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Calibration Methodology for Mapping Within-Field Crop Variability using Remote Sensing

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Abstract.

A successful method of mapping within-field crop variability of shoot populations in wheat (*Triticum aestivum*) and barley (*Hordeum vulgare* L.) is demonstrated. The approach is extended to include a measure of green area index (GAI). These crop parameters and airborne remote sensing measures of the normalised difference vegetation index (NDVI) are shown to be linearly correlated. Measurements were made at key agronomic growth stages up to the period of anthesis and correlated using statistical linear regression based on a series of field calibration sites. Spatial averaging improves the estimation of the regression parameters and is best achieved by sub-sampling at each calibration site using three 0.25 m^2 quadrats. Using the NDVI image to target the location of calibration sites, eight sites are shown to be sufficient, but they must be representative of the range in NDVI present in the field, and have a representative spatial distribution. Sampling the NDVI range is achieved by stratifying the NDVI image and then randomly selecting within each of the strata; ensuring a good spatial distribution is determined by visual interpretation of the image. Similarly, a block of adjacent fields can be successfully calibrated to provide multiple maps of within-field variability in each field using only eight points per block representative of the NDVI range and constraining the sampling to one calibration site per field. Compared to using 30 or more calibration sites, restricting samples to eight does not affect the estimation of the regression parameters as long as the criteria for selection outlined in this paper is adhered to. In repeated tests, the technique provided regression results with a value for the coefficient of determination of 0.7 in over 85% of cases. At farm scale, the results indicate an 80-90% probability of producing a map of within crop field variability with an accuracy of 75-99%. This approach provides a rapid tool for providing accurate and valuable management information in near real-time to the grower for better management and for immediate

adoption in precision farming practices, and for determining variable rates of nitrogen, fungicide or plant growth regulators.

1. Introduction

The aim of precision farming is to target specific amounts of agronomic inputs to optimise the productivity of fields exhibiting within-field spatial variation in both yield potential and quality. In order to understand the causes and the extent of this variability, such that effective management decisions can be made, there is a requirement for an effective method of accurately mapping soil and crop parameters. Proposed methods of precision farming that manage the rate of crop growth to optimise canopy size, yield potential and quality (Wood *et al*., 2002) require accurate, near real-time maps of shoot population and green area index (GAI). Whilst techniques such as electromagnetic induction offer an effective approach for mapping soil parameters (Godwin & Miller, 2002; Earl, *et al.*, 2002), this paper outlines the development of a technique for accurately measuring crop parameters using remote sensing techniques that can be made available to the grower cost-effectively.

Shoot population is an important variable in cereal management because it directly governs canopy size and grain yield (HGCA, 1998). Shoot population is dependent on an interaction of the rate of tillering and initial plant population (Whaley *et al*., 2000) which, in turn, is dependent upon soil physical properties, soil nutrient-water status and temperature (Perry, 1993). These factors vary spatially within single agricultural fields, for example, soil nutrients have been shown to vary over distances down to *c*. 24 m (Taylor *et al*., 2002). Wood *et al*. (2002) have shown that within-field variation in shoot density can have a significant impact upon field management decisions. If accurate methods of measuring within-field variation in canopy-size parameters were possible, it would provide an invaluable diagnostic to guide the use of agronomic inputs such as fertiliser nitrogen

(Sylvester-Bradley *et al*., 1997), plant growth regulators (Berry, *et al*., 1998), and fungicides (Miller, 1998; Bjerre & Secher, 1998). Hitherto, accurate mapping techniques for quantifying within-field variation in canopy-size parameters for crop management have been unavailable.

At the outset of the project it was decided that a system for delivering maps of crop canopy parameters could be offered using optical remote sensing techniques. Previous work (NAS, 1970; Wiegand *et al*., 1991; Chapman & Barreto, 1997) pointed to the use of techniques that utilise empirical relations between ground measurement and spectral reflectance. Typically, measures of red (R) and near infrared (NIR) spectral wavelengths are combined in the form of simple vegetation indices, such as the normalised difference vegetation index (NDVI) as given in Eqn (1) after Goward, *et al*., (1991).

$$I_{NDV} = (\lambda_{NIR} - \lambda_R) / (\lambda_{NIR} + \lambda_R) \quad (1)$$

where: I_{NDV} is the normalised difference vegetation index; and λ_R and λ_{NIR} are the red and near infrared spectral wavebands

The concept of using combinations of red and near infrared measurements to estimate biophysical parameters of vegetation was first introduced by Jordan (1969) who used a simple ratio of canopy transmittance to derive leaf area index. Much research has investigated the spectral properties of vegetation canopies (NAS, 1970; Jacquemoud & Baret, 1990; Buschmann & Nagel, 1993). In particular, the use of red and near-infrared wavelengths has provided a basis for extensive vegetation assessments (Wiegand, *et al*., 1991; Chapman & Barreto, 1997). Numerous spectral vegetation indices have since been defined and empirically related, by ground measurements, to vegetation properties such as percent ground cover, green area index (GAI) and above-ground biomass (Kauth & Thomas, 1976; Richardson & Wiegand, 1977; Miller 1990; Price, 1992; Steven, 1998; Jago *et al*., 1999).

Other approaches are based on radiative transfer models which are used to derive canopy biophysical parameters from a limited set of reflectance measures (Baret, 2001a). This approach offers a very attractive solution to estimating canopy parameters since its aim is to provide estimates without the need for ground calibration. This area of research has contributed much to the understanding of canopy reflectance (Jacquemoud & Baret, 1990; Andrieu *et al*., 1997). However, it is not yet a practical solution since it first has to overcome the implications of differences in genotype and phenological stage on canopy architecture (Baret, 2001b) leaf nutrient and water status, and atmospheric interaction (Baret, 2001a) on model behaviour. For this approach to work, a vast database of respective model parameters must be collected and continuously updated. The interactions of crop management effects through the use of agrochemical inputs that modify the structure and reflectance properties of a canopy, for example, the effect of using nitrogen, plant growth regulators, or fungicides, must also be built into the canopy model processes and characterised in the database of model parameters. This was beyond the scope of this work where immediate integration into the field management processes was important.

This study aims to develop a practical method of producing accurate maps of shoot population and GAI for integration into a larger five-year precision farming project funded by the Home Grown Cereals Authority (HGCA). The initial part of this paper reviews a field study to establish the fundamental relationship between normalised difference vegetation index (NDVI) and shoot population in order to develop a calibration technique to produce maps of canopy variables from NDVI images with minimal ground calibration. From this, a rapid calibration protocol is proposed, evaluated and adopted for use over a four-year period. Examples of the results of its application are presented.

2. Technical approach

2.1. *Equipment*

Remotely sensed image data were collected using the aerial digital photographic (ADP) system, as shown in *Fig.* 1, comprising two Kodak DCS420 digital cameras (Graham, 1994) mounted in the base of a light aircraft's fuselage to provide vertical photography. Optical band-pass filters were selected to correspond to the red and near-infrared bands and fitted in front of each camera's 18 mm, optics respectively. The red waveband was centred at 640 nm with a band width at half the maximum transmission of 10.4 nm, and the near-infrared waveband at 840 nm with a band width at half the maximum transmission of 11.7 nm. Each camera had a 13.8 mm by 9.2 mm charged-coupled device array exposed for 1/125 second at an f-stop of 3.5. Flown at 1000 m above ground level, the system produced a field-of-view of *c*. 500 m by 750 m, with a ground-pixel dimension of 0.5 m by 0.5 m. Using a remote shutter triggering mechanism, image pairs were acquired simultaneously and stored on two separate hard disks.

2.2. *Image processing*

The R-NIR image pairs were geometrically co-registered to remove inherent mis-alignments caused by the cameras' slightly different view-points. Typically, offsets were equivalent to between 5 m and 10 m on the ground. The images were then geo-referenced to the UK Ordnance Survey of Great Britain (OSGB) map coordinate system to within an accuracy of 1 m.

The NDVI is often calculated from derived reflectance values (Wiegand, *et al*., 1991; Price, 1992), alternatively, it can be derived from radiance values or from raw digital number (DN) values (Goward *et al*., 1991) recorded by a sensor. Although each method of calculation leads to different NDVI values, they are linearly inter-correlated. Full radiometric calibration is only required if inter-comparisons of NDVI are to be made between different dates, between different sensors or between different solar zenith angles. This work required only the relative differences of the NDVI across localised areas – individual or adjacent groups of agricultural fields. The NDVI would be used for location-specific and date-specific calibration by empirical relation with ground observations using a regression-based statistical calibration procedure. As such, the use of raw DNs for determining NDVI was appropriate and Eqn (2) was applied to each image to provide the basis for selecting appropriate calibration sites to measure shoot density or GAI.

$$I_{NDV} = (\lambda_{DN840} - \lambda_{DN640}) / (\lambda_{DN840} + \lambda_{DN640}) \tag{2}$$

where: I_{NDV} is the normalised difference vegetation index; and λ_{DN640} and λ_{NDN840} denote the use of digital numbers measured at the red and near infrared spectral wavebands

2.3. *Statistical regression technique*

The number of shoots in wheat and barley can be directly related to the number of developed leaves (Kirkby, 1994) and, hence, to biomass and GAI. Tucker (1979) has shown that during the early phases of crop development the relationship between NDVI and biophysical parameters such as GAI and biomass is linear. According to Asrar *et al*., (1984) when the GAI reaches 4-5 the NDVI saturates, and the relationship becomes asymptotic.

Linear regression was used to determine the relationship between airborne image NDVI image values and ground-based measures of shoot density. The parameters of the regression equation were used to provide the calibration coefficients used in Eqn (3):

$$S_{xy} = \beta I_{NDVxy} + \alpha \tag{3}$$

where S_{xy} is the estimate of shoot population in units of shoots m^{-2}; and I_{NDVxy} is the equivalent image NDVI value at pixel co-ordinate (x,y); and α and β are regression parameters. The calibration equation can be applied to the NDVI image data to make estimates of shoot density at every pixel location in the field. The associated standard error (SE) of the mean is used to produce the appropriate confidence intervals for the estimate.

It is important to note that genotype, phenological stage, tissue nutrient status, atmospheric interactions, irradiance levels and the sun-sensor-target geometry could affect the regression parameters. Thus, the regression parameters are expected to differ between image acquisition dates, requiring each image-set to be calibrated individually.

2.4. *Shoot population*

Shoot population is defined as a count of both the main stem and tillers (Tottman, 1987). Populations were counted in 0.5 m by 0.5 m quadrats. The row spacing of cereal crops could vary between fields from 120 mm to 160 mm depending on the dimensions and settings of the specific seed drill. Hence, a field could have either four or five rows included in each quadrat measurement. In this work, a standard number of rows were selected within each individual field.

3. Initial calibration procedure

The first ADP image (*Fig.* 2) was acquired on 5th May 1996 of a field of winter barley cv. Intro (*Hordeum vulgare* L.). Visual interpretation identified three levels of variation:

(1) a dominating striping effect between tramlines, attributed to an uneven application of nitrogen fertilizer from a spinning-disc spreader;

(2) a low-frequency, field-scale variation from east to west – somewhat masked by the striping; and

(3) localised crop damage attributed to grazing rabbits, glyphosate drift and possible slug damage, all characterised by moderate to severe patches of bare soil.

Sample analyses were conducted at four sites, A, B, C and D, shown in *Fig.* 2, to quantify the across field variation. At each of these four sites a grid of 25 quadrats comprising a matrix five positions each with five replications which were aligned as shown in *Fig.* 2. These were used to assess the localised variation and the between-tramline striping effect. The shoot population was measured in each of hundred 0.25 m^2 quadrats. The locations of the sample sites were fixed by ground measurement relative to the tramline system, which was clearly visible in the ADP images. Equivalent NDVI values were extracted from the images.

3.1. *Results of the initial calibration.*

The relationship between the NDVI values derived by ADPand ground measurements of shoot population for the individual quadrat positions (four sites, each with 25 quadrats) in *Fig.* 4 shows a significant linear trend (probability <0.001) with a standard error (SE) of 121 shoots m^{-2}. The coefficient of determination of 0.37 indicates a high degree of scatter about the regression line, which is especially present at the low NDVI-shoot values taken from site D.

The cause of the scatter in site D (*Fig.* 2) arises due to a high degree of localised variability in crop cover, coupled with a certain degree of error in locating quadrats positions in the field, estimated to be *c*. 1 m.

The effect of the scatter can be reduced significantly by spatially averaging measurements over a larger area. This process also provides a better estimate of the local mean shoot population, reducing the errors introduced by edge-effects (Bloom *et al*., 1985) and counting errors. Averaging the 'replicates' at each site (*Fig.* 3) improved the regression to an coefficient of determination of 0.74, whilst not affecting the overall relationship as shown in *Fig.* 5. Using parallel lines analysis (McConway *et al*., 1999) to test the statistical difference between the regression parameters of two or more lines, the effect of spatial averaging was shown to produce no significant difference (probability of 0.69). By averaging all 25 quadrats at each site, the regression line was not significantly different to the position-level results (probability of 0.61) and the coefficient of determination was improved to 0.99.

The above results show that a high proportion of the scatter in the relationship between NDVI and shoot population is attributable to highly localised variations in the crop canopy at a scale where co-location of the NDVI observations with individual quadrat measurements is not sufficiently accurate. Also, the high number of samples renders the approach uneconomic for operational use presenting a need to investigate the potential for reducing the number of observations. For practical precision farming purposes, highly localised crop variation measured by individual quadrats is not feasible to manage and underlying larger scale trends are more important. Thus localised averaging is justified to mask the small-scale variation and the co-location errors.

At the replicate level five possible quadrats are available for averaging. Figure 6 presents five regression lines based on the arithmetic means derived from including five, four, three and two adjacent quadrats per replicate, it also includes the regression line based on using only one quadrat per replicate. Each regression is calculated with 18 degrees of freedom. The results indicate two distinct groupings: '1' and '2' fall into one group, and '3', '4' and '5' fall into another. Compared to using five replicates, '4' and '3' are not significantly different (probabilities of 0.54 and 0.70, respectively); they also have a similar SE of *c*. 60 shoots m^{-2}. When using only two or one of the replicates, there is a much higher variance and regression lines are significantly different (probability <0.05) with higher associated SEs of 86 and 142 shoots m^{-2}, respectively. From this it was concluded that three replicates (quadrats) can be used to estimate the local mean. The sub-sample of three will be referred to, hence, as a 'triplicate'.

4. Rapid calibration methodology

The previous section identified the appropriate use of local triplicates of quadrat observations to assess crop parameters for correlation with ADP. This section seeks the minimum number of observation sites. Eqn (4) (Burt & Barber, 1996) shows that the standard error (SE) of the regression estimate is a function of the degrees-of-freedom, and that the number of samples required to achieve a certain SE can be determined theoretically, it was on this basis that the 'optimum' sample number was derived.

From Eqn (4) it can be shown that eight calibration points provides an optimum number for linear regression. Assuming a constant variance, the effect of changing the number of calibration points can be expressed as a factor of 1/√n, where n is the sample number. Increasing the number above eight causes a marginal reduction in the SE (<1.0%); whereas, reducing the number below eight causes the SE to increase significantly. The effect of reducing the sample size from 20 down to eight (triplicates) is now evaluated.

$$E = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n-2}} \tag{4}$$

where, E is the standard error; Y_i represents each observed value of the dependent variable; $\hat{Y}_i$ represents its estimate from the regression; n is the sample number.

4.1. *Sample selection.*

Given that five replicates are available for each 'position' (*Fig.* 3), three combinations of triplicates are possible: '1-2-3', '2-3-4' and '3-4-5'. With five positions in each of four sites, 60 possible calibration 'triplicates' are available for selection. For this analysis, eight triplicates were selected on the basis of their NDVI value if they satisfied the following criteria.

(1) Samples must not be spatially auto-correlated (Burt & Barber, 1996) and adjacent positions are avoided.

(2) Samples must represent the complete range in NDVI values, and be equally spread over that range.

(3) Shoot averages derived from replicates '1-2-3', '2-3-4', or '3-4-5' are auto-correlated; if one of out the three is selected, the other two combinations are immediately removed from subsequent selections.

(4) Similarly, each set of eight must be completely independent; once selected for one set of eight, a sample cannot be selected for a subsequent set.

On this basis, using the original data presented in *Fig*. 4, only two independent sets of eight points are possible; these are referred to as 'set 1' and 'set 2'.

4.2. *Rapid calibration results*

As shown in *Fig*. 7, reducing the sample size from 20 to eight led to no significant difference between regression lines (set 1, probability of 0.52; set 2, probability of 0.54). Based on this result, the rapid field calibration protocol, given in Table 1, was proposed and used over the remaining four years of the project. A total of 32 individual ADP calibration surveys were completed at key growth stages in December (early tillering), February (late tillering), March-April (stem extension), and in May (anthesis).

A summary of the ADP linear regression results are presented in Table 2 for both GAI (*Fig*. 9) and shoot population (*Fig*. 10). As expected, the regression line parameters for each date were different, but each had high values for the coefficients of determination (44% with a coefficient of determination over 0.9; 72% over 0.8; and 85% over 0.7) and most had relative standard errors between 10% and 15%.

Fields would ultimately be zoned into broad category ranges, e.g. 200-300 shoots m^{-2}. With standard errors typically in the range of 50-150 shoots m^{-2}, the regression results were considered satisfactory for image calibration in the context of practical precision farming management. *Fig*. 10, is an example, which shows the effects of deliberate changes in shoot population by varying seed rate. The field is zoned in increments of 250 m^{-2} indicating shoot populations less from than 250 shoots m^{-2} to in excess of 1300 shoots m^{-2}.

5. Extension to the farm-scale

In the initial calibration procedure, and for the duration of the project, the 'survey region' was limited to the individual field. If varieties are similar and grown under the same management practices, then the same regression relationship could apply to extended blocks of adjacent or nearby fields. This section investigates the use of a single regression line' for relating NDVI with shoot population with the purpose of calibrating large blocks of fields.

5.1. *Methodology*

Following the procedure of the rapid calibration methodology, 11 fields of winter wheat, cv. Consort and Rialto (*Triticum aestivum*) were surveyed. On 19th April, 2000 an ADP survey was undertaken to capture a series of R-NIR images at *c*. 1 m pixel resolution. The aerial survey was flown in transects designed to provide overlapping imagery: 30% side-lap and 60% end-lap. The survey was flown twice within minutes of each other to ensure a high probability that individual fields were captured in a single frame with similar illumination conditions.

Images were geo-referenced using digitised 1:25,000 map sheets, and Eqn (4) applied to individual frames to calculate the NDVI for all fields. Only one field required two images to be mosaiced to produce a complete NDVI image of that field. The remainder were contained within individual frames. Radiometric balancing between frames was not performed since the time interval between all image frames was minimal and extraneous factors could be assumed to be constant – the normalising effect of the NDVI would reduce errors introduced by extraneous factors (Baret & Guyot, 1991). Field boundaries were digitised from the images and used to extract NDVI images of all eleven fields as shown in *Fig*. 11.

In accordance with Table 1, after image acquisition and prior to ground surveying the farm, eight calibration points were selected based on sample regions at two geographic scales:

(1) field scale – eight points per field were selected in each of the 11 study fields; and

(2) farm scale – eight points were selected to represent the whole farm, such that all 11 fields were treated as one single management block.

Individual regression lines were compared for statistical similarity both between fields and against the farm-scale regression using the technique of parallel lines analysis used earlier (McConway *et al*. 1999).

5.2. *Results of the farm-scale test*

The individual regression lines for each field and at the farm-scale are plotted in *Fig*. 12. The results indicate a range in regression lines, which show that ten fields were not significantly different from the combined regression line, but one was, which is centred at OSGB 532750, 231000 shown in *Fig*. 11. This field was characterised by a high level of medium-scale crop variation attributed to the underlying field drainage system which, when combined with a potential quadrat location error of *c*. 1 m, achieved when using differential global positioning systems, produced a high degree of scatter, resulting in a significantly different regression (probability of 0.045). As a result of the uncertainty associated with the estimation of the regression parameters within this one field, and that all other regression relationships were not significantly different, there was evidence to propose a single, universal farm-scale regression independent of the two varieties

To quantify the effect of varietal differences, all shoot population measurements were split into their respective varieties and regressed with NDVI as shown in *Fig*. 11. This shows that, despite Rialto having a higher value for the coefficient of determination and a lower SE compared to Consort, the two regression lines were not significantly different (probability of 0.51). Pooling both varieties which did not significantly degrade the model fit, demonstrated commonality between Consort and Rialto, in this case.

In comparing the ‘full’ farm-scale regression, using all points, with the farm-scale set of eight in *Fig*. 14, the regression results were shown not to be significantly different (probability of 0.87).

The results above indicate a single farm-scale regression relationship with the possibility that it can be estimated from only eight appropriately selected calibration points. However, to fully evaluate whether the relationship between the farm-scale set of eight and the full farm scale regression is real, and not due to random chance, a statistical simulation study was conducted.

5.3. *Farm-scale simulation study.*

The simulation study was conducted on 60 alternative sets of eight calibration points, extracted from the original 88 field measurements (eleven fields with eight points in each). All 88 data points were ranked by their NDVI value and grouped into eight equal-interval classes and provided the basis for stratified, random sampling. From each class in turn, single points were randomly selected to derive a new set of eight, and repeated 60 times to provide the alternative sets of eight – out of a possible 11^8 combinations.

The individual regressions were then compared to the full farm-scale regression and assessed for statistical similarity. Furthermore, to determine whether there were any practical differences between results, calibrated shoot maps were generated from each set of regression results and zoned to produce a 'typical' nitrogen application map (Wood *et al.*, 2002). A 'definitive' map was derived using the full farm scale regression. Each alternative map was compared to determine the level of correspondence between zones using a measure of 'agreement' (Rosenfield & Fitzpatrick-Lins, 1986).

In addition, the 'full' regression was used to produce a definitive application map against which each 'new' application map would be assessed in terms of its level of agreement. On this basis, an assessment of the 60 combinations would provide a probability distribution indicating the likelihood of successful calibration when using only eight points.

5.4. *Results of the simulation*

By stratifying the data points and constraining the selection to be representative of the full range of NDVI, a high probability of statistical similarity could be expected along with a corresponding high level of agreement between application maps. The results indicated an 83% probability of statistical similarity and a 73% probability that calibration would produce a coefficient of agreement greater than 80%. In reviewing the remaining 20-25%, it was shown that these data sets comprised points with a poor geographical spread. In order to avoid this, a further constraint would be to limit one calibration point per field.

Out of the 60 sets of eight, only 3 satisfied these criteria: the original set of eight selected prior to the farm visit, and two others, referred to as set 1 and set 2 as given in *Fig*. 15. When calibrated, the respective treatment maps had coefficients of agreement of 99%, 76% and

96%. Since this data set is limited, only tentative conclusions can be drawn. However, these results indicate that there is an opportunity to move to a rapid farm-scale calibration procedure with a 75-99% accuracy.

6. Applications

The results presented here demonstrate a practicable means of providing accurate and cost effective shoot population and GAI maps, where the cost is estimated by Godwin *et al.* (2002) to be £7 ha^{-1} for acquiring the ADP images and for undertaking the necessary ground calibration. As such, the approach is suitable for adoption within the agricultural management sector and more specifically for precision farming management.

The benefits of using calibrated images for wheat management has been shown by Wood *et al.* (2002) to reach £60 ha^{-1}. This was achieved by using calibrated ADP images at early growth stages (shoot density in early March, and GAI in late March and April) to monitor the progress of wheat canopy growth and comparing the status at each date to pre-defined benchmark targets for management published by the HGCA (1998). Areas over, under or on-target had fertilizer nitrogen levels adjusted accordingly. Using a more simplistic management approach of adjusting fertilizer nitrogen according to *relative* differences, indicated in the calibrated images, was shown by Welsh *et al.* (2002a) to improve gross margin benefits by up to £23 ha^{-1} in barley, and up to £30 ha^{-1} in wheat (Welsh *et al.*, 2002b). These figures are net margin benefits with the cost of calibrated imagery taken into account.

In a report published by Berry *et al.* (1998), 91% of 340 surveyed fields exhibited some degree of lodging, resulting in 16% of the total area lodged costing the UK wheat industry

£60 million through lost yield, and a further £60 million through lost bread making premium, grain drying costs and delayed harvest. The report adds that, although a variety of weather, crop and soil factors can influence lodging, variation in the structure of wheat crops – including shoots density and GAI – influenced the risk of lodging. Calibrated ADP images could, therefore, serve as a predictive tool for lodging risk and used in conjunction with variable-rate plant growth regulators and variable nitrogen to control lodging.

Images can also be used as a diagnostic. Referring back to Figure 8 shows a GAI map with a distinct low GAI area dominating the field with contrasting linear features of higher GAI corresponding to the tile drain system. A failure in the mole drain system led to severe waterlogging with only those areas directly overlying the tile drains benefiting from free drainage. The northern corner of the field, which occupies a marginally higher elevation, had a GAI > 2.0, which represents the condition that the whole field should have been in to realise its full yield potential. In conjuction with combine yield data, the image was used to identify the worst affected areas which suffered yield penalties of up to 3 t ha^{-1}, which could have been rectified for a one off cost of £50 ha^{-1} (Nix, 2000) for re-moling the site and clearing blocked drain outlets which could have an economic life in excess of 5 years.

Weeds present a problem to the calibration process because they contribute an added reflectance signal that cannot be de-coupled from the crop reflection resulting in over-estimation of shoot density or GAI. The affect on calibration accuracy resulting from different degrees of weed presence was not investigated, although it should be normal management practice to maintain a clean crop and avoid weed problems. However, weeds are persistant and remote sensing can offer a means of assisting in mapping them for the purposes of patch spraying (Godwin & Miller, 2002). The development of patch spraying systems such as that described by Miller *et al.* (1998) provide systems that could deliver a variable rate volume application with a 5:1 range but with no change in spray quality. Based on a time sequence of ADP images within a growing season, a patch of weeds will manifest itself as an anomolous area of high NDVI values, increasing over time at a rate greater than expected for normal crop growth. Equally, a late senescence image will reveal patches of summer weeds, which, although may not affect yields as greatly as winter or spring weeds, may interfer with the harvesting of the crop. Over a number of years a series of images will also reveal patches of weeds that have been shown to be stable for some grass weeds as reported in Godwin and Miller (2002).

Maps of canopy density provide an additional opportunity for targeting more efficient use of foliar fungicides. Bjerre and Secher (1998) state that although the appropriate dosage to control diseases can vary according to a combination of the disease incidence and physiological response of the plant to light conditions and nutritional status, the efficacy of the treatment is related to the concentration of the active ingredient on the leaf surface and, therefore, related to the leaf area index at the time of application. In their experiments Bjerre and Secher adjusted the dose of fungicide in proportion to the canopy density using previous years' yield maps as a surrogate estimate of the current year's canopy density since they had no means of measuring this for the current crop. Their work showed positive results although they acknowledged that historic yield data is a poor surrogate for estimating shoot density and spectral reflectance from vehicle mounted sensors (and potentially ADP could be used in the same way) could privide a basis for varying fungicide doses within a field.

7. Conclusions

The relationship between the normalised difference vegetation index and ground measurements of shoot population or green area index, in wheat and barley, shows a linear trend at crop growth stages up to the end of stem extension (GS39). Modelling the trend by linear regression is greatly improved by spatially averaging measurements over localised geographic areas rather than at single-point locations.

Three 0.25 m^2 quadrat replicates are needed for localised averaging. Increasing the number of quadrats to four or five shows no significant improvement in the subsequent regression, whereas reducing this number to two or one produces erroneous results due to a greater chance of including anomolies such as localised crop damage.

To derive the regression parameters for calibration, eight points were shown to provide an optimum standard error of the estimate whilst retaining the robustness of the regression relationship. The eight points were chosen to represent the range in the NDVI present in a field and had a good geographic distribution, with local sub-samples of three quadrats. This formed the basis of the rapid calibration approach methodology.

Over the duration of four years' repeated application, the rapid calibration methodology provided satisfactory results for the requirements of practical crop management, with over 85% having a value of the coefficient of determination greater than 0.7 and relative standard errors of 10-15%.

For groups of adjacent or nearby fields grown in single management units – similar varieties, sowing date and cultural practice – it may be possible to use a single regression line to calibrate all fields. In this study, winter wheat was tested and only two varieties were available, Consort and Rialto, which exhibited the same regression relationship. Other, smaller shoot-sized varieties could exhibit different a relationship and should be considered seperately before pooling measurements over blocks of mixed varieties.

Providing the selection of calibration sites is constrained to represent the range in NDVI with sites having a good geographic distribution and seperation, there is an 80-95% probability that random selection of sites should produce both stable regression lines and stable management maps (75-99% accuracy).

Whether the field or the ‘management block’ is the sample region, the sampling protocol is otherwise the same.

(1) Zone the field into eight equal ranges of NDVI.

(2) Within each zone, randomly select one calibration site, to provide eight sites in total.

(3) On choosing sites, ensure that each one is geographically distinct and, together, represent the whole sample region (i.e. field or block).

(4) At each calibration site, ground sample shoot density or GAI using three 0.25 m^2 quadrats arranged in a triangle with sides of 2 m; the three will provide a single site average.

Since individually fields will be visited periodically for crop scouting or management purposes, the requirement to make measurements at one site per field, for eight fields, provides a manageable and quick exercise for the farmer, agronomist or technician.

especially considering the enormous value that such management information will provide to the grower. At a cost of £7 ha^{-1} and potential benefits of up to £60 ha^{-1}, the use of calibrated remotely sensed data for precision farming management offers a very attractive approach to cereal production.

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Figures for:

Calibration Methodology for Mapping Within-Field Crop Variability using Remote Sensing

Gavin. A. Wood; John C. Taylor; Richard J. Godwin

Table 1
Rapid field calibration protocol

Step	*Action*
1.	Use a current NDVI image as a basis for selecting calibration sites.
2.	Choose 8 sites that represent the complete range of NDVI, and select sites with values spread equally over that range.
3.	Measurements between calibration sites must not be spatially auto-correlated.
4.	Measurements must be spatially distributed to ensure representation of the whole field.
5.	At each site, measure the crop parameter of interest (e.g. shoot density or GAI). using a sub-sample of 3 x 0.25 m^2 quadrats*.
6.	Extract equivalent NDVI values from the image and regress against the crop parameter measure in ‘5’.
7.	Apply the regression equation to the entire NDVI image.

*Although triplicates were arranged in a straight line in the original survey, a move to a triangular arrangement was proposed so that the three sub-samples are at equal distances (2 m) from each other.

Table 2.
Summary of ADP-NDVI regressions ranked by r^2 value for five fields in the UK.

Survey date	*Field name*	*slope*	*p*	*offset*	r^2	*Standard error (shoots.m^{-2})*	*Standard error (% of mean)*
11-03-99	Onion	3439.0	**	-308.2	0.97	83	11
09-05-98	Onion	4421.0	**	-2964.9	0.97	11	3
04-12-99	Far Highlands	2242.0	**	100.2	0.95	44	12
05-03-98	Onion	11200.7	**	-7228.0	0.95	119	9
12-12-97	Onion	5013.1	**	-2279.7	0.94	68	12
14-03-99	12 Acres	2518.3	**	465.1	0.93	42	7
07-04-00	Far Sweetbrier	1724.9	**	140.2	0.92	86	10
15-04-99	Onion	2267.9	**	-167.4	0.92	106	18
22-12-97	Trent†	10688.6	**	-4975.1	0.91	136	14
25-05-97	12 Acres	1476.2	**	-527.0	0.91	40	12
15-12-99	Trent†	5045.0	**	451.8	0.91	83	11
07-04-00	Trent†	3485.8	**	83.9	0.91	153	11
14-03-99	Trent†	3341.1	**	1313.5	0.90	89	9
30-04-99	Onion	1313.1	**	135.7	0.87	97	16
05-03-00	Far Highlands	2148.1	**	395.6	0.87	152	16
07-04-00	12 Acres	2638.1	**	205.6	0.86	55	10
28-02-98	Trent†	4128.0	**	1555.0	0.84	184	14
27-01-00	Far Highlands	5550.0	**	577.9	0.84	162	19
25-05-99	Trent†	5449.0	**	-2332.7	0.83	53	7
27-06-98	12 Acres	1595.6	**	-469.8	0.82	34	8
05-05-96	Trent†	1435.9	**	-85.2	0.82	55	9
05-03-00	Onion	1716.2	**	298.9	0.82	120	22
05-03-98	Far Sweetbrier‡	4761.8	*	-1568.6	0.78	127	9
02-02-00	12 Acres	3072.7	**	217.7	0.77	71	14
27-05-99	Onion	1885.9	**	-159.3	0.74	82	17
05-03-00	Far Sweetbrier	4143.2	**	1429.7	0.72	310	27
21-01-00	Onion	2752.8	**	408.1	0.72	133	30
28-02-98	12 Acres	1014.1	*	1020.5	0.63	82	8
02-02-00	Trent†	5675.5	*	564.6	0.63	302	30
25-05-99	12 Acres	2030.3	*	-592.2	0.60	63	11
07-04-00	Onion	1281.6	**	-41.2	0.60	114	22
22-12-97	12 Acres	6206.1	*	-2560.7	0.57	246	19

Survey date	*Field name*	*slope*	*p*	*offset*	r^2	*Standard error (GAI)*	*Standard error (% of mean)*
11-03-99	Onion	7.4	**	0.14	0.96	0.20	14
05-03-00	Far Highlands	2.5	**	0.38	0.74	0.28	28
20-05-00	Onion	33.4	0.089	-14.57	0.36	1.00	25
07-04-00	Onion	3.1	0.120	-0.13	0.31	0.50	33

** denotes >99% probability and * denotes >95% probability. All fields were sown with winter wheat (*Triticum aestivum*) except: †winter barley (*Hordeum vulgare* L.) and ‡spring wheat.

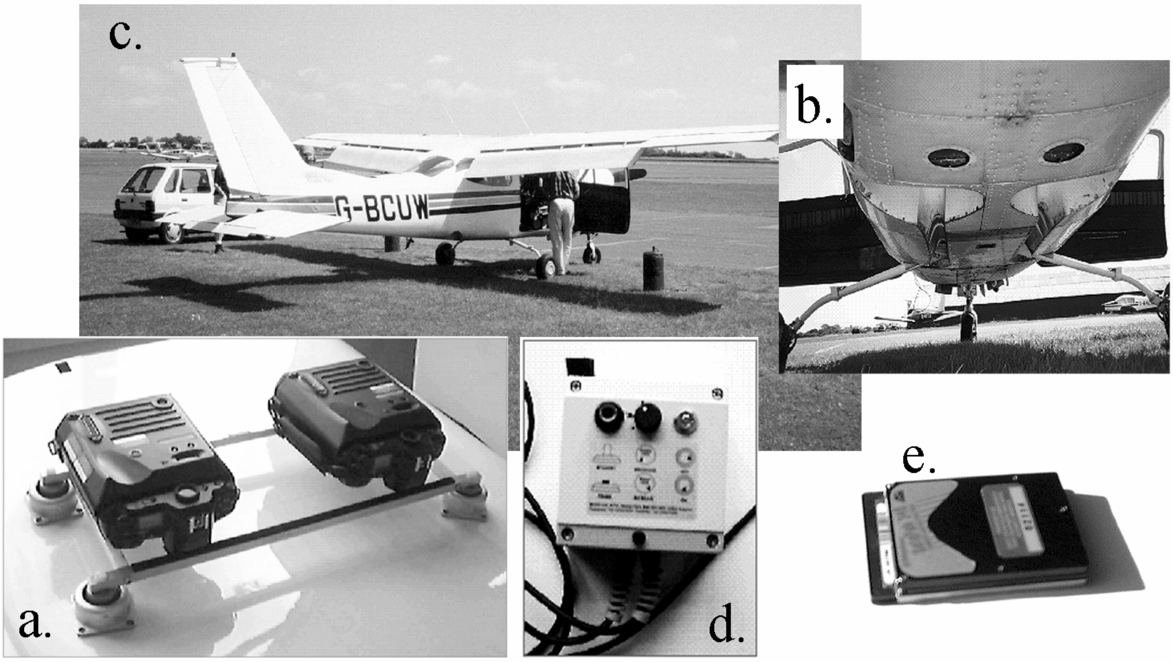

Fig. 1. Airborne digital photographic (ADP) system: two Kodak DCS420 cameras (a), pointed downwards through two camera portholes (b) mounted a light aircraft (c). Camera trigger (d); a camera's internal 520 MB hard disk (e)

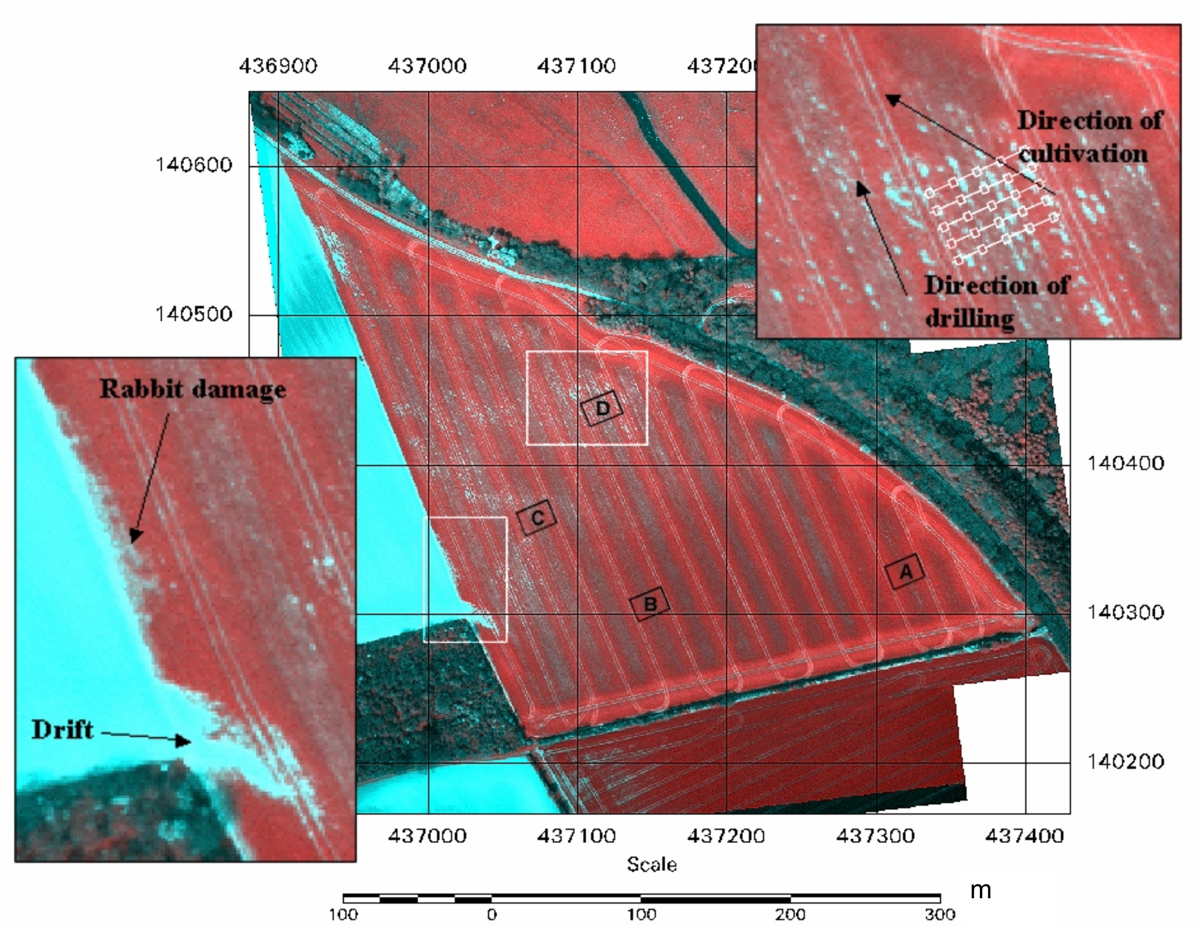

Fig. 2. False colour composite at wavelengths of 640 nm in blue/green, and 840 nm in red of Trent Field, Andover, 5th May 1996 rectified to the Ordanance Survey Great Britain (OSGB) system; the general location of calibration sites A, B C and D is indicated, annotated with examples of crop damage
(Permission to survey courtesy of Roger Dines, Wherwell, Hampshire, UK)

Colour Print and Online

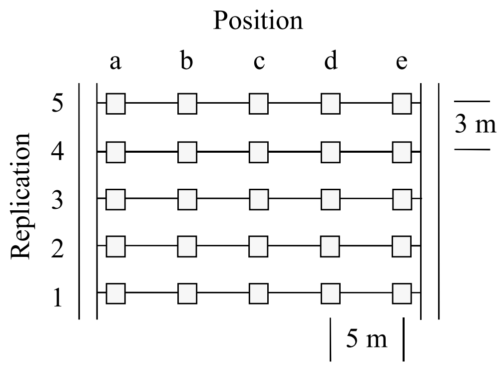

Fig. 3. Pattern of sample sites between tramlines at each of four locations within the study field

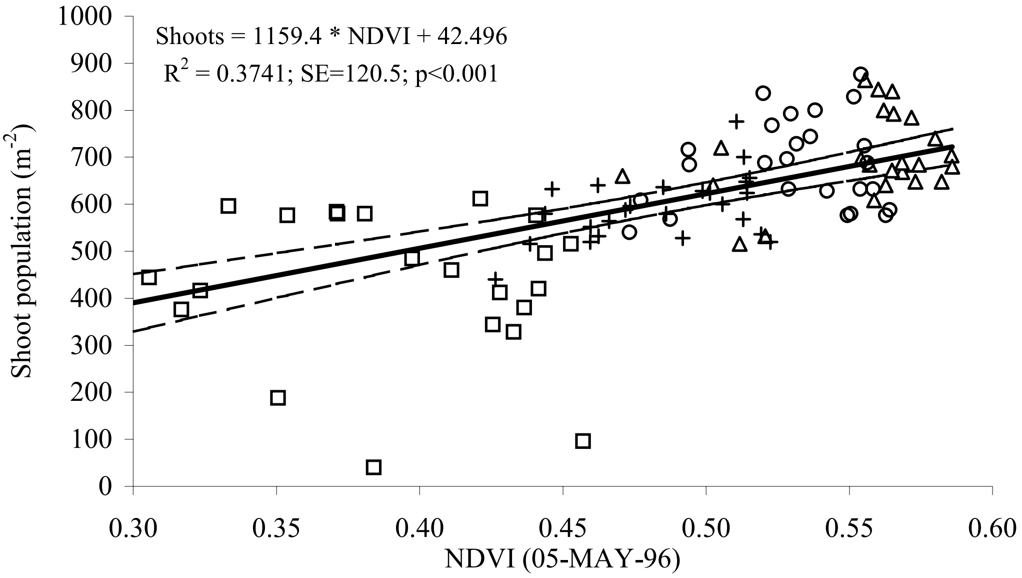

Fig. 4. Normalised difference vegetation index (NDVI) vs. shoot population for Trent Field, 5th May 1996 based on individual quadrat observations; △, Site A; O, Site B; +, Site C; □, Site D; ——, regression line; - - - - -, 95% confidence interval

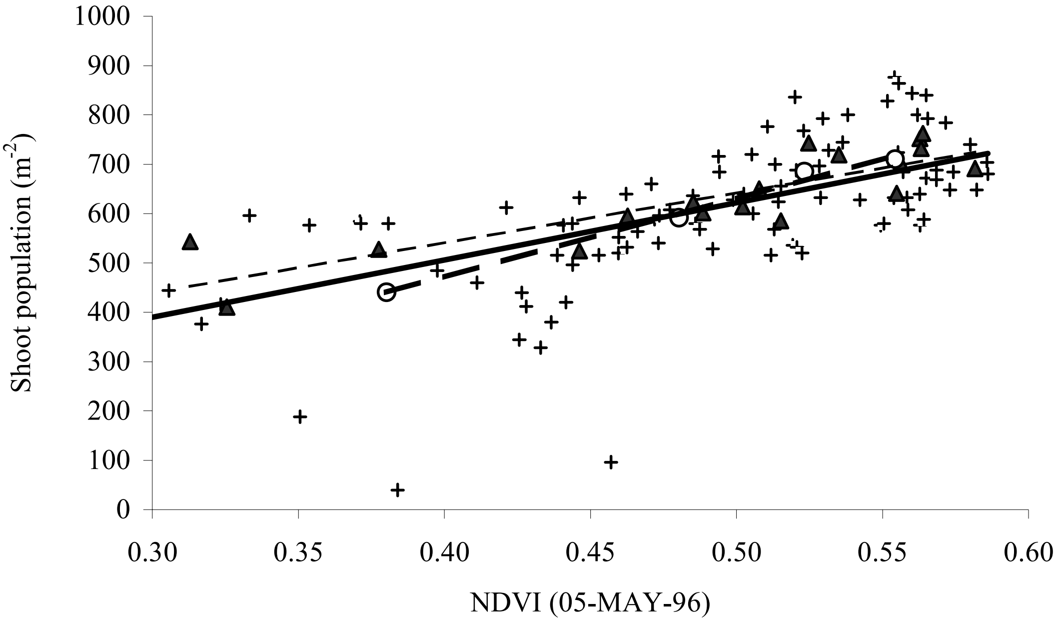

Fig. 5. The effect of spatial averaging on the regression relation between points at individual positions (r^2=0.37), 'replicate' averages (r^2=0.69), or 'site' averages (r^2=0.99): +, Individual quadrats; ▲, Average position; O, Average site; ——, Individual quadrats regression; - - - -, Average position regression; — — —, Average site regression.

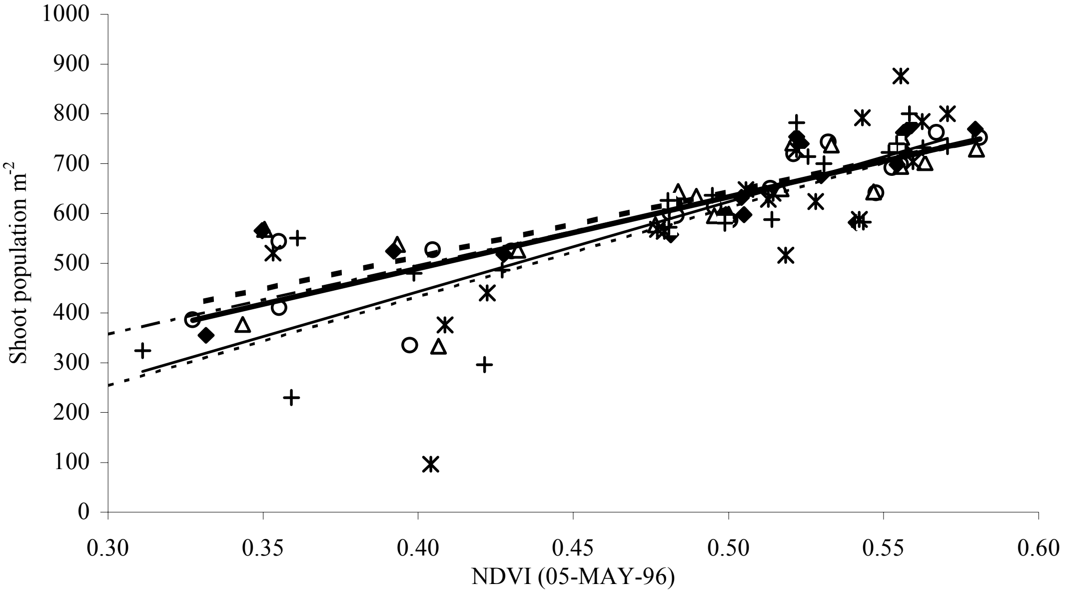

Fig. 6. The regression results at the 'replicate' level representing the effect of estimating local averages using 1, 2, 3, 4 or 5 quadrats; the 5-quadrat regression line represents the 'replicate' result illustrated in Fig. 5:
O, 5 quadrats;, △, 4 quadrats; +, 2 quadrats; ✱, 1 quadrat; ◆, 3 quadrats; ——— 5 quadrats regression; -·-·-, 4 quadrats regression; – – –, 3 quadrats regression; ———, 2 quadrats regression; ...., 1 quadrat regression

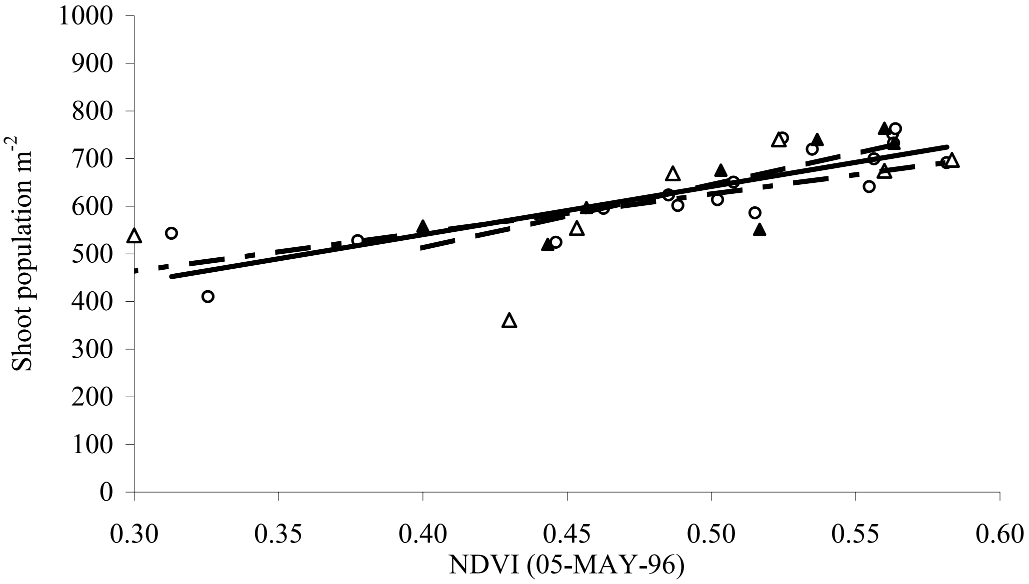

Fig. 7. Relationship between Normalised difference vegetation index (NDVI) and shoot population. The regression lines represent the results using the rapid calibration methodology (sample size=8) compared to the full data set (sample size=20)

○, full-set (sample size=20); ▲,set 1 (sample size=8); △, set 2 (sample size=8); ——, full set regression; — —, set 1 regression; — · -, set 2 regression

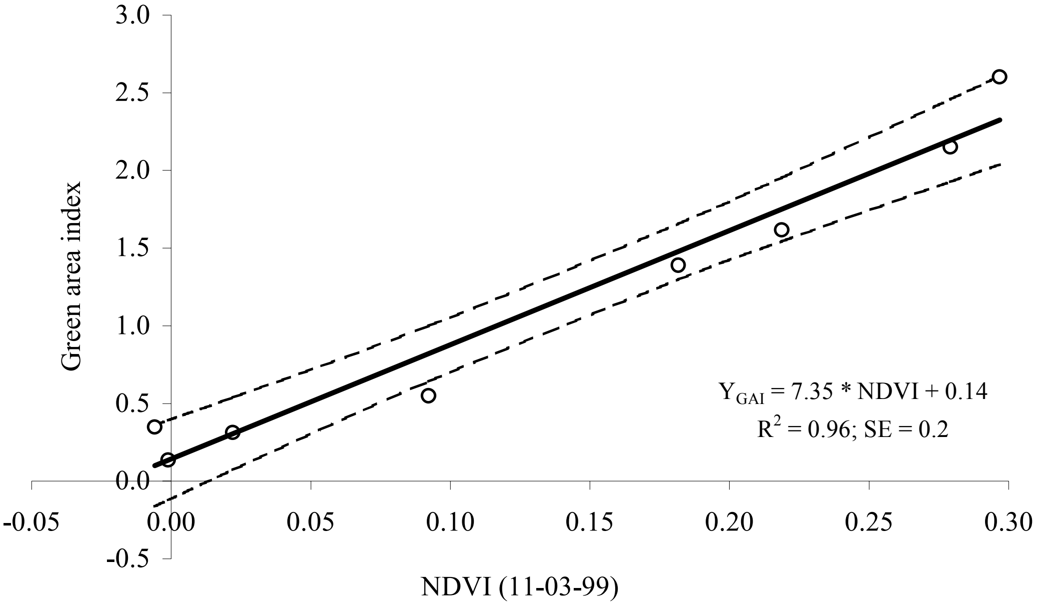

Fig. 8. An example of the relationship between Normalised difference vegetation index (NDVI) and Green area index (GAI) during stem extension in a field of winter wheat in Bedfordshire:

———, regression; – – – ,95% confidence interval

Fig. 9. Normalised difference vegetation index (NDVI) vs. Green area index (GAI) regression relationship and calibrated GAI map for Onion Field, Bedfordshire, winter wheat cv. Malacca (Triticum aestivum), 11th March, 1999

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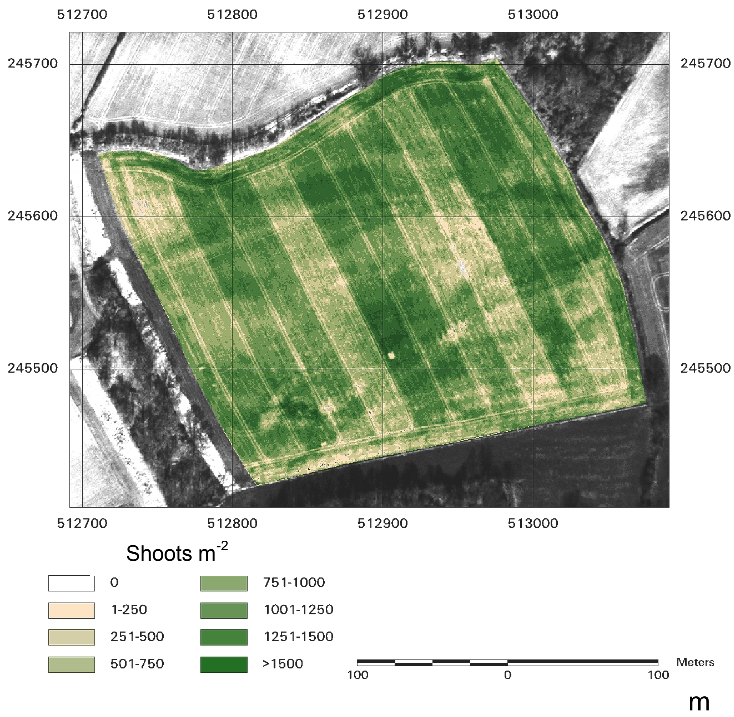

Fig. 10. Shoot population map of Far Highlands, Bedfordshire, winter wheat cv. Consort (Triticum aestivum) derived from calibrated airborne normalised difference vegetation index (NDVI) image, 5th March, 2000

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Fig. 11. Normalised difference vegetation index (NDVI) image of the farm-scale calibration test site derived by aerial digital photography (ADP); light-brown to dark-green indicating increasing NDVI, over-laid on a gre-scale, unbalanced mosaic of 640 nm ADP images
(permission to survey courtesy of John Dingemans, Rushden, UK)

Colour Print and Online

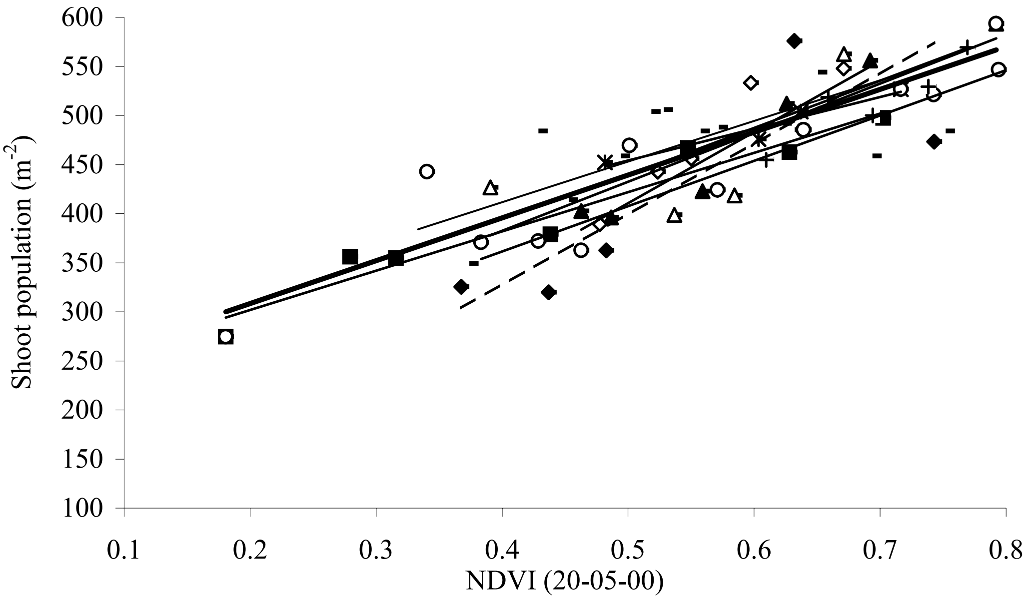

Fig. 12. Individual Normalised Difference Vegetation Index (NDVI) vs. shoot population regression for all fields, sample number=8 per field. The dashed line indicates the only field (field-centre co-ordinate indicated) with a significantly different regression line;○, xxx; △, xxx; ▲, xxx; +, xxx;□; ▪,xxx; ——— ,individual fields; - - - - field 532750,231000; ——— ,farm scale regression

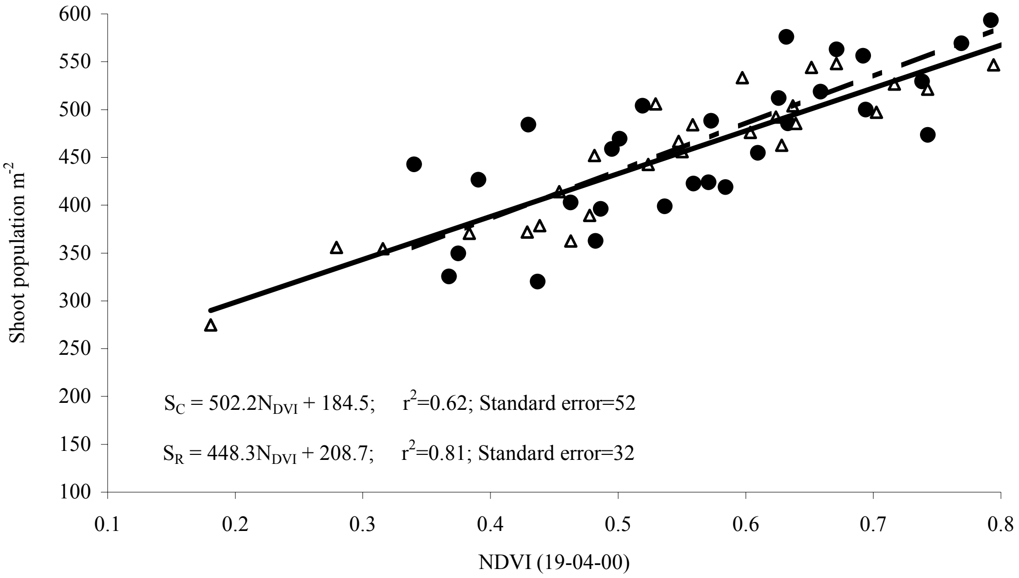

Fig. 13. Normalised Difference Vegetation Index (NDVI) vs. shoot population for Consort (S_C, 6 fields, sample number=48) and Rialto (S_R, 5 fields, sample number=40);

●, *Consort;* △, *Rialto;* — · -, *Consort regression;* ——, *Rialto regression*

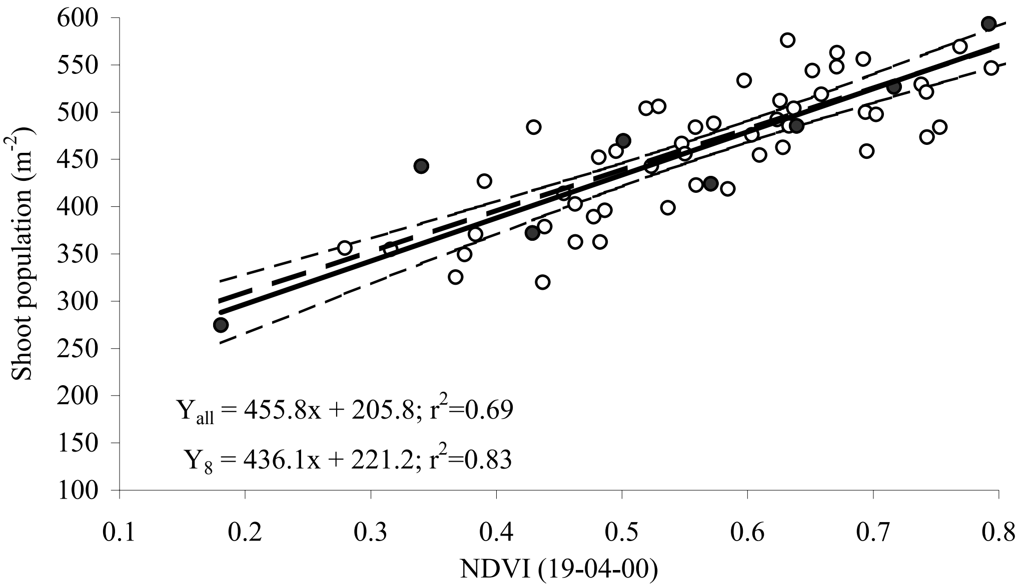

Fig. 14. Individual Normalised Difference Vegetation Index (NDVI) vs. shoot population comparing the full farm-scale set of data points with a reduced set of 8: ○, all data points; ●, a priori data set (sample number=8); – – –, 95% confidence interval; ——, all data points; -----, sample size=8

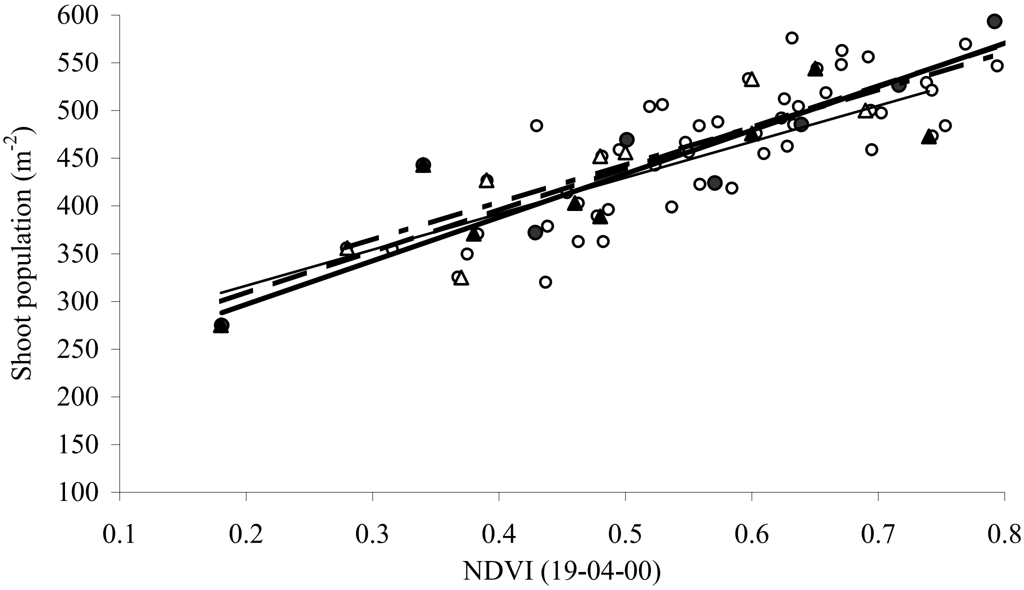

Fig. 15. Individual Normalised Difference Vegetation Index (NDVI) vs. shoot population - Comparison between the farm-scale regression line (derived from using all points) and two alternative reduced-sample regression lines: ○, all data points; ●, a priori data set (sample number=8); △, set 1 (sample number=8); ▲, set 2 (sample number=8); ——, all data points; – – –, a priori (sample number=8); – · –, set 1 (sample number=8)); ——, set 2 (sample number=8)