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# Automating nitrogen fertiliser management for cereals (Auto-N)

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## Abbreviations

| | |
|---|---|
| AFR | Apparent Fertiliser Recovery |
| AN | Ammonium nitrate |
| CCCI | Canopy Chlorophyll Content Index |
| C | Clay |
| CL | Clay Loam |
| CND | Crop Nitrogen Demand |
| CV | Coefficient of Variation |
| DM | Dry matter |
| DEM | Digital Elevation Map |
| EC | Electrical Conductivity |
| EF | Emission factor |
| EMI | Electro-Magnetic Induction |
| FNR | Fertiliser Nitrogen Recovery |
| GAI | Green Area Index |
| GHG | Greenhouse gas |
| GPS | Global Positioning System |
| HI | Harvest index |
| LAI | Leaf Area Index |
| LSD | Least significant difference |
| N | Nitrogen |
| NDVI | Normalised Difference Vegetation Index |
| $N_{opt}$ | Fertiliser Nitrogen optimal N requirement |
| $NO_3$ | nitrate |
| $NH_4$ | ammonium |
| NNI | Nitrogen Nutrition Index |
| OSR | Oilseed rape |
| P | probability |
| RB209 | Reference Book 209 – refers to official fertiliser recommendations published by MAFF or Defra |
| S | Sand |
| SCL | Sandy Clay Loam |
| SD | Standard deviation |
| SE | Standard error of a mean |
| SMN | Soil Mineral Nitrogen |
| SNS | Soil Nitrogen Supply |
| SOM | Soil Organic Matter |
| UAN | Urea Ammonium Nitrate liquid fertiliser |
| WW | Winter Wheat |
| Z | Silt |

# 1 Abstract

Uncertainty in estimating fertiliser N requirements is large, with differences between recommended and measured N optima frequently exceeding 50 kg/ha. Precision farming technologies including yield mapping, canopy sensing, satellite imaging and soil mapping are now common-place on farm. The Auto-N project sought to apply the information readily available from these technologies within an 'Auto-N logic' to improve the precision of N fertiliser decision making. The 'Auto-N logic' was derived from that used to estimate fertiliser N requirements as set out in the AHDB Cereals & Oilseeds guide *Nitrogen for winter wheat – management guidelines*; this guide suggests that N requirements should be calculated by subtracting Soil N Supply (SNS) from Crop N Demand (CND: grain yield x crop N content) and dividing by Fertiliser N Recovery (FNR); thus the 'Auto-N logic' uses yield and protein maps to inform estimates of CND, canopy sensing to inform estimates of SNS and soil sensing to inform estimates of FNR.

Novel chessboard N response experiments were set up on six commercial fields between harvest years 2010 and 2012 to quantify spatial variation in N requirement, to explain it in terms of CND, SNS and FNR, hence to develop the 'Auto-N logic'. At each site, each farmer applied N as liquid urea plus ammonium nitrate (UAN) using the farm sprayer twice, in perpendicular directions, to create a systematic grid of ~400 plots (~12m × 12m) fertilised with N rates of 0, 120, 240 or 360 kg/ha; the area of each experiment exceeded 4 ha. Grain yields were measured by small-plot combine, grain samples were analysed for protein, and N harvest index and total N uptake were determined from pre-harvest grab samples. Values were then estimated for all variates and all N levels for all plots by kriging. Response curves were fitted, and N optima and their components (SNS, CND, FNR) were derived assuming 5 kg grain would pay for 1 kg fertiliser N. Within field variation in optimum N exceeded 100 kg/ha at all sites; spatial variation in optimal yield was greater than 2 t/ha at all sites and variation in SNS was generally greater than 50 kg/ha. Some of the spatial variation in optimum N was explained in terms of SNS and CND. However, the tendency for positive correlations between SNS and optimum yield was striking, and hindered complete explanation of spatial variation in optimum N: i.e. high yielding areas tended to have greater SNS, so the increased requirement from higher crop N demand was counteracted by the reduced requirement from higher SNS.

Spatial variation in CND and SNS was reasonably well estimated from the use of past yield maps and crop sensing, respectively; often, similar within-field patterns showed through for both. However, variation in FNR was also large and was unpredictable. Using clustering techniques, zoning, performance mapping or simple averaging of data from five farms, it was shown that past yield maps could be used usefully to estimate variation in CND. In addition, variation in SNS could be predicted from canopy sensing in early spring (an algorithm was developed based on sensed NDVI and thermal time since sowing). Calibrations for crop N uptake, biomass and crop N status

(Nitrogen Nutrition Index) from canopy sensing were explored, but no rational basis could be found to justify their inclusion in the 'Auto-N logic'.

Validation trials were set up with farmers on 11 fields in 2013 & 2014; these used adjacent tramlines to compare the Auto-N logic with the farm's own practice, 50 kg/ha more N and 50 kg/ha less N.  Evaluation of these trials along with economic analysis of the chessboard trials showed the benefits of precision in judging N requirements to be modest, whereas benefits of accuracy (proximity to the measured mean) were much greater.  Whilst this work demonstrated the feasibility of automating judgements of N requirements within fields using precision information, the variability in CND, SNS and FNR, and crucially the interactions between them, meant that the use of such systems would not guarantee increased accuracy or precision of N use.  The evidence suggests that variable rate N management can give only modest returns, even with a system making perfect predictions, if the field is already receiving the right average N rate.

The results showed that the most important decisions concern N use for whole farms, then for whole fields, then for areas within fields.  Precision technologies can help with all of these, especially through comparisons of crops between and within farms.  However, the most effective aspect of precision farming technologies is probably the empowerment of farmers to test retrospectively the effects of their N decisions (or indeed any decisions) on-farm.  Given the variation in and unpredictability of N requirements between fields and between farms the only way farmers can know for sure whether their chosen N rates were right is to test yield effects of different N rates – this is relatively easy now, by simply applying (say) 60 kg/ha more and 60 kg/ha less to adjacent tramlines.

The chessboard trials initiated here have transformed our understanding of N responses and shown new possibilities for spatial experimentation, not only to empower on-farm testing, but to understand how soil variation affects husbandry outcomes.  These trials show that N use is not the major cause of the very large spatial variation seen in yield.  Thus, understanding the soil-related causes of yield variation should, and can, now become a priority for soil and agronomic research.

# 2 Introduction

The use of nitrogen fertiliser is crucial to modern arable crop production in achieving the yields required to meet the increasing global demands for food, feed and fuel from a rapidly expanding global population (Tilman et al., 2011). However, N fertiliser is associated with a range of environmental impacts (Sutton et al., 2011) including nitrate leaching, energy use through manufacture and greenhouse gas (GHG) emissions, predominantly through nitrous oxide ($N_2O$) emissions from soils (Brentrup et al., 2004; 2008). Indeed, N fertiliser and $N_2O$ can be responsible for more than 70% of GHG costs of arable crops such as wheat and oilseed rape (Berry et al., 2010; Sylvester-Bradley et al., 2014; 2015). Yields per hectare are also important to GHG emissions at a global scale through their indirect effects on land-use-change (Kindred *et al*., 2008); if reduced production from reduced yields in the UK are met by new production via land use change from natural habitat elsewhere in the world the GHG consequences from that land use change can be overwhelming (Carlton et al., 2012). Nitrogen fertiliser forms the biggest single cost in gross margins for wheat production, and it is the input that can have the single biggest influence on yield. Judging the right amount of N fertiliser to apply for the farm, field and within-field is therefore of importance for the farmer to maximise profits, the local environment to minimise leaching and eutrophication risks, the wider environment to minimise GHG emissions and the wider global population to maximise food production and reduce pressure on land use change.

This project aims to use information available from new technologies to develop new approaches to judging N fertiliser requirements in order to improve N management decision making for winter cereals at the within-field to across-farms scales. This should reduce GHG and nitrate emissions and improve crop productivity.

## 2.1 N fertiliser Decision making

The supporting evidence for wheat & barley (Sylvester-Bradley *et al.* 2008) and sugar beet (Jaggard *et al.* 2009) from the last update of the Fertiliser Manual (RB209: Defra, 2010) reveal the difficulties in accounting for variation in optimum N amounts. They show how any recommendation inevitably has considerable uncertainty and hence that in practice fertiliser N is applied with considerable imprecision.

Current cereal nitrogen recommendations are imprecise, and at a field by field and metre by metre level they can be very inaccurate. This is not through lack of effort from N researchers & advisors or negligence on the part of farmers, it is the result of a complex system where only partial information is known when decisions are made. Relevant information is unavailable or too onerous to collate on farms; this indicates a need for automation.

A recent programme of N response experiments showed that the Field Assessment Method (FAM) recommendation system (MAFF, 2000) predicted the N optima to be within 50kg N/ha of the measured N optima in less than 50% of cases (Sylvester-Bradley *et al*., 2008a). Indeed, applying a fixed level of N across all experiments was found to give a better outcome than use of FAM alone (12kg N/ha out on average vs 23kg N/ha out, respectively). The use of soil mineral N to inform prediction of soil N supply was found to improve the prediction of N optima significantly (average 10kg/ha from the measured optimum). However, imprecision is large and SMN analysis of every field is economically unfeasible (Kindred *et al*., 2012a). The imprecision and inaccuracies in the conventional recommendation system and application management not only have large economic costs through wasted fertiliser and foregone yields; they also have large environmental costs. Applications of nitrogen above the optimum increase risks of nitrate leaching into watercourses, potentially resulting in eutrophication and failure to meet legislative water quality limits (NVZs, WFD etc). Wasted N fertiliser also contributes to GHG emissions through emissions associated with fertiliser manufacture and from nitrous oxide emissions from soil without increasing productivity, hence increases GHG emissions per tonne of production. Where N applications are sub-optimal, an opportunity is missed to provide extra grain at marginal economic and environmental cost; this 'lost' productivity could exacerbate pressures for indirect land use change (ILUC) (Kindred *et al*., 2008) in a world where food production needs to double by 2050 (FAO, 2009).

It is therefore clear that a better system for N management is needed urgently. Although the imprecision of the majority of N recommendations is larger than might be liked, the consequences of small imprecisions (<50kg N/ha) are relatively minor in economic and environmental terms. The major economic and environmental gains come from identifying and eliminating the larger errors, where current recommendations would differ by >100kg N/ha from the true N optima; the consequences of getting N management badly wrong in a small number of cases are much worse than those from being a little wrong in the majority of cases (Sylvester-Bradley *et al*., 2008a).

One reason for the poor performance of recommendations is unavailability of relevant information; usable information has normally been limited to soil type, previous crop (which indicates soil N supply), over-winter rainfall, past crop yield and (perhaps) grain N% (which indicates N demand). Ideally, recommendations would be based on direct knowledge of soil N supply, including likely N available from mineralisation and deposition, N demand from the crop and likely fertiliser N recovery. Crucially, it is also important to monitor success of an N management strategy, through grain yields, grain protein contents and occurrence of lodging. TheNitrogen for winter wheat – management guidelines (AHDB Cereals & Oilseeds*,* 2009) sets out how to use information to calculate fertiliser N requirements by estimating crop N demand, soil N supply and fertiliser N recovery with an approach that is compatible with the Fertiliser Manual RB209 (Defra, 2010). This is explained in detail in Chapter 2.

## 2.2 Precision Farming technologies

Precision Agriculture has long held the promise of improving the management of nitrogen (N) fertilisers for arable cropping (Sylvester-Bradley *et al*., 1999), and its use on-farm is now common-place. Fertiliser spreaders and sprayers capable of variable rate application are now used widely and many farms use GPS systems for auto-steering of farm machinery, if nothing else. Modern combines all have the capability to monitor yield, though fewer have GPS systems to enable yields to be mapped. Whilst a range of approaches are now being used on-farm to address spatial variation in N fertiliser application to cereal crops, there is not yet a comprehensive system that determines absolute N amounts and timings for winter cereals.

The 2012 Defra Farm Practices Survey assessed use of precision agriculture technologies by farmers in England. It found that 46% of cereal farm respondents used GPS, 38% used soil mapping, 25% had used yield mapping and 31% used some form of variable rate application.

### 2.2.1 Precision Technologies for Auto-N

In principle, precision agriculture technologies now offer the opportunity to gather information of use for the N Management Guide approach described in previous section and in Chapter 2 and, further, to process it and determine appropriate N management automatically, not only on a field by field basis, but also at a finer within-field scale. For example, grain yield monitors and yield mapping are now common-place on modern combine harvesters. Grain protein sensors and hence grain protein mapping are also commercially available, though uptake in the UK to date is limited. Electro-magnetic induction (EMI) sensors are widely used to produce maps of soil characters, and a host of crop sensing technologies are available to assess growth of the crop, remotely by satellite or with sensors on the tractor. Whilst approaches to use these technologies to inform cereal N management are being used commercially (especially using crop canopy sensing), these are mostly used to vary applications around a preset field norm, they do not currently help determine the absolute N rate to apply for cereals. Furthermore, no system has yet integrated all the available technologies to give an automated system with the best chance of improving N decision making.

The consortium in this project integrated expertise in automatic crop sensing with expertise in determination of N advice, in order to develop and validate, as far as possible, fully automated systems for N management. Our starting point was that these systems should use the same principles that underlie best field-by-field N advice, but that they should be modified according to the character of data available from commercially-available automatic sources.

#### 2.2.1.1 *Variable N management*

A major goal for precision agriculture has been to improve the management of N fertiliser within fields. Much academic research work has been undertaken across the world over the past 20 years to meet this goal (e.g. Lukina et al., 2001; Welsh et al., 2003; Shanahan et al., 2008; Mistele & Schmidhalter, 2008; Samborski et al., 2009; Basso et al, 2011). In addition, there has been much commercial development, for example by Yara with the N sensor (Reusch, 2005; Heege et al., 2008). A range of technologies are potentially useful for precision N management including soil sensing by EMI, yield mapping, canopy sensing and grain protein sensing. The most widely developed and widely adopted of these measures for precision N management to date are canopy sensing measures. Approaches generally use sensor information (eg NDVI) as a gauge of crop N demand to adjust N applications upwards where growth is less, and reduce N applications where crops are lush with increased lodging risks assumed (Bernsten et al., 2006, Zilman et al., 2006). In the UK over 800 farmers are thought to be currently using such sensing technologies. However, relatively little public research has supported the use of these sensor technologies in the UK.

A large AHDB Cereals & Oilseeds-funded study (Godwin et al., 2002, 2003a,b;c Welsh et al 2003a,b; Wood et al., 2003a,b) investigated the application of precision agriculture technologies for crop management, including N fertiliser. Experiments demonstrated that large difference in N optima exist within fields, but that these vary between years (Welsh et al., 2003). It was concluded that the simple use of past yield maps to set N recommendations was not appropriate, but that within season measures, in this case aerial digital photography, could be used to successfully apply variable N application rates. The approach developed by Wood et al. (2003) used remote sensing of NDVI to gauge shoot numbers or green area index (GAI) on a relative basis, with ground truthed measures to allow benchmarking against target GAI as set out in the Wheat Growth Guide (AHDB Cereals & Oilseeds). A similar system is now used commercially by SOYL using satellite imagery.

Whilst Yara market an absolute calibration for oilseed rape using the N sensor, as yet there are no systems available in the UK that give absolute N recommendations for cereals, ie current practice on UK cereals is that the farmer sets the appropriate rate for the field and the system applies this in a spatially variable manner, usually with more N applied to thinner crop areas and less to thicker crop areas.

Most approaches for variable rate N fertiliser management are based on canopy sensing, adjusting N applications by a range of approaches including empirical calibrations, use of nil-N or N rich strips (Samborski et al., 2009), a concept of nitrogen status or nitrogen nutrition index (Mistele & Schmidhalter, 2008) or a concept of target GAI (Wood et al., 2003). These systems have limitations: most do not give absolute recommendations; calibrations and algorithms may be relatively site specific (Samborski et al, 2009); and systems may only work efficiently where N is the major limiting factor (Zilman et al., 2006). It is still not proven whether fertiliser N amounts should be (i) related to estimated yield potential, and / or (ii) increased or decreased in relation to sensed canopy differences (Wiltshire et al., 2002;.Welsh et al., 2003; Zilman et al., 2006). Moreover, precision farming research has not so far tried to reconcile and integrate in full all key aspects of N management invoked field-by-field.

Shanahan et al. (2008) advocate that an integrated approach to variable N management should be taken, using information on soil, past yields and present canopy together. It seems likely that development of a system that can set absolute N amounts for the full range of situations will require separate assessments of crop N demand, soil N supply and fertiliser N recovery. From such a perspective it should be possible to use the available information and technologies to match N fertiliser requirements with accuracy.

#### *2.2.1.2 Canopy sensing*

Over 300 farmers in the UK use the Yara N sensor for in field variable rate applications of N fertiliser, over 500 farmers use satellite sensing services from SOYL, whilst there are smaller numbers of other sensing units such as Crop Circle, Optrx, Greenseeker and Rapidscan used on farm.

Spectral reflectance is widely used to gauge canopy characters such as plant/shoot population, ground cover/GAI, chlorophyll/greeness and biomass, though these characters cannot necessarily be sensed separately from each other (Scotford & Miller, 2004). Commonly, reflectance is sensed at the infra-red and near infra-red wavelengths, allowing various vegetation indices to be calculated (Wiegand et al., 1991; Raun et al., 1998), most commonly Normalised Difference Vegetation Index (NDVI). Ground based sensors such as Greenseeker and Crop Circle measure two or three wavelengths (Govaerts et al., 2007; Havrankova et al., 2008; Raun et al., 2002;2008) whilst the N sensor can measure several wavelengths (Zillman et al., 2006) and spectroradiometers measure many wavelengths (Wiltshire et al., 2002). The use of a colour component in addition to structural information from vegetation indices could give useful extra information (Miller, 2009; 2013). Spectral information can also be gathered remotely from aerial photography (Wood et al., 2003) or satellite imagery (Metternicht, 2004). Each of these systems is used commercially on farm to some extent. Whilst the different sensor platforms give subtlely different values for vegetation indices such as NDVI they are all capable of differentiating crop size and N status (Samborski et al., 2009). Simple digital photographs can also be used to generate vegetation indices (Tillett, 1991), and can be used to predict ground cover or GAI. This is in use commercially for oilseed rape and has been developed for cereals by BASF (Canopy Analyser Tool; [www.totaloilseedcare.co.uk](http://www.totaloilseedcare.co.uk)) and Yara (ImageIT smartphone App).

In addition, a range of other sensors have been suggested as being useful in detecting canopy characters, including fluorescence (Malenovsky et al., 2009), LIDAR (Omasa et al., 2007) and ultrasonic sensors (Scotford & Miller, 2004). Whilst such technologies may prove to give superior sensing of crop characters in the future, perhaps in multiple sensor arrays (Scotford  Miller, 2004b; Miller et al., 2013), this project deals only with proven technologies which are already in commercial use.

An AHDB Cereals & Oilseeds scoping study has shown that canopy sensing over-winter can effectively distinguish between cereal crops with different levels of soil N supply (Sylvester-Bradley et al., 2009b). This is developed in Chapter 2 and Chapter 6.

#### *2.2.1.3 Soil sensors*

Electro-Magnetic Induction (EMI) has been shown to be a useful and reliable method of characterising soil variation in fields (King et al., 2003; 2005). EMI sensors measure the apparent electrical conductivity of the soil, hence indicating available water content and soil texture. If used when the soil has reached field capacity they can be especially useful for interpretation of yield maps and delineation of management zones (King et al., 2005). EMI scanning is conducted commercially in the UK by precision farming providers such as Agrii Soil Quest, SOYL, Soil Essentials and Precision Decisions.

Sensing of soil organic matter and other soil properties has been under development over many years along with other soil characters (Quraishi & Mouazen, 2013; Kuang & Mouazen, 2013; Tekin et al., 2014; Kuang et al., 2015). Such sensors are only recently available for commercial use but could offer a major step forward in estimation of potential mineralisation of N on a spatial basis.

#### *2.2.1.4 Grain protein sensors*

NIR sensors that will monitor grain protein on the combine have been developed by a number of companies and the AccuHarvest sensor has been commercially available from the company Zeltex since 2006 (Taylor & Whelan, 2009). As well as allowing segregation of grain for quality markets, such sensors allow grain protein maps to be generated which, when combined with grain yield, enable the success of N management to be evaluated (Whelan et al., 2009). This could represent a major step forward in tailoring N management strategy on-farm, allowing grain protein to be used as a retrospective guide to whether the crop has been under or over-fertilised in a more sophisticated way than has hitherto been possible (Sylvester-Bradley & Clark, 2009). Other on-farm NIR protein sensors are also commercially available that could be used in a similar vein, such as the FOSS Sofia instrument. Uptake of such protein sensors in the UK has been limited to date, but sales have been greater in USA and Australia.

#### 2.2.1.5 Yield maps

Yield mapping equipment is now readily available, and comes as standard on many combine harvesters. Whilst some difficulties exist with the accuracy of yield monitoring data, especially due to variable bout widths and long lead-in times at the start of bouts, these can be overcome with appropriate adjustments (Blackmore & Moore, 1999). The principal limitation on the use of yield map data is the substantial spatio-temporal complexity that yield maps commonly display. Extracting an underlying signal from these somewhat noisy data is a challenge, but there are statistical methodologies to deal with them. There are two broad approaches. One (e.g. Blackmore et al., 2003; Kleinjan et al., 2006) considers local mean yield and its variability, identifying regions where yield is relatively stable and regions where it is less predictable. Another approach (Lark & Stafford, 1997; Perez-Quezada et al. 2003) uses a more flexible 'clustering' approach in which locations in a field are grouped into classes which show more or less uniform season-to-season patterns of variation (e.g. consistently above-average yields, above average yields except in dry seasons, consistently below-average yields, etc.). These classes have been shown to account for substantial soil variation (e.g. King et al., 2005), since a region with a more-or-less uniform season-to-season pattern of yield variation is likely to be subject to more-or-less uniform constraints on crop performance (e.g. small available water capacity, poor soil structure leading to poor establishment and greater slug damage, etc.). Fridgen et al. (2004) describe a software tool developed to generate management zones for precision agriculture using the approach of Lark & Stafford (1997).

## 2.3 Project objectives

In summary, the main challenges in automating N management of cereal crops in the UK were deemed to be: evaluation of automated grain N% sensor data (Taylor et al., 2005; Long et al., 2008; Whelan et al., 2009) for UK cereals, improved interpretation of previous soil and yield maps (Lark & Stafford, 1997; Blackmore et al., 2003; King et al., 2005; Ross et al., 2008), testing the extent to which N balances predict soil N supplies after both cereals and oilseed rape (Whelan et al., 2009), improved prediction of NDVI with unlimited N supply (accounting for any effects of soil, genotype, sowing date and seed rate), measurement and interpretation of canopy colour in spring as distinct from canopy size (Heege et al., 2008), using variation in canopy size to predict grain yield, and indentifying appropriate predictive relationships between yield potential and other spatial variables that can be applied at different spatial scales (Milne et al., 2006a). This project aimed to address these challenges, then to develop appropriate automated N management systems, validate these on commercial farms, and ensure their commercial viability.

In addressing these challenges it was expected that findings would benefit N management both metre-by-metre and field-by-field because it will prove possible to make more precise tests of relationships within fields than have previously been possible in field trials e.g. the effects of soil variation on fertiliser N recovery and the relationship between yield potential and N requirement.

Spatially intensive measurements of SMN and potentially mineralisable N in the chessboard trials in this project, together with spatially intensive measures of grain yield, N uptake (including N uptake without N applied, hence true SNS) and N optima offer the opportunity to explore this variability in greater detail, potentially allowing better understanding, and hence prediction, of the contribution of SMN and mineralisation to true soil nitrogen supply.

The chessboard trials in this project offer a unique opportunity to better understand the causes of differences in protein content at the optima, and the extent to which N optima are related to yield potential.

## 2.4 Objectives

1. To develop a logic for N fertiliser decision-making that integrates existing 'N balance' and 'canopy management' recommendation systems using (as far as possible) criteria available from commercial automated, spatially-referenced sensors.
2. To develop new protocols (or extend existing approaches) for predicting crop N demands, based on previous yield maps and associated physical data.
3. To test the extent to which the 'N balance' approach explains in-field variation in soil N supplies and optimum fertiliser N amounts.
4. To develop a spring N scheduling system by defining maximum (unlimited by N supply) GAI trajectories (based on thermal time) for autumn-sown cereals, and to calibrate commercial canopy sensors.
5. To validate automated applications of fertiliser N for their effects on gross margins, N Use Efficiency, and N emissions to the environment.

## 2.5 Work Programme

The objectives above were tackled in the 5 Work Packages described below. The first addresses the formulation of the logic in the round; Task 2 deals with issues in judging N demand, using yield and protein maps; Task 3 assesses the impacts of soil N supply and crop N demand on fertiliser N requirements; Task 4 develops calibrations and systems to transfer canopy sensor signals into useable information; and Task 5 tests the value of the systems in commercial practice.

In these tasks, a range of resources were used, with some cross-over between Tasks;

A. Scientific literature and data-sets from recent research

B. Liaison with international groups working on these issues

C. Commercial farm data from 5 farmers who have been using appropriate precision technologies.

   i. Historic yield maps for 5 years for 5 fields.
   ii. Soil maps, EMI maps for these fields to be taken in the project.
   iii. Yield & protein maps (on-board combine protein sensors to be provided in the project) recorded in the first 3 years of the project, with SMN & mineralisable N measured in each field.
   iv. Satellite imagery of crop canopy from February to May to be provided by SOYL for each field. Canopy data from other canopy sensors (eg Crop Circle, N sensor) to be used as available.

D. Chessboard experiments (Task 3) allowing ~400 N optima to be determined spatially per experiment, which can be related to soil N supply, grain yield, grain protein, canopy sensor signals and other measures.

E. Sensor calibration experiments (Task 4) including seed rate, sowing date, variety, N rate and N timing comparisons.

F. System validation trials (Task 5) to give half-field comparisons between 'conventional' (i.e. not spatially adjusted) & 'automated' N management systems.

The issues to be addressed in the 5 tasks of the project, and the proposed approaches to these, are set out in more detail below.

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L. System validation trials (Task 5) to give half-field comparisons between 'conventional' (i.e. not spatially adjusted) & 'automated' N management systems.

The issues to be addressed in the 5 tasks of the project, and the proposed approaches to these, are set out in more detail below.

### 2.6.1 Task 1: Developing a logic for automation

A spreadsheet-based model was developed to demonstrate the feasibility of integrating automatically sensed data on soils, past yields, grain protein, field and weather information, and real-time canopy signals to produce predictions of fertiliser N requirements. This model was developed and refined throughout the project, using literature, previous datasets and on-going work (Tasks 2-4) to:

- Confirm the contribution to soil N supply from atmospheric deposition, soil mineral nitrogen and mineralisation, net of losses due to leaching, denitrification & immobilisation, and whether estimates are improved with knowledge of soil type, weather, geographic location etc.
- Evaluate N%, nitrogen harvest indices & fertiliser N recoveries of a range of crops to inform N balance calculations for previous crops, and whether such balances usefully inform subsequent SNS.
- Evaluate whether grain yield is a useful determinant of grain N demand, hence N requirement, or whether its relationship with N recovery counteracts the usefulness in determining fertiliser N requirement.
- Evaluate the crop fertiliser recovery of modern cereal crops and quantify the effect of soil type, fertiliser & weather on these recoveries.
- Quantify the soil-N limitation of the crop over time from October to March – i.e. to determine at what level of topsoil SNS does N become limiting to crop growth?
- Evaluate whether topsoil SNS assessed by canopy sensing can reasonably be related to SNS for 0–90cm depth.
- Quantify Benchmark GAI through the season to monitor whether growth is 'on-target'.
- Quantify dynamics of N uptake to predict how much previously applied N is still likely to be taken up at the time of subsequent N application.

- Evaluate the use of grain protein and grain yield as a measure of success of N application.

Use was made of past datasets in tackling the questions above including HGCA Optimum N project, report No.438 (RD-3084: Sylvester-Bradley et al., 2008) and associated Defra project IS0223 (especially with regard to crop NHI, N yields, N recoveries & N balances), SNS Best Practice (PR490;; Kindred et al., 2012); (especially with regard to predicting soil N supply, mineralisation, relation between topsoil and subsoil N), Grain signatures project (PR458; Sylvester-Bradley & Clark, 2009) with regard to using yield and protein to predict N demand & hence N requirements, Wheat Growth Guide data sets (Sylvester-Bradley et al., 2008) with regard to GAI and growth over time and thermal time.

### 2.6.2 Task 2: Judging expected yield & N demand

Key issues here were:

- Evaluating best methods for predicting yields
- Evaluating the consistency of grain protein & N demand (kg N/per kg grain) across & within fields, soil types, years etc.
- Evaluating the usefulness of canopy sensors to judge non-N limited grain yields at the time of final N application (~GS 37, May), in order to inform estimates of N demand.

Studies in the literature (e.g. Kleinjan et al., 2006) were firstly reviewed. New datasets were then created by identifying and working with 5 farmers with good field records of grain yield from at least 5 fields going back at least 5 years. Apparent electrical conductivity (EMI) was measured on these soils to map soil properties. Yield, soil and weather data was collated and analysed together to develop methods to predict expected yield. In particular, the potential of a flexible statistical model (multivariate clustering, as proposed by Lark & Stafford, 1997) approaches were explored. This approach identifies the principal patterns of temporal yield variation in a field, which might include consistently large or small yields, but will also include any patterns that reveal susceptibility of regions of a field to particular problems such as drought or poor establishment. This provides a basis for predicting local relative yield and its uncertainty. This task will therefore derive the best means of predicting, on an absolute basis, future grain yield and hence crop N demand of cereals both between and within fields.

The relationships between yield, protein and N demand will also be assessed from the literature. Commercial protein sensors will be fitted to combines of the 5 farmers identified above to allow the spatial relationships to be tested further through the project, as well as from the trials in Tasks 3 & 4.

Past satellite canopy sensed data was also related to yield data to evaluate how well canopy measures at mid growth (~GS37) can predict non-N limiting yield differences and hence final N demand.

### 2.6.3 Task 3: Explaining in-field variation in soil N supplies and optimum N

The core experiments for the Project were the chess-board trials (see below; Lark & Wheeler, 2003; Pringle et al., 2004) in which nitrogen rates are varied within a field with greater replication than in conventional fertiliser experiments. Because these trials can be analysed to model the local nitrogen response of the crop, they allow us to quantify the spatial variation of N requirements (including whether normal field trials accurately reflect N requirements of whole fields), and they provide a test of whether in-field variation in grain N% provides a useful post-mortem on optimum N use (as recommended in the Fertiliser Manual; Defra, 2009). They also allow the evaluation of the use of previous grain yields and protein contents to predict soil N supplies and optimum N amounts of the current crop.

Key issues were to:

- Evaluate the consistency of protein content at the measured N optima.
- Evaluate the usefulness of grain protein and grain yield as a measure of success of N strategy, where high protein indicates super–optimal N applications; low protein/low yield indicates sub-optimal N application.
- Test effects of within-field differences in soil type on N requirements.
- Assess the contribution differences in soil type, organic matter and mineralisation make to differences in soil N supply, and infer differences in leaching/ immobilisation etc.
- Assess relationships between N supply (from soil and fertiliser), canopy signals, growth, green area index, canopy nitrogen requirement, colour and N uptake.
- Test value of EMI (and soil organic matter sensors, if available) for measuring soil characters and informing N management.

One chess-board nitrogen experiment was set up in 2010 growing season, 2 in 2011 and 3 in 2012. Plot size in each experiment was around 10m by 10m, with 4 N rates including zero applied N, applied using 24m spreader with half boom shut off and tramlines both across and up & down the experiment. The design of the experiments means that each plot is always in a grid containing all 4 N rates, allowing N optima to be determined for each plot, but (as noted in the legend to the figure above) model-based estimation of the local response function uses information from neighbouring plots via block kriging, and so achieves greater precision than if each local function were estimated directly from just four yield measurements. This approach can be taken not only to yield, but to other measured responses such as grain N content.

Extensive measurements were taken on the experiments, including sufficient measurements of soil mineral N, potentially mineralisable N, shoots $m^2$, canopy progress, canopy reflectance, GAI, crop DM, N uptake, grain yield, grain protein and nitrogen harvest index to allow causes of differences in N requirements to be evaluated. Regular measurements of canopy signals helped allow calibrations for the above measures to be developed, where appropriate. Grain yield measurements were made by plot combine harvester to ensure greatest possible precision in the experiments.

Where practical sensor assessments of chess-board trials were continued into the succeeding crop to test the capacity of sensors to detect residual or ‘ghost’ effects, particularly on SMN.
Chess-board trial design (using a tramline grid) to test spatial patterns of N responses.

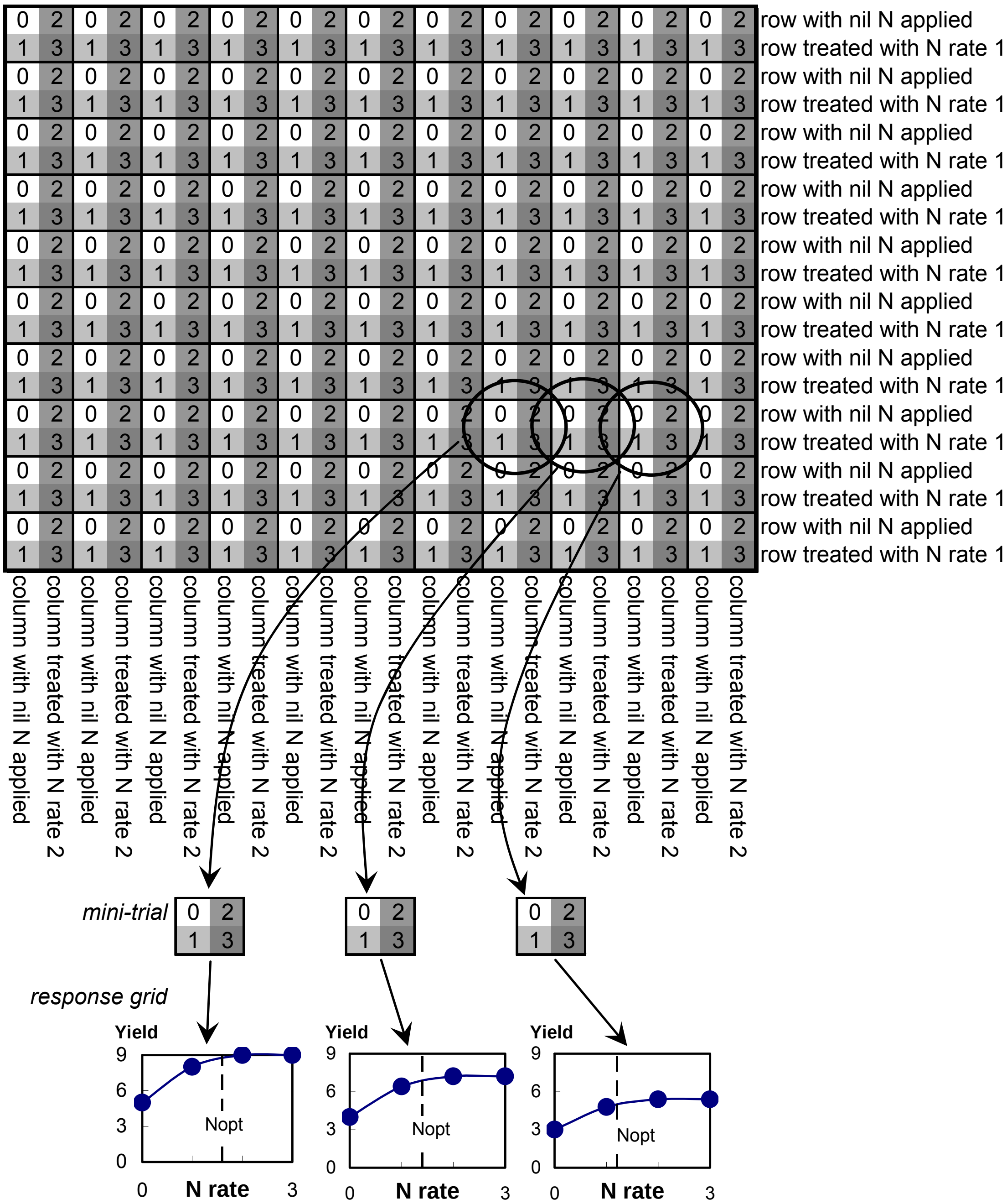



**Figure 1. Chessboard trial: The diagram shows how each component of the 'chess-board' tramline grid includes a mini-trial with N levels of 0, 1, 2 & 3 (2 being the expected N optimum). Hence a N optimum can be determined at each point in the grid, and these can be mapped over the whole field, revealing the spatial variation in N requirements and achievable yields (unconstrained by N) over the whole field, at a maximum spatial resolution of 12-24 metres (depending on the width of the fertiliser spreader used, and the variability in the trial). Note that the methods for analysing such trials (Pringle et al., 2004; Lark and Wheeler, 2003) use model-based methods to map the local N response. This exploits information on the response in neighbouring plots, and so ensures that the local response functions are estimated with less sampling variance than they would be in direct modelling of just four plot yields.**

### 2.6.4 Task 4: Calibrating & interpreting canopy sensor signals

An AHDB Cereals & Oilseeds Scoping Study (Sylvester-Bradley et al., 2009) demonstrated that over winter and early spring NDVI signals for bare ground and fully-fertilised wheat canopies were reasonably consistent over sites and seasons, hence promising scope for absolute calibration of sensor signals. More specific further work was undertaken to account for effects of genotypes (varieties of wheat and barley with contrasting leaf colours and canopy structures), sowing dates and plant establishment on GAI and soil-adjusted vegetation indices (Rondeau et al., 1996; Steven, 1997).

Key issues were to:

- Collate & develop benchmark data for crop growth, GAI, crop N uptake and canopy signals in N unlimited wheat crops, in terms of thermal time after sowing, as affected by variety, sowing date, seed rate and establishment.
- Develop reliable calibrations for canopy signals to gauge crop growth/GAI/crop N uptake, taking account of differences in soil characters etc.
- Develop a reliable system for predicting N-unlimited-growth (dry matter, GAI, N uptake & canopy signals) from sowing date, plant establishment and thermal time.
- Develop a system to quantify soil N limitation over-winter by relating current canopy signals to predicted signals from N unlimited growth, hence allowing estimation of soil N supply.
- Evaluate whether crop colour (or spectral properties) can be used as a measure of crop N status, hence develop a system using canopy sensors to gauge residual N availability after N has previously been applied.

Bespoke experiments were established with sowing date, seed rate, N rate & timing treatments to set-up canopies with different levels of N uptake and N status to be compared, and differences in the dynamics of uptake be assessed.

Digital images were taken and canopy reflectance measured with commercial sensors (e.g. research versions of Crop Circle, N Sensor) through the season.

Data collated in these trials was combined with data from other trials with canopy sensing into a large ‘calibration’ dataset from which relationships were evaluated.

### 2.6.5 Task 5: System validation

A commercialisation group made up of representatives of each of the industry partners convened regularly through the project to ensure that project outcomes could be used commercially. A generic spreadsheet-based system was developed by the project, which partners could use to develop their own software applications to drive variable rate application technology, through factor maps or zone maps using their own systems. Whilst the underlying decision principles are freely available to all and are published in this report, the application of those principles in any commercial software remains the property of the industry partners to allow full exploitation. Whilst not all partners may seek to take outcomes from the project to the market place, all partners committed to not restricting the right of others to do so. Soilessentials, Agleader, Yara, Precision Decisions & Soyl provided application systems developed in the project that can be tested on farm in Task 5.

Tramline comparisons were set up with several growers in 2013 and 2014 comparing 'automated N management' applications with uniform N management.

The potential benefits of automated N management on gross margins were evaluated. As well as economic impacts of such automated-N systems, the potential environmental benefits accrued through reduced GHG emissions from N fertiliser manufacture and soil $N_2O$ emissions, reduced N leaching and ammonia volatilisation were quantified, as well as any land use implications through improved productivity.

## 2.7 Working with 5 farms and 5 fields on each

Real commercial farm data and field sites to answer all the questions above were made available by working closely with 5 precision farmers. On each farm 5 fields were selected to give interesting variability in soil characters, yields and canopy sensing within each field

# 3 A Rational Logic for N Decision Making

Nitrogen (N) management is important for profitability and compliance with legislation; environmental consequences for climate change and water quality are serious. Knowledge of the appropriate rate of N fertiliser to apply to UK arable crops is derived empirically from N response experiments conducted over the past 75+ years (Crowther & Yates, 1941). This knowledge is summarised as recommendations in the Fertiliser Manual (RB209; Defra 2010) and TN625 in Scotland (Sinclair et al., 2009). These use information on previous cropping, soil type and over winter rainfall to give N recommendations through look up tables, known as the "field assessment method". Whilst these recommendations work on average, there is large variation around the averages which cannot currently be predicted; Sylvester-Bradley et al. (2008) found that 50% of N recommendations deviated by more than 50 kg $ha^{-1}$ from measured optima.

The Nitrogen for winter wheat – management guidelines (AHDB Cereals & Oilseeds, 2009) developed an approach whereby N requirements could be *calculated* incorporating best estimates of crop N demand, soil N supply and fertiliser recovery for the farm, field, crop and season. This also advocates monitoring success in order to make better estimates in future years. However, the full guidance for this approach has not been fully developed or validated.

In addition, farmers in nitrate vulnerable zones (comprising the majority of UK arable area) must comply with Nmax rules on the total N rates applied to crop species within the farm.

## 3.1 N responses and the economic N optima

Many N response experiments have been conducted over the past hundred years to determine fertiliser nitrogen (N) requirements of wheat (Board of Agriculture and Fisheries, 1905; Russell 1939; Crowther & Yates 1941; Garner, 1957; Boyd, 1976; Bloom, 1987, Sylvester-Bradley & Kindred, 2009). Early experiments such as those of Lawes & Gilbert (Johnston, 1996) were principally to demonstrate that artificial fertilisers were worthwhile. Since the 1970s the N optima for individual experiments have been determined empirically from fitting an N response curve to yield data from at least four N application rates (including zero) and interpolating the point at which profit to the farmer is maximised (Boyd et al., 1976). This point is dependent on two factors external to the crop experiment, namely the choice of fitted curve and the relative price of grain to fertiliser N (the breakeven ratio: BER). Since George (1984) the standard approach to curve fitting in the UK has been to fit a linear plus exponential function (Equation 1), but other responses are commonly fitted elsewhere and in the literature (Bachmeier et al., 2009). The BER describes the quantity of grain required to pay for a quantity of fertiliser N, and is typically around 5:1 but has varied between 2:1 to 9:1 in recent decades (Sylvester-Bradley & Kindred, 2009). The economic optimum (Equation 2) is the point on the response curve where the slope equals the BER; i.e. the point at which increasing the fertiliser N applied by 1 unit would not increase grain yields sufficiently to pay for the cost of that N fertiliser.

Equation 1: LEXP: $Y = a + b.r^{N} + c.N$

Equation 2: $N_{opt} = [Ln\{(P/1000 - c)/(b \times Ln\ r)\}]/Ln\ r$

Where Y = Yield, N = N applied, P = Price ratio of N (£/kg) and grain (£/kg) and a, b, c & r are parameters determined by statistical fitting.

### 3.1.1 Components of N requirement

By considering crop N uptake as well as yield (Figure 2) the fertiliser N requirement can be considered as a function of 3 components. Crop N uptake with zero fertiliser N applied can be considered as our best estimate of soil N supply (by definition this is N that has got into the crop from soil, not from fertiliser) and can be termed harvested SNS (Kindred et al., 2012). The slope of the increase in crop N uptake with applied N is the apparent fertiliser N recovery (AFR). The maximum crop N uptake is the Crop N Demand. Where crop N uptake intersects the economic N optimum from the yield response can be considered to be the economic crop N demand; i.e. how much N it is worth getting into the crop. In practice the economic CND tends to be similar to the maximum CND.

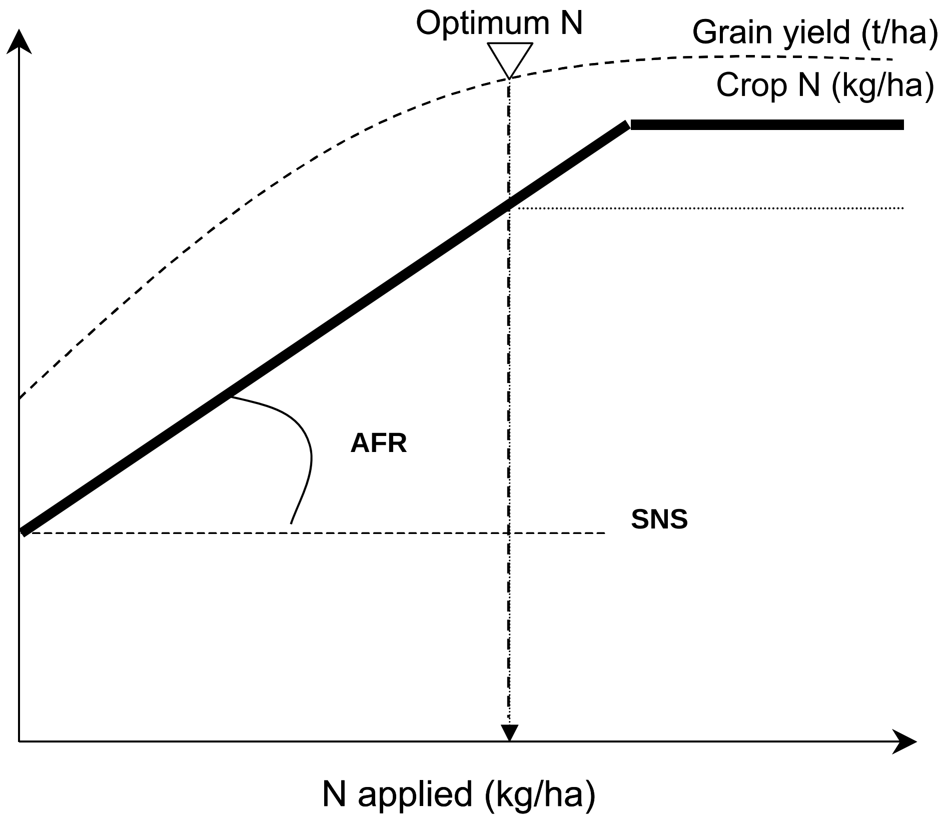



**Figure 2. Schematic of N response with N optima (triangle) and crop N uptake showing Soil N Supply (y intercept), Apparent Fertiliser Recovery (AFR; angle of slope) & Crop N Demand (Crop N uptake at plateau, or at optima)**

By thinking about the yield response and crop N uptake in this way it is possible to both quantify the components to assess their importance in explaining variation in N requirement, and to use estimates of each component to independently estimate an N requirement using Equation 3 below.

## 3.2 AHDB Cereals & Oilseeds Nitrogen Management Guide approach

The basis of field-by-field advice, as set out in the Nitrogen for winter wheat – management guidelines, is to:

1. Judge N demand (from expected yield and optimal N content),
2. Judge N supply (using soil mineral N analysis, or from previous crop N balance, adjusting for any N losses, plus some N deposition),
3. Determine Fertiliser N requirement (the N shortfall, adjusted by fertiliser recovery),
4. Schedule applications (to manage the canopy, accounting for lodging and take-all risks),
5. Monitor Success (by measuring grain yield and grain N content).

Fertiliser N requirements are calculated from the three components:

Equation 3:

$$\text{N requirement (kg N/ha)} = \frac{\text{Crop N Demand (kg N/ha)} - \text{Soil N Supply (kg N/ha)}}{\text{Fertiliser Recovery (\%)}}$$

where Crop N Demand (CND) is the amount of N that it is needed by the crop to optimise yield, grain protein and straw N requirements (assumed to be 23 kg N t grain for feed wheats); Soil N Supply (SNS) is the amount of N available from the soil and fertiliser recovery is the proportion of fertiliser N applied that gets into the crop.

TheNitrogen for winter wheat – management guidelines (AHDB Cereals & Oilseeds, 2009) advocates stepwise estimation of each of these components to determine N requirements of wheat crops. This gives comparable recommendations to RB209, but allows quantitative ‘sliding-scale’ adjustments to be made if yields, proteins, SNSs, or fertiliser recoveries are expected to differ from standard assumptions. It is thus applicable to intra-field variation, as well as to between field variation. In principle, each of the three components on N requirements could be estimated (or at least informed) by information available through precision farming technologies – thus it ought to be possible to automate the estimation of absolute N recommendations for cereals where Precision Farming is practised. The Auto-N project seeks to test this assertion and so provide a system for automated N decision making for use within as well as between fields.

### 3.2.1 Crop N Demand

Crops need N to build green canopy (green area index; GAI) to intercept sufficient light to achieve optimal yields. For wheat, 95% interception of light is achieved with a GAI of 6 or 7, (i.e. 6–7 ha$^{-1}$ green leaf and stem area per ha$^{-1}$). Each unit of GAI contains ~30 kg N ha$^{-1}$; thus 180–210 kg N ha$^{-1}$ in the crop should produce sufficient green canopy. However, crops also need N to satisfy the protein requirements of the seed which, in wheat, are higher for breadmaking varieties than for feed varieties; with optimal N supply, the grain protein of feed wheats is around 11% (1.9%N), that of milling varieties is 12% (2.2%N) (Sylvester-Bradley & Clarke, 2009). It has been shown experimentally that higher protein breadmaking varieties require more fertiliser N for yield than feed varieties (Sylvester-Bradley & Kindred, 2009). Allowing for the N remaining in straw at harvest, 23 kg N is required for each fresh (85% DM) tonne of grain yield for feed wheat, but 25 kg N/t for bread wheat. It is therefore apparent that, with yields above ~9 t ha$^{-1}$, more N is required to satisfy grain protein demand than is needed to build an optimum crop canopy.

### 3.2.2 Soil N supply

Variation in SNS is generally taken to be the major driver of variation in N requirement. Soil N supply is variable spatially and temporally (Dampney & Goodlass, 1997; Baxter et al., 2003), and is currently predicted or measured with poor precision (Harrison, 1995; Sylvester-Bradley et al., 2008). This is due in part to differences in the amount of N mineralised or immobilised through the season which affects N available to the crop (Shepherd et al., 1996; Bhogal et al., 1998; Goulding et al., 2008).

Measured SNS has conventionally been assumed to be used by crops with 100% 'efficiency' (compared to 60% efficiency for fertiliser N; Sylvester-Bradley et al., 2001), though this assumption has been questioned (Knight et al., 2008). The chessboard trials should allow the uptake efficiency of soil N to be assessed across the range of SMN in a field, other factors being constant.

In the field assessment method, SNS is estimated from previous crop, soil type and over-winter rainfall. SNS is all the N that becomes available to the crop from the soil (i.e. not fertiliser or manure N) throughout its growing season, so SNS includes N that will mineralise as well as residual soil N available as nitrate or ammonium. We use the measure of N in an unfertilised crop at harvest as our best measure of total SNS, and we call this 'harvested SNS'. It is possible to measure SNS in autumn or spring before fertiliser N is applied, by testing soil mineral N, as well as using incubation tests to estimate mineralisation. In this sense SNS should be considered as the mineral N in the soil, plus the N already in the crop, plus an estimate of likely N mineralisation. Whilst such testing is useful where SNS is expected to be high or uncertain, and to give an indication of where a field or farm lies in relation to RB209 SNS indices, it does not by itself radically improve predictions of N requirements in 'normal' arable fields (Kindred et al., 2012; Orson, 2010).

The Nitrogen for winter wheat – management guidelines (AHDB Cereals & Oilseeds, 2009) sets out a quantitative basis for predicting SNS using previous crop to set the size of likely N residues in autumn, and soil type with winter rainfall to estimate retention of that residue through to spring (Sylvester-Bradley, 2009). We have formalised this within a spreadsheet tool to give a rational basis to quantify SNS at the field level, but we have also enabled assessments of crops over winter and in early spring to help to adjust or validate predicted levels of SNS. Estimation of N in the crop is an important part of estimating SNS, especially for oilseed rape where more than 100 kg N $ha^{-1}$ can be taken up over winter. In wheat uptake over winter rarely exceeds ~30 kg N $ha^{-1}$. Tools from BASF and Yara are available online and via smart phones to estimate canopy size (GAI) and N uptake for cereals and OSR for the purposes of N and plant growth regulator (PGR) management. The large crop N uptake of OSR is part of the reason why crop sensing techniques (e.g. N sensor) are used successfully to determine its N requirements, perhaps assisted by the weaker influence of seed N content on OSR N demand.

### 3.2.3 Fertiliser N recovery

Whilst fertiliser recovery is known to vary substantially between N response experiments and fertiliser types (Sylvester-Bradley et al., 2014), the majority of this variation is not predictable. Fertiliser recovery is therefore assumed to be 60% for most soils, 70% for sandy and silty soils and 55% for shallow soils over chalk, as in the Fertiliser Manual (RB209; Defra., 2010).

## 3.3 An integrated Auto-N approach

Figure 3 illustrates our initial view of how this N Management Cycle might be integrated with information from precision technologies. Widely used ‘precision farming’ technologies could provide information on likely N demand and N supply even before the crop is sown, through yield maps, grain protein maps and soil maps. Past yields and soil data should together provide a guide to likely future yields (King et al., 2005; Kleinjan et al., 2006) and are routinely mapped on many farms. The current field-by-field approach is to assume a crop N content at the optimum of 23 kg N per tonne of grain [1.9% N in grain (Defra, 2009; Sylvester-Bradley & Clarke, 2009) and 0.7 N harvest index (Sylvester-Bradley & Kindred, 2009)], allowing N demand to be estimated. Soil N supply can be estimated initially from the N balance of the previous crop (fertiliser N used less crop N off-take; Taylor & Whelan, 2007), modified by estimates of additions and losses due to atmospheric exchange, soil organic matter turnover and leaching; these can all be informed by mapped soil data.

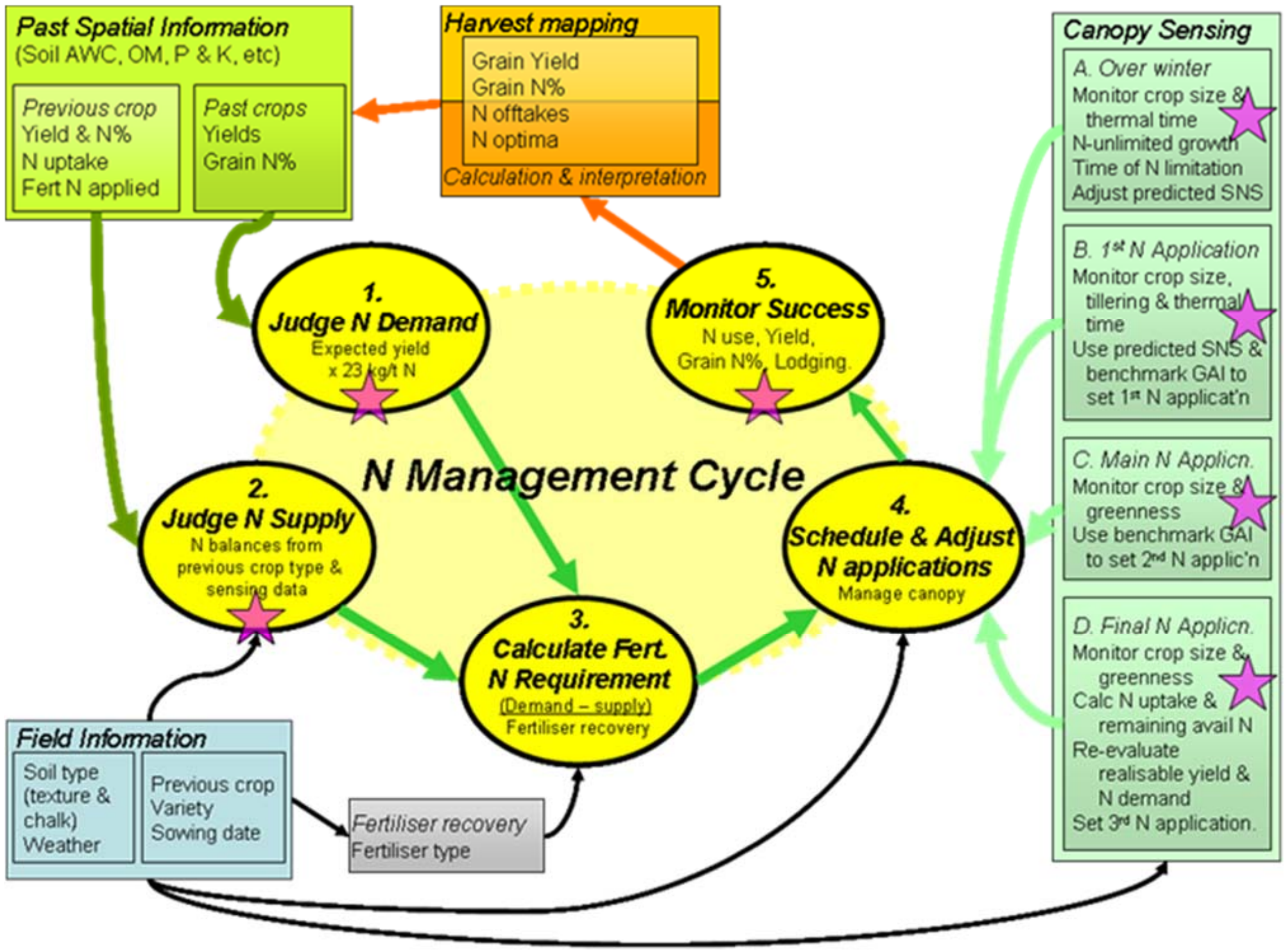



**Figure 3. The N management cycle (yellow), indicating data sources for automation (orange, green & grey), and issues researched in this project (stars).**

Initial estimates of crop N demand and soil N supply can be used to make initial estimates of fertiliser N requirements using fertiliser N recoveries dependent on soil type. Canopy signals over winter and through spring can then be used to refine these estimates, firstly of soil N supply, and later of crop N demand.

### 3.3.1 Initial Auto-N approach for Estimating Crop N Demand

The estimation of CND is possible from estimation of likely yields and protein requirements. Yield maps from previous harvests should enable estimates of yield to be made on a spatial basis, recognising that these estimates can be compromised because, as an extreme example, weather variation can mean that areas that yield best in one year yield worst in another. To deal with this, statistical approaches such as 'fuzzy k means clustering' can be used to group areas into those that behave in a similar manner (Milne et al., 2011). Commercially, simpler functions are used in precision farming software and by service providers to give yield performance maps, zoning areas that consistently perform well, badly or are inconsistent. Alternatively, zones can be defined by growers from any (or a combination of) prior knowledge such as soil surveys, aerial and satellite imagery, electromagnetic induction (EMI) mapping of soil conductivity, digital elevation maps, past field boundaries as well as yield maps. Yield estimates can then be made for each zone. It is also possible that in-season satellite sensing can help fine-tune spatial yield expectations.

Whilst protein sensors on the combine are available (Whelan et al., 2009) they have not so far been widely adopted commercially. Understanding spatial variation in grain protein content and its relationship with grain yield and N supply could improve our estimation of N requirements. The fertiliser manual includes allowance for adjustments to N fertiliser use based on past grain protein results, and many growers use this as a measure of the success of their N management. However, thus far, the dynamics of protein variation have proved too complex to formalise the use of grain protein information into the estimation of N requirement, beyond the well-established impact of variety type (bread vs feed).

#### 3.3.2 Initial Auto-N approaches for Estimating Soil N Supply

The crop can be an indicator of available soil N, especially in terms of indicating spatial variation. Sylvester-Bradley et al. (2008;2009) showed that canopy sensing at visible and near infrared wavelengths (expressed as NDVI: Normalised Difference Vegetation Index) using a Crop Circle (from Holland Scientific) could consistently distinguish plots where previous N response experiments had caused different residual N levels, hence differing SNS. Thus, based on known NDVI values adjusted through thermal time from crops grown with no N-limitation, it is possible to develop calibrations that indicate spatial variation in SNS from their NDVI (or other spectral reflectance measures) in spring.

The AHDB Cereals & Oilseeds study (Sylvester-Bradley et al., 2008; 2009) has shown that, as predicted from classical models of plant growth (Hunt, 1982) and light reflectance by canopies (Wiltshire et al. 2002) the NDVI (normalised difference vegetation index) of wheat crops with unlimited N increases quite consistently with thermal time across sites and seasons (Fig. 4).

Thus, from the difference between measured NDVI and that with unlimited N, crops with small N supplies may be identified by canopy sensors early in the season (Fig. 4), whilst crops with larger N supplies may be identified later. Initial estimates of soil N supply based on previous crop data may thus be verified or modified in spring. However, possible interfering and interacting effects (on sensing signals) of soil colour, stones, genotype, sowing date and seed rate need to be assessed and accommodated (Heege et al., 2008).

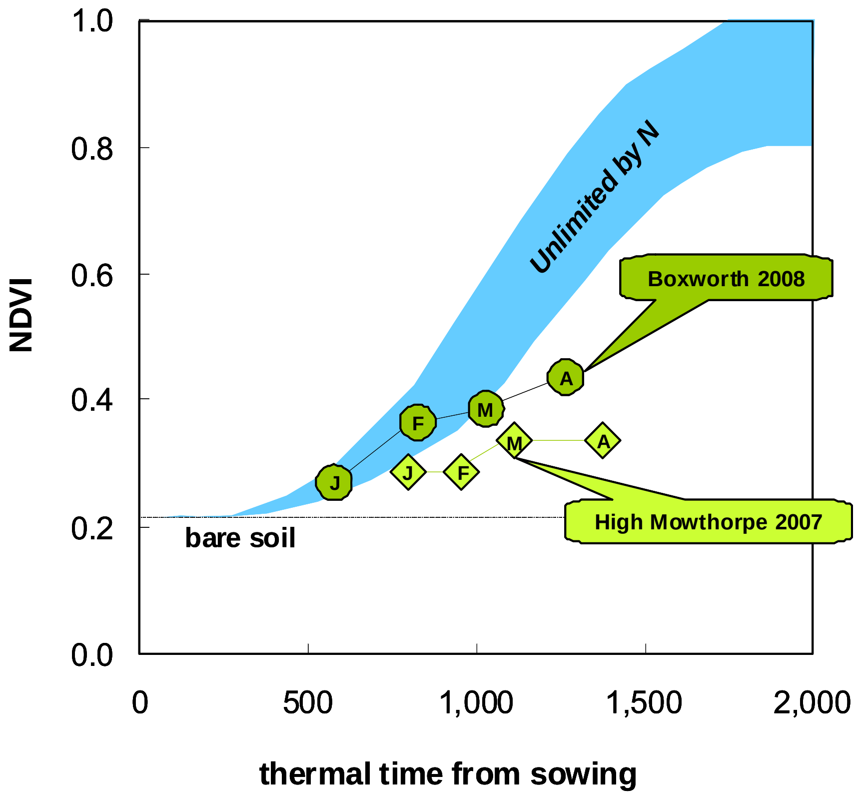



**Figure 4. Two example time-courses for NDVI (by Crop Circle) of unfertilised wheat crops compared to the range of NDVI for crops with unlimited N at 4 sites over 2 seasons, showing how N limitation becomes apparent over time. Symbols show initials of months of measurement: J=January, etc. AHDB Cereals & Oilseeds Project No. 3285 (Sylvester-Bradley et al. 2009).**

### 3.3.3 Initial Auto-N approach for Estimating Fertiliser recovery

In principle soil sensing techniques such as EMI and soil brightness could be used to identify zones in fields where different estimates of fertiliser recovery are evident. However, there is only a minority of fields containing sufficiently contrasting soil types for good distinctions to be made. Currently, evidence is insufficient to assume any quantitative direct relationship of fertiliser recovery with quantitative soil characteristics.

### 3.3.4 Initial Auto-N approach for Scheduling N applications

Monitoring of canopies in later spring with appropriate sensors should enable progress towards a target canopy size (set according to Canopy Management principles; Sylvester-Bradley et al., 1997; Wood et al., 2003) to be gauged, and should also allow initial estimates of crop N demand to be adjusted. Canopy colour is expected to indicate the immediate balance between supply and demand (Lemaire et al., 2008; Heege et al., 2008), hence allowing re-estimation of residual N availability. On this basis N fertiliser decisions may be adjusted automatically at each of three spring application timings.

1. The first N application (0 to ~60 kg N/ha in Feb/March) is used to manage the canopy potential, applying more where tillering is poor and take-all risk high, and applying none where the crop is large and SNS is high, indicating high lodging risk.
2. The main N application (~50% of total N requirement, in April) provides for further canopy expansion, N rates being reduced if a large canopy is sensed.
3. The final N application is the most important as it determines final N rate, and is the most challenging because three features of N requirement need to be estimated; (i) N already in the crop, sensed from canopy size assuming a default canopy N ratio (30 kg N per ha green area; Sylvester-Bradley et al. 1997), and (ii) N still available from the soil including fertiliser N still to be taken up from previous applications, sensed by canopy colour, and (iii) expected yield, hence crop N demand, assuming that a larger crop indicates higher yield potential. Each of these issues requires investigation.

Bread-making crops may require additional late-N to boost grain protein; automation is potentially applicable but this project will mainly target optimisation of grain production, rather than quality.

#### 3.3.5 Initial Auto-N approach to Monitor Success

Monitoring of grain yield and protein (as well as any lodging) at harvest will indicate the success of N use, e.g. low grain yield and high grain N% indicating excess N use due to non-N factors limiting yield. This information should inform future N management (Norng et al., 2005).

However, we don't yet properly understand the relationships between grain yield and N optima, and grain protein and N optima (Sylvester-Bradley & Clarke, 2009), hence the best methods for setting N recommendations remain contentious. Grain N% remains the favoured yardstick by which accuracy of N use on wheat should be judged on farms, though recent work has shown that whilst grain protein is a useful measure of success on average, it can't be taken as a definitive gauge in all situations (Sylvester-Bradley & Clarke, 2009). For example, season-specific conditions and geographic location can impact protein content at the optima in a way which has not yet been explained.

### 3.4 Using past N response data to compare N recommendations

The approach of the N Management Guide has never before been validated by comparison against RB209 or SMN measurement. Data were collated from 53 cereal N response experiments (Figure 5) since 2003 across the UK where Linear plus Exponential response curves (Equation 1) could be fitted and N optima determined (Equation 2) using a break-even ratio of 6:1.

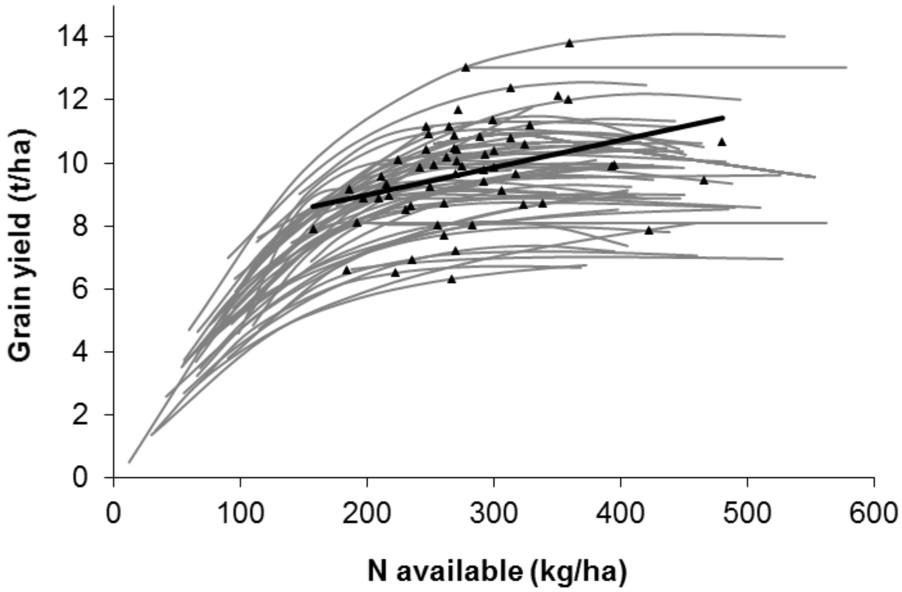



**Figure 5. Responses and optima (triangles) of 53 N response curves from ADAS experiments conducted between 2003 to 2010**

Recommended N rates were determined using 3 approaches:

A. RB209 field assessment method using information on previous crop, soil type and over-winter rainfall.
B. Soil mineral N tests to estimate SNS for the RB209 recommendation.
C. Soil mineral N tests combined with simple crop N demand estimates using the N management guide approach. Yield estimates were reduced for older varieties and a higher crop N content was used for breadmaking varieties.

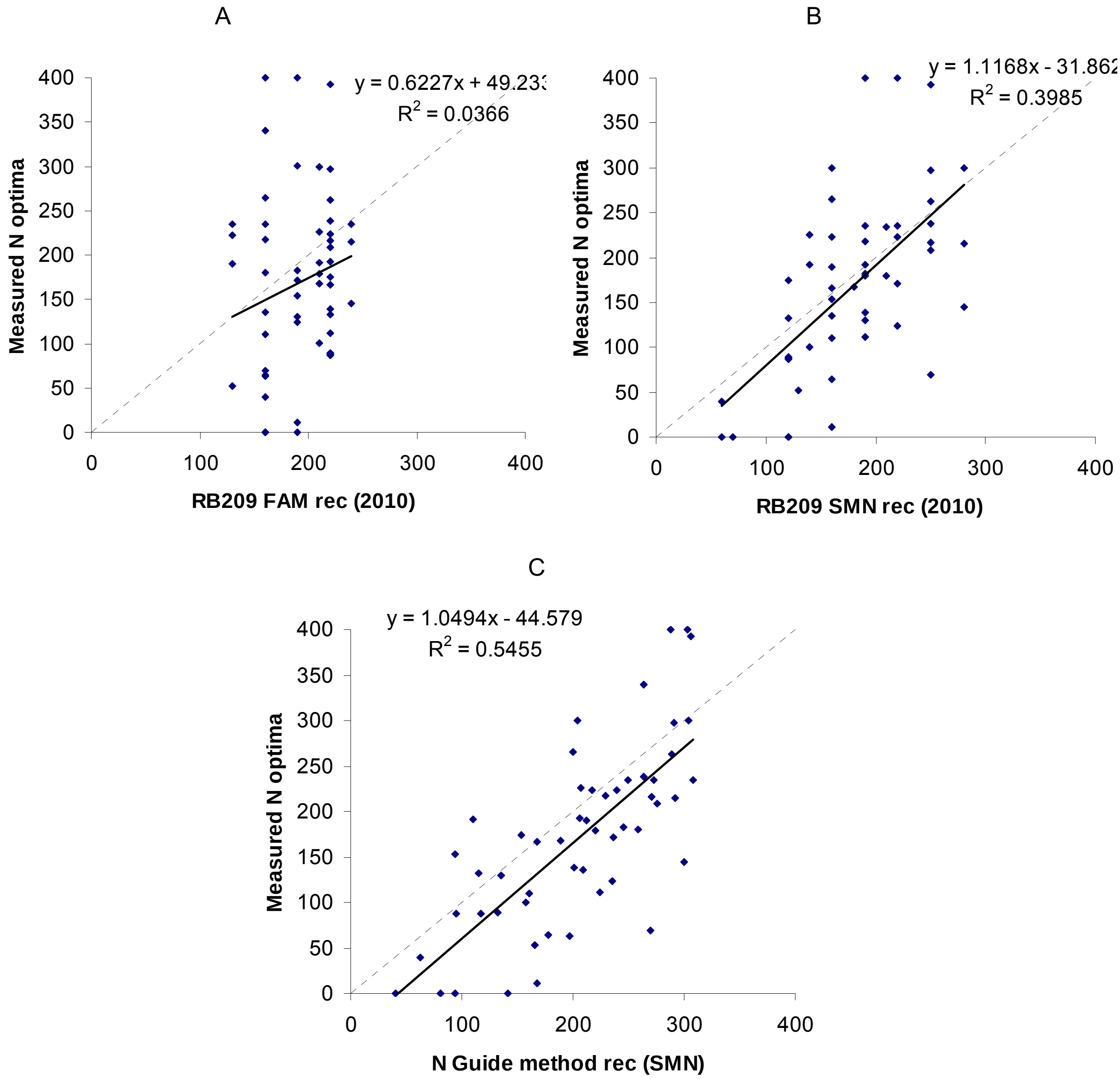



**Figure 6. Measured and predicted N requirements from various N response experiments conducted since 2000 predicted using RB209 field assessment method (A), SMN measurement with RB209 (B) and using the N management Guide approach with SMN (C).**

This shows an improvement in using the N Management Guide approach with SMN over using SMN with RB209 (Figure 6). Detailed 'farmer experience' needs to incorporated into estimates of SNS and fertiliser recovery to fairly compare the N Management Guide approach.

The dataset can also be used to explore the components of N requirement from estimates of harvested SNS, Crop N Demand and Fertiliser recovery and their importance in driving the variation seen in N optima (Figure 7).

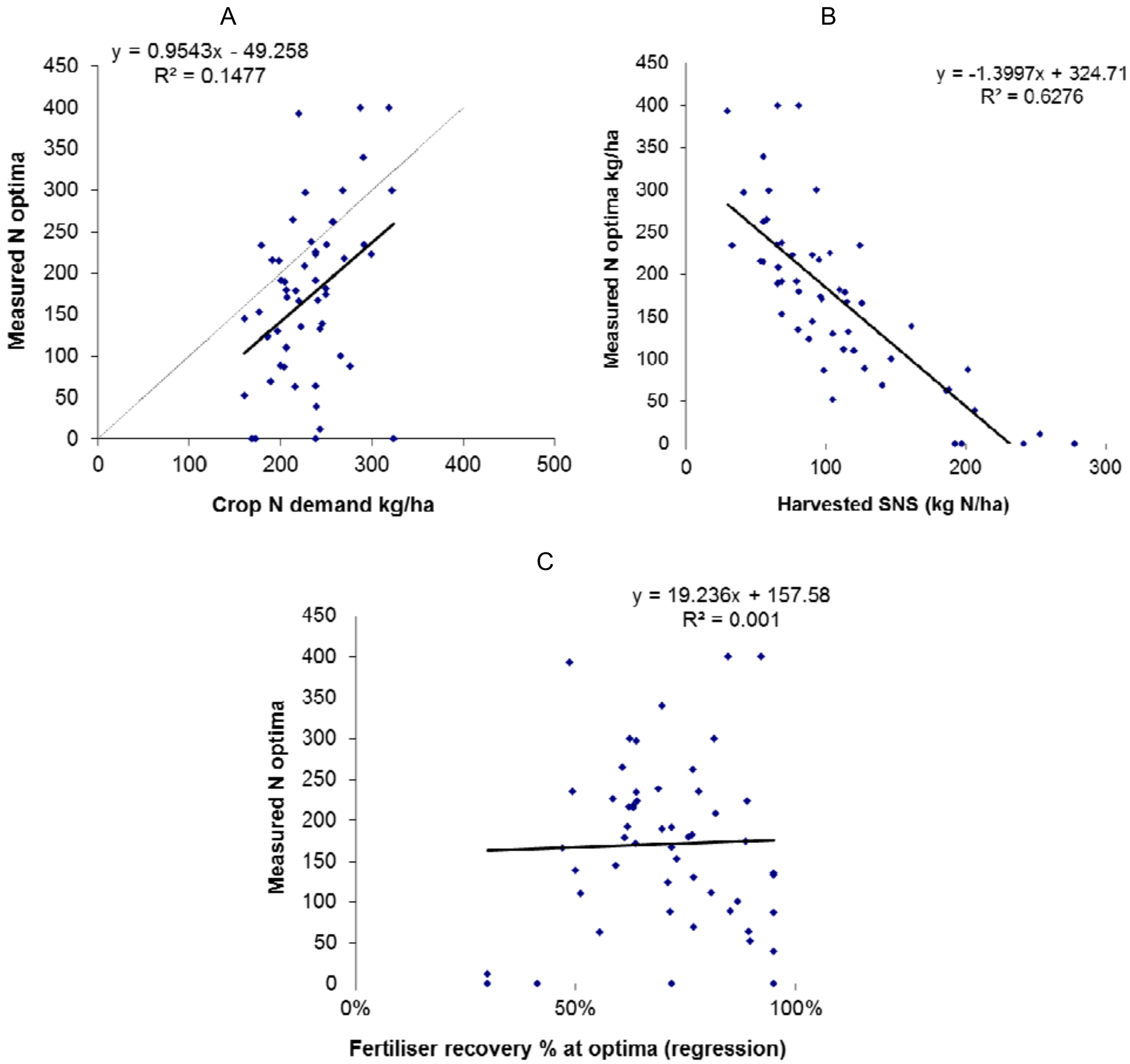



**Figure 7. Relationship between N optima and its components Crop N Demand (A), Soil N Supply (B) and Apparent Fertiliser Recovery (C) for the 53 responses shown in Figure 5.**

This shows that of the components, SNS explains most of the variation in the N optima ($r^2$ = 0.63). Whilst there is a slight positive relationship with Crop N Demand (Figure 7-A), there is no relationship at all with yield at N optima ($r^2$ = 0.01; data not shown). There is no relationship with fertiliser recovery, though it varies greatly.

This indicates that assessing variation in SNS is the most important factor for improving N applications on a field by field basis.

In order to assess the importance of the 3 components in variation in N requirements *within* fields, and to see if this variation could be detected by precision technologies, chessboard experiments were set up.

# 4 Chessboard trials to understand variation in N requirements

## 4.1 Spatial experiments

Spatial N response experiments at a field scale have previously been conducted in the UK (Lark & Wheeler, 2003; Bishop & Lark; 2006; 2007) and Australia (Pringle et al., 2004; 2010; Whelan et al., 2012). By setting up replicated differential rates of N across fields, measuring yields (or other factors, e.g. NDVI), kriging to assess spatial variation at each N rate, then fitting an N response function, the spatial variation in N requirements can be seen. Some of these studies have tended to aim at developing techniques for farmers to generate local response functions using combine yield mapping which they can use for variable rate site specific management in future years (Pringle et al., 2004). Bishop & Lark (2006) recognise the potential for new spatial experimentation techniques to help learn about underlying soil effects on the response of treatments, which is deliberately inhibited by the classical randomised block design and analysis of variance established by Fisher (1930). By measuring the components of N requirement (Crop N Demand, SNS, Fertiliser recovery) along with other crop and soil measures, this spatial experimentation should be able to tell us about soil effects on N requirements generally, not just for the specific site.

## 4.2 Chessboard Experiments

Whilst there are statistical benefits from including randomisation within an experimental design, there are major logistical, practical and management advantages in adopting a simple systematic chessboard (or checkerboard) design as shown in Figure 8. This design is relatively simple to set up using commercial application equipment (sprayer or pneumatic spreader), with half boom shut off and tramlines both across and up & down the experiment. In one direction N rate 1 is applied to one side of the tramline, N rate 0 on the other. In the perpendicular direction N rate 2 is applied to one side and again N rate 0 to the other. This sets up the chessboard pattern (actually a gingham pattern) of alternating squares of N0 (N0+N0) and N1 (N1+N0) plus N2 (N0+N2) and N3 (N1+N2) across the applied area. The size of each square depends on tramline width, a common 24m tramline width giving 12m squares.

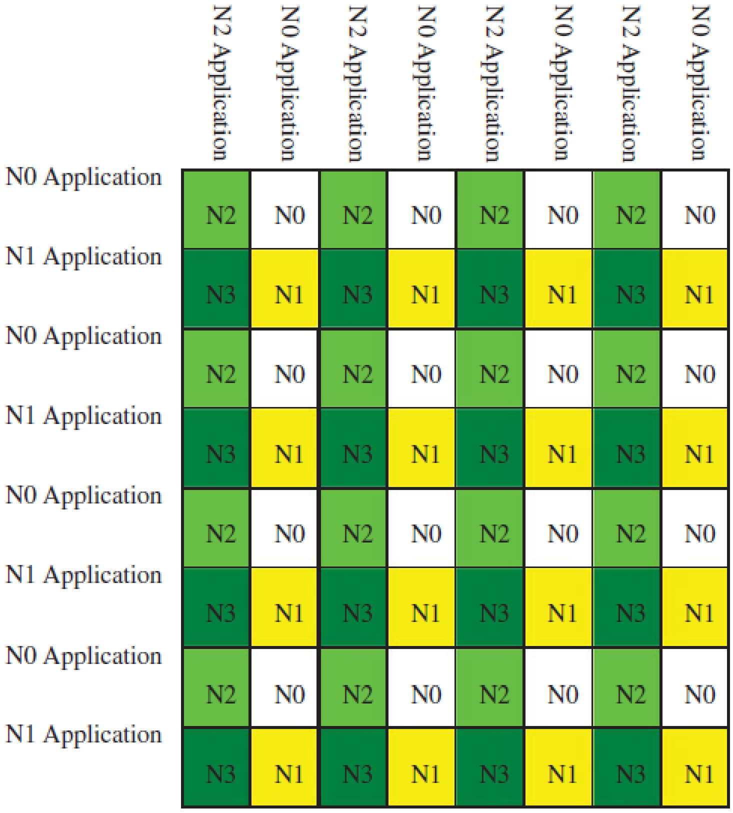



**Figure 8. Chessboard trial: The diagram shows how each N rate of the 'chess-board' tramline grid is attained from cross applications of N rates 0, 1 & 2 to give repeating pattern of N levels of 0, 1, 2 & 3.**

### 4.2.1 Chessboard Sites

Fields in winter wheat were selected as candidates from 5 fields of the 5 Auto-N farms. Fields were sought with interesting underlying variation in yields or crop sensing which might give rise to variation in N requirements. Final decisions on which fields to use were made by the Steering Group. The fields had to be large enough to accommodate the chessboard design of 250 to 500 plots (3 to 5ha plus headlands). Fields where manure had been applied to the current crop were excluded, as were fields recently ploughed out of grass.

**Table 1. Sites and details for the six chessboard trials.**

| Field ID | Parish | Grid Ref | Harvest year | Plot # | Plot length | Soil types | Soil series |
|---|---|---|---|---|---|---|---|
| F1 | Flawborough, Notts | SK777427 | 2010 | 528 | 10m | Clay loam | Worcester, Evesham, Fladbury |
| F6 | Flawborough, Notts | SK781412 | 2011 | 432 | 9m | Clay loam | Evesham, Fladbury |
| A2 | Burford, Oxon | SP236111 | 2011 | 376 | 11m | Cotswold brash | Elmton, Aberford, |
| A3 | Burford, Oxon | SP242112 | 2012 | 400 | 11m | Cotswold brash | Elmton |
| B2 | Sharnbrook, Beds | SP990589 | 2012 | 270 | 10m | Clay loam | St Lawrence, Wickham, Efford, Aberford |
| C | Shipton, N Yorks | SE561576 | 2012 | 250 | 12m | Sandy clay loam | |

### 4.2.2 Setting up plots

Plot size was a minimum of 10m x 10m allowing half of each plot to be used for destructive sampling whilst the other half was used for non-destructive assessments and harvest by plot combine. Harvest lengths were defined by removing tramlines in one direction by plot combine and a single ‘burn out’ mid-way between tramlines using a herbicide application by hand.

### 4.2.3 Nitrogen Applications

Nitrogen treatments were applied by the farmer either pneumatically or as liquid (not by a spinner) using a grid system of tramlines in accordance with the plan (appendix 1a). Nitrogen fertiliser application was applied in two equal doses in March and April (approx. GS30 and 32). At each application date, normal farm tramlines were used to apply Rate 1 (normally 60kg/ha) in one direction on half the tramline, and zero on other half. On tramlines at right angles to these Rate 2 (normally 120 kg/ha) was applied to half the tramline, and zero on other half.

All chessboard trials had treatments of 0, 120, 240, 360 except F6 which had 0, 100, 200, 300 due to high measured SMN and high expected (& achieved) SNS.

### 4.2.4 Measurements

#### *4.2.4.1 Soil sampling.*

Soils were sampled in Autumn or Spring (prior to any fertiliser application) using Eijkelkamp "Stepwise" gouge augurs to 90cm depth in increments of 0–30cm, 30–60cm and 60–90cm. Each sample consisted of 5 cores the first being at the intersection of 4 treatment 'squares'(GPS referenced) and the remaining 4 from the centre of each square. Sampling was carried out either in a grid pattern, or was stratified according to known soil and past yield variations (where sufficient information was available). All samples were analysed for SMN. The 0–30cm sample was also analysed for, total N% by Dumas, SOM (Walkley Black – RB427) and potentially mineralisable-N by anaerobic digestion.

#### *4.2.4.2 Canopy sensing*

We aimed to measure canopy reflectance of all plots using a Crop Circle sensor on at least four occasions per trial, once in autumn or before end February, once 2-3 weeks after first N application (mid-March), once 2–3 weeks after second N application (late April) and once at flag leaf emergence (mid-May). In practice waiting for suitable weather conditions, technical problems with the sensors, and delivery delays between sites meant that exact timings were not always as planned.

On selected plots at each date, canopy measurements were also taken using a hand-held version of the Yara N Sensor, Cropscan, Minolta SPAD (and Yara N tester) and, after GS30, a Sunscan ceptometer. Digital photos were also taken looking vertically down into the crop for use with the BASF canopy assessment tool.

Where possible, sensor assessments of chess-board trials were continued into the succeeding crop to test the capacity of sensors to detect residual or 'ghost' effects, particularly on SMN.

#### *4.2.4.3 Crop dry matter and N uptake.*

Crop dry matter and nutrient uptake was measured on the same selections of plots and timings as the soil samples. Three 0.25m$^2$ quadrats were taken from each plot. Prior to sampling, digital photographs were taken of each quadrat area, chlorophyll content measured by SPAD and light interception measured using the Sunscan ceptometer. The numbers of plants and shoots in each quadrat were counted before the plants were cut at ground level and taken back to the laboratory for drying and weighing. Dried samples were then analysed for N%.

#### *4.2.4.4 Harvest*

At selected plots at each site whole tiller grab samples were taken from each plot immediately prior to harvest, shoots counted then ears separated from straw dried & weighed. Ears were threshed and grain weighed. Chaff was returned to straw samples and sent for analysis of N% by Dumas at Hill Court laboratory. Due to resource limitations and some sample losses not all samples were fully processed at all sites.

To eliminate effects of combine harvest direction being confounded with N treatment two harvest cuts were taken per plot in opposite directions parallel to farm wheelings, using a Sampo plot combine. Cross wheelings were removed prior to harvest cuts being taken and plot lengths measured. A single sample was taken from each plot for grain moisture and specific weight determination by Dickey John Grain meter. Plot yields were calculated at 85% dry matter using averaged yields from the two cuts per plot. Grain samples were analysed for protein by FOSS Infratec NIR analyser.

### 4.2.5 Post-harvest

Where the experimental crop was followed by cereal or oilseed rape, semi-permanent markers were placed in the field and GPS references recorded to allow easy relocation of plots. Crop sensors were then used on every plot in the autumn and in spring before fertiliser application.

### 4.2.6 Statistical analysis

Harvest index (HI) was calculated for each plot by dividing the grain dry matter per shoot by the total dry matter per shoot. Grain N uptake was calculated by multiplying the grain yield by grain protein content divided by 5.7, which is the conversion factor in wheat from grain N% to grain protein content (% dry matter). N harvest index (NHI) was calculated by division of the grain N per shoot by the total N per shoot (straw N plus grain N). Total N uptake was calculated by dividing Grain N uptake by the NHI.

Block kriging was used in Genstat or Matlab to interpolate measures at each N rate for each plot, so that for each plot measures were available for each N rate, even though each plot was conducted at only one N rate. Kriging was conducted for grain yield, grain protein content on all plots at all N rates. HI and straw N% were kriged where sufficient data was available within an N rate. This allowed calculation of grain N yield, NHI and total N uptake for each plot at each N rate (where kriging NHI was not possible it was assumed at the fixed average level per N rate per site, allowing total N uptake still to be estimated from grain N yield).

At each site N responses were fitted to yield for each plot in Genstat using Exponential and Linear plus Exponential (LpE; Equation 1) curves sequentially allowing more parameters to vary within a site and assessing the parsimonious increase in variation explained. N optima were calculated using Equation 2 and a breakeven ratio of 5kg grain per kg N. After examining curves and fits at each site it was decided that the LpE with a fitted common R parameter at each site gave the most representative fits and estimates of N optima. The exponential model is statistically more justifiable for fitting to four N rates given its use of 3 parameters rather than 4 with LpE, but the exponential cannot give a decline at higher N rates and does not allow as much flexibility in the shoulder of the curve where N optima are low. By fixing the R parameter within each site only 3 parameters need to be fitted, leaving one degree of freedom.

Quadratic curves were fitted in Genstat to grain protein concentration. However, these were found to give unsatisfactory responses in many instances. To calculate protein content at the optima simple interpolation was performed in Excel using the forecast function between the N rates either side of the optima for yield.

A broken stick (or split-line) regression analysis was conducted in Genstat on the total N uptake data for each plot. The slope of the second line was restricted to zero so that the Y breakpoint could be used as an estimate of crop N demand and the slope an estimate of fertiliser recovery.

All presentation of spatial data is in ArcGIS.

## 4.3 Chessboard results

### 4.3.1 Weather comments

Both 2010 and 2011 were characterised by having very dry springs (Table 1); it is likely in both years that yields were limited by water availability where soil did not contain sufficient available water. It also meant that fertiliser was not readily taken up after application in April. This was especially evident at Flawborough in 2011 where little visual difference was evident from N applications following only 16.5mm rainfall in all of March and April (Table 2). Such dry conditions could have killed soil microbial activity, giving mineralisation once substantial rainfall fell in late May 2011. The 2012 season began with a continuing drought but became very wet from April onwards. The Shipton site in Yorkshire suffered water-logging for much of the spring and summer. 2012 was also marked by having a very dull late spring and summer, which together with relatively high night time temperatures (7.0°C and 9.7°C for May and June, respectively, compared to long term average mean minimum temperatures of 6.4 and 9.2°C) meant crop respiration was high relative to photosynthesis.

**Table 2. Weather Summary for the three years from Met Office for England**

| Period | 2010 | 2011 | 2012 |
|---|---|---|---|
| *Rainfall (mm/month)* | | | |
| Oct–Dec | 110.7 | 66.6 | 71.8 |
| Jan–Mar | 66.7 | 58.6 | 40.1 |
| Apr–May | 27.0 | 30.0 | 95.3 |
| Jun–Jul | 48.9 | 64.8 | 130.8 |
| *Solar Radiation (hrs/month)* | | | |
| Oct–Dec | 74.4 | 77.9 | 75.7 |
| Jan–Mar | 81.2 | 78.0 | 103.7 |
| Apr–May | 202.3 | 211.9 | 161.9 |
| Jun–Jul | 198.4 | 186.4 | 139.4 |
| *Mean Temperature (°C)* | | | |
| Oct–Dec | 7.5 | 5.0 | 9.1 |
| Jan–Mar | 3.2 | 5.5 | 5.8 |
| Apr–May | 9.7 | 11.9 | 9.3 |
| Jun–Jul | 16.1 | 14.5 | 14.4 |

**Table 3. Weather Summary for Flawborough from John Hawthorne's weather station, Notts**

| Period | 2010 | 2011 | 2012 |
|---|---|---|---|
| *Rainfall* | | | |
| January | 41.4 | 32.8 | 38.6 |
| February | 50.8 | 51.8 | 9.6 |
| March | 40.9 | 9.1 | 24.8 |
| April | 29.7 | 7.4 | 130.7 |
| May | 28.2 | 47.8 | 36.2 |
| June | 40.1 | 35.8 | 110.5 |
| July | 36.8 | 54.9 | 103.4 |
| August | 110.2 | 56.6 | 96.8 |
| | | | |
| *Mean Temperature* | | | |
| January | 1.6 | 3.2 | 5.2 |
| February | 2.4 | 6.1 | 4.1 |
| March | 5.3 | 6.3 | 7.3 |
| April | 8.3 | 10.9 | 7.2 |
| May | 10.2 | 11.9 | 11.5 |
| June | 14.6 | 14.1 | 13.4 |
| July | 16.7 | 15.1 | 15.3 |
| August | 14.6 | 15.5 | 16.5 |

### 4.3.2 Chessboard sites info

All chessboard trials were set-up successfully. A few minor over-applications of fertiliser in Burford 2011 meant a 2 plots were excluded from analyses. Figure 9 shows the fields and layouts of the chessboard trials.

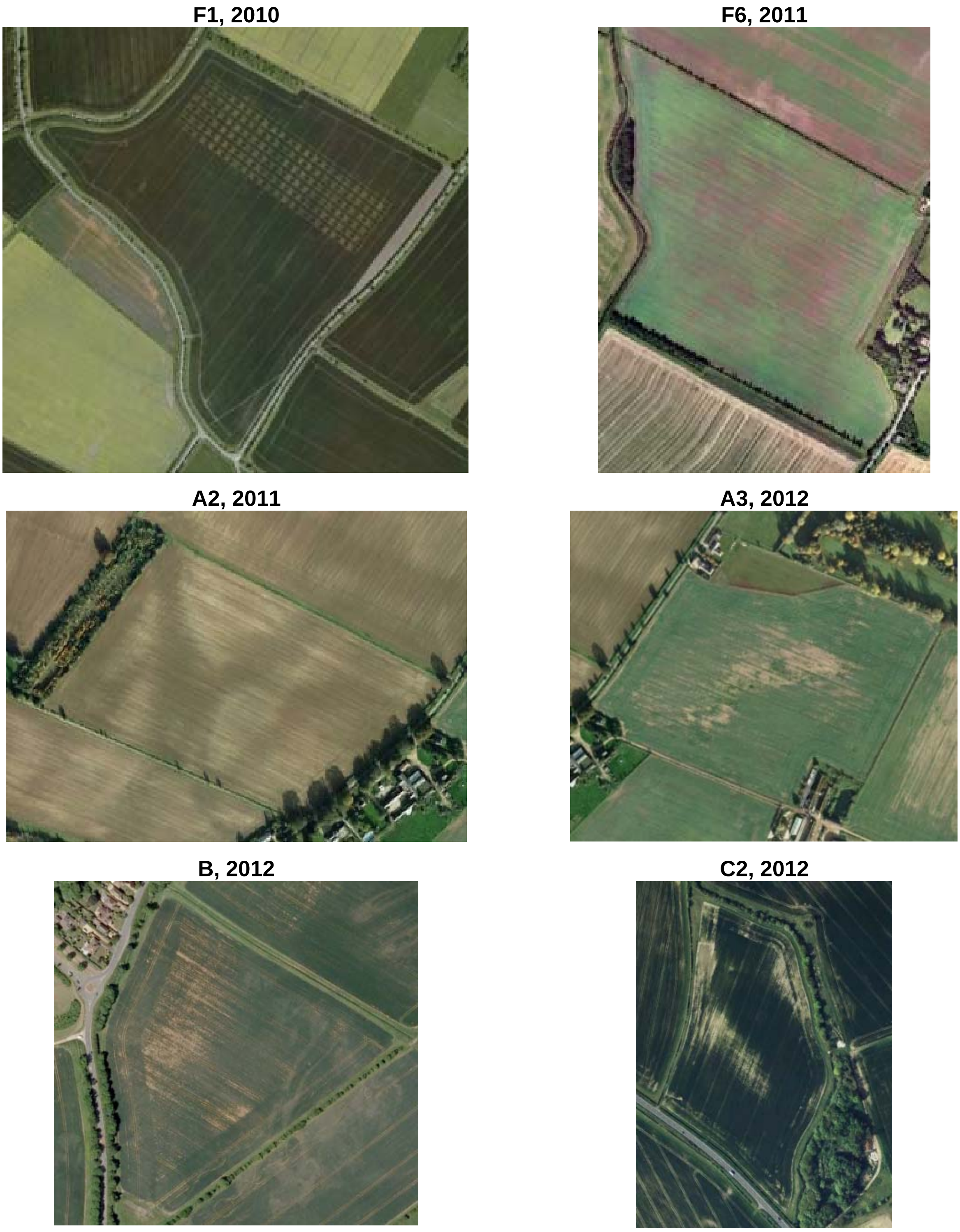
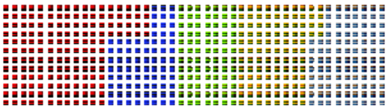



**Figure 9. Fields with Chessboard trials from Google Maps**

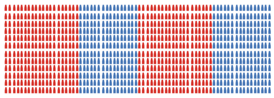
Figure 10 gives estimates of soil series for each plot where soil series differ within the site.

**Flawborough F1, 2010**



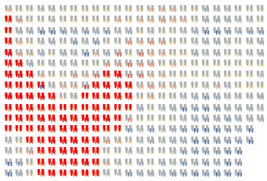
Fladbury-integrade-Evesham-integrade-Worcester

**Flawborough F6, 2011**



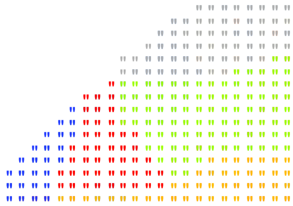
Fladbury-Evesham-Fladbury-Evesham

**Burford, A2, 2011**



Aberford – Elmton

**Bedfordia, B3, 2012**



St Lawrence, Wickham, Efford

**Figure 10. Soil types on chessboard fields**

Figure 11 shows the cluster groups for the chessboard areas from analysis of previous yields described in Chapter 4. Areas within each cluster behaves in a similar way with regard to yields across years. The identity of cluster groups is arbitrary, but these and the soil groups are used to explore the relationships between N optima and its components in Figures 33–38.

The average past wheat yields from past field yield maps for the chessboard areas are shown in Figure 12. Full details are given in Chapter 4.

Figure 13 shows electrical conductivity from EMI mapping of the fields. The distance between paralled soil scans was often somewhat more than the ~10m plot size of the chessboard plots so there are substantial numbers of missing data.

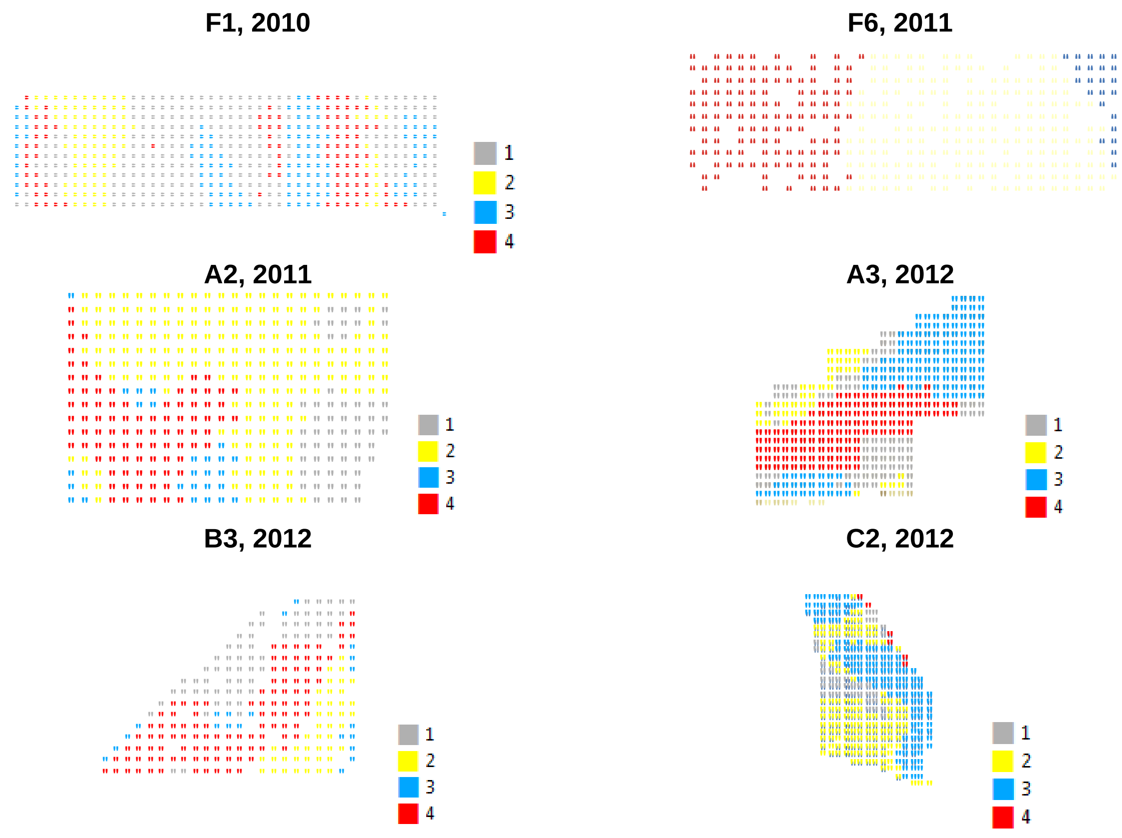



**Figure 11. Cluster groups from previous yield on chessboard fields (see Chapter 4)**

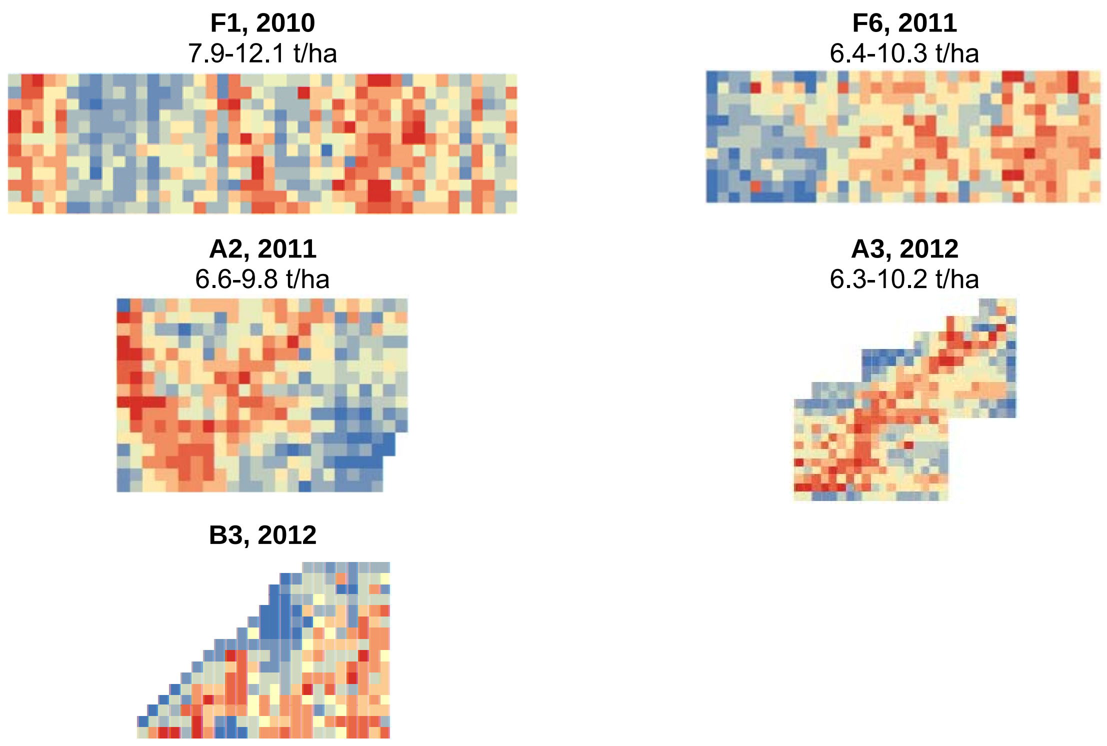



**Figure 12. Averaged past wheat yields on chessboard fields (see Chapter 4)**

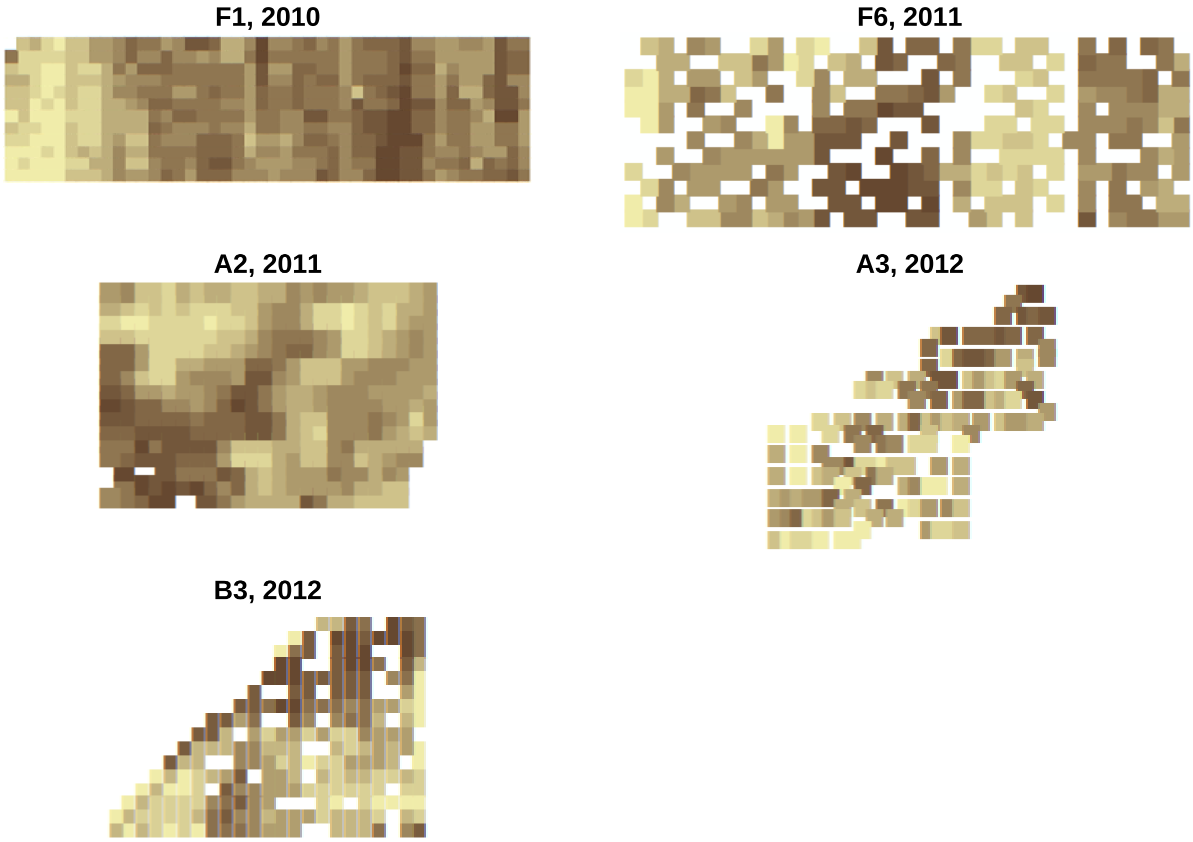



**Figure 13. Soil Electrical Conductivity on chessboard fields. NB soil measures sometimes taken at tramline width not plot width of ~10m so missing values for some plots.**

### 4.3.3 Aerial Photographs

Visual effects of N application and underlying spatial variation were apparent in May/June in all the chessboard trials, though visual effects of N were much more limited at Flawborough in 2011 (Figure 14) .

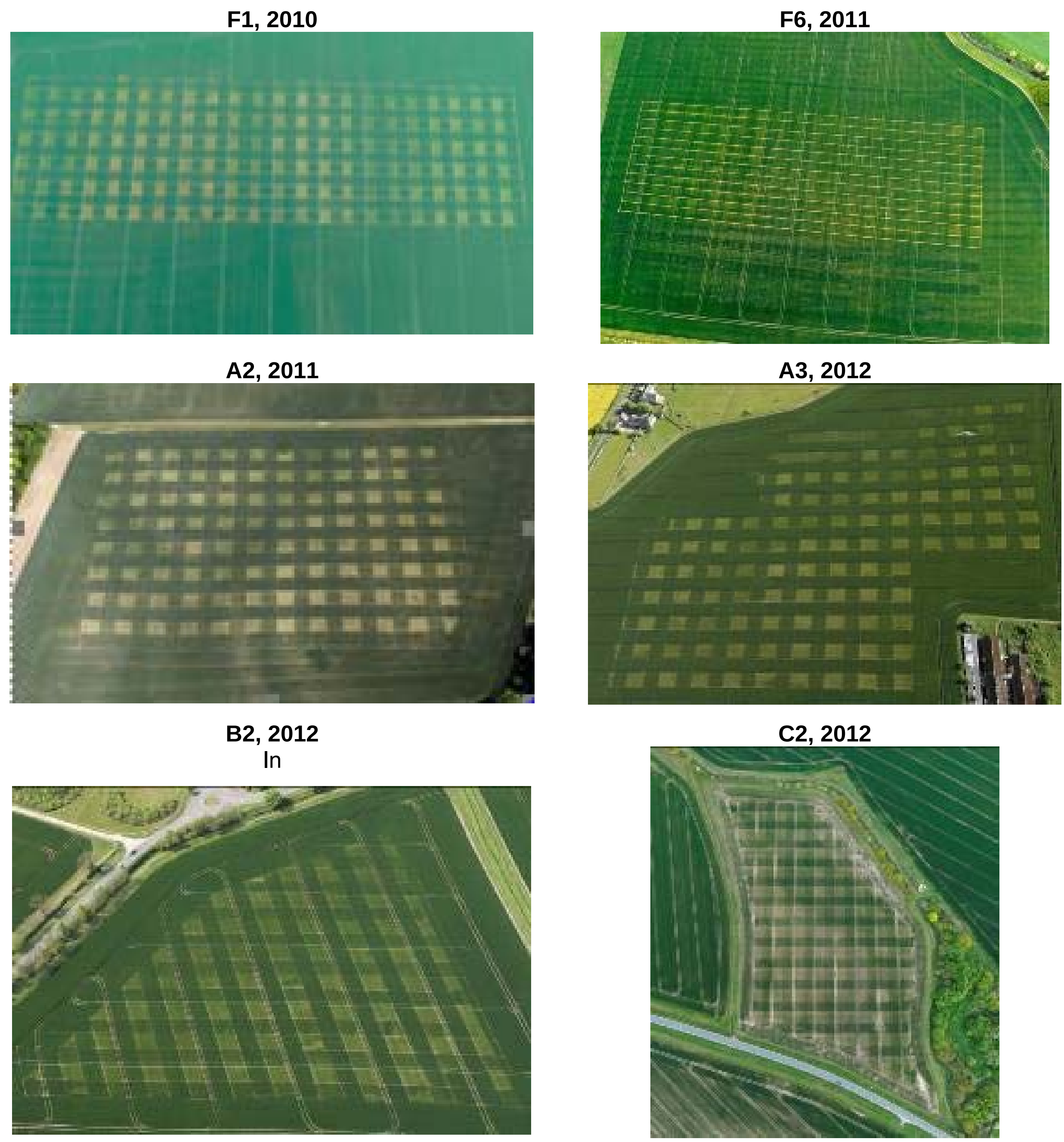


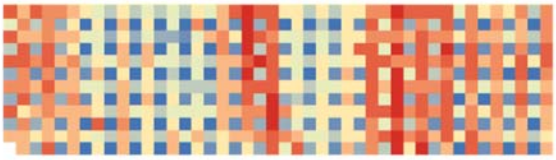

**Figure 14. Aerial images of Chessboard trials with field ID and harvest year.**

### 4.3.4 Plot yields

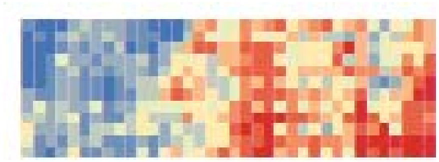
Each site clearly showed strong effects of N on yield as seen by the chessboard pattern showing through in plot yields in Figure 15, with the exception of Flawborough 2011 where there was very little yield response to N, and some very high yields achieved without N. All sites showed large spatial variation in grain yield, both from plot data and from kriged data giving estimated yields at each N rate for each individual plot (Figure 17). Generally the higher yielding areas at each site correspond to the evidently greener areas from the aerial photography. There is some exception in

2012 at Burford and Bedfordia, where the greener areas in June end with the lowest yields. Yields were generally low in 2012.

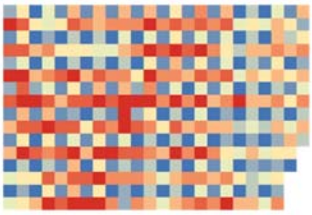
**F1, 2010**
3.9-12.6 t/ha



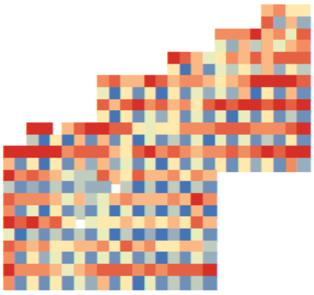
**F6, 2011**
6.1-11.6 t/ha



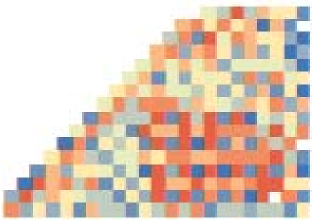
**A2, 2011**
3.4-10.5 t/ha



**A3, 2012**
3.2-9.2 t/ha



**B3, 2012**
3.2-9.2 t/ha



**C2, 2012**
1.0-10.8 t/ha

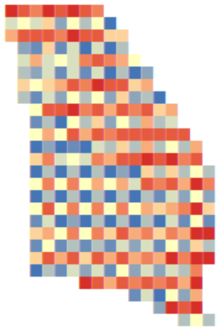


**Figure 15. Plot combine harvester yields of each individual plot in the Chessboard trials. Dark blue corresponds to low yield, dark red to higher yield. Values are given for the range in plot yields. There was some lodging at Flawborough 2010 site at the highest N rates in the highest yielding areas, shown in Figure 16 below. There was no lodging at any other site.**

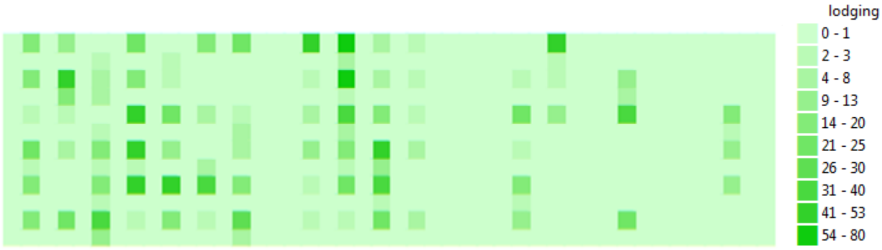



**Figure 16. Plot lodging (% area lodged) at Flawborough 2010**

### 4.3.5 Kriged yields – at each N rate

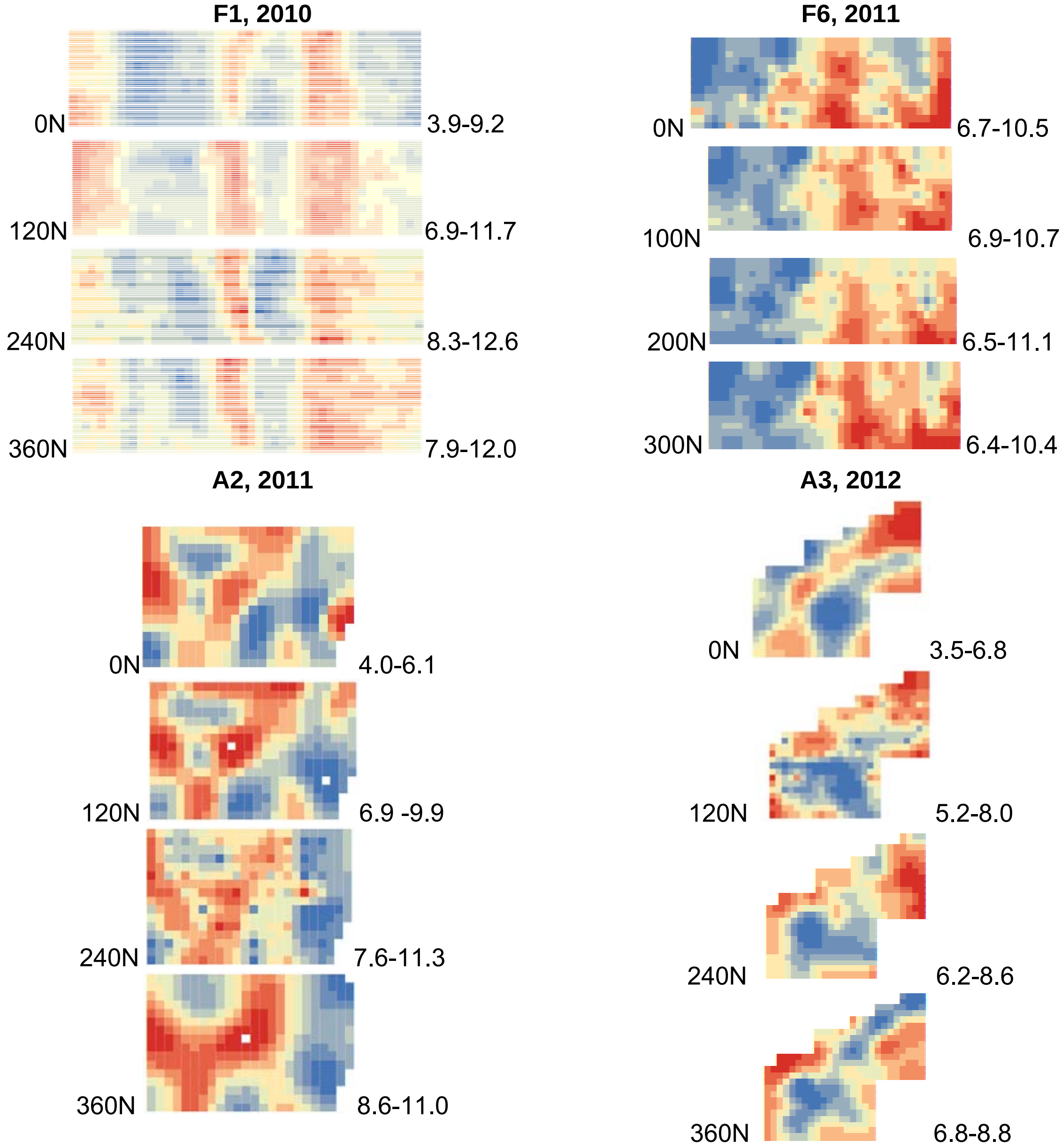



**Figure 17. Kriged yields at each N rate of chessboard trials. Dark blue corresponds to low yield, dark red to higher yield. Values are given for the range in plot yields at each N level.**

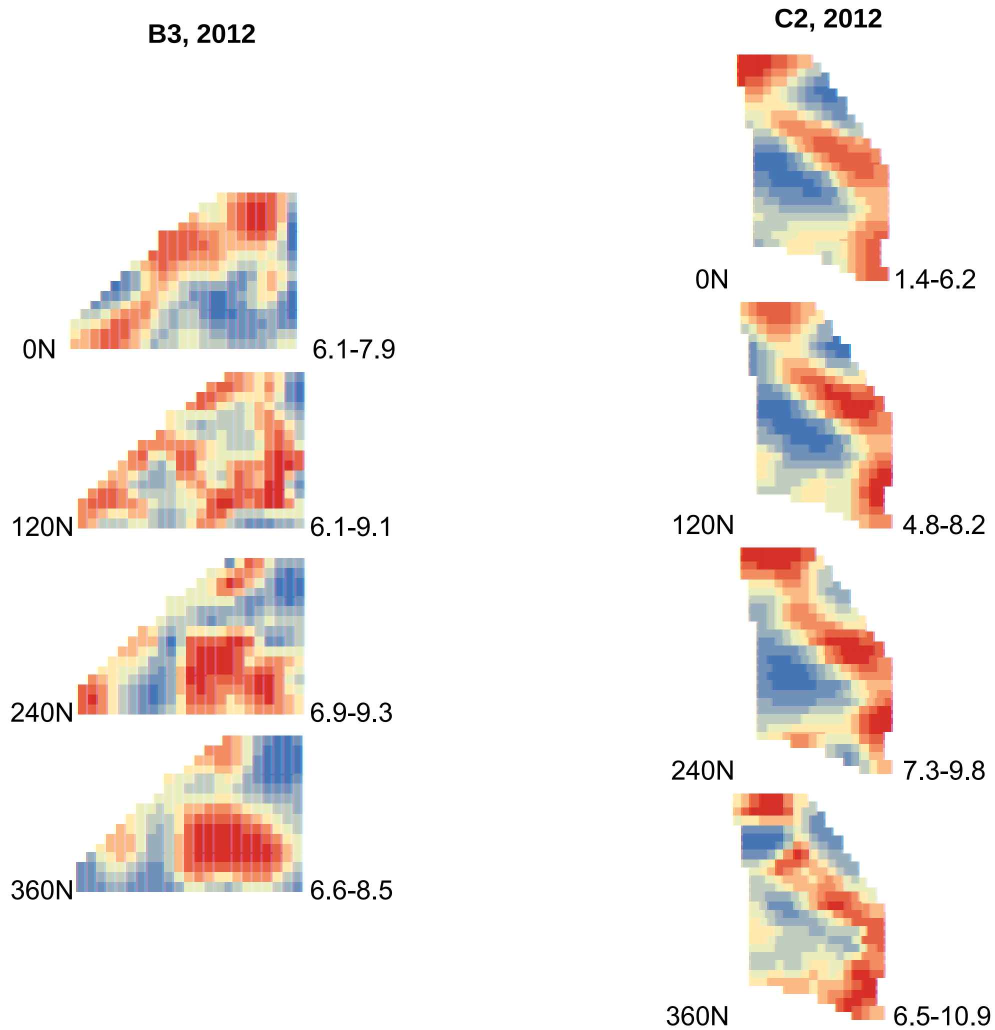



**Figure 17 (cont). Kriged yields at each N rate of chessboard trials. Dark blue corresponds to low yield, dark red to higher yield. Values are given for the range in plot yields at each N level. Spatial variation in yield exceeded 2 t/ha at all sites and 4 t/ha at Flawborough. Generally the patterns of spatial variation were consistent across all levels of applied N, i.e. higher yielding areas yielded more whether or not N fertiliser was applied. However there was a strong exception in 2012 at the Burford and Bedfordia sites where areas yielding the most without N applied, yielded the least with high levels of N applied. This is likely to be due to the abnormally dull and wet summer in 2012, where larger crops generally tended to perform poorly; this is discussed further in sections 3.7.4.**

### 4.3.6 N responses & N optima

For each plot at each site N responses were fitted using Linear plus Exponential function and economic optima determined (Equation 2). A random selection of these responses are shown for each site in Figure 18, with all optima plotted for each site. The differences in shape between sites is striking, but whilst there is substantial variation in N optima within each site, the shape of the response within each site is relatively consistent. Variation in N optima exceeds 100 kg/ha at all sites, and relates more to yield at some sites (e.g. Bedfordia 2012) than at others.

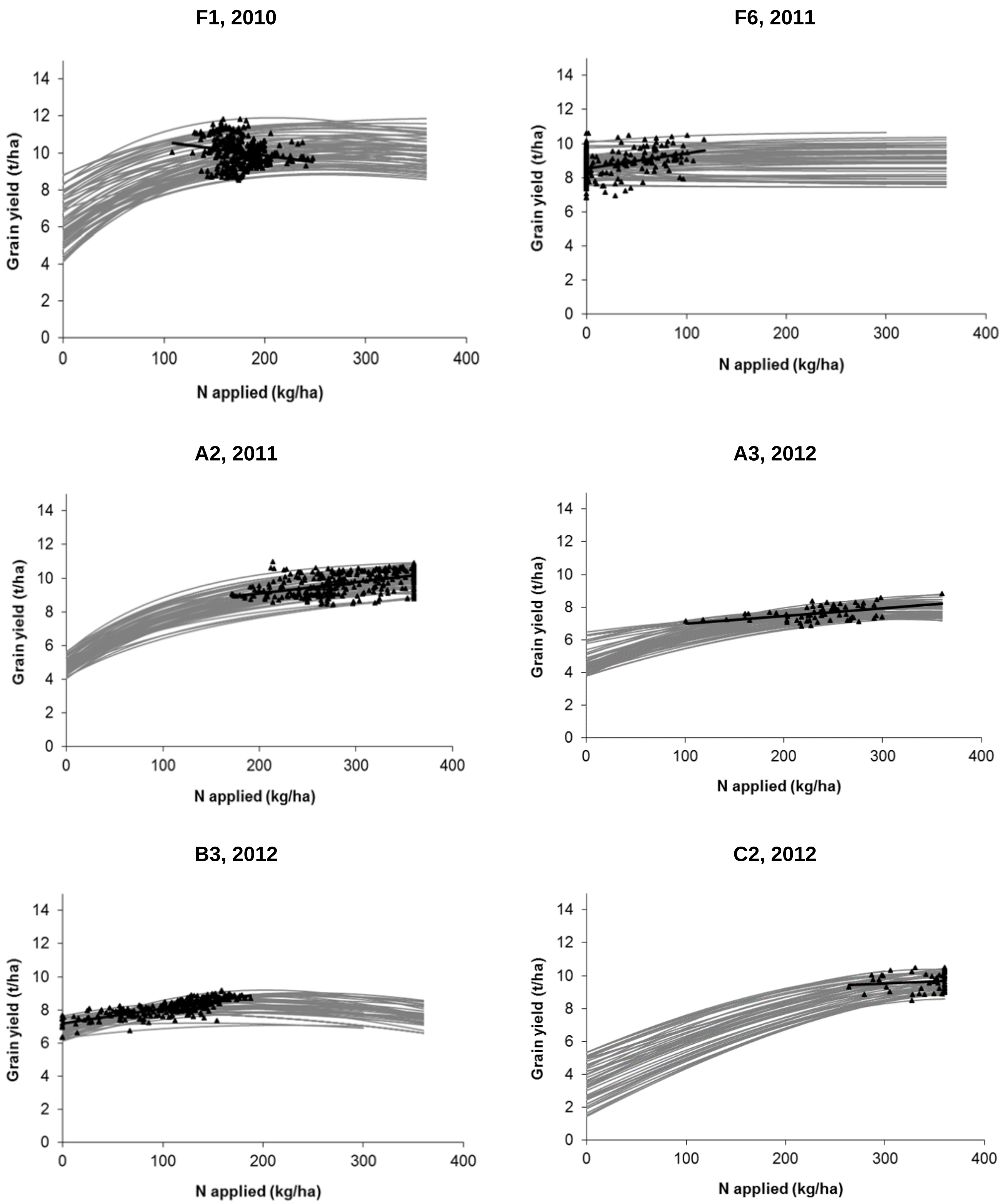



**Figure 18. N responses and N optima (triangles) of Chessboard trials using Linear plus Exponential fits with R fixed at each site. A random subset of the total number of responses is presented for each trial.**

The responses at Flawborough in 2010, Burford 2011 and Shipton in 2012 are reasonably typical of N response curves in the UK, giving N optima between 100 kg N/ha and >340kg N/ha. The lack of response to N is evident at Flawborough in 2011 and is probably partly due to spring drought meaning N fertiliser was not taken up in time to affect grain yield. Responses in 2012 for Burford and Bedfordia became negative at higher N rates, especially so at Bedfordia with some areas yielding as little with 340 kg N/ha as they did with no fertiliser. Whilst such N responses were common in 2012, typically such responses are rare, especially in the absence of lodging.

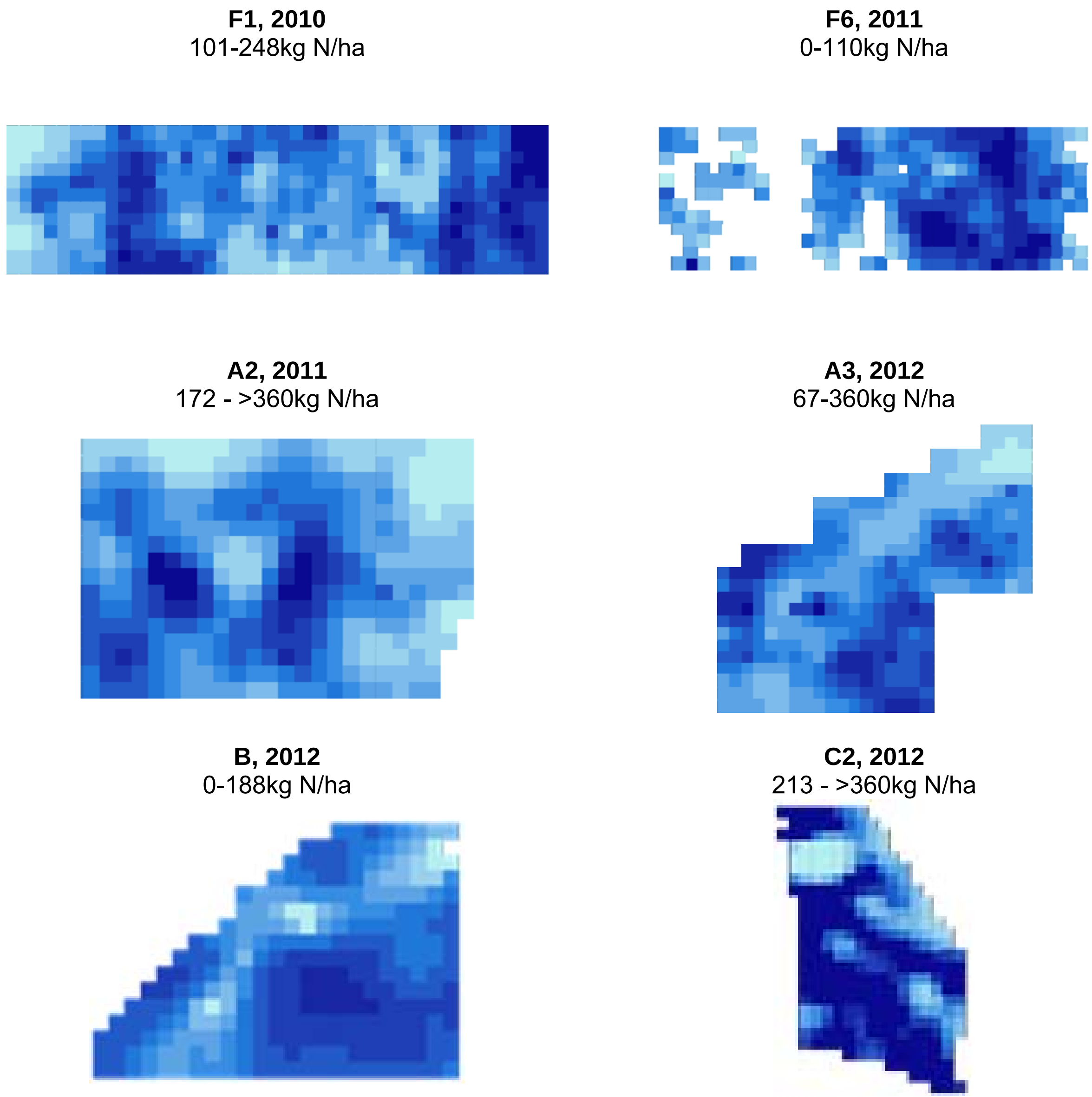



**Figure 19. N optima (BER=5) from fits in Figure 12 of Chessboard trials with field ID and harvest year. Values are minimum and maximum N requirements in trial. Darker colour higher is N requirement.**

Spatial variation in N optima (Figure 19) does not always clearly follow the same patterns that are evident from aerial imagery or from kriged grain yields. The patterns are most consistent for Burford and Bedfordia in 2012 where the lowest yielding bands give the lowest N optima, and vice versa.

### 4.3.7 Yield at optima

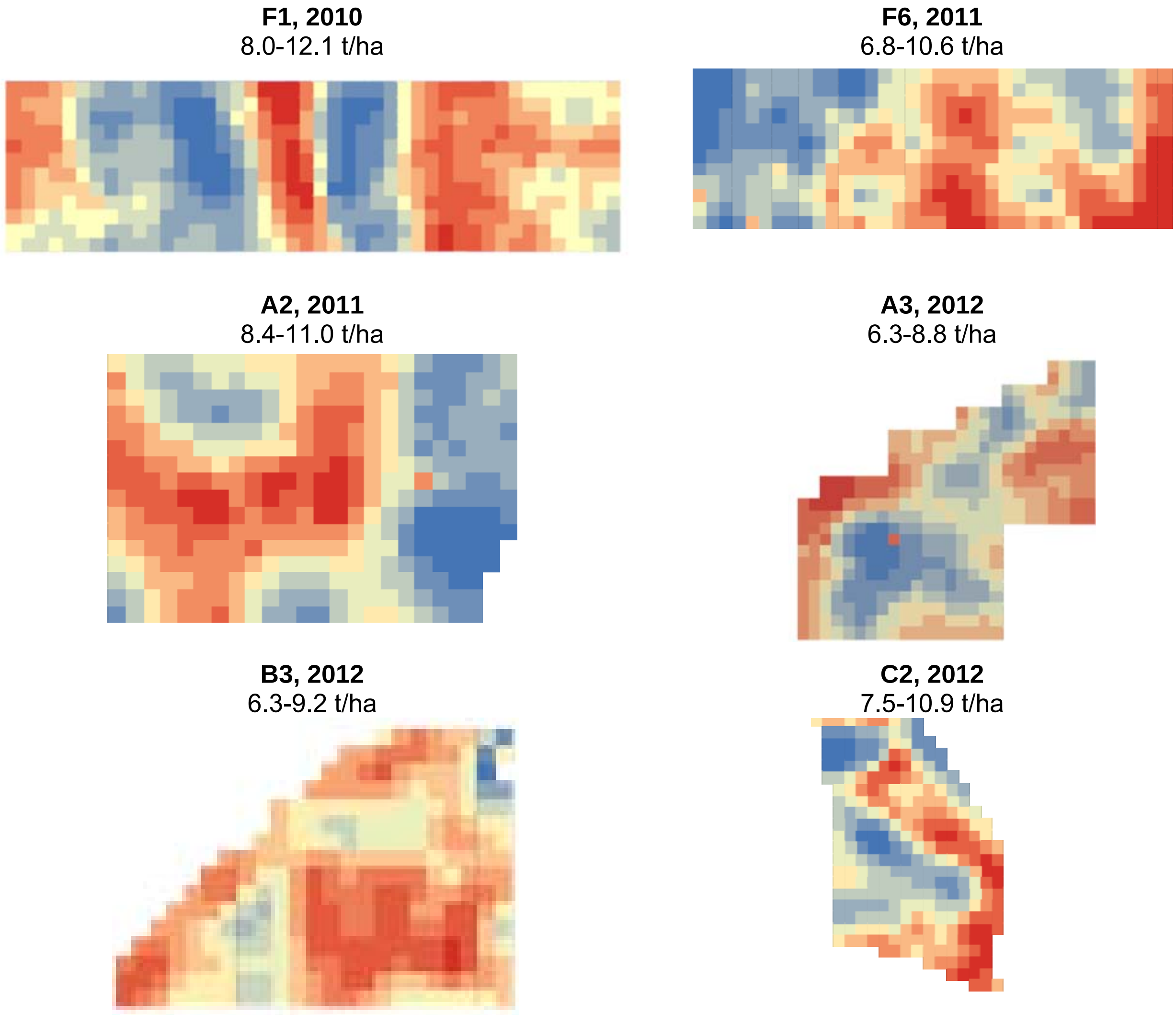



**Figure 20. Yields at N optima of Chessboard trials from fits in Figure 19 with field ID and harvest year. Dark blue corresponds to low yield, dark red to higher yield. Values give minimum and highest yields, excluding outliers.**

The variation in yields at N optima (Figure 20) at each site is greater than 2 t/ha and is similar to the variation in yield at any given N rate. This suggests N limitation is not a major cause of the spatial variation in yield in each of these fields.

### 4.3.8 Plot protein

There is a clear effect of N application on grain protein at each of the sites as the pattern shows through clearly (Figure 21), including for Flawborough 2011 which was unresponsive for yield. There is underlying spatial variation but this isn't generally as clear as that for grain yield and corresponds less clearly to the visible spatial variation from the aerial imagery.

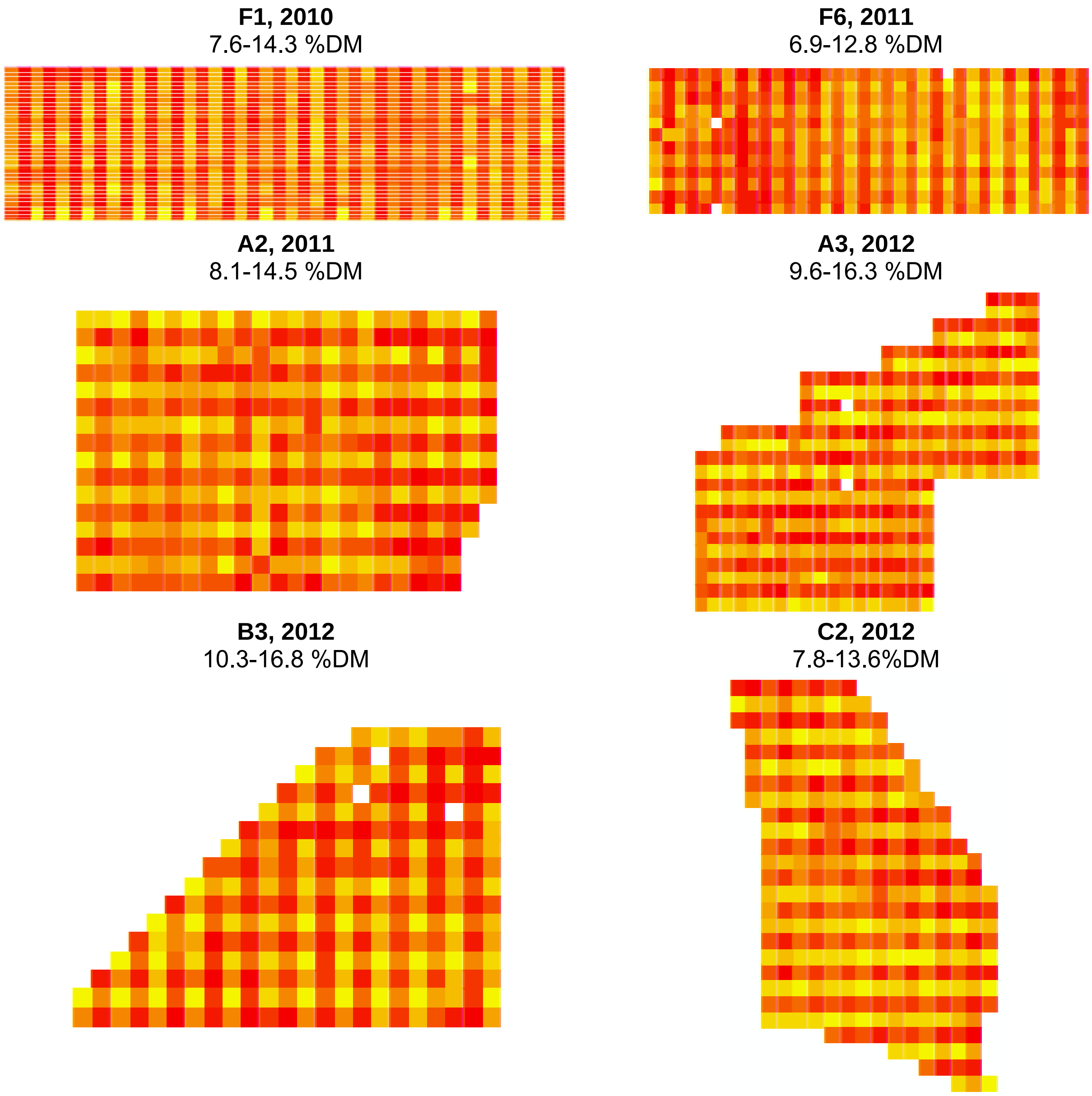
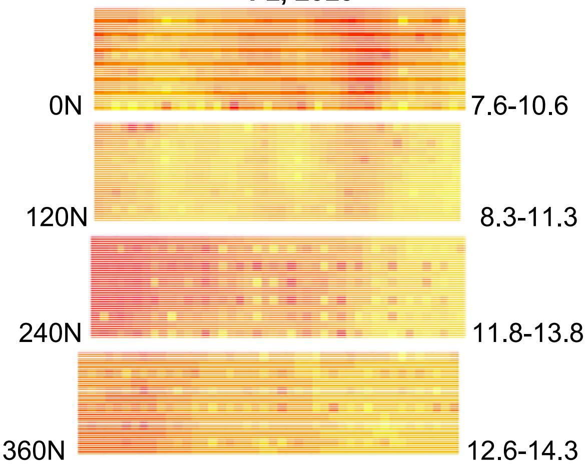



**Figure 21. Grain protein content of each individual plot in the Chessboard trials. Darker colour corresponds to higher protein. Values are given for the minimum and maximum protein in each trial, excluding outliers.**

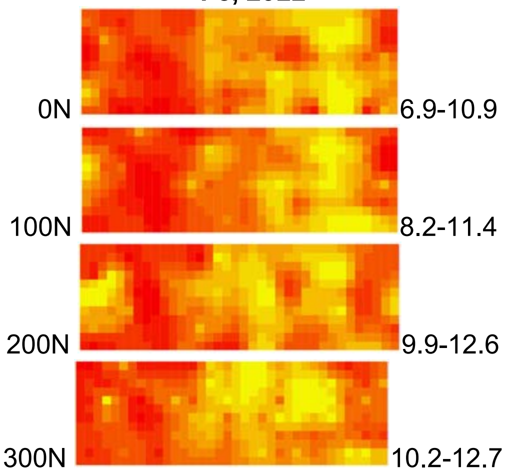
### 4.3.9 Kriged protein at each N rate

The spatial variation in the kriged grain protein content at each N rate is generally less coherent than that for grain yield, and is generally less consistent between N rates (Figure 22). However, variation in grain protein at each N rate is large, always exceeding 2% and often much more.

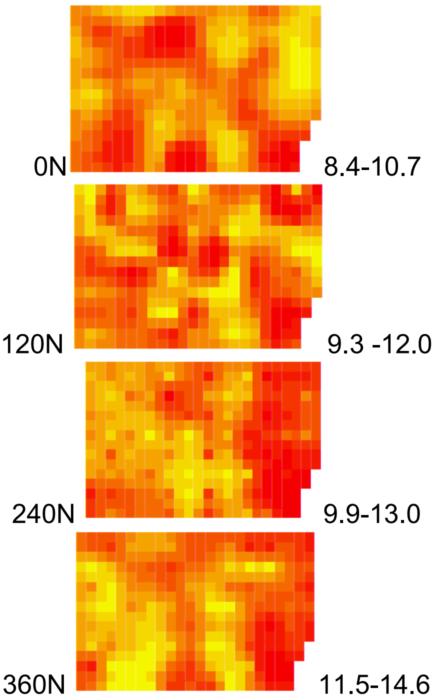
**F1, 2010**



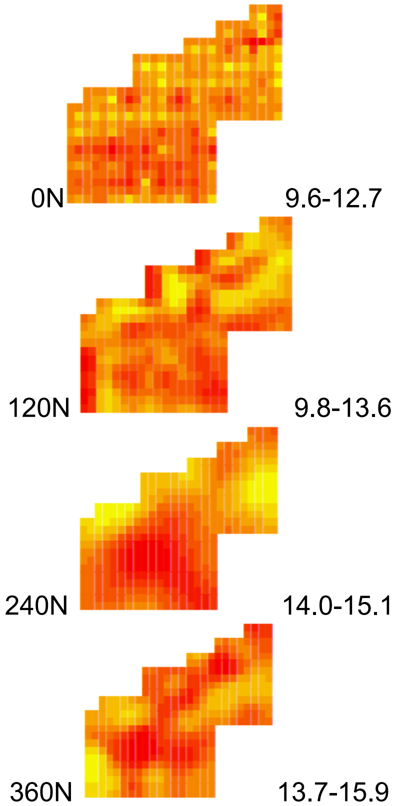

**F6, 2011**



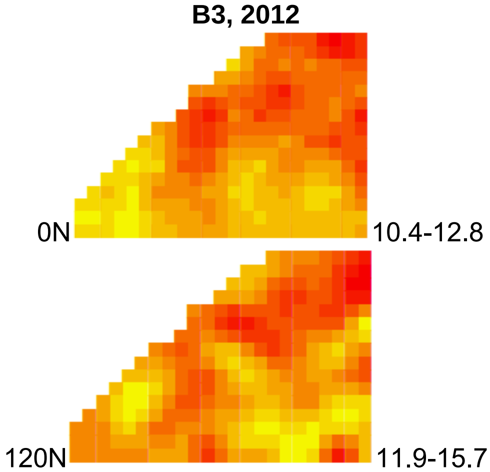

**A2, 2011**



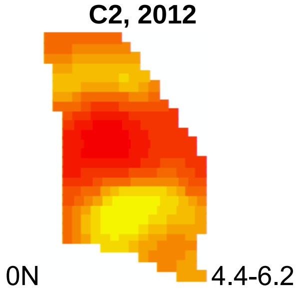

**A3, 2012**




**B3, 2012**




**C2, 2012**



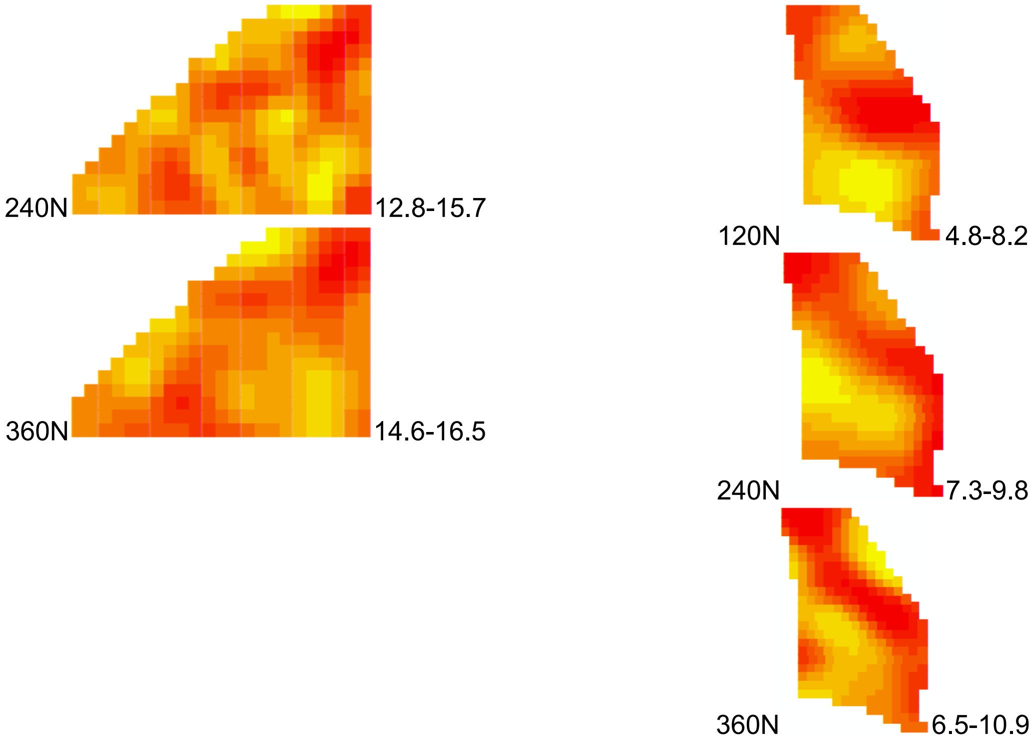



**Figure 22. Kriged protein contents at each N rate of chessboard trials. Darker red corresponds to higher protein. Values are given for the range in kriged plot proteins at each N level, excluding outliers.**

#### 4.3.10 Protein responses

Quadratic curves were fitted to the kriged protein data for each N fertiliser rate in each plot, but these were found to inadequately describe the protein response at Flawborough 2010 (F1) and Burford 2012 (A3) and there are insufficient N rates to fit a more sophisticated model. Therefore, plot figures are shown in Figure 23 and values given for protein at optima interpolated between plot values. At three of the sites (Burford 2011, Bedfordia and Shipton 2012) the protein content continues to increase with N rate with little evidence of levelling off. Where protein contents do clearly level off (Flawborough 2010, Burford 2012) there is a wide range in protein at the optima; the optima does not appear to occur at a consistent point on the protein response curve either within or between sites.

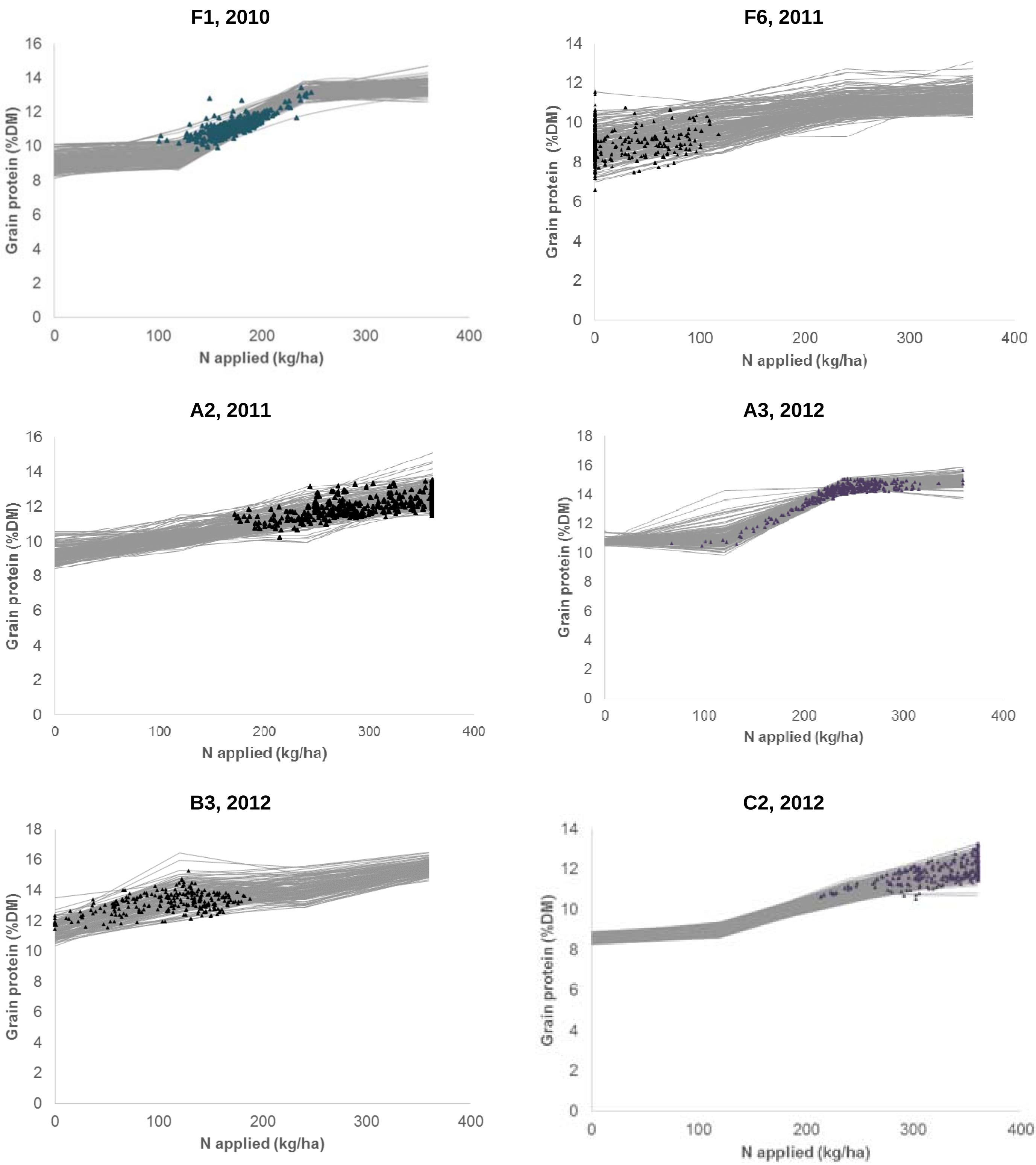



**Figure 23. Protein responses to N and interpolated protein at N optima (triangles) of Chessboard trials**

### 4.3.11 Protein at N optima

Grain protein at the optima varies substantially within each site (Figure 24). Given that protein content is given at the optimum, and that protein content clearly increases with N fertiliser rate, the protein at the optima is not an independent variable and so would be expected to vary with N optima.

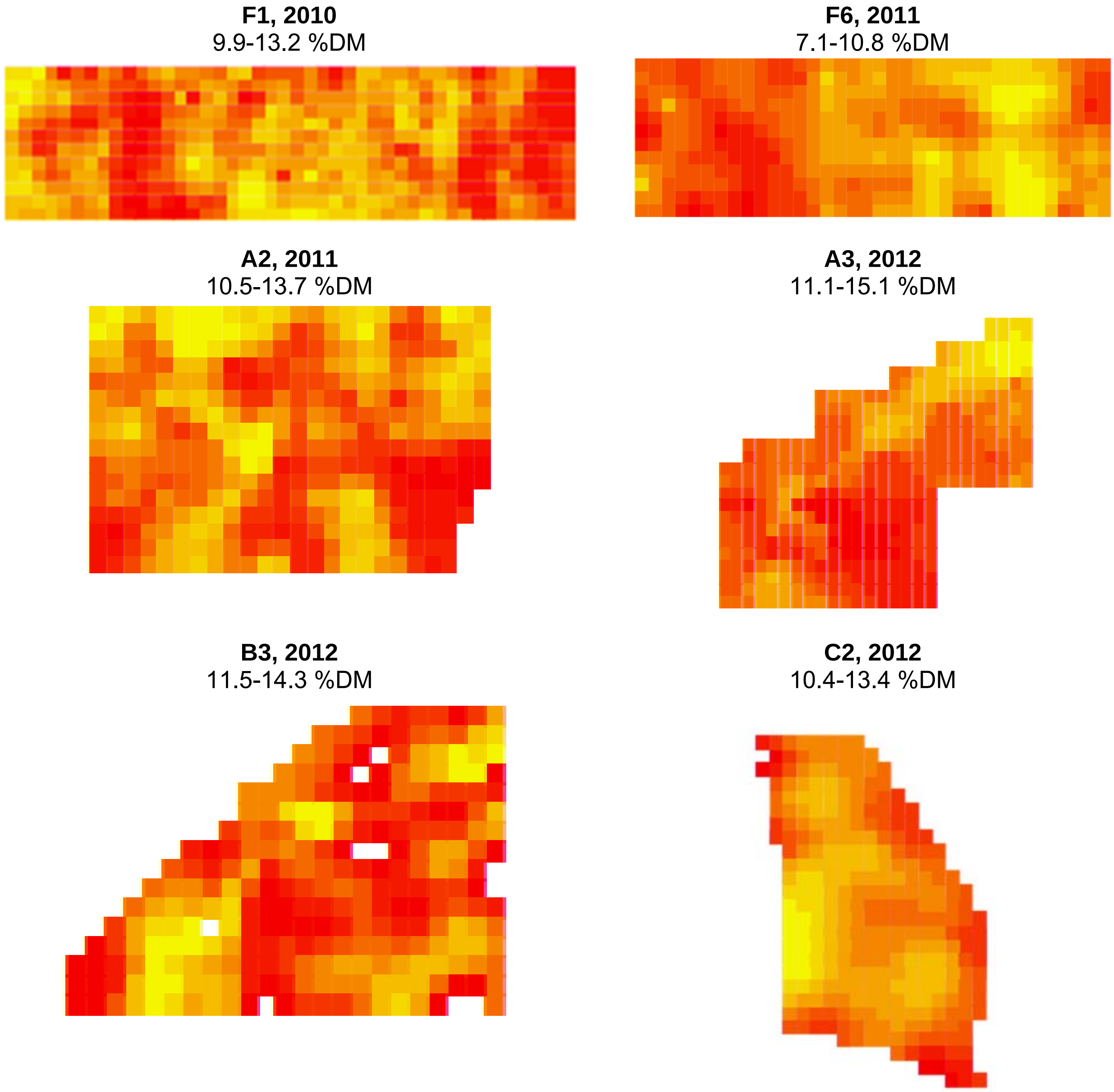



**Figure 24. Grain protein content at N optima of Chessboard trials from quadratic fits in Figure 23 with field ID and harvest year. Darker red corresponds to higher protein. Values are given for the range in proteins at optima for each site, excluding outliers.**

#### 4.3.12 Grab sample measures

Grab samples were taken from selected plots in each experiment to enable calculation of harvest index (proportion of total above ground dry matter (grain + straw) in the grain), straw yields and total N uptake. Full data is available from zero N plots at all sites, other N rates were sampled less intensively and can only be represented at F1, A3 & B3 (Figures 25–27); at the other sites insufficient samples were collected to meaningfully krig to produce maps.

#### *4.3.12.1 Harvest Index*

There is little consistent impact of N fertiliser rate on harvest index (Figure 25), though it tends to reduce markedly at the higher N rates at Burford and Bedfordia in 2012. There are interesting differences in spatial cohesion of variation in Harvest Index, with substantial spatial interactions with N rate at some sites, for example relative areas of high harvest index completely shift from zero N to high N at Flawborough 2010. The patterns in spatial variation in harvest index bear only limited similarity to other measures in each field.

#### *4.3.12.2 Straw N%*

Straw N% generally increased with N application rate and tended to show some spatial coherence within each field between N levels (Figure 26).

#### *4.3.12.3 Nitrogen Harvest Index (NHI)*

Nitrogen Harvest Index (proportion of total crop N in the grain) was little affected by N rate in 2010 but was strongly reduced with increasing N level in 2012 at Burford and Bedfordia, though not Shipton (Figure 27). There was relatively little spatial consistency in NHI across N levels and it was generally not clearly linked to spatial variation evident in other measures.

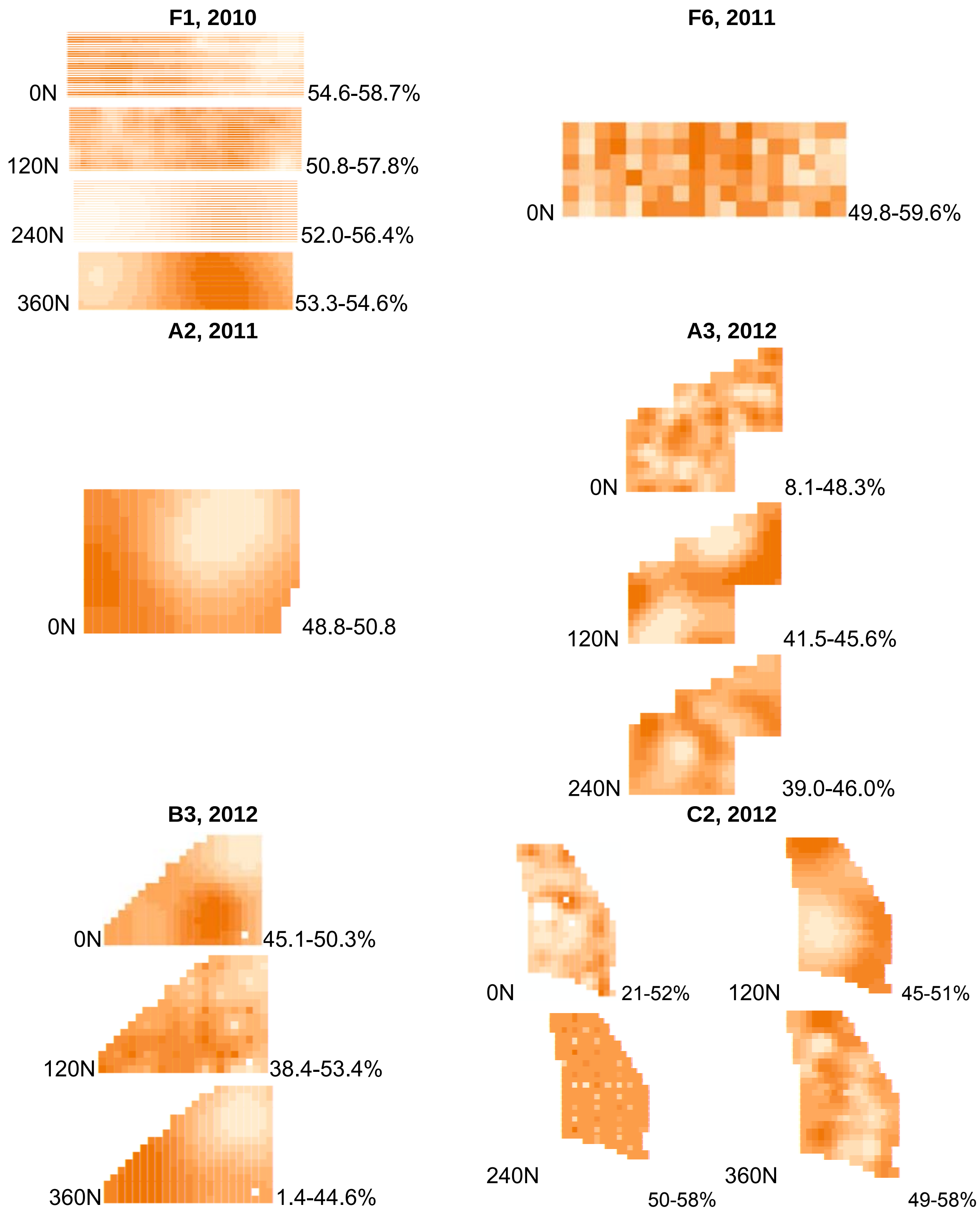



**Figure 25. Kriged Harvest Index (%) for the chessboard trials. All plots were sampled at zero-N at all sites, but only selected plots for other N rates so kriging is not possible for all N rates at all sites. Darker colour is higher value. Values are given for the range in kriged plot proteins at each N level, excluding outliers.**

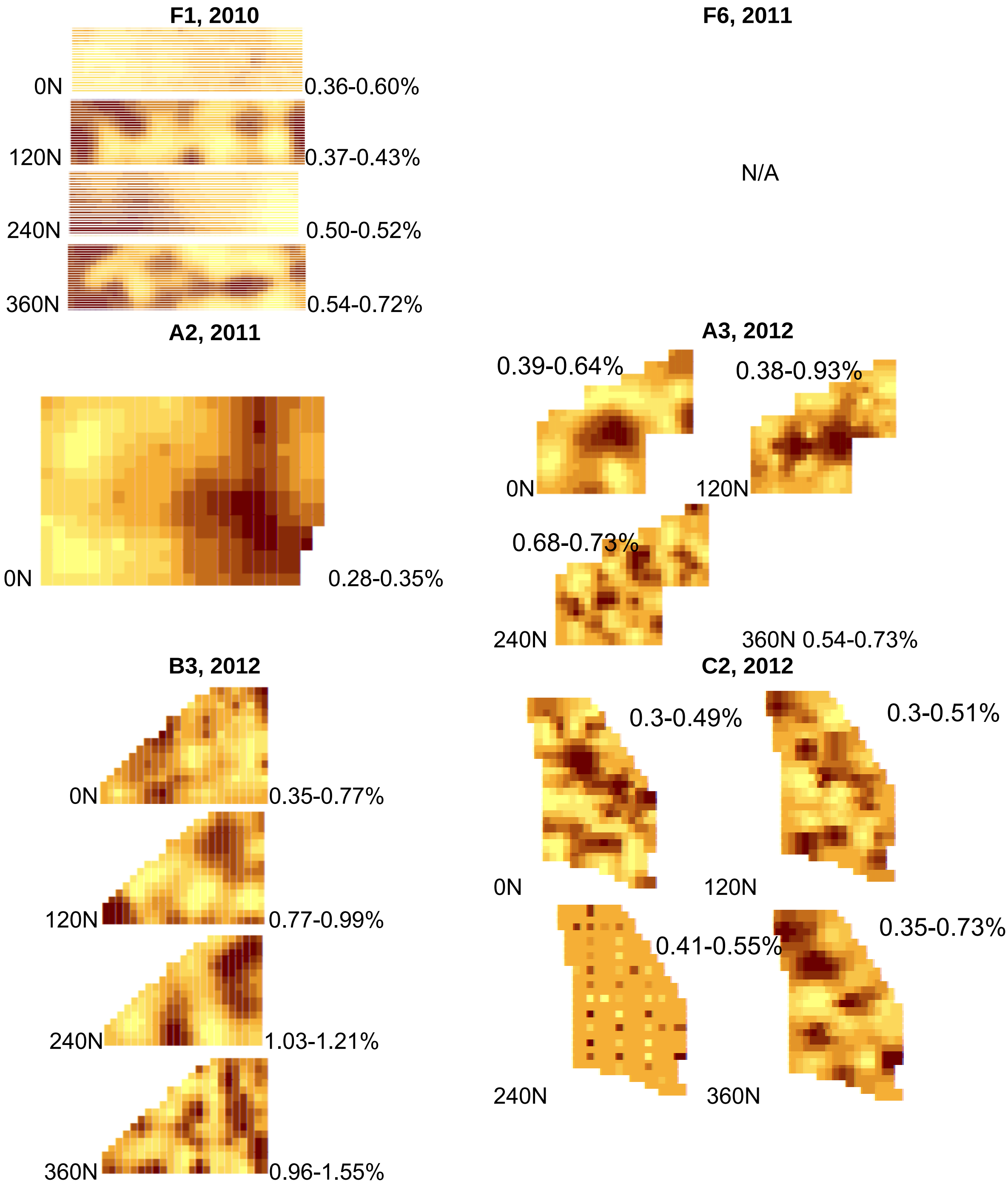



**Figure 26. Kriged Straw N concentration (%) for the chessboard trials. All plots were sampled at zero-N at all sites, but only selected plots for other N rates so kriging is not possible for all N rates at all sites. Darker colour is higher value. Values are given for the range in kriged plot proteins at each N level, excluding outliers.**

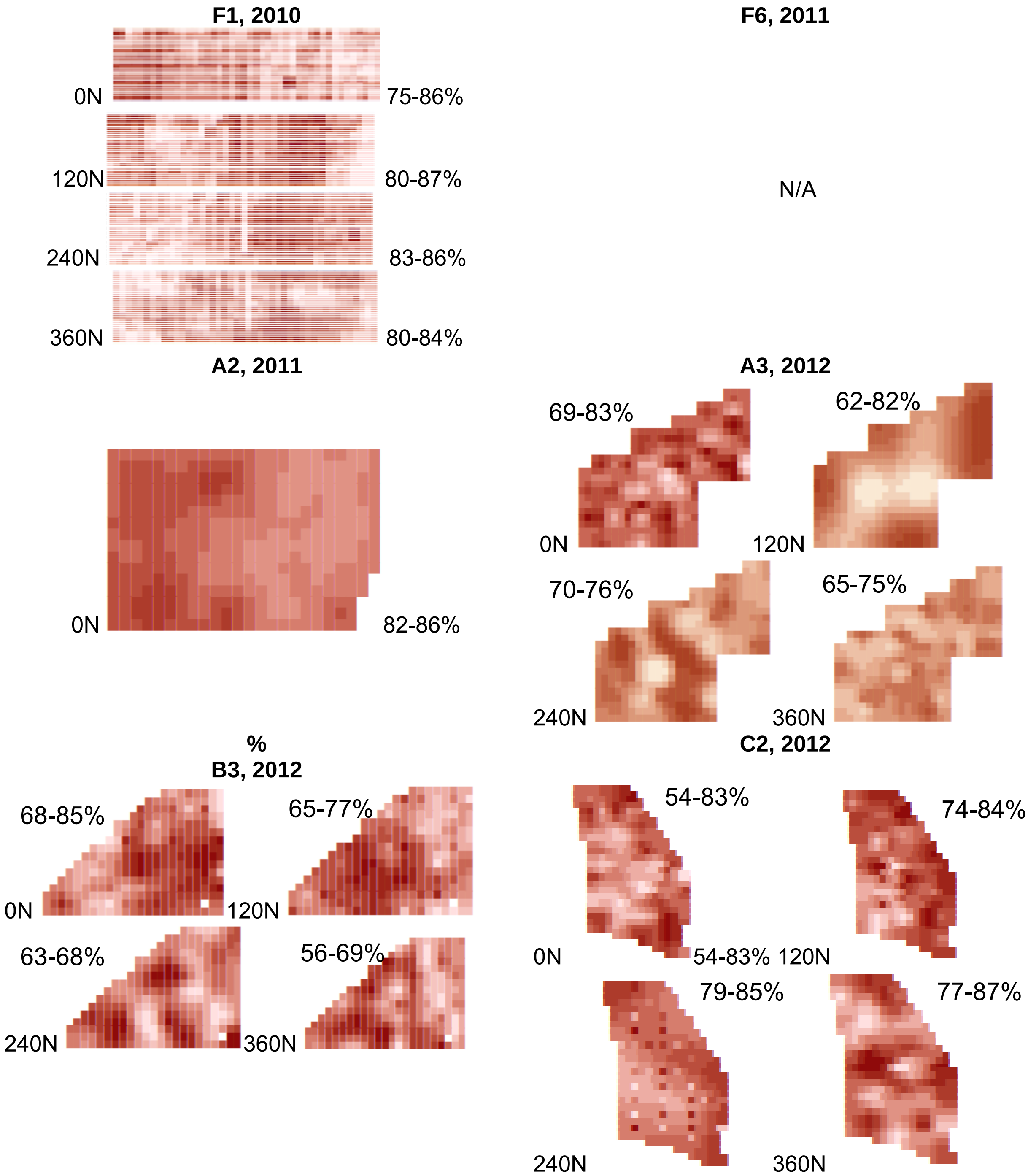



**Figure 27. Kriged N Harvest Index (%) for the chessboard trials. All plots were sampled at zero-N at all sites, but only selected plots for other N rates so kriging is not possible for all N rates at all sites. Darker colour is higher value. Values are given for the range in kriged plot proteins at each N level, excluding outliers.**

### 4.3.13 Total N Uptake

Total N uptake was calculated at each N level for each plot from grain DM yield, grain N% (protein/5.7), straw yield calculated using harvest index and straw N%.

#### *4.3.13.1 Harvested SNS*

Without fertiliser N applied, total N uptake gives the best measure of N available to the crop from the soil throughout the season, hence it is the best measure of Soil N Supply. Figure 28 shows that there was large spatially coherent variation in SNS for each of the fields, variation exceeding 75 kg N/ha in all but one field.

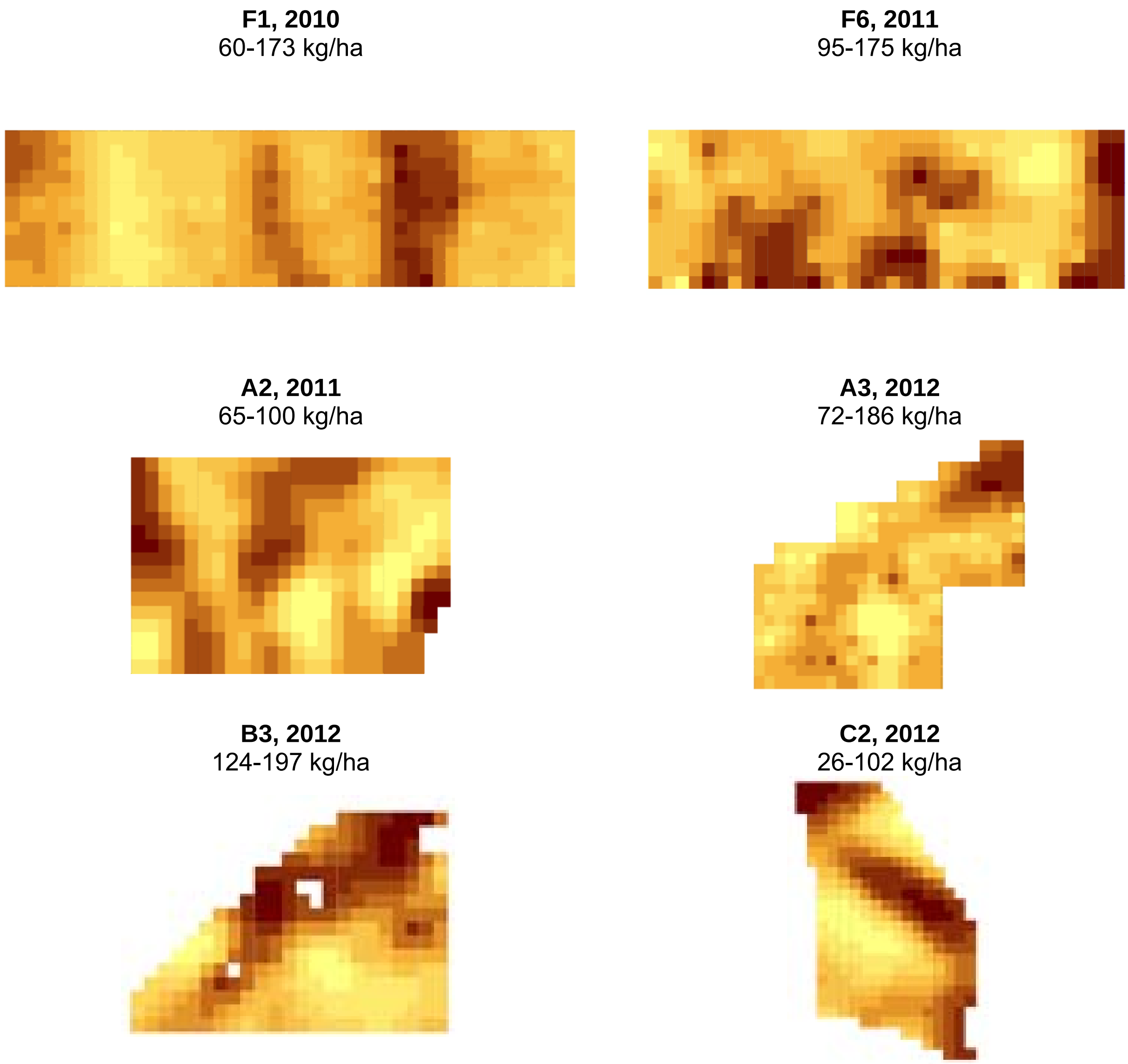



**Figure 28. Harvested SNS (Crop N Uptake with zero N) of Chessboard trials. Darker colour higher value. Values are given for the range in values at each N level, excluding outliers.**

#### *4.3.13.2 Total N uptake with N applied*

Total N uptake for N levels other than zero was calculated using the HI and straw N% values for each plot where available in Figure 21, else using averaged NHI for each N rate within each site.

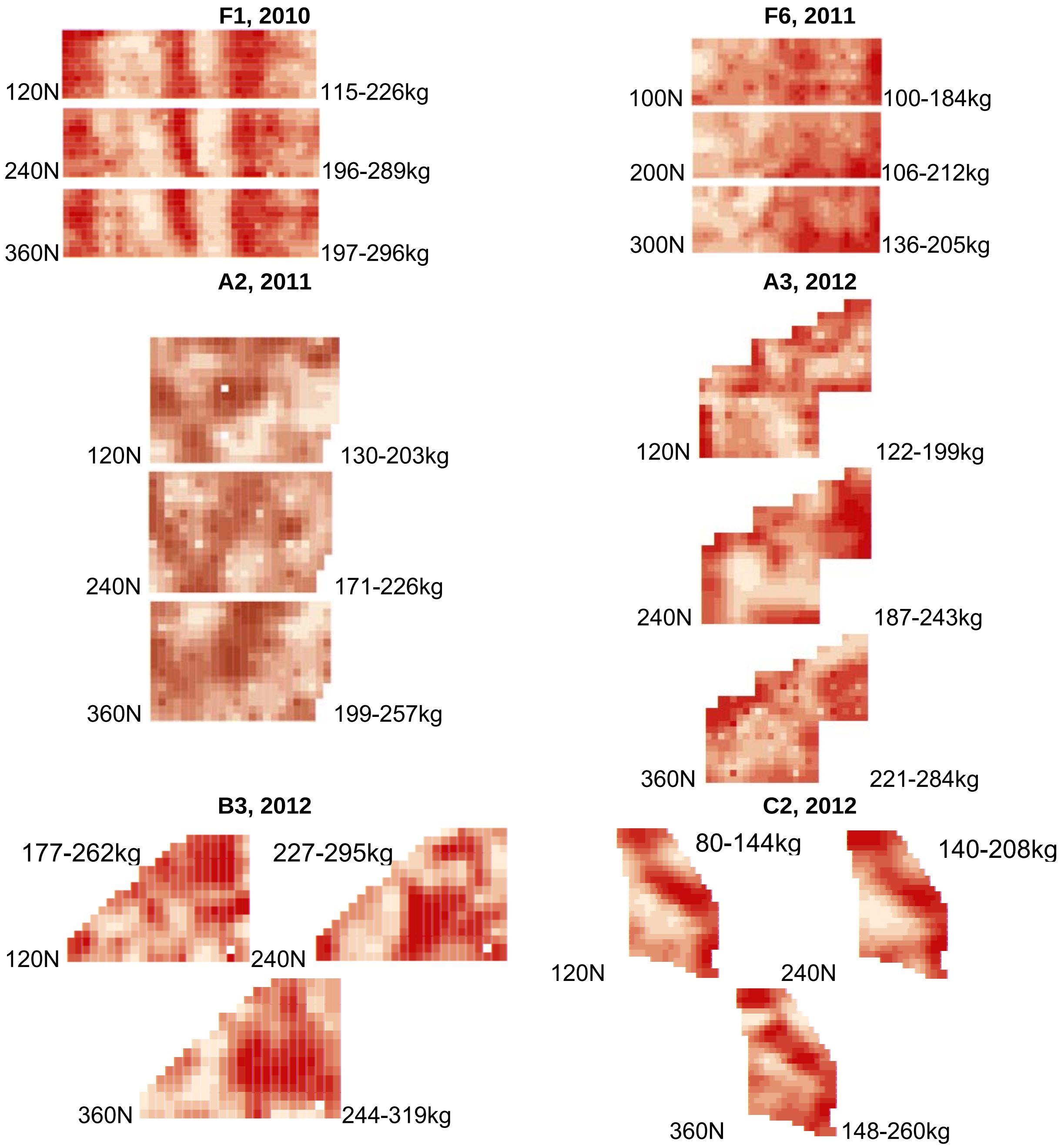



**Figure 29. Kriged N Harvest Index (%) for the chessboard trials. All plots were sampled at zero-N at all sites, but only selected plots for other N rates so kriging is not possible for all N rates at all sites. Darker colour is higher value. Values are given for the range in kriged plot proteins at each N level, excluding outliers.**

#### *4.3.13.3 Broken stick regressions of Total N yield*

In order to assess the response of N uptake to N fertiliser in each plot a split line (broken stick) regression was performed in Genstat restricting the plateau to horizontal (Figure 30). This allows

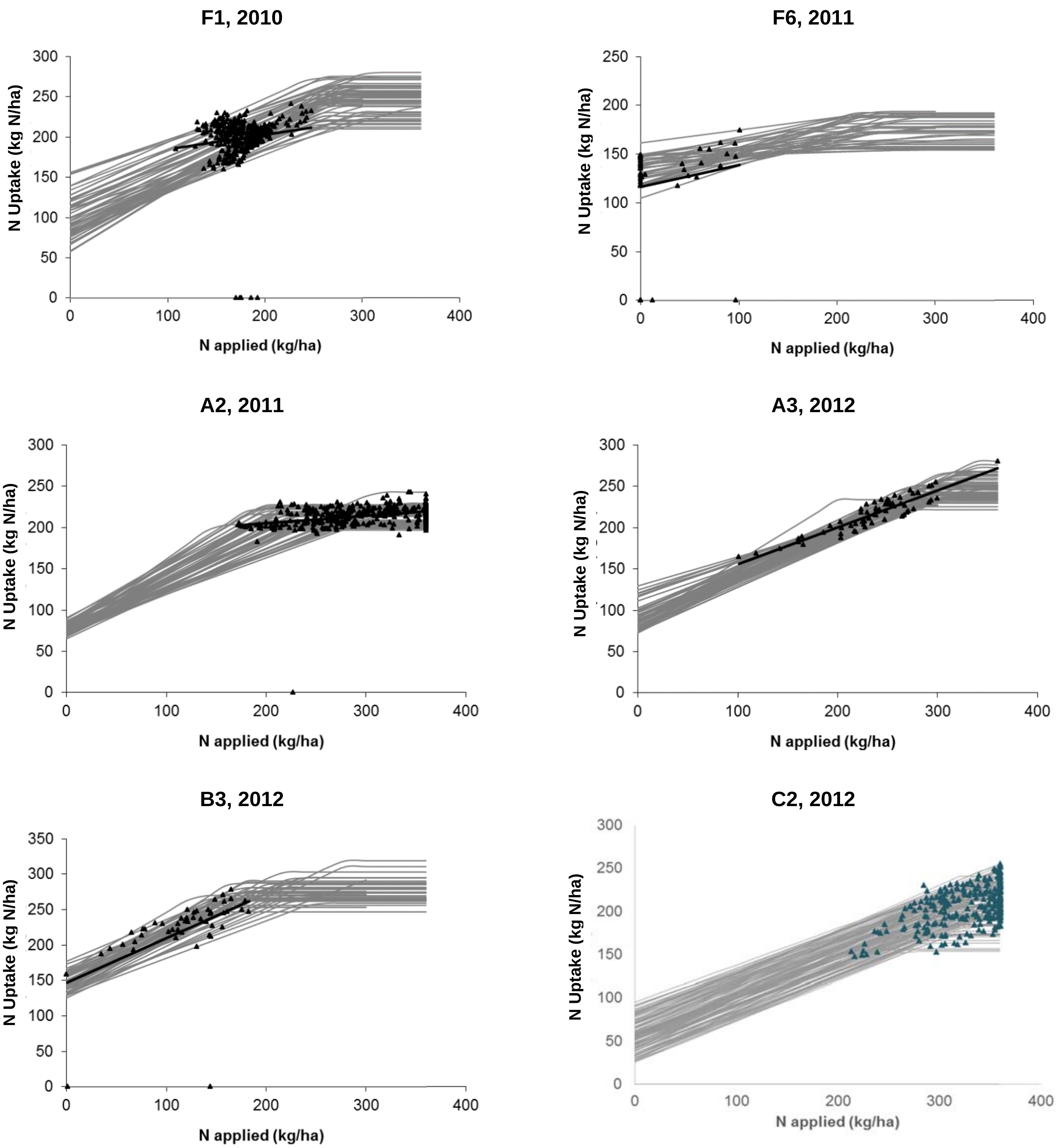



**Figure 30. Broken stick regressions of total crop N uptake for a random set of selected plots for the Chessboard trials. Black triangles show crop N uptake at the optima.**

The crop N uptake responses tend to show more variability in their shape between sites than within sites. How N optima relates to the crop N uptake response and the breakpoint also varies between and within sites. At most sites the majority of N optima occur well before the breakpoint is reached, however at August 2011 the optima for yield for many plots seems to be higher than that required to get maximal N into the crop. At Shipton 2012 crop N uptake continues to increase in many areas beyond the highest N rate of 360kg N/ha. Some caution is needed not to over-interpret these regressions, given that there are only 4 N rates in each.

#### *4.3.13.4 Fertiliser Recovery (slope)*

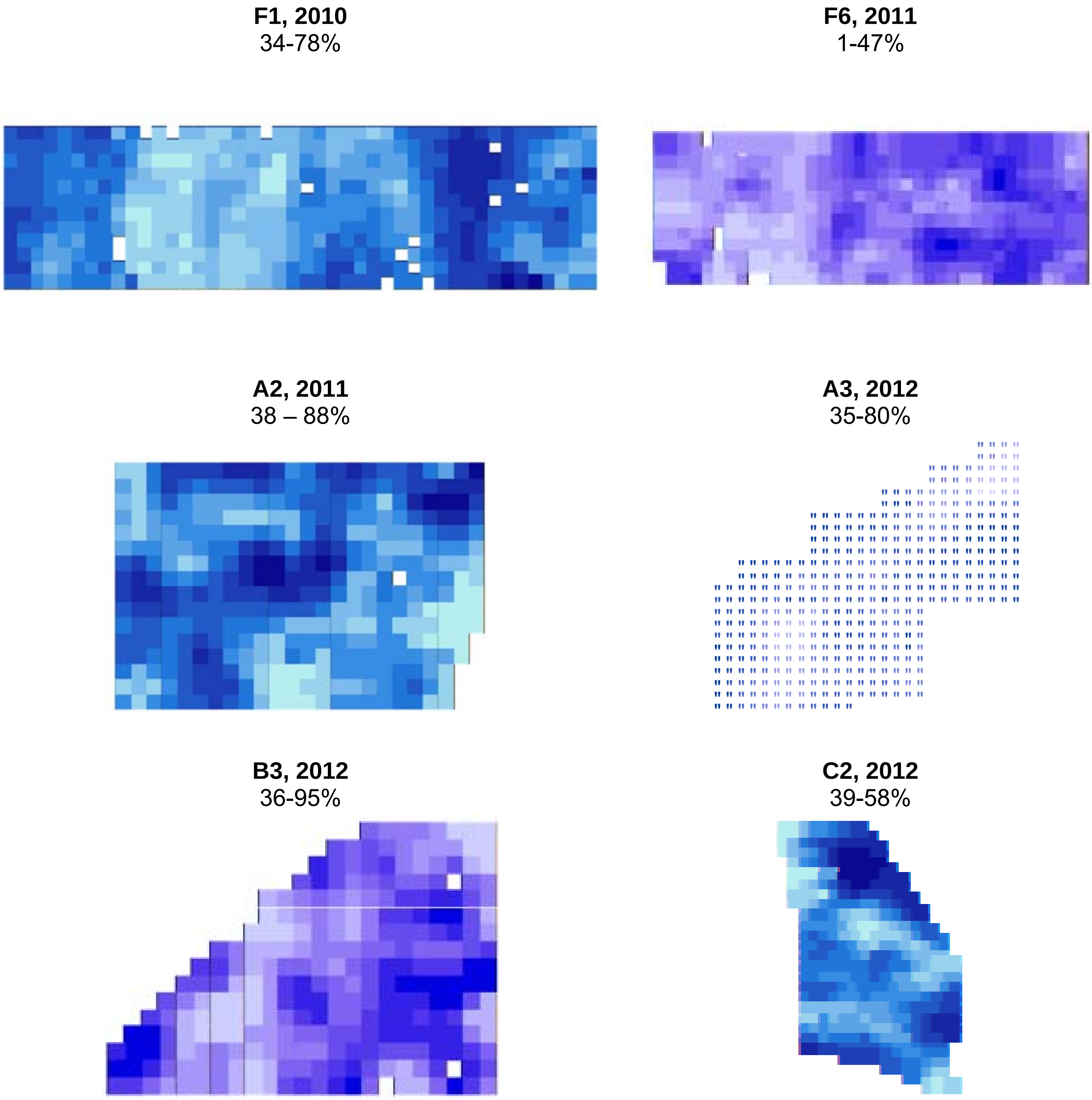



**Figure 31. Fertiliser recovery of chessboard trials from slope of broken stick regression analysis. Darker colour higher value.**

Figure 31 shows large variation in fertiliser N recovery as estimated from the slope of crop N uptake. Fertiliser recovery is typically 60%, the chessboard trials show that it consistently varies by +/-20% around this average. Fertiliser recovery at Flawborough 2011 and Shipton 2012 were both very low, due to drought and waterlogging, respectively.

#### *4.3.13.5 Crop N Demand (plateau)*

Figure 32 shows variation in crop N demand as estimated from the plateau from broken stick regressions exceeding 60 kg/ha at all sites. Spatial variation in crop N demand closely matches that for yield at higher N rates.

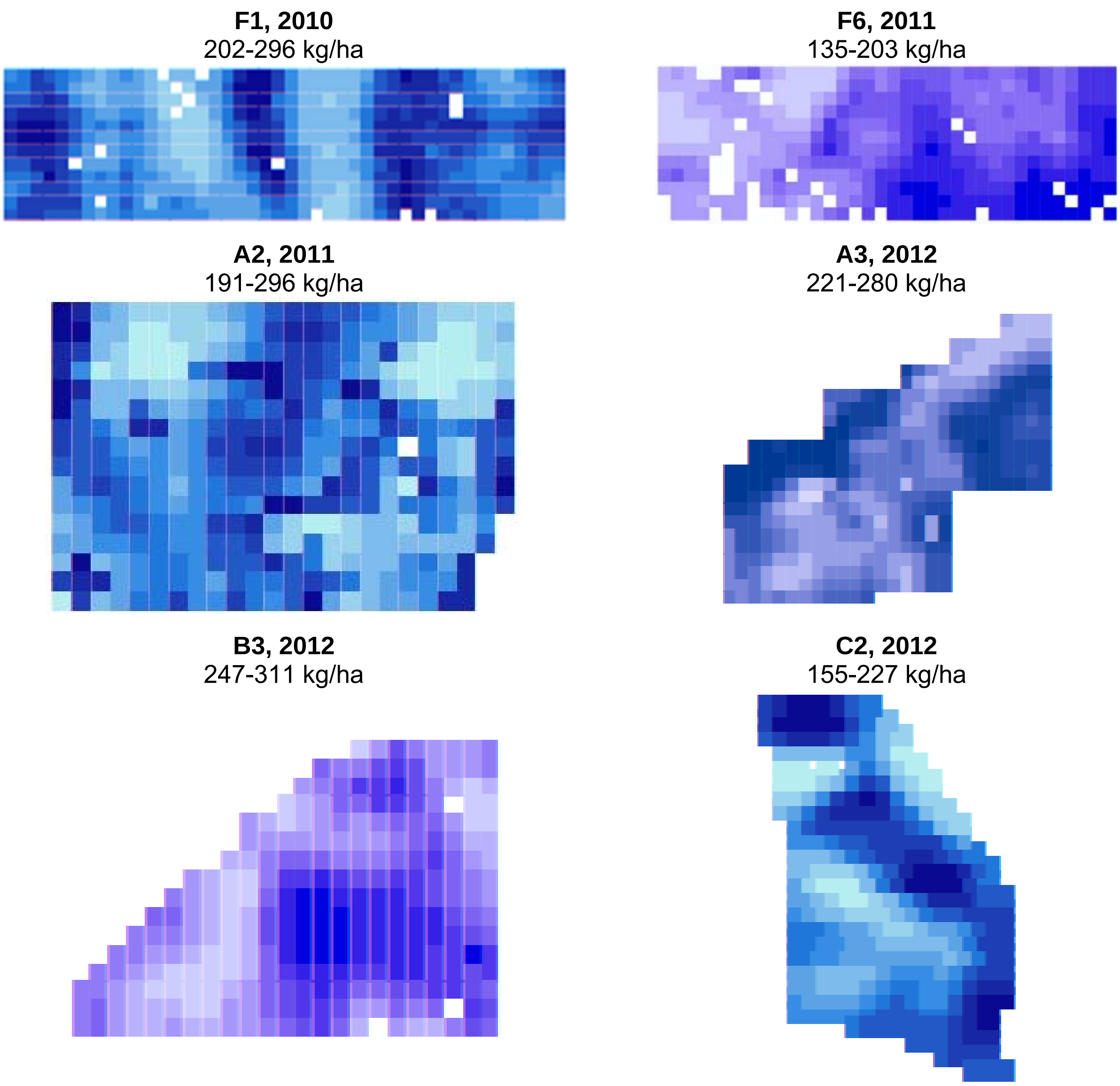



**Figure 32. Crop N Demand of chessboard trials from plateau of broken stick regression analysis. Darker colour higher value.**

## 4.4 Exploring relationships in spatial variation in N optima

In order to understand the prime underlying causes in the variation in N requirement in the chessboard trials the relationships with the three components Crop N Demand, SNS and fertiliser recovery have been assessed in Figures 33 to 35. Recognising that relationships may differ in different parts of the field we have grouped plots from each site by soil type where different soil series are evident, or by cluster groups from analysis of previous yield maps (see Chapter 4).

*Crop N Demand*

There are few strong positive relationships between crop N demand and N optima within the chessboard experiments if average regressions are assessed (Figure 33). Relationships with yield are weaker still (Figure 36). However, at most sites there is some evidence of a positive relationship when assessing within a soil group. For example, Flawborough 2010 appears to show no relationship overall between crop N demand and N optima, but in fact there are a series of positive relationships within the different soil zones. At all sites in 2010 and 2011 some positive relationship is evident using a boundary line approach (Kindred et al., 2015).

*Soil N Supply*

Figure 37 shows there is a strong negative relationship between N requirement and SNS at three sites (F1, A3 and B3) and relationships within some soil groups at two more (A2 and C2). There is no apparent relationship between N optima and N supply at F6, where optima are low and SNS is high. At A3 in 2012 there is clearly a small area in Cluster group 4 which is behaving anomalously, with very high SNS but low yields, and some high yields with lower SNS. It seems likely that in a 'normal' year other than 2012 the areas giving high SNS would also have given high yields.

*Fertiliser Recovery*

Several sites show a relationship between N optima and fertiliser recovery (Figure 35). The negative relationships at two sites (A2 and C2) do seem to be driving some of the variation in N requirement. However, many of the relationships are positive (F1, A3 and B3) with higher recoveries associated with higher N optima, the opposite to that expected if fertiliser recovery is driving differences in N optima.  This may be due to the strong negative association between fertiliser recovery and SNS at all sites except Burford 2011 (Figure 38). At Burford in 2012 the relationship between SNS and fertiliser recovery seems to be non-linear, with very low fertiliser recovery on two plots where SNS was very high, and high fertiliser recovery on some plots with moderate SNS.

There is generally little relationship between fertiliser recovery and yield (data not shown).

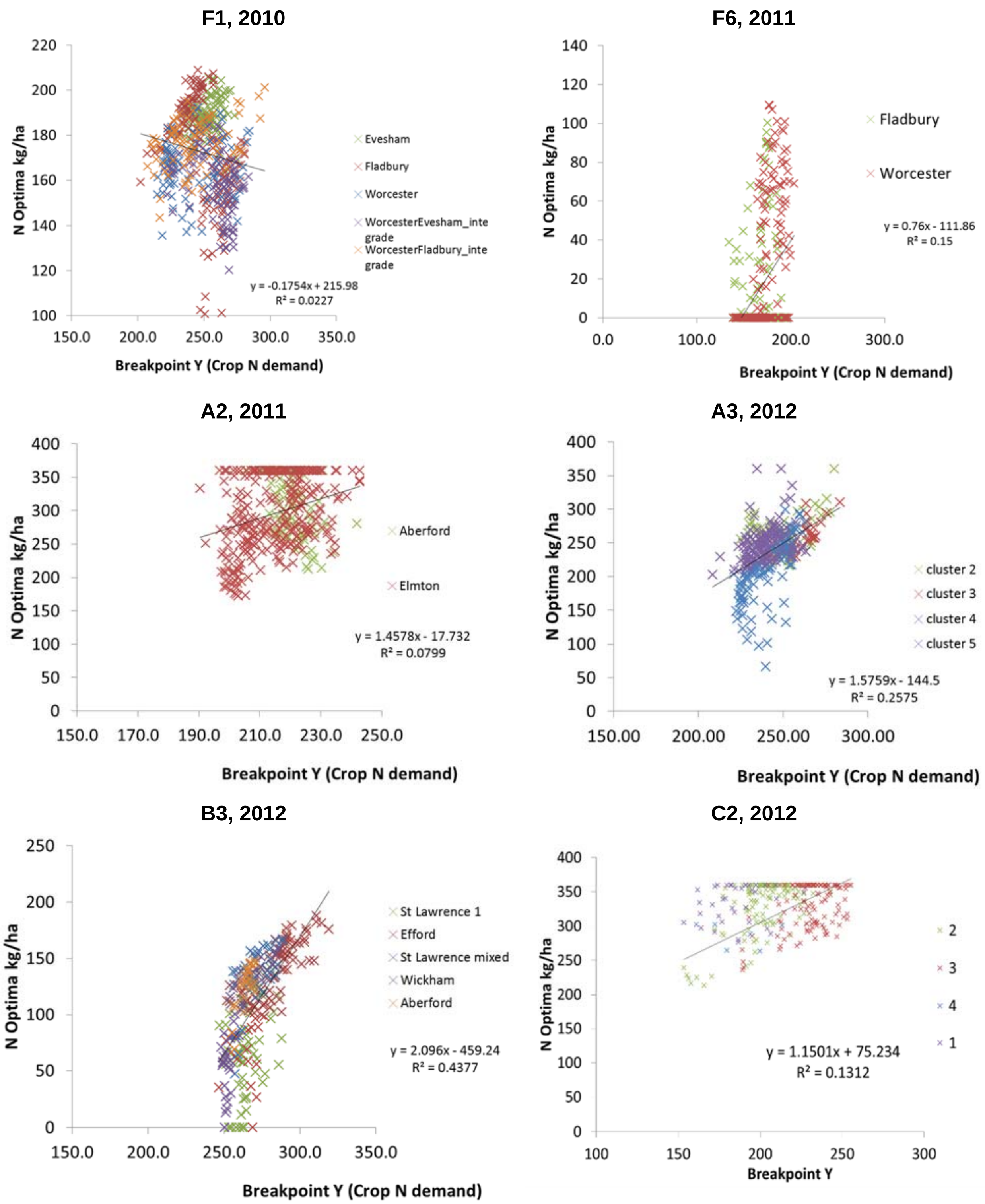



**Figure 33. Relationship of N optima with Crop N Demand as determined by the asymptote of broken stick regression for the Chessboard trials. For each site data is grouped by soil series or cluster groups (see Figs 10 & 11). Solid line shows regression for all data.**

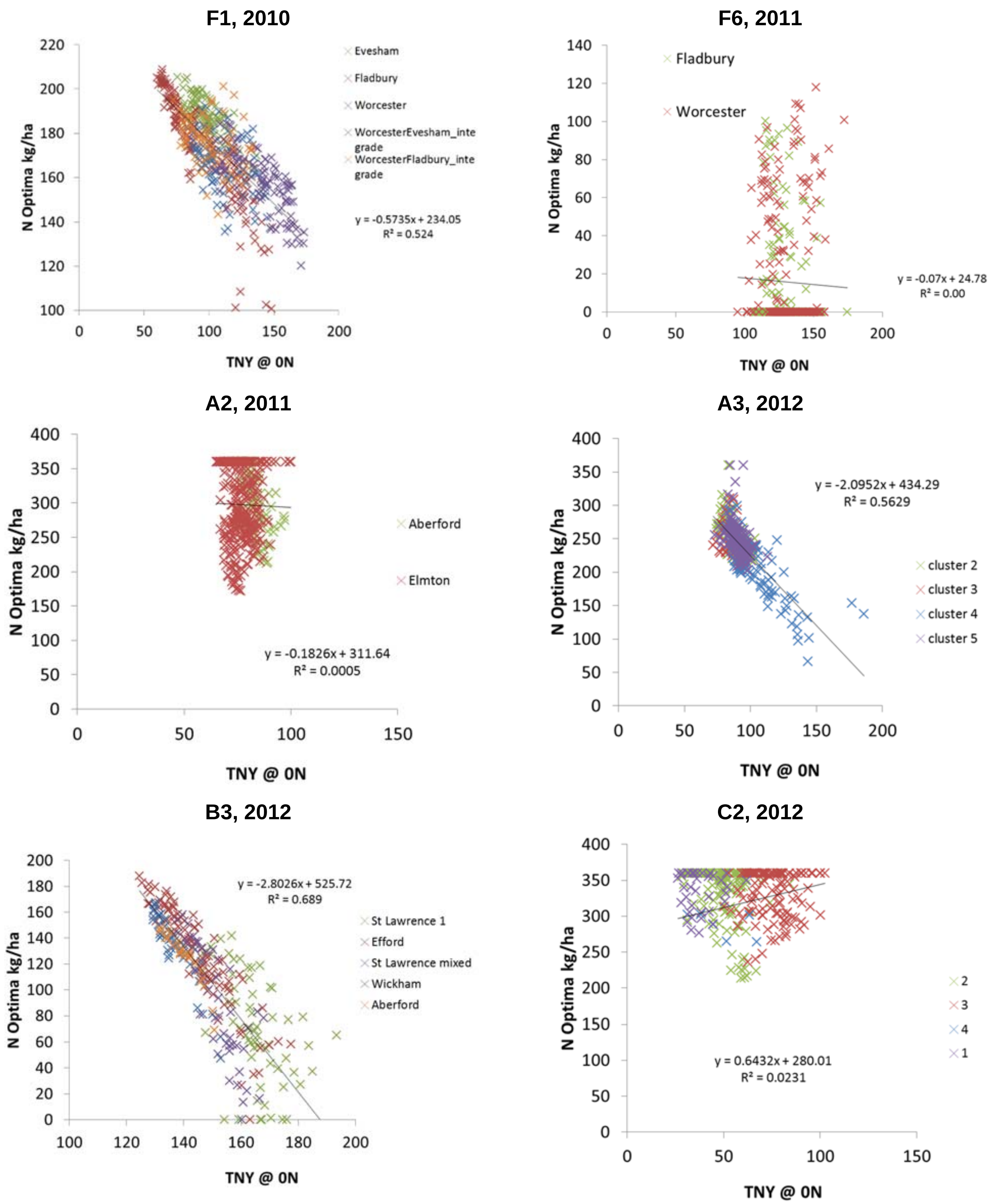



**Figure 34. Relationship of Soil N Supply with N optima for the Chessboard trials. TNY @ 0N = Total N yield with no N applied. For each site data is grouped by soil series or cluster groups (see Figs 10 & 11). Solid line shows regression for all data.**

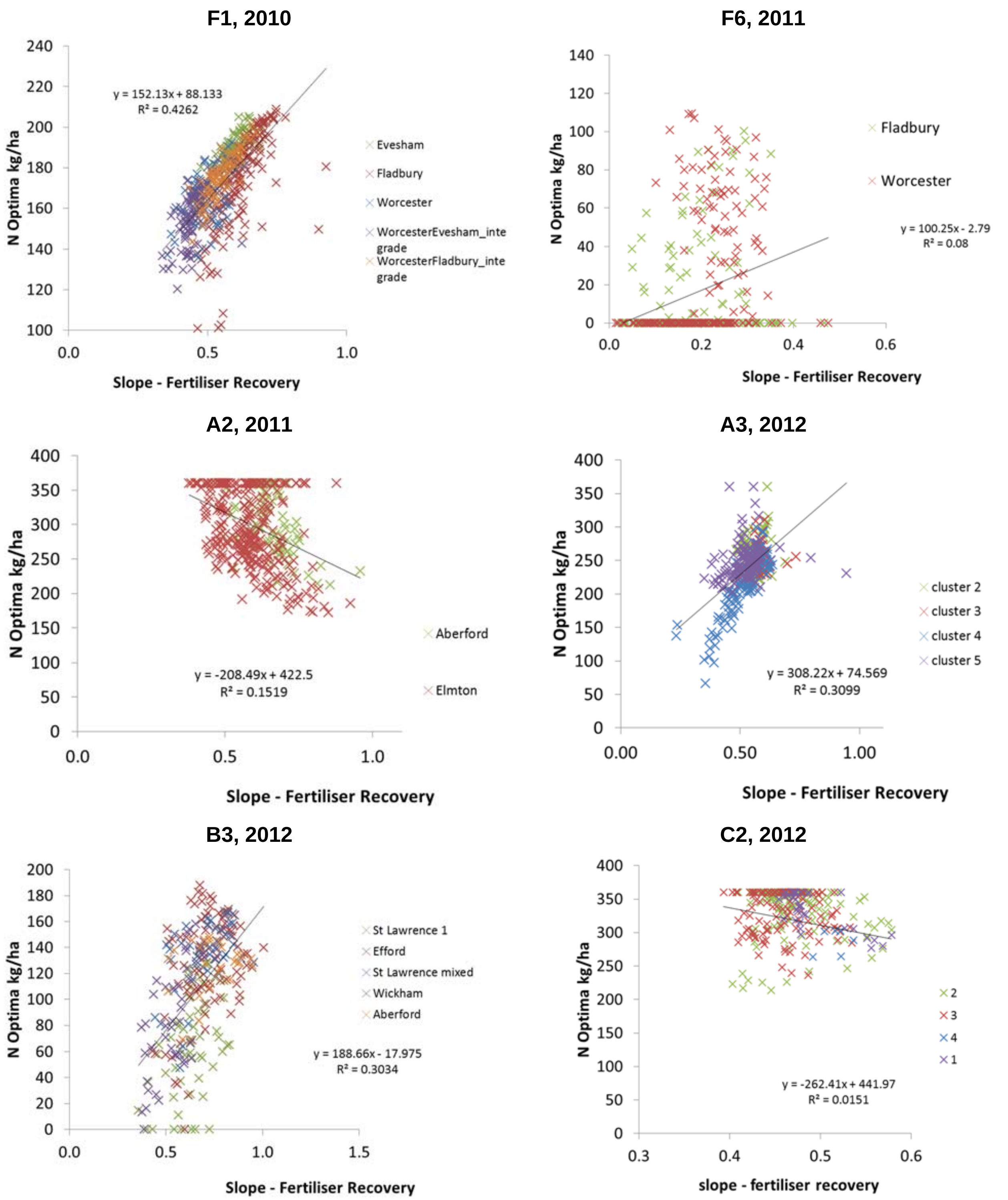



**Figure 35. Relationship of Fertiliser Recovery with N optima for the Chessboard trials. Fertiliser recovery estimated as slope parameter from fitting of broken stick to N uptake data. For each site data is grouped by soil series or cluster groups (see Figs 10 & 11). Solid line shows regression for all data.**

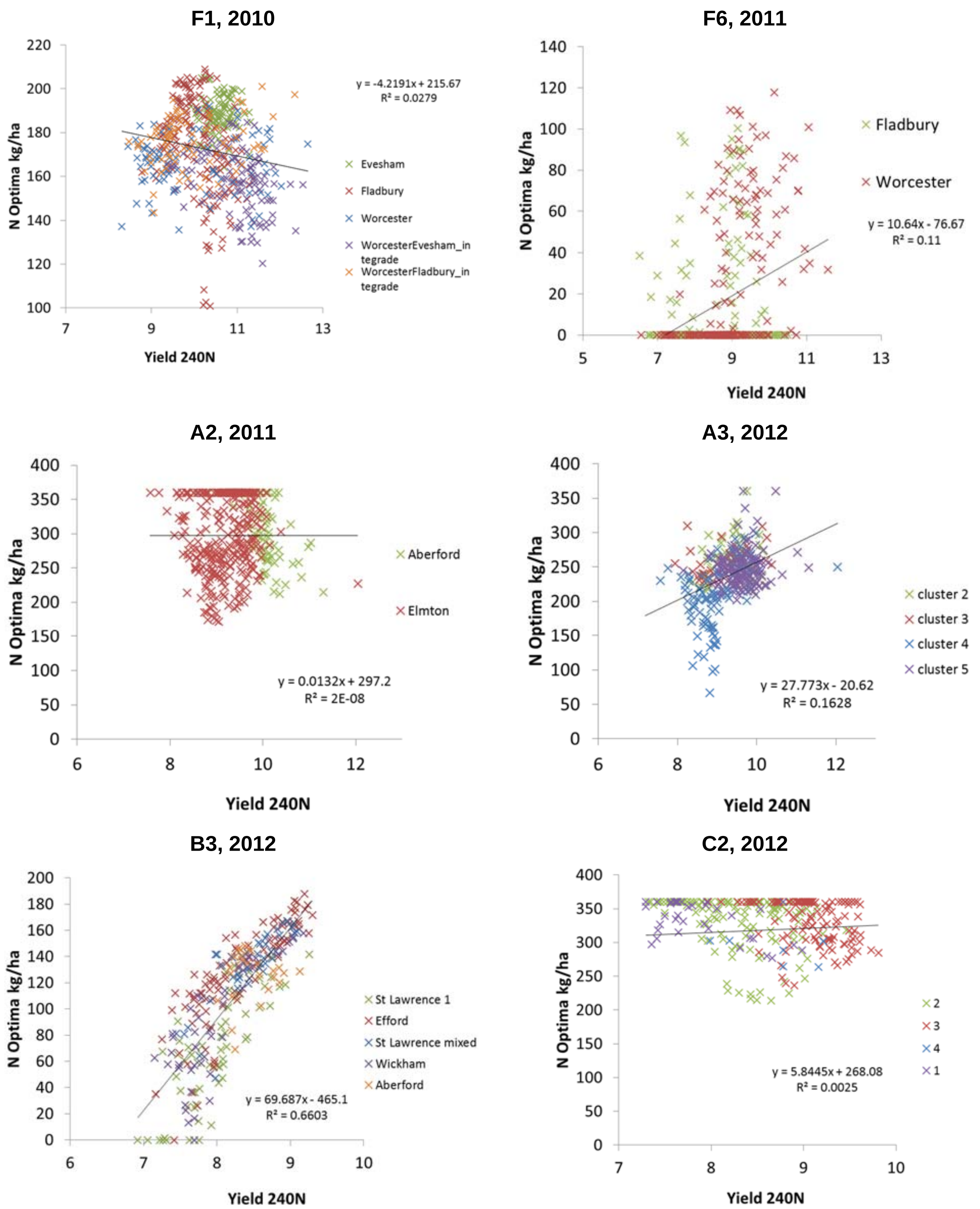



**Figure 36. Relationship of Grain yield at N level 3 with N optima for the Chessboard trials. For each site data is grouped by soil series or cluster groups (see Figs 10 & 11). Solid line shows regression for all data.**

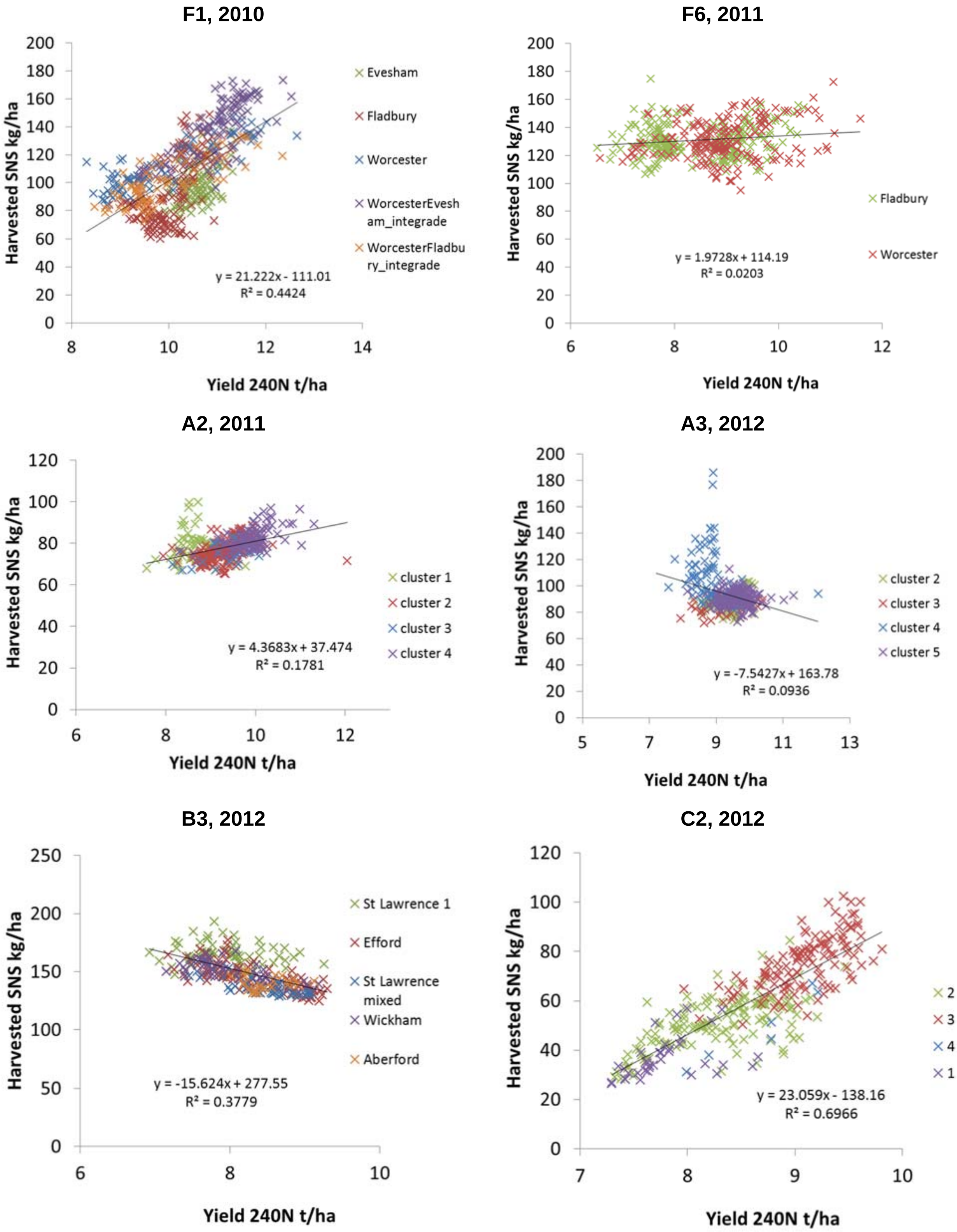



**Figure 37. Relationship of Grain yield at N level 3 with SNS for the Chessboard trials. For each site data is grouped by soil series or cluster groups (see Figures 10 & 11). Solid line shows regression for all data.**

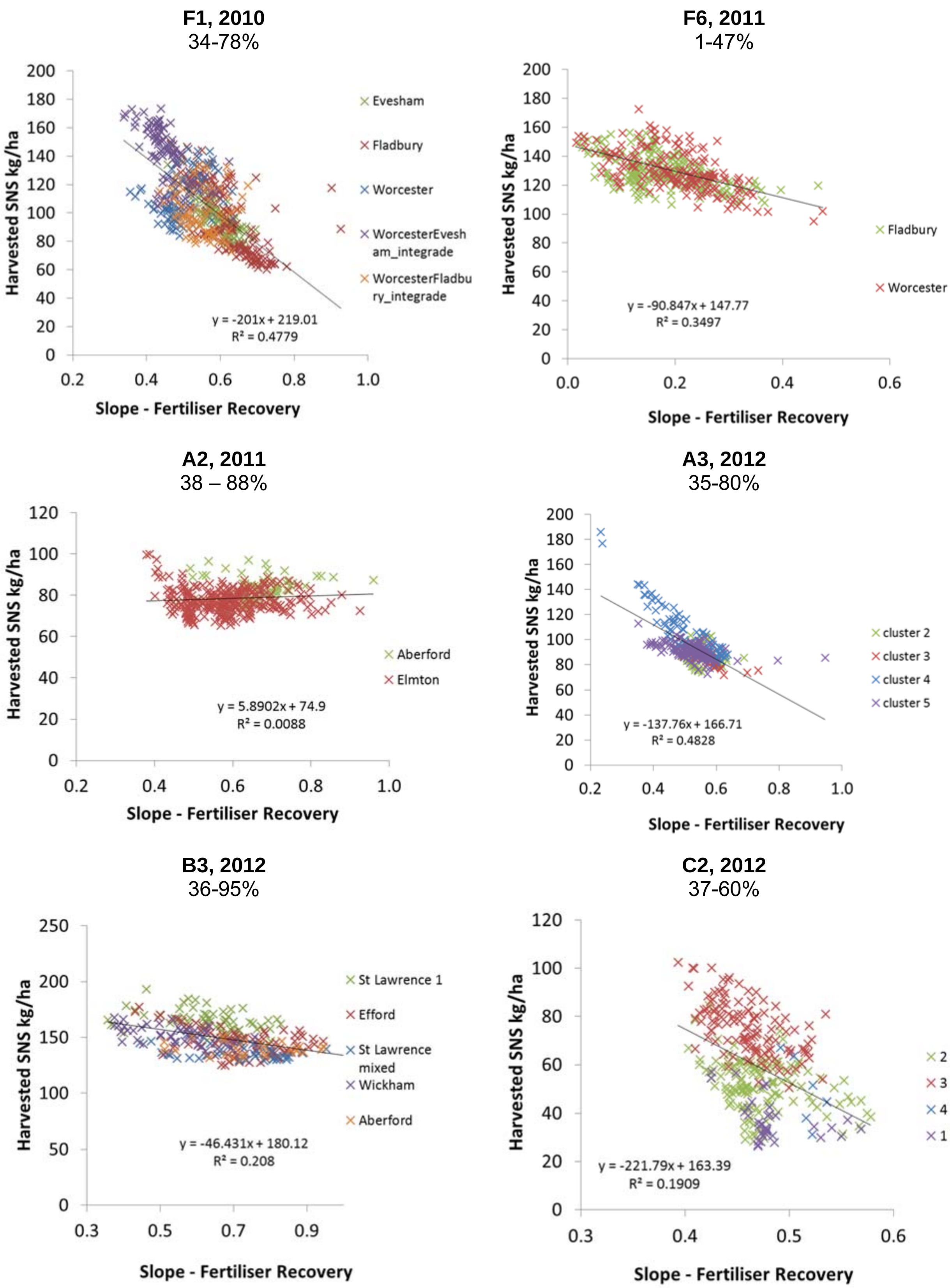



**Figure 38. Relationship of SNS and fertiliser recovery for the Chessboard trials. For each site data is grouped by soil series or cluster groups (see Figures 10 & 11). Solid line shows regression for all data.**

### 4.4.1 Multiple linear regression

Multiple linear regression was conducted in Genstat to assess the statistical importance of each of the components and their interactions. For each site a regression analysis was conducted with N optima as the modelled term, with SNS, crop N demand, fertiliser recovery included as variates and soil series and cluster class as groups. The proportion of variation explained by each term on its own was collated and the best parsimonious model to explain variation in N optima was assessed. A summary of results is given in Table 4 below.

**Table 4. All Subsets regression analysis N optima of chessboards with harvested SNS, CND (defined by N uptake at max N rate) and fertiliser recovery (slope from broken stick analysis) including soil and cluster class as groups to explain variation in N optima.**

| | % variation explained by single terms | | | | | Terms included in final model (significance) | | | | | Variance explained |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Trial | SNS | CND | recovery | soil series | cluster classes | SNS | CND | recovery | soil series | cluster classes | by final model |
| Flawborough 2010 | 46.18 | 2.28 | 35.24 | 22.69 | 17.51 | <0.001 | <0.001 | | <0.001 | | 64.3 |
| Flawborough 2011 | 0.00 | 16.12 | 6.59 | 5.73 | 16.11 | 0.005 | <0.001 | | 0.025 | <0.001 | 22.7 |
| Burford 2011 | 0.00 | 6.56 | 14.96 | 0.98 | 6.29 | <0.001 | <0.001 | <0.001 | | <0.001 | 38.9 |
| Burford 2012 | 56.15 | 26.62 | 30.78 | NA | 25.42 | <0.001 | <0.001 | <0.001 | | <0.001 | 75.9 |
| Bedfordia | 69.74 | 29.22 | 28.37 | 34.86 | 19.25 | <0.001 | <0.001 | 0.007 | | 0.011 | 75.6 |
| Shipton | 0.33 | 13.42 | 1.64 | NA | 2.86 | <0.001 | <0.001 | <0.001 | | 0.019 | 65.8 |

The analysis confirms SNS to be the strongest predictor of N optima at three of the sites. At the other three sites no component is dominant and variation explained tends to be low. At Shipton, whilst the explanatory power of any individual component is very weak, together they account for 65% of the variation, highlighting the importance of the interactions between the components. At all sites spatial classification by soil or cluster group was significant in explaining variation. However, at no site could more than 76% of variation be explained, and for the two sites in 2011 less than 40% of variation was explained

## 4.5 Soil measures at Chessboard sites

Soil samples were taken from selected plots in each experiment. Soil mineral N was measured to 90cm depth and soil organic matter, soil N% and potentially mineralisable N measured on top soil (Figures 39 to 42).

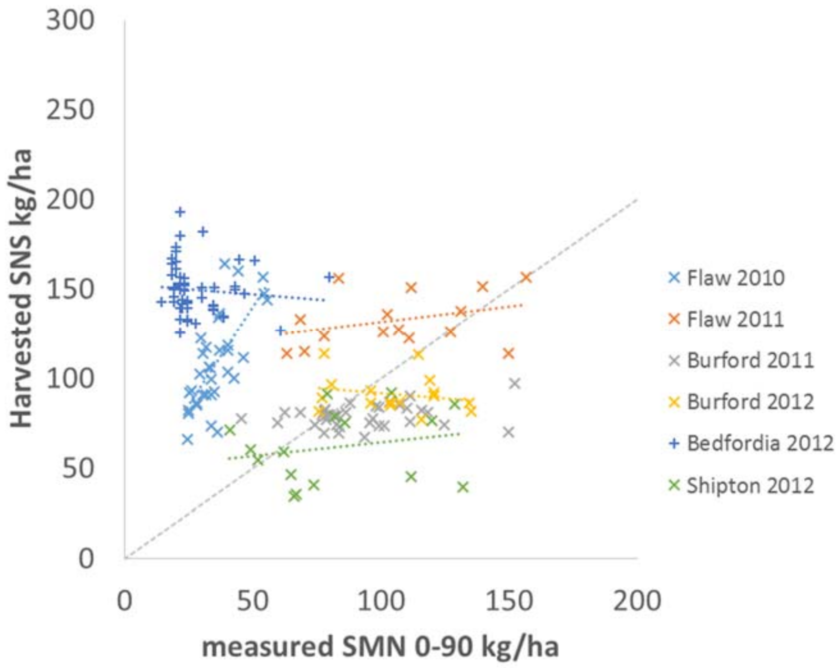



***Figure 39. Relationship between measured SMN and harvest SNS for the Chessboard trials.***

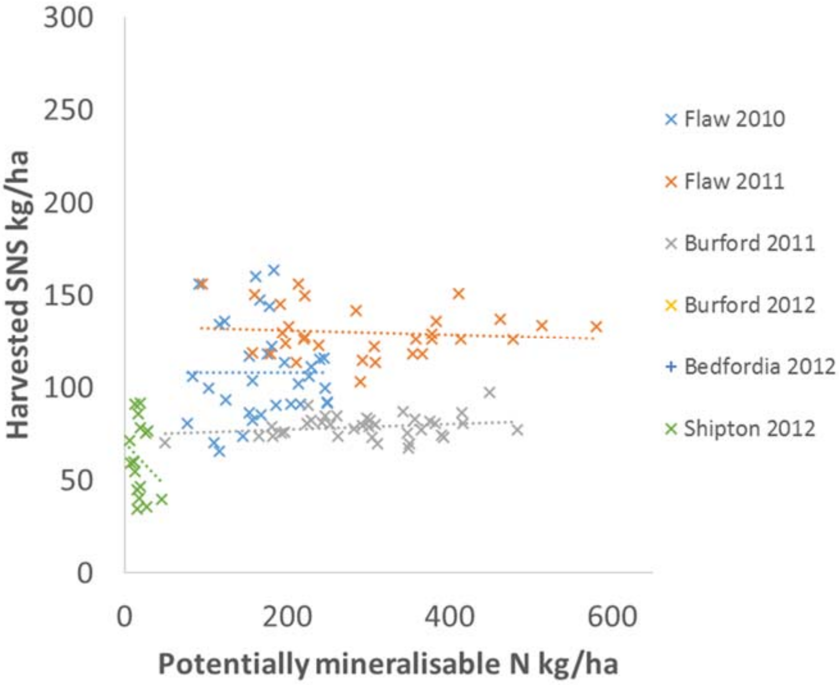



**Figure 40. Relationship between measured potentially mineralisable N (PMN) and harvest SNS for the Chessboard trials.**

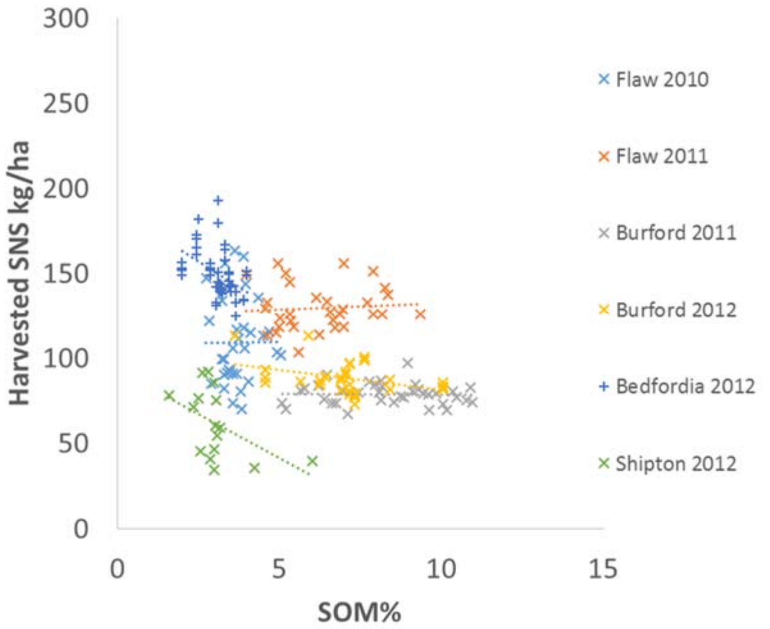



**Figure 41. Relationship between measured SOM% and harvest SNS for the Chessboard trials.**

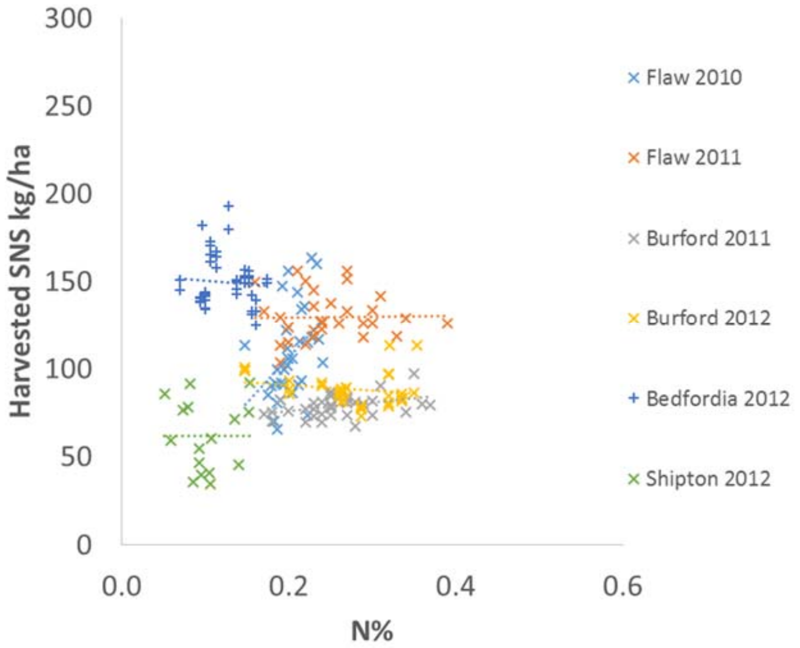
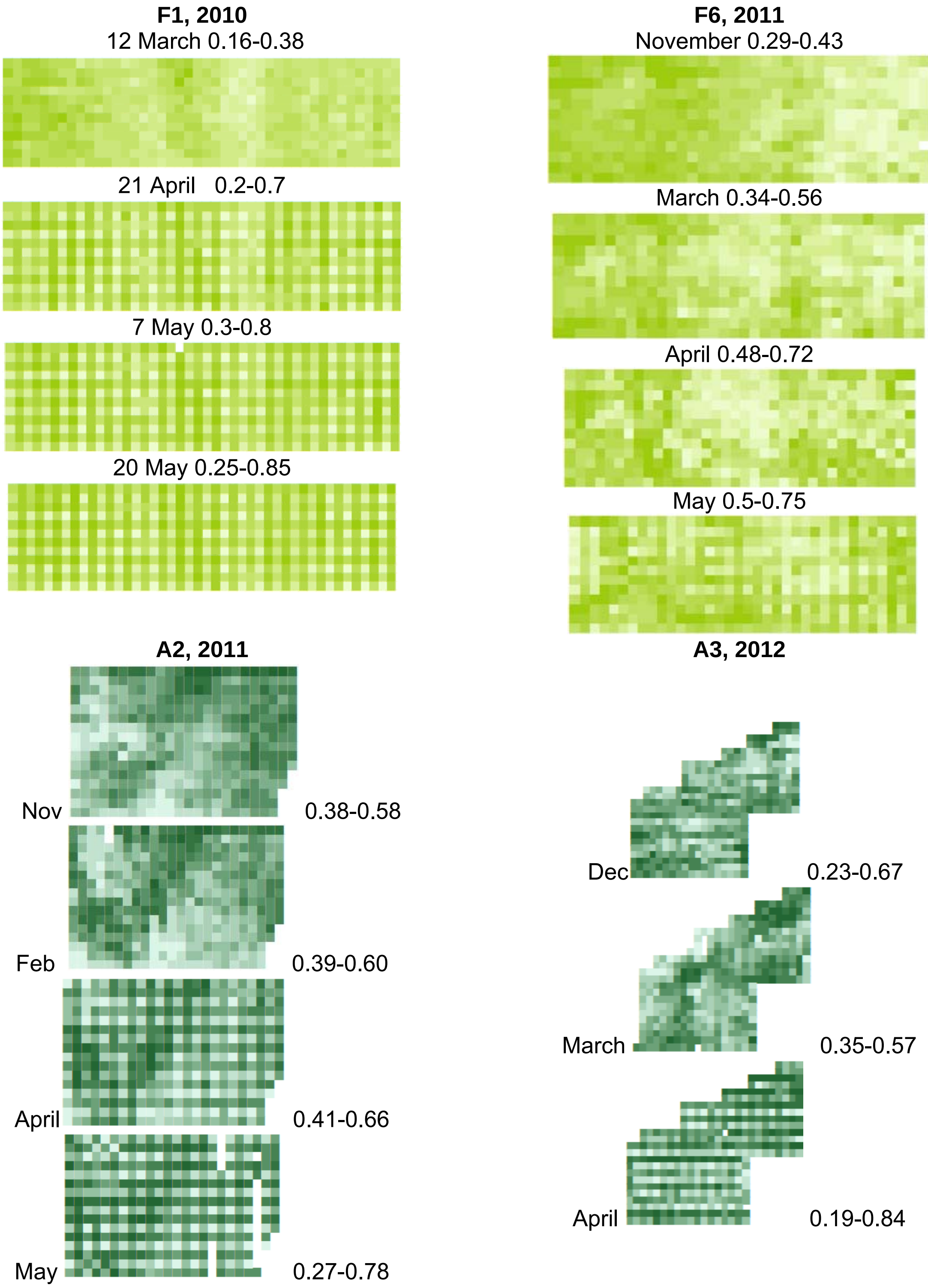



**Figure 42. Relationship between soil total N% and harvest SNS for the Chessboard trials**

It is clear that no soil measure adequately explains the variation in harvested SNS either within fields or between fields. Baxter et al. (2003; 2005) has previously assessed the potential for using surrogate measures such as elevation or clay content to infer variation from limited SMN measures; the results here suggest this is unlikely to succeed.

## 4.6 Canopy measures at Chessboard sites

Each site was assessed with a Crop Circle device to measure spectral reflectance and NDVI on a number of occasions (Figure 43). The patterns ultimately shown in SNS and yield potential are often clear from canopy reflectance early in the season. At most sites the effect of N fertiliser application dominates the canopy reflectance in scans in April and beyond. However, this is not the case at Flawborough 2011 or Shipton (C2) 2012 where drought and waterlogging respectively had large impacts.



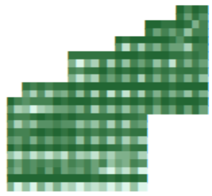



**Figure 43. Crop Circle measures of NDVI for each of the chessboard trials through the season. Darker green corresponds to higher NDVI. Values are given for the range in NDVI at each date.**

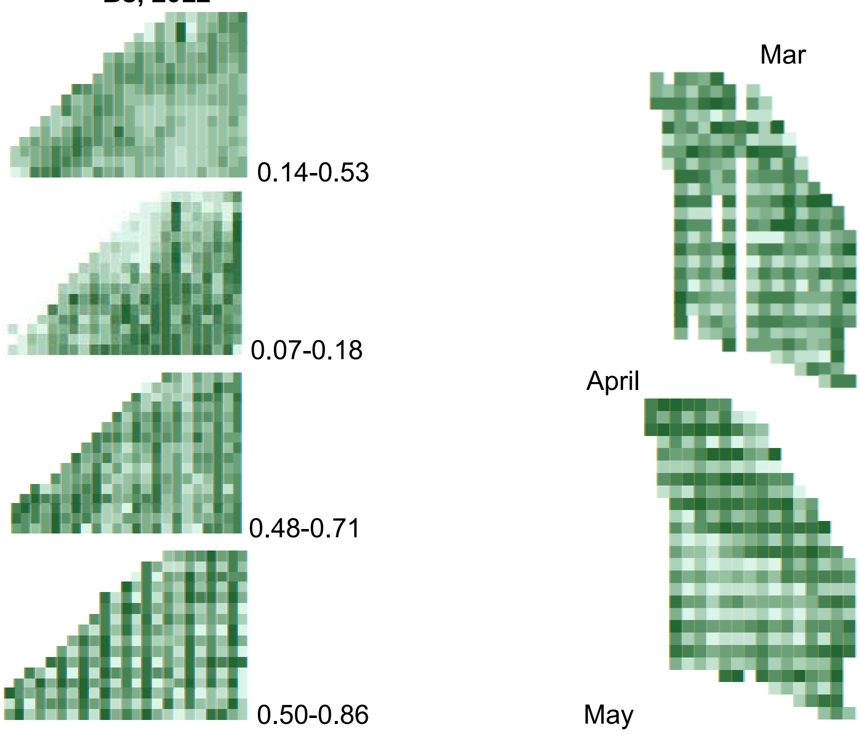



**Figure 43 cont. Crop Circle measures of NDVI for each of the chessboard trials through the season. Darker green corresponds to higher NDVI. Values are given for the range in NDVI at each date. F = Flawborough, A = August (Burford), B = Bedfordia, C= Shipton.**

## 4.7 Explaining variation in N requirement at each site

Using the data shown in Figures 9–43 it is possible to attempt some explanation of the major drivers of variation in each of the chessboard experiments

### 4.7.1 F1 Flawborough 2010

The variation in N optima between 100 and 240 kg N/ha at site F1 is large, spatially coherent and visually matches the trends in variation the soil N supply, crop N demand, AFR and the underlying soil series. Some lodging at the highest N rates in the most fertile parts of the field could have contributed to slight yield declines at the highest N rates in some areas. The variation in optimum N was due predominantly to variation in soil N supply which varies from 60 to 170 kg N/ha. However, there clearly are interactions between the three components at the site, with positive correlation of SNS with grain yields and negative correlation of SNS with fertiliser recovery. The importance of crop N demand and fertiliser recovery in determining the N requirement must therefore be recognised.

The positive association between soil N supply and yield has not been widely acknowledged before. It seems that other attributes of the soil (more water, more of the other plant nutrients, better aeration) have helped to make more N available to the crops and hence boost their yields and demand for N.

Measurements of soil mineral N made in the spring showed little variation (30–60 kg/ha) with no strong spatial coherence pattern. The large variation in the harvested soil N supply was therefore somewhat surprising and remains unexplained; there are no clear differences in soil organic matter or soil total N% to indicate differences in mineralization, yet in certain areas of the field the crop accessed much more nitrogen from the soil. The parts of the field where the soil N supply was largest were where in past years yield was also largest (see Chapter 4). It is possible that the greater crop growth in these areas could have left more organic matter to accumulate in the soil and to mineralise and release N. These areas tended to align with small differences in topography which perhaps are associated with access to deep soil water, which might contain some concentration of nitrate.

#### 4.7.2 F2 Flawborough 2011

The poor response to fertiliser N at Flawborough in 2011 was probably caused by drought. Table 3 (p44) shows rainfall there during March, April and the first 3 weeks of May was only 38.8 mm (compared with long-term average 160.5 mm). This lack of rain severely limited the uptake of fertiliser N and limited crop growth and tillering. The warm dry conditions increased the likelihood of loss of fertiliser N through volatilization of ammonia. Fertiliser recovery varied from zero to 50% but did not appear to explain variation seen in N requirement. The drought is likely to have killed much of the soil's microflora, and rapid mineralisation of N caused by rewetting in late May and June was too late to increase yields substantially; there were too few shoots and leaves to intercept light and photosynthesize. Nitrogen was taken up, however, and this increased protein in the grain.

Areas where N optima was larger than zero were mostly in areas of the Worcester soil series where the soil supplied less N. Across the Worcester soil the variation in N optima visually matches trends in variation seen in soil N supply. The changing patterns of the canopy reflectance (Figure 43) over the season at this site suggest that N was becoming limiting in different areas at different times. The different patterns seen late in the season and finally in harvested SNS perhaps supports the notion that mineralisation occurred late after the drought and rewetting.

### 4.7.3 A2 Burford 2011

The Burford 2011 field has a Y-shaped valley where the soil is much deeper than elsewhere in the field (over 90 cm compared with 30–40 cm elsewhere). The soil is of the Aberford series and yields more than the thinner soil elsewhere. The pattern of N optima for the site is spatially coherent, but cannot perfectly be matched to the patterns of soil N supply, crop N demand, AFR or the soil series. Generally the higher yielding Y shaped valley also gave a higher SNS, but variation in SNS was relatively limited ranging by only 35 kg N/ha from 65 to 100 kg N/ha. Overall the relationship between N optima and SNS is poor, but it is more evident within the Aberford soil series and within other defined areas of the field. Whilst it seems that crop N demand may have some positive relationship with optima in some areas, the negative relationship of fertiliser recovery with N optima is stronger and perhaps is the greater driver at this site. The variation in fertiliser recovery here is large (0.3 to 0.88) and, unlike at other sites, is unrelated to SNS. Instead it is positively related to yield in some areas.

### 4.7.4 A3 Burford 2012

The 2012 season was atypical giving a dry early spring followed by a very wet and dull late spring and autumn. The Burford 2012 field was adjacent to that in 2011 and has a deeper clay bank running diagonally across the field SE to NW. This area had previously given higher yields in the field and was evidently greener throughout the season as seen from the aerial photography (Figure 9) and from the NDVI from the Crop Circle canopy sensor (Figure 43) indicating a larger crop. Without nitrogen applied, this was the highest yielding area of the field, however, with N applied this area gave lower yields. This manifests a peculiarity of the 2012 season where larger crops in normally high yielding situations tended to yield less. Indeed, other N response experiments conducted by ADAS & others in 2012 were unusually flat and often showed higher N fertiliser rates to give reductions in yield. In general, factors that normally give higher yields, such as earlier sowing, heavier land and later higher biomass varieties, tended to give lower in yields in 2012. Grain quality also tended to be very poor in 2012, with specific weight especially badly affected (Marshall, 2013). This indicates poor grain filling. Opinions within the industry for the low yields and quality in 2012 were divided, with many citing water-logging of soils through spring and summer as the major cause, others pointed to the exceptionally high disease pressure in this year resulting from the wet warm conditions. The explanation that best explains the N response and other affects seen in 2012 is that respiration rates were high relative to low levels of solar radiation. Night time temperatures were relatively warm encouraging maintenance respiration, and respiration is greater in larger crops. In this year the light levels were not great enough to pay for the greater carbon costs of a larger canopy intercepting more light, so that crops which were larger in May ended up yielding less. Unfortunately respiration rates are very rarely measured in crops, and we know of no measures made in 2012, so this hypothesis to explain the low yields in 2012 is entirely speculative.

The normally higher yielding areas yielded less at Burford in 2012 and had a lower N requirement than the rest of the field. The low yields gave a lower crop N demand, ranging by 60 kg/ha across the field. The lower yielding areas also had a higher soil N supply, ranging by over 100 kg/ha across the field with very high SNS (100– >150kg/ha) in the North East corner and variation in the rest of the field generally between 70–100kg/ha. Whilst there is a negative relationship between yield and SNS in this field in this year, the relationship between SNS and normal yield potential is positive. There is therefore a strong relationship between N optima and both crop N demand and SNS at this site, but the relationship with SNS is more convincing as the major driver of the variation in N optima ($r^2$ of 0.56). Fertiliser recovery varies greatly at this site but is positively related to N optima so cannot be the major driver of variation in N requirement. Again, fertiliser recovery is low where SNS is high.

It is doubtful that in a more normal year the same variation in crop N demand would be seen, the impact on spatial variation in N response and N requirements on this field in a more normal year can only be speculated on.

#### 4.7.5 B2 Bedfordia 2012

The Bedfordia field in 2012 has given similar anomalous responses to the season as at Burford. The areas which are generally higher yielding were greener in spring, yielded most without fertiliser but yielded least with N applied, and vice versa. The N responses at Bedfordia are very flat and negative at higher N rates, indeed yields at 360 kg N/ha are often lower than at zero N. This again reflects the negative affect of large canopies in 2012. SNS levels are generally high at Bedfordia, exceeding 120 kg/ha across the whole field and reaching nearly 200 kg/ha in the highest regions. These high levels are likely due to a history of manure use on this field combined with warm wet conditions being favourable for mineralisation. However, this is despite low measured SMNs (generally <50 kg/ha) and relatively low SOM and soil N% (Figures 41 & 42).

The variation in yields and N responses generally matches the variation in soil series and cluster groups reasonably well. N optima are lower in the areas where yields are lower, though these are areas that would usually yield better. These areas also have higher SNS levels, so as with Burford 2012, N optima correlates with both crop N demand and SNS. Again, the relationship with SNS is stronger ($r^2$=0.689) and seems to be the major driver in variation in N optima.

Also as with Burford 2012 there is large variation in fertiliser recovery with positive relationship with N optima, presumably due again to a negative correlation between fertiliser recovery and SNS.

### 4.7.6 C2 Shipton 2012

The lower lying parts of the Shipton field were waterlogged for long periods throughout the spring and summer of 2012. These areas are strongly reflected in the yields achieved, with the lower yielding areas to the NE and SW of the higher yielding band running SE-NW being the worst affected.

Unlike the other sites in 2012 there was a strong response to N at Shipton with no negativity at higher N rates, with N optima mostly exceeding 300 kg/ha. This crop was not as thick as those at Burford and Bedfordia, with tillering being severely restricted in parts by waterlogging. Nitrogen application at higher N rates at this site therefore likely had an abnormally large effect on tillering and tiller survival. The yield variation and effect of N is clearly evident on the aerial imagery and canopy reflectance measures.

The spatial variation in N optima generally corresponds to the variation in SNS, but it is evident from Figure 34 that the general relationship between SNS and optima is only apparent within cluster groups. It also appears that yield is having some influence on N optima at this site; some areas with moderately high SNS have lower have low yields and lower optima – for example a circular in the NE of the field and a strip running diagonally SE-NW across the field. Because the N optima was more than 360 kg/ha at much of this site much of the resolution in the variation in N optima in these areas is masked.

Fertiliser N recovery was low across this site, not exceeding 60% anywhere on the field, averaging 47%. It is perhaps surprising that the lowest N recovery here of 39% is no higher than the lowest recovery at all other sites. Again there is a negative association with SNS, fertiliser recovery being lowest where harvested SNS highest. There is however a slight negative relationship between fertiliser recovery and N optima, at least for the soils in Cluster group 1 (Figure 35), suggesting that variation in fertiliser recovery may be driving some of the variation in N requirement in parts of the field.

It seems that the ultimate causes of variation in N requirement at this site are spatially complex and that all components are responsible for the variation, some more than others in different parts of the field, but with interactions between all.

## 4.8 Chessboard discussion & conclusions

### 4.8.1 Variation in N requirement

The chessboard trials demonstrated a surprising amount of variation in yield and N requirements within fields, exceeding 2.5 t/ha and 100kg N/ha, respectively, at all sites.

The chessboard trial approach has been used to assess spatial variation in N requirements by Pringle et al. (2003) in Australia but to our knowledge has not been used elsewhere. The trials have all successfully shown spatially coherent variation in N requirement and allow some understanding to be made of the causes of that variation from the underlying soil.

A set of spatial experiments such as these reported here that allow variation in yield and N requirement to be assessed in the context of their determinants and in the context of soil & crop variation have not been conducted before in the UK. Two N response experiments harvested with a commercial combine in Bedfordshire were conducted in 2000 by Lark and Wheeler (2003). Data from these trials has been reanalysed here using zero-N yield as a surrogate for harvested SNS and yield at the optima as a surrogate for crop N demand (Figure 44). Variation in N optima in these trials was large, varying from 0 to 300 kg at one site and 0 to 200 kg/ha at the other. At one site it seemed that the variation was more due to crop N demand, the other due to variation in SNS.

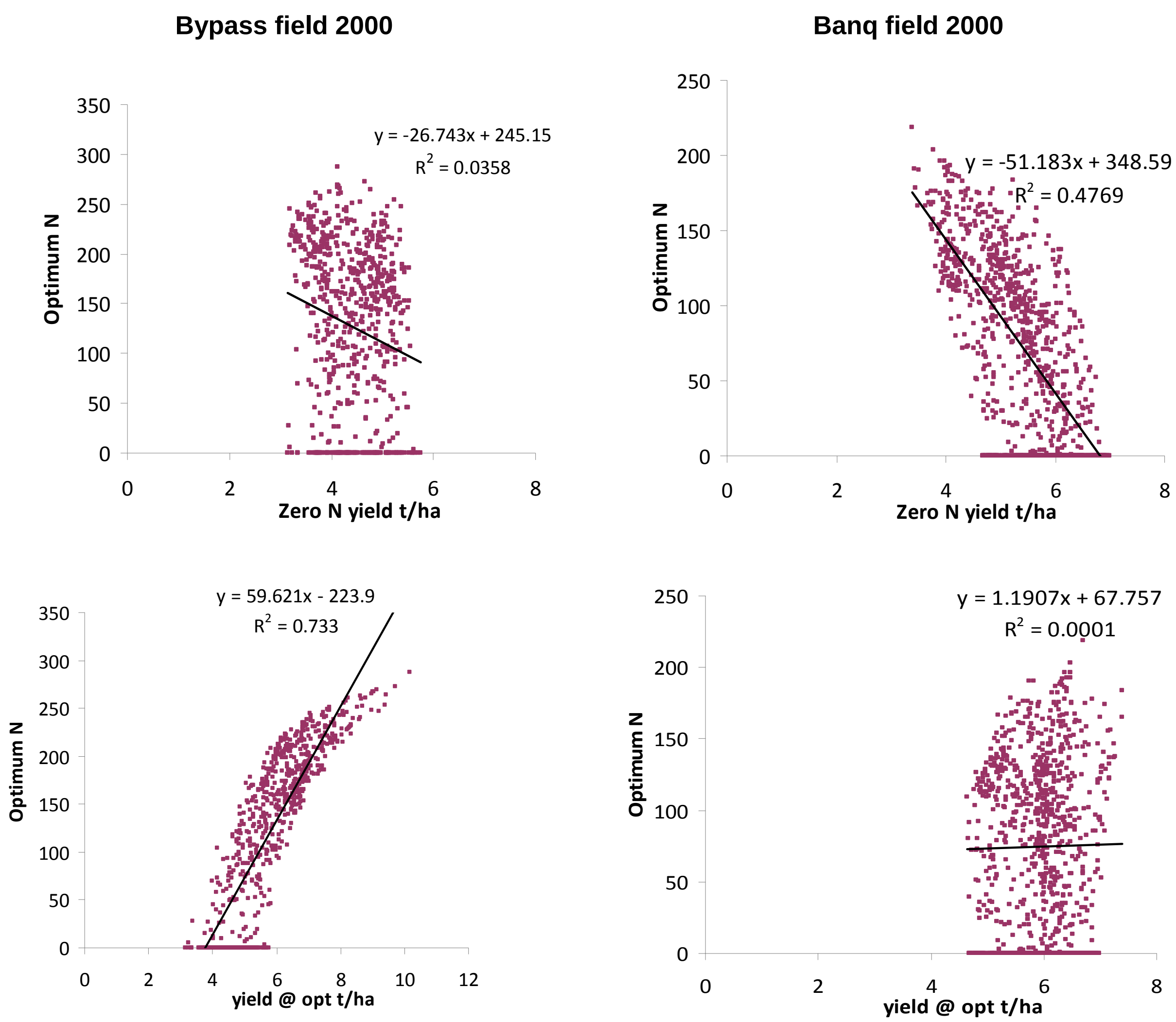


**Figure 44. Regression analysis of N optima from spatial experiments at Silsoe in 2000 conducted by Lark & Wheeler 2003, using yield at zero N as a surrogate for harvested SNS and yield at optima as a surrogate for crop N demand.**

### 4.8.2 Components of N requirement

Within the six chessboard trials, variation in N requirement is strongly associated with variation in SNS at three sites (Flawborough 2010, Burford 2012, Bedfordia 2012) and more loosely associated at all sites, N recovery is suspected to be a major driver at two sites (Burford 2011, Shipton 2012) and crop N demand is implicated in playing an important supporting role at 3 sites (Flawborough 2011, Burford 2011, Shipton 2012).

#### *4.8.2.1 Interaction between components*

The extent to which the three components Crop N demand, SNS and fertiliser recovery are spatially correlated was unexpected and has major implications for estimating fertiliser N requirements. The experiments have demonstrated a clear positive association within fields between yield potential and harvested SNS. It seems that soil conditions that are conducive to higher yields are also able to supply more N from the soil. The reason for higher yield potential is likely to be greater aeration and availability of water through the season, given that soil water contains some level of nitrate then some greater level of N availability might be expected, though probably not to the level seen in some of the fields. High yielding areas would be expected to remove more nutrients from the soil, though this does not appear to be the case with nitrogen. High yielding areas over time will create and return more biomass from roots and straw to the soil thus increasing soil organic matter levels, and higher soil organic matter levels can increase yields through improved soil structure and greater water retentiveness. Where soil organic matter is high greater mineralisation is expected hence a greater supply of N from the through the season. The association with SOM would be the most intuitive explanation for the link between SNS and yield potential, so it is somewhat surprising that there are so few clear relationships with measured SOM, total N% or potentially mineralisable N from soil samples. It is possible that SOM to depth is the causal link, which was not measured.

It is also surprising that the association between SNS and fertiliser recovery is stronger than that between yield and fertiliser recovery. It had previously been assumed that sites with higher yield potential tend to give higher fertiliser recoveries, through the greater demand for N from the crop (Sylvester-Bradley & Kindred, 2009 However, there is no evidence to support this found here. Instead, it seems that a higher SNS tends to be associated with a lower fertiliser recovery. Some care is needed not to over-interpret these data, as the estimation of recovery from broken stick regression is arithmetically connected to SNS (the Y intercept) and Crop N Demand (the asymptote), especially as we only have four N levels, so the relationship could be an artefact.

However, the negative relationship between SNS and recovery could make biological sense where high SNS is a result of high soil organic matter and high levels of microbial activity: Where microbial activity is high N fertiliser may be more readily taken up by soil microbes giving greater immobilisation and reduced fertiliser recovery (King et al., 2001). It is also possible that given the greater N supply from the soil, which may be available at different times to fertiliser N, that crops with higher SNS don't need to take up as much of the fertiliser N available. However, given the normally linear N uptake response to N fertiliser seen in experiments this doesn't seem plausible.

#### *4.8.2.2 Soil N Supply*

Overall, it seems that the most important component determining fertiliser N requirement is the Soil N Supply, both within fields and between fields. In all fields where harvested SNS was less than 120 kg/ha the N optima was generally high, normally more than 200 kg N/ha. Where SNS was greater than 120 kg/ha N optima were generally below 200 kg N/ha.

Unfortunately, current methods for predicting soil N supply are unsatisfactory (Kindred et al., 2012). 'Field assessment' (based on soil type and previous crop) is quick, cheap and correct on average, but it explains less than 50% of field-to-field variation, and it can only be used to predict variation within fields where soil types or past management differ markedly. Tests for mineral N in the soil are more precise, and precision and accuracy might be improved with assessments of mineralization; but it still does not predict more than 50% of field-to-field variation and it is too costly to use repeatedly within fields (Marchant et al., 2012). The predictive power of the soil tests conducted on the chessboard trials here are also disappointing (Figures 39–42). The visual associations between canopy reflectance measures in early spring and final harvested SNS seen in the chessboard trials here are therefore encouraging and point to the potential for successful application of canopy sensing to estimate N supply directly which is presented in Chapter 4.

#### *4.8.2.3 Crop N Demand*

Whilst crop N demand and N optima are generally positively associated (Figure 33, Table 4) there is little evidence from the chessboard trials of a strong driving relationship between yield potential and N optima; the positive relationships between achieved yield and N optima at Burford and Bedfordia in 2012 are confounded by the anomalous effects of the 2012 season and the unusual negative relationship between yield and SNS; in a more normal year the expectation would have been for the lower yielding higher SNS areas to have the higher yield potential. Current fertiliser N recommendations (RB209, Defra 2010) do not explicitly make adjustments for yield potential for cereal crops; rather an allowance can be made for high yielding crops from recording grain protein contents. An explicit link with yield is part of NVZ regulations and the calculation of Nmax limits, with an additional 20 kg N/ha permitted for every 1t increase in grain yield (Defra 2008). Calculation by N Management Guide also has an explicit link with crop yield, with crop N demand calculated as grain yield * 23 kg N/t for feed wheats and * 25kg N/t for bread wheats. Because these figures are divided by fertiliser recovery they actually result in a marginal increase in N fertiliser requirement of 38 to 42 kg N/t extra grain yield. These figures are hard to justify from the evidence from the chessboard trials. This is in part due to the interactions with other components, especially SNS being higher where yields are higher, but it perhaps also implies that as yields increase the marginal crop N content reduces; higher yields might be expected to be associated with lower protein, higher harvest index and lower straw N% so may require less than 23 kg N/t of additional yields. Figure 45 shows the relationship between optimal grain yield and crop N demand determined by broken stick regression to be between 17 and 21 kg/t for 4 of the six sites, with Burford 2011 giving low and Shipton high outliers in the slope.

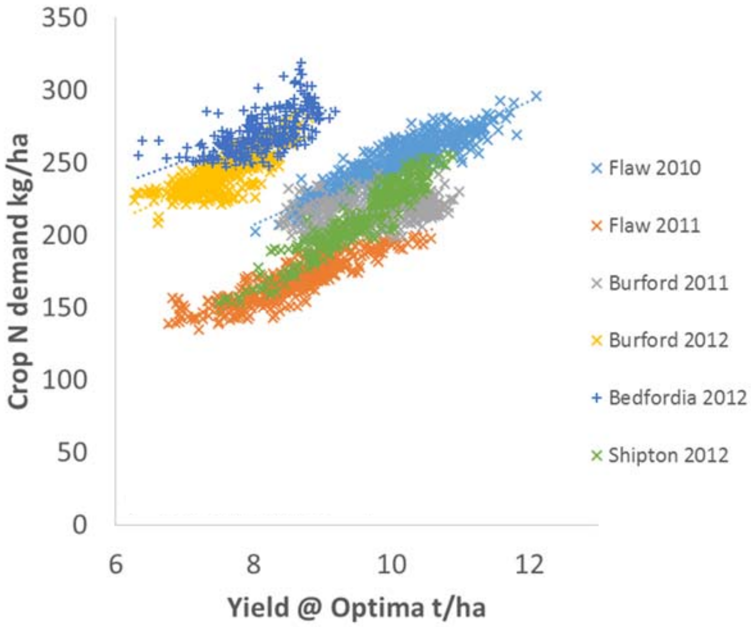



**Figure 45. Relationship between optimal grain yield and Crop N Demand determined by broken stick regression for the six chessboard experiments**

It is clear from the chessboard trials that past yield map information can be used to inform variable yield estimates across the field, though in anomalous years those estimates may be wrong. Without reliable long term weather forecasting it is unlikely to be possible to accurately forecast spatial variability in yields at the time when fertiliser decisions need to be made. In early May 2012 crops look good and expectations were of high yields, it was the later weather that affected final yields. Given the lack of strong relationships between crop N demand and N optima in these trials there is a question mark over whether we should estimate yields as part of the calculation to estimate N requirements on a spatial basis; large adjustments to yield and crop N demand estimates can have large impacts on the calculated N requirement. However, given the association between SNS and yield potential, making adjustments to SNS estimates without also adjusting Crop N Demand estimates can also give misleading predictions of N requirement. It therefore seems that more effort should be given to predicting SNS but estimates of yield and CND should also be made.

#### *4.8.2.4 Fertiliser recovery*

All the experiments showed very large variation in fertiliser N recovery. Whilst this was rarely a driving force in the variation in N requirement, its variation still makes a large difference to calculating predicted N requirements. Apart from the negative association with SNS, the variation in fertiliser recovery remains unexplained and there are no obvious factors which could be used to estimate its variation on a spatial basis.

Overall, despite the strongest relationships existing with SNS, knowing only one component is not enough; we must consider all components together to predict N fertiliser requirement with reasonable precision. The relative importance of these factors varies from site to site and within sites, generally as a function of soil type, and interactions between the components can vary from place to place.

### 4.8.3 Variation in grain protein content

Monitoring grain protein content is advocated in RB209 and the N Management Guide as the best way to gauge whether N fertiliser applications to crops have been appropriate. Previous work has suggested that when the crop is fertilised for a financially optimum yield protein is around 11% for feed varieties and 12% for milling varieties (Sylvester-Bradley & Clarke, 2009). Whilst it has been noted that there is substantial variation around these, and that averaged proteins over fields and years should be used as indicators rather than individual results, it had been hoped that mapping protein content in fields could be a useful surrogate for judging N requirements within fields. However, all of the chessboard trials have shown variation in protein content at the optima exceeding 3% DM, with optimal protein contents seen as low as 7% and as high as 15% across trials. This variation is larger than the variation in grain protein commonly seen in farm, which might typically vary from 9% to 13%. On average the protein at the N optima were 11.2, 9.0, 12.0, 14.1, 13.2 and 12.0% for Flaw 2010, Flaw 2011, Burford 2011, Burford 2012, Bedfordia 2012 annd Shipton 2012, respectively. Apart from Flawborough 2011 which was anomalously non-responsive to N for yield, the average protein values at optima were reasonably close to the benchmarks of 11 and 12% (all fields except Flawborough grew milling varieties). Proteins at Burford and Bedfordia in 2012 were high, perhaps as a result of the poorer grain filling and reduced yields in this year.

The point at which N optima interjects with the protein response curve is not consistent (Figure 23). Generically, the grain protein response to N continues to slightly higher N rates than that for grain yield, so grain protein content at the optima for yield could be expected to generally fall in a similar position on the protein response curve, somewhat before the shoulder is reached. Whilst on average this holds true for most of the sites, the variability apparent from Figure 23 shows that the protein response curve and yield response curves are not always well aligned. This perhaps underlies the complexity and interactions of the system that drives the spatial variation in grain yield and grain protein responses to N fertiliser, from differences in N availability, N uptake, growth, tillering, tiller abortion, spikelet determination, leaf expansion, stem elongation and accumulation of water soluble carbohydrates, floret initiation and survival, numbers of grain set and potential grain size through endosperm cell number, late N uptake of N and remobilisation from leaves and stem to grain, photosynthesis and respiration through grain filling, protein deposition in the grain and starch deposition in the grain. This is the first study to characterise spatial variation in the protein response to N and there is clearly still much more to understand about the drivers for final grain protein content, its relation to yield and to the N optima.

Looking at the spatial patterns in protein at a standard N rate (Figure 22) in relation to the patterns in N optima (Figure 19), there is some negative associations at most of the sites in at least some areas; where protein is high this should indicate optima is low and vice versa. Looking at the relationship formally in Figure 46 a clear negative relationship between protein at 240 kg N/ha and N optima is revealed, with the Flawborough 2011 and Burford 2012 sites standing out as outliers.

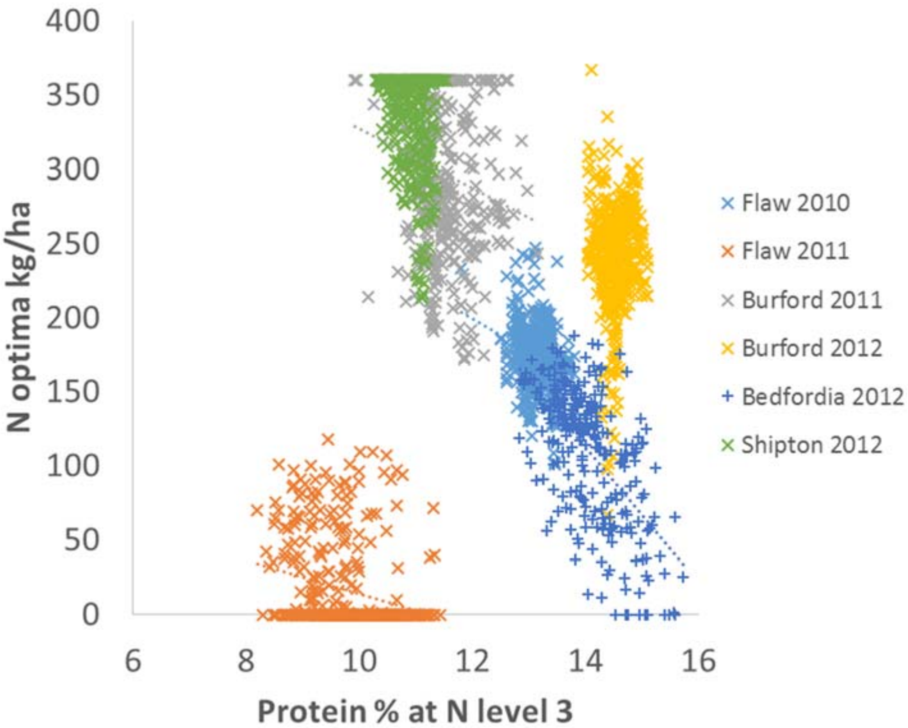



**Figure 46. Relationship between N optima and protein at N level 3 (normally 240 kg N/ha) determined by broken stick regression for the six chessboard experiments**

Whilst the variability in grain protein content, its responses and its value at the N optima have somewhat knocked our confidence in the value of grain protein as a monitor of successful N management, Figure 46 demonstrates that it remains a useful tool in judging N optima, perhaps the best we have available. More caution should perhaps however be advised in inferring conclusions from results in single fields or years.

### 4.8.4 Variation in grain yield

Substantial variation in yield was seen in each of the fields, always more than 2 t/ha and often exceeding 3 t/ha. At every site, the size of spatial variation in yield at sub-optimal N rates was similar to that at higher N rates, or at the optimal N rate. In all cases except the anomalous year of 2012, the highest yielding areas of the field were higher yielding however much N was applied.

Because we know that yields on the lower yielding areas could not be increased to the level of the higher yielding areas by applying more N fertiliser we can therefore conclude that the cause of yield variation within fields in the UK is not predominantly due to N fertiliser limitation. What the major cause of the variation in yield within fields actually is remains largely unexplained. In some fields there are obvious explanations, such as soil depth at Burford 2011 and severity of water-logging due to elevation at Shipton 2012. However, in most cases there is no explanation available from the measures taken; the variation cannot be ascribed to variation in organic matter, pH, P or K. Lark et al., (1998) found much of the spatial variation in a barley field to ultimately be due to differences in soil water holding capacity.

Given the large variability in yield ubiquitously seen in fields investigations into what is causing this variation should be a fundamental question of utmost concern to crop scientists and soil scientists alike. However, we know of no current research tackling this important question. Spatial experimentation provides a unique opportunity to better understand this variation, and hence understand soil effects on yields more generally, as variation in yield can be assessed in the presence and absence of resources suspected of limiting yields. Here we have assessed the impact of N fertiliser on yield, similar experiments could assess the range of nutrients, or even assess the impact of water limitation by providing trickle irrigation.

Variation in grain yield within fields is mostly <u>not</u> due to N limitation. “What is it due to?” remains an important unanswered question.

### 4.8.5 Wider implications from the chessboard trials

The chessboard trials have transformed our understanding of N responses and made us question many previously held assumptions. The underlying cause of the variation is not well understood but chessboard trials give great opportunity to better understand soils and their optimal management.

The variation in yields at N optima at each site is similar to the variation in yield at any given N rate. This suggests N limitation is not a major cause of the spatial variation in yield in each field. Other factors in the soil that affect the amount of water and nutrients available to the crop must be more important than differences in optimal N.

The overall levels of N optima seen in the chessboard trials are fairly consistent with previous plot experiments. Zero-N responses as at Flawborough 2011 and some plots at Bedfordia 2012 are relatively common, with 6 out of 30 N response experiments in recent AHDB Cereals & Oilseeds work showing no response to N (Sylvester-Bradley et al., 2008). The cause for the lack of response is invariably high levels of SNS, which, at least in part, is the cause at Flawborough and Bedfordia. Finding 3 sites out of 6 with some N optima above 360 kg N/ha is perhaps a little more surprising. It is possible that the fitting of the responses in these trials is affected by only having four N rates compared to at least 5 or 6 in conventional N response experiments. If an N rate had been included between 240 and 360 kg N/ha which had given a similar yield to the 360 kg N rate then the optima may have been pulled down. However, the reasonable shapes of the curves and the fits to the plot data points suggests that at least some of the plots did have very high N optima.

The variation in N optima seen in these trials has implications for the interpretation of N responses from small plot trials generally. It is clear that the resulting optima from an N response experiment can be very different depending on where in the field the trial is located. This variation could explain a large part of the notoriously large variation in N optima seen between trials that hinders prediction of optima through factors such as previous cropping, soil type, over-winter rainfall and yield expectation. If within field variation in soil can have such a large impact on N optima there is a need to better understand the causes and nature of this variation. Chessboard type trials provide an exciting opportunity to better understand the effect of soil on N optima as all other factors which normally vary between N response trials (field, variety, history, agronomy, sowing date, seed rate, soil management etc.) are kept constant; the only thing that changes is the soil (and potentially aspect also).

Half of the chessboard trials conducted were in the anomalous season of 2012 where extremely wet and dull weather produced yields, spatial variation and N responses which may be highly atypical. The 2010 and 2011 seasons were also somewhat atypical with both suffering exceptionally dry springs. There would be real value in conducting further chessboard trials in other years, which would hopefully be more representative.

# 5 Estimating N Demand – Predicting Yield & Protein

Whilst seemingly not the most important driver of variation N requirements, the chessboard trials showed that estimation of crop N demand was still important in accurately predicting N requirements. There are various possible approaches to estimate yield potential within fields, either continuously to the minimum definable resolution of the field, or via the delineation of zones within the field that might be expected to yield similarly. Most obviously previous yield maps can be used for this purpose (Robertson et al., 2008), but soil scanning and satellite sensing may also be useful. In order to integrate this data usefully zoning techniques such as clustering may be of value. This chapter assesses how we can best interpret previous soil and yield maps to provide useful yield estimates (Lark & Stafford, 1997; Blackmore *et al.*, 2003; King *et al.*, 2005; Ross *et al.*, 2008).

Analysis was made of selected fields farmed by the 5 farmers with whom we worked with in this project and selected results from the 6 fields used for the chessboard experiments are presented here.

In addition the possibility of mapping grain protein content was examined at three of the farms, the results of which are reported in this chapter.

## 5.1 Yield mapping

Yield mapping equipment is now readily available, and comes as standard on many new combine harvesters. However, there are a range of issues in generating, viewing, transferring and analysing yield maps to make them really useful. Even farmers who have yield maps often do little with them, not having a good answer to the ‘so what?’ question.

### 5.1.1 Dealing with Yield map data

There are multiple issues in dealing with yield map data, both practical and statistical (Birrell et al., 1996; Blackmore & Moore, 1999; Arslan & Colvin, 2002). Many different types of yield monitor are used on-farm from several different manufacturers. Yield is inferred from sensors in the grain elevator either by measurement of mass flow (eg by impact plate or radiometry) or volume flow (eg by optical or NIR sensors). Each is different in its accuracy, precision and frequency. Many yield monitors in the UK assess volumetric flow so require the specific weight of the grain to be input into the calibration on a regular basis. Yield monitors also usually incorporate an in-line moisture meter allowing yield to be adjusted to a traded moisture content, although it is not usually clear from the output of yield map data whether these moisture corrections have been made, or to what ‘dry’ moisture level any correction has been made to. Yield monitors are linked to a digital GPS receiver to give position and speed allowing calculation of yield and associated latitude and longitude for each datapoint. Different GPS systems have differing levels of accuracy; for high accuracy a differentiated signal is required, either from a base station (eg RTK) or from a mobile phone signal. It is not normally clear from raw yield map datafiles how accurate the GPS signal is, or whether it is differentiated.

There is inevitably a delay between the crop being cut and entering the header to it being threshed, sieved and entering the grain elevator & hence the yield measurement being made (Lark & Wheeler, 2000). Depending on where the GPS receiver is located on the combine an appropriate delay can be factored in. Whilst the delay may be adjusted for within the yield monitor system, or may be adjusted in the yield mapping software afterwards, however it is not clear from yield map datasets whether any such adjustments have been made, and if so, what. The dynamics of grain flowing through the combine can be affected by crop type & yield level, forward speed and combine settings for drumspeed, fanspeed and sieves, especially where these affect the amount of grain going through the returns system. Considerable research work has assessed the varying dynamics of grain flow through combines to try to create better reconstructed yield maps, though this is not generally used in commercial yield maps (Arslan & Colvin, 2002; Lyle et al., 2014).

The quality of yield maps can be very dependent on the operator of the combine. This is not just in terms of set-up and calibration of the yield monitor, but also in terms of how the combine is driven. Most important is that the header is constantly cutting a full (or constant) width. Where GPS is used to plot the combines course or a laser on the header is used for auto-steer guidance the width should be reasonably constant within a run. However many operators harvest the crop in lands, often cutting the first cut with the divider in a tramline wheeling then cutting round and round, so that the unloading augur is always on the cut side. Depending on the width of the header relative to tramline width this normally results in the final strips cut not being a full header width. Some systems automatically calculate the cut width from the GPS signals, some sense the cut width and some allow the width to be estimated manually. Whilst the cut width is often recorded in yield map data outputs it is not always clear whether the output yield has been corrected or not. The accuracy of the yield estimates from these widths comparative to yields from full header widths must therefore be questionable. Note that if the estimate of width has been inaccurately used to adjust the yield calculation then these strips can show up as high yield, though they more normally show as low yield.

A wide range of file types and data formats exist for yield map data, dependent on the manufacturer and model. Similarly there are a wide range of software tools for viewing and analysing yield maps. Each manufacturer has software to support their yield data files. However, there is also generic crop management and precision mapping software, such as Gatekeeper, which can handle yield datafiles from the full range of manufactures. In addition, Claas and other manufacturers now operate telematics system whereby yield data (as well as a full suite of combine performance data) is continually relayed to a central server via mobile phone signals, and data can be accessed remotely.

There is little consistency in the format of the data from different yield monitors, even the recorded format of latitude and longitude is not consistent. Most raw yield mapping datafiles will however include:

- Lat, Long & GPS time
- Yield as is
- Moisture
- Adjusted Yield

In addition, many also include elevation, speed, cutter height, cutter width and can include all measures of all sensors from the combine including engine speed, drum speed, temperature etc.

There has been a considerable amount of research effort, especially in the US and Australia, devising post-processing routines to deal with yield map data and the issues above, with the creation of software tools such as Yield Editor (Sudduth & Drummond, 2007), Vesper (Minasny, McBratney & Whelan, 2005) and others (Griffin et al., 2005; Ping & Doberman, 2005). However, a consistent system for post-processing data has not been agreed and is not generally used by growers (Lyle et al., 2014).

An AHDB Cereals & Oilseeds project running in parallel to Auto-N is developing approaches and software for the post -processing of yield data in the UK (RD-2012-3785).

### 5.1.2 Statistical techniques for integrating yield map data

The spatial variation evident in yield maps usually changes considerably between years, so yield maps from several years must be analysed together to get a predictive estimate of yield variation across the field (Blackmore, 2000). This spatio-temporal complexity is largely due to the soil and crop performing differently with different weather and management in different years, but it is somewhat clouded by the noise, errors and variability inherent in yield maps.

Extracting an underlying signal from these somewhat noisy data is a challenge, but there are statistical methodologies to deal with them. There are two broad approaches. One (e.g. Blackmore et al., 2003; Kleinjan et al., 2006) considers local mean yield and its variability, identifying regions where yield is relatively stable and regions where it is less predictable. An approach like this is used by SOYL described as Performance Mapping, which identifies areas which are consistently above average, consistently below average and areas which are highly variable.

Another approach (Lark & Stafford, 1997; Perez-Quezada et al. 2003) uses a more flexible 'clustering' approach with smoothing. Here locations in a field are grouped into classes which show more or less uniform season-to-season patterns of variation (e.g. consistently above-average yields, above average yields except in dry seasons, consistently below-average yields, etc.). These classes have been shown to account for substantial soil variation (e.g. King et al., 2005), since a region with a more-or-less uniform season-to-season pattern of yield variation is likely to be subject to more-or-less uniform constraints on crop performance (e.g. small available water capacity, poor soil structure leading to poor establishment and greater slug damage, etc.).

In the cluster analysis we used only yield monitor data from winter wheat fields as these proved more reliable than those for other crops. First the yield monitor data from $p$ years (typically no more than four) were mapped onto a square grid at intervals of ~10m by taking the average of the yields in the neighbourhood of each grid node in each year. This resulted in $p$ yield values $z_1(\mathbf{x}), z_2(\mathbf{x}), \ldots, z_p(\mathbf{x})$ for each of the grid nodes where $\mathbf{x} = \{x_1, x_2\}$ are the co-ordinates of the grid point.

From these data we can create a classification. We standardise each of the $p$ sets of yield data to have a mean of zero and a standard deviation of 1. We then choose the number of classes ($k$) we wish to impose on the data. Each class $q$, $q = 1,2,\ldots,k$ is characterised by a centroid vector $\bar{\mathbf{z}}_q = \{\bar{z}_{1q}, \bar{z}_{2q}, \ldots, \bar{z}_{pq}\}$, where the elements are the average value of the variates in class $q$. We measure how well a unit $i$ resembles a class $q$ by calculating the Euclidean distance in the vector space

$$\delta_{iq} = \sqrt{\sum_{j=1}^{p} (z_{ij} - \bar{z}_{jq})^2}$$

In a fuzzy k-means clustering each unit belongs to some degree to every class. The classification is made by minimization of

$$\sum_{q=1}^{k} \sum_{i=1}^{n} \delta_{iq}^2 \, u_{iq}^{\omega}$$

where $u_{iq}$ is the membership of unit $i$ to class $q$, and $\omega$ is the fuzziness exponent which we set equal to 1.25. The membership across the classes must sum to 1:

$$\sum_{q=1}^{k} u_{iq} = 1.$$

To choose the number of cluster classifications we apply values of k from 1 to 5 and then use the normalized classification entropy

$$\eta(k) = -\frac{1}{\log k}\sum_{q=1}^{k}\sum_{i=1}^{n}\frac{1}{n}u_{iq}\log u_{iq}$$

where $n$ is the number of units (nodes on the grid). The entropy is plotted against $k$, and we look for a point that falls below the overall trend, such as a local minimum, or the point at which an initial rapid decline is followed by a more gentle decrease.

Once we have chosen how many classifications we which to use we return to the fuzzy membership classification for this number of classes and apply spatial smoothing. This is necessary to create coherent zones in space, otherwise the classification is likely to result in speckled classification maps that are not appropriate for management. The distributions of memberships, $u_{iq}$, are strongly bimodal, and so, following Lark (1998), we converted them to unimodal distributions with a symmetric logratio transform. We then smoothed the transformed memberships, $\tilde{u}_{iq}$, using a weighted average of the transformed memberships in circular neighbourhoods, $R$, of radius $r$:

$$\tilde{u}_{iq}^{*} = \sum_{j\epsilon R} w(i,j)\,\tilde{u}_{kq}.$$

The weights must sum to one and are given by

$$w(i,j) = \frac{1 - f(\mathbf{h}_{ij})}{\sum_{l\epsilon R} 1 - f(\mathbf{h}_{il})} \quad \forall\ j \in R$$

where $f(\mathbf{h})$ describes the spatial structure in the variogram of the yield monitor data

$$\gamma(\mathbf{h}) = c_0 + cf(\mathbf{h})$$

and $\mathbf{h}_{ij}$ is the separation between units $i$ and $j$. For practical purposes a 'hard' classification is needed, and so each unit was assigned to the class for which its membership was greatest.

The size of $R$ affects the results. If $R$ is too small then the classification is likely to remain fragmented; if it is too large then the memberships are likely to be over smoothed. We used the coherence index defined by Lark (1998) to identify an appropriate radius for $R$. It is given by

$$I_c = \frac{\eta_a}{\sum_{q=1}^{k}\psi_q^2}$$

where $\eta_a$ is the proportion of pairs of units within a distance $a = 10\sqrt{2}$ that belong to the same class, and $\psi_q$ is the proportion of units that belong to class q. The larger is the value of $I_c$ the more coherent is the classification. For full details see Milne et al. (2011).

In addition to yield maps other information from soil sensing (EMI) and canopy sensing may be useful in delineating management zone boundaries and in estimating likely yields.

## 5.2 Variation in grain yield between years

Data was collected from the 5 farmers in this project and compiled into a common data file format. The following routine was applied to all yield data:

- Common filename structure, dataformat, column titles & order and units
- Calculated projection from WGS 84 to British National Grid – Eastings & Northings.
- Calculation of combine direction
- Identification of sharp changes in direction and exclusion of data at start and end of runs
- Exclusion of data more than 3 standard deviation from mean
- Calculation of moisture adjusted yield
- Exclusion of anomalous combine runs

Data was viewed and reported using ArcGIS.

### 5.2.1 Flawborough 2010

Figure 47 shows the spatial variation in yields at the Flawborough F1 field between 2002 and 2013. The rectangular whole in the map in 2010 is where the chessboard trial was located. Some features are evident in most years, but other areas show large relative changes between crops and years.

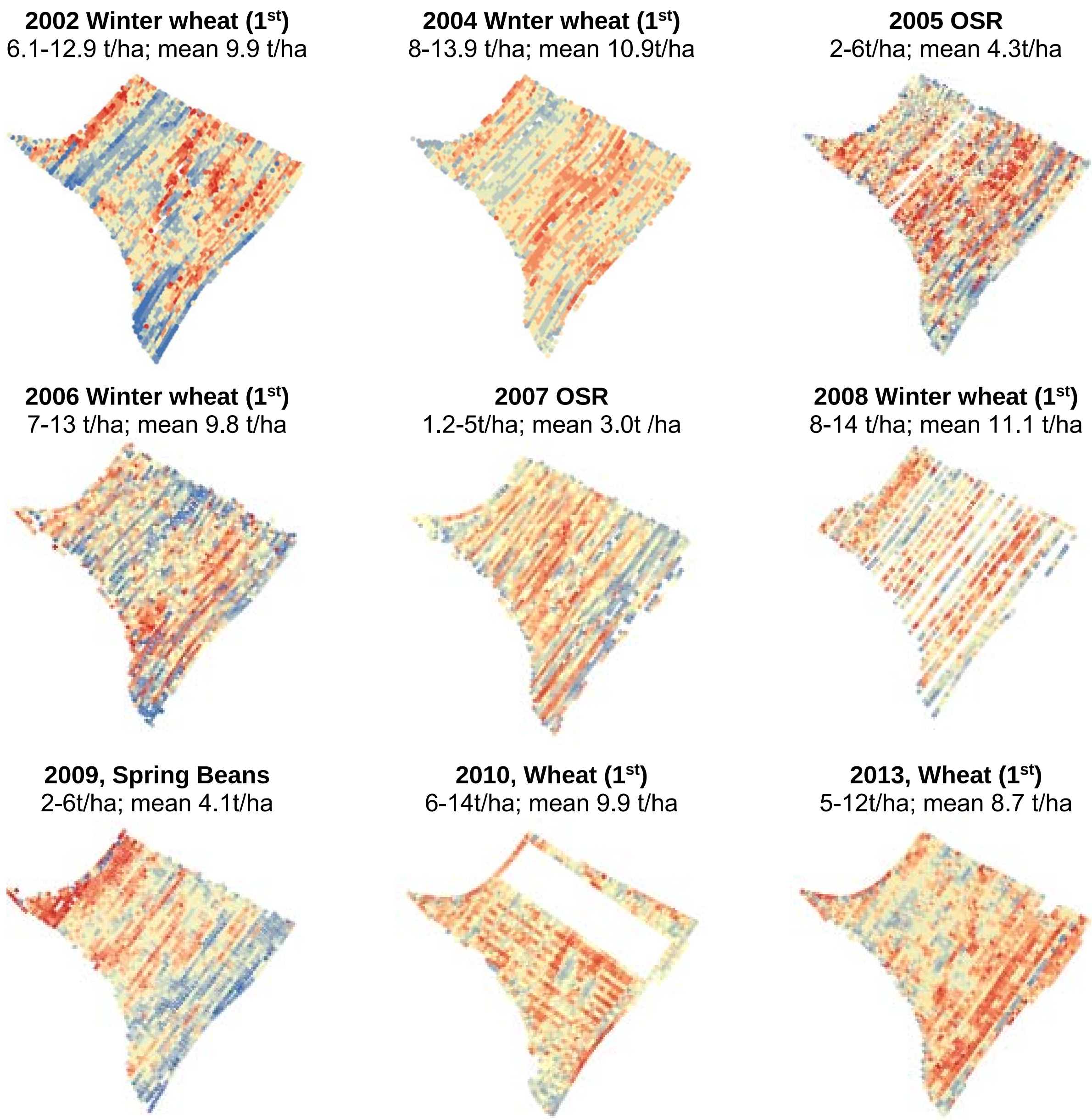



**Figure 47. Yield Maps from field F1. The symbology uses Jenks Natural breaks to best show spatial variation. Blue = low yield; red = high yield. Range and mean is given for each crop.**

A 10 m grid was imposed on the field to allow data from different years to be integrated and compared. The cluster analysis was restricted to only those grid squares where data was available from all years.

The final cluster map is shown in Figure 48, along with simple and normalised averages for each grid square for all crops and just for wheat. Similar patterns are evident for all approaches, though these are more distinct when restricted to wheat and when normalised averages are used.

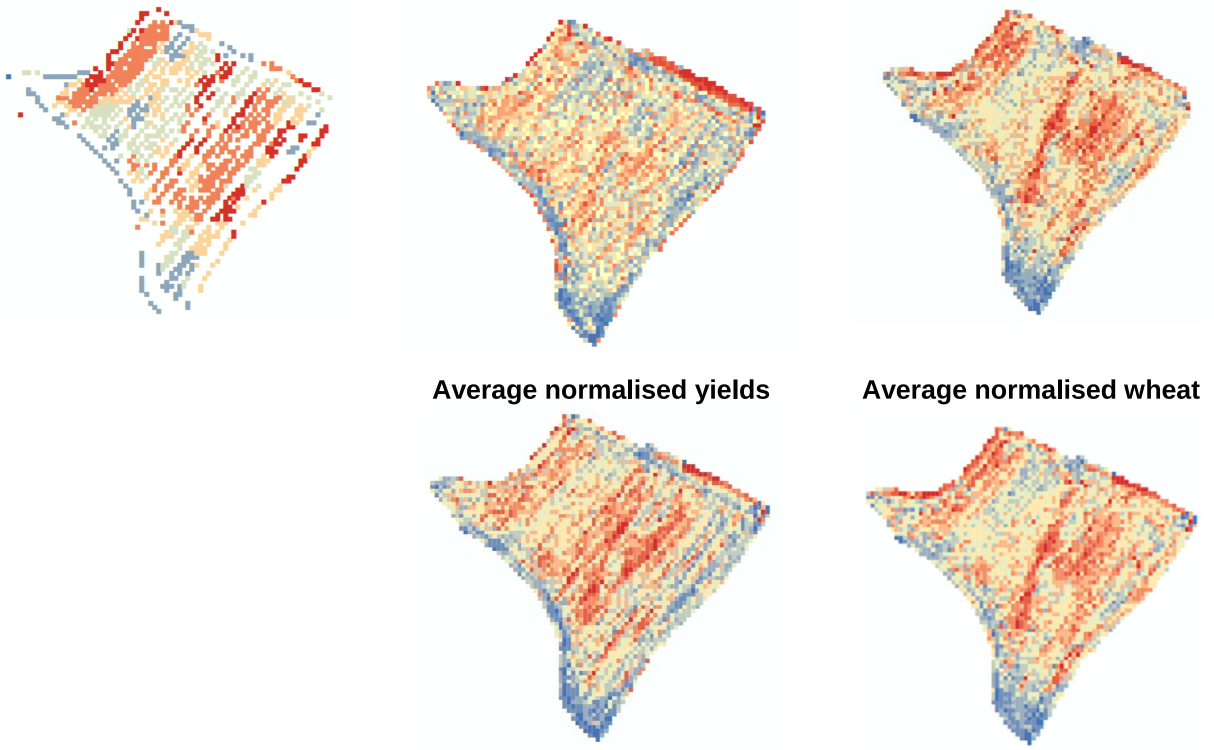



**Figure 48. Integrated Yield Maps from field F1**

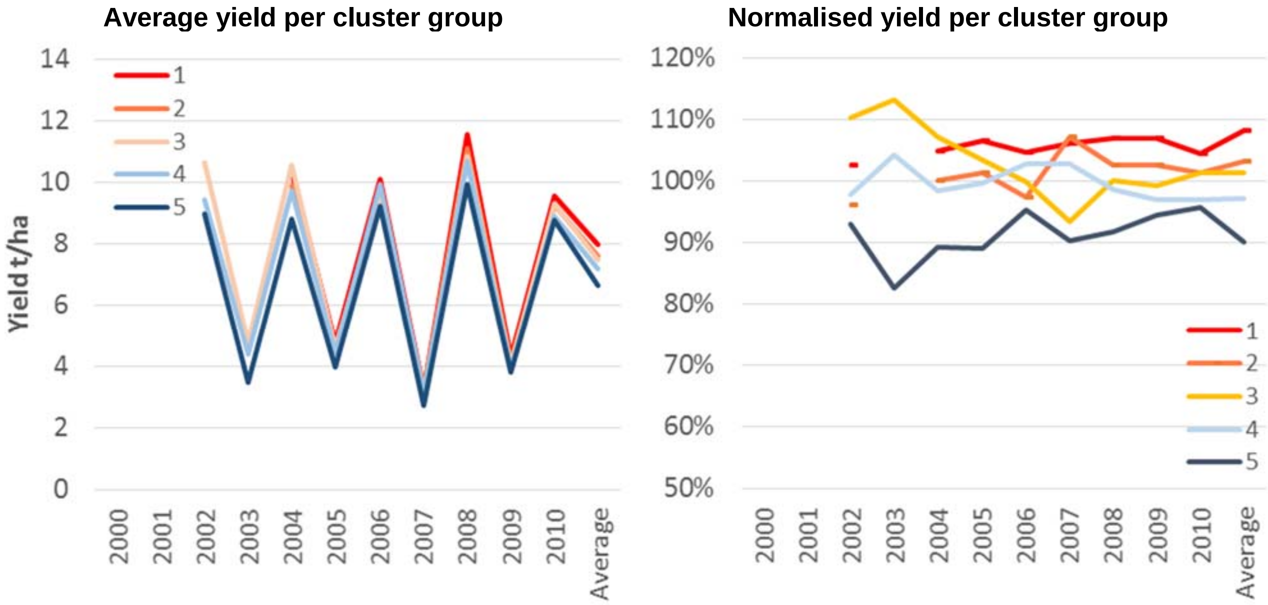



**Figure 49. Mean (a) and Normalised (b) centroid yield values for the Cluster Groups for field A2 for groups shown in Figure 49a**

The line graphs in Figure 49 shows the performance of each cluster group in each year. There is evidently some consistency between groups with cluster group 5 always being lower yielding and group 1 nearly always giving the highest yields. Group 3 is less consistent, having highest yields in 2 years but low yields in 2007.

The past yields, averages, normalised averages and cluster groups for the other chessboard fields are reported below.

### 5.2.2 Flawborough F6 2011


**Figure 50. Yield Maps from field F6. The symbology uses Jenks Natural breaks to best show spatial variation. Blue = low yield; red = high yield. Range and mean is given for each crop.**

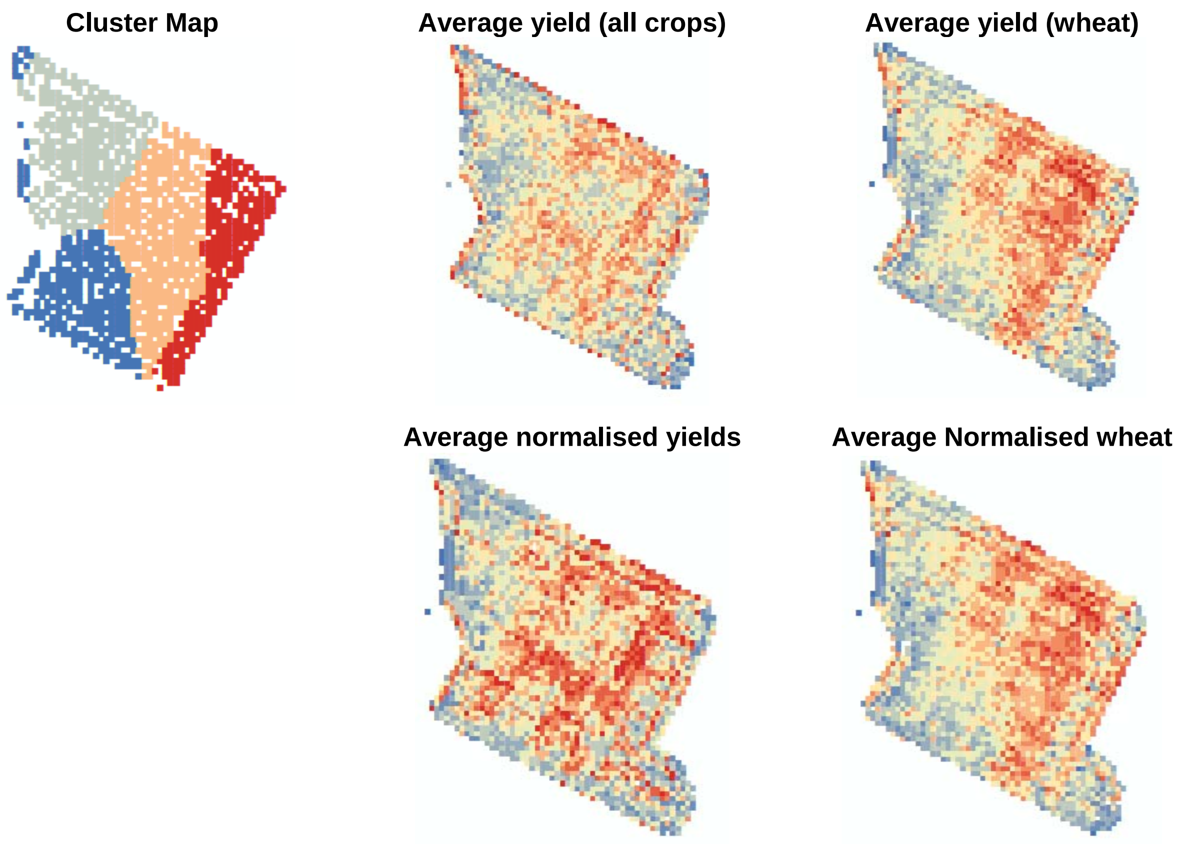



**Figure 51. Integrated Yield Maps from field F6**

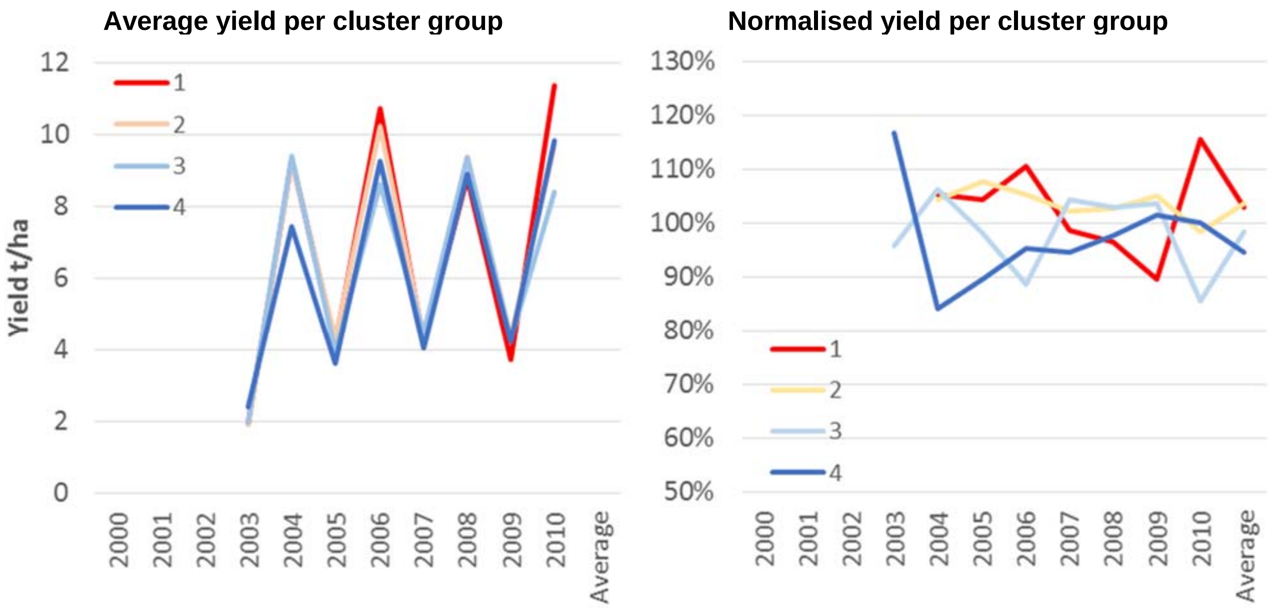



**Figure 52. Mean (a) and Normalised (b) centroid yields for the Cluster Groups for field A2 for groups shown in Figure 51a**

There is considerable spatio-temporal variability in field F6, as shown by Figure 51 and Figure 53, which is not entirely captured by the normalised average yield map. Cluster Group 1 on the eastern edge gives highest yields in some years but lowest in others, whilst group 3 (western corner) is generally lower yielding but has some years with high yields.

### 5.2.3 Burford A2 2011

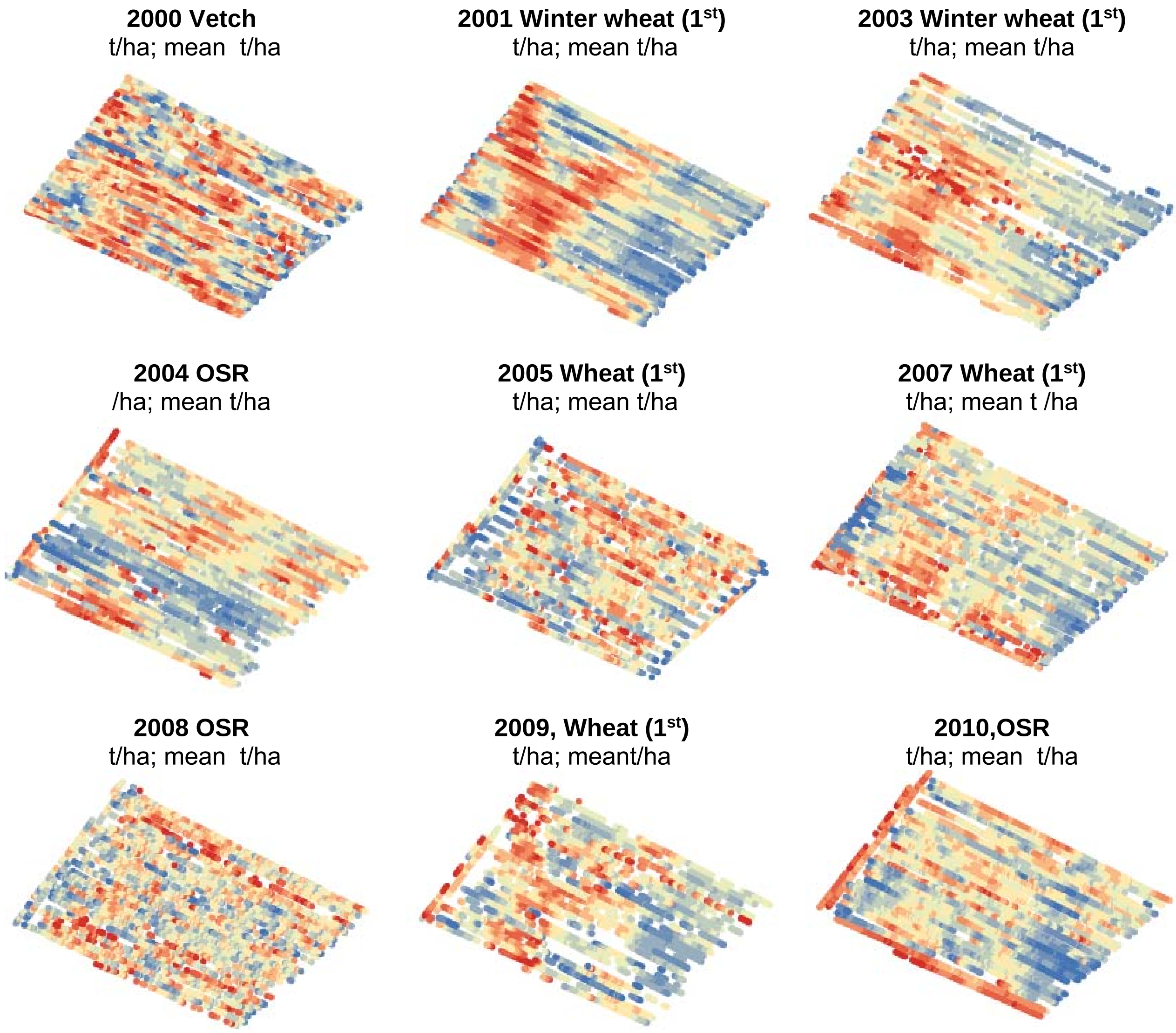



**Figure 53. Yield Maps from field A2. The symbology uses Jenks Natural breaks to best show spatial variation. Blue = low yield; red = high yield. Range and mean is given for each crop.**

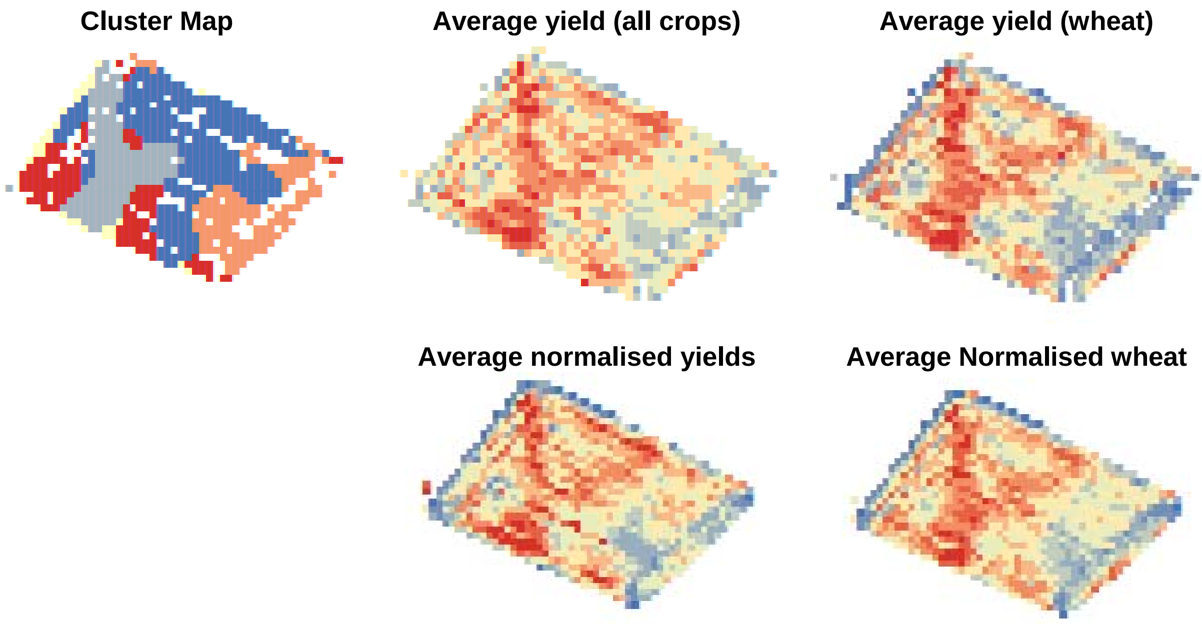



**Figure 54. Integrated Yield Maps from field A2**

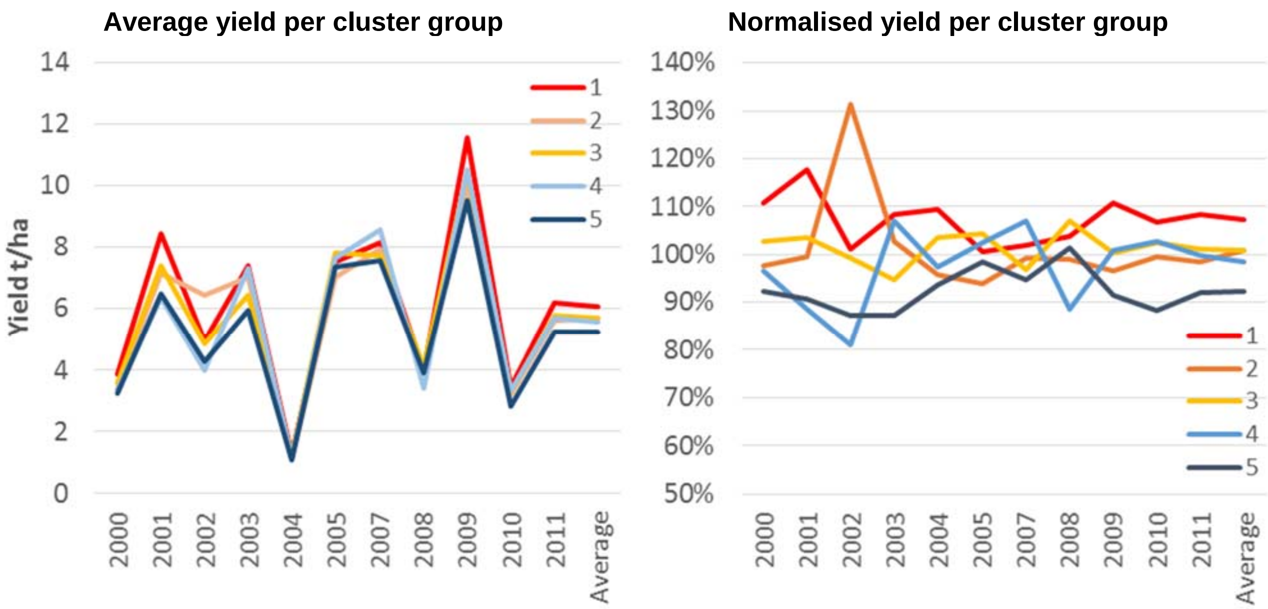
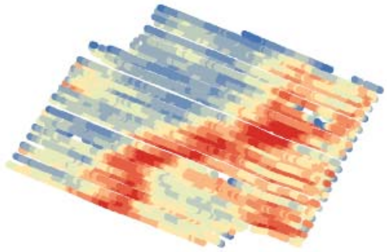



**Figure 55. Mean (a) and Normalised (b) centroid yields for the Cluster Groups for field A2 for groups shown in Figure 54a**

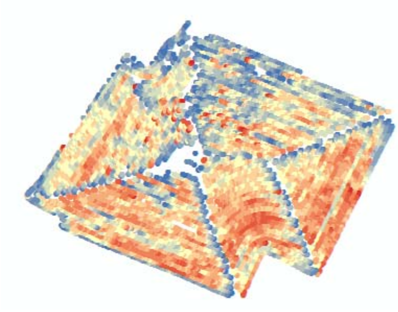
Field A2 also demonstrates substantial spatio-temporal variation. The characteristic Y-shape from the physical valley is clearly apparent from the yield maps in only some years, notably 2001. However it comes through strongly in the averaged yield maps and is present in the cluster map as Group 4, with considerable variability year to year, having high yields in the droughted year of 2007 but less well in other years.

### 5.2.4 Burford A3 2012

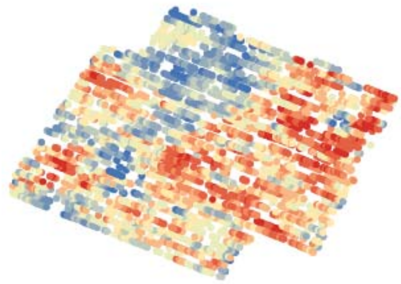
**2000 Winter wheat (1st)**
t/ha; mean  t/ha



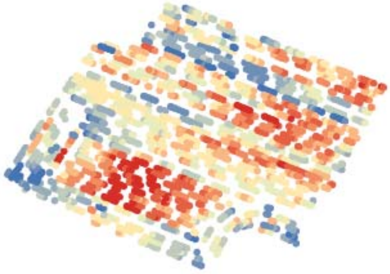
**2001 OSR**
t/ha; mean t/ha



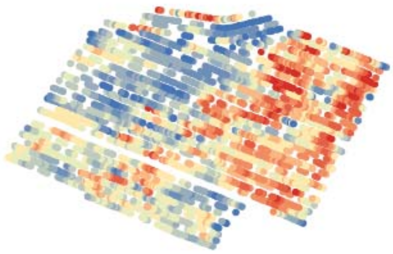
**2002 Winter wheat (1st)**
8-13.9 t/ha; mean 10.9t/ha



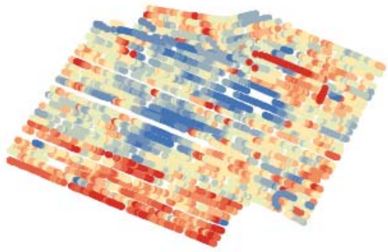
**2003 OSR**
t/ha; mean t/ha



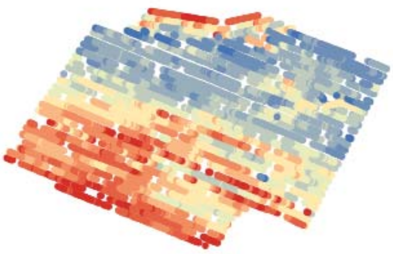
**2006 Wheat (1st) (1st)**
t/ha; mean t/ha



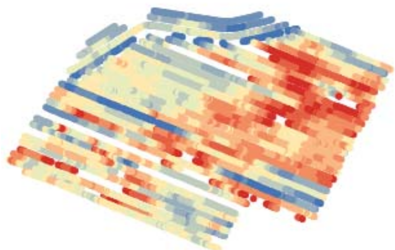
**2007 Wheat (1st)**
t/ha; mean t /ha



**2008 OSR**
- t/ha; mean  t/ha



**2010, Wheat (1st)**
- t/ha; mean t/ha



**2011, peas**
t/ha; mean  t/ha

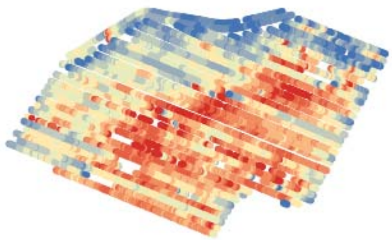


**Figure 56. Yield Maps from field A3. The symbology uses Jenks Natural breaks to best show spatial variation. Blue = low yield; red = high yield. Range and mean is given for each crop.**

There is substantial year to year yield variation in A3. In particular the clay bank that runs E-W across the field is distinctly evident in 2000 but less so in other years. It comes through in the normalised average yield but not in the cluster groups (Figure 58). Figure 59 shows the northern corner (cluster 5) to be consistently low yielding and the eastern corner to be consistently high yielding.

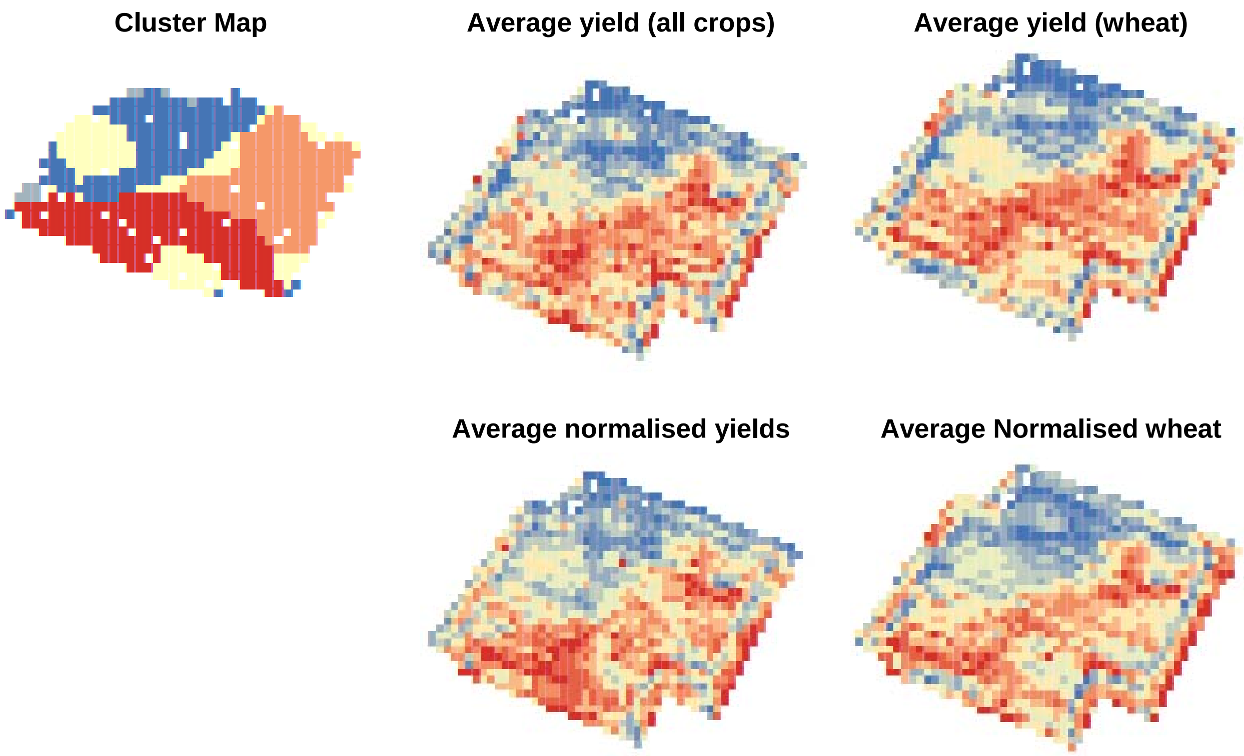



**Figure 57. Integrated Yield Maps from field A3**

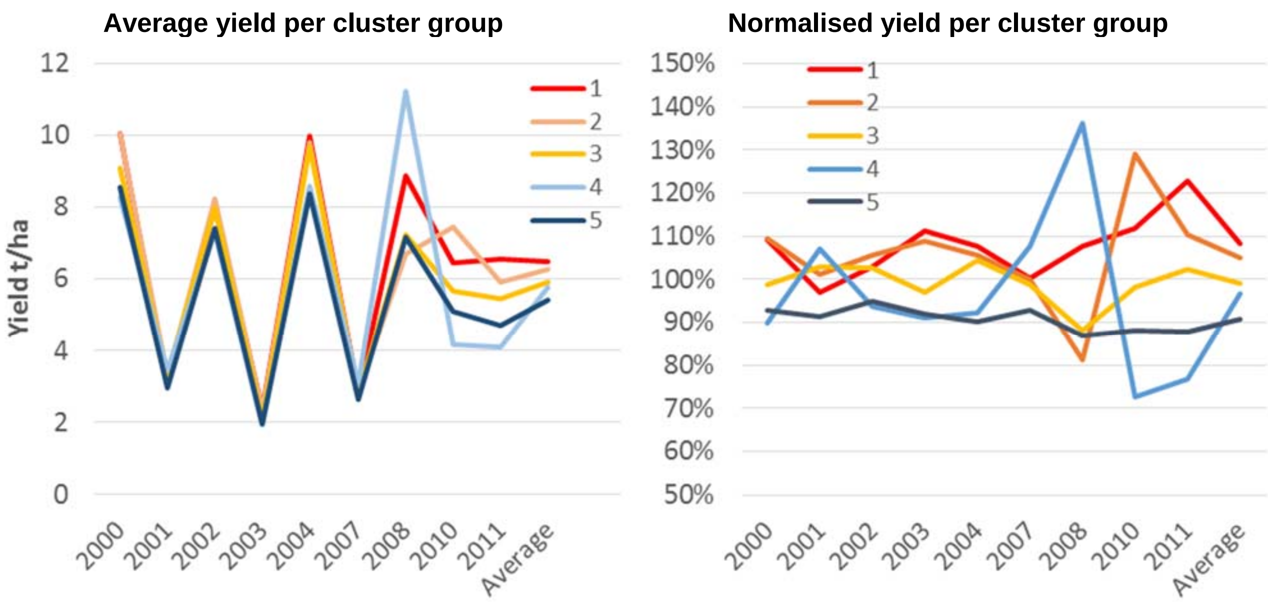



**Figure 58. Mean (a) and Normalised (b) centroid yields for the Cluster Groups for field A2 for groups shown in Figure 57a**

### 5.2.5 Bedfordia B2 2011


**Figure 59. Yield Maps from field B2. The symbology uses Jenks Natural breaks to best show spatial variation. Blue = low yield; red = high yield. Range and mean is given for each crop.**

Despite the large spatial variation there are some distinct areas in field B2, with the western edge consistently lower yielding (cluster groups 4 & 5 in Figure 61) and the central areas in cluster group 1 consistently giving high yields.

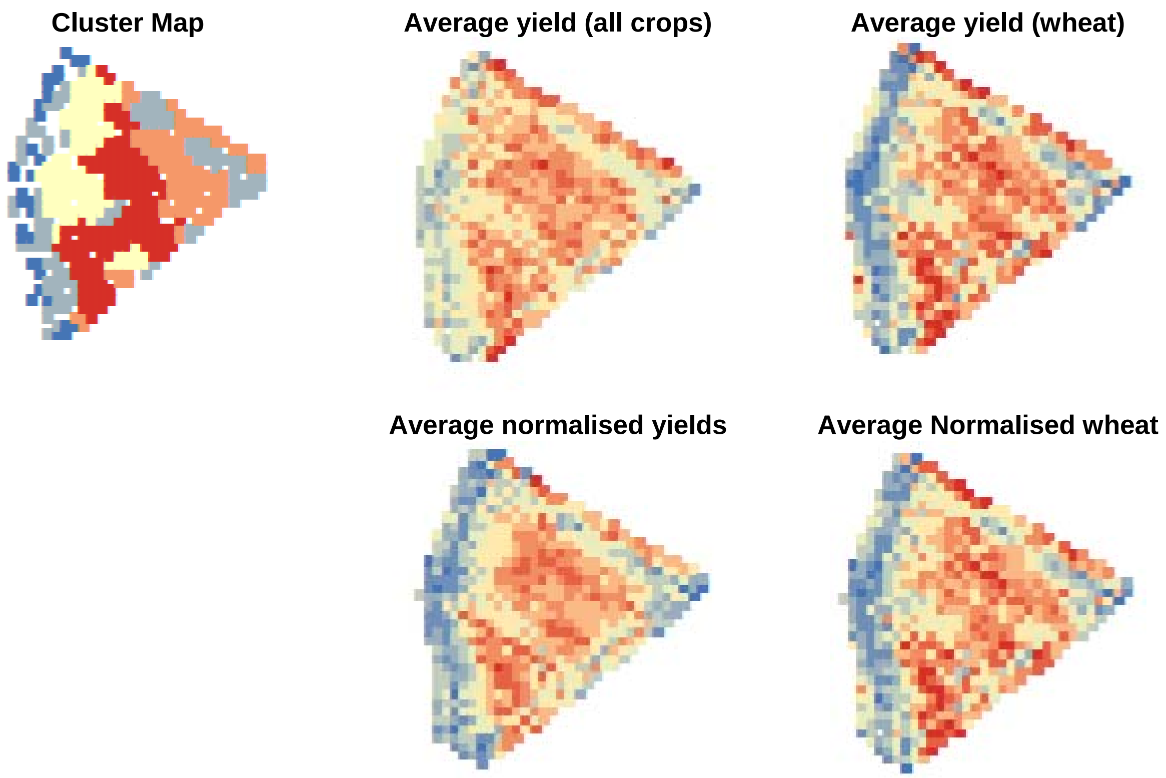



Figure 60. Integrated Yield Maps from field B2

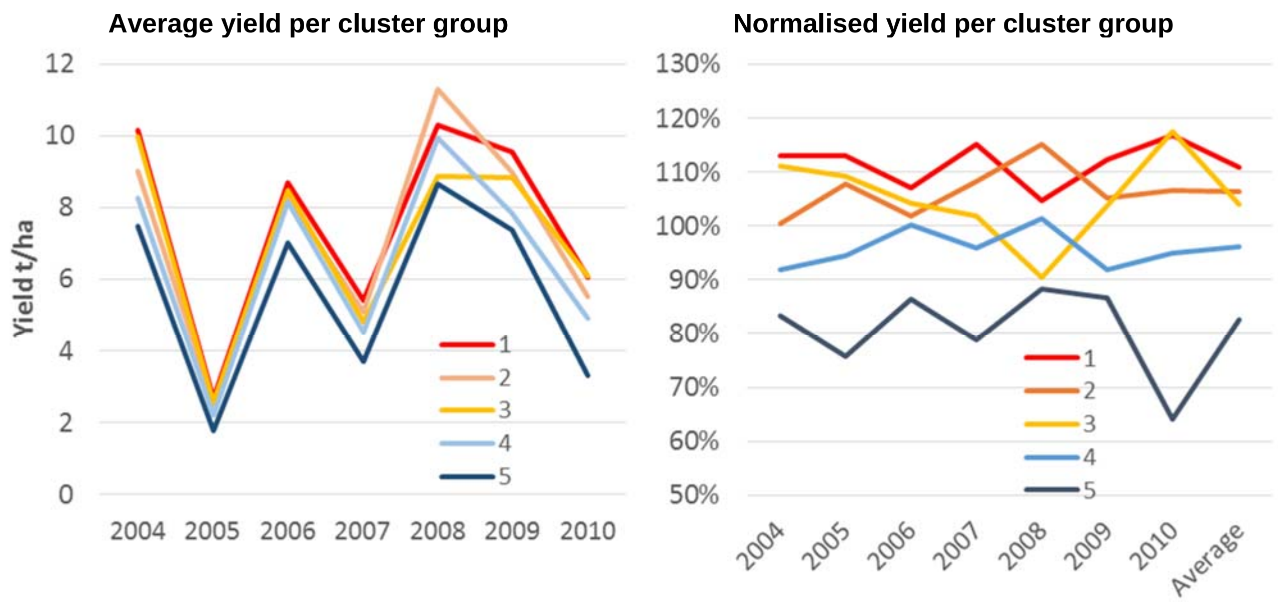



Figure 61. Mean (a) and Normalised (b) centroid yields for the Cluster Groups for field B2 for groups shown in Figure 60a

### 5.2.6 Shipton by Beningborough C2 2011

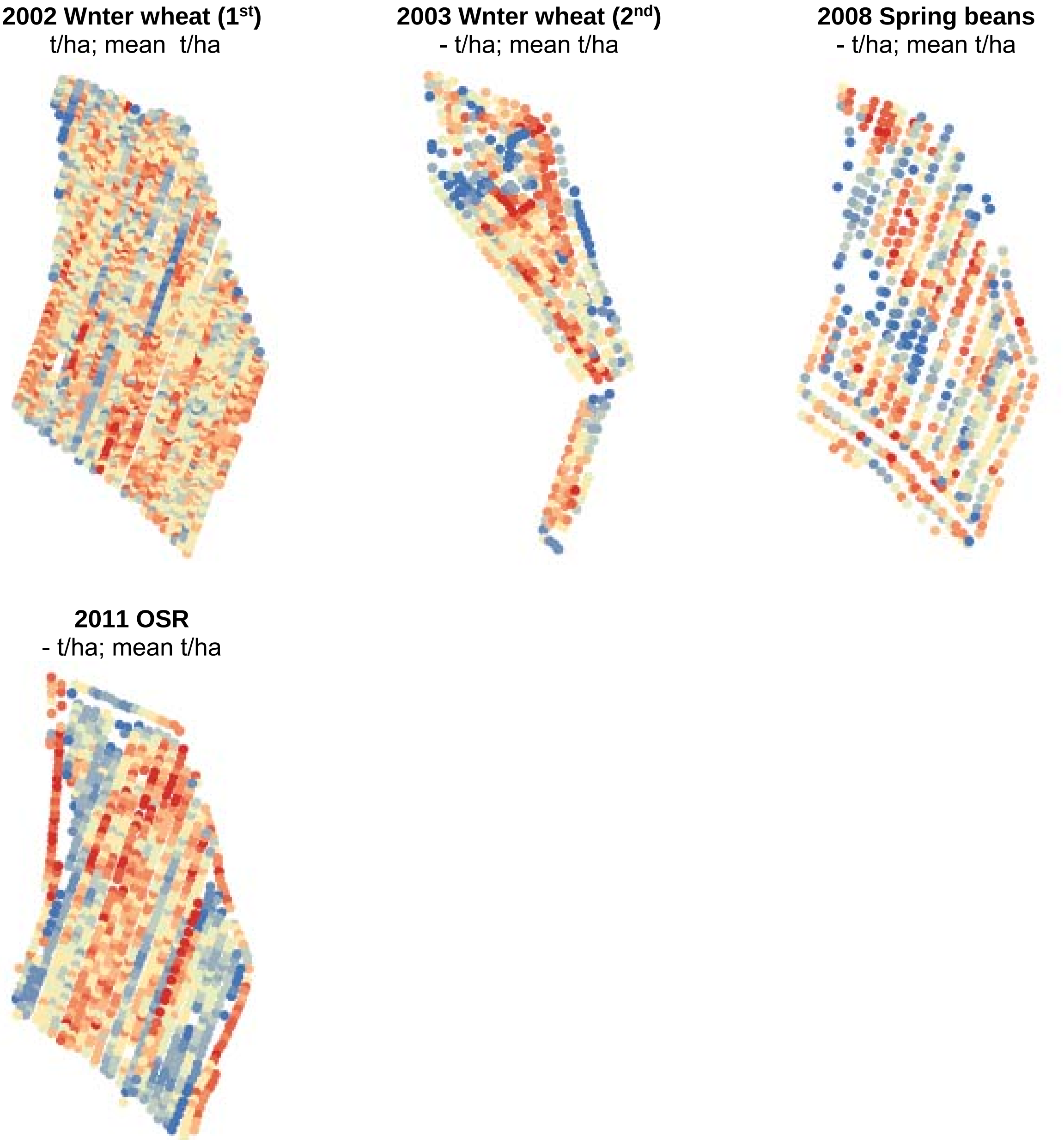
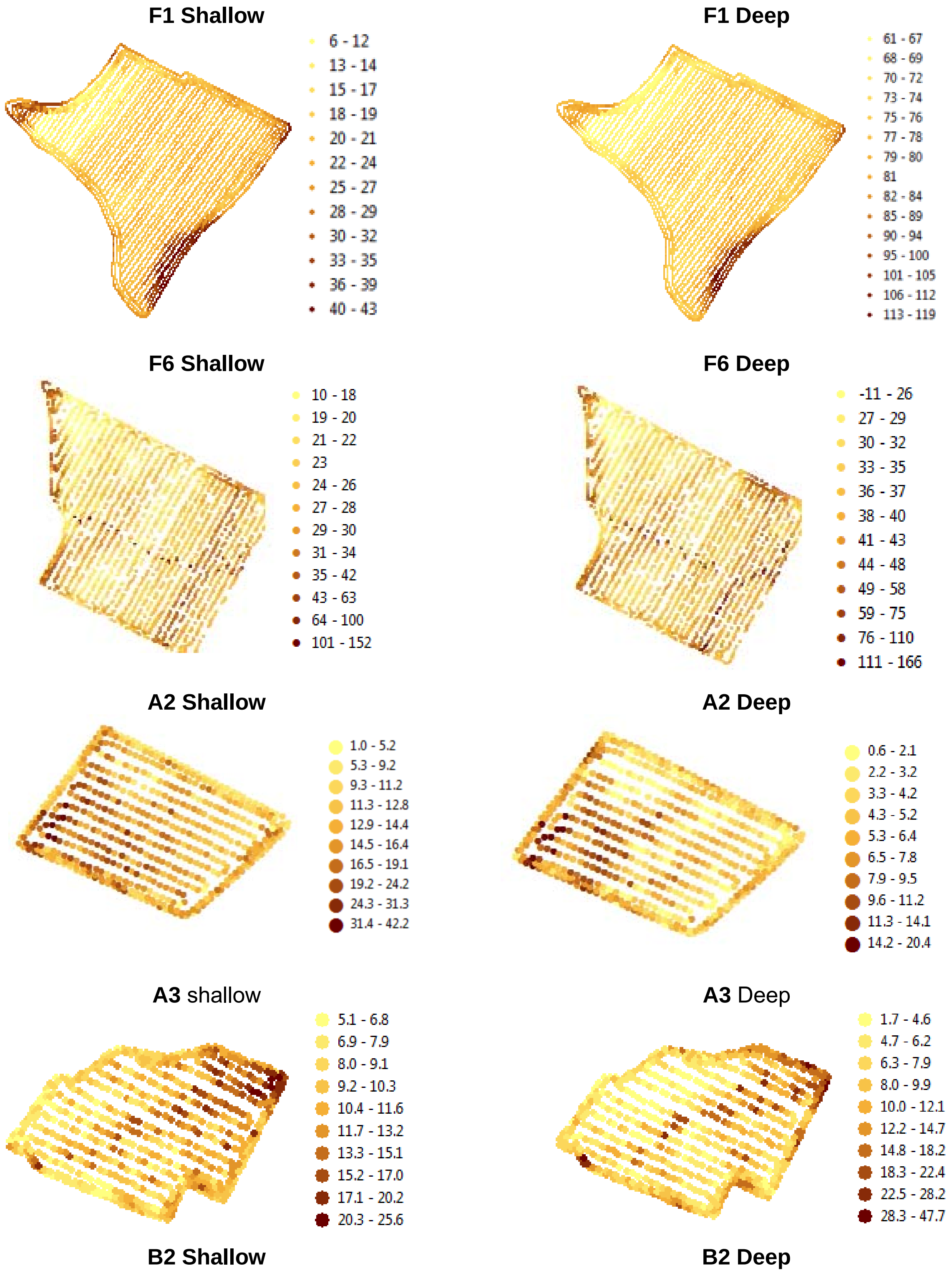



**Figure 62. Yield Maps from field C2. The symbology uses Jenks Natural breaks to best show spatial variation. Blue = low yield; red = high yield. Range and mean is given for each crop.**

Available yield data from C2 was too limited to conduct further analyses.

## 5.3 Soil maps

A range of soil scanning services are available commercially in the UK from providers including Agrii Soil Quest, SOYL, Soil Essentials and Precision Decisions. There are two main types of soil sensor, one uses non-contact Electro-Magnetic Induction (EMI) sensors (such as Geonics EM38), the other uses a contact based approach with a disc or coulter giving electrode contact with the soil (such as Veris 3100) to give Electrical Conductivity (EC) (Sudduth et al., 2003). Soil electrical conductivity has been shown to be a useful and reliable method of characterising soil variation in fields (King et al., 2003; 2005). EMI and EC sensors measure the apparent electrical conductivity of the soil, hence indicating available water content and soil texture. If used when the soil has reached field capacity they can be especially useful for interpretation of yield maps and delineation of management zones (King et al., 2005).



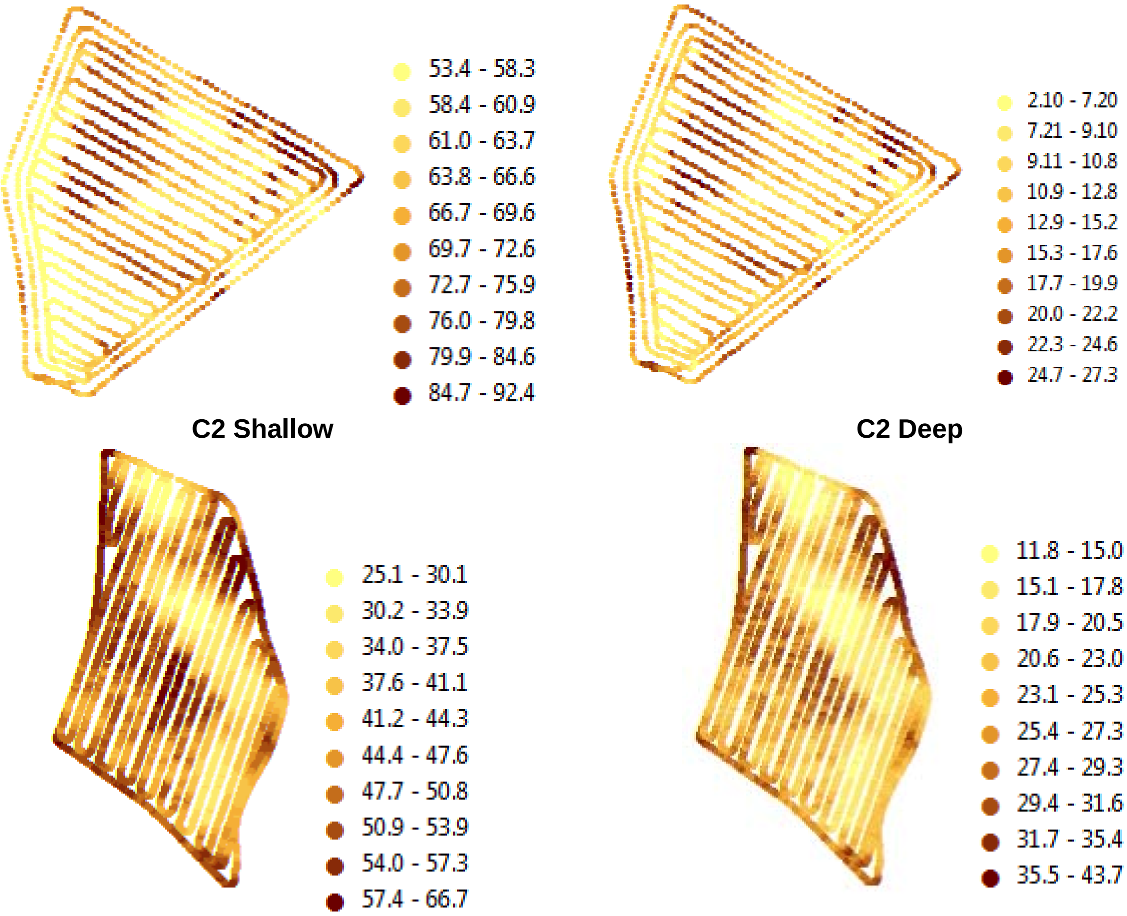



**Figure 63. Soil Electrical conductivity maps from commercial soil sensors**

The variation shown by the soil conductivity maps generally tends to reflect the variation seen in yields and the yield cluster maps.

### 5.3.1 Elevation maps

The topography of fields often closely corresponds to variability in soil properties and crop performance. Figure 64 shows altitude from the 6 fields measured whilst taking the soil EC scans. These can be turned into digital elevation maps and slope angles can be derived, as can change in the angle of slope. Such maps can be useful in defining the boundaries of areas of the field that behave differently.

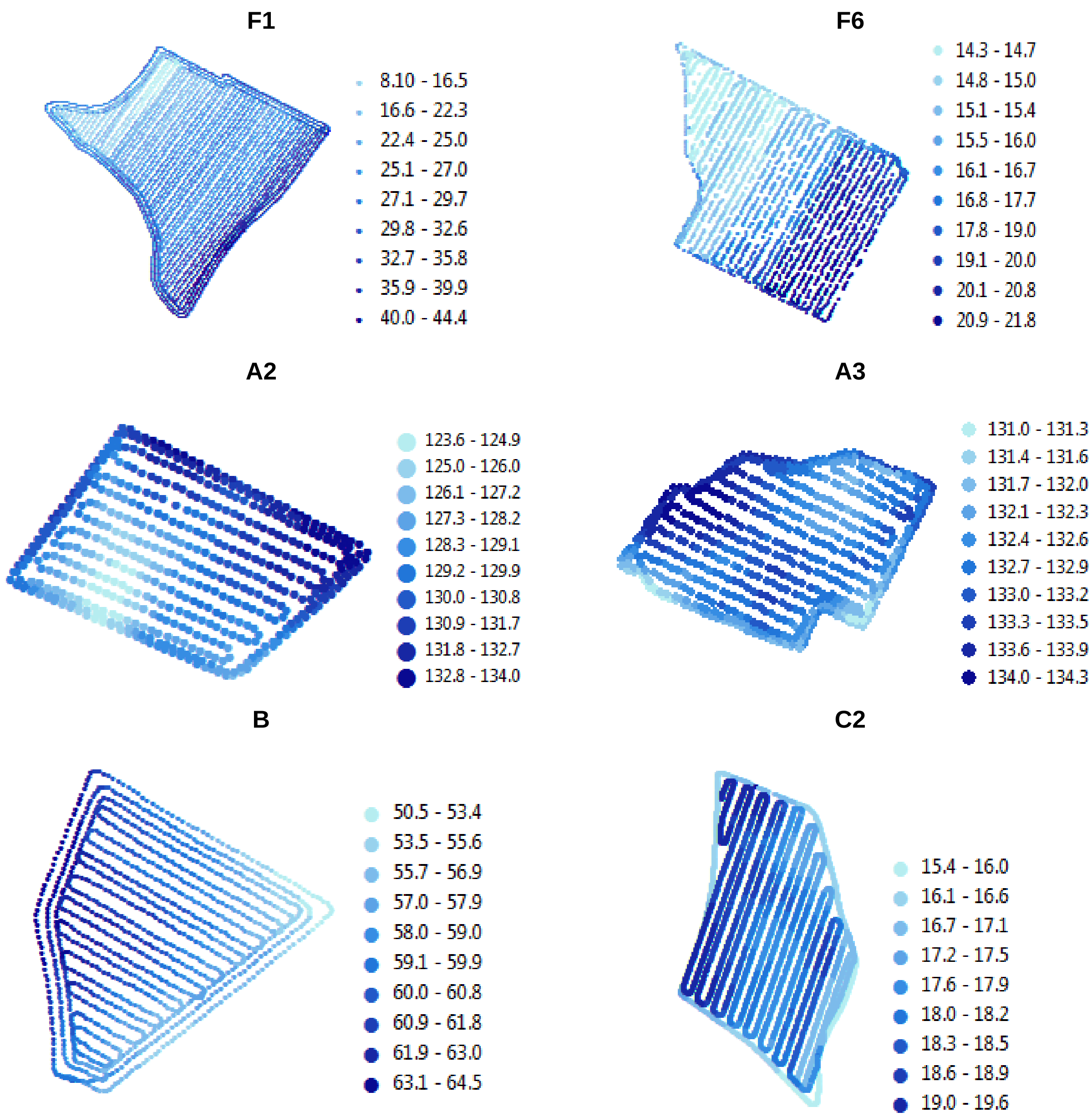



**Figure 64. Altitude maps from commercial soil sensors for the six chessboard fields**

## 5.4 Canopy sensing for yield prediction

Assessment of canopy reflectance through NDVI or similar measures in season could help predict the likely yield, or at least variation in that yield (Ferrio et al., 2004; Panda et al., 2010). The main options for canopy assessment on farm are via proximal sensing with on tractor sensors such as Crop Circle, Optrx and N sensor or satellite sensing, though imagery from manned and unmanned aircraft (eg UAVs) are increasingly available commercially.

Selected N Sensor and satellite NDVI maps for the chessboard fields are shown below.

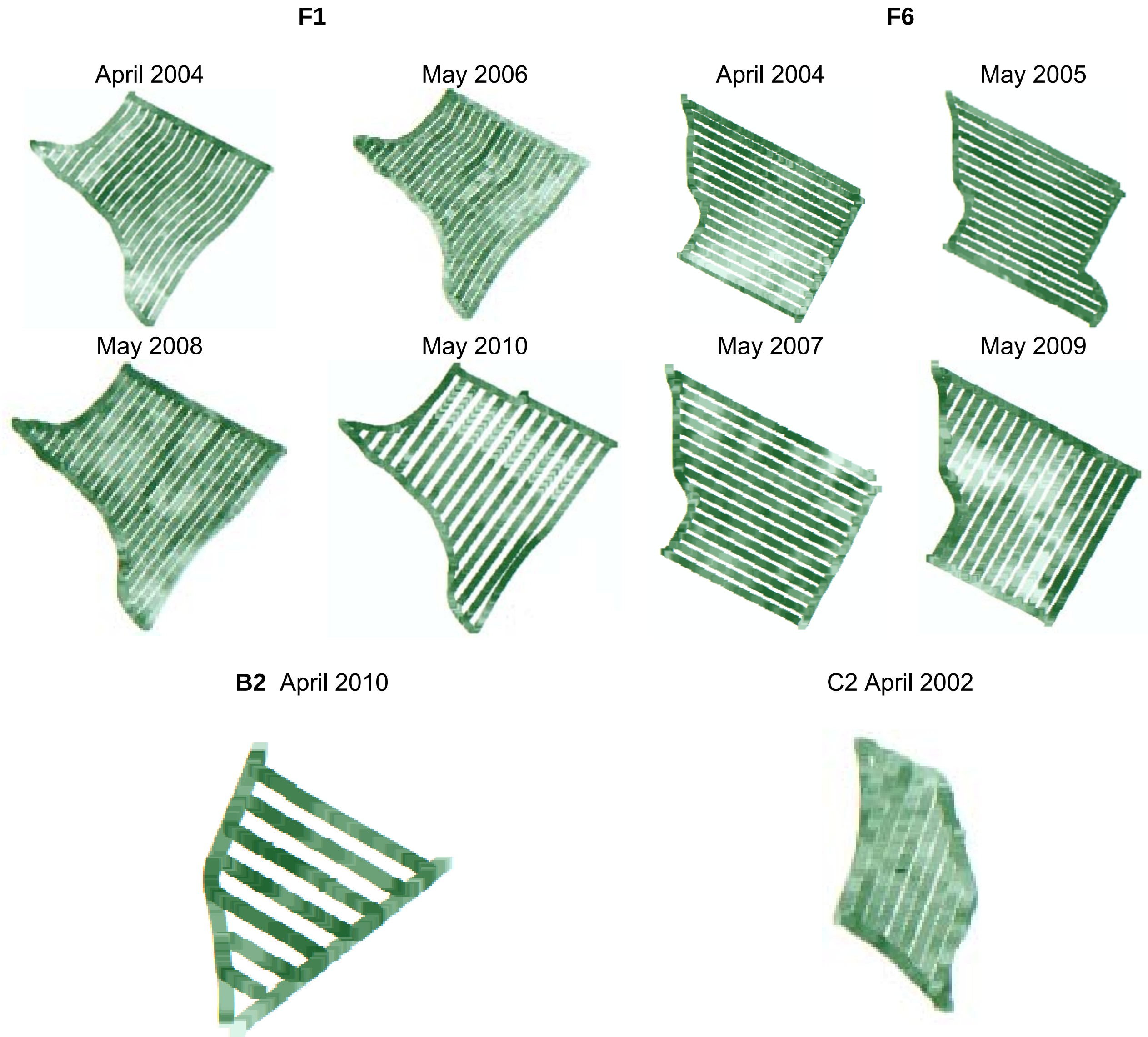



**Figure 65. N sensor 'biomass' maps from some of the chessboard fields in selected years**

Visual comparisons of the canopy reflectance maps with corresponding yield maps in Figures 65 & 66 often show similar spatial patterns, although regression analyses (not shown here) fail to show good relationships between canopy sensing and yield within fields.

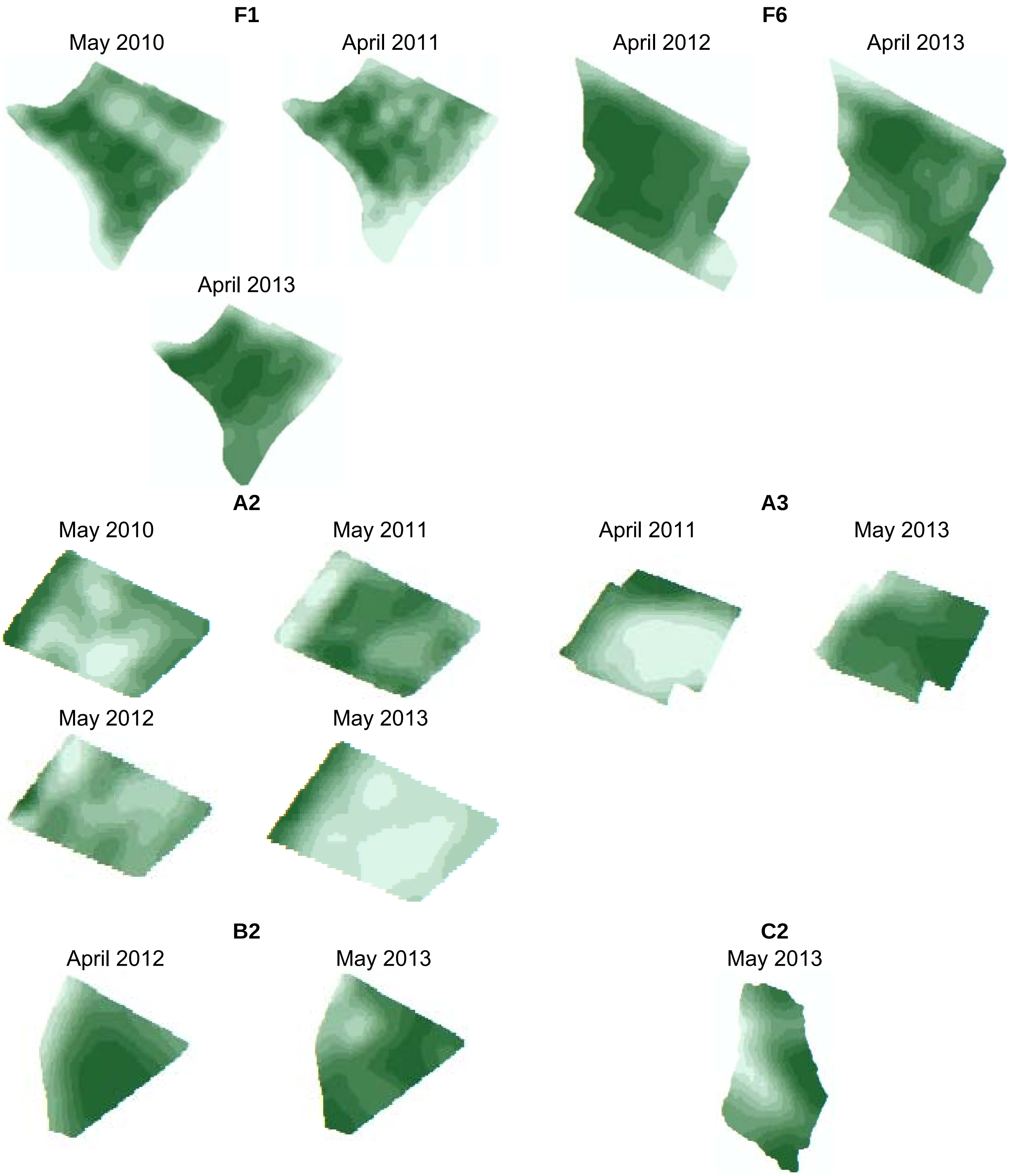



**Figure 66. Selected SOYL Satellite NDVI 'biomass' maps from the chessboard fields**

## 5.5 Best approaches to estimate yield

There tends to be coherent spatial variation in yield within fields, which, whilst relative yields are different in different years and spatial patterns are not exactly the same each year, the general patterns tend to be consistent across years and are often reflected in the spatial variation in soil conductivity, topography and canopy sensing. There seems to be little between different approaches to estimate yield. Whilst a cluster analysis approach may give the most robust method to utilise yield and other information to form zones, simpler methods of averaging yield or using a relative performance basis seem to generally define the variation to an acceptable degree, especially given the relatively modest influence of yield on N optima. Average yields for each zone or each grid square can be predicted from past yield performance at the start of the season, and feasibly can be updated with canopy sensing information through spring, to indicate whether an individual zone is likely to be higher or lower yielding than normal in that year.

## 5.6 Variation in grain protein

#### *5.6.1.1 Accuharvest protein sensor*

On-combine protein sensors were used in this study to assess the spatial variation in grain protein content within and between fields, and whether measurement of grain protein can be usefully used in determining and judging N fertiliser rates. Three Accuharvest On-Combine Grain Analyser protein sensors were acquired from the company Zeltex Inc (Maryland, US) and fitted by Soil Essentials and Precision Decisions to the combines of Nick August, Flawborough Farms and Bedfordia Farms.

Such sensors have previously been evaluated in Australia by Taylor *et al.*, 2005 & Whelan *et al.*, 2009 and in the USA by Long *et al.* (2008; 2015). This was one of the first studies to evaluate the sensors for UK cereals.

The sensor sits outside the casing of the grain elevator of the combine (see picture), with holes and a sampling mechanism to take and return samples from and to the grain elevator. The sensor itself measures reflectance from 16 LEDs with wavelengths in the NIR ranging from 893 to 1045, and uses partial least squared regression analysis to generate calibrations from the NIR reflectance curves.


**Figure 67. Zeltex Accuharvest protein sensor mounted on grain elevator**

#### 5.6.1.2 Protein maps from the Accuharvest

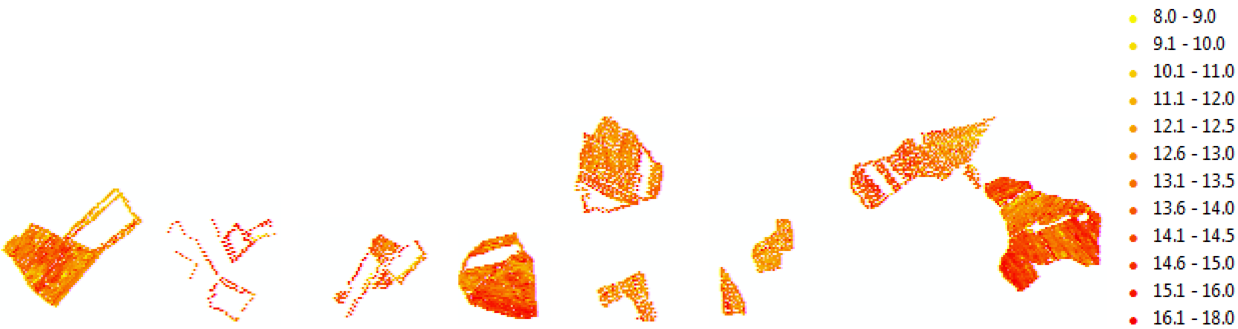
Protein maps from the three farms are presented below.

*Flawborough 2010*

*Flawborough 2012*


*Bedfordia 2010*


*Bedfordia 2011*



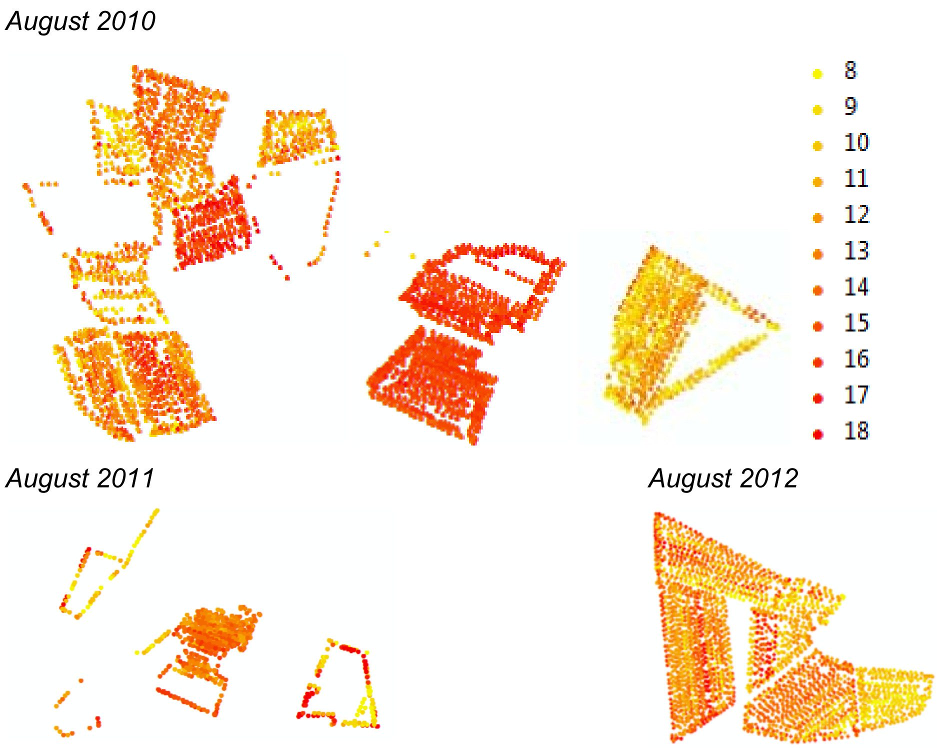



**Figure 68. On-combine protein data from the Accuharvest protein sensor at Flawborough, Bedfordia & Burford**

The variation seen in grain protein tend across the fields in Figure 68 tends to be less than that generally seen for grain yield. Despite efforts unfortunately it was not possible to fully validate the protein sensor calibrations on or off the combine. Various technical difficulties were encountered limiting the amount of data collected from the protein sensors. Figure 69 shows the Accuharvest under-predicting protein in the lab. On farm it often seemed to over-predict protein compared to field scale measures made on-farm.

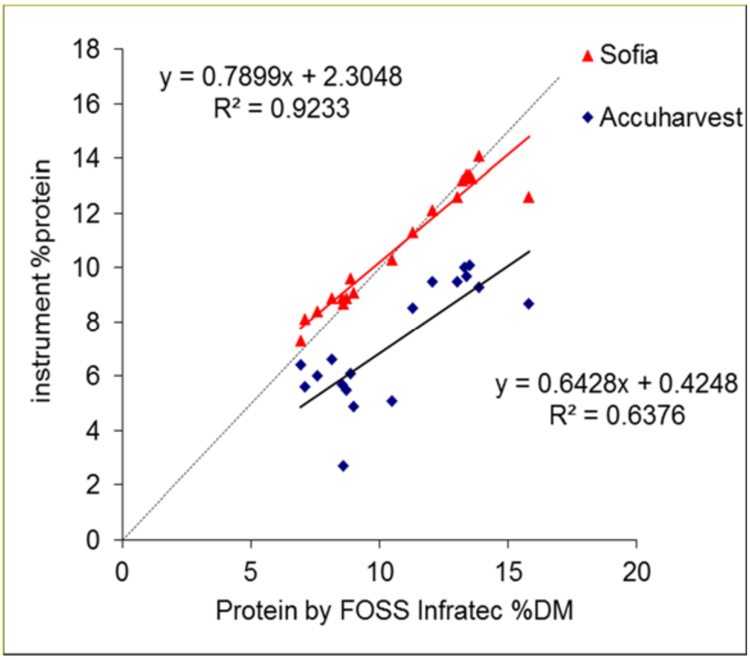



**Figure 69. Results from calibration samples in the lab from an Accuharvest protein sensor and from the FOSS Sofia portable NIR instrument, compared to FOSS Infratec as a reference measure.**

### 5.6.2 Variation in grain protein from field samples

Ear samples were taken by hand from a number of fields at geo-referenced locations and samples threshed and grain analysed for grain protein using FOSS Infratec or Sofia.
Results generally showed limited coherent spatial variation in grain protein content.

### 5.6.3 Conclusions on variation and prediction of grain protein content

The spatial variation seen in grain protein content in the chessboard trials, using the on-combine protein sensor and from geo-referenced hand samples is substantial but is not easily measured, understood or predicted. The expected negative variation between grain yield and grain protein doesn't explain most of the variation in protein. We do not adequately understand the causes of the variation in grain protein, though it is likely to be due to the availability of N from the soil and recovery of fertiliser, especially with regard to the timing of the availability of N and the capacity for late N uptake. Furthermore, the variability in grain protein at the optima seen in the chessboard trials and elsewhere (Sylvester-Bradley & Clarke, 2009) negates the hypothesis set out in this project that knowledge of grain protein content allows useful inference of 'success' in N management. Differences in grain protein within and between fields cannot be taken to imply differences in N optima when taken by themselves in a single year. On average N optima for feed wheat do coincide with ~11% protein content, but the variation around this means that it can only be used as a tool to judge N success on-farm across a number of fields and years. This brings into question the value of spatial measurement of grain protein by on-combine sensing for the purposes of improving N management for feed wheat.

# 6 Calibrations from Canopy Reflectance

## 6.1 Using the crop as a measure of crop N demand, soil N supply, or plant N status

The crop itself has long been expected to indicate soil nutrient status (Hall, 1905). This approach has found most use in horticulture where a plant's value tends to be enhanced (Sylvester-Bradley et al., 2004). A range of approaches has been tried, for example testing N% of plant tissue (Greenwood et al., 1990), sap nitrate (Scaife & Stevens 1983), tissue colour (Matsunaka et al., 1997), and canopy reflectance using NDVI. None of these has yet proved successful on an absolute scale. Often variation between sites, varieties, and development stages prevents easy interpretation.

Two complementary approaches were investigated in this project, the first to estimate soil N supply from the crop over-winter, the second to judge N demand from the crop in spring. Over-winter sensing of NDVI holds promise for estimating soil N supply when compared against predicted NDVI of an N-unlimited crop for a given thermal time after sowing & plant population (Sylvester-Bradley et al., 2009); in spring concepts of canopy management (Sylvester-Bradley et al., 1997) whereby canopy size is taken to indicate progress towards a target optimum canopy, optimum canopy size is relatively conservative but varies slightly with potential yield, and canopy colour indicates the immediate balance between N supply and N demand (Lemaire et al., 2008; Heege et al., 2008).

## 6.2 Approaches for use of canopy signals to guide N decision making

The use of canopy reflectance measures to guide better N decision making has received enormous global attention (e.g. Berntsen et al., 2006; Ortiz-Monasterio & Raun, 2007; Solie et al., 2012; Samborski et al., 2009; 2015; Mulla, 2013; Cao et al., 2015). Canopy reflectance measures, ratios and calibrations can indicate crop N uptake and crop N status. Various approaches have been developed to translate the information from canopy signals into useable N advice. These include the use of nil-N and high-N areas or 'windows' (Raun et al., 2008; Roberts et al., 2010; 2011; Yue et al., 2015), use of the Nitrogen Nutrition Index (NNI), Canopy Chlorophyll Content Index (CCCI; Fitzgerald et al., 2010) and estimation of leaf N concentration (Li et al., 2010; 2016; Wang et al., 2012). Whilst some approaches give a recommendation for how much N to apply given the crops current condition & perhaps using other information such as yield prediction (e.g. Isaria), many approaches vary N around a pre-set mean N rate based on variation in spectral reflectance (e.g. Reusch, 2005).

However, none of the above approaches explicitly calculate N requirement from estimation of Crop N demand, Soil N Supply and Fertiliser Recovery. Within this chapter we try to seek an approach and calibrations that would allow direct estimation of these components, specifically through calibrations for SNS, yield potential, crop N uptake and crop N status within the Auto-N logic.

## 6.3 Principles of Canopy Reflectance

All measures of canopy reflectance make use of the different spectral signature of different crops (see Figure 70). Visible light (400 nm to 700 nm) is absorbed more by larger canopies, so less is reflected back. Light in the Near Infra-Red (NIR) part of the spectrum (700 nm to 1400 nm) is scattered and reflected by structures in plant cell walls, so that larger crops reflect more NIR. The ratio of reflectance of visible light to NIR light can therefore usefully be used to compare the size of crop canopies, in vegetation indices such as Normalised Difference Vegetation Index (NDVI). Whilst measures such as NDVI are often thought of as indicating the ‘greeness’ of the crop, this is not actually what is being measured. Indeed ‘greenness’ is actually a human construct; large ‘green-looking’ crops actually reflect less green light (550 nm) than smaller ‘yellow-looking’ crops, but they appear greener because proportionately more red (650 nm) and blue (450 nm) light is absorbed by the crop.

The different spectral signatures of crops is demonstrated in Figure 70 which shows the spectral reflectance measured by a spectroradiometer of a range of seed rate and N rate treatments in an experiment at Boxworth on the same date in spring 2012. It can be seen that reflectance of bare soil gradually increases with increasing wavelength, where those of the crop treatments all follow a similar shaped curve of less reflection than bare soil at the visible part of the spectrum and greater reflection than bare soil in the NIR portion. A bulge in reflectance can clearly be seen at 550 nm giving the green appearance, and the treatments with larger canopies (higher seed rates or more N) clearly reflect less (absorb more) visible light and reflect more NIR light.

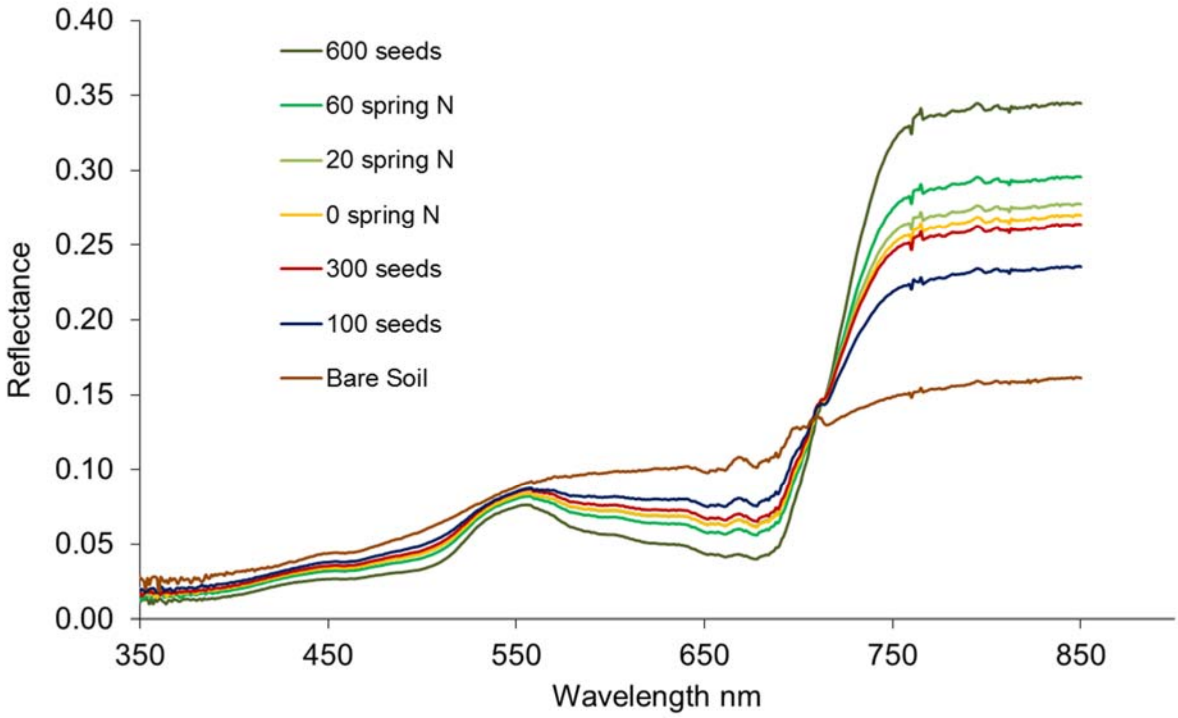



**Figure 70 Example Canopy Reflectance from an Auto-N experiment measured by a LICOR spectroradiometer**

### 6.3.1 Vegetation Indices

A range of vegetation indices have been developed to simplify the comparison of spectral signatures such as above, and to allow cheaper instruments to be used assessing just 2 or 3 individual wavelengths.

The most commonly used vegetation index is NDVI which is simply reflectance in the NIR minus reflectance in visible divided by the sum of NIR and visible reflectance (Haboudane et al., 2004).

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)}$$

The exact wavelengths used for NDVI vary between studies and sensors but are generally around 650nm and 800nm. Values for NDVI can range from 0 to 1, but typically range from 0.1-0.2 for bare soil to 0.8-0.9 for a completely closed canopy. The use of NDVI has two major limitations, firstly it can be affected by the underlying soil, especially by soil wetness; secondly, it becomes saturated with dense canopies, limiting its use to discriminate variability between large canopies (Wang et al., 2012). Various other indices have been developed to help overcome these issues, summarised in Table 5.

**Table 5. Summary of selected vegetation indices**

| Abbrev | Name | Calculation | References | Notes |
|---|---|---|---|---|
| NDVI | Normalised Difference Vegetation Index | (ʎ810ʎ640)/(ʎ810+ʎ640) | Tucker et al., 1979 | |
| NDRE | Normalised Difference Red Edge | (ʎ810-740)/(ʎ810+ʎ740) | Rodriguez et al. 2006 | Chlorophyll and N status |
| SAVI | Soil Adjusted VI | [(ʎnir - ʎred)/(ʎnir + ʎred +L)] (1+L) | Huete, 1988 | L adjusted to minimise noise caused by soil. L=0.5 for most crop conditions, low soil covers L=1 and high soil covers L=0.25 |
| OSAVI | Optimised Soil Adjusted VI | ((NIR-Red) /((NIR+Red+0.16)*(1+0.16)) | Steven 1997 | |
| GNDVI | Green NDVI | (ʎ780-ʎ590)/( ʎ780-ʎ590) | Gitelson & Merzlyak 1996 | |
| GDVI | | (ʎ780-ʎ670)/(ʎ670) | Shanahan 2001 | |
| EVI | Enhanced VI | (2.5*((NIR-red) / (NIR+(6*red)-(7.5*blue)+1)) | Huete et al., 1997 | Optimising NDVI using blue reflectance to correct for soil background & reduce atmospheric influences |
| ARVI | Atmospherically resistant VI | (NIR-(2RED-BLUE)/(NIR+(2RED-BLUE) | Kaufmann et al., 1996 | NDVI resistance to atmospheric factors |
| OVI | Optimal Vegetation Index | (1+0.45)(ʎ800)^2+1)/(ʎ670+0.45) | Reyniers et al 2006 | |
| REIP | Red edge inflection point | 700+40*((((670nm+780nm)/2)-700nm)/(740nm-700nm)) | Guyot et al 1988 | |
| MCARI | Modified chlorophyll absorption ratio index | (ʎ700-ʎ670-0.2(ʎ700-ʎ550))(ʎ700/ʎ670) | Daughtry et al. 2000 | |
| TCARI | Transformed chlorophyll absportion in reflectance index | 3((ʎ700-670)-0.2(ʎ700-ʎ550)(ʎ700/670)) | Haboudane et al., 2002 | |
| CCCI | Canopy Chlorophyll Content Index | $(NDRE-NDRE_{MIN})/ NDRE_{MAX}-NDRE_{MIN})$ | Fitzgerald et al., 2010 | |

## 6.4 Data sources & Measurements

In order to assess canopy signals from UK crops reflectance data was measured and collated from a range of ADAS trials included bespoke experiments to set up differences in canopy structure and canopy N content. The aim was to determine whether it was possible, using non-destructive scanning techniques to assess and predict SNS, yield potential, crop N uptake and N status. In order to achieve this, a series of field trials were established, and data were collected from existing field trials. These are outlined below.

### 6.4.1 Datasets

Various datasets were collated into one Auto N calibration master file, summarised in Table 6. These include data from a total of 52 trials or sites, with 12994 individual data points collected over

Table 6. List of trial data included in the calibration dataset Masterfile.

**Table 6. List of trial data included in the calibration dataset Masterfile.**

| | Project | Site | Location | Year | Treatments | Crop | Sowing date | Soil type | Number of N rates | Number of individual data points |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Green Grain | Terrington | Norfolk | 2006 | Varieties | WW1 | 18/10/2005 | Z | 2 | 160 |
| 2 | Green Grain N study | Terrington | Norfolk | 2006 | N x Variety | WW1 | 18/10/2005 | Z | 6 | 36 |
| 3 | N Ghost | Boxworth | Cambridgeshire | 2006 | Residual N | WW2 | 06/10/2005 | CL | 6 | 26 |
| 4 | N Ghost | Terrington | Norfolk | 2006 | Residual N | WW2 | 11/10/2005 | Z | 6 | 12 |
| 5 | N Ghost | Boxworth | Cambridgeshire | 2007 | Residual N | WW2 | 26/09/2006 | CL | 6 | 68 |
| 6 | N Ghost | High Mowthorpe | North Yorkshire | 2007 | Residual N | WW2 | 30/09/2006 | SCL | 6 | 51 |
| 7 | N Ghost | Rosemaund | Herefordshire | 2007 | Residual N | Winter Barley | 20/09/2006 | SCL | 6 | 72 |
| 8 | N Ghost | Terrington | Norfolk | 2007 | Residual N | WW2 | 27/10/2006 | Z | 6 | 68 |
| 9 | N Ghost | Boxworth | Cambridgeshire | 2008 | Residual N | Wheat | 12/10/2007 | CL | 6 | 96 |
| 10 | N Ghost | High Mowthorpe | North Yorkshire | 2008 | Residual N | Barley | 21/09/2007 | SCL | 6 | 96 |
| 11 | N Ghost | Rosemaund | Herefordshire | 2008 | Residual N | Oats | 31/10/2007 | SCL | 6 | 84 |
| 12 | N Ghost | Terrington | Norfolk | 2008 | Residual N | Wheat | 10/10/2007 | Z | 6 | 96 |
| 13 | MALNA | Boxworth | Cambs | 2009 | N x variety | WW1 | 26/09/2008 | CL | 5 | 60 |
| 14 | N species | Cransford | Suffolk | 2009 | N x Variety | Barley | 15/10/2008 | CL | 5 | 150 |
| 15 | N timing | Seaham | County Durham | 2009 | N x timing | WW1 | 19/11/2008 | SCL | 6 | 16 |
| 16 | N timing | Seaham2 | County Durham | 2009 | N x timing | WW2 | 24/10/2007 | SCL | 6 | 16 |
| 17 | N timing | Terrington | Norfolk | 2009 | N x timing | WW1 | 26/09/2008 | Z | 6 | 192 |
| 18 | N x Fungicide | Terrington | Norfolk | 2009 | N x fungicides | WW1 | 26/09/2008 | Z | 6 | 120 |
| 19 | SNS plots | Terrington | Norfolk | 2009 | N | WW1 | 26/09/2008 | Z | 2 | 26 |
| 20 | SNS plots | Boxworth | Cambridgeshire | 2009 | N | WW1 | 04/10/2008 | CL | 2 | 6 |
| 21 | Soil QC | Ropsley | Lincs | 2009 | Long term N | Wheat | 01/10/2008 | CL | 8 | 64 |
| 22 | Masstock | Fowlmere | Cambs | 2010 | Varieties x N | Wheat | 30/09/2009 | ?? | 5 | 152 |
| 23 | N x Fungicide | Boxworth | Cambridgeshire | 2010 | N x Fungicides | Wheat | 25/09/2009 | CL | 5 | 200 |
| 24 | MINNO | Boxworth | Cambridgeshire | 2010 | N | Wheat | 10/10/2009 | CL | 5 | 72 |
| 25 | MINNO | Terrington | Norfolk | 2010 | N | Wheat | 09/10/2009 | ZL | 5 | 66 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 26 | MINNO | Boxworth | Cambridgeshire | 2011 | N + Autumn N | Wheat | 10/10/2009 | CL | 5 | 26 |
| 27 | MINNO | Terrington | Norfolk | 2011 | N + Autumn N | Wheat | 17/10/2010 | ZL | 5 | 20 |
| 28 | MINNO Residue | Terrington | Norfolk | 2013 | Previous crops & incorporation | Wheat | 18/11/2012 | ZL | 2 | 271 |
| 29 | MINNO Ghost | Boxworth | Cambridgeshire | 2011 | Residual N | WW2 | 18/10/2010 | CL | 6 | 18 |
| 30 | MINNO Ghost | Terrington | Norfolk | 2011 | Residual N | WW2 | 17/10/2010 | ZL | 6 | 6 |
| 31 | CRD | Boxworth | Cambs | 2011 | Seed rate x Autumn N | Wheat | 11/10/2010 | CL | 4 | 84 |
| 32 | HYLO | Terrington | Norfolk | 2011 | N x Variety | Wheat | 14/10/2010 | SZL | 7 | 882 |
| 33 | HYLO | Watlington | | 2011 | N x Variety | WW1 | 05/10/2010 | ZCL | 7 | 254 |
| 34 | HYLO | Boxworth | Cambridgeshire | 2012 | N x Variety | Wheat | 22/09/2011 | Clay | 7 | 147 |
| 35 | HYLO | Rosemaund | Herefordshire | 2012 | N x Variety | Wheat | 05/10/2011 | ZL | 7 | 306 |
| 36 | Auto-N HYLO | Terrington | Norfolk | 2011 | Seed rate x Autumn N x N | Wheat | 14/10/2010 | ZL | 7 | 84 |
| 37 | Additional N strip | Flawborough | Notts | 2011 | Autumn N | WW | 24/09/2010 | CL | 2 | 2 |
| 38 | Unlimited N strip | Flawborough | Notts | 2011 | Unlimited N | WW | 24/09/2010 | CL | 2 | 2 |
| 39 | MINNO Auto-N calibration | Boxworth | Cambridgeshire | 2011 | N | Wheat | 18/10/2010 | CL | 5 | 11 |
| 40 | MINNO Auto-N calibration | Terrington | Norfolk | 2011 | N | Wheat | 17/10/2010 | SZL | 5 | 18 |
| 41 | Chessboard | Flawborough | Notts | 2010 | N x Soil | WW1 | 25/09/2009 | CL | 4 | 153 |
| 42 | Chessboard | Flawborough | Notts | 2011 | N x Soil | WW | 24/09/2010 | CL | 4 | 2598 |
| 43 | Chessboard | Burford | Oxon | 2011 | N x Soil | WW | 20/09/2010 | Cotswold brash | 4 | 1507 |
| 44 | Chessboard | Burford | Oxon | 2012 | N x Soil | Wheat | 20/09/2011 | Cotswold brash | 4 | 1600 |
| 45 | Chessboard | Bedfordia | Beds | 2012 | N x Soil | Wheat | 01/10/2011 | SCL | 4 | 1080 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 46 | Chessboard | Shipton by Beningborough | North Yorkshire | 2012 | N x Soil | Wheat | 20/10/2011 | SCL | 4 | 906 |
| 47 | Chessboard Ghost | Flawborough | Notts | 2011 | Residual N | WW2 | 23/09/2010 | CL | 0 | 530 |
| 48 | Bare soil red | Flawborough | Notts | 2011 | Bare soil | WW | 24/09/2010 | CL | 1 | 1 |
| 49 | Bare soil grey | Flawborough | Notts | 2011 | Bare soil | WW | 24/09/2010 | CL | 1 | 1 |
| 50 | Auto-N Calibration trial | Boxworth | Cambs | 2011 | Seed rate x Autumn N x N | Wheat | 11/10/2010 | CL | 5 | 210 |
| 51 | Auto-N Calibration trial | Boxworth | Cambs | 2012 | Seed rate x Autumn N x N | Wheat | 28/09/2011 | CL | 4 | 198 |
| 52 | Auto-N Calibration trial | Ropsley | Lincolnshire | 2012 | Seed rate x Autumn N x N | Wheat | 30/09/2011 | CL | 8 | 74 |
| | | | | | | | | | **Total** | **12994** |

### 6.4.2 Sensors

Each of the trials listed in Table 6 were assessed in the field using various crop sensors at a range of growth stages. The sensor used depended on the project aims, but where relevant these data were used to increase the data available to use as part of the Auto-N calibration. In each trial one or more of the sensors shown in Table 6 were used. Dependent on the wavelengths available, indices in Table 4 were calculated.

**Table 7. Sensor equipment used to scan the Auto-N calibration, chessboard and other N response trials included in the calibration Masterfile.**

| Sensor | Possible wavelengths/measures | History |
|---|---|---|
| Crop Circle 210 | Measures 2 wavelengths (590, 880nm) with an active light source | Holland Scientific. Used on ADAS trials since 2006 |
| Crop Circle S1 | 590, 880 | Used in 2007 only |
| Crop Circle S4 | 590, 720, 880 | Used in 2007 only |
| Crop Circle 470 | Measures 3 wavelengths at a time with a choice of 6 filters (450, 550, 590, 670,730, 760) with an active light source | Used on ADAS trials since 2009 |
| Crop Circle 430 | Measures 3 wavelengths at a time with a choice of 6 filters (670, 730 and 760) with an active light source | Used from 2010 onwards |
| OptRx Ag Leader | The commercial version of the crop circle 430 with 3 filters | Commercial version of Crop Circle from AgLeader, bought out from Holland Scientific. |
| CropScan | Measures up to 16 wavelengths at a time and incident radiation, but no light source (400 to > 1000 nm) | Mainly used by ADAS on OSR trials, not cereals |
| Yara N Sensor Crop Spec | Active light source full spectroradiometer | |
| LICOR 1800 Spectroradiometer | Measures full range of wavelengths from 400 nm to 1100 nm at 2 or 10 nm intervals. No light source | |
| Digital photographs | GAI | |
| SunScan | light interception/GAI | |

### 6.4.3 Auto-N Calibration Experiments

In order to assess the impact of canopy size, variety and seed rate on canopy reflectance, and to attempt to develop separate calibrations for crop N uptake, biomass, crop N concentration and crop N status the Auto-N calibration trials (Trials 50, 51, and 52 in Table 6) were set up.

Three Auto-N calibration trials were established at Boxworth (2011, 2012) and Ropsley (2012). The two Boxworth trials included 24 unique treatments, consisting of 3 seed rates (100, 300 and 600 seeds per $m^2$), two autumn N rates (0 and 200 kg N/ha), and four spring N rates (0, 100, 200 and 300 kg N/ha). The autumn and spring N applications were made at standard farm practice timings, using a 12m pneumatic spreader. At each application date, the date, crop growth stage, approximate green area index (GAI) and shoots/$m^2$ were recorded. Each trial was arranged in a split-plot design with seed rate in the main plots and autumn and spring N rates randomised within these main plots. There were two replicates of each treatment. Plots were 9 m x 6 m with 3 m discard plots between blocks to enable to fertiliser spreader to be switched off without compromising the treatment applications. The crops received standard treatments other than N fertiliser. There was also a 2 m x 2 m bare soil reference area marked out which was maintained as bare soil by hoeing or spraying with glyphosate at each visit. Autumn N fertiliser applications were applied as soon as possible after sowing/emergence using the pneumatic spreader. The fertiliser was applied to the full plot area. A soil sample was collected for each site to record the pH, % organic matter, soil mineral N analysis, total N% and mineralisation by anaerobic incubation before the end of April and analysed by Hill Court Farm Research.

Available sensors were used on the Auto-N calibration trials approximately 10 days after N applications when reference measurements were collected in late March, mid-April and early May. In addition to sensor use on these trials, a range of reference measurements were also taken on both the Auto-N Calibration and Auto-N Chessboard trials, with quadrat samples taken to measure biomass, crop N concentration and crop N uptake on selected plots with plant samples sent off for N% analysis by DUMAS. Each of the trials were taken to harvest and yield and % dry matter were recorded for each plot. In addition, grain N% was measured using a FOSS Sofia NIR protein analyser. In addition, prior to harvest, grab samples (approx. 50 shoots per plot) were collected, the number of shoots were counted, straw and ears separated, dried, weighed, threshed and grain weight measured. These samples were then also sent off for %N analysis by DUMAS.

#### 6.4.4 Results

Measured and collated data are shown in Figure 71, with NDVI calculated from different sensors using slightly different wavelengths. Figure 72 constrains the data to just one sensor type, the Crop Circle 210, showing more consistency. It can be seen that NDVI increases over time, but that the variation within a measurement date can be very large.

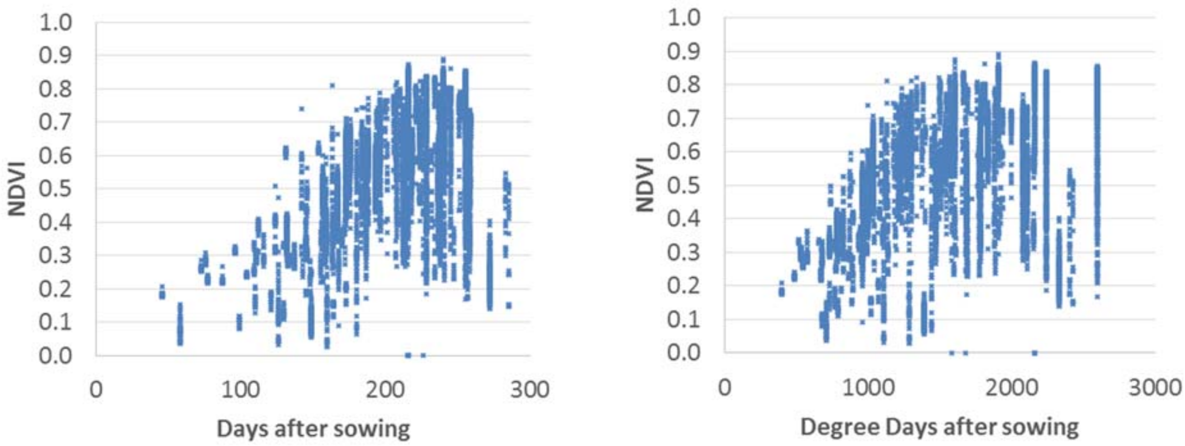



**Figure 71** NDVI Measures from all trials listed in Table 5 made with a range of sensors

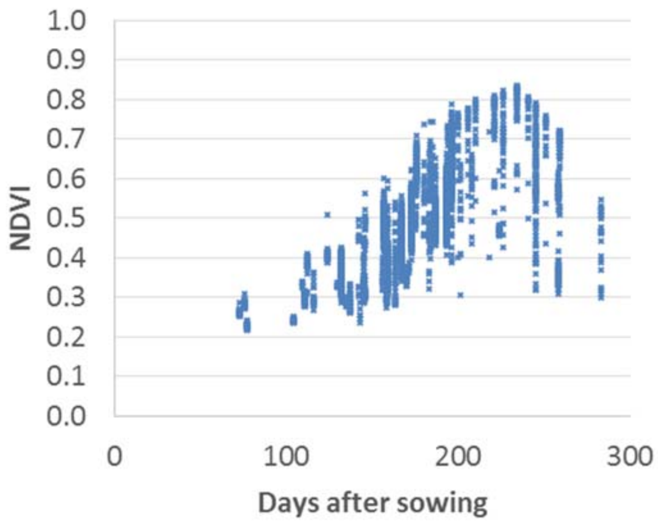



**Figure 72** NDVI Measures from trials using the Crop Circle 210 sensor.

## 6.5 SNS Sensing

The chessboard trials showed, at least indicatively, that the areas with the highest harvested SNS tended to look greenest (have the highest NDVI) throughout the season.

The difference between NDVI of a given crop and the predicted NDVI of an N-unlimited crop should therefore give an indication of N deficiency, so long as nothing other than N has limited potential growth. The extent of N deficiency (hence maximum SNS) that can be detected increases with time; it is only reasonable to expect to detect differences of SNS greater than, say, 100 kg/ha once this level of SNS is beginning to limit crop growth. There are a number of challenges in developing a robust calibration for estimating SNS from canopy signals. The first is to define the course of NDVI of N-unlimited crops against thermal time after sowing. A calibration for SNS then needs to be developed for the difference between N-unlimited NDVI and a given measured NDVI. This calibration needs to be dynamic as associated SNS differences to NDVI differences increase with time. The impact of seed rate, variety, soil type etc on NDVI values needs to be considered to judge whether calibrations can be robust over sites, or whether specific adjustments can be made. The large quantities of canopy reflectance data amassed over a range of trials with associated measures allows us to test this.

The former scoping study (Sylvester-Bradley et al. 2009) found that over winter and early spring NDVI signals for bare ground and fully-fertilised wheat canopies were reasonably consistent over sites and seasons. Here we further develop and test the hypothesis that sensor signals of crop NDVI or other indices could be calibrated to predict soil nitrogen supply (SNS) over winter through the concept of an N-unlimited crop. Measurements were taken from plots which had N fertiliser applied in autumn to ensure they were not limited by N over winter and into spring.

There is a consistent, positive relationship between thermal time and NDVI of an N-unlimited wheat crop, as shown in Figure 73 which includes measures from 8 sites over 2 seasons. It is therefore possible to estimate the NDVI of an N-unlimited wheat crop from the empirical regression relationship, which is simply 0.0005 x thermal time ($P < 0.001$, $r^2 = 0.74$).

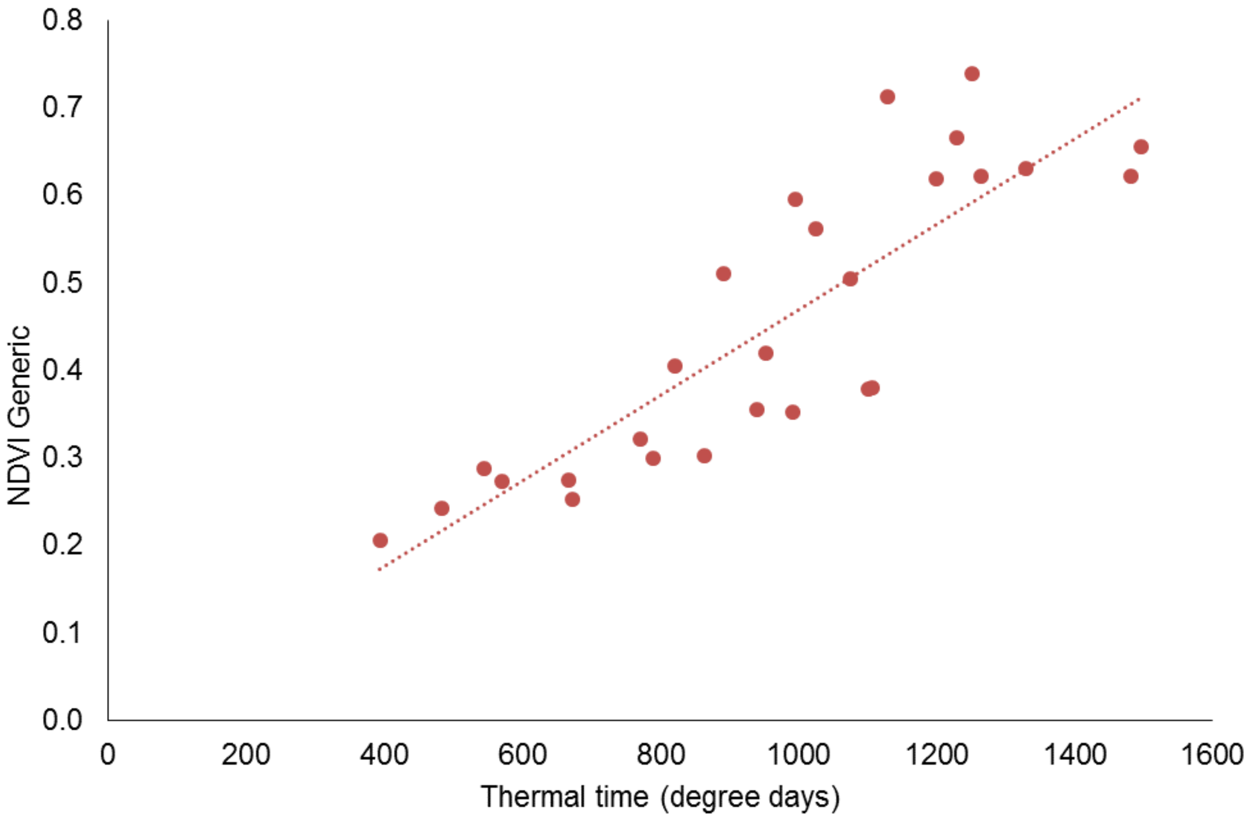



**Figure 73 NDVI of N-unlimited crops over thermal time. Data from ADAS 'N Ghost' trials over two years, four sites per year. The sites were High Mowthorpe (2007), Boxworth (2007, 2008), and Terrington (2007, 2008).**

The Auto-N logic proposes that the difference between the unlimited NDVI and measured NDVI can be indicative of the SNS in a crop that has received no N fertiliser. This theoretical approach is shown in Figure 74, and is presented using trials data in Figures 75 and 76, in which the grey line represents the predicted N unlimited crop NDVI values using equation 1 described above. In each of the experiments shown in Figure 7, a treatment was included in which the crop was not limited for N. This enabled the measurement of NDVI from an N unlimited crop (shown by the cross symbols) under the same conditions as an N limited crop, in which the treatments were exposed to various background soil N supplies. It can be seen in Figures 75b and 76 that the difference between the measured NDVI of an N limited crop and that of an N unlimited crop ('NDVI difference') increases over time. This is as expected, the crop N limitation is unlikely to show as clearly earlier in the season when the crop is still relatively small, and has little requirement for N. As the crop grows, and its N requirement increases, whilst the SNS decreases, the N limitation becomes more distinct, which can be seen by the increase in NDVI difference. In the trials shown below, there were a range of treatments and background SNS, which is why the NDVI values at a given thermal time are varying. This enabled the relationship between NDVI difference and harvested SNS to be evaluated across factors such as soil type, seed rate and variety.

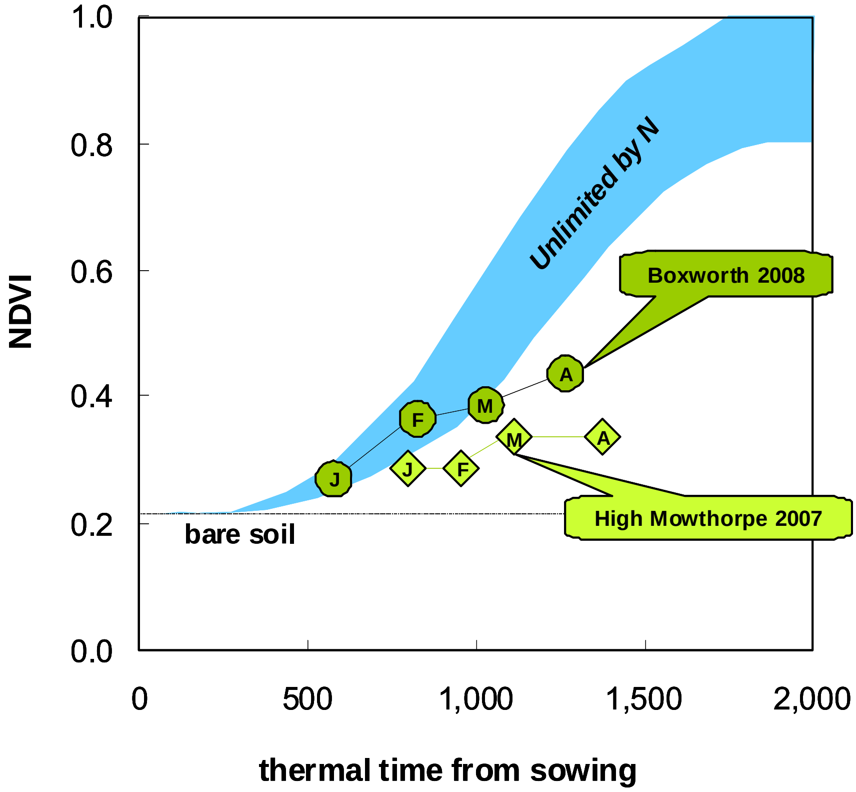



**Figure 74** **The theoretical relationship between the NDVI of an N unlimited crop, and that of an N limited crop**

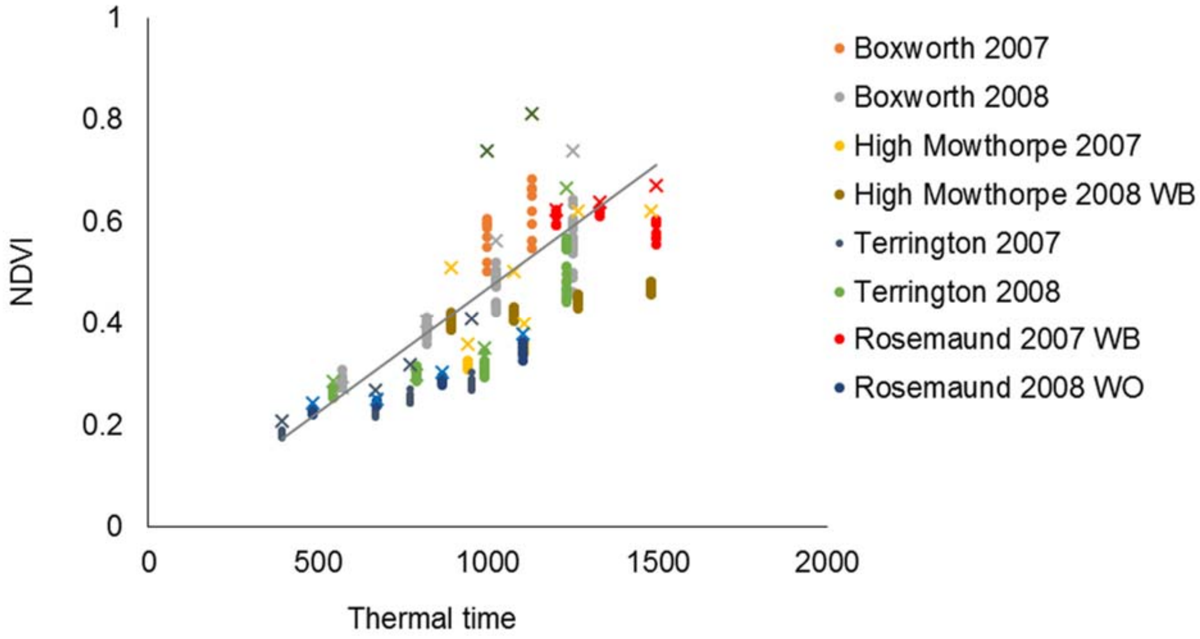



**Figure 75 The relationship using measured experimental data from eight trials over two years including winter wheat, winter barley (WO) and winter oats (WO). Each trial included an N unlimited treatment, which is indicated by the cross. The relationship between these N unlimited values and thermal time can be predicted using a linear equation described in section above, shown here by the grey line**

Figure 75 demonstrates the increase in the difference between the measured NDVI and expected unlimited N NDVI (NDVI difference) over thermal time. This indicates that the ability to predict SNS should increase over time, as the limitation becomes more apparent in the crop.

This can be seen in Figure 76 below for the 'N Ghost' trials. The harvested SNS was measured on these trials by measuring the total N content of the unfertilised crop. Using multiple regression the relationship of harvested SNS with the NDVI difference value (NDVI from N unlimited plots minus measured NDVI) and thermal time was quantified. There is a clear relationship between ‘NDVI difference’ and harvested, but it is clear that the detectable harvested SNS increases with thermal time, as the ability to predict harvested SNS increases. These data were analysed using a multiple regression in GenStat (Version 16.1. 2013, VSN International Ltd.), there was a significant fit ($P<0.001$, $r^2 = 0.324$), and this relationship is shown by the wireframe plot in Figure 76. This equation forms the basis of estimating SNS in the Auto-N logic so is deemed commercially sensitive and has been omitted from this report.

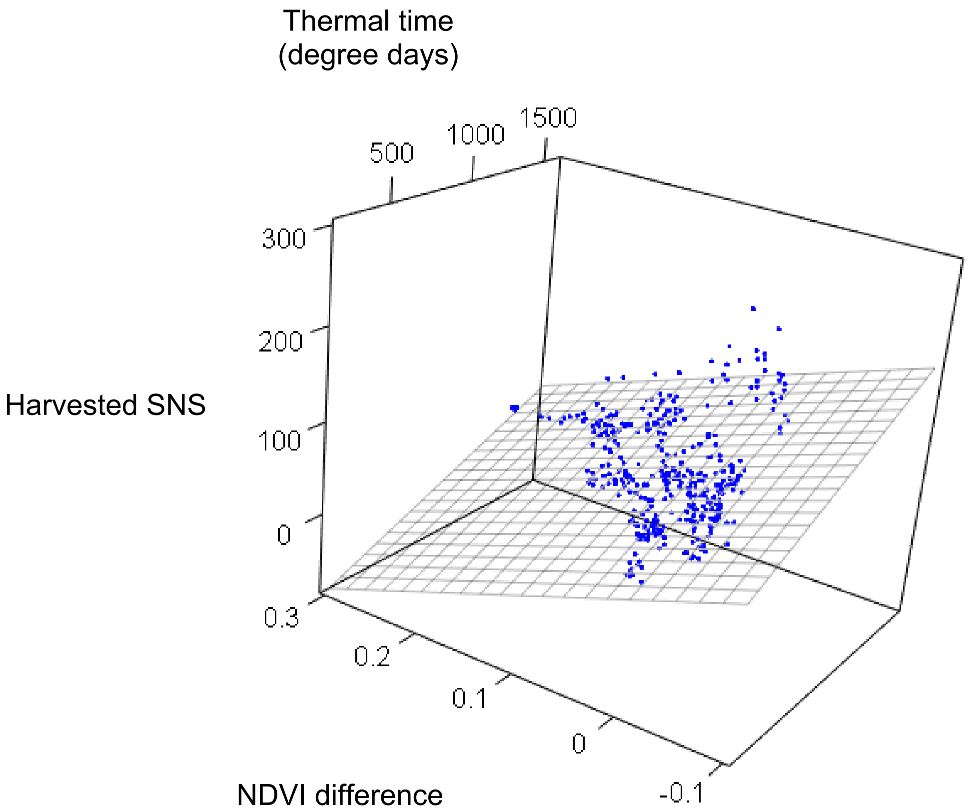



**Figure 76** **The relationship between NDVI difference (NDVI for an unlimited N crop – Measured NDVI), thermal time (degree days) and Harvested SNS (kg/ha) for the eight N ghost experiments. Wireframe surface plot representing the multiple regression of soil nitrogen supply (SNS) at harvest, thermal time, and NDVI difference.**

The relationship between measured, harvested SNS and the SNS predicted using this relationship can be seen for each of the trials in which harvested SNS and NDVI data were available in Figure 77, and the fitted regressions are outlined in Table 8. There is a range in predictive capability, but predictive capability in the chessboard trials is generally poor. It is also evident that the highest predictive power of the SNS equation is highest between 1000 – 2000 degree days. This is as expected, since the crop is expected to show its SNS limitation as the season progresses, but saturation of NDVI is expected as the crop reaches complete canopy closure. The most valuable time for assessing SNS is early spring, and this demonstrates that the equation works most successfully around this time.

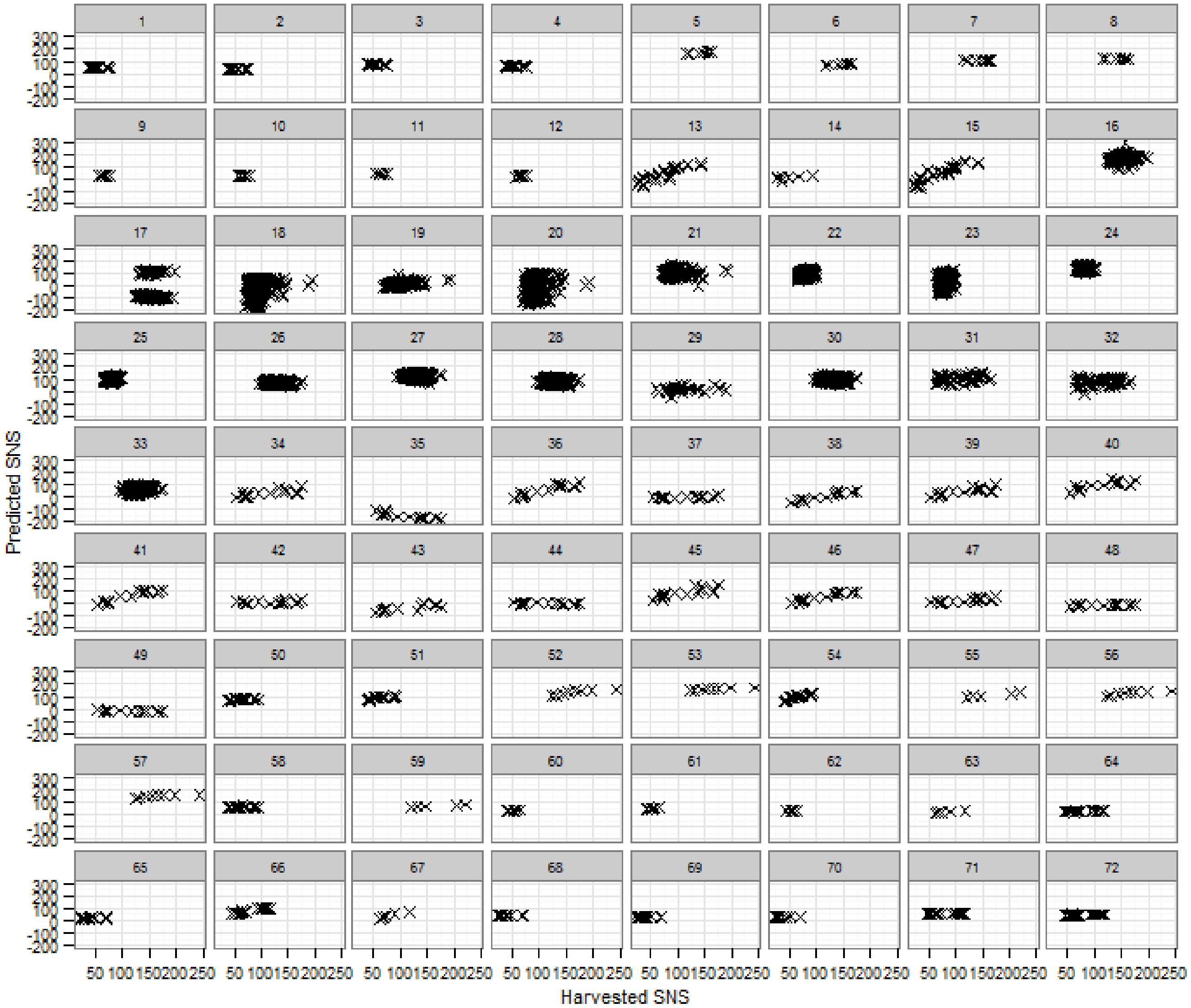



**Figure 77** **Predicted SNS values plotted against measured harvested SNS values for a range of experiments and cereal crops detailed in Table 7. Correlation coefficients and P values are given in Table 5.3.**

Table 8. Correlation coefficients, $r^2$ and P values for Predicted vs Harvested SNS values for each assessment date on a range of cereal trials.

| | Crop | Experiment | Site | Date | Thermal time | Correlation coefficient | $R^2$ | P value |
|---|---|---|---|---|---|---|---|---|
| **1** | Barley | N Ghost | High Mowthorpe | 23/01/2008 | 891.05 | -0.22 | 0.05 | 0.333 |
| **2** | Barley | N Ghost | High Mowthorpe | 26/02/2008 | 1074.9 | -0.29 | 0.08 | 0.203 |
| **3** | Barley | N Ghost | High Mowthorpe | 01/04/2008 | 1263.8 | -0.30 | 0.09 | 0.182 |
| **4** | Barley | N Ghost | High Mowthorpe | 02/05/2008 | 1480.6 | 0.09 | 0.01 | 0.714 |
| **5** | Barley | N Ghost | Rosemaund | 14/12/2006 | 903 | 0.94 | 0.88 | 0.001 |
| **6** | Barley | N Ghost | Rosemaund | 29/01/2007 | 1200 | -0.92 | 0.84 | 0.001 |
| **7** | Barley | N Ghost | Rosemaund | 21/02/2007 | 1330 | -0.90 | 0.81 | 0.002 |
| **8** | Barley | N Ghost | Rosemaund | 15/03/2007 | 1497 | 0.92 | 0.85 | 0.001 |
| **9** | Oats | N Ghost | Rosemaund | 16/01/2008 | 483.85 | -0.64 | 0.41 | 0.088 |
| **10** | Oats | N Ghost | Rosemaund | 12/02/2008 | 672.2 | -0.43 | 0.19 | 0.287 |
| **11** | Oats | N Ghost | Rosemaund | 14/03/2008 | 863.35 | -0.07 | 0.00 | 0.876 |
| **12** | Oats | N Ghost | Rosemaund | 18/04/2008 | 1101.75 | 0.75 | 0.56 | 0.032 |
| **13** | Wheat | Auto-N calibration | Ropsley | 11/03/2012 | 1185.85 | 0.53 | 0.28 | 0.222 |
| **14** | Wheat | Auto-N calibration | Ropsley | 02/05/2012 | 1583 | 0.95 | 0.90 | <0.001 |
| **15** | Wheat | Auto-N calibration | Ropsley | 13/05/2012 | 1681.25 | 0.96 | 0.92 | <0.001 |
| **16** | Wheat | Chessboard | Bedfordia | 11/12/2011 | 750 | 0.32 | 0.10 | <0.001 |
| **17** | Wheat | Chessboard | Bedfordia | 27/02/2012 | 1387 | 0.06 | 0.00 | 0.343 |
| **18** | Wheat | Chessboard | Burford | 11/12/2011 | 973 | -0.02 | 0.00 | 0.650 |
| **19** | Wheat | Chessboard | Burford | 05/03/2012 | 1690 | 0.48 | 0.23 | <0.001 |
| **20** | Wheat | Chessboard | Burford | 05/05/2012 | 2240 | 0.47 | 0.22 | <0.001 |
| **21** | Wheat | Chessboard | Burford | 01/06/2012 | 2600 | 0.55 | 0.30 | <0.001 |
| **22** | Wheat | Chessboard | Burford | 17/11/2010 | 587.75 | -0.01 | 0.00 | 0.887 |
| **23** | Wheat | Chessboard | Burford | 24/02/2011 | 956.95 | 0.32 | 0.10 | <0.001 |
| **24** | Wheat | Chessboard | Burford | 01/04/2011 | 1221.45 | 0.45 | 0.20 | <0.001 |
| **25** | Wheat | Chessboard | Burford | 16/05/2011 | 1780.15 | 0.53 | 0.28 | <0.001 |
| **26** | Wheat | Chessboard | Flawborough | 12/03/2010 | 957.9 | 0.30 | 0.09 | 0.098 |
| **27** | Wheat | Chessboard | Flawborough | 21/04/2010 | 1300.8 | 0.32 | 0.10 | 0.250 |
| **28** | Wheat | Chessboard | Flawborough | 20/05/2010 | 1602.15 | 0.32 | 0.10 | 0.251 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **29** | Wheat | Chessboard | Flawborough | 03/02/2011 | 783.3 | 0.07 | 0.00 | 0.171 |
| **30** | Wheat | Chessboard | Flawborough | 10/03/2011 | 993.65 | -0.01 | 0.00 | 0.780 |
| **31** | Wheat | Chessboard | Flawborough | 16/03/2011 | 1034.8 | -0.05 | 0.00 | 0.274 |
| **32** | Wheat | Chessboard | Flawborough | 08/04/2011 | 1269.8 | 0.06 | 0.00 | 0.510 |
| **33** | Wheat | Chessboard | Flawborough | 23/05/2011 | 1831.2 | 0.41 | 0.17 | <0.001 |
| **34** | Wheat | MINNO crop residues | Terrington | 25/02/2013 | 675.2 | 0.43 | 0.18 | 0.097 |
| **35** | Wheat | MINNO crop residues | Terrington | 08/03/2013 | 729.5 | 0.48 | 0.23 | 0.060 |
| **36** | Wheat | MINNO crop residues | Terrington | 19/03/2013 | 767.85 | -0.27 | 0.07 | 0.308 |
| **37** | Wheat | MINNO crop residues | Terrington | 28/03/2013 | 785.85 | -0.49 | 0.24 | 0.052 |
| **38** | Wheat | MINNO crop residues | Terrington | 15/04/2013 | 889.7 | 0.28 | 0.08 | 0.299 |
| **39** | Wheat | MINNO crop residues | Terrington | 22/04/2013 | 957.55 | 0.73 | 0.53 | 0.001 |
| **40** | Wheat | MINNO crop residues | Terrington | 01/05/2013 | 1044.45 | 0.76 | 0.57 | 0.001 |
| **41** | Wheat | MINNO crop residues | Terrington | 09/05/2013 | 1139.65 | 0.81 | 0.66 | <0.001 |
| **42** | Wheat | MINNO crop residues | Terrington | 13/05/2013 | 1184.5 | 0.81 | 0.66 | <0.001 |
| **43** | Wheat | MINNO crop residues | Terrington | 21/05/2013 | 1264.95 | 0.80 | 0.64 | <0.001 |
| **44** | Wheat | MINNO crop residues | Terrington | 03/06/2013 | 1438.6 | 0.94 | 0.88 | <0.001 |
| **45** | Wheat | MINNO crop residues | Terrington | 14/06/2013 | 1546.65 | 0.94 | 0.88 | <0.001 |
| **46** | Wheat | MINNO crop residues | Terrington | 21/06/2013 | 1655.9 | 0.96 | 0.92 | <0.001 |
| **47** | Wheat | MINNO crop residues | Terrington | 08/07/2013 | 1924.9 | 0.96 | 0.93 | <0.001 |
| **48** | Wheat | MINNO crop residues | Terrington | 17/07/2013 | 2085.2 | 0.80 | 0.65 | <0.001 |
| **49** | Wheat | MINNO crop residues | Terrington | 02/08/2013 | 2402.7 | -0.86 | 0.75 | <0.001 |
| **50** | Wheat | N Ghost | Boxworth | 28/02/2006 | 974.75 | 0.98 | 0.96 | 0.004 |
| **51** | Wheat | N Ghost | Boxworth | 11/04/2006 | 1225.4 | 0.94 | 0.89 | 0.016 |
| **52** | Wheat | N Ghost | Boxworth | 08/12/2006 | 644 | 0.89 | 0.80 | 0.003 |
| **53** | Wheat | N Ghost | Boxworth | 23/01/2007 | 892 | 0.86 | 0.74 | 0.006 |
| **54** | Wheat | N Ghost | Boxworth | 15/02/2007 | 996 | 0.85 | 0.72 | 0.008 |
| **55** | Wheat | N Ghost | Boxworth | 08/03/2007 | 1129 | 0.89 | 0.79 | 0.003 |
| **56** | Wheat | N Ghost | Boxworth | 27/12/2007 | 571.4 | 0.34 | 0.12 | 0.132 |
| **57** | Wheat | N Ghost | Boxworth | 01/02/2008 | 821 | 0.43 | 0.18 | 0.052 |
| **58** | Wheat | N Ghost | Boxworth | 06/03/2008 | 1024.7 | 0.73 | 0.53 | <0.001 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **59** | Wheat | N Ghost | Boxworth | 09/04/2008 | 1251.6 | 0.91 | 0.82 | <0.001 |
| **60** | Wheat | N Ghost | High Mowthorpe | 04/01/2007 | 773 | 0.78 | 0.61 | 0.023 |
| **61** | Wheat | N Ghost | High Mowthorpe | 01/02/2007 | 939 | 0.63 | 0.40 | 0.094 |
| **62** | Wheat | N Ghost | High Mowthorpe | 05/03/2007 | 1106 | 0.43 | 0.18 | 0.292 |
| **63** | Wheat | N Ghost | Terrington | 03/03/2006 | 887.05 | 0.95 | 0.91 | 0.003 |
| **64** | Wheat | N Ghost | Terrington | 12/04/2006 | 1131.2 | 0.97 | 0.95 | 0.001 |
| **65** | Wheat | N Ghost | Terrington | 12/12/2006 | 394 | 0.28 | 0.08 | 0.333 |
| **66** | Wheat | N Ghost | Terrington | 22/01/2007 | 668 | -0.03 | 0.00 | 0.921 |
| **67** | Wheat | N Ghost | Terrington | 13/02/2007 | 771 | -0.01 | 0.00 | 0.975 |
| **68** | Wheat | N Ghost | Terrington | 09/03/2007 | 953 | 0.02 | 0.00 | 0.957 |
| **69** | Wheat | N Ghost | Terrington | 22/12/2007 | 544.2 | 0.69 | 0.48 | <0.001 |
| **70** | Wheat | N Ghost | Terrington | 29/01/2008 | 789 | 0.72 | 0.52 | <0.001 |
| **71** | Wheat | N Ghost | Terrington | 04/03/2008 | 991.05 | 0.64 | 0.41 | 0.002 |
| **72** | Wheat | N Ghost | Terrington | 10/04/2008 | 1229.7 | 0.93 | 0.87 | <0.001 |

testing the extent to which N balances predict soil N supplies after both cereals and oilseed rape; improved prediction of NDVI with unlimited N supply (accounting for any effects of soil, genotype, sowing date and seed rate; Sylvester-Bradley *et al*., 2009); measurement and interpretation of canopy colour in spring as distinct from canopy size (Heege *et al.*, 2008).

Other sources of variation in canopy signals come from illumination angle and time of day. Active sensors such as the Crop Circle/Optrx/RapidScan and Yara N sensor have their own light source so effects of ambient light are mitigated to a large extent. Even so, within experimental measures we aim to use the sensors between 10am to 3pm. The height of the sensor does influence the field of view so maintaining a constant height above the crop is important.

## 6.6 Calibrations for N uptake, biomass, N Nutrition Index

Once variable rate N has been applied measures of canopy reflectance still ought to be useful in judging the N status of the crop even if we don't have, within the Auto-N logic, a rational method to use the information quantitatively to recalculate N requirements. Such measures should help judge the success of N applications so far and provide reassurance that the crop is 'on target' or, conversely, alert the grower to areas where the crop is either not performing or is at risk of lodging allowing remaining fertiliser N applications to be reconsidered.

In considering crop N status it is important to separate the current size of the crop (biomass, GAI, crop N uptake) which indicates how much N has been taken up by the crop so far, from the inherent 'greeness' of the crop, which can be considered to indicate how much N is available to the crop at this instance.

Perhaps the best method of quantifying crop N status is the Nitrogen Nutrition Index (NNI) (Greenwood et al., 1990;1991; Lemaire et al., 2008). The NNI uses the concept of a critical N concentration above which the crop is deemed to have sufficient N and below which N is deemed to be deficient. The critical N concentration reduces over time as the crop grows larger and less photosynthetically active organs such as stems form an increasing proportion of the total biomass (Grindlay, 1997). The relationship between critical N concentration and biomass has been defined empirically by Justes et al (1994) by collating biomass and N concentration measures from N response experiments at sequential growth stages (Fig 78) and is represented by the equation $N_{crit}$ = 5.35*Biomass^-0.442.

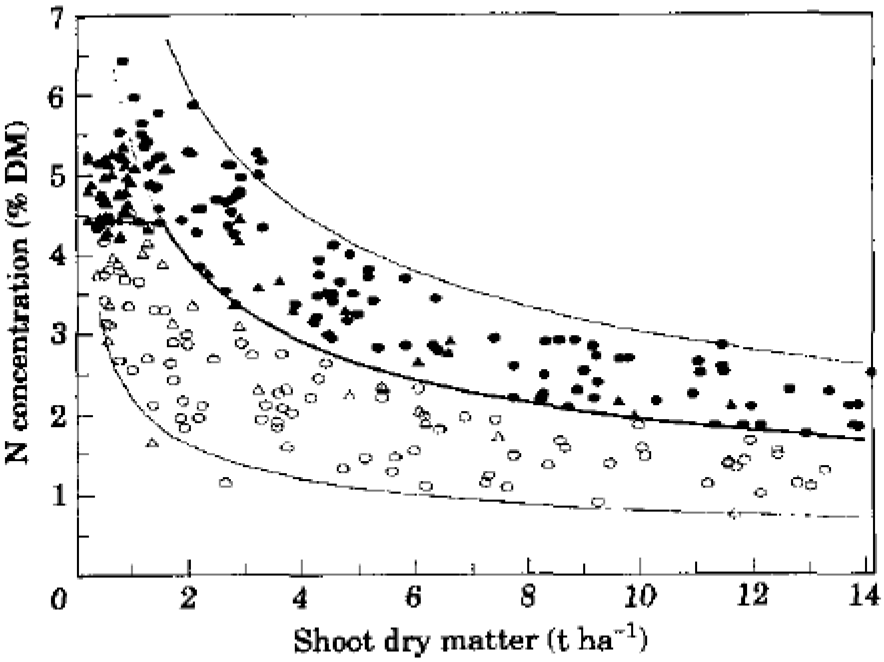



FIG. 5. Diagram representing N concentration versus accumulated dry matter in shoots, for all experimental treatments either N limiting or non-limiting growth. (○), (△) Treatments where N was statistically limiting factor of shoot growth. (●), (▲) Treatments where N was not statistically limiting factor of shoot growth. (○), (●) Analysis by Dumas' method. (△), (▲) Analysis by Kjeldahl's method. (—) Critical dilution curve [eqn (11)]; (——) 'envelope'-curves $N_{min}$ and $N_{max}$ [eqns (16) and (17)].

**Figure 78 Critical Nitrogen Curves for wheat as presented by Justes et al., 1994, Annals of Botany 74, p397-407.**

This allows the calculation of NNI for a given crop of known biomass and N concentration as the proportion of the measured N concentration against the calculated critical N concentration. An NNI of 1 therefore indicates that the crop is at the critical N concentration, an NNI greater than 1 indicates luxury uptake and an NNI below 1 indicates deficiency.

The Auto-N calibration dataset was used to assess the relationships of a range of spectral indices with measures of crop biomass, N uptake, N concentration and NNI. Figures 79-81 shows these relationships using the Crop Circle sensor with growth stages before ear emergence (relationships tend to deteriorate after ear emergence as varietal differences affect canopy signals). Whilst NDVI saturates quickly in its power to differentiate biomass at about 3 t/ha, other indices such as NDRE seem better able to differentiate at higher biomass (Fig 79). Relationships are consistently better expressed on a fresh weight basis than dry weight.

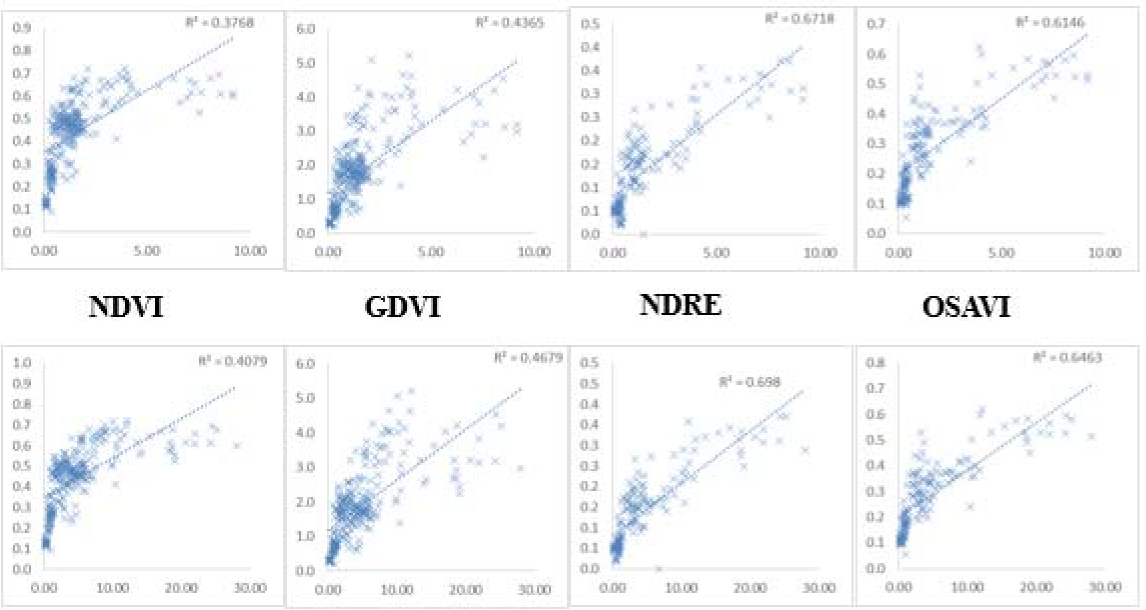



**Figure 79 Relationships of spectral reflectance indices with a) biomass and b) total fresh weight for wheat crops from a range of experiments measured by Crop Circle.**

Reasonable calibrations can be obtained for crop N uptake from reflectance indices (Figure 81), but direct relationships with N concentration are very poor. This reflects the changing ‘appearance’ of N concentration through the season in relation to the size of the crop; canopy reflectance is mostly driven by ground cover and the amount of crop material, rather than the intensity with which an individual leaf absorbs and reflects light. NDRE appears to give the tightest relationships with crop N uptake.

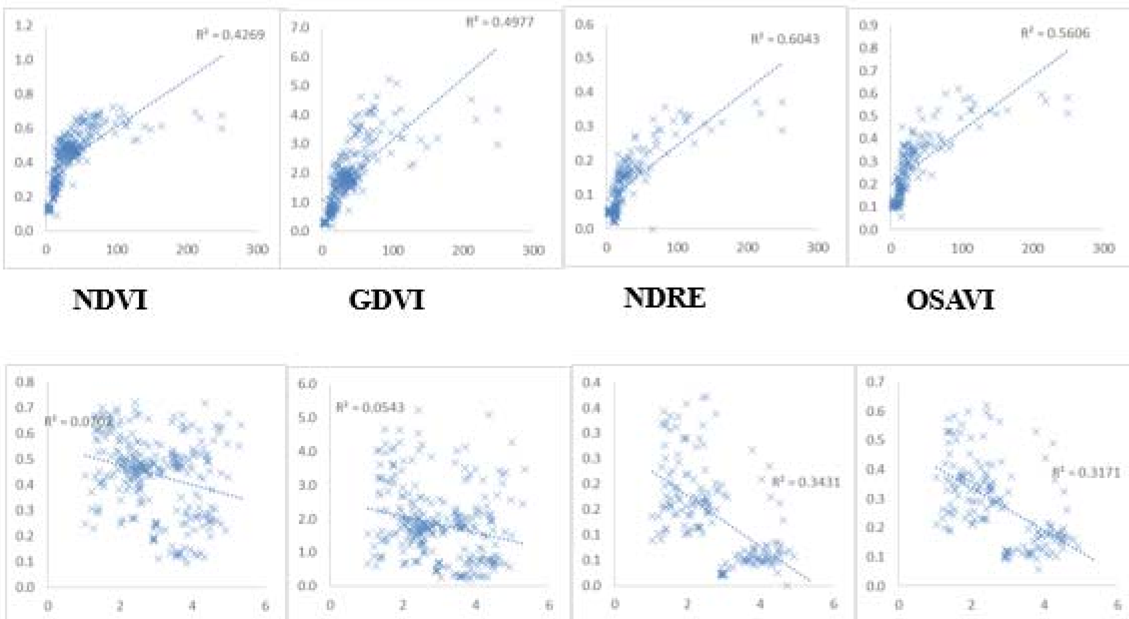



**Figure 80 Relationships of spectral reflectance indices with a) crop N uptake (kg/ha) and b) tissue N concentration for wheat crops from a range of experiments measured by Crop Circle**

The lack of a predictive relationship with N concentration means prohibits the calculation of NNI from independent calibrations for biomass and N concentration. However, direct calibration for NNI does seem feasible with reasonably linear relationships with the reflectance indices (Figure 82). Incorporating thermal time into these relationships could allow greater differentiation of sub- and super-optimal crops. Other approaches such as canopy chlorophyll content index may also be useful in assessing NNI (Gitelson et al., 2005; Fitzgerald et al., 2010; Li et al., 2014; Xu et al., 2014; Basso et al., 2015; Jin et al., 2015; Yao et al., 2015;  Cao et al., 2015; 2016).

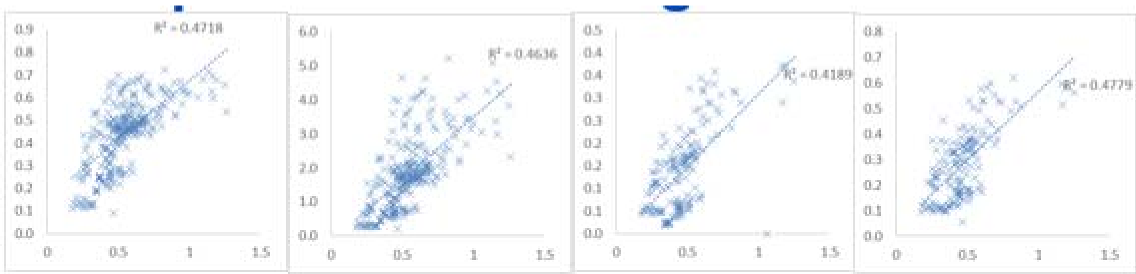



**Figure 81	Relationships of spectral reflectance indices (a. NDVI, b.GDVI, c. NDRE, d., OSAVI) with N nutrition index (crop N status) for wheat crops from a range of experiments measured by Crop Circle**

Evidence from the chessboard trials shows that NNI can be of value in judging optimal N rates, with areas showing lower NNI being those with the higher N requirements (Figure 83)

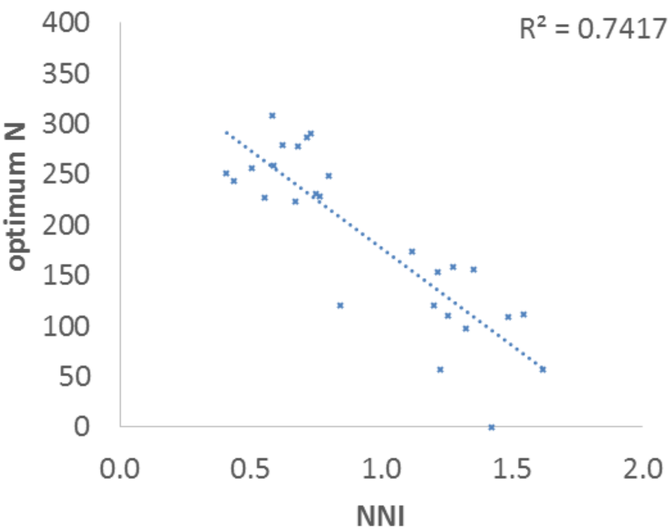



**Figure 82	Relationship between NNI and optimum N for selected plots from chessboard experiments.**

### 6.6.1 Impacts of soil, variety & seed rate on canopy signals

It is clear that there is variation in canopy signals caused by factors other than crop N uptake or N status. There are differences between sites that may relate to soil properties, especially wetness, but these have not shown consistent effects in the datasets here. It seems that soil adjusted indices such as OSAVI do generally give a marginal improvement over straight NDVI.

There are differences in canopy reflectance between varieties that do not evidently relate to differences in biomass, LAI or N status. These differences become bigger through the season and are most evident once ears have emerged. For early season growth the differences are small enough to be ignored but later variety specific adjustments or calibrations may be warranted. Seed rate has a very large effect on canopy reflectance, especially early in the season. We have found no easy correction or adjustment for this, but seed rate and plant establishment differences need to be considered when using canopy reflectance to judge variation in SNS.

## 6.7 Conclusions on canopy signals

We have developed a workable calibration for variation in SNS using NDVI and thermal time since sowing. Whilst the relationship is far from universal across all sites, it does work well at some sites.

We have collated a dataset that gives useful calibrations for biomass, crop N uptake and NNI. Indices such as NDRE are generally better NDVI, saturating at higher levels. Whilst there is strong saturation in signals for biomass and crop N uptake at relatively low levels, there is much less evidence of saturation for NNI. Prediction of NNI by canopy signals appears relatively consistent across the datasets, making it potentially useful. Whilst we can use NNI as a check to monitor success of N management, we don’t however a logical method to include it within the Auto-N system to quantify N requirements.

There is a wide and ever increasing literature around calibrations from canopy signals for crop N uptake, GAI, biomass, N concentration, N status and NNI (Mistele et al., 2008; Samborski et al., 2014; Li et al., 2015. Zhao et al., 2016, Chen, 2015, Cao et al., 2015; Devadas et al., 2015; Feng et al., 2015). Whilst it has been shown that calibrations are feasible there does not yet seem to be a widely proven robust and reliable method to rationally turn this information into recommendations for the economic N requirement.

# 7 Final Auto-N System

Using the findings from Chapters 2, 3, 4 & 5 the final Auto-N system to estimate N requirement integrating information from precision technologies is set out below. This uses information to estimate crop N demand, SNS and fertiliser recovery to improve the estimate of N requirement through the season.

Within the datasets collected in this project large and unexpected interactions between components have been seen. This means that better estimating one component (say SNS) without refining estimates of the other components (demand and recovery) can actually give worse predictions of N requirement than using standard values. Fig 14, using data from the 2010 chessboard experiment, shows that even if SNS was known perfectly less than half of the variation in N requirement would be predicted without perfect knowledge of the other components.

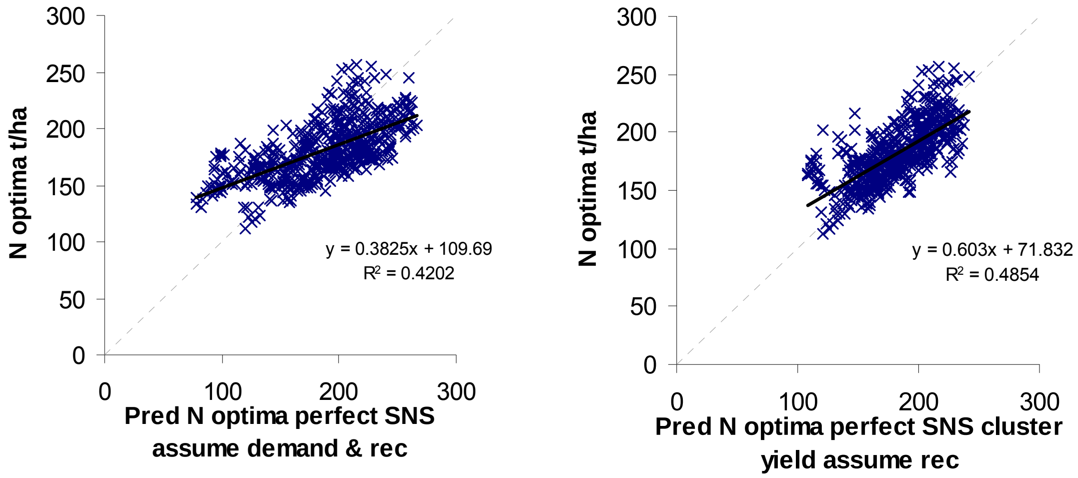



**Figure 83 Prediction of measured N optima using calculated N requirements using knowledge of SNS (a) and SNS and yield (b) from the 2010 chessboard experiment at Flawborough.**

In this case predicted N requirements in areas with high harvested SNS (hence low N optima) tend to be under-predicted, because these areas had higher with-N yields hence higher crop N demand than expected, giving consequently higher measured N optima. The economic performance of such predictions can be worse than using a standard flat rate. This cautions against aiming for spurious precision but shows the importance of getting a good estimate of large scale changes in the N components, getting the average right and accepting that applications will never be perfect everywhere.

## 7.1 Estimating Crop N Demand

The direct link between yield and N requirement has been shown here to be weak, yet it is important to estimate crop N demand not least due to its positive relationship with SNS discovered here: without adjusting for the impact of crop N demand the N requirements of areas with high SNS could be underestimated.

Crop N demand is estimated from yield x crop N content. Crop N content is taken to be 23 kg N/t for feed wheat and 25 kg N/t for milling wheat. There is variation in crop N content between varieties and between sites. Yield level can impact crop N content as higher yielding crops tend to have a higher harvest index and lower grain protein content, giving a lower crop N content. However, such differences are relatively subtle and difficult to predict, so are not included within the Auto-N system. This project has shown there to be large variation in protein content at the optima, both within fields and between fields. These differences do have a substantial impact on the N optima that in principle could be accounted for. However, we not yet well enough understand the dynamics of protein content or consistency of differences between years to be able to use it in predictions of crop N demand.

Our prediction of spatial variation in CND are therefore limited to our predictions in differences of yield. Given the variability in achieved yields between years and the modest association with N requirement, we conclude that only broad indicative estimates of spatial yield differences are necessary, and that the method of achieving those estimates through zones or through a grid system using past average or predicted in-year yields is not critical. What is important is that some attempt to account for yield differences across the field is made.

## 7.2 Estimating SNS

The original intention was to consider an N balance approach for base estimates of SNS, and annual measures of SNS on each field were made on this basis. If previous N applications and N offtakes are known then it should be possible to make some allowances for N leaching and changes to soil organic matter to predict SNS spatially. The expectation would be that areas giving highest yields and proteins with uniform N applications would be areas where N offtakes were higher and resulting SNS would be lower. However, the unexpectedly strong relationship between yield potential and harvested SNS seen in the chessboard experiments refutes the applicability of the N balance hypotheses on a spatial basis, unless full estimation of mineralisation from differences in soil organic matter could be made. An N balance approach may however still give a worthwhile method of judging average field SNS to use as a baseline.

Crop sensing can also be used to judge differences in SNS, assuming that nitrogen has been the major limitation to growth and that other factors have not been responsible for the spatial variation in the crop. Chapter 5 shows there is feasibility of getting an SNS estimate from canopy sensing on an absolute basis by using NDVI with estimated NDVI of an N-unlimited crop from knowledge of thermal time since sowing. Whilst a useable calibration has been developed, the variability in the data suggests that large errors can be associated with SNS predictions, and experience from other work shows that poor prediction of SNS can be costly (Kindred et al., 2012).

We therefore advocate the use of the calibration developed in Chapter 5 to spatially adjust the estimate of SNS around a field average, with constraints on what the maximum and minimum SNS could be in the field.

To estimate the average field SNS we suggest using an N-balance type approach as inferred in the HGCA wheat N Management Guide. First the autumn N residue is estimated based on the balance of N applied (or fixed) and that removed in the crop. Typical OSR and bean crops are expected to leave a residue of around 120 kg N/ha, whereas cereals might leave 80kg/ha. Estimates for other crops is given in Table 9. These estimates may be adjusted based on the amount of fertiliser N applied, its efficiency recovery by the crop (eg was spring very dry so N uptake limited?) and the achieved yield and N offtake in crop & straw.

**Table 9. Estimated typical autumn N residues for a range of previous crops. Values are inferred from N Management Guide.**

| **Previous crop** | Estimated N Residue Kg/ha |
|---|---|
| High N Grass | 150 |
| High N veg | 150 |
| bare land | 130 |
| Med N veg | 125 |
| Potatoes | 125 |
| Oilseed rape | 120 |
| Beans | 120 |
| Peas | 120 |
| Grazed fodder | 100 |
| low N grass | 100 |
| uncropped land with green cover | 90 |
| Wheat | 80 |
| feed barley | 80 |
| malting barley | 70 |
| Triticale | 60 |
| Oats | 60 |
| Forage cut | 60 |
| low N vegetables | 60 |
| sugar beet | 50 |

The amount of residual N available to the following crop will depend on how much is lost to leaching over the winter, which is largely dependent on the retentiveness of the soil and the amount of excess winter rainfall. The HGCA N Management guide infers the retentiveness of soils in high, medium and low rainfall areas as in Table 10. Tools and models such as Irriguide could give more dynamic estimates of retentiveness.

**Table 10. Typical retentiveness of RB209 Soil groups in low, medium and high rainfall conditions.**

| | Rainfall | | |
|---|---|---|---|
| **Soil type** | **low** | **moderate** | **wet** |
| Deep clays | 90% | 80% | 60% |
| Deep silty soils | 100% | 90% | 80% |
| medium soils | 80% | 70% | 50% |
| Sands | 40% | 20% | 10% |
| Sandy loams | 60% | 40% | 20% |
| Shallow soils not over sandstone | 70% | 50% | 30% |
| shallow soils over sandstone | 65% | 45% | 25% |

Multiplying the N residue by retentiveness gives an estimate of the SNS available in spring. An estimate then also is needed for the likely mineralisation of the soil, and also N made available by deposition. The N Management Guide uses an adjustment of 20kg/ha to account for the difference between typical measured spring SNS and that at harvest. Additional mineralisation may be expected on soils with high SOM% or where organic resources (farmyard manure, composts, biosolids etc) have been regularly used in the recent past. There aren't currently reliable & robust methods to estimate the additional N available from mineralisation from knowledge of SOM%, but an indicative relationship of 10kg/ha per 1% increase in SOM above 4% provides a sensible basis for judgement (Kindred et al., 2012). Soil measures using anaerobic incubation can be used to give indicative estimates of Additionally Available N. However, over-estimating N mineralisation can be costly. Mineralisation of N can also be inferred from past experience of fields, for example meadow land or fields which are prone to lodging are likely to have greater mineralisation. Given the relationships seen here between yield potential and SNS, it may be that higher yielding fields could be taken to infer greater mineralisation potential.

In the absence of a robust predictive methodology for mineralisation it is most appropriate to allow a manual adjustment for expected mineralisation, with expected values between 10 and 50 kg/ha for most soils. Mineralisation from organic and peat soils can be much higher.

The residue N multiplied by retentiveness plus the mineralisation estimate gives the baseline SNS.

The canopy sensing methodology comparing measured NDVI with expected N-unlimited NDVI can be used to check the 'baseline' SNS before any fertiliser N has been applied, by estimating the mean, minimum and maximum predicted SNS in the field. This can be a tool to compare to the estimated baseline SNS and adjustments made if the crop seems to be growing faster or slower than expected.

Spatial differences in SNS can be estimated using NDVI differences from the mean NDVI for the field to estimate the difference in SNS using the equation with thermal time developed in Chapter

5. This allows a rational basis for generating variable SNS predictions across the field but ensuring that the field average is based upon sound estimates and that extreme high or low estimates are constrained to a sensible range.

This approach also allows the estimation of variation in SNS even after N has been applied, so long as early N applications are uniform. This is important as the prediction of SNS from canopy sensing increases with time, so estimates of SNS variability can still be made up to late March before the main variable rate applications.

## 7.3 Fertiliser Recovery

The chessboard trials have shown very great variation in fertiliser recovery across fields, between 20-80%. However, we have not yet been able to explain or predict this variability. At present we have no other basis for changing N recovery estimates other than known differences in soil type:
Silts/clay = 60%
Sandy = 65%
Chalk = 55%

It is possible that on Burford soils recovery could be linked to stoniness. At other sites, differences in soil type within a field is probably insufficient to assume different recoveries.

## 7.4 Calculating N requirements & scheduling

The Auto-N system thus integrates two spatial data layers (Crop N Demand & SNS) with a fertiliser recovery estimate to calculate the fertiliser N requirement for each point in the field.

The Crop N Demand layer is calculated simply from estimated yield x crop N content.

The SNS layer is a bit more complex, but basically uses a baseline estimate of SNS modified by a spatial NDVI layer using equation from Chapter 5 using knowledge of thermal time since sowing.

In principle these layers can be created and calculated within precision farm management software such as Gatekeeper.

Once the N requirement has been calculated the timing and splitting of applications needs to be decided. The decisions on early splits of N impact on the information that is subsequently available through canopy sensing later in spring. The splitting and timing of N applications can usefully be used to manage the canopies to help avoid lodging and to achieve optimal canopy size. In essence this means delaying N applications to crops which are well tillered and lush in spring and using early N to promote growth in crops which are thin and backward.

When considering canopy sensed differences after the first application it will always be necessary to know what was applied previously. For this reason ideally the first N application in Feb / early March should be uniform to allow easier interpretation of subsequent canopy scans. A judgement is needed on a whole field or management zone basis whether early N is needed, then either apply 0 or 40 (or 60) kg/ha. Calculating the N requirement in March as above, the remaining fertiliser N to be applied can be split between April and May.

This project has considered the use of canopy sensing through the season to adjust subsequent N applications. However, there are serious difficulties in doing so. As soon as the first variable rate N application has been made there are many measurements and assumptions required in order to recalculate N requirements in terms of CND, SNS and recovery. For each spatial unit knowledge would be needed of:

- Updated crop N demand
- Initial estimated SNS
- N fertiliser already applied
- Crop N uptake
- Soil N still available to be taken up
- Fertiliser N still available to be taken up

Given the variability in the measures and estimates of SNS and of crop N uptake and the variability in fertiliser recovery and dynamics of N uptake, we feel the assumptions required to estimate the above would be too shaky to be worthwhile.

It has not proved possible to reconcile the approach adopted here of calculating fertiliser N requirement on a rational basis by estimating CND, SNS and recovery with a separate approach based on crop N uptake and N status later in the season, without discarding the original calculation of N requirement.

Whilst we have shown in Chapter 5 that canopy sensing can usefully estimate differences in Crop N uptake and crop N status, it is not clear how such information can rationally be used to determine the remaining N fertiliser requirement, whilst it may indicate that N is limiting it doesn’t tell you how much more N it is economically worth applying. Measures that use approaches such as the N Nutrition Index may however be useful tools to measure of success through the season and to judge whether estimates of demand, N supply and recovery are right or not.

Whilst the central Auto-N logic developed in the project is freely available, the equation for SNS prediction from thermal time has been withheld from publication to allow commercial partners to develop and commercialise an Auto-N system accommodating the individual sensor data available to them. We hope these will be applied by the commercial partners in conjunction with software applications and precision technologies. Each commercial partner provided a system for testing commercially in Chapter 7.

Ultimately, any system will need to deal appropriately with spatially variable disturbances such as leaf disease, water-logging, take-all, rabbit grazing etc. The cause of poorer areas of the crop is of fundamental importance to how N management should be adapted. With yield limiting factors such as compaction then yield potential may be compromised so N rates should be cut back, on the other hand patches with poor establishment or suffering compaction, water-logging, take-all, slug damage etc may benefit from greater N applied early to stimulate tillering and root development. Of course, where patches are poor due to low soil N supply, higher N rates would be warranted. Whilst the impacts of non-N factors have been considered in the project, the complexity is too great to deal with each possible cause in detail. Instead, the project focused efforts on the estimated ~80% of cases where growth is limited by N supply. In using the Auto-N system commercially, systems will be required for dealing with poor patches not limited by N supply, with adjustment to N rates based on expected N demand.

# 8 Evaluation of the Auto-N system

The Auto-N approach described in Chapter 6 was evaluated in two ways. Firstly the data sets from the chessboard trials were used to compare predicted N requirements for each plot from previous yield information and in season canopy sensing with the measured N optima, and consequences for profitability, yield and N losses were calculated. Secondly, in 2013 and 2014 validation trials were set up by the commercial partners using the Auto-N system on commercial fields, with tramline comparisons to standard uniform field N rates.

## 8.1 Evaluation from Chessboard trials

The chessboard trials can be used to test potential approaches for predicting N requirements against the measured N optima across the fields, and to evaluate the financial and environmental benefits of improved predictions.

### 8.1.1 Quantifying potential benefits from a perfect system

Firstly we assess the potential for improvement by quantifying the financial benefit of getting N recommendations exactly right, on average for the field and for each ~10x10m area in the field. Comparisons are made against the recommended N rates for these fields as deemed by RB209. The margin over N cost at the optimum and at a given N rate was calculated using a grain price of £120/t and N fertiliser price of £0.75 /kg. This gives a breakeven ratio of 6.2 so quoted N optima here are slightly lower than reported in Chapter 3.

**Table 11. Economic margins from RB209 recommended N rates compared to applying the measured N optima across each of the chessboard trials.**

| Site | RB209 recommended rate *kg N/ha* | Range in measured N opt *kg N/ha* | Average N optima *kg N/ha* | Average margin RB209 *£/ha* | Average margin @ opt *£/ha* | Average Profit foregone *£/ha* |
|---|---|---|---|---|---|---|
| Flaw 2010 | 190 | 115-265 | 185 | 1073 | 1076 | 3.64 |
| Flaw 2011 | 190 | 0-95 | 10 | 910 | 1026 | 116.22 |
| Burford ‘11 | 210 | 162- >360 | 264 | 939 | 950 | 10.87 |
| Burford ‘12 | 210 | 53-359 | 219 | 720 | 725 | 4.90 |
| Bedfordia | 190 | 0-171 | 93 | 853 | 898 | 45.04 |
| Shipton ‘12 | 190 | 207- >360 | 322 | 797 | 897 | 100.02 |

It can be seen from Table 11 that the potential to improve economic margins by more accurately meeting N requirements is large (>£40/ha) at sites where the average measured N optima is very different to the recommended N rate (ie Flawborough 2011, Bedfordia 2012 and Shipton 2012). However, at other sites where the average measured N optima is close to the average recommended rate, the scope for financial benefit is much more modest (<£11/ha) despite each of these sites having large (>100 kg/ha) variation in N optima. This difference between accuracy of the average rate for the field and precision of the application to match variation within the field can be seen in Table 12 where differences in margin and profit foregone are assessed at the average N rate for the field.

**Table 12. Average margins and profit foregone (£/ha) from the chessboard trials when average N rate for the field is same as the average measured N optima.**

| Site | Average N optima *kg N/ha* | Margin with flat rate @ average N opt for field *£/ha* | Average margin @ opt for each plot *£/ha* | Average Profit foregone *£/ha* | 20kg N/ha less than ave opt | 20kg N/ha more than ave opt |
|---|---|---|---|---|---|---|
| Flaw 2010 | 185 | 1073 | 1076 | 3.51 | 5.92 | 5.67 |
| Flaw 2011 | 10 | 1025 | 1026 | 1.73 | 3.14 | 12.22 |
| Burford ‘11 | 246 | 943 | 950 | 6.39 | 7.90 | 6.97 |
| Burford ‘12 | 219 | 720 | 725 | 4.62 | 6.09 | 6.19 |
| Bedfordia ‘12 | 93 | 887 | 898 | 10.71 | 15.02 | 10.60 |
| Shipton ‘12 | 322 | 883 | 897 | 13.40 | 14.86 | 16.67 |

The maximum financial benefit from improved spatial precision of N application, as opposed to improved accuracy on average, for the chessboard trials is between £1.73/ha to £13.40/ha. This is surprisingly small given the size of variation seen in N optima in these trials. It implies that whilst there is large variation in the total range in N optima in the chessboards, only a relatively small proportion of the area is very different to the average N optima. The sites with the greatest profit foregone at Bedfordia and Shipton are those with large areas of very divergent N optima. The fields were of reasonable size and should reasonably reflect the potential benefits for fields in general, except perhaps for large fields with large areas with large differences.

The shape of the N response curve means that under-fertilising can be more costly than over-fertilising. Sylvester-Bradley et al. (2008) calculated over a population of response curves it was worth applying 10-15kg N/ha more than the economic optima in order to minimise this effect. Each chessboard trial here is a population of response curves and the differential effects on profit foregone of under or over applying by 20kg N/ha are shown in the last two columns of Table 12. Whilst at Bedfordia 2012 the cost of under-applying is substantially greater, at other sites the differences are marginal, and at Flawborough 2011 and Shipton 2012 the costs of over-applying by 20kg/ha are bigger than under-applying by 20kg/ha. Overall the evidence from the chessboard trials does not support applying more than the economic optima in order to minimise the perceived risks of under-fertilising.

As well as the potential financial impact from a ‘perfect’ system on N recommendation, it is also possible to quantify the environmental impacts through improved N use and higher yields. Table 13 shows that these impacts are generally very modest, and all accrue from improved accuracy of the average N rate for the field rather than improved precision dealing with the spatial variability. Where measured N optima is higher than recommended, more N is used and yields are higher, where N savings are made the yield penalty tends to be small. Where average N for the field is correct there are no net savings in N fertiliser, as areas requiring less N are compensated by areas requiring more N. The more targeted use of N does give an increase in yield, though this is modest.

**Table 13. Impacts of perfect prediction system on N loss and yield for the chessboard trials.**

| Site | N saved from RB209 *kg N/ha* | Yield difference from RB209 *t/ha* | Yield difference from average *t/ha* |
|---|---|---|---|
| Flaw 2010 | 5 | 0 | 0.03 |
| Flaw 2011 | 180 | -0.16 | 0.01 |
| Burford ‘11 | -54 | 0.42 | 0.05 |
| Burford ‘12 | -8 | 0.09 | 0.03 |
| Bedfordia ‘12 | 97 | -0.24 | 0.09 |
| Shipton ‘12 | -132 | 1.67 | 0.11 |

### 8.1.2 Testing the Auto-N system on the chessboard trials

The use of available data to accurately predict crop N demand, SNS and ultimately N requirement was assessed for each chessboard trial.

Crop N Demand for each site was calculated from past average yields for each plot from previous yield maps, multiplied by crop N content (23 kg N/t feed wheat, 25 kg/t milling wheat). SNS was estimated using the N balance approach to estimate average for the field with variability between plots estimated using the equation from Chapter 5. Cumulative thermal time since sowing was calculated from Irriguide. Fertiliser recovery was assumed constant for each site as detailed in Chapter 6. N requirement was calculated from (CND-SNS) / Fertiliser Recovery and was compared to measured N optima.

Results show varying success in predicting CND (Figure 84) and SNS (Figure 85) between sites. Whilst variation in CND within sites is poorly predicted, average predictions are reasonably accurate except for Flawborough 2011 which was severely affected by drought. Variation in SNS is reasonably predicted at Flawborough 2010 and there is a relationship at Burford 2012. However, relationships are weak at other sites. Absolute predictions are substantially inaccurate at Bedfordia and Burford 2012.

Predictions of N requirement are poor at all the sites (Figure 86), especially at Flawborough 2011 and Bedfordia 2012 where higher SNS and lower CND than expected gives lower N optima than recommended.

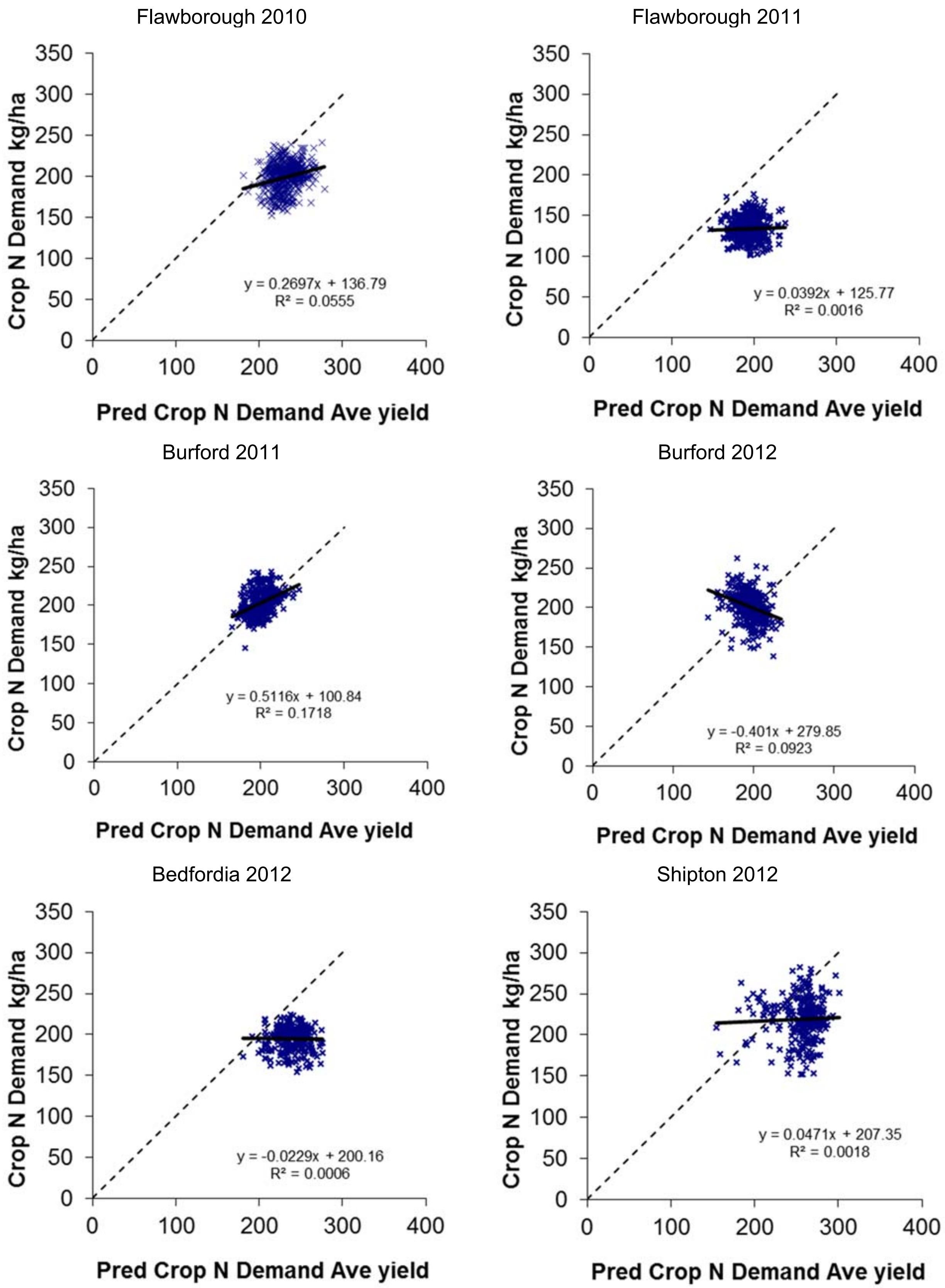



**Figure 84 Prediction of Crop N Demand from past yield data and assumed crop N content (23 kg N/t) for the chessboard trials**

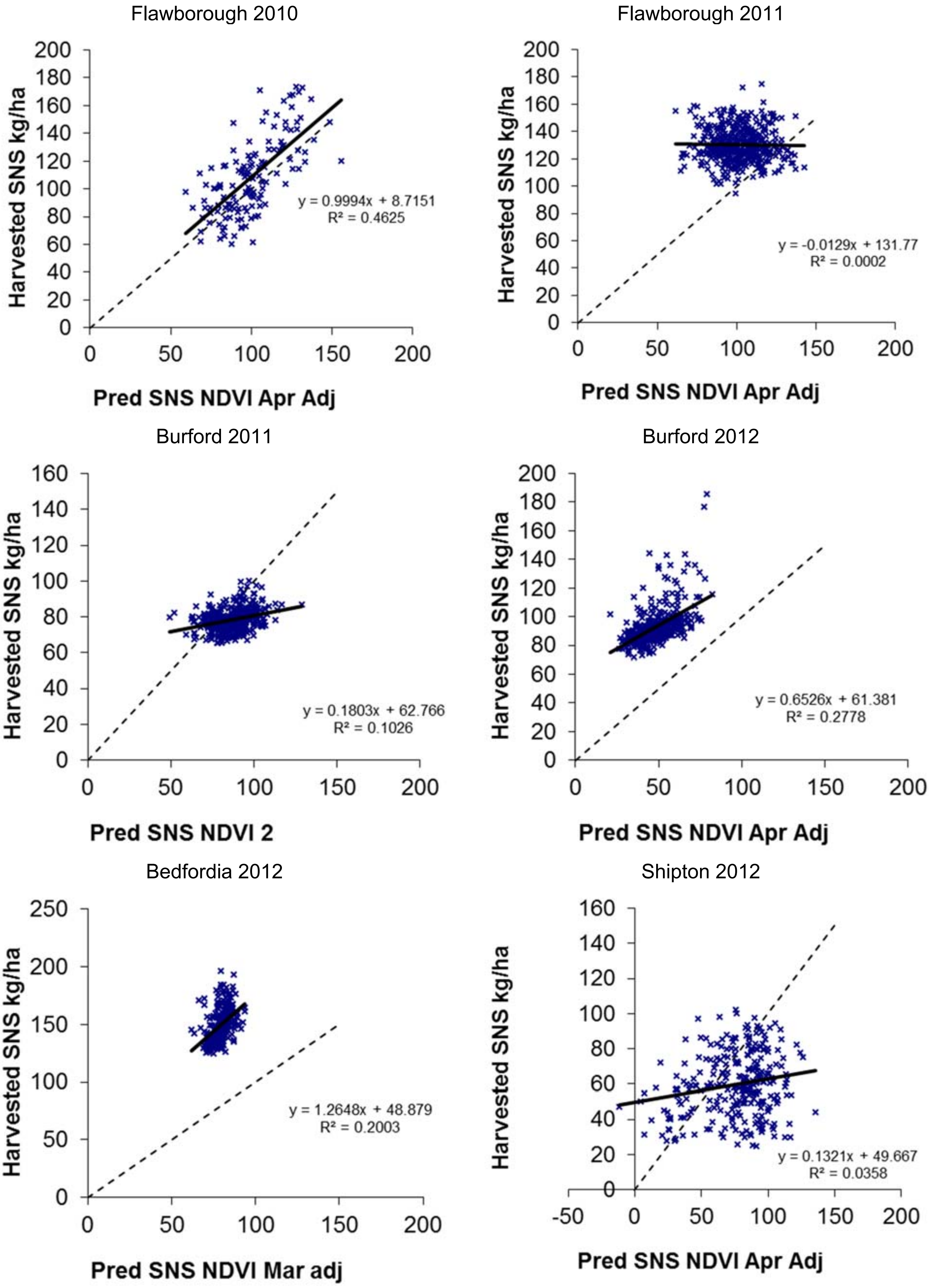



**Figure 85 Prediction of variation in SNS using Crop Circle for the chessboard trials**

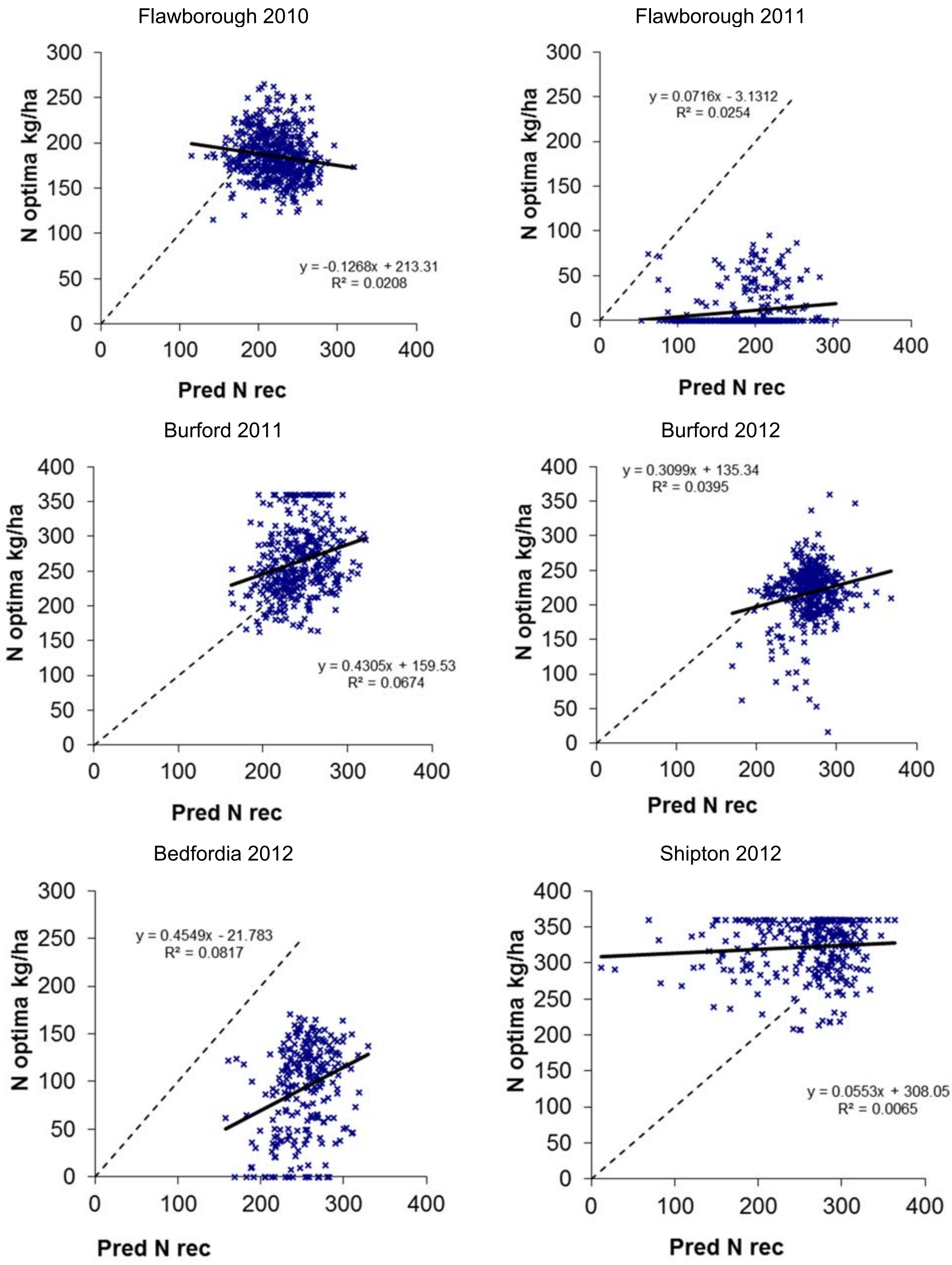



**Figure 86 Prediction of N requirement from Crop N Demand and SNS for the chessboard trials**

The economics of the Auto-N predictions can be compared to flat rate RB209 predictions by comparing margins over N cost and profit foregone from applying the optimum. The economics of the Auto-N system are shown in Table 14 which can be compared to Table 12 for margins at the optima and at RB209 recommended rates.

**Table 14. Impacts of Auto-N prediction system on economic margin, N loss and yield for the chessboard trials.**

| Site | Ave Auto-N recommended rate *kg N/ha* | Average margin Auto-N *£/ha* | Average Profit foregone vs optima *£/ha* | Margin difference to RB209 *£/ha* | N Difference to RB209 Kg/ha | Yield Difference to RB209 t/ha |
|---|---|---|---|---|---|---|
| Flaw 2010 | 221 | 1049 | 26.89 | -23.24 | 31 | 0 |
| Flaw 2011 | 185 | 916 | 110.36 | 5.97 | -5 | 0.02 |
| Burford ‘11 | 243 | 944 | 6.52 | 4.35 | 33 | 0.24 |
| Burford ‘12 | 267 | 711 | 14.09 | -9.19 | 57 | 0.28 |
| Bedfordia | 237 | 783 | 114.84 | -63.40 | 62 | -0.14 |
| Shipton ‘12 | 260 | 851 | 26.89 | 54.55 | 70 | 0.89 |

It can be seen that the economic margins achieved with the Auto-N system are only superior to RB209 flat rate applications at three of the six sites; at the others they are substantially worse. It seems that in trying to improve N recommendations it is easier to get rates ‘more wrong’ than it is to improve accuracy. It is clear again from this that the average N rate for the field is what causes the major economic differences.

## 8.2 Validation trials

In 2013 and 2014 the Auto-N system was tested on eight fields, using either Crop Circle/Optrx or Yara N Sensor tractor mounted crop sensors, or SOYL Nsense satellite imagery to provide SNS estimates using the approach in Chapter 6. Thermal time since sowing for each canopy measurement date was calculated from Irriguide output. For each field spatially variable crop N demand was estimated from previous yield maps, using either estimates for management zones, cluster analysis, calculation of normalised average yields or SOYL performance mapping. SNS for the field was estimated by the N balance technique described in Chapter 6 and checked by SMN testing. Spatial variation in SNS was calculated using the formula developed in Chapter 5. Agrii, SOYL, Yara, Precision Decisions and Agleader each worked with one or more farmers, selecting fields that allowed comparison of at least 4 tramlines, ideally with predominant variation along the length of the tramline.

### 8.2.1 Methodology

To enable some judgement to be made on what the appropriate N rates was, four comparisons were made in each field; the uniform standard N rate to be applied to majority of field representing farm practice; Auto-N variable rate application; flat rate with 60kg N/ha more than standard N rate; flat rate with 60kg N/ha less than standard N rate. The 60kg figure was set in 2014 to match with treatments made in the AHDB LearN project. Each commercial partner worked with the farmer to place the tramline comparisons, create application maps and ensure applications are made appropriately. Where possible fertiliser treatments were preferentially made with pneumatic spreader or applied as liquid UAN, to ensure a distinct cut off at the tramline boundary. Where spinning disc spreaders were used two tramline widths were used for each treatment. Applications were split with generally ~40kg N/ha applied uniformly in February/March and the balance split in two equal applications in April and early May.

Measurement of yield on the tramline comparisons was made by farmer's combine harvester with yield mapping. Where possible we sought to ensure that each tramline width contained at least two combine runs with a completely full header, and that combine runs that span between tramline widths were avoided or data discarded. The harvesting of tramline wheelings was kept consistent between tramlines, and where feasible tramline yield comparison measures were made harvesting in the same direction.  Yield data from the combine was sent to ADAS for statistical analyses. Financial margin over N fertiliser cost was calculated for each yield point assuming grain price of £120/t and N price of £0.75/kg. Yields and margins were averaged for each combine run and each tramline within each field.

### 8.2.2 Results

Details of the validation trials are given below.

Agrii set-up trials with with Nick August at Burford in 2013 & 2014: Yields on the field Sour Corner in 2013 were low due to a hot dry period in June/July which burnt off the crop and meant estimated yield potentials weren't realised. It can be seen from the yield map in Figure 87 that the spatial variation in yield was greater than any imposed treatment difference. The first two tramlines of the eastern side of the field gave lower NDVI measures, was observed to be more 'backward' and gave lower yields than the rest of the field. The spatial variation in this field somewhat compromises fair comparisons between tramlines, but average yields and margins for each are reported in Table 11. Discounting results from tramlines 1 and 10 which are headlands, the results suggest little consistent difference between N rates, with the lowest N rate (130 kg N/ha) actually giving the highest average yields, and therefore the highest margins. The Auto-N system has used a higher N rate on average and seemingly achieved lower yields on this field in this season, giving the lowest gross margin. The higher standard deviations around the Auto-N tramlines, suggest that the lower yield may be due to poorer yielding areas coinciding with these treatments, however further statistical analysis of treatment comparisons either side of the tramline in similarly performing areas do not show any advantage for the Auto-N system.

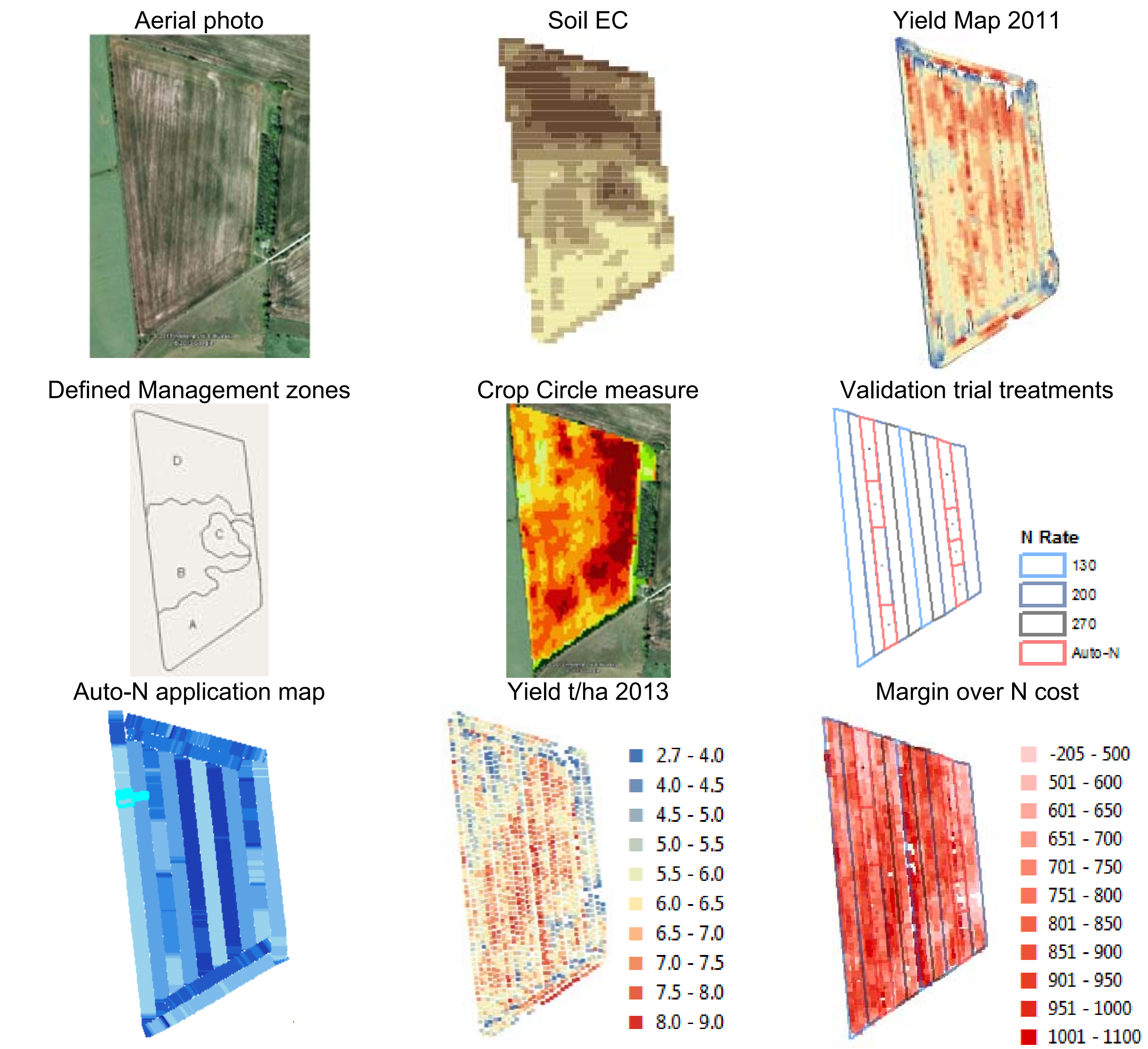



**Figure 87** **Validation trial on field Sour Corner (Nick August, Burford) with Agrii Auto-N system in 2013**

**Table 15. Average Yield and Margin over fertiliser N cost for each tramline for the validation trial in Figure 87.**

| Tramline # from W | N applied | Average Yield t/ha | Standard deviation Yield (t/ha) | Average Margin over N £/ha | Standard Deviation Margin £/ha |
|---|---|---|---|---|---|
| 1 | 130 | 5.99 | 0.823 | 795 | 124 |
| 2 | 200 | 6.43 | 0.667 | 804 | 100 |
| 3 | 245 Auto-N | 5.98 | 1.075 | 701 | 174 |
| 4 | 200 | 6.47 | 1.007 | 810 | 151 |
| 5 | 270 | 6.58 | 0.880 | 771 | 132 |
| 6 | 130 | 7.09 | 0.840 | 959 | 126 |
| 7 | 270 | 6.64 | 0.827 | 781 | 124 |
| 8 | 200 | 6.44 | 0.764 | 807 | 115 |
| 9 | 240 Auto-N | 5.97 | 1.491 | 704 | 231 |
| 10 | 200 | 5.06 | 1.182 | 599 | 177 |

Treatments were set-up in a similar way on this farm in 2014 (see Figure 80). Spatial variation in final yield in this field was much less distinct, but there were not obvious differences between N treatments, only the lower N rate tramline showing a slightly lower yield (Table 16).

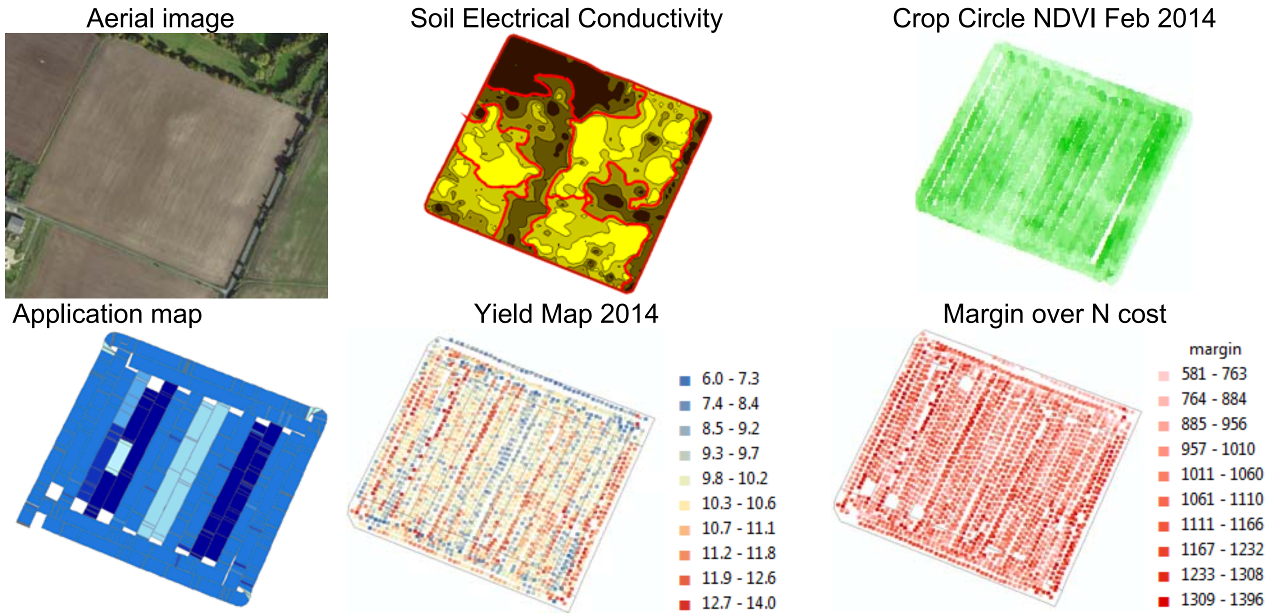



**Figure 88 Validation trial on field Blenheim Hovel (Nick August, Burford) with Agrii Auto-N system in 2014**

**Table 16. Average Yield and Margin over fertiliser N cost for each tramline for the validation trial in Figure 88.**

| Tramline # from W | N applied kg/ha | Average Yield t/ha | Standard deviation t/ha | Average Margin over N £/ha | Standard Deviation £/ha |
|---|---|---|---|---|---|
| 1 | 240 headland | 10.81 | *1.16* | 1130 | *142* |
| 2 | 240 | 10.49 | *0.75* | 1098 | *92* |
| 3 | 240 | 10.03 | *1.39* | 1035 | *160* |
| 4 | Auto-N 238 | 10.40 | *1.01* | 1087 | *124* |
| 5 | Auto-N 267 | 10.16 | *0.53* | 1039 | *71* |
| 6 | 300 | 10.53 | *0.97* | 1056 | *117* |
| 7 | 240 | 10.40 | *0.86* | 1086 | *102* |
| 8 | 240 | 10.20 | *0.63* | 1058 | *77* |
| 9 | 180 | 9.36 | *0.57* | 1004 | *68* |
| 10 | 180 | 10.16 | *0.81* | 1097 | *92* |
| 11 | 240 | 10.59 | *0.79* | 1105 | *91* |
| 12 | 240 | 10.40 | *0.79* | 1082 | *91* |
| 13 | 300 | 10.26 | *0.66* | 1021 | *79* |
| 14 | 300 | 10.49 | *0.70* | 1046 | *81* |
| 15 | 240 | 10.22 | *1.01* | 1057 | *121* |
| 16 | 240 | 9.84 | *0.95* | 1008 | *115* |

Validation trials were set up by SOYL at Bedfordia using SOYL ‘performance mapping’ to estimate potential yield and satellite imagery to estimate variation in SNS. Unfortunately a technical error with the N application meant more N fertiliser was applied than intended compromising the Auto-N comparisons on two fields in 2013 (Fig 89). Spatial variation in final grain yield was greater than any N treatment effect in both fields in 2013.

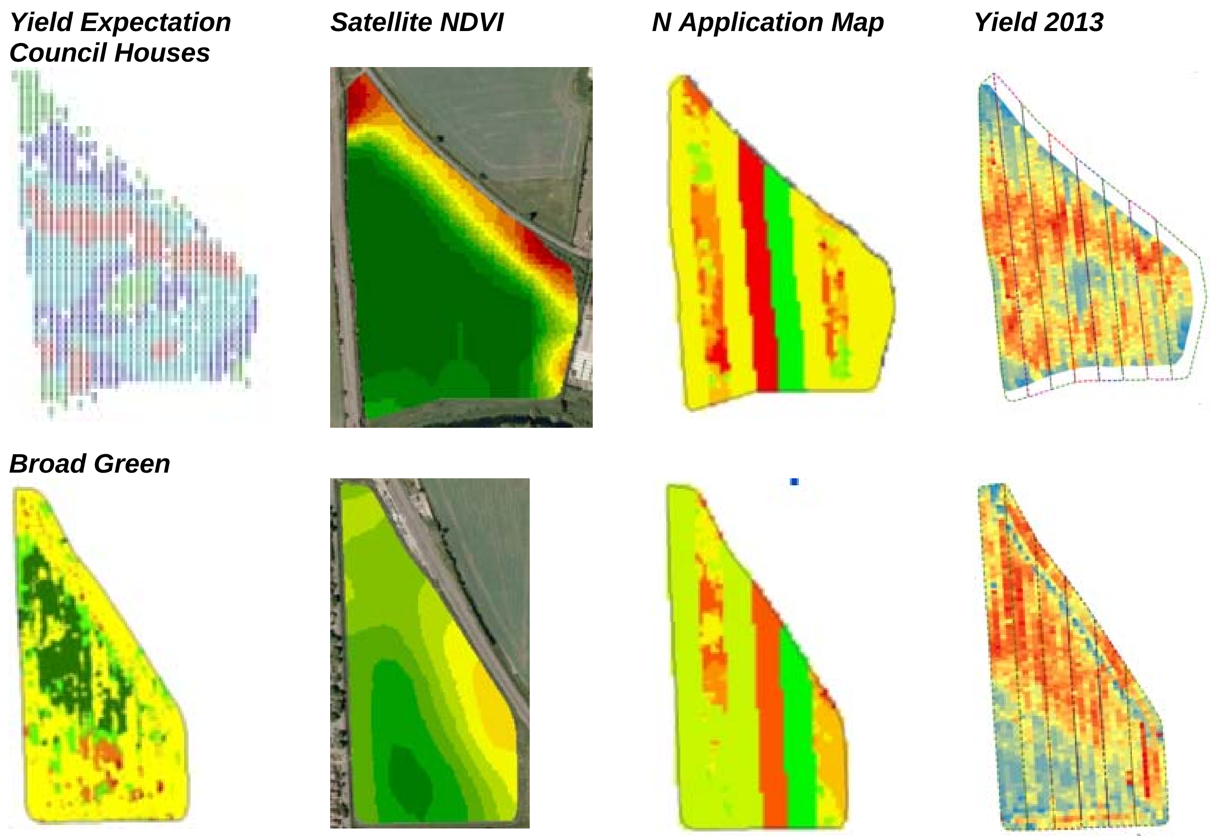



**Figure 89 Validation trials on two Bedfordia Farms fields ('Opposite Council Houses' and 'Broad Green') with Auto-N system utilising SOYL satellite imagery in 2013.**

SOYL conducted two further validation trials at Bedfordia in 2014 (Figure 90). Effects of N rate on yield were limited, with modest impacts of 50kg more or less (Table 17). Comparisons were somewhat compromised by incomplete yield map data, especially in Field 171. In both fields the Auto-N validation area coincided with a lower yielding area and in Field 145 irregular combining severely restricted the useable data points and hampered a fair comparison.

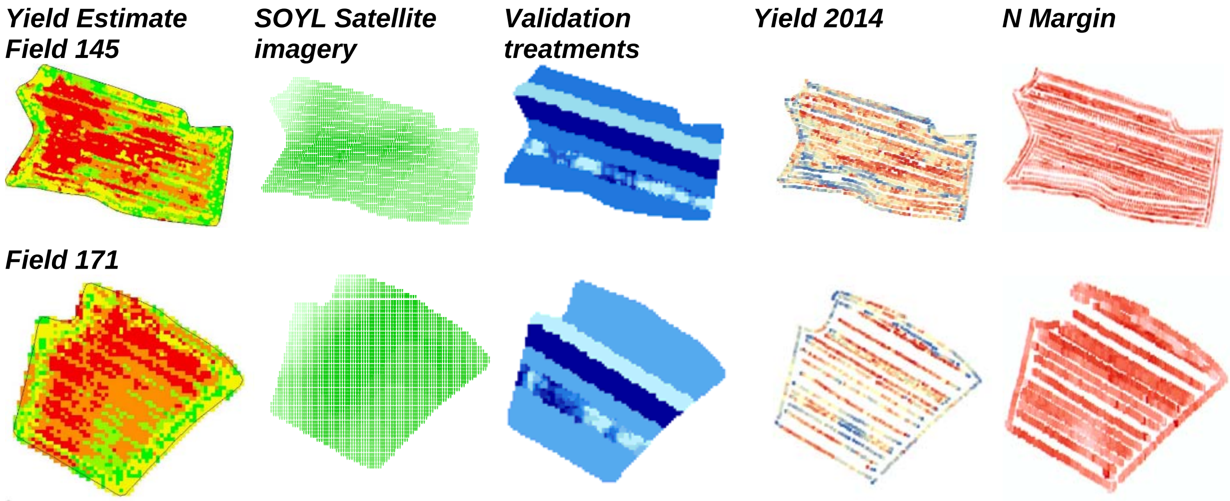



**Figure 90** Validation trial on fields 145 and 171 at Bedfordia Farms with Auto-N system utilising SOYL satellite imagery in 2014

**Table 17. Average Yield and Margin over fertiliser N cost for each tramline for the Bedfordia validation trials in Figure 90.**

| Tramline # from W or N | N applied kg/ha | Average Yield t/ha | Standard deviation t/ha | Average Margin over N £/ha | Standard Deviation £/ha |
|---|---|---|---|---|---|
| *Field 145* | | | | | |
| 1 | Standard (240) | 14.02 | *2.68* | 1514 | *290* |
| 2 | -60 kg | 13.88 | *1.48* | 1514 | *178* |
| 3 | +60kg | 14.26 | *2.16* | 1490 | *250* |
| 4 | Standard (240) | 14.35 | *1.41* | 1535 | *158* |
| 5 | Auto-N (230) | 12.64 | *2.03* | 1371 | *201* |
| | | | | | |
| *Field 171* | | | | | |
| 1 | Standard | 13.37 | | 1359 | *130* |
| 2 | -60 kg | 13.10 | | 1377 | *136* |
| 3 | +60kg | 12.63 | | 1210 | *124* |
| 4 | Standard (240) | 13.03 | | 1318 | *123* |
| 5 | Auto-N (230) | 11.69 | | 1179 | *116* |
| 6 | Standard | 11.47 | | 1131 | *217* |

Further validation trials were conducted by SOYL in 2014 on two other fields comparing farmer's practice with Auto-N and SOYLsense treatments (Fig 91 & 92). Spatial variation dominated the yield maps and there were no strong consistent differences in yield or margin (Tables 18 & 19). The variation in N applied within the Auto-N tramlines was 120-247 kg N/ha at High St Lane and 175-218 kg N/ha at Hamstyles, though on both fields the average applied Auto-N rate was within 10kg of the standard in most tramlines.

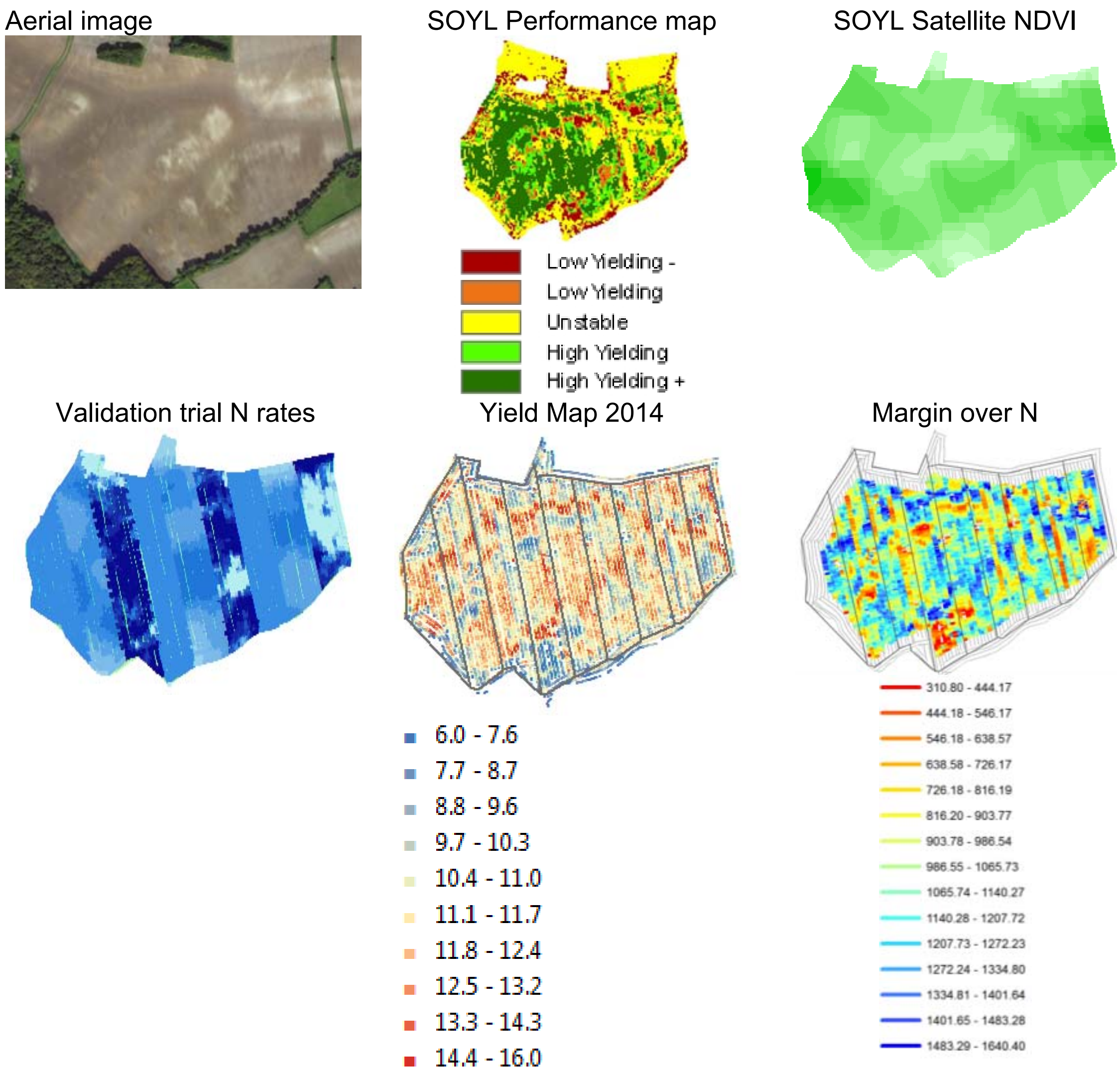



**Figure 91** Validation trial on field High Street Lane with Auto-N system utilising SOYL satellite imagery in 2014

**Table 18. Average Yield and Margin over fertiliser N cost for each tramline for High St Lane SOYL validation trials in Figure 91.**

| Tramline # from W | N applied kg/ha | Average Yield t/ha | Standard deviation t/ha | Average Margin over N £/ha | Standard Deviation £/ha |
|---|---|---|---|---|---|
| 1 | Standard (195) | 10.80 | *1.80* | 1148 | *214.9* |
| 2 | SOYLsense (202) | 11.09 | *1.61* | 1183 | *195.1* |
| 3 | Auto-N (214) | 11.01 | *1.68* | 1162 | *200.0* |
| 4 | Standard (195) | 10.88 | *1.86* | 1147 | *227.5* |
| 5 | SOYLsense (208) | 11.00 | *1.70* | 1141 | *203.6* |
| 6 | Auto-N (212) | 11.25 | *1.53* | 1161 | *180.6* |
| 7 | Standard (195) | 11.31 | *1.44* | 1182 | *172.5* |
| 8 | SOYLsense (202) | 11.25 | *1.57* | 1173 | *186.4* |
| 9 | Auto-N (193) | 11.32 | *1.71* | 1194 | *206.5* |

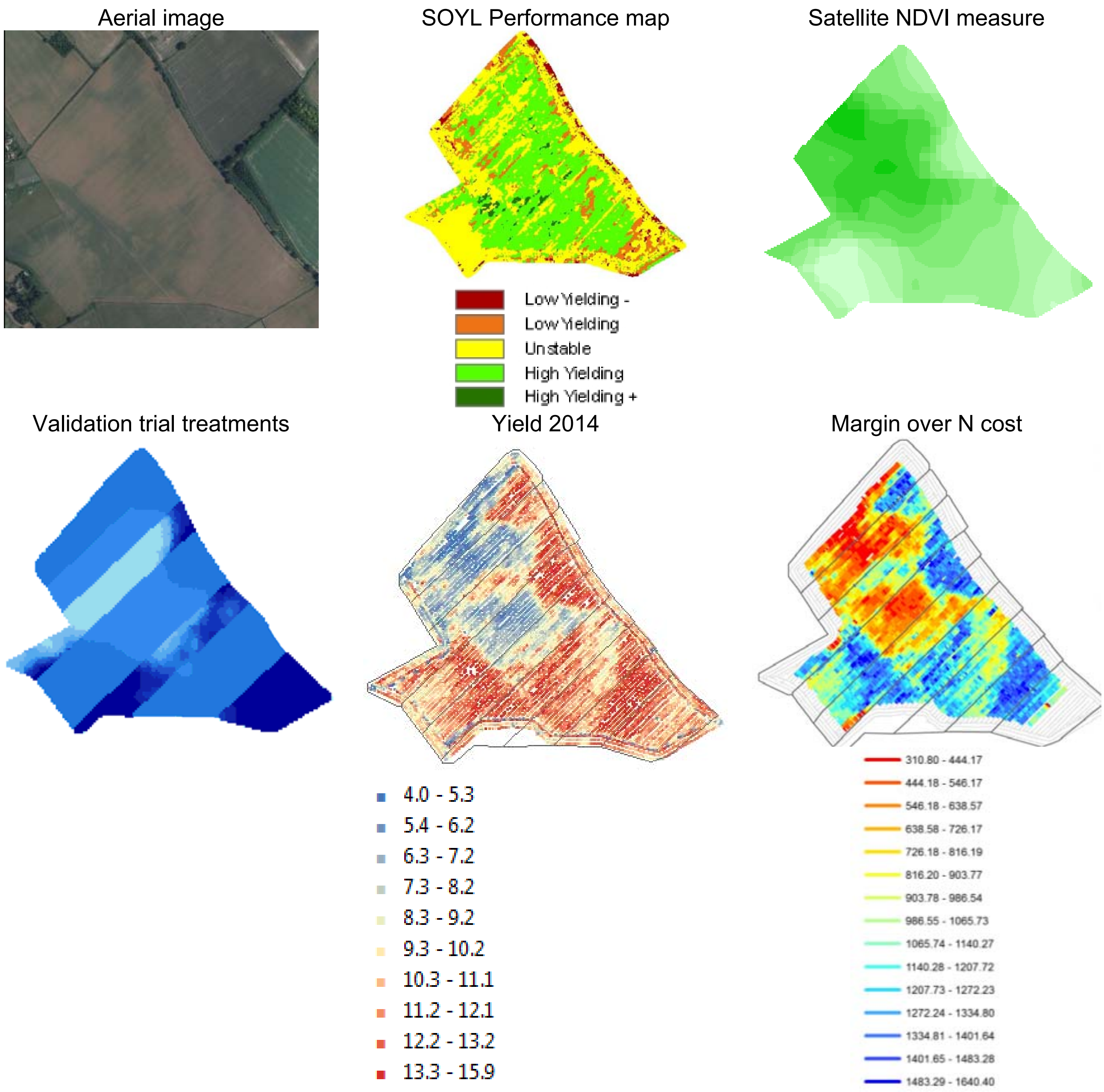



**Figure 92** **Validation trial on field Hamstyles with Auto-N system utilising SOYL satellite imagery in 2014**

**Table 19. Average Yield and Margin over fertiliser N cost for each tramline for Hamstyles field SOYL validation trials in Figure 92.**

| Tramline # from NW | N applied kg/ha | Average Yield t/ha | Standard deviation t/ha | Average Margin over N £/ha | Standard Deviation £/ha |
|---|---|---|---|---|---|
| 1 | Standard (195) | 7.47 | *2.69* | 769 | *322* |
| 2 | SOYLsense (196) | 7.52 | *2.43* | 745 | *291* |
| 3 | Auto-N (182) | 9.15 | *2.14* | 953 | *253* |
| 4 | Standard (195) | 9.56 | *2.72* | 990 | *326* |
| 5 | SOYLsense (197) | 10.09 | *2.17* | 1054 | *261* |
| 6 | Auto-N (203) | 10.84 | *1.79* | 1139 | *216* |
| 7 | Standard (196) | 10.73 | *1.45* | 1130 | *174* |
| 8 | SOYLsense (198) | 10.73 | *1.60* | 1249 | *191* |
| 9 | Auto-N (216) | 10.93 | *1.46* | 1140 | *175* |

There was little evidence that the Auto-N treatment performed better than standard; the majority of variation between tramlines was due to inherent spatial variation.

Precision Decisions tested three fields using the Yara N sensor to estimate SNS and past yields to estimate Crop N Demand. Application maps were generated in Gatekeeper for fields at Flawborough, JSR and with David Blacker.

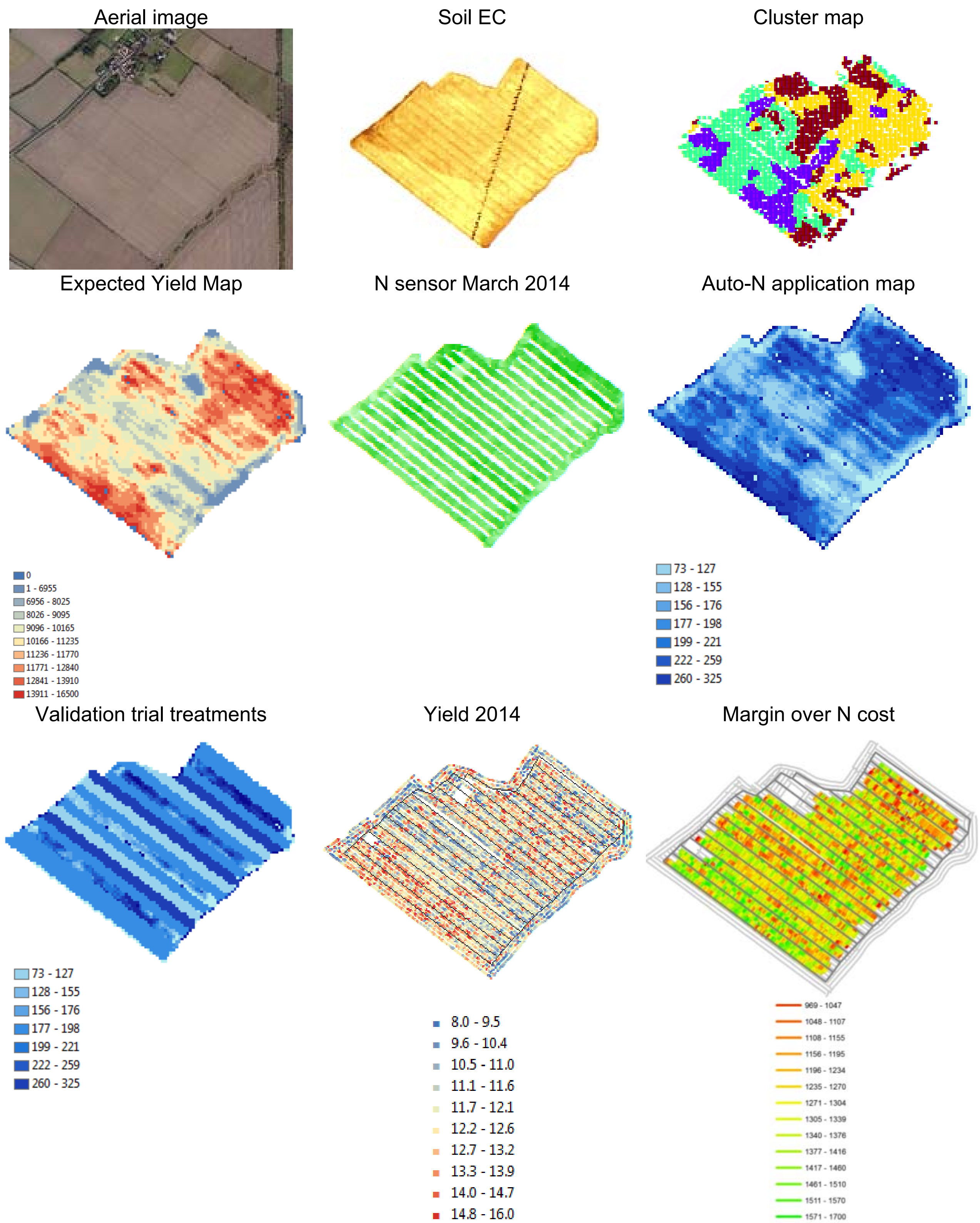



**Figure 93 Validation trial on field Number 5 (Flawborough Farms) with Auto-N system utilising N sensor**

At Flawborough variation in expected yield hence crop N demand was greater than variation in canopy reflectance from the N sensor, so the Auto-N application Map was more driven by variation in yield (Figure 93). The size of field here allowed greater replication of treatments than at other fields tested.

**Table 20. Average Yield and Margin over fertiliser N cost for each tramline for Number 3 field (Flawborough) validation trial in Figure 93.**

| Tramline # from SW | Treatment | N applied kg/ha | Average Yield t/ha | Standard deviation t/ha | Average Margin over N £/ha | Standard Deviation £/ha |
|---|---|---|---|---|---|---|
| 1 | Standard | 180 | 12.61 | *0.99* | 1369 | *119* |
| 2 | Auto-N | 218 | 12.61 | *1.13* | 1339 | *140* |
| 3 | Standard | 180 | 12.31 | *1.07* | 1333 | *129* |
| 4 | High | 240 | 12.22 | *0.83* | 1273 | *101* |
| 5 | Low | 120 | 11.84 | *0.90* | 1328 | *108* |
| 6 | Standard | 180 | 11.68 | *1.26* | 1257 | *151* |
| 7 | Auto-N | 153 | 11.80 | *0.97* | 1293 | *127* |
| 8 | Standard | 180 | 11.82 | *1.02* | 1274 | *122* |
| 9 | Low | 120 | 11.70 | *1.11* | 1310 | *133* |
| 10 | High | 240 | 12.27 | *1.06* | 1278 | *128* |
| 11 | Standard | 180 | 12.03 | *1.06* | 1299 | *127* |
| 12 | Auto-N | 227 | 12.40 | *1.10* | 1307 | *139* |
| 13 | Standard | 180 | 12.30 | *1.09* | 1331 | *131* |
| 14 | Low | 120 | 12.10 | *1.24* | 1358 | *149* |
| 15 | High | 240 | 12.26 | *1.10* | 1277 | *131* |
| 16 | Standard | 180 | 11.54 | *1.21* | 1240 | *146* |
| 17 | Auto-N | 297 | 11.93 | *1.17* | 1195 | *148* |
| 18 | Standard | 180 | 11.76 | *1.20* | 1267 | *144* |
| *Averages* | Standard | 180 | 12.05 | *1.16* | 1302 | *139* |
| | Auto-N | 214 | 12.20 | *1.14* | 1293 | *146* |
| | Low | 120 | 11.84 | *1.07* | 1328 | *128* |
| | High | 240 | 12.25 | *1.16* | 1276 | *118* |

Overall, N applications from the Auto-N system were slightly higher than the standard N rate and yields were also slightly higher, but not high enough to pay for the extra N as the margin was slightly lower (Table 20). The N rate with +60kg N/ha gave the highest yield but the lowest margin, whereas the -60kg N/ha treatment gave the lowest yields but being only 0.4 t/ha lower than the highest rate, the lowest N rate gave the highest margin. This suggest that the optimal N rate for this field was considerably lower than the standard rate applied, at least in this year.

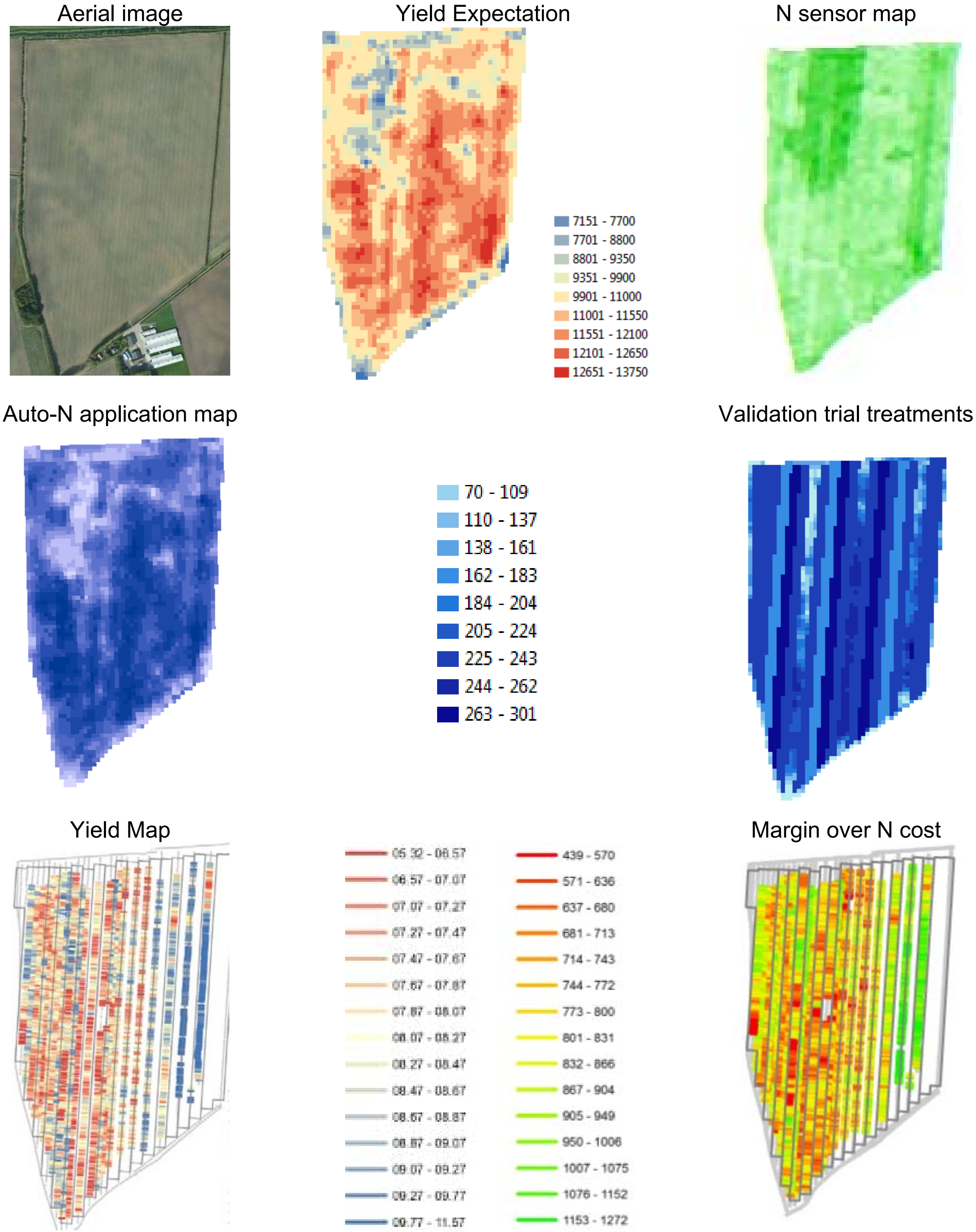



**Figure 94 Validation trial on field Scurfs Decoy at JSR Farms with Auto-N system utilising N sensor**

The field at JSR Farms has an historically lower yielding area at the NW of the field, which also gave the greatest canopy reflectance in spring so indicated the highest SNS. This gave this area the lowest N requirement using the Auto-N system. Yields in this area were not much affected by low or high N rates so the low N rates of the Auto-N system gave a higher margin in this area (tramline 5; Table 21). Yield map data for the eastern half of the field are incomplete, compromising its robustness. Over the field differences in yield between high and low N rates were small, and the lowest N rate gave the highest margin.

**Table 21. Average Yield and Margin over fertiliser N cost for each tramline for Scurfs Decoy (JSR Farms) validation trial in Figure 94.**

| Tramline # from SW | Treatment | N applied kg/ha | Average Yield t/ha | Standard deviation t/ha | Average Margin over N £/ha | Standard Deviation £/ha |
|---|---|---|---|---|---|---|
| 1 | Standard | 205 | 8.02 | *0.83* | 799 | *100* |
| 2 | Low | 145 | 7.81 | *0.63* | 821 | *76* |
| 3 | High | 265 | 8.25 | *0.72* | 778 | *87* |
| 4 | Standard | 205 | 8.00 | *0.92* | 796 | *111* |
| 5 | Auto-N | 144 | 7.90 | *0.95* | 833 | *124* |
| 6 | Standard | 205 | 7.62 | *0.64* | 751 | *77* |
| 7 | Low | 145 | 7.56 | *0.94* | 792 | *113* |
| 8 | High | 265 | 7.96 | *0.69* | 743 | *83* |
| 9 | Standard | 205 | 7.99 | *0.68* | 794 | *82* |
| 10 | Auto-N | 208 | 7.61 | *0.57* | 747 | *69* |
| 11 | Standard | 205 | n/a | *n/a* | n/a | *n/a* |
| 12 | High | 265 | 8.83 | *0.56* | 848 | *67* |
| 13 | Standard | 205 | 8.53 | *0.63* | 860 | *76* |
| 14 | Low | 145 | 9.98 | *0.90* | 1082 | *108* |
| 15 | Standard | 205 | 9.01 | *0.85* | 917 | *102* |
| 16 | Auto-N | 164 | 9.55 | *1.17* | 1015 | *127* |
| *Averages* | Standard | 205 | 8.03 | *0.82* | 799 | *99* |
| | Auto-N | 164 | 8.28 | *1.23* | 863 | *152* |
| | Low | 145 | 8.23 | *1.23* | 872 | *147* |
| | High | 265 | 8.22 | *0.75* | 774 | *90* |

At David Blacker's field the N sensor canopy reflectance showed a less 'green' area on the south-eastern edge indicating a lower SNS and higher N requirement (Figure 88). Historic yields had also been higher in the south of the field, especially in the south-west corner, indicating higher crop N demand and high N requirement. Lower historic yields in the north of the field gave a lower N requirement.

Spatial variation in yield in 2014 roughly matched that from the N Sensor and from previous yield maps. The spatial variation in the south of the field coincided with the treatment boundary between tramlines 1 and 2, with the highest yielding area in the south of the field perhaps overstating the advantage of the Auto-N system in tramline 1 (Table 22). The trend in spatial variation in yield west to east in this field was confounded with the treatments making it difficult to draw conclusions on treatment differences. However the higher N rate in tramline 5 appears to give a substantially higher yield (1 t/ha) than the lower N rate in tramline 6, although the higher margin is given by the standard N rate in tramline 4.

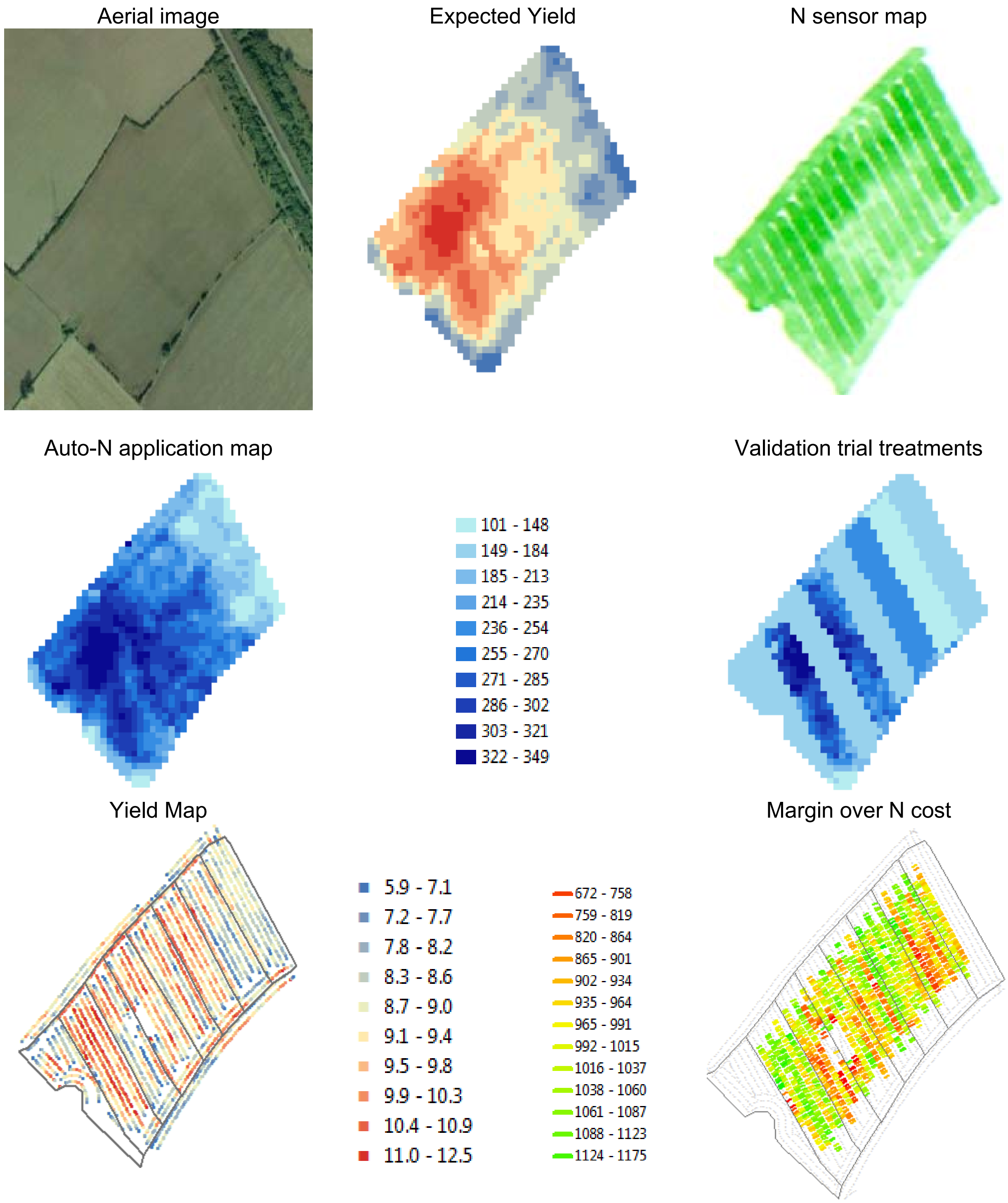



**Figure 95 Validation trial on field Overton at David Blacker's farm with Auto-N system utilising N sensor**

**Table 22. Average Yield and Margin over fertiliser N cost for each tramline for Overton field (David Blacker) validation trial in Figure 95.**

| Tramline # from SW | Treatment | N applied kg/ha | Average Yield t/ha | Standard deviation t/ha | Average Margin over N £/ha | Standard Deviation £/ha |
|---|---|---|---|---|---|---|
| 1 | Auto-N | 276 | 10.28 | *1.56* | 943 | *182* |
| 2 | Standard | 190 | 9.00 | *1.68* | 854 | *201* |
| 3 | Auto-N | 262 | 9.49 | *1.69* | 857 | *208* |
| 4 | Standard | 190 | 9.63 | *1.35* | 930 | *164* |
| 5 | High | 250 | 9.85 | *1.33* | 909 | *160* |
| 6 | Low | 130 | 8.88 | *1.33* | 886 | *160* |
| 7 | Standard | 190 | 9.20 | *0.94* | 884 | *116* |

### 8.2.3 Conclusions from validation trials

We have shown using measures from the chessboard trials and from commercial trials on-farm that it is possible to use precision technologies to calculate N fertiliser recommendations using the principles of CND, SNS and fertiliser recovery. However, it has not been possible to demonstrate that such a recommendation system will inevitably deliver improved yields, profitability or N fertiliser use. Indeed, it seems from the chessboard experiments that systems aimed to improve N fertiliser accuracy can actually lead to larger errors. Whilst there is large variation in N optima it can be easier to make predictions worse rather than better. Caution is required to the extent that N rates are adjusted in field.

The validation trials have demonstrated the many difficulties in conducting tramline comparisons, and the need for careful interpretation. There is a need for better methodologies to deal with yield map data and to analyse, visualise and interpret tramline comparisons. The comparison and evaluation of variable rates is particularly challenging.

It is striking from the validation trials how the inherent spatial variation is so much greater than any variation due to N treatments. Even large differences in N rate (120kg N/ha) in the trials here have given only modest differences in yield, and these differences are often insufficient to pay for the difference in N. This suggests that N is not the major driver of the variation in yield within fields.

The evidence presented here cannot be used to show a large economic benefit of adopting an Auto-N system. It also seems that any potential benefits to the environment through reduced N use or improved yields from more precise variable rate management can only be modest, even with a perfect system. The larger benefits come from improving recommendations at the field or management zone level, but there don’t seem to be quick fixes to robustly aid these decisions. Instead it seems likely that experience over years is required to build confidence in the appropriate N rates for sub-fields, fields and farms. Potential for Precision Farming to improve N management for the benefit of farming and the environment are perhaps not just to be found addressing within field variability, but to help make better decisions field to field, and for the farm as a whole. This should be reflected in future work developing and testing precision farming technologies to improve N management across the farm over the rotation and through differing years.

# 9 Discussion & Conclusions

We have learnt an enormous amount through the course of this project. It has improved our fundamental understanding of N requirements and their determinants. It has highlighted the enormous variability within fields, showing the importance of soil and how little we really understand how the soil impacts crop growth & requirements. It has demonstrated the power of conducting experiments at the field scale, and the potential to work with farmers to set up and measure field-scale trials. And it has shown the value in precision farming datasets to improve on-farm decision making. Variation in N requirements is large, as is the variation in yield, protein, soil N supply and fertiliser recovery.

We have shown that the core principles of the Auto-N system, based on the concepts set out in the AHDB wheat N Management Guide, are sound. It is possible and rational to calculate N requirements based on estimates of Crop N Demand, Soil N Supply and Fertiliser Recovery, whether on a field by field or within field basis. Past yield maps can be used to estimate spatial variation in Crop N Demand and canopy sensing, whether on tractor or from satellite, can be used to estimate spatial variation in Soil N Supply.

However, the large and somewhat unexplained variation in measured N requirements means that any prediction system will inevitably produce errors and improvement over the standard recommendation system (or even a standard figure of, say, 200 kg N/ha) is likely to be relatively modest. It is evident from the chessboard trials that getting an accurate field average is considerably more important financially than precisely dealing with the variation within the field. Indeed, it is surprising how small the calculated benefits of variable rate N application are in terms of profitability, yield, N savings, N leaching and GHG emissions. Other studies have claimed larger benefits (eg Biermacher et al., 2009; Knight et al., 2009). The perception that precision farming technologies will make a large contribution to sustainable intensification through better targeting of fertiliser inputs (Day, 2005) may be challenging to fulfil through variable rate N alone. It is possible that the greater potential for precision farming comes through deriving learnings through shared data and using technologies to evaluate agronomic interventions on farm, rather than just through better targeted variable applications.

This project didn't aim to evaluate current commercial systems for variable rate N management. However, the findings here support the principle that thinner, less 'green' crops are associated with a lower SNS and so warrant extra N application in relation to thicker greener areas. This is the basis of most commercial variable rate systems, albeit not expressed in terms of SNS. Most commercial systems do not explicitly account for variation in yield potential, though given the positive relationship between yield and SNS seen here its estimation can be important to avoid the potential under-application of areas with higher SNS and higher yield potential, or over-application to low SNS areas with low yield potential. However, many commercial systems do advocate switching from ‘Robin Hood’ (rob from the rich, give to the poor) to a ‘King John’ (give to the rich) approach later in the season. Whilst we have not tested such an approach here, it does in principle help account for the higher requirement of higher yielding crops. We have seen that higher yielding areas tend to show greater ‘greenness’ in canopy reflectance measures late in the season, and the application of additional N for yield later in the season is appropriate, once the canopy has been built and lodging risks from extra N minimised. Trials to compare such commercial systems would be of value, but as shown in Chapter 7, it is very difficult to properly compare and evaluate variable rate systems. The measurements made possible by precision farming technologies can provide useful management tools to assess variability within and between fields. However, deciding how to adapt management based on that information is not straight-forward and it seems unlikely that any single algorithm could result in reliable decisions without reliance on human experience. The greatest value of canopy sensing seems to be in its ability to help detect areas and fields with high SNS early in the season, and to monitor N status of crops through the season. It is important to know the cause of the spatial variation seen in order to have confidence that it can be rectified by varying N fertiliser; if the reason for poor performing areas is not known the best response may be to reduce input costs (Oliver et al., 2010). Canopy sensing could usefully give much information about crop status between fields and between years, as well as within fields, through the comparison of curves. Much could be learnt and inferred about the causes of differences in crop performance by comparison to ‘benchmark’ curves, and thus how to remediate poorer crops and manage stronger ones. Systems are required to enable such comparisons to be made, and ultimately decision support tools could be developed.

The chessboard trials have transformed our understanding of fertiliser N requirements. Previously it has been difficult to test the influence of soil induced differences in individual components of N optima; previous N responses came from experiments on different farms and fields and often in different years so that management and variety differences are confounded with inherent soil differences. The chessboard experiments give a unique opportunity to understand how soil variation affects crops' demand for N, the supply of N from the soil, fertiliser recovery and the requirement for N within individual fields. The major learning has been the degree of spatial association between the components, especially the positive relationship between yield and SNS, and negative relation between SNS and fertiliser recovery. These relationships explain much of the variation in N requirement, and explain the difficulty in showing strong relationships between N requirement and any of its individual components. The relative importance of the components varies from site to site and within sites, generally as a function of soil type. Knowing only one component is not enough; we must consider all components together to predict N fertiliser requirement with reasonable precision. Interactions between the components can vary from place to place.

The large variation in fertiliser recovery and absence of any good relationship with N optima requires further examination. We need to understand this so that we can improve fertiliser recovery and the use of fertiliser to obtain larger yields without greater inputs (Sylvester-Bradley & Withers, 2011).

The spatial variation in yield is large, but it is evident from this study and others that the relationship between yield and N requirement is not strong. Whilst the crop in higher yielding areas evidently needs to take up more N to satisfy the demand for protein formation in the grain, these areas tend to also have more N available from soil and perhaps achieve a higher recovery of fertiliser N. The advantages in terms of extra yield of using optimal rather than fixed N rates are generally very small in relation to the spatial variation in yield. It is clear that N is not the major explanatory factor in yield variation within and between fields; whilst variation in N optima was large, spatial variation in yield at the N optimum was also large – lower yielding areas will not yield as much as higher yielding areas, however much N is applied to them. Applying optimal N rates everywhere barely diminishes the spatial variation in yield.

The lack of a strong relationship between yield and N requirement raises some important questions. Firstly, the N Management Guide and Auto-N logic both invoke a direct relationship between yield and N recommendation of around 40 kg N/t extra grain yield (23kg N/t content / 0.6 fertiliser recovery). This is difficult to support with the empirical evidence, and it leads to some very high estimated N requirements for high yielding crops (e.g. >400 kg N /ha for a 15 t/ha crop with 100 kg/ha SNS and 60% recovery). The fact that recent very high yielding crops have been achieved with much more modest N inputs (e.g. Yield Enhancement Network 2015; www.yen.adas.co.uk) demonstrates that high yields aren't synonymous with high N rates. It seems likely that the marginal increase in N demand at high yields is less than 23 kg N/t, as harvest index increases and protein content reduces. This warrants further attention within the review of fertiliser recommendations (RB209), especially for growers targeting high yields.

Whilst nitrogen limitation has been posited as a potential cause of the yield plateau in wheat (Knight et al., 2012), evidence from the trials here would suggests that the size of the impact of any likely sub-optimal N use within-fields is likely to be small.

That N doesn't explain much of the spatial variation in yield, leaves the large and important question of what is the major cause of yield variation within and between fields? This should be a fundamental question of utmost concern to crop and soil researchers. However, we know of no research directly tackling this question. Fundamentally our current understanding of how soils can affect crop yield is through the availability of water and nutrients, although the recent concept of ‘soil health’ apparently invokes additional microbiological effects (Laishram et al., 2012). Spatial experimentation such as the chessboard trials provides a unique opportunity to better understand soil-induced variation, and hence understand soil effects on yields more generally, as variation in yield can be assessed in the presence and absence of resources suspected of limiting yields. Here we have assessed the impact of N fertiliser on yield, but similar experiments could be used to assess the range of nutrients, or even to quantify the impact of water limitation by providing trickle irrigation.

The amount of variation in grain protein at the N optima both between fields and within fields is disappointing. It had been hoped that systems could be developed to use grain protein content as a reliable measure of success of N management between and within fields. Instead it appears that spatial differences in the dynamics of grain protein accumulation may be an important driver in differences in crop N demand and N requirement. There is a need to better understand the drivers of soil & weather induced differences in grain protein content and their impact on N requirements. The Fertiliser Manual RB209 advocates using the deviations in grain protein from 11% as an indicator of how previous N rates have related to optimum N, and this is the only mechanism through which it justifies higher N rates for higher yielding crops. Whilst grain protein is still the best available measure of success, it needs to be used with caution, averaging across fields and years (Sylvester-Bradley & Clarke, 2009).

Consideration of spatial variation raises the question of what is the appropriate scale to measure or manage crops – individual plant scale (e.g. by laser scanning), ~1 $m^2$ (e.g. through individual spray-nozzle control), ~10 m grid (e.g. by spray-boom section), sub-field zones, field, farm, landscape, or region. Whilst the chessboard trials demonstrated large variation in N optima within fields, they also showed large variation between fields, the mean N optimum at Flawborough 2011 being almost zero. From an economic perspective, it appears most important to achieve an accurate average N rate at the largest scale before accounting for variation at a smaller scale. Small errors have small costs, but large errors have disproportionately large costs. It is therefore more important to avoid a few large errors than to correct many small errors, and decisions should generally tend towards the mean. Whilst the shape of the N response curve generally means there is slightly more to be lost from under-fertilising than over-fertilising, and past work has shown that it can be worth over-fertilising on average by around 10–15 kg N/ha (Sylvester-Bradley et al., 2008), the chessboard trials here provided no support for this. It is likely that the perceived need to avoid the risk of yield loss by applying more than the optimum is over-stated in the industry.

It seems the primary aim for N management overall should be to achieve accuracy first for the whole country (e.g. through national fertiliser recommendations), then for whole farms, then field by field, and lastly for areas within fields. The highest impact decisions are made at the largest scale, these therefore require the most care. Assuming larger scale decisions are correct, the value of making adjustments at a finer scale is proportional to the scale being considered; fine scale adjustments have small benefits, dependent on the flatness or relative curvature of the response function of the decision being made (Rogers et al., 2016). However, the crux of the this is in the assumption that “larger scale decisions are correct”. Major opportunities therefore come from the management and aggregation of crop intelligence: if observations at a small scale aggregate to indicate that a larger scale decision is inexact, it is more important to correct all decisions at that larger scale, than just to make corrections where the observations have been made. This could apply across farms as well as within farms, so there could be big pay-backs from networking farms to collate and interpret crop intelligence, and also better representative crop monitoring (of any reasonably predictive metrics) at national and regional scales, for example with satellite data. There is suggestion from analysis of protein content across farms (Weightman et al., 2011) that these may differ in their achieved protein contents and hence N requirements (Kindred & Sylvester-Bradley, 2014). This suggests that some farms may consistently need more N than is advised in the Fertiliser Manual (RB209; Defra, 2010) to achieve optimal yields and quality, whilst others may consistently need less, so could make savings on N fertiliser use. Whilst grain protein is still a useful metric, we need more certain measures of whether N use on farm is too low or too high.

The chessboard trials here have demonstrated that experiments can be conducted at the field scale set up with farm equipment by farmers. Modern fertiliser spreader technology makes it easy for farmers set up simple tramline comparisons for themselves, comparing 50kg N/ha more and less than their standard rate on adjacent tramlines. Canopy sensing and yield mapping on the combine allow the effects of this difference in N rate to be quantified relatively easily. The validation trials here demonstrated the feasibility of this approach in practice, and now a new AHDB project titled ‘LearN’ is testing whether such tramline comparisons can usefully be used by farmers to judge the N requirements on-farm. Such approaches have been successfully demonstrated for N management elsewhere in the world, even in small-scale agriculture without the use of precision farming technologies (Yue et al., 2015).

The use of spatial experimentation and farmer-managed line trials represents a large opportunity for future research, especially for better understanding soils and agronomic interactions. Traditional crop research employs experimental designs that minimise the effects of uncontrolled environmental variables (particularly soil variation) so that measured responses (e.g. in yield) to controllable inputs (seed, tillage, fertiliser, pesticides) can be tested, but the small area of these trial plots commonly restricts the relevance of their results to one soil. We suggest that field scale spatial experiments offer an opportunity for research scientists to investigate the multiple unknowns involved in extrapolation between small and large scales; not least the interactions between agronomic innovations (e.g. in variety, chemistry, machinery) and soil variation. As a result of this realisation, ADAS now has an Innovate UK sponsored project (ref: 101627) which is developing an approach named Agronŏmics to develop rigorous field protocols, data processing software and geostatistical analyses to support the use of tramline trials for scientific research (Kindred et al., 2016; Rudolph et al., 2016) Whilst several studies recognise the need and power of on-farm spatial experimentation to provide local information to drive site specific management (e.g. Whelan et al., 2012 ; Hong et al., 2005), few have recognised its potential role in wider research questions if robust geo-statistical approaches can be developed (Panten et al., 2010; Pringle et al., 2010; Lawes & Bramley, 2012).

The Auto-N Project sought to show how the wide ranging sets of data and information available to growers from precision technologies could be integrated usefully so as to improve N fertiliser management. Whilst we have been able to show the priorities that should be attached to particular datasets for N management purposes, it is clear that an enormous amount of data collected by farmers remains under-utilised. Growers often still do not know how to store, transfer, view and integrate yield map data, let alone know what to do with it once it is processed. However, the opportunities from the 'big data' stored on farm are beginning to be recognised. It is now possible to imagine a future not too far away where a farmer can stand in a field with a smart phone and, via web services on 'the cloud', instantly access all past field records (crop, varieties, agrochemicals, fertilisers, etc.), see underlying soil maps (integrated from national datasets), imagery from satellites (e.g. soil brightness) and from soil scanning (EMI) which define management zones, and data from analyses of soil samples (or possibly even in-field soil sensing) for P, K, Mg, pH SOM% on fine scale. It could also be possible to view past and latest satellite imagery of the crop, all past tractor & machinery movements across the field (with quantified diesel use), all past yield map and crop sensor map data (and useful integrated measures from these – e.g. performance maps with cluster analysis to determine similar zones), along with past meteorological records and future weather forecasts interpolated for this particular point. Via an App Store, a whole suite of potential crop decision support package algorithms could be available that integrate the data sources to provide advice on disease forecasting, pest monitoring, weed management, fertiliser recommendations, best PGR use, etc. This ultimate vision might be termed a 'Global Crop Intelligence System' (GCIS) and whilst its realisation appears eminently feasible, even with currently available technology, this will clearly be an enormous task. The key to ensuring success will be in choosing the most telling initial steps for investment and development. Whilst the Precision Farming industry has mainly focussed on enabling fine-tuning of input rates within fields, the Auto-N Project has provided an invaluable opportunity, working in the context of the most important variable input (nitrogen) for the most extensive UK crop (wheat), to take a broader view, and to assess what the most valuable first steps towards the GCIS might be. It has shown that the largest opportunities are at large rather than fine scales. Thus the initiatives which achieve most effective and valuable successes are likely to be those that integrate these many data into useful information *at a broad scale*, so as to maximise the value of automating better farming decisions.

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