors 1 and 2 of the PCA were plotted (Figure 5.3). As the factors were uncorrelated with each other, they can be clearly seen to represent slightly different parts of the spectral reflectance data. Factor 1 is linked to the wavelength regions 450-500 nm and 600-680nm. Factor 2 is linked to 500-600 nm and 680-850 nm. It is difficult to detect discrete areas of the spectral signatures because of the strong interdependence between the wavelengths.

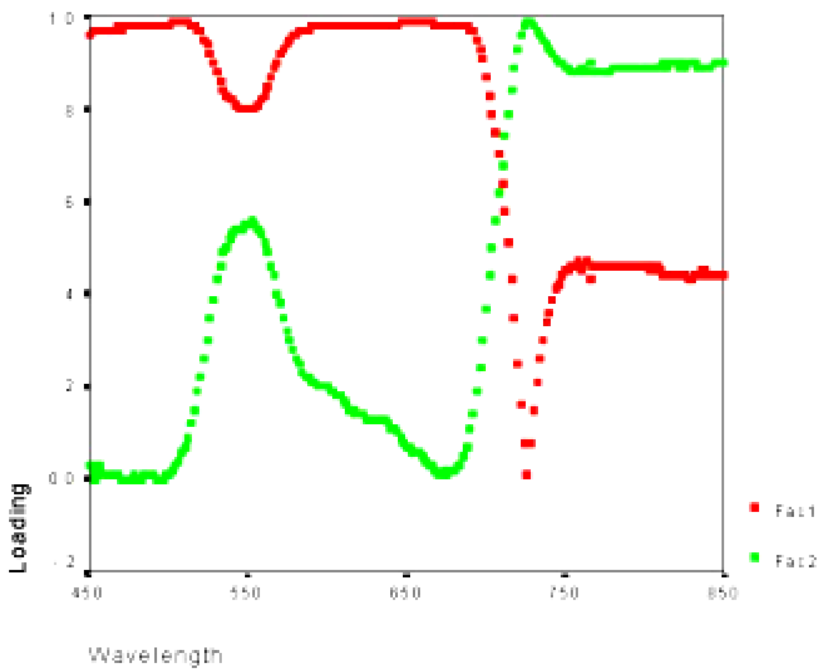


Figure 5.3 Plot of loading of each wavelength on each of Factors 1 and 2 from the PCA for sampling occasion 2 in 2001.

2001 Sampling occasion 3 – Growth Stage 33

As can be seen from Figure 5.4, at growth stage 33 there is a non-linear relationship between LAI and NDVI. Taking the part of the dataset where LAI is less than 2.5, a linear regression between NDVI and LAI was established which is highly significant (R^2 =0.84, p<0.001).

Above an LAI of 2.5 the relationship with NDVI reaches a plateau. LAI is therefore not reliably predictable with NDVI between an LAI of 2.5 and 3.75. The linear relationship between NDVI and LAI up to a LAI of 2.5 is useful in managing nitrogen applications and crop protection inputs. The main nitrogen applications would be applied during this period of crop growth, as would the plant growth regulator applications. The first fungicide application would also be applied during this period of crop growth and an estimate of LAI could be a useful tool in helping decision making. Although estimating LAI above 2.5 would be useful, particularly in crops with large LAI values early in the season, for the majority of crops estimates of LAI up to 2.5 would be adequate.

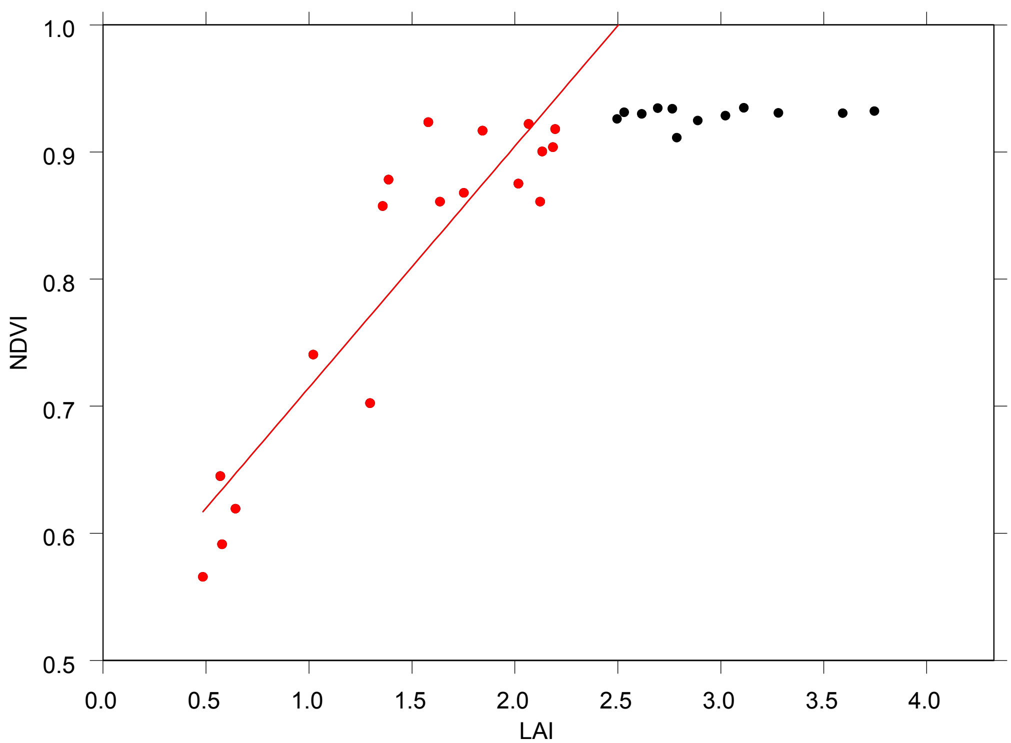


Figure 5.4 Relationship between NDVI and LAI at growth stage 33 in 2001 showing the extent of the linear relationship.

Principal components analysis of the hyperspectral reflectance data found five factors of importance in summarising the variation in the spectral data. The relative importance of each of these factors is shown overleaf:-

	Percentage variance explained	Cumulative percentage variance explained
Factor 1	90.09%	-
Factor 2	7.93%	98.03%
Factor 3	1.86%	99.90%
Factor 4	0.08%	99.98%
Factor 5	0.01%	99.99%

In this case, a very large amount of the variation (90%) is explained on one factor alone (Factor 1), with only small portions of the variation explained by the PCA factors thereafter.

A stepwise multiple regression of these factors with LAI found a highly significant relationship:-

LAI = 2.08 + 0.056 Factor 1 + 0.118 Factor 3

$R^2 = 0.79$ $p<0.001$

This relationship is generally linear (Figure 5.5) and therefore can potentially predict LAI over the range 0.5-4.0 rather than only up to 2.5 as seen by the extent of the linear part of the relationship between LAI and NDVI.

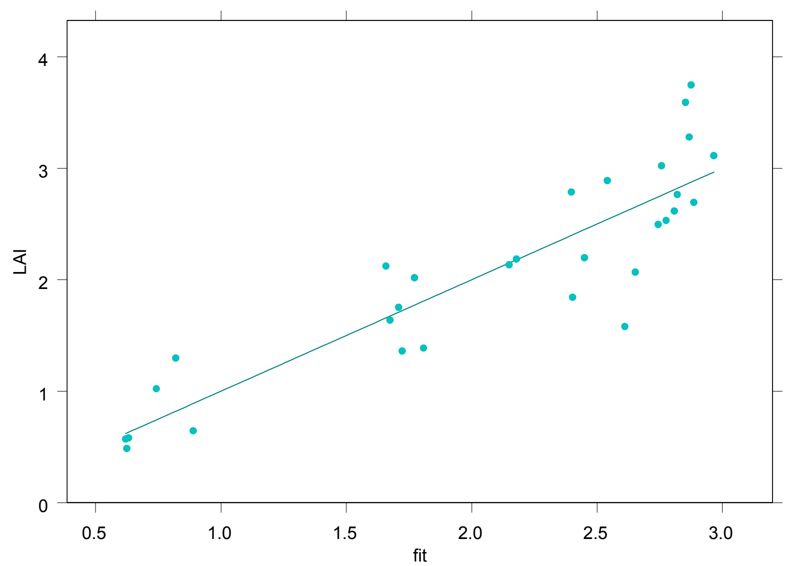


Figure 5.5 Plot of the multiple regression fit of factors 1 and 3 with LAI for sampling at GS33 in 2001

In order to determine whether the wavelengths or wavelength regions of importance in predicting LAI using this regression equation could be determined, the wavelength regions associated with Factors 1 and 3 were examined using a loadings plot as shown in Figure 5.6. Again, no area of the spectrum was not important. Only a small wavelength region represents the input of Factor 3 to this relationship. This is not surprising as Factor 1 is so important in describing the variation in the spectral data, accounting for 90% of the variation and Factor 3 explains less than 2% of the variation.

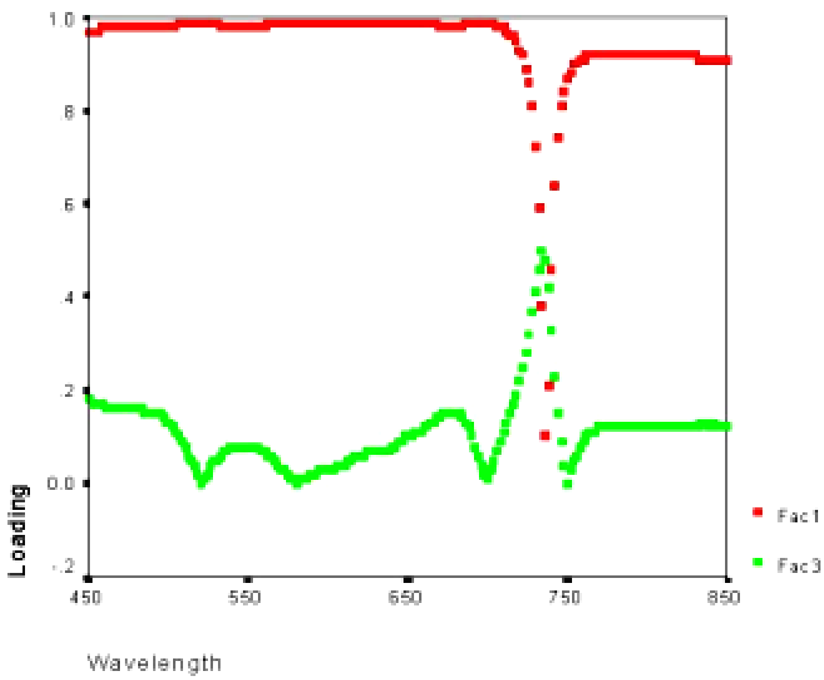


Figure 5.6 Plot of loading of each wavelength on each of Factors 1 and 2 from the PCA for sampling occasion 3 in 2001.

6. SPATIALLY VARIABLE CANOPY SIZE AND USE IN SIMPLE MODELS FOR INPUT MANAGEMENT

6.1 Introduction.

Since the mid 1990's the Global Positioning System (GPS), used to position vehicles on the farm and within fields, has been enhanced to make it more accurate. If necessary GPS systems are now available that can provide centimetre accuracy. The cost of GPS technology has also reduced over the past few years making it more affordable.

Current agricultural computer systems allow the bringing together of advanced agronomic and local knowledge with a number of different technologies. Satellite global positioning systems (GPS), computer Geographical Information Systems (GIS), variable implement technology, and combine yield-mapping systems are just a few examples. Systems such as AGCOs 'Fieldstar' have a significant role, because they provide the farmer with the tools to measure and manage inputs. Inputs such as seed, fertiliser and crop protection products can be varied within a field and matched to canopy size. Such computer systems also allow the opportunity to farmers to automate the process of creating field records providing them with traceability which is rapidly becoming an important feature of marketing farm produce.

The ability to variably apply nitrogen and crop protection inputs relies on having a map of the treatable area showing the variability in the factor which affects the crop input. Canopy size is one key factor which affects many key inputs. The ability to measure and map variation in canopy size across fields would allow the generation of application maps for several crop protection inputs according to rules, some simple, some complex.

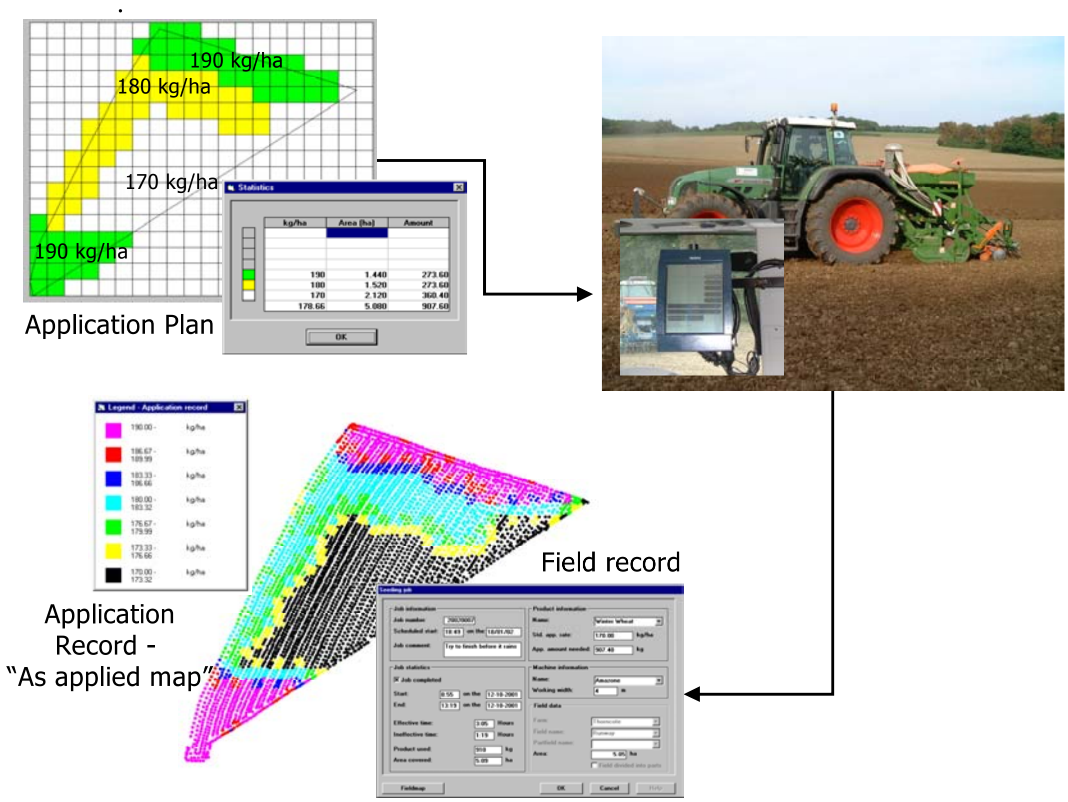
There are many potential benefits of on-board computer technologies and spatially applied crop inputs:

- By applying nitrogen fertiliser spatially according to the needs of the crop nitrate leaching into watercourses may be reduced.

- By spatially applying agrochemicals as and when they are required pesticide residues are reduced and kept to a minimum.

- By applying farm waste, like slurry and farm yard manure, according to a pre-defined application map there is less chance that mistakes are made during spreading - mistakes that could result in run-off into water courses.

The representation below shows how systems such as Fieldstar can use spatial data about a crop to variably apply crop inputs and record those inputs for traceability purposes.



Using IT systems such as the AGCO 'Fieldstar' to create field records and traceability will almost certainly play an ever-increasing role in farm businesses in the near future.

Mapping of canopy using plant canopy analyser and GPS

To illustrate the potential for using canopy size estimates within a field to adjust crop inputs the variation in crop canopy was measured in a field at ADAS Terrington in 1999. A systematic grid of sampling points was designed (Figure 6.1) and measurements of plant canopy size were taken at each of these sampling points throughout the season.

An example of the type of map generated from these data is shown in figures 6.2. The map could be used to vary crop inputs in a crude way, as represented in figure 6.2 but with the use of simple models crop inputs could be adjusted in a more systematic way. Examples of the types of simple models that could be incorporated into such a system are given in section 6.2.

Figure 6.1 Sampling points for spatial measurements taken

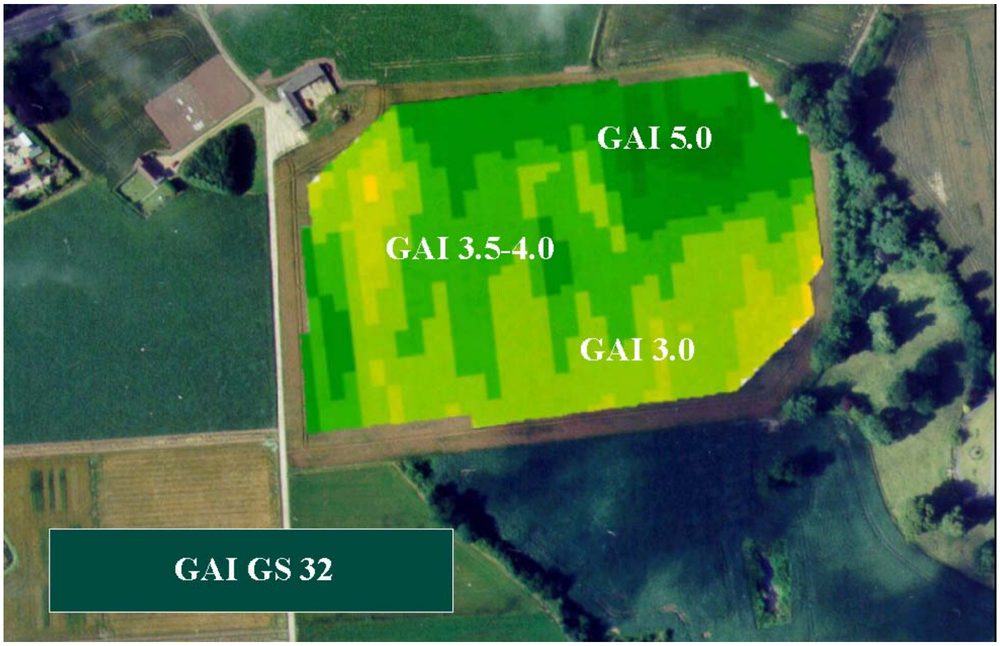


Figure 6.2 Map of GAI at GS32 derived from canopy measurements.

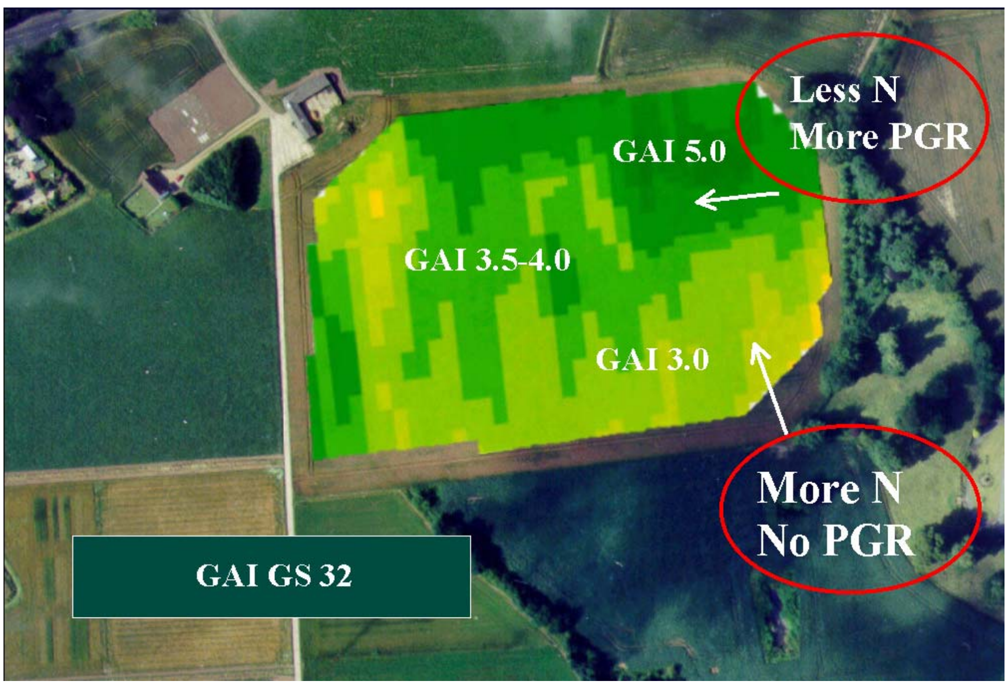


Figure 6.3 Typical recommendations which could be applied using the GAI map

6.2 Simple model using spatial data to assist in decision making on crop inputs

The main factors affected by crop canopy size on crop inputs are:

1. Nitrogen fertiliser
2. Plant Growth regulators
3. Fungicides

A typical map of GAI, such as shown in figure 6.2 could be used to create an application map for these inputs at different stages of crop growth. Typical scenarios are described below.

6.2.1 Nitrogen planning using GAI maps

This example assumes nil soil mineral N available in the spring.

Table 6.1 Nitrogen decisions at GS30 based on crop GAI

First N decision stage: Crop Growth Stage GS30-31

Current GAI	**Target for max. GAI**	**Total N required (kg/ha)**	**1st N application rate (kg/ha)**
1.0	6.0	250	125
2.0	6.0	200	100
3.0	6.0	150	75

Table 6.2 Nitrogen decisions at GS33 based on crop GAI

Second N decision: Crop Growth Stage GS33

Current GAI	**Target for max. GAI**	**Planned N rate (kg/ha)**	**2nd N application rate (kg/ha)**
4.0	6.0	125	100
5.0	6.0	100	50
6.0	6.0	75	Nil

At GS30-31 the variation in GAI across a field could be used to determine the total nitrogen requirement for each ‘area’ of the field (whether these are spreader widths or blocked areas of the field). This total nitrogen requirement will depend on the GAI of the crop at that stage. When GAI is mapped later (at GS33) this could allow more precision in the nitrogen requirement of different areas of the crop. Such variation can arise with variation in soil mineral nitrogen across the field, soil type differences, nitrogen uptake variation etc. Table 6.2 shows how the ‘planned’ nitrogen application could be modified following measurement of GAI at GS33.

These modified nitrogen application rates could result in cost savings to the farmer.

6.2.2 Plant Growth Regulator planning using GAI maps.

Decisions similar to those involving nitrogen could be made for plant growth regulator use as outlined below. The example assumes a high risk lodging variety.

Table 6.3 Plant growth regulator decisions at GS30 based on crop GAI

Plant Growth Regulator decision: Crop Growth Stage GS30

GAI	Plant Growth Regulator programme
1.0	Nil
2.0	Cycocel
3.0	Cycocel split (x2) +/- Terpal

This assumes the principle that the higher GAI areas will have higher plant populations and therefore be at higher risk of lodging. Low GAI areas will have low plant populations and thus very low risk of lodging.

6.2.3 Fungicide planning using GAI maps.

Decisions similar to those involving nitrogen could be made for fungicide use as outlined below. The example assumes a high disease risk variety.

Table 6.4 Fungicide decisions at GS30 based on crop GAI

Fungicide Decisions: GS32

GAI	Fungicide programme GS32
2.0	Strobilurin (0.5 label dose) + triazole 0.25 label dose
3.0	Strobilurin (0.3 label dose) + triazole 0.35 label dose
4.0	Strobilurin (0.3 label dose) + triazole 0.5 label dose

Table 6.5 Fungicide decisions at GS39 based on crop GAI

Fungicide Decisions: GS39

GAI	Fungicide programme GS39
5.0	Strobilurin (0.75 label dose) + triazole 0.25 label dose
7.0	Strobilurin (0.5 label dose) + triazole 0.35 label dose
9.0	Strobilurin (0.5 label dose) + triazole 0.5 label dose

This range of fungicide programmes relies on the principle that in crops with low GAIs the lower leaves contribute more to grain filling than in crops with high GAIs. Leaves 3 and 4 in particular contribute more to yield and it is these leaves which are affected most by strobilurin fungicides applied at GS32, being kept green for longer than under a non-strobilurin programme. Thus, in crop areas with lower GAIs a higher rate of strobilurin is used at GS32. The main fungicide spray timing decision at GS39 is less affected by GAI but a similar principal applies. The crop areas with a sub-optimal GAI of 5 cannot afford to lose any green area – and thus need a higher dose of strobilurin. Areas of high GAI are less likely to be affected by loss of green area and can tolerate more disease. Thus, the rate of strobilurin required is lower in these areas.

Variation in fungicide dose according to canopy size.

There is a school of thought which argues that the dose of fungicide applied to a crop should vary depending on the size of the canopy to which it is applied. This is because as the crop canopy increases, the total amount of active ingredient delivered to a unit area of leaf will decrease. In order to compensate for this dilution effect, in larger canopies a higher dose of fungicide would be applied. Recent HGCA-funded work (HGCA Project Report No. 277 – Optimising fungicide application according to crop canopy characteristics in wheat) suggests that there may be potential to improve the use of fungicides by matching applications to crop growth stage. If canopy size could be measured remotely and mapped, then this map could be used to vary the dose of product applied. This theory has not been tested fully and further development work would be needed before recommendations could be made.

7. TECHNOLOGY TRANSFER ACTIVITIES

The project created considerable interest amongst both the farming community and the agricultural industry in its wider sense. During the first 2 harvest years of the project (1999 and 2000) the results of the project were demonstrated and discussed on the HGCA research demonstration areas at the Cereals 99 and Cereals 2000 events. Crops magazine ran a series of 'Research in Focus' articles which were later bound together into a handout for the Cereals event.

Figure 7.1 Handout for Cereals 2000 event showing article on remote sensing potential

The project was reported on several occasions in the farming press, mainly Farmers Weekly and Crops, throughout the duration of the project.

Figure 7.2 National Cereals 2000 event

Figure 7.3 Article in Agriculture LINK magazine

Conference presentations:

The project helped to bring a UK focus to remote sensing in agriculture and members of the project organised the 'Remote Sensing in Agriculture' conference at the Royal Agricultural College, Cirencester, 2000. This was attended by most of the leading researchers in remote sensing from around the world. The delegates from the conference are shown in figure 7.4. below.

Figure 7.4   Delegates at the Remote Sensing in Agriculture conference 2000

The conference proceedings were published by the AAB in *Aspects of Applied Biology 60, Remote Sensing in Agriculture.* Two papers from the project were presented and published:

The role of remote sensing technologies in UK arable production. R.J. Bryson, J. Clark, W. S. Clark.

Statistical analysis of hyperspectral data: examples from the SPARTAN project. A.E. Riding, R.J. Bryson.

The project team also presented papers at the SCI conferences held in January 2001 and 2002:

SCI Conference January 2001 "In field monitoring of soil and crop factors" M Steven, University of Nottingham.

SCI Conference January 2002   "Optical and radar sensing of wheat crops to aid management decisions" P Dampney, ADAS Boxworth.

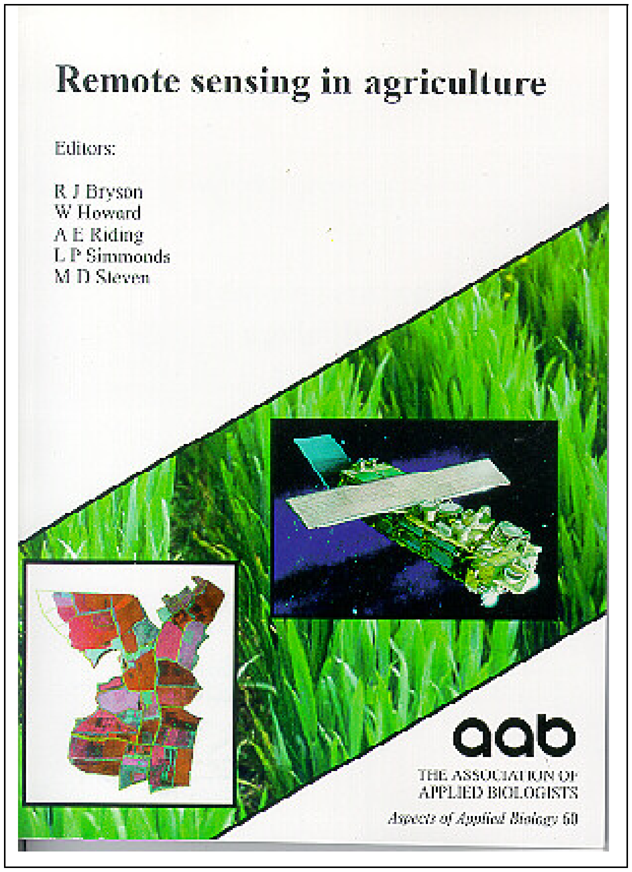


Figure 7.5 Conference proceedings from Remote Sensing in Agriculture conference, 2000

8. ACKNOWLEDGEMENTS

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