University of Reading

Towards More Precise Sugar Beet Management Based on Geostatistical Analysis of Spatial Variability within Fields

Salar A. Mahmood

Thesis submitted for the Degree of Doctor of Philosophy

School of Agriculture, Policy and Development

University of Reading

Reading, Berks RG6 6AR, UK

2015

DEDICATION

I dedicate my thesis to my family, especially my loving children Sarkar, Sarmad, Sooz and Silvan who brighten my life. A special feeling of gratitude to my parents and wife, who have supported me throughout the entire doctorate programme.

Declaration of original authorship

Declaration

I confirm that this is my own work and the use of all materials from other sources has been properly and fully acknowledged.

Salar A. Mahmood

Acknowledgements:

I am very grateful to Kurdistan regional government for providing me with the scholarship and support to study for a PhD Degree.

I would like to acknowledge and thank the School of Agriculture, Policy and Development, University of Reading for allowing me to conduct my research and providing any assistance requested.

I am extremely grateful to my supervisor (Alistair Murdoch) for his valuable supervision, guidance and sharing his professional experiences and time throughout the study period.

Many thanks to Liam Doherty, Caroline Hadley, Richard Casebow and Paul DeLaWarr for their help and technical support.

I would also like to thank Broom’s Barn Research Station and Trumpington Farm Company for providing fields, labs and transportation. Especial thanks goes to Mark Stevens, David Knott, Andrew Creasy and Will Foss of Agrii.

I appreciate the analysis of final harvests done by British Sugar and managed by Colin Walters. I am grateful to Robin Limb for providing me with data and figures of sugar beet production in the UK.

I am also grateful to Margaret Oliver and Richard Webster from Rothamsted Research for providing valuable advice on geostatistical analysis, and Qi Aiming and Tom Osborne for their help on modelling.

I sincerely thank all my friends at Reading for their help, not least at final harvest.

Abstract:

Within-field variation in sugar beet yield and quality was investigated in three commercial sugar beet fields in the east of England to identify the main associated variables and to examine the possibility of predicting yield early in the season with a view to spatially variable management of sugar beet crops. Irregular grid sampling with some purposively-located nested samples was applied. It revealed the spatial variability in each sugar beet field efficiently. In geostatistical analyses, most variograms were isotropic with moderate to strong spatial dependency indicating a significant spatial variation in sugar beet yield and associated growth and environmental variables in all directions within each field. The Kriged maps showed spatial patterns of yield variability within each field and visual association with the maps of other variables. This was confirmed by redundancy analyses and Pearson correlation coefficients. The main variables associated with yield variability were soil type, organic matter, soil moisture, weed density and canopy temperature. Kriged maps of final yield variability were strongly related to that in crop canopy cover, LAI and intercepted solar radiation early in the growing season, and the yield maps of previous crops. Therefore, yield maps of previous crops together with early assessment of sugar beet growth may make an early prediction of within-field variability in sugar beet yield possible. The Broom's Barn sugar beet model failed to account for the spatial variability in sugar yield, but the simulation was greatly improved when corrected for early canopy development cover and when the simulated yield was adjusted for weeds and plant population. Further research to optimize inputs to maximise sugar yield should target the irrigation and fertilizing of areas within fields with low canopy cover early in the season.

Table of Content:

Table of Figures:

List of Tables:

List of Appendices:

List of Abbreviations:

%- Percentage

£- Great Britain pound

γ(h)- Semivariance

µS- Microsiemens

°C- Degree Celsius

a - Range of spatial dependency identified by the variogram

BBRO- British Beet Research Organization

BLUP- Linear unbiased predictor

C1- Sill variance

C0- Nugget variance

$C_0/(C_1 + C_0)$- Nugget to sill ratio

CC- Crop canopy cover

CEDA- Centre for Environmental Data Archival

CGR- Relative canopy growth rate

CV- Coefficient of variation

d- Day

DEM- Digital elevation model

dGPS- Differential global positioning system

EC- Electrical Conductivity

ET- Evapotranspiration

GIS- Geographic information system

GPS - Global positioning system

h- Lag distance

ha- Hectare

IDW- Inverse Distance Methods

K- Potassium

LAI- leaf area index

LOI- Loss-On-Ignition

m- Metre

MaxT- Maximum temperature

Mg- Magnesium

MinT- Minimum temperature

MoM- Methods of moments

MZ- Management zones

N- Nitrogen

NDVI- Normalized differential vegetation index

OK- Ordinary kriging

P- Level of significant (Probability of error)

P- Phosphorus

PA- precision agriculture

PAR- Photosynthetically active radiation

pH- Soil acidity

PP- Plant population

r- Correlation coefficient

R^2- Regression coefficient of determination

RDA- Redundancy analysis

RI- Relative improvement index

RMS- Residual Mean Square

RMEL- Residual Maximum Likelihood

RMS- Residual mean of Square

RTK GPS- Real Time Kinematic Global Positioning System

SD- Standard deviation

SMC- Soil moisture content

SOM- Organic matter

SRI- Solar radiation interception

T- Mean temperature

t- Tonne

VRA- Variable rate application

UK- United Kingdom

US$- United State Dollar

1. Chapter One: Introduction and Literature Review.

1.1 Introduction:

A major concern of agriculturists has been devoted recently to increase land productivity in order to meet the world food demand for increasing world population, which is expected to reach 9 billion by 2050 (Pati *et al*., 2011, Oliver *et al*., 2013). However, the environment and the costs of production are another growing concern; therefore they should be considered when increasing the land productivity. For this purpose, a precise investigation of crop environment such as soil properties and micro-climate which can differ significantly in spatial and temporal scales is required (Heege, 2013). Especially for some crops such as sugar beet, as the world demand of sugar is expected to reach 140 million tons per year (Draycott, 2008, Samson-Bręk, 2010). This thesis considers modelling and mapping the within field variability in sugar beet yield and aims to identify the main driving variables potentially causing within-field variation. Therefore most of the environmental factors that have a potential influence on sugar beet yield have been investigated as well as the interaction between these variables. In addition, the possibility of anticipating the non-uniformity in final economic yield early in the growing season or from yield information of the previous crop has also been examined.

Conventionally, most commercial agricultural fields are generally managed with uniform application of tillage and agronomic inputs which can adversely affect the environment, increase the costs of production and waste natural resources (Montanari *et al*., 2012).

However, it is well-known that there is within-field variability at different spatial and temporal scales (Webster and Oliver, 2007), which affects crop development and is reflected in the non-uniformity in yield (Heege, 2013). This variability could be managed by applying the right amount of inputs in the right place at the right time in order to optimize benefits, increase sustainability and decrease adverse environmental impacts (Mondal *et al*., 2011, Najafabadi *et al*., 2011, Diacono *et al*., 2013). Factors such as soil fertility, pH, water deficit, weeds, pests and diseases could be managed spatially, while others such as soil texture, topography and climate conditions cannot (Sadler *et al*., 1998, Frogbrook *et al*., 2002). Some of these variables are visible and can be seen easily from ground based, airborne and satellite imagery, while others such as temperature and soil chemical composition are difficult to see and require direct measurement and soil analysis (Webster and Oliver, 2007).

In England, recent studies predict that sugar yield is likely to increase in the future by about 0.5-1.5 t/ha in sandy soils and 2 t/ha in loamy soils by 2050 and 4 t/ha by 2080, due to the advances in plant breeding and agronomic progress (Richter *et al*., 2006), but the variation in sugar beet yield due to weather condition is more likely to increase in un-irrigated areas (Freckleton *et al*., 1999), because in these areas the effect of water stress is additional to the effect of temperature and solar radiation (Jaggard *et al*., 2007). The variation within regions is expected to be higher than the variation between regions due to the variability in soil properties (Richter *et al*., 2006). Therefore identifying spatial variation in environmental conditions could provide important information for water and nutrient management and fertilizer application in sugar beet fields (Sağlam *et al*., 2011, Montanari *et al*., 2012) and consequently optimize benefits, increase sustainability and decrease adverse environmental impact. For this purpose various studies have been conducted to address the causes of within-field variation in crop yield. Some of these studies have attributed this variation to soil texture and soil organic matter (Taylor *et al*., 2003, Shaner *et al*., 2008, Karaman *et al*., 2009a), soil nutrients (Vanek *et al*., 2008, Rodriguez-Moreno *et al*., 2014), which have a significant effect on crop yield, to the variation in soil available water in relation soil types, field topography and the proportion of sand and stones (Vanek *et al*., 2008, Zhang *et al*., 2011a, Korres *et al*., 2013), to management practice (Taylor *et al*., 2003) or to some other driving variables such as the diffusion of water and nutrient which are quite complex and are difficult to investigate (Lark, 2012). However, only a few studies have considered the spatial variability in sugar beet fields and most of these studies considered a single environmental variable such as soil organic matter (Karaman *et al*., 2009a), soil nutrient (Franzen, 2004, Karaman *et al*., 2009b), soil moisture content (Zhang *et al*., 2007, Zhang *et al*., 2011a), or diseases and nematodes (Reynolds, 2010, Hbirkou *et al*., 2011). In addition, the spatial relationship between the studied environmental variable and sugar beet growth or yield was not examined, thus the studied variable might not be limiting the yield. The within-field variation could be due to the combined influence of different soil and micro-climate factors and it is quite difficult to isolate the effect of a single environmental factor. These factors can be laid into four main groups as follows: soil texture which can affect soil moisture and soil structure, topography in relation to micro-environment, soil nutrients and, weeds, diseases and pests (Godwin and Miller, 2003). Therefore, detecting the spatial variability in sugar beet yield in relation to the independent and combined effects of different environmental variables is required and likely to be important to achieve the improvement in sugar beet growth and yield.

In addition, crop stress is usually observed and treated when it becomes visible; by which time the damage has already occurred and the crop may not recover fully (Bouma, 1997). For example the appearance of Rhizoctonia crown and root rot in sugar beet fields can be revealed by aerial photographs, but only when it is moderately to severely infected (Reynolds, 2010), when chemical treatments might not reduce its effect on final yield. Also the effect of water stress on the crop is usually seen only when the crop starts wilting (Zhang *et al.*, 2011a), and it has been found that exposing a sugar beet crop to water stress in early growth stages even for short periods can significantly reduce the final sugar yield (Yang *et al*., 2007). Therefore, anticipating the spatial variability in sugar beet yield early in the growing season could help the farmer to take precautions to avoid or mitigate the damage. Furthermore, simulating within-field variability in sugar beet yield using the crop preceding sugar beet in the rotation as a predictor also needs to be assessed, since this might help to reveal expected variation in sugar beet yield and anticipate the spatial and temporal variation over many years. Moreover, modelling the growth of sugar beet crop based on the spatial variability in micro- environmental conditions has not been taken into consideration yet as the current models are usually applied only on a regional basis.

1.2 Sugar beet crop:

Sugar beet along with sugar cane are the two main global sources of sucrose, for which there is a large global market of high economic importance. Sugar beet is considered as a new crop developed from white fodder beet in the 18thcentury, and producing the sugar from sugar beet was one of the important agricultural achievements in the 19th century (Draycott, 2008). It is now grown under a wide range of temperate weather conditions; it is grown as a summer crop in the northern parts of temperate areas and as a winter crop in southern parts of these areas (Draycott, 2008). In most of Europe sugar beet is an un-irrigated crop, it is usually sown in spring and the sugar accumulation starts early in the growing season. The long vegetative growth period increases the sugar percentage in the root due to extending the sugar accumulation period (Jaggard *et al*., 2009). For sugar production the growing season in these areas is usually between 170-200 days. Mild weather during the growing season can significantly increase the root yield, and low temperatures near the end of the season can enhance sucrose accumulation (Samson-Bręk, 2010).

Sugar beet currently supplies approximately 40 million tonnes of sucrose annually which represents 30% of global demand of sucrose, approximately 75% of this amount being produced by Europe and United States, while sugar beet production is not significant in central Asia and Caucasus countries, due to unsuitability of weather conditions (FAO, 2012). The top ten sugar beet producers in Europe with the average area planted by sugar beet, total production, the yield per hectare and the percent global share in 2010 are listed in

Table 1.1 (FAO, 2012). These countries produce more than 60% of sugar and the top country is France which produces approximately 14% of world production of sugar beet.

Table 1.1: The areas planted with sugar beet (1000 ha), total root production (1000 tonnes) and root yield (tonnes/ha) in the world and the ten largest sugar beet producers in Europe 2010 (FAO, 2012).

Country	Area planted (1000 ha)	Roots production (1000 tonnes)	Roots yield (tonnes /ha)	Percent global share
World	4676	228452	48.86	-
France	383	31910	83.32	13.97
Germany	367	23858	65.01	10.44
Russia	924	22256	24.09	9.74
Turkey	329	17942	54.53	7.85
Ukraine	492	13749	27.95	6.02
Poland	200	9823	49.12	4.30
United Kingdom	122	7686	63.01	3.36
Netherlands	71	5280	74.37	2.31
Belgium	59	4465	75.68	1.95
Italy	63	3550	56.35	1.55

In 2010-2011 sugar beet occupied approximately 3% of the UK arable land, and this produced around 1.3 million tonnes of sugar with an average root yield of 75 t/ha (Limb, 2014). Sugar beet yield (t/ha) in UK has significantly increased from the period between 1981 and 2013 (Fig. 1.1a), the significant increase in yield was associated with significant declines in the area planted to sugar beet (Fig. 1.1b) and the number of growers (Limb, 2014). Similar trends were also observed in France for the period between 1980 and 2010, but was associated with decrease in sugar beet prices (Boizard *et al*., 2012). This could be due to the changes in the EU support polices, which reduced sugar beet production in Europe by 20% and the area harvested also reduced to less than 1% of total world arable land in 2009 (FAO, 2012). The recent increase in sugar yield in the UK, which is estimated to be around 0.111 t/ha/year on UK tonnes and about 0.204 t/ha/year in the official varieties trials, is due to the improvements in sugar beet varieties and agronomic practice, in addition to the ability of sugar beet plant to adapt to the recent weather conditions (Jaggard *et al*., 2007, Jaggard *et al*., 2009).

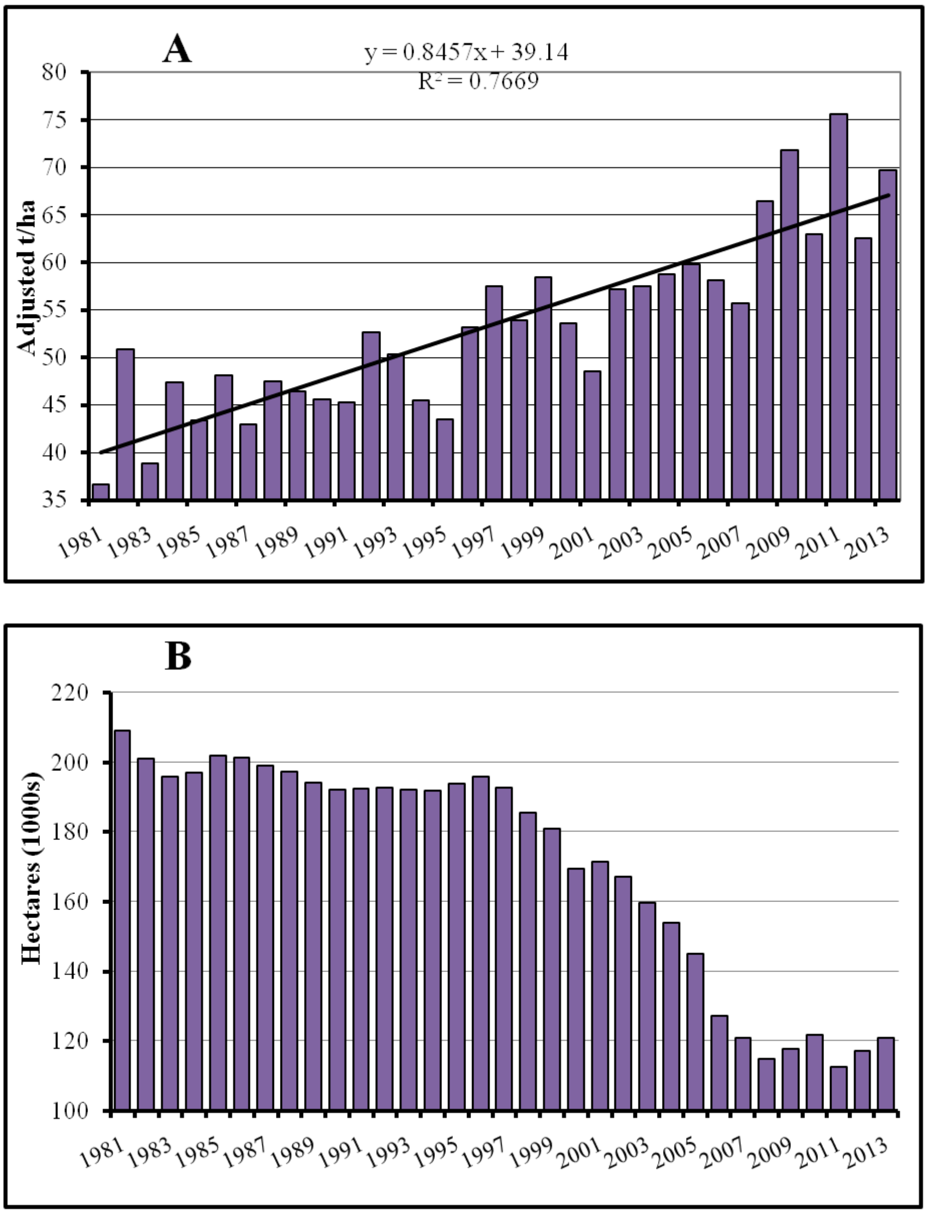


Figure 1.1: Average sugar beet yield (from British Sugar data) from 1981 to 2013 (A), and the UK area harvested (B) (Limb, 2014).

The role of plant breeding appears to be greater than agronomic practices because improved varieties have significantly increased root sugar content from 12% to 20% with improvement in yield and other chemical content as well as increasing sugar beet resistance to diseases and pests. The amount of white sugar produced by sugar beet has therefore increased (Draycott, 2008). Conversely, changes in some other agronomic processes such as extending the period of crop processing by storing beets after harvest and reducing the irrigated areas have reduced sugar beet yield (Jaggard *et al*., 2009).

Despite the significant increases in sugar beet yield per ha over last four decades, sugar beet growers face various challenges and the recent changes in weather conditions are considered to be a major challenge to sugar beet production in the UK. Some of the environmental factors that affect sugar beet growth are outside the grower's control, while others such as plant nutrients can be added in different ways by growers and achieve significant benefits (Draycott and Christenson, 2003). Perhaps the most important factor in Europe is soil moisture, since most sugar beet is rain-fed. In addition sugar beet growers regularly suffer from uneven plant populations due to the lack or delay of irrigation (Sadeghian and Yavari, 2004). On the other hand, in the Mediterranean region the effect of temperature on sugar beet yield is considered to be greater than the effect of drought, due to the increase in the evapotranspiration rate (Abd-El-Motagally, 2004). The effect of some of these factors on sugar beet growth and production might occur at different spatial and temporal scales. Investigating the spatial variation in sugar beet yield and its relation to the soil properties and micro-climate condition is important to maximise the yield, reduce the costs of production and adverse environmental impact.

1.3 Precision agriculture (PA):

Precision agriculture is a modern technique, growing rapidly in western countries. Its scientific goal is to develop a farm's management with the potential of increasing the land productivity based on precise information about spatial variability in environmental attributes that potentially cause yield variation (Mondal *et al*., 2011). Based on this approach the fertilizers, seeds and pesticides can be customized to specific zones rather than uniformly applied across a field by increasing the amount of the inputs where they are required and decreasing where not (Bouma, 1997, Rains and Thomas, 2009, Pati *et al*., 2011, Oliver *et al*., 2013). Conventionally, most of the recommendations about agricultural inputs such as fertilizer and pesticides were derived for uniform application. However, the environmental variables such as solar radiation, available water, soil properties and topography are never uniform even within the field scale (Heege, 2013). As a consequence of uniform application, parts of the field will receive less inputs than required, which might limit the yield, while other parts might receive more than they need, which will waste the natural resources and may adversely affect the environment such as by leaching nutrient and pesticide to the ground water and contaminating it (Oliver *et al*., 2013). This has prompted researchers and farmers to adopt precision agriculture, so that the spatial variation in yield and associated environmental variables can be identified and managed by variable rate application of the inputs, which can enhance the yield uniformity and reduce the adverse environmental impact (Auernhammer, 2001, Najafabadi *et al*., 2011, Oliver *et al*., 2013). Precision agriculture (PA) in relation to climate and soil conditions is expected to have an increasingly important role during the 21st century, which needs the combination of spatial technologies such as global positioning system (GPS), geographic information system (GIS) and remote sensing, as well as the possibility of analysing the spatial relationship between mapped variables in order to conduct management practice according to the spatial and temporal variability across the natural and agricultural landscapes (Berry *et al*., 2003, Najafabadi *et al*., 2011, Clay, 2011).

Precision agriculture has been widely examined for its profitably and accuracy over the last decade and promising results have been achieved. The economic advantages of variable rate nitrogen fertilization in sugar beet fields were estimated to be about US$50 ha^{-1} for grid based sampling and about US$ 113ha^{-1} for zone based sampling compared to uniform application (Franzen, 2004). The average increase in gross incomes, which means the advantages of maximizing the yield with minimizing the inputs, is estimated to be around US$ 150 ha^{-1} in maize field and US $51 ha^{-1} in soybean by applying precision agriculture (Amado and Santi, 2011). In addition the amount of herbicides applied, costs and required working hours were significantly lower compared to uniform application (Pedersen *et al*., 2005, Mohammadzamani *et al*., 2009).

Due to the advances in the spatial technologies that have an important role in the adoption of precision agriculture, it becomes possible and easy to collect information for mapping the yield of many crops. Remote sensing can provide reliable information about the land cover, land use changes and plant growth (Delegido *et al*., 2011). For example it can provide an accurate map of leaf area index or crop cover which might be correlated with the within field variation in yield (Martinez *et al*., 2010). In addition an accurate yield map for combinable crops can be produced cheaply by the combine harvester during the harvest (Griffin, 2010, Heege, 2013). However the map of yield or any other crop growth parameters during growing season provided by these techniques is not sufficient for implementation of precision agriculture, because it does not map the actual stress, but it usually represents the plant response to the stress, and different environmental variables can cause a similar pattern of stress (Jones and Schofield, 2008). Therefore an accurate map of the main environmental variables that have a potential causal influence on yield variation is also required. For some variables such as soil properties and water status, this map cannot be provided by the combine harvester and will not be accurate enough if it provided by remote sensing. For example the soil available water can only be detected by traditional remote sensing techniques for shallow depths, which is not useful to detect the water status for root crops such as sugar beet that absorb the water from 100 cm (Rains and Thomas, 2009). Therefore the field needs to be sampled and all the data should be based on these samples. On the other hand sampling the field intensively to obtain an accurate map for management is difficult and expensive (Webster and Lark, 2012), and the measurements will just represent the locations at which the samples have been taken (Scannavino *et al*., 2011). Using geostatistical methods of interpolation such as Kriging that can predict the value of the property in unsampled locations (Oliver, 2010), but the sampling protocol to obtain the best prediction is still controversial (Kerry, 2003). Therefore precision agriculture needs a combined approach between different techniques to produce an accurate map with reducing the sampling efforts (Kerry *et al*., 2010), because each of these techniques has its limitations if it is applied separately, and combining two or more of these technologies will be complementary to each other, and this will broaden the scope for which they are applicable (Gao, 2002). It has become evident that promising results can be obtained by integrating remote sensing techniques with soil map and crop measurement (Oliver *et al*., 2013). For example using remote sensing techniques for mapping an environmental property can be associated with an error that needs to be statistically quantified by ground truthing (Rocchini *et al*., 2013). The information about spatial variation provided by remote sensing, electrical conductivity scanning and yield mapping by a combine harvester is useful not only for detecting the stress in crop growth or to identify soil types, it is also needed to identify management zones for variable rate applications and to guide sampling schemes for geostatistical analysis (Bouma, 1997, Kerry and Oliver, 2007a, Kerry *et al*., 2010). Using the auxiliary data provided by these techniques as a covariate can enhance prediction of spatial variability in soil properties (Minasny and McBratney, 2007), and it can be a useful to monitor the patterns of variation over time and link it with ground truth data of the soil properties or micro-climate for precision agriculture applications in the following crop in the rotation.

1.3.1 Precision agriculture tools:

As the implementation of precision agriculture requires the adoption of spatial technologies such as GPS, GIS and remote sensing and methods of mapping the spatial patterns, its application has now become more promising as a result of the progress in these techniques.

The availability of these technologies provides an easy way to gather important information about crops and environment. Each of these technologies is described in the following sections.

1.3.1.1 Global Positioning System (GPS):

GPS, was used initially as a navigation system developed by the United States military to identify the position on the earth and it is based on 24 satellites distributed in the earth's orbit (Rains and Thomas, 2009, Chu Su, 2011). The main merits of GPS are that the signal is free and can be used at any time and it works without the effect of weather. Therefore its application has become more popular world-wide and the instruments can identify each satellite's position by receiving its broadcasted signal to provide a triangulated georeference (Auernhammer, 1999, Shanwad *et al*., 2002). Accuracy has now increased from about 100 m to about 10cm (Gavric and Martinov, 2007). As a result of the development of GPS and its integration with other technologies such as remote sensing and GIS, the spatial data about crop condition can be collected easily and efficiently and it can be used by the farmer or their advisors for managing their fields site-specifically (Gao, 2002, Corwin and Lesch, 2005, Aziz *et al*., 2009). The accurate data required for precision agriculture cannot be provided by the raw GPS; therefore it requires an additional signal from known reference to obtain desirable accuracy such as differential GPS that use the additional signal (Rains and Thomas, 2009). In addition to differential GPS, real time kinematic global positioning system (RTK GPS), which is the most accurate generation of GPS is available for agricultural purposes that need more accuracy. The required accuracies of GPS for various agriculture applications are given in Table 1.2.

1.3.1.1.1 Differential Global Positioning System (dGPS):

Differential global positioning system (dGPS) is an enhancement to global positioning system (GPS) which improved the position accuracy of GPS from 15 m to 10 cm in case of the best implementation. In 1987 the U.S. Coast Guard Research and Development (R & D) Centre announced that the accuracy of GPS has been improved significantly by using dGPS correction broadcast to local user equipment within the coverage area of the correction broadcast (Schlechte and Officer, 1994). It operates based on triangulating the signal released from the satellites and it can receive and combined real time correction data provided by the coast guard GPS correction system which made significant improvement in the accuracy of GPS and it can provide resolution within one meter (Nagchaudhuri *et al*., 2005). This resolution is sufficient to determine the position within agriculture fields for different applications and most agricultural equipment used for precision agriculture are provided with this kind of GPS (Rains and Thomas, 2009), and it has been widely used for yield mapping, yield monitoring, soil sampling which are important for describing the spatial variation (Chu Su, 2011). One of the main advantages of using dGPS is that it can solve the digital noise problems with some specifications, but the main drawback of its application in agriculture is that it increases the cost of operation (Mondal *et al*., 2011).

1.3.1.1.2 Real Time Kinematic Positioning System (RTK GPS):

RTK GPS is one of the most accurate kinds of GPS; it can provide the position information within centimetres accuracy (Mondal *et al*., 2011). RTK GPS commercially became available in 1992 with measurement capabilities within 1 to 4 cm accuracy (Buick, 2006). Due to its sensitivity of use (horizontal ±2 cm, vertical ±4 cm), and being easy to be applied, it has become more preferable and most widely used in many studies especially mapping environmental variables and mining survey (Yılmaz *et al.*, 2006). It also can be used effectively for topographic mapping and it has 5cm accuracy for elevation, due to its capability to extract extra information by assessing the carrier of the GPS signal (Sudduth, 1998). However, it is more expensive than some other precision agriculture equipment such as machine vision guidance system (Slaughter *et al.*, 2008). It can provides autonomous systems with better results for robotic weed control and it can be used for more accurate variable rate application, but it is still relatively expensive and it increases the costs for autonomous systems (Pedersen *et al.*, 2005, Chu Su, 2011).

Table 1.2: The required accuracies of GPS signals for agricultural application (Auernhammer, 1999).

Required accuracy	Task	Examples
± 10 m	Navigation	• Targeting of fields (machinery ring, contractor) • Targeting of storage area (forestry)
±1m	Job execution Information Documentation	• Local field operations with yield monitoring, fertilizing, plant protection, soil sampling, action in protected areas • Automated data acquisition
±10 cm	Vehicle guidance	• Gap and overlay control (fertilizing, spraying) • Grain combining
±1cm	Implement (tool) guidance	Mechanical weed control

1.3.1.2 Geographic Information System (GIS):

According to the National Centre of Geographic Information and Analysis (NCGIA), GIS can be defined as “a system of hardware, software and procedures to facilitate the management, manipulation, analysis modelling, representation and display of georeferenced data to solve complex problems regarding planning and management of resources” (Mutluoglu and Ceylan, 2009). The main feature of GIS is that it can integrate, analyse, and model the data from different sources depending on its powerful analytical functionality (Gao, 2002). As most of the environmental variables that relate to agriculture have some form of spatial variation, the adaption of GIS software in precision agriculture provides a great opportunity to visualize these data especially if that might be difficult to present in other ways (Pierce and Clay, 2007). For example, many maps of different variables or different years can be combined to describe the interaction between them and detect the variation patterns over many years (Blackmore, 2003). The integration of GIS with other techniques is important for precision agriculture (Gao, 2002), and the combination of GIS and GPS is most important for creating a map that can show the farmer which parts of the field need more inputs than others (Bullock *et al*., 2002, Nutter *et al*., 2011). In addition, the advanced generation of GIS is provided by the geostatistical analyst toolbar, which has filled the gap between GIS and geostatistics. This is useful to quantify the quality of the surface map by estimating the statistical errors associated with prediction (Johnston *et al*., 2001, Shahbazi *et al*., 2013). However, using GIS is still unreliable for weed mapping, as the different maps of weed distribution produced by GIS based on different sampling schemes and starting points were not related to each other (Backes and Plümer, 2003). This might be a serious issue especially if the map has over or underestimated the actual distribution of weeds, because it will waste the chemical resources and may affect the long term spreading of specific weeds (Backes and Plümer, 2003).

1.3.1.3 Remote sensing:

Remote sensing can provide multispectral information based on emitted radiation from the target point, which could be a bare soil or vegetative cover as a series of narrow wavelength across a geographical location (Diacono *et al.*, 2013, Meroni *et al*., 2009). This information can then be utilized to describe the spatial variation in biotic and abiotic variables of the ecosystem such as land cover, land use, vegetation and soil properties, as well as detecting the changing patterns over time (Rocchini *et al*., 2013). The combination of remote sensing with GPS and GIS increases its capability to detect and map the spatial and temporal variability in crop growth and soil properties and has become an important tool for precision agriculture (Sivarajan, 2011). In addition, it can provide a good explanation of the relationship between crop biophysical data or vegetative indices such as vegetation development, photosynthetic activity, biomass accumulation, leaf area index (LAI), and crop evapotranspiration (ET), with crop production (Jayanthi, 2003). Remote sensing technologies involve different systems such as satellite-based systems (satellite images), airborne-based systems (aerial photography) and ground-based systems (e.g. with vehicle mounted camera). The adaptation of remote sensing imagery for in field decision making has some limitations such as the high cost, non-availability in real time and it requires high scientific knowledge to analyse and interpret data. Providing low or no-cost value-added products that can be interpreted easily is one of the ways to face these challenges (Zhang *et al*., 2010a). The main factor affecting the reliability of remote sensing is that it describes the gradual variation in a property as a set of discrete non-interacting classes which might lead to loss of some information when classifying and processing the images (Rocchini *et al*., 2013).

1.3.1.3.1 Satellite images:

Most kinds of satellite images are originally multispectral, but they have lower spatial resolution compared to other kinds of remote sensing technologies (Reynolds, 2010). Satellite imaging has become a useful tool in precision agriculture. It has many advantages such as that it can capture large areas, the possibility of analysing a single image, it can process rapidly, accurate information is available using different wavebands, the availability of previous images for comparison and the data can be recorded without any administrative limitation by national government (Sivarajan, 2011). The most important source for precision agriculture is QuickBird, due to its high resolution especially the red (630 to 690 nm) and near infrared portions of the spectrum (760 to 900 nm) (Laudien *et al*., 2004). This technique could be used to map leaf area index, which is important for decision making for irrigation and canopy management (Johnson *et al*., 2003, Silva *et al*., 2007). For example Franzen (2004) divided satellite images of a sugar beet field into different green and yellow areas to develop management zones for variable nitrogen fertilization. The same approach was followed by the farmers in Red River Valley in Minnesota. They used Landsat TM derived normalized differential vegetation index (NDVI) of a sugar beet field to create zones to estimate site-specific nitrogen credits, the higher dark green area indicated higher N, which needed less fertilizer for the following crops in these zones and the farmer saved $30 per hectare (Zhang *et al*., 2010a). To identify the optimal number of management zones automatically and delineate them using satellite imagery, the zones based on satellite image with NDVI value were significantly correlated with soil organic matter concentration (Zhang *et al*., 2010b). The NDVI map provided by satellite images can also be used for detecting the damage caused by diseases (Mondal *et al*., 2011), and thus it has successfully detected the area of sugar beet field affected by Rhizoctonia crown and root rot by measuring the chlorophyll content of sugar beet foliage (Reynolds, 2010). For weed detection, satellite imagery is effective for detecting weeds against bare soil in the early growth of row crops (Lamb, 1995), but it is difficult at letter growth stages, due to the small difference between weeds and crop in spectral signature (Mondal *et al*., 2011). The high spatial resolution of soil moisture data (10 m) was achieved only by active remote sensing that have their own energy source for illumination such as the laser and radar (Barrett *et al*., 2009). On the other hand the active sensors have a low temporal resolution and are more sensitive to surface parameters than passive microwave sensors (Lakhankar *et al*., 2009). The spatial information about soil moisture can be provided by remote sensing (Wigneron *et al*., 2003), but only for a few centimetres depth, whereas plants absorb moisture from a depth of more than one metre in some cases (Zhang *et al*., 2011a).

However, using satellite images in precision agriculture has some limitations such as the effect of clouds on the data clarity, low spatial resolution and cannot provide data for real time management (Sivarajan, 2011). In addition, it is not spatially precise enough to map the variables which makes it difficult to superimpose two sets of data such as a yield map and a satellite image (Clay, 2011).

1.3.1.3.2 Aerial photographs:

Aerial photography means the photographs of the ground that taken from an elevated position by some platforms such as fixed-wing aircraft, helicopters, balloons, blimps and dirigibles, rockets, kites, poles, and vehicle mounted poles. These photos have been used more frequently in precision agriculture, due to many advantages such as the flexibility of data collection frequently during growing season, the effect of clouds can be avoided, it can provide high spatial resolution, and it is possible to adjust the altitude and resolution, so that each image can cover a large area to reduce the costs (Sadler *et al*., 1998, Laudien *et al*., 2004, Reynolds, 2010, Mondal *et al*., 2011, Sivarajan, 2011).

The reliability of aerial photography in precision agriculture has been widely assessed and, it can provide good information about spatial variation in soil properties and crop growth with a very high spatial resolution of less than 0.5 m per pixel (Sivarajan, 2011). In a study conducted by Kyvery *et al*. (2012), colour and near infrared aerial photographs were used to predict the final corn nitrogen status. The results indicated the possibility of using normalized late-season to predict final corn N status in large-scale on farm studies. To develop management zones (MZ) for variable rate application, Fleming *et al*. (2000) used aerial photographs as an alternative method to grid sampling. The results of management zones identified by aerial photographs were as effective as grid sampling for variable rate N application and relatively cheaper than grid sampling. In another study, multispectral airborne images were used to detect the within-field variability in sugar beet yield. The flight occurred within 1 hour of solar noon and at 7,500 feet (2,285 m) above the ground surface resulting in 1m pixel resolution, and the results indicate the reliability of this way for estimating sugar beet yield (Gat *et al*., 2000). Despite these positive results of the ability of aerial photography to detect the yield, the data are less reliable and more expensive than can be obtained by a ground platform multi-spectral radiometer (Reyniers *et al*., 2006).

Using unmanned aircraft, Rasmussen *et al*. (2013) carried out weed mapping and they indicated the possibility of unmanned aircraft for site-specific weed management. They also found that the images taken at high altitude covering approximately 3000 m^2 with a resolution of 17 mm per pixel can provide useful information about weeds. However it needs suitable differences in spectral reflectance between weeds and their background soil and plant canopy and sufficient spatial and spectral resolution to detect weed plants (Lamb and Brown, 2001), and it cannot be used to detect weed densities of < 19 plants m^2 (Gerhards and Christensen, 2003).

To detect the spatial variability in soil water content within sugar beet fields, aerial photography for Bury St Edmunds and Thetford in the UK from the years 1946-2003 were obtained and analysed. The results indicated the possibility of using aerial photographs to detect soil available water using wilting of sugar beet as an indicator, but it also needs some soil samples to ensure its reliability, since the wilting may occur due to stress caused by nitrogen deficiency or virus infection (Zhang *et al*., 2011a). Airborne sensing was also used to detect fungal diseases in sugar beet by Laudien *et al*. (2004). After image analysis the healthier patches appeared as lighter areas, while infected areas were darker. It has also been found to be a reliable tool to detect Rhizoctonia crown and root rot (RCRR) in sugar beet crop moderately to severely infected (Reynolds, 2010).

1.3.1.4 Electrical Conductivity (EC):

Recently, the electrical conductivity (EC) scanner has been widely used in precision agriculture to describe within-field spatial variability in some soil properties (Lund *et al*., 1999, Shaner *et al*., 2008), and is considered as a fast, easy, reliable, and cheap method for mapping within field heterogeneity in soil properties (Mondal *et al*., 2011). Due to the strong relationship between soil properties and soil EC (Kitchen *et al*., 2003, Sudduth *et al*., 2005), the variability in soil biophysical characters such as soil texture, organic matter, soil moisture, soil temperature and cation exchange capacity can affect soil EC readings provided by the scanner (Corwin and Lesch, 2005). The changes in EC readings are based on the principals of electromagnetic induction, which can produce an electromotive force across a conductor when it is exposed to a time varying magnetic field. Therefore the spatial variation in these properties can be predicted from the variability in soil EC provided by an electromagnetic induction instruments (Abdu and DA Jones, 2007), and then it can be correlated to the spatial variability in crop yield (Lund *et al*., 1999, Sudduth *et al*., 2005). However, the map of EC alone is not sufficient to predict the variability in soil properties (Johnson *et al*., 2001). It might be reliable to predict the variation in some properties that are strongly correlated with EC (Corwin and Lesch, 2005), but it could not be reliable to identify soil quality and to provide information about soil physicochemical parameters (Mondal *et al*., 2011). The main advantages of EC map is that it can show the scales of the spatial variation, which is useful to direct soil sampling instead of grid sampling, which reduce the costs of intensive sampling (Shaner *et al*., 2008).

1.3.1.5 Yield monitoring:

The spatial variation in the yield is the final consequence of the spatial variation in environmental variables and in plant growth and development at different growth stages. Therefore producing a yield map and evaluating its statistical relationship with other agronomic variables is important for managing the spatial variation in the following crops (Mondal *et al*., 2011). Nowadays, the yield of many crops such as cereal grains, rapeseed, cotton and vegetables can be monitored site-specifically. The attempts to record the yield of cereal crops by combine harvester were started in 1980 and it has been commercially applied since 1990. For yield monitoring, combine harvesters need other technologies to be integrated in addition to the harvesting system (Fig 1.2). These include a product output sensor (t/ha), which needs to be calibrated according to the crop, area sensing (ha/h), which is calculated by measuring the speed of the harvester multiplied by the width of cutting unit, georeferencing system which is usually dGPS, and a storage and processing data system plus a computer for final mapping (Demmel, 2013). When the harvester operates, the output sensor automatically records the yield every few seconds. At the same time the GPS provides positional information and the output of this system represent the spatial yield data that clearly shows how the collected data is spatially auto-correlated (Chu Su, 2011). As a result of availability of yield monitors and GPS, the spatial data of yield based on mass flow or volumetric methods and grain moisture content can be collected easily and cheaply (Griffin, 2010), but most of the farmers do not know how to deal with it. The yield map produced by these data can support the farmer or their advisor with two valuable kinds of information: yield production, and the spatial variation in yield that can be visualized as a coloured map (Rains and Thomas, 2009). These data can also be used for spatiotemporal analysis to predict the spatial variation in a following crop or to improve the prediction of variables sampled sparsely. For this purpose, the values at the neighbouring points of denser data (yield of previous crop) provided by the combine harvester relative to the position of sparse data (sugar beet crop) can be averaged to represent value at the locations of the sparse data (Griffin, 2010). Simmonds *et al*. (2013) used historic yield maps of rice crop in different fields in the Sacramento Valley of California. Their results indicated that the patterns of spatial variation in some fields were temporally constant and related to the distribution of soil organic matter, nitrogen, potassium and salts. These results will allow implementation of precision management in the rice production system, which in turn can increase the productivity and efficiency of using the water and nutrients. Similar results were also found by Amado and Santi (2011) in Southern Brazil. They found almost constant patterns of spatial variability in yield of different crops (soybean, maize and wheat) in a six years rotation, and it was found to be related to soil water infiltration. In a study conducted by Blackmore (2000) in the UK, he found that patterns of the spatial variation over 6 years were more stable when a single crop (winter wheat) was considered than those when multiple crops (winter wheat and oil seed) were considered. However, the spatial variability is not always stable on a temporal basis. The high productive areas in one year may be less productive in the following years (Kleinjan *et al*., 2007), since the within field variation in crop yield is due to the combined effect of different environmental variables (Rains and Thomas, 2009, Griffin, 2010, Hakojärvi *et al*., 2013), and most of the variables especially that relates to weather conditions are not constant temporally. In another study, Blackmore *et al*. (2003) observed a significant pattern of spatial variation in the yield map of a single year, but these patterns were less obvious when the yield maps of six years were combined into a single trend map. This means the spatial variation might not follow the same patterns over many years; therefore the historical yield maps cannot be reliable to predict the spatial variability in the following crop. In addition, managing the field based on the yield map of previous crop is not recommended, but it can be used to estimate the amount of nutrients absorbed by the crop (Blackmore, 2003), and how different parts of the field can be low or high yielding in different years in relation to weather and soil properties (Blackmore *et al*., 2003) .

Despite the ability of this technology to provide a large amount of spatial yield data, transforming these data to useful information for management practice needs care (Griffin, 2010), due to the associated error that can contaminate these data and affect its reliability such as the appearance of outliers (Chu Su, 2011). The main sources of error affecting the yield data listed by Blackmore (2003) are as follows:

- The width of crop entering the cutting system varies,
- Time lag of threshing the grains which may not be in conjunction with georeferencing,
- The accuracy of the data provided by the GPS,
- Losing grains from the combine harvester,

- Other sources of error that are related to calibrating the sensors following the instruction of manufacture and accuracy of the sensor itself.

To produce an accurate map, the raw yield data should go through procedures to identify and remove any unexpected values which are due to one or more of sources mentioned above. Some of these values can be adjusted, while others may not, so they have to be removed from the data set. This procedure has different names; it is usually called data cleaning, data filtering or most commonly called expert-filter, which involves the map of data point that can be assessed by the editor based on his intuition, experience and prior knowledge about the field, combine harvester, crop and GPS (Blackmore, 2003, Griffin, 2010).

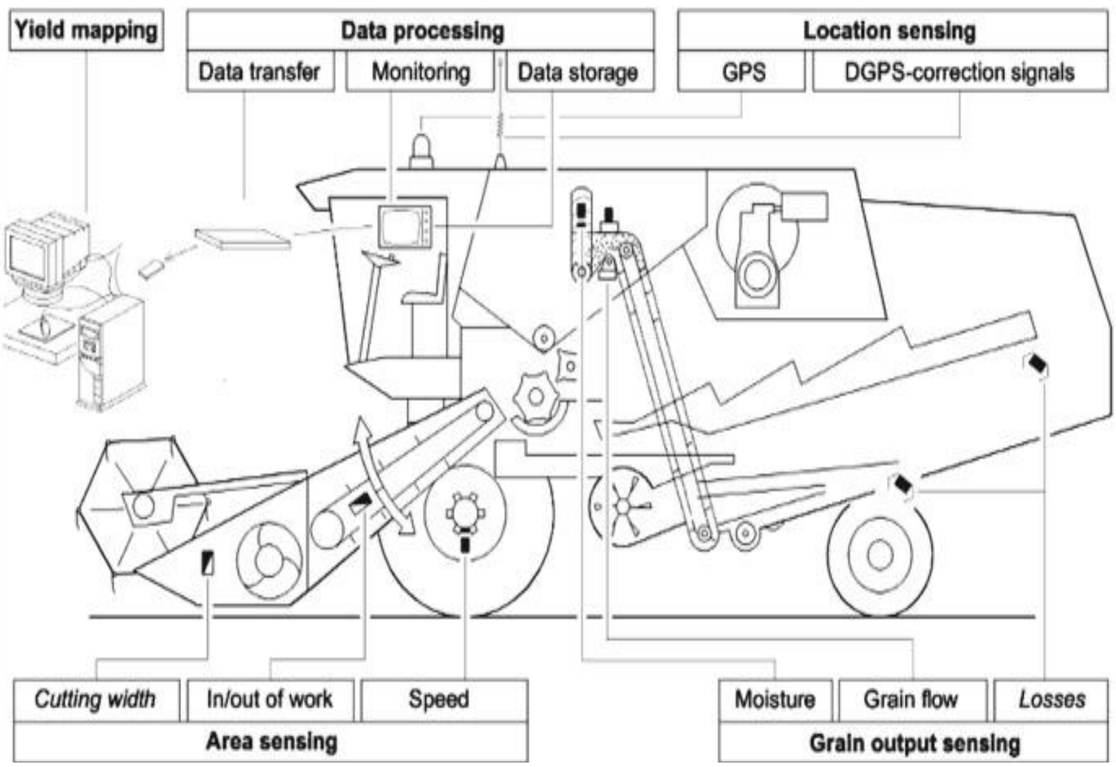


Figure 1.2: Illustration of the sensing systems in combine harvester (Heege, 2013).

1.3.2 Precision agriculture challenges:

Despite the rapid advances in precision agriculture especially in developed countries, and the large numbers of studies that have been conducted to evaluate the reliability, profitability and adaptation of precision agriculture, its application commercially has been limited due to the following challenges:

1. ***Time challenges:*** the time needed for providing and starting the techniques, for training to use them, to overcome the obstacles that may appear and the time needed to achieve the benefit from the investment (Wiebold *et al*., 1998, Reichardt *et al*., 2009, Najafabadi *et al*., 2011)
2. ***Economic challenges:*** this involves the high costs of PA equipment, the cost of developing the hardware and software and the cost of training to use them (Kitchen *et al*., 2002, Lavergne, 2004, Adrian, 2006, Gavric and Martinov, 2007, Najafabadi *et al*., 2011).
3. ***Uncertain achievements:*** this involves the errors that can be associated with using a computer program or any other tools, uncertain profits from the investment, the doubt about the reliability of PA tools and the accuracy of the information, different performance from different kinds of machines, and using incompatible software (Wiebold *et al*., 1998, Kitchen *et al*., 2002, Lavergne, 2004, Adrian, 2006, Gavric and Martinov, 2007, Reichardt *et al*., 2009, Atanasov *et al*., 2010, Najafabadi *et al*., 2011).
4. ***Knowledge and experiences:*** this involves lack of advice on how to use the field map, lack of training, lack of qualification and experts among farmers and the older farmers

with low education and knowledge about computers and new techniques, and lack of knowledge about the role of PA in agriculture, in addition the PA techniques still untaught in most universities (Wiebold *et al*., 1998, Kitchen *et al*., 2002, Lavergne, 2004, Nagchaudhuri *et al*., 2005, Adrian, 2006, Gavric and Martinov, 2007, Reichardt *et al.*, 2009, Mondal *et al*., 2011, Najafabadi *et al*., 2011)

5. ***Exploring and interpreting the data:*** this involves the difficulty in protecting the quality of the data, difficulty to analyse, interpret and present the data in an easy way for the farmers to understand (Bouma, 1997, Kitchen *et al*., 2002).

The economics and a lack of knowledge and experience are considered to be the greatest challenges facing the adoption of precision agriculture commercially. Particularly the lack of qualification and experts among the farmers and initial cost of PA techniques compared to other (Najafabadi *et al*., 2011). Whilst, the crucial one for the scientists is presenting methods that can explore variation in space and time in useful way that can help farmers for their management (Bouma, 1997).

The main limitation of PA application in developing countries such as Iran and India are the lack of knowledge, small size of farms, planting different kinds of crops in specific area, marketing effects and high costs (Shanwad *et al*., 2002, Gavric and Martinov, 2007, Mondal *et al*., 2011, Najafabadi *et al*., 2011). While the main limitation to PA adoption in European countries such as Bulgaria is the lack of required financial resources and limited access of Bulgarian farmers to European funds and the difficulty of using existing resources (equipment, people, warehouse), integrated with current technology entrants and a lack of comprehensive research about PA (Atanasov *et al*., 2010).

1.4 Geostatistics in precision agriculture:

The applications of geostatistics in environmental science were started in 1980 by a British soil scientist, namely Richard Webster and his team when they aimed to create a prediction map of soil properties. However their work was related to the environment more than precision agriculture, and it was adapted for precision agriculture by David Mulla in 1988 (Oliver, 2010). Geostatistics is an analytical tool that deals specifically with the georeferenced data that relies on the spatial correlation in order to predict the values of the variable across the field (Hengl, 2007). As a result of the existence of this tool in environmental research and the availability of various computer packages, it has become possible to overcome the economic problems of large number of samples required for mapping soil properties (Karaman *et al*., 2009b). It can also deal with remote sensing data to predict the spatial variability and to optimize the spatial sampling (Hengl, 2007). However, geostatistics is more sophisticated than conventional statistics in which some other statistical components need to be involved such as the variogram, which is a set of semivariances plotted against the lag distances between the measurements to describe the way in which the property can vary across a geographical location (Fig 1.3), or covariance that describes the spatial correlation between the points as a function of the lag distances (Webster and Oliver, 2007). Understanding and estimating these components are necessary to predict the quantity of the environmental variables at un-sampled locations (Sherman, 2011).

Estimating the variogram is more useful than the covariance because it can be adapted easily, especially when non stationary observations exist and it can be estimated without knowing the mean, therefore it has been considered as a corner stone of geostatistics (Webster and Oliver, 2007, Sherman, 2011).

1.4.1 The variogram:

The geostatistical theory behind the variogram is the Methods of Moment (MoM) (Matheron, 1965), considering the fact that the values of one variable at locations close to each other are more similar than those located further away (Fig 1.3). The experimental variogram needs to be modelled by a suitable mathematical model in order to describe the variation across the whole region, so that the value of the property can be predicted at unsampled locations (Hengl, 2007, Webster and Oliver, 2007). However choosing the best model is controversial, as some people judge it by eye, which is unreliable, because the variance might vary significantly from one point to another. A solution to this is to judge it visually by selecting one or more models with suitable shape and then statistically select the one which gives minimum Residual Sum of Square (RSS) or with mean square error close to the prediction variance (Webster and Oliver, 2007, Oliver and Webster, 2014)

After fitting the model, three components will be identified which are important for the prediction. The maximum variance that the variogram can reach, which is called the ***sill*** (C_1), it is the correlated variance that describe the continuity, the distance at which it reaches 95% of the sill is called the ***range*** (a) (Fig 3.1), which represents the limit of the spatial dependency in which the points separated by distance shorter than the range are spatially dependent and the points located further away are deemed spatially independent. It also represents the average extent of the patches when the variation appears as the patches with low and high values (Hengl, 2007, Webster and Oliver, 2007). The range might vary from a few metres to some kilometres according to both the region and the variable of interest. However, most environmental variables show spatial dependency at a range between 20 and 110 m (Heege, 2013). It has been found to be as short as 40 m for soil biological factors and as long as 90 m for other soil properties and plant production (Groffman, 1997). Identifying the range is essential for site-specific management as it can be used as control distances especially when it depends on a square grid, so that the precision management can be adjusted to not exceed that range (Heege, 2013).

The variogram should intercept the Y axis at the origin (0 variance) as the spatial variation is expected to be continuous and the differences between two samples at 0 distance should be 0. However, quite often it intercepts the Y axis at a positive value constituting that the property is discontinuous. This is called the ***nugget effect*** (C_0) (Fig 1.3) a name which started with gold mining when they noticed that the gold nuggets appeared independently of one another (Clark, 2010, Oliver, 2010). Some statisticians totally attribute it to sampling error which can be avoided by suitable sampling scheme. Others attribute it to the measurement error or white noise that represents the small scale variation which is not covered by the current sampling scheme (Clark, 2010, Colbach and Forcella, 2011). However, the measurement error could be involved, but the main one is the uncorrelated variance that might occur at distances shorter than the minimum sampling interval (Webster and Oliver, 2007, Oliver and Webster, 2014). The positive nugget value should never be replaced by 0 when it appears, as it will affect the reliability of the variogram which in turn will affect the prediction of values at unsampled locations (Clark, 2010).

If the variogram appears as a horizontal line, it is referred to as pure nugget. This indicates non-spatial dependency. Since most environmental variables vary continuously this type of variogram may not be expected (Kerry, 2003), and if it happens then it would be due to the use of large sampling intervals, which exceed the actual scale of the variation in the field (Oliver, 2010).

When the nugget variance exists, not all the variation which occurs in distances shorter than the range will be spatially dependent, therefore the ratio of nugget to sill ($C_0/(C_1+C_0)$) is usually used to quantify the degree of the spatial dependence (Vieira *et al*., 2008, Karaman *et al*., 2009b). On the other hand Oliver and Webster (2014) recommend not relying on this ratio to describe the underlying variation, but rather it can be used for inference of the large measurement error or inefficient sampling intervals or both.

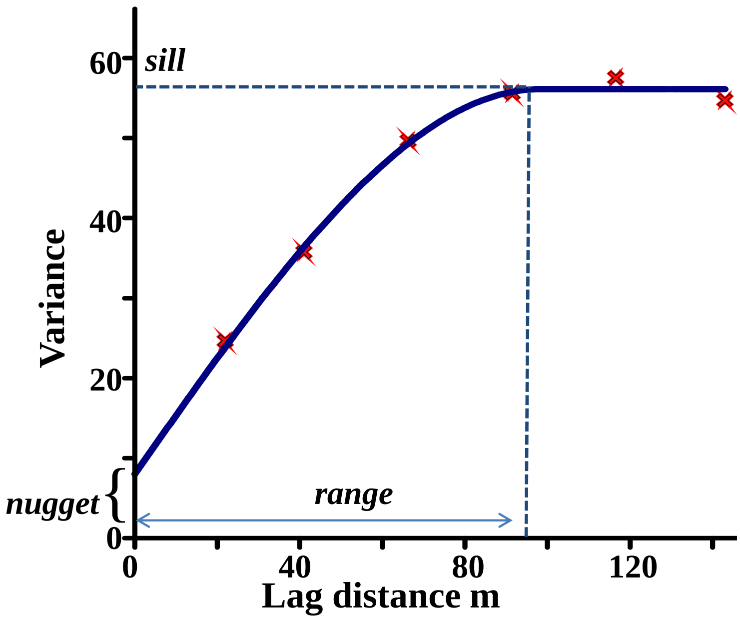


Figure 1.3: The experimental variogram of the data of crop canopy cover in July 2012 in White Path field presented as an example of a typical shape of variogram.

1.4.1.1 The reliability of the experimental variogram:

Since the calculation of the experimental variogram is based on a set of spatial data, its reliability might significantly be affected by the structure, distribution and quality of these data. The main factors that have a potential effect on the reliability of the variogram are asymmetry of the data, number of sampling points and separation distance, anisotropy and the trends (Oliver and Webster, 2014), and it has been explained as follows:

1.4.1.1.1 Asymmetry:

This means the departure from a normal distribution and it can be caused by a long upper or lower tail in the values or by outliers which have unexpected large or small values (Webster and Oliver, 2007). Since the variogram computed by MoM is based on the variances, any departure from normality can overestimate the variances and widen the confidence limit which consequently changes the shape of the variogram. Therefore the data should be explored by histogram, box plot, or coefficient of skewness before computing the variogram (Kerry and Oliver, 2007b, Oliver and Webster, 2014). If any departure from normality is observed, the data may then need to be transformed, so that an approximation to a normal distribution can be achieved and the variogram should then be computed from transformed data. Webster and Oliver (2007) recommend taking the square root of the data which may normalize it if the coefficient of skewness is between 0.5 and 1, while it needs to be transformed to logarithms if it exceeds 1. If the high skewness is due to the presence of outliers they recommend removing them from the analysis. However, transforming the data or removing outliers should not be done before computing the variogram from the original data and then deciding whether to transform it or not. In addition, a high skewness exceeding ±1 may not indicate the necessity of transforming the data especially for a large set of data (Oliver, 2010). In the study conducted by Hbirkou *et al*. (2011) a high coefficient of skewness (1.2) was found in the data set of nematode distribution in a sugar beet field and transforming it to Log10 did not reduce the skewness. Therefore they had to work with original data. The departure from normality is more common in the case of weeds, as the weed density is concentrated largely in some patches and most of the other patches may be weed free or with low weed density. Therefore the outliers in this case are not the result of a single point and cannot be removed to obtain normality (Colbach and Forcella, 2011). Kerry and Oliver (2007b) showed that with the presence of outliers the shape of the variogram did not alter, but the nugget, sill and nugget to sill ratio (C_0, C_1 and $C_0/(C_1+ C_0)$) were increased. This effect was less obvious for large sample sizes than for small ones. They also found constant decrease in the C_0, C_1 and $C_0/(C_1+ C_0)$ by transforming the data to square roots and logarithms. However, for removing the outliers from spatial yield data, Chu Su (2011) recommend using the averaged differences algorithm method. This method is based on comparing the value of each point with the average value at neighbouring points by identifying large numbers of neighbours which is sufficient to cover the area of interest. They considered this as the best method to avoid the effect of both point and regional outliers in which it can involve the spatial autocorrelation and identify the spatial variation between the neighbouring points.

1.4.1.1.2 Sample size and lag intervals:

The experimental variogram computed by MoM can be affected significantly by the sample size and the distance between sampling points. Therefore, for a reliable variogram at least 100 samples per field are required and the sampling intervals should approximately represent the scales of the variation. However a reliable variogram with less than 100 points can be computed by Residual Maximum Likelihood (REML) (Kerry and Oliver, 2007a, Oliver and Webster, 2014). This is explained in more detail in section 1.5.2.

1.4.1.1.3 Trends:

A trend appears as a gradual increase or decrease in the value of the property across the field or in one side rather than a patchy distribution of low and high values, and the mean will therefore change based on the geographical position. Consequently the variogram shape will be affected and will increase steeply and indefinitely with increasing the lag distance which significantly affects the prediction (Oliver and Webster, 2014). As in the case of few sampling points, the effects of trends can be avoided and the reliable variogram can be computed by identifying the trend and then estimating the variogram of the residual by REML methods (Lark, 2012). This method is parametric and accurate, because it depends on the general increase in the lag, which can avoid the effect of trends and rely on the covariance parameter only (Kerry and Oliver, 2007a).

1.4.2 Kriging:

The term Kriging usually refers to the geostatistical methods of prediction based on the weighting average that can provide the best linear unbiased predictor (BLUP) for optimal interpolation in the geographical space (Oliver, 2010, Sherman, 2011). The idea of this method started early in the 1950's in the mining industry by the South African engineer D. G. Krige and the statistician H. S. Sichel. However, the mathematical formula of the method was derived a few decades later by the French mathematician, G. Matheron (Hengl, 2007, Webster and Oliver, 2007, Franzen, 2011). Consequently it has become possible to solve the stochastic problem that is associated with using the mathematical model of interpolation by considering the way that the variable can vary in space from the information provided by the variogram or covariance computed previously, and it can also provide the prediction variance to ensure the reliability of the interpolation (Oliver, 2010, Sherman, 2011). Some people considered Kriging as a sophisticated version of Inverse Distance Methods (IDW) of interpolation (Hengl, 2007). While some others decide between Kriging and IDW method based on the coefficient of variation (CV). They found that IDW methods are more effective than Kriging when the CV < 25%, and the better interpolation can be achieved by Kriging when the %CV is higher (Franzen, 2011). However, more primitive methods such as inverse distance weighting and splines could be easy and useful for initial examination of data, since they do not consider the associated error and spatial structure of data (Lamb and Brown, 2001, Harper and Clark, 2006). Therefore Kriging methods become a promising technique and the key component for precision agriculture in which it can predict and visualize the value of property in the space (Scannavino *et al*., 2011). The main merits of a geostatistical map that separate it from an ordinary map, is that the geostatistical map is a predicted map created based on quantitative statistical methods and it depends on the actual data, while the conventional map is created based on empirical knowledge (Hengl, 2007). Although the interpolated map may not be more precise than the ordinary map (Kempen *et al*., 2012), its use is important to reduce the cost of the sampling with the possibility of quantifying the prediction error statistically (Lamb and Brown, 2001).

Kriging methods embody least square methods that can be used for spatial prediction under different conditions. Ordinary Kriging (OK) is the most robust and commonly used method and it needs only the primary information of the variogram for interpolation, it assumes that the mean is constant and unknown (Oliver and Webster, 2014).

Ordinary Kriging can deal effectively with the assumption of intrinsic stationary. However, it is not applicable when there are strong trends in the data. A solution to this is provided by the Universal Kriging that can deals with non-stationery and random component, but it needs the covariance component to be modelled for residual by incorporating REML methods into Kriging (Lark, 2012). This is also approved by Martinez *et al*. (2010) when they examined different Kriging methods to map spatial variation using auxiliary data, they found that Universal Kriging was the best interpolation method when non-stationary trends exist providing high accuracy under different sample sizes, while optimum results were achieved by Ordinary Kriging under a good stratified sampling design.

Ordinary Kriging can be divided into two kinds, punctual and block Kriging. In the case of block Kriging the mean value for certain block within the map is estimated, while in punctual Kriging the target point could be a point within the field (Heege, 2013). For some agricultural purposes block Kriging was found to be more useful as it helps the farmers for variable rate application of agricultural inputs such as fertilizer and pesticide as long as it does not exceed the effective width of agricultural machinery which is usually 24 m width in Europe (Webster and Oliver, 2007, Oliver and Webster, 2014). In punctual Kriging the overall accuracy can be optimized because the actual sampling locations and sensing points are free from any kind of error, however this could be the only advantage of the punctual Kriging and it cannot be useful for application in commercial fields as there is no machinery that can do a punctual job (Heege, 2013). In practice, with section control on booms, a 6 m block is preferable and the potential resolution required is for the individual nozzle control on a sprayer. On the other hand the predicted variance is larger in punctual Kriging than in block Kriging, because in the punctual method the nugget variance is involved and the predicted variance cannot be less than that, whereas in block method the nugget variance is split into within block variance and so it doesn't associate with the prediction variance (Oliver and Webster, 2014). In addition, ordinary Kriging was also found to be the best unbiased estimator for interpolating soil biological indices (Shahbazi *et al*., 2013).

1.5 Sampling for precision agriculture:

Sampling protocol is an essential step in geostatistics application in which it has a significant influence on the reliability and accuracy of the variogram that relies on the number of the samples and the intervals (Oliver and Webster, 2014), as well as the precise arrangement of the sampling points is essential for precision agriculture (Montanari *et al*., 2012). Inefficient sampling plans are considered to be the main source of error associated with managing agricultural fields and it represents 80-85% of total error (Siqueira *et al*., 2010). Therefore planning ahead for sampling design in environmental studies is essential to support the subsequent analysis of the data and decision making (Oliver, 2010), and this needs to involve some considerations such as the sufficient number of samples, the precise location of each sampling point and a suitable separation distance between sampling points (Martinez *et al*., 2010).

1.5.1 Choice for sampling:

Different approaches to sampling design are available today, and the most commonly used methods can be summarized as follows:

1.5.1.1 Random sampling:

Random sampling is easy to apply. The points are selected separately and all sampling points have the same probability and the mean of the samples can represent the population. However, due to the uneven separation of the points, it has a high variance and therefore it is inefficient to detect the variation especially in patchy distributions such as that of insects and weeds (Mulla, 1997, Bogaert and Russo, 1999, Martinez *et al.*, 2010, Webster and Lark, 2012)

1.5.1.2 Systematic sampling design:

Systematic sampling can provide a uniform cover of the study area and the most popular one is the rectangular grid. It is more efficient than random sampling in which it can provide the same information with lower cost. On the other hand each of the points does not have an equal probability and therefore it might not provide an accurate estimation of the variance (Mulla, 1997, Martinez *et al*., 2010, Webster and Lark, 2012).

1.5.1.3 Nested samples:

This kind of sampling provides the possibility of partitioning the variance into different components which can then be attributed to different spatial scales and identify these scales that are associated with a large proportion of the variance. These are two kinds of sampling schemes: balanced and unbalanced. The latter is more efficient, because it can increase the confidence and estimate the variance at more intervals than balanced ones with the same number of samples. However, it is a more sophisticated design and it needs statistical analysis using Residual Maximum Likelihood (REML) (Webster and Lark, 2012).

1.5.1.4 Stratified random sampling:

This kind of sampling design is considered as the most efficient design, as it can cover the domain evenly by dividing it into blocks based on known distributions of specific environmental factors (Webster and Lark, 2012). Also it can provide an accurate estimate of the variance and the possibility of distributing sampling efforts according to the variability of the phenomenon being assessed and the more variable parts of the field can receive extra sampling effort (Mulla, 1997, Martinez *et al*., 2010, Webster and Lark, 2012).

As mentioned above making a decision about the suitability of any sampling design depends on the purpose of the sampling. For example, to compute a reliable variogram it needs to include some degree of spatial nesting in order to reveal the variation over shorter distances. It can also be designed to be efficient for Kriging which needs an even coverage of the domain, because it relies on the variogram and the distribution of samples around the target point rather than actual values at sampling points (Webster and Lark, 2012). Locating the additional samples purposively based on the previous knowledge provided by a scaled variogram or grid samples can significantly optimize the interpolation of soil properties in which it can reduce the prediction variance in these locations (Pereira *et al*., 2013). The uneven and irregular separation of sampling points is inefficient for mapping the environmental variables and an irregular grid sample was found to be more effective than a regular grid, because the shape of most fields is irregular (Webster and Oliver, 2007). Grid sampling (systematic sampling) has been considered as the most effective design to detect within-field variability in soil properties and creating the map for variable-rate fertilizer application (Kerry *et al*., 2010, Franzen, 2011). It is essential and one of the earliest methods to provide the best information about soil properties for the land users especially when the points are close to each other (Chang *et al*., 2003, Shaner *et al*., 2008). However, Montanari *et al*. (2012) found that grid sampling with uniform intervals did not efficiently reveal the spatial variation in soil properties in the study areas of Oxisols and Alfisols. To provide accurate information it needs to be sampled densely which increases the costs of sampling (Fleming *et al*., 2000, Shaner *et al*., 2008). Attempting to obtain representative sampling based on information about the variability in soil type and crop biomass provided in advance by remote sensing could overcome this problem (Mulla, 1997).

1.5.2 Sample size and intervals:

As mentioned, the reliability of the experimental variogram depends mostly on the sample size and the spatial scale over which samples have been taken. The economic status of the farmer sometimes limits the sample size and taking one sample per hectare as is usual in commercial fields has been found to be inefficient for computing the variogram for a large area and does not represent the actual scales of the spatial variation in fields (Kerry and Oliver, 2007a). Selecting large sampling intervals wider than the scale of the variation may lose a lot of information about the spatial dependency and the experimental variogram could appear as pure nugget. In contrast, selecting small sampling intervals to reveal short-range variation is difficult and cannot be afforded in many cases (Mulla, 1997, Webster and Oliver, 2007). The large difference between the sampling intervals and the scales of the spatial variability is considered as the main problem affecting the efficiency of the grid sampling design (Haberle *et al*., 2004). Therefore sampling intervals should represent the scales of the variation in order to detect the spatial variation efficiently and to increase the detection of spatial dependency (Kerry, 2003, Webster and Oliver, 2007). Webster and Oliver (2007) and Oliver and Webster (2014) pointed out that the accuracy of the variogram can be increased with increasing the number of the samples, because it narrows the confidence limit and decreases the standard deviation, as the same data can be replicated many times when calculating the variogram. They also recommend using at least 100 samples for a variogram with appropriate confidence, and at least 144 samples for more reliable variogram. However, this number may not be adequate if short range variation exists, on the other hand it could be too many if the scales of the variation are long (Kerry *et al*., 2010). Moreover, lower sampling in commercial fields when there is a high concentration of soil nutrients might result in the same recommendations as those that can be derived when sampling densely and there are low concentrations of nutrients. While, Hengl (2007) mentioned that at least 50 sampling points are needed per field to compute a reliable variogram, but an accurate variogram based on less than 100 samples can be calculated using REML rather than MOM. The sample size of 50 with appropriate separation distance is sufficient to estimate the REML variogram and the accuracy of the data is the same as the MOM variogram based on 100 samples (Kerry and Oliver, 2007a). Montanari *et al*. (2012) concluded that the best number of sampling points and the intervals can be identified using a scaled semivariogram for which it can integrate different variables in one variogram and the number of required samples can be identified using the formula developed by Van Groenigen *et al*. (1997) which is based on the %CV of the data as follows:

$$\boldsymbol{n} = \left(\frac{\boldsymbol{t_\alpha}.\mathbf{CV}}{\boldsymbol{D}}\right)^{\mathbf{2}}$$ **Equation 1- 1**

Where n is minimum number of samples required, t_α is the value of student t (at 95% probability), CV is the coefficient of variation and D is the percentage of the variance from an average variance of different attributes.

Furthermore, Kerry and Oliver (2007a) suggested that using the average variogram calculated cheaply from ancillary data provided by remote sensing could be an effective tool to guide sampling as the variation in the property could be due to the interaction between different soil variables. Lark (2012) has also raised the possibility of using a mixed linear model framework to identify efficient methods for sampling which can deal with intrinsic variance. In addition an existing variogram calculated from sampling the field or ancillary data such from remote sensing can explain the range of the variation and guide the future sampling (Kerry *et al*., 2010) as the sampling intervals can be determined by using the half of the variogram range of the available ancillary data (Kerry, 2003). For Kriging interpolation, Li (2010) has found that the accuracy of the prediction of different interpolation methods was significantly improved with reducing the sampling intervals from 500 m to 250 m. In a study conducted in Guariba, in São Paulo State, Brazil , using an additional 20 samples improved the accuracy of the Kriging map with Relative Improvement Index (RI) of 2% for soil chemical properties and 1% for soil physical properties by Pereira *et al*. (2013). The RI can be identified as follows:

$$\mathbf{RI} = \frac{\sigma_{ss}^2 - \sigma_{oss}^2}{\sigma_{oss}^2}\ X\ 100 \qquad \textbf{Equation 1- 2}$$

Where σ_{ss}^2 and σ_{oss}^2 are respectively the prediction variance before and after using additional sampling (Pereira *et al*., 2013) .

In addition, to ensure the reliability and the accuracy of the map produced from the remote sensing data, it also requires some ground based measurements. For this purpose Debaene *et al*. (2014) used different calibration schemes to reduce number of samples required for calibrating the maps of soil properties based on remote sensing data. The maps of most soil properties were best calibrated with 79 samples (1.5 sample/ha) and there was not much difference with the result of using the complete data set of 379 samples. In summary the more data involved, the more reliable the variogram, and the number of the samples depends on the purpose of sampling, the variable of interest, the methods of analysis and availability of previous information about the spatial variability.

1.6 Within-field variability in some environmental variables affecting sugar beet:

The productivity of agricultural lands is not always constant, it might vary temporally between years due to the variability in weather conditions, or spatially within fields due to the variability in the soil properties, aspect, salinity, nutrient management, and across years and within fields induced by the interaction between weather conditions, management practices and soil properties (Oliver *et al*., 2013). The spatial variation in crop yield is usually due to the spatial variability in some environmental factors influencing crop growth and performance that might not be observed or managed precisely by the agronomist (Rains and Thomas, 2009, Griffin, 2010), such as the soil properties, weather conditions during the growing season and the interaction of soil properties and weather conditions on crop growth and development (Hakojärvi *et al*., 2013). It is quite challenging to identify the relationships between these variables (Liu *et al*., 2013). The spatial variation in crop yield and associated environmental variables might not be the same in different years; the high yielding areas in one year may be low yielding in another year due to the variability in weather conditions and the crop response. In general, the constant spatial variability is mainly due to the internal factors such as field topography and soil properties. The temporal variation on the other hand is due to external factors such as climate, pests and disease. In addition, some of the spatial variability might be related to the management practice rather than environmental factors, as almost 50% of the spatial variability in cereal yields found within the distance separating the tramlines (Taylor *et al*., 2003). The interaction among these factors makes it difficult to address the main driving variables (Simmonds *et al*., 2013). Identifying the spatial variation in these factors precisely is important for precision agriculture (Karaman *et al*., 2009b), and evaluating its relationship with the variation in crop yield is a key component for precision agriculture, and it has developed significantly over the last two decades. The patterns of within-field variability in these variables could be randomly distributed throughout the field as small spots or it could be nested variation distributing as a patches of low and high values of the property changing in both distance and direction (Heege, 2013). The potential effect and the spatial variability of each of these factors as well as the possible ways of identifying and managing it are described in detail in the following sections.

1.6.1 Field topography:

Field topography is considered to be one of the main driving variables behind within field variation in which it can affect the crop growth and yield directly from its effect on microclimate condition such as solar radiation and air temperature, or indirectly from its effect on soil properties such as soil nutrients and soil temperature that can affect crop growth and development. However, for most agricultural fields, the field topography cannot be changed, but it rather can be used to understand the variation (Godwin and Miller, 2003) and perhaps to exploit it. The effect of the topography is very significant in the semiarid areas, due to its effect on soil moisture, which is the major problem limiting crop growth in these areas (Zeleke and Cheng, 2004). With the presence of more complex field topography, soil forming factors and erosion will vary accordingly and this might reflect on crop yield (Kumhálová *et al*., 2008). Therefore describing the topographic features such as the slope degree and aspect of the field may be important for implementation of precision agriculture (Pachepsky *et al*., 2001a, Zeleke and Cheng, 2004). Although, the main features of topography can be assessed visually, it is important that they are quantified in order to understand their relation to yield and other environmental variables (Godwin and Miller, 2003).

To identify the direct and indirect effects of field topography on crop yield, different studies have been conducted. Zhang *et al*. (2011b) found spatial variation in soil organic matter (OM), total phosphorus (P) and total nitrogen (N) were related to both the aspect and the steepness of slopes, but this relationship differed when they considered only the aspect or slope. They also found significant increases in the studied variables by 33.8, 23.3 and 22.4% for OM, N and P, respectively when the cross-slope tillage was compared to down-slope tillage. A high dependency of yield and nutrients on field topography was also found by Kumhálová *et al*. (2008). In their study near Brague-Czech Republic, three crops were involved; winter rapeseed, winter wheat and oat in 2004, 2005, and 2006, respectively. They noticed that the effect of field topography in the driest year was greater with correlation coefficient of 60% compared to the 20% correlation coefficient in the wettest years of the studied period. Similar results were also observed by Kleinjan *et al*. (2007) in a maize field located in east-central South Dakota. They found the area at the bottom of a slope that sometimes experiences excess soil moisture, produced high corn yields in dry years and the production was low to moderate in the wet years. This could be due to the effect of topography on the ability of soil to retain moisture during the dry years. This effect has been explained in another study conducted by Pachepsky *et al*. (2001b), based on the results of regression analysis, they found that the field topography accounted for 60% of the variation in soil water content, which could be due to the effect of topography on soil texture which has a direct effect on soil water holding capacity. Due to the effect of field topography on soil water content the upslope length has been considered by Zeleke and Cheng (2004) as a best predictor for grain yield and biomass at different spatial scales and they found high correlation coefficient 93% between scaling indices and grain yield. The distribution of some insects such as sugar beet root maggot, *Tetanops myopaejormis* in relation to field topography was also examined by MacRae (2003) in sugar beet field, in Red River Valley in Minnesota, and the results showed that the emergence of the insect depended on field topography: the population of the insect was significantly reduced in water standing zones of the field which was caused by the topography. In a study conducted by Dixit and Chen (2011) in southern Mallee of Victoria, Australia. They attributed the within field variation in temperature in a wheat field to the field topography. Their results showed that in bare soils only the minimum temperature related to field topography, while both minimum and maximum temperature were related to field topography in the presence of a wheat crop.

Although, the effect of field topography on a crop's yield and micro-environment conditions has been examined in different studies and significant results have been achieved, simulating the yield of some crops such as sugar beet also needs to be examined and modelled based on micro-environmental conditions. These conditions might vary according to the aspect and steepness of the within field slopes which may affect the accumulation of sugar, due to its effect on foliage cover and photosynthesis rate and an attempts is made to investigate this here in this thesis .

1.6.2 Temperature:

Temperature is an important weather variable affecting sugar beet growth and yield. The accumulation of sugar in sugar beet roots is highly affected by temperature. A warm temperature between 15-17°C in July and August with high nitrogen availability is important for sugar beet vegetative growth, while exposing sugar beet to a period of low temperature will stimulate flowering (bolting) causing the stem elongation and will consume the stored sugar in the root for seed development (Draycott, 2008). For successful development of a sugar beet crop in the UK, the thermal time has to be from 2400- 2700 °C d (Samson-Bręk, 2010). A warm temperature early in spring with a low fluctuation between day and night temperatures is important for germination of sugar beet seed and allows early sowing. Low temperature is however important at the end of the growing season to limit the vegetative growth and induce sugar accumulation in the root (Samson-Bręk, 2010). Since 1976 to 2004 the average air temperature in the UK has increased by an average annual rate of 0.045°C which has allowed sugar beet to be sown earlier than 1st of

April, which in turn has extended the period of crop growth and this is associated with an increase the sugar yield by 0.025 and 0.032 t/ha/year sugar in both rain-fed and irrigated areas respectively (Jaggard *et al*., 2007). Extending the growing season of sugar beet is important to avoid the risk of yield losses due to water deficit (Freckleton *et al*., 1999). In addition to the role of temperature in early sowing, warmer summers will have a direct effect on sugar beet canopy cover. The development of sugar beet canopy from emergence to full ground cover is highly dependent on temperature. Therefore warmer conditions in spring would enhance vegetative growth and increase the amount of solar radiation intercepted by the crop canopy (Jaggard *et al*., 2009). Temperature combined with the amount of solar radiation intercepted are considered to be the main factors determining the accumulation of dry matter in sugar beet (Qi *et al*., 2005). Kenter *et al*. (2006) found that increasing temperatures from sowing to July from 14 to 18°C significantly increased the dry weight of both leaves and roots of sugar beet, while crop growth was adversely affected by high temperatures during July and August, then it became independent of temperature at the end of growing season. They also observed that in Germany 18°C was the best average daily air temperature for the development of tap roots. Freckleton *et al*. (1999) stated that the variation in temperature and rainfall are the main factors limiting sugar beet yield in the UK. Their results indicated increase in sugar beet yield with increasing the amount of precipitation and decreasing the temperature, except for the temperature during April, which was found to be positively correlated to the yield. They also found that the crop's response to temperature can be increased by increasing nitrogen fertilization.

From these studies it has become clear that the effect of temperature on sugar beet growth and yield has been well investigated and different models have been derived to simulate sugar beet yield based on weather data. However most of these studies relied on the weather data provided by a small number of weather stations representing whole regions. This weather data may not represent the actual crop micro-climate, as the air temperature in the crop canopy may differ from the air temperature at the weather station (Monestiez *et al*., 2001), and it might vary from one field to another or even within the same field. The within field variability in air temperature was investigated by Dixit and Chen (2011). They installed 25 temperature loggers in 164 ha wheat farm in the southern Mallee of Victoria, Australia near the flowering stage. They attribute the variation in minimum and maximum air temperature to the field topography and variations were more obvious in the presence of a crop canopy than above bare soil. Therefore the differences in air temperature at different locations in a field should be considered when modelling the effect of temperature on sugar beet; an attempt to do this is described in this thesis.

1.6.3 Solar radiation:

Solar radiation interception highly influences the production of dry matter and consequently the accumulation of sugar in the sugar beet root. In the UK, this topic has been investigated at Brooms Barn Research Station (Draycott, 2008). High sugar yield per ha is strongly associated with the amount and duration of insolation, especially during August and September, which are the important times for sucrose accumulation (Samson-Bręk, 2010). Crop growth is a result of the accumulated daily increase in the amount of solar radiation interception and the radiation use efficiency, which could be small in daily rate but it has an essential contribution to the final sugar yield (Jaggard *et al*., 2009). This effect is strongly related to air temperature, such that temperature and solar radiation interception are the main factors determining sugar accumulation in sugar beet when water and fertilizer are optimally available (Qi *et al*., 2005, Kenter *et al*., 2006). The warm summers in the UK have accelerated the crop canopy development which in turn has increased the amount of solar radiation interception (Kenter *et al*., 2006, Jaggard *et al*., 2009). A similar relationship also exists between solar radiation interception and crop water use, as the increase in solar radiation interception is usually associated with increase in the rate of photosynthesis, dry matter production and transpiration, which inevitably increases the crop's requirement for water (Draycott, 2008, Jaggard *et al*., 2009).

Investigating the potential effect of solar radiation on crop growth and yield has been carried out on regional bases assuming an even distribution of solar radiation in a specific geographic area. However, the incident solar radiation can clearly vary at a global scale based on the earth's geometry and the position of the sun. In a small landscape such as in agricultural fields, the distribution of solar radiation is mainly affected by field topography. The presence of slopes at different gradients and orientations may cause significant variation in the received solar radiation which in turn leads to spatial variation in micro-environment such as soil and air temperature, soil moisture, evapotranspiration and photosynthesis (Fu and Rich, 1999). In sloping surfaces, the received solar radiation usually involves three components: the direct beam from the sun received at the surface without the effects of the atmosphere in scattering or absorbing; diffuse radiation which is affected by the atmosphere; and the hemispherical reflected radiation which is a small component reflected from the surface lying at a lower altitude to the point in question (Allen *et al*., 2006). Therefore the information about the orientation and aspect of topography has been considered to describe the relative distribution of solar radiation, but the usual methods did not successfully include the daily and annual variation in solar radiation and shading effect as well as its relation to variation in crop growth (Pierce Jr *et al*., 2005).

A model was developed by Kumar *et al*. (1997) to calculate the incident solar radiation for any location within agricultural fields at any time of the day and year based on the digital elevation model. In addition, a comprehensive geometric map of solar radiation based on a digital elevation model (DEMs) can now be produced by Solar analyst tool developed by Fu and Rich (1999) as an extension in ArcView GIS. This map can explain the effect of elevation, orientation and atmospheric condition on distribution of solar radiation. The same approach was further developed by Pierce Jr *et al*. (2005) to estimate the potential relative radiation based on DEMs and they found significant differences among four comprehensive radiation proxies, and its reliability has been validated when compared with the results of intensive measurements.

Allen *et al*. (2006) developed an analytical extra-terrestrial radiation model based on general algorithms that take into account the effect of atmospheric permeability and slope on the direct beam, diffuse and reflected radiations to produce clear sky solar radiation curves which do not require local calibration. The method was also found useful as a tool to convert global solar radiation on a flat surface to nearby slope. The information about solar radiation is usually provided by a sparse network of stations which are too widely spaced making accurate interpolation almost impossible. Therefore some other related environmental variables such as air temperature can be used to simulate solar radiation.

Montero *et al*. (2009) proposed a numerical model to generate the solar radiation map based on the shadow distribution in each time step. The accuracy of the model depends on the number of points at which the measurements are taken. They recommend improving the interpolation method in the future in order to obtain better results. However, the interpolation methods are usually used to predict solar radiation in areas where there are no weather stations, but these methods are not efficient in the areas where there is complex topography that might be the main source of variation in received solar radiation. The topographic information provided by the DEM is effective to estimate solar radiation in the areas of complex topography (Tovar-Pescador *et al*., 2006). Considering the topographic information provided by the DEM and the map of topographic parameters such as the slope, aspect and hillshade in the radiation transfer model is an efficient and cheap way to predict solar radiation in a specific area (Cioban *et al*., 2013). Bojanowski *et al*. (2013) indicate the feasibility of using daily air temperature to predict daily solar radiation precisely without requiring a site specific empirical coefficient which needs some measurements of solar radiation provided by a weather station. The results obtained by this method were as reliable as these obtained by the ground-based measurements. Bennie *et al*. (2008) have adjusted the incoming solar radiation for the topography, which they used to determine the micro-environment on two chalk grassland fields and its relation to the distribution of some plant species. For this purpose they used two methods to estimate incoming solar radiation: a spatially explicit method, which depends on the information derived by the DEM, while the second method is called spatially implicit, which is based on the statistical distribution of the slope and aspect. The performance of the implicit model was almost the same as the performance of the explicit methods, but it was limited by the parameterization of slope and aspect indicating the importance of the variability in topography to identify the microclimate of the area no previous attempts have used this approaches within a single field as far as known.

1.6.4 Available water:

As with other crops, the available water is one of the important conditions for sugar beet production, because most physiological processes such as cellular functions and turgor pressure depend on water. The current sugar beet varieties are more tolerant of drought than older varieties. The amount of water required for sugar beet production varies from 350 mm per growing season in temperate areas to more than 1000 mm in arid areas (Draycott, 2008). This amount can be increased linearly with increasing solar radiation, and most of this water is absorbed from 0-60 cm deep in the soil and only 5% is absorbed from 100-150 cm (Jaggard *et al*., 2009). In non-irrigated areas such as most of Europe, the water deficit is considered to be the main factor causing yield losses of sugar beet. The potential loss in sugar beet yield due to water stress is expected to increase in the future and is predicted to reach 22% by 2050 and 35% by 2080 (Richter *et al*., 2006) based on current varieties and agronomy. Kenter *et al*. (2006) found a significant relationship between available water and root dry matter of sugar beet during July and August. In a study conducted by Monti *et al*. (2006) near Parano in Italy, a significant reduction in the rate of photosynthesis and accumulation of dry matter under water stress was observed. This reduction was strongly associated with reduction in sugar yield. They concluded that reducing the water to 30% of field capacity for 37 days in early growth stages even for short period, significantly reduced the final sugar yield. The losses in sugar yield were not compensated when water was provided. Therefore any recommendation about irrigation of sugar beet could be useful when water stress can be expected and spatial variability in water supply across the fields could help to improve water use efficiency of the crop.

Soil moisture is highly related to some other environmental variables and therefore it is highly variable at different spatial and temporal scales and the patterns of the variation are usually influenced by different factors such as precipitation, soil properties, topography and some agronomic practices (Korres *et al.*, 2013, Hatfield and Kitchen, 2013). Vieira *et al*. (2008) stated that spatial variation in soil moisture in one year might follow the same patterns in other years in a study conducted near Ottawa in Canada, but the temporal variation and the spatial dependency can be remarkably reduced when the soil becomes drier. This is due to hydrological conductivity affecting the rate of evaporation throughout the field. They also attributed the constant variation in soil moisture over time to the topographical structure. The lowest spatial coefficient of variation (CV=12%) was observed in winter through to the end of March when there is high precipitation with low or no crop canopy, while a high CV was observed in the period from April to June reaching the maximum value of 22% at the beginning of June. This could be due to variability in growth of sugar beet and winter wheat crops which caused variation in the amount of absorbed soil moisture and evapotranspiration, which are considered to be the main factors causing small scale variation in soil moisture (Korres *et al*., 2013). In a study conducted by Pachepsky *et al.* (2001a) in Beltsville Agricultural Research Centre in USA. The results of regression analysis showed that over 60% of the spatial variation in soil moisture related to field topography, and the soil moisture retention was significantly decreased with the increase in slope.

As the soil available water is important for crop growth, it is expected that within field variability in soil moisture can cause spatial variation in crop yield. However in a study conducted by Hakojärvi *et al.* (2013) Agrifood Research Finland, the spatial variation in some crops such as wheat and barley was not sufficiently explained by variability in soil available water. A possible reason for that might be the influence of some other variables such as lodging, cold weather and excess soil moisture.

To detect spatial variation in soil moisture in sugar beet fields, aerial photographs supported with some samples have been used by Zhang *et al.* (2007) and Zhang *et al.* (2011a). They found that the variation in soil moisture can cause spatially variable wilting in sugar beet, which changes the colour and height of the leaves in a way that can be easily detected by aerial images. According to their results, the wilting areas were associated with low soil moisture which was also associated with higher proportions of sand and stones, while unwilted areas were associated with high soil moisture and soil clay content. The variation in total available water at 1 m depth was significantly different between stressed and unstressed areas. Due to the wilting patterns in the sugar beet crop, it can be used as a good predictor to detect within field variability in soil moisture. However the method could not be reliable without some soil sampling because the wilting patterns in sugar beet could be due to other variables. In another study near Missouri in USA, Jiang *et al.* (2007) found a significant relationship between soil electrical conductivity and the available water of 1.2 m soil profile with R^2=0.67 and 0.87 respectively in two fields and it was also highly correlated with topsoil thickness.

1.6.5 Soil properties:

Within the field scale, soil properties are often highly variable causing spatial variation in crop yield and quality which could be due to the variability in soil type, microclimate, drainage, field topography, soil preparation and previous cropping. This variability in soil variables can be associated with spatial and temporal variability in crop biomass, weeds, pests and diseases (Oliver *et al*., 2013). Since crop yield is strongly affected by the variation in soil properties, it is important to map the spatial variability in soil properties over which the farmer has some control for successful application of precision agriculture (Oliver, 2010). Due to the availability of current spatial technology such as remote sensing and electrical conductivity as well as appearance of geostatistical methods for interpolation with different sampling schemes, it has become possible to detect and map the within field variability in soil properties. This information can then be linked to the crop growth in order to derive spatially variable recommendations. Detecting the variation in soil properties is often a complex issue and it is difficult to be modelled by available simple models because it is controlled by different chemical and physical factors (Lark, 2012). Predicting spatial variation in crop biomass based only on soil properties is difficult in the case of high spatial variation, due to the interaction between soil properties, weather conditions and field topography (Hakojärvi *et al*., 2013). Therefore a variety of methods have been examined by soil scientists to detect spatial variability in different soil parameters and their relation to crop variability which is described for each parameter in the following sections.

1.6.5.1 Soil physical properties:

As the emergence of sugar beet seedlings is affected by soil compaction, the sensitivity of sugar beet crop to soil physical properties increases just after emergence because the best yield can be determined by the rapid extension of crop roots early in the season. Therefore sugar beet should be grown in soils with appropriate porosity, a porosity percentage of 50% comprising 25% water and 25% air being ideal for sugar beet crop (Draycott and Christenson, 2003). The most desirable soils for growing sugar beet crop are medium compact, light and medium-heavy clay soils. It can also be grown successively in well-managed heavy clay soils (Samson-Bręk, 2010).

Soil physical properties can directly affect the crop growth and yield through the mechanical resistance to seed emergence and root extension and the porosity. Perhaps the most influential one for many crops is the soil water infiltration capacity as it combines the effect of many other soil physical parameters such as soil structure, porosity, soil resistance, bulk density, and soil compaction. The high infiltration zones had high available water and associated with high yields of soybean, maize and wheat, which followed each other in a six year rotation, while the low infiltration zones had low available water and low yield of these crops (Amado and Santi, 2011). Soil texture is also considered as an important variable and it strongly relates to other soil properties such as porosity, water holding capacity, nutrient availability and soil erosion, therefore mapping the spatial variation in soil texture can be used as an indicator for site specific management and precision agriculture (Safari *et al*., 2013). However, changing soil texture would take a very long time (Draycott and Christenson, 2003). Taylor *et al*. (2003) examined the spatial variability in three cereal fields (winter barley and winter wheat) over four years in England. The spatial variability in yields was found to be related to soil types in dry years, which in turn related to the spatial variability in soil available water. Lamb and Brown (2001) attributed inconsistent patterns of spatial variation in NDVI of a wheat crop measured at two different growth stages to the variation in soil texture and rainfall, which in turn affected the availability of nutrients and water. Hbirkou *et al.* (2011) found a strong correlation between the spatial distributions of the nematode, *Heterodera schachtii,* and soil physical conditions in a variable sugar beet field in the Lower Rhine Basin in Germany. The soil EC and texture maps show that the areas of different soil conditions were associated with different populations of the nematode, indicating that the potential infection of sugar beet by *H. schachtii* may increase in deep soil with light texture (sandy loam) to medium texture (silt loam) as this is the best soil for *H. schachtii*. A high positive correlation coefficient between alkaline phosphomonoesterase enzyme produced by soil microbes and sand content of the soil was found by Shahbazi *et al*. (2013) in different land use conditions in Mirabad area, North West of Iran, indicating the importance of porosity for effective respiration and metabolic activity. Hanse *et al*. (2011b) investigated the reasons for significant differences in sugar beet yield between neighbouring pairs of growers located throughout the Netherlands, which were almost under the same conditions of soil and climate, and they found that the soil physical properties were the main factors associated with the differences. They attributed this difference to soil management practices by the growers during seed bed preparation, which significantly affected the soil physical properties such as soil structure, compaction and porosity. Soil texture reflects many soil attributes such as permeability, water holding capacity, nutrient storage and erosion, and consequently the crop growth and yield, and so mapping the spatial variation in soil texture is important for precision agriculture (Safari *et al*., 2013). Zhu *et al*. (2013) identified two physical soil properties; horizon texture and the depth to clay as related to the crop's yield (maize, soybean winter wheat) in an agricultural landscape located in central Pennsylvania, USA. Therefore, they produced a functional map combining these two physical properties for managing the crops and soil moisture. However, Kempen *et al*. (2012) compared the soil maps created based on spatial and non-spatial models, the validation of results showing that predictions based on spatial models were not more accurate than predictions based on non-spatial models.

1.6.5.2 Soil Organic Matter (SOM)

Soil organic matter has an important role in agricultural fields since it improves soil structure and nutrient status, enhances the ability of soil to hold water, its cation exchange capacity (CEC) and biodiversity. Perhaps the most important role is improving the soil condition for many soil organisms, which in turn is important for nutrient cycling, organic matter decomposition, hydrology and gaseous exchange (Oliver *et al*., 2013). The availability of SOM in a sugar beet field can improve the yield by improving soil properties and providing the crop with nutrients and especially nitrogen at different growth stages (Draycott and Christenson, 2003, Draycott, 2008). As a result of repeated application of farm compost, the soil physical, chemical and biological properties were significantly improved and the yields of studied crops (potato, fodder beet and maize) were also significantly increased. Most of this improvement was correlated to the increase in soil organic carbon and total N, which were therefore considered as the main factors likely to be affecting crop productivity (D'Hose *et al*., 2014). Under different land use conditions Shahbazi *et al*. (2013) found a strong correlation between soil microbial biomass and SOM at different spatial scales. Therefore, mapping spatial variation in SOM could provide the agronomist with useful information to identify degraded locations with the possibility of managing it and doing other agro-environmental improvements accordingly (Lamb and Brown, 2001). For this purpose different studies have been conducted and a variety of methods have been examined. Karaman *et al*. (2009a) used a 20X20 m grid for mapping SOM in a sugar beet field, and they found spatial variation in both the top and the subsoil SOM. They also found that top SOM was more variable (CV=17.8%) than subsoil SOM (CV=13.1%). In a study conducted in southern Brazil, the spatial variability in SOM was found to be related to soil type, field topography and landscape. Most of the spatial variation in SOM was attributed to water erosion in the areas with concave or convex topography, as the water erosion was associated with SOM on the slopes and shoulder areas, but with higher SOM in lower zones (Amado and Santi, 2011). In another study a Kriged map of SOM in a 26 ha field based on 172 samples split the field into three zones, while a map of the same field produced from remote sensing images of bare soil differentiated the field into seven different zones. Low yielding zones were almost always associated with low SOM zones. The remote sensing was found to provide better information about the spatial distribution of SOM than the ground based measurements (Mulla, 1997). A similar conclusion was also obtained by Debaene *et al*. (2014), using a map produced using visible and near-infrared spectroscopy which showed the same patterns of spatial variability in SOM as a map produced from 379 soil samples with the same level of accuracy and lower costs.

1.6.5.3 Soil pH:

Soil pH has a significant effect on crop performance such that low pH can significantly reduce the concentrations of nutrients available to the plant. Sugar beet in particular is very sensitive to acidic soils and it prefers neutral soil pH levels, because low pH can cause poor germination and plant establishment, limiting root growth and leading to unreliable yields (Draycott and Christenson, 2003, Samson-Bręk, 2010). The measurements of soil pH can be used as an indicator of root development and soil condition and are useful to derive some management strategies (Scannavino *et al*., 2011). Spatial variation in soil pH can be associated with spatially variable crop yields. Most of the spatial variation in soil pH is strongly related to field topography, because it exposes the field to the effect of water erosion, which can lead to spatial variation in soil pH (Amado and Santi, 2011). As soil acidity affects the concentration of available nutrients, the interpolation maps produced by Lamb and Brown (2001), showed spatial variation in soil pH and the areas with high pH were associated with a high concentration of magnesium. However, the results did not show any significant relationship with crop yield. The spatial variability in soil pH at different layers in 58 field locations of Kumeu River Winery, New Zealand, was investigated by Scannavino *et al*. (2011), who found that the upper soil layers (5-15 cm) were more acid than the subsoil layers (15-25 and 25-35 cm). However, Cirkel *et al*. (2014) stated that high spatial and temporal variation in soil acidity might be a source of systematic error, and the strong relationship between soil pH and crops yield found in different studies, was associated with high residual variance. They also found that most of this variation in soil pH can be anticipated from soil moisture, as the high correlation between soil pH and crop were observed in the dry plots (93%) and it decreased to 59% in the wet plots.

1.6.5.4 Soil available nutrient:

The main elements that need to be available in large amounts for sugar beet are N, P, S, K, Ca, Mg and Na (Draycott and Christenson, 2003). As the crop growth and yield highly depend on nutrient availability, the within-field variation in some nutrients is associated with spatial variation in yield and quality. For example, a good performance of root crops such as sugar beet, needs uniform distribution of phosphorus in the root zone; therefore the spatial variation in soil phosphorus could potentially lead to spatial variation in sugar beet yield (Karaman *et al*., 2009b). Field topography, weather conditions, soil parent material, management practices and land use are considered to be the main factors causing spatial variation in soil nutrients (Liu *et al*., 2013, Zhang *et al*., 2011b). Perhaps the most influential one is the field topography including both slope degree and aspect (Godwin and Miller, 2003, Zhang *et al*., 2011b), which expose nutrients to water erosion resulting in high nutrient concentrations in some areas and low concentrations in others (Amado and Santi, 2011). However, the areas of low nutrient availability are not necessarily associated with low crop yield; they might rather produce larger yields than areas of high nutrient concentrations. This could be because the yield is limited by factors other than nutrient availability or it could be due to the negative effect of supra-optimal concentration of some nutrients, a problem that can be exacerbated by uniform fertilizer applications (Griffin, 2010). Rodriguez-Moreno *et al*. (2014) investigated the spatial distribution of soil nutrients in two winter wheat fields located in the Czech Republic and its relation to crop growth. They found that soil potassium, calcium and nitrogen were the main factors related to the spatial variability in crop growth in one field, while the related factor was only soil moisture in the other field. They also found that spatial variability in both crop growth and nutrient was related to climate, field topography and soil type. Amado and Santi (2011) observed in their study in Southern Brazil, that areas with high concentration of P were associated with high concentration of K with a correlation coefficient of 0.68. In another study conducted in the Sacramento Valley of California, Simmonds *et al*. (2013) observed temporal change in the spatial distribution of SOM, N, P, K and salts as a result of water movement in four rice fields, but they were related to the yield only in the zones with high salinity. Haberle *et al*. (2004) observed spatial variability in soil N in both top and sub-soil layers with almost the same degree of variation, and the relationship between N levels in top and sub-soil layer was positive. They also mentioned that N leaching to deep sub-soil layers may reduce the negative impact of N on sugar beet, and providing it remains there, it can be utilized later. Liu *et al*. (2006) attribute the variability in available N to soil organic matter and cation exchange capacity, which both control the natural N mineralization, leaching which reduces the N in the root zone, and some other factors that affect N uptake by the crop such as solar radiation and available water. In a study conducted by Mulla (1997), the Kriged map shows that the areas of low phosphorus were associated with areas of low organic matter, but the areas of high phosphorus did not associate with high organic matter. The spatial variation in some soil micro-nutrients such as Fe, Mn and Zn was also observed in the study conducted in northeast China by Zhang *et* *al*. (2013) and they mentioned that the relationship between soil micro-nutrients can vary over different spatial scales.

The nutrient status of the field has a high potential to be one of the main driving variables, or it could interact with other environmental variables and cause spatial variation in crop yield over which the farmer has a control over the duration of a single crop. Therefore, the spatial variability in available nutrients should be mapped and it is essential to investigate their relationship to the variation in crop yield and performance, so that it can be managed accordingly when the nutrient is a limiting factor. The map of nutrient status in relation to the map of crop yield or biomass can help the farmer to avoid the consequences of the uniform fertilization, which may result in over fertilization in some areas and under fertilization in others, which in turn increases the costs, wastes the materials and may adversely affect the environment (Oliver *et al*., 2013). The spatial variation in crop yield in relation to nutrients can be managed by VRA, which is based on dividing the field into different management zones according to nutrient availability. These zones can be identified based on spatial data of soil analysis or the crop response obtained from soil sampling, remote sensing, electrical conductivity or yield monitoring (Chang *et al*., 2003, Franzen, 2004, Zhang *et al*., 2010b). However, VRA technique is usually applied based on the regional recommendations for fertilizer and it needs to be based on very precise local information to avoid any inappropriate application of nutrients, which might lead to the same or worse results as may be obtained from uniform application (Bullock *et al*., 2002).

1.6.6 Weeds:

For sugar beet in particular, the competition for solar radiation by weeds is considered as the most influential, as tall weeds can shade the relatively low crop plants and decrease photosynthetic rate. Small weeds can also affect sugar beet plants shortly after emergence when the crop plants are too small and cannot compete. In both ways weeds affect the amount of light received by the crop, which reduces the dry matter accumulation and consequently reduces the sugar yield (Draycott, 2008). Usually weeds are controlled by the uniform spraying of herbicides, assuming the uniform distribution of weeds throughout the field, while in fact, many weeds tend to appear as patches with a high density in some areas and other areas may be weed free or have a low density of weeds. The location of these patches and weeds species may also change over time (Thornton *et al*., 1990, Nutter *et al*., 2011). In addition, the distribution of weeds can be affected by field management. For example, using an irrigation system such as a split-bed furrow can cause non-uniform weed distribution in the seedline due to the non-uniform distribution of water (Slaughter *et al*., 2008). The information about weed distribution and species is necessary for site specific weed control, and integrating the information of soil properties into the weeds map can be useful to estimate the losses in crop yield due to weed competition (Gerhards and Christensen, 2003). Their results show a significant reduction in the amount of herbicides for controlling weeds in sugar beet field site-specifically by an average 36% for grass weeds and 41% for broad-leaved weeds. However, producing an accurate map of weed distribution is still challenging and a variety of methods have been examined for their reliability in weed mapping. Image capture and analysis are most frequently used as the cost effective methods, but light intensity is considered as the main limitation to distinguishing the sugar beet plants from weeds that can affect the red, green and blue components (Jafari *et al*., 2006, Slaughter *et al*., 2008). Nieuwenhuizen *et al*. (2007) identified about 97% of volunteer potato plants in sugar beet field under cloudy conditions and this percentage reduced to 49% under sunny conditions, due to the higher light intensity. Machine vision has been found as a useful tool for many other agriculture applications, but it cannot be used effectively for weed detection due to overlapping of crop leaves (Jafari *et al*., 2006). Rasmussen *et al*. (2013) referred to the potential of weed detection from altitudes more than 50 m using a fixed wings unmanned aircraft system, at this height the image can cover 3000 m^2 with resolution of 17 m per pixel. However this resolution may not be enough to detect weeds at densities important to the farmer.

1.6.7 Diseases:

Sugar beet is sensitive to the various pests and diseases, although their effects have been mitigated by developing varietal resistance and using effective pesticides, the yield losses due to diseases and pests is a concern. Increasing land productivity usually requires intensive plant rotation and agricultural machinery movements, which might contribute to an increase in crop infection by some soil borne diseases, especially in Europe (Draycott, 2008). As the environmental conditions can spatially vary within the field scale, the suitable condition for development of some diseases can also vary causing variable distribution of biotic constraints. Therefore, considering the spatial variation in some environmental variables especially soil properties may be important for site-specific crop protection (Patzold *et al*., 2008). The appearance of beet cyst nematode, *Heterodera* *schachtii*, which is causing severe sugar beet losses worldwide, is found to be distributed in heterogeneous patches mostly associated with soil texture. In the fields experiencing spatial variation in soil properties the distribution of the nematode was moderately to strongly correlated to soil EC (R^2=0.47 to 0.74) indicating to the potential usefulness of soil mapping for precision crop protection (Hbirkou *et al*., 2011). Producing a map explaining the spatial relationship between environment properties and the distribution of insects, may also be useful in anticipating the outbreak of insect problems and planning for their management (French *et al*., 2011). MacRae (2003) stated that emergence of the adult sugar beet root maggot, *Tetanops myopaejormis*, which is one of the most influential sugar beet insects, is highly affected by field topography, which is in turn affected by soil moisture. The ability of the insect pests to emerge has been significantly reduced in low areas of the field where there is high soil moisture.

In a four year study conducted in the Netherlands by Hanse *et al*. (2011a), the total yield losses of sugar beet due to pests and diseases is estimated to be around 30.2% in clay soils and 13.1% in sandy soils for top sugar beet growers, rising to 37.1 and 16.7% respectively for average growers. This means that the effect of pests and disease on sugar beet may vary according to the soil type as well as the growers. They conclude that the main reason for lower losses in sugar beet fields of the top growers was due to earlier sowing and more fungicide applications compared to the average growers.

Using remote sensing to detect diseases in a sugar beet field has been found to be feasible, as it relates to some vegetative indices such as NDVI that can be measured by remote sensing which are higher in healthy crop and lower in infected areas (Laudien *et al*., 2004, Reynolds, 2010). The changes in vegetative indices can happen, due to the decreases in chlorophyll content which start 3 weeks after infection, but did not appear until the crop was severely infected and its influence on root yield reached 25-50% (Reynolds, 2010). It follows that detection by remote sensing is useful only as historical record, since control would need to be implemented long before the problem was detected by remote sensing. In many cases, disease control has to be implemented prophylactically and also uniformly, due to the rapid distribution of some air borne spores.

1.7 Motivation of the study:

Most agriculturalists are interested nowadays to maximize the yield with the possibility of minimizing the agronomic inputs to reduce the costs of production and protect the environment. This may partly be achieved by applying precision agriculture approaches, which can identify the variation and manage it to improve yields and profitability and also reduce the environmental impacts of food production (Oliver *et al*., 2013). To apply precision agriculture, the within-field variability in crop growth and associated environmental variables need to be determined. However, the intra-field variability in sugar beet yield and quality is generally unknown; therefore, it needs to be quantified in relation to soil properties and micro-climate condition. The observed variability in crop environment can then be managed by customizing the inputs to the areas where they are needed (Lamb and Brown, 2001, Mondal *et al*., 2011, Najafabadi *et al*., 2011).

As a result of the advances in spatial technology such as GPS, remote sensing and machine vision, the intra-field variability in yield and biomass of many crops can now be identified easily and cheaply (Delegido *et al*., 2011, Franzen, 2004, Heege, 2013, Rocchini *et al*., 2013, Zhang, 2011), but yield maps are still not available for sugar beet. However, these data represent the crop's response to stresses, which could have resulted from different kinds of stresses such as water deficit, lack of nutrients, mineral toxicity, salinity or crop protection issues (Blackmore, 2003, Jones and Schofield, 2008), and therefore, the correct interpretation may be unclear without sampling and ground truthing (Zhang *et al*., 2010b). In addition, treating the spatial variability late in the season might be useless, especially in the case of sugar beet, because the accumulation of dry matter and sucrose start early in the season (Draycott, 2008). Therefore, predicting and treating the within field variation in sugar beet growth and development early in the growing season can add great value to the implementation of precision agriculture. Thus identifying the main factors causing early season variation and their correlation with final yield and sugar content was a major topic for study in this thesis.

In addition, the yield map provided by the combine harvester for the crops preceding sugar beet such as winter wheat or rapeseed also need to be examined for their utility in predicting the spatial variation in sugar beet yields. Although, they might not show the same patterns of variation because the crop is different and the environment can differ from one year to another (Blackmore, 2003), the long term variation such as that caused by field topography and soil type can be consistent over many years and the variation in some factors such as soil moisture can follow the same patterns (Vieira *et al*., 2008). Yield maps were available for two out of three fields studied, and so this correlation has been investigated.

The sugar beet growth model developed in Brooms Barn Research Station has been used in various studies to simulate sugar beet yield in relation to weather conditions (Jaggard *et* *al*., 2009, Jaggard *et al*., 2007, Qi *et al*., 2005, Richter *et al*., 2006). However the model used to predict sugar beet yield has always been based on regional weather data considering one soil type, while the incident solar radiation, air temperature, soil moisture, and soil properties can all be affected by field topography including both aspect and slope, which may cause spatial variation in evapotranspiration, photosynthesis and crop yield (Fu and Rich, 1999, Godwin and Miller, 2003, Pachepsky *et al*., 2001a, Zeleke and Cheng, 2004, Zhang *et al*., 2011b). Therefore the sugar beet growth model has been applied and developed here to simulate sugar beet growth and yield based on the micro-climate taking into account the within field variation in solar radiation, air temperature, soil moisture and soil type.

1.8 Study objectives and hypotheses:

Within-field variability in sugar beet yield, growth and associated environmental variables has been investigated under the topic "Towards More Precise Sugar Beet Management Based on Geostatistical Analysis of Spatial Variability within Fields". The general aims were to map within-field variability in sugar beet yield and growth in three commercial fields and identify the main associated variables in order to provide information, which might be useful for precise management of sugar beet crop. A subsidiary objective was to examine the feasibility of modelling and anticipating the spatial variation in sugar beet yield based on early assessment of the micro-environment and crop growth which might add value to spatially variable applications of crop inputs.

1.8.1 Objectives:

1- To identify the main variables associated with spatial variation in sugar beet growth and in root and sugar yield;

2- To examine the possibility of early prediction of spatial variation in sugar beet yield based on measurements of crop condition and biomass taken early in the growing season.

3- To assess the possibility of using the yield map of the crop preceding sugar beet in the rotation to predict the spatial variation in sugar beet crop.

4- To adapt and validate the sugar beet growth model developed in Brooms Barn research station for modelling spatial variation in sugar beet growth and yield across individual field.

1.8.2 General hypothesis:

1- The main variables correlated with spatial variability in sugar beet could be the field topography, soil texture and soil organic matter through their effects on other soil properties and the micro-climate,

2- Variation in some environmental variables and crop biomass observed early in the growing season can be used to predict the spatial variation in the yield and quality of sugar beet at harvest,

3- The yield map of crop preceding sugar beet can be a useful tool for predicting the spatial variation in the yield and quality of sugar beet.

4- The within field variation in sugar beet yield can be simulated using the Broom's Barn sugar beet growth model based on spatial variation in micro-environment in the field .

1.9 Thesis outlines:

- Chapter 2 explain the general materials and methods and the study sites used for this study;

- Chapter 3 present results of statistical and geostatistical analysis of some environmental variables and examines the relationship between them.

- Chapter 4 considers the spatial variation in sugar beet growth, yield and quality in relation to the spatial variability in the studied environmental variables and the possibility of predicting the spatial variability in sugar beet yield at harvest based on early assessments of crop growth and the yield map of the previous crop.

- Chapter 5 considers the methods, the results and discussion of modelling sugar beet growth based on micro-environment.

- Chapter 6 presents the general discussion of the previous chapters and provides an overview for general conclusions from those chapters and hypothesis testing.

2. Chapter Two: Research Methodology.

This chapter considers the general methodologies that have been used in this thesis to obtain the data used in most of the following chapters. However, methods particular to a specific chapter are described in more detail in that chapter.

2.1 Research sites:

The field work has been conducted in the east of England, where sugar beet production is located (Richter *et al*., 2006). The presence of sugar beet factories, sugar beet farmers with efficient equipment and knowledge, and at the time, Brooms Barn sugar beet research station in this region facilitated this study. Three commercial sugar beet fields were selected in collaboration with BBRO, British Sugar, Brooms Barn, Agrii and Trumpington farm company on the basis of known intra-field variability in soil type and aspect that there was likely to be significant spatial variation in factors deemed likely to be important as driving variables for sugar yield. Two of these fields namely White Patch in Brooms Barn research station and T32 in Trumpington estate near Cambridge were selected for the 2012 growing season, and one field, which is called WO3 and located in Great Shelford near Cambridge, was selected for 2013 season. Some details of these three fields and agronomic practices provided by the farmers are presented in Table 2-1 and their locations are identified in Fig. 2-1. Crop management and field operations differed from one field to another, but they were uniform across each field, the farmer being responsible for all operations.

2.1.1 White Patch field in 2012:

The field is located in Broom’s Barn sugar beet research station in the geographic coordinates 52.25 °N and 0.5728 °E. Its area is around 9 ha and it is called White Patch due to the presence of areas with high concentration of chalk, which makes it appear to have a white patch in aerial images. There was a slope in this field starting from the south west corner (82 m above sea level) toward the east and north east corner (65 m above sea level) with an average gradient of 4 % (Fig. 2-2). According to the soil analysis at Brooms Barn farm using a regular 40x40 m soil sampling grid (5 samples per ha), reported by (Draycott and Evans, 2012), the field has three different soil types; loam, calcareous loam and calcareous sandy clay loam (Appendix 1.1). This information provided an initial picture of spatial variation to identify the number and the allocation of samples needed in the present study (Webster and Lark, 2012). Parts of White Patch field were not however, available for this study due to the presence of other experiments, but 91 plots were distributed in the field to represent all three types of soil (Fig. 2-3).

2.1.2 T32 field in 2012:

This field was also selected for the 2012 growing season and it is located in Trumpington estate approximately 2 miles to the south of Cambridge city centre in geographic areas 52.18 °N and 0.105 °E and it belongs to the Trumpington Farm Company. The area of the field is around 12 ha and it includes a small slope in the eastern side with an average gradient of 3% and some areas with gravel (Fig 2-3). Some information about the spatial distribution of some nutrients was also available (Appendix 1.2.), but only based on 12 soil samples (one per ha). Therefore it was not reliable enough to guide sampling, in contrast to White Patch, because the small number of samples with large intervals cannot adequately represent the scales of the variation in an agricultural field (Kerry *et al*., 2010).

2.1.3 WO3 in 2013:

This field was selected for the 2013 growing season. It is located in Great Shelford three miles in the southeast of Cambridge city centre and three miles east of T32 field in the geographic area 52.167 °N and 0.1432 °E. It is also belongs to the Trumpington Farm Company. The total area of the field is around 29 ha, but the study was confined to approximately 12 ha in the western part of the field (Appendix 2.2), which was more variable in soil types according to the recent soil analysis of the field again based on one sample per hectare (Appendix 1.3). It also involves a high slope from southwest (38 m above sea level) toward northeast (18 m above sea level) with an average gradient of 4.3 % (Fig 2.4), and this part of the field was selected due to an expected effect on soil properties and microclimate which might in turn affect the crop yield.

The yield maps produced by the combine harvester for two crops preceding sugar beet (rapeseed and winter wheat) were available for WO3 and for the immediately preceding winter wheat in T32 (Appendix 2.1). These maps were useful for sampling in particular for WO3 in 2013 (Appendix 2.2), as it was helpful to select the part of the field which showed more small scale variation for this study.

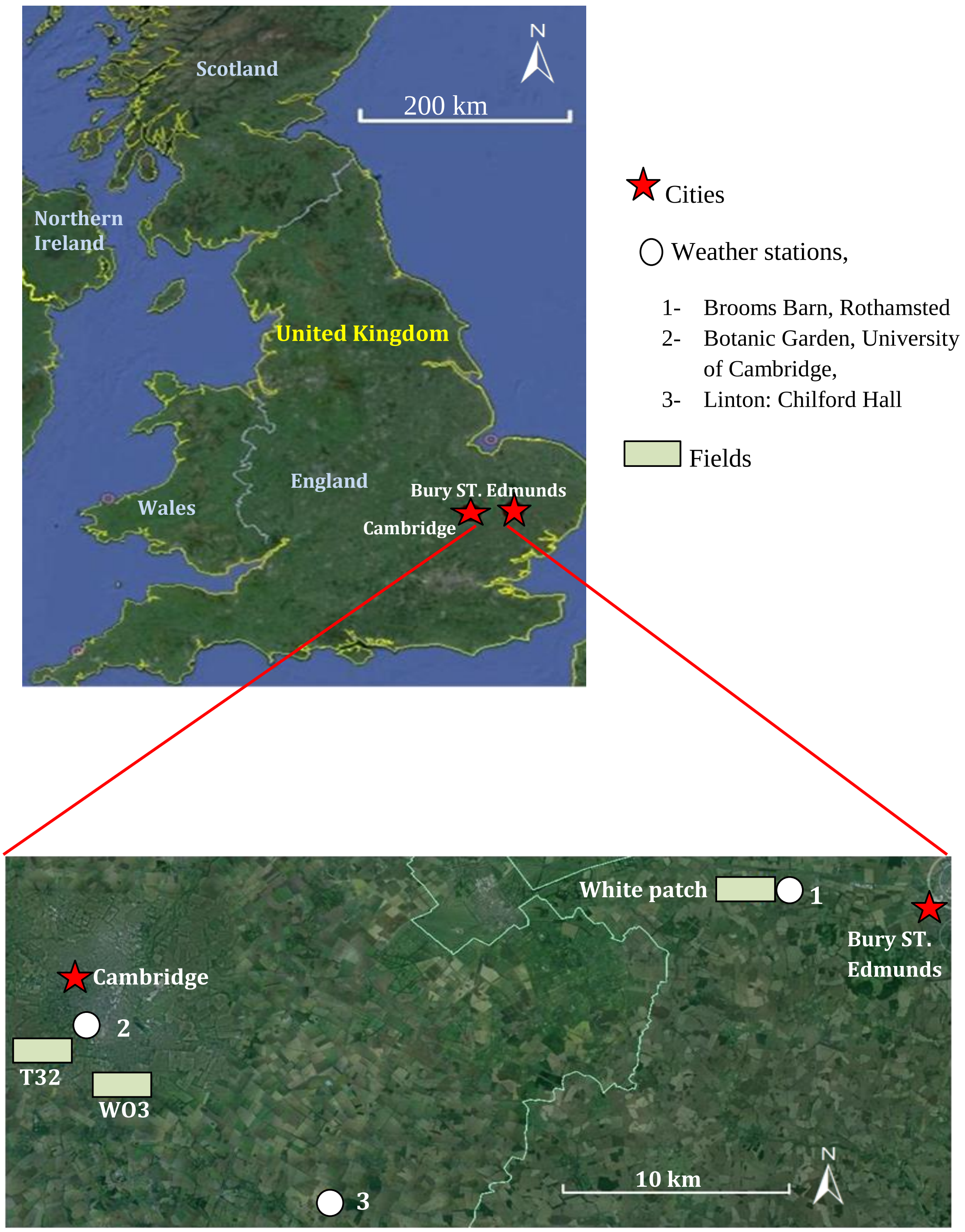


Figure 2.1: Study sites and the locations of the fields and weather stations overlaid on Google Earth map in 8th of September 2014.

Table 2.1: The area, variety planted, number of samples, date of planting and harvesting, previous crop and some field operation during the growing season at each field.

Applications	White Patchfield	T32 field	WO3field
Field area ha	9	12.2	12 ha identified from 29
Variety planted	Valeska	Bullfinch	SY Muse
Number of plots identified	91	90	114
Date of planting	23/03/2012	16/03/2012	05/03/2013
Date of harvesting the plots	24/09/ 2012	02/10/2012	26/11/2013
Previous crop	Winter wheat	Winter wheat	Winter wheat
Nitrogen fertilization	40 kg N/ha on 03/April/2012 80 kg N/ha on 13/April/2012	58.3 kg N/ha on 23/March/2012 80 kg N/ha on 25/May/2012	60 kg N/ha on9/April/2013
Herbicide applications	1. 1.25L Betanal Maxxpro+1L Bettix Flo + Oil at 1L/ha applied on 17/May/2012, 2. 1.25L BetanalMaxxpro+ Venzar at 0.4L /ha applied on 24/May/2012, 3. 1.25L BetanalMaxxpro+ Venzar at 0.4L /ha applied on 24/May/2012.	1. 3L/ha Takron (06237) applied on 22/March/2012, 2. 2.5L/h Beetup+0.39 L/ha Oblix500+20.5g/h Debut+0.4L/ha Venzar Flo+0.5L/h Defiant SC + 1.033L/ha Cropspray 11E applied on 17/May/2012 3. 2.5L/ha OptE Man+5.16 kg/ha Bittersalz+0.55 L/ha Laser+1L/ha Cropspray 11E applied on 22/July/2012	1. 4 L/ha Takron (06237) applied on 14/March/2012, 2. 1 L/ha Beetup+0.45 L/ha Oblix500+0.8 L/ha Target SC+1 L/ha Opteman applied on 25/April/2013, 3. 1.6 L/ha Beetup+1.55 L/ha Defiant SC +0.8 L/ha Target SC+1.13 L/ha Opteman applied on 07/May/2013, 4. 2.46 L/ha Beetup+0.5 L/ha Defiant+1 L/ha Cropspray 11E+0.45 L/ha Oblix500+30 g/ha Debut applied on 17/June/2013

2.2 Sampling strategy:

The sampling scheme followed in this study was designed to assess the spatial dependency in the data and describe within field variation in yield and associated environmental variables (Khosla *et al*., 2010) using geostatistics. To map within field variation, the sampling protocol was designed to represent the scales of the variation (Kerry *et al*., 2010), because the best prediction of spatial variation depends on collecting high quality and representative data (Minasny and McBratney, 2007). Therefore, a suitable number of sampling locations (plots) were identified in each field with some nested samples to quantify the variation over shorter distances and the nugget effect (Webster and Oliver, 2007, Webster and Lark, 2012). The sampling strategy followed in this study was an irregular grid in two dimensions in the three fields, but the number of samples and the intervals differed from one field to another. In the 2012 season, 91 plots were identified in White Patch field, and the sampling intervals for most of the plots ranged between 24 and 40 m for the main plots, and 10 m for nested samples (Fig. 2.2). In the same season, 90 plots were identified in T32 field with 40 m intervals and 20 m for nested samples (Fig. 2.3). In the 2013 season in WO3 field, the number of samples was increased to 114 plots with 36 m intervals for the main plots and 9 m for the nested samples in order to improve the variogram and to represent the scales of the variation (Fig. 2.4). The availability of a yield map of the previous crop in WO3 and a soil map in White Patch was important to guide sampling, especially to identify the location of the nested samples, which can enhance the accuracy of the predicted maps (Pereira *et al*., 2013).

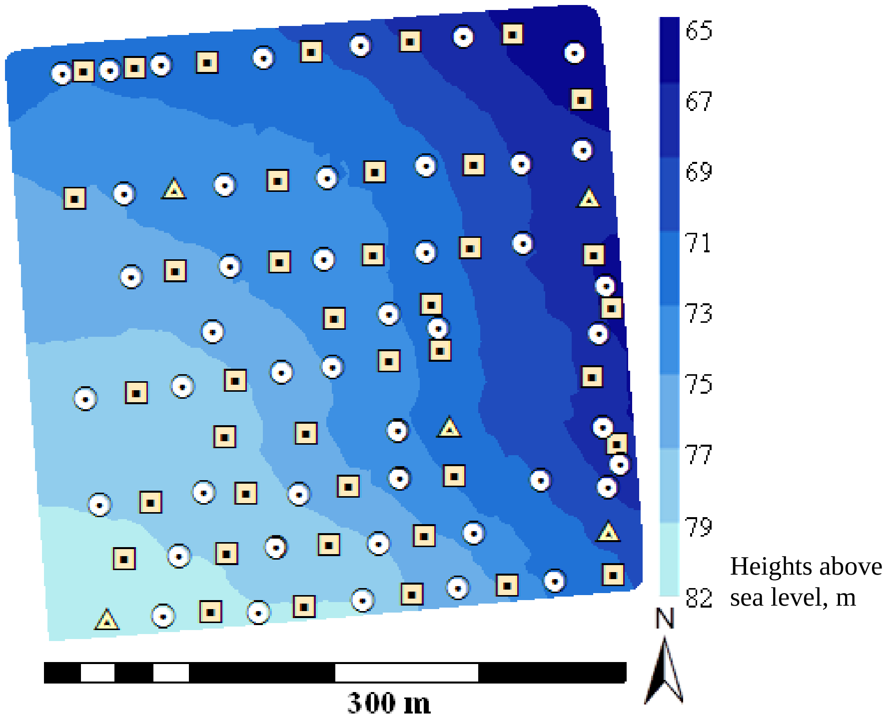


Figure 2.2: The elevation map of White Patch field (9 ha) in 2012 and the distribution of sampling points, (◎) plots without loggers, (▣) plots with air temperature loggers and (△) plots with both soil and air temperature loggers.

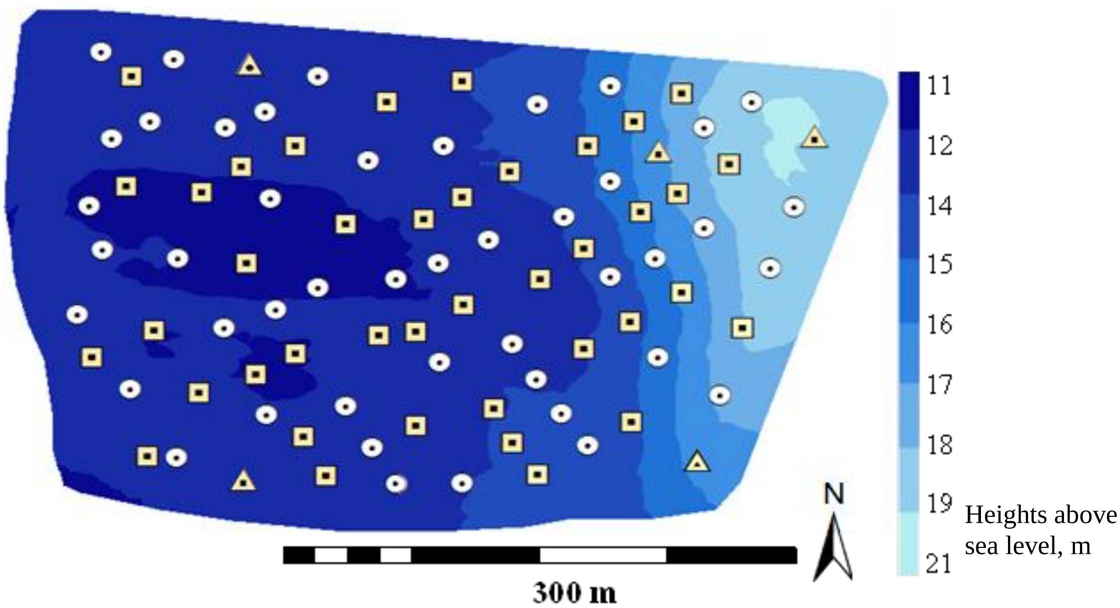


Figure 2.3: The elevation map of T32 field (12 ha) in 2012 and the distribution of sampling points (◎) plots without loggers, (▣) plots with air temperature loggers and (△) plots with both soil and air temperature loggers.

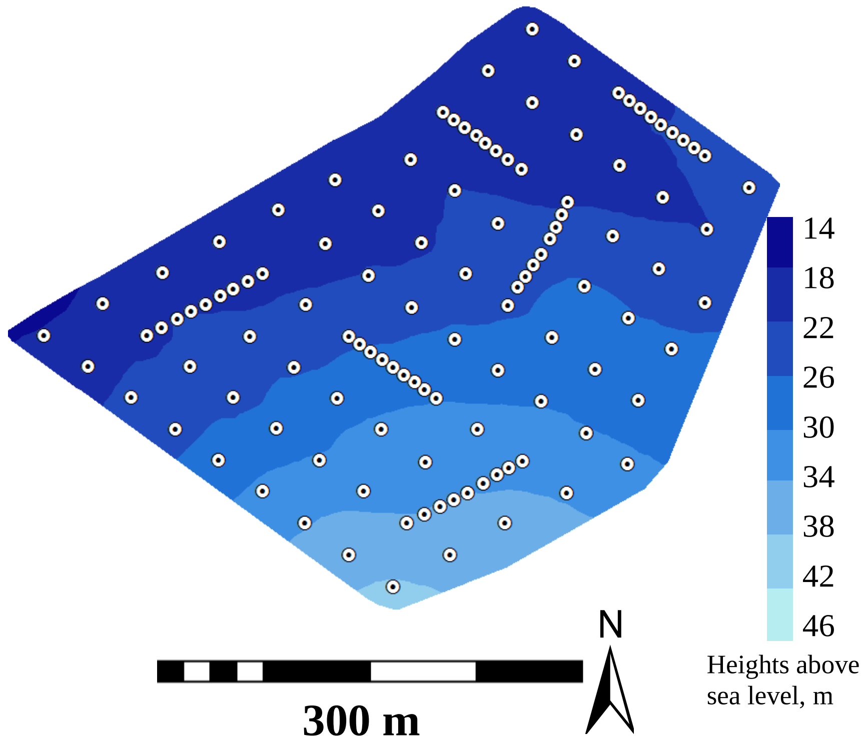


Figure 2.4: The elevation map of WO3 field (12 ha) and the distribution of sampling points (⦿) plots without loggers, (▣) plots with air temperature loggers and (⚠) plots with both soil and air temperature loggers.

Therefore, the nested samples in WO3 field were mostly located in the areas that seemed to have short range variation, but in White Patch field their allocation was designed to represent the different soil types and field aspects in addition to revealing small scale variation. In T32, their location was systematically identified between the main rows, because there was no clear small scale variation in the yield of the previous crop. The field headlands and tractor wheelings were avoided when sampling. The area of each plot was 2x2 m in all three fields and included four rows of crop which was planted with 50 cm between rows in each field.

2.3 Measurements:

2.3.1 Soil properties:

From each of the identified 2X2 m plots, three cores of soil were taken diagonally from 0-30 cm depth using a Dutch auger with 5 cm diameter. The three cores of the soil were mixed thoroughly in one polythene bag to represent the area of the plot. These samples were then air dried by spreading out in the glasshouse with good ventilation for 2 to 4 days according to the wetness of the samples. Once air dry, the samples were ground using a mortar and pestle and sieved through a 2 mm diameter sieve. The samples were again put in the plastic bags and kept in a cold room (2-4°C) prior to laboratory analysis. They were air dried again under laboratory conditions for at least 24 hours before starting each analysis and followed by oven drying for some specific analysis.

2.3.1.1 Soil particle size analysis:

The percentage of each soil particle size were identified using a simplified hydrometer method (Sheldrick and Wang, 1993). This method can identify the percentage of each soil component (clay, sand and silt) based on estimating the density of soil suspension using Bouyoucos hydrometer after 40 seconds of settling the solution and repeating it after 2 hours. However, reading the hydrometer scale is difficult when there is a high concentration of undecomposed organic carbon, but this can be solved by adding one or two drops of octan-2-ol (Loveland and Whalley, 2001).

2.3.1.2 Soil organic matter (SOM):

The total soil organic matter was determined in each sample using the Loss-On-Ignition (LOI) method (Ben-Dor and Banin, 1989, Jones Jr, 1999). Approximately 10 g of 2 mm air dried soil was placed in a ceramic container and weighed. After recording the weight (soil sample + container) the samples were oven dried at 105 °C for at least 4 hours. Then the samples were placed in the desiccators to cool, weighed again and placed in a muffle furnace at 400 °C for at least 8 hours. The difference in weight after drying at 105 °C and 400 °C estimates the total organic matter.

For spatial prediction of soil organic matter, Frogbrook and Oliver (2001) showed that the LOI method overestimated organic matter content compared with acid dichromate oxidation, due to the loss in some other components during the ignition. However the variogram and the produced maps of organic matter estimated by both methods showed similar patterns of the spatial variation indicating to the utility of LOI to describe the spatial variation in soil organic matter (Frogbrook and Oliver, 2001).

2.3.1.3 Soil nutrients:

The available soil nitrate, phosphate, potassium and magnesium in mg/l were estimated for each sieved and air dried soil sample using Soil Test model 10 produced by Palintest Ltd, Palintest House, Kingsway, Team Valley, Gateshead, Tyne & Wear, UKN, E1 1 ONS. The instructions in the Palintest (Soil Test 10) manual were followed for the analyses. A plastic container was filled to 50 ml mark with deionised water, 2.5 ml of N or K extraction powder was added for extracting N or K, while for P and Mg, five P or Mg extractions tablets were added. Then the container was capped and shaken to dissolve the powder/tablet and 2 ml soil was added for each N, P or K, and 10 ml for Mg. The tubes were capped again and shaken for 1 minute before being filtered into another container. From the filtered solutions 10 ml of each N and K solution, 1 ml of Mg solution and 2 ml of P solution were placed in 10 ml photometer tubes. The volume was made up to 10 ml mark with deionised water for Mg and P, and then a specific reagent tablet for each element was added and left for 2 for K and 10 minutes for N, P and Mg for colour to develop. Finally, the photometer reading was reset to zero by inserting a blank tube, then the sample tube inserted and the results were displayed as a form of digital readout.

2.3.1.4 Soil pH and conductivity:

The pH and conductivity (EC) meters of Palintest Soil Test 10 were used to measure soil acidity and electrical conductivity in each sieved and air dried soil sample. For soil pH, 4 ml of soil were placed in the plastic tube and made up to 10 ml with the deionised water. For electrical conductivity the plastic tube was filled with 50 ml deionised water to which 10 ml of soil was added. The plastic tubes were capped and shaken for one minute, then the meters were immersed and readings were taken for pH and the unit of EC was microsiemens (µS) . The meters were rinsed before and after use with deionised water.

2.3.2 Micro-climate factors:

2.3.2.1 Soil temperature:

To record soil temperature, five loggers (MadgeTech, Temp1000IS: Logger Shop Technology, 189 Ashley Road, Poole, Dorset, BH14 9DL, UK) were buried in the soil at a depth of 10 cm at five different locations in White Patch and T32 fields in 2012. These loggers were set up to record the soil temperature at 15 minutes intervals throughout the growing season. Unfortunately, these loggers failed to record the data in WO3 in 2013 due to a fault in the loggers. These five locations were chosen purposefully according to the differences in the soil type and the topography (Fig. 2.2, 2.3, 2.4), and the loggers were put in the field after crop emergence. Five loggers are insufficient to allow geo-spatial analysis of soil temperature, but might give an idea whether it does differed spatially and its relation to air temperature and other variables.

2.3.2.2 Canopy temperature:

To record the crop canopy temperature and humidity 45 data loggers (iButton DS1922L Thermocron temperature and DS1923 Hygrochron temperature) manufactured by Dallas Semiconductor (16 Kingfisher Court, Newbury, Berkshire RG14 5SJ, UK) were distributed in each field in 2012. The number was increased to 90 loggers in WO3 in 2013. These loggers were installed when the plants had a canopy (two pairs of real leaves) at 31st of May 2012 in White Patch and T32 and 22nd of May 2013 in WO3. The loggers were set up to record canopy temperature every 30 minutes during the growing season. There was an attempt made to shield these from direct solar radiation, wind, rain and wild animals by placing them in the crop canopy in 2012 season. In the 2013, loggers in WO3 were covered by polystyrene cups (size 12 oz), and these cups were covered with aluminium foil to reflect the direct solar radiation (Fig. 2.6). Since the memory was not large enough to save the data for entire season, the data were downloaded approximately every month and the heights of the loggers in the canopy were adjusted at the same time. The daily average, minimum and maximum temperature were calculated for each plot along the growing season. Because the canopy temperatures were only recorded in 45 plots in each of White Patch and T32 fields in 2012, the values at the plots where there were no loggers was estimated by averaging the data of the neighbouring sensors located within a 25 m radius.

Figure 2.5: The polystyrene cups covered with aluminium foil to protect the loggers.

In order to understand how the soil temperature is affected by the canopy temperature; these data were compared with soil temperature in plots which included soil and air temperature loggers. In addition, these data were one of the inputs for the sugar beet model as applied to each plot. To visualize the spatial variation in canopy temperature, the average monthly temperatures were calculated for each month and plot and the maps were produced for each field using the ArcGIS software Editor 10 (ESRI, Redlands, CA, USA).

2.3.2.3 Soil volumetric moisture content:

The soil volumetric moisture content was measured at different growth stages and readings were taken at three different locations in each plot. For this purpose a theta probe ML2 manufactured by Delta-T Devices (130 Low Road, Burwell, Cambridge, CB25 0EJ, UK) with 10 cm probe length was used initially in the two fields in 2012, while later readings in 2012 and all readings in 2013 were taken using FieldScout TDR 300 soil moisture meter produced by Spectrum Technologies (3600 Thayer Court, Aurora, IL 60504, USA) with a 20 cm probe length to measure the soil moisture to a greater depth. Although the recorded data were not in time series along the growing season, at each time the soil moisture measured the readings from all plots were taken within a period of 2-3 hours and when it was not raining. This provided some important information about the spatial distribution of soil moisture in the field which relates to the ability of the soil at different locations of the field to retain water and its relation to crop growth and performance.

2.3.3 Crop growth assessment:

2.3.3.1 The percentage of solar radiation interception:

The percentage solar radiation interception was measured for each plot at different growth stages using the Ceptometer AccuPAR model LP-80 produced by Decagon devices (3735 Myrtle Street, Burnaby, BC V5C4E7, Canada). The readings of Photosynthetically Active Radiation (PAR) from above and below the canopy were taken at three different locations in each plot and the differences between above and below values represent the amount of solar radiation intercepted by the crop canopy. The amount of incident radiation can change rapidly causing large differences in the absolute readings. Therefore, data has been normalized by calculating the percentage of solar radiation intercepted by the crop at each location.

2.3.3.2 Leaf Area Index (LAI):

The Leaf Area Index was also estimated by the Ceptometer during measuring solar radiation interception. The AccuPAR calculates LAI based on the equation developed by Norman and Jarvis (1974) to estimate the scattered and transmitted PAR as follows:

$$\boldsymbol{\tau = \exp\left\{\frac{A(1-0.47f_b)L}{\left(1-\frac{1}{2k}\right)f_b-1}\right\}}$$ **Equation 2. 1**

Where τ is the fraction of transmitted PAR, $A=0.283+0.785a+0.159a^2$ where a is the absorptivity of the leaf at PAR wavelengths and is assumed it to be equal to 0.9, f_b is the fraction of incident of PAR, and K is the extinction coefficient of the canopy which can be calculated using the equation simplified by Campbell (1986) as follows:

$$\mathbf{K = \frac{1}{1\cos\theta}} \qquad \textbf{Equation 2. 2}$$

Where θ is the zenith angle of the sun, and LAI can be calculated by inverting the equation 2-1 as follow;

$$\mathbf{L = \frac{\left[\left(1-\frac{1}{2k}\right)f_b-1\right]\ln\tau}{A(1-0.47f_b)L}} \qquad \textbf{Equation 2. 3}$$

All these calculations were done automatically when measuring above and below canopy PAR.

2.3.3.3 Plant population:

The length of the plot was extended another 2 metres (4 X 2 m) for this purpose and the number of plants was counted within 8 m^2 (16 m length of the crop row) in 17 and 18 of May 2012 respectively in White Patch and T32 fields and 13 of June 2013 in WO3 field, and used to estimate the plant population /ha.

2.3.3.4 The percentage of crop canopy cover:

To identify the within-field variability and the temporal changes in crop foliage cover, the images of the plots were captured using a hand held camera (Nikon D90 12MP DSLR Camera with 18-105mm VR Lens) and analysed using WinDIAS 3 software, version 3.2 manufactured by Delta-T Devices. The images were captured at three different stages during growing season; 01/June, 02/July and 13/August 2012 in White Patch and 01/June, 17/July and 17/August in 2012 in T32 field, and 20/June, 16/July and 17/August 2013, in WO3.

The relative canopy growth rate (CGR, $\%d^{-1}$) was calculated from the data of crop canopy cover for the period from 1st of June to 2nd and 17th of July 2012 in White Patch and T32, respectively, and from 20th of June to 16th of July 2013 in WO3 as follows:

$$\mathbf{CGR} = \frac{\textbf{Canopy cover in July} - \textbf{Canopy cover in June}}{\textbf{Canopy cover in June} * \textbf{Number of days}} * \mathbf{100} \qquad \textbf{Equation 2. 4}$$

2.3.3.5 Weed assessment:

Weeds were assessed in each plot and estimated as weed population/m^2. The weed population comprised different weed species associated with growth of sugar beet plant. The main weeds in White Patch and T32 fields in 2012 were Mayweed (*Matricaria sp.*), Speedwell (*Veronica hederifolia*), Fat-hen (*Chenopodium album*), Black-grass (*Alopecurus myosuroides*), and Wild Oat (*Avena fatua*). In WO3 in 2013 the main species were only Black-grass and Brassica (*Brassica napus*).

2.3.4 Post-harvest measurements:

The plots were harvested a few days before the commercial harvest of the field. In White Patch field, T32 and WO3, the plots were harvested on 25th September 2012, 2nd October 2012 in 2012, and 26th November 2013 respectively. The two central rows from each plot were harvested in the 2012 season, while due to the poor plant establishment in WO3 field in 2013; the area was increased for some plots to the whole plot or in some cases double plot (4X2 m) to obtain the required weight of beets for the analysis, which was approximately 15 kg. The leaves were severed from the roots by cutting just below the crown using knives designed for this purpose. The roots were then put in the large white woven polypropylene sacks size 30X45 cm, labelled and then sent within 16 hours to the British Sugar factory in Wissington for analysis in exactly the same way as for commercial farmers.

At the sugar factory the roots were weighed, washed to remove soil and weighed again for final fresh tare weight of roots in kg, which was multiplied by different amounts according to plot area. The clean samples then went through the factory system to determine the sugar content based on polarimetry methods, while the flame photometry was used to measure impurity and the root content of amino acids and potassium in mg/100 gm of beet as for commercial fields. All these processes at the sugar factory are based on the Official and Tentative Methods Recommended by the International Commission for Uniform Methods of Sugar Analysis (ICUMSA) which is described by Whalley and Siegfried (1964).

After estimating the root yield (t/ha) and sugar content for each plot, the sugar yield (t/ha) was then computed as follows;

$$\textbf{Sugar yield (t/ha)} = \textbf{Root yield (t/ha)} \times \textbf{\% Sugar} \qquad \textbf{Equation 2. 5}$$

And the yield value (£/ha) was calculated as follow;

$$\textbf{Yield value (£/ha)} = [\textbf{Roots yield (t/ha)} \times \textbf{the price of tonne of root (£/t)}] \times \textbf{F}$$

Equation 2. 6

The price per tonne of root was £27.53 in the 2012 season and £26.51 in the 2013 season.

F= fixed adjustment to value for each %sugar as applied to commercial sugar beet crops (Appendix 3) (Walters, personal communication).

Since the price per tonne of roots is constant for all plots and the differences in adjustment value were small between the plots, yield values showed similar patterns of the variability between plots as roots or sugar yield. The main advantages of calculating the yield value (£/ha) is to describe the variation in the financial outputs. As the input costs incurred by the farmer were uniform throughout the field, the variation in yield value shows the areas of the field of high and low profitability and areas where possible intervention could improve the economic benefits (Blackmore, 2003).

2.4 Yield map of crop preceding sugar beet crop:

For the spatio-temporal prediction of within field variability in sugar beet yield based on the yield map of the previous crop, the yield maps of crops preceding sugar beet in the rotation from the combine harvester (2007 Claas Lexion 580+ on tracks) were available for

T32 and WO3 fields at the Trumpington farm company (Appendix 2). This harvester estimates the crop yield (t/ha) based on mass flow and assigns the measured yield to georeferenced locations in the field (Demmel, 2013). The yield maps were available for winter wheat in T32 and WO3 in 2011 and 2012, respectively and for oilseed rape in WO3 in 2011. The raw data of yield and the GPS coordinates underlying these maps were obtained and used for further analysis in this study. These data usually contain many outliers, which usually appear as a result of different kinds of errors associated with the harvest operation (Blackmore, 2003, Chu Su, 2011). Therefore the raw data were examined to determine and remove any anomalous values in a process which is usually called data cleaning or data filtering. The procedure followed was to omit points with zero value, values less than half of the mean yield or more than one and half times the mean yield and, points with no georeferencing coordinates (Kerry, 2003).

For correlating the yield map of sugar beet which is measured at points away from each other with the yield map of previous crops, it was important to find the value of previous crops at the points where sugar beet yield was measured. As the yield data of the previous crop is very densely sampled and may not be exactly coincident with plots where sugar beet yield measured, the yield data of previous crop were averaged at four neighbouring points in different directions of each plot (Griffin, 2010). An example of this processing is given in Appendix 4. Since the previous crops are different (winter wheat in T32 field and winter wheat and oilseed rape in WO3), it was necessary to avoid the unit (t/ha) in order to compare between different crops. Therefore, the values at each point were standardised as percentage of the mean value of the field, which show how the yield at each point can deviate from the mean of the field, and it is calculated as described by Blackmore (2000) as follows:

$$\mathbf{s_i} = \left(\frac{\mathbf{y_i}}{\bar{\mathbf{y}}}\right) \mathbf{X\ 100} \qquad \textbf{Equation 2. 7}$$

Where S_i is the standardised yield (%) at point i, y_i is the yield (t/ha) at a certain point and $\bar{y}$ is the mean of the yield for that year. The results of this equation which is also called the relative percentage yield were averaged at each point to produce the spatial trends map.

To identify the parts of the field, which were relatively low output in one year and high output in other year comparing to the mean, the temporal variance for each point was calculated using the equation described by Blackmore *et al*. (2003) as follows:

$$\boldsymbol{\sigma_i^2} = \frac{\sum_{t1}^{t2}(\mathbf{Y_{t,i}} - \bar{\mathbf{y}}_t)^2}{\mathbf{n}} \qquad \textbf{Equation 2. 8}$$

Where σ_i^2 is the temporal variance at plot i, t_1 and t_2 is the time in years between 2011 and 2013 in WO3 field and between 2011 and 2012 in T32 field, Y is the yield in year t at plot i, and $\bar{y}_t$ is the mean of the yield for the whole field in years t, and n the number of year included.

Any part of the field with low temporal variance will be considered as temporally constant, because the yields in different years are close to the mean. Parts with high temporal variance are considered as temporally inconstant, because it tends to be highly productive in some years and low in other years (Blackmore *et al*., 2003).

2.5 Weather data:

The locations of weather stations used in this study are shown in Fig 2.1. The weather data of White Patch field in 2012 season were provided by Rothamsted Research Station based on the weather station located 300 m from White Patch field. For T32 and WO3 fields in 2012 and 2013 seasons, the weather data were downloaded from the Centre for Environmental Data Archival (CEDA) Web Processing Service (http://ceda-wps2.bdc.rl.ac/ui/home), which provides the weather observations throughout the UK from 1859 to the present. The Botanic Garden station at the University of Cambridge was the nearest weather station (approximately 1.3 miles northeast of T32 field and 2.0 miles north of WO3 field). The minimum and maximum temperatures (°C) of each site and season were based on average of daily observations and the rainfall (mm) was based on daily amount. The data of solar radiation was also required for this study, especially for adapting the crop growth model, but it was not available at those stations. The Linton: Chilford Hall in Cambridgeshire was the nearest station to provide the data for solar radiation. This station is located approximately 14 miles southwest of White Patch field and 8-10 miles southwest of T32 and WO3. The summary of weather data for all the sites and season is given in Fig 2.6 and 2.7.

In general, the 2013 season in WO3 was colder than the 2012 season in both sites at the beginning of the growing season (Fig 2.6), and then the maximum temperature increased and became warmer in the middle of growing season compared to the 2012 season. The cold period (<5 °C) in WO3 in 2013 was long (from January to middle of March) compared to the 2012 season in the other two fields. In both sites in 2012 the average, minimum and maximum temperatures followed similar patterns with small fluctuations from one month to another (Fig 2.6 A and B). The highest mean daily temperature recorded was in August 2012 reached 22.55°C in Brooms Barn and 21.2°C in Trumpington, while it reached 23.85°C in August 2013 in Shelford. In 2013 season, the low minimum air temperature during March (<1°C) was associated with low soil temperature (2.7°C), while the mean soil temperature was not affected so much by the air temperature in 2012 and it was much warmer (6 and 8 °C) respectively in Trumpington and Brooms Barn (Fig 2.7. A-C). The highest soil temperature in August in both sites and seasons was 17 and 18 °C respectively in Trumpington and Brooms Barn in 2012 season, while it was higher and reached 20.73 °C at WO3 in 2013. The warmer period (June and July) in 2013 in Shelford was also much drier than the 2012 season in both sites (Fig 2.7 D-F). The amounts of precipitation were lower 14.9 and 43.6 mm in June and July 2013, respectively compared to the same period in 2012. In general the amount of precipitation was higher in 2012 growing season (March to September), as it reached 502 and 441 mm in White Patch and T32 respectively, while in 2013 season in WO3, although the growing season was longer (March to end of November), but the amount of precipitations was only 401 mm.

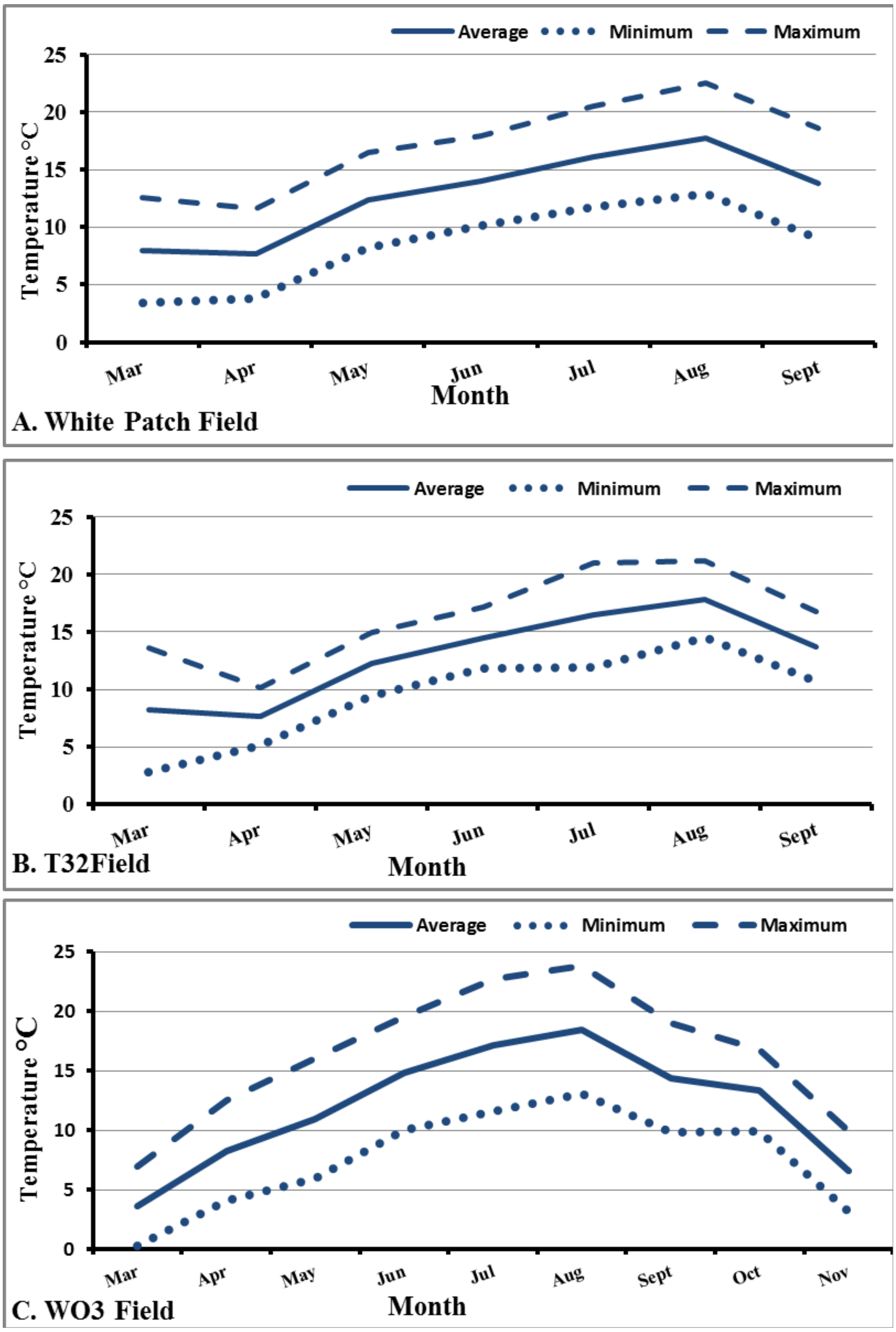


Figure 2.6: The monthly average, minimum and maximum temperatures (°C) at (A) Brooms Barn and (B) Trumpington in 2012, and (C) at Great Shelford in 2013 (Rothamsted and CEDA).

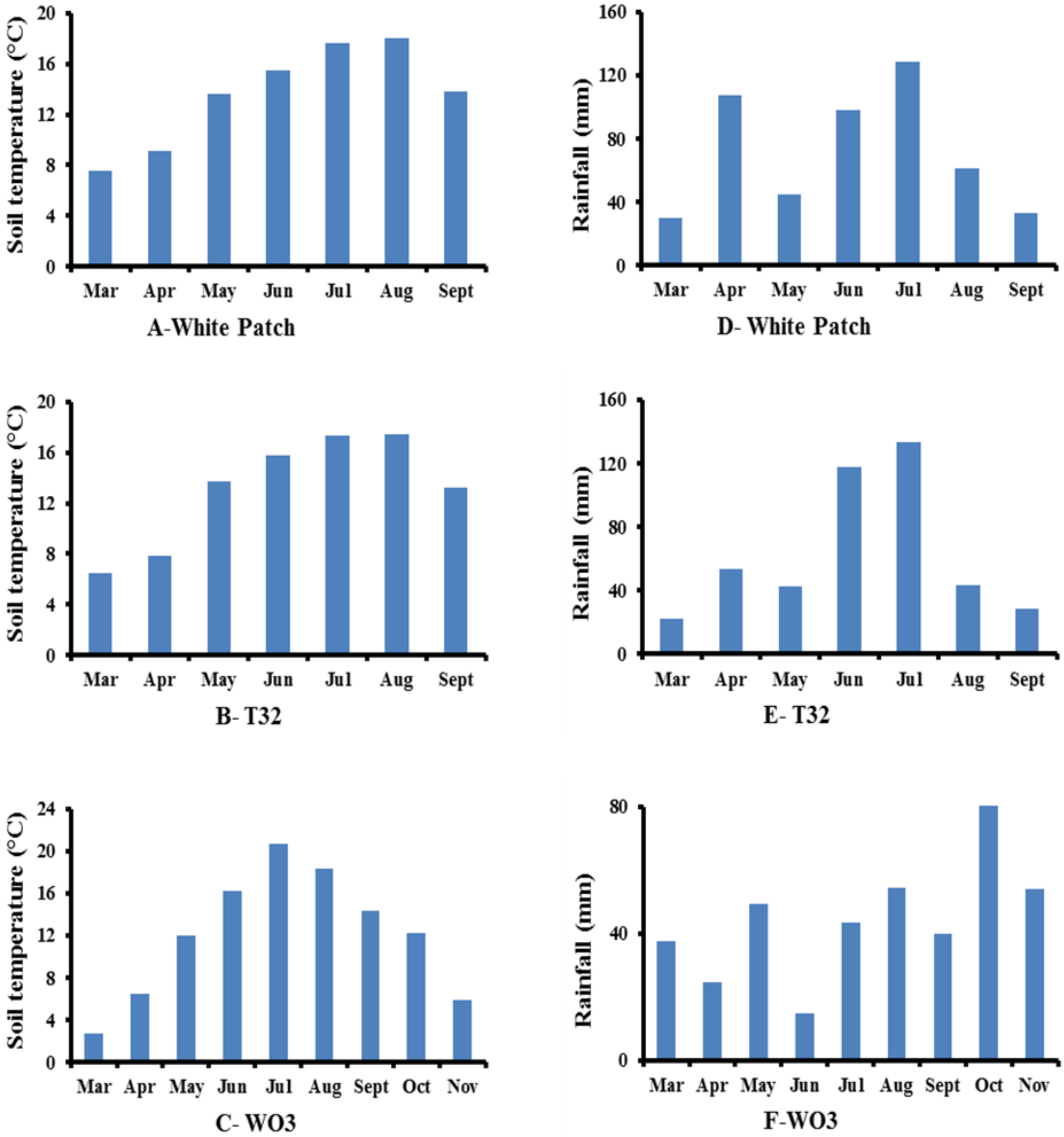


Figure 2.7: The left hand side (A- C) is the soil temperature (degrees Celsius) to 10 cm depth respectively at Brooms Barn and Trumpington in 2012 and Shelford in 2013; the right hand side (D-F) is the monthly amount of precipitation (mm) respectively at these locations (Rothamsted and CEDA).

2.6 Geographic coordinates and altitude data:

An accurate georeferencing of the points at which the measurements were taken was essential for subsequent analysis. For this study differential Global Positioning System (dGPS), Trimble Nomad 900B Mobile Computer (The Barcode Warehouse Ltd, Telford Drive, Newark Industrial Estate, Nottinghamshire, NG24 2DX) was used for georeferencing the plots in White Patch and T32 field in 2012, while in the 2013 season RTK GPS type Topcon grs-1 (Topcon Positioning Systems, Inc., 7400 National Drive, Livermore, CA USA 94550) provided more accurate georeferencing in WO3 field. The device was located in the centre of each plot and the latitude and longitude data were recorded in decimal degrees (WGS 1984) and then transformed to British National Grid Reference. The altitude data for each plot in White Patch field were estimated when georeferencing the plots using the Nomad, while more dense altitude data were available from the yield maps of the previous crops for T32 and WO3 fields. The altitude data were then used to estimate the slope and aspect of each plot and produce the digital elevation map.

2.7 Field topography:

The elevation maps which show some topographic features of each field were created based on the elevation data provide by the GPS in White Patch field and the combine harvester in T32 and WO3 fields using ArcGIS Editor 10 (ESRI, Redlands, CA, USA).

Then the slope and aspect were identified for each point in order to calculate the amount of solar radiation received by each plot from the global solar radiation which in turn was used for spatio-temporal simulation of sugar beet yield and described in detail in Chapter 5. Because the studied areas were relatively small fields, there were no complex topographic features such as a lot of undulations. However, each field included a slope with different heights and aspects, which are likely to influence the micro-environment especially the incident solar radiation and some soil attributes.

2.8 Data Analysis:

2.8.1 Statistical Analysis:

2.8.1.1 Data exploration:

For any statistical analysis, it was important to explore the data and the possible methods of the analysis were then decided. Summary statistics including minimum, mean and maximum values, standard deviation, coefficient of variation and skewness were calculated for each set of data. Calculating the coefficient of variation is important for geostatistical analysis, as it indicates the degree of spatial variation rather than the accuracy as in conventional statistical analysis. A skewness value more than +1 or less than -1 indicates departure from a normal distribution, which can be due to a long upper or lower tail or the presence of outliers in the data set (Oliver and Webster, 2014). To make the skewed data approximately normal for computing the variogram, it was transformed to logarithms and/or the outliers were removed. The outliers were however returned back and the complete original data was used for Kriging interpolation (Webster and Oliver, 2007). If transforming the data or removing outliers did not improve the variogram, the original data was used for computing the variogram (Oliver, 2010).

2.8.1.2 Correlation:

To examine the relationship between different environmental variables and crop parameters, the Pearson Product-Moment Correlation Coefficient was also calculated as follows:

$$\mathbf{r} = \frac{\sum \mathbf{Z_x Z_y}}{\mathbf{n-1}} \qquad \textbf{Equation 2. 9}$$

Where r is the correlation coefficient, Z_x and Z_y are the values of variables X and Y, and n is the number of observations.

The significance of correlation coefficients against zero was tested based on Lowry (2014) as follows,

$$\mathbf{t} = \frac{\mathbf{r}}{\mathbf{sqrt}[(\mathbf{1}-\mathbf{r^2})/(\mathbf{N}-\mathbf{2})} \qquad \textbf{Equation 2. 10}$$

Where *r* is a correlation coefficient, *N* is the number of samples on which an observation of *r* is based.

The correlation coefficients were calculated and tested using GenStat software (15th edition).

The differences between different correlation coefficients were also tested for their significance using a tool provided by Soper (2015), which is based on the method of Fisher (1921).

2.8.1.3 Multivariate analysis:

In order to investigate the interrelationships between sugar beet yield, quality, crop growth parameters and the studied environmental variables, the Redundancy Analysis (RDA) was used to quantify the independent effects of each variable and the partial effect of many variables together on the spatial variability. RDA is a canonical or constrained kind of Principle Components Analysis (PCA) and it closely relates to multiple linear regression analysis (Kenkel *et al*., 2009). It was performed based on a set of response variables (yield and quality of sugar beet) plotted against a set of explanatory variables (measurements of crop biomass and soil properties). It illustrates how the variability in studied variables relates to the variability in sugar beet yield and which variables are more related than others. In addition it may reveal whether the within-field variability is constant over the growing season through examining the relationship between sugar beet yield and some growth parameters such as crop canopy cover and LAI assessed a different times.

The RDA analysis and the orientation diagrams were performed using Canoco 5 (Šmilauer and Lepš, 2014). The analysis was first performed for each field separately, then the root yield was normalized as a percentage of the mean for each field and combined together, the analysis was then performed for all fields together to identify the variables that have a strong association in all fields. In addition, analysis was performed using the normalized crop canopy cover in June as a response variable to identify the relationship between the studied environmental variables and early assessment of crop canopy cover.

2.8.2 Geostatistical Analysis:

After exploring the data statistically, a decision of whether to transform it, remove the outliers or use the original data was made, and the data were then prepared for geostatistical analysis. The methods of geostatistical analysis followed in this study are those recommended by Oliver and Webster (2014) and incorporated the following steps:

After identifying the area of interest, a suitable number and arrangement of sampling locations were identified and the sampling protocol was chosen to be suitable for the purpose of analysis;

The data were explored in the same way as for conventional statistics to identify the outliers and transform the data where necessary;

The experimental semivariances were estimated and modelled by a valid mathematical model, after removing a trend if there is one; and

The points were Kriged and the values in un-sampled locations predicted and mapped.

2.8.2.1 Computing the experimental variogram:

The experimental variogram, which summarizes the way in which the studied variables were spatially varied within field scales was computed based on Matheron's Method of Moments (Matheron, 1965) using the general formula as follows:

$$\boldsymbol{\gamma(h) = \frac{1}{2m(h)} \sum_{i=1}^{m(h)} [Z(x) - Z(x+h)]^2} \qquad \textbf{Equation 2. 11}$$

Where $2\mathrm{m(h)}$ is the number of paired comparisons at lag (*h*), Z(*x*) and *Z*(*x*+*h*) are the values of the property at two locations separated by distance *h*.

Any semivariances computed from this equation at a specific lag distance are only the average of a set of semivariances at that lag and it describes the spatial dependency in a set of discrete data which is itself subject to measurement and sampling error (Webster and Oliver, 2007). The step lengths were slightly different from the actual sampling intervals for some variables, because using the actual intervals sometimes resulted in an erratic experimental variogram, which was difficult to fit a model (Oliver, 2010). This could be due to the fact that the sampling intervals were not exactly the same across the fields, especially in White Patch, and in addition, the lower accuracy of dGPS instruments used in 2012 season. The maximum lag distances modelled also differed from one variable to another because it was changed when the variogram became erratic, but in no case did it exceed more than one half of the field. The experimental variogram was computed and modelled using the GenStat software (15^{th} edition) (Payne, 2009).

However the variogram was not computed for some variables such as air temperature, because it was recorded only at 45 points which is not enough for a reliable variogram (Oliver and Webster, 2014). In addition it was not computed for some other variables such as weed density, which occurred in high density in some plots, but was absent in most of the other plots (Fig 2.8) resulting in large number of outliers, which cannot be removed (Colbach and Forcella, 2011). The value of available phosphorus was also zero for most of the plots in WO3, which made it difficult to compute the variogram. Therefore maps showing the scales of within-field variation in these variables were produced without considering the variogram parameters but their statistical correlations with yield and other variables were still investigated.

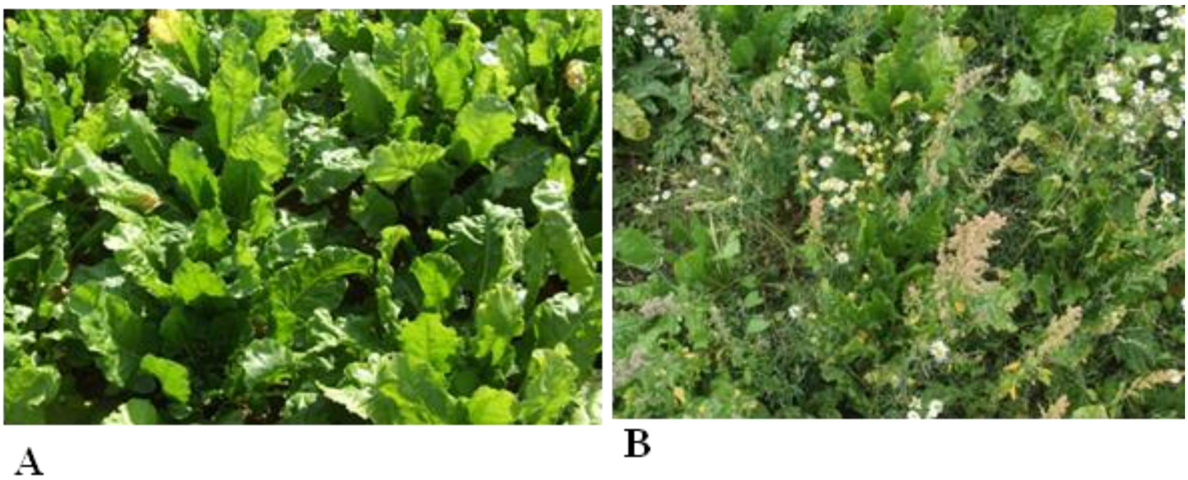


Figure 2.8: Picture (A) a patch from White Patch field which was almost free from weeds and picture (B) is another patch of the same field with high weed density. Both images were captured on 5th of July 2012.

2.8.2.2 Modelling the variogram:

The next step after computing and plotting the experimental variogram was to model it by a suitable mathematical function, so that point to point fluctuations can be smoothed and the variation across the field can be quantified as required for predicting the value in unsampled locations by Kriging (Webster and Oliver, 2007). For each variable, a suitable model was selected, which was best fitted to that variogram from a group of available models in the drop down menu in GenStat software editor 15 and ArcGIS Editor 10 (ESRI, Redlands, CA, USA). The decision on which model was the best was made based on visual assessment first. If more than one model looked appropriate then the model which gave the smallest residual sum of squares (RSS) was selected (an example of fitting the model is given in Appendix 6). If it was still hard to choose, the model was selected from the results of cross validation after Kriging (Johnston *et al*., 2001, Oliver and Webster, 2014). However, in most of the models there is a clear difference in the RSS, and therefore, the selection was made based on RSS. The models which best fitted to the variograms of most variables in this study were spherical, pentaspherical, circular and exponential and their mathematical expressions are as follows:

Spherical model

$$\boldsymbol{\gamma(h) = c\left\{\frac{3h}{2a} - \frac{1}{2}\left(\frac{h}{a}\right)^3\right\}} \quad \textbf{for } \boldsymbol{h \leq a}$$

$$\boldsymbol{= c} \qquad \textbf{for } \boldsymbol{h > a}$$

Equation 2. 12

Where c is the sill variance and a is the range in metres. The spherical model is the most common in geostatistics as it can describe the variation in one, two and three dimensions, and it can explain the variations that are distributed as patches with high and low values and the average extent of these patches is the range of the variogram (Frogbrook *et al*., 2002, Webster and Oliver, 2007).

Pentaspherical model $$\boldsymbol{\gamma}(\mathbf{h}) = \left\{\mathbf{c}\left\{\frac{\mathbf{15h}}{\mathbf{8a}} - \frac{\mathbf{5}}{\mathbf{4}}\left(\frac{\mathbf{h}}{\mathbf{a}}\right)^{\mathbf{3}} + \frac{\mathbf{3}}{\mathbf{8}}\left(\frac{\mathbf{h}}{\mathbf{a}}\right)^{\mathbf{5}}\right\}\right\} \text{ for } \mathbf{h} \leq \mathbf{a}$$

$$= \mathbf{C} \qquad \text{for } \mathbf{h} > \mathbf{a}$$

Equation 2. 13

The pentaspherical model (Equation 2.13) curve more gradual than that of the spherical model

Circular model $$\boldsymbol{\gamma}(\mathbf{h}) = \mathbf{c}\left\{\mathbf{1} - \frac{\mathbf{2}}{\boldsymbol{\pi}}\mathbf{cos}^{-\mathbf{1}}\left(\frac{\mathbf{h}}{\mathbf{a}}\right) + \frac{\mathbf{2h}}{\boldsymbol{\pi}\mathbf{a}}\sqrt{\mathbf{1} - \frac{\mathbf{h}^{\mathbf{2}}}{\mathbf{a}^{\mathbf{2}}}}\right\} \text{ for } \mathbf{h} \leq \mathbf{a}$$

$$= \mathbf{c} \qquad \text{for } \mathbf{h} > \mathbf{a}$$

Equation 2. 14

In the circular model (Equation 2.14) the fitted line curves tightly after reaching the sill and it almost works in a similar way as the bounded linear model:

Exponential model $$\boldsymbol{\gamma}(\mathbf{h}) = \mathbf{c}\left\{\mathbf{1} - \mathbf{exp}\left(\mathbf{1} - \frac{\mathbf{h}}{\mathbf{r}}\right)\right\}$$ **Equation 2. 15**

The exponential (Equation 2.15) model is most commonly used to direct sampling schemes in soil science and it represents an autoregressive relationship. It approximately approaches the sill with parameter r that identifies the spatial extent rather than the range, and the range is approximately $= 3r$ (Webster and Oliver, 2007)

2.8.2.3 Kriging interpolation:

The final step of geostatistical analysis was to predict the value of the property in unsampled locations and present a map showing the within-field variation using Kriging. The method is based on an averaged weighting that can provide best unbiased linear prediction (UBLP) with minimum variance (Oliver, 2010, Sherman, 2011). Because the mean value of the studied variables is unknown and the main aim of Kriging in this study was to visualize the variation in a certain variable and its relation to other variables, the interpolations were made using ordinary punctual Kriging methods (Webster and Oliver, 2007). The prediction by ordinary punctual Kriging and estimating the associated variance were based on the following equations:

$$\check{\mathbf{Z}}(\mathbf{x_0}) = \sum_{\mathbf{i=1}}^{\mathbf{n}} \boldsymbol{\lambda}_\mathbf{i} \mathbf{Z}(\mathbf{x_i}) \qquad \textbf{Equation 2. 16}$$

Where (x_0) is the target point and λ_i is the weight. To guarantee an unbiased estimation the sum of weights is made to equal one, that is,

$$\sum_{\mathbf{i=1}}^{\mathbf{n}} \boldsymbol{\lambda}_\mathbf{i} = \mathbf{1} \qquad \textbf{Equation 2. 17}$$

and the expected error is $E[\check{Z}(x_0) - Z(x_i)] = 0$. The prediction variance can be calculated as follows:

$$\mathbf{Var}\left[\check{\mathbf{Z}}(\mathbf{x_0})\right] = \mathbf{E}\left[\left\{\check{\mathbf{Z}}(\mathbf{x_0}) - \mathbf{Z}(\mathbf{x_i})\right\}^2\right] \qquad \textbf{Equation 2. 18}$$

$$= \mathbf{2}\sum_{\mathbf{i=1}}^{\mathbf{n}} \boldsymbol{\lambda}_{\mathbf{i}} \boldsymbol{\gamma}\left(\mathbf{x_{i,}} \mathbf{x_0}\right) - \sum_{\mathbf{i=1}}^{\mathbf{n}} \sum_{\mathbf{j=1}}^{\mathbf{n}} \boldsymbol{\lambda}_{\mathbf{i}} \boldsymbol{\lambda}_{\mathbf{j}} \boldsymbol{\gamma}\left(\mathbf{x_{i,}} \mathbf{x_j}\right) \qquad \textbf{Equation 2. 19}$$

Where $\gamma(x_{i,}x_0)$ are the semivariances between the value at the i^{th} point and the point that needs to be predicted and $\gamma(x_{i,}x_j)$ are the semivariances between the values of Z at i^{th} and j^{th} points (Webster and Oliver, 2007).

To assess how well the model predicted the value of the property in unsampled locations, cross validation was done for each Kriging map. The components that were identified by cross validation were the mean error (ME), which ideally needs to be close to zero, the root mean square error RMSE, which needs to be as small as possible, and the mean squared deviation ratio (MSDR), which needs to be close to one (Johnston *et al*., 2001, Webster and Oliver, 2007).

The Kriging interpolations and the cross validation were done using the geostatistical Analyst tool in ArcGIS software (10th edition, ESRI, Redlands, CA, USA) which has bridged the gap between GIS and geostatistics by modelling the spatial variation and interpolating it within the study area (Johnston *et al*., 2001, Shahbazi *et al*., 2013). As most agricultural data has some form of spatial component, which might be difficult to visualize, the information provided by ArcGIS was found useful when mapping within field variability (Pierce and Clay, 2007). The model type and its parameters (sill, range and nugget variance) given by GenStat software were used with the original data set for interpolation by ArcGIS.

2.8.3 Ordinary mapping:

Due to insufficient samples or the zero value of most of the points, it was difficult to calculate the variograms for air temperature and weeds, and also the data of the previous crop was very dense, which was not requiring prediction. Therefore the maps were created using an Inverse Distance Weight (IDW) in order to visualize the spatial variation in these variables.

3. Chapter Three: Within-field Variation in Environmental Variables.

This chapter considers the within-field variability in some environmental variables which have a potential influence on sugar beet growth and yield based on geostatistical analysis. The data of each variable was first explored using the descriptive statistics and the spatial variability in the studied variables was described by the variogram and visualized by the maps which presented in this chapter.

3.1 Background:

As most of the environmental variables controlling crop growth and development such as solar radiation, available water, soil properties and topography can vary spatially even over few metres (Heege, 2013), within field variation in crop yield and biomass should also be expected. Thus, identifying the spatial variability in some physical variables, which are likely to be the main driving variables, is important to understand the spatial variation in sugar beet growth and yield. The variability in soil conditions can cause spatial and temporal variability in crop biomass, weeds, pests and diseases (Oliver *et al.*, 2013). The variation in micro-climate such as canopy temperature and solar radiation in addition to soil properties, however, can be mainly due to the field topography (Fu and Rich, 1999, Godwin and Miller, 2003, Zhang *et al*., 2011b). The spatial distribution of some variables may appear to be uniform, but geostatistical methods can precisely visualized their spatial variability and predicted their values in unsampled locations (Zhang *et al*., 2013). The investigated variables were soil texture (percentage of sand, clay and silt), organic matter, soil available nutrients (nitrate, phosphate, potassium and magnesium), pH, electrical conductivity, soil volumetric water content, and canopy temperature. The spatial variability in these variables and the correlation between them are discussed separately for each field.

3.2 White Patch field in 2012:

Based on the descriptive statistics of soil attributes in White Patch field (Table 3.1) most of the variables had low skewness values. Some of the studied variables were therefore normally distributed, which is desirable for geostatistical analysis, because any departure from a normal distribution may overestimate the variance (Kerry and Oliver, 2007b, Montanari *et al*., 2012). However the data of some variables such as soil available nitrate, phosphate and magnesium were positively skewed 0.96, 1.6 and 1.8 respectively, but the approximate normal distribution was achieved by transforming the data to logarithms (Base 10: Appendix 5.1). The CV values were high for most of the variables suggesting significant variability in the spatial distribution of these variables. The CV values were the highest at 88.5 and 136% respectively for soil available phosphate and magnesium. For some other variables such as soil pH and soil moisture in July the spatial distribution was almost uniform with CV of 3.6 and 8% respectively. The pH value was in general high with a mean of 8.4, which could be due to the presence of calcareous patches in this field according to the recent soil map created by (Draycott and Evans, 2012) (Appendix 1), as the pH value in some of these patches reached 9. The soil was much moister in July with a mean value of 53% and less variable with a CV of 8%, due to higher amount of precipitation in July (Fig 2.7 D), while it was the driest in August with mean of 24% and most variable with a CV of 20.3%, due to variability in soil type.

The results of geostatistical analysis confirmed significant spatial variation in most of soil attributes in White Patch field (Table 3.1). The fitted models differed, but for most of the variables in this field the spatial variation was best accounted by the exponential model, which along with the spherical model are usually the best models for describing the spatial variability in soil properties (Webster and Oliver, 2007, Montanari *et al.*, 2012). The variograms for some variables were almost typical (Fig 3.1) as the variance increases with increasing the lag distances and become slightly flat after approaching the sill. The spatial variation in these variables is therefore, expected to be patchy and mostly revealed by the sampling schemes followed in this study. However, the variogram of log-magnesium had a high nugget variance of 0.25, while it was a pure nugget for soil available potassium. Although a pure nugget variogram should not be expected, because the environment is continuous, the value of soil potassium changed over short distances, e.g. from 38 mg/l to 455 mg/l. In addition measurement error could lead to high nugget values (Kerry, 2003, Webster and Oliver, 2007). Most of the observed variation was spatially correlated as there was a strong spatial dependency ($\%C0/(C0+C)<25$), for most of the variables, but it was moderate ranged between 30% for soil organic matter and 71% for Log-magnesium. The range of spatial dependency, which represents the average extent of the variation differed significantly for one variable to another; being as short as 37 m for silt and as long as 220 m for Log-magnesium (Table 3.1).

Table 3.1: Results of statistical and geostatistical analysis of some soil physical and chemical attributes in White Patch field in 2012.

Variables	Descriptive statistics						Geostatistics				
	Mean	**Min**	**Max**	**SD**	**CV%**	**Skew**	**Model**	**Range (m)**	***Sill (C_1)***	***Nugget variance (C_0)***	***%C_0/(C_0+C_1)***
Soil Particles, %											
Clay	28.6	19	40	5.7	19.8	0.035	Spherical	106	29.4	0	0
Sand	67.3	51.3	79.7	7	10.5	-0.05	Exponential	190	49.8	6	10.8
Silt	4.2	0	10	2.3	55.6	0.52	Circular	37	5.2	0	0
Soil Organic Matter, %	3.4	1.9	5	0.5	15.1	0.47	Exponential	69	0.18	0.08	30.8
Soil pH	8.4	7.8	9	0.3	3.6	-0.22	Exponential	123	0.09	0	0
Soil EC, µS	116.8	70	160	19.7	16.8	-0.24	Exponential	115	282.6	88.4	23.8
Soil available nutrients mg/l soil solution											
Nitrate	14.8	4.5	30	6	40.6	0.96	-	-	-	-	-
Log Nitrate	2.6	1.5	3.4	0.39	15	0.06	Spherical	50	0.098	0.067	40
Phosphate	3.4	1	12	3.03	88.5	1.6				-	-
Log Phosphate	0.93	0	2.5	0.73	78	0.75	Spherical	207	0.35	0.26	43
Potassium	330	38	455	130	39.3	-0.6	Pure Nugget	-	-	-	-
Magnesium	24.6	1.5	145	33.5	136	1.8	-	-	-	-	-
Log Magnesium	1	0.18	2.2	0.59	59	0.43	Exponential	220	0.13	0.25	71
Volumetric moisture content, %											
17/ May	34	21	56	6	19.3	0.46	Pentaspherical	82	38	2.3	5.7
02/June	36.7	21	54	6	16.8	0.04	Spherical	64	33	8.6	20
06/July	53	44	68	4	8	0.5	Spherical	119	12.4	4.3	26
13/August	24	14	39	5	20.3	0.57	Exponential	127	24	1.76	6.8

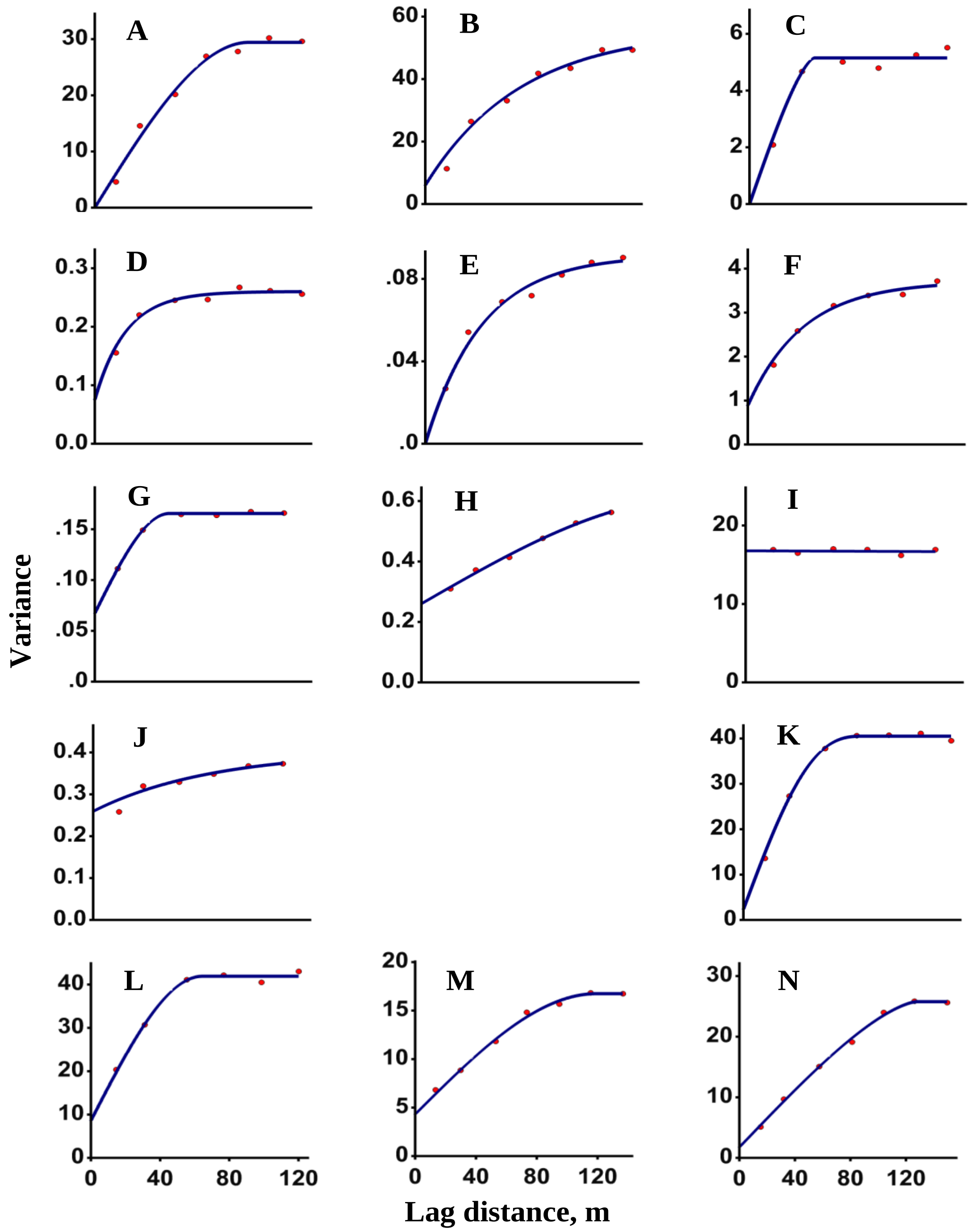


Figure 3.1: The experimental variograms and fitted models for (A) %clay, (B) %sand and (C) %silt, (D) %organic matter, (E) soil pH, (F) EC µS (variance*100), (G) Log nitrate mg/l, (H) log phosphate mg/l, (I) potassium mg/l (variance*1000), (J) Log magnesium mg/l and soil volumetric moisture in (K) May, (L) June, (M) July and (N) August in White Patch Field in 2012. Parameters of fitted models are in Table 3.1.

The patterns of spatial variation in soil attributes are illustrated in the Kriging maps (Fig 3.2). The spatial variability in clay, organic matter, magnesium and soil moisture content at different growth stages had almost similar patterns, as most of the areas with high values of these variables were located along the western site of the field, which is also the most elevated part and extended toward the middle. In addition, some of the patches with low values of these variables were also coincident and located in the lowest part of the field.

The spatial distribution of most soil attributes in this field was positively and significantly correlated to soil clay content (P<0.05: Appendix 9.2). The correlation coefficients of soil clay content were 0.49, 0.36, 0.33 and 0.39 with silt, soil organic matter, soil pH and electrical conductivity, respectively and 0.43, 0.20, 0.51 and 0.41 with soil moisture content in May, June, July and August respectively. On the other hand, soil clay content was negatively associated with the soil available phosphate with significant correlation coefficient -0.30, and not related to soil available potassium with correlation coefficient of 0.06 (Table 3.7 A).

The summary statistics of average canopy temperature are given in Table 3.2 and the spatial variation was illustrated by the maps created based on Inverse Distance Weight (IDW) shown in Fig 3.3. The average mean temperature during the growing season was 16.6°C and ranged from 15 to 18°C at different stages during the growing season. The average minimum temperature for all the season was 12°C and the average maximum was 23°C. In general, the canopy temperature was higher in August and lower and more variable during September with CV of 7.4% compared to 6.2% for the average mean of all the season.

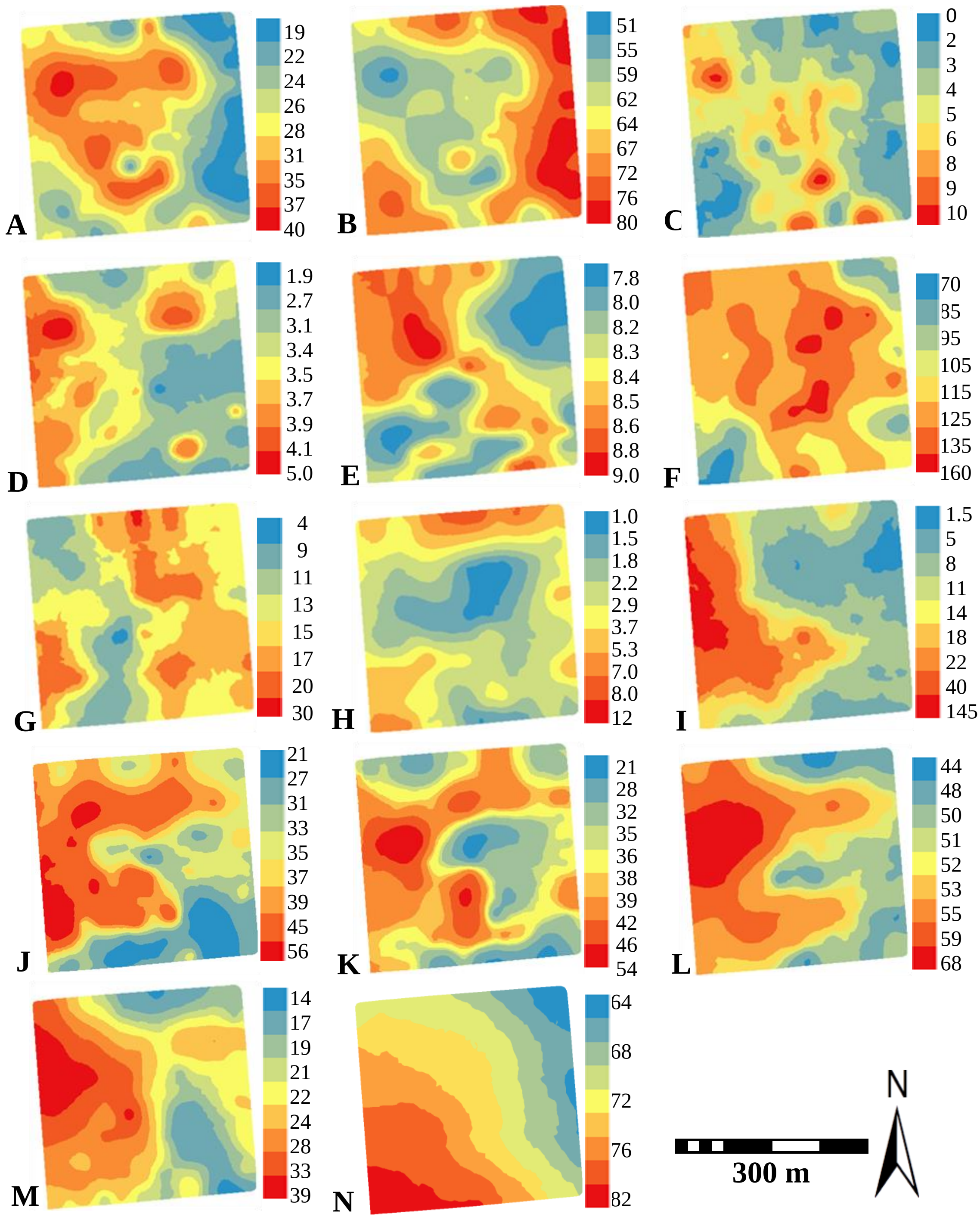


Figure 3.2: Interpolation maps of (A) %clay, (B) %sand and (C) %silt, (D) %organic matter, (E) soil pH, (F) EC µS, (G) available nitrate, mg/l, (H) phosphate mg/l and (I) magnesium mg/l, soil volumetric moisture in (J) May, (K) June, (L) July and (M) August and (N) elevation m in White Patch filed in 2012. The relevant variograms are in Fig. 3.1.

Although the CV values were in general low, small changes in canopy temperature might cause significant differences in crop growth and sugar accumulation. The patterns of spatial variation in average mean temperature were similar at different stages of development as most of the areas with low temperature were located in the west part of the field, and the warmer areas were mostly located in the southeast corner and extended toward the north. Most of the warm areas were coincident with low and steep areas, which are also the same areas of low crop canopy cover. The average maximum temperature during the season was also followed a similar patterns especially for the areas of high value, but it slightly differed from the average minimum.

In addition, the canopy temperature was found to be correlated to soil temperature in the five plots at which the soil temperature was recorded. The highest correlation coefficient between canopy and soil temperature was 0.95 during June and it was 0.90 for all the season (Table 3.7 B). This indicates that the temperature in the root zone was related to canopy temperature and varied in a similar way. Thus, the spatial variation in temperature at the root zone can be predicted within the field from the spatial variability in canopy temperature. Furthermore, the canopy and soil temperature were negatively correlated to soil moisture at different growth stages. The effect of soil temperature on soil moisture seems to be greater than the effect of canopy temperature. The relation between soil temperature and soil moisture was greater in August with r of -0.71 and it was relatively weaker in July with r of -0.45.

Table 3.2: The summary statistics of average mean, minimum and maximum canopy temperature °C at different stages in White Patch field in 2012.

	Average minimum				Average maximum				Average Mean			
Month	**Mean**	**Min**	**Max**	**%CV**	**Mean**	**Min**	**Max**	**%CV**	**Mean**	**Min**	**Max**	**%CV**
June	10.3	9.1	11.4	3.4	22.2	19.2	24.8	6.1	15.5	14.2	17.3	5.7
July	13.5	12.7	15.3	2.8	23.8	19.3	28.3	8.6	17.5	15.7	20.3	7.2
August	13.6	12.8	15.5	2.8	24.3	19.8	32.1	10.1	18	16.2	20.9	6.5
September	10.2	9.3	11.4	4.3	21.3	17.4	30.2	13.1	15	13.3	17.9	7.4
Season	12	11.4	13.5	2.7	23	19.3	28.8	7.9	16.6	15.2	18.9	6.2

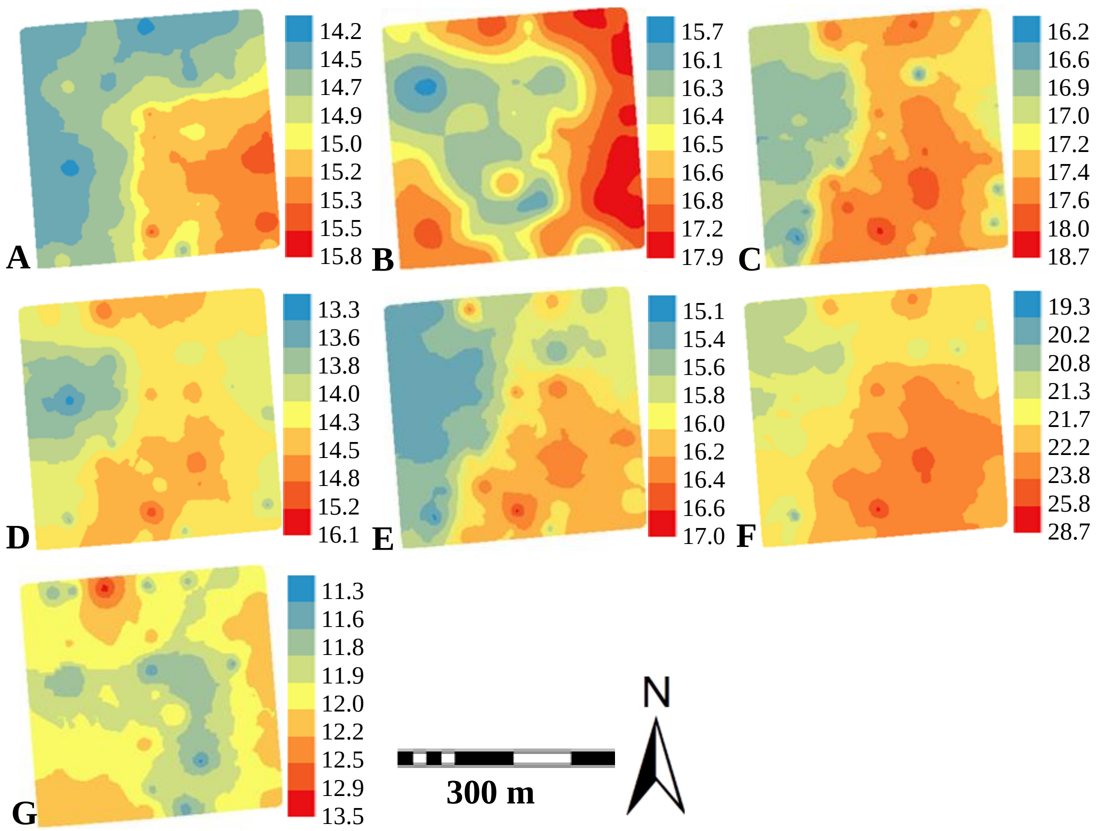


Figure 3.3: The maps of average monthly mean canopy temperature (°C) based on daily records in White Patch field in 2012 season, (A) in June, (B) July (C) August, (D) September and (E) for all the season, and (H and I) are respectively for the average minimum and maximum for all the season.

3.3 T32 field in 2012:

The summary statistics of the soil attributes data are given in Table 3.3. There were high skewness values for silt, soil available phosphate, potassium and magnesium at T32 field which indicates a departure from normal distribution. The high skewness values were also associated with high CV values, which might affect the reliability of the experimental variogram. However, transforming the data significantly improved the distribution of the data (Appendix 5.2) and the CV values were reduced from 61.8, 106, 38.4 and 132% to 32.4, 78, 6.8 and 65% respectively for square root of silt and logarithm of available phosphate, potassium and magnesium. The percentage of sand in T32 field was in general high with mean value of 74.4% and it had almost a uniform distribution with a CV of 4.7%. The soil pH was neutral with a mean of 7.5 and had a low variability with a CV of 5.7%. Although the available magnesium was much more variable, the mean value was in general low (8.4 mg/l), as the concentration of soil available magnesium usually ranges from 10 to 500 mg/l (Draycott and Christenson, 2003). As was the case in White Patch field, the soil was much wetter in July with mean of 41%, but less variable with CV of 12.2%, while it was driest and most variable in August with a mean of 19% and CV of 27%, which suggests that the variation in soil moisture is more evident when the soil is dry, due to the variability in soil types and their ability to retain moisture.

The experimental variograms of the soil variables in T32 field (Fig 3.4) and the model parameters (Table 3.3) indicate significant spatial variation in all variables. The shape of the variogram and fitted models differed from one variable to another.

Table 3.3: Results of statistical and geostatistical analysis of some soil physical and chemical attributes at T32 field in 2012.

Variables	Descriptive statistics						Geostatistics				
	Mean	Min	Max	SD	CV%	Skew	Model	Range (m)	*Sill (C_1)*	*Nugget variance(C_0)*	*%C_0/(C_0+C_1)*
Soil Particles, %											
Clay	20.8	15	28	2.8	13.6	0.18	Pentaspherical	116	5.9	1.66	22
Sand	74.4	65	80	3.5	4.7	-0.28	Pentaspherical	305	6.8	6.2	47.7
Silt	4.8	0.5	13	3	61.8	0.94	-	-	-	-	-
SQR-Silt	2.1	0.7	3.6	0.7	32.4	0.2	Spherical	126	0.23	0.29	55.8
Soil Organic Matter, %	3.4	2.2	4.4	0.4	11.9	0.03	Circular	190	0.11	0.07	38.9
Soil pH	7.5	6.2	8.3	0.4	5.7	-0.57	Circular	141	0.12	0.05	29.4
Soil EC, µS	92.9	50	160	26.5	28.5	0.38	Circular	127	341	284	45.4
Soil available nutrients mg/l											
Nitrate	17.7	9	28	4.3	24.4	0.18	Spherical	164	10.3	9.96	49
Phosphate	8.97	1	38	9.5	106	1.22				-	-
Log Phosphate	1.56	0	3.6	1.2	78	0.03	Pentaspherical	93	0.82	0.51	38
Potassium	185	80	380	71	38.4	1.22	-	-	-	-	-
Log Potassium	2.24	1.9	2.6	0.15	6.8	0.46	Exponential	180	0.013	0.012	48
Magnesium	8.4	1	65	11	132	2.7	-	-	-	-	-
Log Magnesium	1.6	0	4.2	1	65	0.41	Circular	95	0.64	0.44	42
Soil moisture content, %											
06/June	28	16	41	5.2	18.6	0.005	Exponential	266	23.6	13.8	37
06/July	41	30	52	5	12.2	0.15	Exponential	270	27	4	13
13/ August	19	8	28	5	27	-0.54	Spherical	169	18	2.5	12

SD: Standard deviation, a: Range, C_1:Sill, C_0: Nugget variance, Log: Logarithm, SQR: Square root

The variograms for most of the variables became flat after they approached the sill indicating a bounded variation. For some variables, however, there was a large nugget variance which is more likely to be unresolved variation, because the sampling interval was 40 m for most of the plots, which is the main problem in grid sampling (Haberle *et al*., 2004). As a result, the estimation of the degree of spatial dependency was only moderate for most of the variables, but there was strong spatial dependency for soil moisture during July and August and clay with values of 13, 12 and 22% respectively. The ranges of spatial dependency were high for most variables and ranged from 93 m for phosphate to 270 m for soil moisture during July.

The spatial variation in these variables is more evident in the maps created by Kriging (Fig 3.5). The spatial distribution of some variables had almost similar patterns, but as the range value differed, the average extent of variation also differed from one variable to another. Similar patterns of spatial variation were observed for clay, soil pH, electrical conductivity, and soil moisture in June and August, as most of the areas with high values of these variables were on the eastern side of the field, which is also the most elevated side. In addition most areas with low values of these variables were coincident and located on the lower side of the field. The spatial variation in soil available nitrate and to some extent soil moisture followed an almost similar pattern as soil organic matter with significant correlation coefficients of 0.28, 0.25 0.42 and 0.34, respectively with soil nitrate and soil moisture in June, July and August, while the spatial variation in soil available phosphate was similar to the variation in sand with a correlation coefficients of 0.30 (Table 3.8 A).

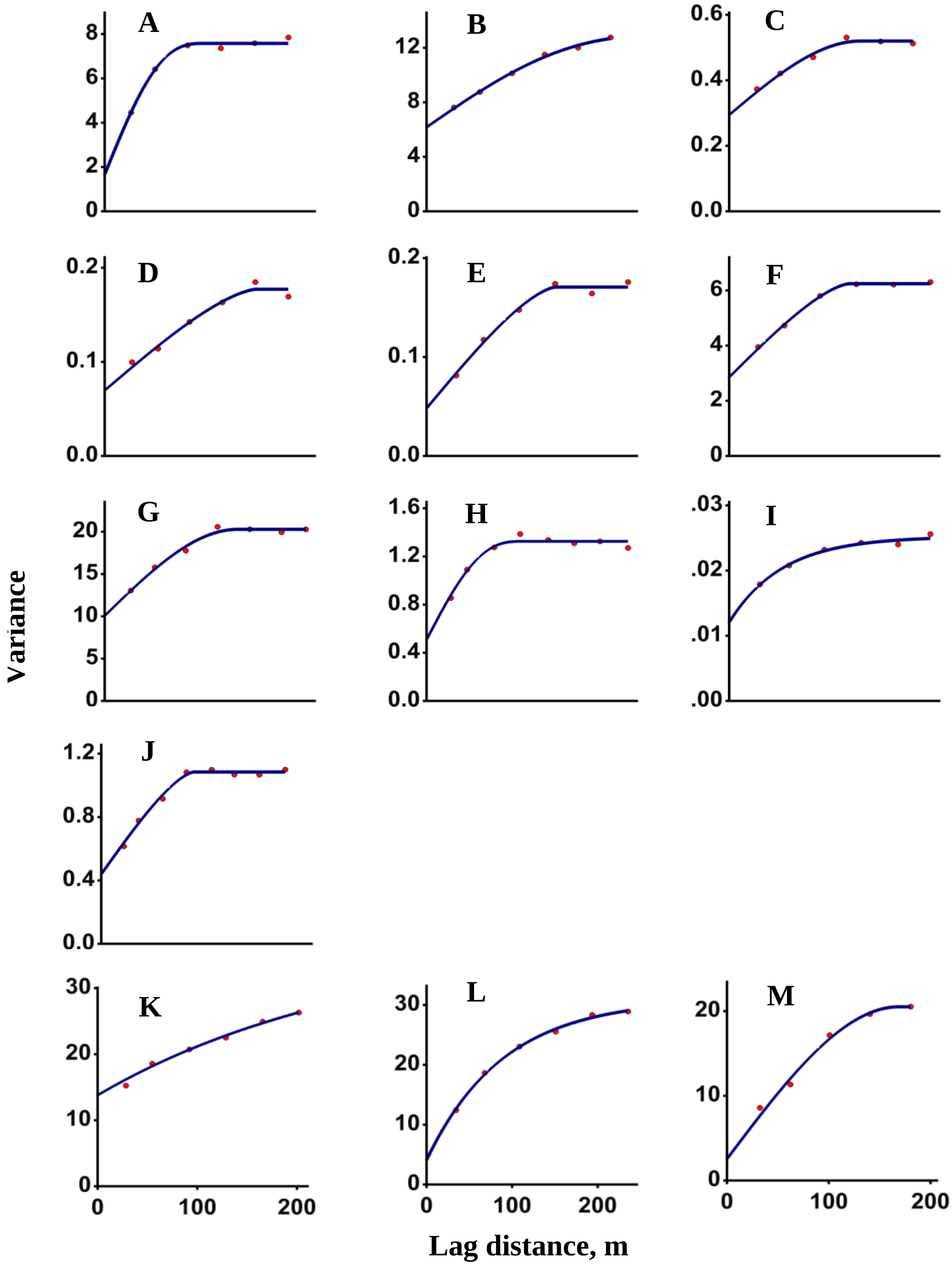


Figure 3.4: The experimental variograms and fitted models for (A) %clay, (B) %sand and (C) SQR-%silt, (D)%organic matter, (E) soil pH, (F) EC µS (variance*100), (G) nitrate mg/l, (H) log phosphate mg/l, (I) Log potassium mg/l, J-Log magnesium mg/l, and soil volumetric moisture content in (K) June, (L) July and (M) August in T32 Field in 2012. Parameters of fitted model are in Table 3.3.

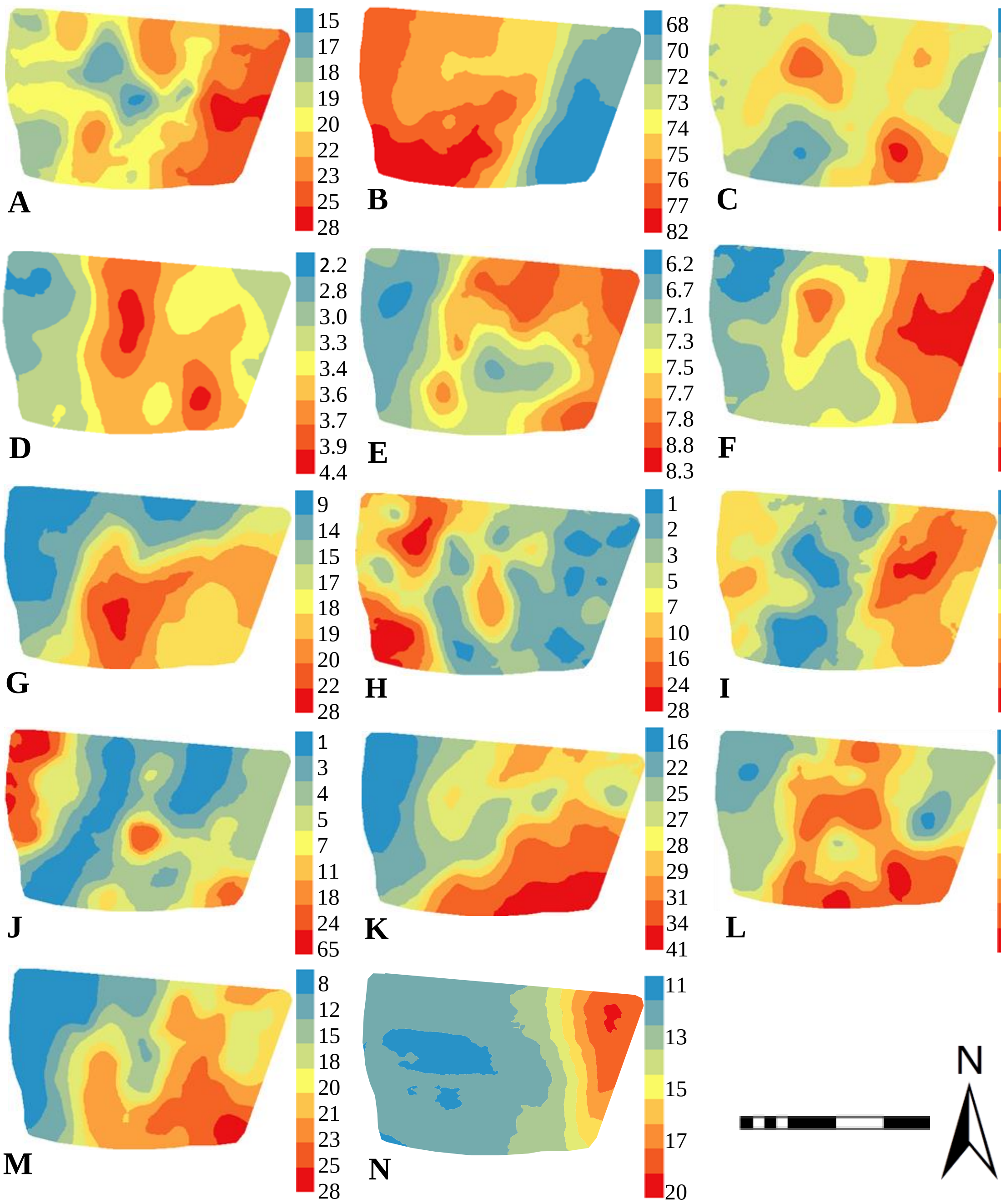


Figure 3.5: Interpolation maps for (A) %clay, (B) %sand and (C) %silt, (D) %organic matter, and (E) soil pH, (F) EC µS, soil available (G) nitrate mg/l, (H) phosphate mg/l, (I) potassium mg/l and (J) magnesium mg/l, %soil moisture content in (K) June, (L) July and (M) August and (N) elevation m in T32 filed in 2012. The relevant variograms are in Fig. 3.4

The mean canopy temperature during the growing season was 16.2°C and ranged from 14.6 to 17.7°C at different stages (Table 3.4). As in White Patch field, the canopy temperature was higher in August and lower in September. In addition, the canopy temperature was more variable during September with CV of 6.4% in T32 field compared to 4.4% for the average mean for whole the season. The mean canopy temperature of T32 was close to that in White Patch but less variable. The patterns of the spatial variation in canopy temperature measured at different times were similar at different growth stages (Fig 3.6), except in June and the maximum temperature for the whole season, which slightly differed from other months. The higher parts of the field were also cooler by almost 2°C than the lower parts, and the warmer areas were also coincident with areas of low crop canopy cover.

The variability in canopy temperature was found to be correlated to the soil temperature with r of 0.91 for the whole season in the five plots where both soil and canopy temperature were recorded (Table 3.8 B). The variability in soil moisture measured at different growth stages was negatively correlated to the variability in soil and canopy temperature, but as in White Patch field the variability in soil moisture was related to soil temperature more than air temperature especially in August with a correlation coefficient of -0.86 (Table 3.8 B).

Table 3.4: The summary statistics of average mean, minimum and maximum canopy temperature °C at different stages in T32 field in 2012.

	Average minimum				Average maximum				Average Mean			
Month	**Mean**	**Min**	**Max**	**%CV**	**Mean**	**Min**	**Max**	**%CV**	**Mean**	**Min**	**Max**	**%CV**
June	12.2	9.6	14.0	8.2	20.3	16.4	23.8	6.0	15.2	13.7	16.5	4.1
July	13.1	12.3	13.9	2.4	22.0	18.4	28.3	9.2	16.8	15.5	19.4	4.9
August	13.1	12.3	13.9	2.4	23.4	19.2	27.1	7.1	17.7	16.3	19.8	4.4
September	9.5	8.3	11.0	6.3	20.8	14.7	29.3	11.8	14.6	12.5	17.9	6.4
Season	12.2	11.4	13.1	3.0	21.7	17.4	25.1	6.3	16.2	14.7	17.9	4.4

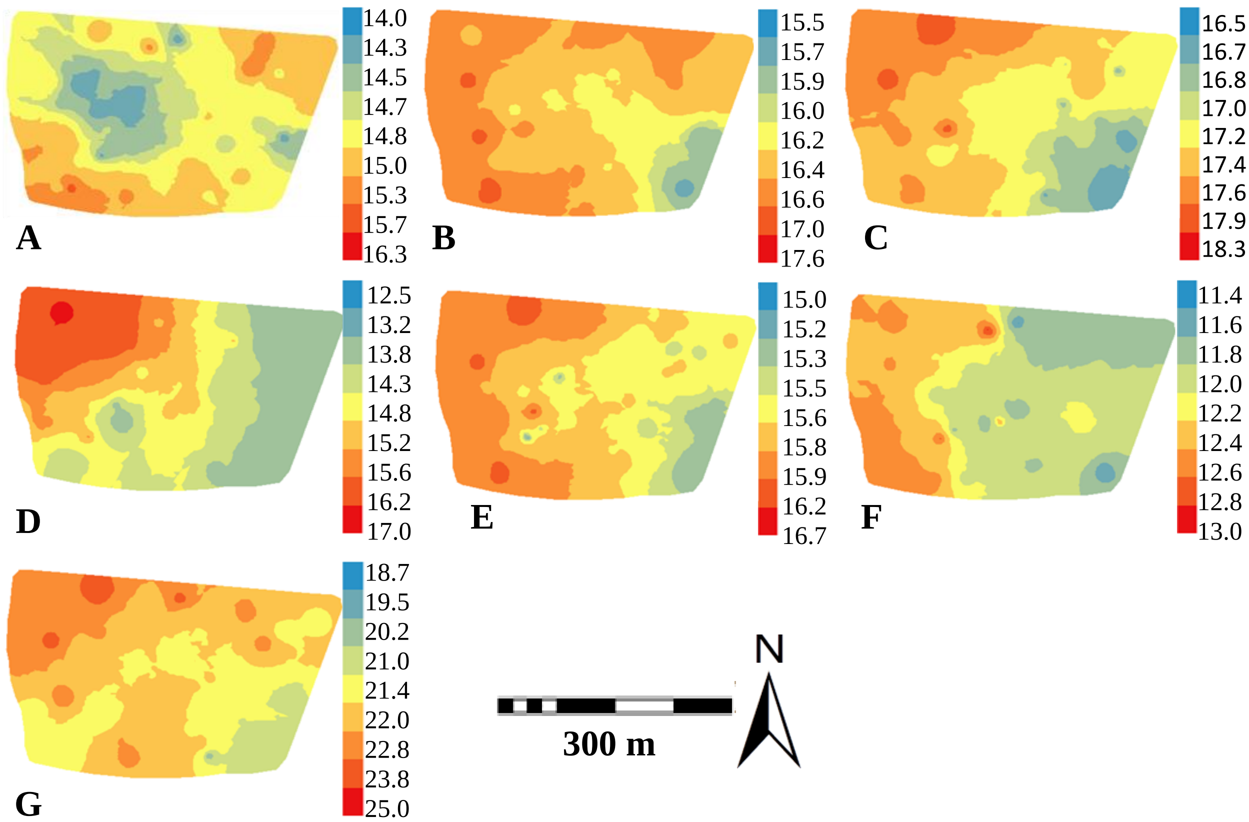


Figure 3.6: The maps of average monthly mean canopy temperature (°C) based on daily records in T32 field in 2012 season, (A, B, C and D) in June, July, August, and September respectively and (E) for all the season, and (F and H) are respectively for the average minimum and maximum for all the season

3.4 WO3 field in 2013:

Based on the summary statistics of the data of soil variables (Table 3. 5), the soil in WO3 field seems to be clayey, as the mean value was 40% and ranged from 29.8 to 52%, but it was not very variable with a CV of 11.6%. The mean value of the available phosphate was 0.55 mg/l, because the value was 0 at more than 90% of the plots and only a few plots gave values between 2 and 13 mg/l, and therefore, the data were strongly and positively skewed and had a high CV value of 356%. The reason for unavailability of phosphate in WO3 could be the high proportion of clay in this field, which increases the adsorption of soil available phosphate by some clay minerals such as goethite and gibbsite (Fontes and Weed, 1996). Some of the studied variables such soil pH and soil EC had a uniform spatial distribution throughout the field with CVs of 2 and 9.3%, respectively. The results also indicate an approximate normal distribution for the data of most variables except for soil available phosphate and magnesium. The availability of soil moisture was in general low and the values were close to each other at different times of year, but it was more variable in July with CV of 25%, due to low precipitation (Fig 2.7 F).

The way in which the soil properties spatially varied in WO3, is described by the experimental variograms (Fig 3.7) for which the model parameters are given in Table 3.5. The spatial variation in most soil attributes was accounted for by the circular model. It was not possible to compute the variogram for soil available phosphate, due to the large number of zero values in the data set, and the variogram for potassium appeared as pure nugget indicating that all the variation was occurring within the minimum sampling intervals.

Table 3.5: Results of statistical and geostatistical analysis of some soil physical and chemical attributes in WO3 field in 2012

Variables	Descriptive statistics						Geostatistics				
	Mean	**Min**	**Max**	**SD**	**CV%**	**Skew**	**Model**	**Range (m)**	**Nugget (C_1)**	**Nugget (C_0)**	***%C0/(C0+C_1)***
Soil Particles, %											
%Clay	40	29.8	52	4.6	11.6	0.32	Circular	81	10.6	8.9	46
%Sand	52.6	36	66.3	5.5	10.5	-0.29	Circular	85	15.4	10.7	41
%Silt	7.4	1.25	17.5	2.7	36.7	0.46	Spherical	69	2.5	3.6	59
Soil Organic Matter, %	4.3	2.9	6.3	0.55	13	0.62	Pentaspherical	112	0.17	0.14	45
Soil pH	7.8	7.3	8.2	0.16	2	0.03	Circular	73	0.016	0.011	40.7
Soil EC, µS	235	180	300	21.8	9.3	0.13	Circular	58	157	270	63.2
Soil Nutrients											
Available phosphate mg/l	0.55	0	13	1.96	356	4.6	-				-
Available potassium mg/l	232	15	455	147	63	0.43	Pure Nugget	-	-	-	-
Available magnesium mg/l	16	3	65	12.3	76	1.54	-	-	-	-	-
Log Magnesium	2.5	1.01	4.2	0.76	30.3	-0.09	Circular	44	0.23	0.34	60
Soil moisture content, %											
06/June	0.27	0.15	0.38	0.06	22.3	0.26	Circular	121	0.0032	0.0005	13.5
06/July	0.22	0. 1	0.34	0.05	25	-0.15	Circular	114	0.0027	0.0005	15.6
11/September	0.20	0.14	0.28	0.03	14.6	-0.13	Circular	169	0.00048	0.00018	27

SD: Standard deviation, *a*: Range, C_1:Sill, C_0: Nugget variance, Log: Logarithm

The degree of spatial dependency was moderate for most of the variables, which could be due to the high levels of clay in this field, which can cause locally erratic variation in other related soil attributes (Kerry, 2003), except for soil moisture in June and July, which had strong spatial dependencies of 13.5 and 15.6% respectively. The range of spatially correlated variation also differed from one variable to another: it was as short as 44 m for magnesium and as long as 169 m for soil moisture in September.

The relation between field topography and some soil attributes is evident in WO3 as in the other two fields in which the most elevated part of the field (southeast corner) was most clayey and also associated with high values of silt and EC (Fig 3.8). However most of the areas of high organic matter content were located in the low and level zones of the fields, perhaps due to the water erosion, which decrease the concentration of organic matter in the back slope and increase it in the low zones (Amado and Santi, 2011). The variation in available magnesium distributed as small patches throughout the field and most of the areas of low magnesium were concentrated in the southeast and northwest corners of the field. However, the interpolation maps for potassium were not created for White Patch and WO3 fields, because the variograms were pure nugget and the mean value of soil potassium in this case can be assumed to be applied throughout the field (Oliver, 2010, Oliver and Webster, 2014).

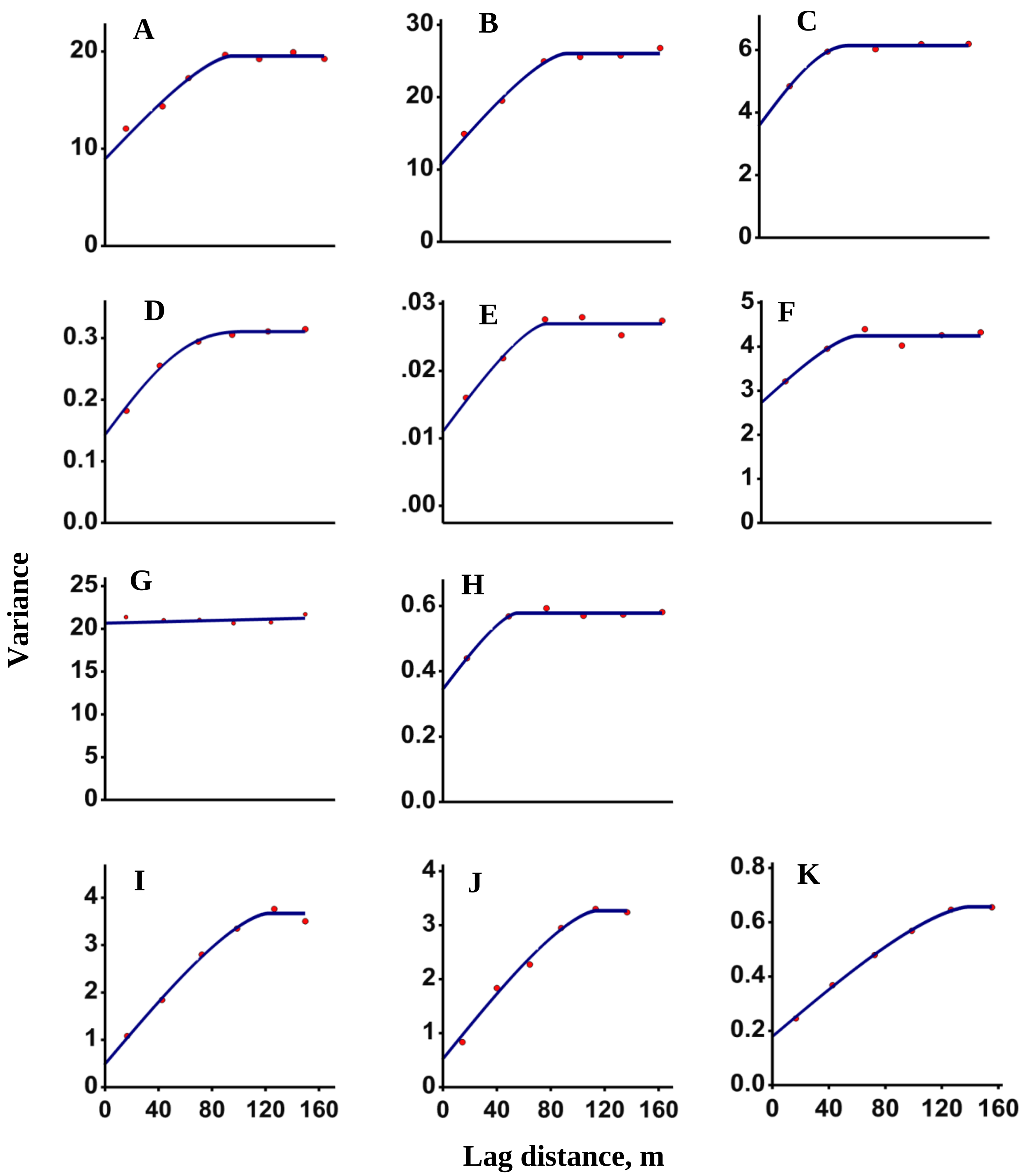


Figure 3.7: The experimental variograms and fitted models for (A) %clay, (B) %sand and (C) SQR-%silt, (D) %organic matter, (E) soil pH, (F) EC µS (variance*100), (G) potassium mg/l (variance*1000), (H) Log magnesium mg/l and soil volumetric moisture content (variance/1000) in (I), June, (J) July and (K) September in WO3 field in 2013. Parameters of fitted models are in Table 3.5.

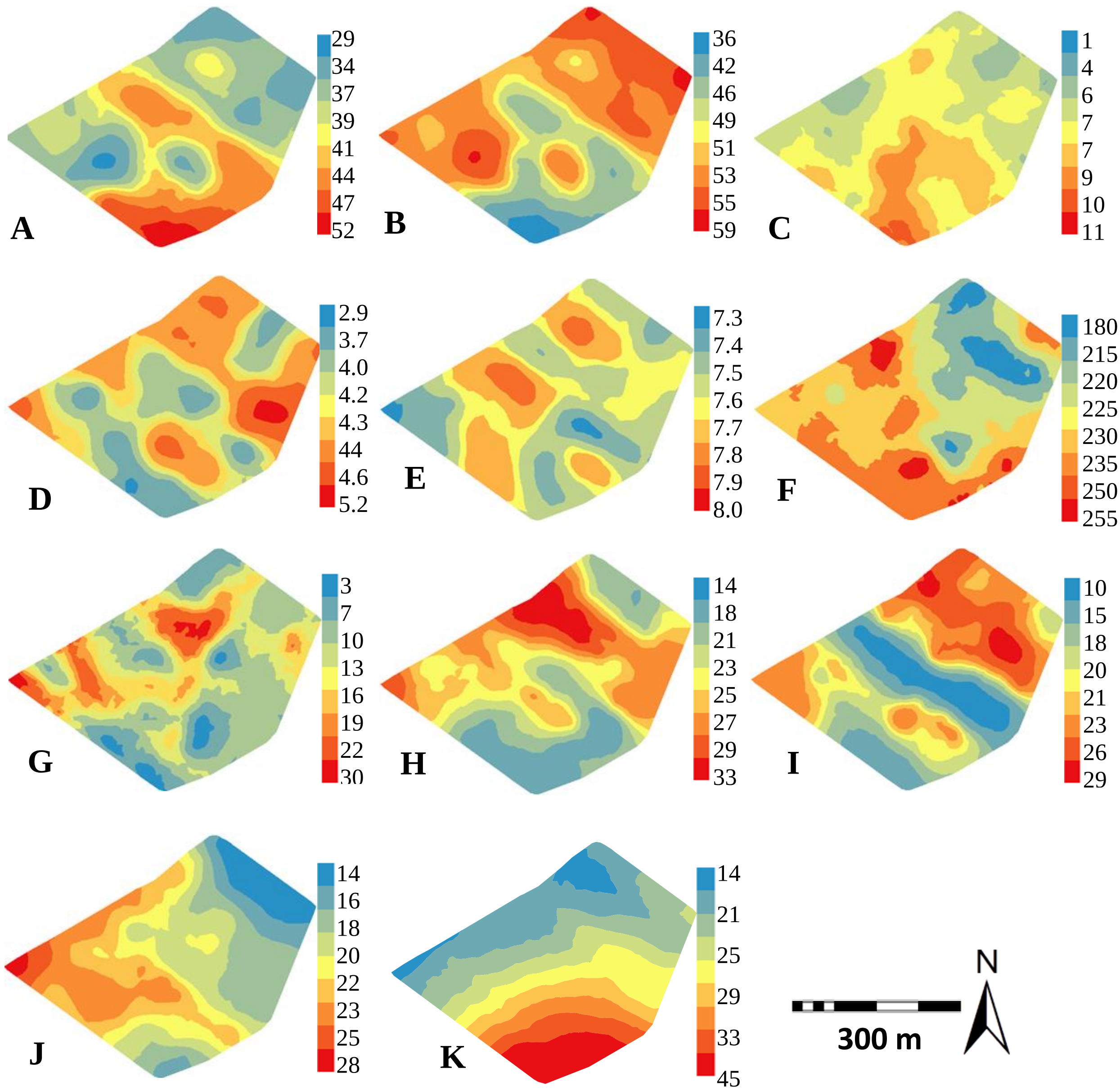


Figure 3.8: Interpolation maps for (A) %clay, (B) %sand and (C) %silt, (D) %organic matter, (E) soil pH, (F) EC µS, (G) available magnesium mg/l, and %soil moisture content in (H) June, (I) July and (J) August and (K) elevation m in WO3 field in 2013. The relevant variograms are in Fig. 3.7.

The mean canopy temperature during the growing season in WO3 was 14.6 °C and ranged from 5.9 to 20.7 °C at different growth stages, with an average minimum temperature of 9.1 °C and a maximum of 21.4°C. This was lower than for the other two fields because the 2013 season was extended to the end of November, which had the lowest minimum temperature of 1.7 °C. The highest CV value for the mean temperature was 3.9% for both August and September and it was in general less variable in 2013 than in 2012 (Table 3.6). In addition the patterns of spatial variation differed in 2013 season compared to 2012 season. The higher areas in WO3 in 2013 had higher canopy temperature except for June and November (Fig 3.9). Whereas in 2012 in White Patch and T32 the warmer areas were coincident with areas of low canopy cover and the cooler areas were mostly associated with high canopy cover.

Table 3.6: The summary statistics of average mean, minimum and maximum canopy temperature °C at different stages in WO3 Field in 2013.

	Average minimum				Average maximum				Average Mean			
Month	**Mean**	**Min**	**Max**	**%CV**	**Mean**	**Min**	**Max**	**%CV**	**Mean**	**Min**	**Max**	**%CV**
June	8.7	8.2	9.3	2.7	22.3	18.1	25	4.2	14.8	13.4	15.9	3
July	13	12.4	14.1	2.6	29.7	25.3	37.3	5.5	20.7	19.1	22.9	2.7
August	11.8	11	12.9	3.5	26.5	21.6	31.6	6.9	18.3	16.6	20.3	3.9
September	8.7	7.6	9.5	5.3	21	17.2	26.1	7.2	14	12.9	15.9	3.9
October	8.4	7.6	9.1	3.9	16.6	14.4	19.6	5.2	12.1	11.4	13	2.2
November	2.6	1.7	3.3	12	9.5	7.9	13.7	7.6	5.9	5.3	6.4	3.4
Season	9.1	8.4	9.8	3.1	21.4	17.8	24.7	4.3	14.6	13.4	15.6	2.5

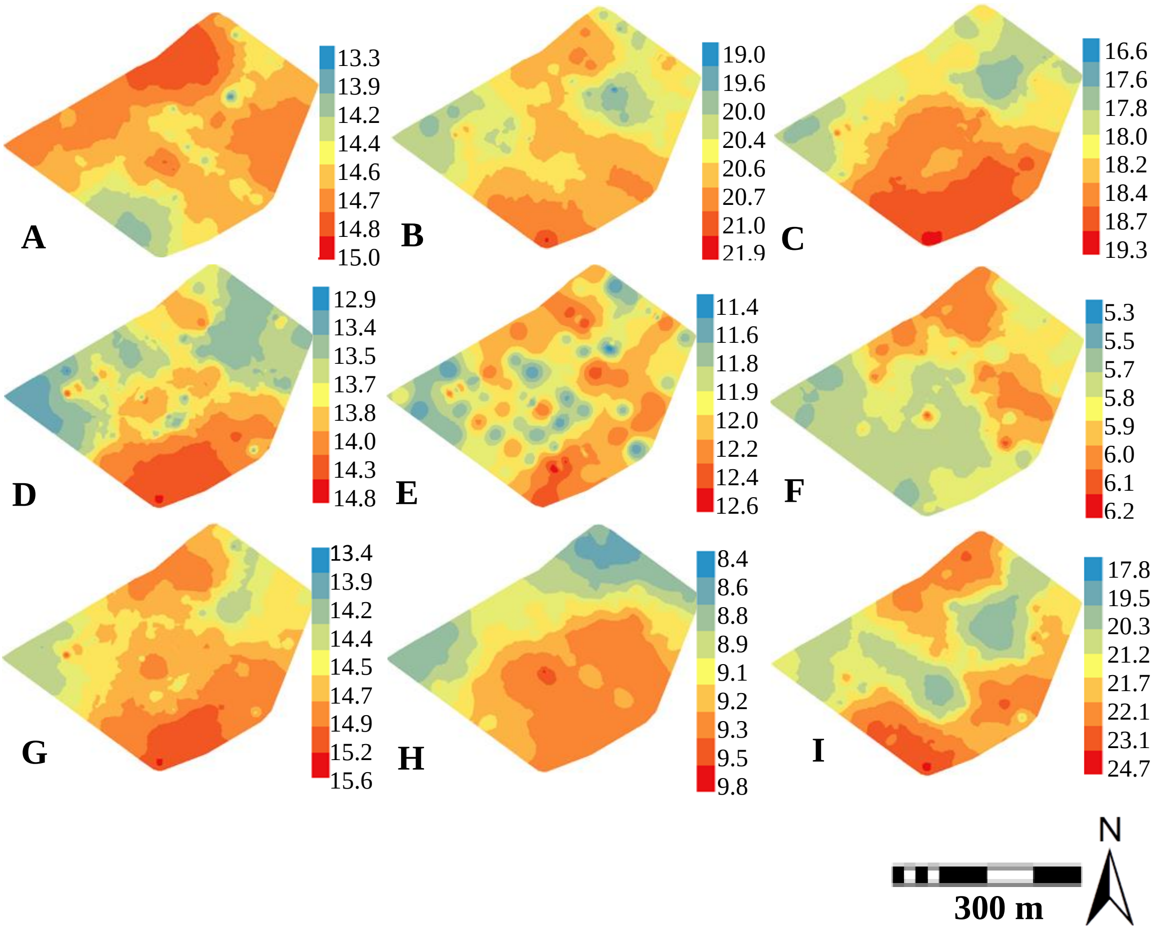


Figure 3.9: The maps of average monthly mean canopy temperature (°C) based on daily records in WO3 field in 2013 season, (A) in June, (B) July (C) August, (D) September, (E) October, (F) November and (G) for all the season, and (H and I) are respectively for the average minimum and maximum for all the season

3.5 Conclusion:

Most measured variables significantly varied across each field, White Patch, T32 and WO3. The soil was in general sandier in T32 field, but also less variable, while it was more clayey in WO3 and more variable. The highest CV values were observed for soil nutrients especially for soil available phosphate and magnesium in all three fields. On the other hand soil pH had almost a uniform spatial distribution with lower CV values, especially in White Patch and WO3 with CV of 3.6 and 2% respectively. The soil at White Patch field had higher mean value of soil pH, while it was neutral in T32 and WO3. The soil volumetric moisture content was lower in WO3 in 2013, but more variable compared to the other fields in 2012, 2012 being a wetter year.

Most of the variation in soil attributes was spatially dependent as the variograms had a low nugget variance and reached the sill semi-variance, albeit at different lag distances. The degree of the spatial dependency detected, was high for most of the variables in White Patch, but it was moderate for most of the studied variables in T32 and WO3, due to higher nugget variance. The high nugget variance could be due to the sampling scheme, which was not able to resolve the variation which occurred over short distances as in T32, or due to high levels of clay as in WO3, which may have caused locally erratic variation in some related attributes.

In all three fields, the most elevated parts were associated with higher clay content. The spatial variation in soil clay content was correlated with soil organic matter, soil available magnesium and soil moisture in White Patch, but with soil pH, electrical conductivity, soil potassium and soil moisture in T32, while it was only correlated with silt and electrical conductivity in WO3. In all three fields, the areas of high soil organic matter were associated with higher soil moisture content.

The canopy temperature also varied spatially across each field. It was less variable in WO3 and the patterns of spatial variation also differed compared to other two fields, as the higher parts were cooler in White Patch and T32, but warmer in WO3. In addition, a strong relationship was observed between the canopy temperature and soil temperature at root zone in the plots where the soil temperature was measured. Therefore, the soil moisture is expected to vary spatially in a similar way as the spatial variability in canopy temperature.

Since the spatial variability in the studied environmental variables is expected to be related to sugar beet growth and yield, the link between these variables and sugar beet growth, yield and quality will be examined and discussed in chapter four. This might help to determine the main associated environmental variables, which might be considered as the potential driving variables.

Table 3.7: Correlation coefficients between (A) soil properties and, (B) between soil and air temperature °C and soil moisture in White Patch in 2012, the bold numbers are significantly different from 0 (see Appendix 9.2 for P values).

(A)		**%Soil particles**			**SOM**	**Soil pH**	**EC**	**Soil available nutrients mg/l**				**Soil moisture content**		
		Clay	Sand	Silt				Nitrate	Phosphate	K	Mg	May	June	July
%Soil particles	%Sand	**-0.96**	-											
	%Silt	**0.49**	**-0.71**	-										
	%OM	**0.36**	**-0.29**	0	-									
	Soil pH	**0.33**	**-0.35**	**0.29**	-0.1	-								
	EC, µS	**0.39**	**-0.42**	**0.33**	0.03	**0.32**	-							
Soil available nutrients mg/l	Nitrate	-0.13	0.13	-0.09	-0.05	-0.17	0.04	-						
	Phosphate	**-0.3**	**0.30**	-0.15	-0.01	-0.07	**-0.28**	0.03	-					
	K	0.06	-0.08	0.13	-0.03	**0.27**	**0.25**	**-0.35**	0.09	-				
	Mg	0.15	-0.16	0.11	0.19	0.10	0.16	0.12	0.03	0.15	-			
%Soil moisture content	17/ May	**0.43**	**-0.35**	0.03	**0.43**	0.0	**0.22**	0.06	0.01	0.06	**0.27**	-		
	02/June	**0.20**	-0.13	-0.09	**0.49**	-0.10	0.03	-0.04	0.10	-0.05	0.19	**0.37**	-	
	06/July	**0.51**	**-0.43**	0.08	**0.43**	**0.30**	0.07	-0.13	**-0.26**	0.01	0.1	**0.38**	**0.41**	-
	13/ August	**0.41**	**-0.36**	0.11	**0.40**	0.10	0.11	**-0.22**	-0.13	0.18	0.2	**0.51**	**0.45**	**0.58**

(B)	**June**	**July**	**August**	**September**	**Season**
Soil moisture with canopy temperature	-0.15	**-0.31**	**-0.29**	-	-
Soil moisture with Soil temperature	**-0.55**	**-0.45**	**-0.71**	-	-
Soil temperature with canopy temperature	**0.95**	**0.86**	**0.87**	**0.84**	**0.90**

Table 3.8: Correlation coefficients between (A) soil properties and, (B) between soil and air temperature °C and soil moisture in T32 in 2012, the bold numbers are significantly different from 0 (see Appendix 9.4 for P values).

(A)		%Soil particles			%OM	Soil pH	EC	Soil available nutrients mg/l				Soil moisture content	
		Clay	Sand	Silt				Nitrate	Phosphate	K	Mg	June	July
%Soil particles	%Sand	**-0.57**	-										
	%Silt	**-0.28**	**-0.63**	-									
	%OM	-0.02	**-0.27**	**0.33**	-								
	Soil pH	**0.30**	-0.18	-0.08	**0.26**	-							
	EC, µS	**0.25**	**-0.49**	**0.34**	**0.33**	**0.43**	-						
Soil available nutrients mg/l	Nitrate	-0.05	0.01	0.04	**0.28**	0.12	**0.30**	-					
	Phosphate	**-0.31**	**0.30**	-0.06	**-0.21**	**-0.45**	**-0.51**	**-0.27**	-				
	K	0.11	-0.14	0.07	0.04	0.05	**0.37**	0.07	-0.19	-			
	Mg	-0.09	0.12	-0.06	-0.13	**-0.29**	**-0.27**	-0.19	0.04	-0.08	-		
Soil moisture content	06/June	**0.37**	**-0.36**	0.07	**0.25**	**0.35**	**0.29**	0.11	**-0.39**	-0.03	0.01	-	
	06/July	-0.05	-0.10	0.17	**0.42**	**0.35**	0.12	**0.21**	-0.19	**-0.23**	-0.15	**0.37**	-
	13/ August	**0.36**	**-0.39**	0.11	**0.34**	**0.53**	**0.49**	**0.33**	**-0.57**	0.10	**-0.24**	**0.61**	**0.44**

(B)	June	July	August	September	Season
Soil moisture with canopy temperature	**0.37**	-0.05	**-0.23**	-	-
Soil moisture with Soil temperature	-0.07	-0.09	-0.86	-	-
Soil temperature with canopy temperature	**0.60**	**0.89**	**0.90**	**0.91**	**0.94**

Table 3.9: Correlation coefficients between some studied soil properties in WO3 filed in 2013, the bold numbers are significantly different from 0 (see Appendix 9.6 for P values).

		%Soil particles			%OM	Soil pH	EC	Soil available nutrients mg/l			Soil moisture content	
		Clay	Sand	Silt				Phosphate	K	Mg	June	July
%Soil particles	Sand	**-0.87**	-									
	Silt	0.05	**-0.54**	-								
	OM	-0.14	0.16	-0.08	-							
	Soil pH	0.10	-0.07	-0.03	-0.04	-						
	EC, µS	**0.34**	**-0.31**	0.05	0.02	**-0.27**	-					
Soil available nutrients mg/l	Phosphate	0.01	-0.01	-0.01	-0.03	0.13	0.11	-				
	K	**-0.22**	0.10	**0.18**	-0.05	**-0.19**	-0.03	-0.05	-			
	Mg	-0.13	0.17	-0.12	0.10	**-0.21**	0.00	-0.05	0.07	-		
Soil moisture content	6-Jun	**-0.27**	**0.28**	-0.11	**0.32**	0.15	**-0.21**	0.00	0.11	**0.35**	-	
	6-Jul	**-0.33**	**0.33**	-0.11	**0.19**	0.10	**-0.40**	-0.10	0.00	0.12	**0.36**	-
	September	-0.04	-0.05	0.16	0.07	0.08	0.07	0.08	-0.05	0.12	**0.24**	0.16

4. Chapter Four: Spatio-Temporal Variation in Sugar Beet Yield and Quality:

The spatial variability in crop yield may arise from the effects of spatial variability in soil attributes, above ground variables and crop parameters (Stafford *et al*., 1996). Mapping within-field variability in crop growth and yield and comparing it with the spatial variation in environmental variables, may indicate those environmental variables which can be considered as the potential driving variables (Rodriguez-Moreno *et al*., 2014). However it is important to examine the relationship between the variability in crop growth and the environment early in the growing season, so that the related environmental variables can be identified and managed before they impair the growth of the crop. Using ground based sensors to assess the crop growth status is considered an effective method to detect the crop stress and requirements within the growing season (Cao *et al*., 2012). In addition, for some fields, yield maps of previous years are available, but most farmers do not know how to deal with them. Therefore this chapter considers the potential of predicting the spatial variability in sugar beet yield and quality based on the variability in some crop growth parameters assessed at different growth stages using ground based sensors. It also aims to examine the relationship between the spatial variability in sugar beet yield and the spatial variability in the yield of preceding crops in order to assess the utility of the yield maps of previous crops to predict the within-field variability in a current sugar beet yield. In addition the relationship between the yield map of sugar beet and the maps of some environmental variables was also investigated.

4.1 Within-variation in sugar beet yield, quality and some biological variables:

The methods of collecting the data used in this chapter are described in Chapter Two. This section concentrates on the results of statistical and geostatistical analysis of these data to describe the spatial variability in some biological measurements assessed during the growing season in addition to the yield, quality and some post-harvest measurements. It also investigates the relationship between the spatial variability in sugar beet yield, quality and the spatial variability in environmental variables described in Chapter Three.

4.1.1 Descriptive statistics:

Most measurements of sugar beet growth, yield and quality had low skewness values ($< \pm 0.7$: Tables 4.1-4.3). Some of the studied variables therefore had an approximate normal distribution. However, some variables such as relative canopy growth rate and weeds density in all three fields as well as the amino acid content in the beets in White Patch were positively skewed with values ranged from 0.85 to 3.35. Transforming the data to logarithms significantly improved the distribution of amino acid content and the canopy growth rate, but it did not improve the distribution of weed density, due to the presence of many outliers that could not be removed, as the weeds usually appear as patches of high density in some parts of the field, while other parts might be weed free or with a low density (Colbach and Forcella, 2011). In addition some growth parameters in WO3 had a higher positive or negative skewness (Table 4.3), indicating a departure from the normal distribution, but transforming these data did not improve the distribution, because the value was too low in some plots compared to others due to the sub-optimal plant population density in these plots. Therefore the original data set was used for the analysis, as highly skewed data does not always require transformation (Kerry and Oliver, 2007b, Hbirkou *et al*., 2011).

The CV values for sugar beet yield and most of growth parameters in all fields exceeded 10%, indicating a significant spatial variation in crop growth and yield. However, the percentage of sugar almost had a uniform distribution in all three fields with CV values ranged from 1.7 to 2.4%, while weed density had the highest CV values ranging from 106 to 165% in all three fields and associated with higher skewness values (Tables 4.1-4.3). In general the variability in sugar beet growth and yield was much higher in WO3 with CV values ranging from 14.7 to 102% (Table 4.3), while they were between 7.9 and 56.4% in White Patch (Table 4.1) and between 2.8 and 37.8% in T32 (Table 4.2).

T32 field had a relatively higher mean yield value of £2500 ha^{-1}, which was also the most uniform among the field with a CV of 11.3% (Table 4.2) compared to White Patch and WO3 fields, which had mean values of £1850 and £1870 $ha^{-1}$and CVs of 21.3 and 32%, respectively (Tables 4.1 and 4.3). The mean plant population in WO3 was very low at only 50800 plants/ha (Table 4.3) indicating poor plant establishment, as the target plant population for optimum sugar yield and economic profits is 80000 to 100000 plants/ha (Jaggard *et al*., 2011). However, the plant establishment varied significantly throughout WO3 field and ranged from 22000 to 81000 plants/ha (Table 4.3). In 2012 season, the plant populations were optimal with mean values of 91000 and 95000 plants/ha in White Patch and T32, respectively (Tables 4.1 and 4.2).

The growth parameters, namely percentage of crop canopy cover, intercepted solar radiation and LAI were more variable early in the growing season than later on. For example, the CV values of crop canopy cover in June were 38.8, 22.5 and 71.5%, respectively in White Patch, T32 and WO3, while it was 9.5, 3.7 and 66.5%, respectively in July and 7.9, 2.8 and 42.2%, respectively in August (Tables 4.1 - 4.3). This is because later in the season most of the ground was covered by the crop foliage, which makes differences less visible, but the variability in LAI and intercepted solar radiation was also mitigated, which might suggest more rapid crop growth in the plots where the growth was weaker early in the growing season as a result of increases in air temperature, incident solar radiation and/or it could be because the crop responded to the uniform application of agronomic inputs applied by the farmer. The crop also bolted to a much more obvious extent in the 2013 season and the number of bolters ranged from 0 to 1.5 plants /$m^2$with a CV of 102% (Table 4.3).

Table 4.1: Summary statistics of sugar beet growth, yield and quality in White Patch in 2012.

Variables	Mean	Min	Max	SD	CV%	Skew
Measurements during growth season						
Plant population/ha	91000	66200	116000	13200	14.5	-0.09
%Crop cover-01/June	8.5	2.87	17.5	3.3	38.8	0.7
%Crop cover-02/July	79	63	92	7.5	9.5	-0.46
%Crop cover-13/Aug.	80.2	65	92	6.3	7.9	-0.63
%Intercepted radiation-01/June	7	0	16	3.96	56.4	0.27
%Intercepted radiation-17/July	72.2	48	92	10.7	14.8	-0.23
LAI-01/June	0.11	0	0.25	0.05	47.9	0.15
LAI-17/July	1.9	0.77	3.45	0.6	31.3	0.32
Relative canopy growth rate, %d^{-1}	30.2	13.3	77.8	13.1	43.3	1.3
Log- Relative canopy growth rate	3.3	2.6	4.4	0.4	12.1	0.26
Weed density/m^2	2.6	0	22	4.34	165	3.35
Post-harvest measurements						
Roots yield t/ha	58.4	36.5	89.5	12.4	21.2	0.47
%sugar	17.7	16.3	18.7	0.42	2.4	-0.13
Sugar Yield t/ha	10.3	6.3	16.6	2.2	21.1	0.43
Yield value £/ha	1850	1120	2990	394	21.3	0.41
Amino acid mg/100g beet	6.45	3	12	1.89	29.3	0.87
Log-Amino acid mg/100g beet	1.83	1.01	2.48	0.28	15.6	0.08
Potassium mg/100g beet	110	90	145	9.9	9	0.71

Table 4.2: Summary statistics of sugar beet growth, yield and quality in T32 in 2012.

Variables	Mean	Min	Max	SD	CV%	Skew
Assessment during growth season						
Plant population/ha	95000	70000	115000	12400	13.1	-0.19
%Crop cover-01/June	25	10	36	5.6	22.5	-0.75
%Crop cover-17/July	87	81	95	3.2	3.7	0.29
%Crop cover-17/Aug.	91	86	96	2.5	2.8	0.16
%Intercepted radiation-17/July	88.9	80	95	3.3	3.7	-0.54
%Intercepted radiation-17/Aug.	85.8	71	97	5.55	6.5	-0.1
LAI-17/July	3.1	1.7	4.7	0.67	21.6	0.4
LAI-17/Aug.	2.9	1.5	4	0.51	17.5	0.03
Relative canopy growth rate, $\%d^{-1}$	8.3	4.4	20	3.15	37.8	1.95
Log- Relative canopy growth rate	2.1	1.5	3	0.31	15.2	1.01
Weed density/m^2	0.58	0	3.2	0.62	106	1.98
Post-harvest assessments						
Roots yield t/ha	75.7	56	98	8.35	11	-0.04
%sugar	18.3	17.6	19.1	0.31	1.7	-0.02
Sugar Yield t/ha	13.8	10.4	16.8	1.45	10.5	-0.13
Yield value £/ha	2500	1870	3320	282	11.3	0.05
Amino acid mg/100g beet	6.2	4	10	1.4	21.9	0.54
Potassium mg/100g beet	121	101	144	8.8	7.2	0.28

Table 4.3: Summary statistics of sugar beet growth, yield and quality in WO3 in 2013.

Variables	Mean	Min	Max	SD	CV%	Skew
Assessment during growth season						
Plant population/ha	50800	22000	81000	10600	20.9	-0.05
Number of bolting plants/ha	0.35	0	1.5	0.35	102	0.95
%Crop cover-20/June	11.5	0.09	45	8.2	71.5	0.82
%Crop cover-16/July	20	0.14	66	13.3	66.5	0.49
%Crop cover-17/Aug.	57.3	8.3	91.7	24.2	42.2	-0.56
%Intercepted radiation-16/July	36.7	1.1	72.7	17.5	47.7	-0.07
%Intercepted radiation-17/Aug.	70.2	15	96.9	17.3	24.7	-1.25
%Intercepted radiation-11/September	78.0	32	94.7	11.4	14.7	-1.4
LAI-16/July	0.9	0.03	2.1	0.49	54.6	0.38
LAI-17/Aug.	2.3	0.1	5.2	0.97	41.6	0.02
LAI-11/Sept.	2.4	0.5	3.8	0.65	27.7	-0.74
Relative canopy growth rate, $\%d^{-1}$	4.4	0.03	16	3.14	70.8	1
Log-Relative canopy growth rate	1.9	0.17	4	0.79	40.2	-0.07
Weed density/m^2	1.1	0	7.8	1.44	136	2.45
Post-harvest assessments						
Roots yield t/ha	68	9	120	21.5	31.6	-0.59
%sugar	16.2	15	17.3	0.36	2.2	0.22
Sugar yield t/ha	11.1	1.4	18.9	3.5	31.8	-0.62
Yield value £/ha	1870	230	3130	596	32.0	-0.63
Amino acid mg/100 beet	14.8	10	21	2.4	15.9	0.53
Potassium mg/100 beet	127	99	162	13.7	10.8	0.56

4.1.2 Geostatistical analysis:

4.1.2.1 The variograms:

The results of geostatistical analysis confirmed that there was significant spatial variation in sugar beet growth, yield and quality parameters in all three fields. The variograms for most of variables reached a sill, indicating a bounded variation in all fields and the maximum variance was generally covered by the sampling scheme for each field (Figs. 4.1-4.3). The main exception was the percentage of sugar, which had a low spatial variability and appeared as pure nugget in T32 and WO3 fields (Figs 4.2 and 4.3). The spatial variation of the various pre and post-harvest parameters was accounted for by different models, which were selected by the best fit to the semivariances with lowest Residual Mean Square (RMS). However, the spatial variation in most parameters in all three fields was most often accounted for by the circular and exponential models (Tables 4.4-4.6). The spatial variability in root yield, sugar yield and yield value was best accounted for by the circular model in all three fields and the exponential model was the best fit to the spatial variation in amino acid beet content. The variogram of root content of amino acid in White Patch field and relative canopy growth rate in all fields were computed based on transformed data, since the original data resulted in an erratic variogram, which was difficult to model.

Most of the observed variation in sugar beet growth and yield was spatially correlated, as the degree of spatial dependency was strong to moderate for most variables (Tables 4.4-4.6). In White Patch, the variation in sugar beet growth and yield was strongly spatially correlated with $C_0/(C_0+C_1)$ ratios ranging from 0 to 31%, but the variation in beet quality parameters (sugar, amino acid and potassium) was only moderately spatially correlated ($C_0/(C_0+C_1)$ = 42 to 55%: Table 4.4)

In T32, most variation was moderately spatially correlated $C_0/(C_0+C_1)$ = 37 to 49%: Table 4.5), but crop canopy cover at different growth stages, LAI in July, log-canopy growth rate and beet content of potassium were strongly spatially correlated $C_0/(C_0+C_1)$ = 4 to 25%: Table 4.5). In WO3, the degree of spatial dependency ranged from 0 to 58%, being strong for some growth parameters and moderate for yield and quality (Table 4.6). The strong and moderate spatial dependencies for the studied variables confirmed that most of the variability in crop yield and growth is mainly due to the separation distance. However, the distance over which the variance was spatially correlated (range) differed from one variable to another, which means the average extent of the variation was not similar for all the variables even within one field. In White Patch, the range parameter for the growth measurements ranged from 61 to 159 m, but it was more similar for the post-harvest measurements and ranged from 90 to 109 m (Table 4.4). While in T32 and WO3, the range parameters were longer for most of the variables and ranged from 176 to 380 m and from 112 to 208 m, respectively (Tables 4.5 and 4.6). The spatial variation in sugar beet yield in White Patch field was patchier than in the other fields, as the maximum variance was reached over shorter distances compared to T32 and WO3.

Table 4.4. Geostatistical analysis of sugar beet growth, yield and quality in White Patch in 2012.

Variables	Model	Range (m)	Sill (C_1)	Nugget (C_0)	$\%C_0/(C_0+C_1)$
Assessment during growth season					
Plant population/ha	Circular	117	$9.77*10^7$	$3.87*10^7$	28
%Crop cover-01/June	Circular	70	10.2	0	0
%Crop cover-02/July	Circular	83	52.8	3	5
%Crop cover-13/Aug.	Circular	130	26.5	12	31
%Intercepted radiation-01/June	Pentaspherical	159	11.9	4.5	27
%Intercepted radiation-17/July	Exponential	152	123	15	11
LAI-01/June	Circular	114	0.002	0.0008	27
LAI-17/July	Spherical	86	0.28	0.09	24
Log- relative canopy growth rate	Circular	61	14	0	0
Post-harvest assessments					
Roots yield t/ha	Circular	94	149	0	0
%sugar	Circular	109	0.116	0.08	42
Sugar Yield t/ha	Circular	93	4.7	0	0
Yield value £/ha	Circular	93	144320	8152	5.3
Log-Amino acid mg/100g beet	Exponential	100	0.03	0.037	55
Potassium mg/100g beet	Circular	90	49	49.4	50

Table 4.5: Geostatistical analysis of sugar beet growth, yield and quality in T32 in 2012.

Variables	Model	Range (m)	Sill (C_1)	Nugget (C_0)	$\%C_0/(C_0+C_1)$
Assessment during growth season					
Plant population/ha	Exponential	315	$9.22*10^7$	$9.03*10^7$	49
%Crop cover-01/June	Pentaspherical	236	33.9	2.5	7
%Crop cover-17/July	Circular	229	13.4	0.55	4
%Crop cover-17/Aug.	Circular	205	6.5	1.5	18
%Intercepted radiation-17/July	Circular	222	6.7	5.6	46
%Intercepted radiation-17/Aug.	Circular	176	17.9	14.8	45
LAI-17/July	Exponential	255	0.40	0.12	23
LAI-17/Aug.	Circular	217	0.19	0.11	37
Log-Relative canopy growth rate	Pentaspherical	265	0.1	0.015	13
Post-harvest assessments					
Roots yield t/ha	Circular	224	45.7	33	42
%sugar	Pure Nugget	-	-	0.09	-
Sugar Yield t/ha	Circular	240	1.5	0.9	38
Yield value £/ha	Circular	241	48933	41956	46
Amino acid mg/100g beet	Exponential	380	1.2	0.99	45
Potassium mg/100g beet	Exponential	255	74.8	24.4	25

Table 4.6: Geostatistical analysis of sugar beet growth, yield and quality in WO3 in 2013.

Variables	Model	Range (m)	Sill (C_1)	Nugget (C_0)	$\%C_0/(C_0+C_1)$
Assessment during growth season					
Plant population/ha	Exponential	126	$6.79*10^7$	$2.12*10^7$	24
Number of bolting plants/ha	Spherical	120	0.05	0.06	58
%Crop cover-20/June	Circular	132	36	16	31
%Crop cover-16/July	Circular	126	122	13.5	10
%Crop cover-17/August	Circular	112	518	26.1	5
%Intercepted radiation-16/July	Circular	132	175	95.9	35
%Intercepted radiation-17/Aug.	Exponential	192	284	22.8	7.5
%Intercepted radiation-11/Sept.	Circular	147	73.2	46.3	39
LAI-16/July	Circular	122	0.10	0.09	48
LAI-17/August	Exponential	131	0.83	0	0
LAI-11/September	Exponential	163	0.28	0.09	25
Log-relative canopy growth rate	Circular	39	0.36	0.18	33
Post-harvest assessments					
Roots yield t/ha	Circular	115	253	141	36
%sugar	Pure Nugget	-	-	0.11	-
Sugar yield t/ha	Circular	116	6.9	3.7	35
Yield value £/ha	Circular	117	190964	113393	37
Amino acid mg/100g beet	Exponential	208	4.4	1.55	26
Potassium mg/100g beet	Pentaspherical	122	93	77	45

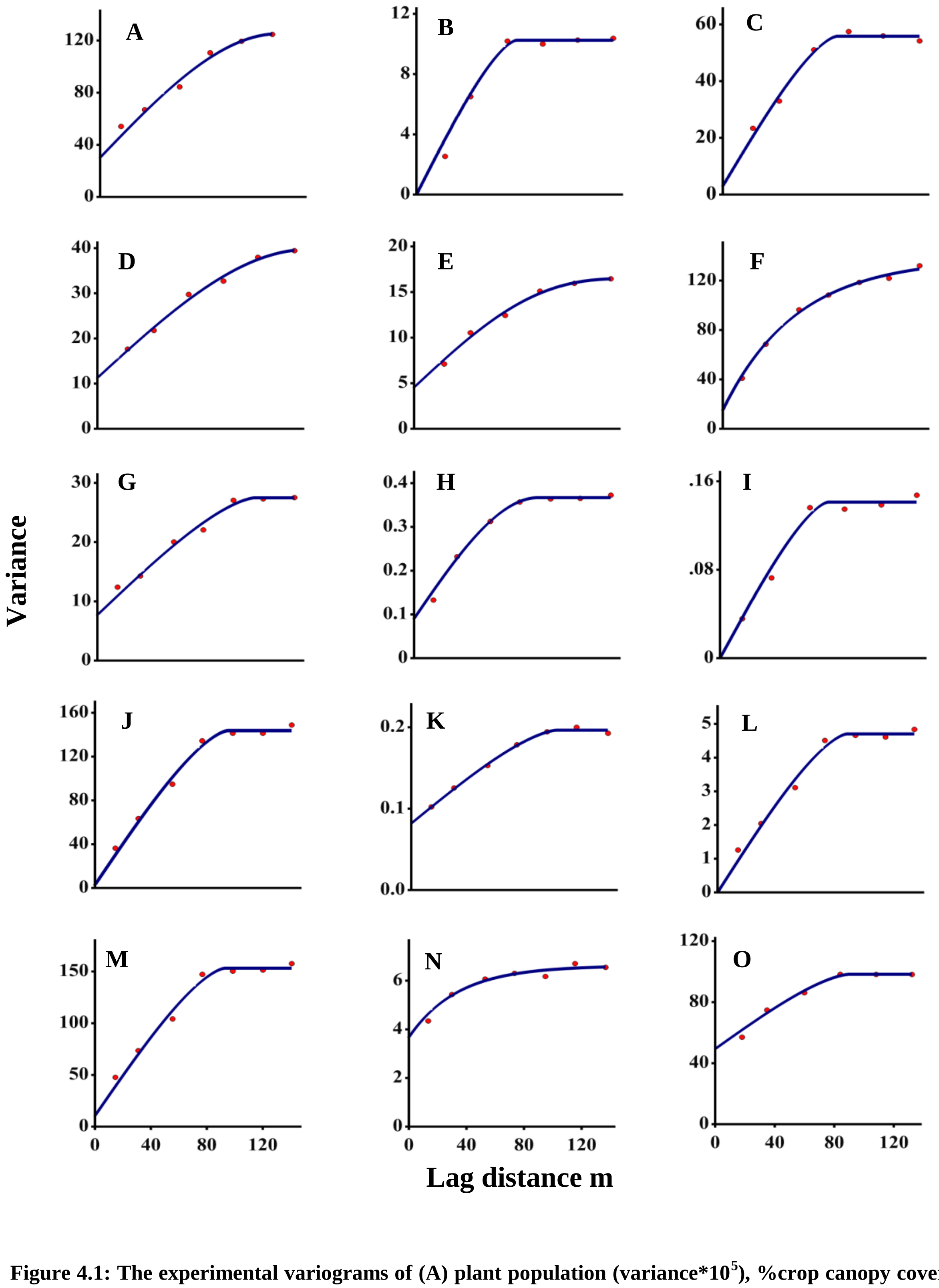


Figure 4.1: The experimental variograms of (A) plant population (variance*10^5), %crop canopy cover (B) in June, (C) in July and (D) in August, %intercepted radiation (E) in June and (F) in July, LAI (G) in June (variance/1000) and (H) in July, (I) Log-relative canopy growth rate, %d^{-1}, (J) root yield (t/h), (K) %sugar , (L) sugar yield (t/h), (M) yield value £/ha (variance *100), (N) log amino acid (variance/100) and (O) potassium (mg/100g beet) in White Patch field in 2012. Parameters of fitted model are in Table 4.4.

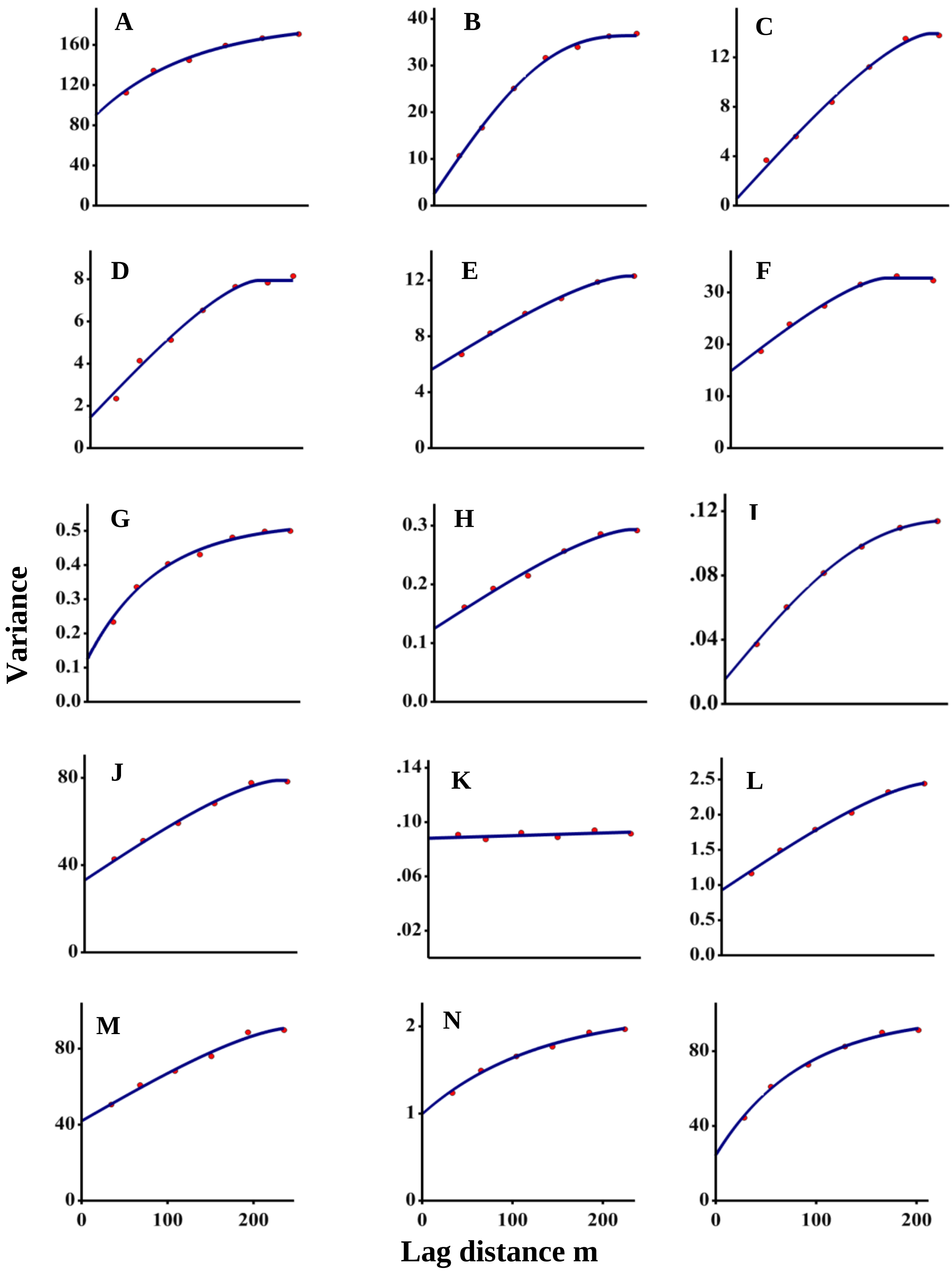


Figure 4.2: The experimental variograms of (A) plant population (variance*10^5), %crop canopy cover (B) in June, (C) in July and (D) in August, %intercepted radiation in (E)in July and (F) in August, LAI (G) in July and (H) in August, (I) Log-relative crop canopy growth rate, %d^{-1}, (J) root yield (t/h), (K) %sugar, (L) sugar yield (t/h), (M) yield value (£/h) (variance *1000), (N) Amino acid and (O) potassium (mg/100g beet) in T32 field in 2012. Parameters of fitted model are in Table 4.5.

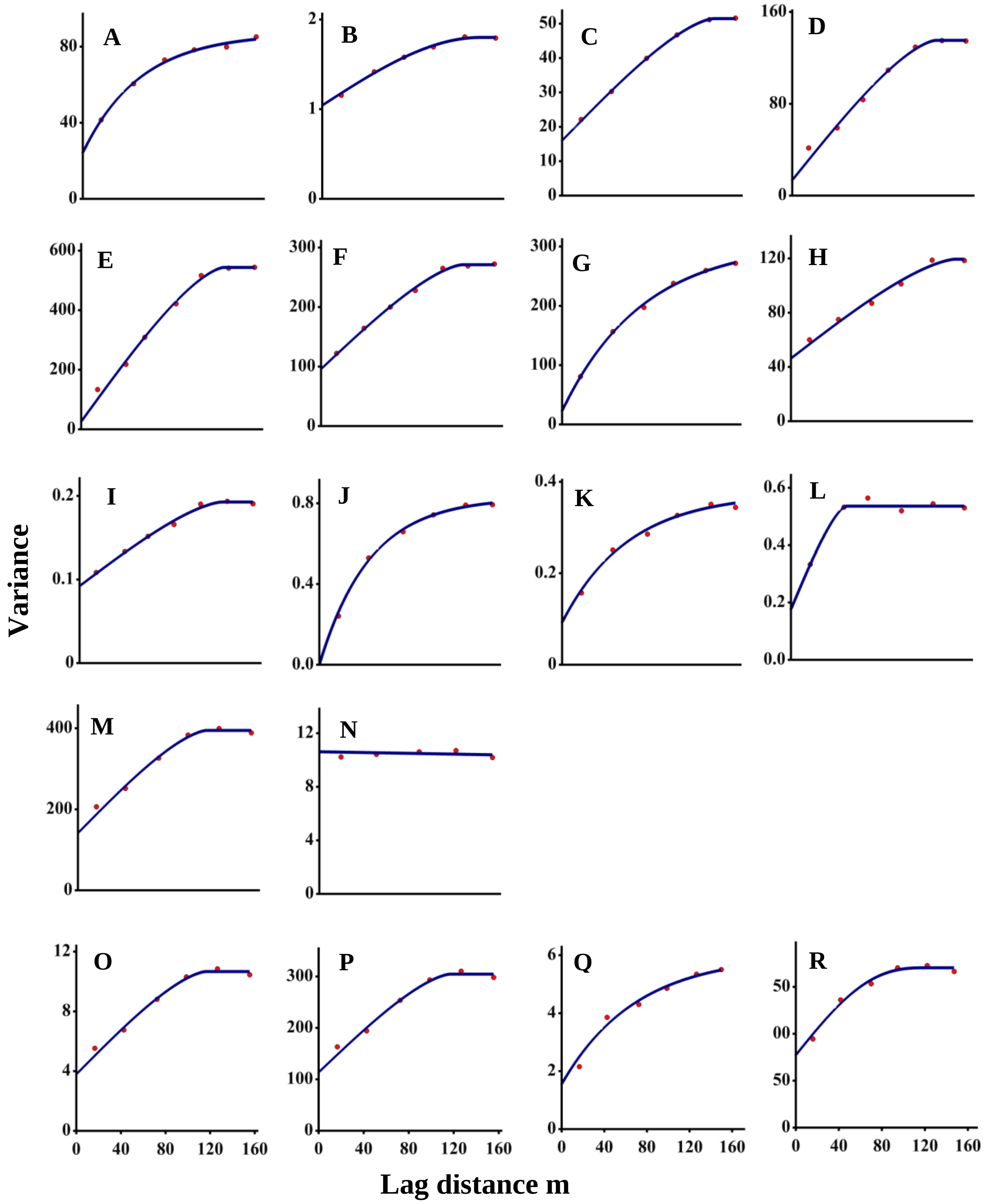


Figure 4.3: The experimental variograms of (A) plant population (10000/ha), (B) number of bolting plants/m^2, %crop canopy cover (C) in June, (D) in July and (E) in August, %intercepted solar radiation (F) in July, (G) in August and (H) in September, LAI (I) in July, (J) in August and (K) in September, (L) Log-relative canopy growth rate, %d^{-1}, (M) root yield (t/h), (N) %sugar (variance/100), (O) sugar yield (t/h), (P) yield value (£/ha) (variance*1000), (Q and R) amino acid and potassium (mg/100g beet) at WO3 field in 2013. Parameters of fitted model are in Table 4.6.

4.1.2.2 Interpolation maps:

The Kriging maps clearly separate low and high yielding zones in each field. In White Patch, the yield value varied from £1120 to 2990 ha^{-1} throughout the field (Table 4.1). The most productive areas (> £1850 ha^{-1}) were located along the western boundary of the field and extended toward the north east, while the less productive areas (< £1850 ha^{-1}) were located in the south east part and extended to the middle with a small patch appearing on the north side (Fig 4.4 M). In T32, the yield value was varied from £1870 ha^{-1} in some part of the field to £3310 ha^{-1} in some other parts (Table 2). The most productive areas (> £2500 ha^{-1}) being located in the south east part of the field and extending toward the middle, while the less productive (< £2500 ha^{-1}) areas were in the west site of the field and in the north east corner (Fig 4.5 L). The variation in yield value was much higher in WO3 being as low as £232 in some parts and as high as £3130 ha^{-1} in others (Table 3). The most productive areas (> £1870 ha^{-1}) were located in the south west of the field and extended toward the north, while the least productive areas (< £1870 ha^{-1}) were mostly found in the south east corner (Fig 4.6 O).

In all three fields, higher yielding areas at final harvest were associated with higher crop canopy cover, interception of solar radiation and LAI as measured in June, July and August, while low yielding areas were associated with low values of these parameters (Figs 4.4-4.6). Although, the observed variability in crop growth parameters was much higher at early growth stages than later on, the patterns of spatial variability in these parameters were almost constant over the growing season and similar to those observed for final yield in all three fields. Maps of sugar beet yields were closer visually to the maps of crop canopy cover as assessed early, on the 1st of June 2012 in White Patch and T32 and in the 20th of June 2013 in WO3 in comparison to the assessment made in July and August

(Figs. 4.4-4.6). These visualizations of the relationship between the spatial variability in root yield and growth parameters were also evident from the strong correlation coefficients (Tables 4.7-4.9), which were significantly different from zero ($P<0.05$: Appendices 7.2-7.6). The correlation coefficients between root yield and crop canopy cover in White Patch, T32 and WO3 were 0.81, 0.66 and 0.80, respectively in June, but only 0.60, 0.65 and 0.74, respectively in July and even lower in August with values of 0.58, 0.54 and 0.72, respectively (Tables 4.7-4.9).

The maps of plant population density also had some spatial association with the maps of root yield. The degree of spatial association was much higher in WO3 with a correlation coefficient of 0.72 (Table 4.9), which means most of the variation in sugar beet growth and yield was due to variability in plant population, but it also accounted for some variability in White Patch and T32 with a significant correlation coefficient of 0.51 in both fields (Tables 4.8 and 4.9).

The maps of some post-harvest quality measurements (amino acid, potassium in all fields and sugar content in White Patch) showed some distinct patterns of spatial variation (Figs. 4.4-4.6), but their relation to sugar beet growth and yield differed from field to field. They were almost not related to the growth and yield in White Patch (Fig 4.4), but in T32 the map of amino acid content showed some association with the map of yield (Fig 4.5) with significant correlation coefficient of 0.36 (Table 4.8), while the root yield was negatively correlated to potassium content in WO3 with correlation coefficient of -0.50 (Table 4.9).

Not surprisingly sugar beet growth and yield were negatively related to the spatial distribution of weeds in the three fields, as weed densities were lower in the high yielding areas of the field and higher in low yielding parts (Figs. 4.4-4.6), with significant correlation coefficients of -0.40, -0.50 and -0.21 in White Patch, T32 and WO3, respectively (Tables 4.7-4-9).

In addition, the maps of relative canopy growth rate from 01/06 to 02/07/2012 in White Patch, 01/06 to 17/7/ 2012 in T32 and 20/06 to 17/07/2013 in WO3 showed some distinct patterns of spatial variability and had a negative association with spatial variability in root yield in all three fields (Figs. 4.4-4.6) with significant correlation coefficients of -0.60, -0.60 and -0.28 in White Patch, T32 and WO3, respectively. In WO3 a map showing the distribution of bolting plants were also produced. A higher number of bolting plants was apparent in the areas at which the plant population and root yield were higher (Fig 4.6 B).

In White Patch, the map of sugar beet yield showed some spatial association with the maps of soil clay content and organic matter with significant correlation coefficients of 0.36 and 0.51, respectively (Table 4.7) and to some extent soil magnesium, but most of soil attributes had a weak association with some quality parameters (Figs 4.4 and 3.2, chapter three). The variability in beet content of sugar and amino acid were negatively related to pH, which was in general high across the White Patch, and the beet content of sugar and potassium were negatively correlated to soil available nitrate (Table 4.7). In T32, the maps of sugar beet yields were related to the maps of soil content of silt, organic matter, available nitrate and soil pH (Figs 4.5 and 3.5, chapter three) with significant correlation coefficients of 0.23, 0.35, 0.36 and 0.25, respectively (Table 4.8). The maps of beet content of amino acid and potassium had some association with the maps of soil clay content, but they negatively related or not related to other soil attributes (Table 4.8). While in WO3, the spatial variability in root yield was associated with spatial distribution of soil content of sand, organic matter and available magnesium (Figs 4.6 and 3.8, chapter three) with correlation coefficients of 0.40, 0.32 and 0.32 respectively (Table 4.9). The areas of high clay content in WO3 associated with lower yield of sugar beet, since it had a lower plant population, but it was associated with higher potassium content of beet (Fig 4.6).

In all three fields the high yielding areas were associated with higher soil moisture content and low yielding areas with lower soil moisture content at different growth stages (Figs 4.4, 4.5, 4.6, 3.2, 3.5 and 3.8). The correlation coefficients between root yield and soil moisture measured at different growth stages were always statistically significant (P<0.05) and ranged from 0.45 to 0.52 in White Patch (Table 4.7), from 0.33 to 0.52 in T32 (Table 4.8) and from 0.24 to 0.55 in WO3 (Table 4.9).

On the other hand, the spatial variation in sugar yield was negatively related to the spatial distribution of canopy temperature in all three fields. Higher yielding areas were associated with lower canopy temperature at different growth stages and vice versa in low yielding parts (Figs 4.4, 4.5, 4.6, 3.3, 3.6 and 3.9). The negative relationship was stronger between the root yield and average maximum canopy temperature for the season in White Patch and T32 with correlation coefficients of -0.56 and -0.25, respectively (Tables 4.7 and 4.8), while in WO3 it was negatively stronger with the average temperature during August with coefficient of -0.48 (Table 4.9).

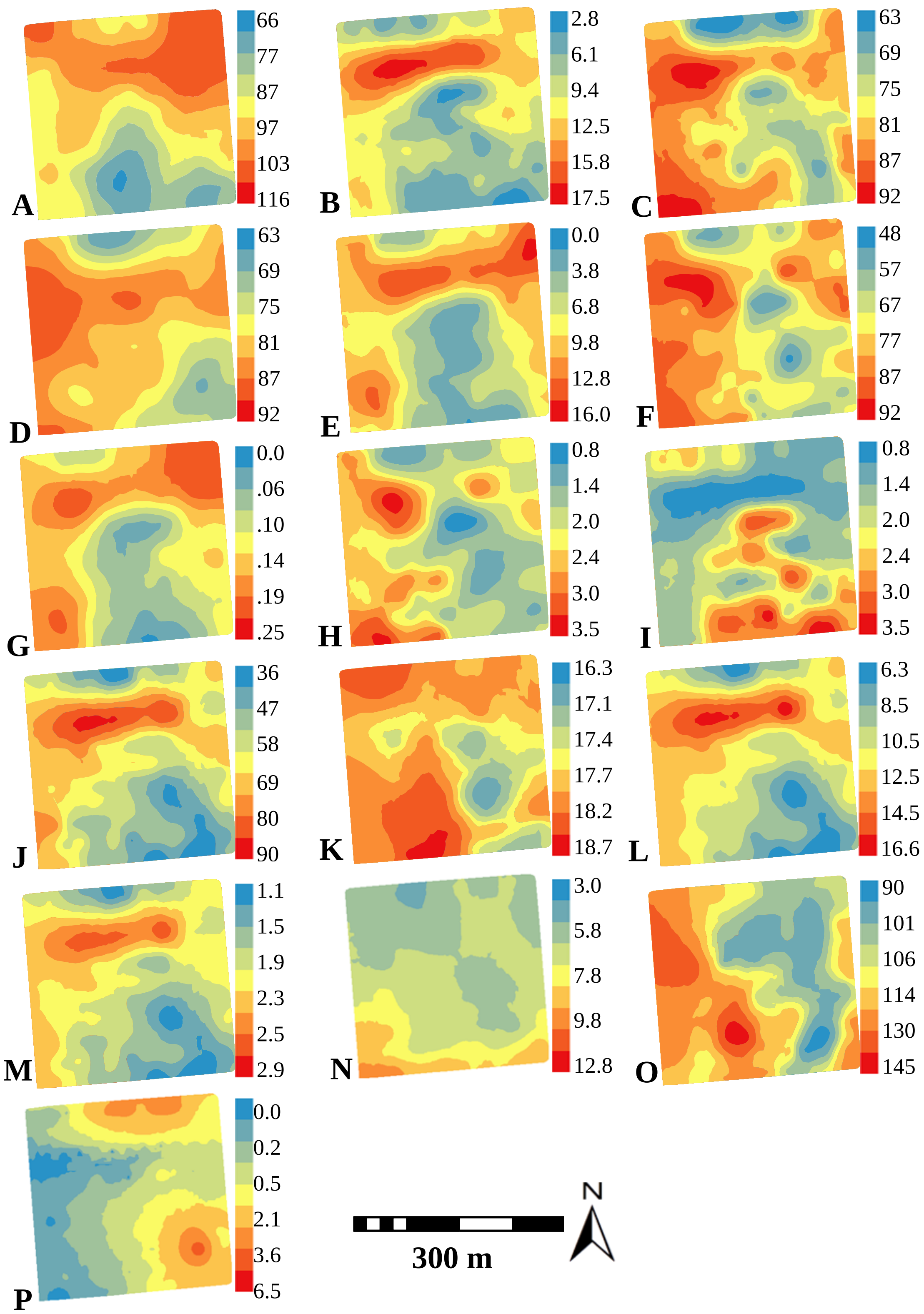


Figure 4.4: Interpolation maps of (A) plant population (1000 plant/ha), %crop canopy cover (B) in June, (C) in July and (D) in August, %intercepted radiation (E)in June and (F) in July, LAI (G) in June and (H) in July, (I) relative canopy growth rate, %d^{-1}, (J) root yield (t/h), (K) %sugar, (L) sugar yield (t/h), (M) yield value (1000 £/h), (N) amino acid and (O) potassium (mg/100g beet), (P) weeds /m^2 in White Patch field in 2012. The relevant variograms are in Fig. 4.1.

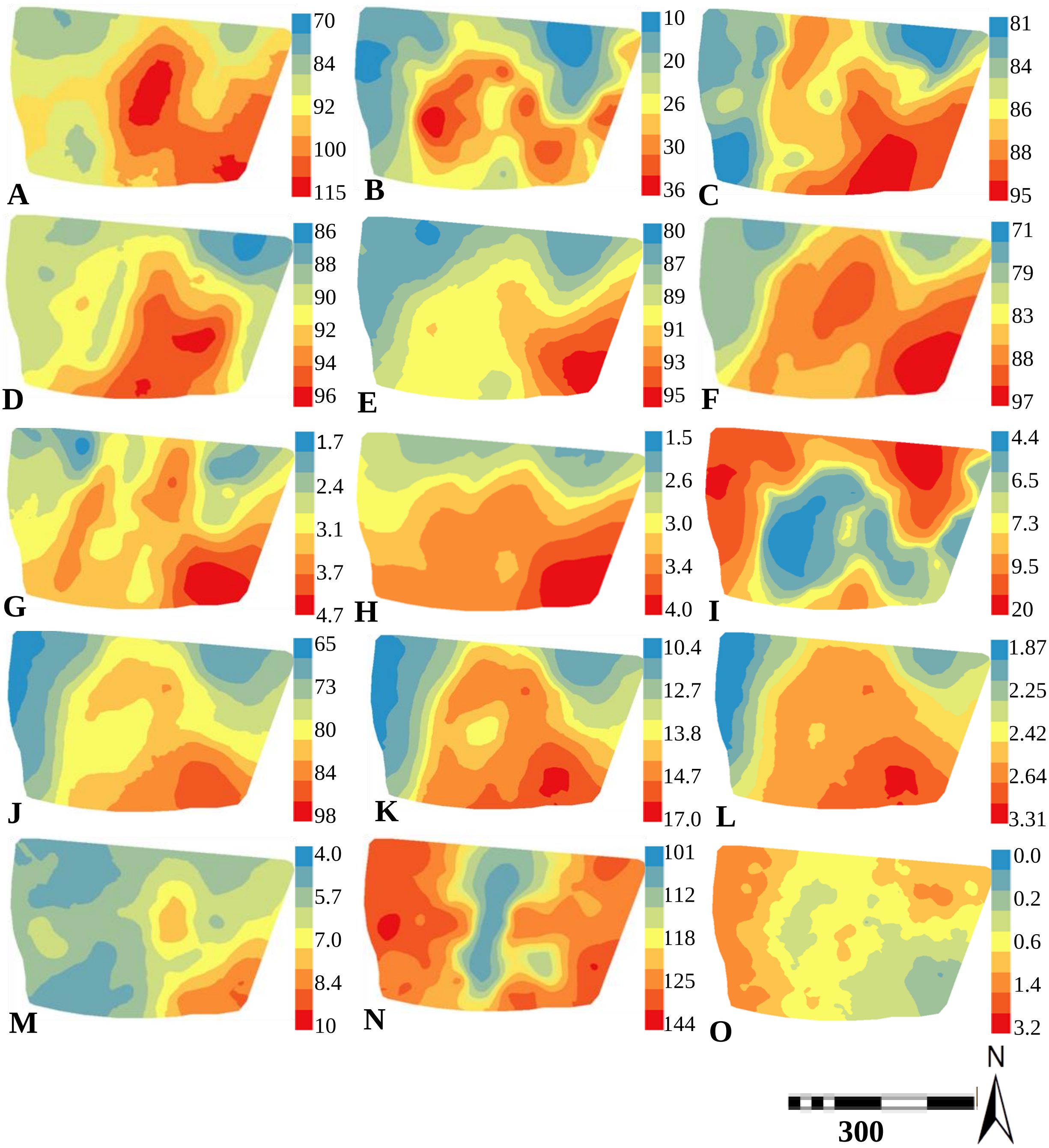


Figure 4.5: Interpolation maps of (A) plant population (1000 plant/ha), %crop canopy cover (B)in June, (C) in July and (D) in August, %intercepted radiation (E) in July and (F) in August, LAI (G) in July and (H) in August, (I) relative canopy growth rate, %d^{-1}, (J) root yield (t/h), (K) sugar yield (t/h), (L) yield value (1000 £/h), (M) amino acid and (N) potassium (mg/100g beet), and (O) weeds m^2 in T32 field in 2012. The relevant variograms are in Fig. 4.2.

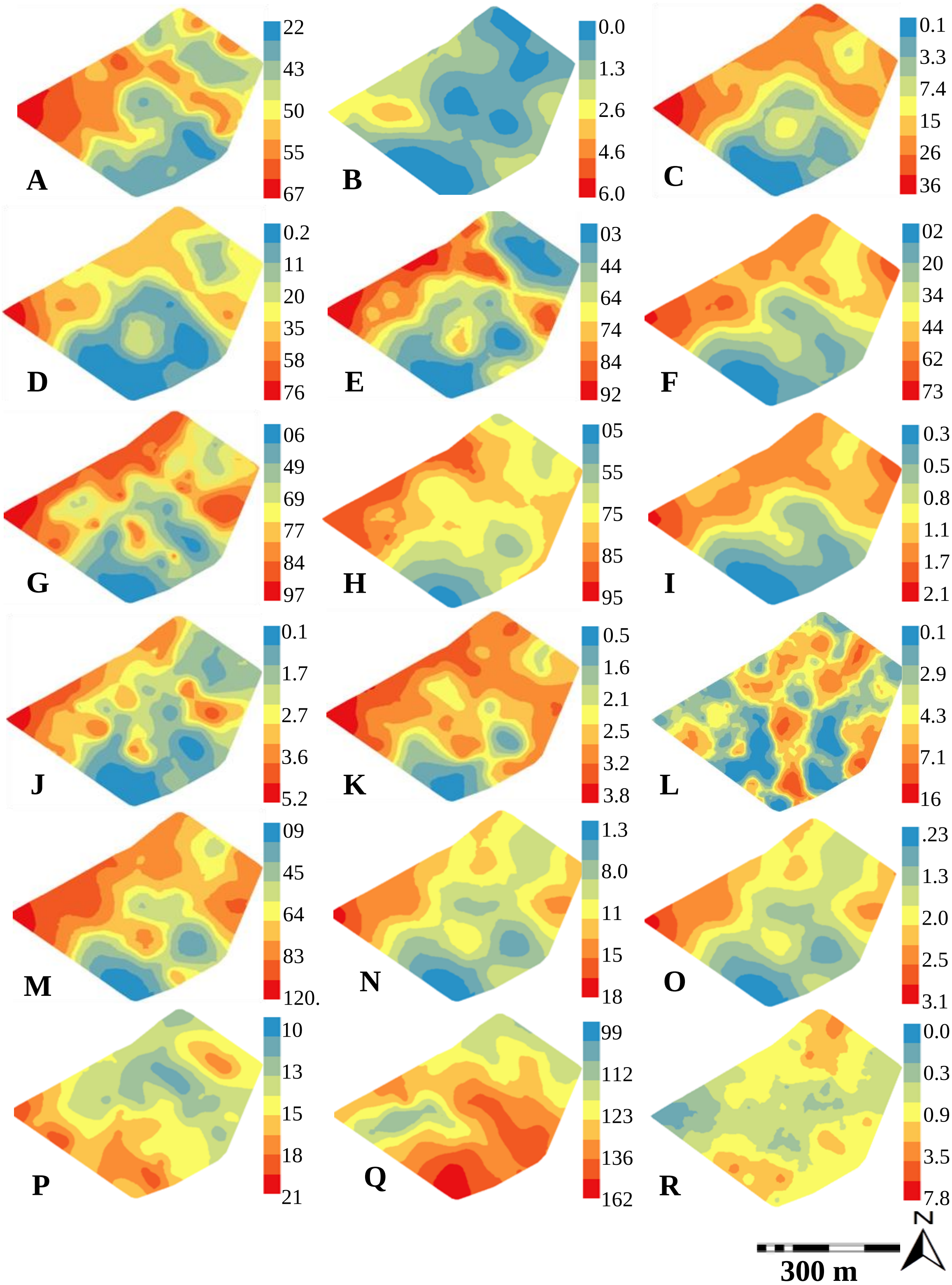


Figure 4.6: Interpolation maps of (A) plant population, (B) number of bolting plants /m2, %crop canopy cover (C) in June, (D) in July and (E) in August, %intercepted solar radiation (F) in July, (G) in August and (H) in September, LAI (I) in July, (J) in August and (K) in September, (L) relative canopy growth rate, %d^{-1}, (M) root yield (t/h), (N) sugar yield (t/h), (O) yield value (1000 £/h), (P) amino acid and (Q) potassium (mg/100g beet), and (R) weeds/m^2 in WO3 field in 2013. The relevant variograms are in Fig. 4.3.

Table 4.7: Correlation coefficients between sugar beet yield and quality, and studied physical and biological variables in White Patch in 2012 (Bold numbers are significantly different from 0).

		Plant density	Root yield	Root content of		
				Sugar	Amino acid	Potassium
Soil properties	%Clay	-0.07	**0.36**	-0.01	-0.06	0.19
	%Sand	0.10	**-0.27**	0.01	0.05	-0.21
	%Silt	-0.11	-0.04	0.00	-0.02	0.15
	%Organic mater	0.17	**0.51**	0.12	0.00	0.08
	pH	-0.02	-0.01	**-0.21**	-0.19	-0.09
	EC, µS	0.02	0.06	-0.09	-0.14	-0.08
	Nitrate, mg/l	0.08	-0.12	**-0.27**	-0.06	-0.21
	Phosphate, mg/l	0.15	-0.03	0.14	0.12	0.09
	Potassium, mg/l	-0.19	-0.13	0.15	0.05	0.13
	Magnesium, mg/l	-0.06	0.04	0.03	-0.10	0.10
Soil moisture, %	17/May	**0.30**	**0.51**	0.02	**-0.23**	0.19
	02/June	0.04	**0.47**	0.15	-0.11	0.16
	06/July	0.10	**0.45**	0.07	-0.09	**0.25**
	13/August	0.13	**0.53**	**0.25**	-0.06	**0.36**
Average canopy temperature	June	**-0.28**	**-0.24**	-0.16	-0.09	-0.17
	July	-0.21	**-0.25**	-0.12	-0.10	-0.14
	August	**-0.23**	**-0.33**	-0.10	-0.20	-0.15
	September	**-0.25**	**-0.41**	-0.02	-0.19	-0.12
	Mean season	**-0.25**	**-0.32**	-0.11	-0.15	-0.16
	Min season	0.02	0.09	**0.28**	-0.03	0.13
	Max season	**-0.40**	**-0.56**	**-0.23**	-0.14	-0.01
Weeds density, m^2		-0.06	**-0.40**	-0.06	**-0.28**	**-0.31**
Crop measurements						
	Plant density/ha	-	**0.51**	-0.06	**-0.25**	**-0.26**
	%Crop cover-01/June	**0.53**	**0.81**	-0.01	-0.16	-0.07
	%Crop cover-02/July	0.16	**0.60**	0.18	**0.34**	**0.23**
	%Crop cover-13/August	**0.24**	**0.58**	-0.01	0.03	0.21
	%Intercepted radiation-01/July	**0.52**	**0.60**	0.09	-0.04	0.00
	%Intercepted radiation-17/Aug.	**0.23**	**0.67**	**0.34**	**0.26**	0.20
	LAI-01/July	**0.52**	**0.46**	0.09	-0.06	-0.04
	LAI-17/August	0.15	**0.55**	**0.33**	**0.36**	0.19
	%Relative canopy growth rate	**-0.51**	**-0.60**	-0.08	**0.27**	0.06
	Roots yield t/ha	**0.51**	-	0.03	-0.02	0.03
	%sugar	-0.06	-	-	0.06	**0.31**
	Amino acid mg/100g beet	**-0.25**	-	-	-	0.12
	Potassium mg/100g beet	**-0.26**	-	-	-	-

Table 4.8: Correlation coefficients between sugar beet yield and quality, and studied physical and biological variables in T32 field in 2012 (Bold numbers are significantly different from 0).

		Plant density	Root yield	Root content of		
				Sugar	Amino acid	Potassium
Soil properties	%Clay	0.08	0.09	0.10	0.19	**0.21**
	%Sand	-0.18	**-0.27**	-0.15	**-0.22**	-0.02
	%Silt	0.13	**0.23**	0.08	0.08	-0.17
	%Organic mater	**0.32**	**0.35**	0.01	0.09	**-0.54**
	pH	0.15	**0.25**	0.05	**0.24**	-0.15
	EC, µS	0.13	0.15	0.06	0.16	-0.04
	Nitrate, mg/l	**0.36**	**0.36**	-0.07	0.08	-0.19
	Phosphate, mg/l	-0.18	-0.17	0.08	**-0.29**	0.03
	Potassium, mg/l	-0.05	-0.14	0.14	0.19	0.09
	Magnesium, mg/l	0.15	-0.19	-0.16	-0.03	0.06
Soil moisture, %	02/June	**0.24**	**0.33**	0.06	**0.27**	-0.02
	06/July	**0.28**	**0.52**	-0.01	0.18	**-0.24**
	13/August	**0.23**	**0.47**	0.08	**0.34**	-0.12
Average canopy temperature	June	-0.13	-0.05	0.16	-0.08	-0.09
	July	-0.07	-0.10	0.11	-0.25	-0.12
	August	**-0.22**	**-0.21**	0.06	-0.27	-0.02
	September	-0.06	-0.06	-0.20	-0.07	0.15
	Mean season	-0.17	-0.16	0.10	-0.24	-0.05
	Min season	**-0.39**	**-0.22**	0.16	-0.37	0.13
	Max season	-0.04	**-0.25**	-0.03	-0.18	0.07
Weeds density, m^2		**-0.24**	**-0.50**	0.11	**-0.39**	**0.03**
Crop measurements						
	Plant density/ha	-	**0.51**	-0.06	**0.38**	**-0.31**
	%Crop cover-01/June	**0.43**	**0.66**	-0.11	**0.23**	**-0.21**
	%Crop cover-17/July	**0.45**	**0.65**	-0.03	**0.46**	-0.13
	%Crop cover-17/Aug.	**0.44**	**0.54**	0.13	0.17	**-0.31**
	%Intercepted radiation-17/July	**0.49**	**0.63**	-0.09	**0.45**	-0.11
	%Intercepted radiation-17/Aug.	**0.43**	**0.50**	0.02	**0.39**	**-0.26**
	LAI-17/July	**0.38**	**0.60**	-0.10	**0.53**	-0.07
	LAI-17/August	**0.44**	**0.54**	0.05	**0.38**	-0.18
	%Relative canopy growth rate	**-0.39**	**-0.60**	0.15	-0.17	0.16
	Roots yield t/ha	**0.51**	-	-0.11	**0.36**	-0.18
	%sugar	**-0.06**	-	-	**-0.32**	-0.16
	Amino acid mg/100g beet	**0.38**	-	-	-	**0.26**
	Potassium mg/100g beet	**-0.31**	-	-	-	-

Table 4.9: Correlation coefficients between sugar beet yield and quality, and studied physical and biological variables in WO3 in 2013 (Bold numbers are significantly different from 0).

		Plant density	Root yield	Root content of		
				Sugar	Amino acid	Potassium
Soil properties	%Clay	**-0.34**	**-0.34**	**-0.26**	0.11	**0.45**
	%Sand	**0.38**	**0.40**	**0.32**	-0.18	**-0.44**
	%Silt	**-0.19**	**-0.24**	**-0.20**	0.16	0.11
	%Organic mater	0.17	**0.32**	0.14	-0.06	-0.06
	pH	-0.10	-0.04	-0.07	**-0.20**	-0.16
	EC, µS	0.07	-0.03	**-0.22**	**0.23**	0.15
	Phosphate, mg/l	0.10	-0.01	-0.17	-0.09	-0.09
	Potassium, mg/l	0.10	0.05	0.13	-0.09	-0.02
	Magnesium, mg/l	**0.29**	**0.32**	0.15	-0.03	-0.09
Soil moisture, %	06/June	**0.40**	**0.55**	**0.30**	**-0.37**	**-0.44**
	06/July	**0.23**	**0.37**	0.17	-0.07	**-0.30**
	11/September	**0.20**	**0.24**	-0.17	0.13	-0.08
Average canopy temperature	June	0.17	**0.29**	**0.24**	-0.16	**-0.19**
	July	**-0.38**	**-0.35**	-0.14	0.08	**0.25**
	August	**-0.40**	**-0.48**	**-0.26**	0.14	**0.36**
	September	**-0.36**	**-0.39**	-0.17	0.10	**0.31**
	October	**-0.22**	-0.17	-0.02	0.02	0.15
	November	-0.07	0.06	0.14	-0.08	-0.03
	Mean season	**-0.30**	**-0.28**	-0.09	0.05	**0.22**
	Min season	**-0.29**	**-0.25**	-0.16	0.10	**0.28**
	Max season	**-0.30**	**-0.33**	**-0.20**	0.11	**0.34**
Weeds density, m^2		-0.11	**-0.21**	-0.12	-0.01	0.16
Crop measurements						
	Plant density/ha	-	**0.71**	**-0.23**	-0.18	**0.45**
	Bolting plants	**0.36**	**0.40**	0.11	-0.10	**-0.24**
	%Crop cover-20/June	**0.71**	**0.80**	**0.30**	**-0.22**	**-0.47**
	%Crop cover-16/July	**0.70**	**0.74**	**0.33**	**-0.24**	**-0.51**
	%Crop cover-17/Aug.	**0.62**	**0.72**	**0.19**	**-0.36**	**-0.38**
	%Intercepted radiation-16/July	**0.60**	**0.67**	**0.45**	**-0.25**	**-0.56**
	%Intercepted radiation-17/Aug.	**0.61**	**0.69**	**0.38**	**-0.31**	**-0.57**
	%Intercepted radiation-11/Aug.	**0.54**	**0.71**	**0.27**	**-0.20**	**-0.43**
	LAI-16/July	**0.58**	**0.64**	**0.41**	**-0.27**	**-0.55**
	LAI-17/August	**0.66**	**0.70**	**0.29**	**-0.29**	**-0.40**
	LAI-11/September	**0.59**	**0.79**	**0.30**	**-0.21**	**-0.41**
	%Relative canopy growth rate	-0.16	**-0.28**	-0.02	0.15	0.02
	Roots yield t/ha	**0.72**	-	**0.33**	-0.18	**-0.50**
	%sugar	**0.23**	-	-	**-0.35**	**-0.30**
	Amino acid mg/100g beet	-0.18	-	-	-	0.14
	Potassium mg/100g beet	**-0.45**	-	-	-	-

4.2 How does within-field variation in the yield of the preceding crop relate to that of the sugar beet crop?

4.2.1 Yield maps of a single year:

The wheat yield in 2011 in T32 field was more variable with a CV of 25% than sugar yield in 2012, which had a CV value of 11%. In WO3 field the CV values were high being 35 and 32% respectively for oilseed rape in 2011 and sugar yield in 2013, while it was lower (13%) for wheat yield in 2012 (Table 4.10). The low CV values in 2012 season in both fields could be due to it being a wet year, which in turn would decrease the spatial variability in water stress related to site-specific water holding capacity and soil hydraulic conductivity. However, some of the spatial variability observed in the yield of the previous crops was associated with the spatial variability of the following sugar beet crop with significant correlation coefficients (P<0.001) in both fields (Figs 4.7 and 4.8). In T32 field, the correlation coefficient for sugar yield in 2012 and wheat yield in 2011 was 0.57 (Table 4.10), while in WO3 the correlations were 0.50 with oilseed rape in 2011 and 0.48 with wheat yield in 2012 (Table 4.10). The sugar beet yield maps for these two fields therefore reflect to some extent those of the previous crops. Nevertheless, the spatial variability in the yield of previous crops visually appears to be patchier than sugar yield (Figs 4.7 and 4.8), which could be because the yield map of the previous crops were based on a very large number of samples, which revealed spatial variation over shorter distances, whereas the map of sugar yield was based on many fewer samples located further apart, especially in T32 field (Table 4.10). Although some of the high yielding areas were not always identical, most of the low yielding areas were coincident. For example, in T32 field the western part of the field, which is at the lowest altitude and has a relatively high percentage of sand, had below average yields (for the field), while most areas in the middle of the field had an above average yield for both wheat and sugar beet (Fig 4.7, A and B). In WO3 field, the south east corner of the field was the low yielding for all crops (oilseed rape, winter wheat and sugar beet), whereas the high yielding areas varied temporally, except for some small patches in the north of the field, which were high yielding in all three years (Fig 4.8, A, B and C). The low yielding areas in WO3 were at the highest altitude and also more clayey, perhaps indicating a clay cap (Figs 4.8 and 3.8 K).

4.2.2 The map of average relative yield and temporal stability:

Since the crops were different each year, yields were normalized as a percentage of the mean for each year at each point. The average standardized yield was taken at each point for different years to produce the map of average relative yield which shows the general patterns of spatio-temporal variation (Figs 4.7 C and 4.8 D). In T32 field the yield of only one preceding crop was available (winter wheat), therefore it was not possible to calculate the temporal variance for this field, but it was possible for WO3, as yield maps for three crops were available. In both fields, the CV values for the average normalized yield were between the highest and lowest CV values for the single crops (Table 4.10). This means that the variability in one year cancelled out some of the variability in other years, because some high yielding areas in one year may have been low yielding in another year. In T32 field, the average relative yield varied from 68 to 131% (Table 4.10). The relative yield map at T32 field had similar patterns to the maps of a single year, especially for the low yielding areas for example in the west part, while the south east corner of the field was consistently high yielding (Fig. 4.7). In WO3 field, the average standardized yield ranged from 46 to 133% (Table 4.10), and again the relative yield map was similar to the yield maps of a single year, especially for oilseed rape and sugar beet (Fig 4.8) with south east of the field consistently low yielding (Fig. 4.8 D). The map of temporal variance in WO3 identified the areas, which had inconsistent patterns over three years. The temporal variance was relatively high along the south side of the field (Fig 4.8 E). In general, the temporal variance tends to be greater in the areas where the yield was much lower or higher than the mean value of the yield. However, the patterns of the spatial variability were almost temporally consistent in the area from middle down towards the north side where the yield was close to the mean value and this involved much of the field. By combining the maps of average relative yield and temporal variance, the map of management zones was manually produced which divided WO3 field to different zones (Fig. 4.8 F): stable and low yielding in the south east corner, unstable and high yielding in the south west corner, stable and medium yielding in the middle with a small patch in the north, a small patch of unstable and medium yielding in the west, and stable and high yielding, which involved most areas in the north and some areas in the west (Fig. 4.8 F).

Table 4.10: The summary statistics and correlation coefficients for sugar yield, previous crops (winter wheat and oilseed rape) and average standardized yield. All the correlation coefficients are statistically significant (*p*< 0.001).

		Summary statistics					Correlation coefficient		
Fields	Crops	No. of points	Mean	Min	Max	CV	Sugar yield	Wheat yield	Oilseed rape
T32	Winter wheat, 2011	1290	8.8	4.2	12.8	25	0.57	…	...
	Sugar beet, 2012	90	13.8	10.4	17	11	…	…	…
	Average standardized yield	90	100	68	131	15	0.78	0.96	…
WO3	Oilseed rape, 2011	1597	3.6	1.2	6.5	35	0.5	0.52	…
	Winter wheat, 2012	1727	8.7	4.6	13.5	13	0.48	…	…
	Sugar beet, 2013	114	11	1.4	18.9	32	…	…	…
	Average standardized yield	114	100	46	133	20	0.68	0.87	0.84

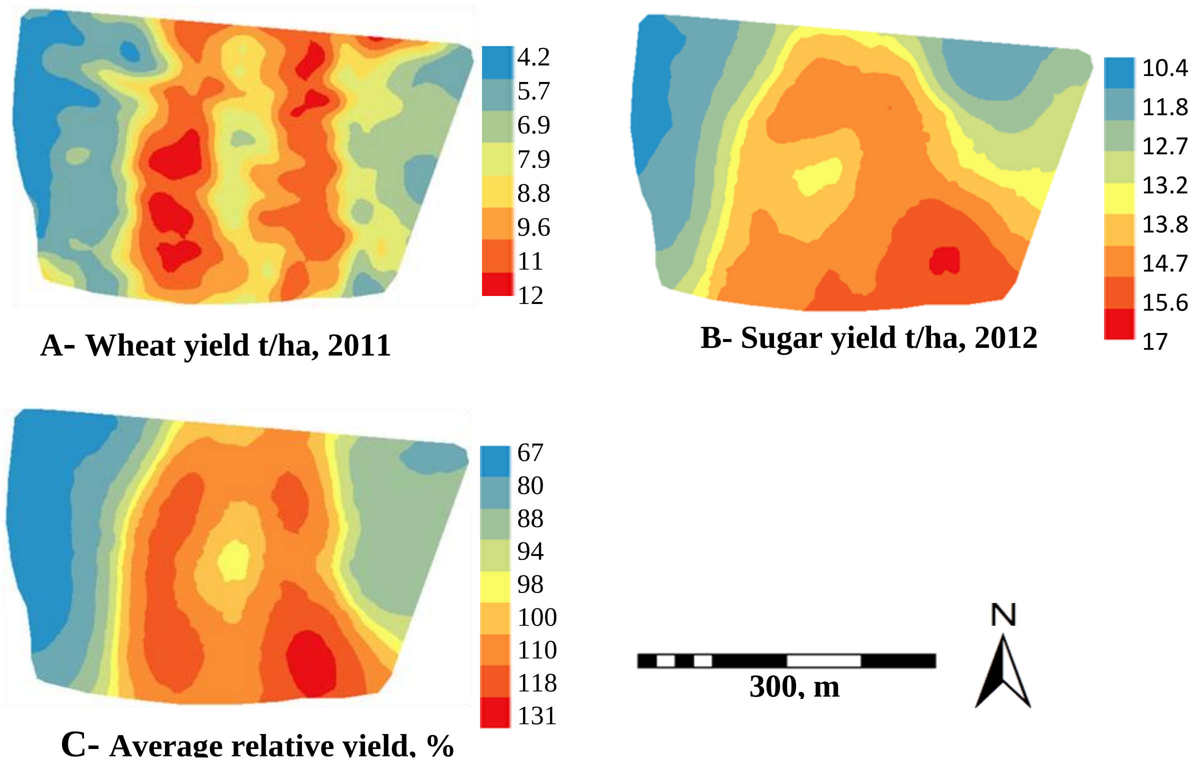


Figure 4.7: The interpolation maps for the yields of (A) wheat in 2011, (B) sugar in 2012, and the average relative yield of both crops (C) in T32 field.

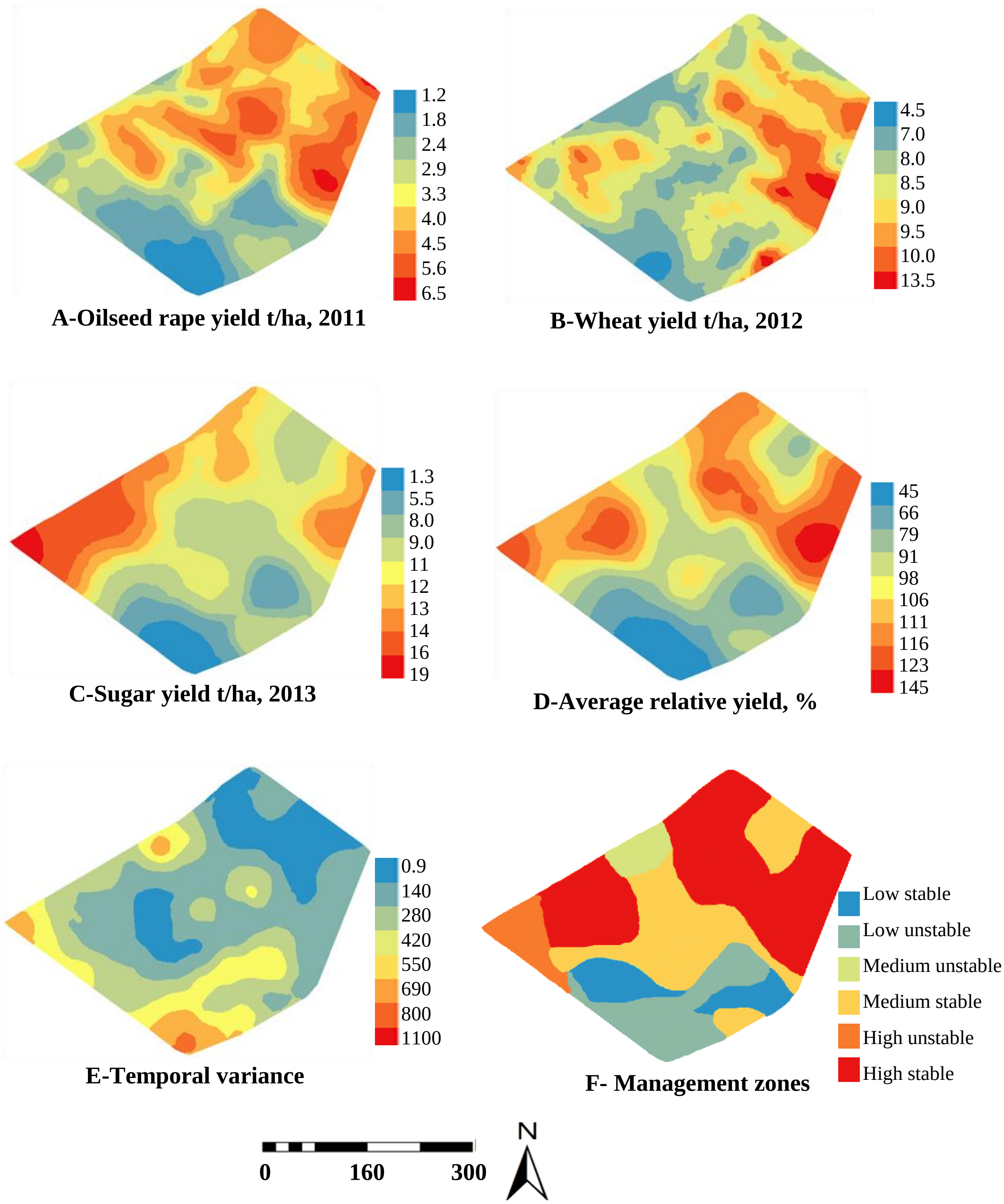


Figure 4.8: The interpolation maps for WO3 for yields of (A) Oilseed rape in 2011, (B) wheat in 2012, (C) sugar in 2013, average relative yield (D), the temporal variance (E), and management zones with low, medium and high yielding zones which may be either stable or unstable from year to year.

4.3 How does within-field variability in sugar beet yield and quality relate to the physical and biological variables?

The relationships between the variability in sugar beet yield and quality and most environmental variables assessed using redundancy analysis were statistically significant in all three fields, although the associated variables differed from one field to another. In White Patch, the total variability accounted for by the first four constrained axes was 50.3%, of which the 38% accounted for by the first two, was statistically significant (P<0.001), which means that the combined effect of the explanatory variables can be explained by only two constrained axes (Table 4.11). The quality parameters (root content of sugar, amino acid and potassium) were closely related to each other, but not related to the root yield, as the angles are almost perpendicular to each other (Fig 4.9). Based on the independent effects of the predictors (Table 4.12), the crop canopy cover in June (CC), plant population (PP), soil organic matter (SOM), soil moisture content (SMC) and soil clay content had a strong positive association with the variability in root yield, ($P \leq 0.006$), while the elevation (Elev), relative canopy growth rate (CGR) ($P \leq 0.001$), soil available magnesium (Mg) and minimum canopy temperature ($P \leq 0.027$) were strongly and positively associated with variability in beet content of sugar, amino acid and potassium. On the other hand, the variability in both yield and quality were negatively well related to the distribution of weeds and averages mean (MeT), maximum canopy temperature (MaxT) and soil available nitrate ($P \leq 0.05$), since the arrows point in opposite directions (Fig 4.9). However, the stepwise analysis identified fewer variables whose partial effects were statistically significant ($P \leq 0.05$).

Table 4.11: The summary statistics of four constrained axes of the redundancy analysis for the sugar beet crop in each field separately and for combined analysis including all three fields. The combined analysis was carried out using normalized values of root yield and canopy cover in June.

	Axis 1	*Axis 2*	*Axis 3*	*Axis 4*
White Patch				
Eigenvalues	0.21	0.17	0.09	0.03
Explained variation	21	38	47.4	50.3
Pseudo-canonical correlation	0.91	0.72	0.62	0.41
Explained fitted variation	41.4	75.5	94.1	100
P values	<0.001	<0.001	0.01	0.97
T32				
Eigenvalues	0.25	0.12	0.05	0.04
Explained variation	25	36.8	41.9	45.5
Pseudo-canonical correlation	0.87	0.62	0.67	0.38
Explained fitted variation	54.2	81	92.2	100
P values	<0.001	0.09	0.89	0.98
WO3				
Eigenvalues	0.33	0.06	0.04	0.03
Explained variation	33	39	43.2	46.1
Pseudo-canonical correlation	0.85	0.59	0.44	0.44
Explained fitted variation	71.7	84.6	93.7	100
P values	<0.001	0.28	0.69	0.92
All fields				
Eigenvalues	0.47	0.16	0.07	0.01
Explained variation	46.9	63	70.1	71.4
Pseudo-canonical correlation	0.95	0.77	0.70	0.47
Explained fitted variation	65.7	88.2	98.1	100
P values	<0.001	<0.001	0.001	0.047
All fields based on canopy cover in June				
Eigenvalues	0.73	0.0	0.0	0.0
Explained variation	73	73	-	-
Pseudo-canonical correlation	0.85	0.55	-	-
Explained fitted variation	100	100	-	-
P values	<0.001	1	-	-

Table 4.12: The percentage of variation accounted for by the explanatory variables and its significance (*P* values) as an independent (single effect) and combined (partial effect) based on redundancy analysis for the sugar beet crop in each field separately or for all fields together, the combined analysis being based on normalized values of root yield and canopy cover in June.

	White Patch		T32		WO3		All fields		Canopy cover	
Variables	***Single***	***Partial***	***Single***	***Partial***	***Single***	***Partial***	***Single***	***Partial***	***Single***	***Partial***
%Crop canopy cover (CC)	16.7 *P*<.001	16.7 *P*<.001	13.6 *P*<.001	13.6 *P*<.001	23.4 *P*<.001	23.4 *P*<.001	11.3 *P*<.001	5.4 *P*<.001	-	-
Plant population/ha (PP)	9.8 *P*<.001	3.9 *P*=.004	12.5 *P*<.001	3.4 *P*=.009	19.4 *P*<.001	2.8 *P*=.004	38.3 *P*<.001	9.3 *P*<.001	-	-
%Relative anopy growth rate (CGR)	13.6 *P*<.001	2.4 *P*=.022	11.2 *P*<.001	0.3 *P*=.8	2.0 *P*=.08	1.1 *P*=.13	4.7 *P*<.001	0.4 *P*=.016	-	-
Previous wheat crop t/ha	-	-	12.6 *P*<.001	2.1 *P*=.043	11.6 *P*<.001	2.0 *P*=.017	-	-	-	-
%Clay	4.3 *P*=.006	2.0 *P*=.021	2.4 *P*=.08	1.5 *P*=.14	8.8 *P*<.001	1.1 *P*=.12	30.3 *P*<.001	2.0 *P*<.001	56.1 *P*<.001	2.7 *P*<.001
%Sand	*3.0* *P*=.035	-	3.5 *P*=.017	2.9 *P*=.019	11.0 *P*<.001	1.8 *P*=.02	32.0 *P*<.001	<0.1 *P*=.7	58.2 *P*<.001	1.1 *P*<.001
%Silt	0.7 *P*=.66	<0.1 *P*=.99	1.3 *P*=.32	0.6 *P*=.5	3.4 *P*=.006	-	22.0 *P*<.001	0.1 *P*=.31	42.7 *P*<.001	0.7 *P*=.004
%Soil organic matter (SOM)	7.2 *P*<.001	0.7 *P*=.75	10.2 *P*<.001	6.5 *P*<.001	3.6 *P*=.007	0.5 *P*=.45	20.1 *P*<.001	0.4 *P*=.017	25.6 *P*<.001	0.1 *P*<.088
Soil pH	2.0 *P*=.11	1.6 *P*=.07	3.6 *P*=.02	0.5 *P*=.6	1.8 *P*=.11	1.7 *P*=.028	7.3 *P*<.001	0.5 *P*=.008	1.2 *P*<.07	0.7 *P*=.011
Electrical conductivity (EC)	0.8 *P*=.62	0.4 *P*=.65	1.4 *P*=.29	0.7 *P*=.46	2.7 *P*=.021	0.9 *P*=.22	39.3 *P*<.001	0.5 *P*=.004	64.6 *P*<.001	64.6 *P*<.001
Nitrate mg/l (N)	3.4 *P*=.021	1.1 *P*=.18	4.3 *P*=.007	0.3 *P*=.75	-	-	-	-	-	-
Phosphate mg/l (P)	1.2 *P*=.38	3.0 *P*=.009	1.7 *P*=.22	0.8 *P*=.36	1.0 *P*=.28	1 *P*=.12	0.3 *P*=.48	0.1 *P*=.27	0.8 *P*=.28	0.1 *P*=.41
Magnesium mg/l (Mg)	3.2 *P*=.027	0.6 *P*=.46	0.7 *P*=.6	0.9 *P*=.3	3.7 *P*=.005	0.7 *P*=.27	17.2 *P*<.001	0.1 *P*=.33	20.2 *P*<.001	0.1 *P*=.75
Potassium mg/l (K)	1.5 *P*=.23	<0.1 *P*=.99	2.1 *P*=.11	1.4 *P*=.14	0.7 *P*=.54	0.8 *P*=.26	3.0 *P*=.001	<0.1 *P*=.57	4.0 *P*<.001	0.1 *P*=.64
Soil moisture content (SMC)	5.2 *P*<.001	0.7 *P*=.39	4.7 *P*=.003	0.8 *P*=.39	18.3 *P*<.001	4.4 *P*<.001	17.5 *P*<.001	1.5 *P*<.001	16.5 *P*<.001	2.9 *P*<.001
Canopy temperature °C										
Mean (T)	4.1 *P*=.005	1.1 *P*=.18	2.3 *P*=.09	1.6 *P*=.1	2.4 *P*=.035	0.5 *P*=.44	27.7 <0.001	0.4 *P*=.011	-	-
Min (Tmin)	2.8 *P*=.024	1.9 *P*=.043	0.8 *P*=.56	0.6 *P*=.5	3.9 *P*=.008	0.7 *P*=.31	42.9 <0.001	42.9 <0.001	-	-
Max (Tmax)	9.3 *P*<.001	1.8 *P*=.06	2.4 *P*=.09	0.6 *P*=.5	5.1 *P*=.002	0.4 *P*=.6	7.1 *P*<.001	0.4 *P*=.026	-	-
Weeds density/m^2 (Weed)	13.3 *P*<.001	8.2 *P*<.001	10.9 *P*<.001	5.1 *P*<.001	3.2 *P*=.018	0.7 *P*=.32	5.7 *P*<.001	1.1 *P*<.001	-	-
Elevation, m (Elev)	7.1 *P*=.001	1.6 *P*=.09	2.6 *P*=.06	0.5 *P*=.6	17.2 *P*<.001	1 *P*=.13	13.4 *P*<.001	6.2 *P*<.001	5.6 *P*<.001	-
Aspect °	1.2 *P*=.39	2.9 *P*=.006	0.5 *P*=.8	0.7 *P*=.4	1.6 *P*=.11	0.4 *P*=.5	6.7 *P*<.001	<0.1 *P*=.45	13.6 *P*<.001	0.2 *P*=.18

The most important explanatory variables in White Patch field were crop canopy cover in June and weed density, which accounted for by 16.7 and 8.2%, respectively of the explained variation in sugar beet yield and quality. Some other variables such as soil available magnesium and phosphate, average minimum canopy temperature, canopy growth rate, soil clay content, field aspect and plant population density also had significant contributions (P<0.05) accounting for 1.9 to 3.9% of variability (Table 4.12).

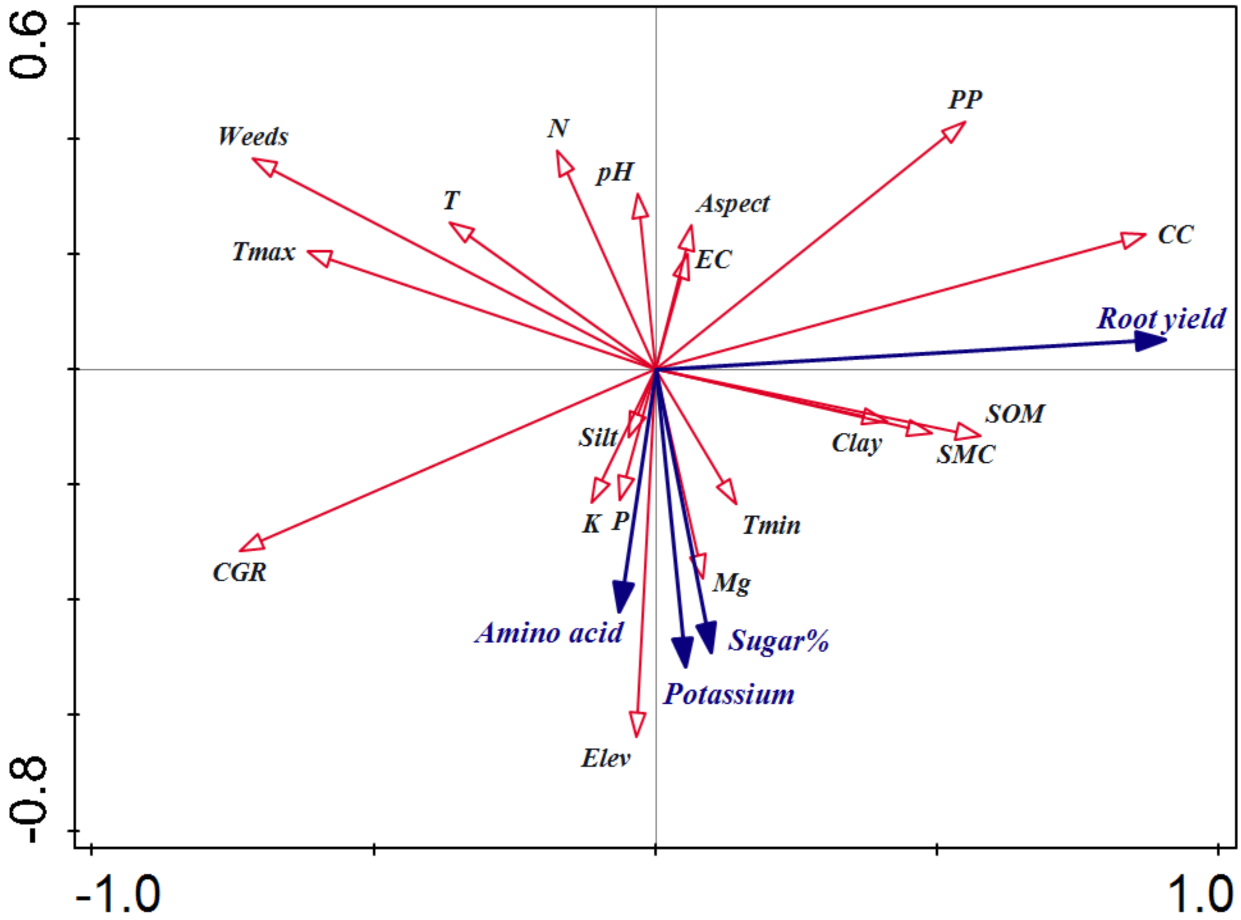


Figure 4.9: Ordination biplots based on redundancy analysis of the sugar beet yield and quality data (filled head arrows) with environmental variables, crop growth parameters and weed density used as explanatory variables (empty head arrows) in White Patch field in 2012 (see Table 4.12 for abbreviations).

Some variables such as weeds, soil organic matter, soil moisture content and elevation were good predictors as independent variables, but their contributions were not significant when added to other predictors in the redundancy analysis. Some soil attributes such as soil available potassium (K), conductivity (EC), soil pH and percentage of silt were not significantly correlated to the variability in yield and quality and the percentage of sand was also redundant when apportioning the variance.

In T32 field, the yield data of the previous wheat crop averaged for the plots where sugar beet measurements were taken was also included as an explanatory variable. The total variation in sugar beet yield and quality captured by the model was 45.5%, but only the first axis was statistically significant (P<0.001), which captured 25% of the variability (Table 4.11). The quality parameters in this field were not as closely related to each other as in White Patch field and the plots with higher root yield had higher root content of amino acid, but lower contents of potassium and sugar (Fig 4.10). The percentage of sugar was not significant, since it had almost a uniform distribution throughout the field with a CV of 1.7% (Table 4.3).

The plots with higher root yield significantly had a higher crop canopy cover, plant population density and wheat yield (P< 0.001) and were positively associated with the distribution of some soil attributes such as organic matter, soil moisture, available nitrate and soil pH ($P \leq 0.05$). On the other hand, a higher root yield was strongly and negatively associated with weed density, relative canopy growth rate (P = 0.001) and percentage of sand (P = 0.02) (Table 4.12). A higher beet content of amino acids and potassium occurred in the elevated parts of the field, which were also associated with higher soil clay content, but did not have a significant effect on fitting the model (Fig. 4.10). However, only a few variables were significant when the combined effect was considered, making a significant partial contribution to the variation explained in the redundancy analysis. The stepwise analysis identified the crop canopy cover, organic matter, weeds, plant population, percentage of sand and wheat yield as the most important predictors for the within field variability in sugar beet yield and quality ($P < 0.05$). The crop canopy cover accounted for 13.6% of the explained variation followed by the soil organic matter and weed density, which contributed by 6.5 and 5.1% respectively, and it ranged from 2.1 to 3.4% for the plant population, percentage of sand and wheat yield (Table 4.12).

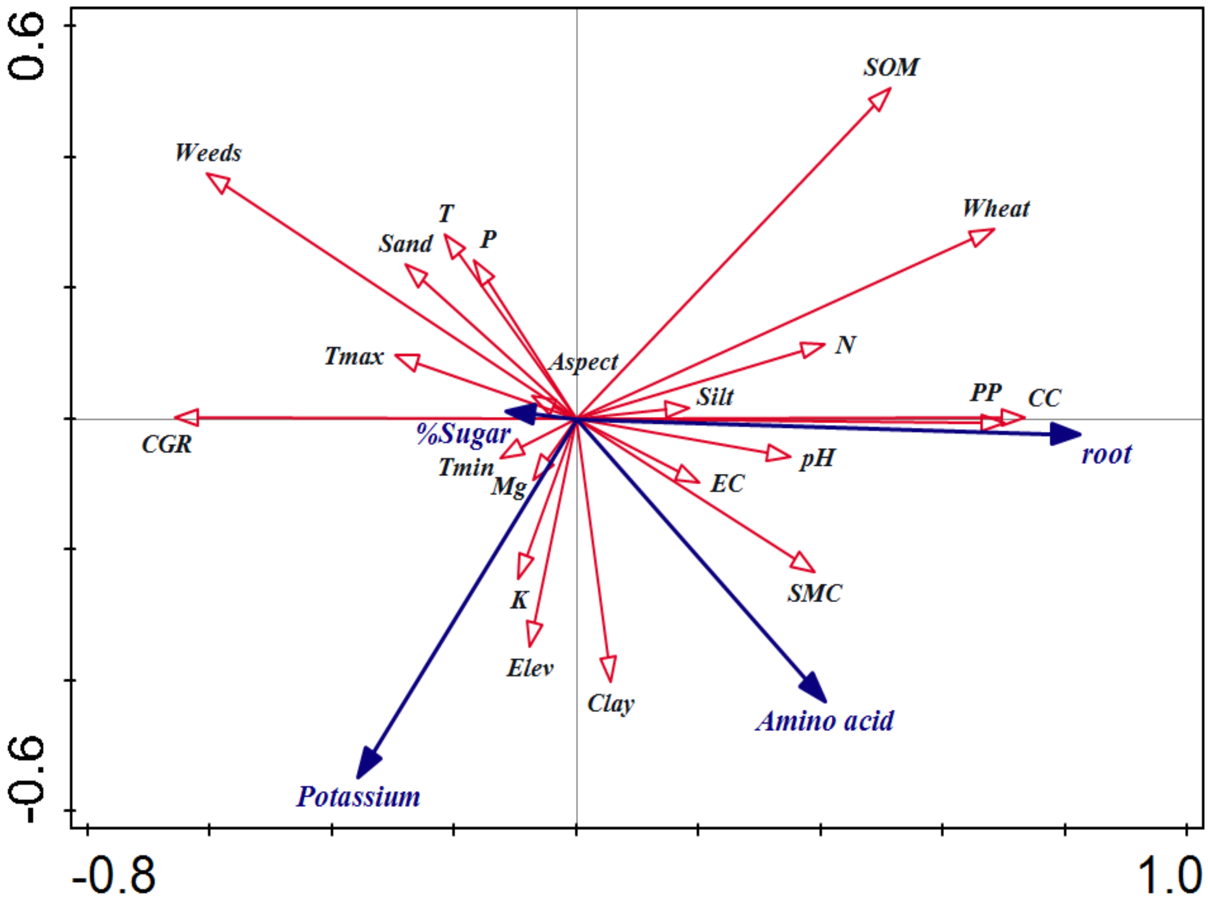


Figure 4.10: Ordination biplots based on redundancy analysis of the sugar beet yield and quality data (filled head arrows) with environmental variables, crop growth parameters and weed density used as explanatory variables (empty head arrows) in T32 field in 2012 (see Table 4.12 for abbreviations).

In WO3 field, the yield data of previous wheat crop was also included in the redundancy analysis as an explanatory variable. The four constrained axes captured 46.1% of the variability in sugar beet yield and quality, but only the first constrained axis was statistically significant (P =0.001) and accounted for 33% of the explained variation in sugar beet yield and quality (Table 4.11). The explanatory variables behaved differently in this field, as the root yield had a negative relationship with beet content of amino acid and potassium and was positively related to the percentage of sugar (Fig 4.11). Most of the selected explanatory variables in this field appeared to be significant independent predictors (P< 0.05), except for canopy growth rate, soil pH and available soil phosphate and potassium (Table 4.12), but only few variables had significant partial effects (P< 0.05) on the fitted model. These variables were crop canopy cover in June, which accounted for 23.4% of the variation followed by soil moisture content, plant population, previous wheat yield, percentage of sand and soil pH (Table 4.12).

A higher root yield occurred in the lower parts of the field, which had lower clay content and yield was strongly associated with higher plant population, crop canopy cover, soil moisture, organic matter, percentage of sand and available magnesium (Fig. 4.11). In addition, the yield data of the previous wheat crop was strongly and positively related to the variability in sugar beet root yield and percentage of sugar (P=0.001), suggesting the usefulness of yield data from the previous crop as a predictor of within field variability in sugar beet yield (Fig 4.11).

The redundancy analysis therefore identified the most important variables associated with sugar beet yield and quality in each field. Some of these variables appeared to be significant predictors in more than one field and the redundancy analysis for all fields together, highlighted the most consistent variables associated with the spatial variability in sugar beet yield and quality (Fig 4.12). The combined explanatory variables accounted for 71.4% of the variability in the combined yield and quality, the four axes being statistically significant (*P*<0.05), but the first axis captured about 47% of the variability (Table 4.11). The model highlighted all the environmental variables as significant independent predictors (*P*<0.001) of variability in yield and quality, except soil available phosphate (*P*=0.48) (Table 4.12). The variability in root yield had a strong positive relationship with crop canopy cover, soil moisture content, soil organic matter, plant population, soil pH and soil available magnesium and potassium (Fig 4.12).

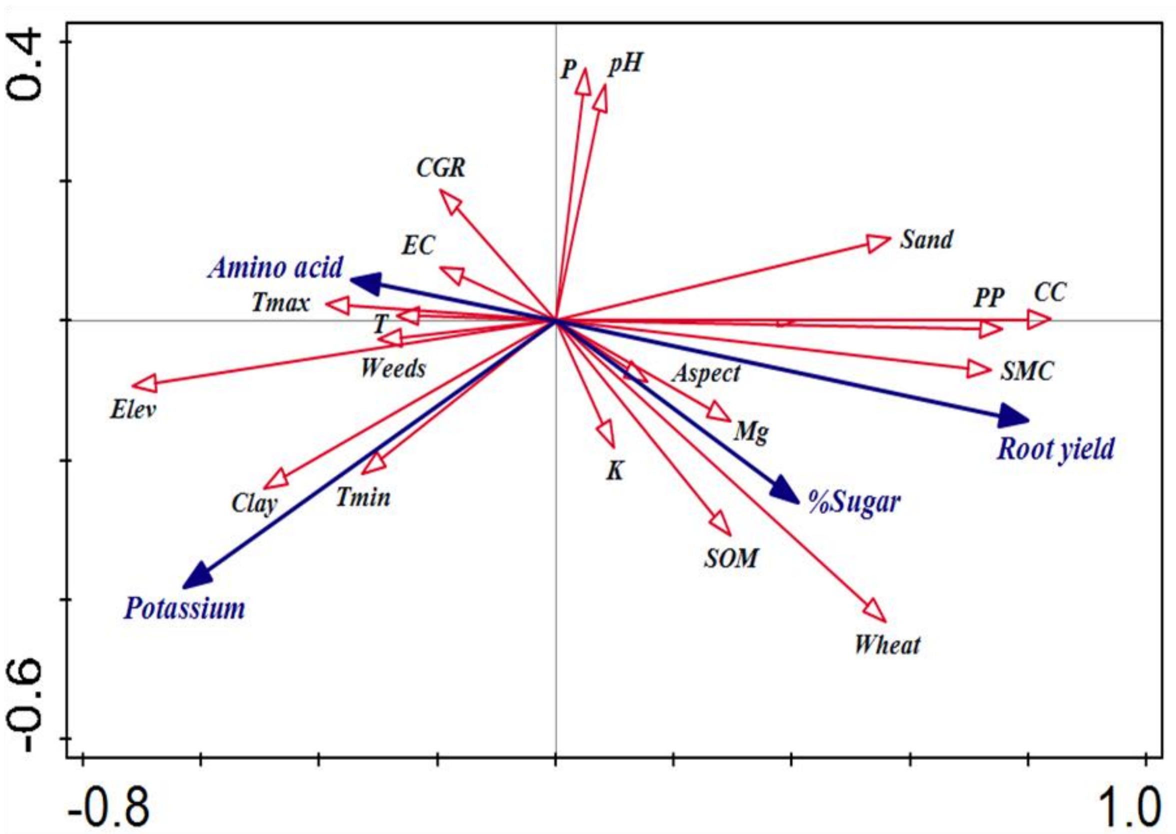


Figure 4.11: Ordination biplot based on redundancy analysis of the sugar beet yield and quality data (filled head arrows) with environmental variables, crop growth parameters, weeds density and previous wheat yield used as explanatory variables (empty head arrows) in WO3 field in 2013 (see Table 4.12 for abbreviations).

On the other hand, relative canopy growth rate, canopy temperature (T, Tmin and Tmax) and weed density were negatively related to the variability in root yield. The plots with a higher percentage of sugar had a lower root content of amino acid and were located in the elevated areas with a high percentage of sand, canopy temperature, canopy growth rate, soil moisture, crop canopy cover and soil pH, while a higher root content of amino acid occurred in the areas with higher soil organic matter, clay and silt content, soil EC and soil available magnesium (Fig 4.12). As the plant population density had always a strong positive association with root yield in the single and combined analysis, it had always a strong negative association with some quality parameters (percentage of amino acid and potassium). Although, most of the explanatory variables were very significant ($P<0.001$) as an independent predictors, the role of some variables such as percentage of sand and silt, soil available phosphate, magnesium and potassium and field aspect became less important in the combined analysis. The stepwise analysis picked up minimum canopy temperature, plant population; elevation and crop canopy cover as the best predictors, contributing 42.9, 9.3, 6.2 and 5.4%, respectively of the explained variability (Table 4.12).

Because of the potential use of early canopy cover for crop management, a further analysis was carried out in which the normalized crop canopy cover in June for all three fields was included as a response variable instead of normalized root yield and the quality parameters were replaced by plant population density, weed density and canopy growth rate. The canopy temperature (T, Tmin and Tmax) and weeds, and crop parameters (canopy cover, canopy growth rate and plant population) were excluded from the analysis as explanatory variables.

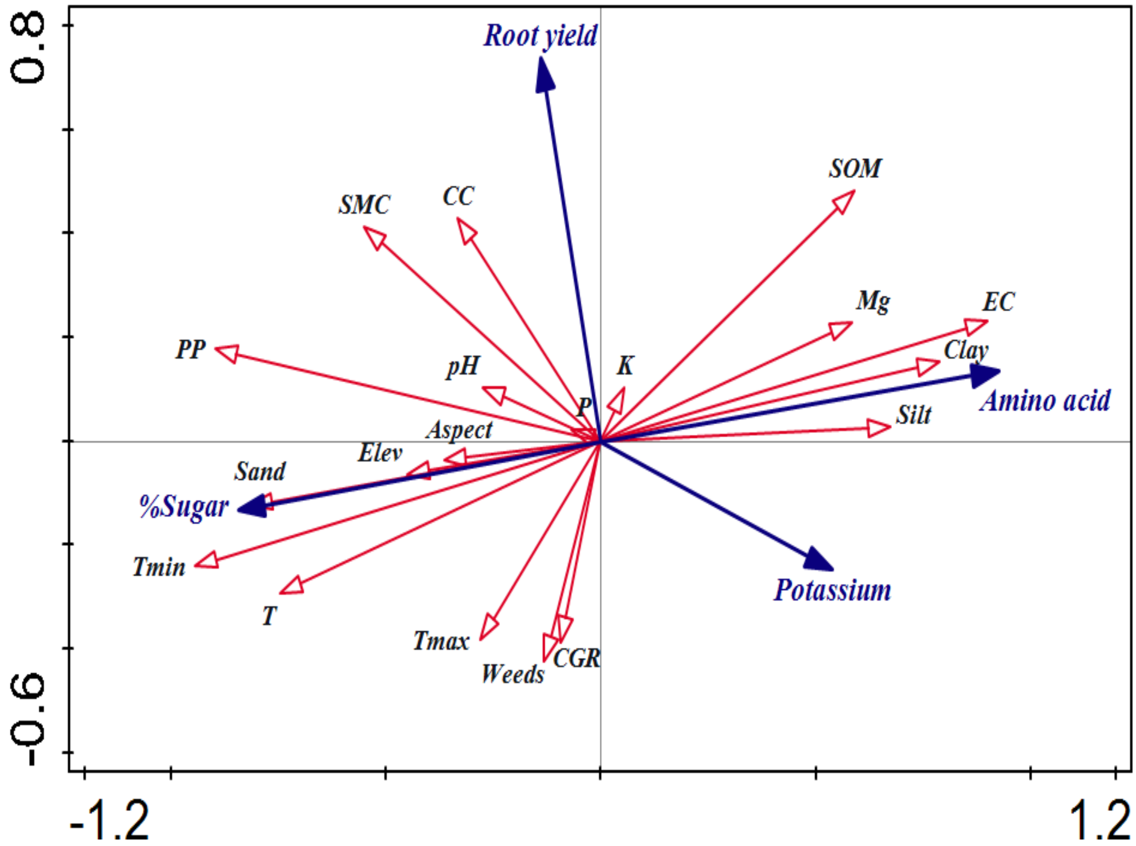


Figure 4.12: Ordination biplot based on redundancy analysis of the normalized and combined root yield for all field and quality data (filled head arrows) with combined environmental variables crop, growth parameters, and weed density used as explanatory variables (empty head arrows) (see Table 4.12 for abbreviations).

The selected soil attributes accounted for 73% of the variation, but all this variation was explained by the first constrained axis only, which was statistically significant (*P*<0.001) (Table 4.11). The combined crop canopy cover behaved in the redundancy analysis in the same way as the combined root yield (Fig. 4.13). A higher canopy growth rate and weed density occurred in the areas of low canopy cover in June. The variability in crop canopy cover and other response variables were significantly related to all the selected environmental variables (*P*<0.001), except soil pH (P=0.07) and available phosphate (*P*=0.12) (Table 4.12). Soil organic matter, soil moisture content and soil available magnesium had a strong positive association with crop canopy cover (Fig. 4.13). However, the role of soil available nutrient (P, K and Mg) was not significant when combined with other variables (Table 4.12). Soil electrical conductivity had a higher partial effect on the explained variation (64%: $P<0.001$) followed by soil moisture content and soil particles (clay, sand and silt) ($P<0.001$). The plant population was highly related to the soil particles and aspect, a higher population occurred in the areas of higher soil content of sand and south facing slopes, which could be warmer and more favorable for seedling emergence.

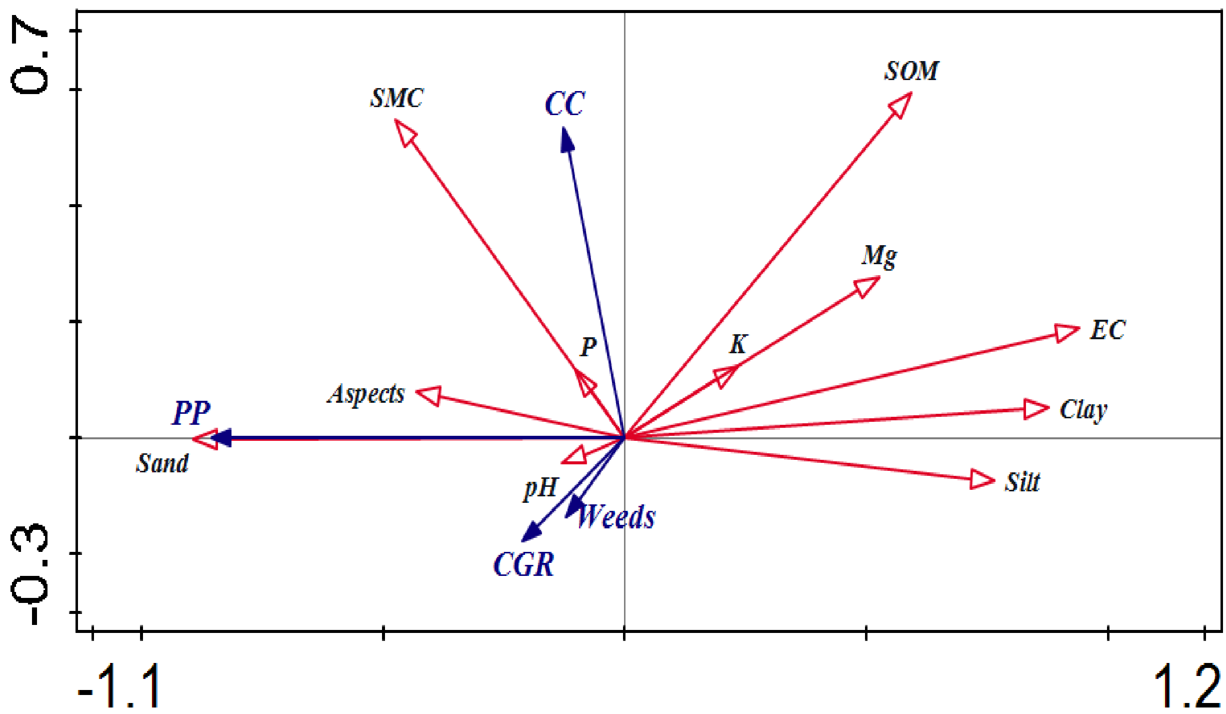


Figure 4.13: Ordination biplot based on redundancy analysis of the normalized and combined crop canopy cover in June for all field and quality data (filled head arrows) with combined environmental variables used as explanatory variables (empty head arrows) (see Table 4.12 for abbreviations).

4.4 Discussion:

The variograms for most of variables reached the sill, indicating a significant spatial variability in sugar beet growth, yield and quality and the variation is therefore expected to be patchy. The nugget variance was high for some variables in T32 and WO3 fields, but the degree of spatial dependency was strong to moderate for most variables.

The patterns of spatial variability in sugar beet growth and yield were clearly visualized by the interpolation maps. These patterns tend to have some visual association with spatial distribution of some environmental factors, which are therefore likely to be the main driving variables. Thus, soil moisture content and organic matter had a consistent positive association with yield variability, while weed density and mean canopy temperature had a negative association in all three fields. Perhaps the most important factor was soil moisture, since the accumulation of dry matter in sugar beet roots is known to be highly related to available soil moisture during June and July (Qi *et al*., 2005, Kenter *et al*., 2006). However, the patterns of spatial variability in sugar yield also had some association with some other environmental variables, although these differed from field to field; they include soil available nutrient, soil particles (clay, silt and sand), pH, electrical conductivity and elevation. The sugar yield was positively correlated to soil clay content in White Patch, but negatively related in WO3 field, which might be accounted for by the poor seedling emergence of sugar beet in clayey soils, especially under the cool conditions, which prevailed in March 2013 with mean temperature of 3.5 °C and not only affected in emergence in WO3, but in many early sown fields of sugar beet in the East of England in 2013 (Stevens, 2015). Since the plant establishment significantly varied throughout WO3, it is expected that another variable interacted with the effect of low temperature on seedling emergence, which is more likely to be soil type, since most of the plots with lower plant population had higher clay content.

In general, the spatial variability in sugar beet yield and quality was not strongly related to any single environmental variable. It appears as though the spatial variability in sugar beet yield might, however be due to the combined effect of different environmental variables, as each of these variables had some contribution to the spatial variability in sugar beet yield and quality. However, some of these variables such as soil organic matter, soil moisture, soil texture and weed density were shown to have consistent effects on the spatial variability in sugar beet yield across all three fields.

It is also important to note that under the uniform management practiced by the farmer the spatial variability in sugar beet growth and yield appeared to be consistent over the growing season, since the patterns of yield variability were similar to those observed for crop canopy cover, intercepted solar radiation and the LAI at different growth stages. These variables as observed early in the growing season could therefore be considered as a good predictor of the likely spatial variability in final sugar yield under uniform field management. A higher variability in crop canopy cover in June and its stronger association is not surprising, since the canopy developed and covered most of the ground by July and August reducing the amount of the variability which could be detected. However, the late development and more uniform canopy cover in July and August might not be associated with more uniform root development and sugar yield across the field, since the accumulation of dry matter starts early in the growing season (Draycott, 2008), so that the early assessment of crop canopy before canopy closure was the best predictor of final yield variability. This was further supported by the negative relationship between the spatial variability in sugar beet yield and relative canopy growth rate from June to July in all three fields, since the plots with low canopy cover in June tend to have a higher growth rate in mid-summer, which made the canopy cover less variable throughout the field in July. Observing the spatial variation in crop canopy cover and some associated environmental variables early in the growing season could therefore help the farmer to identify the areas which might need more or less inputs than other areas to avoid or mitigate the spatial variability in sugar yield or at least reduce the costs of production. Future research is clearly needed to test this hypothesis under field condition.

Although, higher plant populations might increase the dirt tare weight and might not increase the sugar yield (Jaggard *et al.*, 2011), sub-optimal plant populations were particularly associated with areas of relatively low sugar yield at final harvest, especially in WO3.

The research has also shown for the first time how some of the spatial variation in sugar yield can be predicted from the yield map of previous wheat or oilseed rape crop. The yield map of sugar beet in both fields showed some degree of spatial association with the yield map of the previous crop and the yield data of previous wheat crop showed its relevance to the spatial variability in sugar beet yield in the ordination analysis. However, the degree of spatial variability differed from one year to another and the yield maps of single crops also showed some distinct patterns of spatial variability from one year to the next such that the temporal variance map of WO3 in particular showed unstable temporal variation. The annual variability in weather may therefore cause unstable temporal patterns of variation between years (Simmonds *et al*., 2013), which are considered to be the main source of the temporal variability in the crop yield (Oliver *et al.*, 2013). The spatial variation in yield has also been found to be unstable from year to year in other studies (Blackmore *et al*., 2003, Fountas *et al.*, 2004, Simmonds *et al*., 2013), but it is significant that there was some degree of spatial association in this research between the yield maps of sugar beet and the previous crop, especially in the lower yielding parts of the fields, which perhaps need more attention by the farm manger. WO3 field was therefore classified into different zones based on the productivity and stability over three years (Fig. 4.8 F) following (Blackmore *et a*l., 2003), for which it can be treated differently by the farmer, but this might not be reliable enough for two reasons: First, the management zone map is based only on one field and the yield data is of only three years. Secondly, some parts of the fields (south east corner for example) were low yielding in all three years, but it appears in the map to be temporally unstable, because yields in this part largely differed from low for wheat and oilseed rape to very low for sugar beet, and so the farmer might incorrectly consider this as being high yielding in one year and low yielding in another year.

The links between sugar beet yield and quality and early growth and environmental variables as well as previous crop yield, which were visually demonstrated in the maps, were confirmed by the redundancy analysis. This analysis quantified the independent and partial association of explanatory variables with sugar beet yield and quality. The analysis helped to simplify the interpretation, since very few variables had significant partial effects on the explained variation when the combined effects of all variables were taken into account. Hence, although some variables are seem to be important if they are considered individually, they do not improve the prediction when all variables analyzed together (Lepš and Šmilauer, 2003). For example, the clay, sand and silt content of the soil are all related to each other as well as to soil electrical conductivity and soil moisture content, so that not all need to be considered. This is also true to some extent for crop canopy cover, plant population and relative canopy growth rate.

Overall and most consistently in all three fields, the independent and partial effects of crop canopy cover in June was most significant followed by plant population density, which makes them the most important early season predictors for within field variability in crop yield. In T32 and WO3, the yield of the previous winter wheat crop also improved the predictability of the spatial variability in sugar beet yield and quality across these two fields. Although soil moisture, organic matter, clay content, canopy temperature, available nutrient, elevation and weed density were strongly associated with the variability in yield and quality, their partial effects on fitting the overall model were not always significant and inconsistent from one field to another.

Due to the strong relationship between crop canopy cover in June and root yield, the crop canopy cover in June behaved in a similar way as root yield when used as a response variable instead of root yield in redundancy analysis. Since the environmental variables (soil organic matter, soil moisture content and soil available magnesium) associated with root yield were strongly associated with canopy cover in June and the areas with low canopy cover or plant population density are more likely to have a higher weed density. Therefore, it is suggested to look at the spatial variability in these variables as soon as the spatial variability in crop canopy cover is observed and attempts should be made to improve the canopy development. Some of these variables such as soil moisture content, nutrients and weeds can be treated by site-specific irrigation, fertilizer or herbicide applications during the growing season to increase the early canopy development and decrease the spatial variability in final yield, while managing soil organic matter might take more than one growing season, but it is still recommended to add the farm compost repetitively each season to improve soil physical, chemical and biological quality.

4.5 Conclusions:

The main conclusions obtained from the results of this chapter are as follows:

1. A significant spatial variability in sugar beet growth, yield and quality was observed throughout each field. This was particularly and most importantly evident in the yield value, which varied from 1120 to 2990, 1870 to 3320 and 230 to 3130 £/ha^{-1}in White Patch, T32 and WO3, respectively.
2. The spatial variability in sugar beet yield could be correlated with the variability in soil moisture, soil type, soil organic matter, elevation, weeds and canopy temperature in almost all fields, and most of the variables were confirmed to be significant independent predictors in the redundancy analysis. Few of them appeared to be significant when the interaction and confounding effects were taken into account.
3. The variability in sugar beet yield and quality was negatively related to the canopy temperature, but the percentage of sugar had a positive association with minimum canopy temperature
4. The spatial variability in sugar beet yield was found to be strongly correlated to the variability in some growth parameters measured at different times during the growing season. Among these variables, crop canopy cover in June was identified as a good predictor of within field variability in final sugar yield and together with crop plant population if sub-optimal, could be useful in spatially-variable field management by the farmer.
5. The yield map of sugar beet had some degree of spatial association with the yield map of previous crops (winter wheat or oilseed rape), these maps can therefore also be used as a useful tool to predict some spatial variability in sugar beet yield.

6. The spatial variability in crop canopy cover in June was related to soil attributes in a similar way as root yield at final harvest, indicating the possibility of early management of sugar beet.

In order to make the predictability evident in these results from three fields, more generally applicable and useful to farmers as well as to understand the driving variables better, the feasibility of simulating the final sugar yield based on within field variability in air temperature, solar radiation and soil types will be explored in Chapter five, by applying the Broom's Barn sugar beet growth simulation model to the three fields studied. This model has been widely used to simulate sugar beet yield, but only on a regional basis. In chapter five, attempts are made to adapt the model on a spatially variable basis in each field to explore whether it is possible to explain the variation in sugar yield based on weather variables, soil types and also an observation of early canopy development and sugar beet plant establishment.

5. Chapter Five: Within-Field Simulation of Sugar Beet Yield Based on Micro-environment.

5.1 Background:

The sugar beet crop shows significant spatio-temporal variation in crop yield and, as shown in chapters 3 and 4 these variables are correlated with the growth, development and consequently the yield of sugar beet. In this chapter, the effects of these factors on sugar beet growth and yield are simulated on a spatio-temporal basis using the Broom's Barn sugar beet growth simulation model (Jaggard and Werker, 1999, Richter *et al*., 2001), which is described in complete detail by Qi *et al*. (2005). This deterministic model considers the combined influence of temperature, solar radiation, rainfall, potential evapotranspiration and soil available water capacity on accumulation of dry matter and sugar yield and is driven by weather variables on a daily simulation assuming a plant population of more than 75000 plants/ha (Qi *et al*., 2005). The model has been widely applied to simulate sugar beet growth and yield based on weather data and to understand the future of sugar beet production in the UK and Germany under the impact of climate change (Freckleton *et al*., 1999, Pidgeon *et al*., 2001, Richter *et al*., 2001, Kenter *et al*., 2006, Richter *et al*., 2006, Jaggard *et al*., 2007, Jaggard *et al*., 2009). The simulated sugar yield was close to the actual sugar yield under different weather and soil conditions from 1980 to early of 2000s, but it underestimated the sugar yield with beginning of 2008, due to the improvement in varieties and agronomic practice (Qi *et al*., 2013). Therefore, the model was recalibrated recently to match the new varieties and agronomic practices (Qi *et al*., 2013). However, in most of these studies the model was applied for temporal simulation of sugar beet yield and it was applied on regional bases using the weather data collected from weather stations located far from the field and on standard surface.

Whereas, the weather data provided by a standard weather station may significantly vary from weather data provided by weather sensors located in agricultural plots (Monestiez *et al*., 2001). To model the variability in sugar beet yield in the UK under climate change, Richter *et al*. (2006) expected that the variability in sugar beet yield within the regions will be higher than between regions, due to the variability in soil properties. Therefore the spatial variability in the environment should not be ignored when modelling sugar beet. The model was applied based on spatially variable soil properties and weather condition by Launay and Guérif (2003) in France and Kenter *et al*. (2006) in Germany, but the data was not dense enough for spatial interpolation and the spatial variability that might occur within a single field has never been considered for sugar beet as far as known. In another study however, Hakojärvi *et al*. (2013) modelled the growth of spring cereals based on spatial variability in some soil physical properties over three years in Finland. They found that the spatial variability in the simulated crop biomass was much lower than the actual spatial variability in crop biomass. They concluded that the crop biomass cannot be simulated based on spatial variability on some soil physical properties in the case of high variability, because some of the variability could be due to other variables such as weather and field topography. A weakness of these attempts has been the assumption of a uniform distribution of solar radiation across the region or field. Incident solar radiation, however, will vary even within the field scale, controlled by the field topography, especially the slope and aspect (Fu and Rich, 1999, Allen *et al*., 2006), except in completely level fields. The accumulation of dry matter and sugar is therefore predicted to vary within-field, since accumulation of dry matter is a function of intercepted solar radiation (Werker and Jaggard, 1998, Draycott, 2008, Jaggard *et al*., 2009) if provided water is not limiting**.** Different methods are now available to calculate the incident solar radiation and potential evapotranspiration for any location within the field based on a digital elevation model, slope and aspect and the map of spatial variability in solar radiation can also be produced (Kumar *et al*., 1997, Fu and Rich, 1999, Pierce Jr *et al*., 2005, Allen *et al*., 2006). The spatial variability in solar radiation and air temperature can together cause spatial variability in potential evapotranspiration and the crop's requirement of water. This chapter, therefore, investigates the ability of the Broom's Barn model to simulate sugar beet development and yield on a spatially-variable basis. Since the model assumes good crop establishment, satisfactory (non-limiting) conditions of water and nutrients and an absence of pests, weeds and disease (Qi *et al*., 2005), the yield gap between simulated and actual yield is also explained and adjustments necessary to account for the failure to satisfy these assumptions in different parts of each field are identified.

5.2 Methodology:

5.2.1 The components of the model:

The main components of the Broom's Barn sugar beet growth model and the way in which it simulates the crop biomass and accumulation of sugar are described in Figure 5.1 (Qi *et al*., 2005). Under non-limiting growth conditions, the accumulation of dry matter and sugar is mainly accounted for by the solar radiation and temperature. The effect of temperature on the accumulation of crop biomass and sugar is simulated by the model through predicting its effect on the emergence of sugar beet seedlings, the development of crop canopy cover and rooting depth (Qi *et al*., 2005, Jaggard *et al*., 2007). The accumulation of crop biomass was found to be positively related to temperature at the beginning of the growing season, negatively related in July and August and independent at the end of the growing season in Germany (Kenter *et al*., 2006). The increase in average daily temperature over last four decades has allowed sugar beet to be sown earlier in the UK (Jaggard *et al*., 2007) and it is expected to be sown an additional ten days earlier by 2050 (Boizard *et al*., 2012), which might contribute to a significant increase in sugar yield.

The model determines the sugar beet growth as a result of the daily interception of solar radiation and radiation use efficiency, which depends not only on crop foliage cover, but also the available space for the crop canopy to extend (Werker and Jaggard, 1998, Jaggard *et al*., 2009). The final sugar yield results from the daily accumulation of dry matter and its apportioning to sugar (Werker and Jaggard, 1998). It assumes a decrease in the radiation use efficiency with increasing accumulation of dry matter and the age of the crop (Jaggard and Werker, 1999). The model was further developed by Richter *et al.* (2001) to simulate the impact of water stress on the development of crop foliage cover and the influence of diffuse radiation in the canopy on radiation use efficiency. Since the new sugar beet varieties are more droughts tolerant and rhizomania-resistant than older varieties in addition to improvement in agronomy such as seed priming, the model consistently underestimated the sugar yield from 2008. Therefore the model was recalibrated by Qi *et al*. (2013), by reducing the thermal time required from sowing to 50% emergence from 140 °C d to 90 °C d, the influence of drought on potential radiation use efficiency was adjusted to 42% of its possible value calculated in previous study by (Werker and Jaggard, 1998) , and the impact of canopy age on potential radiation use efficiency was adjusted to 50% of its old value.

The model consists of a set of deterministic mathematical functions to estimate a daily accumulation of crop biomass and sugar, the amount of solar radiation intercepted by the crop foliage, total dry matter accumulated based on potential radiation use efficiency and the conversion of dry matter to sugar yield (Fig. 5.1).

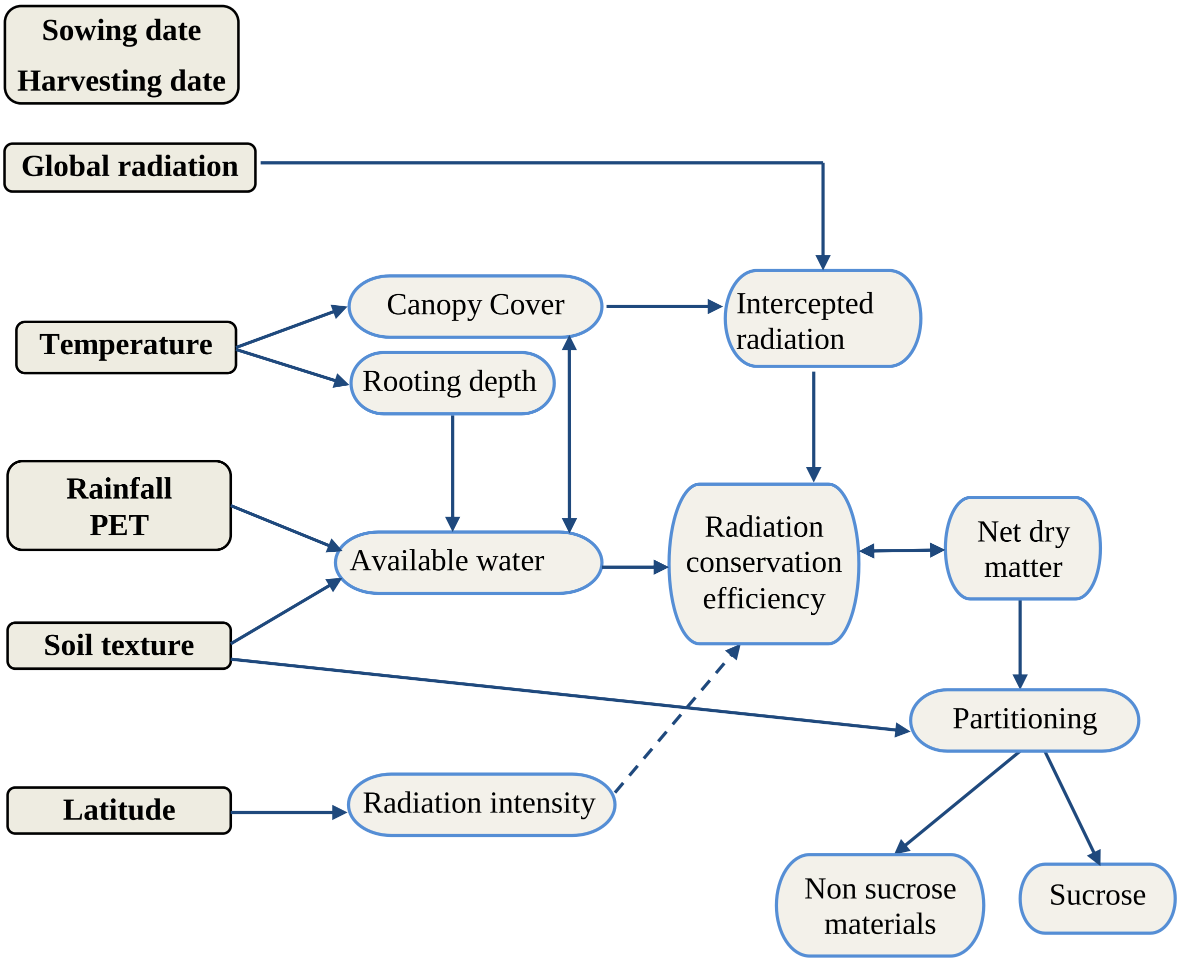


Figure 5.1: Components and controlling environmental variables in the Broom's Barn sugar beet growth simulation model modified from Qi et al. (2005).

All the equations of the model and the ways in which it simulates different crop parameters are described in detail by Qi *et al*. (2005) and summarized in Table 5.1. The specifications and values of some parameters are also given in Table 5.2.

The model simulates the canopy cover and rooting depth as function of daily increment in air temperature above a base temperature of 3°C from the 50% seedling emergence (Werker and Jaggard, 1998).

Table 5.1: The main components and variables of Broom's Barn sugar beet growth model and their mathematical equations (Qi *et al*., 2005). Parameter values of constants are given in Table 5.2.

Parameters	Mathematical equations
Crop canopy cover (f), m^2 m^{-2}	$f = f_0 \exp\left(\mu_{\mathrm{min}}(T - T_0) + \frac{\mu_0 - \mu_{\mathrm{min}}}{\nu}(1 - e^{-\nu(T-T_0)})\right)$
Final net relative growth cover rate (μ_{min}), d^{-1}	$\mu_{\mathrm{min}} = \mu_{\mathrm{min0}}(2 - f_{\mathrm{stress}})$
The rate of change in canopy from μ_0 to μ_{min} (ν), d^{-1}	$\nu = \nu_0(1 + 0.1(1 - f_{\mathrm{stress}}))$
Effect of water stress (f_{stress})	$f_{\mathrm{stress}} = \frac{2}{1 + \exp\{-f_{\mathrm{dt}}(Q_{\mathrm{rel}} - 0.02)\}} - 1$
Rooting depth (D), m	$D = D_{\mathrm{sowing}} + I_0 \exp\left(\frac{\beta_0}{\delta}(1 - e^{-\delta(T-T_0)})\right)$
Daily increase in dry matter (ΔW), gm^{-2} d^{-1}	$\Delta W = \varepsilon f S$
Intercepted radiation use efficiency (ε), gMJ^{-1}	$\varepsilon = \varepsilon_0 \frac{E_a}{E_p}\exp(-\gamma^W)$
Daily increase in sugar yield (ΔY), gm^{-2} d^{-1}	$\Delta Y = \Delta W\left(\frac{K^W}{1 + K^W}\right)$
Total dry matter (W), gm^{-2}	$W = \frac{1}{\gamma}\log\left\{1 + \gamma^{\varepsilon}\sum_{t=t_0}^{t_f}\left(fS\frac{E_a}{E_p}\right)\right\}$
Total sugar yield (Y), gm^{-2}	$Y = W - \frac{1}{k}\log(K^W + 1)$
Evapotranspiration (ET)	
Daily soil surface ET (ΔSSE), mm d^{-1}	$\Delta\mathrm{SSE} = 1.5(1 - f)$
Potential crop ET (E_p), mm d^{-1}	$E_p = 1.25f \times \mathrm{ET}_{\mathrm{grass}}$
Actual crop ET (E_a), mm d^{-1}	$E_a = \min(E_p, E_{\mathrm{max}})$
Daily maximum ET (E_{max}), mm	$E_{\mathrm{max}} = \frac{\psi_{\mathrm{soil}} - \psi_{\mathrm{crop}}}{R_{\mathrm{crop}} + R_{\mathrm{soil}}},$
Resistance of water movement within rooting zone R_{soil} and crop R_{crop},	$R_{\mathrm{crop}} + R_{\mathrm{soil}=c_1+c_2}\frac{1}{D}((\frac{Q}{Q_{\mathrm{fc}}})^{-(2b+3)} - 1)$
Soil texture related water content at field capacity (Q_{fc}), kg m^{-3}	$Q_{\mathrm{fc}} = a_2(\frac{a_2}{5})^{(1/b)}$
Water potential in rooting zone (ψ_{soil}), kPa	$\psi_{\mathrm{soil}} = -5\left(\frac{Q}{Q_{\mathrm{fc}}}\right)^{-b}$
Water content in rooting zone (Q), kg m^{-3}	$Q = Q_{\mathrm{fc}} - \frac{\mathrm{SMD}}{D}$
Soil moisture deficit (SMD), mm	$\mathrm{SMD} = \mathrm{SMD}_{(t-1)} + \Delta\mathrm{SSE} + E_a - R$

Table 5.2: Specifications and values of some parameters and variables used in the original Broom's Barn sugar beet growth model and their mathematical equations (Qi *et al*., 2005).

Parameters	Description	Values	Units
β_0	Rate of increases of *D* when $T = T_0$	0.00935	d^{-1}
δ	Rate of decay in β_0 to 0	0.002715	d^{-1}
ψ_{crop}	Canopy water potential	−1500	kPa
ε_0	Potential radiation use efficiency	1.80	gMJ^{-1}
μ_0	Increasing rate in canopy cover at $T = T_0$	0.06556	d^{-1}
μ_{min0}	Rate of decay in canopy cover at $T = T_0$	−0.000169	d^{-1}
μ_{min}	μ_{min0} as affected by water stress		d^{-1}
γ	decaying coefficient of radiation conversion coefficient	0.00014	$g^{-1}m^2$
b	Soil texture related values (2-18)	This parameter varies across each field according to the variability in soil texture	
D_{sowing}	Root depth at sowing	0.02	m
f_0	Initial canopy cover when $T = T_0$	0.0015	$m^{-2}\,m^2$
f_{dt}	Response factor	Increase linearly from 6 to 12 with increasing the thermal time from 700 to1700 °C	
I_0	Length of epicotyls when $T = T_0$	0.0491	m
k	Sugar partitioning coefficient	0.00148	$g^{-1}m^2$
M_p	Regression coefficient of the relationship between observed sugar yield and plant population	0.000081, 0.00006 and 0.00023 in White Patch, T32 and WO3, with standard error of 0.00002, 0.00001 and 0.00002, respectively	
M_w	Regression coefficient of the relationship between observed sugar yield and squared root of observed weed density	3.1, 2.0 and 1.4 in White Patch, T32 and WO3, respectively with standard error of 0.42, 0.3 and 0.5 respectively	
P_{obs}	Observed plant population	Variable across each field	Plant/ha
P_w	Observed weed density	Variable across each field	Plant/ha
Q_{rel}	Relative water content	Calculated as ratio of the daily available water content and available water content at field capacity	
R	Rainfall	Obtained from the nearest weather station for each field	$mm\ d^{-1}$
S	Incident solar radiation,	Field value obtained from local weather station and this calculated for each plot based on slope degree and aspect (see text)$MJ\ m^{-2}d^{-1}$	
T	Thermal time above base temperature of 3 °C from sowing	Recorded every 30 minutes from 45 sensors distributed in each of White Patch and T32 fields, and 89 sensors in WO3 field °Cd	
T_0	Thermal time above base temperature of 3 °C from sowing to 50% crop emergence	90	°Cd
t	Time		
t_0 and t_f	The crop emergence and final harvest, respectively in which the ΔW is calculated		
ν_0	Rate of change of μ, from μ_0 to μ_{min}	0.005866	d^{-1}
ν	ν_0 as affected by water stress		d^{-1}

To quantify the influence of water stress, the soil water stress factor (f_{stress}, Table 5.1) is simulated as a logistic function, which changes between 1 and 0 according to relative water content (Q_{rel}) (Qi *et al*., 2005). The relative water content is the percentage of daily available water content from the available water at field capacity. The response factor (f_{dt}) has a value, which starts initially from 6 and increases up to 12 with increase in thermal time from 700 to 1700 °Cd (Richter *et al*., 2001). The yield loss due to water stress is to some extent compensated by early sowing and extending the growing season (Freckleton *et al*., 1999, Richter *et al*., 2006)

The evapotranspiration (ET) from the bare soil is assumed to be constant (1.5 mm d^{-1}). However, the model does not allow the ET from the soil surface (ΔSSE) to exceed that from standard grass (ET_{grass}), which is calculated based on the Penman–Monteith equation for a standard grass sward (Allen *et al*., 1998). The daily actual ET is assumed to be the same as daily potential ET, but if the available water in the rooting zone is not enough or slow moving, then the actual ET will be equal to the daily maximum ET ($E_{\max}$) that might occur. The value of ($E_{\max}$) can vary according to the differences in water potential in the soil rooting zone (ψ_{soil}) and crop canopy (ψ_{crop}) and water movement between rooting zone (R_{soil}) and canopy (R_{crop}) (Qi *et al*., 2005). The values of R_{soil} and R_{crop} are calculated based on rooting depth (D), soil parameter (b) which can be changed according to soil type, available water at rooting zone in a given day (Q) and available water at field capacity (Q_{fc}) (Jaggard and Werker, 1999).

5.2.2 Crop and environment data:

The model was applied separately for each studied field (White Patch and T32 in 2012 and WO3 in 2013) based on spatially-variable environmental data collected from different locations within the field. The information about the studied fields, method of sampling and collection of crop and environmental data is described in detail in chapter two and Figures 2.4, 2.5 and 2.6 and summarized as follows:

1. The latitude, longitude and mean altitude above sea level were 52.25°N, 0.57°W and 68 m respectively for White Patch, 52.18°N, 0.10 °W and 15 m for T32, and 52.16°N, 0.14°W and 35 m for WO3,
2. The model was applied for 91, 90 and 114 different locations in White Patch, T32 and WO3 fields respectively,
3. The soil texture, crop biomass and sugar yield were identified at each of these locations,
4. Air temperature was recorded every 30 minutes at 45 locations in White Patch and T32 fields and at 90 locations in WO3. The value of air temperature for other plots, where there were no loggers was calculated by averaging the data of the neighbouring plots located within a 25 m radius,
5. Daily data for rainfall, incident solar radiation, relative humidity and wind speed were obtained from the Broom's Barn weather station for White Patch in 2012 and from the Botanic Garden near Cambridge (52.19°N, 0.126°W) for T32 in 2012 and WO3 in 2013. The data for rainfall, relative humidity and wind speed were assumed to be the same for all plots across each field,

6. The incident radiation was calculated for each location within field from the slope and aspect of each location following the equation developed by Kumar *et al*. (1997) as follows:

$$\boldsymbol{S_{\mathrm{p}} = S_{\mathrm{s}} \cos i} \qquad \textbf{Equation 5- 1}$$

Where S_{p} is the shortwave solar radiation, which is visible and contains a high amount of energy received by a skewed surface, S_{s} is the shortwave solar radiation falling on a surface normal to the sun's rays and i is the angle between the normal to the surface and the direction to the Sun calculated as follows:

$$\boldsymbol{\cos i = \sin\Omega_s(\sin L \cos\beta - \cos L \sin\beta)}$$
$$\boldsymbol{+\cos\Omega_s \cos h_s(\cos L \cos + \sin L \sin\beta \cos a_w)\cos\Omega_s \sin\beta \sin a_w \sin h_s}$$

Equation 5- 2

Where β and a_w, are respectively the tilt and azimuth angles of the soil surface (slope and aspect) for each plot, L is the latitude of plot, Ω_{s} is a solar declination and h_s is the hour angle.

For each field, the hourly observations of incident radiation of which the daily sum is based were recorded at a horizontal plane (i.e. β= 0:0). The incident radiation for this reference point can be written as follows:

$$\boldsymbol{S_{\mathrm{p,reference}} = S_{\mathrm{s}}(\cos i)_{\mathrm{reference}}\, cloud\ cover} \qquad \textbf{Equation 5- 3}$$

Since the slope and aspect for each plot within the fields is known, the incident radiation for each plot can be written as follow:

$$\boldsymbol{S_{\mathrm{p,plot}} = S_{\mathrm{s}}(\cos i)_{\mathrm{plot}}\, cloud\ cover} \qquad \textbf{Equation 5- 4}$$

The physical measurement of S_p at the reference point integrates the effect of clouds. Hence, using Equation 5.2 to determine $(\cos i)_{\mathrm{plot}}$ and $(\cos i)_{\mathrm{reference}}$, and their ratio can be used to scale up or down observations of radiation $S_{\mathrm{p,reference}}$ to provide $S_{\mathrm{p,plot}}$ as follows:

$$\boldsymbol{S_{\mathrm{p,plot}} = \frac{S_{\mathrm{p,reference}}(\cos i)_{\mathrm{plot}}}{(\cos i)_{\mathrm{reference}}}} \qquad \textbf{Equation 5- 5}$$

7. Since the incident solar radiation and air temperature could thus be estimated for each plot within the field, the potential evapotranspiration for each plot was calculated following Allen *et al*. (1998).

The model parameters and variables, which varied within each field, were therefore soil *b* parameter and soil available water at field capacity, which relates to soil texture, air temperature, solar radiation and potential evapotranspiration (Tables 5.1 and 5.2).

5.1.1. Model performance:

Model performance for each plot in each of the three studied fields was evaluated as follows:

1. The simulated and measured sugar yields at each point were plotted against each other.
2. The goodness of the relationship between the simulated and measured sugar yields was determined by estimating the correlation coefficient (r) and the main parameters of the linear regression (slope, intercept and their standard errors, coefficient of determination (R^2)) and Residual Mean Square (RMS), which estimate the scatter of the data around 1:1 line. These indicators were identified using GenStat software (15th edition).
3. To identify the locations within each field at which the model over or under estimated the yield, the relative yield gap (Y_g) between the simulated ($\breve{y}_i$) and measured (y_i) sugar yield was calculated for each point as follows,

$$\boldsymbol{Y_g = \left(1 - \frac{y_i}{\breve{y}_i}\right) \times 100} \qquad \textbf{Equation 5- 6}$$

4. To visualize the model performance spatially within each field, the simulated yields were analyzed geostatistically (Appendix 7) and the Kriging maps were produced for the simulated and actual sugar yields and the yield gap and compared.

5.1.2. Improving model performance:

Since the simulation model assumes a plant population density of at least 75000/ha, the crop is weed free and rapid expansion of the crop canopy, some adjustments were made on the model inputs and outputs as follows in order to see if these assumptions affected model performance:

1. To compensate for variability in crop establishment and early canopy expansion (Fig 5.2), the sowing date was changed for most of the plots, so that the simulated crop canopy cover corresponded to the observed canopy cover on the 1st June 2012 in White Patch and T32 fields and on the 20th June 2013 in WO3 field evidenced by the 1:1 relationship (Figure 5.3 D-F). The sowing date was therefore delayed for some plots from Julian day 85 up to 117 in White Patch, from 76 to up to 90 days for a few plots in T32 and from 64 to up to 130 days in WO3 field in order to compensate for much slower early canopy development in the field compared to the simulation.
2. In case the spatial variability in observed sugar yield was affected by weeds and plant population, the simulated yield was adjusted based on the following regression analysis:

a) The simulated sugar yield was adjusted for plant population ($\breve{y}_{adjp}$) for each field using the equation of linear regression analysis between observed sugar yield and plant population density (Fig 5.4 A-C) as follows:

$$\breve{y}_{adjp} = \breve{y} - \{\mathbf{M_p} \times (\mathbf{75000} - \mathbf{P_{obs}})\} \qquad \textbf{Equation 5- 7}$$

Where 75000 is minimum plant population/ha assumed by the model. Therefore this adjustment was only applied for the plots where the plant population <75000 plants/ha and P_{obs} is the observed plant population density in each plot.

a) The simulated sugar yield was also adjusted for weed density ($\check{y}_{adjw}$) for each field based on the equation of linear regression analysis between observed sugar yield and weed density (Fig 5.4 D-F) as follows:

$$\check{y}_{adjw} = \check{y} - \left(\mathbf{M_w} \times \sqrt{\mathbf{P_w}}\right) \qquad \textbf{Equation 5- 8}$$

Where $\sqrt{P_w}$ is the square root of the observed weed density in each plot, since the data of weeds was highly skewed (Chapter 4, Tables 4.1-4.3), the root square of the data was taken (see Table 5.2 for meanings of the symbols and their values).

The significance of the differences between the different adjustments was tested by calculating the *p* values for the differences between the correlation coefficients using a tool provided by Soper (2015), which is based on the method of Fisher (1921).

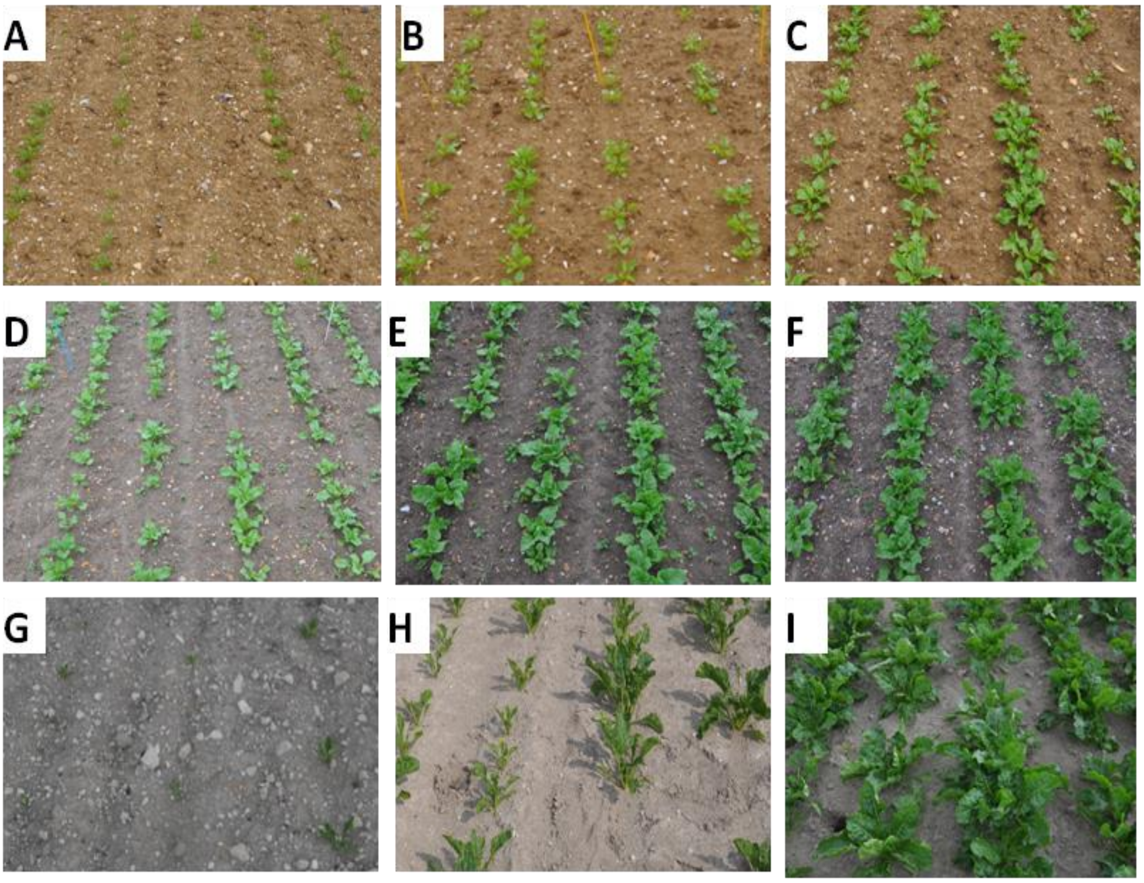


Figure 5.2: Images of the minimum (A, D, G), mean (B, E, H) and maximum (C, F, I) canopy cover in White Patch (A, B and C) and T32 (D, E and F) fields assessed on 1st of June 2012, and in WO3 (G, H and I) field assessed on 20th of June 2013. The canopy cover was lower than predicted by the model and also more variable.

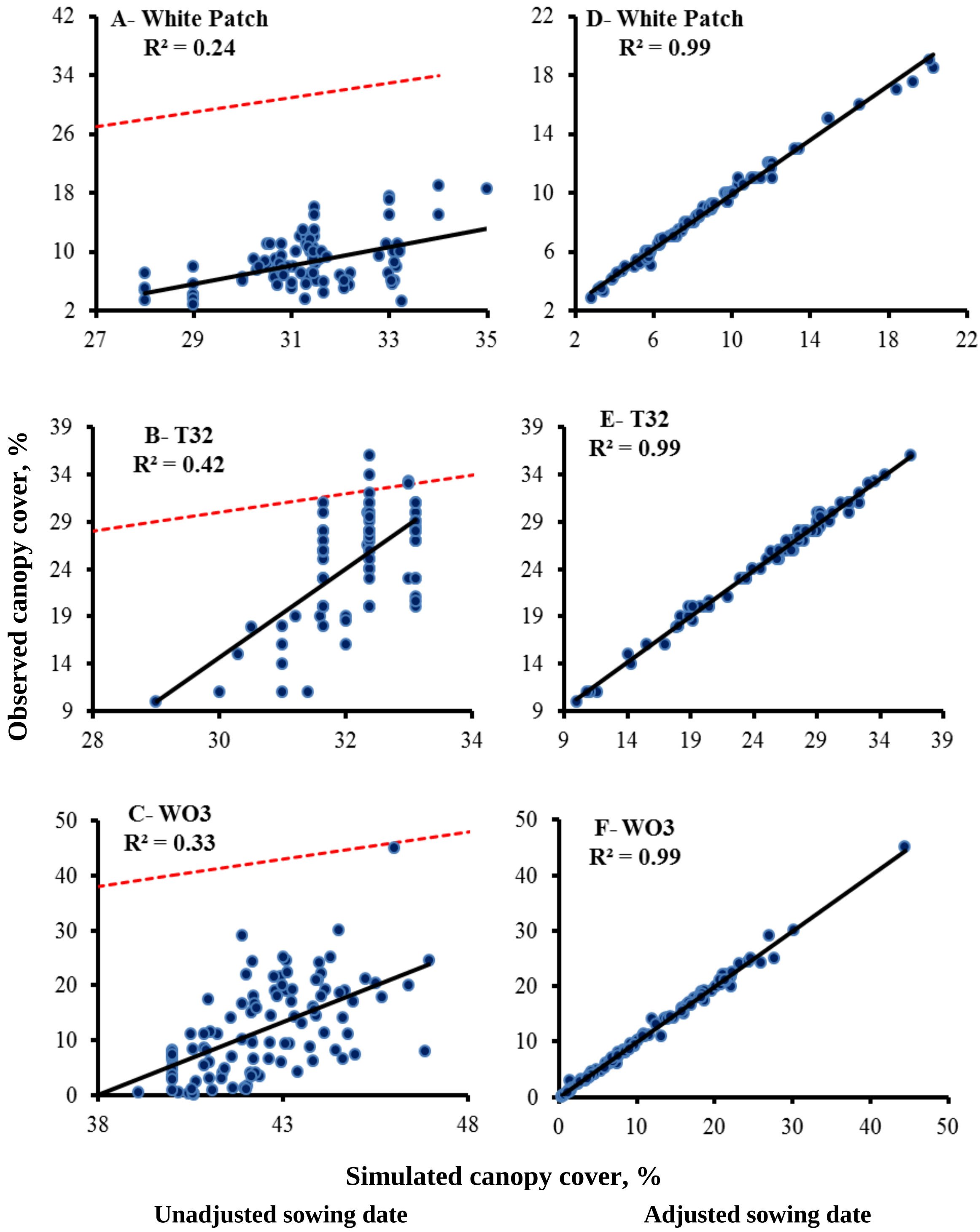


Figure 5.3: The relationships between observed and simulated crop canopy covers in June before (A-C) and after (D-F) adjusting the sowing date at White Patch (A, D), T32 (B, E) and WO3 (C-F). The one-to-one relationships were obtained by manually adjusting the sowing date for most plots, so that the simulated canopy in June was as close to the observed canopy as possible. In A-C the solid line is the regression line and the dashed line is the 1:1 relationship. In D-F the regression and 1:1 line are coincident.

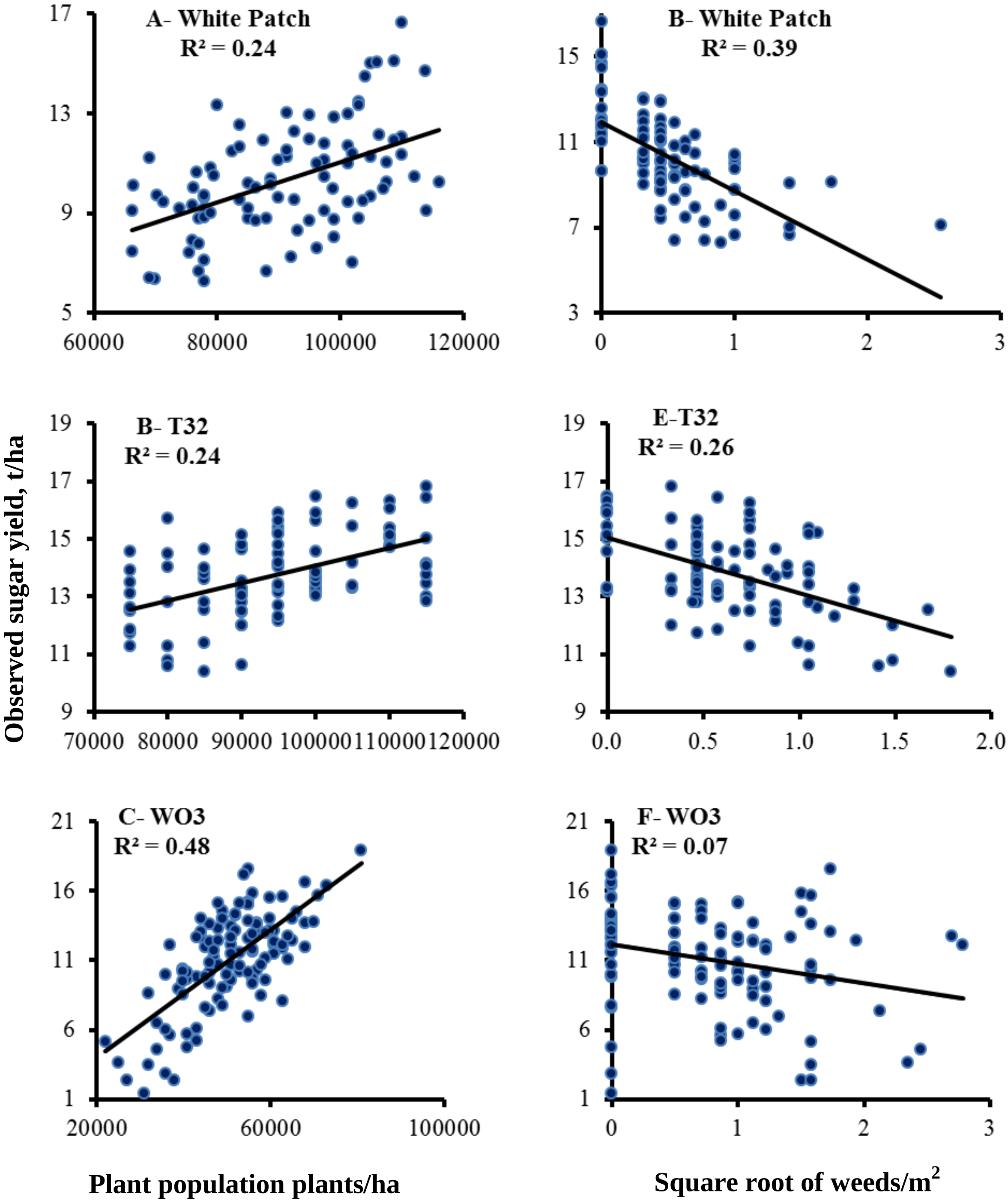


Figure 5.4: The relationships between observed sugar yield and plant population (A-C) and weed density (D-F) in White Patch (A, D), T32 (B, E) and WO3 (C, F). These relationships were used to adjust the simulated sugar yield in order to account for the effect of weeds and sub-optimal plant population.

5.3 Results:

In general, the unadjusted Broom's Barn sugar beet growth simulation model did not perform well to predict the sugar yield on a spatially variable basis within any field (Figs 5.5-5.7 A). In all three fields, the model overestimated the sugar yield in low yielding parts and, in White Patch and T32, underestimated it in high yielding parts. The relationship between simulated and observed sugar yields were therefore far from the one-to-one relationship, especially in WO3 field. The observed sugar yield ranged from 6.3 to 16.6, 10.4 to 16.8 and 1.4 to 18.9 t/h in White Patch, T32 and WO3 fields respectively, while the simulated sugar yields were much less variable ranging from 12.1 to 14.7, 13.1 to 15.8 and 15 to 21.1 t/ha respectively (Table 5.3). Therefore, the observed spatial variation was much higher than the simulations in all three fields, and the observed yields had higher CV values ranging from 10.5 to 31.8% compared to 4.3 to 5.3% for the simulations.

Although, the model over or under estimated sugar yield, some of the spatial variability in the observed yield was accounted by the simulated yield (Figs 5.5-5.7 A) and the maps of the simulated yield had some similar patterns of spatial variability as that for the observed sugar yields (Figs. 5.8-5.9 A and B), as some of low yielding areas had relatively low simulated yields and some high yielding areas were associated with higher simulated yield. The correlation coefficients between the simulated and observed sugar yield also significantly differed from 0 ($P<0.001$: Table 5.5) in all three fields. However, the performance of the model for spatial simulation differed from one field to another. Its performance was better in T32 field compared to the other fields, since the simulated yield accounted for 45% of the spatial variability in observed sugar yield with a lower Residual Mean Square (RMS) of 1.2 and a correlation coefficient (r) of 0.67 compared to other two fields (Table 5.4).

Table 5.3: Summary statistics of observed and simulated sugar yields t/ha and the relative yield gap between observed and simulated sugar yield.

	Mean	Min	Max	SD	CV
White Patch					
Observed sugar yield t/ha	10.3	6.3	16.6	2.2	21.1
Simulated sugar yield t/ha (Unadjusted)	13.3	12.1	14.7	0.6	4.3
Simulated sugar yield (t/ha)adjusted for					
Canopy in June	11.4	9.98	13.6	0.7	6.1
Weed density in July	12.6	9.64	14.7	0.91	7.3
Plant population	13.2	11.4	14.7	0.67	5.1
Canopy and weeds	10.3	6.8	14.3	1.3	12.7
Canopy and plant population	11.4	9.3	14.2	0.94	8.2
%Relative yield gap based on					
Original sowing date	22.6	-13	50.7	14.9	66
Adjusted for canopy in June	9.93	-22	39.6	14.8	149
For weeds	12.8	-13.1	42.9	12.2	95.9
For plant population	21.9	-13.1	47.7	14.3	65.2
For canopy and weeds	0.05	-17.9	28.2	11.4	23224
For canopy and plant population	10.5	-17.0	38.1	13.2	125.5
T32					
Observed sugar yield t/ha	13.8	10.4	16.8	1.4	10.5
Simulated sugar yield t/ha (Unadjusted)	14.3	13.1	15.8	0.7	4.6
Simulated sugar yield (t/ha)adjusted for					
Canopy in June	14.1	11.8	16.2	1.0	7.1
Weed density in July	13.0	10.1	15.6	1.2	8.9
Plant population	14.3	13.0	15.8	0.68	4.7
Canopy and weeds	12.7	9.1	16.2	1.5	11.8
Canopy and plant population	14.0	11.6	16.2	1.0	7.3
%Relative yield gap based on					
Original sowing date	3.9	-15.4	23.8	7.9	201
Adjusted sowing date	2.1	-7.1	19.5	5.6	260
For weeds	3.7	-15.4	23.8	7.7	208
For plant population	-6.2	-24.8	8.3	7.2	116
For canopy and weeds	1.9	-7.1	18.4	5.4	283
For canopy and plant population	-8.7	-26.6	6.3	6.5	75
WO3					
Observed sugar yield t/ha	11.1	1.4	18.9	3.5	31.8
Simulated sugar yield t/ha (Unadjusted)	19.2	15	21.1	1.0	5.3
Simulated sugar yield (t/ha)adjusted for					
Canopy in June	16.4	12.7	19.5	1.2	7.6
Weed density in July	18.1	13.2	21	1.5	8.4
Plant population	14.4	6	21	2.6	18.1
Canopy and weeds	15.3	9.9	19.5	1.8	11.7
Canopy and plant population	11.5	4.0	19.5	3.1	26.6
%Relative yield gap based on					
Original sowing date	42.9	10.0	90.7	17.3	40
Adjusted sowing date	33.6	3.1	89.3	18.2	54
For weeds	39.6	3.4	90.2	17.7	45
For plant population	24.6	-3.5	76.7	17.8	72
For canopy and weeds	28.9	-5.1	87.6	18.6	65
For canopy and plant population	5.1	-32.2	65.2	18.9	378

Table 5.4: Correlation coefficients and the parameters of linear regression between observed and simulated sugar yield t/ha, and adjusted simulated yield.

	Intercept	Slope	Se_c	Se_a	*r*	R^2	RMS
White patch							
Simulated sugar yield t/ha (unadjusted)	-14.7	1.9	4.7	0.35	0.50	23	3.6
Simulated sugar yield (t/ha)adjusted for							
Canopy in June	-18.7	2.6	2.2	0.19	0.81	66	1.6
Weed density in July	-12.1	1.8	2.1	0.17	0.75	56	2.1
Plant population	-16.6	2.0	3.6	0.27	0.63	39	2.9
Canopy and weeds	-5.1	1.5	0.8	0.08	0.90	81	0.9
Canopy and plant population	-12.2	2.0	1.5	0.13	0.85	72	1.3
T32							
Simulated sugar yield t/ha (unadjusted)	-7.6	1.5	2.5	0.18	0.67	45	1.2
Simulated sugar yield (t/ha)adjusted for							
Canopy in June	-3.7	1.2	1.1	0.08	0.86	75	0.5
Weed density in July	1.2	0.97	1.1	0.08	0.77	59	0.8
Plant population	-8	1.5	2.3	0.16	0.70	48	1.1
Canopy and weeds	3.1	0.84	0.6	0.05	0.87	75	0.5
Canopy and plant population	-3.5	1.2	1	0.07	0.87	76	0.5
WO3							
Simulated sugar yield t/ha (unadjusted)	-28	2	5.1	0.27	0.58	34	8.2
Simulated sugar yield (t/ha)adjusted for							
Canopy in June	-29.6	2.5	2.1	0.13	0.87	77	2.9
Weed density in July	-14	1.4	3.2	0.17	0.61	36	7.9
Plant population	-4.8	1.1	1.1	0.07	0.81	66	4.2
Canopy and weeds	-13	1.6	1.7	0.1	0.81	65	4.2
Canopy and plant population	-0.3	0.98	0.67	0.06	0.86	73	3.3

c: intercept, a: slope, Se_c and Se_a: standard error for the intercept and slope, *r*: correlation coefficient, R^2:determination coefficient and RMS: residual mean square.

In WO3, the simulated yield accounted for 34% of the variation in the observed yield, which was higher than 24% in White Patch, but the relationship was closer to 1:1 in White Patch (Table 5.4). However, the correlation coefficient between the observed and simulated yield in T32 does not significantly differ from those in White Patch and WO3 (*P*= 0.08 and 0.3, respectively).

The difference between the observed and simulated yields throughout each field is expressed by the relative yield gap, which also indicates the model performance in different parts of field (Figs 5.8-5.10 D). The mean relative yield gap was higher 42.9% in WO3 and ranged from 10-90.7%, while it was lower and ranged from -13 to 50.7 % in White Patch and lowest in T32, where it ranged from -15.4 to 23.8 %. This means that the model overestimated the yield throughout WO3, but it was overestimated in some parts and underestimated in other parts in White Patch and T32 fields (Table 5.3). These results suggest that although the model was not efficient enough for spatial simulation within-field, its efficiency was less in the case of high spatial variability, as it performed better in T32 field, which had lower spatial variability compared to the other fields. Furthermore, the amount of spatial variation in observed sugar yield accounted for by the model might reflect the effect of spatial variation in some inputs driving sugar beet growth and yield such as air temperature, solar radiation, potential evapotranspiration and soil texture.

5.3.1 Where the simulation was poor and why?

In all three fields, the relative yield gap between observed and simulated sugar yield was higher in the low yielding parts of the field. Although the simulated yield did not match the observed yield in most parts of the field, the differences were much higher in low yielding parts, since the yield was highly overestimated in these parts (Figs 5.8-5.10 C). This could be because the model simulates the spatial variability in sugar beet growth and yield as a function of temperature, solar radiation, evapotranspiration and soil type, which was not sufficient to account for the majority of the variability in observed sugar yield. A higher simulated sugar yield in low yielding parts of the field, is because the model assumes a favorable growth condition and it takes no account of other factors that might cause significant losses in yield. These factors could be a biotic stress such as diseases, pests and weeds, inadequate crop nutrients or sup-optimal crop density. For example, most of the higher positive yield gaps occurred in the areas where there was a higher weed density and lower soil organic matter content in White Patch and T32 fields (Figs 5.8 and 5.9 D), which means that some of the differences between observed and simulated sugar yield was caused by weeds and low organic matter. In WO3 field however, the higher yield gaps occurred mainly in the areas where there was poor plant establishment and soil available magnesium. The model assumes a plant population of >75000 plants/ha, but the observed plant population in WO3 field ranged from 22000 to 67000 plants/ha for the majority of plots. Therefore the yield gap was in general positive and high in WO3 field, especially in the southeast part of the field which had the lowest plant population. In addition, the model assume a rapids expansion in crop canopy cover immediately after 50% of crop emergence as a result of accumulated air temperature, which means an increase in radiation use efficiency and accumulation of dry matter and consequently the sugar yield. However, the observed canopy cover measured in June spatially varied throughout each field and was generally much lower than the simulated canopy cover on the same day. The differences between the observed and simulated canopy covers are evident in Figure 5.2. A reason for poor simulation for crop canopy development could be that the model accounts for the variability in soil types in relation to soil available water only, but it does not consider the variability in crop development caused by the variability in soil types (Qi *et al*., 2005), and the effect of soil type on crop emergence which might cause variability in crop density and consequently crop cover. Therefore the crop cover was over estimated in most cases and the crop behaves as though as it was sown later than the actual sowing date in most of the plots in each field.

Table 5.5: The significance (*P* values) of the correlation coefficients between observed and simulated sugar yield (adjusted and unadjusted) against 0 and against unadjusted simulated sugar yield and adjusted for canopy cover in June:

	Zero	Simulated yield (unadjusted)	Simulated yield adjusted for Canopy in June
White patch			
Simulated sugar yield (unadjusted)	<0.001	-	
Simulated sugar yield adjusted for			
Canopy in June	<0.001	<.001	-
Weed density in July	<0.001	<.005	N
Plant population	<0.001	0.20	N
Canopy and weeds	<0.001	<.001	0.02
Canopy and plant population	<0.001	<.001	N
T32			
Simulated sugar yield (unadjusted)	<0.001	-	
Simulated sugar yield adjusted for			
Canopy in June	<0.001	0.0014	-
Weed density in July	<0.001	0.16	N
Plant population	<0.001	0.71	N
Canopy and weeds	<0.001	<0.001	0.79
Canopy and plant population	<0.001	<0.001	0.79
WO3			
Simulated sugar yield (unadjusted)	<0.001	-	
Simulated sugar yield adjusted for			
Canopy in June	<0.001	<0.001	-
Weed density in July	<0.001	0.73	N
Plant population	<0.001	<0.001	N
Canopy and weeds	<0.001	<0.001	N
Canopy and plant population	<0.001	<0.001	N

*N: means the test is not performed, since the correlation is less than the previous one.

5.3.2 Adjustments made to model inputs and simulated yield:

The initial use of the model based on the actual sowing dates resulted in a poor simulation of sugar yield, which is mainly associated with poor simulation of crop canopy development. To improve the simulation of sugar yield, the crop canopy was corrected by adjusting the sowing date for each plot in order to obtain a 1:1 relationship between the observed and simulated canopy covers in June (Fig 5.2 and 5.3).

After adjusting the sowing dates for June canopy cover, the simulation of sugar yield significantly improved ($P < 0.001$) in all three fields (Figs 5.5-5.7, B). The percentage of spatial variability in observed sugar yield accounted for by the simulated yields was increased by adjusting the sowing date from 23, 45 and 34% respectively in White Patch, T32 and WO3 to 66, 75 and 77% respectively (Table 5.4). The CVs of simulated yields were, however, still lower than for the observed yields (Table 5.3), the patterns of spatial variability in simulated sugar yield were similar to that for observed sugar yield, since most of high yielding areas were associated with high values of simulated yield and the same is true for low yielding areas (Figs 5.8-5.10, C). The mean relative yield gap between the observed and simulated sugar yield was decreased (Table 5.3). However, the relation between observed and simulated yield was improved in terms of spatial variability only, and the yield gap was still high, especially in low yielding areas (Figs 5.8-5.10, E). Despite these improvements, it was still far from a one-to-one relationship, since the simulated yields were not matching the observed yields in White Patch and WO3 (Figs 5.5 and 5.7 B), although it was much better for T32 (Fig 5.6 B) with an RMS of 0.5 (Table 5.4). This suggests that further adjustments are needed. Therefore, the simulated sugar yield based on original and adjusted sowing date was further adjusted based on the relationship between the observed sugar yield and plant population and weeds.

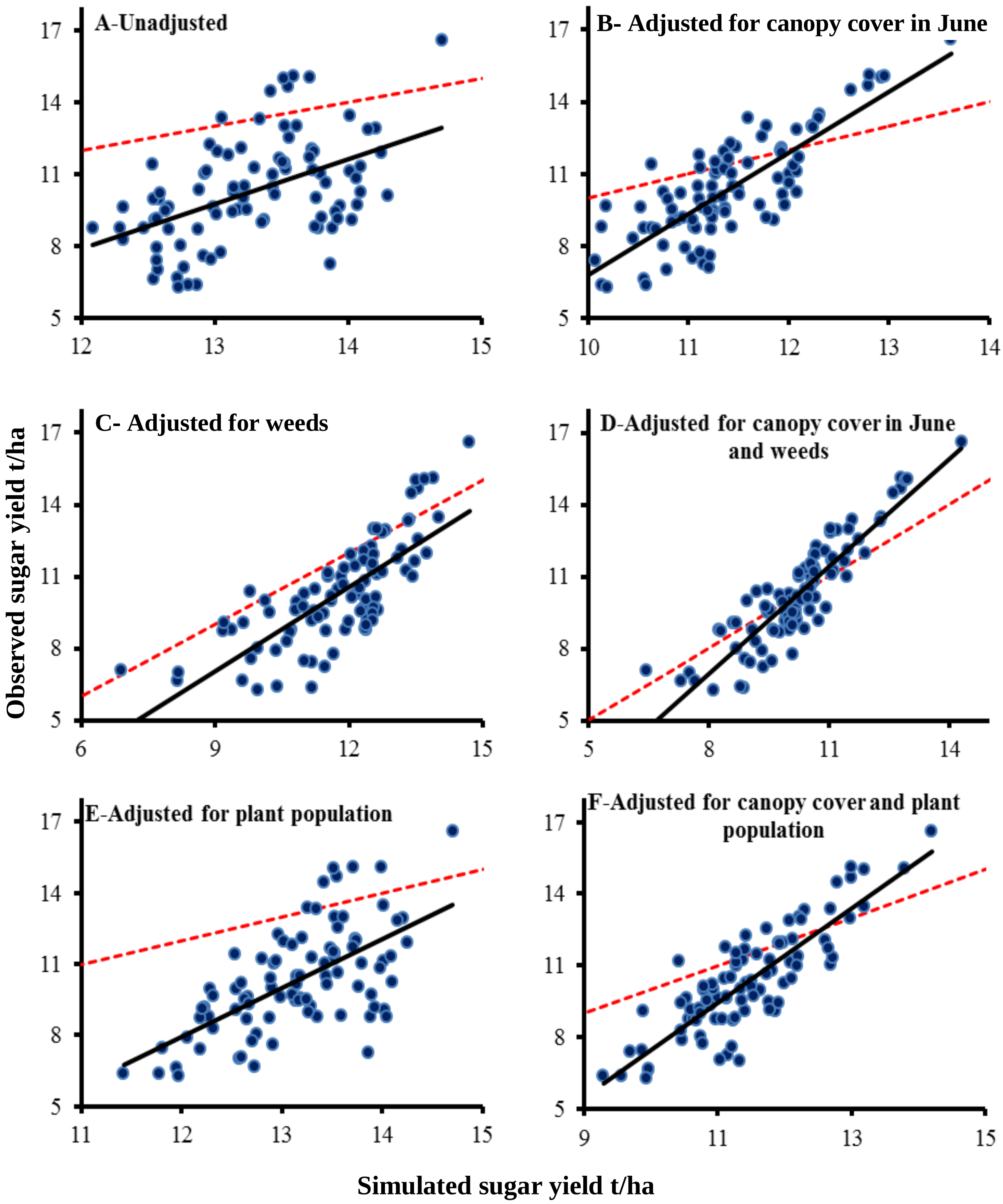


Figure 5.5: The linear relationships between observed and simulated sugar yield (A) unadjusted, (B) adjusted for canopy cover in June, (C) adjusted for weeds, (D) adjusted for canopy cover and weeds, (E) adjusted for plant population and (F) adjusted for canopy cover and plant population in White Patch field in 2012. The solid line is the regression line and the dashed line is the one-to-one relationship.

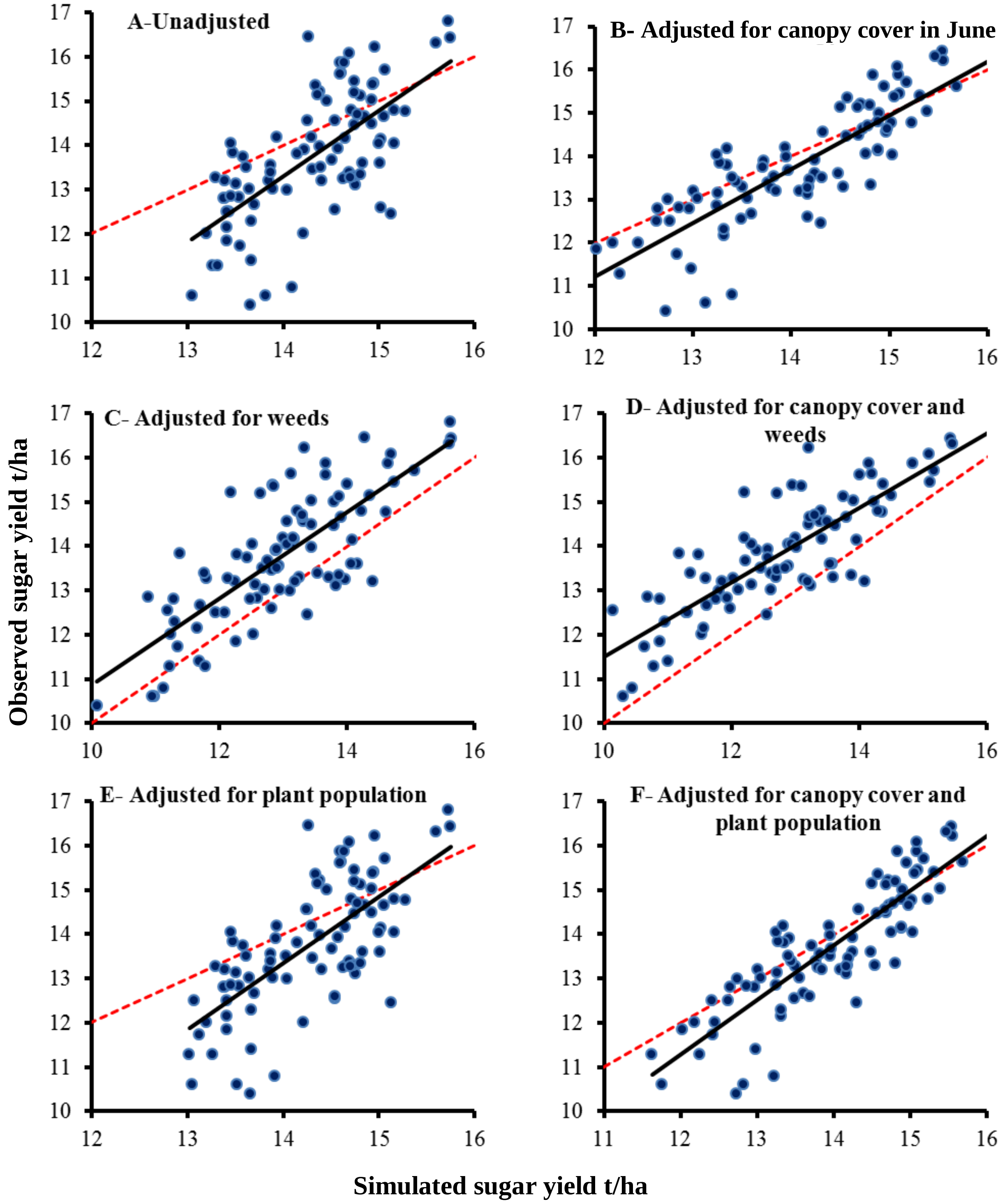


Figure 5.6: The linear relationships between observed and simulated sugar yield (A) unadjusted, (B) adjusted for canopy cover in June, (C) adjusted for weeds, (D) adjusted for canopy cover and weeds, (E) adjusted for plant population and (F) adjusted for canopy cover and plant population in T32 field in 2012.The solid line is the regression line and the dashed line is the one-to-one relationship.

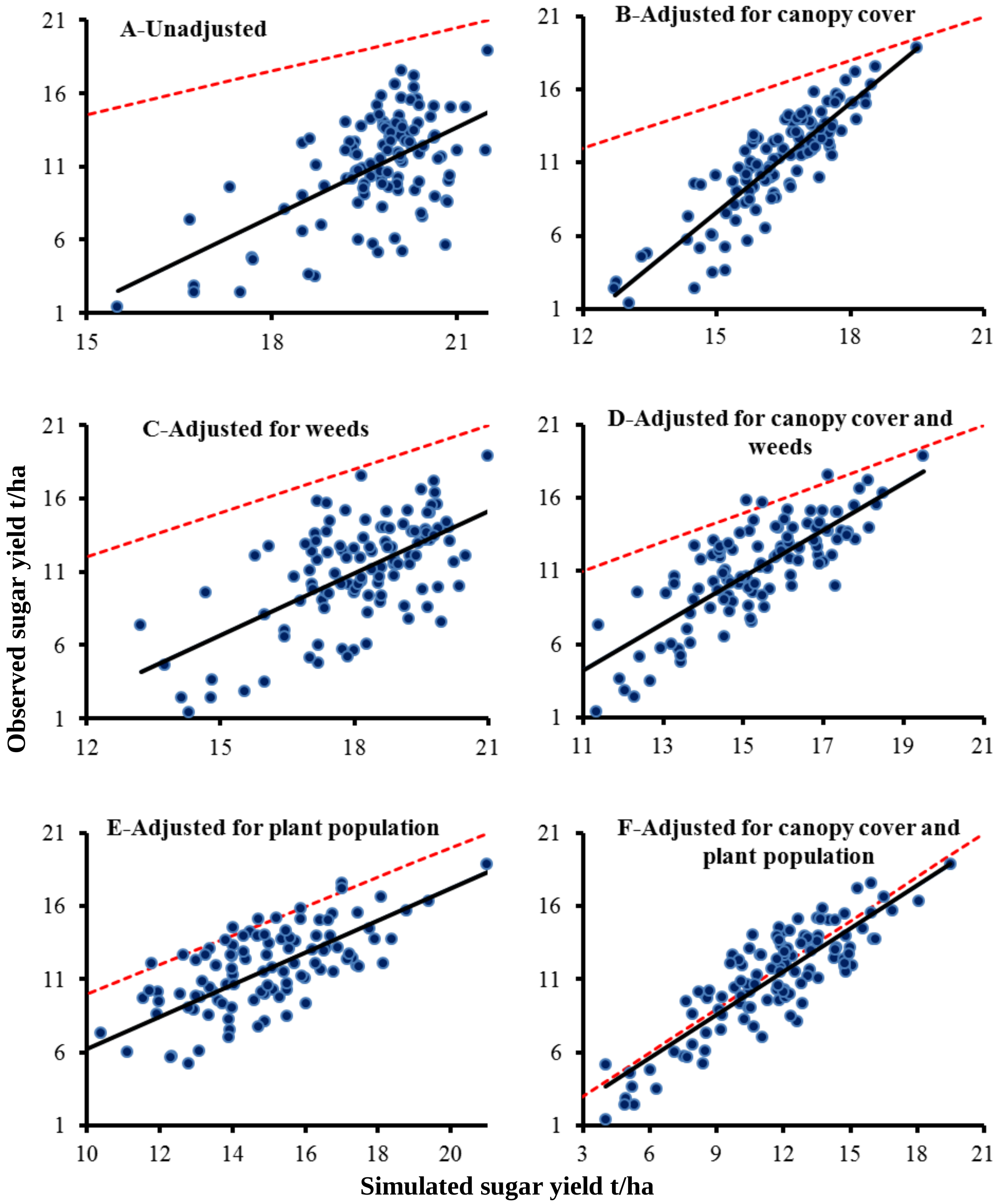


Figure 5.7: The linear relationships between observed and simulated sugar yield (A) unadjusted, (B) adjusted for canopy cover in June, (C) adjusted for weeds, (D) adjusted for canopy cover and weeds, (E) adjusted for plant population and (F) adjusted for canopy cover and plant population in WO3 field in 2013.The solid line is the regression line and the dashed line is the one-to-one relationship.

The relationship between observed and simulated yield based on original sowing date was improved when the effects of weeds and plant density were both considered in all three fields (Figs 5.5-5.7, C and E). The patterns of the spatial variability became more similar to that for observed yield compared to unadjusted simulated sugar yield and reduced the yield gap in the areas where some of the yield losses due to weeds or sub-optimal plant population density (Appendices 8), but the improvements were smaller than by adjusting the sowing date. Adjusting the simulated yield based on weeds improved the correlation between the observed and adjusted simulated yield in all three fields (Table 5.4), but the improvement was statistically significant only in White Patch field (P<0.005: Table 5.5) (Fig. 5.5 C).

On the other hand, the correlation coefficient was significantly improved only in WO3 (P<0.001: Table 5.5) and the differences between observed and simulated sugar yield significantly decreased when the simulated yield was adjusted for plant population (Table 5.3 and 5.4), which makes the relationship closer to 1:1 (Fig 5.7E).

In T32, the relationship between observed and simulated yields was improved when the simulated yield based on corrected canopy cover was adjusted for plant population or weeds (Fig 5.6 E and F), compared to unadjusted simulated yield, but the improvements were not significantly different (Table 5.5) from that obtained by adjusting for canopy cover only (Table 5.4). Therefore, adjusting the sowing date for corrected crop canopy cover can be considered as the best adjustment that can be made to obtain the simulation by the model.

In White Patch field, the simulated yield based on corrected canopy cover was further improved when adjusted based on weeds (Fig. 5.5 D). It accounted for 81% of the variation in observed yield with the lowest RMS of 0.9. The correlation coefficient between observed and simulated yield was also improved and reached 0.90, which was statistically higher (P<0.02: Table 5.5) than the 0.81 (Table 5.4), which was obtained by adjusting sowing date only. Therefore, this can be considered as a best relationship, since it also reduced the yield gap between simulated and observed yield (Table 5.3) (Appendix 8.1).

In WO3, the best relationship between observed and simulated yields was obtained when the simulated yield based on corrected canopy cover was adjusted for plant population (Fig 5.7 F), although the correlation was not statistically different (Table 5.5) from that obtained by adjusting for canopy cover only (Table 5.4), but the relationship became very close to 1:1 when adjusted for plant population and the patterns of variation became more similar to that for the observed yield (Appendix 8.3), suggesting that most of the variability in sugar yield in this field was due to the variability in plant population density.

The relationship between simulated and observed sugar yield was also tested by combining all three adjustments (canopy cover, weeds and plant population) to simulated yield. The relationships was not significantly different than those obtained based on one or two adjustments in all three fields, therefore it was not included in the results and the figures were not presented.

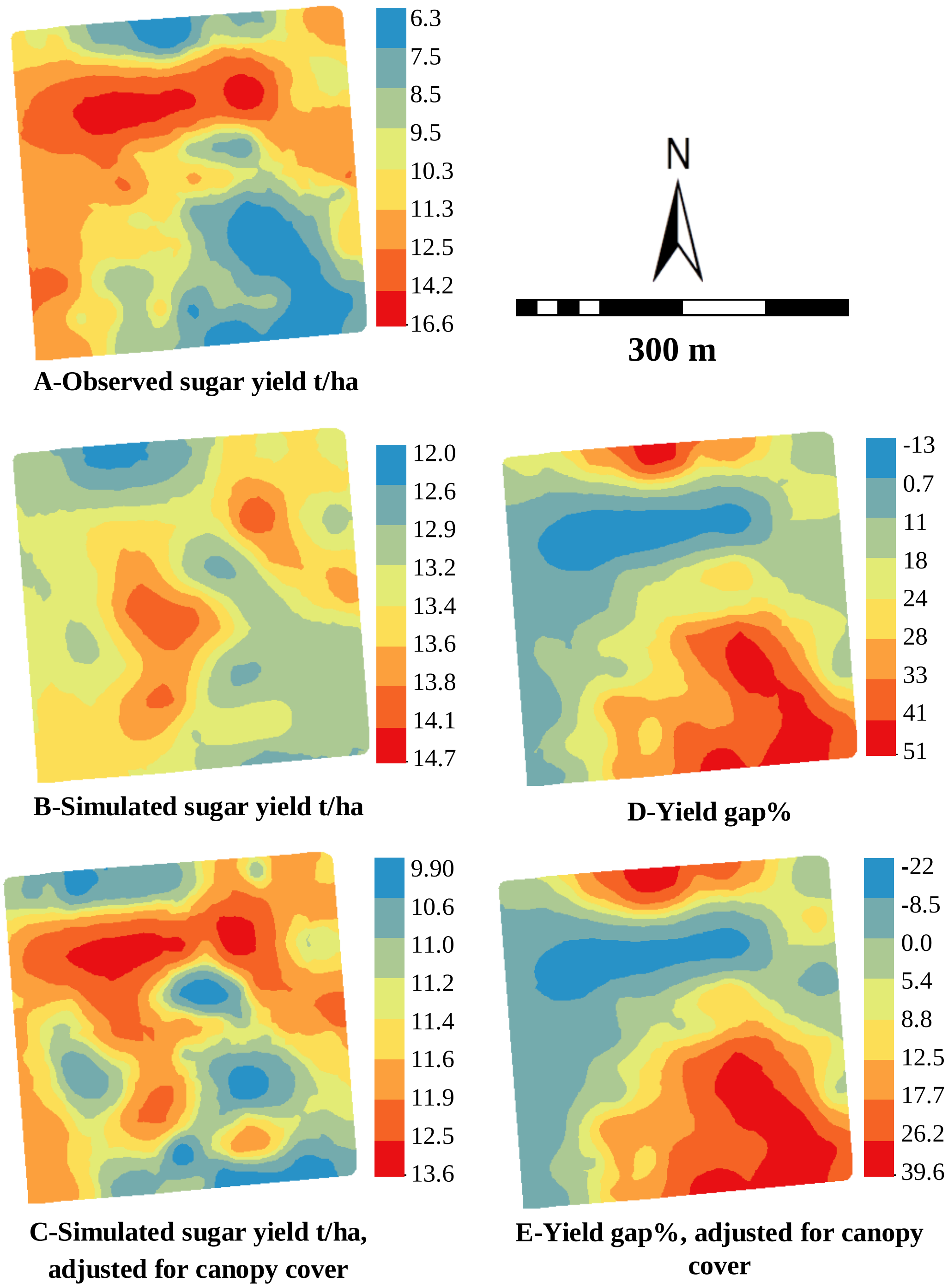


Figure 5.8: The interpolation maps for the observed and simulated sugar yield t/ha and the relative yield gap based on adjusted and unadjusted sowing dates in White Patch field in 2012. Variograms and model parameters are in Appendix 7.1 and 7.2.

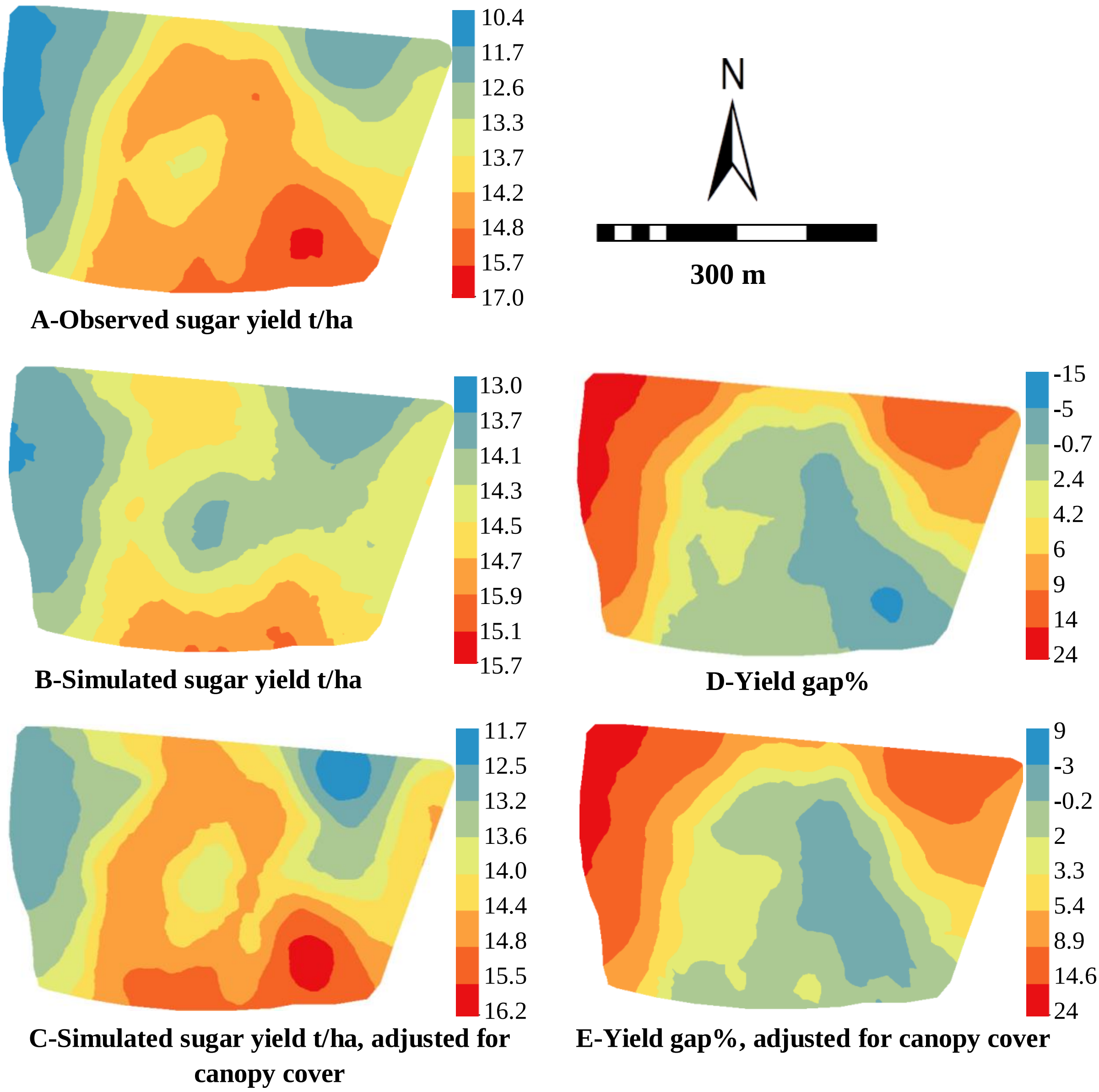


Figure 5.9: The interpolation maps for the observed and simulated sugar yield t/ha and the relative yield gap based on adjusted and unadjusted sowing dates in T32 field in 2012. Variograms and model parameters are in Appendix 7.1 and 7.2.

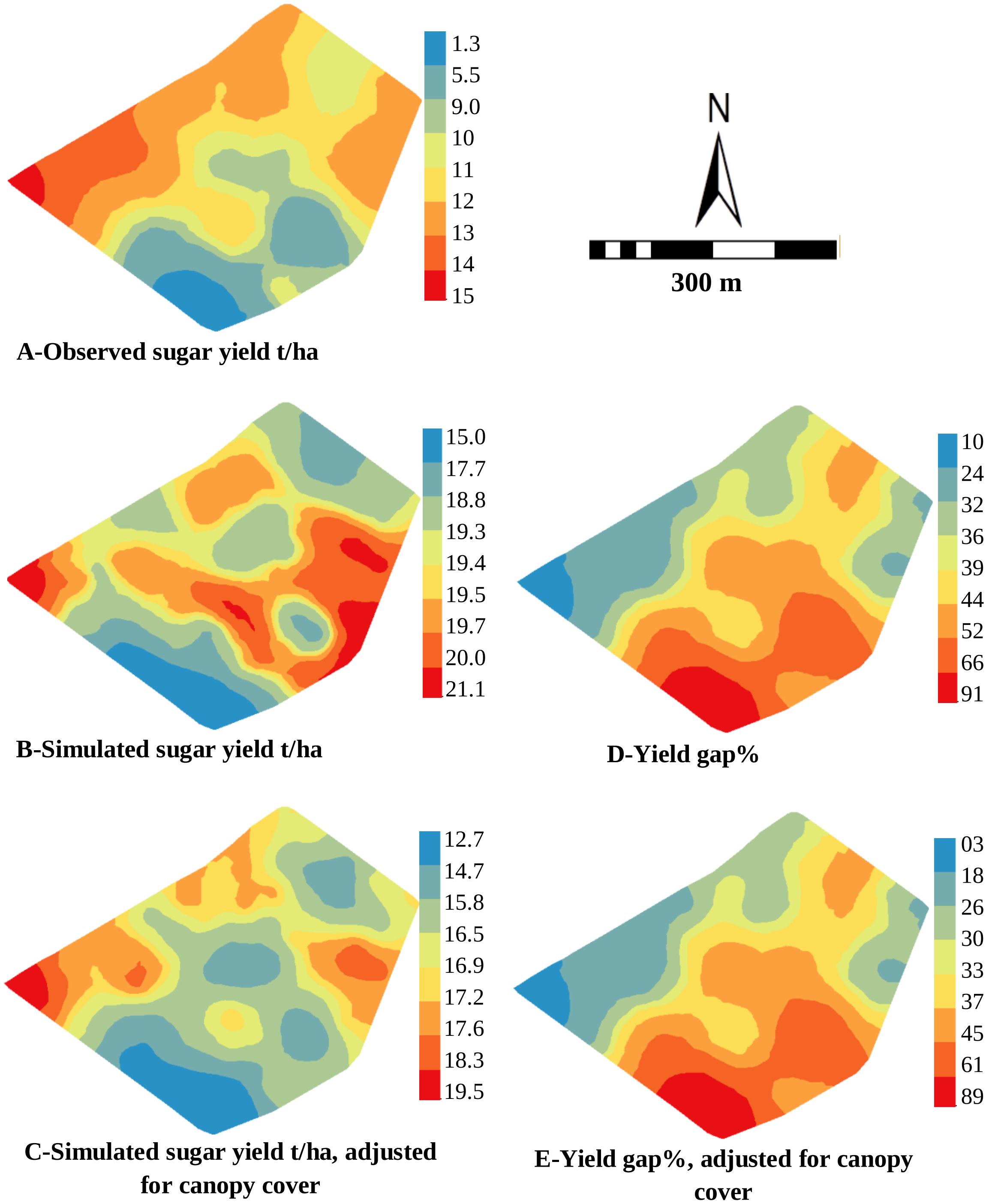


Figure 5.10: interpolation maps for the observed and simulated sugar yield t/ha and the relative yield gap based on adjusted and unadjusted sowing dates in WO3 field in 2013. Variograms and model parameters are in Appendix 7.1 and 7.2.

5.4 Discussion:

Using the Broom's Barn sugar beet growth simulation model, with its initial parameters on a spatially variable basis, the sugar yield was overestimated in some parts and underestimated in others. The spatial variability was much lower in simulated yield than in observed sugar yield. However, the model was able to account for some of the spatial variability in sugar yield and the simulated yield had some similar patterns of spatial variability as that for the observed yield. Although the percentage of variation accounted by the model was not as high as that obtained when applying the model on a regional basis (Qi *et al*., 2005, Jaggard *et al*., 2007), a stronger relationship might not be expected, since it reflects only the effect of variability in weather variables and soil types. In addition the performance of the model for spatial simulation of sugar yield differed from one field to another, which had different soil types and weather conditions. It performed better in T32 field in 2012, which had lower spatial variability compared to other fields and it highly overestimated the sugar yield in WO3, which had a higher spatial variability. This suggests that the model was less efficient to simulate the sugar yield in case of higher spatial variability than low spatial variability, especially when the crop is rain-fed, since it reflects the variability in rainfall and evapotranspiration in addition to temperature, radiation and soil types (Jaggard *et al*., 2007). Hakojärvi *et al*. (2013) used another model to simulate the yield of cereal on a spatially variable basis, and they also found that the model performed better in the case of lower spatial variability. The low performance of the Broom's Barn model in this study might be due to some other factors such as weeds and diseases, since the model ignores the yield losses due to these causes. Secondly, nutrient status, the model assumes adequate availability of all soil nutrients, whereas in fact the distribution of soil nutrients might spatially vary and could be inadequate in some parts of the field. Finally, sub-optimal crop density, since the model assumes a plant population of >75000, while in some plots it might be much less than this, and this was evident in WO3 field. Therefore, the relative yield gap was higher in low yielding areas which had a higher weed density and low organic matter in White Patch and T32 fields and poor plant establishment in WO3, while the simulated yield did not match observed yield in high yielding parts, which might have had better growth conditions.

Most of unresolved variation could be explained by a poor simulation of early crop canopy development by the model, since the model takes into account the effect of different soil types in relation to available water, but it does not account for the variability in soil types in relation to canopy development (Qi *et al*., 2005) and its effect on availability of nutrients. Adjusting the sowing date to make the simulated canopy cover match the observed canopy cover on a specific day early in the growing season with one-to-one relationship significantly improved the simulation in all three fields. The patterns of spatial variability in the simulated and observed sugar yield became more alike when the simulated crop canopy was corrected. Therefore, the availability of measurement of early crop canopy cover is important to obtain a better simulation of within-field variability in sugar yield. The relationship between observed and simulated sugar yield after correcting the canopy cover was further improved in White Patch when the effect of weeds was considered, while in WO3 the differences between simulated and observed yield was decreased and became very close to 1:1 relationship with considering the variability in plant population, but it did not improved the correlation, since most of the variability in plant population was already reflected by the crop canopy cover, therefore, adjusting the sowing date for correcting crop canopy cover an adequate adjustment to improve the simulation of sugar yield early in the growing season. In a study conducted by (Jégo *et al*.,

2012) on modelling the growth of some crops (soybean, corn and spring wheat) over ten years, they found a significant improvement in the performance of the models when they re-initialized some input parameters based on the data of LAI provided by remote sensing. They found a great improvement in the simulated yield and biomass when they re-initialized the sowing date to correct the simulated LAI based on actual LAI provided by the remote sensing.

The initial use of model without any adjustments cannot therefore provide a reliable simulation of sugar yield within-field, but rather it can be useful to isolate the effects of weather conditions and soil type from the effects of abiotic factors and other soil properties. For reliable spatial simulation, an assessment of crop biomass is required, so that the simulated biomass can be adjusted accordingly or it needs further development to take into account the potential effect of other variables, which may significantly improve the efficiency of the model to simulate sugar yield under variable growth condition.

5.5 Conclusion:

Applying the Broom’s Barn sugar beet growth model based on spatially variable inputs of weather and soil type, the simulated yield accounted for 23, 45 and 34% of the variability in observed sugar yield. This means that the model can predict the variability in sugar yield to some extent that is related to some of the inputs driving the crop growth and yield such as temperature, solar radiation, potential evapotranspiration and soil type. However, the simulated yield was much higher than the observed yield and much less variable, since the model takes no account of some other factors than can significantly reduce the yield such as weeds, diseases and nutrient status. The simulation was significantly improved when the sowing date was adjusted to correct the crop canopy cover. After correcting the canopy cover the simulated yield accounted for 66, 75 and 77% of the variation in observed yield. The simulation was further improved and the yield gap was decreased when the effect of weeds and plant population were considered, especially in White Patch and T32 fields. Therefore, to use the model on a spatially variable basis, an assessment of crop canopy should be available and the simulated crop canopy cover can then be calibrated accordingly. In addition, the model needs to be further developed to include the effect of some other factors such as weeds, diseases, nutrient availability and plant population, and to allow it to be linked to LAI data obtained by remote sensing early in the growing season.

6. Chapter Six: General Discussion and Conclusions.

Within-field variability in sugar beet yield is still unknown and the uniform management of agronomic inputs is still the common approach in most commercial sugar beet fields in the UK. A uniform application of agronomic inputs might increase the yield, but it can also be associated with an increase in the costs of production and may adversely affect the environment, which are other growing concerns nowadays. Therefore, a precise investigation of within-field variability in crop growth conditions such as soil properties, field topography and canopy temperature and how they relate to each other was undertaken to understand the nature of each field (Chapter three).

It was also important to investigate the within-field variability in sugar beet growth, yield and quality and link it to the variability in environmental variables, so that the main associated environmental variables, which are likely to be the main driving variables can be addressed. The spatial variability in sugar beet fields was also investigated in some other studies, but most of these studies considered only a single environmental variable such as soil organic matter (Karaman *et al*., 2009a), soil nutrients (Franzen, 2004, Karaman *et al*., 2009b), soil moisture content (Zhang *et al*., 2007, Zhang *et al*., 2011a), or diseases and nematodes (Reynolds, 2010, Hbirkou *et al*., 2011). Most importantly and surprisingly, the spatial relationship between the studied environmental variable and sugar beet growth or yield was not examined, and thus it is not known if the studied variable was actually limiting the yield. Nevertheless, detecting the spatial variability in sugar beet yield in relation to the independent and combined effects of different environmental variables is highly desirable and is likely to be important to achieve optimal sugar beet growth and yield. In addition, an early prediction of the spatial variability in crop yield could add great value to the implementation of precision agriculture as it will inform management practices, which can be carried out on a spatially-variable basis early in the growing season. Therefore, the within-field variability in sugar beet growth was monitered early in the growing season and the relationship between the spatial variability in sugar beet yield and the yield of the previous crop was also examined (Chapter four).

Since the sugar beet crop growth simulation model simulates the sugar yield as a function of some environmental factors such as air temperature, solar radiation and soil type in relation to soil available water, all of which might spatially vary within-field, the potential of simulating the sugar yield on a spatially variable basis using the Broom's Barn sugar beet growth model was also investigated (Chapter five). This new application of the model was used to simulate the potential yield in different parts of the field, which, in conjunction with the prediction and relationships identified in chapter four can help to determine whether any site-specific interventions would be useful or not.

To achieve these objectives, two commercial sugar beet fields (White Patch and T32) in 2012 and one (WO3) in 2013 were selected based on known intra-field variability and sampled using an irregular grid with some nested samples. The sugar beet growth and yield and associated environmental variables were measured at each plot and the data were analysed statistically and geostatistically.

6.1 Was there any spatial variability?

The distribution of most environmental variables was found to be variable and appeared as patches with high and low values throughout each field. Most of the growth parameters also varied spatially at different growth stages. Consequently, the yield value of sugar beet, which is the ultimate interest of the farmer, also spatially varied throughout each field. A significant spatial variability in sugar beet growth, yield and some associated environmental variables in all three fields was confirmed by the experimental variograms and high CV values, the latter referring to the degree of spatial variability in the field rather than the accuracy as in conventional statistics. The variability in final yield within each field was related to the spatial distribution of environmental variables. Some variables such as weed density and available soil nutrients had the highest spatial variability, while some others such as soil pH and percentage of sugar had the lowest. A high spatial variability in available soil nutrients was also found in some other studies and they indicate the importance of site specific fertilizer application for crop management (Wortmann *et al*., 2009, Montanari *et al.*, 2012).

The maps produced by ordinary punctual Kriging clearly identified the high and low yielding areas of each field. Although, ordinary block Kriging is recommended for precision agriculture, since the agricultural machinery cannot vary inputs on a continual basis (Heege, 2013, Oliver and Webster, 2014), the main aim of using Kriging maps in this study is to understand the spatial variability in crop growth and yield in relation to some environmental variables rather than for managing the field. Therefore, it was important to look at the spatial variability at points rather than within large management blocks.

Despite the uniform management across each field with the farmer being responsible for all operations, the observed spatial variability in the final economic yield was significant within each field and some parts of each field looked as though as they were not responding to the treatments. Therefore, a uniform management of sugar beet fields is no longer recommended; it would be better to increase the inputs in some parts of the field and decrease them in others (Bouma, 1997, Pati *et al*., 2011, Oliver *et al*., 2013). Optimizing sugar beet yield with possibility of reducing the amount of the inputs can significantly increase the gross margin of the farmer, especially, if this variability is linked to identifiable variables, which can be managed, as the map of sugar beet growth and yield does not represent the actual stress, but rather the crop's response to stress (Jones and Schofield, 2008).

6.2 Was the sampling scheme efficient?

The observed variation was almost isotropic in all three fields and mostly spatially dependent, which means the variation was similar in all directions and a function of the separation distances between sampling points (Piccini *et al*., 2014). Therefore the irregular grid sampling scheme followed in each field was efficient, since it accounted for the majority of the spatial variation which occurred in each field. Grid sampling was found to be an efficient sampling design to detect the within-field variability in environmental variables and to develop a map for variable rate applications (Kerry *et al*., 2010, Franzen, 2011). It is also considered as the most appropriate design for geostatistical applications, since it provides an even distribution of the spatial data for Kriging interpolation (Webster and Lark, 2012, Webster and Oliver, 2007), especially the irregular grid, as the shapes of many agricultural fields are irregular (Webster and Oliver, 2007). Locating some nested samples purposively in this study based on the previous yield map in WO3 and soil map in White Patch, improved the prediction and represented the scale of the variation (Pereira *et al*., 2013), by reducing the prediction error and the nugget variance. However, the nugget variance was high for some variables in T32 field, which could be the unresolved variation due to the larger sampling intervals than in the other two fields or measurement error (Webster and Oliver, 2007, Oliver, 2010), which suggests that the minimum sampling intervals for detecting within-field variability, should not be as much as 20 m as it was in

T32 field. The nugget variances for root yield and yield value were also high in WO3, which could be due to high spatial variability in plant population density, which caused erratic variation over short distances.

In general, the variograms for almost all variables reached the sill in all fields, which means the maximum variance was covered by the sampling scheme. In addition, the degree of spatial dependency was strong to moderate for most of the studied variables in all three fields, indicating that the distribution of the samples and their separation distances were optimum. However, a reliable variogram requires at least 100 samples (Webster and Oliver, 2007, Oliver and Webster, 2014) and this may not be affordable by sugar beet farmers. Therefore, attempts should be made to predict the final root yield from the spatial variability in crop growth parameters such as canopy cover and LAI (Jayanthi, 2003, Zhang, 2011, Cao *et al*., 2012, Jégo *et al*., 2012). In addition, a reliable map of soil attributes can be achieved from remote sensing by calibrating the data with some ground truth measurements (Debaene *et al*., 2014), but this study needs to be repeated for different soil types and different weather conditions to identify the optimum number of calibration points.

6.3 The main associated environmental variables (Objective one):

Determining the main environmental variables associated with the variability in sugar beet yield and quality is the key for site specific management, since some of the associated variables are likely to be the main factors driving growth and development of sugar beet. Although, the spatial variability in sugar yield was not highly related to any one environmental factor, such a relationship is not expected under field conditions, since within field variation can be due to the combined influence of different biotic and abiotic variables (Griffin, 2010, Zhang *et al*., 2011b, Hakojärvi *et al*., 2013, Oliver *et al*., 2013). It would therefore be quite surprising to be able to attribute the within field variability to a single environmental variable. Indeed, although some environmental variables showed some spatial association with the maps of sugar yield, they also had distinct patterns of spatial variability, which suggests that the limiting factors in some parts of the field could differ from other parts.

Different methods have been examined to identify the spatial association between environmental variables and crop yield such as a regression Kriging which is based on the regression analysis between the variable of interest and related auxiliary variables (Hengl, 2007, Piccini *et al*., 2014), functional soil map by overlaying different soil properties in one map to identify the variables associated with the yield of corn and soybean (Zhu *et al*., 2013), factorial Kriging with step-wise multiple regression analyses to detect the association of different soil attributes at different spatial scales (Liu *et al*., 2013) and using classification methods with a regression tree to identify the underlying cause of the spatial variability in rice yield within a field (Roel and Plant, 2004, Simmonds *et al*., 2013). However, regression kriging depends on auxiliary data which is usually dense and provided by remote sensing and the factorial kriging needs sampling at different scales. Therefore, Redundancy Analysis has been used here, for the first time as far as is known, to identify the key environmental variables, which was also confirmed by the visual assessment of Kriging maps and correlation coefficients. Soil organic matter, soil moisture content, weeds and canopy temperature were the most important variables associated with spatial variability in sugar beet yield. Some variables became less significant when combined in the redundancy analysis, since they could be explaining the same variability explained by other variables. This has been considered as one drawback of any analysis based on stepwise selection, since it depends on which factor is first selected or deleted from the model (Lark *et al*., 2007), especially when the two variables are highly correlated with each other (Derksen and Keselman, 1992). Rodriguez-Moreno *et al*. (2014) stated that if two variables are strongly related to the yield, they are also expected to be strongly related to each other such as the relationship between soil type, soil moisture content and elevation. Therefore, a further investigation of the reliability of Redundancy Analysis in precision agriculture is required.

Large spatial variability was observed in soil moisture content (SMC) measured in June, July and August in all three fields and it was highly related to the variability in final economic yield of sugar, which was also documented in some other studies (Zhang *et al*., 2007, Zhang *et al*., 2011a, Zhu *et al*., 2013). A strong association was also observed between the spatial variability in SMC and sugar beet canopy cover in June suggesting the necessity of early monitoring of the water status in sugar beet fields, which might relate to site-specific variation in water holding capacity and hydraulic conductivity (Hakojärvi *et al*., 2013). Thus site-specific irrigation of sugar beet field early in the growing season can enhance the canopy cover and reduce the yield losses due to water stress. Monti *et al*. (2006) found that exposing sugar beet to water stress even for a short time can significantly reduce the sugar yield.

Soil organic matter (SOM) is another important variable identified in all three fields. The spatial variation in SOM and its relation to sugar beet yield is well documented in some other studies (Karaman *et al*., 2009a, Amado and Santi, 2011, Debaene *et al*., 2014). Such a relationship is not surprising, as SOM can affect physical, chemical and biological soil quality attributes, which makes it an important variable positively associated with the crop yield (D'Hose *et al*., 2014), and one which can be used as a good indicator for within-field variation in yield and quality of crops (Moghadam, 2002) and to identify and manage the degraded parts of field. However, managing SOM site-specifically by adding compost or farm yard manure to the degraded parts may take a few seasons. However, the low yielding areas of the previous crop in this study occurred in the areas of low SOM identified in the following year, which suggests that adding more farm yard manure before sowing sugar beet could be useful. Since the canopy cover in June is positively related to SOM, it is also suggested to increase nitrogen fertilizer in the areas of low SOM, which had also low canopy cover early in the season, as the sugar beet crop can respond better to the nitrogen fertilizer in the soils with low SOM (< 2%) early in the growing season, because it can be absorbed easily and may accelerate the canopy growth (Malnou *et al*., 2006).

Soil texture also had a great spatial variability throughout each field, but its relation to the sugar beet was not consistent in the three fields. In White Patch field the high yielding areas had a higher soil clay content (maximum value of 40% clay (Table 3.1)), while in T32, the high yielding areas might not be associated with higher clay content, but the low yielding areas had a higher percentage of sand (maximum value of 80% sand (Table 3.4)). In WO3, the lowest yields occurred in the most clayey areas (maximum value of 52% clay (Table 3.7)), due to lower plant population density in these areas. Therefore, it might be difficult to anticipate the spatial variability in sugar yield from the soil type, since the impact of soil type might differ under different weather conditions, which might in turn affect the water holding capacity, nutrient availability and consequently the yield (Horta and Thomas, 2013). In England, the yield of cereals was found to be related to soil type only in dry years through which it was related to soil available water (Taylor *et al*., 2003). Clearly, managing the spatial variability in soil texture is not feasible (Draycott and

Christenson, 2003), but it still important for precision agriculture, since it can be used to understand the spatial variability in some other environmental variables, which are related to soil texture such as porosity, water holding capacity and nutrient availability (Safari *et al*., 2013, Shahbazi *et al*., 2013, Zhu *et al*., 2013).

Soil available nutrients also varied within each field, but they were not strongly related to the sugar beet yield in any field, except soil available nitrate in T32 and soil available magnesium in WO3. This could be because the yield was limited by factors other than nutrient availability or due to the negative effect of a supra-optimal concentration of some nutrients, a problem which can be exacerbated by uniform fertilizer applications (Griffin, 2010). In addition the soil samples were collected in July, and the crop in high yielding areas might have absorbed a higher amount of nutrient before collecting the samples. The observed spatial variability in root content of amino acids and potassium confirms the spatial variability in nutrient uptakes by sugar beet plant. Moghadam (2002) observed spatial variability in soil available nutrients, but it was also not related to spatial variability in grain yield of cereals in the UK, while Rodriguez-Moreno *et al*. (2014) found it to be related to the yield variability of winter wheat only in one field in Czech Republic and not in three other fields. Therefore, it is recommended for future study on the spatial relationship between the yield of sugar beet and soil available nutrient, to collect the soil samples before the emergence of the crop and application of fertilizers with measuring the concentration of these nutrients in both shoot and root of sugar beet crop.

Weeds were distributed as patches and since the sugar beet crop is highly sensitive to weed infestation at early growth stages (Draycott, 2008), the patches with high weed densities were less productive than others. The uniform application of herbicides is therefore important early in the growing season, but any appearance of weeds late in the season could be treated site-specifically if a reliable map of weed distribution obtained. Different techniques have been examined for weed mapping in agriculture fields (Jafari *et al*., 2006, Nieuwenhuizen *et al*., 2007, Slaughter *et al*., 2008, Rasmussen *et al*., 2013), but distinguishing the weeds from the crop and the costs were still the major challenges facing the adoption of these techniques. Therefore, it is suggested to develop and commercialize a cost-effective technique that can clearly identify the weeds from sugar beet plants and treated site-specifically. Since the patches of low canopy cover in June had a high weed density in July, improving the canopy cover early in the growing season or perhaps increasing the seed rate might limit the occurrence of weeds. The losses in sugar yield due to weed infestation can be significantly reduced, if the crop was kept weed-free for at least one month after crop emergence (Kropff and van Laar, 1993).

The canopy temperature was less variable during the growing season, but it was negatively related to the spatial variability in sugar beet yield, especially in July and August. The higher air temperature in July and August was also found by Kenter *et al*. (2006) to have a negative influence on sugar beet growth and yield. The negative relationship between canopy temperature and root yield could be due to the effect of air temperature on the evapotranspiration rate and consequently the root content of water. The relation between air temperature and sugar beet yield was reported in many previous studies (Werker and Jaggard, 1997, Freckleton *et al*., 1999, Qi *et al*., 2005, Kenter *et al*., 2006, Jaggard *et al*., 2007, Draycott, 2008, Jaggard *et al*., 2009), but the within-field variability in canopy temperature and its relation to the yield and quality of sugar beet is shown for the first time in this study. Although, managing the canopy temperature may not be possible, it is still important to understand how it can affect the growth, yield and quality of sugar beet on a spatially variable basis. In addition, the negative correlation between canopy temperature and soil moisture content may suggest irrigating the areas of higher canopy temperature to compensate for the amount of water evaporated or/and increase the amount of nitrogen fertilizer to accelerate the canopy cover.

The above mentioned variables acted together and accounted for the majority of the spatial variability in sugar beet yield. Some of the variability can also be related to some other variables not assessed in this study such as the diffusion of soil water and nutrients (Lark, 2012), and management operations, as Taylor *et al*. (2003) found 50% of the spatial variation in three cereal fields occurred between the tramlines and they attributed it to the management practices rather than environmental variables. Identifying the limiting factors under field conditions is quite challenging and need to be supported by the results of experiments under glass house conditions. Since some associated variables differed from one field to another, the relationship between the spatial variability in sugar beet yield and environmental variables should be examined in some other sugar beet fields with different soil types and field topography, and under different weather conditions. In addition for future research, it is also suggested to detect some other variables and their association with sugar beet, which were not included in this study such as the availability of soil boron and some other micro-nutrients, soil infiltration, and diseases, which might also vary within the field.

6.4 An early prediction of within-field variability in sugar beet yield based on early assessment of crop growth (Objective two):

In this study, the Kriging maps, correlation coefficients and ordination analysis confirmed a strong association between the spatial variability in crop canopy cover, intercepted solar radiation and LAI measured in June, July and August and the spatial variability in final economic yield. Perhaps the most important was the crop canopy cover assessed on 1st of June 2012 in White Patch and T3 and 20th of June 2013 in WO3, which was more variable and related to the same variables as those related to root yield.

Treating the stress in sugar beet fields when the damage has already happened might not compensate the yield losses, as the sugar beet crop starts to accumulate dry matter early in the growing season (Draycott, 2008). Therefore, this relationship may be of great value in precision agriculture, as it can be used to predict the spatial variability in final economic yield and manage it early in the growing season if the underlying causes of the variation were identified.

However, the environmental variables correlated with the spatial variability in crop canopy might differ from one season to another or from one field to another due to the variability in weather condition, soil types and field topography. Rodriguez-Moreno *et al*. (2014) assessed the spatial variability in some growth parameters of winter wheat (plant height and leaf chlorophyll content) using (Yara N-Tester). They found the patterns of the spatial variability in these parameters were consistent with final yield, but the related environmental variables differed from one to another. They also suggested that the observed spatial variability in crop growth parameters in relation to environmental variables can be useful to create the interpolation map for variable rate application with minimum sampling efforts. The feasibility of managing the spatial variability in sugar beet field based the spatial variability in some growth parameters such as LAI and NDVI provided by satellite images was documented in some other studies (Franzen, 2004, Zhang *et al*., 2010a), but the main purpose was to develop a map of management zones for variable rate nitrogen fertilization according to the differences in canopy colour without identifying the main causes, while in fact, different kinds of stress might have similar symptoms, and the relationship between the observed spatial variability in growth parameters and final yield was not examined.

Based on the relationships observed in this study between canopy cover in June, root yield at final harvest and some environmental variables, it is recommended to assess the spatial variability in some growth parameters early in the growing season such as crop canopy cover, intercepted solar radiation and LAI that can be measured easily and cheaply using ground based sensors (Cao *et al*., 2012) or remote sensing (Jayanthi, 2003, Silva *et al*., 2007). In addition, attempts should be made to improve the crop canopy cover by site-specific irrigation or fertilizer application as soon as the main associated variables are identified, since a good yield of sugar beet at final harvest highly depends on a good development of crop canopy cover early in the growing season (Scott and Jaggard, 1993), which in turn increases the intercepted solar radiation and accumulation of dry matter (Jaggard *et al*., 2009). The maximum intercepted daily radiation by the sugar beet canopy can reach 15-25 MJ/m^2 and this is usually in June (Watson, 1952), but most commercial sugar beet crops in the UK might not have enough canopy cover before late July or the beginning of August for full interception of the radiation (Draycott, 2008), which was also observed in most areas of each field in this study. To advance the canopy cover early in summer, the farmer might sow the crop early, as the developing of bolting-resistant varieties and the recent increases in air temperature may allow that (Jaggard *et al*., 2007).

However an early sowing might not always be successful, especially if the crop experienced cold weather during seed germination, which was evident in WO3 in 2013 season in this study and resulted in very poor plant establishment and low yields in some parts of the field. The rapid expansion in crop canopy cover early in summer was found to be related to nitrogen uptake by sugar beet crop and it requires 120 Kg N/ha^{-1} to reach the maximum canopy cover by late May or early June (Scott and Jaggard, 1993, Malnou *et al*., 2006). In another study Malnou *et al*. (2008) stated that the nitrogen fertilizer is more important to accelerate the canopy development early in summer than to maintain it to late summer, especially in areas with low organic matter (Malnou *et al*., 2006), as the lower canopy cover mostly occurred in this study in the areas of low soil organic matter. Therefore it is necessary to make sure that the areas with lower canopy cover receive a sufficient amount of nitrogen fertilizer early in the growing season, which can also increase the ability of sugar beet for absorbing water and cover most of the ground to limit weed occurrence.

6.5 Predicting the spatial variability in sugar beet yield based on the spatial variability in the previous crop (Objective three).

It has been expected that some patterns of spatial variability in crop yield might be temporally consistent, due to the assumption that the behaviour of different soil attributes can be temporally stable over years (Blackmore *et al*., 2003). Therefore, the relationship between the yield maps of sugar beet and previous crop was examined, which indicated the possibility of predicting some of the spatial variability in sugar beet yield from the variability in the yield of previous crop. The extent of this prediction is dependent on the season, however, and for example, in 2012, the sugar yield in T32 and the wheat yield in WO3 were less variable, which could be due to the high rainfall in that season, since the available water in dry season is related to the ability of soil to retain water (Taylor *et al*., 2003, Hakojärvi *et al*., 2013), which might in turn vary within each field. The prediction based on previous year's crop must therefore be treated with caution. The possibility of using the historical yield maps for predicting and managing the following crops has been examined in previous studies, but none of these studies included the sugar beet crop in the rotation and indeed yield maps are not available for sugar beet in the literature. Some of these studies found the patterns of spatial variability were temporally instable (Blackmore, 2000, Blackmore, 2003, Blackmore *et al*., 2003, Kleinjan *et al*., 2007) and managing the fields based on historical data was therefore rejected in these studies. Nevertheless, the results of this study indicate the possibility of using the yield map of the previous crop to predict ***some*** of the spatial variability in sugar beet yield, especially in the low yielding areas, which appeared to be temporally consistent.

Most interestingly, a lower canopy cover of sugar beet occurred in the low yielding areas of previous crop; therefore, the yield data of previous crop combined with early measurements of the current sugar beet crop can significantly improve the prediction of final sugar yield. Thus, by identifying the main associated environmental variables, the spatial variability can be managed early in the growing season with more confidence. A temporally stable pattern of spatial variability in some rice fields was found by Simmonds *et al*. (2013) and it was attributed to the variability in soil organic matter and soil nitrogen, and also found by Amado and Santi (2011) in a field involving different crops (soybean, maize and wheat) and attributed to soil infiltration. In addition, the historical yield maps can also be used to determine the areas, which are consistently low yielding, due to soil organic matter, soil texture and field topography and undertake a long-term management plan to improve soil quality. The management plan might involve adding the farm compost repeatedly or applying conservation agriculture for other crops in the rotation and reduce soil management practices, since the high yielding areas of sugar beet were found to be highly related to soil structure, which in turn is related to soil management practices (Hanse *et al*., 2011b).

To manage the current sugar beet crop based on the previous yield map, it is recommended to irrigate these potentially low yielding areas if an irrigation source and system are available, as the low yielding areas of previous crop and areas with a low canopy cover of sugar beet had lower soil moisture content. In addition, adding extra nitrogen fertilizer to the low yielding areas early in the growing season can improve the sugar beet canopy cover, especially in the areas of low organic matter (Malnou *et al*., 2006), which might increase the amount of intercepted radiation and radiation use efficiency. Since most of the low yielding areas in WO3 field had low plant population, and were also the most clayey parts, it is also recommended to increase the seed rate in the areas expected to have a lower plant establishment.

However, the yield map of only two crops was available in T32 and three crops in WO3, which might not be sufficient to constitute reliable recommendations. Therefore, these recommendations need to be investigated in other sugar beet fields using the yield maps of several years, where farmers have had access to the yield mapping technology. For future research it is also suggested to involve some management experiments, such as assessing the spatial response of sugar beet to fertilizer application in different parts of some fields based on the historical yield map, and to see how it can improve the canopy cover of sugar beet. Commercial sugar beet harvesters cannot currently monitor and map the yield during harvest, which makes it difficult to get the yield map of sugar beet. The farmers who monitor their crop yields over years will therefore have a gap of one year when they include the sugar beet in the rotation. Therefore, a further development of the sugar beet harvester to monitor the yield of sugar beet site-specifically is also suggested.

6.6 Simulating the yield of sugar beet using Broom's Barn sugar beet growth simulation model on a spatially variable basis (Objective four):

The sugar beet growth simulation model developed at Broom's Barn was able to account for some of the spatial variability in the observed sugar yield across each field. The model has been widely used to simulate sugar beet yield on regional basis in previous studies (Freckleton *et al*., 1999, Pidgeon *et al*., 2001, Richter *et al*., 2001, Kenter *et al*., 2006, Richter *et al*., 2006, Jaggard *et al*., 2007, Jaggard *et al*., 2009), while the main objective of using the model in this study is to examine the utility of the model for simulating the within-field variability in sugar yield, and to find the potential yield and the yield gap between the simulated and observed sugar yield throughout each field. This could help sugar beet farmers to make a decision whether to exclude some parts of the field from sowing or to explore whether there is a potential to improve the productivity in these parts. Since the model is mainly weather and soil driven (Qi *et al*., 2005), the observed spatial variability in sugar yield might reflect the variability in weather conditions and soil type. Although, the model accounted for some of the variability in observed sugar yield within each field, the variability was much lower in the simulated sugar yield and the yield gap was high in most parts of each field, especially where they were consistently low yielding (Fig. 6.1). This suggests that the weather condition and soil type were optimum throughout each field to obtain better sugar yield than observed in low yielding areas, and most of the yield losses in these areas is perhaps, due to some agronomic variables not considered by the model such soil fertility, weeds, diseases and sub-optimal plant population density. This has become more evident when the sowing date was adjusted to correct the crop canopy cover in June or the simulated yield was adjusted for weeds and plant population, as these adjustments significantly improved the relationship between the observed and simulated yields. Although the simulated yield was much higher than the observed yield in WO3, the low air temperature during seed germination resulted in a poor plant establishment, especially in the most clayey parts of the field, which had a very high yield gap up to 91% (Table 5.3: Fig. 6.1 D). The model did not consider the effect of air temperature on seed germination and the most clayey parts of the field were accounted by the model to have more available soil water. To avoid sub-optimum plant population, the farmer might need to avoid an early sowing or increase the seed rate in the areas where a low plant population might be expected based on soil type. Contrary to weather variables, the agronomic variables can be managed to some extent by the farmer to improve the yield in low yielding areas. For example the farmer cannot manage the incident solar radiation, but it can be possible to increase radiation use efficiency by improving the canopy cover early in the summer and its ability to compete with weeds by site-specific irrigation, fertilization and perhaps herbicide application.

The input parameters of the Broom's Barn sugar beet growth model were not enough for efficient simulation of sugar beet yield on a spatially variable basis. Another model was used by Hakojärvi *et al.* (2013) to simulate the spatial variability in cereal yields, but they also found that the selected input parameters (radiation and water) were not enough to predict the yield of cereal crops on a spatially variable basis. Therefore, to simulate the spatial variability in crop yield, the model should consider the effect of some other soil and biotic variables potentially causing yield losses. Since the model was developed by Richter *et al*. (2001) to account for the effect of water stress, and it was improved recently by Qi *et al*. (2013) to match the growth and yield of new varieties, it is also important for it to be developed further to account for the yield losses caused by biotic constraints.

Therefore, a further development of the model is now needed to allow modelling the sugar beet yield on a spatially variable basis. This development could include the potential yield losses due to the weeds and diseases based on the research results of for example (Kropff and van Laar, 1993), which showed a good agreement between the observed and simulated losses in sugar yield due to weed competition. The crop growth rate from sowing to June can be adjusted based on soil properties. Further research is also needed to explore the plant population response to different soil types and weather conditions and how it can affect the simulation of sugar yield on a spatially variable basis. For example, the model assumes a consistent plant population of at least 75000 plants/ha, while Jaggard *et al*. (2011) recently found 100000 plants/ha as the best plant population density for maximum root yield and 80000 plants/ha for maximum economic return, any plot with plant population density out of this range should be assumed by the model to have negative influence on simulated yield.

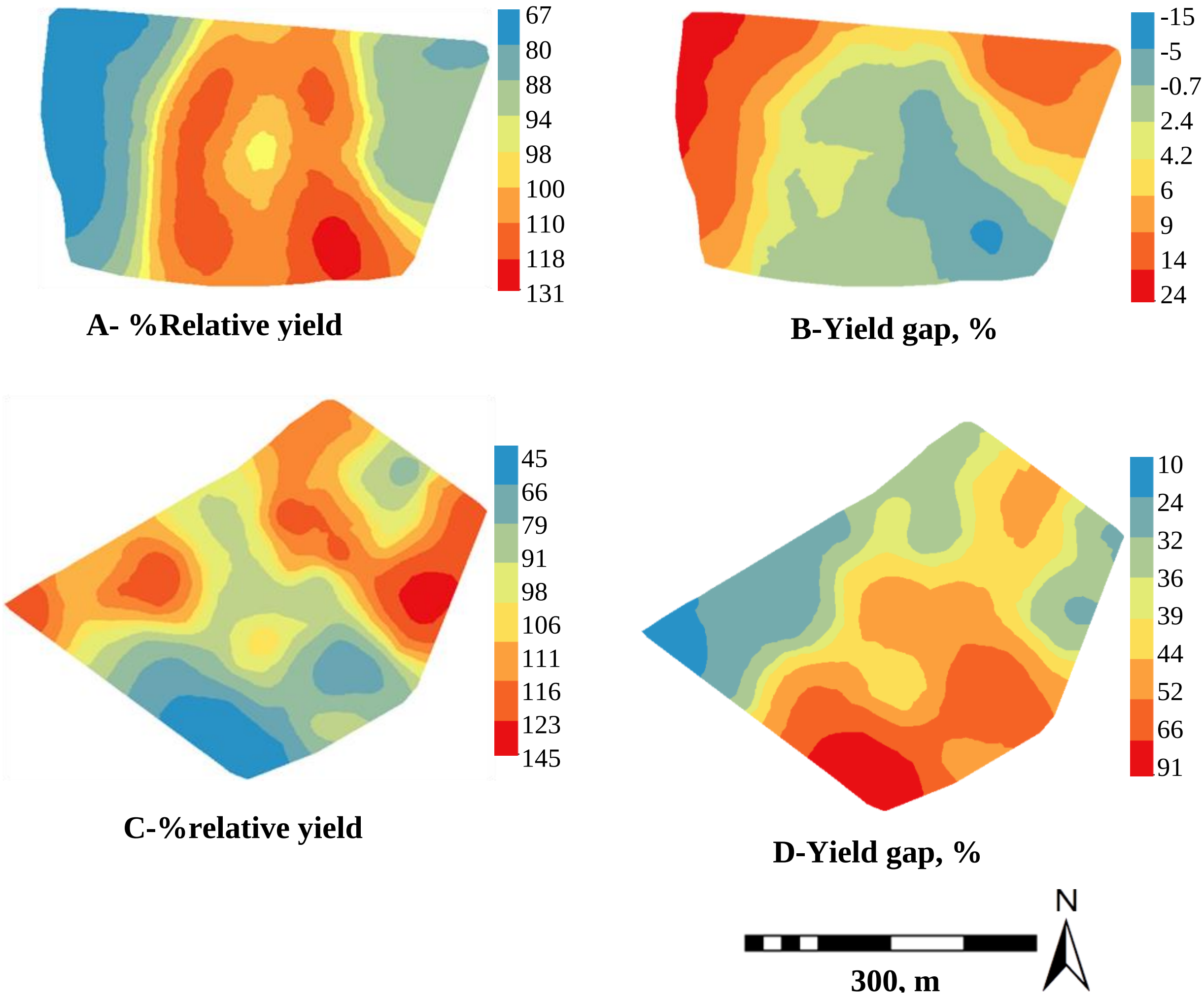


Figure 6.1: The Kriging maps of relative yield of (A) sugar beet with previous winter wheat crop in T32, and (C) sugar beet with previous winter wheat and oilseed rape in WO3 (see chapter two, equation 2.6 for calculation), and the Kriged map of yield gap between the simulated and observed sugar yield (B) in T32 and (D) in WO3 (see chapter 5, equation 5.6 for the calculation).

6.7 Summary of the findings and conclusions from the whole thesis:

1. Irregular grid sampling with some nested samples located purposively based on the expected spatial variability in soil type and the yield of the previous crop followed in this study was sufficient to reveal the majority of the spatial variability in three sugar beet fields, which represented the scale of the variation.
2. Given the uniform application of agronomic inputs, the observed spatial variability in the final economic yield of sugar was significant and varied by £1870, 1450 and 2900 per hectare in White Patch, T32 and WO3, respectively. In some areas, the predicted sugar yield according to the Broom's Barn Simulation Model was lower or close to the observed yield, which suggests the growth conditions were optimum, while in low yielding areas, the potential yield was much higher, which means these areas need extra care to optimize the growth condition; therefore the uniform management of sugar beet fields is not recommended.
3. The Redundancy Analysis (RDA), which is a kind of multiple linear regression analysis, proved to be a powerful method to identify the main environmental variables associated with variability in sugar beet root yield.
4. Most of the studied environmental variables were related to the spatial variability in sugar beet growth and yield, but the key environmental variables were soil type, soil organic matter, soil moisture content, weed density and canopy temperature, since they were related to the spatial variability in sugar beet yield in all three fields. The relation of sugar beet yield with soil type, soil available nutrient, soil EC, soil pH, field aspect and elevation differed from one field to another.
5. The spatial variation in sugar beet growth occurred early in the growing season and was reflected in final yields, since the variability in canopy cover in June was strongly

related to the final root yield, and also related to the same environmental variables as those related to root yield. This observation could be of great value to predict and manage the spatial variability in sugar beet early in the growing season to avoid or mitigate the yield losses.

6. Using the yield map of the previous crop did not appear to be reliable enough for managing the spatial variability in the following sugar beet crop, but it can be more reliable if it is combined with some early measurements of the current crop. It was also useful to identify the areas of the field which were consistently low yielding, especially where low yield was related to soil type and field topography, which might require long term management.
7. Using the Broom’s Barn sugar beet growth simulation model on a spatially variable basis, it was possible to simulate some of the spatial variability in sugar yield, especially when related to weather conditions and soil types in relation to soil available water. This was useful to find the potential yield in different parts of each field and whether making any intervention (fertilization, irrigation, herbicide application, seed rates) might optimize the final yield.
8. The performance of the model was significantly improved if the simulated canopy cover in June was corrected and if the effects of weeds and sub-optimal plant population were considered, which was confirmed that the weather condition was optimum and the final sugar yield can be improved by agronomic interventions.

6.8 Possible recommendations:

The finding of this study may provide the sugar beet farmer with some helpful recommendations, which were stated as follows:

1. For applying precision agriculture in sugar beet field, it is always recommended to have an early assessment of crop growth such as LAI, which could be provided by remote sensing. This will provide an initial picture about the expected spatial variability in the final yield, and by knowing the potential cause of the variation from the farmer's experience about the field or from the soil map; it might be possible to maximize the economic returns by site-specific application of fertilizer or irrigation. Further research is needed to validate this recommendation.
2. For the farmers who have access to yield mapping techniques, it is recommended to use the yield map of previous crops to determine the areas, which are consistently low yielding and to manage them accordingly. Since this is usually related to soil quality, the management might be adding the farm compost and/or reducing soil disturbance as far as applicable.
3. If the low yielding areas also have low potential yield and cannot be improved, it is recommended to exclude from cropping or at least to reduce inputs in such areas.
4. An early sowing of sugar beet might result in a sub-optimal plant population, therefore it is recommended to avoid sowing in suboptimal conditions (seed bed too cold and/or wet) and to increase the seed rates in the areas of heavy soil texture.
5. A site-specific irrigation of the areas of low soil moisture content, low canopy cover or expected to be low yielding based on previous yield map is recommended if a source of water is available with considering the soil type and soil moisture content.

6. Increase the nitrogen doses up to 120 Kg/ha in the areas of low canopy cover or expected to be low canopy cover by applying 30-40% just after sowing and the remainder after full emergence to accelerate the canopy expansion and increase radiation use efficiency.
7. Since the weeds mostly occurred in the areas of low crop canopy cover, improving the canopy development early in summer might reduce weed occurrence, but if it still occurred, the areas with high weed density should be identified as soon as they appear and extra herbicidal treatments applied to these areas only. This could significantly improve the yield and reduce the costs and the adverse environmental impact.

6.9 Suggested work for future research:

1. The study needs to be repeated in several sugar beet fields using grid sampling with different intervals and to identify the number of samples required for calibration and validating the maps of sugar beet growth parameters such as LAI that could be provided by remote sensing early in the growing season.
2. Detecting the spatial variability early in the growing season may need new techniques such as developing a package to provide a map of crop foliage cover from images provided by a handheld camera or an automated system.
3. Collecting and analysing the soil samples before the emergence of sugar beet seedlings, so that it can be linked to any spatial variability observed early in the growing season and undertake a management experiment accordingly, and the relationship between the concentration of nutrients in sugar beet crop and soil should also be examined on spatially variable basis.

4. The main associated environmental variables were identified in this study under field conditions and it was therefore impossible to state definitely that they were limiting or not, therefore, their independent and combined effects on sugar beet need to examined under controlled conditions such as an experiment in pots or a glass house.
5. The effect of some other variables, which were not included in this study such as soil micro-nutrients, soil infiltration and pests and diseases on sugar beet crop also need to be investigated on a spatially variable basis.
6. The reliability of Redundancy Analysis to link between the spatial data of crop and environmental variables needs to be examined further and compared to the results of other methods such as factorial and regression Kriging.
7. The relationship between an early development of crop canopy and the occurrence of weeds later in the season needs to be further investigated on a spatially variable basis.
8. The relationships between the yield maps of sugar beet and the previous crops need to be investigated in some other sugar beet fields and for several years, and the sugar beet harvester also need to be developed to monitor the yield of sugar beet site-specifically.
9. Some experiments need to be conducted about the spatial response of sugar beet to fertilizer application based on the historical yield map.
10. The Broom's Barn sugar beet simulation model needs further development to account for the effects of some other variables potentially causing yield losses such as soil fertility, weeds and sub-optimal plant population.

References:

ABD-EL-MOTAGALLY, F. M. F. 2004. *Evaluation of two sugar beet cultivars (Beta vulgaris L.) for growth and yield under drought and heat conditions.* PhD Thesis, Justus Liebig University.

ABDU, H. R. & DA JONES, S. 2007. Comparing bulk soil electrical conductivity determination using the DUALEM-1S and EM38-DD electromagnetic induction instruments. *Soil Science Society of America Journal,* 71**,** 189.

ADRIAN, A. M. 2006. *Factors influencing adoption and use of precision agriculture.* PhD Thesis, Auburn University.

ALLEN, R. G., PEREIRA, L. S., RAES, D. & SMITH, M. 1998. Crop evapotranspiration-Guidelines for computing crop water requirements. *Irrigation and drainage paper 56,* UN-FAO, Rome.

ALLEN, R. G., TREZZA, R. & TASUMI, M. 2006. Analytical integrated functions for daily solar radiation on slopes. *Agricultural and Forest Meteorology,* 139**,** 55-73.

AMADO, T. J. C. & SANTI, A. L. 2011. Using precision farming to overcome yield-limiting factors in southern Brazil Oxisols: A case study. *In:* CLAY, D. E. & SHANAHAN, J. F. (eds.) *GIS application in precision agriculture, nutrient management for energy efficiency.* Boca Raton-USA: CRC Press.

ATANASOV, A., KANGALOV, P., STOIANOV, K. & ANGELOV, I. Some aspects in preparation of transport and field operations in large Bulgarian farms by using GPS and GOOGLE EARTH. 9th International Scientific Conference Engineering for Rural Development 27-28.05. 2010. 2010 Jelgava, Latvia. 62-66.

AUERNHAMMER, H. 1999. Precision farming for site-specific fertilisation. *Zeitschrift für Agrarinformatik,* 7**,** 58-66.

AUERNHAMMER, H. 2001. Precision farming--the environmental challenge. *Computers and Electronics in Agriculture,* 30**,** 31-43.

AZIZ, A. S., STEWARD, B., TANG, L. & KARKEE, M. 2009. Utilizing repeated GPS surveys from field operations for development of agricultural field DEMs. *Transactions of the ASAE,* 52**,** 1057-1067.

BACKES, M. & PLÜMER, L. On the adequacy of GIS-Generated weed maps for precision farming. ScanGIS, 2003. 261-268.

BARRETT, B. W., DWYER, E. & WHELAN, P. 2009. Soil moisture retrieval from active spaceborne microwave observations: An evaluation of current techniques. *Remote Sensing,* 1**,** 210-242.

BEN-DOR, E. & BANIN, A. 1989. Determination of organic matter content in arid-zone soils using a simple "loss-on-ignition" method. *Communications in Soil Science & Plant Analysis,* 20**,** 1675-1695.

BENNIE, J., HUNTLEY, B., WILTSHIRE, A., HILL, M. O. & BAXTER, R. 2008. Slope, aspect and climate: spatially explicit and implicit models of topographic microclimate in chalk grassland. *Ecological Modelling,* 216**,** 47-59.

BERRY, J. K., DELGADO, J. A., KHOSLA, R. & PIERCE, F. 2003. Precision conservation for environmental sustainability. *Journal of Soil and Water Conservation-USA,* 58**,** 332-339.

BLACKMORE, S. 2000. The interpretation of trends from multiple yield maps. *Computers and Electronics in Agriculture,* 26**,** 37-51.

BLACKMORE, S. 2003. *The role of yield maps in precision farming.* PhD Thesis, Cranfield University.

BLACKMORE, S., GODWIN, R. J. & FOUNTAS, S. 2003. The analysis of spatial and temporal trends in yield map data over six years. *Biosystems Engineering,* 84**,** 455-466.

BOGAERT, P. & RUSSO, D. 1999. Optimal spatial sampling design for the estimation of the variogram based on a least squares approach. *Water Resources Research,* 35**,** 1275-1289.

BOIZARD, H., DUVAL, R., LEMAITRE, T., MACHET, J. M., MARY, B., BEAUDOIN, N., CARIOLLE, M., ESCRIOU, H., GOSSE, G., RICHARD-MOLARD, M. & BOIFFIN, J. 2012. Sugar beet, a sustainability factor of arable crop

systems in northern France. *International Sugar Beet Journal,* 114**,** 711–714.

BOJANOWSKI, J. S., DONATELLI, M., SKIDMORE, A. K. & VRIELING, A. 2013. An auto-calibration procedure for empirical solar radiation models. *Environmental Modelling & Software,* 49**,** 118-128.

BOUMA, J. 1997. Precision agriculture: introduction to the spatial and temporal variability of environmental quality. *In:* 210, C. F. S. (ed.) *CIBA foundation symposium 210-precision agriculture: spatial and temporal variability of environmental quality*. Chichester, UK: Wiley

BUICK, R. 2006. RTK base station networks driving adoption of GPS+/-1 inch automated steering among crop growers. *Trimble White Paper***,** 1-9.

BULLOCK, D. S., LOWENBERG-DEBOER, J. & SWINTON, S. M. 2002. Adding value to spatially managed inputs by understanding site-specific yield response. *Agricultural Economics,* 27**,** 233-245.

CAMPBELL, G. 1986. Extinction coefficients for radiation in plant canopies calculated using an ellipsoidal inclination angle distribution. *Agricultural and Forest Meteorology,* 36**,** 317-321.

CAO, Q., CUI, Z., CHEN, X., KHOSLA, R., DAO, T. H. & MIAO, Y. 2012. Quantifying spatial variability of indigenous nitrogen supply for precision nitrogen management in small scale farming. *Precision Agriculture,* 13**,** 45-61.

CHANG, J. C., CARLSON, D. E., CLAY, C. G., MALO, S. A., BERG, D. D., KLEINJAN, R. & JON WIEBOLD, W. 2003. Different techniques to identify management zones impact nitrogen and phosphorus sampling variability. *Agronomy Journal,* 95**,** 1550.

CHU SU, P. 2011. *Statistical geocomputing: Spatial outlier detection in precision agricultur.* MSc. Thesis, University of Waterloo.

CIOBAN, A., CRIVEANU, H., MATEI, F., POP, I. & ROTARU, A. 2013. Aspects of Solar Radiation Analysis using ArcGis. *Bulletin of University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca. Horticulture,* 70**,** 437-440.

CIRKEL, D. G., WITTE, J. P. M., BODEGOM, P. M., NIJP, J. J. & ZEE, S. E. 2014. The influence of spatiotemporal variability and adaptations to hypoxia on empirical relationships between soil acidity and vegetation. *Ecohydrology,* 7**,** 21-32.

CLARK, I. 2010. Statistics or geostatistics? Sampling error or nugget effect? *The Journal of The South African Institute of Mining and Metallurgy***,** 307-312.

CLAY, S. A. 2011. *GIS applications in agriculture* Boca Raton-USA, CRC Press Inc.

COLBACH, N. & FORCELLA, F. F. 2011. Adapting geostatistics to analyze spatial and temporal trends in weed populations. *In:* CLAY, S. A. (ed.) *GIS applications in agriculture.* Boca Raton-USA: CRC Press.

CORWIN, D. & LESCH, S. 2005. Apparent soil electrical conductivity measurements in agriculture. *Computers and Electronics in Agriculture*, 46**,** 11-43.

D'HOSE, T., COUGNON, M., DE VLIEGHER, A., VANDECASTEELE, B., VIAENE, N., CORNELIS, W., VAN BOCKSTAELE, E. & REHEUL, D. 2014. The positive relationship between soil quality and crop production: A case study on the effect of farm compost application. *Applied Soil Ecology,* 75**,** 189-198.

DEBAENE, G., NIEDŹWIECKI, J., PECIO, A. & ŻUREK, A. 2014. Effect of the number of calibration samples on the prediction of several soil properties at the farm-scale. *Geoderma*, 214**,** 114-125.

DELEGIDO, J., VERRELST, J., ALONSO, L. & MORENO, J. 2011. Evaluation of sentinel-2 red-edge bands for empirical estimation of green LAI and chlorophyll content. *Sensors*, 11**,** 7063-7081.

DEMMEL, M. 2013. Site-specific recording of yields. *In:* HEEGE, H. J. (ed.) *Precision in crop farming: Site specific concepts and sensing methods: Applications and results*

Heidelberg-Germany: Springer

DERKSEN, S. & KESELMAN, H. 1992. Backward, forward and stepwise automated subset selection algorithms: Frequency of obtaining authentic and noise variables. *British Journal of Mathematical and Statistical Psychology*, 45**,** 265-282.

DIACONO, M., DE BENEDETTO, D., CASTRIGNANÒ, A., RUBINO, P., VITTI, C., ABDELRAHMAN, H., SOLLITTO, D., COCOZZA, C. & VENTRELLA, D. 2013. A combined approach of geostatistics and geographical clustering for delineating homogeneous zones in a durum wheat field in organic farming. *NJAS-Wageningen Journal of Life Sciences*, 64**,** 47-57.

DIXIT, P. N. & CHEN, D. 2011. Effect of topography on farm-scale spatial variation in extreme temperatures in the Southern Mallee of Victoria, Australia. *Theoretical and Applied Climatology*, 103**,** 533-542.

DRAYCOTT, A. P. 2008. *Sugar beet*, Oxford-UK, Wiley

DRAYCOTT, A. P. & CHRISTENSON, D. R. 2003. *Nutrients for sugar beet production: Soil-plant relationships*, London-UK, CABI.

DRAYCOTT, P. & EVANS, B. 2012. Soil of Brooms barn Farm. *British Sugar Beet Review,* 80**,** 35-38.

FAO 2012. Area harvested and crop production. *In:* ORGANIZATION, F. A. A. (ed.) *Year book 2012.*

FISHER, R. A. 1921. On the" Probable Error" of a coefficient of correlation deduced from a small sample. *Metron,* 1**,** 3-32.

FLEMING, K., WESTFALL, D. & BAUSCH, W. Evaluating management zone technology and grid soil sampling for variable rate nitrogen application. 2000. 16-19.

FONTES, M. & WEED, S. 1996. Phosphate adsorption by clays from Brazilian Oxisols: relationships with specific surface area and mineralogy. *Geoderma,* 72**,** 37-51.

FOUNTAS, S., BLACKMORE, S., GEMTOS, T. & MARKINOS, A. Trend yield maps in Greece and the UK. HAICTA 2002: Proceedings of the 2nd international conference on information systems & innovative technologies in agriculture, food and environment, 2004 Thessaloniki-Greece. 309-319.

FRANZEN, D. 2004. Delineating nitrogen management zones in a sugar beet rotation using remote sensing-A Review. *Journal of Sugar Beet Research,* 41**,** 47-60.

FRANZEN, D. W. 2011. Collecting and analyzing soil spatial information using kriging and inverse distance. *In:* CLAY, D. E. & SHANAHAN, J. F. (eds.) *GIS application in agriculture: Nutrient management for energy efficiency.* Boca Raton-USA: CRC Press.

FRECKLETON, R., WATKINSON, A., J WEBB, D. & THOMAS, T. 1999. Yield of sugar beet in relation to weather and nutrients. *Agricultural and forest meteorology,* 93**,** 39-51.

FRENCH, B. W., REITSMA, K. D., BECKLER, A. A., CHANDLER, L. D. & CLAY, S. A. 2011. Geographic information systems in corn root worm management. *In:* CLAY, S. A. (ed.) *GIS application in agriculture:Invasive Species.* Boca Raton-USA: CRC Press.

FROGBROOK, Z. & OLIVER, M. 2001. Comparing the spatial predictions of soil organic matter determined by two laboratory methods. *Soil Use and Management,* 17**,** 235-244.

FROGBROOK, Z., OLIVER, M., SALAHI, M. & ELLIS, R. 2002. Exploring the spatial relations between cereal yield and soil chemical properties and the implications for sampling. *Soil Use and Management*, 18**,** 1-9.

FU, P. & RICH, P. M. Design and implementation of the Solar Analyst: an ArcView extension for modeling solar radiation at landscape scales. Proceedings of the 19th annual ESRI user conference, San Diego, USA, 1999.

GAO, J. 2002. Integration of GPS with remote sensing and GIS: reality and prospect. *Photogrammetric Engineering and Remote Sensing*, 68**,** 447-454.

GAT, N., ERIVES, H., FITZGERALD, G. J., KAFFKA, S. R. & MAAS, S. J. Estimating sugar beet yield using AVIRIS-derived indices. *In:* GREEN, E. B. R. O., ed. 9th JPL Airborne Earth Science Workshop, 2000 California-USA.

GAVRIC, M. & MARTINOV, M. 2007. Low cost GPS-based system for site-specific farming at flat terrains-case study. *International Commission of Agricultural Engineering (CIGR)* [Online], 9. [Accessed 07/07/2014].

GERHARDS, R. & CHRISTENSEN, S. 2003. Real-time weed detection, decision making and patch spraying in maize, sugarbeet, winter wheat and winter barley. *Weed Research*, 43**,** 385-392.

GODWIN, R. & MILLER, P. 2003. A review of the technologies for mapping within-field variability. *Biosystems Engineering*, 84**,** 393-407.

GRIFFIN, T. W. 2010. The spatial analysis of yield data. *In:* OLIVER, M. A. (ed.) *Geostatistical applications for precision agriculture*. London-UK: Springer.

GROFFMAN, P. M. 1997. Ecological constrains on the ability of precision agriculture to improve the environmental performance of agriculture production system. *In:* LAKE, J. V., BOCK, G. R. & GOOD, J. A. (eds.) *precision agricultur: spatial and temporal variablity of environmental quality*. UK: Wiley.

HABERLE, J., KROULÍK, M., SVOBODA, P., LIPAVSKY, J., KREJCOVA, J. & CERHANOVÁ, D. 2004. The spatial variability of mineral nitrogen content in topsoil and subsoil. *Plant, Soil and Environment* 50**,** 425-433.

HAKOJÄRVI, M., HAUTALA, M., RISTOLAINEN, A. & ALAKUKKU, L. 2013. Yield variation of spring cereals in relation to selected soil physical properties on three clay soil fields. *European Journal of Agronomy*, 49**,** 1-11.

HANSE, B., SCHNEIDER, J., TERMORSHUIZEN, A. & VARRELMANN, M. 2011a. Pests and diseases contribute to sugar beet yield difference between top and averagely managed farms. *Crop Protection,* 30**,** 671-678.

HANSE, B., VERMEULEN, G., TIJINK, F., KOCH, H.-J. & MÄRLÄNDER, B. 2011b. Analysis of soil characteristics, soil management and sugar yield on top and averagely managed farms growing sugar beet (*Beta vulgaris* L) in the Netherlands. *Soil and Tillage Research,* 117**,** 61-68.

HARPER, W. V. & CLARK, I. Visualization tool to aid in the understanding of geostatistics *In:* ICOTS, ed. 7th international conference on teachin statistics, 2006 Salvador, Brazil.

HATFIELD, J. L. & KITCHEN, N. R. 2013. Precision agriculture in food production and security *In:* OLIVER, M., BISHOP, T. & MARCHANT, B. (eds.) *Precision agriculture for sustainability and environmental protection* Abingdon, Oxon-UK: Routledge.

HBIRKOU, C., WELP, G., REHBEIN, K., HILLNHÜTTER, C., DAUB, M., OLIVER, M. & PÄTZOLD, S. 2011. The effect of soil heterogeneity on the spatial distribution of *Heterodera schachtii* within sugar beet fields. *Applied Soil Ecology,* 51**,** 25-34.

HEEGE, H. J. 2013. Precision in crop farming. *In:* HEEGE, H. J. (ed.) *Site specific concepts and sensing methods: Applications and results* Heidelberg-Germany: Springer.

HENGL, T. 2007. A practical guide to geostatistical mapping of environmental variables. *JRC Scientific and Technical Reports. European Commission, Joint Research Centre, Luxemburg*.

HORTA, A. & THOMAS, F. A. B. 2013. Spatio-temporal analysis to improve agriculture managment. *In:* MARGARET A. OLIVER, AND, T. F. A. B. & MARCHANT, B. P. (eds.) *Precision agriculture for sustainability and environmental protection.* Abingdon, Oxon-UK: Routledge.

JAFARI, A., MOHTASEBI, S. S., JAHROMI, H. E. & OMID, M. 2006. Weed detection in sugar beet fields using machine vision. *International Journal of Agriculture & Biology,* 8**,** 602-605.

JAGGARD, K., QI, A. & OBER, E. 2009. Capture and use of solar radiation, water, and nitrogen by sugar beet (*Beta vulgaris* L.). *Journal of Experimental Botany,* 60**,** 1919.

JAGGARD, K., QI, A. & SEMENOV, M. 2007. The impact of climate change on sugarbeet yield in the UK: 1976–2004. *The Journal of Agricultural Science,* 145**,** 367-375.

JAGGARD, K. & WERKER, A. 1999. An evaluation of the potential benefits and costs of autumn-sown sugarbeet in NW Europe. *The Journal of Agricultural Science,* 132**,** 91-102.

JAGGARD, K. W., QI, A., MILFORD, G., CLARK, C., OBER, E., WALTERS, C. & BURKS, E. 2011. Determining the optimal population density of sugarbeet crops in England. *International Sugar Journal,* 113**,** 114-119.

JAYANTHI, H. 2003. *Airborne and ground-based remote sensing for the estimation of evapotranspiration and yield of bean, potato, and sugar beet crops.* PhD Thesis, Utah State University.

JÉGO, G., PATTEY, E. & LIU, J. 2012. Using Leaf Area Index, retrieved from optical imagery, in the STICS crop model for predicting yield and biomass of field crops. *Field Crops Research,* 131**,** 63-74.

JIANG, P., ANDERSON, S. H., KITCHEN, N. R., SUDDUTH, K. A. & SADLER, E. J. 2007. Estimating plant-available water capacity for claypan landscapes using apparent electrical conductivity.

JOHNSON, C. K., DORAN, J. W., DUKE, H. R., WIENHOLD, B. J., ESKRIDGE, K. M. & SHANAHAN, J. F. 2001. Field-scale electrical conductivity mapping for delineating soil condition. *Soil Science Society of America Journal*

65**,** 1829-1837.

JOHNSON, L., ROCZEN, D., YOUKHANA, S., NEMANI, R. & BOSCH, D. 2003. Mapping vineyard leaf area with multispectral satellite imagery. *Computers and Electronics in Agriculture,* 38**,** 33-44.

JOHNSTON, K., VER HOEF, J. M., KRIVORUCHKO, K. & LUCAS, N. 2001. *Using ArcGIS geostatistical analyst,* California-USA, Esri Redlands.

JONES, H. & SCHOFIELD, P. 2008. Thermal and other remote sensing of plants stress. *General Applied Plant Physiology,* 34**,** 19-32.

JONES JR, J. B. 1999. *Soil analysis handbook of reference methods,* Boca Raton-USA, CRC Press

KARAMAN, M. R., SUSAM, T., ER, F., YAPRAK, S. & KARKACIER, O. 2009a. Simulation of organic matter variability on a sugar beet field using the computer based geostatistical methods. *Engineering and Technology,* 56**,** 724-727.

KARAMAN, M. R., SUSAM, T., YAPRAK, S. & ER, F. Computer based geostatistical strategies in assessing of spatial variability of agricultural phosphorus on a sugar beet field. International conference of information management and engineering 2009b Kuala Lumpur. IEEE, 201-204.

KEMPEN, B., BRUS, D. J. & HEUVELINK, G. 2012. Soil type mapping using the generalised linear geostatistical model: A case study in a Dutch cultivated peatland. *Geoderma,* 189**,** 540-553.

KENKEL, N., DERKSEN, D., THOMAS, A. & WATSON, P. 2009. Review: Multivariate analysis in weed science research. *Weed Science Society of America,* 50**,** 281-291.

KENTER, C., HOFFMANN, C. M. & MARLANDER, B. 2006. Effects of weather variables on sugar beet yield development (Beta vulgaris L.). *European Journal of Agronomy,* 24**,** 62-69.

KERRY, R. 2003. *Determining the effect of parent material and topography on the structure of spatial variation in soil properties for precision agriculture.* PhD Thesis, University of Reading.

KERRY, R. & OLIVER, M. 2007a. Comparing sampling needs for variograms of soil properties computed by the method of moments and residual maximum likelihood. *Geoderma,* 140**,** 383-396.

KERRY, R. & OLIVER, M. 2007b. Determining the effect of asymmetric data on the variogram. II. Outliers. *Computers & Geosciences,* 33**,** 1233-1260.

KERRY, R., OLIVER, M. A. & FROGBROOK, Z. L. 2010. Sampling in precision agriculture. *In:* OLIVER, M. A. (ed.) *Geostatistical applications for precision agriculture.* London-UK: Springer.

KHOSLA, R., WESTFALL, D. G., REICH, R. M., MAHAL, J. S. & GANGLOFF, W. J. 2010. Spatial variation and site-specific management zones. *In:* OLIVE, M. A. (ed.) *Geostatistical applications for precision agriculture.* London-UK: Springer.

KITCHEN, N., DRUMMOND, S., LUND, E., SUDDUTH, K. & BUCHLEITER, G. 2003. Soil electrical conductivity and topography related to yield for three contrasting soil–crop systems. *Agronomy Journal,* 95**,** 483-495.

KITCHEN, N., SNYDER, C., FRANZEN, D. & WIEBOLD, W. 2002. Educational needs of precision agriculture. *Precision Agriculture,* 3**,** 341-351.

KLEINJAN, J., CLAY, D. E., CARLSON, C. G. & CLAY, S. A. 2007. Developing productivity zones from multiple years of yield monitor data. *In:* PIERCE, F. J. & CLAY, D. (eds.) *GIS application in agriculture.* Boca Raton-USA: CRC Press.

KORRES, W., REICHENAU, T. & SCHNEIDER, K. 2013. Patterns and scaling properties of surface soil moisture in an agricultural landscape: An ecohydrological modeling study. *Journal of Hydrology,* 498**,** 89-102.

KROPFF, M. J. & VAN LAAR, H. 1993. *Modelling crop-weed interactions,* Wallingford Oxon-UK, CAB and International Rice Research Insititute.

KUMAR, L., SKIDMORE, A. K. & KNOWLES, E. 1997. Modelling topographic variation in solar radiation in a GIS environment. *International Journal of Geographical Information Science,* 11**,** 475-497.

KUMHÁLOVÁ, J., MATEJKOVA, S., FIFERNOVÁ, M., LIPAVSKY, J. & KUMHÁLA, F. 2008. Topography impact on nutrition content in soil and yield. *Plant Soil and Environment,* 54**,** 255.

KYVERY, P. M., BLACKMER, T. M. & PEARSON, R. 2012. Normalization of uncalibrated late-season digital aerial imagery for evaluating corn nitrogen status. *Precision Agriculture (2012),* 13**,** 2-16.

LAKHANKAR, T., KRAKAUER, N. & KHANBILVARDI, R. 2009. Applications of microwave remote sensing of soil moisture for agricultural applications. *International Journal of Terraspace Science and Engineering,* 2**,** 81-91.

LAMB, D. & BROWN, R. 2001. PA--Precision agriculture:: remote-sensing and mapping of weeds in crops. *Journal of Agricultural Engineering Research,* 78**,** 117-125.

LAMB, D. W. Aerial video and spatial data. *In:* INFORMATION, R. O. C., ed. Riverinal Outlook Conference Information, 1995 Australia. Wagga Wagga, 45-54.

LARK, R. 2012. Towards soil geostatistics. *Spatial Statistics,* 1**,** 92-99.

LARK, R., BISHOP, T. & WEBSTER, R. 2007. Using expert knowledge with control of false discovery rate to select regressors for prediction of soil properties. *Geoderma,* 138**,** 65-78.

LAUDIEN, R., BARETH, G. & DOLUSCHITZ, R. Comparison of remote sensing based analysis of crop diseases by using high resolution multispectral and hyperspectral data–case study: Rhizoctonia solani in sugar beet. 12th International conference on geoinformatics −geospatial information research: bridging the pacific and atlantic, 2004 University of Gävle, Sweden,. 670-676.

LAUNAY, M. & GUÉRIF, M. 2003. Ability for a model to predict crop production variability at the regional scale: an evaluation for sugar beet. *Agronomie*, 23**,** 135-146.

LAVERGNE, C. B. 2004. *Factors determining adoption or non-adoption of precision agriculture by producers across the cotton belt.* MSc. Thesis, Texas A&M University.

LEPŠ, J. & ŠMILAUER, P. 2003. *Multivariate analysis of ecological data using CANOCO,* Cambridge university press.

LI, Y. 2010. Can the spatial prediction of soil organic matter contents at various sampling scales be improved by using regression kriging with auxiliary information? *Geoderma*, 159**,** 63-75.

LIMB, R. 2014. *RE: The UK sugar industry: Personal communication; British sugar Plc.*

LIU, Y., LV, J., ZHANG, B. & BI, J. 2013. Spatial multi-scale variability of soil nutrients in relation to environmental factors in a typical agricultural region, Eastern China. *Science of the Total Environment*, 450**,** 108-119.

LIU, Y., SWINTON, S. M. & MILLER, N. R. 2006. Is site-specific yield response consistent over time? Does it pay? *American Journal of Agricultural Economics*, 88**,** 471-483.

LOVELAND, P. J. & WHALLEY, W. R. 2001. Particle size analysis. *Soil and environmental analysis: physical methods (revised and expanded),* 2**,** 281-315.

LOWRY, R. 2014. Concepts and applications of inferential statistics. http://vassarstats.net/textbook/.

LUND, E., CHRISTY, C. & DRUMMOND, P. 1999. Practical applications of soil electrical conductivity mapping. *Precision Agriculture,* 99**,** 771-779.

MACRAE, I. 2003. Effect of within field topography on emergence of adult sugar beet root maggot, Tetanops myopaeformis (Roder) (Diptera: Otitidae) *Sugar Beet Research,* 40**,** 88-102.

MALNOU, C., JAGGARD, K. & SPARKES, D. 2006. A canopy approach to nitrogen fertilizer recommendations for the sugar beet crop. *European Journal of Agronomy,* 25**,** 254-263.

MALNOU, C., JAGGARD, K. & SPARKES, D. 2008. Nitrogen fertilizer and the efficiency of the sugar beet crop in late summer. *European Journal of Agronomy,* 28**,** 47-56.

MARTINEZ, B., CASSIRAGA, E., CAMACHO, F. & GARCIA-HARO, J. 2010. Geostatistics for mapping leaf area index over a cropland landscape: Efficiency sampling assessment. *Remote Sensing,* 2**,** 2584-2606.

MATHERON, G. 1965. *Les variables régionalisées et leur estimation: une application de la théorie des fonctions aléatoires aux sciences de la nature,* Masson Paris.

MERONI, M., ROSSINI, M., GUANTER, L., ALONSO, L., RASCHER, U., COLOMBO, R. & MORENO, J. 2009. Remote sensing of solar-induced chlorophyll fluorescence: Review of methods and applications. *Remote Sensing of Environment,* 113**,** 2037-2051.

MINASNY, B. & MCBRATNEY, A. B. 2007. Spatial prediction of soil properties using EBLUP with the Matérn covariance function. *Geoderma,* 140**,** 324-336.

MOGHADAM, M. S. 2002. *Yield and quality of cereals in responce to inputs and spatial variablity* PhD Thesis, Reading UK.

MOHAMMADZAMANI, D., MINAEI, S., ALIMARDANI, R., ALMASSI, M., RASHIDI, M. & NOROUZPOUR, H. 2009. Variable rate herbicide application using the global positioning system for generating a digital management map. *International Journal of Agriculture and Biology,* 11**,** 178-182.

MONDAL, P., BASU, M., BHADORIA, P., EMAM, A. A., SALIH, M. H., ADEGBITE, A. A., AYINDE, T. B., OMOLEHIN, R., IBRAHIM, U. & FOLA, A. J. 2011. Critical review of precision agriculture technologies and its scope of adoption in India. *American Journal of Experimental Agriculture,* 1**,** 49-68.

MONESTIEZ, P., COURAULT, D., ALLARD, D. & RUGET, F. 2001. Spatial interpolation of air temperature using environmental context: application to a crop model. *Environmental and Ecological Statistics,* 8**,** 297-309.

MONTANARI, R., SOUZA, G. S. A., PEREIRA, G., MARQUES, J., SIQUEIRA, D. & SIQUEIRA, G. 2012. The use of scaled semivariograms to plan soil sampling in sugarcane fields. *Precision Agriculture,* 13**,** 542-552.

MONTERO, G., ESCOBAR, J., RODRÍGUEZ, E. & MONTENEGRO, R. 2009. Solar radiation and shadow modelling with adaptive triangular meshes. *Solar Energy,* 83**,** 998-1012.

MONTI, A., BRUGNOLI, E., SCARTAZZA, A. & AMADUCCI, M. 2006. The effect of transient and continuous drought on yield, photosynthesis and carbon isotope discrimination in sugar beet (Beta vulgaris L.). *Journal of Experimental Botany,* 57**,** 1253-1262.

MULLA, D. J. 1997. Geostatistics, remote sensing and precision farming. *In:* LAKE, J. V., BOCK, G. R. & GOODS, J. A. (eds.) *Precision agriculture: Spatial and temporal variablity of environmental quality.* London-UK: Wiley.

MUTLUOGLU, Ö. & CEYLAN, A. 2009. Accuracy and cost comparison of spatial data-acquisition methods for the development of geographical information systems. *Journal of Geography and Regional Planning,* 2**,** 235-242.

NAGCHAUDHURI, A., MITRA, M., BROOKS, C., EARL, T., LADD, G. & BLAND, G. Initiating environmentally conscious precision agriculture at UMES. Annual Conference of American Society of Engineering Education, 2005 Portland Oregon.

NAJAFABADI, M. O., HOSSEINI, S. J. F. & BAHRAMNEJAD, S. 2011. A Bayesian confirmatory factor analysis of precision agricultural challenges. *African Journal of Agricultural Research,* 6**,** 1219-1225.

NIEUWENHUIZEN, A., TANG, L., HOFSTEE, J., MÜLLER, J. & VAN HENTEN, E. 2007. Colour based detection of volunteer potatoes as weeds in sugar beet fields using machine vision. *Precision Agriculture,* 8**,** 267-278.

NORMAN, J. & JARVIS, P. 1974. Photosynthesis in Sitka spruce (Picea sitchensis (Bong.) Carr.). III. Measurements of canopy structure and interception of radiation. *Journal of Applied Ecology***,** 375-398.

NUTTER, F. W., EMMANUEL Z. BYAMUKAMA, ROSALEE A. COELHO-NETTO, SHARON K. EGGENBERGER, GLEASON, M. L., , A. G., ALISON E. ROBERTSON & RIJ, N. V. 2011. Integrating GPS, GIS,and remote sensing technologies with disease management principles to improve plant health. *In:* CLAY, S. (ed.) *GIS applications in agriculture.* Boca Raton-USA: CRC Press.

OLIVER, M., BISHOP, T. & MARCHANT, B. 2013. *Precision agriculture for sustainability and environmental protection,* Abingdon, Oxon-UK, Routledge.

OLIVER, M. & WEBSTER, R. 2014. A tutorial guide to geostatistics: Computing and modelling variograms and kriging. *Catena,* 113**,** 56-69.

OLIVER, M. A. 2010. *Geostatistical applications for precision agriculture,* London-UK, Springer.

PACHEPSKY, Y. A., TIMLIN, D. & RAWLS, W. 2001a. Soil water retention as related to topographic variables.

PACHEPSKY, Y. A., TIMLIN, D. & RAWLS, W. 2001b. Soil water retention as related to topographic variables. *Soil Science Society of America Journal,* 65**,** 1787-1795.

PATI, F. M., CLAY, D. E. & CARLSON, G. 2011. Nutrient management for improved energy efficiency. *In:* CLAY, D. E. & SHANAHAN, J. F. (eds.) *GIS applications in agriculture, nutrient management for energy efficiency.* Boca Raton-USA: CRC Press.

PATZOLD, S., MERTENS, F. M., BORNEMANN, L., KOLECZEK, B., FRANKE, J., FEILHAUER, H. & WELP, G. 2008. Soil heterogeneity at the field scale: a challenge for precision crop protection. *Precision Agriculture,* 9**,** 367-390.

PAYNE, R. W. 2009. GenStat. *Wiley Interdisciplinary Reviews: Computational Statistics,* 1**,** 255-258.

PEDERSEN, S. M., FOUNTAS, S., HAVE, H. & BLACKMORE, B. 2005. Agricultural robots: an economic feasibility study. *Precision Agriculture,* 5**,** 589-595.

PEREIRA, G. T., SOUZA, Z. M. D., TEIXEIRA, D. D. B., MONTANARI, R. & MARQUES JÚNIOR, J. 2013. Optimization of the sampling scheme for maps of physical and chemical properties estimated by kriging. *Revista Brasileira de Ciência do Solo,* 37**,** 1128-1135.

PICCINI, C., MARCHETTI, A. & FRANCAVIGLIA, R. 2014. Estimation of soil organic matter by geostatistical methods: Use of auxiliary information in agricultural and environmental assessment. *Ecological Indicators,* 36**,** 301-314.

PIDGEON, J., WERKER, A., JAGGARD, K., RICHTER, G., LISTER, D. & JONES, P. 2001. Climatic impact on the productivity of sugar beet in Europe, 1961-1995. *Agricultural and Forest Meteorology,* 109**,** 27-37.

PIERCE, F. J. & CLAY, D. 2007. *GIS applications in agriculture,* USA, CRC Press.

PIERCE JR, K. B., LOOKINGBILL, T. & URBAN, D. 2005. A simple method for estimating potential relative radiation (PRR) for landscape-scale vegetation analysis. *Landscape Ecology,* 20**,** 137-147.

QI, A., ERIC, E. S. & JAGGARD, K. W. 2013. Updating the BBRO/Broom's Barn sugar beet growth model. *British Sugar Beet Review* 81**,** 29-32.

QI, A., KENTER, C., HOFFMANN, C. & JAGGARD, K. 2005. The Broom's Barn sugar beet growth model and its adaptation to soils with varied available water content. *European Journal of Agronomy*, 23**,** 108-122.

RAINS, G. C. & THOMAS 2009. Precision farming an introduction. *In:* ATHENAEUM@UGA (ed.) *Cooperative extension.* University of Georgia: Athenaeum@UGA.

RASMUSSEN, J., NIELSEN, J., GARCIA-RUIZ, F., CHRISTENSEN, S. & STREIBIG, J. C. 2013. Potential uses of small unmanned aircraft systems (UAS) in weed research. *Weed Research*, 53**,** 242-248.

REICHARDT, M., JÜRGENS, C., KLÖBLE, U., HÜTER, J. & MOSER, K. 2009. Dissemination of precision farming in Germany: acceptance, adoption, obstacles, knowledge transfer and training activities. *Precision Agriculture*, 10**,** 525-545.

REYNIERS, M., VRINDTS, E. & DE BAERDEMAEKER, J. 2006. Comparison of an aerial-based system and an on the ground continuous measuring device to predict yield of winter wheat. *European Journal of Agronomy*, 24**,** 87-94.

REYNOLDS, G. J. 2010. *Remote Sensing for Detection of Rhizoctonia Crown and Root Rot in Sugar Beet and the Impact of the Disease on Chlorophyll Content.* MSc. Thesis, University of Minnesota.

RICHTER, G., QI, A., SEMENOV, M. & JAGGARD, K. 2006. Modelling the variability of UK sugar beet yields under climate change and husbandry adaptations. *Soil Use and Management*, 22**,** 39-47.

RICHTER, G. M., JAGGARD, K. W. & MITCHELL, R. A. 2001. Modelling radiation interception and radiation use efficiency for sugar beet under variable climatic stress. *Agricultural and Forest Meteorology*, 109**,** 13-25.

ROCCHINI, D., FOODY, G. M., NAGENDRA, H., RICOTTA, C., ANAND, M., HE, K. S., AMICI, V., KLEINSCHMIT, B., FÖRSTER, M. & SCHMIDTLEIN, S. 2013. Uncertainty in ecosystem mapping by remote sensing. *Computers & Geosciences*, 50**,** 128-135.

RODRIGUEZ-MORENO, F., LUKAS, V., NEUDERT, L. & DRYŠLOVÁ, T. 2014. Spatial interpretation of plant parameters in winter wheat. *Precision Agriculture*, 15**,** 1-19.

ROEL, A. & PLANT, R. E. 2004. Factors underlying yield variability in two California rice fields. *Agronomy Journal,* 96**,** 1481-1494.

SADEGHIAN, S. & YAVARI, N. 2004. Effect of water-deficit stress on germination and early seedling growth in sugar beet. *Journal of Agronomy and Crop Science,* 190**,** 138-144.

SADLER, E. J., BUSSCHER, W. J., BAUER, P. J. & KARLEN, D. L. 1998. Spatial scale requirements for precision farming: a case study in the southeastern USA. *Agronomy Journal,* 90**,** 191-197.

SAFARI, Y., BOROUJENI, I. E., KAMALI, A., SALEHI, M. H. & BODAGHABADI, M. B. 2013. Mapping of the soil texture using geostatistical method (a case study of the Shahrekord plain, central Iran). *Arabian Journal of Geosciences,* 6**,** 3331-3339.

SAĞLAM, M., ÖZTÜRK, H., ERŞAHIN, S. & ÖZKAN, A. 2011. Spatial variation of soil physical properties in adjacent alluvial and colluvial soils under Ustic moisture regime. *Hydrology and Earth System Sciences Discussions,* 8**,** 4261-4280.

SAMSON-BRĘK, I. 2010. Sugar beet production. *In:* CBE (ed.) *Basic data of technology description.* European Union: ERDF.

SCANNAVINO, F. A., PEREZ-KUROKI, A. J., GHOBAKHLOU, A., SALLISC, P., SHANMUGANATHAN, S. & CRUVINEL, P. E. 2011. Spatial variability on soil pH gradient: A case study in vineyards. *In:* TECHNOLOGY, A. U. O. (ed.) *19th International Congress on Modelling and Simulation.* Perth, Australia.

SCHLECHTE, G. L. & OFFICER, D. O. P. 1994. Design Process for the United States Coast Guard's Differential GPS Navigation Service.

SCOTT, R. K. & JAGGARD, K. W. 1993. Crop physiology and agronomy. *In:* COOKE, D. A. & SCOTT, R. K. (eds.) *The sugar beet crop.* Chapman and Hall: London-UK.

SHAHBAZI, F., ALIASGHARZAD, N., EBRAHIMZAD, S. & NAJAFI, N. 2013. Geostatistical analysis for predicting soil biological maps under different scenarios of land use. *European Journal of Soil Biology,* 55**,** 20-27.

SHANER, D., KHOSLA, R., BRODAHL, M., BUCHLEITER, G. & FARAHAM, H. 2008. How well does zone sampling based on soil electrical conductivity maps represent soil variability. *Agronomy Journal,* 100**,** 1472- 148.

SHANWAD, U., PATIL, V., DASOG, G., MANSUR, C. & SHASHIDHAR, K. Global Positioning System (GPS) in Precision Agriculture. The Asian GPS Conference 24–25 October 2002 New Delhi-India.

SHELDRICK, B. H. & WANG, C. 1993. Particle Size Distribution *In:* CARTER, M. R. (ed.) *Soil sampling and methods of analysis.* Boca Raton-USA: CRC Press.

SHERMAN, M. 2011. *Spatial statistics and spatio-temporal data: covariance functions and directional properties,* USA, John Wiley & Sons.

SILVA, A. M., NALON, M. A., KRONKA, F. J. N., ALVARES, C. A., CAMARGO, P. B. & MARTINELLI, L. A. 2007. Historical land-cover/use in different slope and riparian buffer zones in watersheds of the State of São Paulo, Brazil. *Scientia Agricola,* 64**,** 325-335.

SIMMONDS, M. B., PLANT, R. E., PENA-BARRAGÁN, J. M., VAN KESSEL, C., HILL, J. & LINQUIST, B. A. 2013. Underlying causes of yield spatial variability and potential for precision management in rice systems. *Precision Agriculture,* 14**,** 512-540.

SIQUEIRA, D., MARQUES JR, J. & PEREIRA, G. 2010. The use of landforms to predict the variability of soil and orange attributes. *Geoderma,* 155**,** 55-66.

SIVARAJAN, S. 2011. *Estimating Yield of Irrigated Potatoes Using Aerial and Satellite Remote Sensing.* PhD Thesis, Utah State University.

SLAUGHTER, D., GILES, D. & DOWNEY, D. 2008. Autonomous robotic weed control systems: a review. *Computers and Electronics in Agriculture,* 61**,** 63-78.

ŠMILAUER, P. & LEPŠ, J. 2014. *Multivariate analysis of ecological data using CANOCO 5,* Cambridge-UK, Cambridge university press.

SOPER, D. S. 2015. Significance of the Difference between Two Correlations Calculator [Software]. Available from http://www.danielsoper.com/statcalc

STAFFORD, J., AMBLER, B., LARK, R. & CATT, J. 1996. Mapping and interpreting the yield variation in cereal crops. *Computers and Electronics in Agriculture,* 14**,** 101-119.

STEVENS, M. 2015. 2013 emergence issue-a review by the BBRO. *In:* LIMB, R. (ed.) *Sugar Beet Review.* UK: British Beet Research Organization

SUDDUTH, K., KITCHEN, N., WIEBOLD, W., BATCHELOR, W., BOLLERO, G., BULLOCK, D., CLAY, D., PALM, H., PIERCE, F. & SCHULER, R. 2005. Relating apparent electrical conductivity to soil properties across the north-central USA. *Computers and Electronics in Agriculture,* 46**,** 263-283.

SUDDUTH, K. A. 1998. Engineering for Precision Agriculture-Past accomplishments and future directions.

TAYLOR, J., WOOD, G., EARL, R. & GODWIN, R. 2003. Soil factors and their influence on within-field crop variability, part II: spatial analysis and determination of management zones. *Biosystems Engineering,* 84**,** 441-453.

THORNTON, P., FAWCETT, R., DENT, J. & PERKINS, T. 1990. Spatial weed distribution and economic thresholds for weed control. *Crop Protection,* 9**,** 337-342.

TOVAR-PESCADOR, J., POZO-VÁZQUEZ, D., RUIZ-ARIAS, J., BATLLES, J., LÓPEZ, G. & BOSCH, J. 2006. On the use of the digital elevation model to estimate the solar radiation in areas of complex topography. *Meteorological Applications,* 13**,** 279-287.

VAN GROENIGEN, J., STEIN, A. & ZUURBIER, R. 1997. Optimization of environmental sampling using interactive GIS. *Soil Technology,* 10**,** 83-97.

VANEK, V., BALIK, J., SILHA, J. & CERNY, J. 2008. Spatial variability of total soil nitrogen and sulphur content at two conventionally managed fields. *Plant Soil and Environment,* 54**,** 413-419.

VIEIRA, S. R., GREGO, C. R. & TOPP, G. C. 2008. Analyzing spatial and temporal variability of soil water content. *Bragantia,* 67**,** 463-469.

WATSON, D. 1952. The physiological basis of variation in yield. *Advance in Agronomy,* 4**,** 101-145.

WEBSTER, R. & LARK, M. 2012. *Field sampling for environmental science and management,* Abingdon, Oxon-UK, Routledge.

WEBSTER, R. & OLIVER, M. A. 2007. *Geostatistics for environmental scientists,* West Sussex-UK, Wiley

WERKER, A. & JAGGARD, K. 1997. Modelling asymmetrical growth curves that rise and then fall: applications to foliage dynamics of sugar beet (*Beta vulgaris L.*). *Annals of Botany,* 79**,** 657-665.

WERKER, A. & JAGGARD, K. 1998. Dependence of sugar beet yield on light interception and evapotranspiration. *Agricultural and Forest Meteorology*, 89**,** 229-240.

WHALLEY, D. & SIEGFRIED, H. C. 1964. *ICUMSA methods of sugar analysis*, New York-USA, Elsevier

WIEBOLD, W., SUDDUTH, K., DAVIS, J., SHANNON, D. & KITCHEN, N. 1998. Determining barriers to adoption and research needs of precision agriculture. *Retrieved December from http://www. fse. missouri. edu/mpac/pubs/parpt. pdf*.

WIGNERON, J. P., CALVET, J. C., PELLARIN, T., VAN DE GRIEND, A., BERGER, M. & FERRAZZOLI, P. 2003. Retrieving near-surface soil moisture from microwave radiometric observations: current status and future plans. *Remote Sensing of Environment,* 85**,** 489-506.

WORTMANN, C. S., DOBERMANN, A. R., FERGUSON, R. B., HERGERT, G. W., SHAPIRO, C., TARKALSON, D. & WALTERS, D. T. 2009. High-yielding corn response to applied phosphorus, potassium, and sulfur in Nebraska. *Agronomy Journal*, 101**,** 546-555.

YANG, D., SUN, F., LIU, Z., CONG, Z., NI, G. & LEI, Z. 2007. Analyzing spatial and temporal variability of annual water-energy balance in nonhumid regions of China using the Budyko hypothesis. *Water Resources Research,* 43.

YıLMAZ, I., TIRYAKIOGLU, I., TAKTAK, F. & UYSAL, M. Using RTK GPS method in creation of Digital Terrain Models". International conference on cartograpgy and GIS, January 25-28 2006 Bulgaria.

ZELEKE, T. B. S. & CHENG, B. 2004. Scaling properties of topographic indices and crop yield. *Agronomy Journal,* 96**,** 1082.

ZHANG, F., YIN, G., WANG, Z., MCLAUGHLIN, N., GENG, X. & LIU, Z. 2013. Quantifying spatial variability of selected soil trace elements and their scaling relationships using multifractal techniques. *PloS one,* 8**,** e69326.

ZHANG, L., CLARKE, M., STEVEN, M. & JAGGARD, K. 2011a. Spatial patterns of wilting in sugar beet as an indicator for precision irrigation. *Precision Agriculture,* 12**,** 296-316.

ZHANG, L., STEVEN, M., CLARKE, M. & JAGGARD, K. 2007. Mapping soil water holding capacity at a within-field scale for precision irrigation. 7th UK CARE annual general meeting, 15 September 2007 Greenwich-UK. UK Chinese Association of Resources and Environment 1-9.

ZHANG, S., ZHANG, X., HUFFMAN, T., LIU, X. & YANG, J. 2011b. Influence of topography and land management on soil nutrients variability in Northeast China. *Nutrient Cycling in Agroecosystems*, 89**,** 427-438.

ZHANG, X. 2011. Digital northern great plains and zone mapping application for precision agriculture. *In:* CLAY, D. E. & SHANAHAN, J. F. (eds.) *GIS application in agriculture.* Boca Raton-USA: CRC Press.

ZHANG, X., SEELAN, S. & SEIELSTAD, G. 2010a. Digital northern great plains: a web-based system delivering near real time remote sensing data for precision agriculture. *Remote Sensing,* 2**,** 861-873.

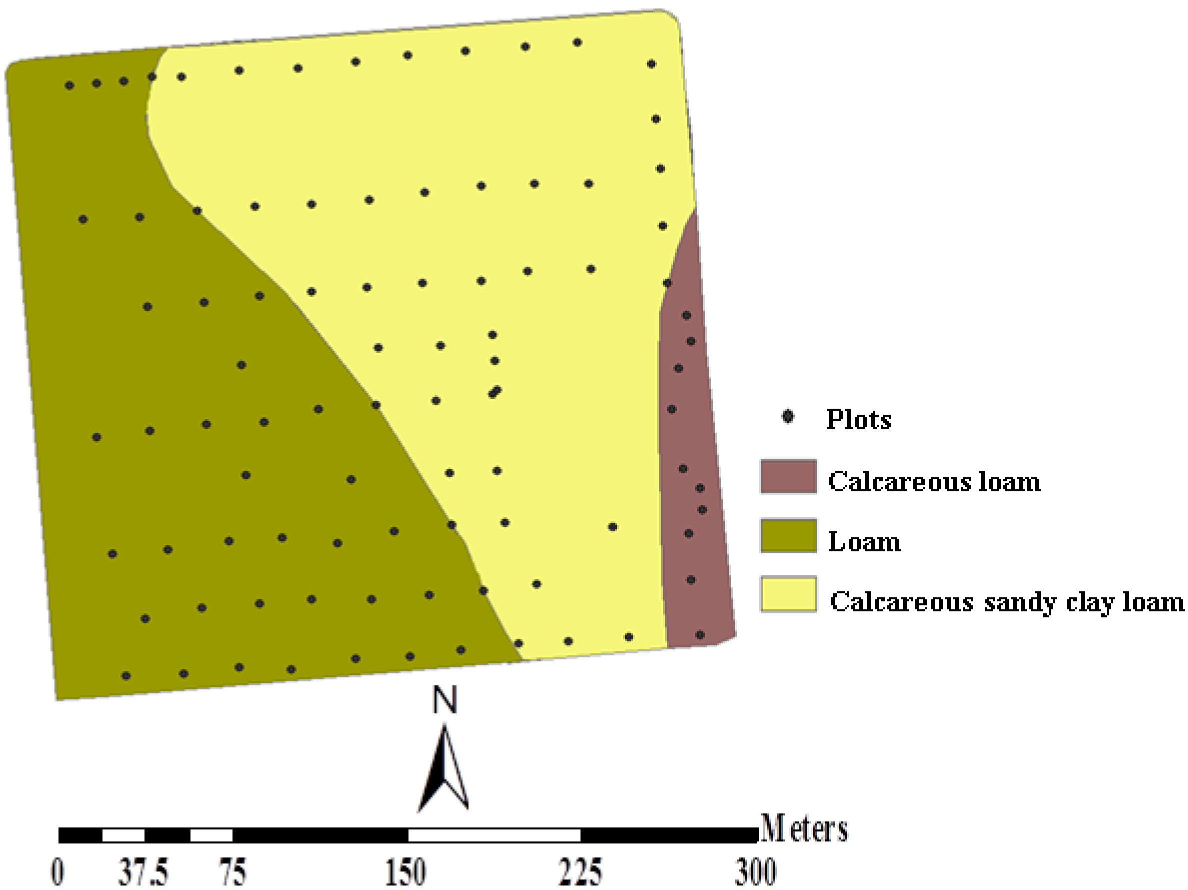
ZHANG, X., SHI, L., JIA, X., SEIELSTAD, G. & HELGASON, C. 2010b. Zone mapping application for precision-farming: a decision support tool for variable rate application. *Precision Agriculture,* 11**,** 103-114.

ZHU, Q., LIN, H. & DOOLITTLE, J. 2013. Functional soil mapping for site-specific soil moisture and crop yield management. *Geoderma,* 200**,** 45-54.

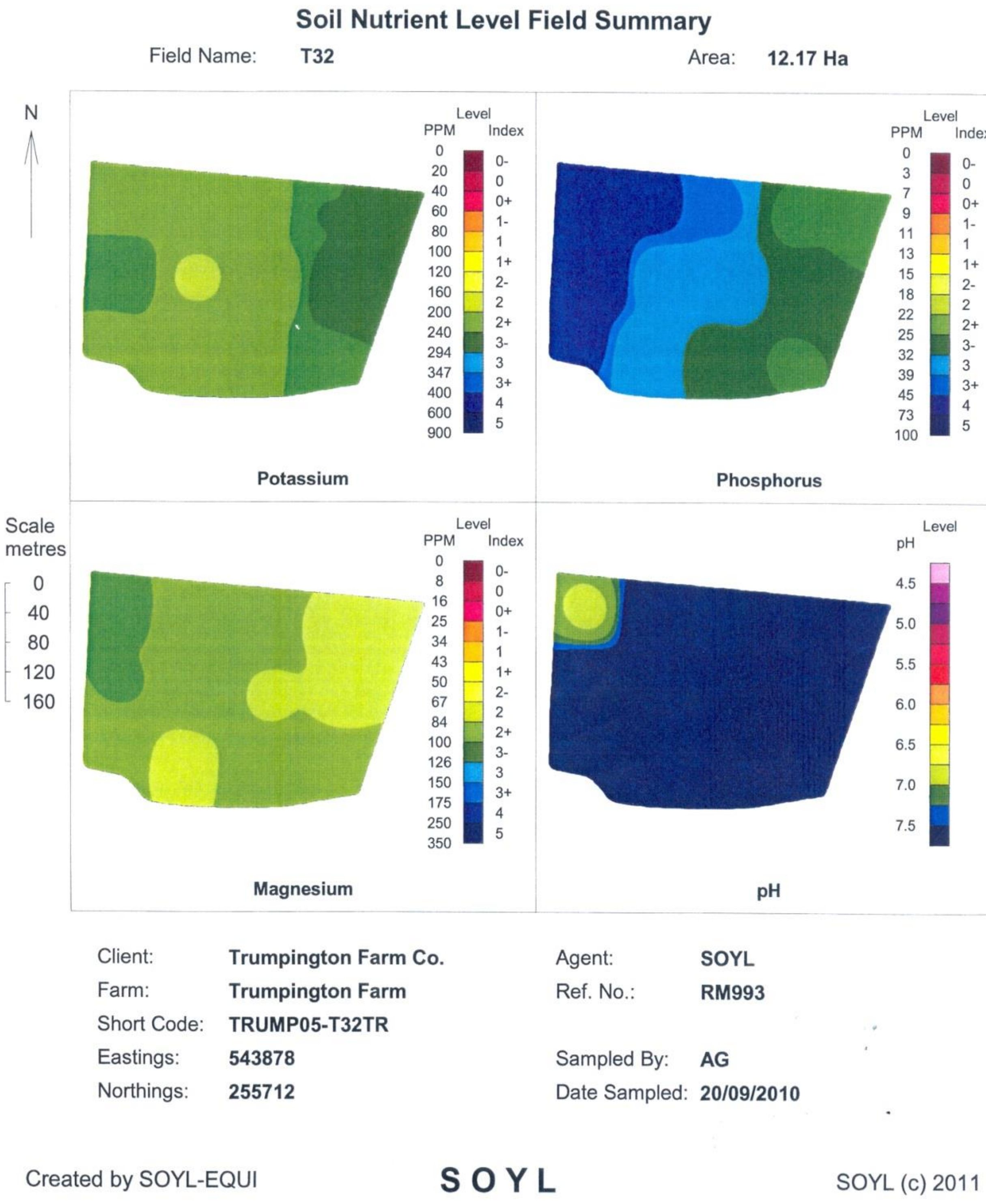
Appendixes:

Appendix 1: The maps of some soil properties of the fields:

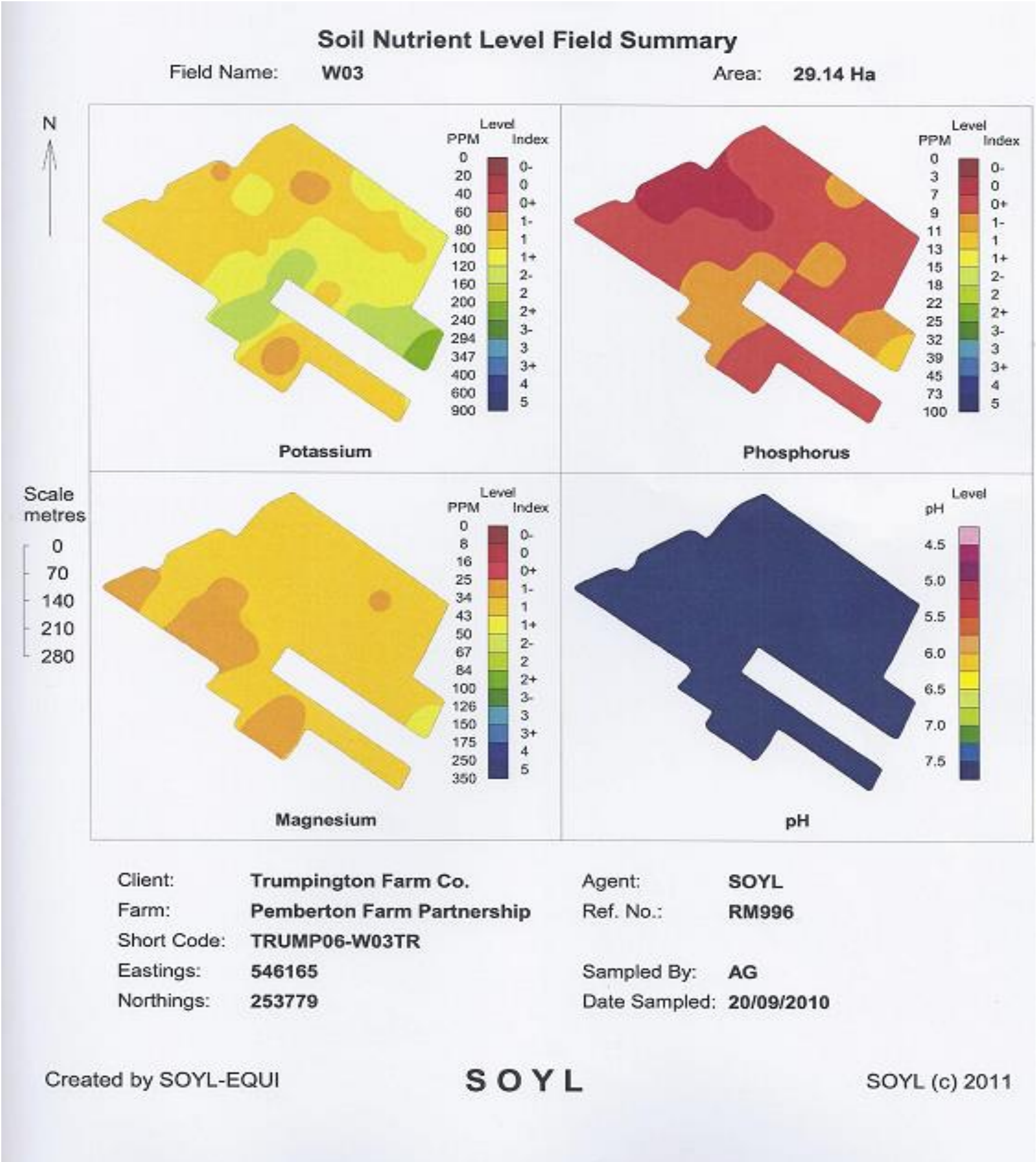
Appendix 1.1: The map of main soil types at White Patch field in 2012 created by (Draycott and Evans, 2012) based 49 samples (40X40 m grid with five samples per hectare) and the locations of plots where the measurements of sugar beet have been taken in this study.



Appendix 1.2: The map of main soil nutrients and pH at T32 field in 2011 crated based on 12 samples (one sample per hectare) as provided by Trumpington farm company:

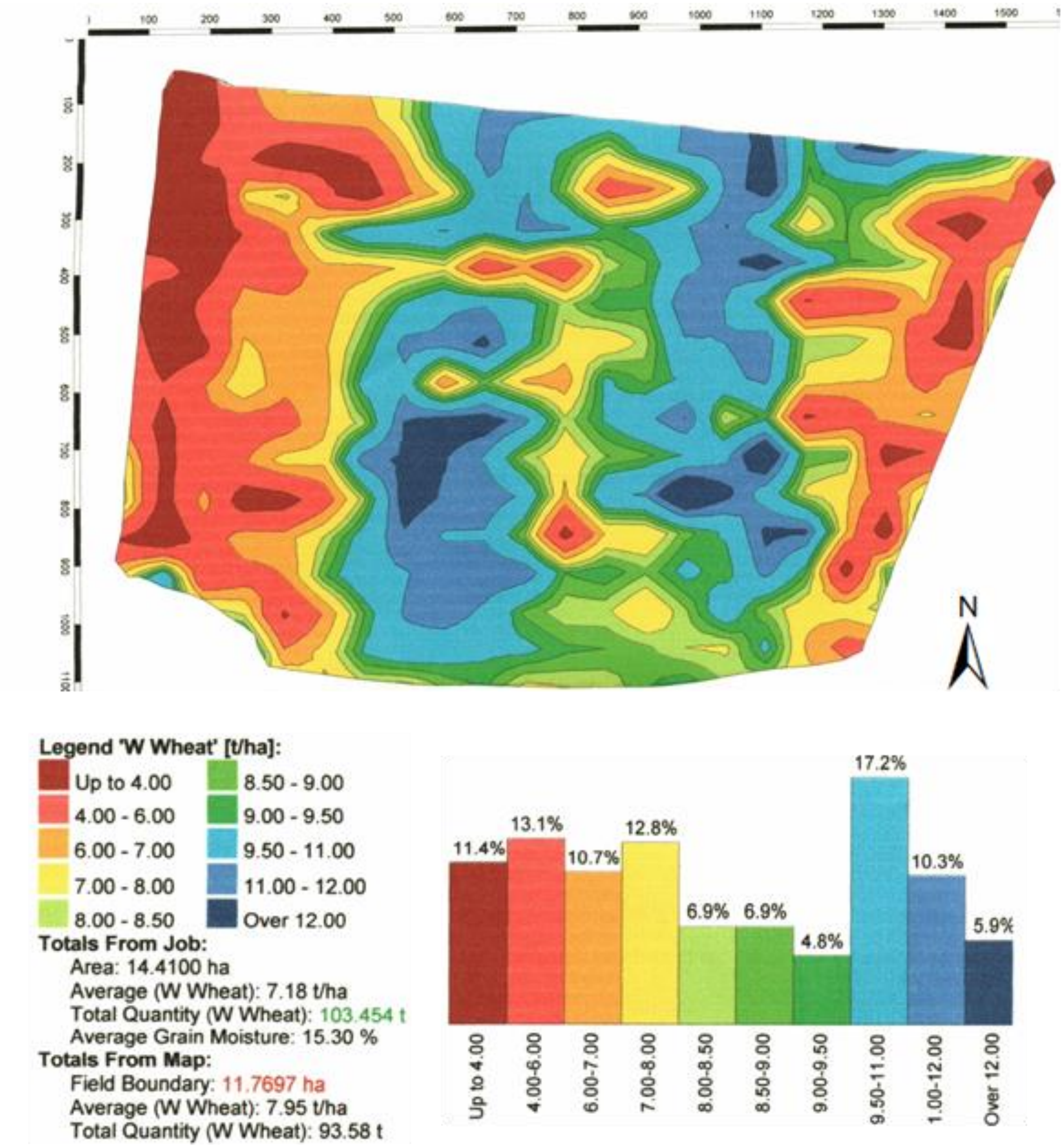


Appendix 1.3: The map of main soil nutrients and pH at WO3 field in 2013 crated based on 30 samples (one sample per hectare):

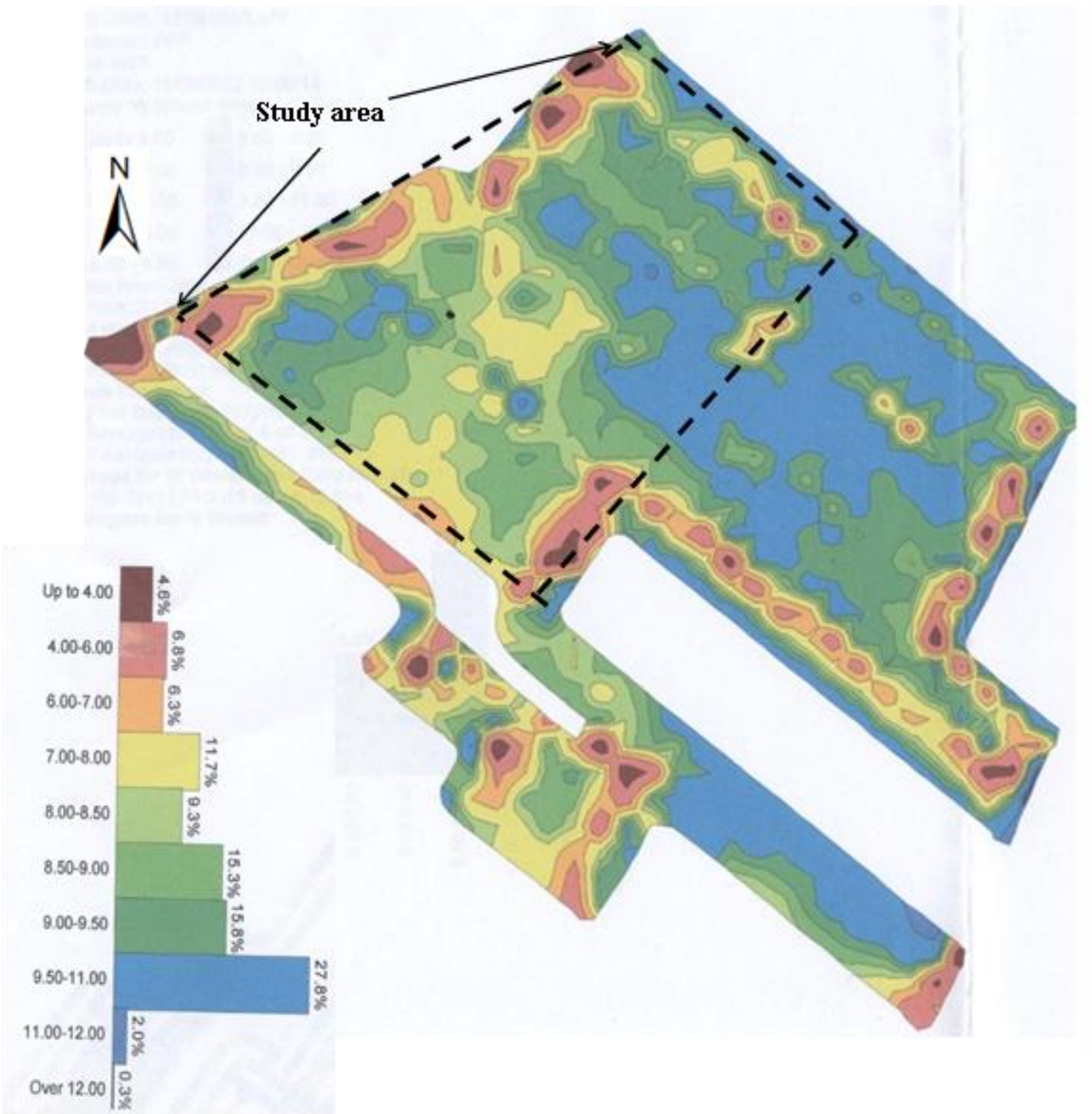


Appendix 2: The maps of crops preceding sugar beet crop provided by the combine harvester:

Appendix 2.1: The yield map of winter wheat in T32 in 2011 preceding sugar beet crop:



Appendix 2.2: The yield map of winter wheat in WO3 in 2012 preceding sugar beet crop, the dished black line shows the identified for the study which is approximately 12 ha and it appears more variable than the other parts of the field therefore it was selected:



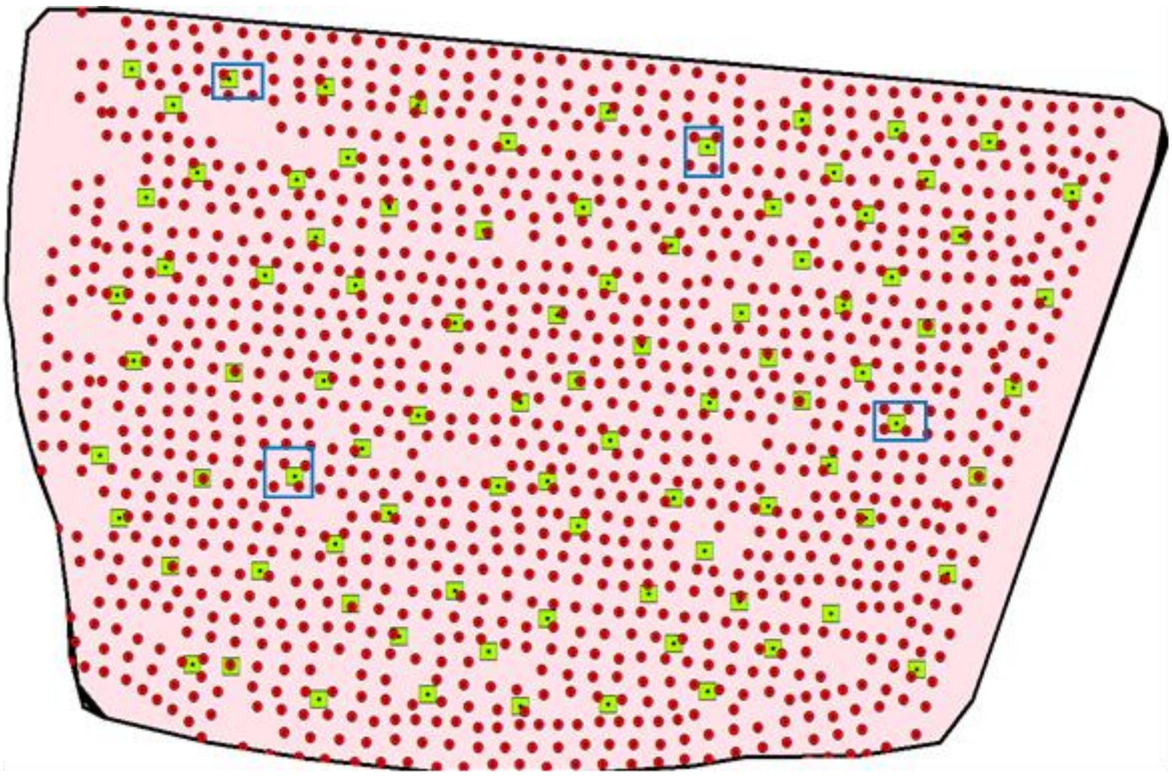
Appendix 3: Conversion of actual beet tonnage into adjusted beet tonnage by reference to actual sugar content:

Column 1 is the actual sugar content and column 2 is the adjusted factor identified for each sugar percentage to adjust tonnage based on the factor in column 2 (British Sugar).

Actual sugar content (1)	Factor (2)	Actual sugar content (1)	Factor (2)
13	0.715	16.6	1.064
13.1	0.725	16.7	1.073
13.2	0.735	16.8	1.082
13.3	0.745	16.9	1.091
13.4	0.755	17	1.1
13.5	0.765	17.1	1.108
13.6	0.775	17.2	1.116
13.7	0.785	17.3	1.124
13.8	0.795	17.4	1.132
13.9	0.805	17.5	1.14
14	0.815	17.6	1.148
14.1	0.825	17.7	1.156
14.2	0.835	17.8	1.164
14.3	0.845	17.9	1.172
14.4	0.855	18	1.18
14.5	0.865	18.1	1.187
14.6	0.875	18.2	1.194
14.7	0.885	18.3	1.201
14.8	0.895	18.4	1.208
14.9	0.905	18.5	1.215
15	0.915	18.6	1.222
15.1	0.925	18.7	1.229
15.2	0.935	18.8	1.236
15.3	0.945	18.9	1.243
15.4	0.955	19	1.25
15.5	0.965	19.1	1.257
15.6	0.974	19.2	1.264
15.7	0.983	19.3	1.271
15.8	0.992	19.4	1.278
15.9	1.001	19.5	1.285
16	1.01	19.6	1.292
16.1	1.019	19.7	1.299
16.2	1.028	19.8	1.306
16.3	1.037	19.9	1.313
16.4	1.046	20	1.32
16.5	1.055		

Appendix 4: Identifying the yield (t/ha) of previous crop (winter wheat) in the plots where the sugar beet measurements were taken in T32 field:

The value of wheat yield (t/h) where identified in the plots at which all the sugar beet measurements were taken ( ) by averaging the value at the nearest 4 points at which the wheat yield was measured ( ) by the combine harvester and identified by the blue square ( ).

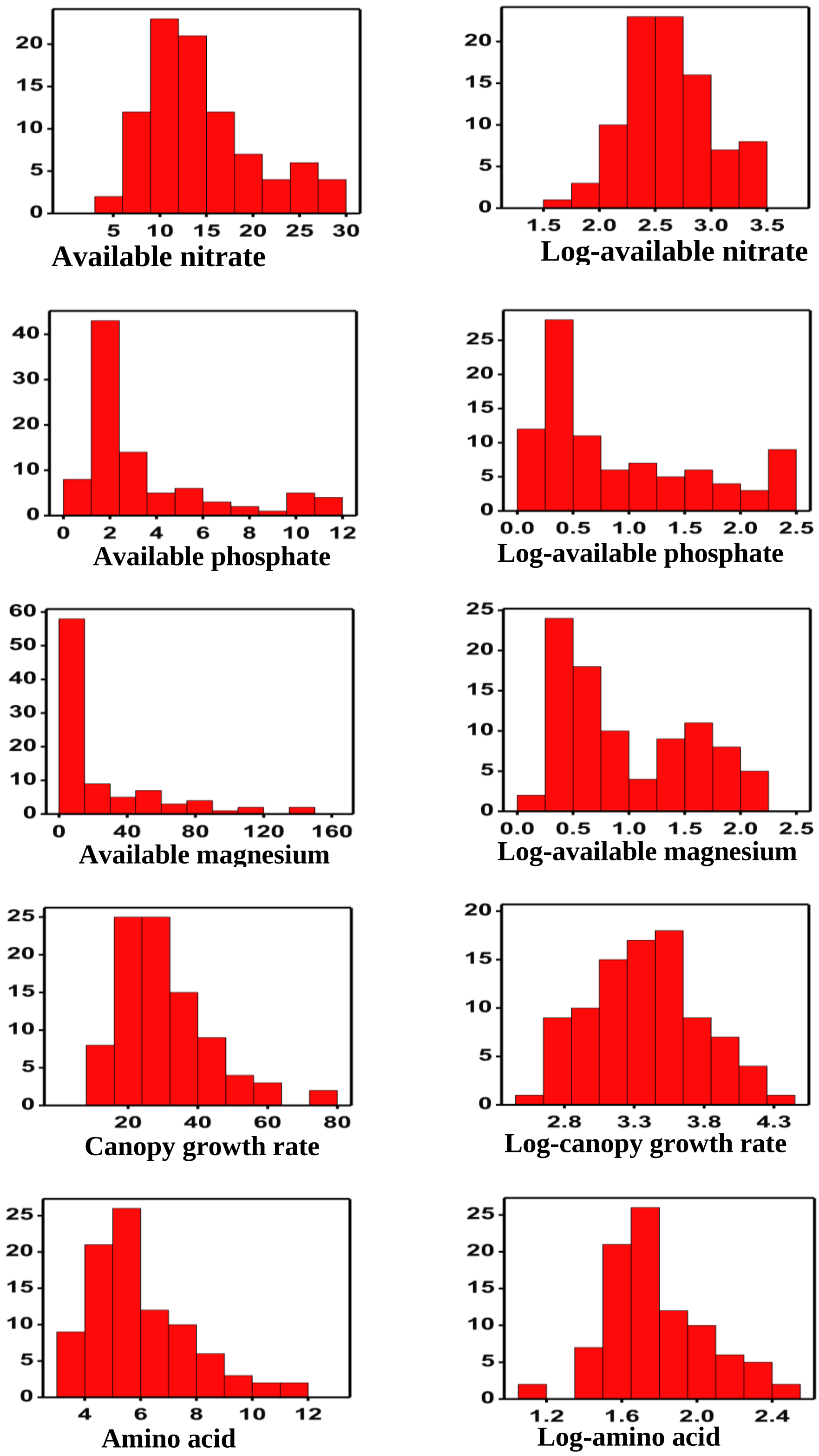


The identified plots for this study at which sugar beet measurement is based

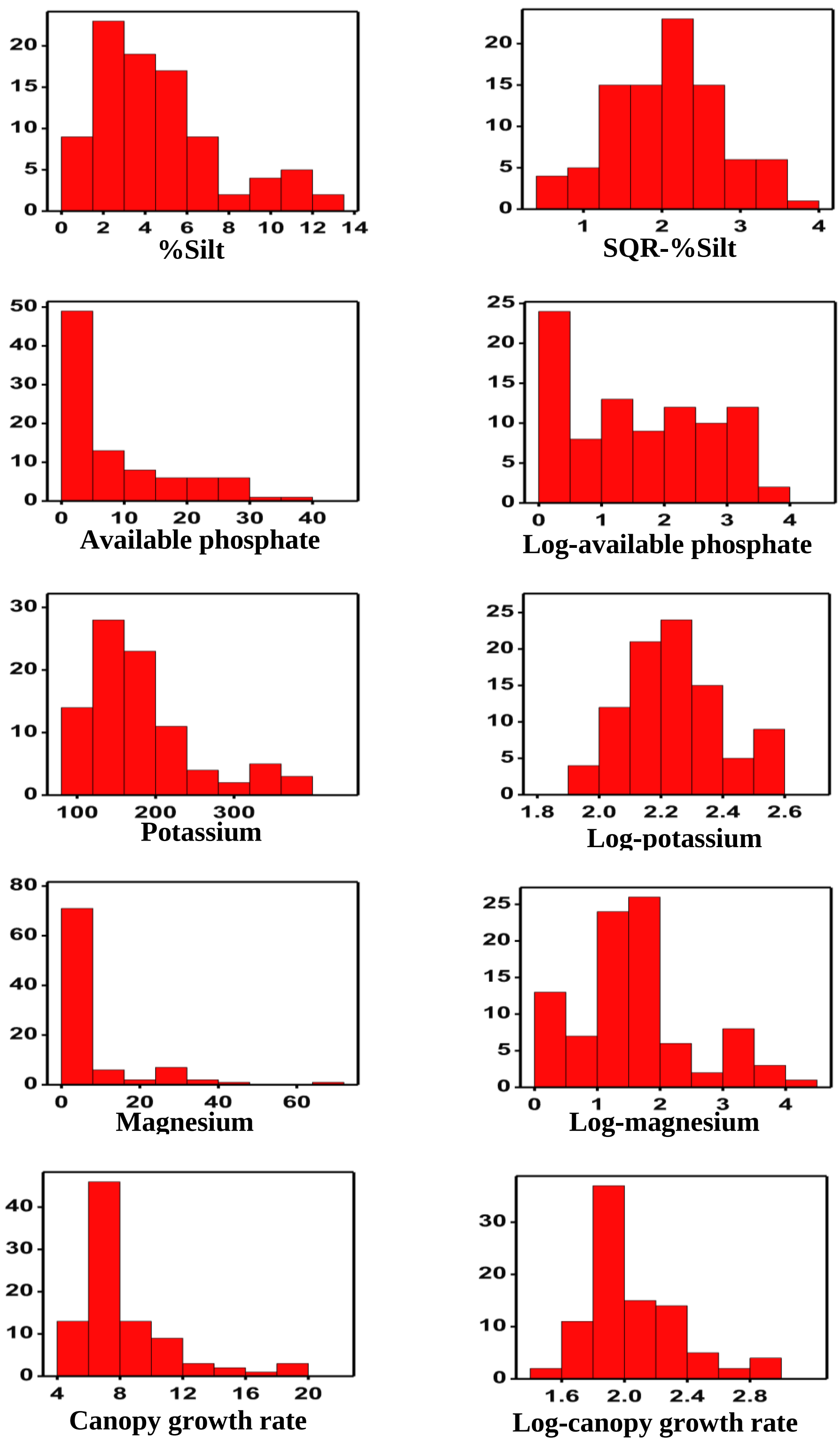
The points at which the wheat yield was measured by the harvester

Appendix 5: The histograms of original and transformed data:

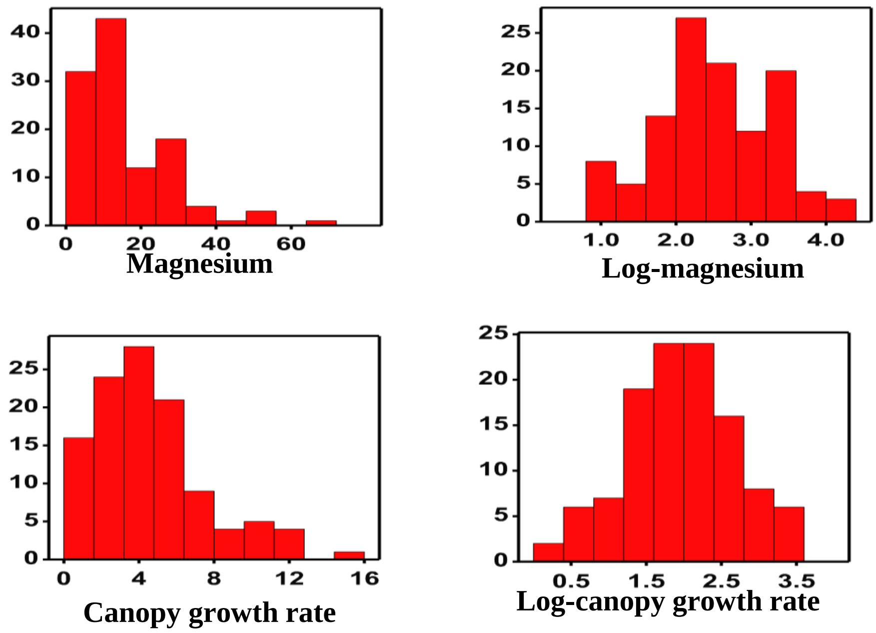
Appendix 5.1: The histograms of original (A) and transformed data (B) for some variables in White Patch field,



Appendix 5.2: The histograms of original (A) and transformed data (B) for some variables in T32 field,

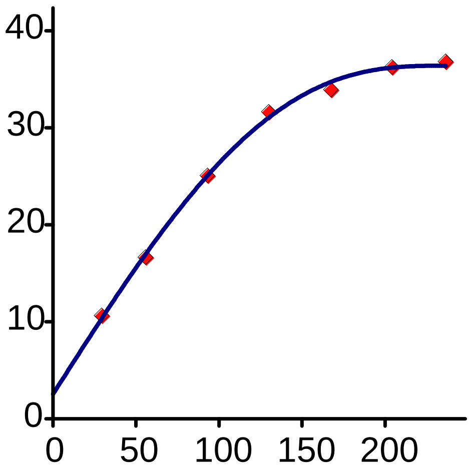


Appendix 5.3: The histograms of original (A) and transformed data (B) for some variables in WO3 field,

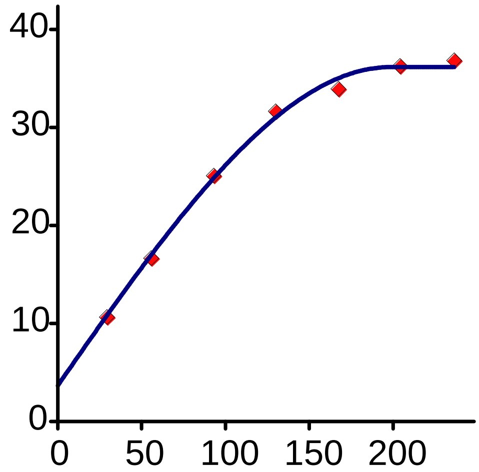


Appendix 6: The experimental variogram fitted with different models:

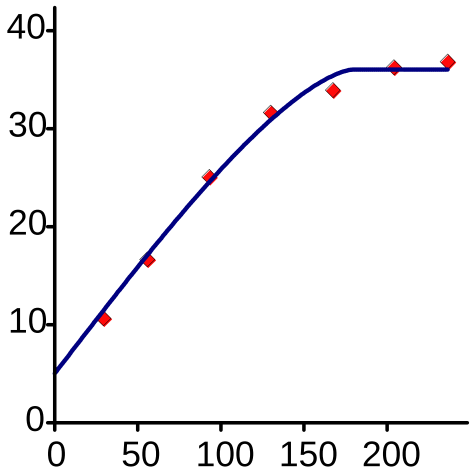
D- Pentaspherical RMS=183



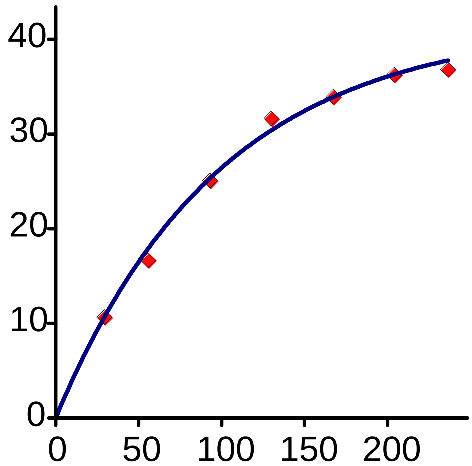
C- Spherical RMS=310



B- Circular RMS=571



A- Exponential RMS=328

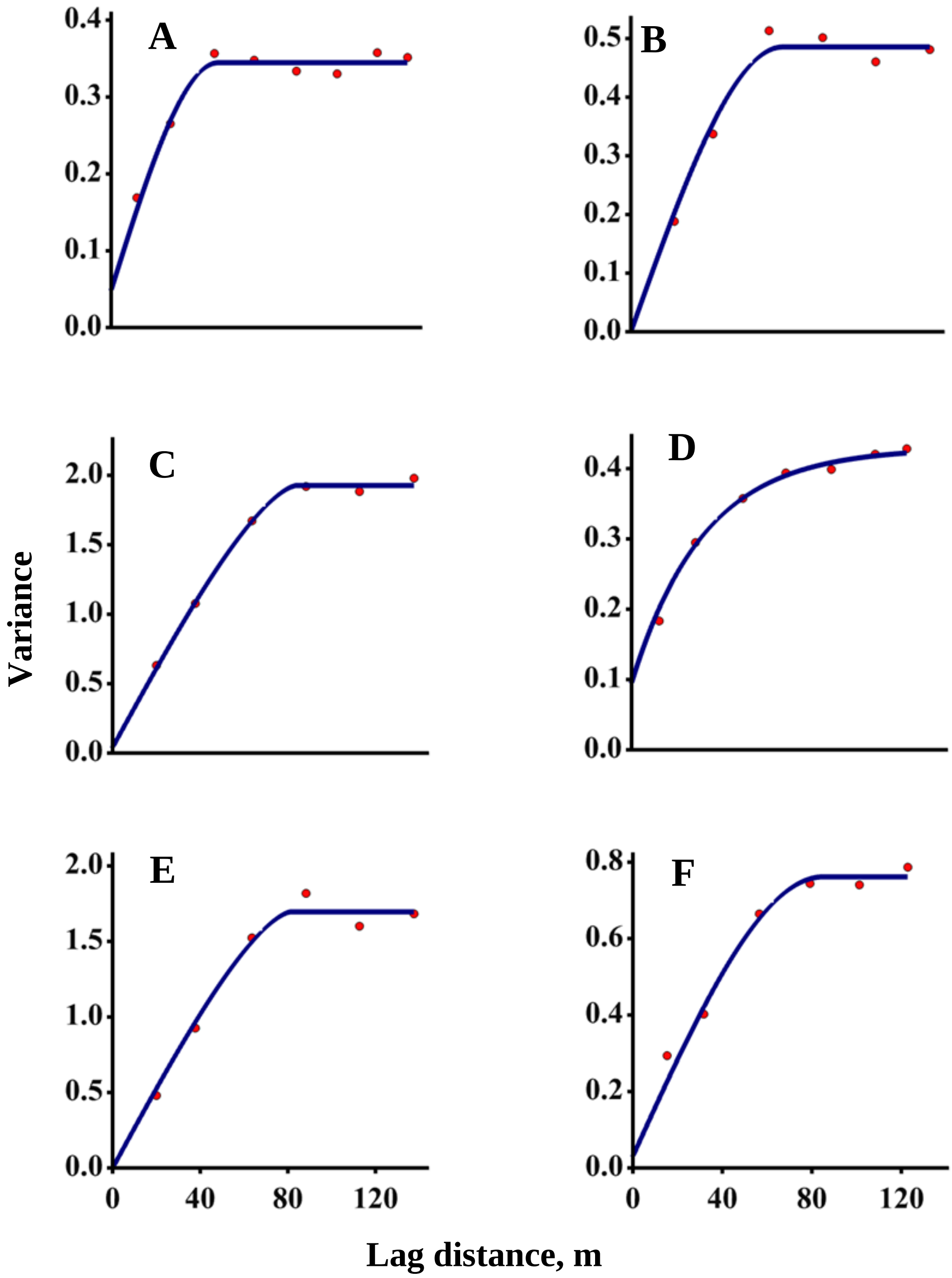


Appendix 7: The model parameters and the excremental variograms for the simulated yields in all three fields.

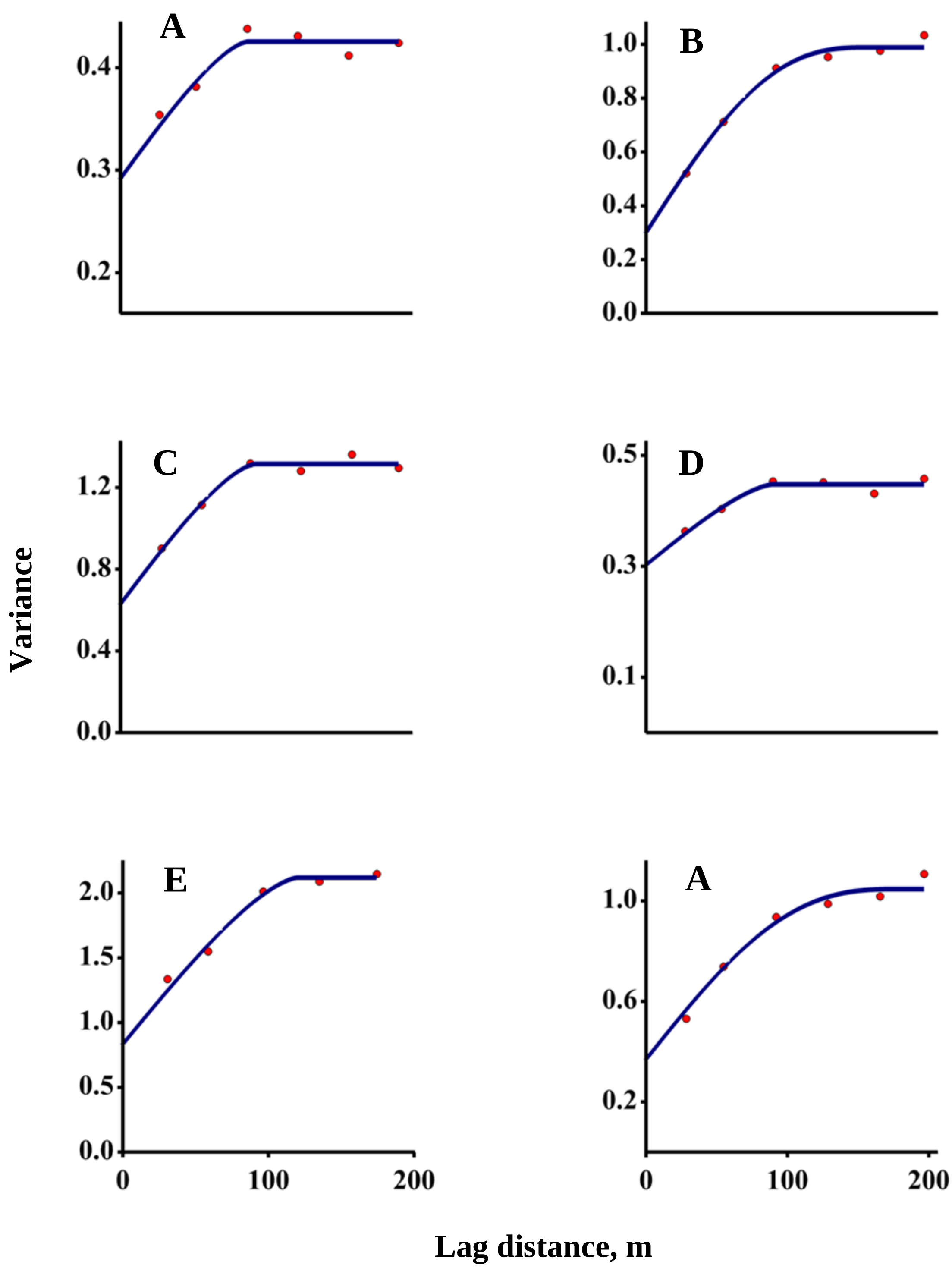
Appendix 7.1: The model parameters for the variograms of simulated yields in the three fields:

	Model	Range, m (a)	Sill (C1)	Nugget (C0)	C0/(C0+C1)
White patch					
Simulated sugar yield t/ha (unadjusted)	Spherical	52	0.30	0.05	0.14
Simulated sugar yield (t/ha)adjusted for					
Canopy cover in June	Spherical	70	0.50	0	0
Weed density in July	Circular	84	1.9	0.04	2
Plant population	Exponential	98	0.33	0.1	23
Canopy and weeds	Circular	81	1.7	0	0
Canopy and plant population	Spherical	85	0.73	0.03	4
T32					
Simulated sugar yield t/ha (unadjusted)	Circular	92	0.13	0.29	69
Simulated sugar yield (t/ha)adjusted for					
Canopy cover in June	Pentaspherical	158	0.69	0.30	30
Weed density in July	Circular	112	0.69	0.62	47
Plant population	Circular	92	0.15	0.30	67
Canopy and weeds	Circular	120	1.3	0.83	39
Canopy and plant population	Pentaspherical	180	0.68	0.37	35
WO3					
Simulated sugar yield t/ha (unadjusted)	Circular	140	0.78	0.25	24
Simulated sugar yield (t/ha)adjusted for					
Canopy cover in June	Circular	112	1.1	0.22	17
Weed density in July	Circular	129	1.3	1.03	44
Plant population	Spherical	134	4.4	1.2	21
Canopy and weeds	Circular	114	1.7	1.2	41
Canopy and plant population	Spherical	105	6.04	0.88	12

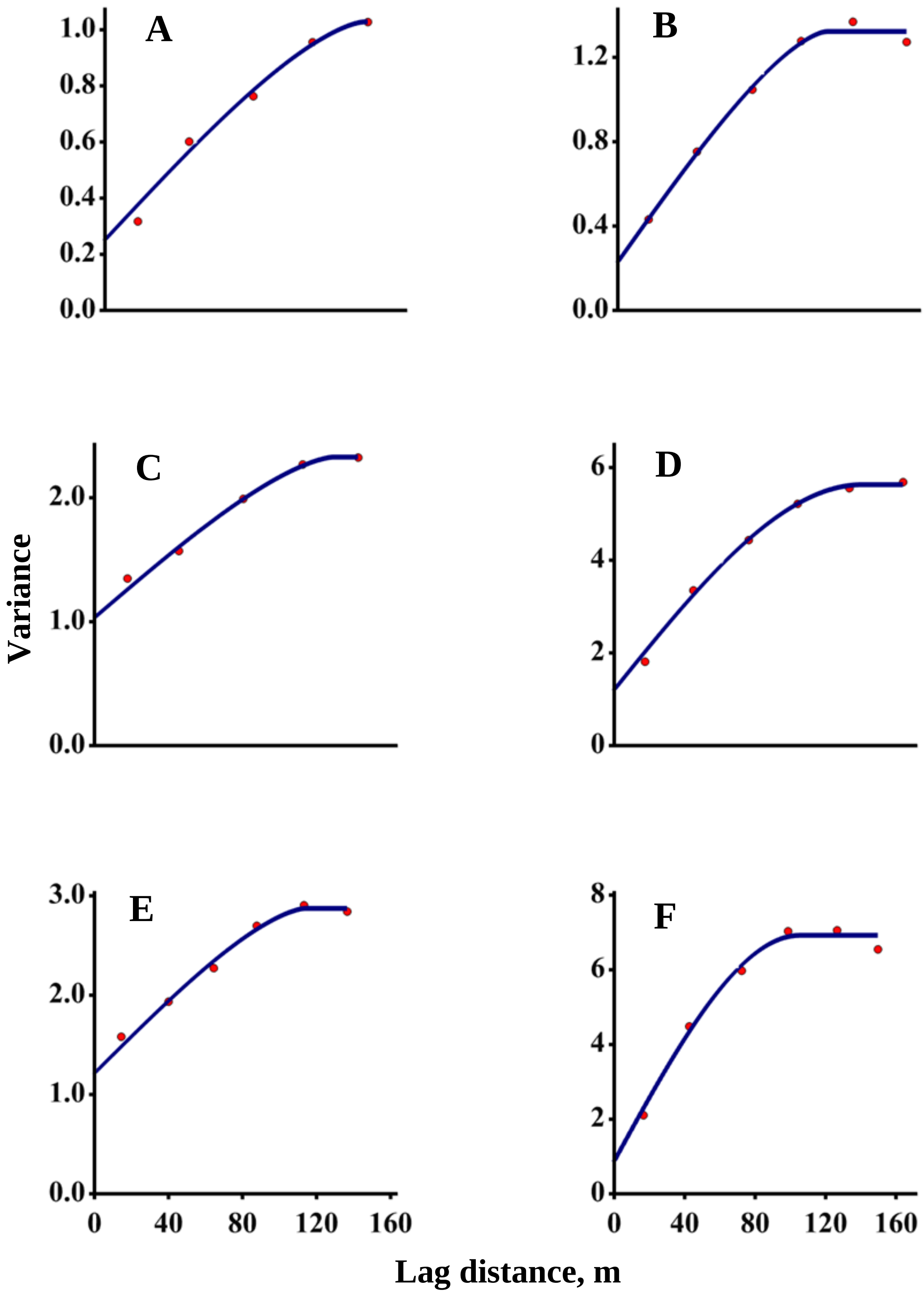
Appendix 7.2: The experimental variograms of simulated yields White patch field, (A) simulated yield (unadjusted), and adjusted for (B) canopy cover in June, (C) weeds, (D) plant population, (E) canopy cover and weeds and (F) canopy cover and plant population.



Appendix 7.3: The experimental variograms of simulated yields T32 field, (A) simulated yield (unadjusted), and adjusted for (B) canopy cover in June, (C) weeds, (D) plant population, (E) canopy cover and weeds and (F) canopy cover and plant population.

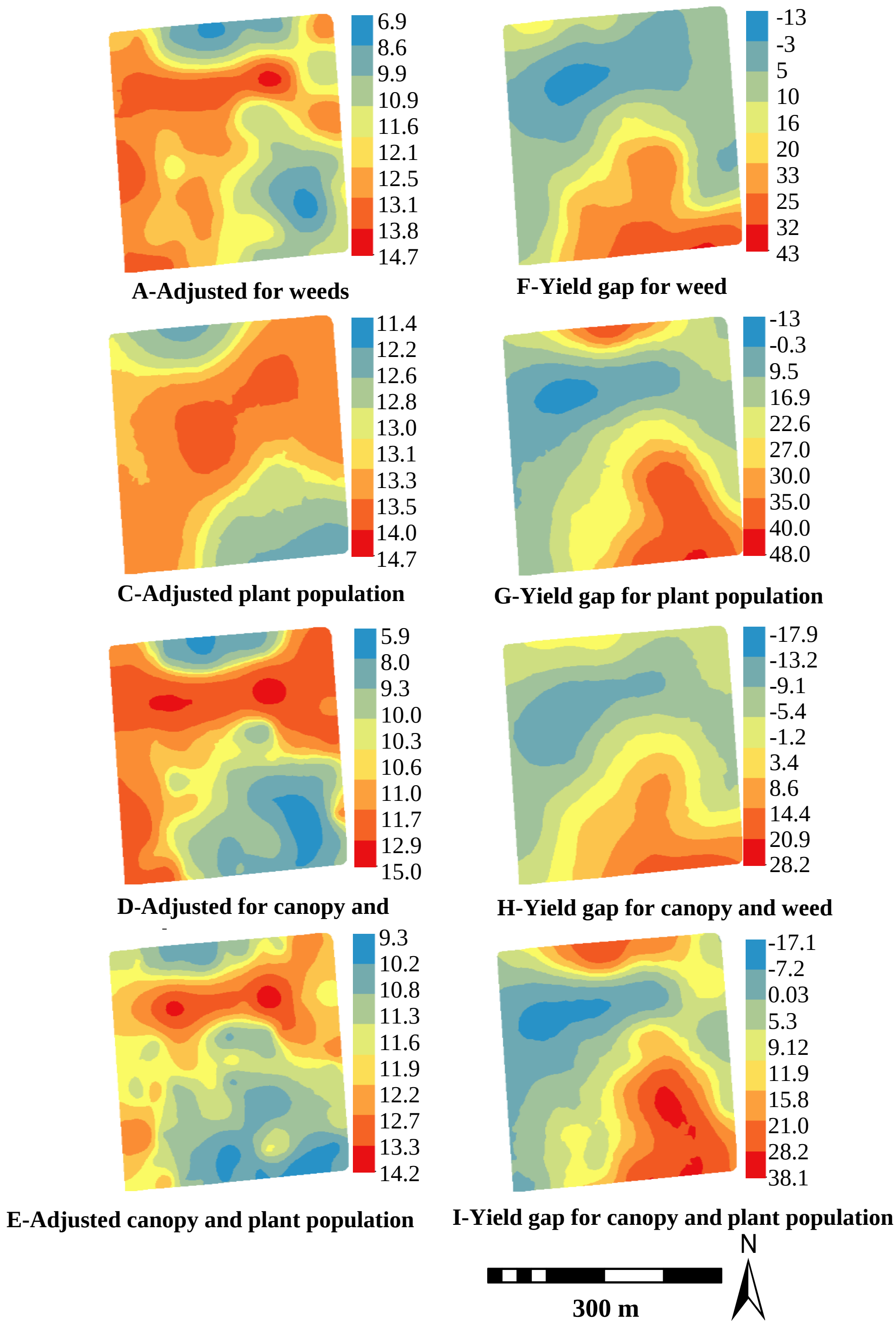


Appendix 7.4: The experimental variograms of simulated yields WO3 field, (A) simulated yield (unadjusted), and adjusted for (B) canopy cover in June, (C) weeds, (D) plant population, (E) canopy cover and weeds and (F) canopy cover and plant population.

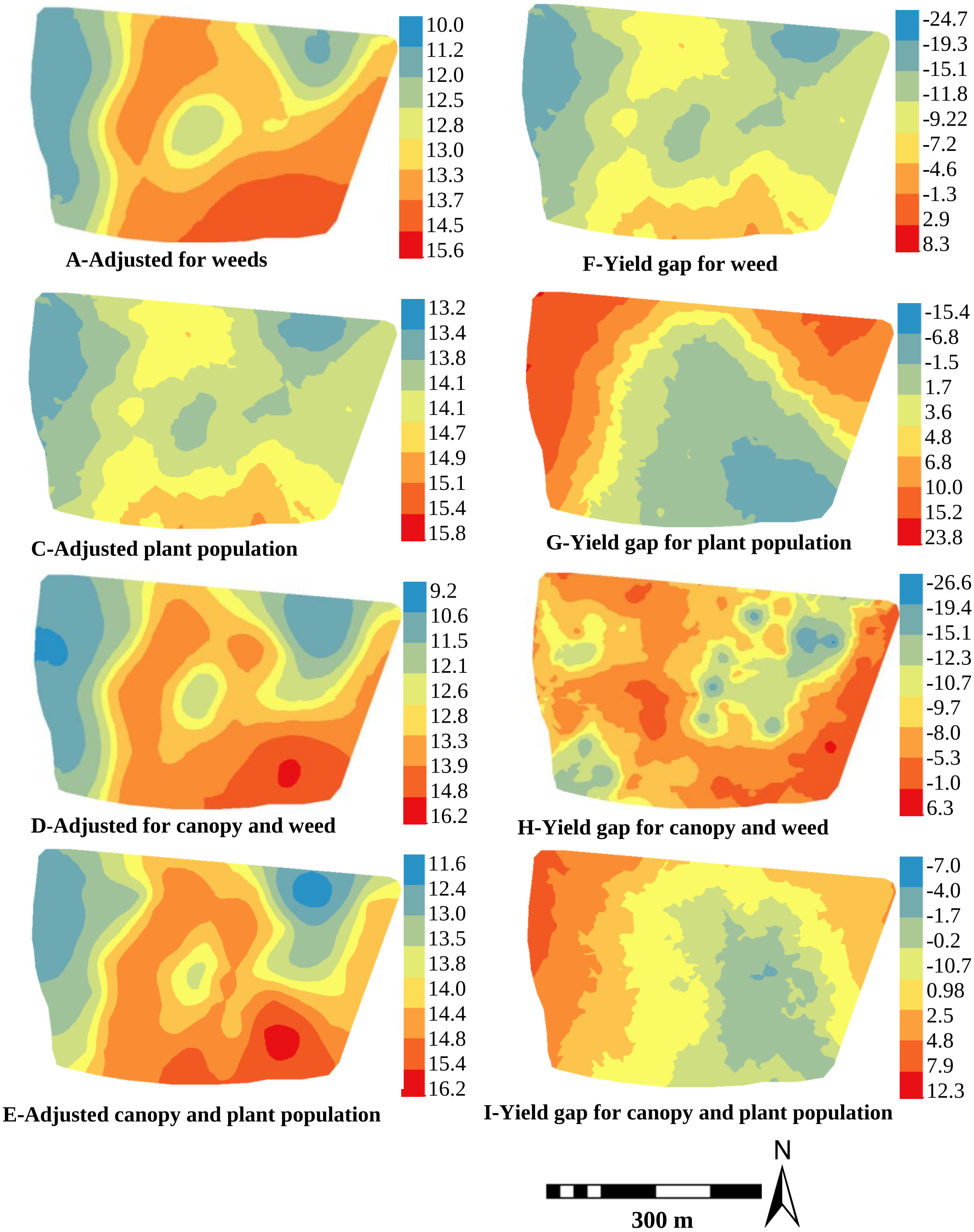


Appendix 8: The interpolation maps for the adjusted simulated yields and yield gaps:

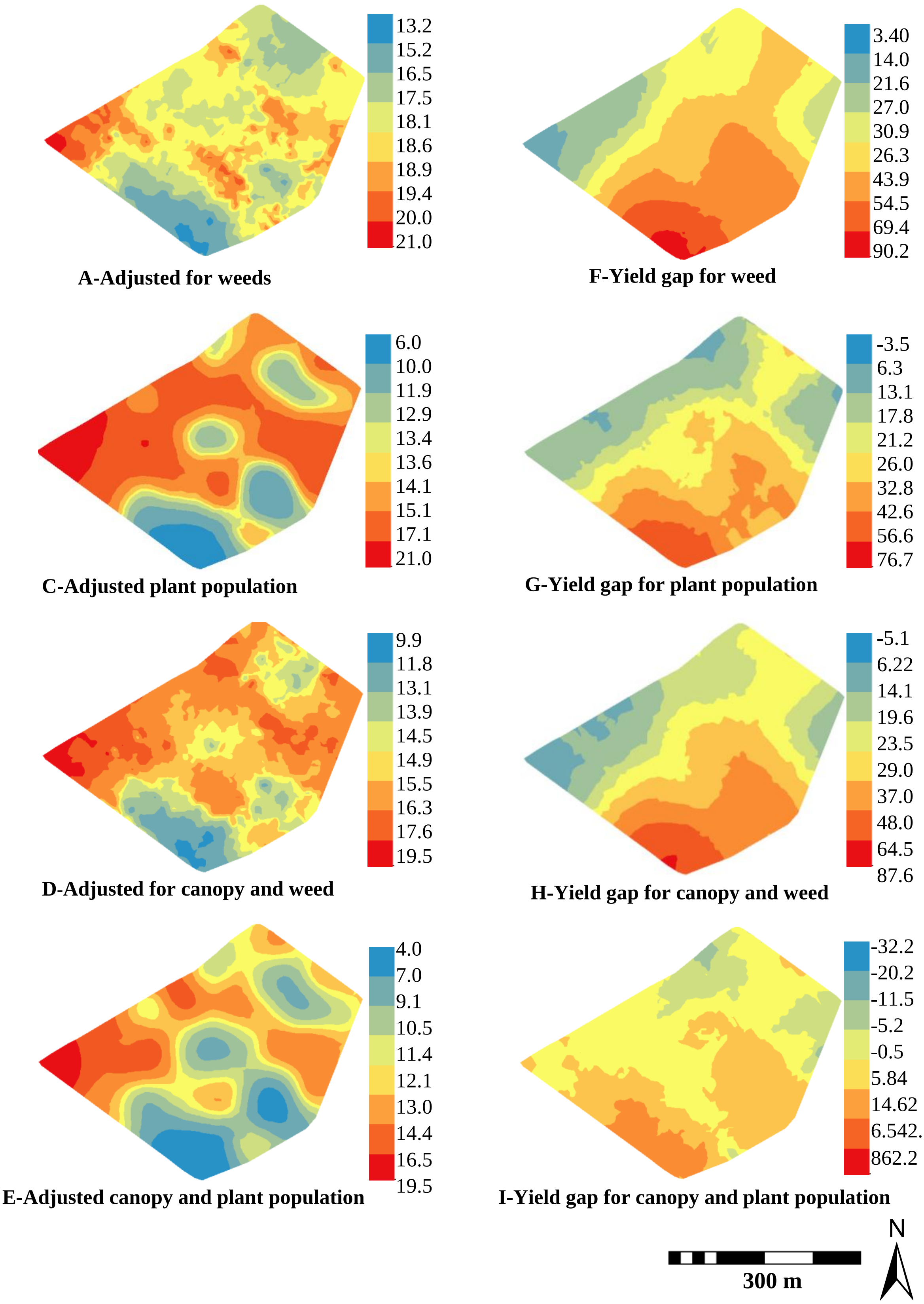
Appendix 8.1: The interpolation maps for the adjusted simulated yields (A-E) and yield gaps (F-I) in White Patch in 2012. The relevant variograms are in appendix 7.2.



Appendix 8.2: The interpolation maps for the adjusted simulated yields (A-E) and yield gaps (F-I) in T32 in 2012. The relevant variograms are in appendix 7.3.



Appendix 8.3: The interpolation maps for the adjusted simulated yields (A-E) and yield gaps (F-I) in WO3 in 2013. The relevant variograms are in appendix 7.4.



Appendix 9: The correlation coefficients and their significance against zero for the studied variables.

Appendix 9.1: Correlation coefficients between the studied variables in White Patch.

	%Clay	%Sand	%Silt	%SOM	pH	EC	Nitrate	Phosphate	K	Mg	SMC-May	SMC-June	SMC-July	SMC-August
%Sand	**-0.96**	-												
%Silt	**0.48**	**-0.71**	-											
%OM	**0.36**	**-0.28**	-0.01	-										
pH	**0.33**	**-0.35**	**0.28**	-0.12	-									
EC	**0.39**	**-0.42**	**0.33**	0.03	**0.33**	-								
Nitrate	-0.12	0.12	-0.09	-0.04	-0.16	0.05	-							
Phosphate	**-0.30**	**0.30**	-0.15	-0.01	-0.06	**-0.28**	0.02	-						
K	0.05	-0.07	0.12	-0.04	**0.24**	**0.25**	**-0.34**	0.09	-					
Mg	0.15	-0.16	0.11	0.19	0.09	0.16	0.12	0.03	0.15	-				
SM-May	**0.45**	**-0.36**	0.03	**0.44**	0.02	**0.23**	0.04	0.00	0.07	**0.26**	-			
SM-June	**0.23**	-0.16	-0.08	**0.52**	-0.08	0.04	-0.08	0.08	-0.03	0.19	**0.34**	-		
SM-July	**0.52**	**-0.43**	0.08	**0.44**	**0.31**	0.08	-0.14	**-0.27**	0.01	0.09	**0.38**	**0.40**	-	
SM-August	**0.41**	**-0.36**	0.11	**0.40**	0.11	0.11	**-0.22**	-0.14	0.18	**0.20**	**0.51**	**0.46**	**0.58**	-
AVT-June	-0.10	0.03	0.14	**-0.21**	-0.01	0.03	0.01	**-0.24**	-0.01	-0.12	**-0.22**	-0.17	**-0.28**	-0.16
AVT-July	-0.07	0.02	0.08	-0.18	-0.10	-0.01	0.08	-0.12	-0.15	-0.09	-0.17	-0.19	**-0.32**	**-0.22**
AVT-Aug.	0.04	-0.07	0.12	**-0.21**	0.07	0.07	0.06	-0.06	-0.11	-0.06	-0.16	**-0.20**	**-0.23**	**-0.29**
AVT-Sept.	0.01	-0.03	0.09	**-0.22**	0.10	0.07	0.04	0.04	-0.08	-0.05	-0.17	**-0.23**	**-0.25**	**-0.35**
AVT-Season	-0.03	-0.02	0.11	**-0.22**	0.01	0.04	0.06	-0.10	-0.10	-0.08	-0.19	**-0.21**	**-0.29**	**-0.27**
MIT	**-0.23**	**0.25**	-0.17	-0.03	-0.19	-0.12	-0.18	**0.22**	0.19	-0.04	0.01	0.09	-0.09	0.03
MXT	-0.04	-0.01	0.08	**-0.35**	0.05	0.09	**0.25**	-0.10	-0.07	0.01	**-0.29**	**-0.27**	**-0.28**	**-0.41**

	%Clay	%Sand	%Silt	%SOM	PH	EC	Nitrate	Phosphate	K	Mg	SMC-May	SMC-June	SMC-July	SMC-August
Weeds	**-0.34**	**0.34**	**-0.21**	-0.13	0.12	-0.14	0.11	0.16	0.04	-0.01	**-0.24**	-0.09	-0.31	**-0.40**
Plant population	-0.07	0.10	-0.11	0.18	-0.02	0.02	0.08	0.15	-0.19	-0.06	**0.30**	0.04	0.10	0.13
Crop cover-June	**0.24**	-0.14	-0.14	**0.46**	0.00	0.04	-0.08	0.03	-0.16	-0.03	**0.48**	**0.45**	**0.44**	**0.35**
Crop cover-July	**0.20**	-0.19	0.06	**0.31**	-0.12	-0.20	**-0.25**	-0.07	-0.05	-0.02	0.10	**0.30**	**0.40**	**0.47**
Crop cover-August	**0.45**	**-0.42**	0.19	**0.21**	0.04	0.06	-0.16	-0.18	-0.17	0.07	**0.39**	**0.25**	**0.49**	**0.48**
SRI-June	-0.08	0.17	**-0.29**	**0.36**	-0.17	-0.17	-0.02	0.10	**-0.21**	-0.13	**0.31**	**0.39**	**0.29**	**0.27**
SRI-July	0.17	-0.10	-0.11	**0.37**	-0.15	-0.18	**-0.27**	0.12	-0.04	0.10	**0.23**	**0.43**	**0.38**	**0.54**
LAI-June	-0.10	0.19	**-0.33**	**0.32**	-0.09	-0.15	-0.01	**0.20**	-0.19	-0.06	**0.33**	**0.35**	**0.27**	0.17
LAI-July	0.16	-0.10	-0.08	**0.31**	-0.09	-0.13	**-0.30**	0.12	-0.02	0.05	0.14	**0.36**	**0.38**	**0.47**
Canopy growth rate	-0.07	-0.03	**0.25**	**-0.40**	0.02	-0.01	0.01	-0.14	0.13	-0.02	**-0.47**	**-0.43**	**-0.27**	**-0.28**
Roots yield	**0.36**	**-0.27**	-0.04	**0.51**	-0.01	0.06	-0.12	-0.03	-0.13	0.04	**0.51**	**0.47**	**0.45**	**0.53**
%Sugar	-0.01	0.01	0.00	0.12	-0.21	-0.09	**-0.27**	0.14	0.15	0.03	0.02	0.15	0.07	**0.25**
Sugar yield	**0.36**	**-0.28**	-0.03	**0.52**	-0.04	0.04	-0.14	-0.03	-0.12	0.05	**0.50**	**0.48**	**0.47**	**0.55**
Yield value	**0.36**	**-0.27**	-0.04	**0.51**	-0.04	0.04	-0.15	-0.01	-0.11	0.04	**0.51**	**0.48**	**0.45**	**0.54**
Amino in beet	-0.06	0.05	-0.02	0.00	-0.19	-0.14	-0.06	0.12	0.05	-0.10	**-0.23**	-0.11	-0.09	-0.06
Potassium in beet	0.19	**-0.21**	0.15	0.08	-0.09	-0.08	**-0.21**	0.09	0.13	0.10	0.19	0.16	**0.25**	**0.36**

	Weeds	Plant pop.	Crop cover-June	Crop cover-July	Crop cover-August	LAI-June	LAI-July	SRI-June	SRI-July	Canopy growth rate	Roots yield	%Sugar	Sugar yield	Yield value	Amino acid in beet	Potassium in beet
T-June	0.14	**-0.28**	**-0.33**	**-0.20**	**-0.27**	**-0.41**	**-0.27**	**-0.35**	**-0.27**	**0.30**	**-0.24**	-0.16	**-0.26**	**-0.26**	-0.09	-0.17
T-July	0.18	**-0.21**	**-0.32**	**-0.26**	**-0.27**	**-0.39**	**-0.27**	**-0.29**	**-0.29**	**0.26**	**-0.25**	-0.12	**-0.27**	**-0.27**	-0.10	-0.14
T-Aug.	**0.26**	**-0.23**	**-0.34**	**-0.36**	**-0.27**	**-0.45**	**-0.36**	**-0.29**	**-0.34**	**0.28**	**-0.33**	-0.10	**-0.35**	**-0.34**	**-0.20**	-0.15
T-Sept.	**0.25**	**-0.25**	**-0.41**	**-0.42**	**-0.30**	**-0.46**	**-0.40**	**-0.29**	**-0.36**	**0.34**	**-0.41**	-0.02	**-0.41**	**-0.40**	-0.19	-0.12
T-Season	**0.22**	**-0.25**	**-0.36**	**-0.33**	**-0.30**	**-0.45**	**-0.34**	**-0.32**	**-0.33**	**0.31**	**-0.32**	-0.11	**-0.34**	**-0.33**	-0.15	-0.16
Tmax	-0.09	0.02	0.12	0.06	-0.14	0.20	0.14	0.17	0.19	-0.13	0.09	**0.28**	0.13	0.12	-0.03	0.13
Tmax	**0.23**	**-0.40**	**-0.54**	**-0.36**	**-0.25**	**-0.58**	**-0.60**	**-0.47**	**-0.56**	**0.46**	**-0.56**	**-0.23**	**-0.58**	**-0.58**	-0.14	-0.01

	Weeds	Plant population	Crop cover-June	Crop cover-July	Crop cover-Aug.	SRI-June	SRI-July	LAI-June	LAI-July	Canopy growth rate	Root yield	%sugar
Plant population	-0.06	-										
Crop cover-June	-0.15	**0.53**	-									
Crop cover-July	**-0.53**	0.16	**0.48**	-								
Crop cover-August	**-0.55**	**0.24**	**0.40**	**0.48**	-							
SRI-June	-0.13	**0.52**	**0.71**	**0.46**	**0.26**	-						
SRI-July	**-0.32**	**0.23**	**0.56**	**0.66**	**0.39**	**0.52**	-					
LAI-June	0.01	**0.52**	**0.74**	**0.34**	0.16	**0.83**	**0.43**	-				
LAI-July	-0.31	0.15	**0.51**	**0.67**	**0.36**	**0.48**	**0.90**	**0.42**	-			
Canopy growth rate	-0.05	**-0.51**	**-0.85**	**-0.21**	**-0.21**	**-0.62**	**-0.43**	**-0.72**	**-0.34**	-		
Root yield	**-0.40**	**0.51**	**0.81**	**0.60**	**0.58**	**0.60**	**0.67**	**0.46**	**0.55**	**-0.60**	-	
%Sugar	-0.06	-0.06	-0.01	0.18	-0.01	0.09	**0.34**	**0.09**	**0.33**	-0.08	0.03	-
Sugar yield	**-0.42**	**0.49**	**0.80**	**0.63**	**0.58**	**0.61**	**0.71**	**0.46**	**0.59**	**-0.59**	**0.99**	0.14
Yield value	**-0.41**	**0.50**	**0.80**	**0.61**	**0.57**	**0.61**	**0.71**	**0.47**	**0.59**	**-0.61**	**0.99**	0.15
Amino in beet	**-0.28**	**-0.25**	-0.16	**0.34**	0.03	-0.04	**0.26**	-0.06	**0.36**	**0.27**	-0.02	0.06
Potassium in beet	**-0.32**	**-0.26**	-0.07	**0.23**	**0.21**	0.00	0.20	-0.04	0.19	0.06	0.03	**0.31**

Appendix 9.2: Test the significance of the correlations against zero in White Patch

	%Clay	%Sand	%Silt	%SOM	PH	EC	Nitrate	Phosphate	K	Mg	SMC-May	SMC-June	SMC-July	SMC-August
%Sand	<0.001	-												
%Silt	<0.001	<0.001	-											
%OM	<0.001	0.007	0.9558	-										
Soil pH	0.0017	<0.001	0.0083	0.2714	-									
EC	<0.001	<0.001	0.0014	0.7962	0.0018	-								
Nitrate	0.259	0.2508	0.4172	0.6887	0.1367	0.6656	-							
Phosphate	0.004	0.0048	0.1547	0.9188	0.5478	0.0074	0.8333	-						
K	0.6428	0.4929	0.2786	0.6955	0.0217	0.017	<0.001	0.3882	-					
Mg	0.1671	0.1289	0.2966	0.0714	0.393	0.1408	0.2829	0.7959	0.1718	-				
SM-May	<0.001	<0.001	0.7464	<0.001	0.8539	0.0327	0.7358	0.9762	0.4955	0.0122	-			
SM-June	0.0304	0.1397	0.4428	<0.001	0.4603	0.7421	0.483	0.4694	0.7881	0.0755	0.0013	-		
SM-July	<0.001	<0.001	0.458	<0.001	0.0028	0.4811	0.1793	0.0099	0.924	0.3958	<0.001	<0.001	-	
SM-August	<0.001	<0.001	0.3012	<0.001	0.3255	0.2854	0.0355	0.2019	0.0846	0.0575	<0.001	<0.001	<0.001	-
AVT-June	0.3487	0.8062	0.1808	0.0464	0.9163	0.7851	0.9581	0.025	0.8951	0.2634	0.0411	0.1203	0.0073	0.1294
AVT-July	0.5384	0.8632	0.4843	0.0897	0.3534	0.9317	0.4453	0.2687	0.164	0.4257	0.1216	0.0824	0.0021	0.0349
AVT-Aug.	0.7176	0.4897	0.2639	0.0454	0.4969	0.4988	0.5457	0.6021	0.3028	0.5673	0.1351	0.058	0.0287	0.0054
AVT-Sept.	0.9617	0.7472	0.4034	0.0396	0.3636	0.5269	0.6782	0.7216	0.4309	0.6361	0.1191	0.0288	0.02	<0.001
AVT-Season	0.7736	0.8676	0.2986	0.0414	0.9422	0.7106	0.5952	0.3511	0.3364	0.435	0.0817	0.0512	0.0059	0.0101
MIT-Season	0.0289	0.019	0.1102	0.7602	0.0762	0.2716	0.101	0.038	0.0707	0.7253	0.9023	0.418	0.4286	0.8096
MXT-Season	0.7163	0.9366	0.446	<0.001	0.6394	0.3849	0.0203	0.3359	0.5187	0.9082	0.0061	0.0109	0.009	<0.001

	%Clay	%Sand	%Silt	%SOM	PH	EC	Nitrate	Phosphate	K	Mg	SMC-May	SMC-June	SMC-July	SMC-August
Weeds	<0.001	<0.001	0.0523	0.2307	0.2529	0.1916	0.301	0.126	0.7162	0.9374	0.0213	0.4164	0.0036	<0.001
Plant population	0.5312	0.3346	0.2853	0.0944	0.8471	0.8672	0.4353	0.1537	0.0726	0.6084	0.0041	0.7224	0.3668	0.2103
Crop cover-June	0.0259	0.1935	0.1917	<0.001	0.9729	0.731	0.4672	0.8131	0.1414	0.7558	<0.001	<0.001	<0.001	<0.001
Crop cover-July	0.0547	0.0824	0.598	0.0032	0.283	0.0565	0.0188	0.5069	0.6152	0.8821	0.359	0.0047	<0.001	<0.001
Crop cover-August	<0.001	<0.001	0.0819	0.0533	0.7097	0.5534	0.1241	0.0989	0.1144	0.5096	<0.001	0.0191	<0.001	<0.001
SRI-June	0.4563	0.1113	0.0056	<0.001	0.1014	0.117	0.8474	0.3511	0.054	0.2415	0.0027	<0.001	0.0053	0.0099
SRI-July	0.105	0.342	0.3152	<0.001	0.1655	0.0927	0.0119	0.2797	0.7355	0.3578	0.0309	<0.001	<0.001	<0.001
LAI-June	0.3564	0.0679	0.0015	0.0026	0.3963	0.156	0.8974	0.0668	0.0812	0.5893	0.0019	<0.001	0.0119	0.1063
LAI-July	0.138	0.3579	0.4715	0.0029	0.3859	0.2302	0.0044	0.2662	0.8277	0.6755	0.1851	<0.001	<0.001	<0.001
Canopy growth rate	0.5352	0.7599	0.0165	<0.001	0.8677	0.9157	0.8949	0.2031	0.2123	0.8771	<0.001	<0.001	0.0096	0.0084
Roots yield	<0.001	0.0094	0.6973	<0.001	0.9033	0.6068	0.2771	0.8069	0.2317	0.7208	<0.001	<0.001	<0.001	<0.001
%Sugar	0.9588	0.9075	0.9765	0.2463	0.047	0.3829	0.011	0.1878	0.1592	0.795	0.8878	0.1746	0.5025	0.0174
Sugar yield	<0.001	0.0088	0.7518	<0.001	0.6942	0.7014	0.1781	0.805	0.2603	0.6526	<0.001	<0.001	<0.001	<0.001
Yield value	<0.001	0.0099	0.6959	<0.001	0.7245	0.6893	0.1633	0.9619	0.2874	0.6764	<0.001	<0.001	<0.001	<0.001
Amino in beet	0.5778	0.66	0.829	0.9646	0.0703	0.2067	0.5759	0.2723	0.6543	0.3723	0.034	0.2863	0.4083	0.6007
Potassium in beet	0.0691	0.0533	0.1588	0.4289	0.4267	0.4615	0.0537	0.4084	0.2378	0.3336	0.0705	0.1312	0.0203	<0.001

	Weeds	Plant pop.	Crop cover-June	Crop cover-July	Crop cover-August	LAI-June	LAI-July	SRI-June	SRI-July	Canopy growth rate	Roots yield	%Sugar	Sugar yield	Yield value	Amino acid in beet	Potassium in beet
T-June	0.1848	0.0073	0.0017	0.0647	0.0118	<0.001	0.0094	<0.001	0.0092	0.0037	0.0252	0.1382	0.0156	0.0134	0.4205	0.1034
T-July	0.0863	0.0519	0.0025	0.0127	0.0097	<0.001	0.0106	0.0067	0.0067	0.013	0.0171	0.2557	0.0097	0.0101	0.3427	0.1765
T-Aug.	0.0154	0.0319	0.0011	<0.001	0.0098	<0.001	<0.001	0.0054	<0.001	0.0083	0.0017	0.3564	<0.001	0.0011	0.0627	0.1713
T-Sept.	0.0174	0.0203	<0.001	<0.001	0.0037	<0.001	<0.001	0.0061	<0.001	0.0013	<0.001	0.8808	<0.001	<0.001	0.0688	0.2585
T-Season	0.0366	0.0177	<0.001	0.0018	0.005	<0.001	0.001	0.0022	0.0014	0.0033	0.0022	0.3132	0.0012	0.0013	0.1512	0.1455
Tmax	0.4039	0.8403	0.2651	0.5735	0.184	0.0582	0.1953	0.1033	0.0805	0.217	0.3892	0.0089	0.2406	0.2608	0.7703	0.2298
Tmax	0.0338	<0.001	<0.001	<0.001	0.0185	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.0322	<0.001	<0.001	0.2064	0.9165

	Weeds	Plant pop.	Crop cover-June	Crop cover-July	Crop cover-Aug.	SRI-June	SRI-July	LAI-June	LAI-July	Canopy growth rate	Root yield	%sugar
Crop cover-June	0.56	-										
Crop cover-July	0.16	<0.001	-									
Crop cover-August	<0.001	0.1307	<0.001	-								
SRI-June	<0.001	0.0263	<0.001	<0.001	-							
SRI-July	0.2228	<0.001	<0.001	<0.001	0.0145	-						
LAI-June	0.0024	0.0328	<0.001	<0.001	<0.001	<0.001	-					
LAI-July	0.9543	<0.001	<0.001	0.0013	0.1464	<0.001	<0.001	-				
Canopy growth rate	0.0033	0.1722	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-			
Root yield	0.6721	<0.001	<0.001	0.0535	0.0482	<0.001	<0.001	<0.001	<0.001	-		
%Sugar	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	
Sugar yield	0.5853	0.5993	0.9326	0.0867	0.9011	0.4251	0.0013	0.4257	0.0013	0.4719	0.8053	-
Yield value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.1933
Amino in beet	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.1712
Potassium in beet	0.0086	0.019	0.1429	0.0013	0.7575	0.7292	0.0128	0.5981	<0.001	0.0117	0.8481	0.591

Appendix 9.3: Correlation coefficients between the studied variables in T32.

	%Clay	**%Sand**	**%Silt**	**%SOM**	**pH**	**EC**	**Nitrate**	**Phosphate**	**K**	**Mg**	**SMC-June**	**SMC-July**	**SMC-August**
%Sand	**-0.56**	-											
%Silt	**-0.29**	**-0.63**	-										
%OM	-0.03	**-0.26**	**0.33**	-									
pH	**0.30**	-0.17	-0.08	**0.26**	-								
EC	**0.25**	**-0.49**	**0.34**	**0.32**	**0.43**	-							
Nitrate	-0.06	0.02	0.04	0.27	0.12	0.30	-						
Phosphate	**-0.30**	**0.29**	-0.05	**-0.21**	**-0.45**	**-0.51**	**-0.27**	-					
K	0.09	-0.12	0.06	0.03	0.04	0.37	0.06	-0.18	-				
Mg	-0.08	0.12	-0.06	-0.13	**-0.29**	**-0.27**	-0.19	0.04	-0.07	-			
SM-June	**0.38**	**-0.38**	0.08	**0.25**	**0.36**	**0.29**	0.12	**-0.40**	-0.02	0.01	-		
SM-July	-0.04	-0.12	0.18	**0.43**	**0.36**	0.12	**0.22**	-0.20	**-0.21**	-0.16	**0.37**	-	
SM-August	**0.37**	**-0.41**	0.12	**0.34**	**0.54**	**0.49**	**0.34**	**-0.58**	0.11	**-0.25**	**0.61**	**0.44**	-
AVT-June	0.01	-0.11	0.12	0.03	-0.17	-0.05	0.02	0.05	0.01	-0.11	0.06	-0.06	-0.06
AVT-July	-0.09	-0.06	0.15	-0.01	-0.30	-0.17	-0.04	0.14	-0.02	0.00	-0.08	-0.18	**-0.24**
AVT-Aug.	-0.12	0.08	0.01	-0.10	-0.40	-0.24	-0.14	**0.24**	-0.02	-0.02	**-0.22**	**-0.25**	**-0.40**
AVT-Sept.	**-0.22**	0.18	0.00	**-0.22**	**-0.26**	**-0.31**	**-0.26**	**0.30**	-0.05	0.11	**-0.27**	**-0.25**	**-0.41**
AVT-Season	-0.10	0.01	0.09	-0.05	**-0.37**	-0.20	-0.09	0.21	-0.02	-0.03	-0.14	**-0.23**	**-0.34**
MIT	-0.17	0.18	-0.05	**-0.21**	**-0.39**	**-0.24**	**-0.22**	**0.41**	0.06	0.11	**-0.44**	**-0.32**	**-0.48**
MXT	-0.18	0.15	-0.01	-0.16	**-0.41**	**-0.28**	**-0.25**	0.09	-0.05	0.20	-0.16	**-0.30**	**-0.46**

	%Clay	%Sand	%Silt	%SOM	PH	EC	Nitrate	Phosphate	K	Mg	SMC-June	SMC-July	SMC-August
Weeds	**-0.22**	**0.27**	-0.11	**-0.23**	**-0.32**	**-0.35**	**-0.32**	**0.27**	-0.07	**0.34**	**-0.27**	**-0.28**	**-0.47**
Plant population	0.08	-0.18	0.13	**0.32**	0.15	0.13	**0.36**	-0.18	-0.05	0.15	**0.24**	**0.28**	**0.23**
Crop cover-June	-0.04	0.06	-0.03	**0.36**	0.17	0.00	**0.42**	-0.12	-0.19	-0.11	**0.22**	**0.50**	**0.39**
Crop cover-July	0.19	**-0.32**	0.19	**0.36**	**0.24**	**0.25**	**0.39**	**-0.39**	0.03	-0.05	**0.45**	**0.53**	**0.49**
Crop cover-August	0.01	-0.11	0.11	**0.30**	-0.03	0.02	**0.27**	-0.18	-0.02	0.09	**0.30**	**0.31**	**0.29**
SRI- July	0.07	-0.14	0.09	**0.24**	**0.27**	0.15	**0.32**	**-0.30**	-0.09	-0.04	**0.24**	**0.32**	**0.44**
SRI-August	0.04	-0.20	0.19	**0.43**	**0.34**	0.19	**0.32**	**-0.23**	-0.14	-0.04	**0.26**	**0.35**	**0.37**
LAI-July	0.00	-0.13	0.15	**0.23**	**0.22**	-0.02	0.17	-0.17	-0.10	-0.03	**0.30**	**0.40**	**0.39**
LAI-August	0.05	-0.23	0.22	**0.34**	0.12	0.13	**0.26**	-0.14	-0.03	0.03	**0.27**	**0.37**	**0.34**
Canopy growth rate	0.09	-0.14	0.08	**-0.27**	-0.08	0.12	**-0.34**	-0.03	**0.22**	0.05	-0.12	**-0.39**	**-0.25**
Roots yield	0.09	**-0.27**	**0.23**	**0.35**	**0.25**	0.15	**0.36**	-0.17	-0.14	-0.19	**0.33**	**0.52**	**0.47**
%Sugar	0.10	-0.15	0.08	0.01	0.05	0.06	-0.07	0.08	0.14	-0.16	0.06	-0.01	0.08
Sugar yield	0.10	**-0.25**	0.18	0.38	0.28	0.17	**0.39**	-0.17	-0.13	**-0.23**	**0.33**	**0.53**	**0.48**
Yield value	0.07	**-0.30**	**0.27**	**0.35**	**0.23**	0.15	**0.34**	-0.14	-0.12	-0.20	**0.32**	**0.49**	**0.47**
Amino in beet	0.19	-0.22	0.08	0.09	**0.24**	0.16	0.08	**-0.29**	0.19	-0.03	0.27	0.18	**0.34**
Potassium in beet	0.21	-0.02	-0.17	**-0.54**	-0.15	-0.04	-0.19	0.03	0.09	0.06	-0.02	**-0.24**	-0.12

	Weeds	Plant pop.	Crop cover-June	Crop cover-July	Crop cover-August	LAI-June	LAI-July	SRI-June	SRI-July	Canopy growth rate	Roots yield	%Sugar	Sugar yield	Yield value	Amino acid in beet	Potassium in beet
T-June	-0.10	-0.13	-0.14	0.03	0.15	-0.01	-0.07	-0.07	0.01	0.12	-0.05	0.16	-0.03	-0.02	-0.08	-0.09
T-July	0.07	-0.07	**-0.27**	-0.20	0.08	**-0.22**	**-0.23**	**-0.25**	-0.20	**0.21**	-0.10	0.11	-0.10	-0.07	**-0.25**	-0.12
T-Aug.	0.13	**-0.22**	**-0.28**	**-0.25**	-0.03	**-0.31**	**-0.29**	**-0.30**	**-0.26**	**0.21**	**-0.21**	0.06	-0.21	-0.19	**-0.27**	-0.02
T-Sept.	0.14	-0.06	-0.15	-0.15	-0.05	-0.13	-0.10	-0.10	-0.14	0.07	-0.06	-0.20	-0.11	-0.09	-0.07	0.15
T-Season	0.07	-0.17	**-0.26**	-0.19	0.04	**-0.24**	**-0.24**	**-0.25**	-0.20	0.20	-0.16	0.10	-0.15	-0.13	**-0.24**	-0.05
Tmax	**0.30**	**-0.39**	-0.14	**-0.23**	-0.03	**-0.25**	**-0.25**	**-0.25**	-0.09	0.06	-0.22	0.16	-0.18	-0.20	**-0.37**	0.13
Tmax	**0.25**	-0.04	**-0.42**	**-0.27**	-0.10	**-0.38**	**-0.35**	**-0.34**	**-0.35**	**0.35**	**-0.25**	-0.03	**-0.29**	**-0.23**	-0.18	0.07

	Weeds	Plant pop.	Crop cover-June	Crop cover-July	Crop cover-Aug.	SRI-June	SRI-July	LAI-June	LAI-July	Canopy growth rate	Root yield	%sugar
Plant population	**-0.24**	-										
Crop cover-June	**-0.40**	**0.43**	-									
Crop cover-July	**-0.48**	**0.45**	**0.61**	-								
Crop cover-August	-0.20	**0.44**	**0.45**	**0.65**	-							
SRI-June	**-0.33**	**0.49**	**0.64**	**0.59**	**0.47**	-						
SRI-July	**-0.28**	**0.43**	**0.52**	**0.52**	**0.50**	**0.70**	-					
LAI-June	**-0.23**	**0.38**	**0.57**	**0.61**	**0.44**	**0.82**	**0.68**	-				
LAI-July	**-0.22**	**0.44**	**0.57**	**0.57**	**0.54**	**0.70**	**0.84**	**0.73**	-			
Canopy growth rate	**0.34**	**-0.39**	**-0.95**	**-0.49**	**-0.42**	**-0.58**	**-0.43**	**-0.51**	**-0.51**	-		
Root yield	**-0.50**	**0.51**	**0.66**	**0.66**	**0.54**	**0.63**	**0.50**	**0.60**	**0.54**	**-0.61**	-	
%Sugar	0.11	-0.06	-0.11	-0.03	0.13	-0.09	0.02	-0.10	0.05	0.15	-0.11	-
Sugar yield	**-0.51**	**0.49**	**0.70**	**0.67**	**0.59**	**0.62**	**0.51**	**0.58**	**0.54**	**-0.64**	**0.98**	0.02
Yield value	**-0.46**	**0.51**	**0.63**	**0.64**	**0.58**	**0.61**	**0.50**	**0.57**	**0.55**	**-0.57**	**0.98**	0.04
Amino in beet	**-0.39**	**0.38**	**0.23**	**0.46**	0.17	**0.45**	**0.39**	**0.53**	**0.38**	-0.18	**0.36**	**-0.32**
Potassium in beet	0.03	**-0.31**	**-0.21**	-0.13	**-0.31**	-0.11	**-0.26**	-0.07	-0.18	0.17	-0.18	-0.16

Appendix 9.4: Test the significance of the correlations against zero in T32.

	%Clay	%Sand	%Silt	%SOM	pH	EC	Nitrate	Phosphate	K	Mg	SMC-June	SMC-July	SMC-August
%Sand	<0.001	-											
%Silt	0.0055	<0.001	-										
%OM	0.78	0.013	0.0016	-									
pH	0.005	0.1069	0.4533	0.0144									
EC	0.019	<0.001	0.0013	0.0019	<0.001	-							
Nitrate	0.57	0.8627	0.7419	0.0095	0.2641	0.0041	-						
Phosphate	0.004	0.006	0.6405	0.0532	<0.001	<0.001	0.0116	-					
K	0.39	0.2481	0.6086	0.7601	0.6805	<0.001	0.5959	0.0874	-				
Mg	0.45	0.2807	0.6033	0.2424	0.0055	0.0101	0.0722	0.7172	0.4896	-			
SM-June	<0.001	<0.001	0.4792	0.0161	<0.001	0.0056	0.2716	<0.001	0.8761	0.899	-		
SM-July	0.6925	0.2705	0.1002	<0.001	<0.001	0.2597	0.0345	0.0632	0.0438	0.1439	<0.001	-	
SM-August	<0.001	<0.001	0.2669	<0.001	<0.001	<0.001	0.0012	<0.001	0.2996	0.0193	<0.001	<0.001	-
AVT-June	0.9322	0.293	0.2516	0.7475	0.1119	0.6672	0.8418	0.6624	0.9184	0.2834	0.5837	0.5844	0.58
AVT-July	0.4178	0.5878	0.1613	0.9406	0.0047	0.1084	0.6839	0.2038	0.8568	0.9839	0.4602	0.0875	0.023
AVT-Aug.	0.2806	0.4391	0.8955	0.3512	<0.001	0.0255	0.1852	0.0226	0.821	0.8365	0.0398	0.0176	<0.001
AVT-Sept.	0.0369	0.0999	0.9671	0.0341	0.0129	0.0034	0.0143	0.0046	0.656	0.2932	0.0096	0.0189	<0.001
AVT-Season	0.3393	0.9377	0.4128	0.6159	<0.001	0.0545	0.4158	0.0437	0.8676	0.7633	0.1844	0.0273	0.001
MIT-Season	0.1222	0.0939	0.6469	0.0508	<0.001	0.0256	0.0386	<0.001	0.5544	0.305	<0.001	0.0025	<0.001
MXT-Season	0.093	0.1543	0.9406	0.1459	<0.001	0.007	0.0202	0.411	0.6305	0.0664	0.1311	0.004	<0.001

	%Clay	%Sand	%Silt	%SOM	PH	EC	Nitrate	Phosphate	K	Mg	SMC-June	SMC-July	SMC-August
Weeds	0.041	0.0098	0.3143	0.0283	0.0026	<0.001	0.0026	0.0111	0.5022	<0.001	0.0094	0.0078	<0.001
Plant population	0.4603	0.0949	0.2274	0.002	0.1672	0.2101	<0.001	0.0839	0.63	0.1522	0.0216	0.0069	0.034
Crop cover-June	0.6856	0.5462	0.7463	<0.001	0.1146	0.9755	<0.001	0.2791	0.0673	0.2996	0.0372	<0.001	<0.001
Crop cover-July	0.0746	0.0025	0.0785	<0.001	0.0251	0.0198	<0.001	<0.001	0.7828	0.6177	<0.001	<0.001	<0.001
Crop cover-August	0.9224	0.3087	0.2904	0.0037	0.7976	0.8268	0.0116	0.0923	0.8201	0.3947	0.0039	0.0027	0.0064
SRI- July	0.4893	0.1949	0.3994	0.0222	0.0114	0.1512	0.0024	0.0044	0.377	0.6918	0.0227	0.0024	<0.001
SRI-August	0.7143	0.0631	0.0735	<0.001	0.0011	0.0704	0.0021	0.0286	0.1983	0.6912	0.015	<0.001	<0.001
LAI-July	0.9793	0.2255	0.1512	0.0295	0.0408	0.8587	0.122	0.116	0.3314	0.7607	0.0041	<0.001	<0.001
LAI-August	0.6254	0.0284	0.0393	0.0011	0.258	0.208	0.0157	0.1831	0.7535	0.7861	0.0092	<0.001	0.0012
Canopy growth rate	0.3929	0.1802	0.4553	0.0102	0.4725	0.2797	0.0013	0.813	0.0421	0.6455	0.2628	<0.001	0.0171
Roots yield	0.4187	0.0109	0.0329	<0.001	0.0182	0.1494	<0.001	0.1033	0.2052	0.0739	0.0015	<0.001	<0.001
%Sugar	0.3573	0.1528	0.4302	0.9283	0.6217	0.5886	0.5248	0.4609	0.192	0.1256	0.5755	0.9383	0.4624
Sugar yield	0.329	0.0194	0.0832	<0.001	0.0091	0.1127	<0.001	0.1114	0.2392	0.0288	0.0016	<0.001	<0.001
Yield value	0.4923	0.0049	0.0105	<0.001	0.0274	0.159	0.0012	0.1849	0.2584	0.0635	0.0019	<0.001	<0.001
Amino in beet	0.0825	0.0366	0.4453	0.4261	0.024	0.1348	0.4362	0.0055	0.0817	0.7581	0.0094	0.0892	0.0013
Potassium in beet	0.049	0.8344	0.1131	<0.001	0.1676	0.6827	0.0768	0.7798	0.3862	0.5894	0.8804	0.0256	0.2527

	Weeds	Plant pop.	Crop cover-June	Crop cover-July	Crop cover-August	LAI-June	LAI-July	SRI-June	SRI-July	Canopy growth rate	Roots yield	%Sugar	Sugar yield	Yield value	Amino acid in beet	Potassium in beet
T-June	0.3757	0.2273	0.1866	0.7771	0.1568	0.9016	0.515	0.5086	0.9127	0.2695	0.6625	0.1421	0.7661	0.8892	0.4384	0.381
T-July	0.505	0.5254	0.0115	0.0627	0.4826	0.0354	0.028	0.0183	0.0575	0.0504	0.3563	0.3255	0.3709	0.49	0.0185	0.271
T-Aug.	0.2302	0.0422	0.0069	0.0194	0.7976	0.0031	0.0068	0.0045	0.0142	0.0499	0.0434	0.5608	0.0513	0.0718	0.01	0.8622
T-Sept.	0.1836	0.5456	0.1567	0.1539	0.613	0.228	0.3278	0.3709	0.1961	0.5301	0.5654	0.060	0.3108	0.4177	0.4962	0.1728
T-Season	0.5168	0.1131	0.0123	0.075	0.6957	0.0248	0.0254	0.0163	0.061	0.0634	0.1381	0.336	0.1595	0.2254	0.0261	0.6214
Tmax	0.0049	<0.001	0.1807	0.033	0.812	0.0182	0.0179	0.0181	0.3943	0.5768	0.0408	0.1439	0.0854	0.0666	<0.001	0.2315
Tmax	0.0205	0.7228	<0.001	0.0115	0.3756	<0.001	<0.001	0.0013	<0.001	<0.001	0.0167	0.816	0.0066	0.0311	0.101	0.5296

	Weeds	Plant pop.	Crop cover-June	Crop cover-July	Crop cover-Aug.	SRI-June	SRI-July	LAI-June	LAI-July	Canopy growth rate	Root yield	%sugar
Plant population	0.0241	-										
Crop cover-June	<0.001	<0.001	-									
Crop cover-July	<0.001	<0.001	<0.001	-								
Crop cover-August	0.0541	<0.001	<0.001	<0.001	-							
SRI-June	0.0015	<0.001	<0.001	<0.001	<0.001	-						
SRI-July	0.0073	<0.001	<0.001	<0.001	<0.001	<0.001	-					
LAI-June	0.0304	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-				
LAI-July	0.0396	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-			
Canopy growth rate	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-		
Root yield	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	
%Sugar	0.2857	0.5613	0.2885	0.7683	0.2081	0.4119	0.8857	0.3444	0.6261	0.1727	0.3103	-
Sugar yield	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.8772
Yield value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.6949
Amino in beet	<0.001	<0.001	0.031	<0.001	0.1055	<0.001	<0.001	<0.001	<0.001	0.0918	<0.001	0.0023
Potassium in beet	0.7591	0.0032	0.0508	0.2229	0.0028	0.3055	0.0128	0.4933	0.0912	0.1196	0.0855	0.1323

Appendix 9.5: Correlation coefficients between the studied variables in WO3

	%Clay	**%Sand**	**%Silt**	**%SOM**	**pH**	**EC**	**Phosphate**	**K**	**Mg**	**SMC-June**	**SMC-July**	**SMC-August**
%Sand	**-0.87**	-										
%Silt	0.05	**-0.54**	-									
%OM	-0.14	0.16	-0.08	-								
pH	0.10	-0.07	-0.03	-0.04	-							
EC	**0.34**	**-0.31**	0.05	0.02	**-0.27**	-						
Phosphate	0.01	-0.01	-0.01	-0.03	0.13	0.11	-					
K	**-0.22**	0.10	0.18	-0.05	-0.19	-0.03	-0.05	-				
Mg	-0.13	0.17	-0.12	0.10	**-0.21**	0.00	-0.05	0.07	-			
SM-June	**-0.27**	**0.28**	-0.11	**0.32**	0.15	**-0.21**	0.00	0.11	**0.35**	-		
SM-July	**-0.33**	**0.33**	-0.11	0.19	0.10	-0.40	-0.10	0.00	0.12	**0.36**	-	
SM-September	-0.04	-0.05	0.16	0.07	0.08	0.07	0.08	-0.05	0.12	**0.24**	-0.05	-
AVT-June	-0.10	0.15	-0.13	**0.20**	0.13	-0.06	-0.12	0.13	0.11	**0.36**	**0.31**	0.16
AVT-July	**0.43**	**-0.40**	0.07	-0.13	0.09	0.19	-0.10	-0.10	-0.12	**-0.20**	**-0.21**	0.00
AVT-Aug.	**0.44**	**-0.41**	0.07	-0.14	0.06	0.16	-0.09	-0.08	-0.18	**-0.44**	**-0.27**	0.02
AVT-Sept.	**0.35**	**-0.31**	0.04	-0.10	0.02	0.12	-0.12	-0.06	-0.15	**-0.30**	-0.09	0.01
AVT-Oct.	0.13	-0.12	0.03	0.02	0.04	0.08	-0.15	0.00	-0.13	-0.06	0.12	0.01
AVT-Nov.	-0.08	0.07	0.00	0.05	0.02	0.00	-0.07	0.10	-0.04	0.17	0.17	-0.05
AVT-Season	**0.32**	**-0.28**	0.02	-0.05	0.09	0.13	-0.14	-0.02	-0.12	-0.17	-0.05	0.05
MIT-Season	0.10	-0.16	0.15	0.00	0.01	0.04	-0.15	-0.05	-0.11	-0.04	-0.10	**0.25**
MXT-Season	**0.36**	**-0.37**	0.13	-0.10	0.03	0.07	0.02	0.03	-0.19	**-0.26**	**-0.21**	-0.11

	%Clay	**%Sand**	**%Silt**	**%SOM**	**PH**	**EC**	**Phosphate**	**K**	**Mg**	**SMC-June**	**SMC-July**	**SMC-August**
Weeds	0.19	-0.16	0.00	-0.04	0.09	-0.04	0.05	-0.05	-0.14	-0.10	-0.02	**-0.20**
Plant population	**-0.34**	**0.38**	-0.19	0.17	-0.10	0.07	0.10	0.10	**0.29**	**0.40**	**0.23**	**0.20**
Crop cover-June	**-0.39**	**0.44**	**-0.22**	**0.32**	-0.12	-0.08	0.06	0.12	**0.33**	**0.54**	**0.43**	0.14
Crop cover-July	**-0.40**	**0.45**	**-0.23**	**0.32**	-0.14	-0.10	0.05	0.15	**0.33**	**0.60**	**0.41**	0.11
Crop cover-August	-0.19	**0.21**	-0.10	**0.34**	0.05	0.01	0.10	0.05	**0.24**	**0.69**	0.18	**0.43**
Crop cover-September	**-0.33**	**0.34**	-0.13	**0.24**	-0.01	-0.01	0.07	0.02	**0.28**	**0.53**	0.17	**0.31**
SRI- July	**-0.41**	**0.48**	**-0.28**	**0.24**	-0.08	-0.06	0.06	**0.20**	**0.21**	**0.53**	**0.37**	0.07
SRI-August	**-0.50**	**0.54**	**-0.24**	**0.37**	0.16	-0.15	0.09	0.05	0.20	0.61	0.39	0.17
SRI-September	**-0.37**	**0.39**	-0.15	**0.27**	0.02	0.00	0.08	0.17	0.28	0.54	0.23	**0.29**
LAI-July	**-0.42**	**0.48**	**-0.26**	**0.26**	-0.11	-0.06	0.08	**0.20**	**0.24**	**0.58**	**0.33**	0.06
LAI-August	**-0.38**	**0.43**	**-0.21**	**0.33**	0.05	-0.07	0.15	0.11	0.18	0.55	0.29	**0.30**
LAI-September	**-0.36**	**0.37**	-0.14	**0.33**	-0.03	-0.05	-0.05	0.19	0.32	0.56	0.30	**0.25**
Canopy growth rate	0.15	-0.10	-0.07	-0.09	-0.01	0.07	-0.08	-0.06	-0.04	-0.07	-0.13	-0.14
Roots yield	**-0.34**	**0.40**	**-0.24**	**0.32**	-0.04	-0.03	-0.01	0.05	0.32	0.55	0.37	**0.24**
%Sugar	**-0.26**	**0.32**	**-0.20**	0.14	-0.07	**-0.22**	-0.17	0.13	0.15	0.30	0.17	-0.17
Sugar yield	**-0.34**	**0.41**	**-0.24**	**0.32**	-0.05	-0.04	-0.02	0.06	**0.32**	**0.56**	**0.38**	**0.22**
Yield value	**-0.34**	**0.41**	**-0.25**	**0.32**	-0.05	-0.05	-0.02	0.06	**0.33**	**0.56**	**0.37**	**0.21**
Amino in beet	0.11	-0.18	0.16	-0.06	**-0.20**	**0.23**	-0.09	-0.09	-0.03	**-0.37**	-0.07	0.13
Potassium in beet	**0.45**	**-0.44**	0.11	-0.06	-0.16	0.15	-0.09	-0.02	-0.09	**-0.44**	**-0.30**	-0.08

	Weeds	**Plant population**	**Crop cover-June**	**Crop cover-July**	**Crop cover-August**	**Crop cover-August**	LAI-July	**LAI-Augu.**	**LAI-Sept.**	**SRI-July**	**SRI-Aug.**	**SRI-Sept.**	**Canopy growth rate**	**Roots yield**	**%Sugar**	**Sugar yield**	**Yield value**	**Amino acid in beet**	**Potassium in beet**
T-June	-0.03	0.17	**0.28**	**0.25**	**0.27**	0.18	**0.24**	**0.29**	**0.28**	**0.25**	0.19	0.18	-0.09	**0.29**	**0.24**	**0.30**	**0.30**	-0.16	-0.19
T-July	0.11	**-0.38**	**-0.36**	**-0.40**	**-0.30**	**-0.39**	**-0.41**	**-0.42**	**-0.37**	**-0.33**	**-0.40**	**-0.47**	0.01	**-0.35**	-0.14	**-0.34**	**-0.34**	0.08	**0.25**
T-Aug.	0.13	**-0.40**	**-0.48**	**-0.55**	**-0.43**	**-0.54**	**-0.54**	**-0.56**	**-0.45**	**-0.53**	**-0.52**	**-0.54**	0.04	**-0.48**	**-0.26**	**-0.48**	**-0.47**	0.14	**0.36**
T-Sept.	0.17	**-0.36**	**-0.34**	**-0.41**	**-0.37**	**-0.52**	**-0.40**	**-0.50**	**-0.44**	**-0.39**	**-0.45**	**-0.54**	-0.04	**-0.39**	-0.17	**-0.39**	**-0.38**	0.10	**0.31**
T-Oct	0.11	**-0.22**	-0.12	-0.17	-0.19	**-0.32**	-0.17	**-0.22**	**-0.25**	-0.14	**-0.22**	**-0.37**	-0.05	-0.17	-0.02	-0.17	-0.15	0.02	0.15
T-Nov.	0.11	-0.07	0.10	0.06	-0.01	-0.08	0.06	0.04	-0.01	0.11	0.01	-0.12	-0.11	0.06	0.14	0.07	0.07	-0.08	-0.03
T-Season	0.12	**-0.30**	**-0.26**	**-0.33**	**-0.26**	**-0.40**	**-0.33**	**-0.36**	**-0.31**	**-0.29**	**-0.35**	**-0.43**	-0.03	**-0.28**	-0.09	**-0.28**	**-0.27**	0.05	**0.22**
Tmax	-0.07	**-0.29**	**-0.40**	**-0.41**	-0.13	-0.16	**-0.32**	**-0.24**	-0.14	**-0.32**	**-0.25**	**-0.24**	0.08	**-0.25**	-0.16	**-0.26**	**-0.26**	0.10	**0.28**
Tmax	**0.22**	**-0.30**	**-0.22**	**-0.32**	**-0.33**	**-0.44**	**-0.36**	**-0.41**	**-0.37**	**-0.29**	**-0.36**	**-0.40**	-0.16	**-0.33**	**-0.20**	**-0.33**	**-0.33**	0.11	**0.34**

	Weeds	Plant pop.	Crop cover-June	Crop cover-July	Crop cover-Aug.	Crop cover-Sep	SRI-July	SRI-Aug.	SRI-Sept.	LAI-July	LAI-Aug.	LAI-Sept	Canopy growth rate	Root yield	%sugar
Plant population	-0.11	-													
Crop cover-June	-0.11	**0.71**	-												
Crop cover-July	-0.16	**0.70**	**0.92**	-											
Crop cover-August	**-0.21**	**0.62**	**0.67**	**0.72**	-										
Crop cover-Sep	**-0.23**	**0.68**	**0.61**	**0.65**	**0.79**	-									
SRI-July	**-0.29**	**0.60**	**0.73**	**0.80**	**0.55**	**0.57**	-								
SRI-Aug.	-0.18	**0.61**	**0.63**	**0.69**	**0.66**	**0.72**	**0.65**	-							
SRI-Sept.	-0.16	**0.54**	**0.52**	**0.53**	**0.67**	**0.72**	**0.51**	**0.66**	-						
LAI-July	**-0.22**	**0.58**	**0.72**	**0.78**	**0.54**	**0.54**	**0.93**	**0.63**	**0.51**	-					
LAI-Aug.	**-0.23**	**0.66**	**0.74**	**0.78**	**0.77**	**0.73**	**0.62**	**0.84**	**0.57**	**0.58**	-				
LAI-Sept	**-0.23**	**0.59**	**0.64**	**0.65**	**0.72**	**0.78**	**0.57**	**0.72**	**0.89**	**0.54**	**0.67**	-			
Canopy growth rate	-0.07	-0.16	**-0.34**	-0.06	-0.11	-0.06	-0.03	-0.07	-0.09	-0.05	-0.10	-0.13	-		
Root yield	**-0.21**	0.72	**0.80**	**0.74**	**0.72**	**0.76**	**0.67**	**0.69**	**0.71**	**0.64**	**0.70**	**0.79**	**-0.28**	-	
%Sugar	-0.12	0.23	**0.30**	**0.33**	0.19	**0.28**	**0.45**	**0.38**	**0.27**	**0.41**	**0.29**	**0.30**	-0.02	**0.33**	-
Sugar yield	**-0.21**	0.71	**0.80**	**0.74**	**0.72**	**0.76**	**0.69**	**0.69**	**0.71**	**0.65**	**0.70**	**0.79**	**-0.28**	1.00	**0.39**
Yield value	**-0.21**	0.71	**0.80**	**0.73**	**0.71**	**0.75**	**0.69**	**0.69**	**0.70**	**0.65**	**0.69**	**0.78**	**-0.28**	1.00	**0.41**
Amino in beet	-0.01	-0.18	**-0.22**	**-0.24**	**-0.36**	**-0.21**	**-0.25**	**-0.31**	**-0.20**	**-0.27**	**-0.29**	**-0.21**	0.15	-0.18	**-0.35**
Potassium in beet	0.16	-0.45	**-0.47**	**-0.51**	**-0.38**	**-0.44**	**-0.56**	**-0.57**	**-0.43**	**-0.55**	**-0.40**	**-0.41**	0.02	**-0.50**	**-0.30**

Appendix 9.6: Test the significance of the correlations against zero in WO3.

	%Clay	%Sand	%Silt	%SOM	pH	EC	Phosphate	K	Mg	SMC-June	SMC-July	SMC-August
%Sand	<0.001	-										
%Silt	0.614	<0.001	-									
%OM	0.169	0.130	0.480	-								
pH	0.399	0.570	0.768	0.738	-							
EC	<0.001	0.002	0.635	0.829	0.003	-						
Phosphate	0.939	0.977	0.942	0.747	0.196	0.265	-					
K	0.012	0.259	0.048	0.642	0.040	0.651	0.559	-				
Mg	0.160	0.078	0.250	0.335	0.026	0.948	0.617	0.470	-			
SM-June	0.003	0.002	0.325	<0.001	0.139	0.021	0.992	0.317	<0.001	-		
SM-July	<0.001	<0.001	0.263	0.048	0.298	<0.001	0.300	0.972	0.210	<0.001	-	
SM-September	0.795	0.569	0.107	0.508	0.386	0.420	0.413	0.678	0.198	0.008	0.616	-
AVT-June	0.340	0.189	0.306	0.052	0.125	0.604	0.203	0.194	0.322	<0.001	0.001	0.084
AVT-July	<0.001	<0.001	0.441	0.175	0.328	0.045	0.327	0.312	0.210	0.031	0.034	0.991
AVT-Aug.	<0.001	<0.001	0.544	0.148	0.519	0.085	0.359	0.465	0.064	<0.001	0.006	0.864
AVT-Sept.	<0.001	<0.001	0.729	0.328	0.791	0.198	0.217	0.592	0.120	0.002	0.381	0.954
AVT-Oct.	0.209	0.229	0.775	0.826	0.684	0.412	0.116	0.970	0.175	0.553	0.220	0.936
AVT-Nov.	0.345	0.411	0.960	0.560	0.931	0.949	0.432	0.324	0.669	0.094	0.075	0.622
AVT-Season	<0.001	0.003	0.799	0.618	0.342	0.183	0.162	0.813	0.219	0.076	0.580	0.645
MIT-Season	0.225	0.064	0.097	0.962	0.807	0.578	0.138	0.699	0.273	0.754	0.320	0.010
MXT-Season	<0.001	<0.001	0.199	0.338	0.880	0.583	0.845	0.861	0.052	0.006	0.030	0.280

	%Clay	%Sand	%Silt	%SOM	PH	EC	Phosphate	K	Mg	SMC-June	SMC-July	SMC-August
Weeds	0.055	0.102	0.979	0.699	0.367	0.672	0.586	0.617	0.151	0.302	0.838	0.042
Plant population	<0.001	<0.001	0.049	0.074	0.286	0.482	0.323	0.310	0.003	<0.001	0.017	0.036
Crop cover-June	<0.001	<0.001	0.021	<0.001	0.234	0.403	0.518	0.212	<0.001	<0.001	<0.001	0.141
Crop cover-July	<0.001	<0.001	0.016	<0.001	0.157	0.285	0.611	0.126	<0.001	<0.001	<0.001	0.277
Crop cover-August	0.055	0.033	0.311	<0.001	0.641	0.956	0.306	0.635	0.013	<0.001	0.063	<0.001
Crop cover-September	<0.001	<0.001	0.185	0.013	0.902	0.956	0.468	0.814	0.003	<0.001	0.088	0.001
SRI- July	<0.001	<0.001	0.004	0.013	0.397	0.531	0.525	0.038	0.031	<0.001	<0.001	0.496
SRI-August	<0.001	<0.001	0.014	<0.001	0.099	0.131	0.339	0.586	0.043	<0.001	<0.001	0.074
SRI-September	<0.001	<0.001	0.117	0.005	0.806	0.984	0.434	0.082	0.003	<0.001	0.019	0.003
LAI-July	<0.001	<0.001	0.008	0.007	0.270	0.534	0.415	0.040	0.013	<0.001	<0.001	0.537
LAI-August	<0.001	<0.001	0.027	<0.001	0.623	0.466	0.114	0.258	0.068	<0.001	0.002	0.002
LAI-September	<0.001	<0.001	0.167	<0.001	0.759	0.622	0.617	0.047	<0.001	<0.001	0.002	0.009
Canopy growth rate	0.120	0.329	0.494	0.347	0.926	0.459	0.407	0.527	0.672	0.494	0.186	0.165
Roots yield	<0.001	<0.001	0.014	<0.001	0.655	0.751	0.942	0.586	<0.001	<0.001	<0.001	0.015
%Sugar	0.007	<0.001	0.035	0.148	0.490	0.026	0.084	0.169	0.121	0.002	0.074	0.089
Sugar yield	<0.001	<0.001	0.012	<0.001	0.646	0.648	0.854	0.569	<0.001	<0.001	<0.001	0.026
Yield value	<0.001	<0.001	0.011	<0.001	0.633	0.600	0.818	0.563	<0.001	<0.001	<0.001	0.032
Amino in beet	0.241	0.070	0.099	0.529	0.041	0.016	0.337	0.346	0.797	<0.001	0.446	0.184
Potassium in beet	<0.001	<0.001	0.268	0.524	0.097	0.113	0.366	0.863	0.347	<0.001	0.002	0.410

	Weeds	Plant population	Crop cover-June	Crop cover-July	Crop cover-August	Crop cover-August	LAI-July	LAI-Aug..	LAI-Sept.	SRI-July	SRI-Aug.	SRI-Sept.	Canopy growth rate	Roots yield	%Sugar	Sugar yield	Yield value	Amino acid in beet	Potassium in beet
T-June	0.777	0.085	0.004	0.010	0.005	0.060	0.013	0.003	0.003	0.010	0.052	0.065	0.374	0.003	0.012	0.002	0.002	0.107	0.055
T-July	0.263	<0.001	<0.001	<0.001	0.002	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.898	<0.001	0.162	<0.001	<0.001	0.419	0.010
T-Aug.	0.201	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.695	<0.001	0.008	<0.001	<0.001	0.144	<0.001
T-Sept.	0.076	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.717	<0.001	0.077	<0.001	<0.001	0.325	0.001
T-Oct	0.253	0.024	0.227	0.078	0.051	<0.001	0.088	0.022	0.009	0.148	0.027	<0.001	0.583	0.083	0.839	0.090	0.116	0.816	0.117
T-Nov.	0.248	0.461	0.291	0.509	0.938	0.399	0.540	0.719	0.911	0.273	0.880	0.218	0.267	0.550	0.156	0.507	0.462	0.418	0.760
T-Season	0.206	0.002	0.006	<0.001	0.006	<0.001	<0.001	<0.001	0.001	0.002	<0.001	<0.001	0.773	0.004	0.355	0.004	0.006	0.627	0.022
Tmax	0.457	0.003	<0.001	<0.001	0.172	0.095	<0.001	0.013	0.143	<0.001	0.009	0.014	0.430	0.009	0.105	0.008	0.008	0.326	0.003
Tmax	0.024	0.002	0.023	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.002	<0.001	<0.001	0.104	<0.001	0.039	<0.001	<0.001	0.243	<0.001

	Weeds	Plant pop	Crop cover-June	Crop cover-July	Crop cover-Aug.	Crop cover-Sep	SRI-July	SRI-Aug.	SRI-Sept.	LAI-July	LAI-Aug.	LAI-Sept	Canopy growth rate	Root yield	%sugar
Plant population	0.270	-													
Crop cover-June	0.271	<0.001	-												
Crop cover-July	0.108	<0.001	<0.001	-											
Crop cover-August	0.032	<0.001	<0.001	<0.001	-										
Crop cover-Sep	0.019	<0.001	<0.001	<0.001	<0.001	-									
SRI-July	0.003	<0.001	<0.001	<0.001	<0.001	<0.001	-								
SRI-Aug.	0.059	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-							
SRI-Sept.	0.104	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-						
LAI-July	0.026	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-					
LAI-Aug.	0.017	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-				
LAI-Sept	0.015	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-			
Canopy growth rate	0.479	0.108	<0.001	0.510	0.256	0.555	0.771	0.472	0.357	0.608	0.303	0.197	-		
Root yield	0.034	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.004	-	
%Sugar	0.236	0.016	0.002	<0.001	0.057	0.004	<0.001	<0.001	0.005	<0.001	0.003	0.002	0.875	<0.001	-
Sugar yield	0.032	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.004	<0.001	<0.001
Yield value	0.033	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.004	<0.001	<0.001
Amino in beet	0.883	0.059	0.024	0.013	<0.001	0.035	0.011	0.001	0.039	0.006	0.003	0.028	0.125	0.068	<0.001
Potassium in beet	0.110	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.801	<0.001	0.002