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Understanding the Relative Impacts of Climate Change on Crop Production using Data from the Rothamsted Long-Term Experiments

Doctor of Philosophy

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Declaration

I confirm all work and analyses using the Rothamsted Long-Term Experiment data presented within this Thesis is my own. This Thesis has used data from the Electronic Rothamsted Archive. All data regarding the Rothamsted Long-Term Experiments which was used was either from the Electronic Rothamsted Archive or from correspondence with the Electronic Rothamsted Archive team Dr Margaret Glendining and Dr Sarah Perryman. Data from the Rothamsted Meteorological Station was also provided through the Electronic Rothamsted Archive.

The version of Sirius used within Chapter 7 is version 15.0.6494.28556. Future climate scenarios within Chapter 7 was generated using the Long-Aston Research Station Weather Generator by Dr Mikhail Semenov.

Statistical analysis within Chapters 3, 4, 5, 6 and 7 were performed in `R` (R Core Team, 2018) and Genstat® 18 (VSN International, 2017). Three dimensional surface plots were created by using the `rgl` package in R (https://cran.r-project.org/web/packages/rgl/rgl.pdf). Statistical model validation was achieved by using the `car` package in R (https://cran.r-project.org/web/packages/car/car.pdf).

All other data used within this Thesis has been properly and fully acknowledged within each chapter.

John W. G. Addy

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Abstract

Crop yields are affected by many variables. In the context of climate change, higher temperatures tend to reduce yield. The Rothamsted Long-Term Experiments on winter wheat (*Triticum aestivum*) (in Broadbalk), spring barley (*Hordeum vulgare*) (Hoosfield), and herbage (Park Grass) are some of the world's oldest continuous agricultural experiments. This Thesis investigates inter-annual variability in yield in the response to climate change, and principally, variations in weather.

A multivariate approach to quantify climate change was developed in which 10 different clusters of similar annual weather characteristics from 1892 to 2016 were identified. Most years in the 21st century had their own distinct cluster of a generally warmer climate, which occurred infrequently in the 20th century. FYM treatments of wheat and barley from these warm and dry years had a total biomass of 3.05 and 1.18 t ha^{-1} lower compared to years from a typical 20*th* century climate. Between-year variations in temperature and rainfall were associated with variations in the yield of wheat, barley and forage. Warmer temperatures in the early-summer were shown to have a negative effect on the yield of cereal crops. By modelling variations in a Nitrogen response curve, annual yields of wheat and spring barley to Nitrogen were also influenced by variations in rainfall and temperature, where warmer temperatures reduced asymptotic yield of the response to Nitrogen. Simulated wheat yields were estimated to increase by 9.12 to 9.87% from 1892 to 2016 due to rises in atmospheric CO_2 when all other variables were fixed, but this effect was largely negated by the actual rise in temperature over this period.

The Rothamsted Long-Term Experiment data provided a unique insight into the association between weather and yield and potential mitigations to increase food production. The statistical approaches developed within this Thesis may be applied to other long-term crop-weather datasets.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

By 2050 the world population is projected to reach 9.8 billion and 11.2 billion by 2100 (UN, DESA, 2017). Ending hunger and achieving food security for all is recognised as the second Sustainable Development Goal by the United Nations (UN, 2018). Food security was defined by the World Food Summit (1996) as "when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life". Therefore, to meet the food demand of a growing global population crop production worldwide will need to increase 60% by 2050, in comparison with today, with farmers required to produce more with fewer inputs and no more land (FAO, 2017).

This intensification of agriculture must be achieved during a period of global climate change; as 2016 saw the average global land temperature rise to 1.43°C above the 20$^{\text{th}}$ century average (NOAA, 2017). In 2015, the Paris Climate Agreement (UNFCCC, 2015) was agreed by the United Nations Framework Convention on Climate Change (UNFCCC) to limit the rise of global temperatures this century well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5°C (UNFCCC, 2015).

1.1 Crop Production and Food Security

Globally, the total area of harvested cereals in 2016 was 718 million ha, with world wheat and barley yields at 3,405 and 3,011 kgha^{-1}, respectively (FAOSTAT, 2018b). The top three highest yielding crops in 2016 were maize (5,640 kgha^{-1}), rice (4,637 kgha^{-1}) and wheat (3,405 kgha^{-1}) (FAOSTAT, 2018b). In the UK, 71% of land is used for farming, with 19% of land used for arable farming (National Statistics, 2016). In 2016, milk, wheat and barley production

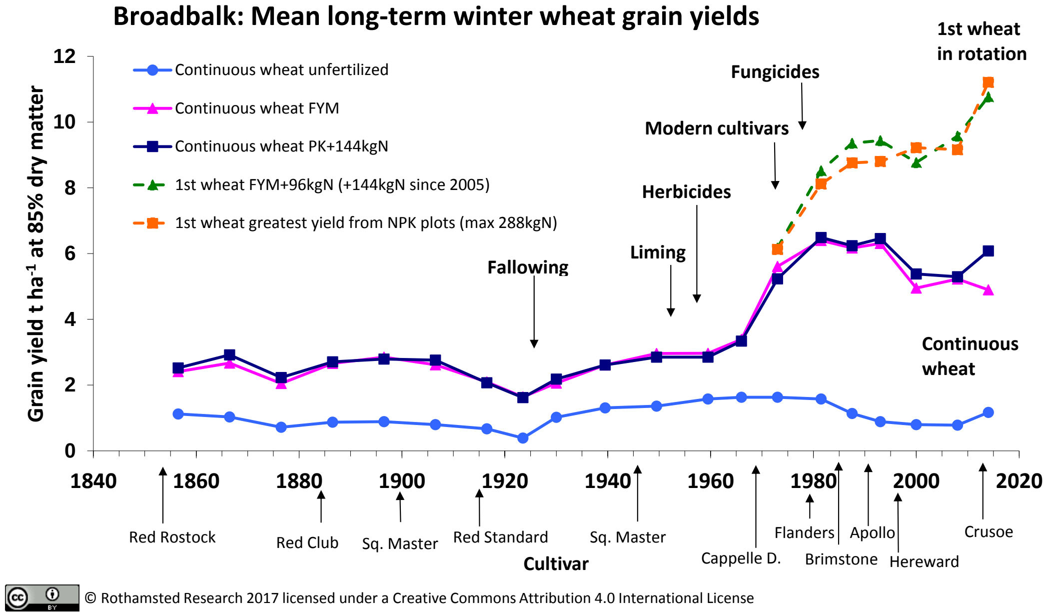


Figure 1.1: Mean long-term grain yields of the Broadbalk winter wheat experiment from 1852 to 2016, illustrating the effects of changes in agricultural practice (arrows) on wheat production (Rothamsted Research, 2017a).

were the three highest agricultural outputs in the UK, with a production of 14.9, 14.4 and 6.7 million tonnes (FAOSTAT, 2018a). With the production of these agricultural outputs, any change could threaten food security within the UK. The five-year harvest mean (2012 to 2016) for wheat (*Triticum aestivum*) and barley (*Hordeum vulgare*) in the UK was 14.5 and 7.4 million tonnes, with an 5.4% and 10.6% increase in 2017 compared to 2016, respectively (National Statistics, 2017a). In 2017, 10,124 thousand ha of agricultural land in the UK was permanent grassland with a 0.4% increase compared to 2016 (National Statistics, 2017b). The current global agricultural output from harvested land will have to increase by 2050 to meet a growing population demand and any threats to crop production could have disastrous effects on the global food security.

The Green Revolution of Agriculture in the 1960s saw an increase in the agricultural production of cereals through the use of short-strawed cultivars and the use of agrochemicals such as pesticides. Short-strawed cultivars were bred to include semi-dwarfing genes and allowed higher applications of Nitrogen to be applied with a lower risk of lodging. The effects of the

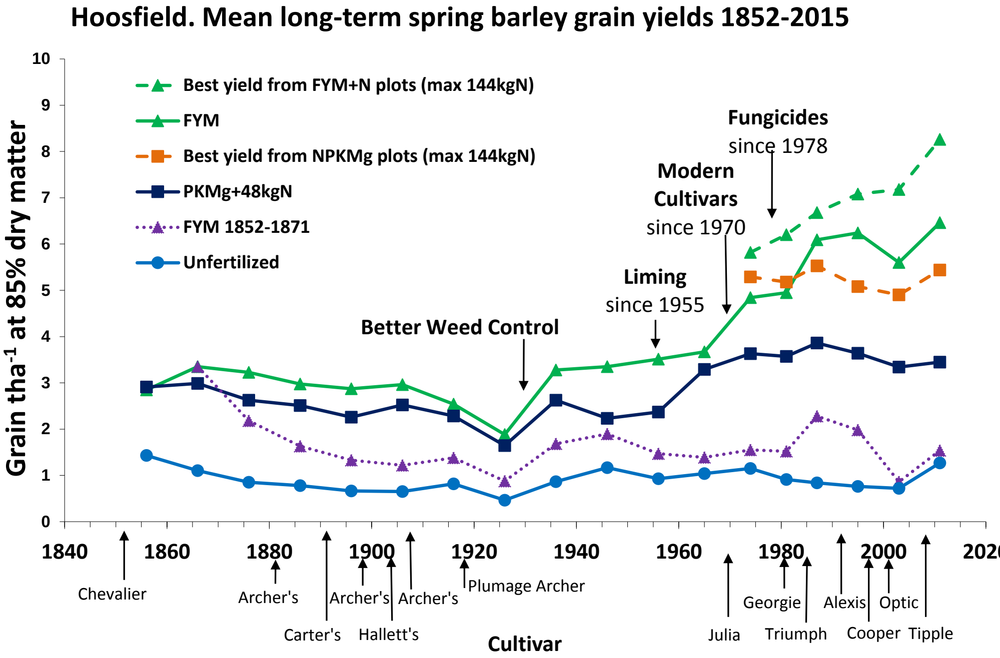


Figure 1.2: Mean long-term grain yields of the Hoosfield spring barley experiment from 1852 to 2016, illustrating the effects of changes in agricultural practice (arrows) on spring barley production (Rothamsted Research, 2017b).

Green Revolution, together with changes in agricultural management practices from 1852 to 2016, can be seen in the yields of the Rothamsted Long-Term Experiments of wheat (Broadbalk) and spring barley (Hoosfield) in Figures 1.1 and 1.2. Broadbalk and Hoosfield have been sown continuously since 1843 and 1852, respectively, and provide an invaluble resource to show and understand how the agricultural outputs of wheat and spring barley have changed since the mid-19th century.

Between 1968 and 1996, the UK production of wheat and barley increased. But, since 1997 onwards the production of these cereals has stagnated (FAOSTAT, 2018b). Rice and wheat yields remained relatively constant in 72% and 85% of long-term rice and wheat experiments in Bangladesh, China, India and Nepal (Ladha et al., 2003). In France, climate has been considered an important factor in the stagnation of yield, however, agronomic changes, such as the decline in legumes in cereal rotation, may have contributed to yield stagnation (Brisson et al., 2010).

Increasing night-time temperatures have been shown to negatively influence yields from 1988 to 2002 from a study of climate trends in Mexico (Lobell et al., 2005). Although the stagnation of crop production has occurred on a national level, any trend in local UK yields, due to yearly and spatial variations in weather or changes in climate, may have been smoothed-out resulting in no change in crop production being observed over time.

It has been estimated that for every 1°C increase in mean global temperature, global wheat production is estimated to fall, on average, by 6% (Asseng et al., 2015). Overall, there has been a rise in food insecurity due to weather-related events affecting food availability (FAO, IFAD, UNICEF, WFP and WHO, 2017). The overall impact of climate change on food production will vary globally (Lobell et al., 2011) and food security will differ among global and socio-economic regions (Schmidhuber & Tubiello, 2007).

1.2 An Introduction to Climate Change

Earth is considered to have a rare balance of life-supporting conditions such as heat, liquid water and its atmospheric composition. Any changes to the balance of these optimal conditions on Earth could impact climate and world food security, where climate change was shown to increase food production in developed countries and reduce it production in developing countries (Rosenzweig & Parry, 1994). The Intergovernmental Panel on Climate Change (IPCC) was founded in 1988 by the United Nations Environmental Programme (UNEP) and the World Meteorological Organization (WMO) with the objectives that the IPCC would assess ”the scientific basis of risk of human-induced climate change, its potential impacts and options for adaptation and mitigation” (IPCC, 2013).

In the 5th IPCC assessment, the global mean surface temperature anomalies (where anomalies were defined as the annual temperature differenced from a relative period of climatology), relative to a 1961-1990 climatology, have increased at a positive linear rate between 1951 and 2012 of 0.106 °C per decade (Hartmann et al., 2013). In 2016, the average global temperature was 1.43 °C above the 20th century average (NOAA, 2017), with temperatures predicted to rise throughout the 21st century, depending on future climate emissions scenarios (Kirtman et al., 2013). Kovats et al. (2014) observed a greater change of European temperature over the last decade, with the decadal average European temperature between 2002-2011 being 1.3 °C (± 0.11 °C) above the 1850-1899 average. The Mean UK decadal temperatures between 2007 and 2016 was 9.1 °C compared to a 1961 to 1990 average of 8.3 °C (Kendon et al., 2017).

The global air temperature over the last 30 years has been increasing faster than any other period over the last 150 years, with night-time temperatures rising at a faster rate than daytime temperatures (Hartmann et al., 2013). In 2010 the occurrence of warmer night anomalies increased by approximately 20 days, compared to the 1961-1990 average, and the occurrence of colder night anomalies decreased by approximately 15 days, compared to the 1961-1990 average (Hartmann et al., 2013).

There has been evidence to show that over a shorter period of 25 years in Holbart, Australia average temperature has not increased compared to a 1964 to 2013 dataset (Keatinge et al., 2015). This hiatus has also been detected and explained by the strong relationship between El Niño Southern Oscillation (ENSO) and temperature, and once the ENSO variation has been removed, temperature has been shown to increase at a linear rate from 1970 to 2012 (Trenberth and Fasullo, 2013). This is an example of the complexity surrounding the variability associated with rising temperatures and climate change.

One human contributing factor linked to the rise in global temperature includes the increasing amounts of greenhouse gas emissions in the atmosphere. The total UK greenhouse gas emissions in 2016 was an estimated 467.9 $MtCO_2e$ (million metric tons of CO_2 equivalent) which was down 5.0% from 2015 (National Statistics, 2018). Although the annual UK greenhouse gas emissions seems to have fallen, the cumulative greenhouse gas emissions in the Earth's atmosphere have increased. Atmospheric CO_2 emissions were first measured in 1959 at 315.97 ppm by the Mauna Loa Observatory in Hawaii, with the amount of atmospheric CO_2 passing 350 ppm in the mid-1990s and 400 ppm in April 2014 (NOAA, 2018). Etheridge et al. (1998) conducted a study in the Law Dome, East Antarctica from 1987 to 1993 to extract atmospheric CO_2 reconstructions from 1006 A.D. to 1978 A.D. The reconstructed CO_2 estimate in 1892 was 295.6 ppm (Etheridge et al., 1998), which was less than the first observed atmospheric CO_2 level of 315.97 ppm (NOAA, 2018).

The IPCC (2014) has predicted CO_2 levels to rise by 2050 and 2100, with predictions varying depending on future scenarios of economic and population growth. High population growth and less emphasis on the use of cleaner technologies would result in higher levels of atmospheric CO_2 by the end of the 21^{st} century (IPCC, 2014). With increases in atmospheric CO_2, global mean surface temperatures between 2081 and 2100 would rise between 1.1 to 2.6°C for Representative Concentration Pathway (RCP) 4.5 and 2.6 to 4.8°C for RCP 8.5, compared to a 1986 and 2005 average (Collins et al., 2013).

1.3 Influence of Climate Change on Crop Production

Crop yields are affected by many variables, principally: soils and crop nutrition, previous cropping, the cultivar and its agronomy, the impact of pests and diseases and the effect of climate and weather. Generally, climate change will influence agriculture and global food security through changes in agroecological conditions (Schmidhuber & Tubiello, 2007). However, the impact of one variable, such as increases in temperature, on crop production over a long-time series may be confounded by potential variations of abiotic and biotic stresses.

Increases in temperature, at the time of flowering, have been shown to reduce the potential number of grains that contribute to crop yield (Wheeler et al., 2000). The impact of increasing temperatures from anthesis to harvest maturity have further been shown to reduce the seed dry weight of winter wheat (Wheeler et al., 1996). It has also been suggested that grain fertilisation was sensitive to high temperatures at the mid-anthesis stage of wheat development (Ferris et al., 1998). Other phenological stages of crop development, such as the vernalisation of winter wheat tends to occur most effectively at 3°C but can occur very slowly at 0°C (Gooding & Davies, 1997).

Plant phenology has also been impacted by the rise in night-time temperatures. Spring wheat experienced a decrease of 0.25 grain dry weight (g plant^{-1}) for every 1°C increase in night-time temperature (Prasad et al., 2008). Rice leaves respired more in the early grain fill period of plant growth in higher night-time temperatures compared to ambient night-time temperatures (Mohammed & Tarpley, 2009). Therefore, any impacts of temperature on yield may be confounded by within-day variations of temperature.

A positive trend of some crop yields over time within Northern Europe may be explained by how the impact of increasing temperatures are being negated by the positive effects of increasing CO_2 within the atmosphere (Olesen et al., 2011; Schmid et al., 2015; Wheeler et al., 2000). Crops grown in increased CO_2 experience a higher rate of photosynthesis and a greater water-use efficiency (Beadle et al., 1993). Review studies from the 1980s showed that the doubling of CO_2 from ambient levels resulted in a 29% to 33% increase in grain yield (Cure & Adcock, 1986; Kimball, 1983). More recent studies have shown an increase of 17% in crop yields with an enrichment (475 to 600 ppm) of CO_2 (Ainsworth & Long, 2005). A review study, across multiple experimental methods, detected a 31% increase in wheat yield from the doubling of CO_2 from 350 ppm to 700 ppm (Amthor, 2001). A comparison between different methodologies in identifying a CO_2 response in controlled experiments was given by Long et al. (2006) and Tubiello et al. (2007). A doubling of CO_2, from 350 ppm to 700 ppm, was shown to increase potential crop growth by 25% in C3 crops and 10% in C4 crops (Tubiello et al., 2000). Where C3 crops were shown to benefit more from elevated levels of CO_2 compared to C4 crops (Bowes, 1993).

Furthermore, wheat grown in an enrichment of CO_2 (comparison of ambient levels to 700 μmol mol^{-1}) was shown to increase grain weight across multiple temperatures (Wheeler et al., 1996). But generally, European agricultural systems will see an increase in productivity due to climate change effects and further developments of in technology and crop management (Olesen & Bindi, 2002). Overall, crop biomass was shown to increase with CO_2 and decrease with higher temperatures (Batts et al., 1997).

The use of process-based models allows the identification of the potential impacts of climate change on crop productivity given known studied and modelled biological processes. Process-based models coupled with future climate projections can inform the state of crop productivity, given future emission scenarios, and the potential mitigation against a loss in future crop yield. Generally, in the absence of enriched CO_2, a simulation-based approach of future weather scenarios showed, future yields at Rothamsted in 2055 are expected to decrease (Semenov & Shewry, 2011). A further simulation study in Southern Denmark showed, across several wheat models, without the increase of atmospheric CO_2 over the 21st century there was an observed yield reduction (Ozturk et al., 2017). The development of heat-tolerant idiotypes for southern and central Europe suggest, to cope with an acceleration of crop physiology due to higher temperatures, higher and more stable wheat yields could be achieved by adapting wheat to extend the duration of the grain filling period (Semenov et al., 2014; Stratonovitch & Semenov, 2015). Although process-based models may inform about how the potential losses of yield due to climate change directly influence the crop, other sources of variability may indirectly influence crop growth through a change in the environment.

Soil water content falling outside the least limiting water range has been shown to contribute to moisture conditions which limit plant growth (da Silva & Kay, 1997). Changing weather patterns can increase the vulnerability of crops by infection, pest infestations, and weeds (Rosenzweig et al., 2001). Any direct gains in yield due to increasing atmospheric CO_2 could be offset by the growth of weeds (Coakley et al., 1999). Overall the estimated losses of yield due to weeds was approximately US$4.9 billion in Europe and US$8.4 billion in North America between 1988 and 1990 (Rosenzweig et al., 2001). By analysing weed populations on the Long-Term Broadbalk experiment high spring temperatures and milder winters saw an increase in the weed species *Tripleurospermum inodorum* and *Rosa arvensis*, respectively, with weed communities becoming more competitive during mild springs resulting in a higher wheat yield loss (García De León et al., 2014). Therefore, if the environment is becoming more suited to increase plant growth we may expect to see more competition between crops and pests.

The use of controlled experiments and simulation-based modelling approaches, to identify the effects of climate change on crop production, provide valued insight into the biological processes driving crop growth in different environmental conditions. However, the study of crop variability on long-term field trials may provide further insight into how climate change has and will affect crop production on an agricultural system, rather than a reduced hypothesis driven approach of well-designed experiments. Long-term field experiments allow for the investigation of the effects of climate change, and the biological responses found in controlled experiments, on a larger scale, where these effects may be occurring in the presence of other abiotic or biotic stresses. Therefore, any impact of one variable on crop production due to climate change may be confounded by one or many other variables, which may or may not be influenced by variations in weather or climate change.

1.4 Studies in Crop Yield Variation

The influence of weather on crop production and variability was investigated before the discovery of human induced climate change in the mid to late-20$^{\text{th}}$ century. Two Victorian scientists, John Bennet Lawes and Joseph Henry Gilbert devised the Broadbalk Experiment (hereafter Broadbalk) at Rothamsted in 1843 to test the effects of inorganic fertilisers and organic manures on the growth of wheat (Lawes, 1847) in response to a theory of agricultural chemistry and the acquisition of Nitrogen in crops given by Justus Freiherr von Liebig at that time (Lawes & Gilbert, 1851). It was in Lawes & Gilbert (1851) where the yearly variations in yield (since 1843 Broadbalk has been in continuous wheat) of continuously sown crops can be first observed.

A drought year in 1870 resulted in a comparison of the effects of drought on crop yields across multiple years at Rothamsted by Lawes & Gilbert (1871), with an absence of rainfall over a harvest season leading to a reduction in yield, where the magnitude of yield loss varied between wheat, barley and grassland. The harvest season 1879 saw excess rainfall at Rothamsted and across Hertfordshire. This, combined with a decline in agricultural production of the Long-Term Experiments from 1868 to 1879, led to a publication on how climate influences the wheat yield of Broadbalk, ”climate have been exhibited in unusual frequency” which contributed to ”the worst for the wheat-crop since the commencement of our experiment” (Lawes & Gilbert, 1880b). In 1919, Rothamsted hired their first statistician, Ronald J. Fisher, to investigate if more information could be obtained from the accumulation of data from Rothamsted’s Long-Term Experiments. This appointment lead to a study in crop variation (Fisher, 1921) and later the influence of rainfall on the yield of wheat, where variations in weather within the early harvest season of wheat are negatively associated with yield (Fisher, 1925a). The motivation for some of the methodology within Fisher (1925a), was driven from Hooker (1907), where similar results of variations in weather and their associations with yield were found.

Further studies in crop variation at Rothamsted showed how rainfall influenced the grain yield of the Hoosfield Barley Experiment (Wishart & Mackenzie, 1930) and hay yield of the Park Grass Experiment (Cashen, 1947). Previous studies into variations in grassland yield have determined excess rainfall led to increased biomass and the dominance of grasses over other species on the Park Grass Experiment (Silvertown et al., 1994). The influence of maximum May and June temperatures have been shown to be negatively correlated with wheat yields, from 1854 to 1967 (Chmielewski & Potts, 1995). It should be noted that crop processes may be affected by temperature and temperature variability, but this may not necessarily be the same process, such as the rate of crop development, photosynthesis and respiration (Porter & Semenov, 2005). These relationships must be considered when analysing long-term yield datasets. Further associations in larger climate systems, such as the North Atlantic Oscillation, and the summer to autumn grassland (Park Grass) growth rate (Kettlewell et al., 2006) have been observed.

In previous studies of crop yield variability at Rothamsted, rainfall was identified as the most studied meteorological variable. Consideration as to why rainfall may have been the most studied may be because mean surface temperatures at Rothamsted may not have increased for there to be an adequate variability to determine a yield and temperature correlation (Chmielewski & Potts (1995) was the most recent study in crop variation on Broadbalk). Although, inter-year variation in rainfall and not temperature was shown to explain significant levels of wheat yield variability across the Great Plains of the United States of America from 1952 to 2016 (Hatfield & Dold, 2018). A similar comment could be made about the effect of CO_2 on the Rothamsted LTEs. No influence of the increase in atmospheric CO_2 was observed on the Park Grass Experiment between 1891 and 1992 (Jenkinson et al., 1994). However, there was no variation around the increasing trend of atmospheric CO_2, as there has been an increase every year since 1959 (NOAA, 2018). Therefore, due to a lack of variability around increasing atmospheric CO_2 and how the effect of increased CO_2 are masked in the observed data, identifying an association between increases in CO_2 and yield from long-term experiment data may become difficult.

Although the Rothamsted Long-Term Experiments have a long data time-series, they were devised before the development of the statistical principles of designed experiments (Fisher, 1926; 1925b). Some of the issues with the design of the LTEs are the lack of replication, but more importantly randomization of treatments (see Sections 2.2, 2.3 and 2.4). Other issues with continuously cropped experiments is the serial auto-correlation of yields, where auto-correlation of yield is defined as the correlation of yield in time at year t with year $t - 1$. The auto-correlation of Park Grass herbage yields was found and discussed by Coleman et al. (1987), Jenkinson et al. (1994) and Kettlewell et al. (2006).

1.5 The Value of Long-Term Experiments

The Rothamsted LTEs have provided a unique insight into the effects of long-term environmental changes on crop production from shortly after their inception (Lawes & Gilbert, 1880a; Lawes & Gilbert, 1871) to the present day. I have previously discussed the effects of weather variability on crop yields from the Rothamsted LTEs. However, other long-term changes have been shown to influence the LTEs. Changes in our climate has lead to an environment where weed competitiveness has increased (Storkey et al., 2018). The presence of antimicrobial resistance in fungal pathogens of barley has increased since 1985 (Hawkins et al., 2014). The decline of Nitrogen deposition in the atmosphere since the 1980s has led to an increase in the species diversity of grasses on some parts of the Park Grass Experiment (Storkey et al., 2015). Several of the Rothamsted Experiments have been used to examine the potential for increasing soil organic carbon as a method for mitigation against climate change (Poulton et al., 2018). The strength of the Rothamsted LTEs is their longevity and not their design. These resources make it possible to test hypotheses how long-term variation in the crops environment influences the agricultural system, although the Rothamsted LTEs are located on one site at Rothamsted, Hertfordshire, England.

The data from Rothamsted LTEs is widely disseminated. Requests for data from the Electronic Rothamsted Archive have increased in recent years, with data mainly being used in research applications (Perryman et al., 2018). Although the Rothamsted LTEs are the oldest agricultural field experiments in the world they are a living scientific resource which has adapted over time (Owens, 2013). In a review of the Rothamsted LTEs, Johnston & Poulton (2018) concluded that the value of the Rothamsted long-term experiments increases over time, and the experiments provide an invaluable resource and insight in the sustainability of food production and the associated impacts of climate change.

1.6 Objectives

The Rothamsted LTEs allow for studies in inter-annual crop variation, whether they be soil, pest or weather orientated. Studies into crop variation provide insight into how long-term experiments are influenced by weather and climate. They do not provide the degree of accuracy of well-designed, hypothesis driven experiments discussed in Section 1.3, but provide a resource to identify agricultural and environmental trends over time, which would not otherwise be possible (Figures 1.1 and 1.2).

The study undertaken within this PhD attempts to identify how much of the yield variability of Broadbalk (wheat), Hoosfield (spring barley) and Park Grass (grassland) can be explained by climate change and principally variations in weather, notwithstanding the variability associated with changes in management or experiment methodology. Various statistical methodologies have been applied, such as: multivariate analyses, response function analyses and multiple regression. Criticism of the use of statistical methods to detect the effects of climate change on crop production have been given by Katz (1977), where some of these criticisms include the non-linearity of yield and explanatory variables and correlated predictor variables. Considerations and explorations of these criticisms will be given within the General Discussion where other issues with statistical methods to detect the effect of climate change on crop production will be given, such as: auto-correlation of yields at lag 1, gained inference between treatments, a confounding of explanatory variables and smoothing-out local variability from national yield statistics. Other methods of detecting the effects on climate change involve the use of process-based models. Both methods ask different questions. One asks how much of the variability of observed yield can be associated with other variables. The other asks how much variability in yield do we observe given a known studied biological process under given constraints and projections of climate change. Both are needed to understand the full complexity of the relative impacts of climate change on crop production. A comparison between both methodologies and a review of statistical approaches to identifying the effects of climate change on crop development is given in the General Discussion.

Although there may be many sources of variation influencing crop yield, to observe an association between variations in weather and yield illustrates the precedence of how changes in climate can be detrimental to agricultural production. Within this Thesis, multivariate methods, response surface functions, multiple regression modelling and a mechanistic process model of wheat, Sirius, were used.

1.6.1 Research Aims

Research Aim 1: The effects of human induced climate change over multiple variables have been observed in univariate analysis, therefore the effect of a changing climate can be observed through a multivariate study, where the effects of climate are classified objectively through the clustering of years.

The IPCC reports have shown how climate has changed, over multiple variables, from the late 20th and early-21st century (see Section 1.2). However, crop development has been shown to be influenced by many weather variables, for example rainfall and temperature (see Section 1.4). Understanding how climate has changed across multiple weather variables combined provides an understanding of how the agricultural climate has changed, in comparison to univariate analysis, and how this influences yield.

Multivariate methods have been applied to previous climate studies. Cluster analysis was used to partition climate zones of the Conterminous United States over temperature and precipitation variables from 1931 to 1980 (Fovell & Fovell, 1993). Using data from 1950 to 2002, cluster analysis was used to describe cyclone trajectories in the western North Pacific, (Camargo et al., 2007). The use of multivariate methods can provide insight into how the whole climate system is changing, and not just over one variable. The clustering of years based on their weather will be addressed in Chapter 3, along with a comment on the current use of clustering indices, where a change in cluster membership over time will illustrate how climate has changed over multiple variables. Chapter 3 will also involve a comparison of the yields from clustering of years from Broadbalk, Hoosfield and Park Grass, to determine if there has been a similar response to climate between cereals and herbage, and among treatments. A univariate analysis of the Rothamsted Meteorological Station data will be provided in Chapter 2, as an overview of the climate of Rothamsted.

Research Aim 2: Given that environmental stresses, such as temperature and rainfall, on crop development have been shown to affect yield in controlled experiments, then the year-to-year variability in the yields of wheat, spring barley and permanent pastures, from the Rothamsted Long-Term Experiments, will also be associated with increases in temperature and variations in rainfall.

Previous studies into the yield response of LTEs to weather, at Rothamsted and elsewhere, have shown increases in temperature, but more importantly, variations in rainfall, to influence crop productivity (see Section 1.4). The latest studies on the influence of weather on Rothamsted crop yield variability of wheat, barley and pastures were by Chmielewski & Potts (1995), Wishart & Mackenzie (1930) and Sparks & Potts (2003), respectively. (Rothamsted LTE data has been used in other studies to identify the influences of climate change on crop production, most importantly the influence on soil characteristics, but are the most recent regarding the direct comparison between yield and weather data.)

Since these studies, global temperatures have risen further and there has been a greater understanding of the effects of climate on crop production through well-designed controlled experiments (see Section 1.2. and 1.3). With an increase in the length of yield data and weather time-series, the associations between yield and weather variations may differ from previous studies, and the associations may differ in magnitude. Can the associations between yield and weather be explained by the influences of climate found on crop production within the literature, such as sensitive stages of crop development (see Section 1.3). This research aim will be first addressed in Chapter 3, after the clustering of years (see Research Aim 1), to determine if climate change, over multiple variables, can be observed. In Chapters 4, 5 and 6, the association between total rainfall and mean temperatures, summarised monthly, will be addressed. This research aim is the foundation of Research Aim 3 below.

Research Aim 3: Year-to-year and within-year variations in temperature and rainfall over a harvest season (October to September) affect the Nitrogen response of Broadbalk wheat and Hoosfield spring barley.

The Rothamsted LTEs were never designed to test the effects of weather variability or climate change on crop production, although shortly after their inception yearly variations in yield were observed (see Section 1.4). The longevity and standardisation of treatments from each experiment allows for the investigation of sources of weather variability that influence crop development (see Research Aim 2). As previously mentioned the LTEs were devised to test the effects of organic and inorganic fertilisers on crop growth, and therefore careful consideration of the year-to-year variability in fertiliser response should be considered.

From Research Aim 2, there are stages of crop development which have associations with increases in temperature and variations in rainfall (Chapters 3, 4 and 5). Also, the functional response of yield to Nitrogen has been shown to vary depending on the year, soil, crop and weather (Roques et al., 2017; Sylvester-Bradley & Kindred, 2009; Vold, 1998). The yield response to weather variability has been shown to be greater in unfertilized plots compared to treatments with higher nutrient availability (van der Bom et al., 2017). The crop response to Nitrogen can be modelled by the Linear-By-Exponential function (George, 1982) using fewer parameters and allows for a more comparable biological interpretation. In this method of statistical modelling, the Nitrogen response curve for each year becomes the unit variable. And 3-dimensional surface plots can be obtained to understand the crop response to Nitrogen with increases in temperature and variations in rainfall. This research aim will be addressed in Chapter 4 (for Broadbalk wheat) and Chapter 5 (for Hoosfield barley).

Research Aim 4: An increase in yield over 125 years, from 1892 to 2016, is associated with rises in atmospheric CO_2 and any future rise in CO_2 will influence the crop productivity of Broadbalk yields at least till the end of the 21st century.

From Hypotheses 1, 2 and 3 the association between weather and crop yield variability on the Rothamsted Long-Term Experiments have been discussed. However, the potential influence of increases in atmospheric CO_2 on Rothamsted LTE yields has not. 2016 saw atmospheric CO_2 levels reach 404.21 ppm compared to 315.97 ppm in 1959 (NOAA, 2018). The influence of the negative effects of climate change on crop production, such as increases in temperature, could be outweighed by the positive effects of an enrichment of CO_2 (see Section

1.4).

This research aim intends to investigate the potential increase in yield due to rises in atmospheric CO_2 at Rothamsted from 1892 to 2016. Further analysis investigates the potential future influence of atmospheric CO_2 on grain yield at Rothamsted using data from the Coupled Model Intercomparison Project phase 5 from the mid (2041 to 2060) to late (2081 to 2100) 21st century. This research aim will be addressed in Chapter 7. The overall influences of weather and CO_2, their modelling implications and sources of variability, will be addressed in the General discussion.

Chapter 2

The Rothamsted Long-Term Experiments

This Chapter provides a summary of the Rothamsted Long-Term Experiments (LTEs), where an attempt was made for the reader to understand the design and data before the analysis Chapters 3, 4, 5 and 6.

2.1 Introduction

Founded in 1843, Rothamsted Research, previously known as Rothamsted Experimental Station and The Institute of Arable Crops Research, is located in Harpenden, Hertfordshire and is home to three long-term agricultural experiments on wheat, barley and permanent pasture, named Broadbalk, Hoosfield and Park Grass, respectively. These experiments, together with several others are known as the Classical Field Experiments. They were originally established by John Lawes and Henry Gilbert to examine the effect of inorganic fertilisers and organic manures on crop yield (Lawes, 1847; Lawes & Gilbert, 1859; Lawes & Gilbert, 1857). The same crop has been grown each year (with the exception of a few years) on each of the three experiments, but in Broadbalk additional crops have been introduced on some sections. Samples of the crop from each year have been collected and stored in the Rothamsted Sample Archive; it now contains more than 300,000 samples. The Rothamsted Electronic Archive (e-RA) stores experiment data, especially yield and weather data.

Along with physical samples of the crop, soil samples of have been kept for chemical analysis, such as Soil Organic Carbon (SOC) and soil pH. The Rothamsted LTEs have not been immune to changes in agricultural practice. Some examples of changes, over the lifetime of these experiments, include the introduction of a tractor pulled plough, the application of pesticides and the introduction of semi-dwarf varieties during the green revolution. Weather data at Rothamsted has been collected by the Rothamsted Meteorological Station (RMS) since the 1850s. It was recognised in 2017 by the World Meteorological Organisation as a Long-Term Observing Station (WMO, 2018). The RMS first started collecting daily rainfall measurements in 1853, followed by temperature and sunlight in subsequent years, to understand how weather contributed to the yield of crops. In a review of the Rothamsted LTEs by Johnston & Poulton (2018), they concluded the value of the Rothamsted long-term experiments increases over time, and the experiments provide an invaluable resource and insight in the sustainability of food production and the associated impacts of climate change. A map of Rothamsted Research is given in Figure 2.1. All data within this Chapter and within this Thesis was provided by e-RA. I derived my hypotheses by reviewing the literature and used the data within e-RA to test them.

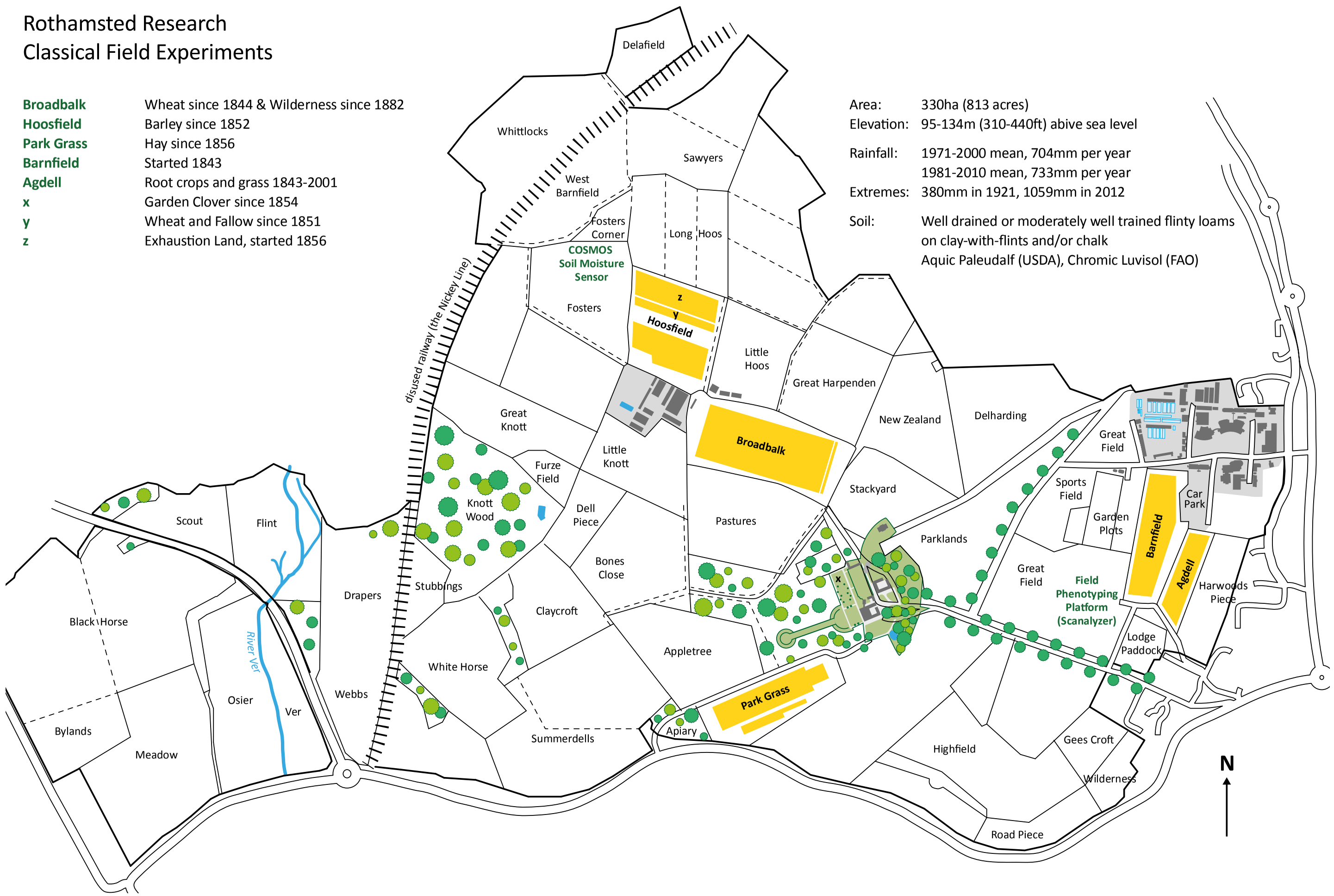


Figure 2.1: A map of Rothamsted from Macdonald et al. (2018), Guide to the Classical and other Long-Term experiments, Datasets and Sample Archive - Rothamsted Research, April 2018. ISBN 978-1-9996750-0-4.

2.2 The Broadbalk Experiment

2.2.1 Introduction

The Broadbalk Experiment (hereafter Broadbalk) was first sown in the autumn of 1843, and harvested in the following year, to measure the effect of and inorganic fertilisers and organic manures on the yield of continuous winter wheat (Lawes, 1847). Although the experiment started in 1843 it was not until 1852 that a full set of treatments was decided upon (Garner & Dyke, 1968). The Broadbalk Experiment originally had 19 treatment strips, the current amount of treatment strips is 20 (Figure 2.2). In 1926, Broadbalk was divided into five sections in an attempt to reduced yield loss due to weeds, by fallowing one section each year in rotation. In the 1960s other major changes were implemented to keep the experiment relevant to modern agricultural practices. The implementation of herbicides was introduced in 1964 followed by the introduction of modern, short-strawed cultivars in 1968 (Table 2.1). The National Institute of Agricultural Botany (NIAB) variety descriptions are given in Table 2.1 for wheat varieties grown since 1968. Broadbalk is currently separated into 10 sections (See the Broadbalk plan Figure 2.2). Sections 0, 1 and 9 are all continuous wheat sections. Section 0 has had straw from the previous crop incorporated into the soil since 1986. Sections 6 and 8 are also in continuous wheat, with the absence of fungicides and herbicides, respectively. Sections 2, 3, 4, 5 and 7 are the rotational sections of Broadbalk. Rotational cropping was introduced in 1968. Since 1968 the highest N application on Broadbalk was 192 kg N ha^{-1}, in the 1985 N applications of 240 and 288 kg N ha^{-1} were added. More information about the Broadbalk treatment plan can be seen in Figure 2.2 and Table 2.3. Since 2001, P has been withheld from some plots. This was because of a build-up of P within the soil (Table 2.3). The level of P currently within the soil in these plots is not considered limiting for crop growth. Since 1968, sowing of continuous wheat on Broadbalk occurs in October (however, it has occurred in the last and first days of September and November, respectively). The application of N occurs in March or April and harvest occurs in late-August to early-September. In 2013 winter wheat was sown very late, but in 2015 a spring variety was sown due to the wet autumn.

Table 2.1: Wheat varieties grown on Broadbalk from 1968 to 2016.

Year	Cultivar	Description
1968-1978	Cappelle desprez	Short and moderately stiff straw variety with a high resistance to eyespot but susceptible to yellow rust (NIAB, 1968).
1979-1984	Flanders	High grain protein with moderately high bread making quality and high resistance to yellow rust (NIAB, 1982).
1985-1990	Brimstone	High yielding and high bread making quality variety, with weak straw and a potential risk of lodging (NIAB, 1986).
1991-1995	Apollo	Good grain quality and early maturing variety with susceptibility to mildew, yellow and brown rust (NIAB, 1993).
1996-2012	Hereward	Good bread making variety which is susceptible to yellow rust (NIAB, 1993).
2014, 2016	Crusoe	Short, relatively stiff straw variety with good grain quality and protein content with resistance to mildew, yellow rust and *Septoria tritici* (NIAB TAG Network, 2014).

2.2.2 Soil Properties and Yields

The soil on Broadbalk is a flinty silty clay loam overlying chalk at a depth of about 2 m (Avery and Catt, 1995). The top-soil (0 - 23 cm) texture, is 25% sand, 50% silt and 25% clay (Gregory et al., 2010). The clay content of Broadbalk soil ranges from 19 to 39%, with the mean clay content for Section 1 being about 28% (Watts et al., 2006). The soil pH of Broadbalk is maintained at around 7.0 to 7.5. The soil organic carbon (SOC) content of selected plots from 1966 to 2010 is given in Table 2.2. The Farm Yard Manure (FYM) treatment on Broadbalk has the largest % SOC in contrast, the plot which receives no inputs had the lowest SOC, whereas the plot with the highest Nitrogen inputs (since 1987) has the highest SOC of the inorganic fertilisers. From Table 2.3 the changes in plant available P (Olsen P) in the soil on selected plots on Section 1 of Broadbalk can be observed.

The grain yield and total biomass from Broadbalk Section 1, from 1968 to 2016, are given in Figure 2.4 (a), (b), (c), (d), (e), (f), (g), (h) and (i), respectively. The mean grain yield for treatments Nil, FYM, PKNaMg, 48 kgNha^{-1} + PKNaMg, 96 kgNha^{-1} + PKNaMg, 144 kgNha^{-1} + PKNaMg, 192 kgNha^{-1} + PKNaMg, 240 kgNha^{-1} + PKNaMg and 288 kgNha^{-1} + PKNaMg between 1968 and 2016, were 1.27, 5.51, 1.34, 3.26, 5.04, 5.61, 6.21, 6.73 and 7.01 t ha^{-1}, respectively. The mean total biomass for treatments nil, FYM, PKNaMg, 48 kgNha^{-1} + PKNaMg, 96 kgNha^{-1} + PKNaMg, 144 kgNha^{-1} + PKNaMg, 192 kgNha^{-1} + PKNaMg, 240 kgNha^{-1} + PKNaMg and 288 kgNha^{-1} + PKNaMg between 1968 and 2016, were 1.97, 9.53, 2.12, 5.24, 7.98, 8.96, 9.95, 10.17 and 10.73 t ha^{-1}, respectively. From Figure 2.4, large year-to-year variability in grain yield and total biomass can be observed, with larger variability for treatments which have a higher yield.

Table 2.2: The top-soil (0 - 23 cm) organic carbon content (% in air-dry soil) on selected plots on the Broadbalk experiment, Section 1.

Treatment	1966	1987	1992	1997	2000	2005	2010
FYM	2.49	2.84	2.70	2.94	2.83	3.03	2.81
Nil	0.88	0.98	0.81	0.71	0.89	0.89	0.88
PKNaMg	0.90	0.94	1.01	0.86	0.90	0.89	0.88
48kgNha^{-1} + PKNaMg	0.96	1.00	1.03	0.94	1.03	1.00	1.03
96kgNha^{-1} + PKNaMg	1.04	1.16	1.08	1.02	1.12	1.12	1.06
144kgNha^{-1} + PKNaMg	1.10	1.18	1.05	1.00	1.13	1.07	1.04
192kgNha^{-1} + PKNaMg	0.92	1.07	1.04	1.02	1.13	1.10	1.05
240kgNha^{-1} + PKNaMg	0.94	1.05	1.13	1.01	1.12	1.09	1.04
288kgNha^{-1} + PKNaMg	0.95	1.04	1.04	1.06	1.20	1.14	1.12

Table 2.3: The amount of Olsen P (mgkg^{-1}) in 0 to 23 cm of the Broadbalk experiment Section 1.

Treatment	1966	1987	1992	1997	2000	2005	2010	2015
FYM	79	87	85	95	91	96	103	123
Nil	6	4	7	7	5	7	8	11
PKNaMg	63	72	96	94	95	82	84	74
48kgNha^{-1} + PKNaMg	75	65	99	95	100	86	86	82
96kgNha^{-1} + PKNaMg	88	98	115	100	101	87	90	75
144kgNha^{-1} + PKNaMg	80	79	83	83	77	70	69	59
192kgNha^{-1} + PKNaMg	71	51	76	73	73	61	55	50
240kgNha^{-1} + PKNaMg	73	67	80	75	71	64	65	57
288kgNha^{-1} + PKNaMg	67	65	73	66	67	53	47	48

Figure 2.2: The current treatment plan of the Broadbalk Wheat Experiment from Macdonald et al. (2018).

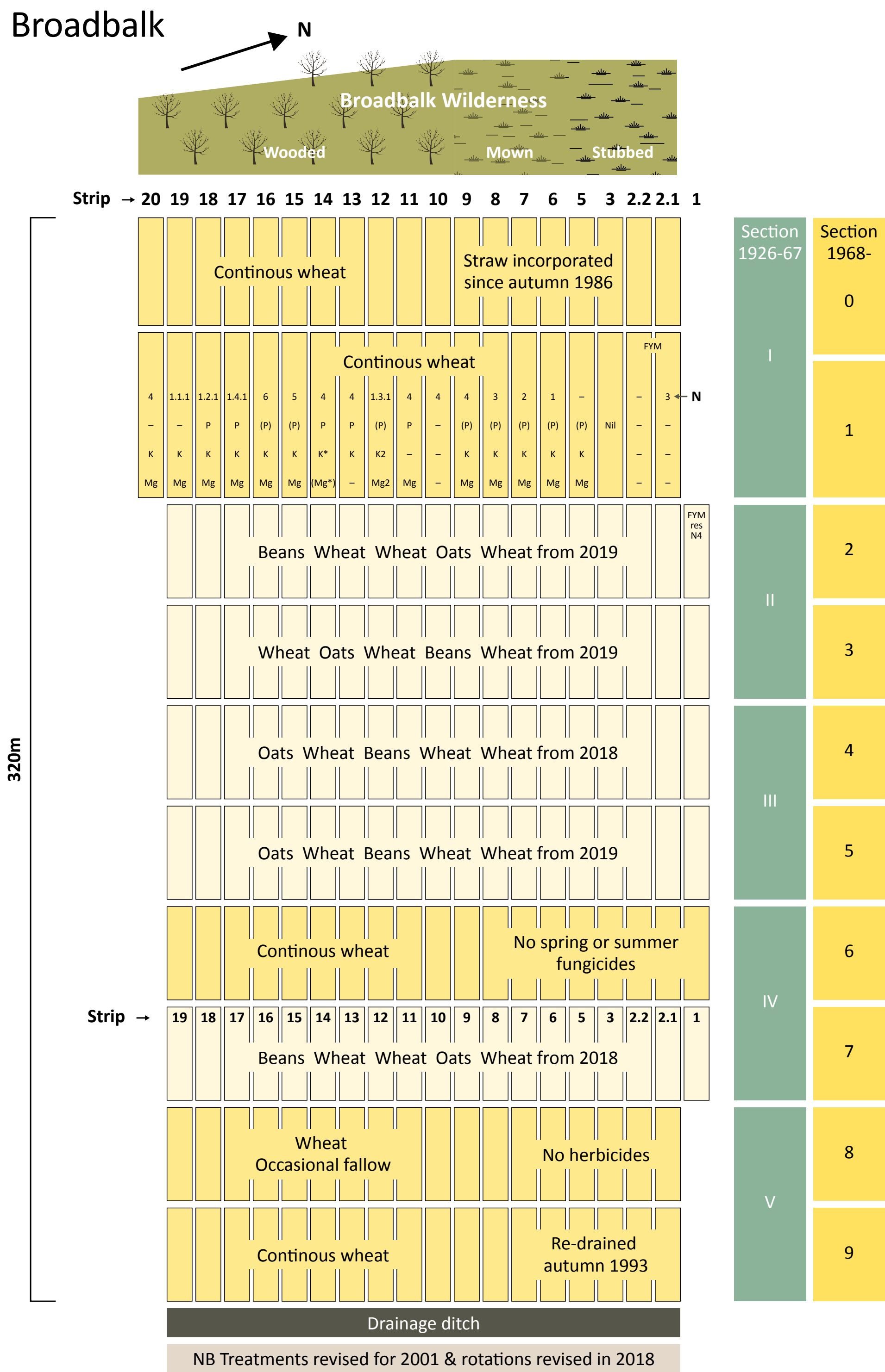


Figure 2.3: The reference table of treatments of the Broadbalk Experiment from 1852 to 2016 from Macdonald et al. (2018).

Strip	Treatmants until 1967	Treatments from 1968	Treatments from 1985	Treatments from 2001
01	-	FYM N2 PK	FYM N4 PK	(FYM) N4
2.1	FYM since 1885	FYM N2	FYM N2	FYM N3(1)
2.2	FYM	FYM	FYM	FYM
03	Nil	Nil	Nil	Nil
05	PKNaMg	PK(Na)Mg	PKMg	(P)KMg
06	N1 PKNaMg	N1 PK(Na)Mg	N1 PKMg	N1 (P)KMg
07	N2 PKNaMg	N2 PK(Na)Mg	N2 PKMg	N2 (P)KMg
08	N3 PKNaMg	N3 PK(Na)Mg	N3 PKMg	N3 (P)KMg
09	N*1 PKNaMg	N4 PK(Na)Mg	N4 PKMg	N4 (P)KMg
10	N2	N2	N2	N4
11	N2 P	N2 P	N2 P	N4 P Mg
12	N2 P Na	N2 P Na	N2 P Na	N1+3+1(P)KMg(2)
13	N2 PK	N2 PK	N2 PK	N4 PK
14	N2 P Mg*	N2 PK Mg*	N2 PKMg*	N4 PK*(Mg*)
15	N2 PKNaMg	N3 PK(Na)Mg	N5 PKMg	N5 (P)KMg
16	N*2 PKNaMg	N2 PK(Na)Mg	N6 PKMg	N6 (P)KMg
17	N2(A)	N2 ½[PK(Na)Mg]	N0+3 ½[PKMg](A)	N1+4+1 PKMg
18	PKNaMg(A)	N2 ½[PK(Na)Mg]	N1+3 ½[PKMg](A)	N1+2+1 PKMg
19	C	C	(C)	N1+1+1 KMg
20	N2 KNaMg	N2 K(Na)Mg	N2 KMg	N4 KMg

(A) Treatment to strips 17 & 18 alternating each year. From 1968 both strips received N2 and ½-rate PK(Na)Mg;
from 1980 wheat on strips 17 & 18 received N1+3 i.e. autumn N1 in alternate years plus N3 in spring.

Annual treatment per hectare

FYM :	Farmyard manure at 35t
(FYM) :	Farmyard manure at 35t 1968-2000 only
P :	35kgP as triple superphosphate
(P) :	35kgP as triple superphosphate until 2000; to be reviewed in 2021
K :	90kgK as potassium sulphate
K2 :	180kgK as potassium sulphate, 2001-2005. (plus 450 kgK in autumn 2000 only)
K* :	90kgK as potassium chloride
Mg :	12kgMg as Kieserite.Was 35kgMg every 3rd year 1974-2000.Previously 11kgMg as magnesium sulphate until 1973
Mg2 :	24kgMg as Kieserite, 2001-2005. (plus 60 kg Mg in autumn 2000 only)
(Mg*) :	30kgMg as Kieserite 1974-2000.Previously 31kgMg as magnesium sulphate until 1973
(Na) :	16kgNa as sodium sulphate until 1973; 55kgNa on strip 12 only until 2000 (57kgNa until 1973)
(C) :	Castor meal to supply 96kgN until 1988

N to wheat as single applications (mid-April)
N1, N2, N3, N4, N5, N6 : 48, 96, 144, 192, 240, 288 kgN

Split N to wheat (mid-March, mid-April, mid-May)
N1+1+1 : 48+48+48 kgN (strip 19)
N1+2+1 : 48+96+48 kgN (strip 18)
N1+3+1 : 48+144+48 kgN (strip 12)
N1+4+1 : 48+192+48 kgN (strip 17)

N to oats at ½-rate, as a single application (mid-April)
½N1, ½N2, ½N3, ½N4, ½N5, ½N6 : 24, 48, 72, 96, 120, 144 kgN
Oats on strips 19, 18, 12 and 17 also receive N as a sing application; ½N3, ½N4, ½N5, ½N6 respectively

No N or FYM to beans from 2018

N as ammonium nitrate (Nitram, 34.5% N) since 1986; calcium ammonium nitrate (Nitro-chalk, c.26% N) 196 ammonium sulphate or sodium nitrate (N*) until 1967

(1) : FYM N2 from 1968-2004

(2) : N1+3+1 (P)K2Mg2 from 2001-2005

Note : S has been added, by default (except on strip 14 since 2001), as part of the potassium sulphate, magnesium sulphate, Keiserite, FYM and ammonium sulphate applications. S last applied to strip 14 in 2000.

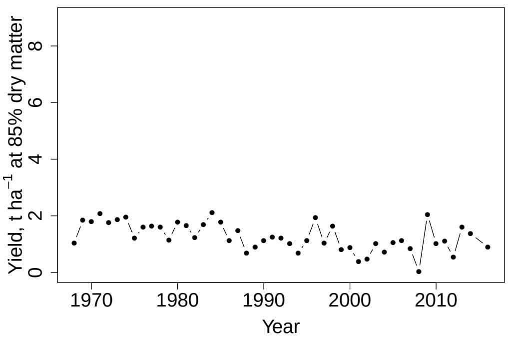
In 2018 the rotation on five sections of the experiment changed to Wheat, Wheat, Oats, Wheat, Beans. The oats will receive N at half of the normal rate (see above); the beans will not receive N or FYM.

In the previous rotation, Wheat, Wheat, Wheat, Oats, Maize from 1996-2017, oats did not receive N or FYM.
In earlier rotations from 1968-1995, beans did receive N, FYM (and PK etc.); fallows in the rotations (and on Section 8) did receive FYM, PK etc. but no N was applied. Between 1926-1967 no fertilisers or manures were applied to those sections which were fallov to control weeds. For detailed information on treatments and management until 1967, see Rothamsted Report for 1968, Part 2, pp215.

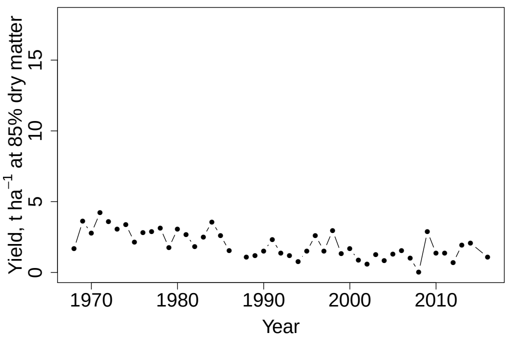
Figure 2.4: Winter wheat grain yield and total biomass from Section 1 of the long-term Broadbalk Experiment, from 1968 to 2016 (excluding 2013 and 2015 because of late sowing). Nine different treatments are shown here, Nil (a), PKMaNg (b), FYM (c), 48kgNha^{-1} + PKNaMg (d), 96kgNha^{-1} + PKNaMg (e), 144kgNha^{-1} + PKNaMg (f), 192kgNha^{-1} + PKNaMg (g), 240kgNha^{-1} + PKNaMg (h) and 288kgNha^{-1} + PKNaMg (i).

Nil (a)

Grain Yield

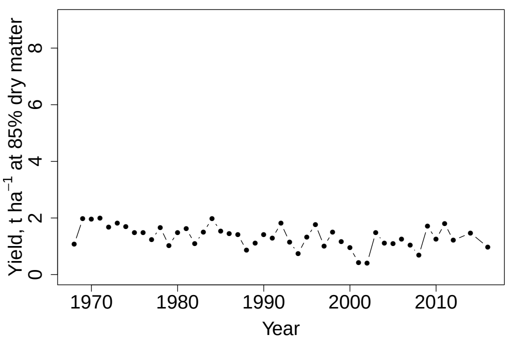


Total Biomass

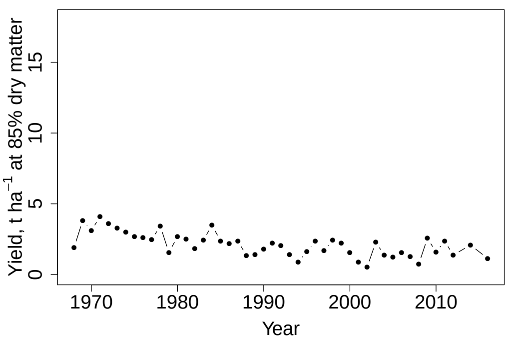


PKMaNg (b)

Grain Yield

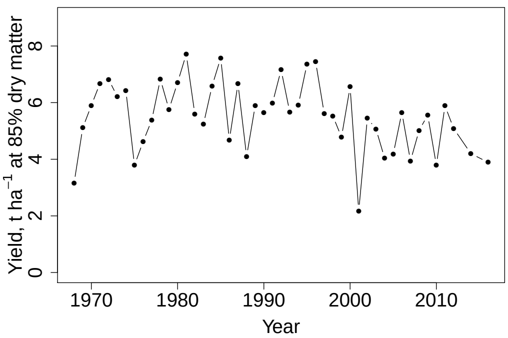


Total Biomass

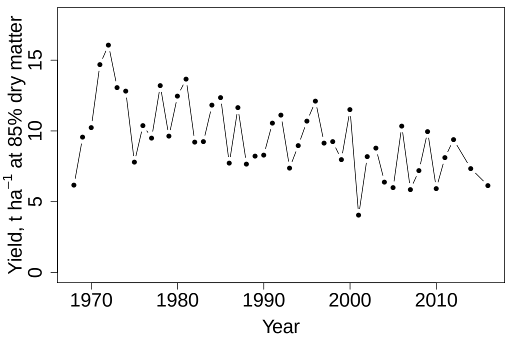


FYM (c)

Grain Yield

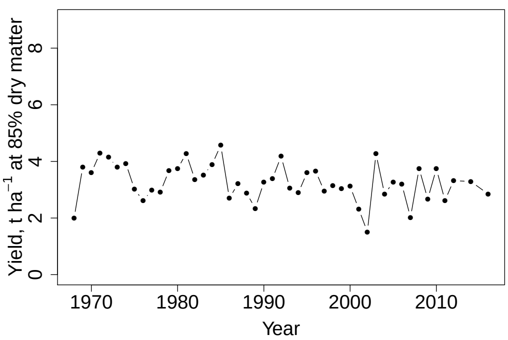


Total Biomass

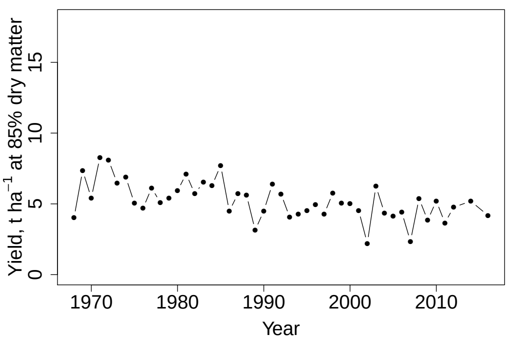


48 kg N ha^{-1} + PKNaMg (d)

Grain Yield

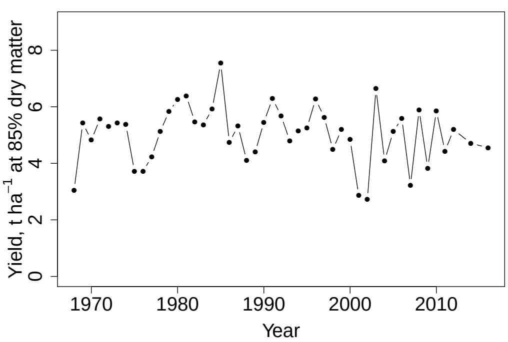


Total Biomass

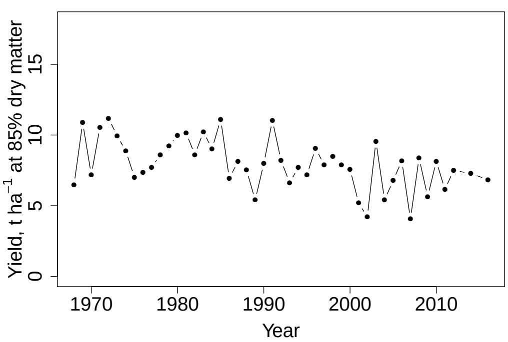


96 kg N ha^{-1} + PKNaMg (e)

Grain Yield

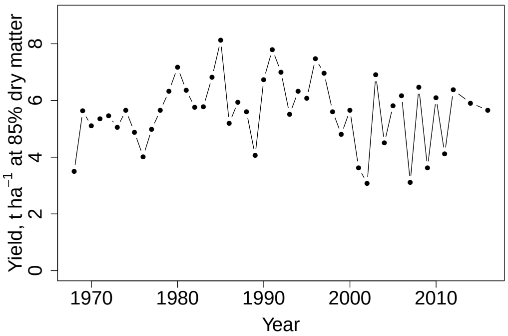


Total Biomass

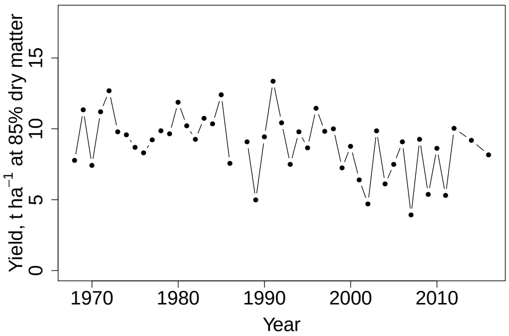


144 kg N ha^{-1} + PKNaMg (f)

Grain Yield

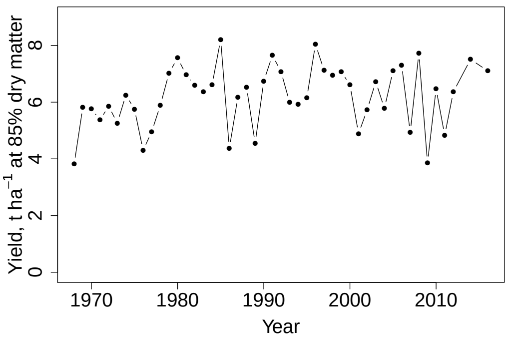


Total Biomass

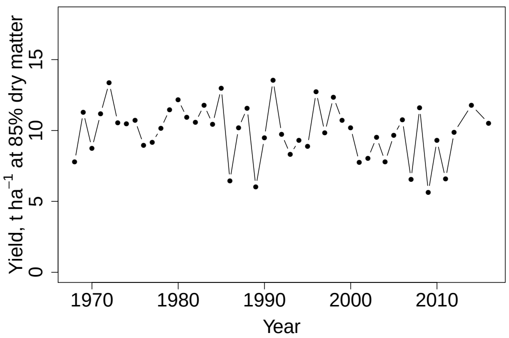


192 kg N ha^{-1} + PKNaMg (g)

Grain Yield

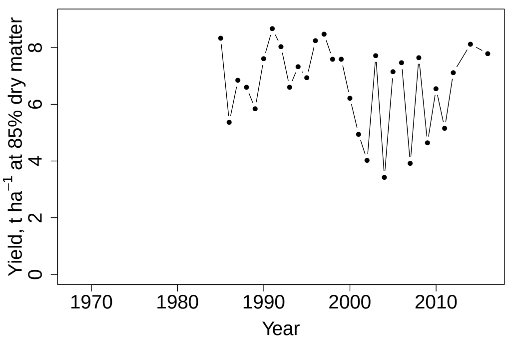


Total Biomass

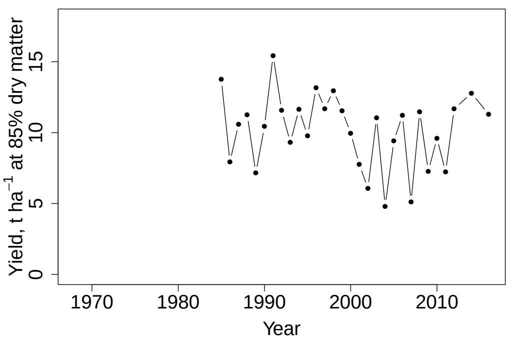


240 kg N ha^{-1} + PKNaMg (h)

Grain Yield

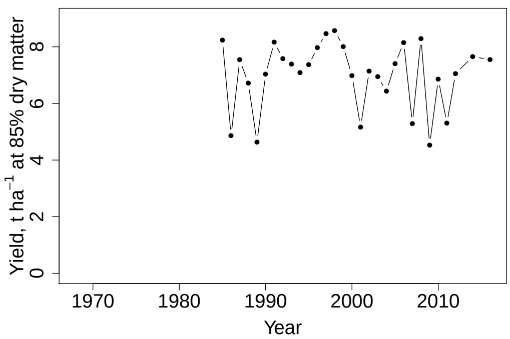


Total Biomass

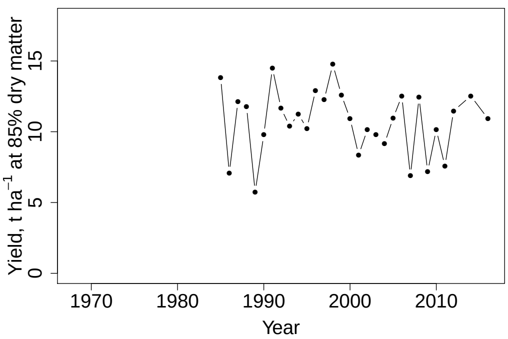


288 kg N ha^{-1} + PKNaMg (i)

Grain Yield



Total Biomass



2.3 The Hoosfield Experiment

2.3.1 Introduction

The Hoosfield Spring Barley Experiment (hereafter Hoosfield) was first sown in 1853 to measure the effects of mineral fertilisers and organic manures on the yield of spring barley (Lawes & Gilbert, 1857). From 1852 to 1967, Hoosfield comprised of four main fertiliser treatments (0, P, KMgNa and PKMgNa) crossed with three series Nitrogen treatments (Figure 2.5) and two different organic amendments; farm yard manure and rape cake. Treatments included: Series O (no N); Series A (N as ammonium sulphate); Series AA (N as sodium nitrate); and Series C (rape cake, later replaced by castor meal. Similar to Broadbalk, Hoosfield was modified in 1968, when modern short-strawed cultivars were introduced (Table 2.4) and each plot was subdivided to included different rates of N application (0kgNha^{-1}, 48kgNha^{-1}, 96kgNha^{-1} and 144kgNha^{-1}). The NIAB information about the modern spring barley varieties are given in Table 2.4. Initially (1968 - 1973) N rates were fixed for each plot, but rates of N have rotated in the order 144-96-48-0 kgNha^{-1}, with a transitional period between 1974 and 1980. Since 2001, P has been withheld from some plots. Similar to Broadbalk, this was because of a build-up of P within the soil (Table 2.6). Information about the rates and application of N and mineral fertilisers on Hoosfield can be found in Table 2.6. Since 1968, the sowing of continuous spring barley occurred in either February or March (Although in 1979 the crop was sown in April), N application occurs in April or early May and harvest occurs in August or early September (in 1976 the harvest was in late-July).

2.3.2 Soil Properties and Yields

The soil on Hoosfield is a flinty silty clay loam overlaying chalk at a depth of about 2 m (Avery and Catt, 1995). The top-soil (0 - 23 cm) texture of plots 42 and 72 (see Figure 2.5) is 28% sand, 52% silt and 20% clay (Blake et al., 2003). The soil pH of Hoosfield is maintained at about 7.0 to 7.5. The Hoosfield plan (Figure 2.5) shows the current experimental design together with the old series. Some key soil properties, including SOC and Olsen P have been determined in soils collected from the experiment. The FYM plot has the highest % SOC and Olsen P from 1965 to 2013 (Tables 2.5 and 2.6). The no fertiliser plot has the lowest % SOC and Olsen P. The plot

Table 2.4: Spring barley varieties grown on Hoosfield from 1968 to 2016.

Year	Cultivar	Description
1968-1969	**Maris Badger**	High malting quality (NIAB, 1968).
1970-1979	**Julia**	Liable to ear loss when ripe and susceptible to mildew and and yellow rust (NIAB, 1978).
1980-1983	**Georgie**	Short strawed variety which is susceptible to mildew (NIAB, 1982).
1984-1991	**Triumph**	High yield and high malting quality with a resistance to yellow rust but very susceptible to mildew (NIAB, 1986).
1992-1995	**Alexis**	Malting variety with a high resistance to mildew (NIAB, 1993).
1996-1999	**Cooper**	Short, stiff straw malting variety with good ear retention and resistance to brown rust but susceptible to *Rhynchosporium* (NIAB, 2001).
2000-2007	**Optic**	Good malting quality with resistance to brown and yellow rust but very susceptible to *Rhynchosporium* (NIAB, 2001).
2008-2015	**Tipple**	Very short, stiff malting variety with good resistance to mildew and brown rust but is susceptible to yellow rust and *Rhynchosporium* (NIAB Association, 2008).
2016	**Irina**	Very high yielding, short, stiff variety with good resistance to mildew but is susceptible to *Rhynchosporium* (NIAB TAG Network, 2016)

which receives both P and KMgNa fertiliser has the highest % SOC and Olsen P, from 1965 to 2013, compared to other inorganic fertilisers.

The grain yield and total biomass, between 1968 and 2016 from Hoosfield, are given in Figure 2.7 (a), (b), (c), (d) and (e). The FYM treatment had the highest mean grain yield of 5.53 t ha^{-1} from 1968 to 2016. The highest grain yield from an inorganic treatment was 144 kg N ha^{-1} + PKNaMg of 5.05 t ha^{-1}. The lowest grain yield was 0.99 t ha^{-1} from the nil plot. Across all N rates, PK had the highest grain yield of 3.73 t ha^{-1}, compared to 2.95, 2.13 and 1.48tha^{-1} from P, K and no mineral fertiliser, respectively. The highest average total biomass, between 1968 and 2016, was 8.21tha^{-1} on the FYM plot. The total biomass from the nil plot, from 1968 to 2016, was the lowest, on average, of 1.34 t ha^{-1}. The highest mean total biomass from inorganic fertiliser was 7.64 t ha^{-1} from plot 144 kg N ha^{-1} + PKNaMg. Across all N rates, the average total biomass, from 1968 to 2016, was 5.48, 4.16, 3.10 and 2.12 t ha^{-1} for treatments PKNaMg, P, KNaMg and no mineral inputs.

Table 2.5: Top-soil (0 - 23 cm) organic carbon content (% air-dry soil) on selected plots on the Hoosfield experiment sections 11 (Nil), 21 (P), 31 (KMg), 41 (PKMg) and 72 (FYM).

Treatment	1965	1982	1998	2008	2013
FYM	3.37	3.26	3.58	3.53	3.74
Nil	0.81	0.78	0.92	0.82	0.89
P	0.82	0.84	0.95	0.85	0.85
KMgNa	0.91	0.93	1.09	0.94	0.95
PKMgNa	0.97	0.99	1.12	1.04	1.04

Table 2.6: The amount of Olsen P (mgkg^{-1}) in the top-soil (0 - 23 cm) on selected plots of the Hoosfield experiment sections 11 (Nil), 21 (P), 31 (KMg), 41 (PKMg) and 72 (FYM).

Treatment	1965	1982	1998	2008	2013
FYM	102	137	95	98	144
Nil	5	2	2	3	2
P	78	94	89	73	76
KMgNa	9	7	4	5	5
PKMgNa	126	138	115	100	99

Figure 2.5: The current treatment plan of the Hoosfield Spring Barley Experiment from Macdonald et al. (2018).

Figure 2.6: The reference table of treatments of the Hoosfield Experiment from 1852 to 2016 from Macdonald et al. (2018).

Annual treatment per hectare

Nitrogen (applied in spring)

N 0, 1, 2, 3	0, 48, 96, 144 kg N as calcium ammonium nitrate (Nitro-chalk) N rates rotate in the order: N3 > N2 > N1 > N0

Organics (applied before ploughing in autumn)

FYM 1852	Farmyard manure at 35 t since 1852
FYM 2001	Farmyard manure at 35 t since 2001
FYM 1852-71	Farmyard manure at 35 t, 1852-1871 only

Minerals (applied before ploughing in autumn)

P2	4 kg P as triple superphosphate since 2001
(P)	35 kg P until 2002 (to be reviewed for 2020)
K	90 kg K as potassium sulphate
(Mg)	35 kg Mg as Kieserite every 3 years until 2002 (to be reviewed for 2020)
Mg	35 kg Mg as Kieserite since 2001
Si	450 kg sodium silicate since 1980
(Si)	450 kg sodium silicate 1862-1979

Note: Na as sodium sulphate discontinued in 1974 (applied with K and Mg),
P, K and Mg last applied to Series C for 1979

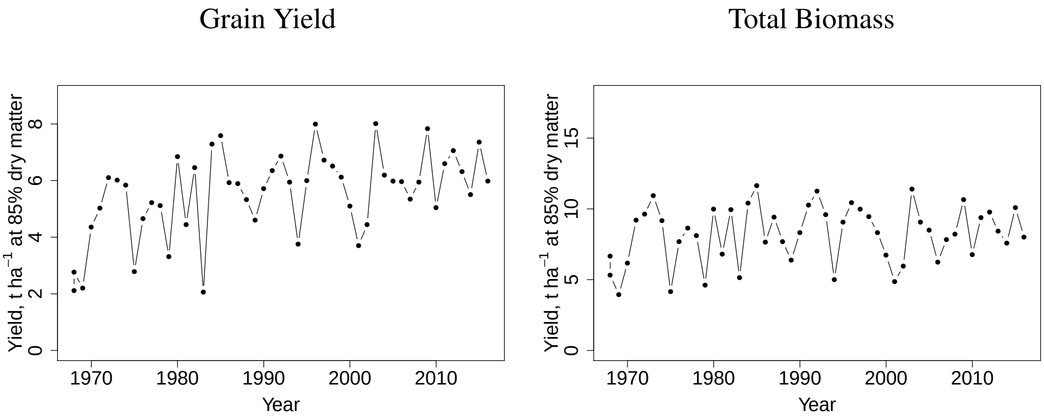
Series treatments (last applied 1966; 1967 for parts of Series C)

0	None
A	48 kg N as ammonium sulphate
AA	48 kg N as sodium nitrate
C	48 kg N as castor bean meal

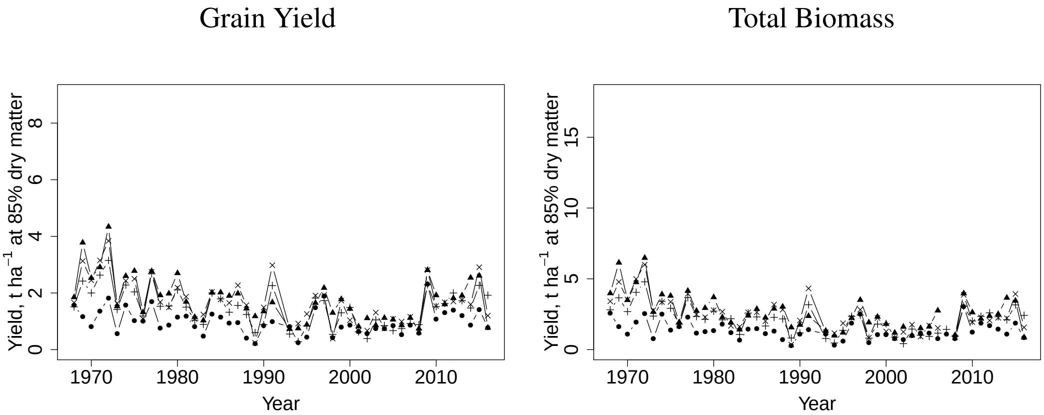
Note: Old Series C and Strip 5 used as a "P" Test since 2003. These plots and those on the Silicate Test (on old Series AA) receive 144 kg basal N

Figure 2.7: Spring barley grain yield and total biomass from Series O (for the inorganic treatments) and Series A (for the FYM treatment) of the long-term Hoosfield Experiment. Yields from five different treatments were shown here, FYM (a), Nil (b), KNaMg (c), P (d), and PKNaMg (e). Mineral treatments for the inorganic Nitrogen applications are 0 kg N ha^{-1} (dots), 48 kg N ha^{-1} (crosses), 96 kg N ha^{-1} (diagonal crosses), and 144 kg N ha^{-1} (triangles).

FYM (a)



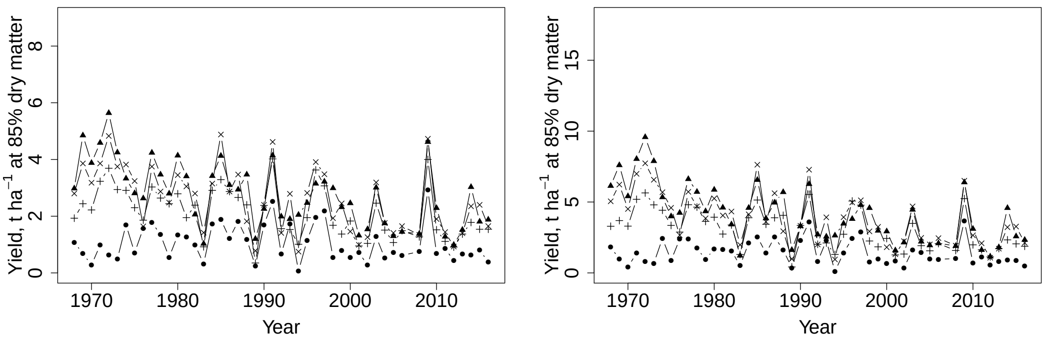
Nil (b)



KNaMg (c)

Grain Yield

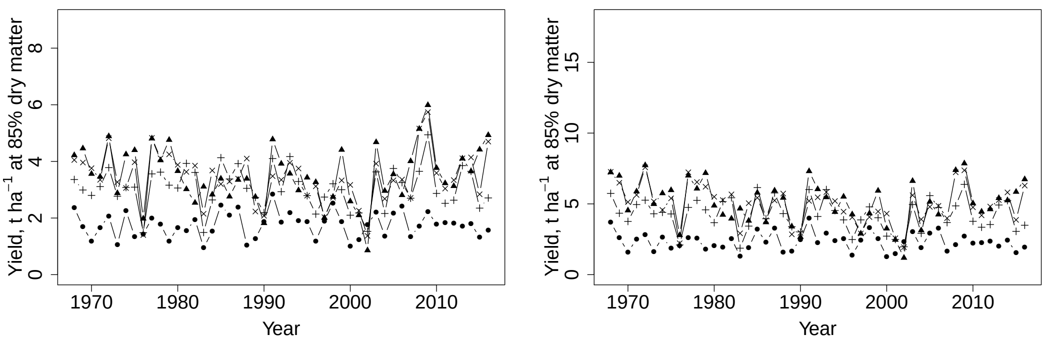
Total Biomass



P (d)

Grain Yield

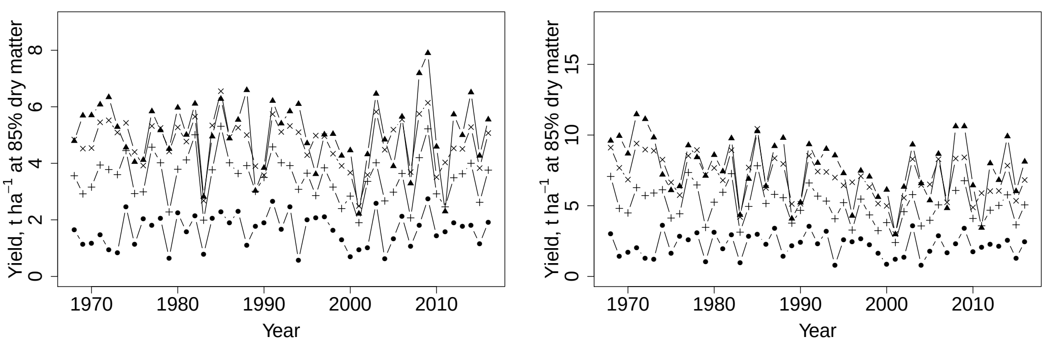
Total Biomass



PKNaMg (e)

Grain Yield

Total Biomass



2.4 The Park Grass Experiment

2.4.1 Introduction

The Park Grass Experiment (hereafter Park Grass) started in 1856 to measure the effects of inorganic fertilisers and organic manures on permanent grassland (Lawes & Gilbert, 1859). This is still a current aim of the experiment, but the effects of liming have also been included (Anon, 1971). Fertiliser treatments include different amounts and combinations of N, P, K, Na, Mg and Si. In addition, some plots measure organic manures, including FYM and poultry manure (replaced by fishmeal in 2003). Before 1856, the experiment had been in permanent pasture for 100 years. Shortly after the experiment was implemented, it became apparent that different fertiliser treatments affected the species diversity of the plots (Lawes & Gilbert, 1880a; Lawes & Gilbert, 1859). The experiment design is shown in Figure 2.8 and further information about the fertiliser treatments can be found in Table 2.9. Since 2001 P applications have been withheld on selected plots due to a build-up of P within the soil.

Liming was introduced on Park Grass in 1903 in an attempt to maintain the soil pH, where plots were split into limed (b) and unlimed (b) halves. In 1965, plots were split again and lime applied to maintain a target soil pH of 7 (a), 6 (b), 5 (c) and unlimed (d). Park Grass differs from Broadbalk and Hoosfield as two separate cuts of herbage are taken from Park Grass each year. The first cut is in mid-June whilst the second cut is in the autumn.

2.4.2 Soil Properties and Yields

The soil of Park Grass is classified as silty clay loam (Avery & Catt, 1995). The soil texture of plots 3a & d, 4.1a and 4.2d (see Figure 2.8) are 23% clay, 58% silt and 19% sand (Blake et al., 2003). The soil pH of plots 12, 3, 2.2, 13, 7.2, 16 and 14.2 can be seen in the Appendix Tables A.1, A.2, A.3, A.4, A.5, A.6 and A.7. Since 1960, the soil pH of subplots a, b and c are maintained at 7, 6, and 5, respectively. Subplot d is unlimed. Plot 12d has never received any fertiliser or lime since 1853. The soil pH of d subplots of 12, 3, 2.2, 13, 7.2 and 16 has been around 5 since 1876. Plot 14.2d has the highest soil pH, of around 6, compared to other d subplots. Before the separation of plots from limed and unlimed to a, b, c and d, the soil pH of the limed plots (12, 3, 2.2, 13, 7.2, 16, 16.2) had a range of 5.70 to 7.30.

From 1856 to 1900 the harvesting of Park Grass was done by hand with scythes. A mowing machine was first used for the first cut in 1901, although this method of harvesting was used for the second cut since 1881. Before 1960, hay from the whole plot was weighted for the first cut. Since 1960, this method of harvesting has been replaced by a forage harvester, where a strip of the plot is cut and weighed fresh and a subsample is dried to calculate yield at 100% dry matter. To adjust for the changes in harvesting methods in 1960, a correction factor based on the relationship between herbage yield (Y_{Herbage}) and hay yield (Y_{Hay}) has been derived by comparing both methods in four harvest seasons (1992, 1993, 1994 and 1959),

$$(Y_{\text{Hay}}) = 0.2743 \times (Y_{\text{Herbage}}^{1.662}) \tag{2.1}$$

(Bowley et al., 2017). The second cut data from 2003 is missing.

The first cut hay yields and total cut herbage yields of plots 12, 3, 2.2, 13, 7.2, 16 and 14.2 of Park Grass are given in Figure 2.10 (a), (b), (c), (d), (e), (f) and (g). Hay yields from limed plots start from 1903. All hay yields from 1960 onward have been adjusted from herbage yields (Equation 2.1). 12b is omitted here due to the treatment being introduced in 1965. The hay yields from the first cut of the limed plots (b) were, on average, higher than the unlimed plots (d), across all treatments. The lowest yielding limed plot was 3b (no fertiliser treatment), with a yield of 1.21 t ha^{-1}, compared to 4.51 t ha^{-1} from plot 14b (96 kg N ha^{-1} + PKNaMg). The lowest yielding unlimed plot was 3d (no fertiliser treatment), with a yield of 0.82 t ha^{-1}, plots 12d (no fertiliser treatment) and 2.2d (no fertiliser treatment) had similar low yields of 0.99 t ha^{-1} and 0.93 t ha^{-1}, respectively. Plot 14d had the highest mean hay yield of 4.48 t ha^{-1}. The yield from plot 13d (FYM unlimed) was 3.26 t ha^{-1} compared to 3.52 t ha^{-1} from plot 13b (FYM limed).

From the total cut, yields from subplot d were, on average, the lowest across all treatments from 1960 to 2016. The highest yielding subplot from Park Grass, between 1960 and 2016, was 13b (FYM, pH 6). Plots which had no inputs (12, 3 and 2.2) were the lowest yielding on average compared to plots 13, 7.2, 16 and 14.2. The relative difference in herbage yield between subplots c and d were larger than those between subplots a and b. However, the difference in herbage yields between subplots b and c were the largest. In this Thesis only a study of yield in relation to weather parameters was considered. A discussion of the potential for species diversity to affect yield in given in Chapter 6 and in the General Discussion.

Figure 2.8: The current treatment plan of the Park Grass Experiment from Macdonald et al. (2018). (Note: The alignment of Plots 14.2, 14.1, 15, 16 and 17 should be aligned with the left column of Plot 1.)

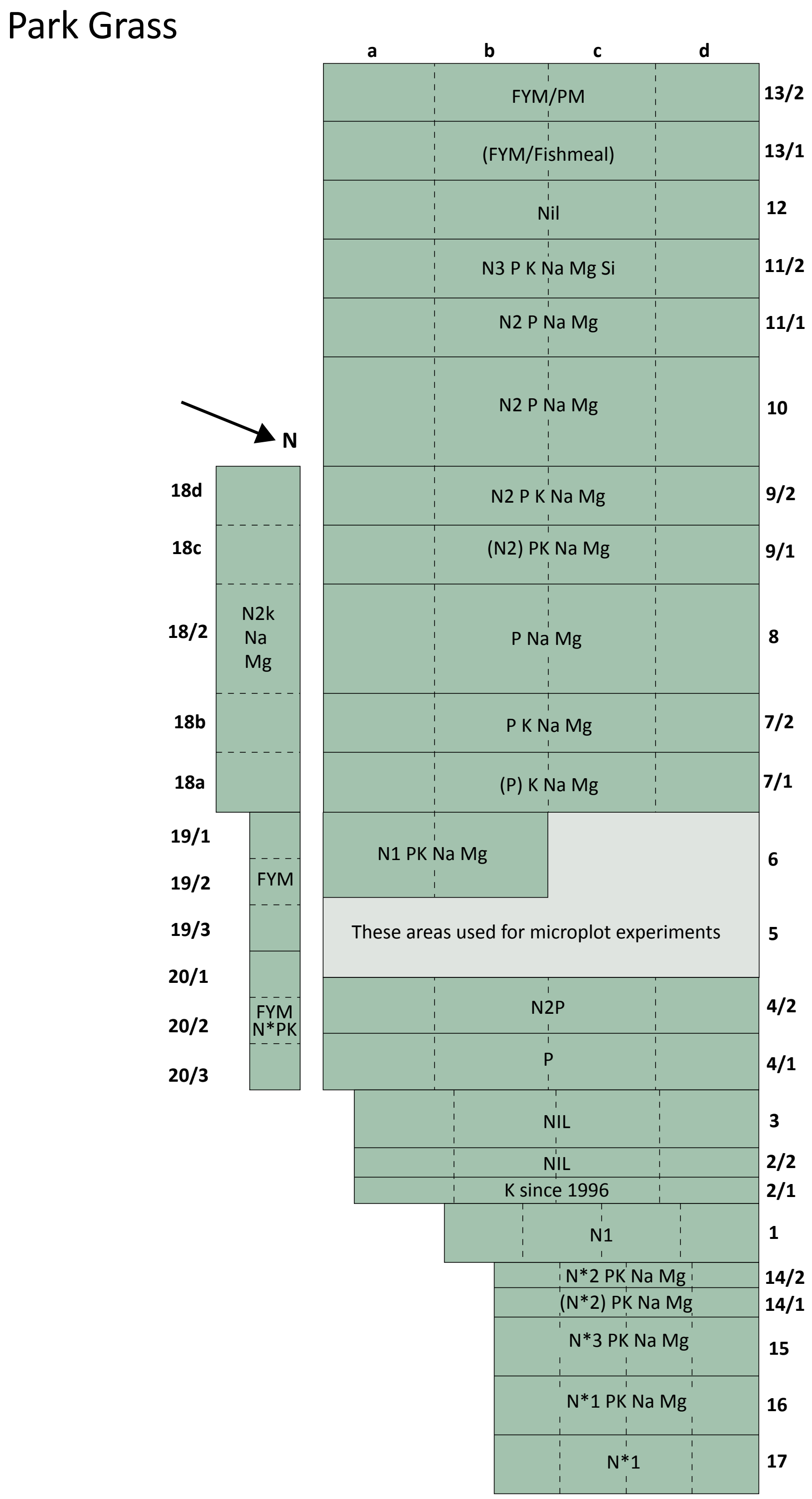


Figure 2.9: The reference table of treatments of the Park Grass Experiment from 1856 to 2016 from Macdonald et al. (2018).

Nitrogen (applied in spring)

N1, N2, N3	48, 96, 144 kg N as ammonium sulphate
N*1, N*2, N*3	48, 96, 144 kg N as sodium nitrate
(N2) (N*2)	last applied 1989

Minerals (applied in winter)

P	17 kg P as triple superphosphate since 2017, previously 35 kg P
K	225 kg K as potassium sulphate
Na	15 kg Na as sodium sulphate
Mg	10 kg Mg as magnesium sulphate
Si	450 kg of sodium silicate
Plot 20	30 kg N*, 15 kg P, 45 kg K in years when FYM is not applied

In 2013, plot 7 was divided into 7/1 and 7/2; P applications on 7/1 stopped
Since 2013, plot 15 has also received N*3 (previously PKNaMg but no N)

Organics (applied every fourth year)

FYM	35 t ha^{-1} farmyard manure supplying c.240 kg N, 45 kg P, 350 kg K, 25 kg Na, 25 kg Mg, 40 kg S, 135 kg Ca
PM	Pelleted poultry manure (replaced fishmeal in 2003) supplying c.65 kgN

On plot 13/2 FYM and PM (previously fishmeal) are applied in a 4-year cycle i.e.:
FYM in 2017, 2013, 2009, 2005 etc.
PM in 2015, 2011, 2007, 2003, fishmeal in 1999, 1995 1991 etc.

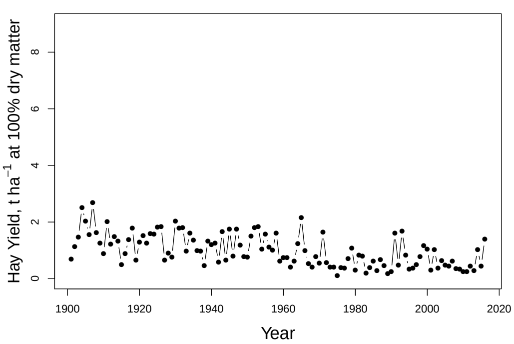
(FYM/Fishmeal) FYM and fishmeal last applied in 1993 and 1995 respectively

Lime (applied every third year)
Ground chalk applied as necessary to maintain soil (0-23 cm) at pH 7, 6 and 5
on sub-plots “a”, “b” and “c”.
Sub-plot “d” does not receive any chalk

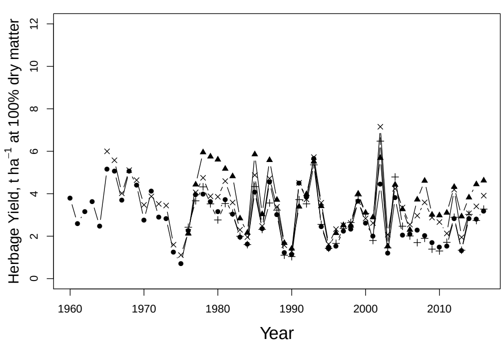
Figure 2.10: First cut hay yields (where yields between 1901 and 1959 have been adjusted) and total cut herbage yields of the Park Grass Experiment from 1901 to 2016 and 1960 to 2016, respectively. Yields from seven different treatments are shown here, Nil_{12} (a), Nil_3 (b), Nil_{12} (c), FYM (d), PKNaMg (e), 48 kg N ha^{-1} + PKNaMg (f) and 96 kg N ha^{-1} + PKNaMg (g). Hay yields from 1901 to 2016 were limed (crosses) and unlimed (dots) compared to herbage yields with a pH of 7.2 (triangles), 6 (diagonal crosses), 5 (crosses) and unlimed (dots).

Nil_{12} (a)

First Cut Hay Yield

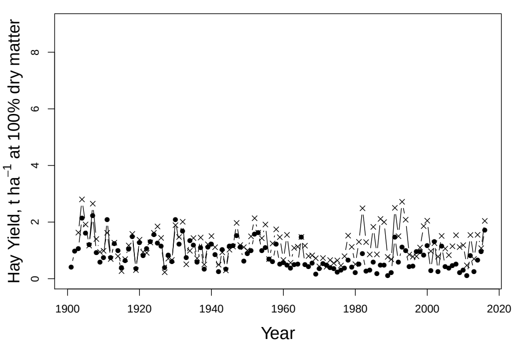


Total Cut Herbage Yield

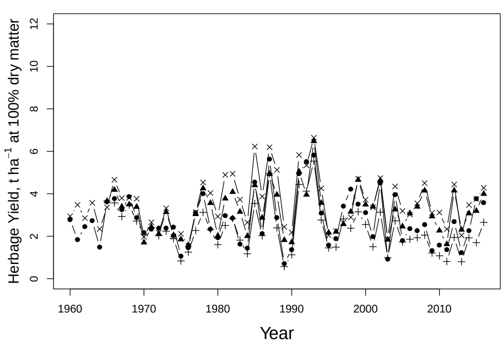


Nil_3 (b)

First Cut Hay Yield

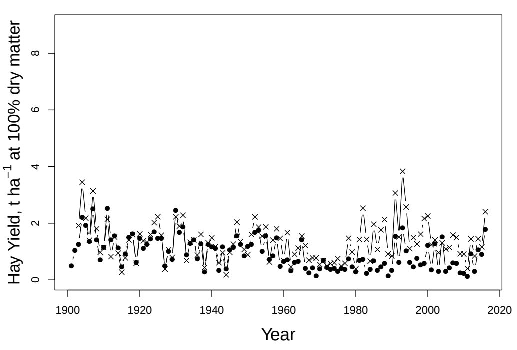


Total Cut Herbage Yield

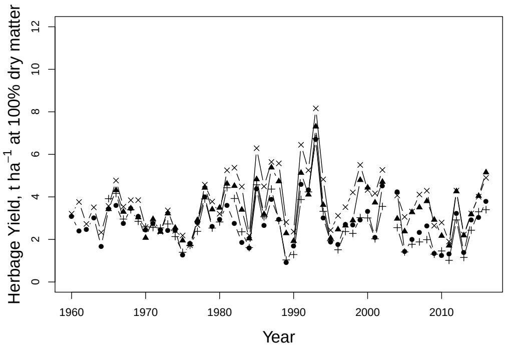


Nil$_{2.2}$ (c)

First Cut Hay Yield

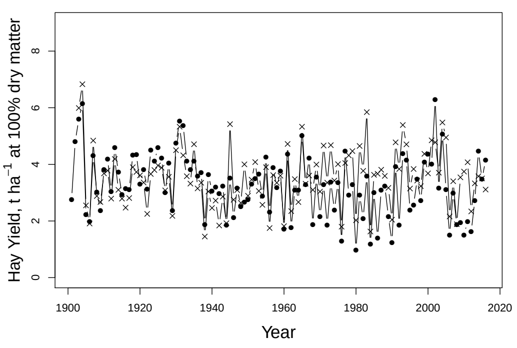


Total Cut Herbage Yield

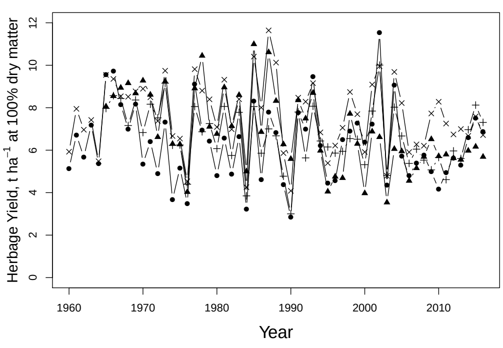


FYM (d)

First Cut Hay Yield

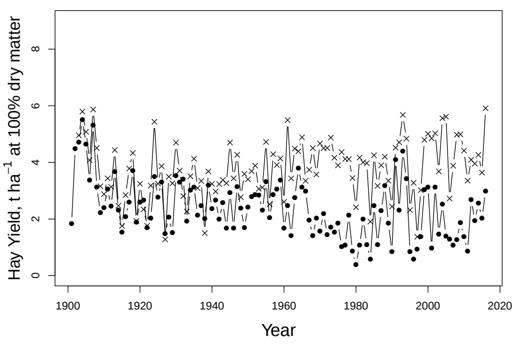


Total Cut Herbage Yield

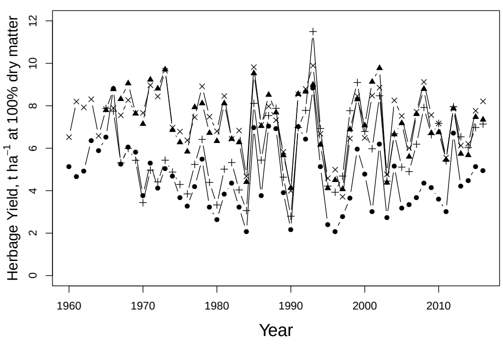


PKNaMg (e)

First Cut Hay Yield

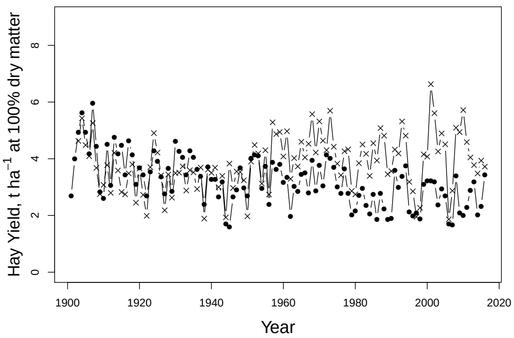


Total Cut Herbage Yield

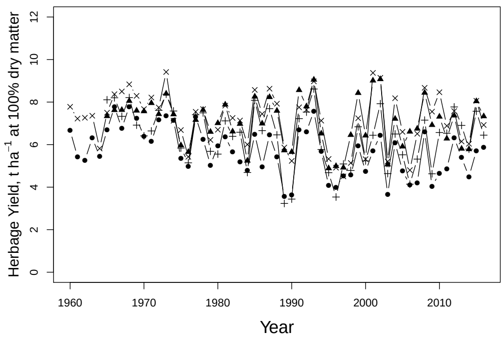


48 kg N ha^{-1} + PKNaMg (f)

First Cut Hay Yield

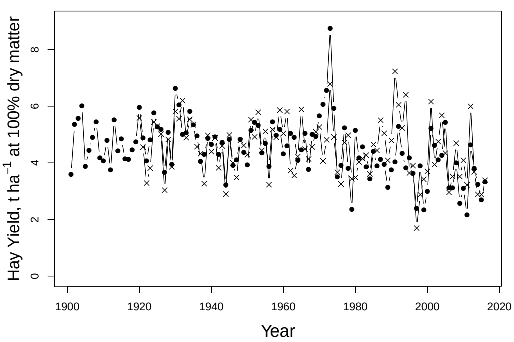


Total Cut Herbage Yield

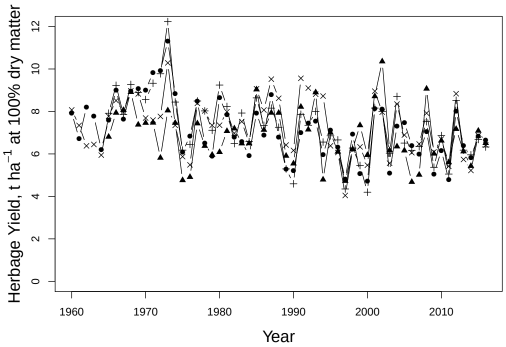


96 kg N ha^{-1} + PKNaMg (g)

First Cut Hay Yield



Total Cut Herbage Yield



2.5 Rothamsted Meteorological Station

2.5.1 Introduction

The Rothamsted Meteorological Stations (RMS) first started recording total daily rainfall in 1853 and by 1890, the RMS was recording hours of direct sunlight (started 1890) along with maximum and minimum temperature (started 1878). With advances in technology, RMS joined the Environmental Change Network in 1992 and became fully automated, with electronic sensors, in 2004 (Scott et al., 2015). Rothamsted is a unique resource in identifying the effects of weather variability and climate change on crop yield development as Rothamsted has been recording long-term meteorological data (RMS) in parallel with the LTEs on the same site since 1853 (Figure 2.1). All information about the recording of meteorological data from the RMS was provided by Scott et al. (2015), unless stated otherwise and all data was provided by e-RA.

2.5.2 Rainfall Records

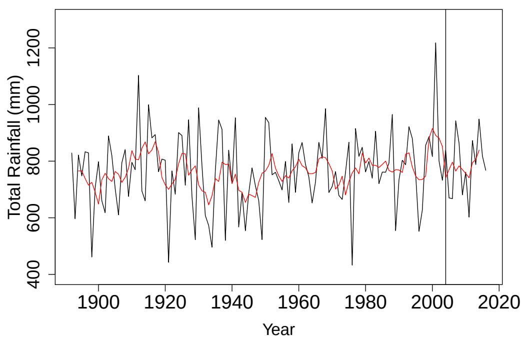
First recorded in 1853, the five-inch rain gauge measurements have been updated several times. The first change to the five-inch rain gauge measurements came in 1948 where the five-inch rain gauge was replaced with a five-inch copper rain gauge, of the Meteorological Office standard (type, MKII), and surrounded by a turf wall. Further changes to the recording of rainfall data came in 2004 where the rainfall measurements became automated and a ten-inch aerodynamic ARG100 tipping bucket rain gauge was installed within the turf wall.

The five-inch copper rain gauge is still in use today, however, data is recorded every several days whilst the data from the ten-inch tipping bucket is recorded every day. Due to the change in rain gauge size in 2004 there has been an observed increase, of approximately 10.54%, in rainfall capture per year by the ten-inch tipping bucket rain gauge compared to the five-inch copper rain gauge. The 10.54% increase in rainfall, due to the increased efficiency of the measurements since 2004, was derived by the RMS Caretaker by a method of double-mass curves (Scott, personal communications). All rainfall recordings from before 2004 were adjusted up.

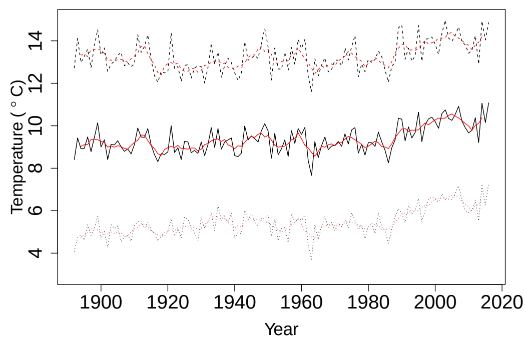
The total annual rainfall throughout a harvest season (October to September) at Rothamsted from 1892 to 2016 is given in Figure 2.11a. Since 1892 there has been no trend in the amount of rainfall over time, with a mean of 766.66mm of total rainfall over a harvest season. The minimum rainfall measured in a harvest season was 432.87mm in 1976 with most rainfall observed, over a harvest season, in 2001 with 1217.71mm. Compared to total annual rainfall from Figure 2.11a, the mean total Autumn, Winter, Spring and Summer rainfall were 216.39, 200.87, 162.52 and 186.61mm, respectively (Figure 2.12a, b, c and d). Although there was no trend in rainfall over time, there was a large amount of year-to-year variability compared to average temperature (Figure 2.11 (b)) and total hours of direct sunlight (Figure 2.11 (c)).

Figure 2.11: Yearly summary of mean (solid), maximum (dashed) and minimum (dots) temperature at Rothamsted, for each year (black) and five-year means (red), from 1892 to 2016.

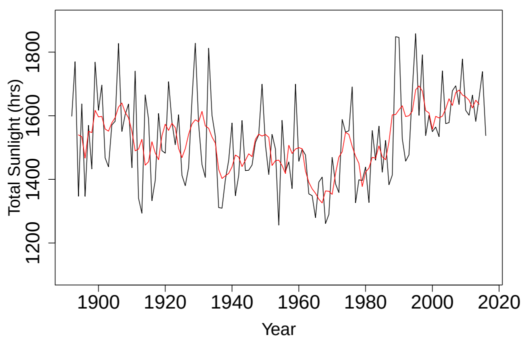
(a)



(b)



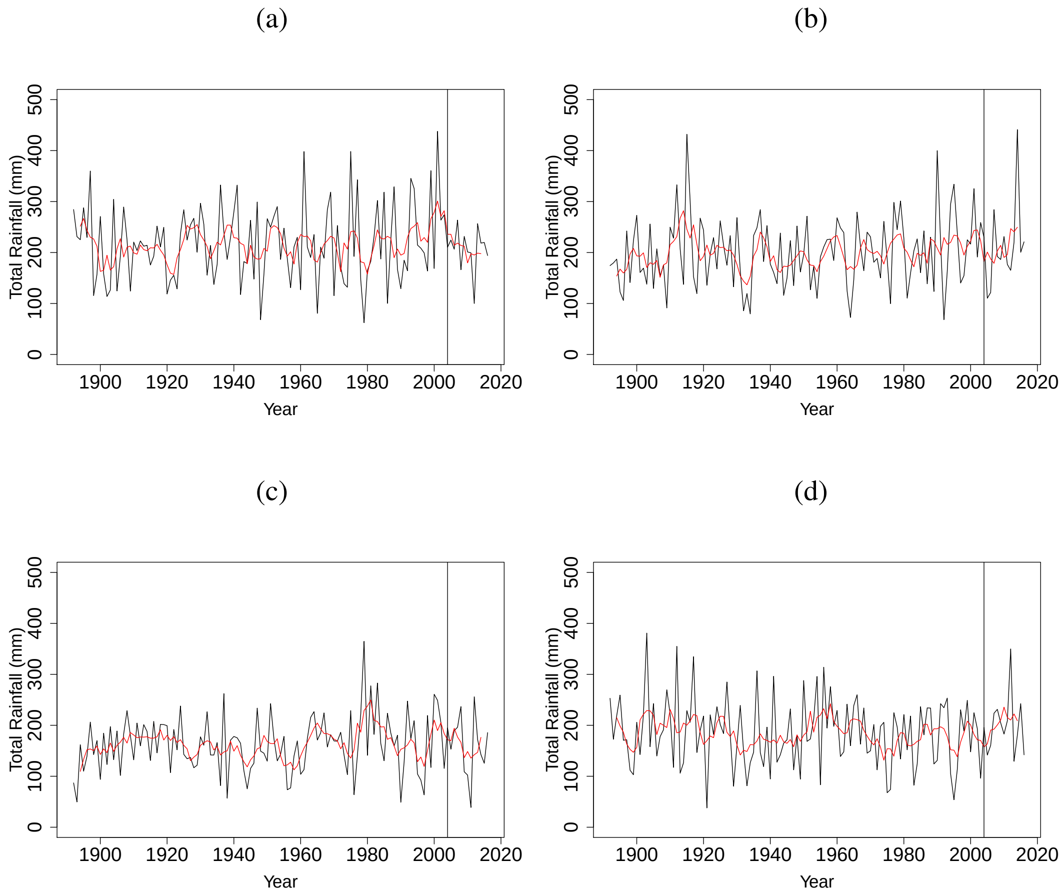
(c)



2.5.3 Temperature Records

Rothamsted started recording temperature measurements in 1878. Since 2004 maximum and minimum temperatures (°C) have been measured by a single dry bulb thermistor (Campbell

Figure 2.12: Seasonal summaries of total Autumn (a), Winter (b), Spring (c) and Summer (d) rainfall at Rothamsted, for each year (black) and five-year means (red), from 1892 to 2016.



Scientific, type 107) replacing the glass sheathed mercury bulb maximum thermometer and a glass sheathed spirit bulb minimum thermometer. Only caretaker measurements, twice weekly, are made using the glass thermometers now to validate measurements from the electronic thermistor. Both thermometers are enclosed within a Stevenson Screen. This is to shield the instruments against precipitation and direct heat radiation in order to gain true estimates of air temperature. The process of recording temperature measurements was automated in 2004 with manual measurements still being recorded by Rothamsted's Meteorological caretaker. Manual measurements are still recorded as a way to validate measurements from the automated thermometers.

The 2007 to 2016 decadal mean annual mean temperature at Rothamsted was 10.19 °C compared to the 100-year average (1892 to 1991) of 9.16 °C (Figure 2.11 (b)). In comparison, the decadal average (2007 to 2016) for mean minimum and maximum annual temperature was 0.88 °C and 1.17 °C above the 1892 to 1991 average of 13.10°C and 5.23 °C. The hottest recorded mean annual temperature, between 1892 and 2016 at Rothamsted, was 11.08 °C in 2016, where 1963 had the coldest recorded mean temperature of 7.66 °C. The mean autumn, winter, spring and summer decadal (2007 to 2016) temperature was 11.11, 4.51, 9.18 and 16.08 °C compared to the century mean (1892 to 1991) of 9.74, 3.47, 8.05 and 15.27 °C. The mean decadal minimum temperature of autumn, winter, spring and summer was 1.63, 1.04, 1.14 and 1.13 °C higher than the 1892 to 1991 average of 6.03, 0.64, 3.67 and 10.45 °C, where the mean decadal maximum temperatures were 1.12, 1.05, 1.13 and 0.49 °C in autumn, winter, spring and summer, compared to the 1892 to 1991 mean (13.45, 6.29, 12.43 and 20.08 °C). Therefore, from 2007 and 2016, across the seasons, minimum temperatures increased more than maximum temperatures.

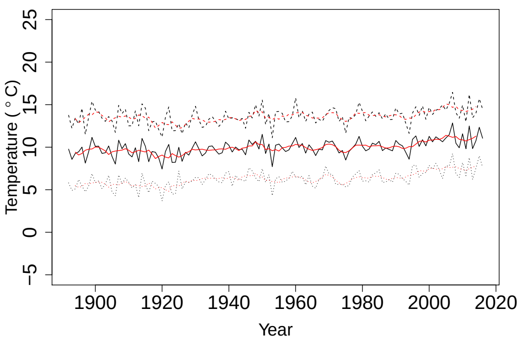
2.5.4 Sunlight Records

Sunshine recordings were first recorded at Rothamsted in 1890 by a Campbell-Stokes recorder. The Campbell-Stokes recorder consists of a glass sphere through which sunlight passes burning a trace onto a sunshine card appropriate to the time of year. Cards are measured to the hour, noon is located in the centre, and the card is burnt by the sunlight depending on the time of day. The length of the burn mark therefore depicts how long (in hours) there was direct sunlight on that day. Since the automation of the RMS in 2004 the hours of direct sunlight have been calculated from the total solar radiation per day (J cm^{-2}). Solar radiation is measured using a pyranometer. The calculation takes into account the time of sunrise and sunset and Earth's latitude and longitude.

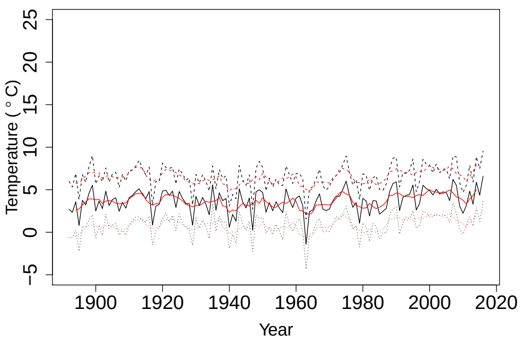
From 1892 to 1968 the annual total hours of direct sunlight at Rothamsted decreased from 1565.29 hours (1892 to 1900 mean) to 1416.99 hours (1958 to 1968 mean). The 2007 and 2016 decadal mean of total annual direct sunlight was 1650.66 hours and has been increasing steadily since 1968 (Figure 2.11 (c)). The lowest recorded annual hours of direct sunlight over a harvest season was 1954 of 1256.10 hours. 1995 was the harvest season with the most recorded hours of direct sunlight of 1858.2 hours. The increase in hours of direct sunlight after 1968 was thought

Figure 2.13: Seasonal summaries of mean Autumn (a), Winter (b), Spring (c) and Summer (d) mean (solid), maximum (dashed) and minimum (dots) temperature at Rothamsted, for each year (black) and five-year means (red), from 1892 to 2016.

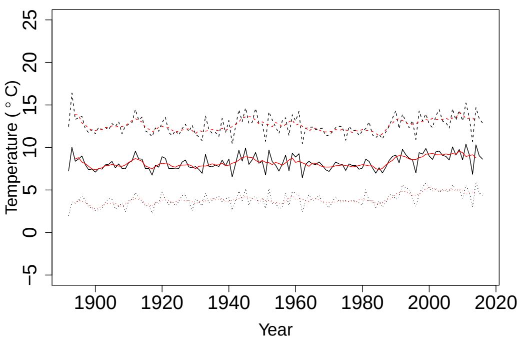
(a)



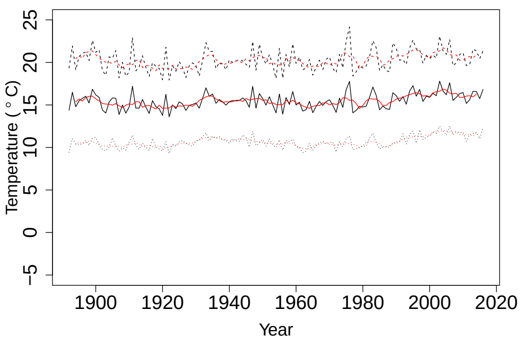
(b)



(c)

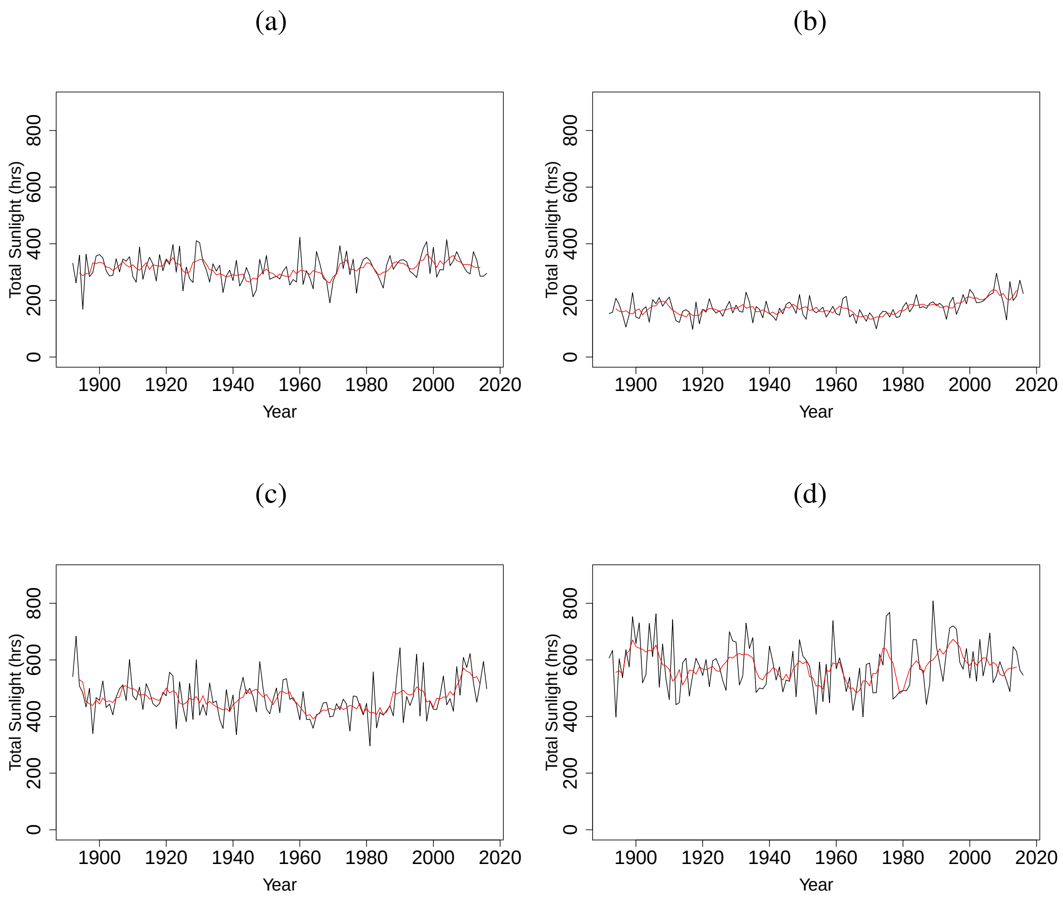


(d)



to be a response to the Clean Air Act of 1956 and 1968. The 2007 to 2016 decadal average for autumn, winter, spring and summer total hours of direct sunlight were 19.41, 63.53, 126.22 and 24.36 hours greater than the 1958 to 1968 mean of 301.97, 162.57, 417.43 and 537.81 hours (Figure 2.14 (a), (b), (c) and (d)). Winter and spring have the greatest increase in hours of direct sunlight compared to all other seasons.

Figure 2.14: Seasonal summaries of total Autumn (a), Winter (b), Spring (c) and Summer (d) hours of direct sunlight at Rothamsted, for each year (black) and five-year means (red), from 1892 to 2016.



Chapter 3

A multivariate study into Rothamsted's weather from 1892 to 2016 and the yield of the Long-Term Experiments

3.1 Introduction

In 2016, the average global temperature was 1.43°C above the 20th century average (NOAA, 2017), with temperatures predicted to rise throughout the 21st century, depending on future climate emissions scenarios (Kirtman et al., 2013). The UK decadal average temperature between 2007 and 2016 was 9.1°C compared to a 1961 to 1990 average of 8.3°C (Kendon et al., 2017). At Rothamsted, the decadal temperature between 2007 and 2016 was 1.03 °C greater than a 1961 to 1990 average with no consistent increasing or decreasing trend in rainfall at Rothamsted since 1892 (Chapter 2).

Studies into crop variation from time-series yield data show associations between variations in weather with these in the yield of wheat, barley and pastures (Chmielewski & Potts, 1995; Fisher, 1925a; Hatfield & Dold, 2018; Hooker, 1907; Silvertown 1994; Wishart & Mackenzie, 1930). Understanding how climate has changed across multiple weather variables provides an understanding of how the agricultural climate has changed, in comparison to univariate analysis, and potentially how this influences yield. Multivariate methods have been applied to previous climate studies. Cluster analysis was used to partition climate zones of the conterminous United States over temperature and precipitation variables from 1931 to 1980 (Fovell & Fovell, 1993). Using data from 1950 to 2002, cluster analysis was used to describe cyclone trajectories in the western North Pacific (Camargo et al., 2007). The use of multivariate methods can provide insight into how the whole climate system has changed over several variables.

Rothamsted Meteorological Station (RMS) has weather records dating back to 1853. From 1890, the RMS started collecting hours of direct sunlight records to add to the rainfall (1853) and maximum and minimum temperature (1878) records already being measured (Chapter 2). The purpose of this study was to apply multivariate analysis to monthly summarised rainfall, temperature and sunlight duration data, from the RMS, to see if climate could be objectively categorised and to test how climate has change, over multiple variables, from 1892 to 2016. This study also used wheat, barley and pasture total biomass data from the Rothamsted Long-Term Experiments (Broadbalk, Hoosfield and Park Grass) to investigate if and how the yield from years within different defined clusters varies.

3.2 Aims and Objectives

3.2.1 Aim

This study aims to investigate, objectively, how the climate at Rothamsted has changed, from 1892 to 2016, over multiple variables using multivariate analysis. I investigated the impacts of climate change on wheat, spring barley and herbage yields from Rothamsted's Long-Term Experiments and identified how the interaction between climate and yields of these crops differs.

3.2.2 Objectives

Within this chapter I:

- Identified the key components of variations in weather over years by reducing the dimensionality of the Rothamsted weather data by the use of Principal Components Analysis.
- Identified clusters of years with different characteristics depending on their weather patterns to understand how climate had change across multiple variables at Rothamsted since

1892.

- Given the clustered years, I assessed whether the yields of wheat, spring barley and herbage from the Broadbalk, Hoosfield and Park Grass experiments varied across these defined clusters over five common treatment groups PKNaMg (Mineral), 48 kg N ha^{-1} + PKNaMg (N1 + Mineral), 96 kg N ha^{-1} + PKNaMg (N2 + Mineral), farmyard manure and no inputs (Nil).

3.2.3 Hypotheses

- Univariate analyses of the RMS data show increasing temperatures in the late-20th and early-21th century, therefore objectively classifying these changes in climate through cluster analysis showed distinct weather characteristics from other years in the 20th century.

- The classification of years based on weather showed a loss in the yield of wheat, spring barley and herbage in clusters which had weather characteristics which were less suited to crop growth, such as those in in the early-21st.

3.3 Methods

3.3.1 Rothamsted Meteorological Data

To form a complete dataset, rainfall, temperature and sunlight data from 1892 to 2016 were used. In this analysis, I considered seven meteorological variables, summarised for each month over a growing year from October to September. Some meteorological variables included: total rainfall (mm), rain intensity (mm/days), mean daily maximum temperature (°C), mean daily minimum temperature (°C), and total sunlight hours. To include the amplitude of low and high temperatures within a month, minimum daily minimum temperature (°C) and days maximum temperature was over 31°C were considered. Heat stress over 31°C was known to lead to a loss in crop growth. Only four months had an observed temperature over 31(°C), these were June, July, August and September. Monthly summaries of weather were chosen because phenological data was not collected on the Rothamsted LTEs and larger windows would smooth-out within year variability. In total 76 variables ($12 \times 7 + 4$) were selected over 125 years.

3.3.2 Rothamsted Long-Term Experiment Data

To make comparisons across experiments over multiple years, total biomass (85% dry matter) was used from Broadbalk wheat Section 1, Hoosfield spring barley Series O and Park Grass Section A from 1968 onwards (see Section 2). Treatments PKNaMg (Mineral), 48 kg N ha^{-1} + PKNaMg (N1 + Mineral), 96 kg N ha^{-1} + PKNaMg (N2 + Mineral), farmyard manure and no inputs (Nil) were considered for this analysis because they were consistent across experiments. Total biomass was considered for this analysis to minimise the cultivar effect of Broadbalk and Hoosfield. An example of this was a comparison between short-strawed and long-strawed cultivars showed no clear difference in total biomass on the Broadbalk experiment within the same years (Austin & Ford, 1989). Although we have clustered weather data since 1892, yield data before 1968 was not considered due to a lack of homogeneity of agricultural practices such as the introduction of herbicides and short strawed cultivars in the 1960s.

3.3.3 Statistical Analysis

Principal components (PCs) analysis was used as a dimension reduction tool to identify key sources of variability within the dataset. Due to the seven underlying variables being measured on different scales, PCs were constructed from the correlation matrix. A k-means clustering procedure (Hartigan & Wong, 1971), where data was clustered into 2 to 50 clusters to determine the optimum cluster number, was used on the scores of the PC analysis to group years together dependent on their weather. The Hartigan & Wong (1971) procedure results in minimising the within-cluster sum of squares by the following algorithm: 1. partition the data at random into k sets, 2. calculate the centroid of each set, 3. assign each point to a cluster corresponding to the closest centroid, and 4. repeat stages 2 and 3 until convergence is met or the maximum iterations has been met.

Multiple indices were considered for optimum cluster number. However, due to the large variability of the Rothamsted weather data few gave an optimum cluster number which did not result in clusters having very small membership or years being allocated their own cluster. The optimum cluster number should result in clusters having a large enough size to include multiple years but not so big that few clusters were observed. The R package clusterCrit was used to investigate indices which could optimise cluster number. Multiple indices were considered for optimum cluster number. However, some cluster indices were based on the within-cluster sums of squares and therefore the C-Index was preferred as it considers the range of values within a cluster. The within-cluster sum of squares and the C-Index were both used to choose an optimum cluster number. The C-Index was used alongside the within-cluster-sum-of-squares figure as an index to define optimum clusters size. The C-Index is defined by Desgraupes (2013) as

$$C = \frac{S_W - S_{min}}{S_{max} - S_{min}}$$

Where: S_W is the sum of the distances between all pairs of points within each cluster; S_{min} is the sum of the smallest distances within each cluster; and S_{max} is the sum of the maximum distances within each cluster. The C-Index was calculated for all clusters, 2 to 50. The optimum cluster number was chosen from an elbow in the within-cluster-sum-of-squares and C-Index plot. It should be stated that cluster analysis and selecting optimum cluster number is subjective, given multiple indices available, and it is my opinion that further methodological developments are needed. The issue of optimum cluster number links with the philosophy of these type of analyses, years do not naturally form clusters, the approach taken was a method of objectively classifying changes in climate and sources of weather variability. Further analyses show how the climate within these clusters influences the yield over three crops.

Once a cluster number was achieved, by viewing the within-cluster sums of squares and the C-Index, a linear mixed model (LMM) (Equation 3.1) was used to determine if there was a difference between total biomass across clusters, experiments (Broadbalk, Hoosfield and Park Grass) and treatments (Nil, PKNaMg, 48 kg N ha^{-1} + PKNaMg, 96 kg N ha^{-1} + PKNaMg and FYM)

$$y = X\beta + U\gamma + \varepsilon \tag{3.1}$$

with y the response variable yield, X the fixed effects design matrix, β the fixed effects, U the random effects design matric, γ the random effects and ε the associated error. A LMM was preferred due to the lack of cluster membership within clusters. Without a LMM, a year effect could confound a cluster effect and therefore lead to a bias analyses. The fitted model was expressed as

$$\begin{aligned} y_{ijklm} = &\beta_0 + \beta_{1i}x_i + \beta_{2j}x_j + \beta_{3k}x_k + \beta_{4ij}x_{ij} + \beta_{5ik}x_{ik} + \beta_{6jk}x_{jk} + \beta_{7ijk}x_{ijk} + \\ &\gamma_{1l}u_l + \gamma_{2lm}u_l u_m + \varepsilon_{ijklm} \end{aligned} \tag{3.2}$$

with, y_{ijklm} the yield for the i^{th} cluster, j^{th} experiment ($j = 1, 2, 3$; 1 = Broadbalk, 2 = Hoosfield, 3 = Park Grass), k^{th} treatment ($k = 1, 2, 3, 4, 5$; 1 = Nil, 2 = PKNaMg, 3 = 48 kg N ha^{-1} + PKNaMg, 4 = 96 kg N ha^{-1} + PKNaMg, 5 = FYM), l^{th} plot, and m^{th} year ($m = 1968, ..., 2016$). The overall mean was β_0, β_1 the effect of cluster, β_2 the effect of experiment, β_3 the effect of treatment, β_4 the interaction between cluster and experiment, β_5 the interaction between cluster and treatment, β_6 the interaction between experiment and treatment, and β_7 the three way interaction between cluster, experiment and treatment. γ_1 was the fixed effect of plot and γ_2 the nested effect of year within plot. Years were clustered regarding their weather, therefore any variability associated with year must be taken into account within the random model. Model validation was achieved. Total biomass from all experiments was square rooted to satisfy the assumption of homogeneous variance of the residuals across all treatment groups.

3.4 Results

3.4.1 Principal Components Analysis

The first 19 PCs explained 70% of the overall variability of the weather dataset. PC1 explained 10.00% of the variability whilst PC2 and PC3 explained 6.53% and 5.80%. The loadings of total rainfall, mean daily maximum temperature, mean daily minimum temperature, total sunlight, rain intensity and minimum daily minimum temperature and days over 31°C for each month are provided in Figure 3.1 (a), (b), (c), (d), (e) and (f). The first 16 PCs are given in the Appenix Tables A.10 and A.10. PC1 had a negative loading for mean maximum and minimum temperature for every month (Figure 3.1 (b) and (c)). PC1 separated out a temperature effect. Therefore, due to the negative loadings of temperature, years which had warmer months had a negative score over PC1. PC2 had a positive loading for mean maximum and minimum temperature for April, May, June, July, August, September and November, and a negative loading for December, January, February and March. Therefore, PC2 separates out a seasonal effect of temperature. The magnitude of loadings, over PC1 and PC2, for January, February, July and August temperature were large (September minimum temperature and November maximum temperature also have large loadings over PC1 and PC2), and therefore years with warmer temperatures within these months were given larger scores. A seasonal effect in temperature was also observed in the loadings of minimum daily temperature and days over 31°C (3.1f). December, January, February and March loadings were negative for minimum daily minimum temperature and were positive for all other months.

The months June, July and August had positive loadings for total rainfall and negative loadings for December, January and February over PC1 (3.1a and e). Therefore, PC1 is separating a seasonal effect of rainfall and rain intensity. All months, except October and May had negative loadings for hours of direct sunlight (3.1 (d)), therefore, PC1 not only separated out a temperature effect, but also a sunlight effect. PC2 had a positive loading for November and March rainfall and rain intensity, and August and October sunlight. December, February, August and September rainfall had negative loadings over PC2 (Figure 3.1a), and November sunlight had a negative loading over PC2 (Figure 3.1 (d)). PC1 and PC2 therefore separated a temperature and sunlight effect, and seasonal effect of weather of temperature, rainfall and sunlight, respectively.

PC3 separated out a seasonal effect but gave more magnitude to maximum temperature variables and hours of direct sunlight in July, August and September. Temperature variability within the early growing was captured in PC4 and 7, where PC7 also captures rainfall variability in the early harvest season, with wetter October, November and December had a larger negative score. PC5 separated out a seasonal spring effect, where April mean daily maximum temperature was given a positive loading and spring rainfall variables given a negative loading. The seasonal effect of temperature in early-summer was separated out in PC6, PC8, 9 and 11. PC9 and 12 separated out the seasonal effect of rainfall and rain intensity in the winter and spring, respectively. Seasonal variation in rainfall and rain intensity around the early harvest season and summer were explained by PC10 and 19.

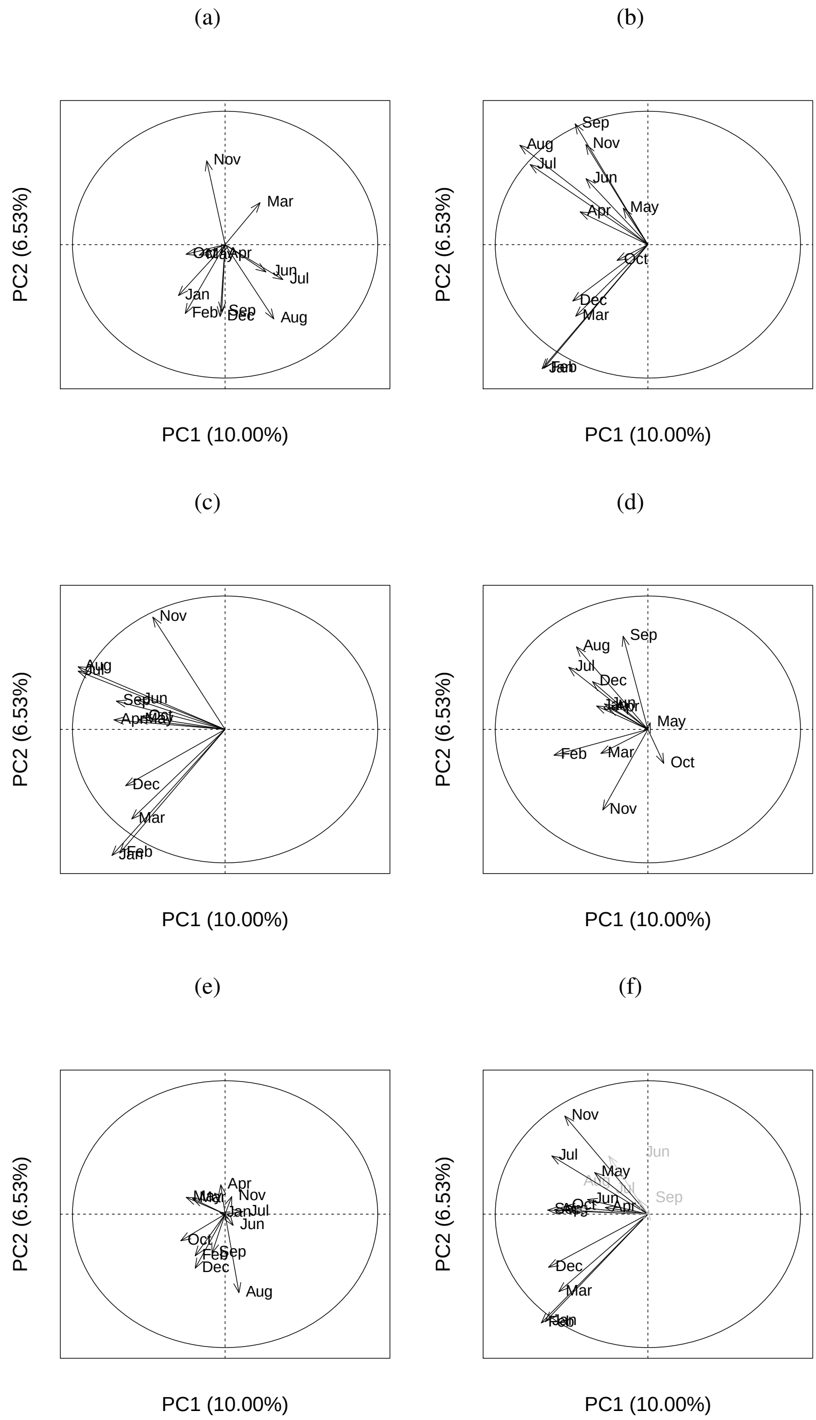
Interpretation of the loadings proved more difficult the more PCs included. The PC loadings are given in the Appendix. A cut-off of 70% was preferred because before 70% some informative PC may have been lost in further analyses, a cut-off after 70% may have resulted in non-informative information dominating the cluster analysis. From the first 19 PC, all PCs explained variations in temperature but separated a within-year effect. For example, PC3 separated out a seasonal effect of temperature but also a maximum and minimum temperature effect, giving more magnitude to mean daily maximum temperature for August and July compared to daily minimum temperature.

3.4.2 Cluster Analysis

From Figure 3.2 (a) and Figure 3.2 (b) the within-cluster sum of squares and C-Index relationship as cluster number increases. No distinct elbow from Figure 3.2 (a) was observed, although the rate of decline of the within-cluster sum of squares changed between a cluster number of 7 to 15, there was an elbow at cluster number 5, 7 and 10 from the C-Index in Figure 3.2 (b). From combining 3.2a and 3.2 (b), a cluster number of 10 was chosen as the optimum number of clusters with C-Index of 0.19. A cluster number of 7 could have been proposed but was rejected because the rate of decline of the within-cluster sum of squares around a cluster number of 7 was still high in comparison to cluster number 10. The membership of clusters since 1892 is shown in Figure 3.3 (a) and are given explicitly in Table 3.1. Years throughout the 20th century tended to be within Cluster 2, 3, 7 and 10, with their score across PC1 being more positive than negative (see score Figure 3.3). 25, 16 and 23 out of 100 years, between 1900 to 1999, were in Cluster 2, 3 and 10, respectively (Table 3.1). The scores from years within Cluster 1 tended to be more negative on the PC1 axis (Figure 3.3 (b)). With the negative loadings of temperature variables from the loadings plot (Figures 3.1 (b) and (c)) over PC1, years within Cluster 1 were generally warmer.

From Figures 3.4, 3.5, 3.6, and 3.7 the weather characteristics of monthly mean daily maximum and minimum temperature, total rainfall, rain intensity and hours of sunlight for each cluster are given. Generally, Cluster 1, which most membership years fall within the 21st century, had the highest mean daily maximum temperature from November to February compared to all other clusters. Cluster 1 also had a higher mean daily maximum temperature across all months compared to Cluster 10, who's membership spans the 20th century. The hottest and coolest mean daily maximum temperature was 23.29°C and 2.17°C from August Cluster 9 and

Figure 3.1: A representation of the loadings of (a) total rainfall, (b) mean daily maximum temperature, (c) mean daily minimum temperature, (d) total sunlight, (e) rain intensity, and (f) minimum daily minimum temperature (black) and days over 31°C (grey) weather variables summarised each month over PC1 and PC2 at Rothamsted (1892 to 2016).



February Cluster 4, respectively. Cluster 4 had the coldest January and February mean daily maximum temperature, whereas Cluster 8 had the coldest and July to August mean daily maximum temperature period. The daily mean daily minimum temperature for Cluster 1 was the warmest for all months compared to Clusters 2, 3, 7, 8 and 10. Cluster 4 had the coldest December to March mean daily minimum temperatures compared to all other clusters. The cluster which had the coldest late-spring to early-summer period was Cluster 2, where Cluster 8 had the summer period late-summer. Summarised days where temperature went over 31°C and minimum daily minimum temperature captured the same information as the mean daily maximum and minimum temperature. For example, Cluster 9 had the warmest mean daily maximum August temperature compared to the other clusters of 23.29°C. It also had the most days where temperature went over 31°C of 10. Therefore, mean daily maximum and minimum temperature captured the same variability as days when temperature went over 31°C and monthly minimum daily minimum temperature.

Cluster 1 had the wettest harvest season of 848.92mm of rainfall, compared to 671.95mm from the driest Cluster 7. Clusters 5 and 6 had a total rainfall of 643.88 and 432.87mm, but these clusters were omitted from further summaries due to their cluster size of four and one, respectively. The wettest month for a cluster was December Cluster 1 with 104.48mm. the driest month was August from Cluster 9, where only 27.92mm of rain fell. The radar plots from Figure 3.5 show the distribution of rainfall across all clusters, where Cluster 1 was generally wetter across all months. Cluster 8 had the wettest late-summer period compared to all other clusters. However, Cluster 3 had the wettest June where Cluster 1 experienced the wettest May. The driest late-summer period was Cluster 9, with Cluster 1 having the driest June and Cluster 4 having the driest May. In collusion with rainfall, Cluster 1 had the most intense rainfall harvest season of 6.66mm $days^{-1}$, so when rainfall occurred it happened, on average, over a shorter period than any other cluster. The most intense rainfall month within Cluster 1 was October, with an intensity of 9.74mm $days^{-1}$. The least intense rainfall month, over all clusters, was February from Cluster 4 with a rain intensity of 3.91mm $days^{-1}$. Cluster 9 had the most hours of direct sunlight, across the whole harvest season, of 1681.66 hours. The cluster with the least hours of direct sunlight was Cluster 10 of 1426.18 hours. June, from Cluster 1 had the longest hours of direct sunlight of 216.37 hours compared to any other cluster and month. The month and cluster with the shortest duration of sunlight hours was December, Cluster 3 with 36.92 hours.

A summary of each cluster is given in Table 3.2. Generally, k-means cluster analysis does not consider potential outliers and clusters them on their own or with other outliers. For example, the membership of Cluster 6 was one. This was the year 1976. Within 1976, there was less rainfall in October through to August than there was in any other cluster (August had only 9.84mm of rain), there was also more rainfall in September compared to any other cluster. Also, Cluster 6 had the most hours of direct sunlight from June to August, with the warmest mean June and July maximum and minimum temperature compared to all other clusters of 25.10°C. Although the harvest year 1976 had a warm dry summer, the winter was relatively cool compared to other warmer clusters, such as 1, 7 and 9. Also, for months October, November, February, March, April, August and September, the mean minimum temperature for 1976 was less than those of Cluster 7 and 9. Therefore, 1976, and Cluster 6, could be defined as a year of extreme drought and intense sunlight and temperature in the summer, with a cool winter. This resulted in 1976 being closer to the centroid of Cluster 6 (1976) than any other cluster. An opposite to this result was 1943. Although 1943 was not as warm as 1976, the harvest season was generally wetter and had characteristics of a warm-wet year, therefore clustered within Cluster 1.

Table 3.1: The cluster membership of years between 1892 and 2016 after a cluster number of 10 was chosen.

Cluster	Year
1	1943, 1994, 1999, 2000, 2001, 2002, 2004, 2005, 2006, 2007, 2008, 2014, 2015
2	1892, 1900, 1901, 1904, 1907, 1908, 1909, 1915, 1928, 1929, 1941, 1946, 1954, 1955, 1956, 1962, 1969, 1971, 1977, 1978, 1979, 1980, 1985, 1987, 1991, 1996, 2013
3	1896, 1897, 1902, 1903, 1905, 1912, 1913, 1916, 1920, 1921, 1923, 1935, 1938, 1948, 1957, 1960, 1974, 1984
4	1895, 1940, 1942, 1947, 1963, 1964
5	1898, 1906, 1911, 1990
6	1976
7	1893, 1914, 1934, 1945, 1952, 1982, 1992, 1997, 2009, 2010, 2011
8	1917, 1919, 1922, 1924, 1931, 1965, 1966, 1970, 1986
9	1899, 1933, 1949, 1959, 1975, 1983, 1989, 1995, 1998, 2003, 2012, 2016
10	1894, 1910, 1918, 1925, 1926, 1927, 1930, 1932, 1936, 1937, 1939, 1944, 1950, 1951, 1953, 1958, 1961, 1967, 1968, 1972, 1973, 1981, 1988, 1993

Table 3.2: A brief summary table of weather characteristics of each cluster.

Cluster	Summary
1	Most cluster membership was within the 21st century. This cluster had the highest temperature, on average, across all the harvest season, with more rainfall which fell over a shorter period of time compared to all other clusters. Also had the most hours of direct sunlight, on average, across all months.
2	Most common cluster with membership spanning the late-19th century to throughout the 20th, with 2013 being the only year in the 21st century. The temperature between December and March was colder than Clusters 3, 7, 9 and 10, for mean daily maximum temperature. February and March also had the lowest mean daily minimum temperature compared to Clusters 3, 7, 9 and 10. Therefore, the defining trait of Cluster 2 was the cold winter and early-spring period.
3	Most of the cluster membership spans the 20th century, including 1896 and 1897. The temperature between August and September was the coldest in Cluster 3 compared to 2, 5, 9 and 10. Other defining periods within the harvest season of this cluster include the lowest period of rainfall intensity around April of 4.10mm day^{-1}, although overall rainfall was 40.19mm, not the lowest compared to other clusters.
4	A cluster of only six years which spans the mid-20th century, including 1895. This cluster had a cold December to February period of both mean daily maximum and minimum temperatures. Other characteristics include a general absence of rainfall throughout the harvest season as a total of 691.62mm fell across years within this cluster. Therefore, this cluster was defined as years which were both cold and had a drought.
5	Cluster membership of only four. Considered an outlier cluster as the years within this cluster follow no real temporal pattern. A general summary shows this cluster had a warm mean daily maximum temperature from July to September but a relatively cold March through to June. The years within this cluster also had a general absence of rainfall, over the harvest season, but more also the most hours of direct sunlight.

6	A cluster with membership one, which was 1976. This year had a warm drought summer with warmest mean daily maximum and minimum temperatures for June and July with the longest hours of direct sunlight between the months June and August.
7	The cluster membership spans the 19^{th}, 20^{th} and 21^{st} centuries. Years within Cluster 7 tended to have a warmer March to June mean daily maximum temperature compared to Clusters 2, 3 and 9. Cluster 7 also had the coldest mean daily minimum temperature January and December compared to Clusters 2, 3, 9 and 10. December, January, March, April and May were the driest compared to Clusters 1, 2, 3, 6, 8, 9 and 10.
8	Membership of years spans the 20^{th} century. The defining characteristics of this cluster are that it had a cold mean daily maximum temperature for January and February. Cluster 8 is similar to those years within Cluster 2 but had a slightly warmer and drier harvest season.
9	A cluster membership which spans the 19^{th}, 20^{th} and 21^{st} centuries. The defining traits of this cluster include a warmer November to February mean daily maximum temperature, and November to December mean daily minimum temperature. This cluster also had the warmest July to September mean daily maximum and minimum temperatures compared to Clusters 2, 3, 7 and 10. There was also a general absence of rainfall between July and August.
10	Second largest cluster size, with membership spanning the 19^{th} and 20^{th} centuries. The only defining characteristics of this cluster include, the lowest mean maximum temperature and the lowest amount of rainfall experience in March, compared to Clusters 2, 3, 7 and 9. This cluster may be considered a *typical* 20^{th} century climate, with characteristics shown in Figures 3.4, 3.5, 3.6, and 3.7.

Figure 3.2: Scree plots of the within-cluster sums of squares (a) and C-Index (b) as cluster number varies from 0 to 50. The vertical line at cluster number 10 is discussed in the text. The red symbol in Figure b represents the C-Index value of 0.19 at cluster 10.

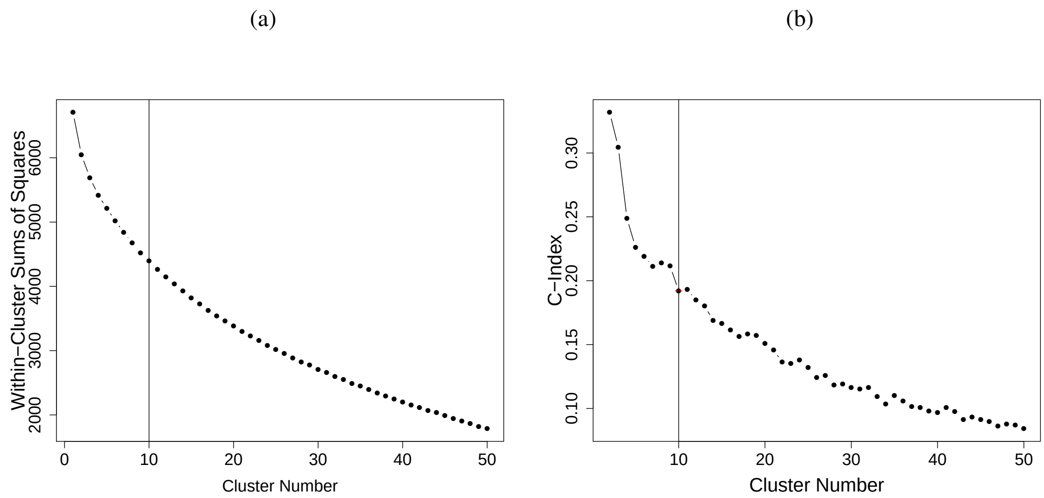


Figure 3.3: The cluster membership of years (a) and the PC1 and PC2 scores given to each year by cluster membership. The season October 1891 to September 1892 is shown here as 1892, etc.

(a)

(b)

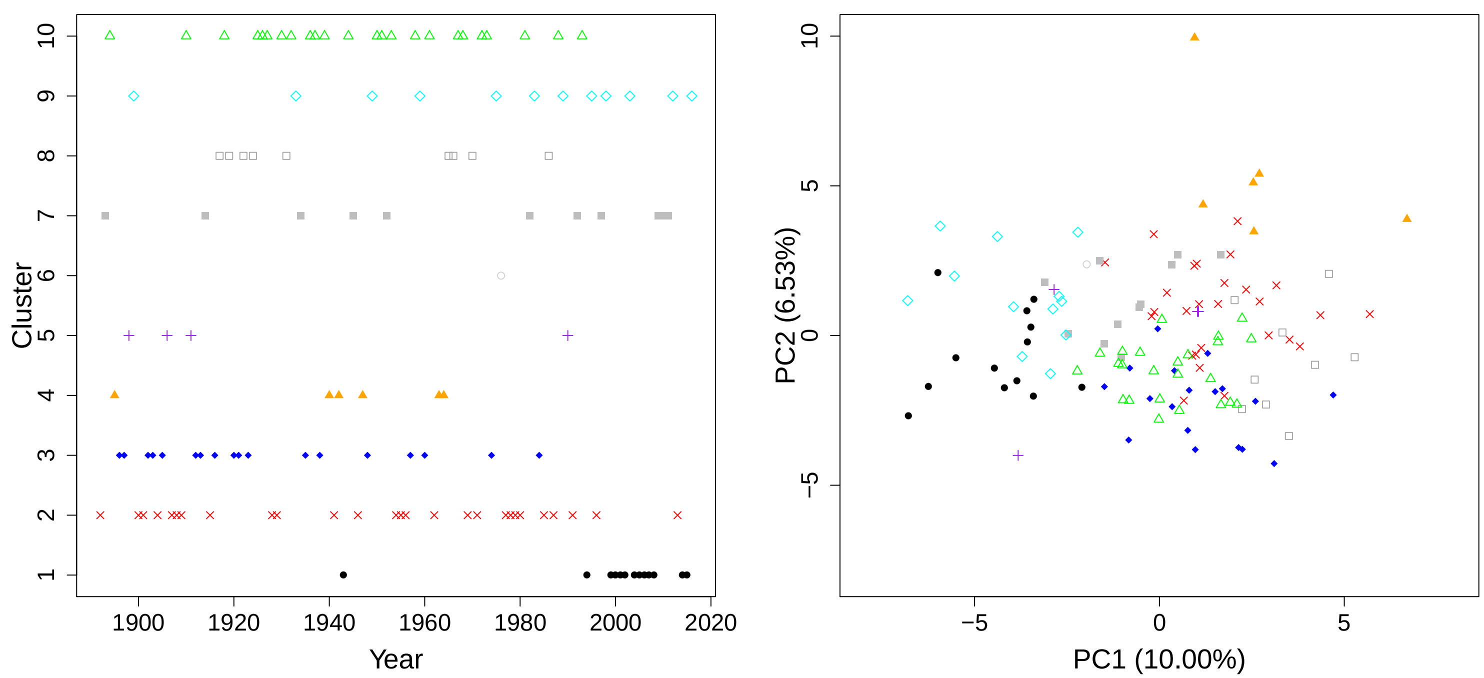
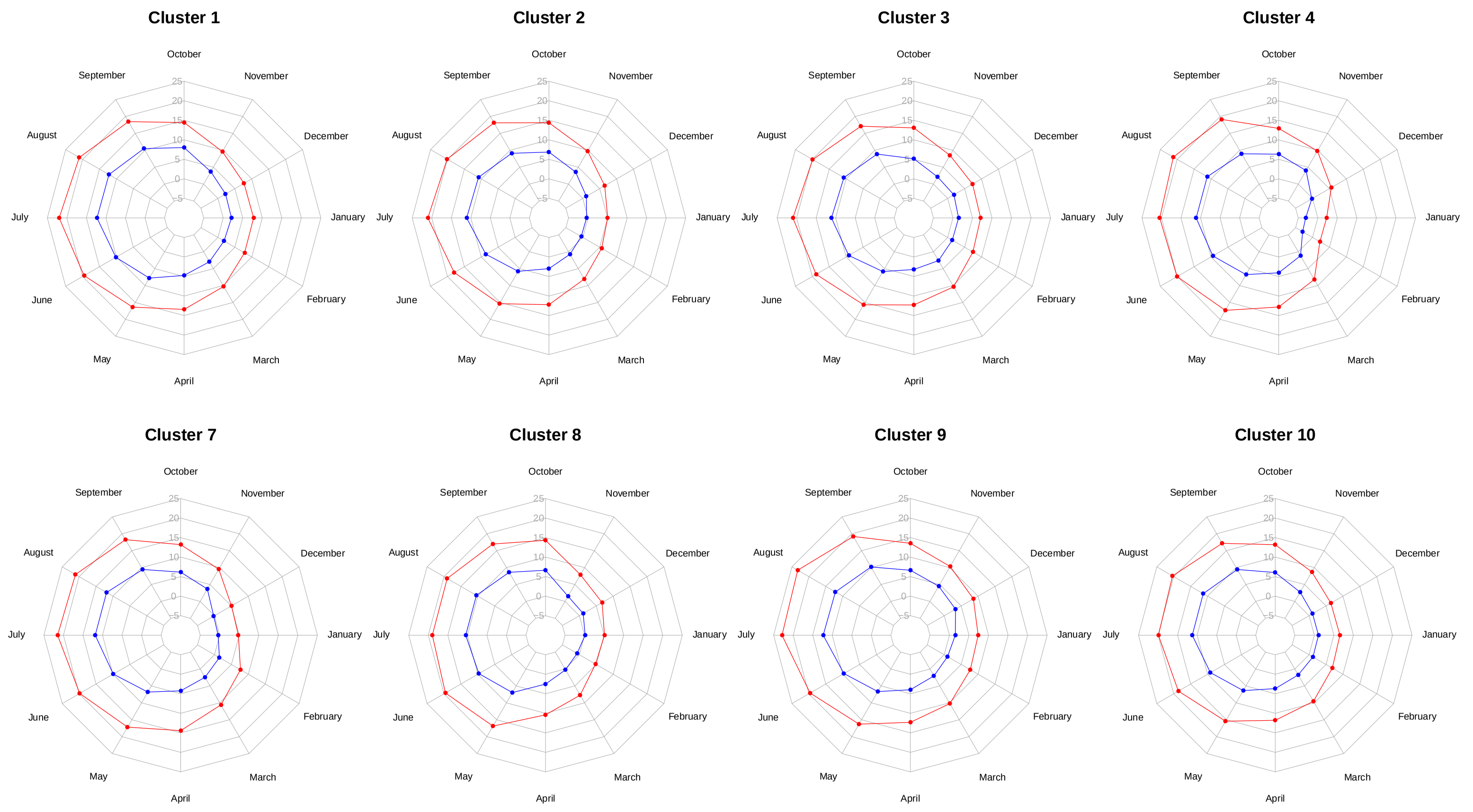


Figure 3.4: A representation of mean daily maximum and minimum temperature (°) over each month, within a harvest season (October to September), for each cluster. The standard deviation for each cluster is available in Appendix A.1 for maximum temperature and Appendix A.2 for minimum temperature.



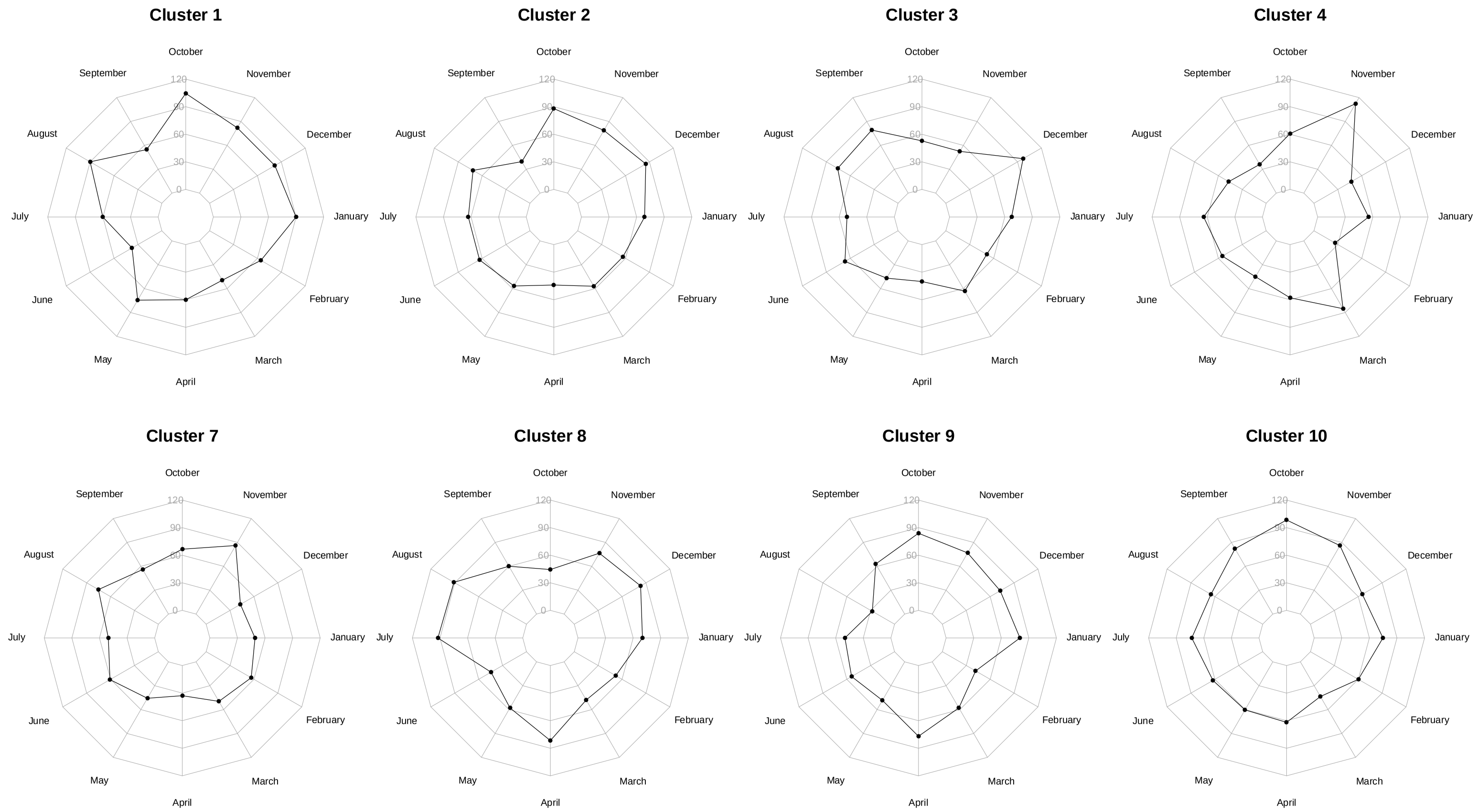


Figure 3.5: A representation of mean total rainfall (mm) over each month, within a harvest season (October to September), for each cluster. The standard deviation for each cluster is available in Appendix A.3.

Figure 3.6: A representation of mean rainfall intensity (mm/days, calculated monthly) over each month, within a harvest season (October to September), for each cluster. The standard deviation for each cluster is available in Appendix A.4.

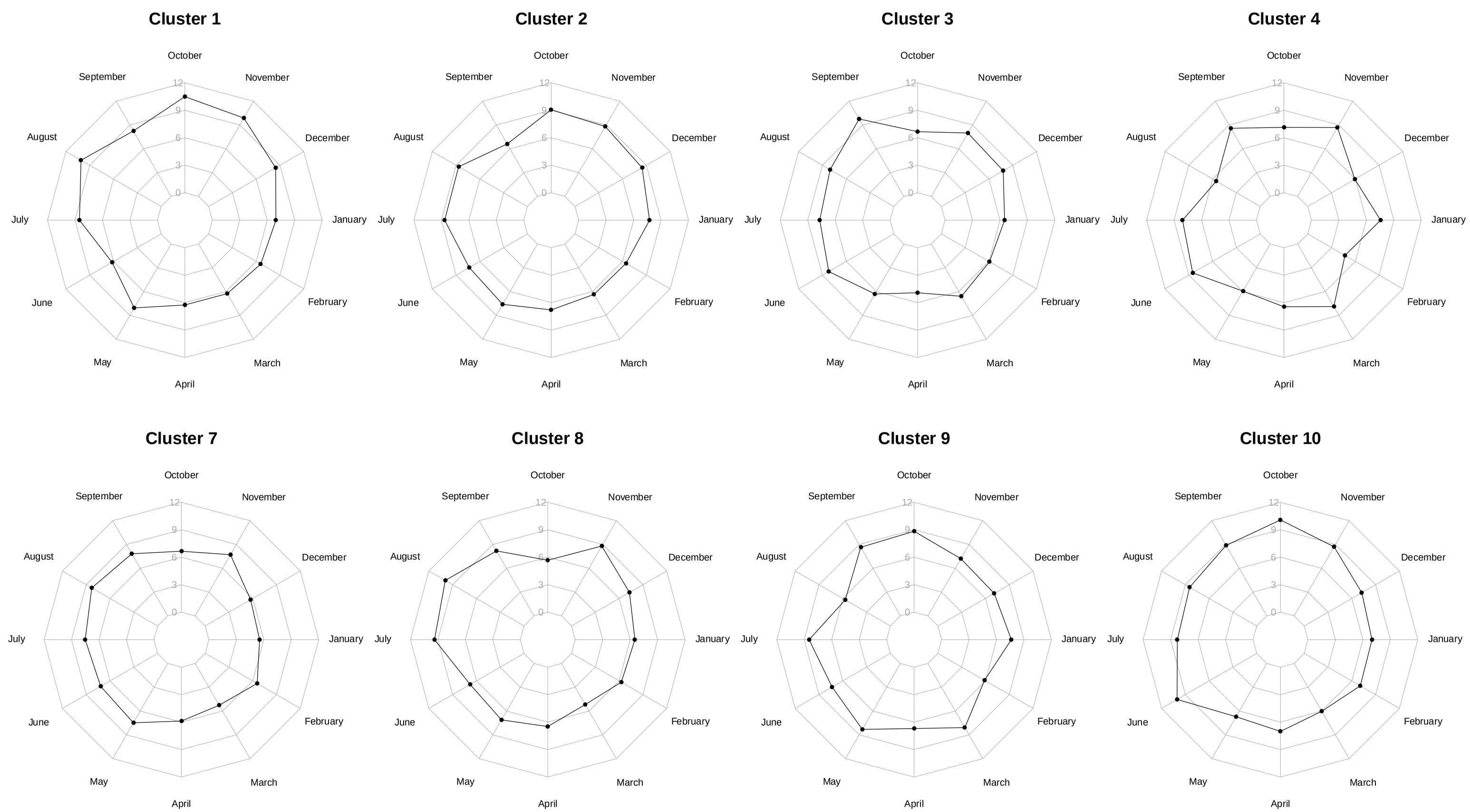
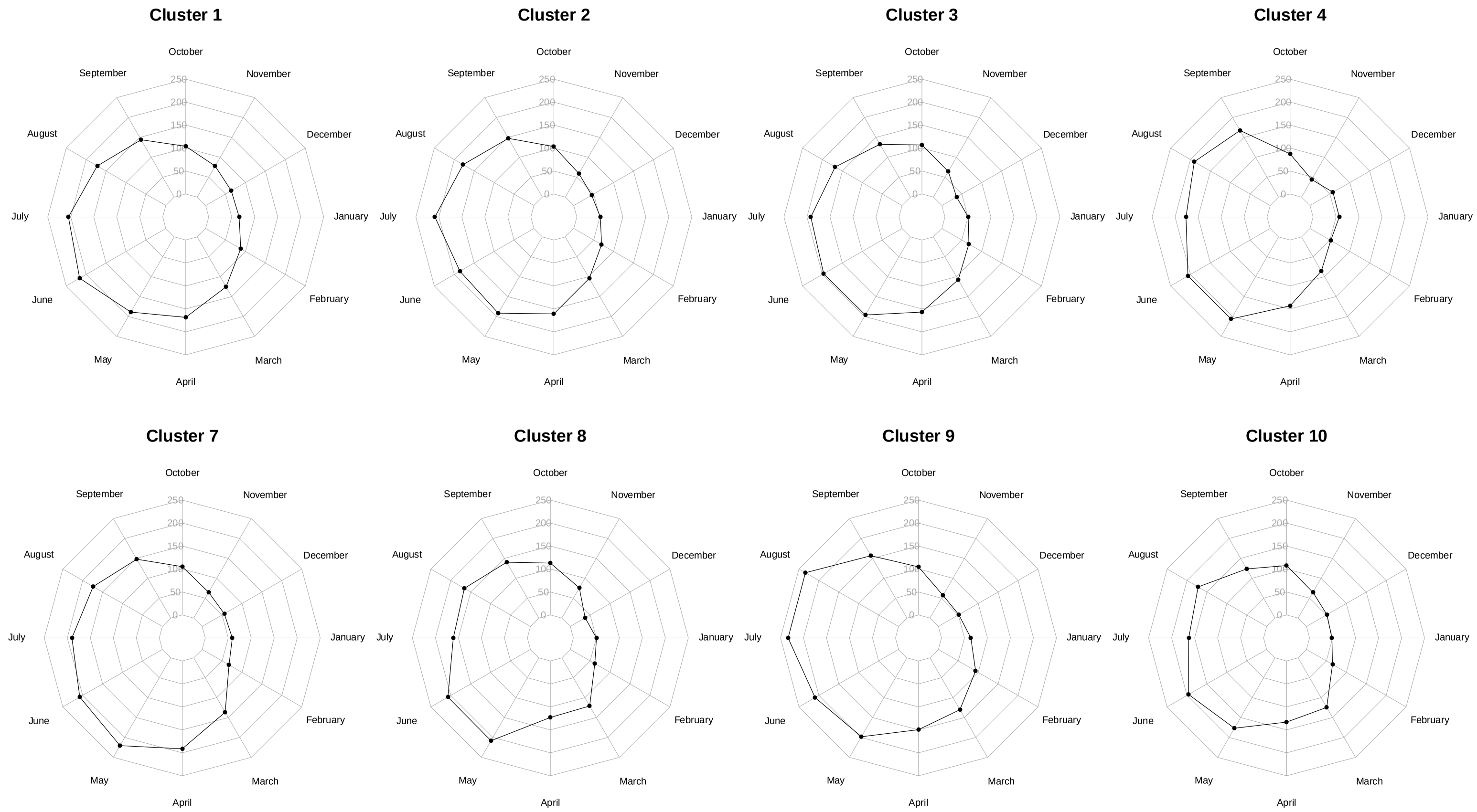


Figure 3.7: A representation of mean total sunlight (hours) over each month, within a harvest season (October to September), for each cluster. The standard deviation for each cluster is available in Appendix A.5.



3.4.3 Comparison of yields between weather clusters and yields

From our clustered years, Rothamsted LTE data was clustered given the membership of years from the above analysis. Clusters 1, 2, 7, 9 and 10 were considered for this analysis due to their membership including more than six years post-1968. The wheat and spring barley FYM plots were the highest yielding plots across all clusters (Figures 3.8 and 3.9). Yields from years within Cluster 2 from the FYM treatment had the highest wheat total biomass of 11.57 t ha^{-1} (Figure 3.8). Cluster 7 treatment FYM was the highest mean total biomass of spring barley of 9.67 t ha^{-1} (Figure 3.9). All treatments of wheat and spring barley (except the Nil treatment of spring barley for Cluster 1 compared to Cluster 7) had a lower average yield in Cluster 1 compared to clusters 2, 7, 9 and 10. Years within Cluster 2 had the highest average total biomass of wheat across all treatment groups. The lowest mean total biomass of herbage yield was the Nil treatment from years within Cluster 9 of 2.44 t ha^{-1}. Cluster 10 treatment PKNaMg had the greatest mean total biomass of herbage of 7.41 t ha^{-1}. Years within Cluster 10 had the largest mean herbage yield, across all treatments, compared to Clusters 1, 2, 7 and 9.

From the cluster summary given in Table 3.2 and mean effect on yield from each cluster, discussed above, the above cluster and yield summaries suggest a hot and wet climate (Cluster 1) was not beneficial to the growth of wheat or spring barley. In comparison, a cooler climate (Clusters 2 and 10) showed a greater yield across both wheat and spring barley. Cluster 7, although it had a warmer March to June similar to Cluster 1 but experienced less rainfall, had a greater yield compared to Cluster 1 across all treatments for both wheat and spring barley. Similar to Cluster 7, years within Cluster 9 had a warmer late-summer to harvest and dry July, August period and had a greater yield in all treatments of wheat compared to Cluster 1, which was generally wetter throughout the harvest season. In comparison to Clusters 2 and 10, Clusters 7 and 9 had a lower average cluster yield for treatments 48 kg N ha^{-1} + PKNaMg and 96 kg N ha^{-1} + PKNaMg. Therefore, a combination of increases in temperatures and the extremes of rainfall may contribute a loss in yield. The response of herbage to climate was different compared to cereals. For example, across all fertilisers, warm dry clusters (Cluster 7 and 9) were the lowest yielding (Table 3.10) (except from the Cluster 1, FYM treatment). However, in high fertiliser plots, years which had both high temperature and rainfall saw a loss in herbage yield. It may be suggested a general absence of rainfall may be the major contributor to herbage loss, followed by temperature.

We have considered the mean yield of each experiment and cluster. However, wheat yields from Broadbalk had the greatest variance across all clusters (2.17) compared to spring barley yields from Hoosfield (1.60) and herbage yields from Park Grass (1.02). Yields from Cluster 10 had the greatest variance for wheat (5.12) and the lowest for spring barley (1.16) and herbage (0.77). Cluster 2 had the highest yield variance for spring barley (2.02) and herbage (1.46) (wheat 1.41).

The ANOVA table for the LMM was given in Table 3.3 and the model coefficients are given in Table A.12 within the Appendix. The main effect of Cluster was highly significant (F(4, 552, 37.74), $P < 0.001$), therefore there was an overall significant difference in the impact of Cluster averaging over all three experiments. This can be observed in the estimated β_1 coefficients of the model, where Cluster 1 was fitted as the baseline and all other Cluster estimated effects are positive (Table A.12). The Experiment main effect and the Experiment and Treatment interaction were not significant (F(2, 552, 1.71), $P = 0.427$, F(8, 552, 14.76), $P = 0.066$), suggesting there were no significant difference in yield from wheat, spring barley and herbage averaged across clusters and treatments and the effect of each treatment was the same on all Experiments. The main effect of Treatment was highly significant (F(4, 552, 55.58), $P < 0.001$), showing significant differences in yield between Treatments averaging over Experiment and Cluster. The interaction between Cluster and Experiment was significant (F(8, 552, 64.70), $P < 0.001$), therefore there was an overall difference in the impact of Cluster between experiments averaging over treatments. This can be observed from Figure 3.11, the total biomass of wheat and spring barley, averaged across all treatments, in Cluster 1 (years were generally warmer and wetter) were lower than those of herbage. Years within Cluster 2 (years within this Cluster were cooler) also experienced the highest wheat yield, whilst years within Cluster 7 (warm early-summer and drier) and 10 (*typical* 20$^{\text{th}}$ century climate) experienced the highest spring barley and pasture yield, respectively, compared to other clusters. The Cluster and Treatment interaction was not significant (F(16, 552, 8.30), $P = 0.938$), suggesting the impact of climate change to not be very similar amongst all treatments. The three-way interaction Cluster, Experiment and Treatment was not significant (F(32, 552, 23.58), $P = 0.855$), therefore the impact of climate on the Cluster and Experiment interaction was similar for all treatments.

Figure 3.8: Boxplots of the total biomass (t ha^{-1}) of Nil, PKNaMg, 48 kg N ha^{-1} + PKNaMg, 96 kg N ha^{-1} + PKNaMg and FYM plots of continuous wheat from the Broadbalk Experiment (1968-2016).

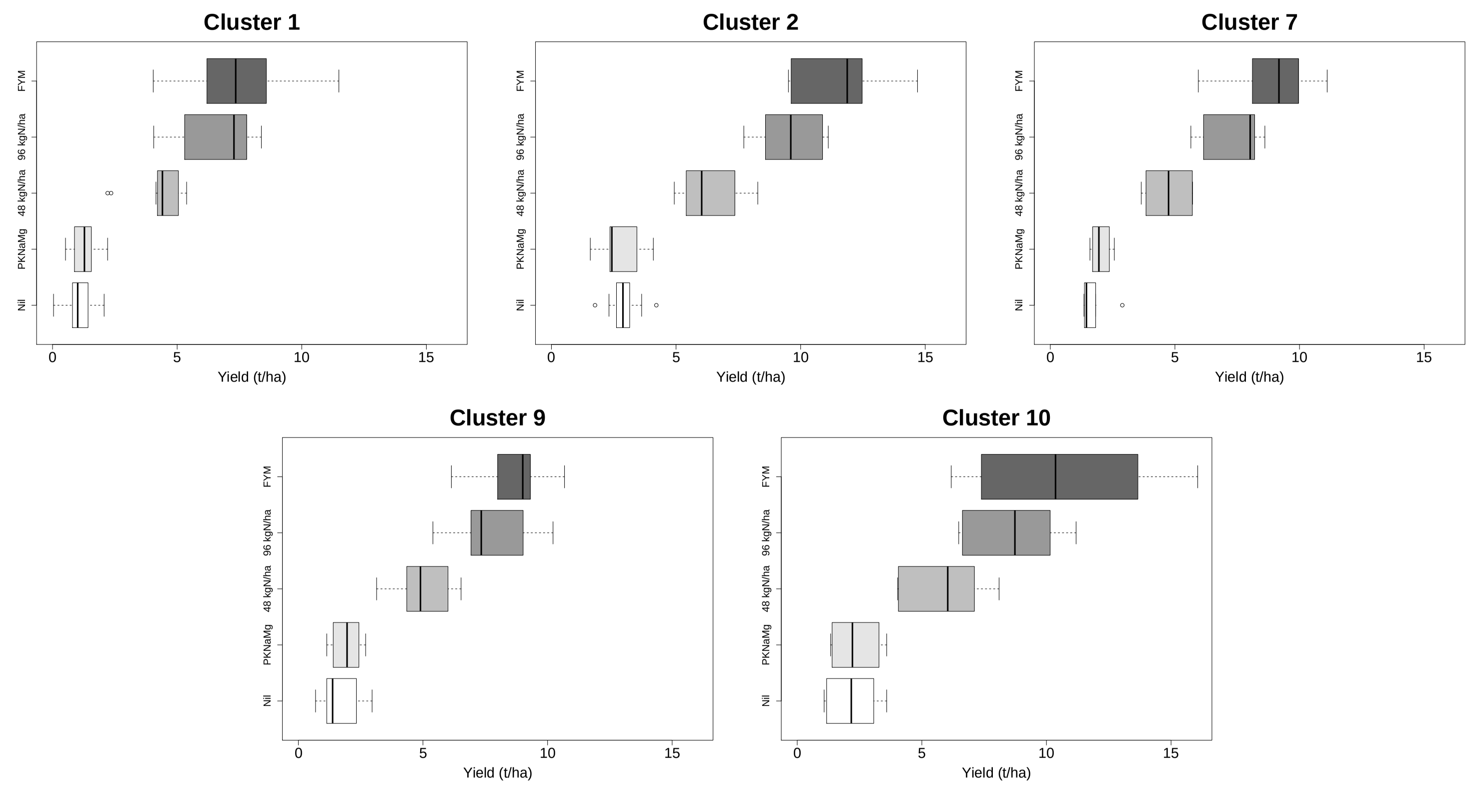


Figure 3.9: Boxplots of the total biomass (t ha^{-1}) of Nil, PKNaMg, 48 kg N ha^{-1} + PKNaMg, 96 kg N ha^{-1} + PKNaMg and FYM plots of continuous spring barley from the Hoosfield Experiment (1968-2016).

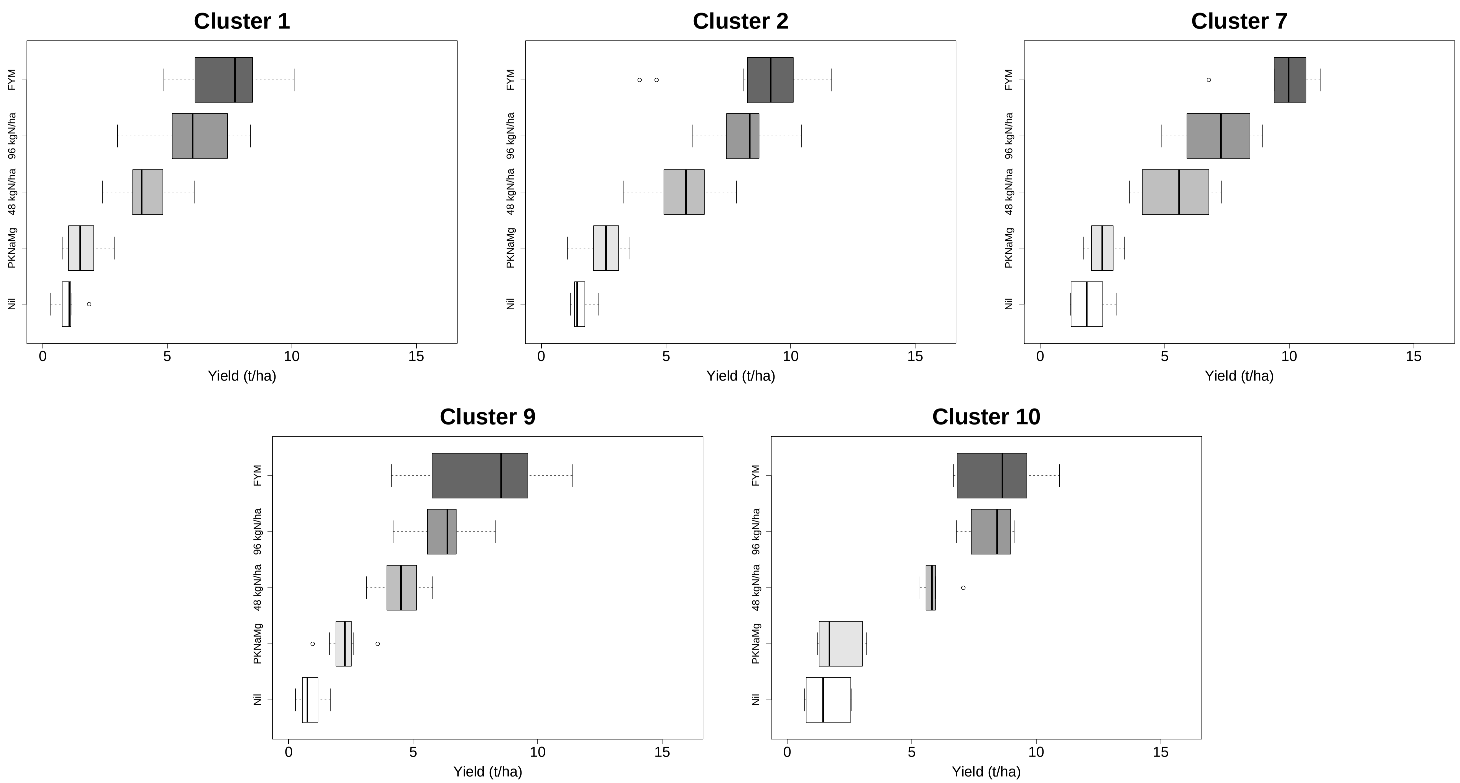


Figure 3.10: Boxplots of the total biomass (t ha^{-1}) of Nil, PKNaMg, 48 kg N ha^{-1} + PKNaMg, 96 kg N ha^{-1} + PKNaMg and FYM plots of herbage from the Park Grass Experiment section A (1968-2016).

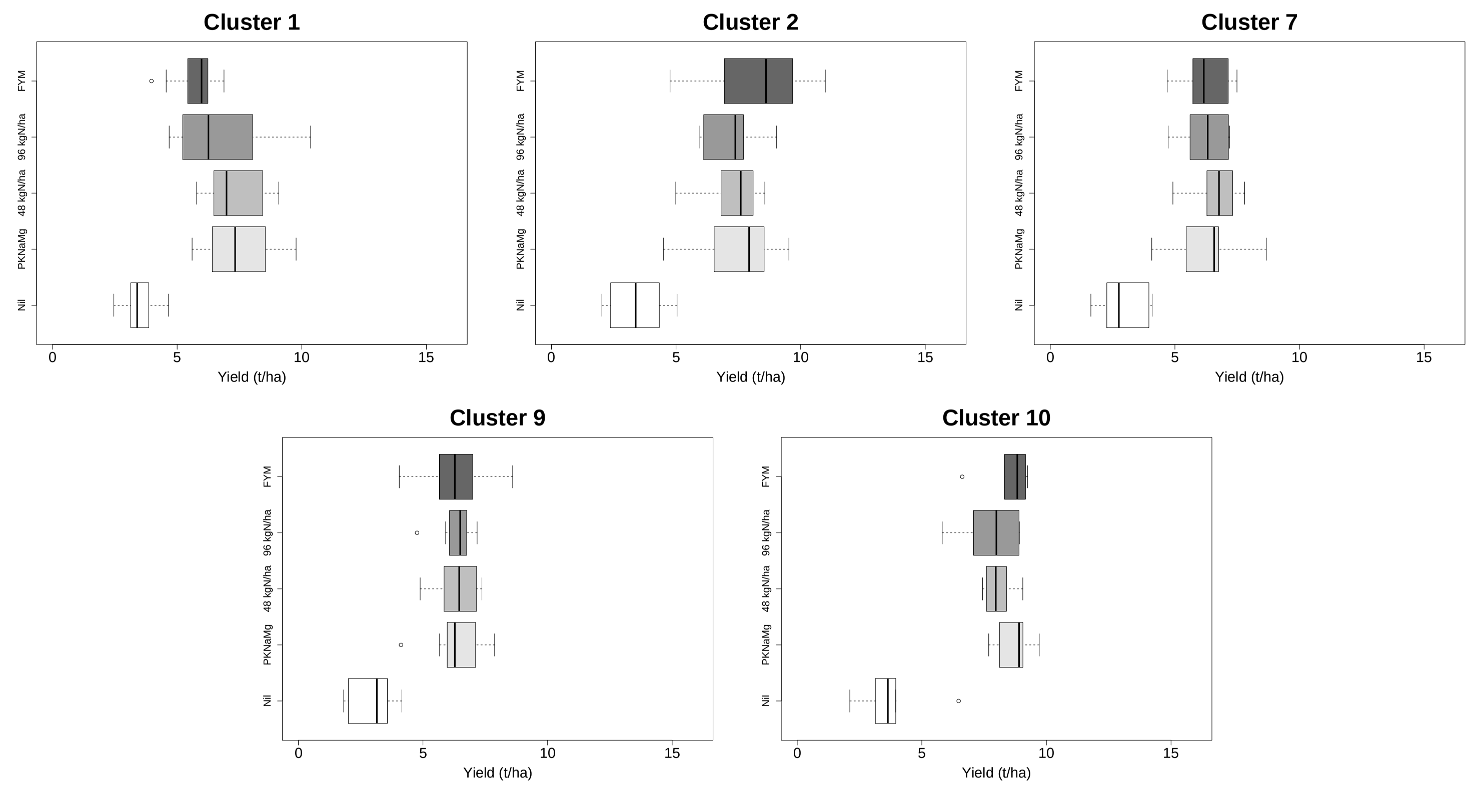
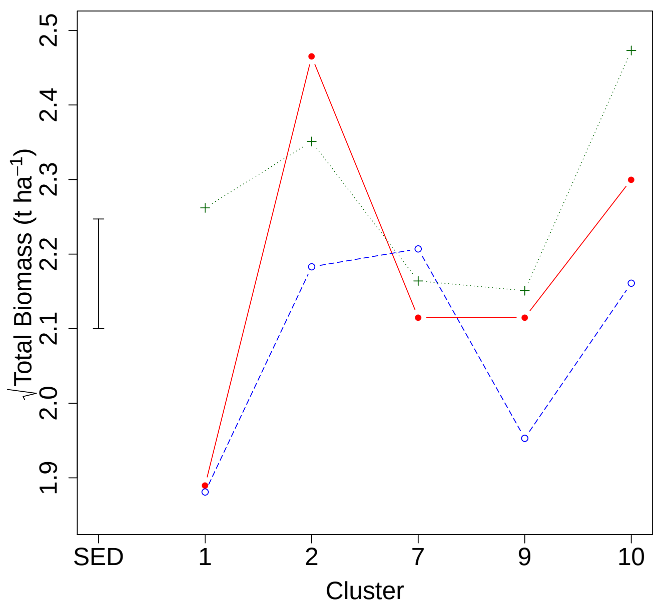


Table 3.3: Wald statistics and approximate F-statistics with estimated denominator degrees of freedom (ddf) and observed significant levels for the cluster by experiment by treatment analysis.

Term	df	Wald	F	ddf	P(F)
Cluster	4	150.98	37.74	552.0	<0.001
Experiment	2	1.71	0.85	552.0	0.427
Treatment	4	55.58	13.89	552.0	<0.001
Cluster.Experiment	8	64.70	8.09	552.0	<0.001
Cluster.Treatment	16	8.30	0.52	552.0	0.938
Experiment.Treatment	8	14.76	1.84	552.0	0.066
Cluster.Experiment.Treatment	32	23.58	0.74	552.0	0.855

Figure 3.11: Estimated standard error of the difference (SED) and cluster means, over all treatments, for wheat (red), spring barley (blue) and herbage (green) total biomass per annum.



3.5 Discussion

Hypothesis 1: Univariate analyses of the RMS data show increasing temperatures in the late-20th and early-21th century, therefore objectively classifying these changes in climate through cluster analysis showed distinct weather characteristics from other years in the 20th century.

Although years, depending on their weather, do not naturally form into clusters, this multivariate approach of objectively detecting changes in climate has led to a grouping of years, which have similar weather, in the late-20th and early-21st century. The methods of PCA and cluster analysis has also made comparisons between climates (clusters) more meaningful, rather than an average temperature being compared to a moving baseline climatology. PCA takes potentially correlated variables within a dataset and forms uncorrelated linear combinations of these variables. One issue with identifying sources of variation which potentially influence the yields of crops by statistically modelling long-term experimental data was the collinearity of explanatory variables. By constructing uncorrelated linear combinations sources of variability within the RMS data can be identified. For example, PC1, which explains most of the variability of the RMS dataset for one PC, separates out a temperature and sunlight effect, suggesting years, from 1892 to 2016, can be first separated out into warmer and cooler. This was expected in a 125-year weather time-series dataset as it has been shown elsewhere (Hartmann et al., 2013; Kendon et al., 2017; Kirtman et al., 2013; Kovats et al., 2014; NOAA, 2017) and at Rothamsted (Chapter 2) that temperatures have risen over time. A comparison of this method of analysis and those within Chapters 4, 5 and 6 is given in the General Discussion.

Due to the variability of the Rothamsted weather data (Chapter 2), objectively categorising the best number of clusters proved difficult. No distinct elbow was observed from the within-cluster-sum-of-squares as cluster number increased. A C-Index calculation was used for each cluster number along with the within-cluster sum of squares to determine a cluster number of 10.

The cluster membership of each year stated within this analysis was not definite and does not represent a fixed climate but that groups of years, which have been clustered, experienced similar weather. Cluster 1's membership was 12 out of the past 24 years with one year in the mid-20th century, where years within this cluster experienced a warmer temperature compared to other clusters. A explanation of the Euclidean distance of most years within the 21st being closer to the centroid of Cluster 1 than any other cluster is evidence of climate change (Figure 3.3). These results were similar to the univariate analysis, as the mean annual temperature between 2007 and 2016 was 1.03 above the 1961 to 1990 average (Chapter 2), and Cluster 1 had a mean daily maximum and minimum temperature of 14.04 and 6.55°C compared to 12.88 and 5.41°C from Cluster 10 (a *typical* 20th century climate). This method of analysis also shows an insight into the type of weather which Rothamsted has experienced. Since 1892, years at Rothamsted were becoming warmer (Chapter 2), but from these analyses it can be concluded there were fluctuations between years which were dry, and years which were wet, this can also be concluded in the 20st century.

From Table 3.1, the fluctuation of climate in the 21st century at Rothamsted was between Clusters 1, 7 and 9 (Cluster 2 also has one year, 2013). In comparison to Cluster 1, Clusters 7 and 9 both experience periods of higher temperatures, of early and late-summer respectively, but generally have a drier harvest season. From Table 3.1, there was also evidence to suggest the climate at Rothamsted, in the early and mid-20th century, mainly varied between a cool, to slightly warm, to cool and wet (Clusters 2, 3 and 10), although there were years of increased temperatures with wet and dry periods (Clusters 4, 7, 8 and 9).

1976 was considered a year of hot weather with a general absence of rainfall and high June and July temperatures. From our results within this Chapter, it has been shown that the climate during the 20th century varied between a warm-wet to a warm-dry climate, where 1976 was considered to be more dissimilar to other years within the 20th century.

One suggestion why 1976 was not clustered within Clusters 7 or 9 may be given by the temperatures summaries over the winter for each cluster. Generally, 1976 had a warm June and July but a relatively cool winter compared to Clusters 7 and 9. If 1976 was considered as a 21st century climate, a period increased warming, it would have been grouped within Clusters 1, 7 or 9. Therefore, due to a lack of high temperatures in the winter of the 1976 harvest season, 1976 may be considered an outlier for a 20th century climate, rather than a precursor to a 21st century climate. One explanation to why the winter temperature of the 1976 harvest season was generally cooler than years within Clusters 7 and 9 may be given by lower atmospheric CO_2 levels, where more heat could escape the atmosphere compared to years within the 21st century.

This type of analysis proposes interesting insights into capturing sources of weather variability and the type of climate Rothamsted had experienced over time. However, atmospheric CO_2 was not considered within this analysis. Several reasons for this were: the collection of atmospheric CO_2 started in 1959 (NOAA, 2018) and the reconstruction dataset (Etheridge et al., 1998) does not include monthly or seasonal values; if data was available, cumulative atmospheric CO_2 has been increasing every year since 1959, and therefore a lack of variability exists across the yearly trend-line to potentially detect how this increase in CO_2 was associated with year-to-year variations in weather. For example, year-to-year variability in warm and cool years has been observed while atmospheric CO_2 has increased, therefore, we are adding a variable to this analysis which lacks variability and would be non-informative within the clustering of years.

An optimum cluster number was difficult to detect because years do not *naturally* form into clusters and due to large variability in weather, within and between years. Also, the lack of outlier clusters within k-means cluster analysis forces potential outlier years to be within a cluster, either with others or on its own, potentially influencing the within sum of squares and C-Index calculations. However, this k-means approach to clustering years based on their weather data proved the least bias, as a hierarchical cluster analysis approach would have depended on an arbitrary cut off point. Although years have been clustered, the method of optimising cluster size and number has also been shown and therefore further methods of cluster validation, not based on within-cluster sums of squares, may be needed.

Hypothesis 2: The classification of years based on weather showed a loss in the yield of wheat, spring barley and herbage in clusters which had weather characteristics which were less suited to crop growth, such as those in in the early-21st.

The mean total biomass across all treatments, of wheat and spring barley in years within Cluster 1, was lower than those of clusters 2, 7, 9 and 10. Generally, Cluster 1 was warmer in April, May, June, July and August and experienced a drier June compared to clusters 2, 3 and 10. However, more rainfall was experienced over the total harvest season from years within Cluster

1. Between 1854 and 1967, high grain yields of Broadbalk wheat occurred in dry-warm and dry-cold years (Chmielewski & Potts, 1995). Previous analysis into the studies of crop variation at Rothamsted showed excess rainfall, for short periods in the summer, was beneficial to barley yields (Wishart & Mackenzie, 1930). Yields from years which were warm and dry (Clusters 7 and 9) had a lower wheat and spring barley yield compared to years which were cooler (Clusters 2 and 10). Yields from years which were warmer (Clusters 1, 7 and 9) may have experienced periods of heat stress. Heat stress from anthesis to crop development of wheat has been shown to result in a decline of yield (Ferris et al., 1998; Wheeler et al., 1996). Therefore, as warmer years have been more common in the 21st century, more heat stress on wheat and spring barley may have occurred.

Although heat stress may have influenced the yield from years which were warmer, the average spring barley yield for Cluster 7 (early-summer warm and dry), across all treatment groups, was higher than Cluster 9 (late-summer warm and dry) where 186.32 and 131.81 mm of summer rainfall fell on average. Cluster 1 experienced more rainfall, on average, in July and August (150.15 mm) compared to Cluster 7 (125.61 mm), with Cluster 1 having a lower estimated spring barley yield compared to Cluster 1. However, the average June rainfall from years within Cluster 1 was 37.37 mm compared to 60.71mm from Cluster 7, therefore the absence of rainfall in June, for Cluster 1, may have offset the benefits of rainfall in other months, for spring barley. Years were warm and could have experienced periods of heat stress, excess rainfall may have contributed the yields of wheat and spring barley to decline due to the potential leaching of fertilisers into the soil.

In comparison to wheat and spring barley, total biomass of herbage from years within Cluster 1 was not the lowest yielding. Therefore, suggesting herbage was less susceptible to changes in climate. A positive relationship between rainfall and biomass, along with changes in the dominance of grasses, was observed on the Park Grass Experiment (Silvertown, 1994). With the yield of herbage from the Park Grass experiment within Cluster 1 not as low as wheat and spring barley, the effects of increases in temperature may have offset by increases in rainfall and the changes of the botanical composition of the Park Grass Experiment. This was also illustrated within Figure 3.11, years which experienced warmer temperatures which were drier (Clusters 7 and 9) had a lower yield, averaged over all Park Grass treatments, compared to years which experienced warmer temperatures and were wet (Cluster 1). Herbage yields from Park Grass had a negative association with high temperatures in July and August, but had a positive association with rainfall (Sparks & Potts, 2003). From Figure 3.11, we observe Clusters 7 and 9, which were warm and dry clusters, have a lower yield compared to Cluster 1. The results from Sparks & Potts (2003) support our findings that both variations in temperature and rainfall influence the yield of Park Grass, where high temperatures are associated with lower yields.

Membership of Clusters 2 and 10 were throughout the 20th century. An average 20th century climate was shown to yield higher total biomass of wheat, spring barley and herbage compared to a late-20th and early-21st century climate. A lack of interaction between Cluster and Treatment suggests that the effects of climate change across all treatments were the same.

Given the results presented within this chapter, these analyses do not account for a cultivar effect, changes to soil organic matter or potential loss of yield due to pests. Although the total biomass of short-strawed and long-strawed cultivars have been shown to yield the same on low fertilised plots from the Broadbalk Experiment (Austin & Ford, 1989), this may not be true between short-strawed cultivars. Further, the soil organic matter of the FYM plots has been shown to vary over time for the Hoosfield Experiment (Chapter 2), evidence of the Take-all disease (Etheridge, 1969) and the problem of weed management of Black Grass (Fisher, 1921) has been observed on the Rothamsted LTEs potentially leading to other sources of variability influencing total biomass. This study also does not take into account the yield from high Nitrogen plots, as higher Nitrogen plots may have a loss of Nitrogen due to an over application nutrients (This will be discussed in Chapter 4 and the in General Discussion).

Multivariate analyses of long-term climate and total biomass data determined wheat and spring barley yields from a late-20th and early-21st century climate were lower than a 20st century climate across all treatment groups. However, this analysis does not determine the magnitude of a single weather variable. The individual influence of temperature and rainfall variables on yield using univariate methods have been documented within the literature (Chmielewski & Potts, 1995; Fisher, 1925a; Hooker 1907; Wishart & Mackenzie 1930). From this multivariate approach to identifying climate change, the conclusions of the individual effect of a weather variable cannot be made. However, conclusions over how climate has changed over multiple weather variables throughout the late-19th, 20th and early-21st centuries can. Due to the large output from this analysis making informative comparisons of the potential effect of climate change proved difficult, as sensitive stages of crop development may be confounded within a cluster. For example, stresses in crop growth due to weather in the early harvest season may be cancelled out by benefits in crop growth due to variations in weather in the late harvest season.

This study demonstrates the application of multivariate cluster analysis, not just to spatial weather data (Fovell & Fovell, 1993) but also temporal weather datasets, to objectively observe how climate has changed over multiple variables. Within this section, I have discussed the limitations of both univariate and multivariate statistical analyses in objectively defining how climate has changed. However, by acknowledging how climate has changed over multiple variables both between and within years, this study potentially shows a more informative analysis regarding the characteristics of climate change.

Generally, the membership of years for Clusters 2 and 10 (membership spans the 20th century) was less in the 21st century compared to any other time since 1892 (3.1). If these trends continue more years such as Clusters 1, 7 and 9 (generally warmer and lower yielding) would be expected throughout the 21st century with fewer years such as Clusters 2 and 10 (generally cooler and higher yielding).

3.6 Conclusion

Climate change can be identified by the application of multivariate analysis, especially cluster analysis, to long-term weather datasets. This chapter shows that there is not only an increasing trend in warmer temperatures at Rothamsted (Chapter 2, univariate analyses) but the climate in the late 20th and early 21st century was identified to be distinctly different to the rest of the 20th century (Hypothesis 1). Clusters of years within the 21st century were identified to be warmer with more extreme rainfall compared to years from the 20th century.

The response of crop yields wheat, barley and grassland to these clusters were typically the similar, with a climate typical of the 20th century providing higher yields than a climate from the 21st century (Hypothesis 2). However, the loss in yield due to increases in temperature seemed to impact the yield of cereal crops more so than the yield of grasslands. Therefore, suggesting grasslands were more resilient to changes in climate.

Chapter 4

How weather variation changes the functional response of cereals to Nitrogen using Rothamsted's Long-Term Experiment data: Broadbalk wheat

4.1 Introduction

From Chapter 3 it was concluded warm-wet and warm-dry years from the 21st century had a lower total biomass compared to cooler years of the 20th century across three Rothamsted Long-Term Experiments (wheat, spring barley and herbage). With 19% of land used for arable farming within the UK (Anon, 2016) and wheat being the third most produced worldwide crop behind rice and maize (FAOSTAT, 2018b) any loss of yield could be potentially disastrous for global food security. Although an effect of temperature on crop production was found, the magnitude of the effect of increases in temperature was not investigated within Chapter 3 due to the limitations of multivariate analysis.

It has been estimated that for every 1°C increase in mean global temperature global wheat production would fall, on average, by 6% (Asseng et al., 2015). At the time of flowering, increased temperatures reduced the potential number of grains that contribute to crop yield (Wheeler et al., 2000). The impact of increasing temperatures from anthesis to harvest maturity have been shown to reduce the winter wheat seed dry weight (Wheeler et al., 1996). It has also been suggested that grain fertilisation is sensitive to the high temperatures at the mid-anthesis stage of wheat development (Ferris et al., 1998). Vernalisation of winter wheat tends to occur most effectively at 3°C (Gooding & Davies, 1997).

The global population is expected to continue to rise throughout the 21st century with future demand for crop production expected to increase 60% by 2050 in comparison with today, with farmers required to produce more output with fewer inputs and no more land (FAO, 2017). This intensification of agriculture must be obtained with a changing global climate, 2016 saw the average global temperature rise to 1.43°C above the 20th century average (NOAA, 2017).

Other studies of crop variation on Broadbalk wheat showed maximum May and June temperatures to be negatively correlated with annual yield in the period from 1854 to 1967 (Chmielewski & Potts, 1995). Further historical analysis of crop variation on long-term yields showed rainfall during the early harvest season to be negatively associated with wheat yield (Fisher 1925a, Hooker, 1907). Historical associations between drought and high rainfall have been identified as resulting in a reduction in yield from the Long-Term Experiments (Lawes & Gilbert, 1880b; 1871). Across the Great Plains of the United States of America, inter-year variation in rainfall, but not temperature, were shown to explain significant levels of wheat yield variability (Hatfield & Dold, 2018).

Although weather variation may directly influence the crop development, other sources of variability may indirectly influence crop growth through a change in the environment. Soil water content falling outside the least limiting water range may contribute to moisture conditions which limit plant growth (da Silva & Kay, 1997). Milder springs saw weed communities become more competitive on the Broadbalk experiment (García de Leon et al., 2014). Increasing levels of atmospheric CO_2 from the mid-20th century onwards (NOAA, 2018) may also influence the heterogeneity of long-term what yields. Wheat grown with an enrichment of CO_2 saw an increase of the overall grain yield per ear (Wheeler et al., 1996). The incidence of take-all has been detected on the Broadbalk experiment, with more crops infected within the 48 kg N plus minerals plots compared to the minerals only plot (Etheridge, J., 1969), and this could also influence the heterogeneity of long-term yields.

The Broadbalk Wheat Experiment was first sown in the autumn of 1843 at Rothamsted to test the effects of mineral fertilisers (N, P, K, Na and Mg) and organic manures on wheat yields. One of the objectives of the Broadbalk experiment was to study the effects of organic and inorganic manures on continuous winter wheat (Anon, 1971) and therefore wheat's relationship with Nitrogen should be considered in future analyses. Since 1968, short-strawed wheat varieties have been sown annually with the application of 0, 48, 96, 144 and 196kg of kg N ha^{-1}, with the increased levels of 240 and 288kg N/ha included since 1985 (Chapter 2). A Linear-By-Exponential (LEXP) function has been shown adequately model the Nitrogen response to wheat (George, 1982) by four estimable parameters of a curve (Sylvester-Bradley & Murray, 1982). Studies into Nitrogen response curves show how varied a functional response curve can be depending on the year, soil type and crop (Roques et al., 2017; Sylvester-Bradley & Kindred, 2009; Vold, 1998).

4.2 Aims and Objectives

4.2.1 Aim

This study aims to investigate how inter-annual variability in weather contributes to that in wheat yield, of the Broadbalk Experiment, through the response of wheat to applied Nitrogen, allowing for differences between cultivars, from 1968 to 2016.

4.2.2 Objectives

Within this chapter I:

- Calculated Pearson's correlation values and their significance levels between yield (grain yield and total biomass) and monthly summarised total rainfall and mean temperature, from October to September, from plots 5, 6, 7, 8, 9, 15 and 16 between 1968 and 2016 (plots 15 and 16 from 1985 to 2016).

- Fitted a local Nitrogen response curve to yield (grain yield and total biomass) to all years using a LEXP function.

- Fitted a Nitrogen response curve, using a LEXP function, to yield (grain yield and total biomass) for all years and tested if there was significant year-to-year variability of the Nitrogen response to wheat.

- Built a maximal and parsimonious model for both grain yield and total biomass, including cultivar and monthly summarised weather variables, which identified key weather variables which influenced parameters of the Nitrogen response curve of the Broadbalk Experiment from 1968 to 2016.

4.2.3 Hypotheses

- Yearly variations in Broadbalk total biomass have been observed (Chapter 3). Do we observe yearly variations in the Nitrogen response to yield (grain yield and total biomass) of the Broadbalk Experiment, from 1968 to 2016.

- Do inter-annual variations in weather affect the Nitrogen yield response curve in wheat and therefore suggest optimum weather conditions, along with Nitrogen to maximise yield.

4.3 Methods

4.3.1 Long-Term Experiment Data

Data considered for this study are grain yield and total biomass (t ha^{-1} at 85% dry matter) from continuous wheat Section 1 of the Broadbalk Experiment at Nitrogen applications of 0, 48, 96, 144, 196, 240 and 288 kg N ha^{-1} plus minerals, between 1968 to 2016. Plots only received 240 and 288 kg N ha^{-1} from 1985 onwards and previous application on these plots were 144 and 96 kg N ha^{-1}, respectively. Yields from 2013 and 2015 were omitted from these analyses due to late sowing dates where spring wheat was sown. Nitrogen was applied to the experiment in April each year. Information about the different cultivars sown onto the experiment over time was used as a factor variable (Table 2.1).

4.3.2 Rothamsted Weather Data

Daily mean temperature ((maximum daily temperature + minimum daily temperature)/2, °C) and daily rainfall (> 1 mm) data from the Rothamsted Meteorological Station were summarised monthly for each harvest season, where a harvest season was defined as October to September. Mean daily temperature was chosen as an explanatory variate and not daily maximum and minimum temperatures. This was because daily maximum and minimum temperatures are both collinear.

4.3.3 Statistical Analyses

A linear-plus-exponential (LEXP) function (George, 1982) was used to fit a Nitrogen (N) response curve to yield (t at 85% dry matter ha^{-1}) (y):

$$y = a + br^N + cN \tag{4.1}$$

where a, b, c and r define the upper yield asymptote (a), magnitude of the yield response to increased Nitrogen above 0 kg N ha^{-1} (b), the rate of yield loss due to over application of Nitrogen (c) and the curvature of the response. The effects of a varying c parameter on the Nitrogen response curve, which explains the potential loss of yield due to an over application of N, was previously investigated by Sylvester-Bradley & Murray (1982). Common modelling functions including linear-plateau relationships, quadratics and exponentials have been examined in the literature and tend to produce a poor fit beyond optimum Nitrogen application (Cerrato & Blackmer, 1990). Inverse polynomial functions have been shown to provide adequate fits for Nitrogen dose responses (Nelder, 1966). However, a LEXP relationship was preferred as it allows the response function to be modelled using fewer parameters and allows for a more comparable biological interpretation over parameters a, b and c.

Pearson's correlation coefficients and significance levels (α <0.05) between yield (grain yield and total biomass) and monthly weather variables were derived for each Nitrogen dose (0, 48, 96, 144, 192, 240 and 288) from 1968 to 2016. This was achieved to determine if some of the within-year variation in yield could be associated with within-year variations in weather.

A backwards elimination stepwise procedure was used to determine if there was within-year variation in the shape of the Nitrogen response (Equation 6.1). This resulted in monthly summarised mean temperatures (°C), total rainfall (mm) and variety becoming added to Equation 6.1 to form a maximal model

$$y_{f(W+V)} = a_{f(W+V)} + b_{f(W+V)}r^N + c_{f(W+V)}N \tag{4.2}$$

where $f(W + V)$ is a function of weather (W) and variety (V).

Below is a step-by-step model description of the analysis achieved within this chapter. This procedure was achieved for a grain yield and total biomass model. It should be noted steps 1, 2 and 3 are steps when fitting standard exponential curves in Genstat® (VSN International, 2017).

1. A local Nitrogen response curve (Equation 4.1) was fitted to yields (grain yield and total biomass) for all years from 1968 to 2016.

2. By using year as a factor variable, an individual LEXP curve was fitted to each year, allowing for parameters a, b, c and r to vary.

3. The non-linear term r was fixed across all years and estimated by the Gauss-Newton method. Once r was fixed, a partial F-test was conducted to determine if allowing r to vary explained significant amounts of variability.

4. Correlations between yields (grain yield and total biomass) and monthly weather summaries were calculated for all Nitrogen doses (0, 48, 96, 144, 192, 240 and 288) from 1968 to 2016. Monthly weather summaries included total rainfall and mean daily mean temperature.

5. Once r was shown to explain insufficient amounts of model variability, a maximal model (equation 4.2) was fitted to yields (grain yield and total biomass) including explanatory variables cultivar, total rainfall and mean temperature ($f(W + V)$). Those weather variables with the highest mean absolute correlation across all Nitrogen doses were ranked

into the model first. Because the non-linear parameter r was shown to explain insufficient amounts of model variability, the model selection procedure becomes a multiple regression model selection problem.

6. After terms were included some weather variables were omitted if they had a high correlation ($\rho >\mid 0.3 \mid$) due to collinearity of explanatory variables. The rejection level ($\rho >\mid 0.3 \mid$) was selected because the correlation values between yield and weather variables were low - this was expected and more explanation of this will be in use of statistical methods within the General Discussion.

7. The relationship between yield and a weather variable was investigated. If the relationship was considered non-linear, it was fitted as a quadratic. Typically, this was a quadratic with a negative squared term resulting in a maximum.

8. $f(W + V)$ does not include an interaction between cultivar and weather or between weather variables themselves. A reason for the exclusion of a cultivar and weather interaction was because of a lack of range over the explanatory variable. For example, a separate interaction term for cultivar may be confounded if the years a particular variety was sown were few and/or had a small range of monthly rainfall or temperature. Combinations of weather variables were not considered for several reasons. First, due to a lack of biological meaning these comparisons would have made, for example understanding the magnitude effect of October temperature for variations in June rainfall. Second, combinations of total rainfall and mean temperature from the same month could result in a potential confounding as their main effect may lack independence.

9. From a maximal model, variable selection methods were used to achieve a reduced model. Omitting variables from the model one-by-one until convergence. The Akaike Information Criterion (AIC) (Akaike, 1971) was used to omit these terms. For each iteration the AIC becomes smaller until convergence occurs, meaning the AIC does not reduce for every additional variable omitted.

10. After the AIC selection procedure, a further model selection process, using partial F-tests, was used to test whether model parameters within the reduced model explained signifi-

cant amounts of model variability (significance level $\rho < 0.05$) and therefore a parsimonious model. If, after the omission of a term, an explanatory variable was nonsignificant (compared to a model including that term) it was concluded that variable did not explain significant model variability and was omitted.

11. After a parsimonious model was found, a final step of model validation was achieved to assess if the model was adequate. This involved a residual vs fitted, a Q-Q and a scale-location plot with a histogram of the residuals, these figures are considered non-essential to the overall conclusions of our results and are given in the Appendix.

After the first iteration of this procedure, it was found the residuals of the model lacked constant variance of the residuals. Residuals at the highest yielding plots were more variable than the lowest yielding plots. To deal with this lack of constant variance a square root transform of the yield data was used and the model procedure stated above (steps 1 to 11) was repeated. Therefore, all model parameters stated within the results are on the square-root scale. All predictions from the model on figures with the yield scale were transformed back to the yield scale. As the response was transformed and higher yielding plots were more variable than lower yielding plots we sacrifice potential variables explaining the loss at high Nitrogen doses (parameter c) for model adequacy.

It should be noted here that this model selection procedure was similar to that from Chapters 5 and 6. There were however, subtle differences such as the modelling of a response and the modelling of a response over multiple mineral fertilisers.

4.4 Results

4.4.1 Common Nitrogen Response

The average variance of grain yield across years for Nitrogen treatments lower than 144 kg N ha^{-1}, between 1985 and 2016, was 0.56 t ha^{-1}, for applications above 144 kg N ha^{-1} the average variance was 1.58 t ha^{-1}. In comparison, the average variances of total biomass for Nitrogen treatments lower than 144 kg N ha^{-1} and greater than 144 kg N ha^{-1} were 1.46 and 5.43 t ha^{-1}, respectively. Therefore, there was more variability in yields from higher inputs. The common

Nitrogen response curve for grain yield (Figure 4.1 (a)) and total biomass (Figure 4.2 (a)) fitted to data for all years shows an asymptotic exponential relationship, with small evidence of a decline an optimum Nitrogen input. Although yields from higher Nitrogen doses are more variable, the LEXP function provides an adequate fit to data from all years.

4.4.2 Yearly Fitted Nitrogen Response

Fitting individual curves to each year, fixing the non-linear component, to both grain yield and total biomass (Figure 4.1 (b), Figure 4.2 (b)), provided the best fit to the data compared to the common fit (GY: F(9.69, 138, 153), P < 0.001, TB: F(15.35, 138, 152), P < 0.001). Allowing r to vary with each year explained the same model variation compared to fixing r for each year (GY: F(0.392, 46, 107), P $= 0.999$, TB: F(0.580, 46, 106), P $= 0.980$). The estimate of r between all treatments was 0.988 and 0.986 for grain yield and total biomass. Further analysis was conducted with the non-linear component fixed, this step refers to modelling step 3 from the methods. Grain yields from 1985 had the highest estimated asymptote relationship between Nitrogen and yield with an estimated a and b parameters of 3.60 and -2.37. The total biomass from 1981 had the highest asymptotic relationship with Nitrogen of 4.15. 1968 and 2002 both had shallow Nitrogen response curves for grain yield with estimated a and b parameters of 1.91 and 1.51 and -0.89 and -0.86, respectively. Years 2002 and 2007 had the lowest estimated a parameters of 1.88 and 1.88, respectively, along with b parameters with values of -1.15 and -0.7738. The Nitrogen response for total biomass for 2002 was the most linear compared to all other years. 1973 has the smallest estimated c parameter of -0.0039, this suggests this year had a high potential of loss due to an over application of Nitrogen. The year with the smallest c parameter for total biomass was 1981 with an estimate of -0.0037.

Figure 4.1: Common fitted LEXP (Equation 4.1) of grain yield and total biomass in response to applied Nitrogen from 1968 to 2016. Coefficients (S.E.) of grain yield LEXP: $a = 2.402(0.225)$, $b = -1.261(0.222)$, $c = 0.00085(0.0008)$ and $r = 0.985(0.003)$. Coefficients (S.E.) of total biomass LEXP: $a = 3.229(0.388)$, $b = -1.809(0.382)$, $c = 0.00014(0.0013)$ and $r = 0.986(0.003)$. All coefficients were estimated on the square-root scale, the fitted LEXP (red) function was back transformed to the yield scale.

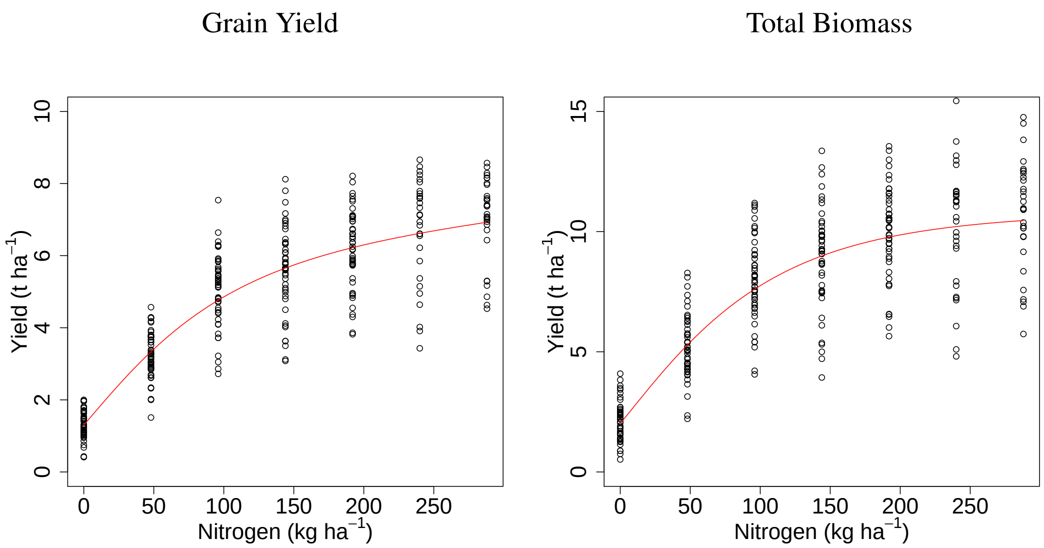
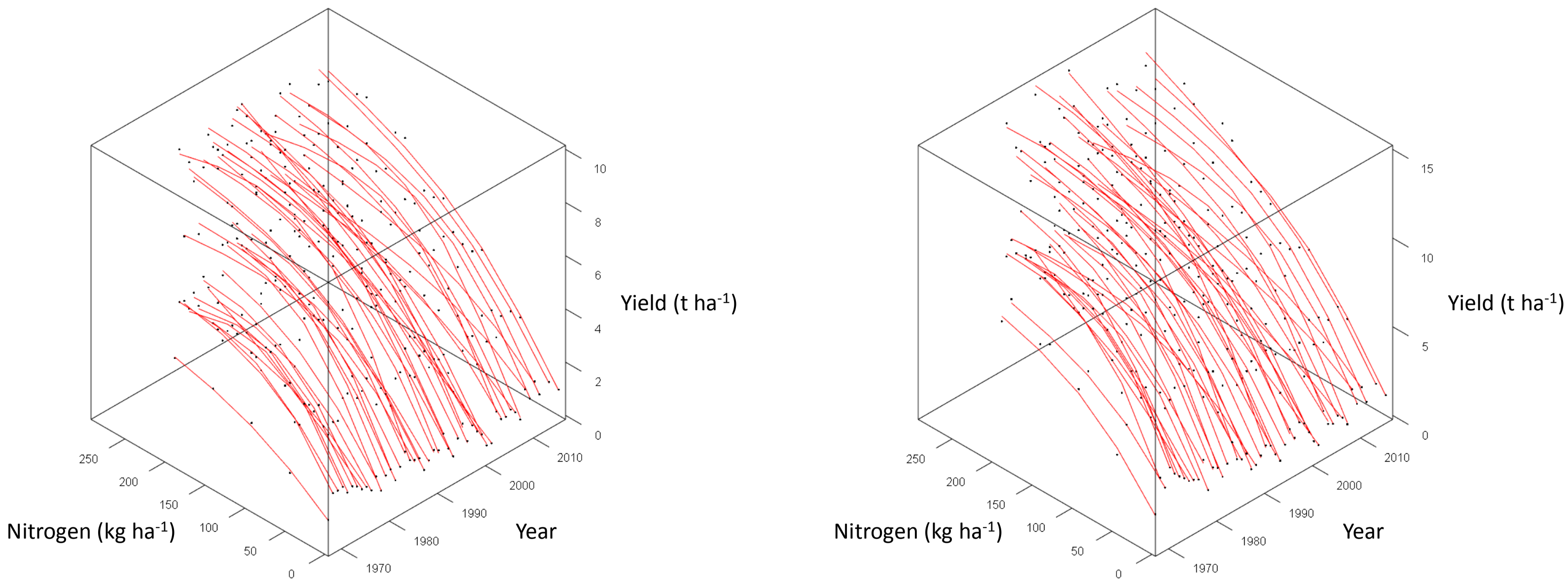


Figure 4.2: Fitted LEXP to grain yield and total biomass data for each year between 1968 and 2016 with $r = 0.988(0.0009)$ (grain yield) and $r = 0.986(0.0014)$ (total biomass), allowing parameters a, b and c to vary. All coefficients were estimated on the square-root scale, the fitted LEXP (red) function was back transformed to the yield scale.

Grain Yield　　　　Total Biomass



4.4.3 Yield and Weather Correlations

Tables 4.1 and 4.3 show the correlation between grain yield and total rainfall and mean temperature at Nitrogen levels 0, 48, 96, 144, 192, 244 and 288 kg N ha^{-1}. Total biomass correlations were provided within Tables 4.2 and 4.4. Correlations between mean May and June temperature with grain yield and total biomass were negative across all Nitrogen dose levels. Mean April temperatures had a significant negative correlation with total biomass at Nitrogen levels 48, 96 and 144 kg N ha^{-1}. For grain yield and total biomass, high Nitrogen doses of 240 and 288 kg N ha^{-1} did not have a significant correlation with any weather variables. There was a negative correlation between mean January temperature with both grain yield and total biomass.

The correlation between total July rainfall and yield for both grain yield and total biomass was negative across all Nitrogen levels. Grain yields from Nitrogen treatments 0, 48 and 96 kg N ha^{-1} (Table 4.1) and total biomass from treatments 0 kg N ha^{-1} (Table 4.2) had a significant negative correlation with total October rainfall. All treatments had a negative correlation between grain yield and total October rainfall. It should be noted here that the correlations between yield (grain yield and total biomass) and weather variables presented within Tables 4.3, 4.4, 4.1 and 4.2 are associations with yield and have a relatively low correlation. An explanation of this low correlation will be given within the General Discussion.

Table 4.1: Pearson's correlation coefficient between grain yield and total monthly rainfall at different Nitrogen response levels (values in *Italic* have $P < 0.05$). The degrees of freedom for treatments 0, 48, 96, 144 and 192 kg N ha^{-1} was 45. The degrees of freedom for treatments 240 and 288 kg N ha^{-1} was 28. Corresponding P-values are provided within the Appendix.

Treatment	October	November	December	January	February	March	April	May	June	July	August	September
0 kg N ha^{-1}	*-0.4846*	-0.0207	-0.0835	-0.0552	-0.1455	-0.1392	-0.2319	-0.1360	0.0732	-0.2726	-0.2042	-0.0356
48 kg N ha^{-1}	*-0.3641*	0.0640	0.1013	-0.0438	-0.2072	0.1559	-0.1179	0.0371	0.0765	-0.2761	-0.0957	-0.0551
96 kg N ha^{-1}	*-0.3437*	-0.0925	0.1793	-0.1514	-0.2245	0.0338	-0.1271	-0.0339	0.1583	-0.1932	-0.1107	-0.2083
144 kg N ha^{-1}	-0.2254	-0.1267	0.2337	-0.0637	-0.1217	0.0211	-0.0560	-0.0276	0.1537	-0.1329	-0.1129	-0.1035
192 kg N ha^{-1}	-0.0659	-0.0943	0.1430	0.0155	-0.0561	0.1049	-0.0426	0.0792	0.0933	-0.0527	0.0029	-0.1016
240 kg N ha^{-1}	-0.0913	-0.1842	0.0509	-0.0456	-0.1299	-0.2442	-0.0730	-0.1948	0.2158	-0.2215	-0.1342	0.1910
288 kg N ha^{-1}	-0.0678	-0.0188	-0.0505	-0.0711	-0.2007	-0.1889	-0.0386	0.0448	0.2283	-0.0702	-0.0511	0.2907

Table 4.2: Pearson's correlation coefficient between total biomass and summarised monthly rainfall at different Nitrogen response levels (values in *Italic* have $P < 0.05$). The degrees of freedom for treatments 0, 48, 96 and 192 kg N ha^{-1} was 45. The degrees of freedom for treatment 144 kg N ha^{-1} was 44. The degrees of freedom for treatments 240 and 288 kg N ha^{-1} was 28. Corresponding P-values are provided within the Appendix.

Treatment	October	November	December	January	February	March	April	May	June	July	August	September
0 kg N ha^{-1}	*-0.3459*	0.0556	-0.0967	-0.0033	-0.0893	-0.0084	-0.2207	-0.1166	0.1387	-0.2854	-0.2185	-0.0498
48 kg N ha^{-1}	-0.1529	0.1097	0.0165	0.0222	-0.1762	0.2148	-0.0566	0.0263	0.1621	-0.2382	-0.0762	-0.0112
96 kg N ha^{-1}	-0.2144	-0.0709	0.0920	-0.0873	-0.2212	0.1172	-0.0563	0.0079	0.1667	-0.1995	-0.2220	-0.0633
144 kg N ha^{-1}	-0.1625	-0.0996	0.1303	-0.0473	-0.1376	0.0928	-0.0045	0.0028	0.1789	-0.1308	-0.2103	0.0068
192 kg N ha^{-1}	-0.0239	-0.0812	0.0547	0.0599	-0.1148	0.1907	0.0009	0.0749	0.1338	-0.0986	-0.1658	-0.0013
240 kg N ha^{-1}	-0.0314	-0.2020	0.0716	0.0388	-0.1602	-0.1358	0.0305	-0.1751	0.2789	-0.1026	-0.1381	0.2182
288 kg N ha^{-1}	0.0169	-0.0614	-0.0479	-0.0158	-0.2301	-0.0715	0.0571	-0.0009	0.2919	-0.0002	-0.0312	0.3054

Table 4.3: Pearson's correlation coefficient between grain yield and mean monthly temperature at different Nitrogen response levels (values in *Italic* have $P < 0.05$). The degrees of freedom for treatments 0, 48, 96 and 192 kg N ha^{-1} was 45. The degrees of freedom for treatments 240 and 288 kg N ha^{-1} was 28. Corresponding P-values are provided within the Appendix.

Treatment	October	November	December	January	February	March	April	May	June	July	August	September
0 kg N ha^{-1}	-0.0205	-0.1292	-0.1865	-0.1352	-0.2740	*-0.3618*	-0.1245	-0.1987	-0.1234	-0.1452	-0.1454	-0.0874
48 kg N ha^{-1}	-0.1193	0.1922	-0.0553	-0.2546	-0.2394	-0.2570	-0.2041	-0.1813	-0.2444	-0.0308	-0.0754	-0.1531
96 kg N ha^{-1}	0.0397	0.1456	-0.0963	*-0.3547*	*-0.3057*	-0.1327	-0.1705	-0.2419	-0.2350	0.0339	-0.0427	-0.0085
144 kg N ha^{-1}	0.0509	0.2036	0.0076	-0.2875	-0.2288	-0.0651	-0.1999	*-0.2945*	-0.2281	0.0394	0.0579	-0.0740
192 kg N ha^{-1}	0.1646	*0.3368*	0.0773	-0.0744	0.0495	0.0326	0.0405	-0.0691	-0.0931	0.0900	0.0929	0.2317
240 kg N ha^{-1}	0.0435	-0.0417	-0.0431	-0.1651	-0.1585	0.0565	-0.2355	-0.2209	-0.2366	0.2180	0.0343	0.0088
288 kg N ha^{-1}	0.1256	0.1780	-0.1747	-0.0562	0.0643	0.0050	-0.0202	-0.2184	-0.1679	0.0786	0.0750	0.1263

Table 4.4: Pearson's correlation coefficient between total biomass and summarised monthly temperature at different Nitrogen response levels (values in *Italic* have $P < 0.05$). The degrees of freedom for treatments 0, 48, 96 and 192 kg N ha^{-1} was 45. The degrees of freedom for treatment 144 kg N ha^{-1} was 44. The degrees of freedom for treatments 240 and 288 kg N ha^{-1} was 28. Corresponding P-values are provided within the Appendix.

Treatment	October	November	December	January	February	March	April	May	June	July	August	September
0 kg N ha^{-1}	-0.0589	-0.2423	-0.1655	-0.2081	*-0.2987*	*-0.4096*	-0.2780	*-0.3193*	*-0.3255*	-0.2416	-0.1883	-0.1607
48 kg N ha^{-1}	-0.1744	-0.0124	-0.0913	-0.2839	*-0.3320*	*-0.3107*	*-0.3759*	*-0.3198*	*-0.4994*	-0.1589	-0.2118	-0.2383
96 kg N ha^{-1}	-0.0336	-0.0118	-0.1216	*-0.3180*	*-0.4158*	-0.2433	*-0.3771*	*-0.3969*	*-0.4525*	-0.0598	-0.1346	-0.1462
144 kg N ha^{-1}	0.0022	0.0514	-0.0366	*-0.2957*	*-0.3464*	-0.1845	*-0.4105*	*-0.4675*	*-0.4567*	-0.0525	-0.0654	-0.2225
192 kg N ha^{-1}	0.0726	0.1619	0.0496	-0.1259	-0.1578	-0.1695	-0.2303	*-0.3378*	*-0.3842*	-0.0266	-0.0689	0.0100
240 kg N ha^{-1}	0.0760	0.0528	0.0472	-0.1997	-0.2458	-0.0158	-0.2852	-0.2832	-0.3386	0.1270	-0.0164	0.0455
288 kg N ha^{-1}	0.1181	0.1955	-0.0546	-0.1419	-0.0727	-0.0666	-0.1129	-0.2660	-0.2813	0.0073	-0.0227	0.1694

4.4.4 Weather Fitted Nitrogen Response

Fixing the non-linear parameter of the LEXP function (Figure 4.1) for all years reduced the model selection procedure of Equation 6.2 to a stepwise multiple linear regression problem. This was step 5 of the statistical analyses.

Grain Yield

There was no significant difference between the amount of variability explained by the maximal (Equation 6.2) and the parsimonious model (Table 4.5) for grain yield (F(1.42, 40, 272), P $=$ 0.057). All weather terms within the maximal model included total October rainfall, mean May temperature, total July rainfall, mean November temperature, total February rainfall, mean April temperature, total June rainfall, total December rainfall, total August rainfall, total November rainfall, total May rainfall, mean December temperature and total January rainfall, all ranked within this order. The weather terms absent from the maximal model but were included within the correlations were absent due to their high collinearity. The AIC for the maximal model was -977.79 compared to -1017.14 from the parsimonious model, along with the partial F-test, the parsimonious model stated within Table 4.5 provides a desired level of explanation with as few predictor variables as possible.

Variety was a significant term within the parsimonious model and influenced the asymptote (a) and the rate of yield loss due to over application (c). Cappelle desprez had the largest estimated a parameter of all varieties of 0.15 bigger than Hereward. However, Cappelle desprez had the lowest estimated c parameter of all varieties of -2.25×10^{-3} lower than Hereward. Crusoe had the highest estimated c parameter of 0.93×10^{-3} greater than Hereward.

The relationship between grain yield and mean November temperature followed a quadratic relationship, with an estimated negative quadratic term, and was shown to influence the a parameter of the LEXP (Figure 4.3 (a)). mean November temperature was not shown to influence the b or c parameters. Therefore, the relationship between yield and mean November temperature was the same across all Nitrogen treatments, suggesting for optimum grain yield mean November temperatures should be between 6 and 7°C. Mean April temperature was also fitted into the model with a negative quadratic term and influenced the a and b parameters of the

LEXP function. Therefore, the relationship between yield and mean April temperature was not the same across all Nitrogen doses. The negative quadratic term for mean April temperature within the parsimonious model suggests an optimum April temperature between 8 and 8.5°C to maximise grain yield (Figure 4.3 (b)). Higher temperatures in May and more rainfall in October and February were shown to negatively influence the a parameter within the parsimonious model and lead to a reduction in grain yield (Table 4.5). A drier June was shown to have a lower asymptote of the Nitrogen response curve and therefore a smaller grain yield (Table 4.5).

Total Biomass

Similar to the grain yield parsimonious model, there was no significant difference between the amount of variability explained by the maximal model (Equation 6.2) and the parsimonious model (Table 4.6) for total biomass (F(1.41, 40, 268), P $= 0.062$). Weather variables included within the total biomass parsimonious model include mean June temperature, mean April temperature, mean January temperature, total February rainfall, total August rainfall, total July rainfall, total October rainfall, mean November temperature, total November rainfall, mean December temperature and total May rainfall. All these terms within the maximal model influenced the a, b and c parameters of the LEXP function. Explanatory variables omitted from the maximal model had a high collinearity with other terms within the model. The AIC of the maximal total biomass model was -862.20 compared to -897.31 of the parsimonious model.

Variety was a significant term within the model, influencing the asymptote (a) and the rate of yield loss due to over application (c). Crusoe had the highest estimated a and c parameter for total biomass of 0.42 and 1.46×10^{-3} greater relative to Hereward, respectively. Hereward had the lowest estimated a parameter. Cappelle desprez had the lowest estimated c parameter of -2.39×10^{-3} lower than Hereward.

The relationship between mean December temperature and total biomass followed a quadratic relationship, with a maximum between 2 and 3°C, was shown to influence the a parameter of the LEXP function (Figure 4.4 (a)). Mean April temperature was fitted to the parsimonious model by a quadratic relationship with total biomass and influenced both the a and b parameters (Table 4.6, Figure 4.4 (b) (b)). Therefore, the effect of April temperature varied across Nitrogen levels. The quadratic relationship had an estimated negative second term, therefore an optimum mean April temperature of around 7.5 to 8.5 °C maximised yield. Mean June temperature was modelled with a negative linear relationship and influenced the a and c parameter within the model (Table 4.6, Figure 4.4 (c)). This suggests the effect of high June temperatures was not the same across treatments. Treatments with a higher dose of Nitrogen had a greater loss of yield in years with a warmer June. More rainfall in February, July and October was shown to negatively influence total biomass (Table 4.6). The quadratic relationship between total rainfall in November and total biomass suggests an optimum rainfall for total biomass (Table 4.6) between 75 and 100mm.

Table 4.5: The final parsimonious model for grain yield with model coefficients and standard errors ($R^2 = 89.92\%$). Values in the term columns refer to weather variables influencing the a, b and c parameters (left) of the LEXP function. This model is a first level parametrisation, such that wheat variety Hereward was fitted as the baseline and the effects of all other varieties are in reference to this, the intercept. (Second order polynomial terms (2), * Terms $\times 10^3$, ** Terms $\times 10^5$). Total rainfall and mean temperature are labelled TR and MT, respectively. Terms (1) and (2) refer to the linear and second order term of a quadratic relationship. Weather variables are ranked into the table depending on their model order.

	Parameter	Coef	S.E.
a	Intercept	3.16	0.16
	Variety Apollo	0.11	0.06
	Variety Brimstone	0.11	0.06
	Variety Cappelle desprez	0.15	0.06
	Variety Crusoe	0.08	0.09
	Variety Flanders	0.13	0.07
	TR October	-1.65*	0.26*
	MT May	-0.04	0.01
	MT November (1)	-0.25	0.24
	MT November (2)	-0.59	0.23
	TR February	-0.58*	0.36*
	MT April (1)	-0.80	0.33
	MT April (2)	-1.80	0.31
	TR June	0.61*	0.29*
b	Intercept	-1.55	0.16
	MT April (1)	1.28	0.65
	MT April (2)	2.48	0.57
c	Intercept	0.19	0.30
	Variety Apollo	-0.59**	0.37*
	Variety Brimstone	-0.35*	0.37*
	Variety Cappelle desprez	-2.25*	0.46*
	Variety Crusoe	0.93*	0.53*
	Variety Flanders	-0.43*	0.55*

Table 4.6: The final parsimonious model for total biomass with model coefficients and standard errors ($R^2 = 91.37\%$). Values in the term columns refer to weather variables influencing the a, b and c parameters (left) of the LEXP function. This model is a first level parametrisation, such that wheat variety Hereward was fitted as the baseline and the effects of all other varieties are in reference to this, the intercept. (Second order polynomial terms (2), * Terms $\times 10^3$, ** Terms $\times 10^5$). Total rainfall and mean temperature are labelled TR and MT, respectively. Terms (1) and (2) refer to the linear and second order term of a quadratic relationship. Weather variables are ranked into the table depending on their model order.

	Parameter	Coef	S.E.
a	Intercept	4.57	0.34
	Variety Apollo	0.01	0.08
	Variety Brimstone	0.11	0.09
	Variety Cappelle desprez	0.37	0.08
	Variety Crusoe	0.42	0.13
	Variety Flanders	0.22	0.09
	MT June	-0.08	0.02
	MT April (1)	-1.37	0.38
	MT April (2)	-2.56	0.33
	TR February	-3.10*	0.50*
	TR July	-2.47*	0.57*
	TR October	-1.02*	0.33*
	TR November (1)	-0.28	0.26
	TR November (2)	-0.60	0.24
	MT December (1)	-1.45	0.30
	MT December (2)	-1.44	0.29
b	Intercept	-1.75	0.09
	MT April (1)	1.95	0.76
	MT April (2)	3.29	0.68
c	Intercept	7.18*	2.20*
	Variety Apollo	-5.41**	0.45*
	Variety Brimstone	-1.24*	0.49*
	Variety Cappelle desprez	-2.39*	0.58*
	Variety Crusoe	1.46*	0.65*
	Variety Flanders	-0.79*	0.68*
	MT June	-0.42*	0.15*

Figure 4.3: Response surface of the effect of Nitrogen on wheat yield from the parsimonious model (Table 4.5) as affect by: (a) Mean November temperature; (b) Mean April temperature; (c) Mean May temperature. Further 3-dimensional surface plots are available in Appendix Figure A.11

(a) (b) (c)

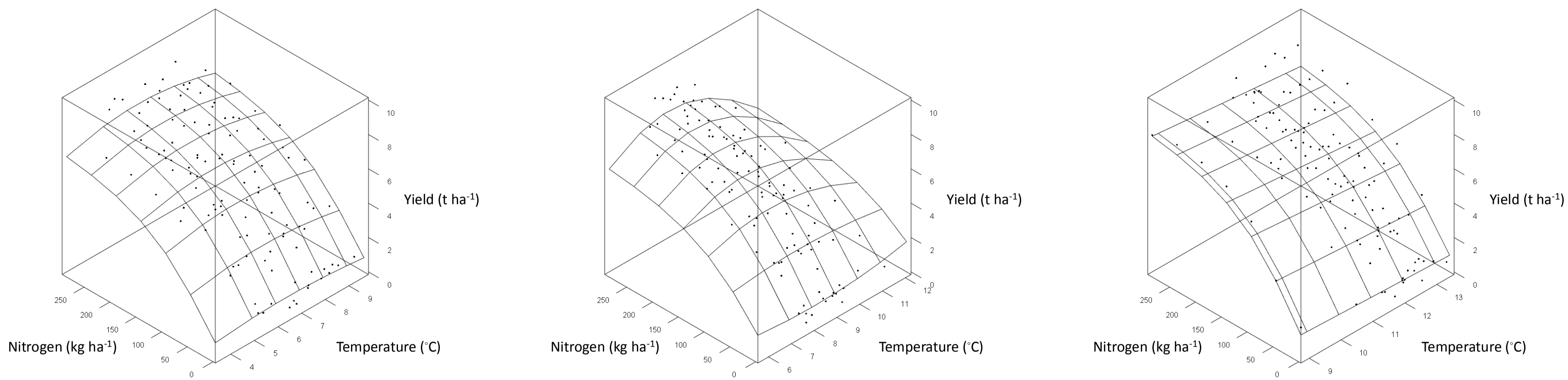
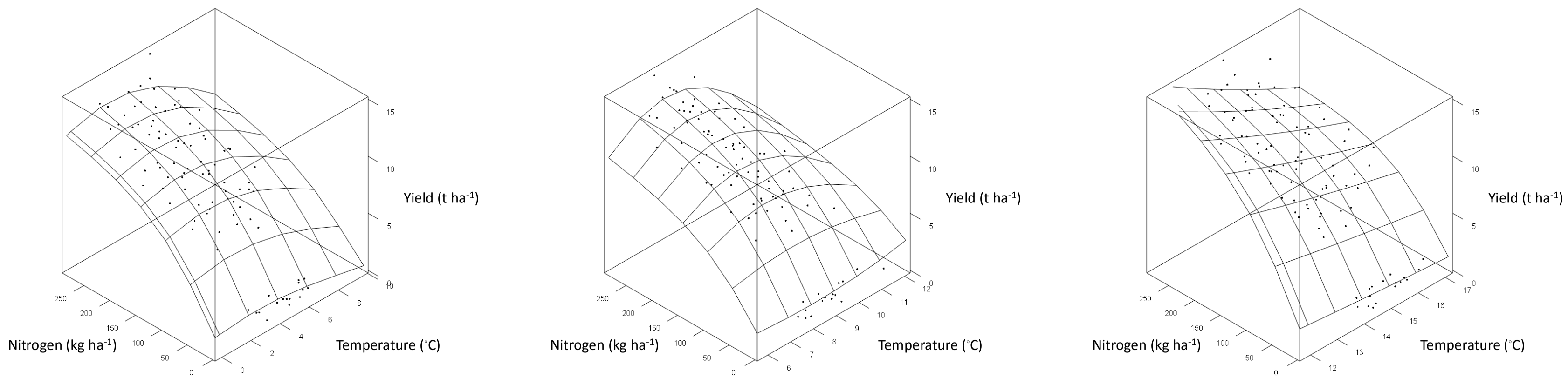


Figure 4.4: Response surface of the effect of Nitrogen on wheat yield from the parsimonious model (Table 4.6) as affect by: (a) Mean December temperature; (b) Mean April temperature; (c) Mean Jun temperature. Further 3-dimensional surface plots are available in Appendix Figure A.12

(a) (b) (c)



4.5 Discussion

Hypothesis 1: Yearly variations in Broadbalk total biomass have been observed (Chapter 3). Do we observe yearly variations in the Nitrogen response to yield (grain yield and total biomass) of the Broadbalk Experiment, from 1968 to 2016.

Grain yield and total biomass of continuous wheat of the Broadbalk Experiment were shown to vary among years from 1968 to 2016. Previous analysis of studying sources of variation in wheat yield from the Broadbalk Experiment only considered yield as a response variable (Chmielewski & Potts 1995; Fisher, 1925a; Fisher, 1921). Since 1843, the Broadbalk Experiment has tested the different effects of non-organic fertilisers on wheat. Consideration of this relationship should be acknowledged when analysing the Broadbalk yield dataset.

By fitting a Nitrogen response curve across Nitrogen dose for yield a test between the yearly variations in the LEXP function parameters could be achieved. There was significant evidence to suggests there was year-to-year variation in the Nitrogen response of wheat and therefore grain yield and total biomass. A simple test of year-to-year variations in yield would not be possible if a Nitrogen response curve was not fitted, this is because there would be insufficient degrees of freedom. A possible identification of variation overtime would be to fit a trend-line between yield and year. A method of fitting a trend-line to yield over time would not be preferred due to the assumption of the shape of the trend-line over time and the lack of information driving the trend-line. Within these analysis seven data points, or Nitrogen doses (five before 1985), were reduced to three parameters a, b and c (after fixing r) and inference, about yield, was gained across Nitrogen doses. This should not be considered as replication (due to each plot not being randomised across the field see Chapter 2) but as taking instances of a known response. Therefore, the lack-of-fit around N response curves can be used as a basis for assessing for differences between years in the shape of the response curve. Other modelling functions have been investigated (Cerrato & Blackmer, 1990; Nelder, 1966). However for these analyses, the LEXP function provided the best fit as there were fewer parameters to estimate, there was an asymptotic and loss due to excess Nitrogen parameter, the function was non-symmetrical, and once the non-linear parameter was fixed, fitting the curve over weather variables became a backwards modelling procedure. Variations in the Nitrogen response has been observed in other studies depending on year, soil, crop and weather (Roques et al., 2017; Sylvester-Bradley & Kindred, 2009; Vold, 1998).

By analysing the year-to-year variation of the Nitrogen response curve, there was evidence to show significant variations in yield each year. This year-to-year variation could be driven by variations of within-year weather or changes in the agronomy such as changes in cultivar. In an attempt to end hunger and achieving food security (UN, 2018) and to produce a sustainable agricultural system. year-to-year variations in yield need to be minimised. Within the Broadbalk Experiment, year-to-year variations in yield, more so grain yield, need to be minimised where the only source of year-to-year variability should be changes in cultivar.

Hypothesis 2: Do inter-annual variations in weather affect the Nitrogen yield response curve in wheat and therefore suggest optimum weather conditions, along with Nitrogen to maximise yield.

Grain yield and total biomass of continuous wheat, of the Broadbalk Experiment varied amongst years, from 1968 to 2016. Similar to the analyses from Chmielewski & Potts (1995) of the pre-1968 Broadbalk data, there was a negative correlation between May and June temperature and yield from 1968 onwards. Vernalisation and anthesis processes of wheat are both sensitive to changes in temperature which may affect yield (Ferris et al., 1998; Gooding & Davies, 1997; Long et al., 2006; Wheeler et al., 2000). Although phenology data was not collected from the Broadbalk experiment, it is known vernalisation and anthesis occur in the late autumn or early winter, and early summer, respectively (Gooding & Davies, 1997). The known relationships between yield and temperature during vernalisation and anthesis may explain why November and December, April and May and June mean temperatures explain significant amounts of variability within the parsimonious model (Figures, 4.3 and 4.4).

The association of rainfall explaining variability in long-term yield datasets has been well documented (Chmielewski & Potts, 1995; Fisher, 1925a; Hatfield & Dold, 2018; Hooker, 1907). October and February rainfall were negatively correlated with grain yield, across all Nitrogen treatments, and had a negative effect on the a coefficient of the LEXP function. Total rainfall in October, and July were negatively correlated with total biomass and negatively influenced the a parameter of the LEXP function (Tables 4.2 and 4.6). The correlations between October rainfall and yield, for both grain yield and total biomass, had a higher negative correlation for plots which receive lower Nitrogen inputs. This suggested low fertilised plots are more dependent on the environment. Total rainfall in November had a quadratic effect on the a parameter of the LEXP function, suggesting an optimum rainfall of between 75 and 100mm for maximising total biomass. Although weather may be explaining some levels of crop variability, the relationship between monthly rainfall variables and yield may be due to indirect changes to the crops environment, such as changes in the soil water content and least limiting water range, not providing adequate aeration of the soil (da Silva & Kay, 1997), and potential Nitrogen loss from the soil. Since the relationship between variations in April weather was quadratic, with a maximum and the magnitude of loss was greater for higher Nitrogen doses, this suggests a potential leaching or evapotranspiration of fertiliser rather than the direct physiological stresses to the crop during certain developmental stages.

Within the parsimonious model for grain yield (Table 4.5), total rainfall in June gave a positive estimated a coefficient. Therefore, with more rainfall in June the estimated asymptote of the Nitrogen response curve would increase and therefore result in more yield. Within the method of model selection for the grain yield parsimonious model mean June temperature was omitted from this model due to its high correlation with mean May temperature, as May temperature had a higher mean absolute correlation across all treatment groups. Therefore, the variability associated with mean June temperature was not accounted for directly within the grain yield parsimonious model. Mean June temperature and total June rainfall had a large negative correlation. Therefore, a wetter June tends to be a colder June. This issue of collinearity of weather variables was one limitation of statistical modelling within the regression framework as the model itself was built on the linear, or quadratic, associations between the response and explanatory variables. This was an issue raised by Katz (1977) in assessing the impact of climate change on food production.

Another similar issue of identifying sources of variability within long-term yield datasets is confounding of variables. From Tables 4.5 and 4.6 changes in cultivar explains significant amounts of model variability of the a and c parameters of the LEXP function. It has been observed different varieties of Triticale vary in the optimum Nitrogen application rate (Roques et al., 2017). However, higher Nitrogen treatments of the Broadbalk Experiment have a slightly higher soil organic carbon level soil compared to lower Nitrogen treatments (Chapter 2; Watts et al., 2006). Also, atmospheric CO_2 has increased, each year, alongside the Broadbalk experiment (NOAA, 2018). Although variety was included within our model, a true estimate of the cultivar effect cannot be obtained due to other influencing variables changing over time. The factor variable cultivar also captures information about weather. For example, from the yearly fitted model the year with the highest fitted Nitrogen response curve for grain yield was 1985 and 2002 and 2007 had the shallowest Nitrogen response curve. Therefore, in conjunction with the results from Chapter 3, if cultivars were sown during a period of warming their yield may be influenced by stress in crop development and may not be a true cultivar effect. Every variety had a window of within-year weather variability. Some cultivars have more variability over a weather variable than others. Therefore, by not including a varying interactions term (a different estimated slope for each cultivar for each weather variable) each cultivar borrows inference of the effect of weather and it has been assumed the effect of weather was the same across all cultivars.

The issue of confounding and collinearity of explanatory variables has limited these analyses. By averaging minimum and maximum temperature, the independent variability of each has not been accounted for. A rise in night-time temperature has been shown to increases dark respiration an decrease grain dry weight of spring wheat (Prasad et al., 2008). Incorrect parameterisation of regression coefficients may be obtained within our parsimonious models as rising atmospheric CO_2 may have offset some of the loss in yield due to rises in temperature. However, no evidence of increasing atmospheric CO_2 affecting yields from a Rothamsted Long-Term Experiment was found between 1891 and 1992 (Jenkinson et al., 1994).

Among these limitations, the analyses and results presented within this chapter show how more information about yield production can be obtained by acknowledging a known response across treatments. From these results, variations in weather around potential phenological dates (anthesis and grain-filling) showed losses in yield across all Nitrogen doses. And it could be suggested that, along with more heat tolerant varieties, reducing the loss of yield due to weather variability around management practices (Nitrogen application) would be beneficial. For example, from Figure 4.3 (b) it was shown higher temperatures around high Nitrogen treatments led to a greater loss in grain yield than at lower doses. Therefore, minimising this loss of yield due around management and cultivar stress would lead to higher yields and a less variable temporal yield dataset.

4.6 Conclusion

There was significant variation in the Nitrogen response on Broadbalk, from 1968 to 2016, due to inter-annual variations in weather (Hypothesis 1). Warmer temperatures and an absence of rainfall in the early-summer resulted in a lower yield of wheat from Broadbalk. By acknowledging inferences between Nitrogen treatments within Broadbalk, a Nitrogen response curve could be adequately fitted to the model. By modelling a Nitrogen response curve and not yield, variations in weather around nitrogen application resulted in a loss in yield.

Therefore, to achieve higher levels of wheat production, efforts to make wheat more heat and drought tolerant in the early-summer and better able to take up Nitrogen from drier or wetter soils should be considered (Hypothesis 2).

Chapter 5

How weather variation changes the functional response of cereals to Nitrogen using Rothamsted's Long-Term Experiment data: Hoosfield barley

5.1 Introduction

From Chapter 3, warm-wet and warm-dry growing conditions have been shown to produce lower yields across all of Rothamsted's Long-Term Experiments. It was concluded within Chapter 4 that both variations of within-year rainfall and mean temperature result in variations of wheat's response to Nitrogen. Wetter conditions around Nitrogen application were shown to influence yields from treatments which received higher doses of Nitrogen compared to lower doses. Whereas the magnitude of loss, for wheat, due to higher temperatures was the same for all doses of Nitrogen (Chapter 4).

Climate change will influence agriculture and global food security through changes in agro-ecological conditions (Schmidhuber & Tubiello, 2007). Mean UK barley (*Hordeum vulgare*) yield in 2017 saw a 2.7% increase to 6.1 tonnes per hectare compared to 5.9 tonnes per hectare in 2016 (Anon, 2017). The overall land used for barley production in UK was measured at 1.2 million hectares in 2017 (Anon, 2017). As discussed in Chapter 1 and Section 4.1, the intensification of agriculture will have to increase by 2050, to meet food demand and cope with increases in temperature and rises in atmospheric CO_2 throughout the 21^{st} century.

Analyses into the study in crop variation from long-term experiments show associations between variations in weather with variation in yield (Chapter 4; Fisher, 1925a; Hooker, 1907). Increased temperatures during a crop harvest season have been shown to reduce the winter wheat seed dry weight and reduce grain number potential (Wheeler et al., 2000; Wheeler et al., 1996). Excess rainfall or drought during a harvest season may contribute to the soil water content falling outside the least limiting water range, therefore limiting plant growth (da Silva & Kay, 1997).

The Hoosfield Barley Experiment was first sown in the autumn of 1852 at Rothamsted to test the effects of mineral fertilisers (N, P, K, Na and Mg) and organic manures on spring barley yields. One of the main objectives of the Hoosfield experiment was to study the effects of organic and inorganic manures on continuous spring barley (Anon, 1971). Since 1968, short-strawed spring varieties have been sown annually with the application of 0, 48, 96 and 144 kg N ha^{-1} and different combinations of mineral fertilisers, PKNaMg, P, KNaMg and Nil (the absence of fertiliser) (Chapter 2). The functional response of cereal grain yield to Nitrogen has been shown to vary depending on the year, soil, crop and weather (Chapter 4; Roques et al., 2017; Sylvester-Bradley & Kindred, 2009; Vold, 1998). Common modelling functions have been shown to inadequately fit the Nitrogen response curve due to the asymptotic and symmetrical assumptions of quadratics and exponentials (Cerrato & Blackmer, 1990). Inverse polynomial functions have been shown to provide adequate fit for Nitrogen dose response (Nedler, 1966). However, within these analyses a Linear-By-Exponential (LEXP) (George, 1892) was preferred as it allows the response function to be modelled using fewer parameters and allows for a more comparable biological interpretation (Chapter 4). This study aims to investigate how weather contributes to variability in annual crop yield through the functional response of spring barley to applied Nitrogen, allowing for differences between mineral treatments (PKNaMg, P, KNaMg and Nil) and cultivars, from 1968 to 2016.

5.2 Aims and Objectives

5.2.1 Aim

This study aims to investigate how inter-annual variability in weather contributes to that in spring barley yield, of the Hoosfield Experiment, through the response of spring barley to applied Nitrogen, allowing for differences between cultivars and mineral fertiliser treatments (PKNaMg, P, KNaMg and Nil), from 1968 to 2016.

5.2.2 Objectives

Within this Chapter I:

- Calculated Pearson's correlation values and their significance levels between yield (grain yield and total biomass) and monthly summarised total rainfall and mean temperature, from October to September, from plots within Series O of the Hoosfield Experiment at Nitrogen applications 0, 48, 96 and 144 kg N ha^{-1} between 1968 and 2016.
- Fitted a local Nitrogen response curve to yield (grain yield and total biomass) to each mineral fertiliser treatment (PKNaMg, P, KNaMg and Nil) for all years using a LEXP function.
- Fitted a Nitrogen response curve, using a LEXP function, to yield (grain yield and total biomass) to each mineral fertiliser treatment (PKNaMg, P, KNaMg and Nil) for all years and tested if there was significant year-to-year variability of the Nitrogen response to spring barley.
- Tested if allowing the non-linear parameter r, within the LEXP function with yield (grain yield and total biomass), to vary between each year explained significant amounts of variability compared when r was fixed.
- Built a maximal model for both grain yield and total biomass, including mineral fertiliser treatment, cultivar and monthly summarised weather variables.
- Ran a backwards model selection procedure, minimising the Akaike Information Criterion to both maximal models to omit explanatory variables which did not explain large

amounts of model variability.

- Produced a parsimonious model for grain yield and total biomass, which identified key weather variables which influenced parameters of the Nitrogen response curve of the Hoosfield Experiment from 1968 to 2016.

5.2.3 Hypotheses

- Yearly variations in cereal Nitrogen response has been observed on wheat from a Rothamsted Long-Term Experiment. Do we observe yearly variations in the Nitrogen response to yield (grain yield and total biomass) of the Hoosfield Experiment across various mineral fertilisers, from 1968 to 2016.

- Do inter-annual variations in weather affect the Nitrogen yield response curve in spring barley across various mineral fertilisers and therefore suggest optimum weather conditions, along with Nitrogen to maximise yield.

5.3 Methods

5.3.1 Long-Term Experiment Data

Data considered for this study are grain yield and total biomass (t ha^{-1} at 85% dry matter) from the continuous spring barley Series O of the Hoosfield Experiment at Nitrogen applications of 0, 48, 96 and 144 kg N ha^{-1} and at mineral treatments Nil, P, KMgNa and PKMgNA, from 1968 to 2016 (see Section 2 for a complete plan). Grain yields for 1992, on the Nil mineral applied plots are missing. Straw yields from 2007 were not recorded for each Nitrogen level, therefore total biomass yields from 2007 were omitted. Spring barley was sown around February each year. Nitrogen was applied to the experiment around April each year. Information about the different cultivars sown on the experiment since 1968 was used as a factor variable (Table 2.4)

5.3.2 Rothamsted Weather Data

Daily temperature ((maximum daily temperature + minimum daily temperature)/2, °C) and daily rainfall data from Rothamsted Meteorological Station were summarised monthly for each harvest season, where a harvest season was defined as October to September. Weather data within the harvest season February to September was considered for these analyses. Daily temperature was averaged over daily maximum and minimum daily temperature due to the collinearity of independent daily temperature measurements.

5.3.3 Statistical Analyses

Similar to the analysis within Chapter 4, a Linear-By-Exponential (LEXP) function (George, 1982) was used to model a Nitrogen response curve to yield (t ha^{-1}). However, since the Hoosfield experiment tests different levels of mineral fertiliser, a local Nitrogen response curve was fitted to each mineral fertiliser by a factor variable. A local Nitrogen response curve was modelled for yield (t ha^{-1}) (y) as defined:

$$y_{f(T)} = a_{f(T)} + b_{f(T)}r^N + c_{f(T)}N \tag{5.1}$$

where a defines the asymptote (t ha^{-1}), b the magnitude of the yield response to Nitrogen, c the rate of yield loss due to over application of Nitrogen, and r the curvature of the response (see Section 5.1) for each mineral treatment. Equation 5.1 is a modification of Equation 4.1 where $f(T)$ is a function of mineral treatment (T). The methodology within this chapter is similar to those in Chapter 4, where we test how the shape of the Nitrogen response curve differs for mineral treatments over fewer Nitrogen applications. A comment on the use of the LEXP function and other functions was given in Chapter 4.

Pearson's correlation coefficients and significance levels ($\alpha < 0.05$) between yield (grain yield and total biomass) and monthly weather variables were derived for each Nitrogen dose (0, 48, 96, 144 kg N ha^{-1}) and each mineral treatment from 1968 to 2016. This was achieved to determine if there some of the within-year variation in yield could be associated with within-year variations in weather.

A further analysis assessed how much of the year-to-year variation in the linear parameters of these Nitrogen response curves could be explained be variation in weather and changes in cultivar. Monthly summarised mean temperatures (°C), total rainfall (mm) and variety were added to Equation 4.2 to form a maximal model

$$y_{f(T+V+W)} = a_{f(T+V+W)} + b_{f(T+V+W)}r^N + c_{f(T+V+W)}N \tag{5.2}$$

where $f(T + V + W)$ is a function of mineral treatment (T), weather (W) and variety (V). Weather variables with the largest mean absolute correlation between all treatments were included into the model fit first. To reduce collinearity among the explanatory variables, variables with a high correlation, greater than 0.3, were omitted from the model. A maximal model including treatment, variety and weather variables was fitted to yield. Interaction terms between treatment and variety, and treatment and weather variables were tested. Due to a limited replication of variety over years of variety over multiple years, the interaction between weather variables and variety were omitted from this analysis. All terms remaining within the maximal model were investigated as linear or quadratic.

It should be noted yields from 1993, 1998, 2000 and 2012 were omitted from the grain yield and total biomass maximal models. 2015 yields were omitted from the total biomass maximal model due to large July rainfall values. The omission of these data points was due to the interaction of the polynomial relationship of April rainfall (for grain yield and total biomass) and the polynomial relationship of July rainfall (for total biomass) with variety. The inclusion of these large rainfall values and few years of the same variety result in the incorrect parameterisation model coefficients and a systematic lack of fit.

A step-by-step modelling description of the analysis achieved within this chapter is given below. This procedure was achieved for grain yield and total biomass of spring barley. Again, it should be noted steps 1, 2 and 3 are steps when fitting standard exponential curves in Genstat® (VSN International, 2017).

1. A local Nitrogen response curve (Equation 5.1) was fitted to yields (grain yield and total biomass) for all mineral treatments (PKNaMg, P, KNaMg and Nil) and years from 1968 to 2016.

2. By using year as a factor variable, an individual LEXP curve was fitted to each mineral treatment (PKNaMg, P, KNaMg and Nil) and year, allowing for parameters a, b, c and r

to vary.

3. The non-linear term r was fixed across all treatments but not years (due to only four dose levels) and was estimated by the Gauss-Newton method. Once r was fixed between treatments, a partial F-test was conducted to determine if allowing r to vary explained significant amounts of variability.

4. Correlations between yields (grain yield and total biomass) and monthly weather summaries were calculated for all Nitrogen doses (0, 48, 96, 144 kg N ha^{-1}) and mineral treatments (PKNaMg, P, KNaMg and Nil) from 1968 to 2016. Monthly weather summaries included total rainfall and mean daily mean temperature.

5. Once r was shown to explain insufficient amounts of model variability, a maximal model (equation 5.2) was fitted to yields (grain yield and total biomass) including explanatory variables treatment, cultivar, total rainfall and mean temperature ($f(T+V+W)$). Those weather variables with the highest mean absolute correlation across all mineral treatments and Nitrogen doses were ranked into the model first. Because the non-linear parameter r was shown to explain insufficient amounts of model variability, the model selection procedure becomes a multiple regression model selection problem.

6. After terms were included some weather variables were omitted if they had a high correlation ($\rho >|0.3|$) due to collinearity of explanatory variables. The rejection level ($\rho >|0.3|$) was selected because the correlation values between yield and weather variables were low.

7. The relationship between yield and a weather variable was investigated. If the relationship was considered non-linear, it was fitted as a quadratic. Typically, this was a quadratic with a negative squared term resulting in a maximum.

8. $f(T + V + W)$ does include an interaction between treatment and all other explanatory variables. Therefore, the effects of variety and weather on parameters a, b and c could be investigated. Whereas, $f(T + V + W)$ does not include an interaction between cultivar and weather or between weather variables themselves. Reasons for this omission were given in the Statistical Analysis section of Chapter 4.

9. From a maximal model, variable selection methods were used to achieve a reduced model. Omitting variables from the maximal model one-by-one until convergence. The Akaike Information Criterion (AIC) (Akaike, 1971) was used to omit these terms. For each iteration the AIC becomes smaller until convergence occurs, meaning the AIC does not reduce for every additional variable omitted.

10. After the AIC selection procedure, a further model selection process, using partial F-tests, was used to test whether model parameters within the reduced model explained significant amounts of model variability (significance level $\alpha < 0.05$) and therefore a parsimonious model. If, after the omission of a term, an explanatory variable was non-significant (compared to a model including that term) it was concluded that variable did not explain significant model variability and was omitted.

11. After a parsimonious model was found, a final step of model validation was achieved to assess if the model was adequate. This involved a residual vs fitted, a Q-Q and a scale location plot with a histogram of the residuals, these figures are considered nonessential to the overall conclusions of our results and are given in the Appendix.

After the first iteration of this procedure, it was found the residuals of the model lacked constant variance of the residuals. Residuals at the highest yielding plots were more variable than the lowest yielding plots. To deal with this lack of constant variance a square root transform of the yield data was used and the model procedure stated above (steps 1 to 11) was repeated. Therefore, all model parameters stated within the results are on the square-root scale. All predictions from the model on figures with the yield scale were transformed back to the yield scale. As the response was transformed and higher yielding plots were more variable than lower yielding plots we sacrifice potential variables explaining the loss at high Nitrogen doses (parameter c) for model adequacy.

It should be noted here that this model selection procedure was similar to that from Chapters 4 and 6. Steps 5 to 11 are identical to those given in Chapter 4.

5.4 Results

5.4.1 Common Nitrogen Response

Table 5.1: Estimated model coefficients (and standard errors) of the LEXP function, for grain yield, fitted to each treatment group. The non-linear parameter was fixed at r = 0.985 (S.E. 0.0076) for all treatments (* Terms $\times 10^3$).

	PKNaMg	P	KNaMg	Nil
a	2.59 (0.18)	2.33 (0.25)	1.98 (0.25)	1.42 (0.25)
b	-1.33 (0.19)	-1.01 (0.28)	-1.00 (0.28)	-0.45 (0.28)
c	-1.36* (1.24*)	-2.52* (1.75*)	-1.69* (1.76*)	-0.51* (1.76*)

Table 5.2: Estimated model coefficients (and standard errors) of the LEXP function, for total biomass, fitted to each treatment group. The non-linear parameter was fixed at r = 0.988 (S.E. 0.0075) for all treatments (* Terms $\times 10^3$).

	PKNaMg	P	KNaMg	Nil
a	3.55 (0.30)	3.11 (0.42)	2.73 (0.42)	1.85 (0.43)
b	-2.10 (0.32)	-1.59 (0.46)	-1.60 (0.46)	-0.72 (0.46)
c	-3.13* (1.91*)	-4.29* (2.71*)	-3.51* (2.71*)	-1.12* (2.72*)

Allowing the non-linear component of the LEXP function, r, to vary between mineral treatments did not explain any more model variation as fitting a common r to all treatments for grain yield (F(0.44, 3, 760), P $=$ 0.723) and total biomass (F(0.26, 3, 748), P $=$ 0.853). The estimated r for all treatments was 0.985 for grain yield and 0.988 for total biomass. Allowing a, b and c coefficients to vary between mineral treatments explained significantly more model variability compared to a common Nitrogen response curve fitted to all treatments for grain yield (F(62.88, 9, 763), p $<$ 0.001) and total biomass (F(92.18, 9, 751), p $<$ 0.001). The PKNaMg treatment had a larger estimated asymptote (a) and yield response to Nitrogen (b), of 2.59 and -1.33, and 3.55 and -2.10 for grain yield (Table 5.1) and total biomass (Table 5.2), compared to other treatment groups. From Figures 5.1 and 5.2 the estimated Nitrogen response curve, over all years, was more linear for treatments KNaMg and Nil compared to PKNaMg and P treatments. This may be explained by an effect of P, however, a factorial analysis approach in identifying a true effect of P was not investigated as there was confounding of variables such as more soil organic carbon (see Section 2) in the PKNaMg and P plots compared to KNaMg and nil.

5.4.2 Yearly Fitted Nitrogen Response

Estimating individual parameters a, b and c for each year and treatment, fixing the non-linear component, to both grain yield and total biomass for each year and treatment explained significantly more variability than fitting a common curve over all years to each treatment (grain yield: F(19.27, 579, 193), P $<$ 0.001; total biomass: F(12.74, 582, 190), P $<$ 0.001). Due to only four doses of applied Nitrogen the parameter r could not be estimated for each year. The non-linear parameter was fitted across all years due to only four Nitrogen doses and therefore estimating a fourth model parameter for each year was not possible. The estimated r parameter across all years and treatments was 0.989 and 0.988 for grain yield and total biomass, respectively. These estimates differed from those given in Section 5.4.1, as 0.989 and 0.988 account for variability between year along with treatment. A final test of model parameters for both grain yield and total biomass models was conducted on parameter c and whether allowing c to vary among both treatment and year explained significant amounts of model variability. Allowing c to vary with each year and treatment did not explain significant amounts of model variability (grain yield: F(1.20, 190, 194), P = 0.099; total biomass: F(1.21, 187, 191), P = 0.096) compared to a model where c was estimated for each treatment across all years. The estimated c coefficients for grain yield were -4.51 $\times 10^{-3}$ (PKNaMg), -4.83 $\times 10^{-3}$ (P), -3.98 $\times 10^{-3}$ (KNaMg) and (Nil), and -1.53 $\times 10^{-3}$, and -5.41 $\times 10^{-3}$ (PKNaMg), 11.12 $\times 10^{-3}$ (P), 5.20 $\times 10^{-3}$ (KNaMg) and 1.87 $\times 10^{-3}$ (Nil) for total biomass.

From Figures 5.3 and 5.4 the Nitrogen response curve was fitted to each year. Similar to fitting a common Nitrogen response curve to all years (Figures 5.1 and 5.2), mineral treatment PKNaMg had a more asymptotic relationship with applied Nitrogen for both grain yield and total biomass. The KNaMg and Nil treatment both had flat year-to-year Nitrogen response curves. From treatment PKNaMg, 2009 had the largest estimated a parameter of 3.82, 1972 had the lowest estimated b parameter of -1.56. Also, year had the lowest asymptotic relationship between Nitrogen and grain yield with an estimated a parameter of 2.51, for treatment PKNaMg.

Figure 5.1: LEXP function, Equation 5.1, fitted to grain yield for treatments: (a) PKNaMg, (b) P, (c) KNaMg, and (d) Nil, from 1968 to 2016. The non-linear parameter was fixed at r = 0.985 (S.E. 0.0076) for all treatments.

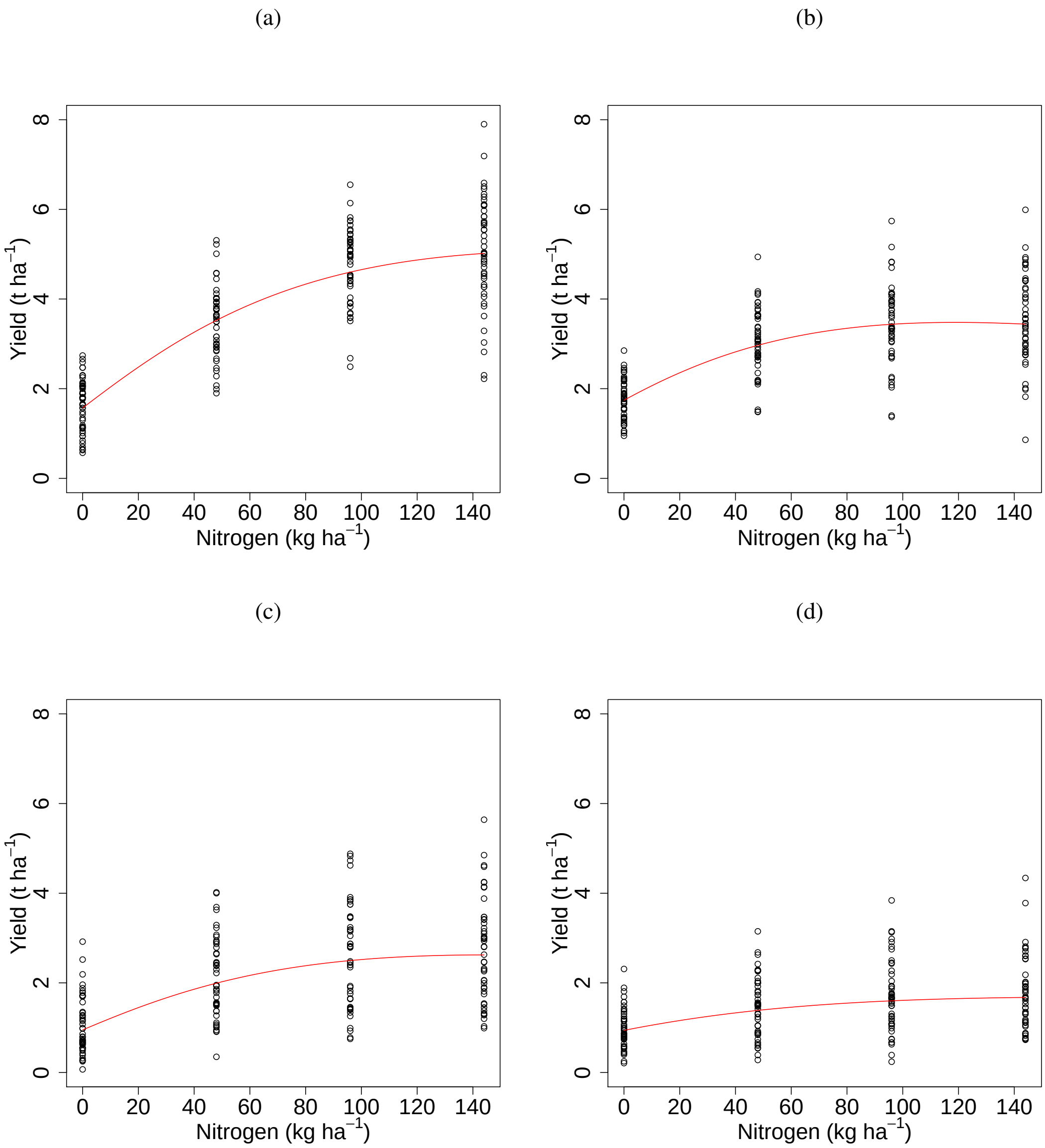


Figure 5.2: LEXP function, Equation 5.1, fitted to total biomass for treatments: (a) PKNaMg, (b) P, (c) KNaMg, and (d) Nil, from 1968 to 2016. The non-linear parameter was fixed at r = 0.988 (S.E. 0.0075) for all treatments.

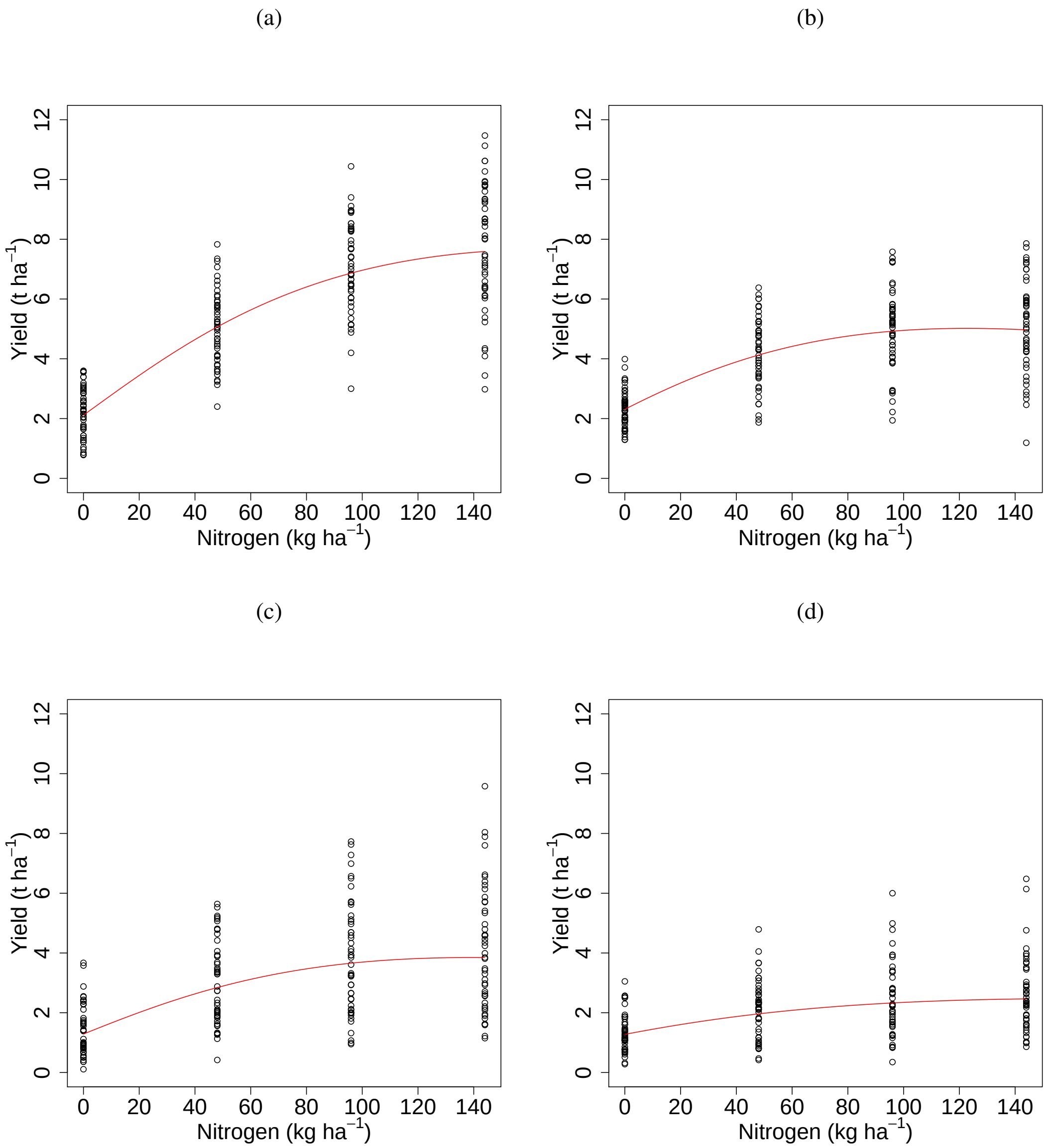


Figure 5.3: Fitted LEXP function to grain yield for each year and treatment ((a) PKNaMg, (b) P, (c) KNaMg and (d) Nil) from 1968 and 2016.

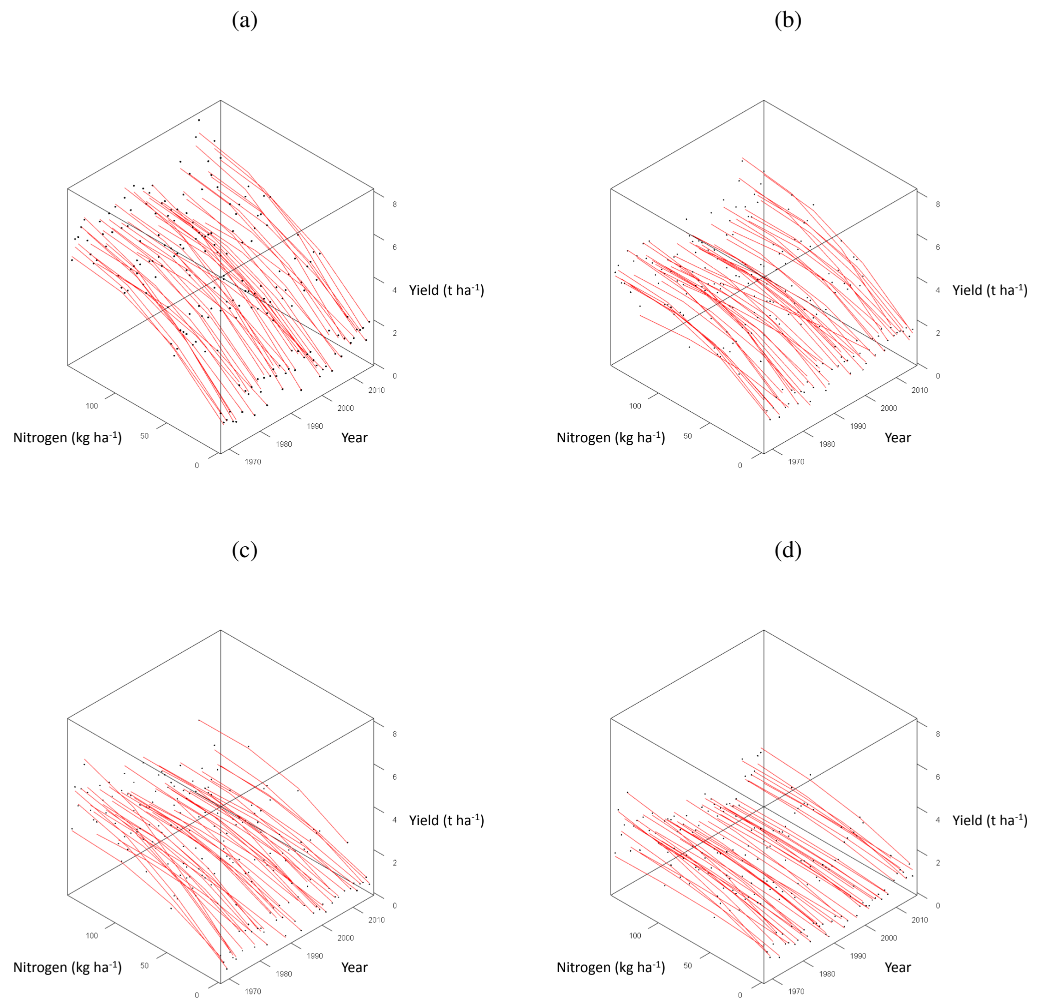
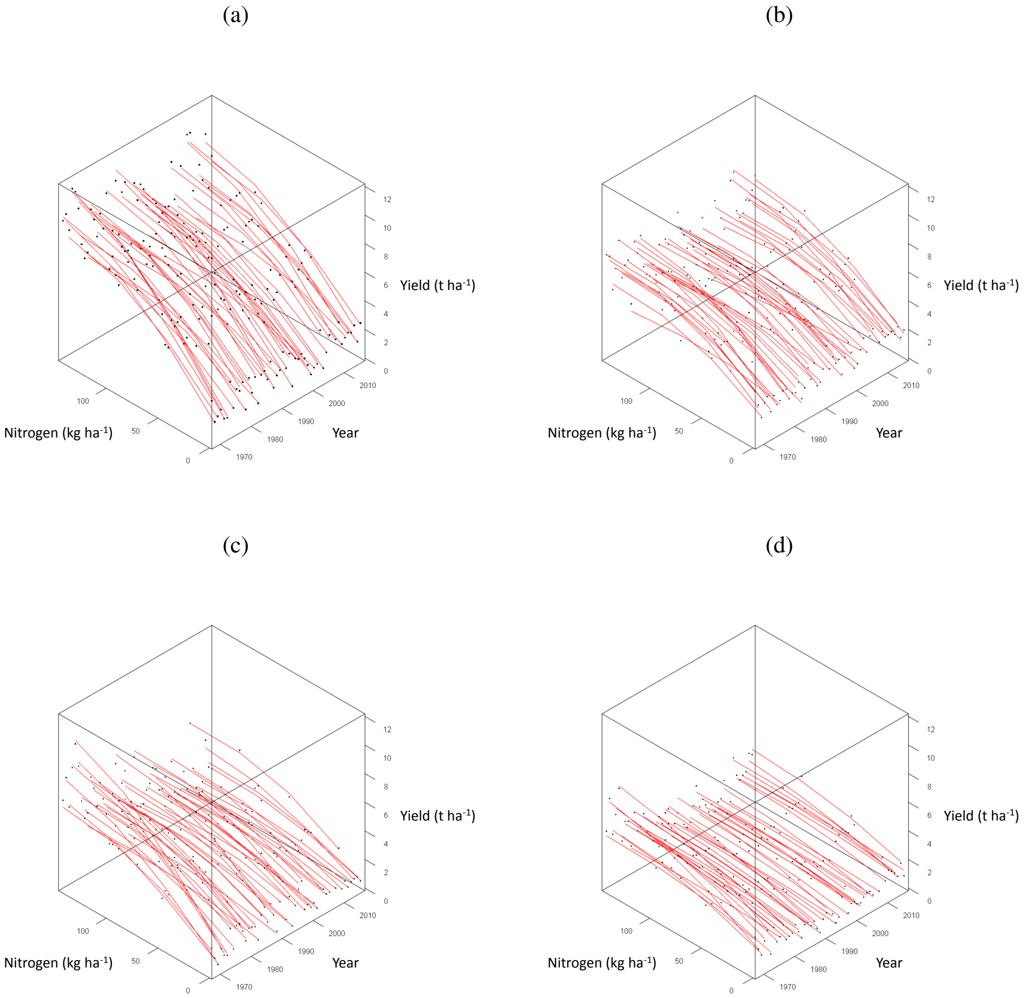


Figure 5.4: Fitted LEXP function to total biomass for each year and treatment ((a) PKNaMg, (b) P, (c) KNaMg and (d) Nil) from 1968 and 2016.



5.4.3 Yield and Weather Correlations

Grain yield and total biomass from all Nitrogen and mineral treatments showed a negative correlation with April rainfall (Tables A.17, A.18, A.19, A.20, A.25, A.26, A.27 and A.28). June rainfall was positively correlated with grain yield and total biomass across all Nitrogen and mineral treatments.

Grain yield from all Nitrogen treatments for mineral treatment PKNaMg was not significantly correlated with any monthly temperature weather variables (Table A.21). The correlation between each of grain yield and total biomass with May, June and July temperatures was negative for all Nitrogen and mineral treatments (Tables A.21, A.22, A.23, A.24, A.29, A.30, A.31 and A.32), with more significant negative correlations where P was not provided. All May and July temperatures had a significant negative correlation with grain yield and total biomass at every N dose for KNaMg and Nil mineral treatments. Grain yield and total biomass from Nitrogen treatments 48, 96 and 144 kg N ha^{-1} for mineral treatments KNaMg and Nil had a significant negative correlation with June temperature.

5.4.4 Weather Fitted Nitrogen Response

Grain Yield

The AIC of the maximal model for grain yield was -2204.5 compared to -2255.3 of the reduced model, where there was no significant difference between the amount of variability explained by the maximal model (Equation 5.2) and the parsimonious model (Table 5.3; F(1.19, 84, 563), P = 0.136)). Terms fitted within the maximal model included mineral treatment and variety as factor variables along with weather variables mean June temperature, total April rainfall, mean February temperature, total May rainfall, total September rainfall and total July rainfall.

Mineral treatment and variety were significant terms within the parsimonious model and influenced the asymptote (a) and the magnitude of the yield response to Nitrogen (b). Treatments P and Nil had an estimated 0.43 and 0.29 larger a parameter than the PKNaMg treatment (Table 5.3). Also, the estimated b parameter for treatments P and Nil were 0.55 and 0.84 greater than PKNaMg. Although a greater a parameter was estimated for mineral treatments P and Nil, the estimated b parameters for P and Nil were more positive than PKNaMg. Therefore, P and Nil treatments were less efficient at utilising Nitrogen at lower doses suggesting more Nitrogen is required for P and Nil plots to achieve optimum yield than the PKNaMg treatment.

Alexis had the largest estimated a parameter of all varieties and 0.15 bigger than Tipple. Alexis also had a lower estimated b parameter compared to Tipple of -0.26. This suggests Alexis was more efficient at utilising Nitrogen at lower doses and has a higher grain yield Nitrogen asymptote compared to Tipple. Maris Badger had the lowest estimated b coefficient, of -0.44 smaller than Tipple, suggesting this variety was the most efficient at facilitating Nitrogen at lower doses. The interaction between mineral treatment and variety on the a parameter was significant, therefore suggesting varieties respond differently to certain mineral treatments.

Higher temperatures in June were shown to negatively influence the a parameter for mineral treatments P, KNaMg and Nil within the parsimonious model (Table 5.3). Total rainfall in April was fitted to the model by a negative quadratic relationship for grain yield and influenced the a parameter of the LEXP function (Figure 5.5). Total rainfall in April was also shown to have a significant interaction with mineral treatments, where treatment PKNaMg had the largest negative estimation of the second order polynomial term (Table 5.3). From Figure 5.5, the influence of excess rainfall in April was more severe for treatments which received more mineral inputs. The relationship between mean February temperature and grain yield was shown to negatively influence the a parameter and no interaction with treatment was found, suggesting the impact of higher temperatures in February was the same across all mineral treatments. Excess rainfall in September was shown to negatively influence the a parameter and positively influence the b parameter of the LEXP function, suggesting wetter conditions in September result in a more linear Nitrogen response function (Appendix A.18).

Total Biomass

The AIC of the maximal model for total biomass was -1756.9 compared to -1816.1 of the reduced model, where there was no significant difference in the model variability explained by the parsimonious model compared to the maximal model for total biomass (Table 5.5; Equation 5.2, F(1.26, 96, 624), P = 0.096). Weather variables included within the maximal model for total biomass included: mean June temperature, total April rainfall, mean August temperature, total February rainfall, mean March temperature, total May rainfall and total July rainfall. Terms

Table 5.3: The final parsimonious model for grain barley yield with model coefficients and standard errors ($R^2 = 83.17\%$). Values in the parameter column refer to weather variables influencing the a, b and c parameters (left) of the LEXP function. This model is a first level parametrisation, such that spring barley variety Tipple was fitted as the baseline and the effects of all other varieties are in reference to this, the intercept. (Second order polynomial terms (2), * Terms $\times 10^3$, ** Terms $\times 10^5$). Total rainfall and mean temperature are labelled TR and MT, respectively. Terms (1) and (2) refer to the linear and second order term of a quadratic relationship. Weather variables are ranked into the table depending on their model order.

	Parameter	Coef	S.E.
a	Intercept	3.27	0.25
a	Treatment P	0.43	0.31
a	Treatment K Na Mg	-0.03	0.31
a	Treatment Nil	0.29	0.31
a	Variety Alexis	0.22	0.10
a	Variety Cooper	-0.19	0.09
a	Variety Georgie	0.16	0.09
a	Variety Irina	0.18	0.15
a	Variety Julia	0.17	0.07
a	Variety Maris Badger	0.09	0.12
a	Variety Optic	-0.18	0.07
a	Variety Triumph	0.07	0.07
a	MT June	0.01	0.01
a	TR April (1)	-2.57	0.43
a	TR April (2)	-3.08	0.42
a	MT February	-0.04	0.01
a	TR September	-2.01*	0.44*
a	Treatment P:Variety Alexis	-0.14	0.10
a	Treatment K Na Mg:Variety Alexis	-0.08	0.10
a	Treatment Nil:Variety Alexis	-0.50	0.11
a	Treatment P:Variety Cooper	-0.16	0.10
a	Treatment K Na Mg:Variety Cooper	0.36	0.10
a	Treatment Nil:Variety Cooper	0.07	0.10
a	Treatment P:Variety Georgie	-0.28	0.09
a	Treatment K Na Mg:Variety Georgie	0.10	0.09
a	Treatment Nil:Variety Georgie	-0.22	0.09
a	Treatment P:Variety Irina	-0.06	0.15
a	Treatment K Na Mg:Variety Irina	-0.13	0.15
a	Treatment Nil:Variety Irina	-0.15	0.15
a	Treatment P:Variety Julia	-0.16	0.07
a	Treatment K Na Mg:Variety Julia	0.31	0.07
a	Treatment Nil:Variety Julia	0.09	0.07

Table 5.3 continues overleaf

Table 5.3 continued

	Parameter	Coef	S.E.
a	Treatment P:Variety Maris Badger	3.11*	0.12
a	Treatment K Na Mg:Variety Maris Badger	0.33	0.12
a	Treatment Nil:Variety Maris Badger	0.22	0.12
a	Treatment P:Variety Optic	-0.09	0.08
a	Treatment K Na Mg:Variety Optic	0.10	0.08
a	Treatment Nil:Variety Optic	-0.12	0.08
a	Treatment P:Variety Triumph	-0.32	0.08
a	Treatment K Na Mg:Variety Triumph	0.14	0.08
a	Treatment Nil:Variety Triumph	-0.31	0.08
a	Treatment Nil:MT June	-0.09	0.02
a	Treatment K Na Mg:MT June	-0.06	0.02
a	Treatment P:MT Jun	-0.05	0.02
a	Treatment Nil:TR April (1)	-0.06	0.60
a	Treatment K Na Mg:TR April (1)	-1.22	0.62
a	Treatment P:TR April (1)	1.72	0.60
a	Treatment Nil:TR April (2)	2.72	0.60
a	Treatment K Na Mg:TR April (2)	1.12	0.63
a	Treatment P:TR April (2)	1.17	0.60
b	Intercept	-2.07	0.14
b	Treatment P	0.55	0.07
b	Treatment K Na Mg	0.42	0.07
b	Treatment Nil	0.84	0.07
b	Variety Alexis	-0.26	0.13
b	Variety Cooper	0.18	0.12
b	Variety Georgie	-0.06	0.11
b	Variety Irina	-0.15	0.18
b	Variety Julia	-0.30	0.08
b	Variety Maris Badger	-0.44	0.14
b	Variety Optic	0.16	0.09
b	Variety Triumph	0.08	0.09
b	TR September	2.78*	0.70*
c	Intercept	-3.91*	0.64*

were ranked within the maximal model in this order as described in modelling step 5. within the Methods section.

Similar to the parsimonious model for grain yield, variety and mineral treatment were significant terms within the model, influencing the asymptote (a) and the magnitude of the yield response to Nitrogen (b). For total biomass, mineral treatments P, KNaMg and Nil all had lower estimated a coefficients compared to the PKNaMg treatment (Table 5.4). Mineral treatments P, KNaMg and Nil also had a larger estimated b coefficients compared to the PKNaMg treatment. This variation in a and b suggests P, KNaMg and Nil treatments were less efficient at facilitating Nitrogen at lower doses and had a lower Nitrogen asymptote.

Maris Badger had the largest estimated a coefficient, of 0.33 bigger than Tipple, and the lowest estimated b coefficient, of -0.38 compared to Tipple (Table 5.4). Varieties Cooper and Optic had the lowest estimated a parameter (-0.36 and -0.34 compared to Tipple) and largest estimated b parameter (0.23 and 0.40 compared to Tipple).

Higher temperatures in June were shown to negatively influence the a parameter for all mineral treatments within the total biomass parsimonious model (Table 5.4). It was estimated the slope between mean June temperature and treatment was the same across all mineral treatments, suggesting the impact of higher temperatures in June are the same among all mineral treatments (Figure 5.8). Total rainfall in April was fitted to the model by a negative quadratic relationship with total biomass and influenced the a and b parameter of the LEXP function (Figure 5.7). Total rainfall in April was also shown to have a significant interaction with mineral treatments for parameter a, with treatment PKNaMg having the lowest estimation of the second order polynomial term (Table 5.4). From Figure 5.7, the influence of extreme rainfall was more severe for treatments which received more mineral inputs.

Table 5.4: The final parsimonious model for grain spring barley yield with model coefficients and standard errors ($R^2 = 82.46\%$). Values in the parameter column refer to weather variables influencing the a, b and c parameters (left) of the LEXP function. This model is a first level parametrisation, such that spring barley variety Tipple was fitted as the baseline and the effects of all other varieties are in reference to this, the intercept. (Second order polynomial terms (2), * Terms $\times 10^3$, ** Terms $\times 10^5$). Total rainfall and mean temperature are labelled TR and MT, respectively. Terms (1) and (2) refer to the linear and second order term of a quadratic relationship. Weather variables are ranked into the table depending on their model order

	Parameter	Coef	S.E.
a	Intercept	4.75	0.22
a	Treatment P	-0.52	0.09
a	Treatment K Na Mg	-1.15	0.09
a	Treatment Nil	-1.49	0.10
a	Variety Alexis	0.04	0.13
a	Variety Cooper	-0.36	0.13
a	Variety Georgie	0.16	0.12
a	Variety Irina	-0.06	0.20
a	Variety Julia	0.21	0.10
a	Variety Maris Badger	0.33	0.15
a	Variety Optic	-0.34	0.11
a	Variety Triumph	0.02	0.10
a	MT June	-0.05	0.01
a	TR April (1)	-1.90	0.78
a	TR April (2)	-5.29	0.79
a	Treatment P:Variety Alexis	-0.11	0.13
a	Treatment K Na Mg:Variety Alexis	-0.08	0.13
a	Treatment Nil:Variety Alexis	-0.45	0.14
a	Treatment P:Variety Cooper	-0.10	0.13
a	Treatment K Na Mg:Variety Cooper	0.55	0.13
a	Treatment Nil:Variety Cooper	0.28	0.13
a	Treatment P:Variety Georgie	-0.29	0.12
a	Treatment K Na Mg:Variety Georgie	0.20	0.12
a	Treatment Nil:Variety Georgie	-0.11	0.12
a	Treatment P:Variety Irina	-0.14	0.20
a	Treatment K Na Mg:Variety Irina	-0.19	0.20
a	Treatment Nil:Variety Irina	-0.20	0.20
a	Treatment P:Variety Julia	-0.19	0.10
a	Treatment K Na Mg:Variety Julia	0.45	0.10
a	Treatment Nil:Variety Julia	0.21	0.10
a	Treatment P:Variety Maris Badger	-0.05	0.16

Table 5.4 continues overleaf

Table 5.4 continued

	Parameter	Coef	S.E.
a	Treatment K Na Mg:Variety Maris Badger	0.38	0.16
a	Treatment Nil:Variety Maris Badger	0.33	0.16
a	Treatment P:Variety Optic	-0.21	0.12
a	Treatment K Na Mg:Variety Optic	0.13	0.12
a	Treatment Nil:Variety Optic	-0.10	0.12
a	Treatment K Na Mg:Variety Triumph	0.32	0.10
a	Treatment P:Variety Triumph	-0.26	0.10
a	Treatment Nil:Variety Triumph	-0.12	0.10
a	Treatment Nil:TR April (1)	0.22	0.81
a	Treatment K Na Mg:TR April (1)	-1.21	0.80
a	Treatment P:TR April (1)	2.48	0.80
a	Treatment Nil:TR April (2)	2.38	0.81
a	Treatment K Na Mg:TR April (2)	0.69	0.81
a	Treatment P:TR April (2)	0.26	0.81
b	Intercept	-2.58	0.19
b	Treatment P	0.75	0.10
b	Treatment K Na Mg	0.59	0.10
b	Treatment Nil	1.11	0.10
b	Variety Alexis	-0.07	0.16
b	Variety Cooper	0.23	0.16
b	Variety Georgie	-0.05	0.15
b	Variety Irina	0.13	0.25
b	Variety Julia	-0.29	0.12
b	Variety Maris Badger	-0.38	0.19
b	Variety Optic	0.40	0.14
b	Variety Triumph	0.09	0.12
b	TR April (1)	-1.52	0.97
b	TR April (2)	3.51	0.98
c	Intercept	-4.87*	0.87*

Figure 5.5: Response surface of the effect of Nitrogen on spring barley yield from the grain yield parsimonious model (Table 5.3) as affected by mean April rainfall for treatments: (a) PKNaMg, (b) P, (c) KNaMg and (d) Nil.

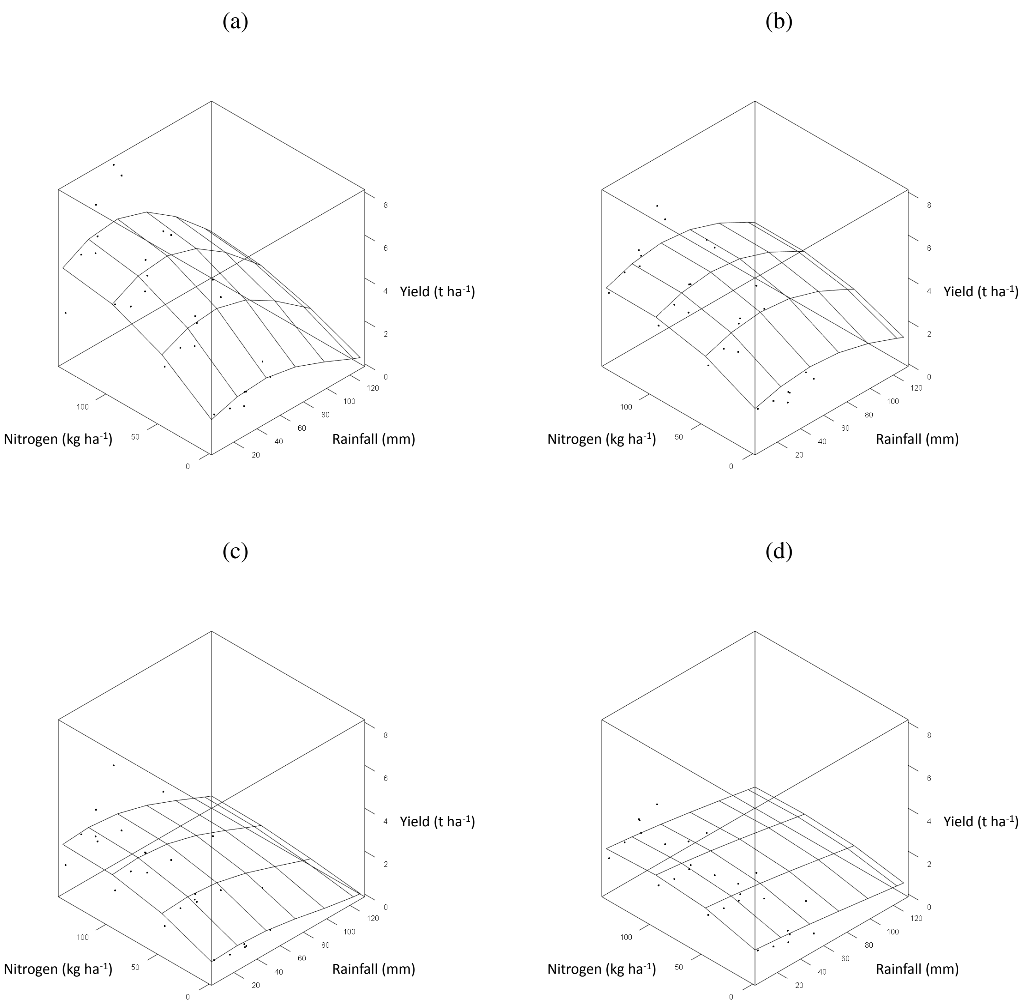
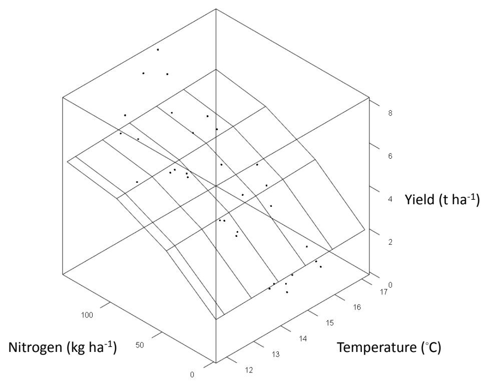
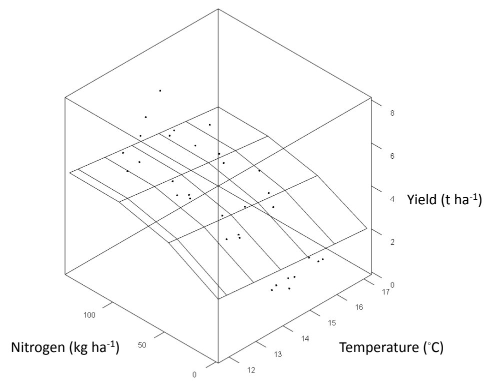


Figure 5.6: Response surface of the effect of Nitrogen on spring barley yield from the grain yield parsimonious model (Table 5.3) as affected by mean June temperature for treatments: (a) PKNaMg, (b) P, (c) KNaMg and (d) Nil.

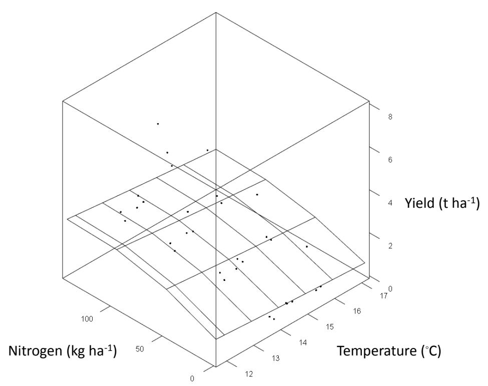
(a)



(b)



(c)



(d)

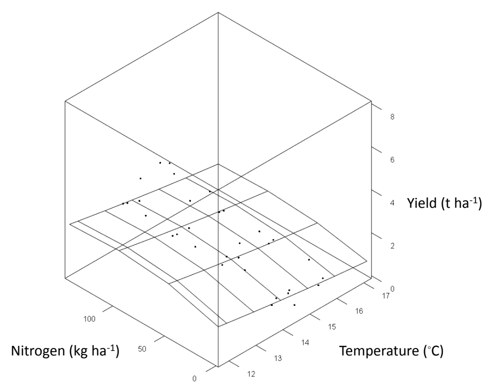
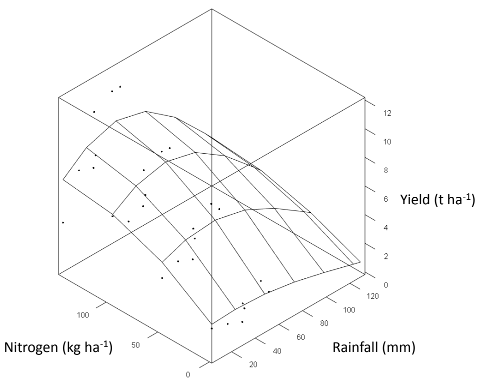
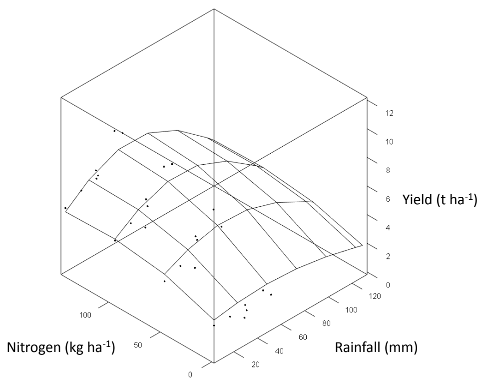


Figure 5.7: Response surface of the effect of Nitrogen on spring barley yield from the total biomass parsimonious model (Table 5.4) as affected by mean April rainfall for treatments: (a) PKNaMg, (b) P, (c) KNaMg and (d) Nil.

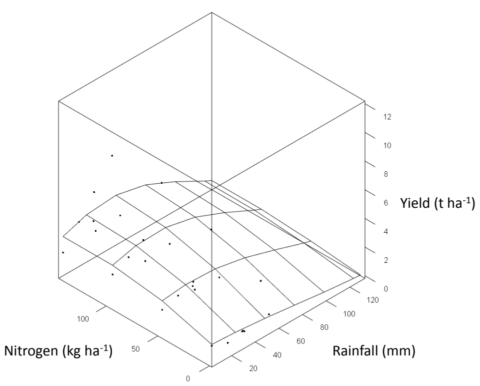
(a)



(b)



(c)



(d)

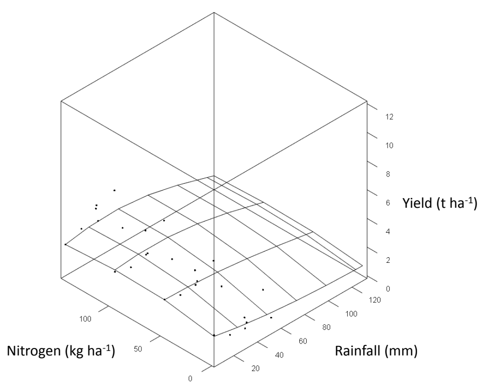
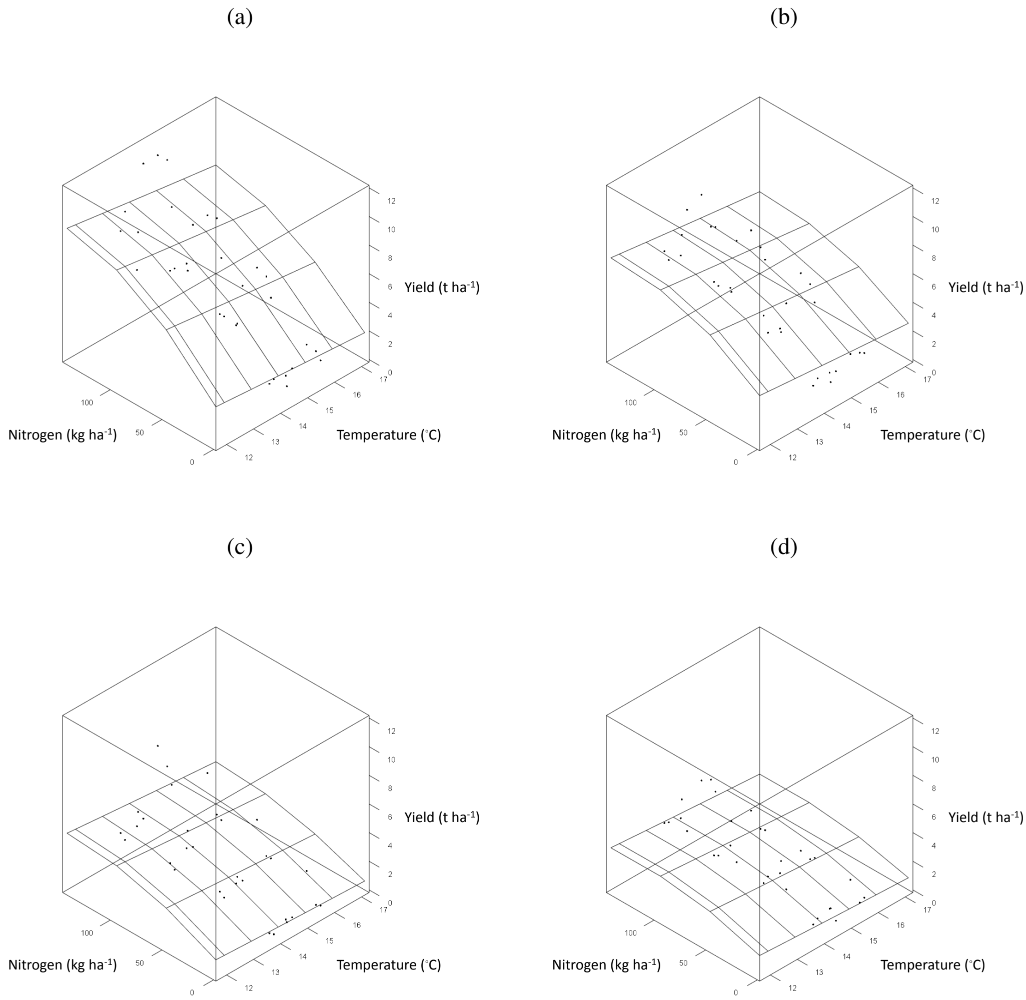


Figure 5.8: Response surface of the effect of Nitrogen on spring barley yield from the total biomass parsimonious model (Table 5.4) as affected by mean June temperature for treatments: (a) PKNaMg, (b) P, (c) KNaMg and (d) Nil.



5.5 Discussion

Hypothesis 1: Yearly variations in cereal Nitrogen response has been observed on wheat from a Rothamsted Long-Term Experiment. Do we observe yearly variations in the Nitrogen response to yield (grain yield and total biomass) of the Hoosfield Experiment across various mineral fertilisers, from 1968 to 2016.

For both grain yield and total biomass, the Nitrogen response to yield for spring barley of the Hoosfield Experiment was shown to have significant year-to-year variations over all mineral treatments, between 1968 and 2016. From Chapter 4, it was shown there was significant variation in the Nitrogen response to wheat yield over the same period.

Following the same conclusions from Chapter 4, the LEXP function has, within these analyses, three estimable parameters. Therefore, there was an extra degree of freedom (four Nitrogen doses, three parameters) to test if the Nitrogen response, and therefore yield, varied between years. Since spring spring barley yields were shown to have significant year-to-year variability, this should be minimised in order to create a less variable agricultural production system. However, consideration into the sources of crop variability should be given. For example, since 1968, nine spring barley varieties have been sown on Hoosfield, therefore, how much were variations in yield due to variations in weather and potentially climate change (this will be discussed within Hypothesis 2 of this Chapter and the effect on wheat was discussion within the Discussion of Chapter 4). Within the General Discussion a comparison of the Nitrogen response curve between wheat and spring barley will be given.

Furthering the method of fitting a Nitrogen response curve to each year over one mineral treatment (Chapter 4). The analyses within this section show how estimating the parameters of the LEXP function can be achieved within different mineral treatments and therefore experimental design and show potential for this type of response curve analyses over larger, more complex, designed experiments.

Hypothesis 2: Do inter-annual variations in weather affect the Nitrogen yield response curve in spring barley across various mineral fertilisers and therefore suggest

optimum weather conditions, along with Nitrogen to maximise yield.

Amongst mineral treatments, grain yield and total biomass of continuous spring barley was shown to vary between years from 1968 to 2016. The mineral treatment PKNaMg had the largest estimated a coefficient and lowest estimated b coefficient for both grain yield and total biomass (Tables 5.1 and 5.2). The P treatment had the second largest estimated a, coefficient compared to KNaMg and Nil, suggesting P was more important for spring barley production than the combination of KNaMg. However, due to the layout of the experiment, isolating a true P effect from a $2{\times}2$ factorial design structure would not be robust, due to the established plot characteristics such as soil organic carbon being higher on the PKNaMg plots confounding the true effect of P. This was a consideration of interest, as there may be long-term effects of treatment which may confound year-to-year variations in yield.

Increases in mean June temperature was negatively correlated with increases in yield, suggesting this stage of crop development was sensitive to heat stress. Phenology data was not collected from the Hoosfield Experiment, however anthesis, in wheat, may occur in early summer (Gooding & Davies, 1997) and heat stress around anthesis has been shown to be sensitive to temperature (Ferris et al., 1998). Correlations between mean June temperature and yield were more negative for treatments which receive fewer mineral inputs. Also, the estimated effect of mean June temperature on the a coefficient, in the parsimonious grain yield model, was more negative for treatments which receive fewer mineral inputs. Therefore, low input plots were more susceptible to temperature variability in June, suggesting low fertilised plots were more dependent on the environment. Since a Nitrogen response curve was fitted between Nitrogen doses, and it has been discussed (Chapter 4) that with higher doses of Nitrogen yield has a higher variance, inference of the effect of June temperature and yield was borrowed from lower doses of Nitrogen, where an effect may have occurred but other sources of variability has confounded this relationship.

The association of rainfall explaining variability in long-term yield datasets has been discussed in Chapter 4 and its documentation within the literature (Chmielewski & Potts, 1995; Fisher, 1925a; Hatfield & Vold, 2018; Hooker, 1907). April rainfall was negatively correlated with grain yield and total biomass across all mineral and Nitrogen treatments (Tables A.17, A.18, A.19, A.20, A.25, A.26, A.27 and A.28). Within both parsimonious models, April rainfall had a quadratic effect on the a coefficient for grain yield and the a and b coefficient for total biomass, suggesting there was an optimum April rainfall which maximises spring barley yield of between 50 and 70mm. There was also a significant interaction between April rainfall and mineral treatments for the a parameter in both grain yield and total biomass models. The quadratic relationship between April rainfall and yield was more linear in treatments which received fewer mineral inputs (Figures 5.5 and 5.7). Therefore, the effects of increased rainfall and drought in April was less in low mineral plots due to the potential of less fertiliser being potentially leached into the soil or possibly lost by evapotranspiration.

September rainfall was more negatively correlated with grain yield and total biomass from low fertilised plots. Within the parsimonious model for grain yield (Table 5.3), September rainfall had more positive estimated b coefficient. Therefore, as more rain fell as the crop matured yields from lower Nitrogen doses were reduced compared to higher Nitrogen doses. Another explanation for this relationship may be considered from the use of a square-root transform of yield and potential variability in yield from higher Nitrogen doses could be lost. Mean February temperature, when the crop was sown, was negatively correlated with grain yield and total biomass across all mineral and Nitrogen treatments (Tables Appendix A.21, A.22, A.23, A.24, A.29, A.30, A.31 and A.32). Within the parsimonious model for grain yield (Table 5.3), mean February temperature influenced the a parameter but did not interact with treatment. Therefore, warmer temperatures around sowing saw a decline in grain yield. This relationship of weather around sowing and yield has been detected in previous studies on crop variability (Chmielewski & Potts, 1995; Fisher, 1925a; Hooker, 1907). Including variable variables around sowing may be considered as a proxy and may be capturing variations in sowing data (which may be driven by weather).

Although parameter c did not interact with any variable, c explained significant amounts of variability within the parsimonious model. Allowing c within the model, even at few Nitrogen doses (0, 48, 96 and 144 kg N ha^{-1}kg N ha^{-1}), allowed the Nitrogen response curve to be estimated without an asymptotic assumption. Nitrogen response curves with an asymptotic assumption we shown to provide a poor fit beyond optimum Nitrogen application (Cerrato & Blackmer, 1990). Therefore, although it may not vary between years, an estimated c parameter was why the Linear-by-Exponential function was an adequate function in modelling a Nitrogen response curve to yield.

Confounding of variables and collinearity of explanatory variables discussed in Chapter 4, to identify weather variability in wheat yields. These issues persist within these analyses of the Hoosfield spring barley dataset. Alexis is a spring barley variety used in the brewing industry. It was sown at Hoosfield between the years 1992 and 1995. Within these analyses Alexis was estimated to have the largest estimated a coefficient for grain yield, the conclusion being it would provide the greatest spring barley yield given non-limiting growing conditions. Similarly, Maris Badger, an early dwarfing variety sown between 1968 and 1969, had the lowest estimated b parameter compared to other varieties, suggesting this was the best variety for Nitrogen uptake and utilisation at low doses for grain yield.

Over the lifetime of the Hoosfield experiment Rothamsted temperatures have increased (Chapter 3) and atmospheric CO_2 has risen above 400 ppm (NOAA, 2018). Although variety was included as a factor within the model, the true estimate of the cultivar effect cannot be estimated due to other influencing variables changing over the decades. The issues of estimating a variety effect within Hoosfield also differ from that of Broadbalk. Since 1968, Hoosfield has had nine spring barley varieties sown compared to six wheat varieties at Broadbalk. Therefore, there were fewer observations to test the variety-LEXP interaction within the Hoosfield analysis. Fewer observations for each variety makes a true estimation of the impact of weather variability more biased towards extreme weather events.

Within these analyses, the interaction between variety and weather was omitted. Therefore, only the intercept was estimated for each variety. The reason for this omission of an interaction does not only depend on how long a variety was sown for but also if, during the time the variety was sown, there was enough variability along the weather variable axis. For example, if a variety was sown for 15 years and the weather variable of interest only varied $+-0.5°$C within these years it would be inappropriate to compare the interaction with a variety which was sown for 15 years and the weather variable varied $+-3°$C as the relationship may not be linear and the estimation of the effect for the first variety would be more weighted around the mean. The issue of non-linearity of weather variables against yield was discussed by Katz (1977). Therefore, as temperatures increase throughout the 21st century, the bivariate relationship between yield and temperature may become more complex, and varieties may need to be sown over a longer time period in order to detect future effects of climate change.

An example of this was given by the need to exclude yields from 1993, 1998, 2000, 2012 from the grain yield and total biomass analysis, due to extreme April rainfall values inverting the negative quadratic relationship to positive. There were not enough observed years between the observed outlier of rainfall and the rest of the dataset, and for most rainfall variables the relationship was a negative quadratic. Therefore, the estimation of the polynomial coefficients was heavily weighted around one extreme observation for varieties which have five or less observations. These years were only omitted from the maximal and parsimonious models and were included in the year model and correlations.

Also, the summarisation of the weather variables themselves may have been an issue. Within one year, April may have experienced large amounts of rainfall but over the whole spring average (relative to a baseline climate) rainfall may have been experienced. With regards to these analyses, to include these years, which influenced the model parameters, within the parsimonious model would have resulted in incorrect parametrisation of model coefficients and led to incorrect conclusions. A potential approach to overcome this issue, of outliers influencing model parameters, would have either been to use mean April temperature as a proxy as temperature and rainfall were highly colinear, or to use a lasso-regression approach where weights were given to model coefficients.

The ability to test the effects of weather variability on the yield Rothamsted Long-Term Experiments is invaluable and shows the importance of these experiments as a resource to provide insight into the sustainability of food production and the associated impacts of climate change over various cropping systems. This study builds upon the findings of Chapter 4, where it was investigated how weather influences the shape of Nitrogen responses in wheat. From this study, a Linear-by-Exponential function has provided a good representation of the response of spring barley yield to applied Nitrogen and shown how the response was affected by inter-annual variation in weather and mineral application. Within this chapter, the year-to-year variability in yield between mineral treatments was shown to be influenced by both annual variations in rainfall and underlying long-term changes temperature. A comparison between the results from these analyses and Chapter 6 will be provided in the General Discussion.

5.6 Conclusion

Similar to the conclusion of Chapter 4, there was significant variation in the Nitrogen response on Hoosfield, from 1968 to 2016, due to inter-annual variations in weather (Hypothesis 1). Warmer temperatures and an absence of rainfall in the early-summer resulted in a lower yield of barley from Hoosfield. By acknowledging inferences between nitrogen treatments for each mineral treatment within Hoosfield, a nitrogen response curve could be adequately fitted to the model. Variations in weather around nitrogen application resulted in a loss in barley yield, where a greater loss of yield due to variations in weather around nitrogen application were found in the mineral fertilised plots compared to the non-mineral fertilised plots.

Therefore, to achieve higher levels of barley production, efforts to make barley more heat and drought tolerant in the early-summer and to produce an agricultural system barley can take up Nitrogen more efficiently from drier and wetter soils (Hypothesis 2). The conclusions reached within this Chapter were very similar to those of wheat within Chapter 4. Therefore, by analysing the Hoosfield experiment, similar evidence was found to support the conclusions within Chapter 4 and therefore illustrating the validity of the method of analysing variations in a Nitrogen response curve due to inter-annual variations in weather.

Chapter 6

The influence of weather variability on the first-cut hay and total-cut herbage yield of Park Grass

6.1 Introduction

Previous studies into variations in grassland yield have concluded that increases in rainfall have led to increased biomass production and the dominance of grasses on the experiment (Silvertown et al., 1994). Higher rainfall generally led to increased herbage yields and lower wheat and spring barley yields, in a study on the influence of weather over three Rothamsted Experiments (Chapter 3). Variations in monthly rainfall patterns have been previously shown to influence the hay yield of the Park Grass Experiment (Cashen, 1947; Lawes & Gilbert, 1880a). Bigger climate systems, such as the North Atlantic Oscillation, have also been shown to influence the forage growth rate, between the first and second cuts (Kettlewell et al., 2006). Previous studies have shown herbage yields from Park Grass to have high auto-correlation at lag one (Jenkinson et al, 1994; Kettlewell et al., 2006; Silvertown et al, 1994), therefore yields from each year may be dependent on the previous year. No influence of the increase in atmospheric CO_2 was observed on the yield of hay and herbage from Park Grass from years between 1891 and 1992 (Jenkinson et al., 1994). Rainfall was not the only influential weather variable on herbage yields.

A negative correlation was observed between mean maximum temperatures in July and August with herbage yields from Park Grass, between 1965 and 2002 (Sparks & Potts, 2003). Most years from the mid-1990s onwards, at Rothamsted, have been grouped into a climate cluster which was warmer and wetter compared to periods in the 20th century (Chapter 3). Previous studies into variations of herbage yields from the Park Grass Experiment have not considered the most recent data over this time period.

The Park Grass Experiment was established in 1853 to study the effect of organic, inorganic manures and liming on permanent grassland (Chapter 2) (Anon, 1971). Shortly after the experiment started it was realised that the botanical composition of the experiment changed with the fertiliser treatment applied and therefore the experiment is considered an ecological experiment. Plots on the experiment are cut twice a year, once in early-summer and again in early-autumn. Since 1960 the plots have been assessed by harvesting a single strip of the whole plot by using a forage harvester (herbage yield). Between 1901 and 1959, a mowing machine was used to harvest the first cut of the experiment (hay yield). Comparisons of these harvest methods have determined a correction factor discussed in Chapter 2, Equation 2.1. No previous studies on Park Grass, where investigations of how much weather variations influence the summer hay yield, have considered this correction factor and therefore no analysis has considered the first cut Park Grass dataset as one continuous time-series from 1902 to 2016.

6.2 Aims and Objectives

6.2.1 Aim

This study aims to investigate, from 1901 to 2016, and how inter-annual variability in weather contributes to variation in hay and herbage yields, on selected plots of the Park Grass Experiment.

6.2.2 Objectives

Within this chapter I:

- Calculated Pearson's correlation values and their significance levels between the summer hay yields of plots 3, 12, 2.2, 7.2, 16, 14.2 and 13.2 (subplots (b) and (d)) with seasonal (autumn, winter and spring) total rainfall and mean daily mean temperature.

- Calculated Pearson's correlation values and their significance levels between the herbage yields of plots 3, 12, 2.2, 7.2, 16, 14.2 and 13.2 (subplots (a), (b), (c) and (d)) with seasonal (autumn, winter, spring and summer) total rainfall and mean daily mean temperature.
- Built separate maximal models for both hay and herbage yield, including soil pH values and seasonal summarised weather variables.
- Ran a backwards model selection procedure to both maximal models to omit explanatory variables which did not explain large amounts of model variability.
- Produced a parsimonious model for hay and herbage yields, which identified key weather variables that influenced the yield on the Park Grass Experiment.

6.2.3 Hypotheses

- Previous studies have shown hay yields of the Park Grass Experiment to be influenced by weather. Do we observe the same relationships between hay yields and variations in weather by extending the time-series from 1901 to 2016.
- With most years since the mid-1990s, at Rothamsted, becoming more warmer and wetter (Chapter 3), do we observe associations between warmer temperatures and Park Grass total-cut herbage yield and the weather variability of seasonal rainfall and temperature.

6.3 Methods

6.3.1 Long-Term Experiment Data

Data considered for this study are first and second cut yields (t ha^{-1} at 100% dry matter) from plots 12, 3, 2.2, 7.2, 16, 14.2 and 13.2 (hereafter Nil_{12}, Nil_{3}, $Nil_{2.2}$, PKNaMg, N1 + PKNaMg, N2 + PKNaMg and FYM; where N1 was a dose of 48 kg N ha^{-1} and N2 96 kg N ha^{-1}) of the Park Grass Experiment for all liming applications (a, b, c and d). Other plots were considered for this analysis, however, soil pH measurements over time were too few to capture the variability of soil pH in more acidic plots. Limed subplots (d) had the longest time series starting in 1901 and plots (b) start in 1923 when the first soil pH measurements were taken. Plots (a) and (c) have a time-series starting in 1971 and 1977, respectively, as these were the first year's soil pH measurements were taken. To adjust for the changes in harvesting methods in 1960, a correction factor from herbage yield (Y_{Herbage}) to hay yield (Y_{Hay}) was used, given in Equation 2.1.

This study comprises of two separate analyses. The first examines how weather variability effects first-cut hay yields followed by a similar analysis for total-cut herbage yields (first-cut + second-cut). The correction factor stated in Equation 2.1 was calculated with yields from (b) and (d) subplots for plots Nil_{12}, Nil_3, $\text{Nil}_{2.2}$, PKNaMg, N1 + PKNaMg, N2 + PKNaMg and FYM, from years 1959 and 1992 to 1994. As the time-series of subplots (a) and (c) only start in 1971 and 1977 (after the change in harvesting methods) only liming subplots (b) and (d) were considered for the first-cut analyses.

6.3.2 Rothamsted Weather Data

Total rainfall (mm) and mean temperature (°C) data from the Rothamsted Meteorological Station, from 1901 onwards, were summarised into the seasons autumn (September, October and November), winter (December, January and February), spring (March, April and May) and summer (June, July and August). This was because plots within the Park Grass Experiment have different botanical compositions and potentially flower at different times during the harvest season. Taking monthly summarised variables may lead to incorrect conclusions. For example, a species which flowers in early spring may result in one variable being included within a model and omit another variable which may influence a species which flowers in late spring. Summer weather variables were not considered for the first cut analysis as the experiment is harvested in early June.

6.3.3 Statistical Analyses

Pearson's correlation coefficients and significance levels ($\alpha < 0.05$) between yield and seasonal weather variables were derived for each combination of fertiliser and liming treatments for both first-cut hay (1901 to 2016) and total-cut herbage (1960 to 2016). After observing correlations between yield and weather, a regression analysis was conducted to understand which weather variables are related to hay and herbage yield and which type of relationship they have. A step-by-step regression modelling procedure for first-cut hay and total-cut herbage yields are given below. It should be noted the first-cut hay yield model only considers autumn, winter and spring variables whereas the total-cut herbage yield model considers all seasons.

1. Correlations between yield and seasonal weather summaries were calculated for all fertiliser and liming treatments. Seasonal weather summaries included total rainfall and mean daily mean temperature.

2. A model was constructed which included a factor variable of plot (12a, 12b, 12c, 12d, 3a, etc...), a continuous variable for soil pH (values given in Chapter 2) and seasonal weather summaries.

3. Seasonal weather summaries were ranked within the model. An absolute correlation was calculated for each correlation and averaged across all plots to create a mean absolute correlation for each weather variable. Those weather variables with the highest mean absolute correlation were ranked into the model first.

4. After terms were included, some weather variables were omitted if they had a high correlation ($\rho >\mid 0.3 \mid$) due to collinearity of explanatory variables. The rejection level $\rho >\mid 0.3 \mid$ was selected because the correlation values between yield and weather variables were low - this was expected and more explanation of this will be in use of statistical methods within the General Discussion.

5. The relationship between yield and a weather variable was investigated. If the relationship was considered non-linear, it was fitted as a quadratic. Typically, this was a quadratic with a negative squared term.

6. Interactions between treatment, soil pH and weather were included within the model. Interactions between treatment involved the test to whether values had a significantly different slope and intercept. Combinations of weather variables were not considered for several reasons. First, due to a lack of biological meaning these comparisons would have made, for example understanding the magnitude effect of autumn temperature for variations in summer rainfall. Second, combinations of total rainfall and mean temperature

from the same month could result in a potential confounding as their main effect may lack independence.

7. A model with explanatory variables plot (factor), pH (continuous) and seasonal summarised variables, with weather variables omitted due to collinearity, and their interactions was considered as a maximal model.

8. From the maximal model, variable selection methods were used to achieve a reduced model. Omitting variables from the model one-by-one until convergence. The Akaike Information Criterion (AIC) (Akaike, 1971) was used to omit these terms. For each iteration the AIC becomes smaller until convergence occurs, meaning the AIC does not reduce for every additional variable omitted.

9. After the AIC selection procedure, a further model selection process, using partial F-tests, was used to test whether model parameters within the reduced model explained significant amounts of model variability (significance level $\alpha < 0.05$) and therefore a parsimonious model. If, after the omission of a term, an explanatory variable was non-significant (compared to a model including that term) it was concluded that variable did not explain significant model variability and was omitted.

10. After a parsimonious model was found, a final step of model validation was achieved to assess if the model was adequate. This involved a residual vs fitted, a Q-Q and a scale-location plot with a histogram of the residuals, these figures are considered non-essential to the overall conclusions of our results and are given in the Appendix.

After the first iteration of this procedure, it was found the residuals of the model lacked constant variance. Residuals at the highest yielding plots were more variable than the lowest yielding plots. To deal with this lack of constant variance a square root transform of the yield data was used and the model procedure stated above (steps 1 to 10) was repeated. Therefore, all model parameters stated within the results are on the square-root scale. All predictions from the model on figures with the yield scale were transformed back to the yield scale. Auto-correlation at lag 1 was conducted on the yields (both first and total cut) for each plot and the residuals for each parsimonious models. Auto-correlation here was calculated as the correlation of yield in time at year t with $t-1$.

6.4 Results

6.4.1 Relationship Between Weather and Park Grass First Cut

Hay Yield and Weather Correlations

Table 6.1 shows the correlation between first-cut hay yields and seasonal total rainfall and mean temperature for treatments Nil_{12}, Nil_3, $\text{Nil}_{2.2}$, PKNaMg, N1 + PKNaMg, N2 + PKNaMg and FYM for liming treatments b (limed) and d (unlimed). The correlations between autumn rainfall, spring rainfall and hay yield were positive across all treatments. Hay yields from treatments Nil_3(b), $\text{Nil}_{2.2}$(b), PKNaMg(b), N1 + PKNaMg(b), FYM(b) and FYM(d) had significant positive correlations with autumn rainfall. Hay yields from treatments Nil_3(b), $\text{Nil}_{2.2}$(b), PKNaMg(b), FYM(b) and FYM(d) had significant positive correlations with spring rainfall. Treatment PKNaMg(d) was the only plot to have a significant negative correlation between hay yield and winter rainfall, although all treatments except N1 + PKNaMg(b), N2 + PKNaMg(b), FYM(b) and FYM(d) had a negative correlation.

The correlations between autumn temperature and hay yield from all plots were negative except plot PKNaMg(b). Hay yields from treatments Nil_{12}(d), $\text{Nil}_{2.2}$(d), PKNaMg(d), N1 + PKNaMg(d), N2 + PKNaMg(b), N2 + PKNaMg(d) and FYM(d) all had significant negative correlations with mean autumn temperature. No treatments had significant correlations between hay yield and mean winter temperature and all correlations between hay yield and mean winter temperature for other treatments were low. Only treatment N1 + PKNaMg(d) had significant negative correlation between hay yield and mean spring temperature. From Table 6.1, the correlations between hay yield and mean spring temperature for other treatments were low.

Hay Yield Regression Model

Starting with a maximal model for first-cut hay yield, terms included within this maximal model include a factor variable for plot (12(a), 12(b), 12(c), 12(d), 3(a),...), pH as a continuous term. Weather terms included, ranked in order, were total rainfall in spring, mean autumn temperature, total rainfall in autumn, mean temperature in spring and total rainfall in winter. Interactions between the factor plot, pH and weather variables were included within the maximal model. Mean winter temperature was omitted from the model due to its high correlation with total winter rainfall and mean spring temperature. An interaction between factor and a weather variable resulted in a separate intercept and slope for said variable. Total rainfall in spring and mean temperature in spring were fitted as quadratics, where the second order term was negative indicating an optimum spring rainfall and temperature to maximise first-cut hay yield.

The AIC of the maximal model for hay yield was -3792.1 compared to -3890.7 of the reduced model, where the parsimonious model for hay yield explained the same model variability as the maximal model ($F(1.21, 151, 1319)$, $P > 0.05$). Table 6.2 and Figures 6.1, 6.3 and 6.2 show the parameters for the parsimonious model and the weather variables by yield plots. Weather variables total spring rainfall, mean autumn temperature and mean spring temperature were shown to explain significant amounts of variability within the parsimonious model for first-cut hay yield. Total spring rainfall and mean spring temperature were fitted into the model with a negative second order quadratic term suggesting an optimum to maximise yield. A separate linear and quadratic term was fitted for each plot for mean spring temperature. Therefore, the effect of mean spring temperature on yield was not the same across all treatment groups. From Figure 6.2, the relationship between hay yield and mean spring temperature was more linear compared to other treatments. With maximum yield occurring around mean spring temperatures between 7.5°C and 8.5°C. Ph was also shown to influence the relationship between mean spring temperature and hay yield. The model estimate effect between soil pH and mean spring temperature was -0.41 for the linear term and 1.85 for the quadratic term (Table 6.2). Therefore, more neutral the soil pH the more flat and linear the relationship between mean spring temperature and hay yield and less yield loss at warmer and cooler temperatures.

From Table 6.2 the effect of mean spring temperature becomes more linear for plots with lower fertiliser. Total spring rainfall of between 200 to 250mm provides optimum conditions for maximising hay yield. Mean autumn temperature was fitted as a negative relationship to hay yield, with different estimated intercepts but the same slope, or loss, as temperatures increase. The range of autumn temperature since 1901 to 2016 was between 7.44 and 12.84°C, the loss in hay yield over this range was around 0.5t ha^{-1}.

All treatments except FYM(b) had a positive auto-correlation of first-cut hay yields at lag 1 (Table 6.3). Treatments Nil_{12} (d), Nil_{3}(d), $\text{Nil}_{2.2}$(b), $\text{Nil}_{2.2}$(d), PKNaMg(d), N1 + PKNaMg(b), N1 + PKNaMg(d), N2 + PKNaMg(b) and N2 + PKNaMg(d) all had significant positive auto-correlation. From Table 6.3, all unlimed plots had a higher positive auto-correlation compared to limed plots. After the parsimonious model was fitted the only treatments which had a significant positive auto-correlation of the residuals were N1 + PKNaMg(b), N1 + PKNaMg(d), N2 + PKNaMg(b) and N2 + PKNaMg(d). Which therefore means some of the positive auto-correlation at low or no input plots were captured within this model. The fitted parsimonious model of first-cut Park Grass hay yield captures information regarding the year-to-year variation of yield and its relationship with soil pH and weather. This parsimonious model does not capture any information about the positive auto-correlation, however, we were able to capture some of the auto-correlation from low or no input plots from soil pH and weather.

Figure 6.1: First-cut hay yield Vs. total spring rainfall for limed (b) and unlimed (d) treatments. Treatments Nil_{12} (black), Nil_3 (light grey), $Nil_{2.2}$ (dark grey), PKNaMg (green), N1 + PKNaMg (orange), N2 + PKNaMg (red), FYM (blue). Points refer to observed yield, lines refer to fitted slope from the parsimonious model.

(a) (b)

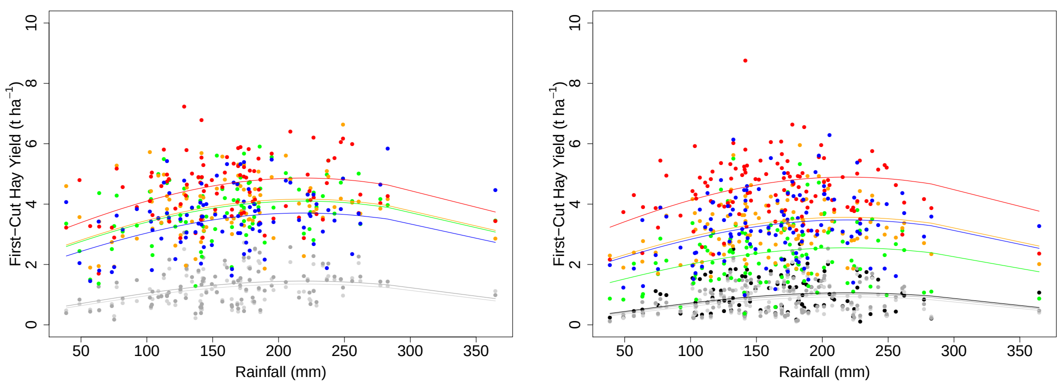


Figure 6.2: First-cut hay yield Vs. mean spring temperature for limed (a) and unlimed (b) treatments. Treatments Nil_{12} (black), Nil_3 (light grey), $Nil_{2.2}$ (dark grey), PKNaMg (green), N1 + PKNaMg (orange), N2 + PKNaMg (red), FYM (blue). Points refer to observed yield, lines refer to fitted slope from the parsimonious model

(a) (b)

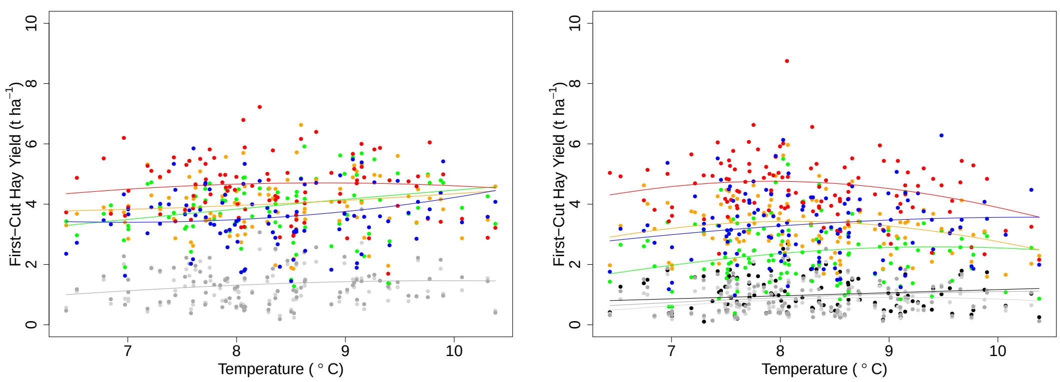


Table 6.1: Pearson's correlation coefficient between the first-cut hay yield of the Park Grass and summarised seasonal rainfall and temperature for different fertiliser treatments (values in *Italic* have $p < 0.05$). Degrees of freedom and significance levels for each fertiliser treatment are provided within the Appendix. Nil_{12}, Nil_3 and $Nil_{2.2}$ refers to nil treatment on plots 12, 3 and 2.2. (b) are the limed plots and (d) are the unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively.

	Total Rainfall			Mean Temperature		
Plot	Autumn	Winter	Spring	Autumn	Winter	Spring
Nil_{12}(d)	0.0338	-0.1560	0.0966	*-0.2735*	-0.1206	-0.0960
Nil_3(b)	*0.2228*	-0.0149	*0.3399*	-0.0165	0.0308	0.0973
Nil_3(d)	0.0363	-0.1355	0.1313	-0.1723	-0.0050	-0.0112
$Nil_{2.2}$(b)	*0.2543*	-0.0032	*0.2846*	-0.0407	0.0911	0.0923
$Nil_{2.2}$(d)	0.0583	-0.0633	0.1322	*-0.2206*	0.0282	-0.0463
PKNaMg(b)	*0.2291*	-0.0412	*0.3075*	0.0699	0.0995	0.1691
PKNaMg(d)	0.1258	*-0.1852*	0.1233	*-0.2662*	-0.0621	-0.0084
N1 + PKNaMg(b)	*0.2269*	0.1013	0.1946	-0.0732	0.0345	0.0859
N1 + PKNaMg(d)	0.0817	-0.0569	0.1187	*-0.3631*	-0.0500	*-0.2348*
N2 + PKNaMg(b)	0.0837	0.0270	0.1708	*-0.2108*	-0.0055	-0.1364
N2 + PKNaMg(d)	0.0048	-0.0711	0.0387	*-0.2991*	-0.0520	-0.2634
FYM(b)	*0.3071*	0.0340	*0.2905*	-0.0924	0.0753	0.0884
FYM(d)	*0.3014*	0.0586	*0.1920*	*-0.1891*	0.0897	0.0131

6.4.2 Relationship Between Weather and Park Grass Total Cut

Herbage yield and weather correlations

Table 6.4 shows the correlation between total-cut herbage yields and seasonal total rainfall and mean temperature for treatments Nil_{12}, Nil_3, $Nil_{2.2}$, PKNaMg, N1 + PKNaMg, N2 + PKNaMg and FYM for liming treatments (a), (b), (c), and (d). The correlations between autumn rainfall, spring rainfall, summer rainfall and herbage yield were positive across all plots, however none were significantly different from zero. Winter rainfall had a negative correlation with herbage yields for all plots, although no relationships were significantly different from zero. Herbage yields from all plots had a significant positive correlation with summer rainfall except plots N1 + PKNaMg(c), (d) and FYM(c). Plots Nil_{12}(a), Nil_3(a), Nil_3(b), $Nil_{2.2}$(a), $Nil_{2.2}$(b), PKNaMg(a),

Table 6.2: The final parsimonious model for first cut hay yield with model coefficients and standard errors ($R^2 = 81.04\%$). Total rainfall and mean temperature are labelled TR and MT, respectively. Weather variables with the highest mean absolute correlation with yield were included into the model first. This parsimonious model as a first level parametrisation, such that plot 12d was set as the baseline and the effect of all other plots are in reference to this, the intercept. Terms (1) and (2) refer to the linear and second order term of a quadratic relationship. Weather variables are ranked into the table depending on their model order. MT refers to mean temperature and TR total rainfall.

Parameter	Coef	S.E.
Intercept	-2.35	0.64
$Nil_{2.2}$(b)	5.22	0.71
$Nil_{2.2}$(d)	1.25	0.75
Nil_3(b)	5.44	0.80
Nil_3(d)	1.27	0.85
PKNaMg(b)	4.72	0.80
PKNaMg(d)	1.38	0.79
N1 + PKNaMg(b)	5.53	0.78
N1 + PKNaMg(d)	3.25	0.89
N2 + PKNaMg(b)	4.17	0.83
N2 + PKNaMg(d)	3.38	0.94
FYM(b)	4.41	0.71
FYM(d)	5.46	0.80
pH	0.71	0.12
TR Spring (1)	2.38	0.25
TR Spring (2)	-2.34	0.24
MT Autumn	-0.04	0.01
MT Spring (1)	3.78	4.57
MT Spring (2)	-9.76	4.22
Nil_3(b):Ph	-0.95	0.14
Nil_3(d):Ph	-0.26	0.16
$Nil_{2.2}$(b):Ph	-0.92	0.13
$Nil_{2.2}$(d):Ph	-0.26	0.14
PKNaMg(b):Ph	-0.71	0.14
PKNaMg(d):Ph	-0.14	0.15
N1 + PKNaMg(b):Ph	-0.82	0.14
N1 + PKNaMg(d):Ph	-0.47	0.16
N2 + PKNaMg(b):Ph	-0.60	0.14
N2 + PKNaMg(d):Ph	-0.46	0.17
FYM(b):Ph	-0.67	0.13
FYM(d):Ph	-0.90	0.16

Table 6.2 continues overleaf

Table 6.2 continued

Nil_3(b):MT Spring (1)	0.25	1.72
Nil_3(d):MT Spring (1)	0.01	1.22
$Nil_{2.2}$(b):MT Spring (1)	0.50	1.55
$Nil_{2.2}$(d):MT Spring (1)	0.53	1.24
PKNaMg(b):MT Spring (1)	1.49	1.64
PKNaMg(d):MT Spring (1)	0.56	1.23
N1 + PKNaMg(b):MT Spring (1)	0.31	1.81
N1 + PKNaMg(d):MT Spring (1)	-2.54	1.24
N2 + PKNaMg(b):MT Spring (1)	-0.67	1.73
N2 + PKNaMg(d):MT Spring (1)	-2.80	1.41
FYM(b):MT Spring (1)	0.82	1.45
FYM(d):MT Spring (1)	-0.08	1.33
Nil_3(b):MT Spring (2)	-3.17	1.65
Nil_3(d):MT Spring (2)	-1.30	1.20
$Nil_{2.2}$(b):MT Spring (2)	-2.56	1.53
$Nil_{2.2}$(d):MT Spring (2)	-0.69	1.21
PKNaMg(b):MT Spring (2)	-2.33	1.57
PKNaMg(d):MT Spring (2)	-0.81	1.21
N1 + PKNaMg(b):MT Spring (2)	-2.56	1.67
N1 + PKNaMg(d):MT Spring (2)	-2.24	1.23
N2 + PKNaMg(b):MT Spring (2)	-3.11	1.65
N2 + PKNaMg(d):MT Spring (2)	-3.02	1.38
FYM(b):MT Spring (2)	-0.79	1.43
FYM(d):MT Spring (2)	0.60	1.26
pH:MT Spring (1)	-0.41	0.86
pH:MT Spring (2)	1.85	0.79

Table 6.3: Autocorrelation coefficients at lag one for first-cut hay yields and residuals from parsimonious model. Nil_{12}, Nil_3 and $Nil_{2.2}$ refers to nil treatment on plots 12, 3 and 2.2. (b) are the limed plots and (d) are the unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively. The degrees of freedom for significance tests for the unlimed and limed subplots were 113 and 91. Individual P-values are given in the Appendix (values in *Italic* have a P-value < 0.05).

Plot	First-Cut Hay Yield	Parsimonious model residuals
Nil_{12}(d)	*0.4422*	0.1808
Nil_3(b)	0.1857	0.0937
Nil_3(d)	*0.3056*	0.1898
$Nil_{2.2}$(b)	*0.2828*	0.1265
$Nil_{2.2}$(d)	*0.3959*	0.1687
PKNaMg(b)	0.1169	0.0668
PKNaMg(d)	*0.4066*	*0.2590*
N1 + PKNaMg(b)	*0.3931*	*0.3784*
N1 + PKNaMg(d)	*0.5232*	*0.3352*
N2 + PKNaMg(b)	*0.2592*	*0.2438*
N2 + PKNaMg(d)	*0.4228*	0.1617
FYM(b)	-0.0881	-0.0959
FYM(d)	0.1524	0.0508

PKNaMg(b), N2 + PKNaMg(b), N2 + PKNaMg(c), FYM(c) and FYM(d) had significant positive correlations between spring rainfall and herbage yields. Only herbage yield from FYM(a) treatment had a significant positive correlation with total autumn rainfall.

All plots had a negative correlation between herbage yield and both mean winter temperature and mean summer temperature. Only plots Nil_3(a), $Nil_{2.2}$(b) and PKNaMg(c) did not have significant correlations with mean summer temperature. Plots from 7(c), 14.2(c), 14.2(d) and 13(a) had a significant negative correlation between herbage yields and mean spring temperature. Only herbage yields from plot 13a had a significant negative correlation with mean winter temperature. No significant correlation was found between mean autumn temperature and herbage yields across all plots.

Herbage Yield Regression Model

The maximal model for total-cut herbage yield included a factor variable for plot, pH as a continuous term and weather variables, ranked in order, total summer, spring, autumn and winter rainfall and mean winter and autumn temperature. Total spring rainfall was fitted with quadratic terms. All weather variables stated within the maximal model interacted with plot, pH and plot and pH together. Mean spring and summer temperature were omitted do to their high collinearity with total spring and summer rainfall. The interaction between plot and weather variables resulted in a separate slope and intercept fitted for each variable.

The AIC of the maximal model for herbage yield was -3601.1 compared to -3835.9 of the reduced model, where the parsimonious model for herbage yield explained the same model variability as the maximal model ($F(1.05, 386, 1264)$, $P > 0.05$). Table 6.5 and Figures 6.4, 6.5 and 6.6 show the parameters for the parsimonious model and the weather variables by yield plots. Weather variables total summer rainfall, mean autumn temperature and total spring rainfall were shown to explain significant amounts of variability within the parsimonious model for total-cut herbage yield. The estimated slope for the effect of mean autumn temperature and pH was shown to vary for each treatment within the parsimonious model. An interaction between mean autumn temperature and pH was found. Therefore, as a plots pH becomes more neutral the effect of mean autumn temperature changes. For example, the estimate effect of the interaction pH and mean autumn temperature was -0.04 for treatment Nil_{12}(a) compared to -0.1, 0.3 and -0.1 of treatments Nil_{12}(b), Nil_{12}(c) and Nil_{12}(d) (Table 6.5). The interaction effect of pH and mean autumn temperature was the lowest for treatments Nil_3(d) and $Nil_{2.2}$(d) with an estimate of -0.10 for both. From inorganic fertiliser, the effect of mean autumn temperature was more severe for low fertilised plots and unlimed plots (Table 6.4, Figure (6.5)). The estimated effect of mean autumn temperature was more negative for FYM(a) compared to the high fertilised plots. For every 1 mm increase in total summer rainfall a 0.00247 increase in herbage yield was estimated across all plots, as there was no strong evidence to suggest the slope of total summer rainfall varied for each treatment. Total spring rainfall was fitted into the model with a quadratic relationship for herbage yield (Figure 6.6). There was no evidence to suggest the linear and quadratic term for total spring rainfall varied for each treatment. Therefore, the optimum spring rainfall to maximise total-cut herbage yield was between 225 and 275mm.

The auto-correlation of the total-cut herbage yield and residuals from the parsimonious model for each plot are in Table 6.6. All treatments had a positive auto-correlation at lag one. The treatment with the highest lag one auto-correlation was N1 + PKNaMg(d) of 0.4617, followed by treatment N2 + PKNaMg(d) of 0.4153. The auto-correlation at lag one from the residuals of each treatment were generally lower than the total-cut herbage, therefore weather variable capture some of the auto-correlation. From the residuals of the parsimonious model, treatments Nil_{12}, N1 + PKNaMg(b), N1 + PKNaMg(d), N2 + PKNaMg(b) and N2 + PKNaMg(d) still had auto-correlation coefficients significantly different from zero. In the case of N1 + PKNaMg(b) and N1 + PKNaMg(d) the auto-correlation of the residuals at lag one was more positive compared to total-cut herbage yield. Therefore, the parsimonious model added some auto-correlation with the absence of a variable explaining this potential auto-correlation.

Figure 6.3: First-cut hay yield Vs. mean autumn temperature for limed (a) and unlimed (b) treatments. Treatments Nil_{12} (black), Nil_{3} (light grey), $Nil_{2.2}$ (dark grey), PKNaMg (green), N1 + PKNaMg (orange), N2 + PKNaMg (red), FYM (blue). Points refer to observed yield, lines refer to fitted slope from the parsimonious model

(a) (b)

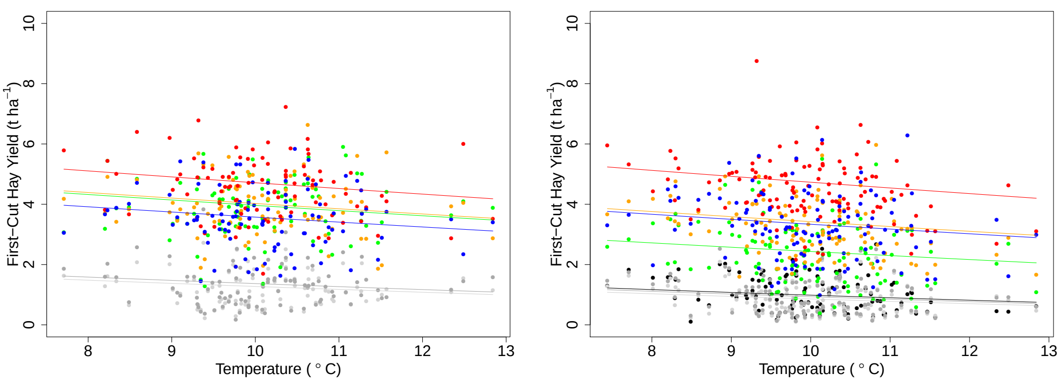


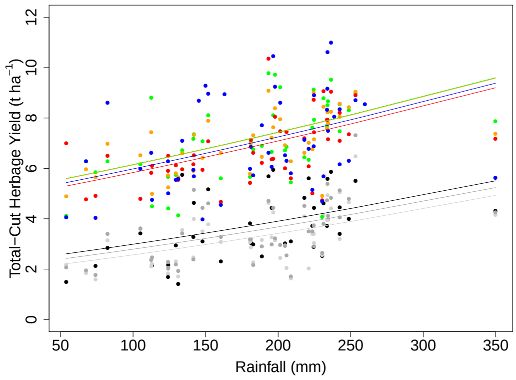
Table 6.4: Pearson's correlation coefficient between the total-cut herbage yield of Park Grass and summarised seasonal rainfall and temperature for different plots (values in *Italic* have $p < 0.05$). Degrees of freedom and significance levels for each fertiliser treatment are provided within the Appendix. Nil_{12}, Nil_3 and $Nil_{2.2}$ refers to nil treatment on plots 12, 3 and 2.2. (b) are the limed plots and (d) are the unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively.

	Total Rainfall				Mean Temperature			
Plot	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer
Nil_{12}(a)	0.0618	-0.1182	*0.3955*	*0.5110*	0.0036	-0.2269	-0.0364	*-0.6203*
Nil_{12}(b)	0.0566	-0.1793	0.2642	*0.5444*	0.0973	-0.1705	0.1361	*-0.4907*
Nil_{12}(c)	0.1721	-0.1767	0.2668	*0.3924*	-0.0854	-0.0610	0.0813	*-0.4073*
Nil_{12}(d)	0.0269	-0.1411	0.2065	*0.5146*	-0.0971	-0.3084	0.0581	*-0.5497*
Nil_3(a)	0.2194	-0.1339	*0.3780*	*0.5625*	0.0715	-0.0945	0.1945	-0.2778
Nil_3(b)	0.1851	-0.1337	*0.3336*	*0.5368*	-0.0243	-0.1086	0.1661	*-0.2788*
Nil_3(c)	0.1828	-0.2837	0.1988	*0.4198*	-0.2210	-0.1337	0.0453	*-0.3589*
Nil_3(d)	0.0331	-0.1996	0.1640	*0.5464*	-0.0044	-0.0730	0.1452	*-0.3413*
$Nil_{2.2}$(a)	0.2097	-0.1583	*0.3442*	*0.5454*	0.0489	-0.0560	0.1393	*-0.3326*
$Nil_{2.2}$(b)	0.2303	-0.1190	*0.3107*	*0.4742*	-0.0149	-0.0171	0.1799	-0.2014
$Nil_{2.2}$(c)	0.1715	-0.2235	0.3075	*0.4161*	-0.2044	-0.1406	-0.0230	*-0.4542*
$Nil_{2.2}$(d)	0.0378	-0.0812	0.2150	*0.5135*	-0.0321	-0.0551	0.1085	*-0.3706*
PKNaMg(a)	0.2075	-0.2691	*0.3629*	*0.5227*	0.0142	-0.0486	0.0657	*-0.5070*
PKNaMg(b)	0.1844	-0.2358	*0.3630*	*0.4376*	-0.0593	-0.1136	-0.0036	*-0.4349*
PKNaMg(c)	0.3449	-0.2716	0.1274	*0.5775*	-0.0288	0.1507	*0.3546*	-0.2020
PKNaMg(d)	0.1437	-0.2258	0.1680	*0.5927*	-0.2004	-0.1554	0.0603	*-0.4396*

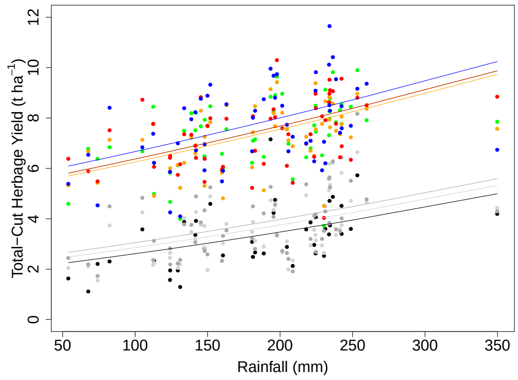
N1 + PKNaMg(a)	0.2352	-0.1733	0.2835	*0.5996*	0.0062	-0.0751	0.1088	*-0.4415*
N1 + PKNaMg(b)	0.2316	-0.0541	0.1802	*0.4743*	-0.1592	-0.1501	-0.0515	*-0.4207*
N1 + PKNaMg(c)	0.2675	-0.2189	0.2504	*0.5809*	-0.0913	-0.2124	-0.0086	*-0.4554*
N1 + PKNaMg(d)	0.0750	-0.1573	0.1763	*0.4573*	*-0.3144*	-0.2062	-0.2012	*-0.5433*
N2 + PKNaMg(a)	0.1907	-0.0896	0.1346	*0.4925*	0.0173	-0.1199	-0.0543	*-0.3914*
N2 + PKNaMg(b)	0.0821	-0.0391	*0.2880*	*0.3975*	-0.1499	-0.1393	-0.1922	*-0.4356*
N2 + PKNaMg(c)	0.1549	-0.0809	*0.3785*	0.3070	-0.0253	-0.2381	*-0.3940*	*-0.4389*
N2 + PKNaMg(d)	-0.0439	-0.1208	0.1018	0.2231	-0.1290	-0.1605	*-0.3963*	*-0.4555*
FYM(a)	0.1246	-0.1493	0.2327	*0.3342*	*-0.3090*	*-0.4050*	*-0.3159*	*-0.6561*
FYM(b)	0.2151	-0.1458	0.2343	*0.4153*	-0.1613	*-0.2755*	-0.0912	*-0.4722*
FYM(c)	0.2485	-0.0252	*0.3121*	0.2496	-0.0300	-0.1338	-0.1233	*-0.3618*
FYM(d)	*0.2855*	-0.0760	*0.2706*	*0.4305*	-0.0750	-0.0974	0.1125	*-0.3087*

Figure 6.4: Total-cut Herbage yield Vs. total summer rainfall for subplots kept at a pH of 7 (a), 6 (b), 5(c) and unlimed (d) treatments. Treatments Nil_{12} (black), Nil_{3} (light grey), $Nil_{2.2}$ (dark grey), PKNaMg (green), N1 + PKNaMg (orange), N2 + PKNaMg (red), FYM (blue). Points refer to observed yield, lines refer to fitted slope from the parsimonious model.

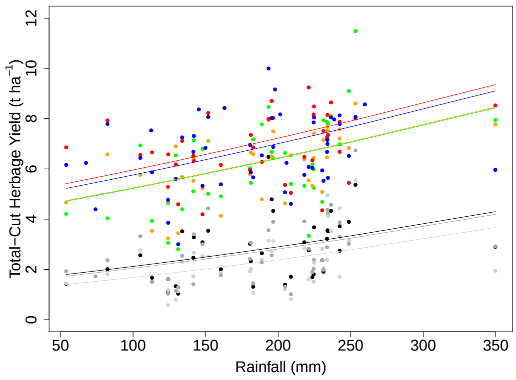
(a)



(b)



(c)



(d)

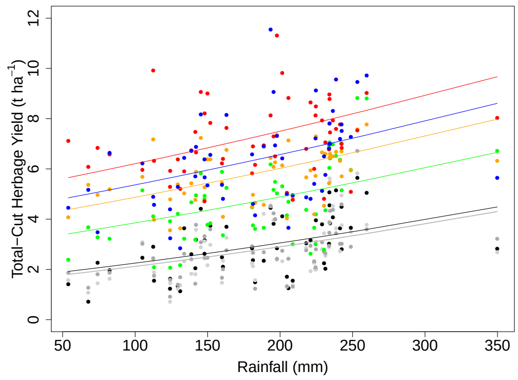


Figure 6.5: Total-cut Herbage yield Vs. mean autumn temperature for subplots kept at a pH of 7 (a), 6 (b), 5(c) and unlimed (d) treatments. Treatments Nil_{12} (black), Nil_3 (light grey), $Nil_{2.2}$ (dark grey), PKNaMg (green), N1 + PKNaMg (orange), N2 + PKNaMg (red), FYM (blue). Points refer to observed yield, lines refer to fitted slope from the parsimonious model.

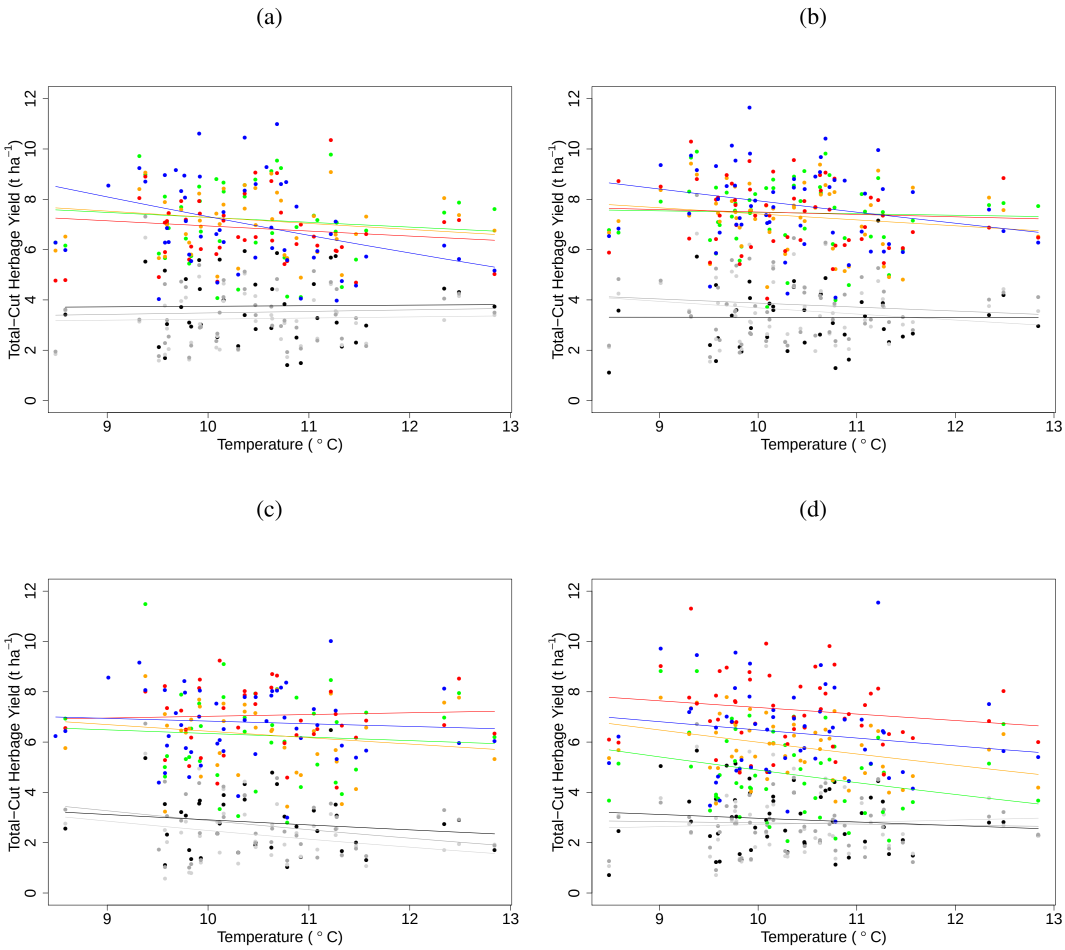


Table 6.5: The final parsimonious model for total-cut herbage yield with model coefficients and standard errors ($R^2 = 80.47\%$). Total rainfall and mean temperature are labelled TR and MT, respectively. Weather variables with the highest mean absolute correlation with yield were included into the model first. This parsimonious model as a first level parametrisation, such that plot 12a was set as the baseline and the effect of all other plots are in reference to this, the intercept. Terms (1) and (2) refer to the linear and second order term of a quadratic relationship. Weather variables are ranked into the table depending on their model order. MT refers to mean temperature and TR total rainfall. (* Terms $\times 10^3$).

Plot	Coef	S.E.
Intercept	0.78	2.25
Nil_{12}(b)	0.02	0.74
Nil_{12}(c)	0.57	0.92
Nil_{12}(d)	0.43	0.85
Nil_3(a)	-0.20	0.67
Nil_3(b)	0.72	0.66
Nil_3(c)	0.97	0.91
Nil_3(d)	-0.34	0.84
$Nil_{2.2}$(a)	-0.18	0.67
$Nil_{2.2}$(b)	0.55	0.66
$Nil_{2.2}$(c)	1.07	0.89
$Nil_{2.2}$(d)	0.09	0.85
PKNaMg(a)	1.19	0.71
PKNaMg(b)	1.00	0.68
PKNaMg(c)	1.07	0.90
PKNaMg(d)	1.66	0.91
N1 + PKNaMg(a)	1.28	0.65
N1 + PKNaMg(b)	1.31	0.69
N1 + PKNaMg(c)	1.28	0.84
N1 + PKNaMg(d)	1.67	0.80
N2 + PKNaMg(a)	1.14	0.65
N2 + PKNaMg(b)	1.04	0.68
N2 + PKNaMg(c)	0.70	0.78
N2 + PKNaMg(d)	1.40	0.71
FYM(a)	2.23	0.64
FYM(b)	1.79	0.69
FYM(c)	1.09	0.86
FYM(d)	1.48	0.94
Ph	0.09	0.32
TR summer	2.47*	0.12*
TR spring (1)	3.34	0.25

Table 6.5 continues overleaf

Table 6.2 continued

TR spring (2)	-1.93	0.26
MT autumn	0.25	0.24
Nil_{12}(b):MT autumn	-0.19	0.14
Nil_{12}(c):MT autumn	-0.49	0.18
Nil_{12}(d):MT autumn	-0.28	0.16
Nil_{3}(a):MT autumn	-0.07	0.14
Nil_{3}(b):MT autumn	-0.08	0.11
Nil_{3}(c):MT autumn	-0.51	0.19
Nil_{3}(d):MT autumn	0.26	0.18
$Nil_{2.2}$(a):MT autumn	-0.04	0.13
$Nil_{2.2}$(b):MT autumn	-0.10	0.11
$Nil_{2.2}$(c):MT autumn	-0.36	0.20
$Nil_{2.2}$(d):MT autumn	0.25	0.20
PKNaMg(a):MT autumn	-0.20	0.21
PKNaMg(b):MT autumn	-0.29	0.11
PKNaMg(c):MT autumn	-0.33	0.17
PKNaMg(d):MT autumn	-0.53	0.22
N1 + PKNaMg(a):MT autumn	-0.33	0.20
N1 + PKNaMg(b):MT autumn	-0.29	0.11
N1 + PKNaMg(c):MT autumn	-0.23	0.26
N1 + PKNaMg(d):MT autumn	-0.22	0.21
N2 + PKNaMg(a):MT autumn	-0.15	0.26
N2 + PKNaMg(b):MT autumn	-0.32	0.11
N2 + PKNaMg(c):MT autumn	0.18	0.24
N2 + PKNaMg(d):MT autumn	-0.15	0.20
FYM(a):MT autumn	-0.25	0.17
FYM(b):MT autumn	-0.25	0.11
FYM(c):MT autumn	-0.13	0.16
FYM(d):MT autumn	-0.31	0.17
Ph:MT autumn	-0.04	0.03
Nil_{12}(b):Ph:MT autumn	0.03	0.02
Nil_{12}(c):Ph:MT autumn	0.07	0.03
Nil_{12}(d):Ph:MT autumn	0.03	0.02
Nil_{3}(a):Ph:MT autumn	0.01	0.01
Nil_{3}(b):Ph:MT autumn	0.96*	0.01
Nil_{3}(c):Ph:MT autumn	0.06	0.03
Nil_{3}(d):Ph:MT autumn	-0.06	0.03
$Nil_{2.2}$(a):Ph:MT autumn	0.01	0.01
$Nil_{2.2}$(b):Ph:MT autumn	0.01	0.01
$Nil_{2.2}$(c):Ph:MT autumn	0.04	0.03
$Nil_{2.2}$(d):Ph:MT autumn	-0.06	0.03
PKNaMg(a):Ph:MT autumn	0.02	0.02
PKNaMg(b):Ph:MT autumn	0.04	0.01
PKNaMg(c):Ph:MT autumn	0.05	0.03
PKNaMg(d):Ph:MT autumn	0.07	0.04

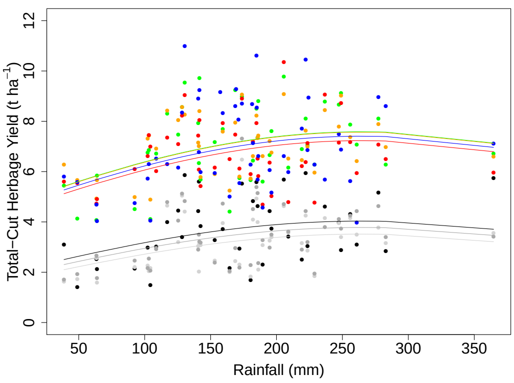
Table 6.5 continues overleaf

Table 6.2 continued

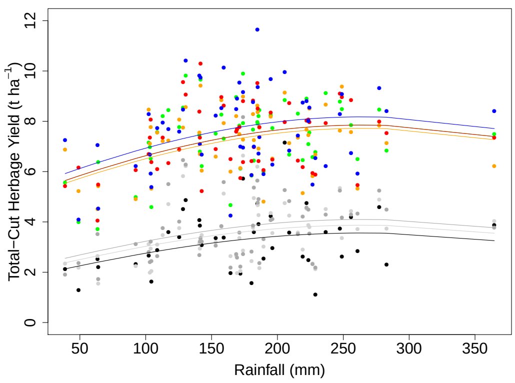
N1 + PKNaMg(a):Ph:MT autumn	0.04	0.03
N1 + PKNaMg(b):Ph:MT autumn	0.04	0.01
N1 + PKNaMg(c):Ph:MT autumn	0.02	0.04
N1 + PKNaMg(d):Ph:MT autumn	0.01	0.03
N2 + PKNaMg(a):Ph:MT autumn	0.02	0.04
N2 + PKNaMg(b):Ph:MT autumn	0.04	0.01
N2 + PKNaMg(c):Ph:MT autumn	-0.03	0.03
N2 + PKNaMg(d):Ph:MT autumn	0.01	0.03
FYM(a):Ph:MT autumn	0.02	0.02
FYM(b):Ph:MT autumn	0.02	0.01
FYM(c):Ph:MT autumn	0.01	0.02
FYM(d):Ph:MT autumn	0.04	0.02

Figure 6.6: Total-cut Herbage yield Vs. total spring rainfall for subplots kept at a pH of 7 (a), 6 (b), 5(c) and unlimed (d) treatments. Treatments Nil_{12} (black), Nil_3 (light grey), $\text{Nil}_{2.2}$ (dark grey), PKNaMg (green), N1 + PKNaMg (orange), N2 + PKNaMg (red), FYM (blue). Points refer to observed yield, lines refer to fitted slope from the parsimonious model.

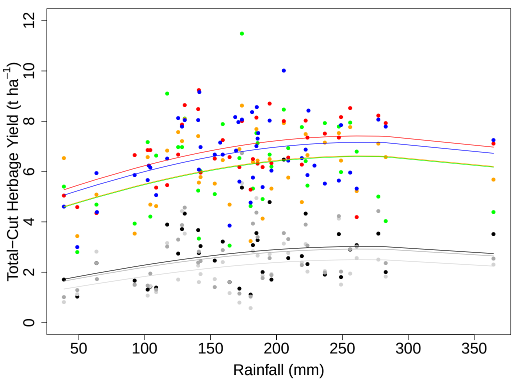
(a)



(b)



(c)



(d)

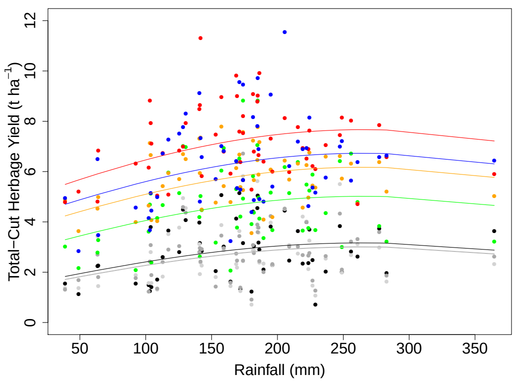


Table 6.6: Autocorrelation coefficients at lag 1 for total-cut herbage yields and residuals from the herbage parsimonious model. Nil_{12}, Nil_3 and $Nil_{2.2}$ refers to Nil treatment on plots 12, 3 and 2.2. (a) refer to plots kept at a pH of 7, (b) 6, (c) 5 and (d) unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively. The degrees of freedom for significance tests for the unlimed and limed subplots were 113 and 91. Individual P-values are given in the Appendix. Values in *Italic* have a P-value < 0.05.

Plot	Total-cut Herbage Yield	Parsimonious Model Residuals
Nil_{12}(a)	*0.3184*	0.1113
Nil_{12}(b)	0.1243	0.0068
Nil_{12}(c)	0.2644	0.1409
Nil_{12}(d)	*0.3896*	*0.3310*
Nil_3(a)	0.1666	-0.0769
Nil_3(b)	0.2981	0.0826
Nil_3(c)	0.2909	0.1536
Nil_3(d)	0.2960	0.1710
$Nil_{2.2}$(a)	0.2199	-0.0096
$Nil_{2.2}$(b)	*0.3270*	0.1069
$Nil_{2.2}$(c)	*0.3552*	0.2604
$Nil_{2.2}$(d)	0.2505	0.1580
PKNaMg(a)	0.2709	0.1436
PKNaMg(b)	0.2283	0.0791
PKNaMg(c)	0.3000	0.3212
PKNaMg(d)	*0.2690*	0.0624
N1 + PKNaMg(a)	0.0291	-0.1115
N1 + PKNaMg(b)	*0.3228*	*0.4115*
N1 + PKNaMg(c)	0.1618	0.2289
N1 + PKNaMg(d)	*0.4617*	*0.4945*
N2 + PKNaMg(a)	0.2291	-0.0329
N2 + PKNaMg(b)	*0.3494*	*0.3420*
N2 + PKNaMg(c)	0.2499	0.0206
N2 + PKNaMg(d)	*0.4153*	*0.3621*
FYM(a)	0.3052	0.1175
FYM(b)	0.1153	-0.0379
FYM(c)	0.1571	0.1339
FYM(d)	0.1835	0.0254

6.5 Discussion

Hypothesis 1: Previous studies have shown hay yields of the Park Grass Experiment to be influenced by weather. Do we observe the same relationships between hay yields and variations in weather by extending the time-series from 1901 to 2016.

Table 6.1 gives the correlation of seasonal weather variables and first cut hay yields of the Park Grass Experiment. Total autumn and spring rainfall had a positive correlation with hay yield across all plots. The correlation between mean autumn temperature and hay yield was negative for all plots except FYM(b). Within the regression model for hay yield (Table 6.2) both total spring rainfall and mean spring temperature explained significant amounts of model variability, compared to the maximal model, and were fitted by a quadratic relationship (Figures 6.2). Treatments Nil_{12}(d), Nil_3(b), Nil_3(d), $Nil_{2.2}$(d), $Nil_{2.2}$(b), PKNaMg(d) and FYM(d) had a more linear relationship with mean autumn temperature, suggesting weather variability within these months was more influential in higher input hay treatments. The effect of mean autumn temperature was -0.04 for every 1°C increase in temperature across all treatments. These results suggest wetter cooler weather conditions lead to greater yield of hay in early-summer. These results support those concluded from the multivariate approach within Chapter 3. Considered over a continuous scale, the negative relationship between mean autumn temperature and first-cut hay yield results in a lower yield from warmer temperatures. However, the amount of total rainfall within spring was quadratic with a maximum with an optimum value of between 200 and 250mm to maximise hay yield. This was also observed in Chapter 3, where wet and dry conditions, along with warmer temperatures, both had a lower yield compared to moderate rainfall.

Between 1858 and 1920 the effect of soil pH and rainfall on hay yield was not found (Cashen, 1947). A suggestion for the absence of a rainfall effect may be there was inadequate variation in the extreme tails of the explanatory variable rainfall to detect a possible quadratic relationship. Therefore, producing a flat, approximately zero, linear relationship between rainfall and hay yield. An example of this was from the total spring rainfall vs hay yield Figures 6.1. Most of the rainfall values fall between 100 and 250mm of rainfall. If this relationship was quadratic then adequate observations in the tails of spring rainfall are needed. This can only be observed in an experiment which has been running for a long period to have observed multiple variations of weather. Therefore, future analyses of these data with more years added, with the potential for more rainfall between the range 300 and 350mm of total spring rainfall to be observed, may result in different results and therefore different conclusions.

Although there have been small changes in the pH on the limed and unlimed plots (Chapter 2), pH was shown to have a positive linear effect on hay yield which was closer to 0 for limed treatments. There was also a liming effect influencing both hay yield and the effect of weather on hay yield. The quadratic relationship between mean spring temperature and first-cut hay yield was more linear in limed (b) plots compared to unlimed (d) plots. Therefore, with a more neutral soil the effects of warmer and cool autumn temperature are less compared to more acidic soil. It may be argued that as limed plots have a more stable pH compared to the unlimed, variations in soil pH which affect yield are more likely to be found in the unlimed plots. This relationship was also observed with organic and inorganic fertilisers. With the FYM treatment the effects of warm and cold autumn were less compared with inorganic fertilisers.

Hypothesis 2: With most years since the mid-1990s, at Rothamsted, becoming more warmer (Chapter 3), do we observe the same associations between Park Grass total-cut herbage yield and the weather variability of seasonal rainfall and temperature.

Table 6.4 gives the correlation of seasonal weather variables with total cut herbage yields. All plots had a positive correlation between total herbage yield and total spring and summer rainfall, and a negative correlation with total winter rainfall, mean winter and summer temperature. These results are consistent with Sparks & Potts (2003), where yields from Park Grass were negatively correlated with mean maximum temperatures in July-August and positively correlated with rainfall, from 1965 to 2002. Similarly, the summer growth rate on Park Grass was shown to be associated with the availability of soil moisture (Kettlewell et al, 2006). The correlation between total herbage yield and total autumn rainfall was positive for all plots except N1+PKNaMg(d) (-0.0439). Total spring rainfall was included into the parsimonious model by a quadratic relationship, with a negative second order term (Figures 6.6). The effect of total summer rainfall was linear and there was no evidence for an interaction with treatment. Therefore, after an early-summer harvest, these results suggest that a wetter summer conditions lead to a greater total yield of herbage.

The influence of weather variability on hay and herbage yield suggest cool conditions in spring lead to high yields across all plots. This was also found across Park Grass yields from a multivariate approach within Chapter 3. Over a continuous scale, the negative correlation and model coefficients for temperature suggest a lower hay and herbage yield with warmer temperatures. However, this was not the only weather effect. The influence of rainfall was shown to have a quadratic effect, with an optimal rainfall, in both first-cut hay and total-cut herbage yields. Previous studies into the effects of rainfall variation on the yield from Park Grass have shown high rainfall in spring leads to increased yield (Cashen, 1947; Lawes & Gilbert, 1880a). However, a lack of variation over the explanatory variable in earlier analyses may have prevented the detection of a significant quadratic effect. Compared to the regression model for first-cut hay yields, mean autumn temperature had a significant interaction with treatment and pH for the total-cut herbage yield model. Mean autumn temperature had a negative relationship with yield from hay yield and no interaction was found. The interpretation of mean autumn temperature within the total cut herbage analysis may be due the limitations of statistical methods in identify how weather variability influences long-term yields and the high auto-correlation of yields at lag one.

Overall, there was a negative association between temperature, within certain seasons, with first-cut hay and total-cut herbage yields. As temperatures increase the yield of Park Grass would be expected to decrease. However, any decline in yield due to increases in temperature may be offset by high rainfall or an enrichment of CO_2. The measured effect of increases in temperature were less in plots which were limed compared to those which were unlimed. The direct effect of a more neutral soil may influence the effect of weather and Park Grass yields. Although, the indirect effect of liming, such as an increase in the biodiversity of limed plots compared to unlimed plots (Chapter 2), may influence the relationship between limed plots and yield, indicating more diverse plots were less susceptible to variations weather.

Statistical Implications of Identifying Weather Variability on the Hay and Herbage Yield of the Park Grass

From these analyses we have modelled and discussed the effects of weather variability on the yield from the Park Grass Experiment for both first-cut hay and total-cut herbage yields. However, there may be other variables which were contributing to the yields of the Park Grass Experiment which have not been investigated within this study. Variations in the winter North Atlantic Oscillation were shown to influence the summer growth rate of Park Grass (Kettlewell et al, 2006). Declines in atmospheric Nitrogen deposition since the 1980s had led to a decline in grasses and an increase in legumes in low Nitrogen plots on the Park Grass experiment (Storkey et al., 2015). 2016 saw an increase in atmospheric CO_2 to 404ppm compared to 316 ppm in 1959 (NOAA, 2018). Enrichment of atmospheric CO_2 was shown to increase yield across multiple crops (Kimball, 1983). No influence of increasing atmospheric CO_2 on yield was found on the Park Grass Experiment, however, an explanation into the limitations of statistical methods into detecting climate change effects was given in Jenkinson et al. (1994) and the confounding benefits of increasing CO_2 and loss of yield due to increases in temperature are given in Chapter 7 and discussed in the General Discussion.

Hay and Herbage yields and parsimonious model residuals, from selected plots were found to have a positive auto-correlation, resulting in a lack of independence of yield response between years. Autocorrelation of yields were also found and discussed by Coleman et al. (1987), Jenkinson et al. (1994) and Kettlewell et al. (2006). This auto-correlation of yield can be defined as the correlation of yield in time at year t with year $t-1$. To put the importance of auto-correlation into context, the auto-correlation between N1 + PKNaMg(d) for total-cut yield was 0.4617 and the highest correlated weather variable was mean summer temperature with -0.5433. Therefore, including an autoregressive terms within the model may produce a better fit. A uniform crop is not sown to Park Grass every year, with each plot consisting of a mixture existing of legumes and grasses. Therefore, it may be suggested the auto-correlation values are driven by a dominance of a species. The method of fitting an autoregressive processes (AR(1)) to the Park Grass data was considered. However, since yearly measurements of species diversity and their relative yield were not taken, an estimation of a autoregressive coefficient would not be appropriate on just yield alone due to differences between treatments. Capturing some of the auto-correlation through the use of weather variable at time $t-1$ may be considered, although this could result in aliasing of explanatory variables due to collinearity of weather variables at time $t-1$.

The method of using a correction factor given by Bowley et al. (2017), provides a method of comparing yields from two different methods of harvesting from 1901 to 1959 with yield from 1960 to 2016. However, the use of a conversion factor may have resulted in a smoothing of 1960 to 2016 herbage yields. In the conversion, variability may have been lost which could have been contributed by weather which may have given bias results within the first-cut hay analysis. However, this conversion factor provides a method of including more data from the Park Grass Experiment in investigating the effect of weather variability on yield by extending the time-series and has furthered the understanding of how weather variability influences the growth of hay yield on the Park Grass Experiment.

6.6 Conclusion

Inter-annual variations in rainfall and temperature explain year-to-year variations in Park Grass yields. Spring rainfall was found to have a significant relationship with forage yields, where rainfall between 200 and 250mm were shown to maximise summer yield (Hypothesis 1). Increases in temperature were shown to have a negative effect on both the summer yield and the total yield (Hypothesis 1; Hypothesis 2). Therefore, as most years within the 21st century were warmer with more extreme rainfall, forage yields were shown to decrease. If this pattern of climate extends throughout the 21st century, of warmer years with more extreme rainfall, forage yields are expected to decrease further.

Year-to-year variations in forage yields due to inter-annual variations in weather were more severe from plots which received more fertiliser and had more acidic soils. Further evidence of this was found by the high auto-correlation of plots 16.2 and 14 after modelling for variations in weather. Yields from higher input plots seemed to be influenced by the success of the crop in the previous year. High input plots also had the lower biodiversity. Therefore, increased forage biodiversity may alleviate some of the effects climate change by increasing the resilience of the crop.

Chapter 7

Can Sirius be used to address the influence of atmospheric CO_2 on simulated wheat yields at Rothamsted

7.1 Introduction

The association between weather and crop yield variability on the Rothamsted Long-Term Experiments (LTEs) was investigated in Chapters 3, 4, 5 and 6. However, I have not addressed the potential influence of increases in atmospheric CO_2 on the yields of the Rothamsted LTEs. 2016 saw atmospheric CO_2 levels reach 404.21 ppm compared to 315.97 ppm in 1959 (NOAA, 2018). Along with increases in atmospheric CO_2, the 2007 to 2016 average temperature at Rothamsted was 1.03°C greater than the 1961 to 1990 average (Chapters 2 and 3). This study investigates the potential increase in yield due to rise in atmospheric CO_2 at Rothamsted from 1892 to 2016. The potential future influence of atmospheric CO_2 on grain yield at Rothamsted is also investigated using climate projections from the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al., 2011) from the mid (2041 to 2060) to late (2081 to 2100) 21st century.

The effect of increasing atmospheric CO_2 on crop yields was discussed within Section 1.3. A brief summary is given below. Both photosynthesis and water-use efficiency increase when a crop is grown in elevated CO_2 (Beadle et al., 1993). A doubling of CO_2 from 350 to 400 ppm was shown to increase crop yield by 31% (Amthor, 2001). Although the benefits of an enrichment of CO_2 were less for C4 crops compared to C3 crops (Bowes, 1993).

There was a negative association between within-year temperature and yield from the Broadbalk wheat and Hoosfield barley experiments (Chapters 3, 4 and 5). However, wheat grown in an enrichment of CO_2 (comparison of ambient levels to 700 μmol mol-1) was shown to increase grain weight regardless of temperature increases (Wheeler et al., 1996). Overall, crop biomass was shown to increase with greater CO_2 and decrease with higher temperatures (Batts et al., 1997).

The Rothamsted Meteorological Station has daily rainfall, maximum temperature, minimum temperature and total sunlight hours recordings dating from 1891 to the present (Chapter 2, Chapter 3). Along with this weather time-series, the NOAA have yearly atmospheric CO_2 measurements from 1959 to 2016 (NOAA, 2018). Ice core analysis has provided an estimation of atmospheric CO_2 to extend the National Oceanic and Atmospheric Administration (NOAA) time-series back to 1892 (Etheridge et al., 1998).

A simulation-based approach of future weather scenarios, using the wheat process-based model Sirius, showed, in the absence of enriched CO_2, future yields at Rothamsted in 2055 are expected to decrease (Semenov & Shewry, 2011). A study in Southern Denmark showed, across several wheat models, without the increase of atmospheric CO_2 over the 21st century there was an observed yield reduction, compare to a baseline climate (Ozturk et al., 2017).

7.2 Aims and Objectives

7.2.1 Aim

This study aims to investigate how much wheat yields at Rothamsted may have benefitted from an enrichment of atmospheric CO_2 from 1892 to 2016 by using a wheat process model: Sirius. This was achieved by allowing CO_2 to vary and fixing CO_2 at the estimated 1892 level (ppm) (Etheridge et al., 1998) and calculating a percentage difference for each year. However, comparing yields of enriched and fixed CO_2 levels for every year from 1892 to 2016 may not be considered representative as the effect of increased CO_2 may be limited by other environmental factors within a year. Therefore, as a supplement to the 1892 to 2016 analysis, 99 years of a baseline (1980 - 2010) climate was compared to 99 years of future climate emissions scenarios based on Representative Concentration Pathways (RCP; Moss et al., 2010) 4.5 and 8.5, where data was generated from the LARS-WG weather generator.

7.2.2 Objectives

Within this Chapter I intend to:

- Use Rothamsted's Meteorological time-series dataset together with atmospheric CO_2 measurements from Etheridge et al. (1998) and NOAA (2018) to simulate wheat yields, using the process based model Sirius, for each year from 1892 to 2016 where CO_2 was increasing with each year and CO_2 was fixed at a reference (1892) level of 295.6ppm.
- Compare the relationship between the % difference in yield simulations and CO_2 among three wheat varieties (Avalon, Claire and Mercia).
- Simulate wheat yields at Rothamsted in the mid-21st and late-21st century using data from HadGEM2 and GISS GCMs and compare these to a baseline climate.
- Investigate the potential loss of yield in the mid-21st and late-21st century, across both GCMs, without the enrichment of CO_2, across three varieties.
- Investigate the potential increase in yield from the projected RCP 4.5 and 8.5 CO_2 levels on a baseline climate, across three varieties.

7.2.3 Hypotheses

- Since 1892, has there been a positive effect of increase in CO_2 on wheat yield at Rothamsted and has the positive effect of CO_2 enrichment been observed through year-to-year variations in weather.
- Using future climate scenarios, do simulations indicate a positive effect on wheat yield from increases in atmospheric CO_2 at Rothamsted in the mid-to-late 21st century under projected HadGEM2 and GISS climates from RCPs 4.5 and 8.5?

7.3 Methods

Weather and CO_2 data were used to simulate yield data from a wheat process model Sirius (Jamieson et al., 1998) from 1892 to 2016. A simulation of wheat yield from 1892 to 2016, where CO_2 was increasing over time, was compared to a simulation where CO_2 was fixed at a reference 1892 level (295.6 ppm).

7.3.1 A Brief Description of Sirius

The key literature cited within this description of the wheat crop simulation model Sirius is Jamieson et al. (1998) and Semenov et al. (2014). The version of Sirius used within this study is 15.0.6494.28556. Sirius was applied to identify how much of the variability in wheat yield can be explained by increases in atmospheric CO_2 from 1892 to 2016 and from future climate scenarios.

Within Sirius, biomass production is calculated as a product of the amount of intercepted photosynthetically active radiation (PAR) and the radiation use efficiency (RUE), with the total above ground biomass (B) over a harvest season being the sum of PAR $\times$ RUE, from emergence to maturity (Jamieson et al., 1998). Generally, the RUE is proportional to atmospheric CO_2, therefore increases in CO_2 result in a greater RUE. However, there are many underlying processes driving the positive effects of CO_2 on simulated yields within Sirius. Some include the total leaf area, minimum leaf size, maximum leaf size and length of grain-filling period.

The phenology of pre-emergence, grain filling and maturation are calculated within Sirius from days in thermal time of air temperature, whereas phenology of leaf production and anthesis are calculated from the duration (in thermal time) of three and one phyllochron, respectively, where temperature is the canopy temperature (based upon air temperature) (Jamieson, et al,. 1998). Variations in phenology can occur with different set thermal time and phyllochron parameters from varieties. Grain yield from Sirius simulations is calculated by allowing all growth (PAR $\times$ RUE) between the grain filling period to be allocated to the grain, plus of 25% of the biomass at anthesis (Jamieson et al., 1998). The additional 25% of biomass added to grain yield at anthesis is inversely proportional to the grain filling period, longer grain filling periods result in a lower remobilisation of biomass to the grain (Semenov et al., 2014). Further information about the simulation of grain yield within Sirius is provided in Brooks et al. (2001). Variations in the maximum leaf size, through variety parameters, influence leaf area index and therefore the amount of intercepted radiation. Water or temperature stress influences the drought stress factor (daily calculation of actual and potential evapotranspiration). The presence of drought stress shortens the daily addition of thermal time and therefore accelerates leaf senescence (Semenov et al., 2014).

It should be noted that simulated yields within Sirius may be subject to error. The formulation of the model itself is driven by relationships, between input variables and yield, observed from experiments. An appreciation of the residual (predicted - observed) error of each experiment is not considered within Sirius and is therefore not considered within these analyses.

7.3.2 Varieties and Management Dates

Varieties chosen for this study were Avalon, Claire and Mercia. These varieties were chosen as they were already calibrated into Sirius. Avalon, Claire and Mercia have a short, moderate and long thermal time requirement from anthesis to beginning of grain filling, respectively. Mercia has a higher potential leaf size compared to Avalon and Claire. Claire has the longest accumulated day degree phyllochron period compared to Avalon which has the shortest. Both Claire and Mercia have the lowest minimum possible leaf number of 8 compared to 8.55 for Avalon. Claire has the lowest possible maximum leaf number of 18 compared to 24 for both Avalon and Claire. Avalon has a larger day-length response in leaves (h^{-1}) compared to Claire and Mercia.

Sowing date was set to the 15th of October and Nitrogen application date was set to the 15th of April with a single application of 192 kg N ha^{-1}. In all Sirius simulations water, Nitrogen, grain heat and grain drought limitations were activated (this is the Sirius default setting).

7.3.3 The Influence of atmospheric CO_2 at Rothamsted from 1892 to 2016

Daily rainfall, maximum temperature, minimum temperature and hours of direct sunlight from the Rothamsted Meteorological Station (RMS) from 1891 to 2016 were used. To accompany the weather dataset, CO_2 data from 1959 to 2016 from the Moana Loa Observatory CO_2 time-series dataset were used (NOAA, 2018). Atmospheric CO_2 data from 1892 to 1959 were taken from

Etheridge et al. (1998) to match the RMS time-series. Two simulations using the RMS dataset were conducted. A simulation of the RMS data where CO_2 was varied as observed (Figure 7.1) was compared against a simulation of the RMS data with CO_2 fixed at a reference level of the observed 1892 CO_2 level (295.6 ppm). A percentage difference between yields from a varying and reference CO_2 levels was calculated for each year as

$$\%\Delta y_i = 100 \times \left(\frac{y(CO_2Vary)_i}{y(CO_2Reference)_i} - 1 \right) \tag{7.1}$$

where y is grain yield and i is year from 1892 to 2016.

7.3.4 Future Simulations

One of the issues with the above analysis was that climate was not sampled from an underlying distribution. Therefore, potential increases in yield by increases in CO_2 may be limited by within-year variations in weather. Comparisons of wheat simulations between a baseline climate (1980 - 2010) and a number of future climate scenarios was conducted. Two global circulation models (GCMs) were selected from the Coupled Model Intercomparison Project phase 5 (CMIP5) ensemble. The two selected GCMs were the Hadley Centre Global Environmental Model-Earth System, version 2 (HadGEM2-ES; hereafter HadGEM2; Collins et al., 2011; Jones et al., 2011; Martin et al., 2011) and the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Sciences couples general circulation model (hereafter GISS; Chandler et al., 2013), over the two time periods 2041 - 2060 and 2081 - 2100 were considered from RCP 4.5 and 8.5. 100 years of weather were simulated for every future time period, RCP and GCM from the LARS-WG, along with 100 years of a baseline climate (1980 - 2010). Therefore, there are 9 sets of 100-year datasets.

From all GCMs and RCPs, four separate analyses where conducted in an attempt to investigate the effect of weather and CO_2 on yield. These four analyses were:

1. Future weather scenarios + future projected CO_2 (Analysis 1).
2. Future weather scenarios + baseline CO_2 (Analysis 2).
3. Baseline weather + future projected CO_2 (Analysis 3).

4. A comparison between future weather scenarios + future projected CO_2 and future weather scenarios + baseline CO_2 (Analysis 4).

7.3.5 Statistical Analysis

Weighted regression analysis through the origin was used to investigate the mean increase in the % yield difference of simulations between varying and fixed CO_2 for every unit increase in atmospheric CO_2 from 1892 to 2016. Weighted regression was used because of the systematic increase in variability as % yield difference increased. The weights for each observation of the analysis were the reciprocal of the squared residuals $(1/(r_i^2))$ from a fitted regression. Within the regression framework, Variety was fitted as a factor to determine if Avalon, Claire or Mercia had a different yield response to increase in CO_2. The effect of increasing CO_2 on % yield difference was fitted as a curvilinear relationship using a quadratic function.

An analysis of variance (ANOVA) framework was used to test if yields from future weather scenarios were significantly different to yields for the baseline climate (1981 - 2010). For the future weather scenarios + future projected CO_2 (Analysis 1) and future weather simulations + baseline CO_2 (Analysis 2) analyses, the explanatory component was fitted as:

$$y_{ijk} = \beta_0 + \beta_{1i}x_i + \beta_{2j}x_j + \beta_{3ik}x_{ik} + \beta_{4ij}x_{ij} + \beta_{5ijk}x_{ijk} + \varepsilon_{ijk} \tag{7.2}$$

with, y_{ijk} the yield from the i^{th} future scenario ($i = 1, 2, 3, 4, 5$; $1 =$ Baseline, $2 =$ 2041 - 2060 RCP 4.5, $3 =$ 2081 - 2100 RCP 4.5, $4 =$ 2041 - 2060 RCP 8.5, $5 =$ 2081 - 2100 RCP 8.5), j^{th} variety ($j = 1, 2, 3$; $1 =$ Avalon, $2 =$ Claire, $3 =$ Mercia) and k^{th} GCM ($k = 1, 2, 3$; $1 =$ baseline, $2 =$ GISS, $3 =$ HadGEM2). The overall mean effect was β_0, β_1 the effect of future climate scenario, β_2 the effect of variety, β_3 the interaction between future climate scenario and GCM, β_4 the interaction between future climate scenario and variety, and β_5 the interaction between future climate scenario, variety and GCM. An estimation of a main effect of GCM was not considered within these analysis. This was because both GISS and HadGEM2 were taken from an RCP. Therefore, the effect of GCM was nested within future scenario. The model given in Equation 7.2 was also fitted for days to anthesis and maturity.

For the baseline weather + future projected CO_2 (Analysis 3) analysis, the explanatory component was fitted as:

$$y_{ij} = \beta_0 + \beta_{1i}x_i + \beta_{2j}x_j + \beta_{3ij}x_{ij} + \varepsilon_{ij}$$

with, y_{ij} the yield from the i^{th} future scenario ($i = 1, 2, 3, 4, 5$; $1 =$ Baseline, $2 =$ 2041 - 2060 RCP 4.5, $3 =$ 2081 - 2100 RCP 4.5, $4 =$ 2041 - 2060 RCP 8.5, $5 =$ 2081 - 2100 RCP 8.5) and j^{th} variety ($j = 1, 2, 3$; $1 =$ Avalon, $2 =$ Claire, $3 =$ Mercia). The overall mean effect was β_0, β_1 the effect of future climate scenario, β_2 the effect of variety, and β_3 the interaction between future climate scenario and variety.

Analysis 4 (A comparison between future weather scenarios + future projected CO_2 and future weather scenarios + baseline CO_2) had an explanatory component fitted as:

$$y_{ijkl} = \beta_0 + \beta_{1i}x_i + \beta_{2j}x_j + \beta_{3ik}x_{ik} + \beta_{4ij}x_{ij} + \beta_{5ikl}x_{ikl} + \beta_{6ijk}x_{ijk} + \beta_{7ijkl}x_{ijkl} + \varepsilon_{ijkl}$$

with, y_{ijk} the yield from the i^{th} future scenario ($i = 1, 2, 3, 4, 5$; $1 =$ Baseline, $2 =$ 2041 - 2060 RCP 4.5, $3 =$ 2081 - 2100 RCP 4.5, $4 =$ 2041 - 2060 RCP 8.5, $5 =$ 2081 - 2100 RCP 8.5), j^{th} variety ($j = 1, 2, 3$; $1 =$ Avalon, $2 =$ Claire, $3 =$ Mercia), k^{th} GCM ($k = 1, 2, 3$; $1 =$ baseline, $2 =$ GISS, $3 =$ HadGEM2) and l^{th} CO_2 simulation ($l = 1, 2$; $1 =$ CO_2 fixed (368.30 ppm), $2 =$ CO_2 varying). The overall mean effect was β_0, β_1 the effect of future climate scenario, β_2 the effect of variety, β_3 the interaction between future climate scenario and GCM, β_4 the interaction between future climate scenario and variety, β_5 the interaction between future climate scenario, GCM and CO_2 simulation, β_6 the interaction between future climate scenario, variety and GCM, and β_7 the interaction between future climate scenario, variety, GCM and CO_2 comparison. Similar to Equation 7.2, GCM was nested within future climate scenario. The effect of a CO_2 comparison was nested within future scenario and GCM. For all analysis variety was fitted as an interaction term. The significant level (α) within this analysis was set at 0.05.

It should be noted that all variety simulations were conducted under the same future scenario and GCM (99 years) weather simulated data. Therefore, the variability between varieties was more similar at a lower nested stratum. However, this cannot be adjusted for within these analyses due to future period (e.g. 2041 to 2060 and 2081 to 2100) being nested within GCM and RCP.

7.4 Results

7.4.1 Past Analysis

Simulation modelling by Sirius showed Claire to be the highest yielding variety, from 1892 to 2016, with a mean of 9.79 t ha^{-1} compared to 9.04 and 8.25 t ha^{-1} of Mercia and Avalon, respectively (Figures 7.2 (a), (b) and (c)). Avalon had the largest mean harvest index from 1892 to 2016 of 0.52 compared to 0.49 and 0.48 for Claire and Mercia, respectively (Figures 7.2 (d), (e) and (f)). The 25-year mean grain yield of simulations from 1991 to 2016, for varying CO_2 concentrations, was 8.50, 10.18 and 9.38 t ha^{-1} for Avalon, Claire and Mercia, compared to 7.92, 9.48, 8.75 t ha^{-1} against simulations at a reference CO_2 level. A percentage difference was calculated between simulated yields where CO_2 increased over time and with CO_2 at a 1892 (294.50 ppm) reference level (Equation 7.1) (Figure 7.3).

Weights were used within the regression analyses due to the systematic increase in variability as CO_2 increases (Figures 7.3 (a), (b) and (c)). The relationship between % difference in yield and CO_2 was fitted as a quadratic relationship. This curvilinear suggests that the benefits of increased CO_2 at lower levels were greater compared to higher levels of atmospheric CO_2. There was a significant difference (see Table 7.1) between this relationship amongst varieties (however this analysis of variance lacks constant variance among residuals and was compensated by weighted regression).

The relationship with CO_2 for Claire was more linear compared to that in Avalon and Mercia (Table 7.2). This would suggest the cultivar, Claire, would benefit from further increases in atmospheric CO_2 more than Avalon and Mercia. The predicted % increase in yield in 2016, from an increase in CO_2 concentrations since 1892, was 9.36%, 9.87% and 9.12% for Avalon, Claire and Mercia, respectively. The estimated quadratic effect of increasing CO_2 on the % difference in yield for Claire was slightly positive (0.00001335; Table 7.1). However, this estimated quadratic effect was considered small compared to the estimated linear effect (0.088; Table 7.1) and may be considered as a limitation to the statistical methods applied to this dataset. As testing for a difference in linearity of a varieties response to increasing CO_2 a quadratic term must be estimated for each variety, even if such term may not exist. A curvilinear effect may be observed for Claire as atmospheric CO_2 levels continue to increase.

From all simulations from 1892 to 2016, one year (1956) from the Avalon simulation had a lower yield from the varying CO_2 simulation of 7.739 t ha^{-1} compared to 7.744 t ha^{-1} from the reference CO_2 simulation. This decrease in yield from the greater CO_2 concentration was because more of the simulated growth of the crop went into non-grain biomass. The total biomass for the CO_2 varying run was 15.52 t ha^{-1} compared to 15.36 t ha^{-1} from the reference CO_2 run. One year (1903) from the Mercia simulation had a lower total biomass from the varying CO_2 simulation of 18.81 t ha^{-1} compared to 18.84 t ha^{-1} from the reference CO_2 simulation. The increase in total biomass from the lower CO_2 simulation was because the varying CO_2 simulation had a shorter harvest season of 2 days compared to the reference CO_2 simulation. This reduced harvest season was due to an increase in leaf production of the varying CO_2 simulation and therefore increasing the potential to intercept radiation. Figures 7.3 (a), (b) and (c) have potential outliers, however, since weights were used in this analysis they were not omitted from these analyses.

Figure 7.4 (a), (b) and (c) show the simulated changes in the start of anthesis in days after sowing from 1892 to 2016 for Avalon, Claire and Mercia. The 100-year mean (1892 to 1991) of simulated anthesis date for Avalon, Claire and Mercia was 242, 250 and 251 days after sowing. In comparison, the 25-year mean for simulated time to anthesis for Avalon, Claire and Mercia from 1992 to 2016 was 8 (234), 7 (243) and 7 (244) shorter compared to the 1892 to 1991 average. Similar results were found for time to maturity. The 100-year mean maturity date was 300, 310 and 315, where the 1992 to 2016 mean was 10 (290), 10 (300) and 10 (305) days earlier in comparison.

Figure 7.1: The mean yearly atmospheric CO_2 concentration recorded at the Moana Loa Observatory between 1959 to 2016 (NOAA, 2018) (solid line). The yearly atmospheric CO_2 reconstructed concentration measurements between 1892 to 1958 (Etheridge et al., 1998) (dashed line).

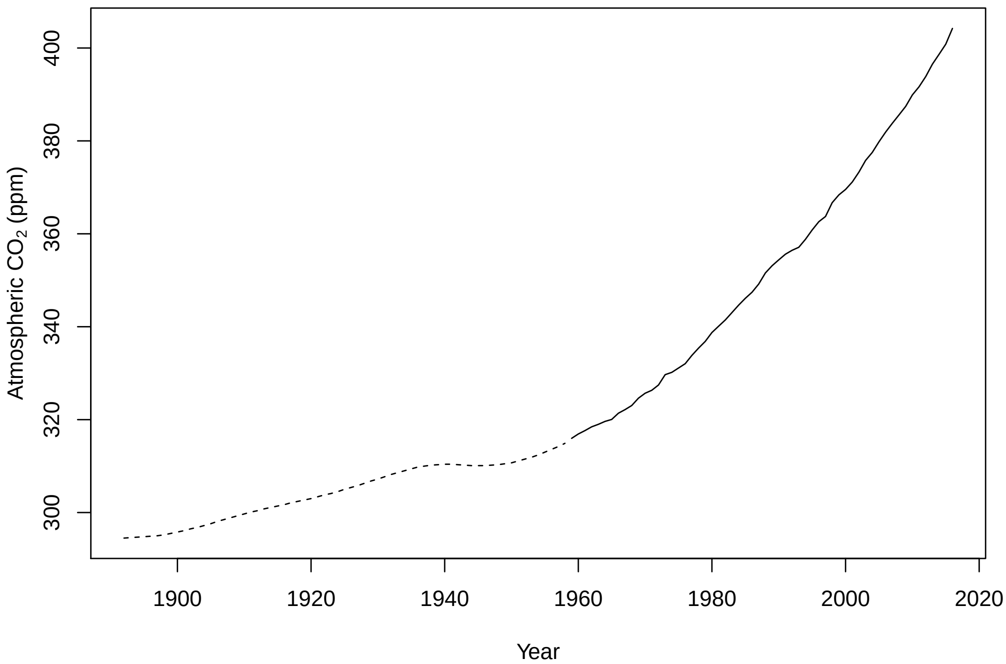


Figure 7.2: The simulation of wheat yield and harvest index by Sirius from 1892 to 2016 for varieties Avalon, Claire and Mercia. Black solid lines indicate five-year means of simulated yields where CO_2 has increased. Grey solid lines indicate five-year means of simulated yields where CO_2 was fixed at 294.5 ppm.

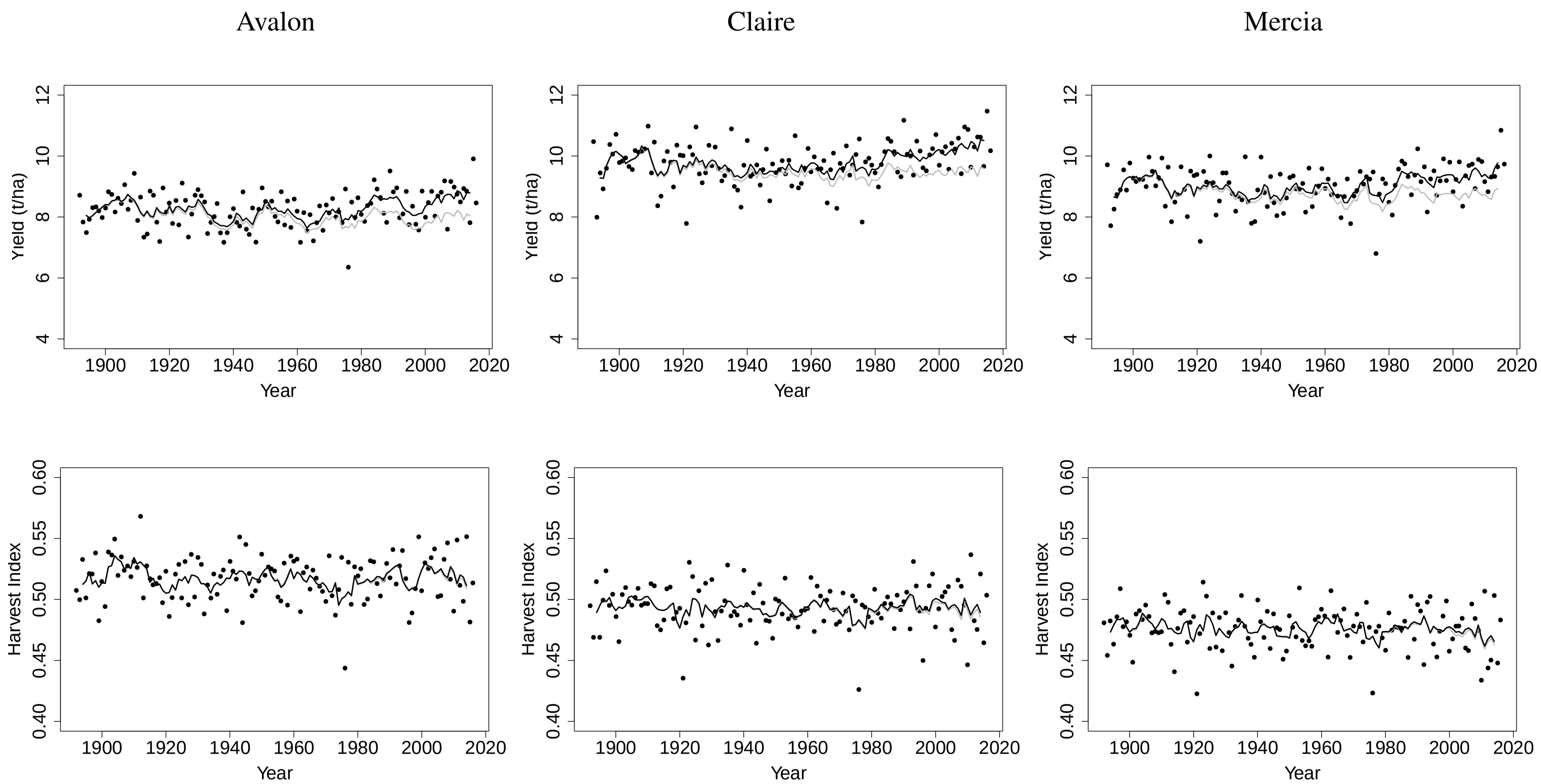


Figure 7.3: The % difference in wheat yields against difference in CO_2 concentration (from 294.50 ppm) for Avalon (a), Claire (b) and Mercia (c) from Sirius (see Figure 7.2). The fitted weighted regression line is constrained through the origin (red).

Avalon Claire Mercia

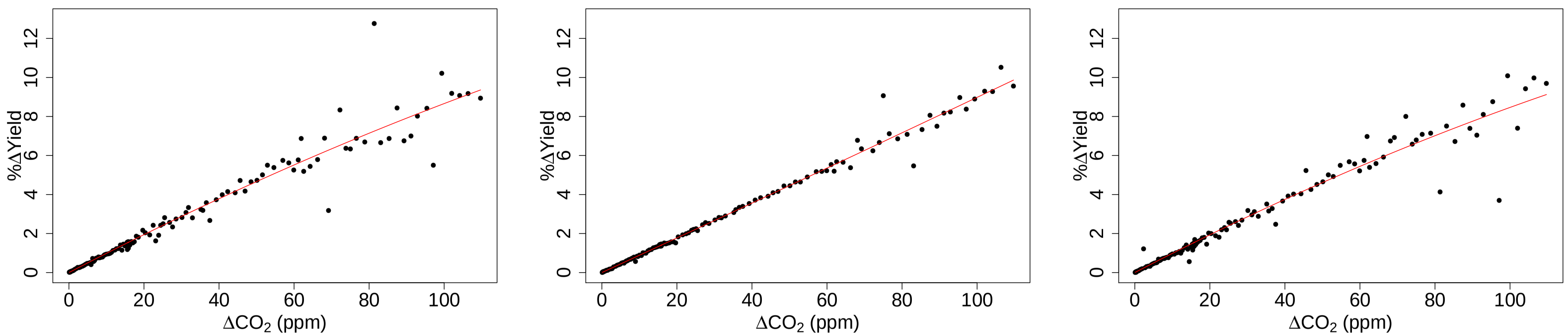


Figure 7.4: The simulation of date of anthesis in days after sowing for Avalon, Claire and Mercia from 1892 to 2016. The simulation of date of maturity in days after sowing for Avalon, Claire and Mercia from 1892 to 2016. Y-axis refers to days after sowing. Solid lines indicate five-year means.

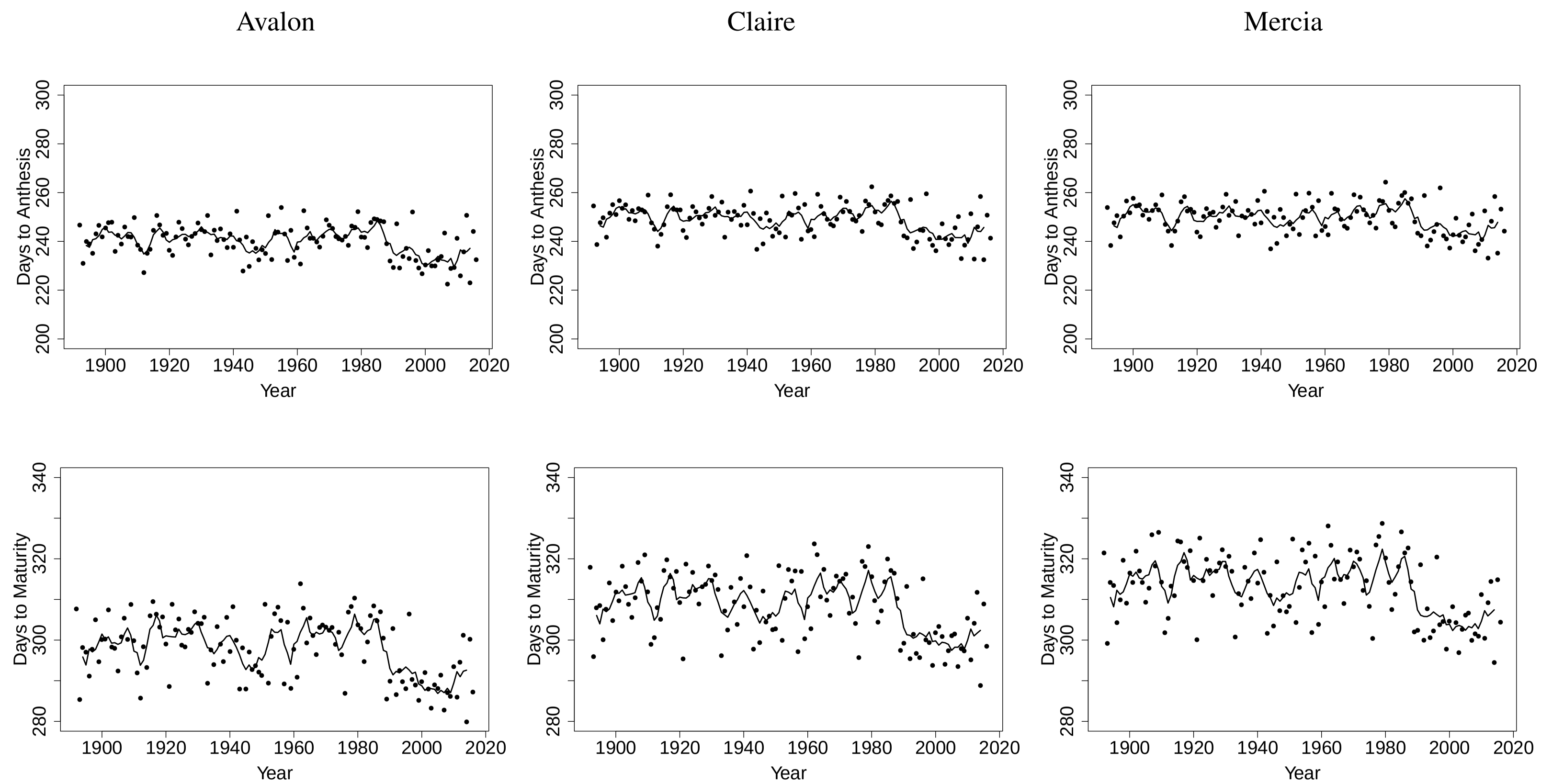


Table 7.1: The analysis of variance table for the influence of CO_2 on the percentage difference in yield from 1892 to 2016 (without weights).

Parameter	DF	SS	MS	F	P
CO_2	1	5795.2	5795.2	16518.41	< 0.001
$(CO_2)^2$	1	3.9	3.9	11.14	< 0.001
CO_2:Variety	2	0.40	0.20	0.56	0.57
$(CO_2)^2$:Variety	2	2.60	1.30	3.72	0.03
Residuals	365	128.1	0.40		

Table 7.2: The estimated main effect of increasing atmospheric CO_2 on the yield in Avalon, Claire and Mercia varieties from 1892 to 2016 with weights $= 1/r_i^2$. R^2 = 97.84% from the analysis without weights. (Values * are $\times 10^3$, Values ** are $\times 10^5$).

Coefficient	Estimate	SE
CO_2:Avalon	0.010	0.107*
$(CO_2)^2$Avalon	-0.133*	0.19**
CO_2:Claire	0.088	0.10*
$(CO_2)^2$:Claire	1.335**	0.19**
CO_2:Mercia	0.010	0.10*
$(CO_2)^2$:Mercia	-0.152*	0.52**

7.4.2 The Influence of Atmospheric CO_2 at Rothamsted in the mid to late-21st Century

The future projections of climate at Rothamsted are given in Figure 7.5. The baseline mean total rainfall was 724.51 mm, rainfall from future scenario HadGEM2 2081 to 2100 provides the lowest mean total rainfall. The range of mean total rainfall for each scenario is between 694.95 mm and 743.88 mm. The baseline climate (Figure 7.5 (b) and (c)) had the lowest mean maximum and minimum temperature of 13.60°C and 5.89°C. HadGEM2, from RCP 8.5 and between 2081 and 2100, had the highest simulated maximum and minimum temperature of 18.85°C and 10.26°C. Simulations from HadGEM2 had a warmer simulated climate compared to GISS for both maximum and minimum temperatures across both RCPs. All temperatures from RCP 8.5 were warmer than RCP 4.5. All future climate projections from GCM HadGEM2 had a greater mean radiation compared to GISS and the baseline.

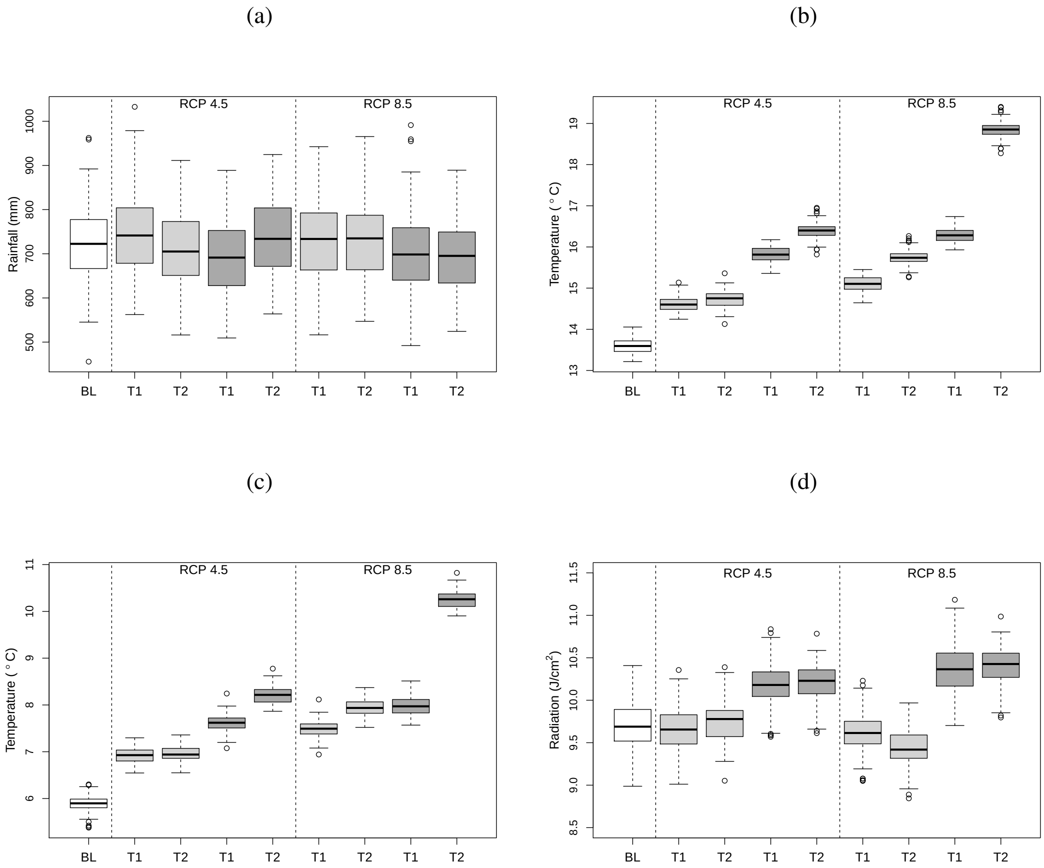
The baseline climate scenario had an atmospheric CO_2 value of 363.80 ppm, compared to 487.00 ppm and 533.00 ppm from RCP 4.5 time periods 2041 to 2060 and 2081 to 2100. The expected CO_2 values from RCP 8.5 were 533.00 and 844.00 ppm from time periods 2041 to 2060 and 2081 to 2100, respectively.

Analysis 1

Figures 7.6, provides the simulated yield from future weather scenarios + future projected CO_2 for varieties Avalon, Claire and Mercia. Similar to the 1892 to 2016 simulations, Avalon was the lowest yielding variety with a mean of 11.18 t ha^{-1} across all future scenarios, compared to 12.58 and 11.94 t ha^{-1} from Claire and Mercia.

Mean simulated yield for all future scenarios and GCMs were higher yielding than the baseline. Simulated yields from RCP 8.5 scenarios, where CO_2 was 844.0 ppm, were the highest yielding across all varieties. Mean simulated yields from GCM HadGEM2 were higher yielding than GISS across all varieties. The between Scenario and Variety interaction was not significant (F(1.25, 8, 2646), $P > 0.05$; Table 7.3), however, the interaction between Variety and the nested effect of GCMs within climate scenario was significant (F(10.05, 8, 2646), $P < 0.001$). Therefore, the effect of variety did not vary at the scenario level, however, there is strong evidence of an overall difference in yield from GCMs HadGEM2 and GISS between varieties. All pairwise

Figure 7.5: Simulated climate scenarios for GISS (light grey) and HadGEM2 (dark grey). Baseline (BL), 2041-2060 (T1) and 2081-2100 (T2).



comparisons for yield are shown in Figure 7.10 (a). Although grain yields are greater from RCP 8.5 2081 to 2100 for HadGEM2 compared to GISS, the mean harvest index for HadGEM2 was smaller than GISS (Figures 7.5 (d), (e) and (f)). This suggests as the growth potential increases, due to increased atmospheric CO_2, more growth was allocated to non-grain specific parts of the crop under a warmer climate (HadGEM2) compared to cooler climate (GISS).

Figures 7.7 (a), (b) and (c) show the anthesis dates for the future weather scenarios + future projected CO_2 simulations. From ANOVA (Table 7.4) there was significant difference to suggest a different time to anthesis from the nested GCM structure for each variety (F(14.59, 8, 2646), $P < 0.001$). Avalon had the earliest time to anthesis compared to Claire and Mercia. All future scenarios had an earlier time to anthesis compared to the baseline climate (Figure 7.10 (e)). RCP

8.5 at time period 2081 to 2100 had the earliest time to anthesis across all varieties, where GISS was earlier on average than HadGEM2.

Time to maturity, from future weather scenarios + future projected CO_2 simulations was given in Figures 7.7 (d), (e) and (f). From ANOVA Table (7.5) there was evidence to suggest a significant difference between the time to maturity within the nested structure of scenario and GCM for each variety ($F(9.93, 8, 2646)$, $P < 0.001$). All pairwise comparisons are given in (Figure 7.10 (f)). Similar to time to anthesis, RCP 8.5 at time period 2081 to 2100 had the earliest time to maturity, where HadGEM2 was earlier on average than GISS.

Figure 7.6: Simulated wheat yields (a, b and c) and harvest index (d, e and f) from future weather scenarios + future projected CO_2 provided by Sirius for Avalon (a and d), Claire (b and e) and Mercia (c and f). GISS (light grey) and HadGEM2 (dark grey), Baseline (BL), 2041-2060 (T1) and 2081-2100 (T2).

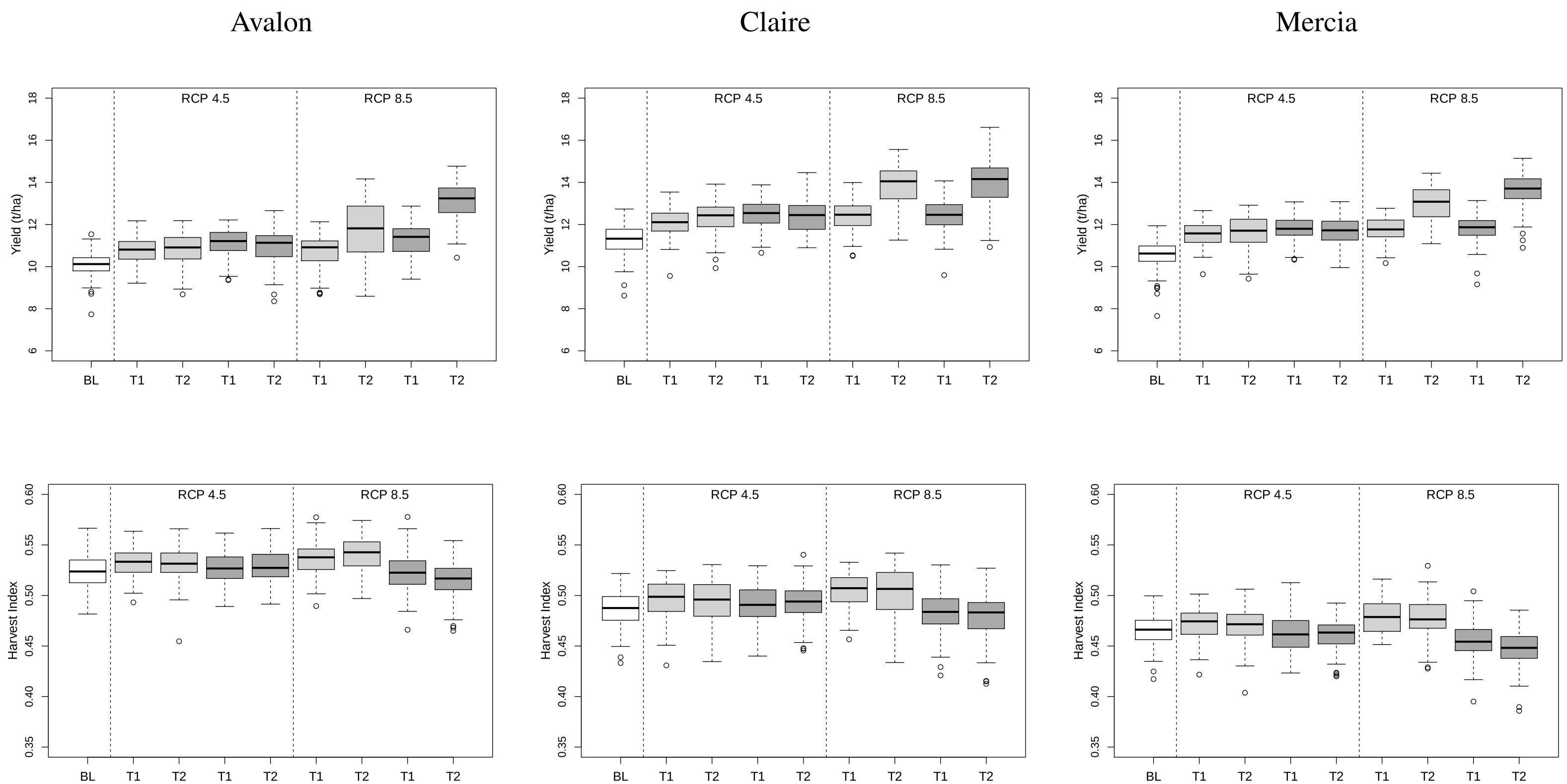


Table 7.3: The ANOVA table for the yield (t ha^{-1}) of wheat at different climate scenarios (future weather scenarios + future projected CO_2) where the effect of HadGEM2 and GISS is nested.

Source	df	SS	MS	F	P(F)
Scenario	4	33.35	8.34	656.34	< 0.001
Variety	2	18.62	9.31	732.93	< 0.001
Scenario:GCM	4	2.15	0.54	42.40	< 0.001
Scenario:Variety	8	0.13	0.02	1.25	0.264
Scenario:GCM:Variety	8	1.02	0.13	10.05	< 0.001
Residual	2646	33.62	0.01		
Total	2672	88.90			

Figure 7.7: Simulated time to anthesis (a, b and c) and maturity (d, e and f), after sowing, from future weather scenarios + future projected CO_2. For Avalon (a and d), Claire (b and e) and Mercia (c and f). GISS (light grey) and HadGEM2 (dark grey), Baseline (BL), 2041-2060 (T1) and 2081-2100 (T2).

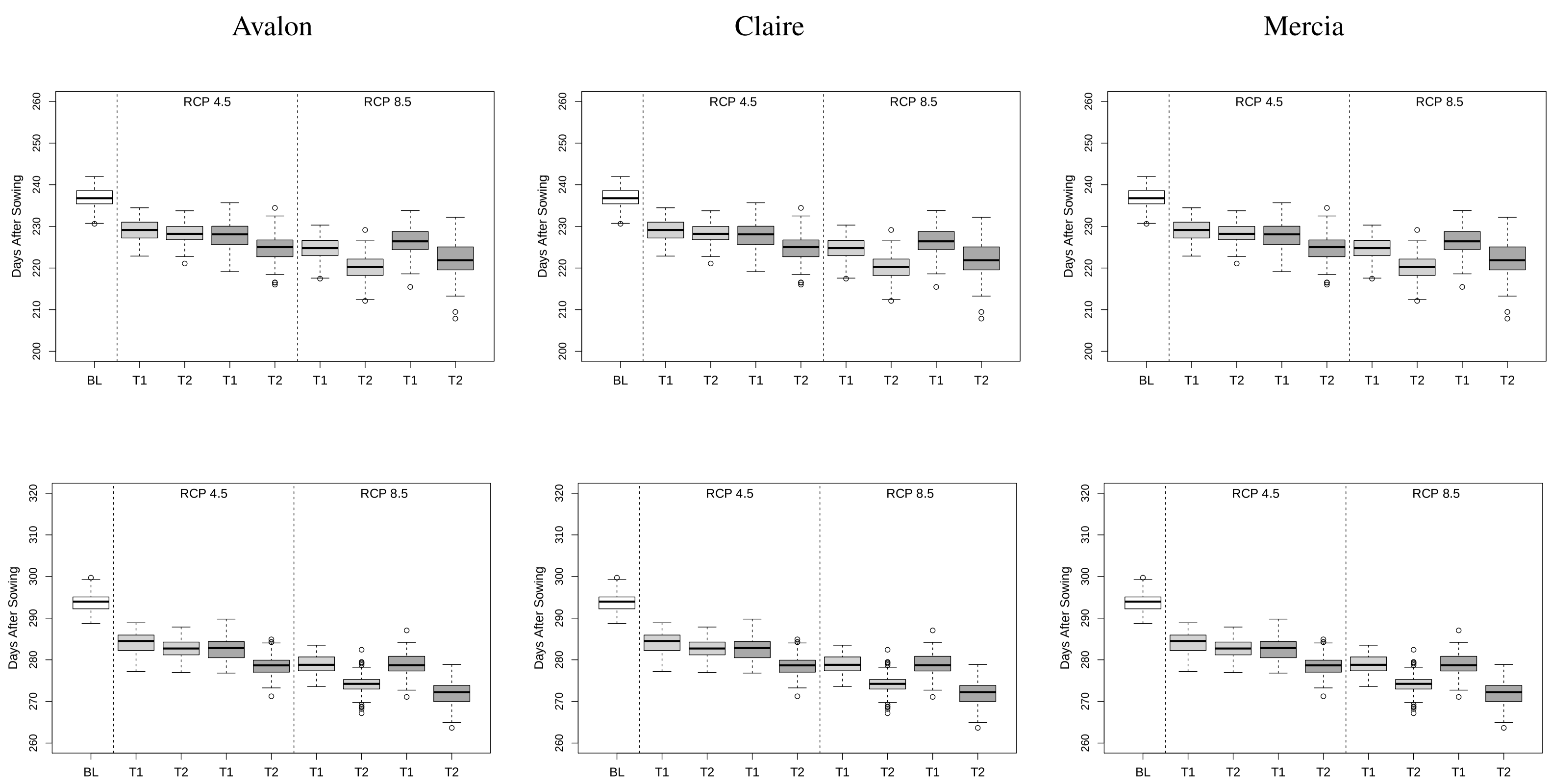


Table 7.4: The ANOVA table for time to anthesis of wheat at different climate scenarios (future weather scenarios + future projected CO_2) where the effect of HadGEM2 and GISS is nested.

Source	df	SS	MS	F	P(F)
Scenario	4	51101.37	12775.34	1464.40	< 0.001
Variety	2	65078.87	32539.44	3729.90	< 0.001
Scenario:GCM	4	2235.05	558.76	64.05	< 0.001
Scenario:Variety	8	702.68	87.8	10.07	< 0.001
Scenario:GCM:Variety	8	1018.32	127.29	14.59	< 0.001
Residual	2646	23083.53	8.72		
Total	2672	143219.82			

Table 7.5: The ANOVA table for time to maturity of wheat at different climate scenarios (future weather scenarios + future projected CO_2) where the effect of HadGEM2 and GISS is nested.

Source	df	SS	MS	F	P(F)
Scenario	4	100526.18	25131.55	3937.25	< 0.001
Variety	2	98738.05	49369.02	7734.43	< 0.001
Scenario:GCM	4	5597.20	1399.30	219.22	< 0.001
Scenario:Variety	8	511.10	63.89	10.01	< 0.001
Scenario:GCM:Variety	8	506.88	63.36	9.93	< 0.001
Residual	2646	16889.46	6.38		
Total	2672	222768.88			

Analysis 2

Similar to the future weather scenarios + future projected CO_2 analysis (Analysis 1), the interaction between Variety and Scenario was not significant (F(1.93, 8, 2646), $P > 0.05$; Table 7.6), however, the interaction between Variety and the nested effect of GCMs within climate scenarios was significant (F(9.16, 8, 2646), $P < 0.001$). Therefore, for the future weather scenarios + baseline CO_2, there was strong evidence of an overall difference in yield from GCMs HadGEM2 and GISS between varieties. Without the enrichment of projected future CO_2 levels, all future scenarios and GCMs had a lower yield on average, compared to the baseline climate, except yields from RCP 4.5 at time period 2041 to 2060 from GCM HadGEM2.

Figures 7.5 (b) and (c) future predicted temperatures are greater for HadGEM2 than compared to GISS. This would therefore potentially shorten the harvest season for HadGEM2 simulations more and therefore reduce the potential intercepted radiation and hence yield. However, Figure 7.5 (d) shows future HadGEM2 radiation to be greater than GISS, across all time periods. Therefore, the potential loss in yield due to a shortening of the harvest season, by increases in temperature from HadGEM2 simulations, may be offset by the increase in potential light radiation intercepted.

Figure 7.8: Simulated wheat yields (a, b and c) and harvest index (d, e and f) from future weather scenarios + baseline CO_2 provided by Sirius, for Avalon (a and d), Claire (b and e) and Mercia (c and f). GISS (light grey) and HadGEM2 (dark grey), Baseline (BL), 2041-2060 (T1) and 2081-2100 (T2).

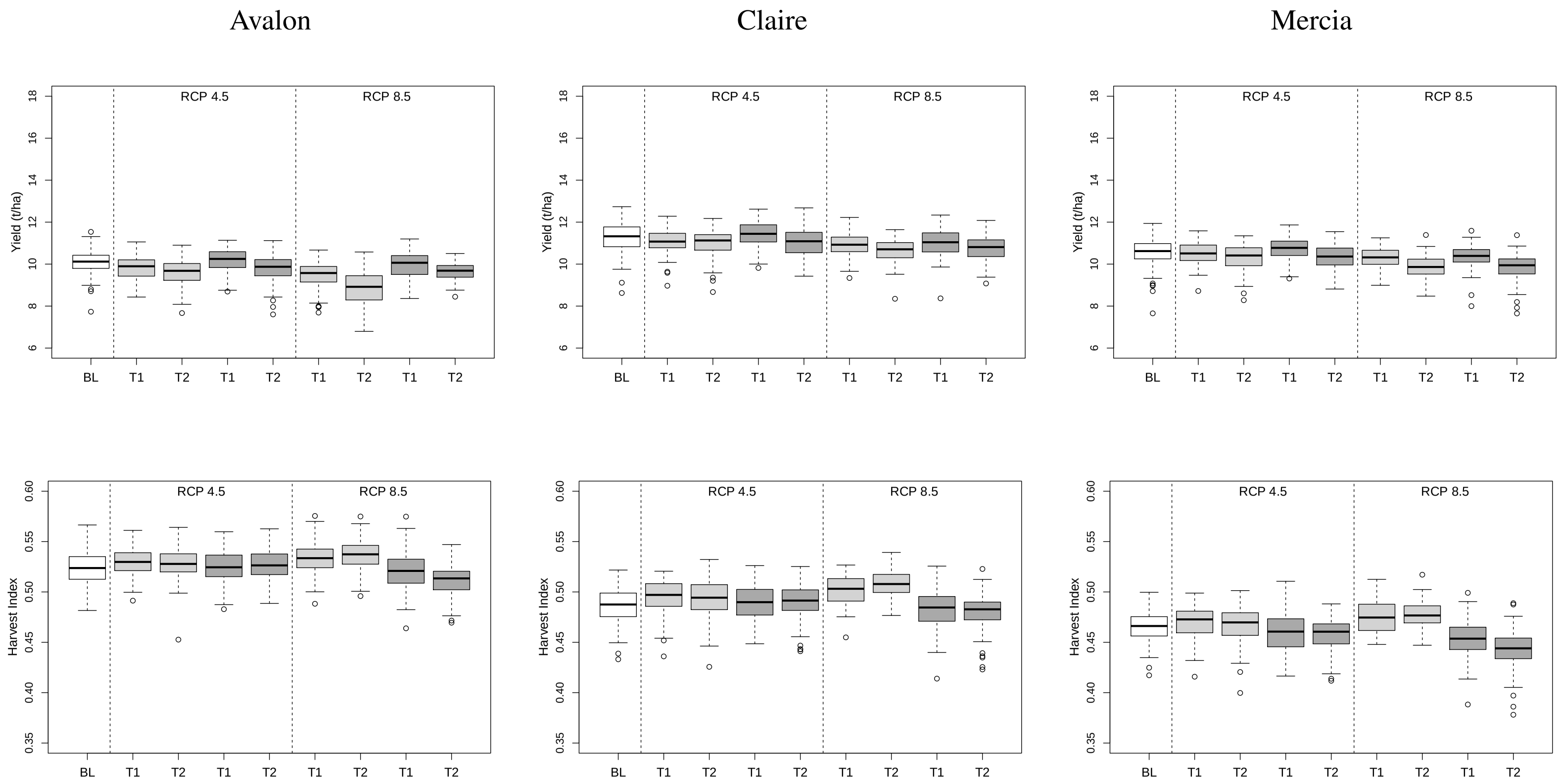


Table 7.6: The ANOVA table for the yield (t ha^{-1}) of wheat at different climate scenarios with a baseline CO_2 (future weather scenarios + baseline CO_2) where the effect of HadGEM2 and GISS is nested.

Source	df	SS	MS	F	P(F)
Scenario	4	4.25	1.06	120.14	< 0.001
Variety	2	18.05	9.02	1019.42	< 0.001
Scenario:GCM	4	0.87	0.22	24.43	< 0.001
Scenario:Variety	8	0.14	0.02	1.93	0.052
Scenario:GCM:Variety	8	0.65	0.08	9.16	< 0.001
Residual	2646	23.42	0.01		
Total	2672	47.38			

Analysis 3

Figure 7.9 shows the simulation of baseline weather + future projected CO_2. For every future scenario there was an increase in yield compared to the baseline. From Table 7.7, the interaction between Scenario and Variety was significant (F(18.29, 8, 1470), $P < 0.001$). Therefore, the response to enriched CO_2 varied among each variety. All pairwise comparisons were given in Figure 7.10 (c). From Figure 7.7, we observe yield from variety Avalon from RCP 8.5 at time period 2081 to 2100 to be the highest yielding future scenario across all varieties at 12.97 t ha^{-1}. The same positive effect of 844 ppm was not experienced for the other varieties. The highest mean yield scenario for Claire was RCP 8.5 2041 to 2060 of 12.49 t ha^{-1} and RCP 8.5 2081 to 2100 the second highest mean yield of 12.44 t ha^{-1}. Claire had a smaller absolute maximum leaf number compared to Avalon and Mercia. Therefore, it may be suggested that with a smaller maximum leaf potential more of the accumulated biomass was going into stem growth rather than leaf production rather than grain production. From Figures 7.9 (d), (e) and (f), the mean harvest index for RCP 8.5 2081 to 2100 scenario was lower than all other time periods from the baseline weather + future projected CO_2 simulations. Therefore, through the enrichment of CO_2 more of the intercepted radiation was allocated non-grain specific biomass.

Figure 7.9: Simulated wheat yields (a, b and c) and harvest index (d, e and f) from baseline weather + future projected CO_2 provided by Sirius for Avalon (a and d), Claire (b and e) and Mercia (c and f). Baseline (BL), 2041-2060 (T1) and 2081-2100 (T2).

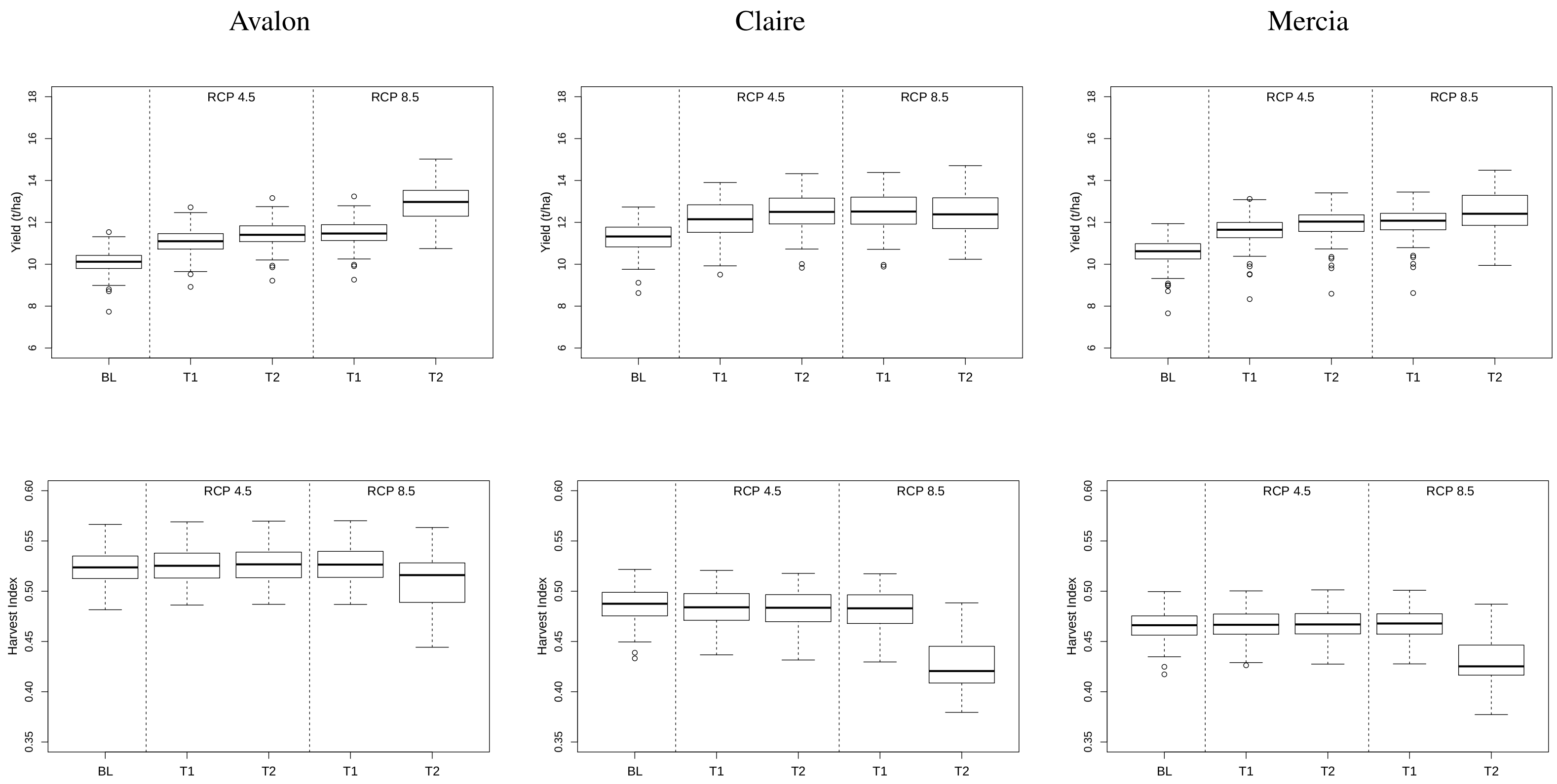


Table 7.7: The ANOVA table for the yield (t ha^{-1}) of wheat at a baseline weather scenario with a future projected CO_2 levels (baseline weather scenarios + future projected CO_2).

Source	df	SS	MS	F	P(F)
Scenario	4	13.67	3.42	257.89	< 0.001
Variety	2	3.18	1.59	120.20	< 0.001
Scenario:Variety	8	1.94	0.24	18.29	< 0.001
Residual	1470	19.47	0.01		
Total	1484	38.26			

Analysis 4

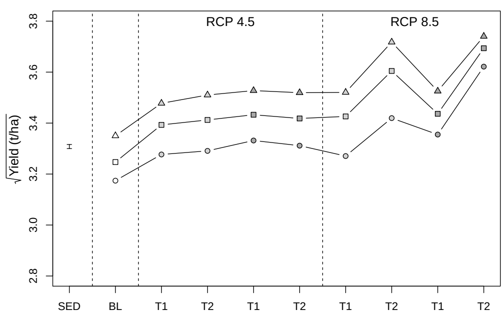
Without the enrichment of CO_2, future weather scenarios + baseline CO_2 (Figure 7.8 (a), (b) and (c)) had a lower yield compared to future weather scenarios + future projected CO_2 simulations (Figure 7.10 (d)). From the ANOVA Table (7.8), there was enough evidence to suggest a significant difference within the nested effect between simulations which had an enrichment and baseline CO_2 levels (F(1173.84, 8, 4704), $P < 0.001$). Therefore, there was a decline in future simulations of yield without an enrichment of CO_2. The interaction between the nested effect of CO_2 levels and Variety was not significant (F(1.47, 16, 4704), $P > 0.05$). Therefore, there was no significant evidence to suggest the loss of absolute yield (t ha^{-1}) due to future weather scenarios + baseline CO_2, for future scenarios, differed among all varieties.

Table 7.8: The ANOVA table for the yield (t ha^{-1}) of wheat of future weather scenarios + future projected CO_2 compared with future weather scenarios + baseline CO_2. A comparison of future projected CO_2 and baseline CO_2 is given in by Simulation.

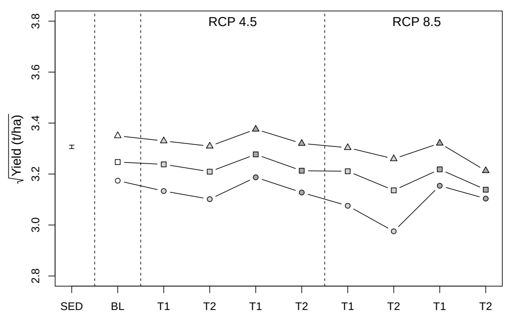
Source	df	SS	MS	F	P(F)
Scenario	3	4.57	1.52	141.36	< 0.001
Variety	2	33.62	16.81	1559.76	< 0.001
Scenario:GCM	4	2.78	0.70	64.52	< 0.001
Scenario:Variety	6	0.05	0.01	0.84	0.542
Scenario:GCM:Simulation	8	101.22	12.65	1173.84	< 0.001
Scenario:GCM:Variety	8	1.58	0.20	18.32	< 0.001
Scenario:GCM:Simulation.Variety	16	0.25	0.02	1.47	0.103
Residual	4704	50.70	0.01		
Total	4751	194.79			

Figure 7.10: All pairwise comparisons given in Tables 7.3, 7.4, 7.5, 7.6, 7.7 and 7.8 between: grain yield of future weather scenarios + future projected CO_2 (a); grain yield of future weather scenarios + baseline CO_2 (b); grain yield of baseline weather + future projected CO_2 (c); a comparison between the yield of future weather scenarios + future projected CO_2 and future weather scenarios + baseline CO_2 (d); days to anthesis of future weather scenarios + future projected CO_2 (e); and days to maturity of future weather scenarios + future projected CO_2 (e). GISS (light grey) and HadGEM2 (dark grey), Baseline (BL), 2041-2060 (T1) and 2081-2100 (T2), Avalon (circle), Claire (triangle), Mercia (square). Standard error of the difference from each analysis is provided on the appropriate Figure. Figures (a), (b), (c) and (d) are presented on the same scale as their analyses, the transformed square-root scale.

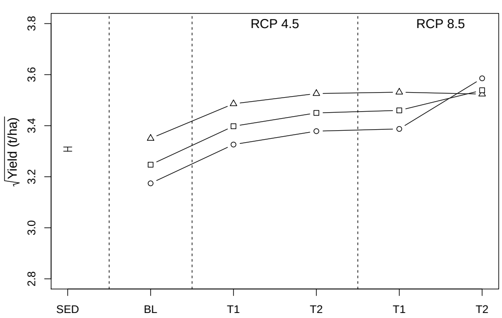
(a)



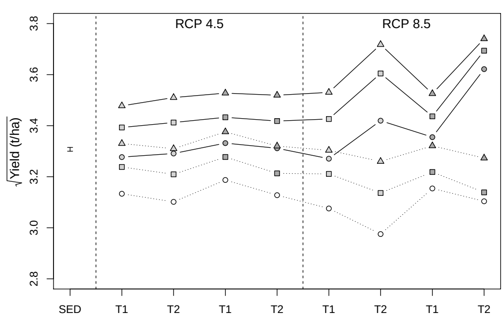
(b)



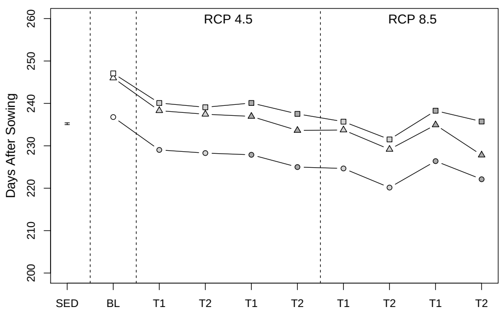
(c)



(d)

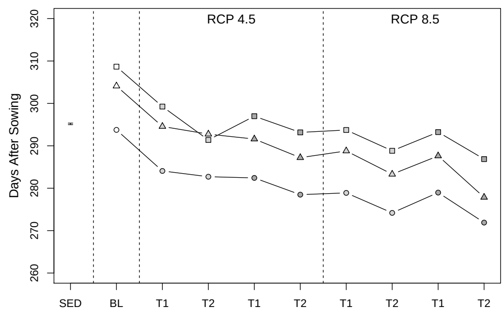


(e)



RCP 4.5
RCP 8.5
Days After Sowing
200
210
220
230
240
250
260
SED
BL
T1
T2
T1
T2
T1
T2
T1
T2

(f)



RCP 4.5
RCP 8.5
Days After Sowing
260
270
280
290
300
310
320
SED
BL
T1
T2
T1
T2
T1
T2
T1
T2

7.5 Discussion

Hypothesis 1: Since 1892, has there been a positive effect of increase in CO_2 on wheat yield at Rothamsted and has the positive effect of CO_2 enrichment been observed through year-to-year variations in weather.

The mean simulated increase in grain yield from 1892 to 2016 across all three varieties was 9.42%. For varieties Avalon and Mercia, the relationship between increases in CO_2 and % difference in yield was more variable and slightly curvilinear compared to Claire. The relationship between increase in CO_2 and % increase in yield has been described as a curvilinear relationship within the literature (Long et al., 2006; Tubiello et al., 2007), where the investigated CO_2 levels are over the maximum CO_2 (404.21 ppm) considered within the first part of the analysis within the Chapter. From investigating the potential enrichment of yield due to increases in atmospheric CO_2 from 1892 to 2016, the start of a curvilinear relationship was around 100 ppm above the reference level (1892), and could therefore suggest the potential for a diminished benefit of increases in CO_2. This conclusion may be variety specific, as Claire had a more-linear estimation of the positive effects of CO_2 compared to both Avalon and Mercia. The decadal average temperature (2001 to 2016) was 1.03°C greater than the 1961 to 1990 average (Chapter 2). A temperature increase of 1°C was reported to reduce yield by an estimated 3.5% (Kristensen et al., 2011). A comparison of the results and conclusions within this chapter are compared with those from Chapters 3, 4, 5 and 6 in the General Discussion. On average, an increase in crop yield occurred due to increases in CO_2 from 1892 to 2016, sources of weather variability nevertheless influenced contributed to large year-to-year variations in yield. Wheeler et al. (1996) showed there was still a positive effect of CO_2 on the yield of wheat grown at various temperatures. These results suggest there would still be year-to-year variations in the yields of the Rothamsted Long-Term Experiments as atmospheric CO_2 increases.

The results from this study (% increase per ppm CO_2) do not reject nor support the exact % increase in yield due to increases in CO_2 found in Cure & Adcock (1986), Kimball (1983), Ainsworth & Long (2005), Amthor (2001) and Tubiello et al. (2000) (see Section 1.3). This may be because their reference CO_2 was not the same as that considered in this analysis and the maximum CO_2 level within this study was 404.21 ppm. However, the results from this study do support the literature of the potential increase in yield due to an enrichment of CO_2. There was also evidence to support a variety specific curvilinear relationship, and how this relationship may not be reached by some varieties of wheat. However, the relationship between CO_2 and yield from the 1892 to 2016 may be a product of the process-based model Sirius. These results suggest was that the relationship between CO_2 and yield was more linear for the variety Claire and therefore may benefit more from increased levels of CO_2 throughout the 21st century compared to Avalon and Mercia. The results from this Chapter suggest there has been a positive effect of CO_2 on yield, on average, at Rothamsted from 1892 to 2016.

Hypothesis 2: Using future climate scenarios, do simulations indicate a positive effect on wheat yield from increases in atmospheric CO_2 at Rothamsted in the mid-to-late 21st century under projected HadGEM2 and GISS climates from RCPs 4.5 and 8.5?

Enrichment of CO_2 increases simulated yield throughout the 21st century. Nonetheless, accelerated phenology and the consequent reduction in intercepted radiation may also reduce grain yield. HadGEM2 simulations of future climate scenarios had a warmer climate, on average, compared to GISS and a higher mean solar radiation. HadGEM2 yield simulations experienced a shorter period to anthesis and maturity, compared to GISS simulations. Therefore, less light potential was intercepted and converted to biomass due to a shorter harvest season for HadGEM2 simulations compared to GISS. Without the enrichment of CO_2, 21st century wheat yields were shown to decline (Semenov & Shewry, 2011), grain Nitrogen also shown to decline towards the end of the 21st century (Ozturk et al., 2017). In the absence of enriched CO_2, HadGEM2 yield simulations did not experience a greater decline in yield compared to GISS yield simulations. With greater predicted CO_2 in the future more of the biomass was shifted into non-grain specific parts of the crop and a lower harvest index was observed. The development of heat-tolerant ideotypes for southern and central Europe suggest higher and more stable wheat yields could be achieved by adapting wheat to extend the duration of the grain filling period (Stratonovitch & Semenov, 2015; Semenov et al., 2014). However, this should be achieved by cultivars which have a larger leaf number and leaf size, to avoid biomass allocation to non-grain specific parts of the crop (although leaves are considered non-grain specific parts of the crop, leaves contribute to the accumulation of grain yield). Also, further wheat breeding suggestions within the literature suggest wheat be bred to be resistant to high temperatures around flowering (Semenov & Shewry, 2011).

Within this study I have used an ANOVA framework to test the significance between future climate scenarios with enriched and fixed CO_2 levels. Although a significant difference between a baseline climate and future climate scenarios was tested, the standard error of the difference for all pairwise comparisons was narrow (Figure 7.10). This was because 99 years of simulated data was generated for each scenario. A significance level of 0.05 may, therefore, be too high and an adjustment of the significance level should be considered. It should be noted that reducing the significance level also increases the statistical power of the hypothesis test (where statistical power is the probability that a statistical test correctly rejects the null hypothesis). However, any adjustment of the significance level should consider what level of difference in yield, from future climate scenarios, would be significant from a biological, socio-economical, technological and population food demand perspective. It may therefore be recommended that although statistical significance was found, it may be preferred if biological or economic significance was considered.

7.6 Conclusion

There has been a mean estimated 9.42% increase in wheat crop production due to rises in atmospheric CO_2 at Rothamsted between 1892 and 2016, removing other factors such as management, weather and other environmental (Hypothesis 1). The increase in atmospheric CO_2 from 1892 to 2016 was 109.71 ppm. The estimated relationship between increasing CO_2 and % increase in yield was curvilinear, with a plateau forming at around a 90 ppm increase compared to a 1892 baseline level. Therefore, future increase in atmospheric CO_2 may not be as beneficial as increases in CO_2 during the mid to late-20$^{\text{th}}$ century. What this chapter suggests is the negative relationships with temperature and yield shown and discussed within Chapters 4, 5 and 6 may be confounded with CO_2 and their true effect of increasing temperatures on yield may be more severe than the estimated effect.

This chapter also concludes that without the future increase in atmospheric CO_2 future grain yields will decline due to increasing warming temperatures (Hypothesis 2). Future simulated yields from RCP 8.5 also showed a decline in the harvest index of wheat. Warmer temperatures from future climate scenarios shortened the *window* of which biomass could be allocated to the grain. Therefore, more crop production was allocated to non-grain specific parts of the crop. Efforts should be made to heat-tolerant varieties which also lengthen the grain-filling period such that more of the crop biomass can be allocated to the grain.

Further Comments

The only sources of variability within this analysis were through the RMS dataset, future climate scenarios and varying variety parameters. No variability in yield was contributed by Sirius as it is a process-based model. Therefore, variations in weather from the early harvest season may offset phenology dates and lead to difference in yield. So any difference in yield may be confounded by changing the window over which temperature and radiation is used to derive yield within a year. This was observed in the 1892 to 2016 analysis, where one year had a lower grain yield in enriched CO_2 compared to fixed CO_2. Although the difference was small, the increase in CO_2 caused the simulated crop to mature two days earlier. One possible way to investigate this would be to add stochasticity into Sirius around phenology dates. However, this would require a very detailed experiment to parameterise Sirius (MA Semenov 2018, personal communication).

For the 1892 to 2016 analysis, the difference in atmospheric CO_2 (ppm) was increasing with every additional year. For example, differences in CO_2 between 2015 and 2016 was 3.38 ppm compared to 0.94 ppm between 1959 and 1960. Also, there was a systematic increase in the variability of % difference in yield as CO_2 increased. Therefore, future analyses at further time points, to identify the effects of enrichment of CO_2 on yield at Rothamsted, may prove more difficult as there will be greater increments along the CO_2 axis paired with greater systematic variability in the % difference in yield at higher CO_2.

Also, these simulations only considered how increasing atmospheric CO_2 influences the yield of wheat from 1892 to 2016 and for future climate scenarios. Other crops may have had a different observed effect due to increases in CO_2. Such as C4 crops, as C4 crops were shown not to benefit less from increased CO_2 compared to C3 crops (Bowes, 1993).

Changing weather patterns may influence the vulnerability of crops to infection, pest infestation, and weeds (Rosenzweig et al., 2001). Any gains in yield, due to increasing atmospheric CO_2, could be offset by phytophagous insects, plant pathogens or weeds (Coakley et al., 1999). Modelling any potential loss of yield due to weeds without considering the adaptation of weeds may lead to an underestimate of the loss of yield (Stratonovitch et al., 2012). Therefore, the mean 9.42% increase in grain yield, from an enrichment of CO_2 between 1892 and 2016, may not be observed in practice due to the influence and prevalence of pests and diseases, which are not simulated by Sirius.

Chapter 8

General Discussion

Within this thesis I have shown how the climate at Rothamsted has changed from 1892 to 2016 (Chapters 2 and 3). I have also examined the associated effect of weather variability (Chapter 3) on the yield of wheat (Chapters 4 and 7), spring barley (Chapter 5) and permanent grassland (Chapter 6). The implications for statistical modelling of long-term field experiment data has also been discussed, where statistical models are used to model the association between yield and of weather. Generally, with variations in weather, there were many variables which affect crop yield, but the two I have emphasised within this Thesis were total rainfall and mean temperature. Both variables contribute to the growth of crops in different ways, however, both have different trends over time. There was no trend in rainfall over time, but large year-to-year variability was observed at Rothamsted since 1968, whereas mean annual temperature was shown to be increasing along with year-to-year variability during this period (Chapters 2 and 3). Year-to-year variations in yield were shown to be associated with weather during a period of increasing atmospheric CO_2 from 1892 to 2016 (Chapter 7). Therefore, any direct gains in crop yield due to increases in CO_2 may be limited by other environmental pressures, such as weather, within a year. A discussion of the general findings within Chapters 3, 4, 5, 6 and 7 and their relation to the overall research hypotheses in Chapter 1 are given within this section.

Research Aim 1: The effects of human induced climate change over multiple variables have been observed in univariate analysis, therefore the effect of a changing climate can be observed through a multivariate study, where the effects of climate are classified

objectively through the clustering of years.

From the Rothamsted Meteorological Station (RMS) weather records, it was shown that there has been no general trend over time in the amount of rainfall experienced at Rothamsted, although there was large year-to-year variability. The mean annual total rainfall over a harvest season (October to September) from 1892 to 2016 was 766.66 mm. The driest and wettest harvest seasons, between 1892 and 2016, were 1976 and 2001, with 432.87 and 1217.71mm of rainfall. There was also within-year variability of rainfall at Rothamsted. The mean seasonal total rainfall for autumn, winter, spring and summer rainfall was 216.39, 200.87, 162.52 and 186.61 mm, respectively. In contrast to rainfall, mean daily temperatures have increased between 1892 and 2016, more so since the late-1980s. The 100-year mean annual (October to September) temperature (1892 to 1991) was 9.16°C compared to the most recent decadal mean (2007 to 2016) of 10.19°C. This constitutes of a warming of 1.03°C at Rothamsted, the mean UK decadal temperatures between 2007 and 2016 of 9.1°C compared to a 1961 to 1990 average of 8.3 (Kendon et al., 2017). Along with rises in mean annual daily mean temperature, compared to a mean 1892 to 1991 climate, the 2007 to 2016 decadal mean for daily maximum temperatures and daily minimum were 0.88 and 1.17°C, respectively. Finally, hours of direct sunlight had increased steadily since 1968; the 2007 to 2016 decadal mean was 1651 hours compared to 1417 hours for the 1958 to 1968 decadal mean.

Although univariate analyses methods show how climate has changed, they did not provide insight into how climate variables change together. For example, annual rainfall was shown to have no trend over time but varied year-to-year and annual temperatures were shown to be increasing over time with some year-to-year variability. Therefore, the multivariate approach within Chapter 3 allowed for the investigation of associations between year-to-year variations and long-term trends by the use of principal components analysis (PCA) by the clustering of similar years and an investigation of the distribution of cluster membership over time.

PCA provided a method of analysis which forms uncorrelated linear combinations of correlated variables. Within Chapter 3, it was shown how the first principal component (PC), which explained the most variability of a single component, separated out warm and cool years. Therefore, the first defining characteristic of the RMS dataset was temperature. This could also be concluded from the univariate summaries within Chapter 2, as they detected the increase in temperature since the late-20th century. However, from the univariate analysis it proved difficult to identify any trend within rainfall, as a moving average (of 5 years) detects no change over time, but there were large amounts of year-to-year variability associated with rainfall. The second PC, from the analysis within Chapter 3, separated out a seasonal effect of both temperature, rainfall and sunlight. Therefore, it was shown how within groups of years some months, which were warmer, also had more rainfall. Suggesting a combined pattern of rainfall and temperature which was not identified in univariate analyses. An example of this was given by Cluster 1 compared to Clusters 7 and 9. All three clusters had years which were in the 21st century and were warm but Cluster 1 was wetter, on average throughout the whole harvest season, than all other clusters. By selecting PCs accounting for 70% of the RMS dataset variability, further separations due to temperature could be observed. For example, 1976 experienced the warmest mean maximum daily June and July temperatures compared to the mean of each cluster. However, within other parts of the harvest season, 1976's mean daily minimum temperatures were less than those years in clusters which were warm (Clusters 1, 7 and 9). Therefore, 1976, although a warm dry year, did not have warm night-time temperatures similar to those years within Clusters 1, 7 and 9. This approach, of analysing multiple weather variables together provides more informative comparisons and conclusions about climate change. For example, 1976 was a warm year, but the analysis within Chapter 3 suggests it was a 20th century outlier, not a precursor for a 21st century climate as observed in Clusters 1, 7 and 9. The results from Chapter 3 show most years from the late-20th century and early-21st century fluctuate from warm-wet (Cluster 1) to warm-dry (Clusters 7 and 9). It was also shown how the climate in the 20th century varied from cool (Cluster 2) to slightly-warm (Cluster 3) to cool and wet (Cluster 10).

Although cluster analysis may show these relationships, averaging responses over multiple years within one cluster may smooth out the dataset but could miss important variations in climate leading to incorrect conclusions. Also, varying the number of clusters may lead to different summaries of clusters. Although a change in temperature over time has been shown within Chapter 2, the classification of any given change in climate in Chapter 3 was difficult due to the variability of the weather dataset, more specifically rainfall. The classification of years based on climate was difficult because methods to determine the number of optimum cluster were more difficult the more variable the dataset. As climate has changed over time, years do not naturally group or cluster in time, however, considering the similarity between years climate change may be quantified over time by considering the membership of these clusters. Also, it may be suggested that current metrics used to optimise cluster number need to be developed for large variable datasets, because current methods to quantify change were shown to be inadequate due to the large variability of the Rothamsted weather dataset.

A baseline climate of a selected range of 30 years is typically used to classify the °C increase in temperature (Hartmann et al., 2013; Kendon et al., 2017; NOAA, 2017). This method was adequate for defining change. However, issues arise when more years get added to a temperature dataset over time, as the baseline moves from an average for between 1961 and 1990 to 1971 and 2000 and now 1981 and 2010. It was understood that the baseline moves to see how climate has changed with regards to *now*, where *now* refers to the most recent 30-year period. A trend-line over time has also been used (Hartmann et al., 2013) to classify change over time. There is an issue of linearity in using a trend line, as change over time may be non-linear. For example, the change of hours of direct sunlight was shown to decrease until the 1960s after which hours of direct sunlight then increased. A multivariate approach of cluster analysis takes all available data and groups of years which have a similar climate, therefore a potential stationary baseline. Although optimum cluster number may change depending on how variable a weather data was or if a *new* climate emerges. From the conclusions of Chapter 2 together with Chapter 3, the evidence presented within this Thesis showed, that between 1892 and 2016, climate becoming warmer and how there were fluctuations between wet and dry harvest seasons within the 20th century.

Research Aim 2: Given that environmental stresses, such as temperature and rainfall, on crop development have been shown to affect yield in controlled experiments, then the year-to-year variability in the yields of wheat, spring barley and permanent pastures, from the Rothamsted Long-Term Experiments, will also be associated with increases in temperature and variations in rainfall.

The drought of 1870 motivated a publication on the effects of drought on some of the experimental crops at Rothamsted (Lawes & Gilbert, 1871). Data from the electronic-Rothamsted Archive showed the amount of rainfall which fell over the harvest season (October to September) for 1870 was 480.90 mm (unadjusted). In comparison, the driest year between 1892 and 2016 was 1976 with 432.87 mm of rainfall throughout the harvest season. The conclusions from the study of 1870, drought on crops caused a greater reduction in hay yield from the Park Grass experiment compared to those of winter wheat on the Broadbalk Experiment (Lawes & Gilbert, 1871). The 1879 harvest season had extreme levels of rainfall where rain fell on 223 days (> 0.01 inches) and 42.29 inches (1074.17 mm, direct conversion) of rainfall was recorded throughout the whole harvest season. This season resulting in a reduction in the yield of continuous wheat yield from the Broadbalk Experiment, relative to the preceding years (Lawes & Gilbert, 1880b). Therefore, over nine years there were periods of both drought and excess rainfall each of which both led to yield losses on the continuous experiments at Rothamsted (Lawes & Gilbert, 1880b; 1871).

Broadbalk, allowed for the direct comparisons between years and an exploration of year-to-year variations of yields and how they can be explained by climate. Further analyses from Fisher (1925a; 1921) took the ideas of crop variability further. In his analyses of the influence of rainfall on the yield of wheat at Rothamsted, it was shown how certain stages of crop growth, over a harvest season, were affected by rainfall, for example, in the early harvest season (Fisher, 1925a). Results presented within Chapters 4 and 5 showed how variations in weather within the early harvest season affect yield and the Nitrogen response curve for both wheat and spring barley.

I believe these early studies in crop variation were driven by a different philosophy about the effects of climate and weather on crop development due to the lack of understanding of human induced climate change that is accepted within modern literature. Although briefly discussed in Lawes & Gilbert (1880b; 1871), an understanding of the impact of high temperatures on crop production was not presented as comprehensive as it has been in modern literature (see Section 1.3). Within Section 1.3 I discussed the influence of climate change on crop production. To conclude, it is now better understood how high temperatures impact crop development. For example: at flowering, increased temperatures were shown to reduce the potential number of grains (Wheeler et al., 2000); high temperatures from anthesis to harvest maturity were shown to reduce the seed dry weight of winter wheat (Wheeler, et al., 1996); and grain fertilisation was sensitive to high temperatures at the mid-anthesis stage of wheat development (Ferris et al., 1998). Other approaches, such as simulation-based studies, have suggested that wheat cultivars with an extended grain filling period could achieve higher and more stable wheat yields (Semenov et al., 2014; Stratonovitch & Semenov, 2015). There is also a better understanding of how atmospheric CO_2 has changed over time and the impact on yield this will be discussed within Research Aim 4.

Analyses of the Rothamsted Long-Term Experiment yield data and their association with weather has been revisited since Fisher (1925a). Where there were high negative correlations between temperature and yield. For example, Maximum May and June temperatures were shown to be negatively correlated with wheat yields from Broadbalk between 1854 to 1967 (Chmielewski & Potts, 1995). However, rainfall was still shown to influence the yield of the Rothamsted Long-Term Experiments (see Section 1.4).

The results presented within this Thesis show that some variation in long-term yields which could be explained by weather. For example, through the clustering of years (Chapter 3), years which were warmer (Cluster 1), on average, had a lower total biomass across all treatments and experiments, from 1968 to 2016. Furthermore, total biomass of wheat and spring barley in years which were warm and dry (Clusters 7 and 9) were lower compared to years which were cooler. Although heat stress may have influenced the total biomass from years which were warmer, there was evidence to suggest that within-year variations in weather also influence total biomass. For example, the average spring barley total biomass for Cluster 7 (warm early-summer and dry), across all treatment groups, was higher than Cluster 9 (warm late-summer and dry). Also from Chapter 3, grassland was shown to be more resilient to warmer years across all treatments than both wheat and spring barley. A positive relationship between rainfall and biomass, along with changes in the dominance of grasses, was observed on the Park Grass Experiment (Silvertown, 1994). The multivariate approach to identifying how climate change influences crop production in the Rothamsted Long-Term Experiments provides insight into how multiple variables act together to influence yield. However, this approach lacks an understanding of how the magnitude of the increases in temperature on yield. To conclude, years in the 20th century had a higher total biomass, across all treatments and experiments, compared to most years within the 20th century (Chapter 3).

Considering monthly summaries of total rainfall and mean temperature for a harvest season (October to September), showed how within-year variations in weather were associated with changes in wheat and spring barley yields (Chapters 4 and 5). For example, correlations for May and June temperatures with grain yield and total biomass for wheat were negative across all Nitrogen application rates (0, 48, 96, 144, 192, 240, 288 kg N ha^{-1}) (Chapter 4). Similar results were found from the Hoosfield Experiment, with correlations between spring barley yields (grain yield and total biomass) and mean May, June and July temperatures being negative for all Nitrogen treatments (0, 48, 96, 144 kg N ha^{-1}) and all mineral treatments (PKNaMg, P, KNaMg, Nil). However, mean May and June temperatures only influenced the a parameter (the asymptote) of the Linear-By-Exponential function Nitrogen response curve (Equation 4.1). Hence, the effect of mean May and June temperature was similar at every Nitrogen dose. Therefore, it would be beneficial to develop heat tolerant varieties of wheat and spring barley in an attempt to make this relationship less severe and maintain high yield productivity at high temperatures.

Associations between rainfall and wheat yield were found within Chapter 4. There was a negative correlation between grain yield and October rainfall, a relationship also found by both Fisher (1925a) and Hooker (1907). Variations in April weather (more so rainfall) was found to influence the Nitrogen response curve for both wheat and spring barley, where, the more Nitrogen applied (both wheat and spring barley) and greater the mineral fertiliser applied (spring barley) the more loss associated with variations in April weather. Therefore, the relationship between April weather and cereal yield would need to become more linear, where at drought or extreme rainfall the loss in yield was not as large, in order to improve crop production (Figures 4.3 (a), 4.4 (a), 5.5 and 5.7).

Although weather was shown to influence the total herbage yield of Park Grass the effects of liming and soil pH with weather were also shown to influence yield (Chapter 6). Generally, limed plots (high pH) had a lower loss of yield with more extreme mean autumn temperatures. Whilst, the direct effect of more neutral soils may have resulted in more resilience of the species of grasses and legumes grown, although the indirect effect of increased plant species biodiversity on the limed plots may also have resulted in greater resilience (Chapter 6). Long-term plant species biodiversity data is needed to validate this conclusion, although gathering this data for all plots may be both time consuming and expensive. Further conclusions from Chapter 6 showed yields on farm yard manure plots on Park Grass were less susceptible to extreme variations in mean autumn temperature compared to those receiving inorganic fertilisers. Similar conclusions may be made from the limed and unlimed comparisons, as the plant biodiversity of the farm-yard manure plots was generally higher than the inorganic fertiliser plots (Macdonald et al., 2018). The higher plant species diversity of the farm yard manure plots on Park Grass may have increased the adaptability of the plots and therefore the capacity of the plot to adapt to variations in weather without loss of yield. This result was also found within Chapter 3, where a comparison between Rothamsted Long-Term Experiments showed herbage yields to be less susceptible to increases in temperature compared to cereals such as wheat and spring barley.

Possible evidence of the adaptive nature of each plot of the Park Grass Experiment was given by the increased positive auto-correlation at lag 1 in plots which received more inorganic fertiliser and were less biodiverse. Hence, plots with a lower plant species diversity were more likely to have yields at time t positively associated with yields at time $t-1$. After a parsimonious model was fitted for first-cut hay and total-cut herbage there was still high auto-correlation in the high inorganic input plots compared to the Nil and farm yard manure treatments. It may be concluded that, without the biodiversity to adapt, herbage plots with high inorganic inputs were more susceptible to increases in temperature compared to plots with a higher biodiversity. In recent decades some plots on the Park Grass Experiment have also become more diverse due to a reduction in Nitrogen inputs from fertiliser and atmospheric Nitrogen (Storkey et al., 2015). Therefore, the effects of weather variations on the Park Grass Experiment may be less extreme as atmospheric Nitrogen deposition decreases and biodiversity increases, although this was not formally tested within this Thesis. The results from Chapter 6 further the understanding of how weather influences the Park Grass Experiment, as previous analyses have not addressed the auto-correlation issue of the data in context with plot species biodiversity.

One issue with the modelling approaches taken within Chapters 4, 5 and 6 was the separation of a main effect of temperature (increasing over time with small variability) and rainfall (no change over time with large variability). By taking instances from a Nitrogen response curve and allowing for a relationship between Nitrogen treatments presented within Chapters 4 and 5, it may be suggested, as a method to maximise yield productivity, that more heat tolerant crop varieties (Semenov et al., 2014; Stratonovitch & Semenov, 2015) should be sown on the experiment, but also a farming system where lower yield loss around variations in weather at the time of fertiliser application.

For example, in all parsimonious models of wheat (Chapter 4) and spring barley (Chapter 5) there was an optimum April weather (temperature and rainfall) at which yield was maximal. Lower or higher April temperature or rainfall resulted in a loss of yield. Therefore, if a flatter response around optimum rainfall could be achieved, the rate of yield loss due to variations in April weather may be reduced. This may be achieved by increasing cereal varieties capacity to take up more nutrients through deeper rooting systems or soil which can hold more nutrients before they are potentially lost.

Research Aim 3: Year-to-year and within-year variations in temperature and rainfall over a harvest season (October to September) affect the Nitrogen response of Broadbalk wheat and Hoosfield spring barley.

In previous analyses of how climate and weather influence the yields of the Rothamsted Long-Term Experiments, the relationship between yield and Nitrogen fertiliser was not considered. From Chapters 4 and 5, fitting a Nitrogen response curve for yield at different doses provided more information about how the yield of wheat and spring barley varies between years. It was shown within Chapters 4 and 5 that yields of wheat and spring barley from Rothamsted's Long-Term Experiments had significant year-to-year variability, where some years had a higher estimated yield asymptote compared to other years.

It was found, in both wheat and spring barley, that although there were significant year-to-year variations in the shape of the Nitrogen response curves. Variations in the non-linear parameter (r) of the Linear-By-Exponential function did not explain significant amounts of model variability, and, this parameter was therefore fixed across years. The estimated r parameter for grain yield of wheat was 0.988 compared to 0.989 of spring barley. The estimated r parameter for total biomass was 0.986 and 0.990 for wheat and spring barley. These terms were estimated on the square-root transformed yield scale and therefore differences between r values were small. However, the estimated r parameter for wheat was smaller than spring barley for grain yield. This suggested the response to Nitrogen for spring barley was more linear for grain yield compared to wheat. These results were expected as for wheat there were seven (as from 1985 onward) Nitrogen doses compared to four for spring barley. If higher Nitrogen doses were considered in the future the relationship between spring barley yield and Nitrogen may become less linear. The smaller r parameters resulted in the Nitrogen response curve for total biomass to be more linear than those for grain yield for wheat, suggesting a more linear relationship between Nitrogen and total biomass.

Variations in weather were shown to influence the parameters of a Linear-By-Exponential Nitrogen response curve for both wheat and spring barley. For the parsimonious models for grain yield and total biomass, variations in weather around sowing, Nitrogen application and in early summer were shown to influence both response curves for wheat and spring barley.

For all analyses, increased temperatures around May and June resulted in a lower estimate of the asymptote (a parameter) of Nitrogen response curve. Therefore, increases in temperature around sensitive stages of crop development (see Section 1.3) decreased wheat and spring barley's response to Nitrogen.

The quadratic relationship between variations in April weather with grain yield and total biomass was shown to influence the asymptote (a) and the relationship between Nitrogen and yield at low doses of Nitrogen (b). With more Nitrogen applied the loss of yield due to variations in April weather became more severe. This was because April weather (rainfall and temperature) was fitted to the models (parameter b) within Chapters 4 and 5 as a quadratic with an optimum (discussed within Research Aim 2). The rate of loss around this optimum was steeper for treatments which received more Nitrogen (wheat and spring barley) and more mineral treatments (spring barley). Therefore, it may be suggested that at higher Nitrogen doses, more nutrients were lost to the soil with variations in weather around fertiliser application. It may be suggested (as suggested from the outcome of Research Aim 2) that if less nutrients were lost around nutrient application yield production would increase.

A wetter and cooler sowing time led to a reduction in grain yield for both cereals, October weather may be confounded by variations in sowing date and the relationship between yield and variations in weather around sowing has been identified in previous studies (Fisher 1925a;

Hooker, 1907).

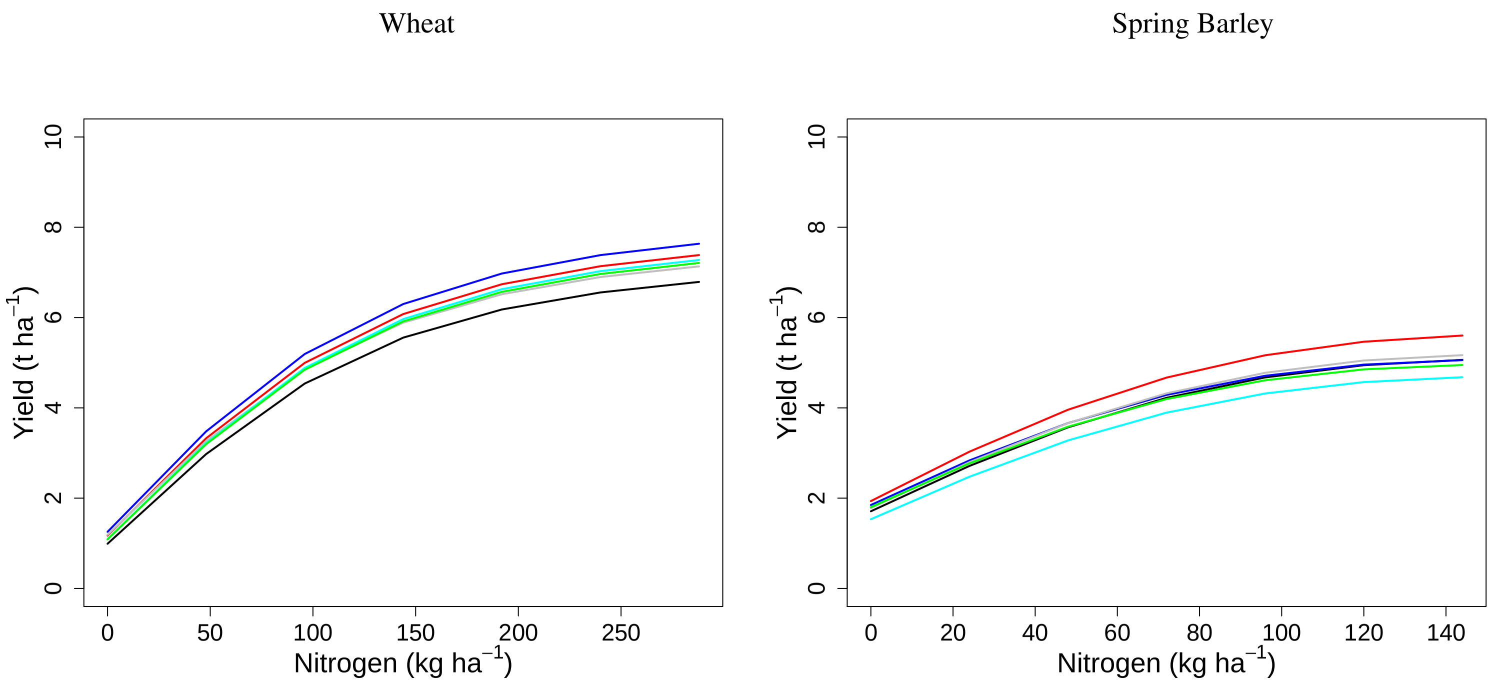
The effect of climate change on the Nitrogen response curve can be seen by combining the cluster summaries and membership of years from Chapter 3 with the parsimonious models fitted in Chapters 4 and 5 (Figure 8.1). Warmer and wetter years experienced within the 21st century (Cluster 1) had a lower predicted asymptotic Nitrogen response for the grain yield of wheat compared to any other period between 1892 and 2016. Cluster 3, a cluster whose membership spans the 20th century and generally has a cooler and drier harvest season, had the highest estimated asymptotic (a parameter) Nitrogen response curve. For the grain yield of spring barley, a typical late-19th and 20th century climate of a cold early-spring period (Cluster 2) had a higher estimated asymptotic Nitrogen response curve. A climate consisting of a dry July and August period also resulted in a shallower Nitrogen response from spring barley (Cluster 9). Therefore, from combining the results of Chapter 3 with Chapters 4 and 5 (Figure 8.1), it may be suggested that changes in climate (1892 to 2016) may have created an environment where the efficiency of wheat and spring barley to facilitate Nitrogen has decreased compared to other periods in the 20th century.

However, issues with this comparison include the disadvantages of using a parsimonious model as a predictive model. Some identifying characteristics of a cluster may not be included within the predictions from the predictive parsimonious model due to the omission of that weather variables due to its collinearity.

For the predictions shown in Figures 8.1, the winter wheat variety Hereward and the spring barley variety Tipple were used as a method of removing the variety effect and making a direct climate change comparison. However, variety was a significant term within all wheat and spring barley yield (grain yield and total biomass) parsimonious models. As discussed within Chapters 4 and 5, the estimated effects of these varieties were potentially confounded by variations in weather, atmospheric CO_2 and possible prevalence of pests.

Therefore, it has been shown that climate change and variations in weather have affected not only the overall yields of wheat and spring barley but also the relationship between yield and fertiliser inputs. A possible approach to increase production of wheat and spring barley may include methods to increase the efficiency of wheat and spring barley to facilitate Nitrogen in a changing global climate. Broadbalk and Hoosfield were unique as the homogeneous treatments applied each year at different fertiliser applications allowed for the comparison of variations in Nitrogen response over time.

Figure 8.1: The predicted Nitrogen response curve for Broadbalk Hereward wheat grain yield (left; Chapter 4) and Hoosfield Tipple spring barley grain yield (right; Chapter 5) for Clusters 1 (black), 2 (red), 3 (blue), 7 (grey), 9 (cyan) and 10 (green) derived from the analyses from Chapter 3. Cluster by Nitrogen response curve.



Research Aim 4: An increase in yield over 125 years, from 1892 to 2016, is associated with rises in atmospheric CO_2 and any future rise in CO_2 will influence the crop productivity of Broadbalk yields at least till the end of the 21st century.

From Chapters 3, 4, 5 and 6 the investigation of how weather variations were associated with variations in the yield of wheat, spring barley and hay did not consider how increases in atmospheric CO_2 over the 20th and 21st centuries may influence crop production. Wheat grown within an enriched CO_2 environment (comparison of ambient levels to 700 μmol mol^{-1}) was shown to have increased grain weight (Wheeler et al., 1996). A doubling of CO_2 from 350 ppm to 700 ppm resulted in an increase of 31% in wheat yields (Amthor, 2001).

Between 1892 and 2016 there was an estimated increase 9.12 to 9.87% in the simulated grain yield of wheat at Rothamsted, depending on variety, due to increases in atmospheric CO_2 from 295.6 to 404.21 ppm (Chapter 7). These results suggest that the associations between yield and weather from the Rothamsted Long-Term Experiments (Chapters 3, 4, 5 and 6) may be confounded by changes in CO_2, where the estimated negative effects of reduced rainfall and increased temperature on the Rothamsted Long-Term Experiments may actually have been more severe.

The relationship between CO_2 levels and % difference in yield (between runs where CO_2 was fixed and when CO_2 varied) was also curvilinear with systematic increases in between-year variance as CO_2 levels increased. Therefore, the positive effects of CO_2 on crop yield seen in the early-21st century were not as great during the 20th century. This curvilinear relationship between CO_2 and yield was also discussed within the literature (Long et al., 2006; Tubiello et al., 2007). The increasing variability of the % in yield difference as CO_2 levels increase was also of interest. From this Thesis an understanding of how variations in rainfall, variations and trends in temperature (Chapters 3, 4, 5 and 6), and an increasing trend of CO_2 (Chapter 7) influence on yield was investigated. Although an enrichment of CO_2 was shown to increase yields from 1892 to 2016, year-to-year variation in yields was also observed and was shown to increase as CO_2 increased. An explanation of an increase of variability as atmospheric CO_2 increased may be given since as atmospheric CO_2 was increasing it became less of a limiting factor on crop production (see results from elevated CO_2 future Sirius simulations from Chapter 7). Therefore, year-to-year weather variations limiting crop production (Chapters 4, 5 and 6) were becoming more frequent as CO_2 was becoming less limiting.

From future climate simulations of the crop production of wheat, grain yield and total biomass were shown to increase. However, the biomass production was shown to shift to non-grain specific parts of the crop. It has been suggested that by adapting wheat to extend the duration of the grain filling period the amount of light intercepted over the grain filling period would increase and lead to an increase in yield (Semenov et al., 2014; Stratonovitch & Semenov, 2015). Chapter 7 supports this finding. However, the concentration of atmospheric CO_2 increases it may become less of a limiting factor on crop production. Consequently, future yields from the Rothamsted Long-Term Experiments may not reach their growing potential due to year-to-year variations in weather which may also limit crop production (as found from Chapters 4, 5, and 6). Therefore, to maintain an increase long-term crop production, future crop varieties must have high resilience against year-to-year variations in adverse weather conditions (see Research Aims 2 and 3).

It may also be suggested that as yields from the Rothamsted Long-Term Experiments become more variable in the future due to increases in CO_2, the capacity to detect an association between rainfall or temperature and yield may become more difficult. The CO_2 and weather main effects may become more confounded and so isolating the effect of each source of crop variability may become more difficult if the yield dataset becomes more variable. However, if global temperatures were limited to below 2 °C above pre-industrial levels throughout the 21st century (UNFCCC, 2015), then the associated variability in yield from the Rothamsted Long-Term Experiments from increasing temperatures would be less due to limit of temperature variability. As levels atmospheric CO_2 become less limiting on crop production (Chapter 7) and global temperatures becoming limited to below 2 °C above pre-industrial levels throughout the 21st century (UNFCCC, 2015), it may be concluded that more of the variability in future yields of Rothamsted Long-Term Experiments would be more associated with variations in rainfall. It may be suggested that in order to maximise future yields from the Rothamsted Long-Term Experiments attempts should be made to minimise the loss associated with extreme rainfall or drought (see Research Aims 2 and 3).

Issues of using statistical methods to identify the effects of weather variability on crop production

Some issues to be considered when using statistical modelling to identify the effects of weather variability on crop production using data from the Rothamsted Long-Term experiments include collinearity and confounding of explanatory variables. Further criticisms such as non-linearity of explanatory variables was also discussed by Katz (1977). From the conclusions within Chapters 3, 4, 5, 6 and 7 I have briefly stated the limitations of statistical analyses, such as: collinearity and confounding of explanatory variables; the use of trend-lines summarising yield over time and smoothing-out variability; a lack of replication and randomisation of treatments; and auto-correlation of yields at lag 1.

The issue of collinearity of explanatory variables within a regression model results in the incorrect estimated of parameter coefficients as the variables are not independent. For example, temperature and rainfall for a particular month may be partially collinear, cooler April also was wet and a warm April was also dry. The multivariate approach discussed in Chapter 3 attempted to explore with this issue. Collinear weather variables were taken into consideration within principal components analysis as new uncorrelated components were derived from correlated data, pulling out associations between multiple weather variables. However, consideration on regressing PC against yield was not considered due to the complex interpretation of each PC and the potential of non-informative analyses.

From the PC scores from these analyses, years which experienced similar weather were grouped together, and a cluster-by-crop by treatment comparison was made (see Chapter 3). However, due to this being data-driven with little consideration of agronomic effects, meaningful interpretation between clusters, with regards to total biomass of wheat, spring barley and herbage, proved time consuming and difficult. Also, because groups of years were considered the analysis was not conducted on a continuous scale, where the magnitude of the effect of a weather variable could not be assessed. Therefore, it could only be determined that a few grouped years were lower or higher yielding given their climate. Given this, the method taken within Chapter 3 provided comparisons across several crops and gave insight into how combinations of weather variables impacted crop production.

Similar to the issue of collinearity, confounding of variables was also an issue with the analyses conducted within this Thesis. Within Chapters 4 and 5 the issue of confounding was discussed in the context of estimating a true cultivar effect separately from weather effects. The cultivar effect influencing the parameters of the parsimonious model may be influenced by weather. For example, there was 16 observations for the variety Hereward (1996 to 2012) on the Broadbalk Experiment but only 4 for Apollo (1991 to 1995). The variability of those explanatory variables may have been too narrow to detect a true effect of weather. This was why an interaction between variety and weather was not investigated within the models within Chapters 4 and 5. However, if more years for each variety were included, which covered an appropriate range over each explanatory variable, then a model including a separate effects (slopes) for each variety may have been considered. The models within Chapters 4 and 5 assume that the effect of weather on yield was the same across all varieties and inference was borrowed between cultivars.

Other examples of confounding include the estimate of soil pH effect on hay and herbage yields from Chapter 6. Data on soil pH levels on Park Grass before 1960 were sparse, and consequently only plots with relatively stable soil pH were chosen for analyses. More acidic plots were originally selected. However, due to the relative scarcity of pH data there was not enough variability in the pH values to capture year-to-year variations in yield and therefore the pH effect for these acidic plots was confounded by observations in time, leading to large residuals and a lack of fit.

Also the issue of the effect of increasing CO_2 potentially confounding the parameter estimate of temperature variables from Chapters 4, 5 and 6. Within Chapter 7, there was an estimated 9.12 to 9.87% increase in yield, depending on variety, due to increase in atmospheric CO_2 from 295.60 ppm in 1892 to 404.21 ppm in 2016. Therefore, any negative estimated effect of temperature on yield from 1968 to 2016 may not be a true effect and could be underestimated due to the confounding effect of CO_2.

The issue of the non-linearity of relationships between explanatory variables with yield was identified by Katz (1977) as a limitation of statistical methods. For example, the relationship between two variables from well-designed experiments within the literature may be identified as non-linear, however, using national yield data or data from long-term experiments this relationship may be discovered as linear. Two reasons may be considered for this linearity, a non-linear effect may have happened but was not observed due to increased amounts of variability due to the confounded effects of other variables. Or, insufficient range of variability along the axis of the explanatory variable was observed and therefore resulted in a linear trend over a short range. An extension of this limitation can be considered for fitting trend-lines through yield over time. For example, from Chapter 2, variations in annual (October to September) sunlight was decreasing from 1892 to 1968, but from 1968 onwards this trend was increasing. If a linear trend-line was fitted to all 125 years no trend over time may have been observed but would show a lack of fit. Using year as a factor variable (Chapters 4 and 5) allowed for direct comparison between the yield of wheat and spring barley with other years. This was achieved by reducing the dimension of the data to three parameters (from seven Nitrogen treatments for wheat and four Nitrogen treatments for spring barley) and therefore was no assumption that the effects of climate were linear over time.

The lack of replication and randomisation was addressed within Chapters 4 and 5. A lack of randomisation of treatments prohibited the direct test for an effect of Phosphorus on the Nitrogen response curve of spring barley (Chapter 5) due to the application of treatments over-time influencing the characteristics of each plot and therefore a main effect of Phosphorus could not be investigated. For example, a test of presence or absence of the effect of Phosphorus could be obtained, however, a dose effect could not be achieved due to the build-up of Phosphorus within the soil of certain plots of the Hoosfield Experiment (see Chapter 2). The issue of a lack of replication was addressed and by taking instances of a known Nitrogen response curve inference between Nitrogen doses was obtained. This method also allowed for an investigation of how weather variations may influence the Nitrogen response of winter wheat and spring barley with respect to the grain yield.

The issue of auto-correlation of yields was addressed within Chapter 6. Although previous studies into the effect of weather on Park Grass (Coleman et al., 1987; Jenkinson et al., 1994; Kettlewell et al., 2006) stated there was high positive auto-correlation at lag 1. In this Thesis, this issue has been addressed with an attempt at a biological interpretation. Within Long-Term Experiments, where the crop was not sown, it may be considered that auto-correlation occurs. For example, if a species had high abundance in one year it may have a better capacity to grow in the next. Autocorrelation should be considered in such datasets. However, if the auto-correlation cannot be explained by other data from the experiment, such as species prevalence, then the use of an autoregressive model (which includes a term which explains the auto-correlation) may be considered. However, as discussed within Chapter 6, the use of an autoregressive term may only be necessary within one or more set of treatments and including such a term in all treatments may lead to an over fitting of the data.

Autocorrelation was not considered as a negative result within this Thesis, but as another description of the dataset. By considering the auto-correlation of both yields and residuals, it was shown how the inorganic fertiliser treatments on Park Grass Experiment may be more susceptible to variations in weather than other treatments due to a lack of biodiversity. Therefore, auto-correlation of yields and residuals, although it may influence the parameterisation of coefficients and model building, were results to comment on.

It was stated by Katz (1977) that coefficients of statistical models were ”estimates subject to several sources of error”. The same argument may be applied to process based models. Known biological relationships and estimates from well-designed experiments were used to build process based models. These well-designed experiments were subject to sources of variability when estimating a true effect. Therefore, if variation around an estimated effect was not included within a process based model this may influence its predictive ability. Building a stochastic processes or sampling from a distribution rather than an expected value within a process based model may be considered to overcome this issue. However, this may result in an over complex model with large variability around predictions and the need for a very detailed experiment to study variability or a distribution around certain crop processes.

Due to the standardisation of treatments, the Rothamsted Long-Term Experiments has a higher potential of identifying a true climate effect than national and regional statistics. However, an extrapolation of all conclusions from Rothamsted, Hertfordshire, England are needed for the results presented within this Thesis. With national or regional data, trends in yield over time may be driving advancements in technology which may take years for the whole nation or region to adapt. For example, the Broadbalk grain yield of treatment 192 kg N ha^{-1} from 1968 were relatively stable, but had some year-to-year variations. The FAOSTAT (2018b) statistics for UK wheat production show, for the UK production of wheat, increases in yield from 1968 to 1996 but a stagnation in yield from 1997 onwards. The increase in the late-20th century may be a result of the change in agricultural practice due to the green revolution in the 1960s where there was a general shift to the use of higher yielding short-strawed cultivars and increasing use of herbicides. Therefore, any year-to-year variations in the FAOSTAT dataset due to weather are confounded by trends in increased productivity due to changes in agricultural practice.

One method of dealing with trends over time is to de-trend long-term summaries and assess the variation associated around a trend-line by modelling the residuals. This is a two-stage analysis where potential year-to-year variability due to weather may have been smoothed out and information has been lost before the second modelling step. This approach was conducted by Kukal & Irmak (2018). Their results show that after de-trending yield over several crops between 1900 to 2014 using county data from the continental United States, there was a linear relationship between growing day degrees and de-trended yield residuals over several variables. Emphasis should not just be put onto the presence of a trend-line, but also the adequacy of fit around the trend-line and if there is normality and homogeneity of residuals. Also, caution must be taken with analysis at a regional level, as sources of within-year variation may smoothed over and therefore not accounted for. Although trend-lines over time may smooth-out variability, there are benefits of using within year analyses. Within Chapters 4 and 5, year was fitted as a factor variable where a Nitrogen response curve was fitted to each year. In this approach inference between yields was gained and a potential *replication* was found by taking instances of a response curve. Also, three parameters were estimated for each year rather than seven, so more degrees of freedom could be allocated to assess the goodness of fit. Modelling year effects using weather in Chapters 4 and 5 provided a better understanding of the relationship between climate change and crop production.

Suggestions for Future Work

The multivariate cluster analysis in Chapter 3 provided an insight into how the climate has changed at Rothamsted from 1892 to 2016. Similar to the partitioning climate zones of the conterminous United States by Fovell & Fovell (1993), a multivariate analysis approach to all long-term United Kingdom meteorological data should be considered. This approach would determine not only how climate has changed among multiple variables but also spatial characteristics of the weather experienced in the United Kingdom. Therefore, would there be similar cluster membership of years allowing for both temporal and spatial variability.

It may be suggested that traditional clustering metrics to determine an optimal number of clusters could also be developed. For example, a common method for optimising the number of clusters includes identifying an *elbow* in the within-cluster-sum-of-squares plot (this *elbow* occurs when the relationship between within-cluster-sum-of-squares and increased numbers of cluster becomes shallower). However, from Figure 3.2(a) no clear *elbow* could be identified, therefore another clustering metric (not based on the within-cluster-sum-of-squares) was used. The reason for this lack of *elbow* was due to the variability of the Rothamsted Meteorological dataset. Therefore, if cluster analysis is used as a method to quantify climate change, then better metrics of optimum cluster number should be developed.

By allowing a Linear-by-Exponential relationship between Nitrogen applications for each year on Broadbalk wheat and Hoosfield spring barley, the effects of weather variability can be investigated by modelling the a, b and c coefficients. This allows for more inference to be obtained on the effects of weather, not only on yield, but also on the Nitrogen and yield relationship. This methods of fitting a Nitrogen response curve to each year is an approach already conducted in the literature (Roques et al., 2017). However, estimating the coefficients of a Linear-by-Exponential function may be applied to further studies of the effect of weather on yield. This approach may be considered on the rotational plots of the Broadbalk Experiment (Figure 2.2) to determine if similar effects of variations in the Nitrogen response were observed on first wheat in rotation as shown on continuous wheat within Chapter 4.

Further investigations in to the loss of yield in high Nitrogen plots due to variations in weather around Nitrogen application should be investigated. As this may be considered as a potential mitigation against loss in yield due to weather variations.

As discussed within *Issues of using statistical methods to identify the effects of weather variability on crop production*, the application of stochastic processes within process-based models may be considered as a potential for future work. However, appropriate variability of biological stages of crop growth should be considered from well-designed experiments rather than deviations around a unit normal distribution.

To suggest future work of the Rothamsted Long-Term Experiments in regard to weather variability and climate change is difficult. This is because the experiments themselves represent a current sustainable agricultural system which changes over time (see Figures 1.1 and 1.2) and is subject to year-to-year variations in yield. The work presented in this Thesis is an attempt to explain variability in yield from a current agricultural system by variations in weather. Therefore, future studies in crop variation using data from the Rothamsted Long-Term Experiments will be responsive analyses depending on threats to agricultural production given in that time.

8.1 Concluding Remarks

How the use of statistical approaches to identify the effects of weather variability on crop production using data from the Rothamsted Long-Term Experiments has changed over time

From 1864 to 1899, John Lawes published annual summaries of the wheat crop yield of Broadbalk in the *Agricultural Gazette*. These publications (35 in total) were early examples of an attempt to study sources of crop variability in wheat yields over time. The drought of 1870 (Lawes & Gilbert, 1871) and the very wet year of 1879 (Lawes & Gilbert, 1880b), mentioned above, were used to explain the effects of weather on the yield of crops. However, the statistical methods used were a simple comparison of means and did not consider the broader weather variability between years. Lawes and Gilbert (1880a) expressed the need for ”very detailed consideration of climate statistics” when identifying the influence of weather on the Park Grass Experiment.

Studies In Crop Variation by Fisher (1921) was the first attempt to understand the year-to-year variability of Broadbalk wheat grain yields which considered more than a simple comparison of one year against a long-term mean. This led to further studies of the influence of rainfall variations on crop production on barley (Wishart & Mackenzie, 1930) and hay (Cashen, 1947). These studies focused on the influence of rainfall on crop production as little was known at the time about the consequences of human induced climate change.

The influence of variations in rainfall on crop production on the Long-Term Experiments has been revisited more recently by Silvertown et al. (1994) and with related studies on the effect of variations in temperature (Chmielewski and Potts, 1995; Jenkinson et al., 1994; Sparks and Potts, 2003). From these studies correlations were used to comment on the associated between of variations in weather on yield. Regression models were also used to test the effect of temperature and rainfall on the yields of wheat on Broadbalk from 1854 to 1967, where high temperatures in May and June were associated with lower yields (Chmielewski & Potts, 1995). Similar analyses was achieved with yield data from the Park Grass Experiment, where CO_2 was not shown to be influencing herbage yield at Rothamsted (Jenkinson et al., 1994).

General Conclusion

The major conclusion of this thesis can be separated out into contributions to two subjects:

1. **Agricultural**
   The climate at Rothamsted has not only experienced a period of warming since 1892, but years within the 21st century seem to be warmer with either periods of drought or more extreme rainfall compared to years from the 20th century (Research Aim 1). Inter-annual variations in monthly temperature and rainfall were association with variations in the yield of wheat, barley and grassland yield (Research Aim 2). Warmer temperatures in the early-summer were shown to have a negative effect on the yield of cereal crops. There was an interaction between the effects of Nitrogen application and weather on wheat and barley yields, such that extreme rainfall and warmer temperatures led to lower yields at high Nitrogen application rates, therefore flattening the fitted Nitrogen response curve (Research Aim 3). To maximise yield production of wheat and barley an agricultural system where the loss of yield due variations in weather around Nitrogen application should be implemented on the Long-Term Experiments. Warmer temperatures also led to a reduction in forage yields from the Park Grass Experiment (Research Aim 2). However, high positive auto-correlation (at lag 1) was observed in plots which received more mineral fertilisers and which were less biodiverse. Therefore, more biodiverse plots

were more resilient against variations in weather. Generally, the negative effect of warmer temperatures and climate change on the yield of Park Grass (forage) was less compared to Broadbalk (wheat) and Hoosfield (barley). From 1892 to 2016 there was a mean estimated 9.42% increase in crop production due to rises in atmospheric CO_2 at Rothamsted, having kept management, weather and other environmental factors stationary (Research Aim 4). The estimated relationship between increasing CO_2 and % increase in yield was slightly curvilinear. Concluding, the future benefits of further increases in atmospheric CO_2 on yield may less than those during the mid to late-20th century. This was supported by the observation of more biomass production being allocated to non-grain specific parts of the crop under future climate scenarios.

2. **Statistical analysis to Long-Term Experiment data**

   Fitting trends to climate data over time risks smoothing-out year-to-year variation which may not be a function of time. By investigating the similarity of each year, based on their within-year weather, clusters of years may be obtained. Considering the distribution of these weather clusters over time is clear evidence of a changing climate.

   By acknowledging each treatment, within a year, experienced the same weather, we can therefore gain statistical inference by modelling instances of a Nitrogen response curve. This allows yield over multiple Nitrogen levels, within a year, to be summarised by a Nitrogen response curve. Year-to-year variations in a Nitrogen response curve due to inter-annual variations in weather may be investigated. Therefore, inference on the effect of weather variations on yield is gained as yields from different treatments are considered as not independent and are sampled from a response curve.

   Yearly variations in yield are not the same when considering data from an experiment where a cereal crop is sown compared to an experiment where forage yield is harvested each year. Careful consideration should be considered between year-to-year variations in forage yields due to crop being a semi-permanent community of grasses, and not a single sown mono-crop. Serial auto-correlation of forage yield should be understood and stated as this will influence the independence of the residuals and therefore conclusions of any statistical model. However, caution is given against using auto-regressive models on forage yield data alone due to a lack of understanding in the year-to-year variation of forage yield of each treatment. Further species identification data should be collected along with forage yield to better understand the auto-correlation at lag 1.

The methods of analysing Long-Term Experiment data proposed within this thesis could be implemented in other Long-Term Experiments, especially those with varying levels of Nitrogen.

My Contribution to the Study of the Association between Crop and Weather Variation on the Rothamsted Long-Term Experiments

Overall, when identifying changes in climate over long time-series datasets, combinations of variables may be considered to look for a combined effect over multiple weather records to better inform our understanding of how climate has changed and the response of crop yield to these changes. As discussed, this approach was taken within Chapter 3. The main findings from Chapter 3 include that not only are years becoming warmer, but within the 21st century there are periods of dry and wet years. Also, the negative effects of higher temperatures were less on grassland systems than cereals.

The Rothamsted Long-Term Experiments generally had the same treatments applied each year (except when major changes in the agricultural system occur and they needed to be updated) and by acknowledging similar variations in yield occurring over multiple treatments, where only the Nitrogen application rate changed, inference was gained about differences between these treatments and a Nitrogen response curve was modelled, with the Nitrogen response of wheat and spring barley shown to be influenced by within-year variations in weather. The Rothamsted Long-Term Experiments do not have detailed phenological data regarding the stages of crop development of wheat and spring barley collected regularly, but variations in mean temperature associated with the sensitive stages of crop development, such as anthesis, were shown to negatively influence crop yield. Variations in monthly total rainfall around management application of Nitrogen were also shown to influence yield. Increased rainfall in April may lead to a decline in yield suggesting a potential leaching of fertiliser into the soil, with this effect being more severe for higher Nitrogen plots.

The benefits of increased biodiversity on grassland plots was also discussed. The results from Chapter 6 showed that in less diverse plots of the Park Grass Experiment, having accounted for variations in weather, there was still an auto-correlative component which was unexplained. Therefore, concluding that in less biodiverse plots they may be less resilient to variations in weather as the effects of weather in the previous year (lag 1) may be contributing to yield.

Atmospheric CO_2 has increased since 1892 (Etheridge et al., 1998; NOAA, 2018), where year-to-year variations in crop yield were still observed, which suggests, as future yields from the Rothamsted LTEs may be expected to change (depending on future weather scenarios), there will also be year-to-year variations in yield due to weather.

The results and conclusions presented within this Thesis illustrate the need for long time-series datasets, with constant homogeneity between years. Along with appropriate analyses to separate the influence of short-term variations of weather and long-term trends in climate on the Rothamsted Long-Term Experiments. Further, studies in crop variation may lead to the effects of multiple variables being modelled, some of which may not be weather or climate variables (such as soil or pests), and some variables may be used as a proxy for weather such as year. The use of Long-Term Experiment data still provided insight into how variations in yield from a current sustainable agricultural system may still be attributed to variations in weather, and the modelling of these data provided insight into factors causing yield loss and help identify potential mitigations to minimise these losses and hence maximise yield.

This Thesis has attempted to address year-to-year variations in yield of three of the Rothamsted's Long-Term Experiments (LTEs). I have not been the first to address this in the 175-year history of these experiments and as they continue into the mid and late-21st century and more years of data are added to the archive this work should be revisited. It was expressed by Lawes and Gilbert (1880a) that there was a need for "very detailed consideration of climate statistics" when identifying the influence of weather on the Park Grass Experiment. An attempt of this was made throughout this Thesis through my contribution to the study of the associations of weather variations with crop yield variations on the Rothamsted LTEs (Chapters 3, 4, 5, 6 and 7).

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Appendices

Appendix A

Supplementary Material

Within this appendix contains supplementary material from the analyses in Chapters 2, 3, 4, 5, 6 and 7.

A.1 The Rothamsted Long-Term Experiments

Table A.1: The soil pH of plots 12 (Nil) a, b, c and d of the Park Grass Experiment, from 1876 to 2014.

Plot	1876	1923	1959	1967	1970	1971	1974	1975	1976	1977	1979	1984	1991	1995	1998	2002	2005	2008	2011	2014
a	.	.	.	.	.	5.40	.	5.30	.	6.60	6.10	6.70	7.00	7.00	7.00	7.10	7.10	6.80	7.20	6.82
b	.	.	.	.	.	.	.	5.30	.	6.00	6.10	5.60	6.10	6.30	6.60	6.00	6.00	5.90	6.20	6.00
c	.	.	.	.	.	.	.	.	.	5.20	.	5.10	4.80	5.30	5.20	5.10	5.10	4.90	5.00	5.10
d	5.30	5.50	5.20	.	.	.	.	.	5.20	5.20	.	5.00	4.80	5.20	5.20	4.90	5.20	5.10	5.00	5.04

Table A.2: The soil pH of plots 3 (Nil) a, b, c and d of the Park Grass Experiment, from 1876 to 2014.

Plot	1876	1923	1959	1967	1970	1971	1974	1975	1976	1977	1979	1984	1991	1995	1998	2002	2005	2008	2011	2014
a	.	.	.	.	.	7.20	.	7.10	.	.	.	6.30	6.40	7.10	7.10	7.30	7.30	7.20	7.20	7.11
b	.	6.80	7.20	.	.	.	.	.	.	6.50	.	6.10	6.40	6.50	6.50	6.30	6.40	6.10	6.30	6.06
c	.	.	.	.	.	.	.	.	.	5.10	.	4.90	5.00	5.40	5.30	5.20	5.10	4.90	5.10	5.16
d	5.30	5.60	5.20	.	.	.	.	.	5.30	.	.	5.00	4.80	5.20	5.20	5.30	5.30	5.20	5.30	5.14

Table A.3: The soil pH of plots 2.2 (Nil) a, b, c and d of the Park Grass Experiment, from 1876 to 2014.

Plot	1876	1923	1959	1967	1970	1971	1974	1975	1976	1977	1979	1984	1991	1995	1998	2002	2005	2008	2011	2014
a	.	.	.	.	.	7.30	.	7.10	.	.	.	6.30	6.50	6.90	6.90	7.40	7.50	7.30	7.10	7.11
b	.	7.10	7.30	.	.	.	.	.	.	6.70	.	6.10	6.20	6.00	6.00	6.00	6.20	6.00	6.20	6.12
c	.	.	.	.	.	.	.	.	.	5.20	.	4.90	5.10	5.10	5.30	5.20	5.20	5.00	5.30	5.30
d	5.60	5.80	5.20	.	.	.	.	.	5.20	.	.	5.10	4.80	5.00	5.20	5.10	5.20	5.10	5.10	5.12

Table A.4: The soil pH of plots 13 (FYM) a, b, c and d of the Park Grass Experiment, from 1876 to 2014.

Plot	1876	1923	1959	1967	1970	1971	1974	1975	1976	1977	1979	1984	1991	1995	1998	2002	2005	2008	2011	2014
a	.	.	.	.	.	7.10	.	6.90	.	.	.	6.50	6.70	6.70	6.80	7.00	7.00	6.90	7.00	6.84
b	.	5.70	7.00	.	.	.	.	.	6.20	.	.	6.20	6.30	6.10	6.20	5.90	6.00	5.90	6.10	5.98
c	.	.	.	4.90	5.20	5.40	5.00	.	.	.	5.10	5.40	4.90	5.30	5.50	5.20	5.30	5.10	5.20	5.28
d	4.50	4.50	4.70	.	.	.	.	.	4.90	.	.	4.70	4.60	5.10	5.10	5.10	5.20	5.20	5.00	5.20

Table A.5: The soil pH of plots 7 (PKNaMg) a, b, c and d of the Park Grass Experiment, from 1876 to 2014.

Plot	1876	1923	1959	1967	1970	1971	1974	1975	1976	1977	1979	1984	1991	1995	1998	2002	2005	2008	2011	2014
a	.	.	.	.	.	6.90	.	6.60	.	.	6.70	6.60	6.40	6.90	6.90	7.00	7.00	6.90	7.00	7.02
b	.	6.60	7.00	.	.	.	.	.	.	6.30	.	6.20	6.20	6.00	5.90	5.80	6.00	6.10	6.20	6.30
c	.	.	.	.	.	.	.	.	.	5.20	.	4.80	5.20	5.10	5.00	5.00	4.90	4.90	5.20	5.19
d	5.40	5.30	4.90	.	.	.	.	.	4.80	.	.	4.80	4.80	5.00	4.70	4.90	4.90	4.90	4.90	5.10

Table A.6: The soil pH of plots 16 (48kg Nha^{-1}PKNaMg, where N was applied as sodium nitrate) a, b, c and d of the Park Grass Experiment, from 1876 to 2014.

Plot	1876	1923	1959	1967	1970	1971	1974	1975	1976	1977	1979	1984	1991	1995	1998	2002	2005	2008	2011	2014
a	.	.	.	.	.	7.20	.	6.80	.	.	6.90	6.80	6.80	.	6.70	6.70	6.90	6.90	7.00	7.08
b	.	7.10	7.10	.	.	.	.	.	.	6.50	.	6.50	6.60	.	6.20	6.10	6.10	6.00	6.10	6.00
c	.	.	.	.	.	.	.	.	.	5.30	.	5.50	5.40	.	5.40	5.50	5.40	5.40	5.30	5.58
d	5.50	5.80	5.40	.	.	.	.	.	5.20	.	.	5.40	5.30	.	5.30	5.50	5.50	5.60	5.40	5.58

Table A.7: The soil pH of plots 14 (96kg Nha^{-1}PKNaMg, where N was applied as sodium nitrate) a, b, c and d of the Park Grass Experiment, from 1876 to 2014.

Plot	1876	1923	1959	1967	1970	1971	1974	1975	1976	1977	1979	1984	1991	1995	1998	2002	2005	2008	2011	2014
a	.	.	.	.	.	7.20	.	7.00	.	.	.	6.90	6.80	6.80	6.90	7.00	7.00	7.00	7.00	7.02
b	.	6.60	7.30	.	.	.	.	.	.	6.70	.	6.70	6.80	6.40	6.50	6.30	6.30	6.30	6.20	6.30
c	.	.	.	.	.	.	.	.	.	5.80	.	5.80	6.00	6.10	6.10	6.00	6.10	6.00	5.90	6.10
d	5.90	6.30	6.00	.	.	.	.	.	5.80	.	.	5.80	5.80	5.70	6.10	6.00	6.10	6.10	6.00	6.12

Table A.8: The correlation of monthly summarised meteorological variables. The top right corner is the correlation between monthly summaries of total rainfall. The bottom left corner is the correlation between monthly summaries of mean temperature.

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Oct	1	0.1272	-0.0616	0.2811	0.1217	0.0666	-0.099	0.0482	-0.0752	0.1642	0.0430	0.1362
Nov	0.1265	1	-0.0066	0.053	-0.1367	-0.0109	-0.0775	-0.0258	0.0859	-0.1191	0.0926	-0.1131
Dec	-0.0311	0.2047	1	0.1946	0.2938	0.0283	0.0421	0.0259	-0.1669	-0.201	0.1206	-0.2059
Jan	-0.0869	-0.0173	0.2847	1	0.269	0.1246	-0.1569	-0.0092	-0.0486	-0.1695	0.0168	-0.0307
Feb	-0.0565	0.1507	0.0884	0.3740	1	-0.0947	-0.2789	-0.029	-0.2351	-0.2064	0.2162	-0.3015
Mar	-0.0127	0.0142	0.0995	0.3423	0.4464	1	0.0810	0.3343	-0.1470	-0.1051	0.0059	-0.0015
Apr	0.0663	0.2746	-0.1548	0.0936	0.4441	0.2497	1	0.1183	0.0585	0.1994	-0.0195	0.1816
May	0.0862	0.0072	0.1242	0.3822	0.5005	0.354	0.1875	1	-0.2512	0.1531	0.1470	0.0331
Jun	-0.0360	0.1009	-0.0028	0.2684	0.1277	0.0286	0.2335	0.4117	1	0.1603	-0.1349	-0.0202
Jul	-0.0093	0.1351	0.1601	0.2376	0.0019	0.0003	0.0681	0.1349	0.3177	1	0.0297	-0.0148
Aug	-0.112	0.3049	0.2069	0.2775	0.3612	0.1812	0.0681	0.1333	0.2309	0.4618	1	-0.0847
Sep	0.1741	0.1421	0.0171	0.0620	0.2726	0.1571	0.2624	0.3886	0.3212	0.2797	0.2532	1

Table A.9: The correlation between monthly summarised meteorological variables total rainfall and mean temperature.

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Oct	-0.1685	-0.1023	0.1115	0.1678	0.1243	0.2086	0.2112	-0.1084	-0.2053	0.1231	0.0247	0.0862
Nov	-0.2033	0.2781	0.065	-0.0466	0.0662	-0.1178	0.1772	0.0387	0.0744	0.1395	0.1837	0.0111
Dec	0.1691	0.1514	0.1619	-0.1575	-0.1292	-0.1511	-0.097	-0.1579	-0.0089	0.1019	0.0634	-0.1026
Jan	-0.0947	0.0289	0.2586	0.34	0.0913	0.1081	0.1001	0.0532	-0.1779	0.0675	-0.0291	-0.1902
Feb	0.3673	-0.0777	-0.0882	-0.0131	0.314	0.141	0.1277	-0.0247	-0.1474	0.084	0.0887	-0.1026
Mar	-0.221	0.0408	0.2199	-0.2297	-0.1701	-0.3	-0.33	-0.1102	-0.2883	-0.0915	-0.1936	-0.1205
Apr	-0.0355	0.0942	0.2247	0.1261	-0.2008	0.1983	-0.4033	0.1699	0.0299	-0.0664	-0.0311	0.0207
May	0.1005	0.1497	0.032	0.0299	-0.2153	-0.0471	0.0704	-0.0874	0.0856	0.0164	-0.2103	-0.0715
Jun	-0.0875	0.1526	-0.1105	-0.1386	0.1288	0.2186	0.0807	0.0167	-0.3225	-0.4217	-0.1208	0.0453
Jul	0.3128	0.1111	0.0025	0.0746	-0.054	0.1801	0.1234	0.1234	0.039	-0.3871	-0.1168	-0.0904
Aug	0.1900	-0.2233	-0.1926	-0.1549	0.0154	0.066	0.143	0.2087	-0.0112	-0.0647	-0.4103	0.0394
Sep	-0.4832	-0.0315	0.1112	0.2561	0.0475	0.0481	-0.0948	-0.0529	0.1967	-0.0313	0.0189	-0.126

A.2 A multivariate study into Rothamsted's weather from 1892 to 2016 and the yield of the Long-Term Experiments

Table A.10: The principal components (PCs) from the principal components analysis within Chapter 3. Table A.10 continues overleaf.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC 15	PC16
Total Rainfall (mm) Oct	-0.0640	-0.0180	0.0825	-0.0708	0.0721	-0.0839	-0.2073	0.0748	0.2587	0.2309	0.1493	0.0136	0.0946	-0.0344	-0.0254	0.1495
Total Rainfall (mm) Nov	-0.0301	0.1570	0.1181	-0.0132	-0.0922	-0.0275	-0.2073	-0.0084	0.1682	-0.2484	0.0122	-0.0129	0.1516	0.0968	0.0894	-0.0758
Total Rainfall (mm) Dec	-0.0081	-0.1345	-0.1127	-0.1878	-0.0323	0.0028	0.0012	-0.0872	0.0123	0.0555	-0.1795	0.0086	0.1203	0.0029	0.1735	-0.0066
Total Rainfall (mm) Jan	-0.0764	-0.0954	0.0020	-0.0508	-0.0546	-0.1835	-0.1252	-0.0343	0.1541	-0.0423	-0.1169	-0.1069	0.0126	-0.3161	-0.1350	-0.1110
Total Rainfall (mm) Feb	-0.0652	-0.1289	-0.0332	-0.1787	0.1539	-0.0020	-0.1293	0.0168	0.0951	-0.0753	0.0576	0.2452	0.0858	0.1906	-0.1855	-0.1456
Total Rainfall (mm) Mar	0.0573	0.0787	0.0306	-0.0218	-0.2041	-0.1376	-0.0759	-0.1119	-0.2154	-0.1694	-0.0015	0.2866	0.0098	-0.0452	-0.0523	0.0610
Total Rainfall (mm) Apr	-0.0066	-0.0180	0.0940	0.0436	-0.3263	0.0634	0.2201	0.1317	0.1281	0.0584	0.0073	0.0955	-0.1177	0.0179	0.0327	-0.0635
Total Rainfall (mm) May	-0.0425	-0.0198	0.0513	-0.1769	-0.0837	0.0259	0.0237	0.2249	-0.0345	-0.0564	-0.2846	-0.0312	0.0276	0.0953	0.1362	0.2404
Total Rainfall (mm) Jun	0.0669	-0.0510	0.0561	0.1171	0.0603	-0.2412	0.1880	0.0670	-0.0590	-0.2094	0.1693	0.0239	0.2340	0.0285	-0.0576	0.0731
Total Rainfall (mm) Jul	0.0947	-0.0655	0.1753	-0.0523	-0.0858	0.0842	0.0494	-0.0735	0.1431	0.2140	0.1560	-0.0875	0.1286	0.0596	-0.1060	0.2481
Total Rainfall (mm) Aug	0.0798	-0.1391	0.1740	-0.1765	0.0333	0.0711	-0.1395	-0.2090	-0.0997	-0.1696	0.1759	-0.0290	-0.0155	-0.0603	0.0959	0.0418
Total Rainfall (mm) Sep	-0.0056	-0.1258	0.1071	0.2126	-0.1479	0.0731	-0.1716	0.0134	-0.1225	0.0296	-0.0471	-0.0852	0.0143	0.1639	-0.0624	-0.0007
Mean Max Temperature (°C) Oct	-0.0505	-0.0295	0.0396	-0.3142	0.0667	0.0278	0.2998	-0.0388	-0.1257	0.0218	-0.0184	-0.1134	0.0389	0.0375	-0.1104	-0.1359
Mean Max Temperature (°C) Nov	-0.1015	0.1877	0.0905	-0.0301	-0.0315	-0.2361	0.0233	-0.0823	-0.1368	0.0008	-0.0594	-0.1878	0.0945	0.1390	-0.1059	-0.0701
Mean Max Temperature (°C) Dec	-0.1231	-0.1057	-0.0900	-0.0894	-0.2645	-0.1198	0.0074	-0.1767	-0.0882	0.1643	-0.0186	-0.0074	0.0764	0.1484	0.1657	-0.0090
Mean Max Temperature (°C) Jan	-0.1732	-0.2324	-0.1209	0.0729	-0.0964	-0.0204	-0.0244	0.0390	-0.0501	-0.0442	-0.0430	-0.1942	-0.1414	-0.0107	-0.2304	0.0281
Mean Max Temperature (°C) Feb	-0.1702	-0.2315	-0.0117	0.1115	0.1189	-0.0695	0.0413	-0.0049	0.0234	-0.0108	-0.0264	0.1355	0.0088	-0.0157	-0.0454	0.1558
Mean Max Temperature (°C) Mar	-0.1182	-0.1341	0.0659	0.1977	0.1809	-0.0582	0.1217	-0.0452	0.0829	0.1798	0.0884	-0.0646	0.1263	-0.0031	0.2075	-0.0801
Mean Max Temperature (°C) Apr	-0.1109	0.0614	0.0373	-0.0079	0.3185	-0.1452	-0.0730	-0.1631	-0.0972	0.0853	-0.1037	-0.0145	-0.1328	-0.0221	0.0149	0.0021
Mean Max Temperature (°C) May	-0.0403	0.0684	0.0202	0.0967	-0.0276	0.0367	0.1471	-0.4428	0.1554	-0.1039	0.1068	0.0574	-0.0598	-0.0887	-0.0611	0.1389
Mean Max Temperature (°C) Jun	-0.1013	0.1237	0.0057	0.0826	0.0043	0.3171	-0.0828	-0.2203	0.0929	0.0443	-0.2021	-0.0457	0.1113	0.0711	0.1017	-0.0450
Mean Max Temperature (°C) Jul	-0.1928	0.1500	-0.1635	-0.0067	0.0475	0.1422	-0.1523	0.0702	-0.1945	-0.0107	0.0760	0.0536	0.0538	-0.1413	0.0587	-0.0311
Mean Max Temperature (°C) Aug	-0.2098	0.1863	-0.2084	0.0765	-0.0220	-0.0553	0.0237	0.0542	0.0270	0.0107	0.0242	0.0589	-0.1034	0.1826	-0.0358	-0.0230
Mean Max Temperature (°C) Sep	-0.1191	0.2263	-0.1032	0.0014	0.0449	-0.0054	0.1941	0.0801	0.0855	-0.0676	0.0774	-0.0831	0.0397	-0.2031	0.1488	-0.1294
Mean Min Temperature (°C) Oct	-0.1364	0.0242	0.0647	-0.3370	0.0769	0.0788	0.2047	0.0286	-0.0497	0.0226	0.0277	-0.0175	0.0843	0.0173	-0.1075	-0.0118
Mean Min Temperature (°C) Nov	-0.1184	0.2105	0.1532	-0.0143	-0.0297	-0.2384	-0.0098	-0.0314	-0.1035	0.0677	-0.0708	-0.1770	0.0861	0.0626	-0.1072	-0.0818
Mean Min Temperature (°C) Dec	-0.1630	-0.1055	-0.1185	-0.0894	-0.2705	-0.1199	-0.0036	-0.1653	-0.0612	0.1385	0.0031	0.0205	0.1026	0.0965	0.1214	-0.0873
Mean Min Temperature (°C) Jan	-0.1853	-0.2362	-0.1106	0.0514	-0.0794	0.0406	-0.0316	0.0644	-0.0277	-0.1168	-0.0384	-0.2335	-0.0939	0.0119	-0.1859	-0.0167
Mean Min Temperature (°C) Feb	-0.1725	-0.2317	0.0301	0.1202	0.1423	-0.0349	0.0212	0.0413	0.0394	-0.0301	-0.1053	0.1960	0.0258	0.0007	-0.0997	0.1095
Mean Min Temperature (°C) Mar	-0.1529	-0.1678	0.1073	0.1652	0.0260	-0.0636	0.0345	-0.0704	-0.0941	0.0291	0.1735	0.0938	0.1542	-0.0589	0.1037	-0.0949
Mean Min Temperature (°C) Apr	-0.1820	0.0179	0.1873	0.0449	0.0712	-0.0558	0.0173	0.0233	0.0020	0.0878	-0.2076	0.1972	-0.1382	-0.1101	0.0598	-0.0936
Mean Min Temperature (°C) May	-0.1427	0.0183	0.1377	0.0242	-0.1410	0.0641	0.1116	-0.2211	0.2513	-0.1226	-0.0188	0.0034	-0.0904	-0.0624	-0.1377	0.1507
Mean Min Temperature (°C) Jun	-0.1454	0.0555	0.1822	0.1016	0.0292	0.1533	0.0890	-0.0887	0.0265	-0.1494	-0.1494	-0.0656	0.1902	0.1415	0.1355	0.0230
Mean Min Temperature (°C) Jul	-0.2407	0.1092	0.0383	0.0073	-0.0048	0.1129	-0.1493	0.0515	-0.1337	-0.0086	0.1093	0.0763	-0.0031	-0.0048	-0.0067	0.0443
Mean Min Temperature (°C) Aug	-0.2407	0.1173	-0.0201	-0.0222	0.0449	-0.0055	-0.0405	0.0407	0.0420	-0.1334	0.1017	-0.0394	-0.1432	0.1462	0.0134	0.0685
Mean Min Temperature (°C) Sep	-0.1782	0.0531	0.1217	0.0373	0.0119	0.0983	0.0643	0.1705	-0.0168	-0.0698	0.0636	-0.1384	-0.0133	-0.1776	0.1238	-0.0593

Table A.11: Table A.10 continued.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC 15	PC16
Sun Duration (hrs) Oct	0.0261	-0.0636	0.0538	0.1193	-0.0580	-0.0282	0.1295	0.0102	-0.0338	0.1459	0.0431	-0.1465	-0.2193	0.1258	-0.0394	-0.1802
Sun Duration (hrs) Nov	-0.0739	-0.1510	-0.0233	-0.1167	0.0490	0.1438	0.1758	-0.0031	0.0035	-0.1773	0.0897	0.0545	-0.0313	0.1314	0.0819	-0.0477
Sun Duration (hrs) Dec	-0.0906	0.0895	0.2307	-0.0300	0.0209	-0.0248	-0.0153	0.0964	-0.0314	0.0781	0.0733	-0.0233	-0.1518	0.2110	0.0054	0.0969
Sun Duration (hrs) Jan	-0.0841	0.0440	0.0559	0.0318	-0.0222	-0.0856	0.0629	-0.0963	-0.1360	0.1326	0.0554	0.0539	-0.0569	0.0344	-0.0138	0.2701
Sun Duration (hrs) Feb	-0.1539	-0.0483	-0.0369	-0.0597	-0.0708	-0.0926	0.1242	-0.0603	-0.0373	-0.0393	0.0843	-0.2485	-0.0922	-0.1205	0.0176	0.1444
Sun Duration (hrs) Mar	-0.0771	-0.0450	0.0468	0.0790	0.2197	-0.0283	0.1313	0.0298	0.1957	0.1618	-0.0618	-0.1250	0.0475	0.1076	0.1352	0.0309
Sun Duration (hrs) Apr	-0.0643	0.0408	-0.0784	-0.0834	0.2715	-0.1090	-0.1286	-0.1957	-0.1492	0.0102	0.0830	-0.1692	-0.0773	0.0585	-0.0615	0.0794
Sun Duration (hrs) May	0.0039	0.0125	-0.0376	0.0682	0.0723	0.0164	0.1684	-0.3181	0.0345	0.0005	0.1142	0.1302	-0.0989	-0.0420	0.1541	-0.0329
Sun Duration (hrs) Jun	-0.0711	0.0479	-0.0478	0.0195	-0.0522	0.2686	-0.1939	-0.1342	0.1436	0.1347	-0.1797	-0.0430	-0.0558	-0.0381	0.0228	0.0009
Sun Duration (hrs) Jul	-0.1297	0.1166	-0.2301	-0.0408	0.0499	0.0953	-0.0749	0.1076	-0.0863	-0.0146	0.1324	0.0376	0.1006	-0.1965	0.0941	0.0751
Sun Duration (hrs) Aug	-0.1171	0.1548	-0.2435	0.1200	-0.0976	-0.0278	0.0093	0.0388	0.0914	0.1004	0.0860	0.1172	-0.0508	0.1031	-0.1006	0.0250
Sun Duration (hrs) Sep	-0.0405	0.1746	-0.1988	-0.0384	0.0212	-0.0514	0.1799	-0.0159	0.1493	-0.0436	0.0906	0.0258	0.0010	-0.0608	0.0351	-0.0315
Rain Intensity (mm/days) Oct	-0.0726	-0.0499	0.0734	-0.0886	-0.0002	-0.1157	-0.1726	0.0956	0.2145	0.1688	0.1454	-0.0633	0.0190	-0.0017	-0.0663	0.0638
Rain Intensity (mm/days) Nov	0.0109	0.0330	0.1024	-0.0840	-0.0610	0.0242	-0.2555	0.0033	0.1307	-0.2503	0.0923	-0.1066	0.1361	-0.0398	0.0661	-0.0905
Rain Intensity (mm/days) Dec	-0.0490	-0.1013	-0.1003	-0.2380	0.0307	0.0953	0.0165	0.0173	-0.0202	0.0940	-0.2244	-0.0517	0.0729	-0.0117	0.0199	0.0353
Rain Intensity (mm/days) Jan	-0.0086	0.0028	0.0225	-0.0763	-0.0767	-0.2053	-0.0640	0.0337	0.2034	0.0937	-0.0791	-0.0182	0.0682	-0.3307	-0.1152	-0.1037
Rain Intensity (mm/days) Feb	-0.0490	-0.0781	-0.0288	-0.1324	0.1031	0.0083	-0.0820	0.0727	0.1128	-0.0261	0.1488	0.1866	0.0759	0.2858	-0.1212	-0.2542
Rain Intensity (mm/days) Mar	-0.0533	0.0294	-0.0032	-0.0523	-0.1551	-0.2075	0.0072	-0.1037	-0.2108	-0.1349	-0.1313	0.1441	0.0112	-0.0940	-0.1001	0.1283
Rain Intensity (mm/days) Apr	-0.0071	0.0551	0.0779	0.0188	-0.2398	0.0608	0.1766	0.2521	0.0167	0.0744	0.1079	0.1174	-0.0890	-0.0286	-0.0053	-0.0212
Rain Intensity (mm/days) May	-0.0637	0.0316	0.0223	-0.1374	-0.1115	0.0012	0.0020	0.0828	-0.0386	-0.0119	-0.1524	-0.0043	0.0561	0.0178	0.2217	0.2983
Rain Intensity (mm/days) Jun	0.0133	-0.0210	-0.0278	0.1794	-0.0549	-0.0349	0.0992	0.1033	0.0453	-0.1855	-0.0082	0.0037	0.3399	0.0670	-0.1142	0.1534
Rain Intensity (mm/days) Jul	0.0292	0.0047	0.0772	-0.0271	-0.0598	0.2107	-0.0267	-0.0205	-0.0706	0.2238	0.2106	-0.0606	0.2148	-0.1580	-0.1417	0.2452
Rain Intensity (mm/days) Aug	0.0228	-0.1472	0.0694	-0.2078	-0.0494	0.0627	-0.1050	-0.1135	-0.0507	-0.0716	0.1869	0.0499	-0.1957	-0.0446	0.1006	-0.0268
Rain Intensity (mm/days) Sep	-0.0213	-0.0727	0.0675	0.1523	-0.1618	0.0692	-0.0744	-0.0429	-0.1163	-0.0150	0.0723	-0.1452	0.0072	0.1347	0.0752	-0.1588
Min Min Temperature (°C) Min Min Oct	-0.1356	0.0152	0.0030	-0.2662	0.0451	0.1006	0.2059	0.0049	0.0349	0.0076	-0.0365	0.1214	0.1063	0.0049	-0.1869	-0.0019
Min Min Temperature (°C) Min Min Nov	-0.1361	0.1840	0.1493	-0.0113	-0.0488	-0.1848	-0.0757	0.0231	0.0055	0.1135	0.0213	-0.0260	0.1293	0.0038	-0.0526	-0.0573
Min Min Temperature (°C) Min Min Dec	-0.1628	-0.0995	-0.0974	-0.0996	-0.2194	-0.0269	-0.0246	-0.0646	0.0403	0.1154	0.1025	0.0764	0.1395	0.0263	0.1275	-0.1699
Min Min Temperature (°C) Min Min Jan	-0.1679	-0.2012	-0.1537	0.0142	-0.0605	0.0347	-0.0295	-0.0002	0.0082	-0.1108	0.0501	-0.2221	-0.0445	-0.0354	-0.0489	-0.0181
Min Min Temperature (°C) Min Min Feb	-0.1745	-0.2038	0.0315	0.1191	0.0757	0.0359	-0.0494	0.0908	0.0230	-0.0566	-0.1748	0.1919	-0.0032	-0.0900	-0.0522	0.0815
Min Min Temperature (°C) Min Min Mar	-0.1460	-0.1452	0.0205	0.0946	-0.0406	-0.0639	0.0016	-0.0096	-0.0779	0.0319	0.1367	0.1316	0.1779	-0.1190	0.1386	-0.0724
Min Min Temperature (°C) Min Min Apr	-0.0698	0.0123	0.1954	0.0273	0.0152	-0.0525	-0.0398	0.0359	-0.0733	0.0721	-0.1451	0.1681	-0.2045	-0.1025	0.0696	-0.1052
Min Min Temperature (°C) Min Min May	-0.0872	0.0779	0.0984	-0.0467	-0.1333	0.0484	0.0291	-0.1518	0.2493	-0.1022	-0.0687	0.0607	-0.1019	-0.0367	-0.2253	-0.1180
Min Min Temperature (°C) Min Min Jun	-0.0990	0.0274	0.2204	0.0329	0.0770	0.0242	0.0626	-0.0326	-0.0163	-0.1457	-0.1466	-0.0480	0.1832	-0.0030	0.0089	-0.0515
Min Min Temperature (°C) Min Min Jul	-0.1574	0.1090	0.0936	-0.0379	-0.0351	0.0638	-0.0828	0.0178	-0.0575	0.1185	0.0857	0.1844	-0.0834	0.0322	-0.0192	0.1350
Min Min Temperature (°C) Min Min Aug	-0.1530	0.0082	0.1313	-0.0645	0.0228	0.0333	-0.0400	0.0898	0.0529	-0.1497	0.1928	-0.0597	-0.2028	0.1062	0.0305	0.1387
Min Min Temperature (°C) Min Min Sep	-0.1642	0.0077	0.1669	0.0211	-0.0218	0.1354	0.0098	0.1184	-0.0847	-0.1061	0.0757	-0.0574	-0.0399	-0.1637	0.0441	-0.1089
Max Over 31°C Jun	-0.0153	0.1145	-0.0548	0.1453	-0.0055	0.2274	0.0032	-0.0832	-0.1226	0.0545	-0.0666	0.0379	0.1539	0.0997	-0.3191	-0.0563
Max Over 31°C Jul	-0.0639	0.0462	-0.0686	0.0786	0.0369	0.2185	0.0132	-0.0366	-0.1912	0.1250	0.0451	-0.0235	0.1073	-0.1655	-0.2066	-0.0716
Max Over 31°C Aug	-0.1166	0.0602	-0.2039	0.0320	-0.0122	-0.1045	-0.0850	-0.0620	0.1644	-0.0571	-0.0533	0.0033	0.0238	0.1427	0.1131	0.0986
Max Over 31°C Sep	0.0013	0.0293	-0.2371	0.0560	0.0113	-0.0534	0.0082	0.0444	0.0900	-0.1371	0.0083	-0.0572	-0.0154	0.0074	0.0624	0.1859

Figure A.1: A representation of the standard deviation for maximum temperature (°) over each month, in a harvest season, for each cluster.

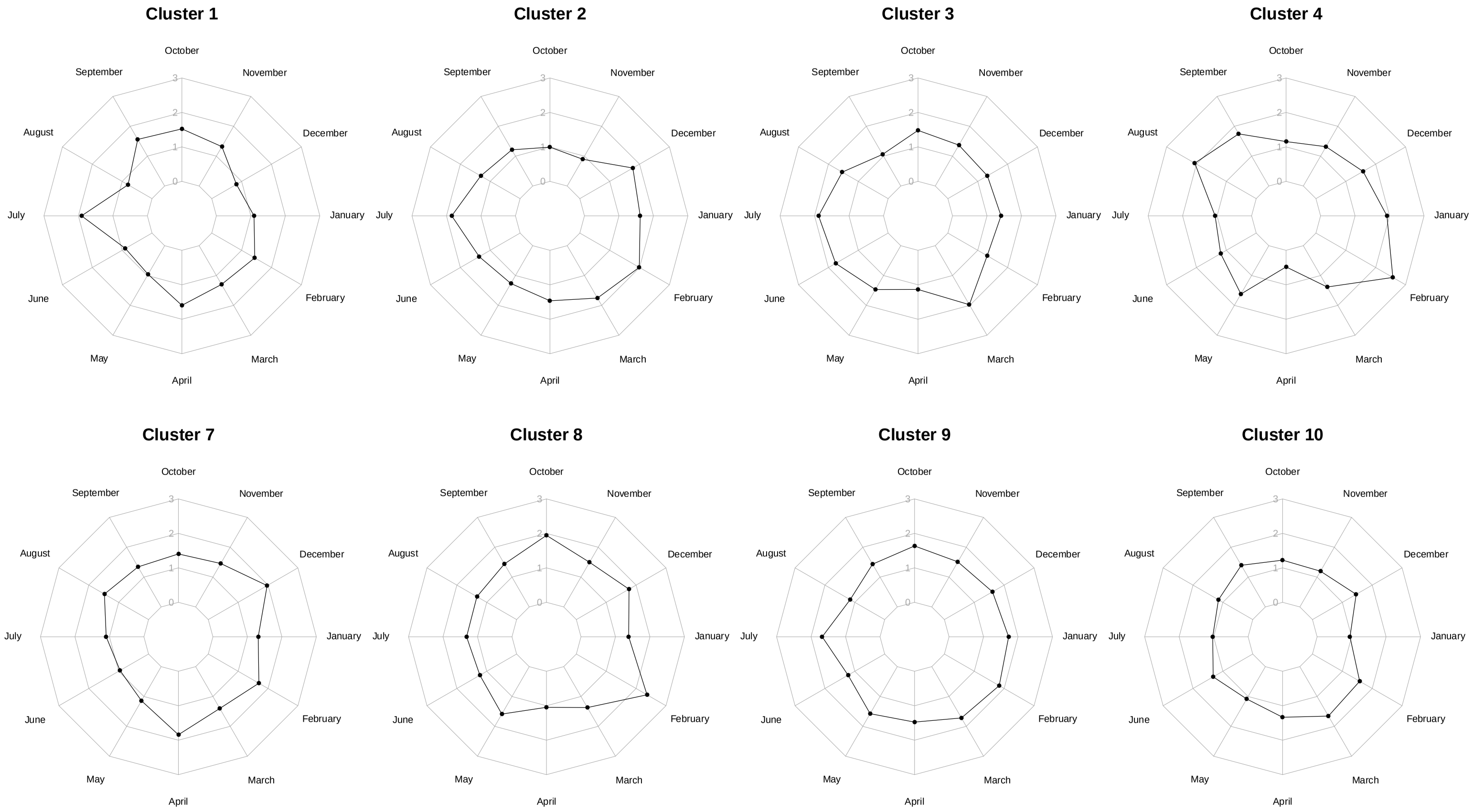


Figure A.2: A representation of the standard deviation for minimum temperature (°) over each month, in a harvest season, for each cluster.

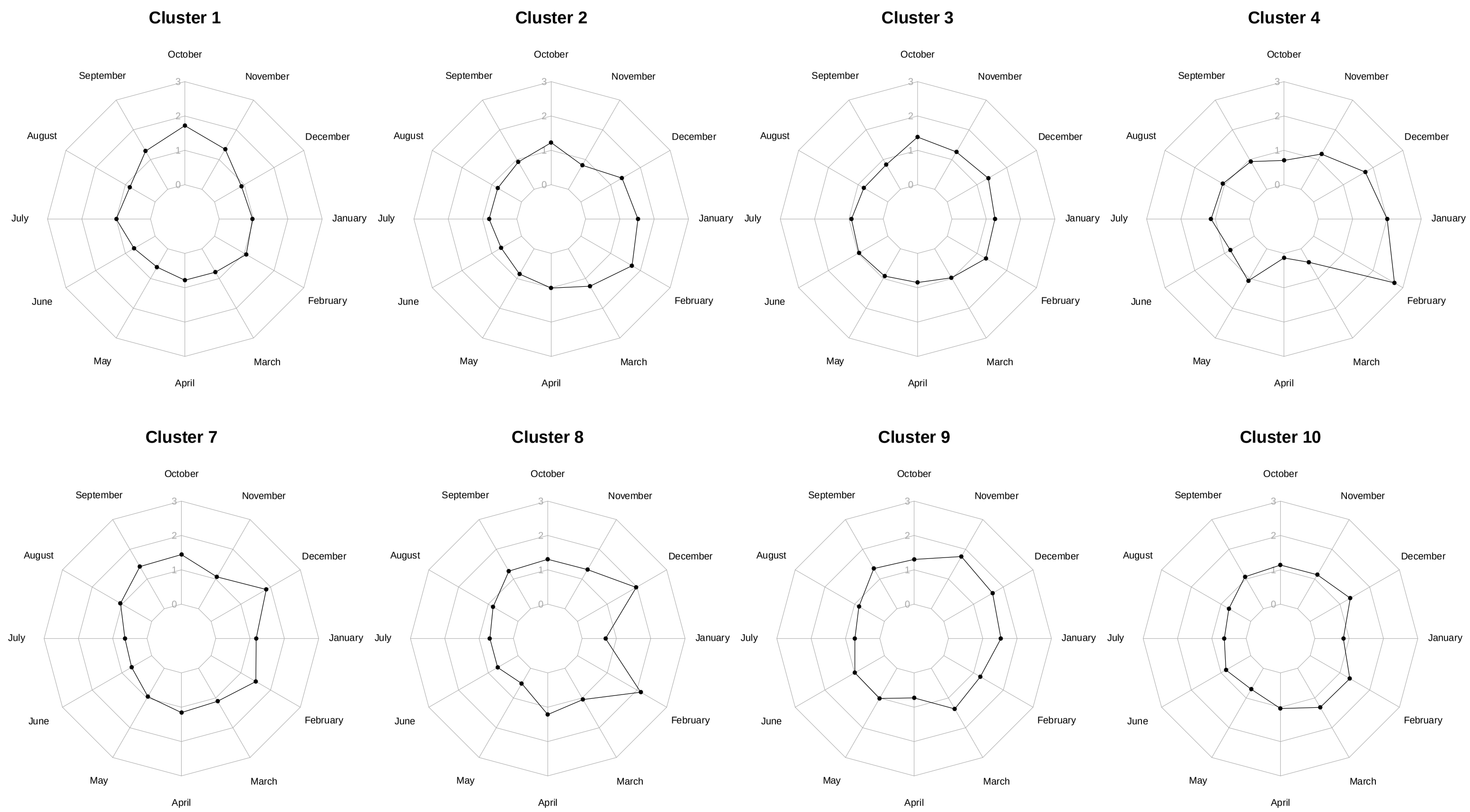


Figure A.3: A representation of the standard deviation for rainfall (mm) over each month, in a harvest season, for each cluster.

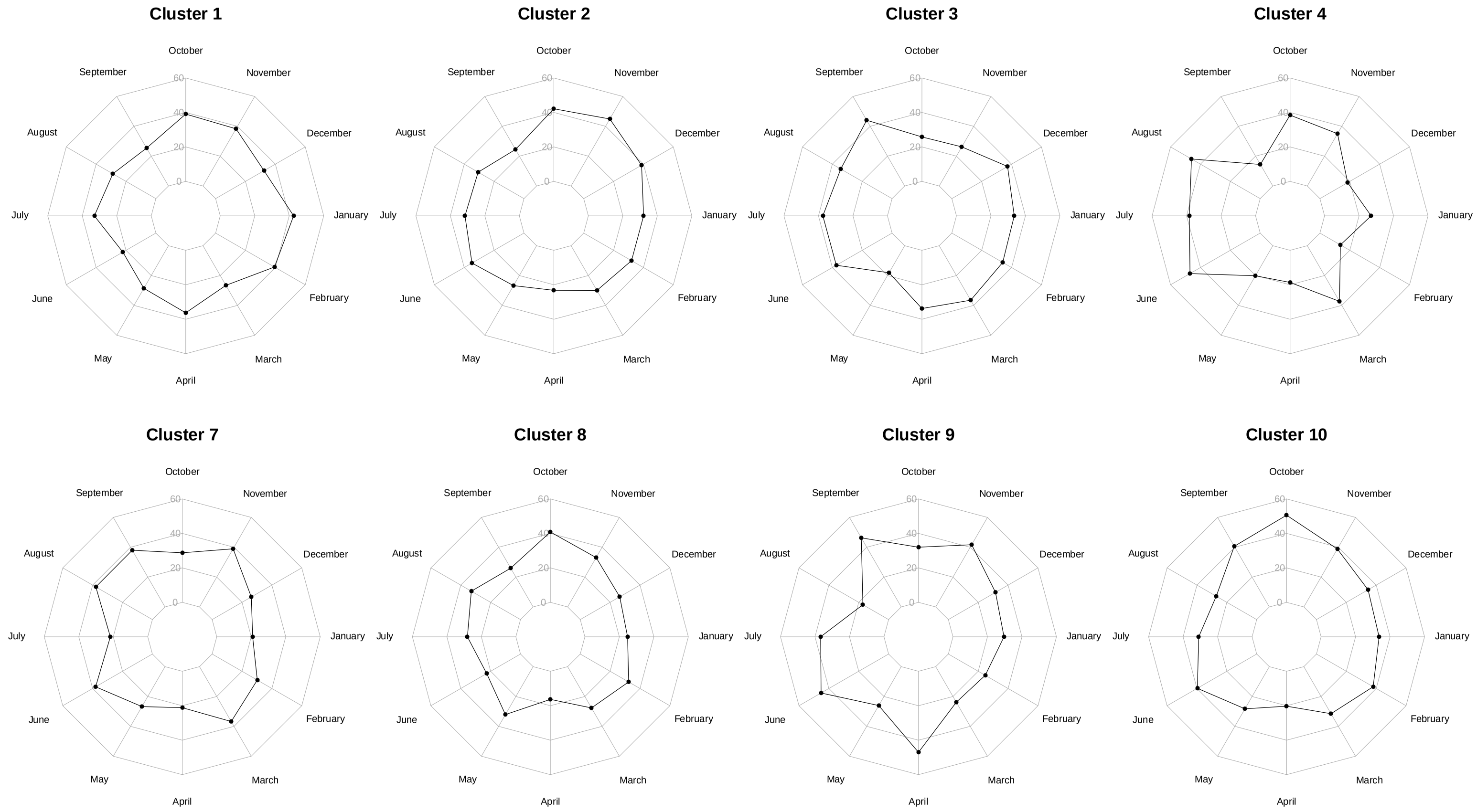


Figure A.4: A representation of the standard deviation for rainfall intensity (mm/days) over each month, in a harvest season, for each cluster.

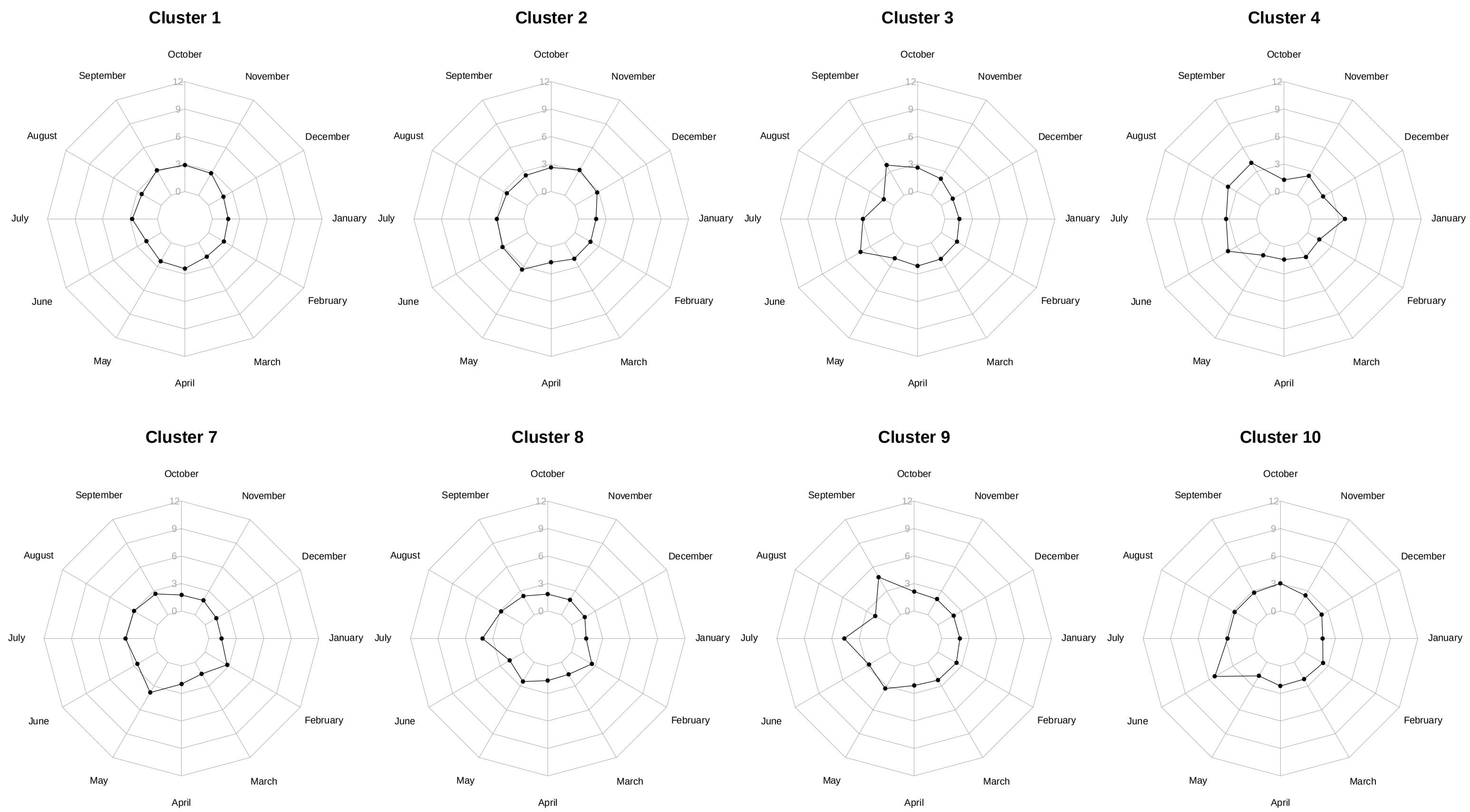


Figure A.5: A representation of the standard deviation for total sunlight (hours) over each month, in a harvest season, for each cluster.

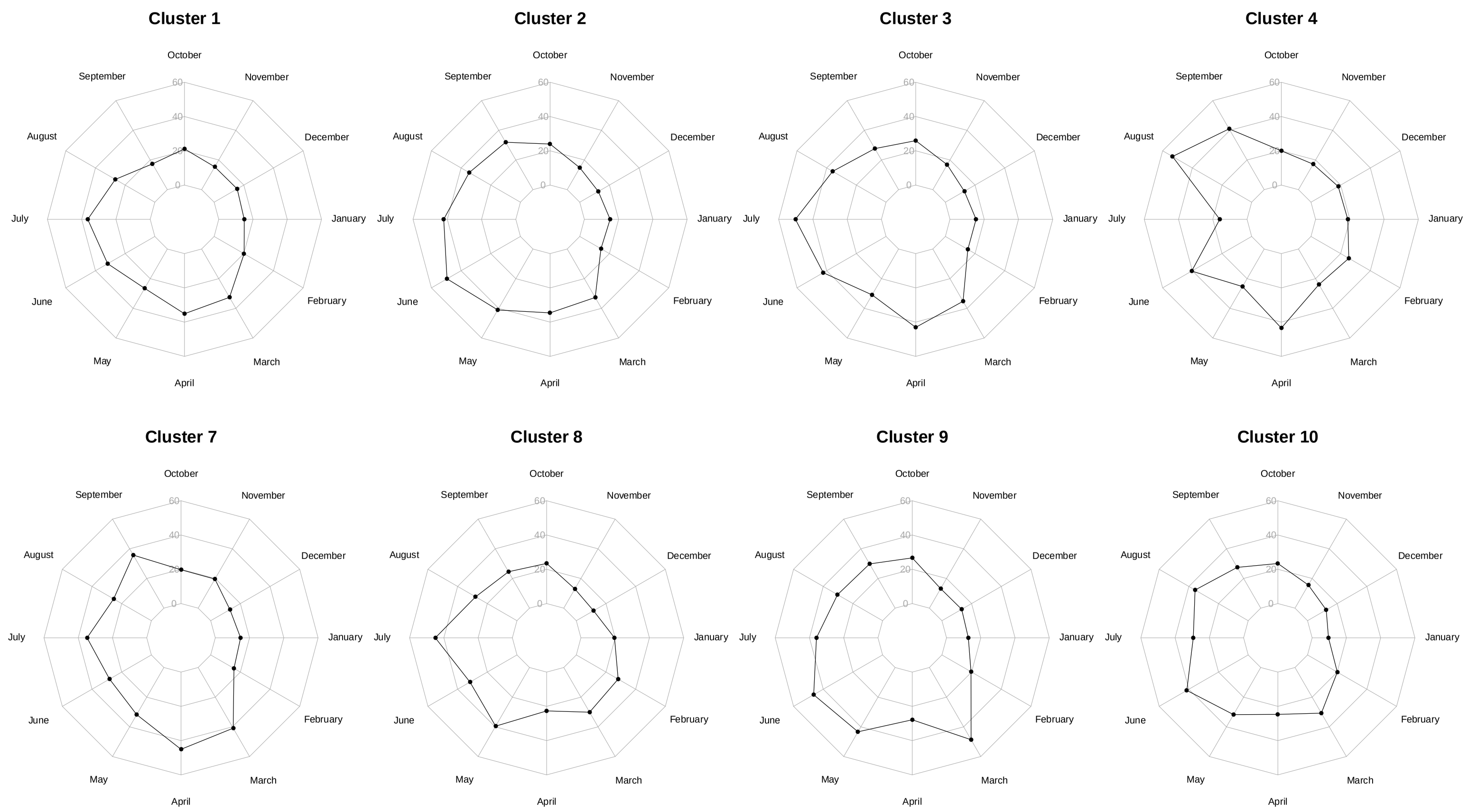


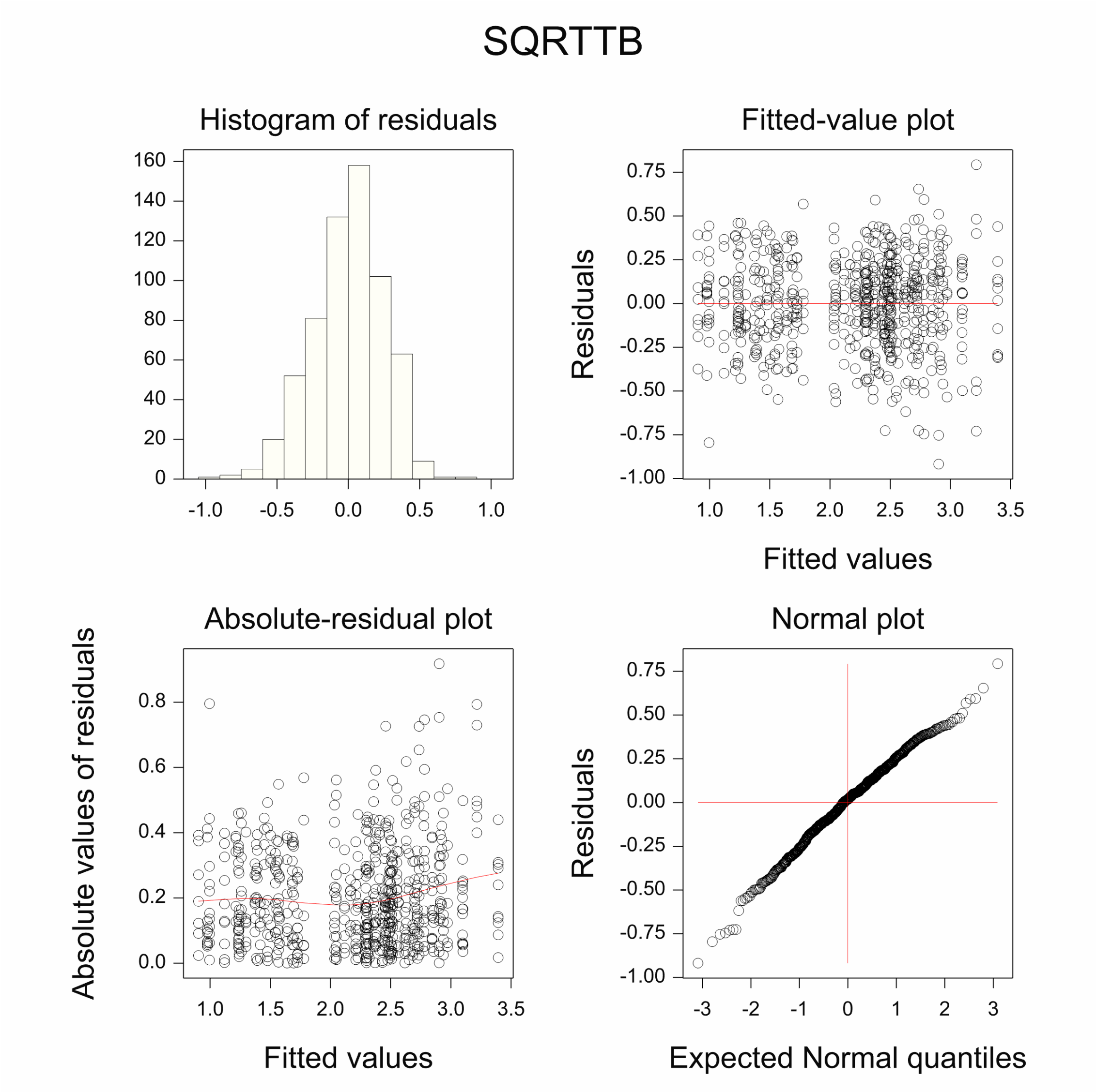
Table A.12: The fitted REML model fixed effect coefficients given in Equation 3.2 where Cluster 1, Broadbalk and the Nil treatment were all fitted as the baseline for their treatments.

Parameter	Coef	S.E.
β_0	1.00	0.28
$\beta_{1\text{Cluster 2}}$	0.70	0.12
$\beta_{1\text{ Cluster 7}}$	0.30	0.14
$\beta_{1\text{ Cluster 9}}$	0.26	0.13
$\beta_{1\text{ Cluster 10}}$	0.45	0.14
$\beta_{2\text{ HF}}$	-0.02	0.40
$\beta_{2\text{ PG}}$	0.73	0.40
$\beta_{3\text{ PKNaMg}}$	0.12	0.40
$\beta_{3\text{ 48kg Nha}^{-1}\text{ + PKNaMg}}$	1.05	0.40
$\beta_{3\text{ 96kg Nha}^{-1}\text{ + PKNaMg}}$	1.56	0.40
$\beta_{3\text{ FYM}}$	1.74	0.40
$\beta_{4\text{ Cluster 2 HF}}$	-0.44	0.17
$\beta_{4\text{ Cluster 7 HF}}$	0.10	0.20
$\beta_{4\text{ Cluster 9 HF}}$	-0.34	0.18
$\beta_{4\text{ Cluster 10 HF}}$	-0.22	0.19
$\beta_{4\text{ Cluster 2 PG}}$	-0.74	0.17
$\beta_{4\text{ Cluster 7 PG}}$	-0.48	0.19
$\beta_{4\text{ Cluster 9 PG}}$	-0.45	0.18
$\beta_{4\text{ Cluster 10 PG}}$	-0.40	0.19
$\beta_{5\text{ Cluster 2 PKNaMg}}$	-0.18	0.17
$\beta_{5\text{ Cluster 2 48kg Nha}^{-1}\text{ + PKNaMg}}$	-0.25	0.17
$\beta_{5\text{ Cluster 2 96kg Nha}^{-1}\text{ + PKNaMg}}$	-0.15	0.17
$\beta_{5\text{ Cluster 2 FYM}}$	-0.04	0.17
$\beta_{5\text{ Cluster 7 PKNaMg}}$	-0.01	0.19
$\beta_{5\text{ Cluster 7 48kg Nha}^{-1}\text{ + PKNaMg}}$	-0.18	0.19
$\beta_{5\text{ Cluster 7 96kg Nha}^{-1}\text{ + PKNaMg}}$	-0.13	0.19
$\beta_{5\text{ Cluster 7 FYM}}$	-0.07	0.19
$\beta_{5\text{ Cluster 7 PKNaMg}}$	-0.01	0.18
$\beta_{5\text{ Cluster 7 48kg Nha}^{-1}\text{ + PKNaMg}}$	-0.08	0.18
$\beta_{5\text{ Cluster 7 96kg Nha}^{-1}\text{ + PKNaMg}}$	-0.04	0.18
$\beta_{5\text{ Cluster 7 FYM}}$	-0.06	0.18
$\beta_{5\text{ Cluster 10 PKNaMg}}$	-0.07	0.19
$\beta_{5\text{ Cluster 10 48kg Nha}^{-1}\text{ + PKNaMg}}$	-0.09	0.19
$\beta_{5\text{ Cluster 10 96kg Nha}^{-1}\text{ + PKNaMg}}$	-0.08	0.19
$\beta_{5\text{ Cluster 10 FYM}}$	0.25	0.19
$\beta_{6\text{ HF PKNaMg}}$	0.13	0.56
$\beta_{6\text{ HF 48kg Nha}^{-1}\text{ + PKNaMg}}$	0.00	0.56
$\beta_{6\text{ HF 96kg Nha}^{-1}\text{ + PKNaMg}}$	-0.07	0.56
$\beta_{6\text{ HF FYM}}$	-0.02	0.56

Table A.12 continues overleaf.

$\beta_{6\ \mathrm{PG\ PKNaMg}}$	0.66	0.56
$\beta_{6\ \mathrm{PG\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	-0.29	0.56
$\beta_{6\ \mathrm{PG\ 96kg\ Nha^{-1}\ +\ PKNaMg}}$	-0.91	0.56
$\beta_{6\ \mathrm{PG\ FYM}}$	-1.26	0.56
$\beta_{7\ \mathrm{Cluster\ 2\ HF\ PKNaMg}}$	0.25	0.23
$\beta_{7\ \mathrm{Cluster\ 2\ HF\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	0.31	0.23
$\beta_{7\ \mathrm{Cluster\ 2\ HF\ 96kg\ Nha^{-1}\ +\ PKNaMg}}$	0.27	0.23
$\beta_{7\ \mathrm{Cluster\ 2\ HF\ FYM}}$	-0.02	0.23
$\beta_{7\ \mathrm{Cluster\ 2\ PG\ PKNaMg}}$	0.23	0.23
$\beta_{7\ \mathrm{Cluster\ 2\ PG\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	0.27	0.23
$\beta_{7\ \mathrm{Cluster\ 2\ PG\ 96kg\ Nha^{-1}\ +\ PKNaMg}}$	0.27	0.23
$\beta_{7\ \mathrm{Cluster\ 2\ PG\ FYM}}$	0.50	0.23
$\beta_{7\ \mathrm{Cluster\ 7\ HF\ PKNaMg}}$	-0.06	0.28
$\beta_{7\ \mathrm{Cluster\ 7\ HF\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	0.07	0.28
$\beta_{7\ \mathrm{Cluster\ 7\ HF\ 96kg\ Nha^{-1}\ +\ PKNaMg}}$	-0.08	0.28
$\beta_{7\ \mathrm{Cluster\ 7\ HF\ FYM}}$	0.06	0.28
$\beta_{7\ \mathrm{Cluster\ 7\ PG\ PKNaMg}}$	-0.02	0.27
$\beta_{7\ \mathrm{Cluster\ 7\ PG\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	0.23	0.27
$\beta_{7\ \mathrm{Cluster\ 7\ PG\ 96kg\ Nha^{-1}\ +\ PKNaMg}}$	0.22	0.27
$\beta_{7\ \mathrm{Cluster\ 7\ PG\ FYM}}$	0.32	0.27
$\beta_{7\ \mathrm{Cluster\ 9\ HF\ PKNaMg}}$	0.33	0.25
$\beta_{7\ \mathrm{Cluster\ 9\ HF\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	0.24	0.25
$\beta_{7\ \mathrm{Cluster\ 9\ HF\ 96kg\ Nha^{-1}\ +\ PKNaMg}}$	0.14	0.25
$\beta_{7\ \mathrm{Cluster\ 9\ HF\ FYM}}$	0.22	0.25
$\beta_{7\ \mathrm{Cluster\ 9\ PG\ PKNaMg}}$	-0.01	0.25
$\beta_{7\ \mathrm{Cluster\ 9\ PG\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	0.09	0.25
$\beta_{7\ \mathrm{Cluster\ 9\ PG\ 96kg\ Nha^{-1}\ +\ PKNaMg}}$	0.15	0.25
$\beta_{7\ \mathrm{Cluster\ 9\ PG\ FYM}}$	0.33	0.25
$\beta_{7\ \mathrm{Cluster\ 10\ HF\ PKNaMg}}$	-0.01	0.27
$\beta_{7\ \mathrm{Cluster\ 10\ HF\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	0.26	0.27
$\beta_{7\ \mathrm{Cluster\ 10\ HF\ 96kg\ Nha^{-1}\ +\ PKNaMg}}$	0.24	0.27
$\beta_{7\ \mathrm{Cluster\ 10\ HF\ FYM}}$	-0.05	0.27
$\beta_{7\ \mathrm{Cluster\ 10\ PG\ PKNaMg}}$	0.23	0.27
$\beta_{7\ \mathrm{Cluster\ 10\ PG\ 48kg\ Nha^{-1}\ +\ PKNaMg}}$	0.17	0.27
$\beta_{7\ \mathrm{Cluster\ 10\ PG\ 96kg\ Nkg\ Nkg\ Nha^{-1}\ +\ PKNaMg}}$	0.22	0.27
$\beta_{7\ \mathrm{Cluster\ 10\ PG\ FYM}}$	0.40	0.27

Figure A.6: The model assumptions of the REML model fitted in Chapter 3.



A.3 How weather variation changes the functional response of cereals to nitrogen using Rothamsted's Long-Term Experiment data: Broadbalk wheat

Figure A.7: Model assumptions for a nitrogen response fitted to grain yield for each year.

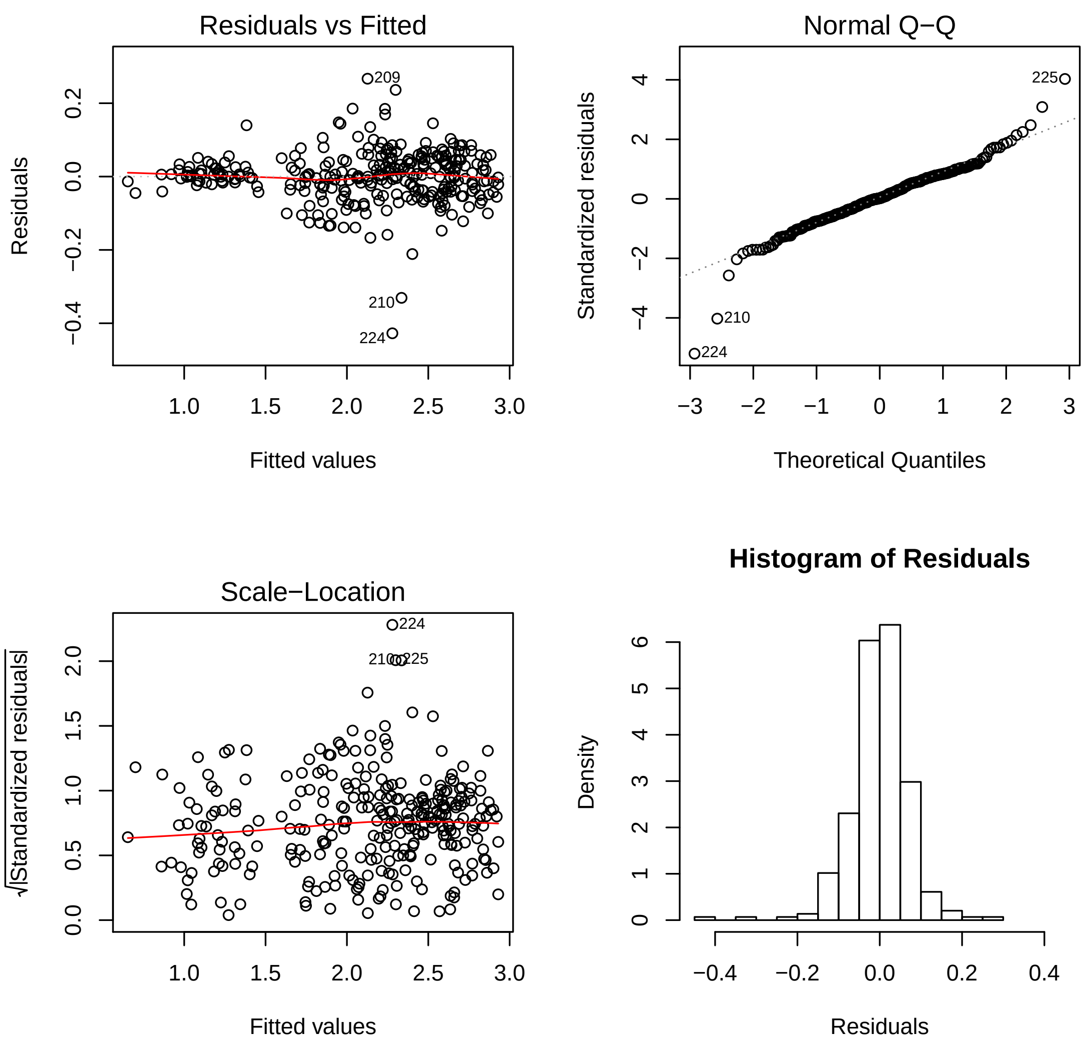


Figure A.8: Model assumptions for a nitrogen response fitted to total biomass for each year.

(a)

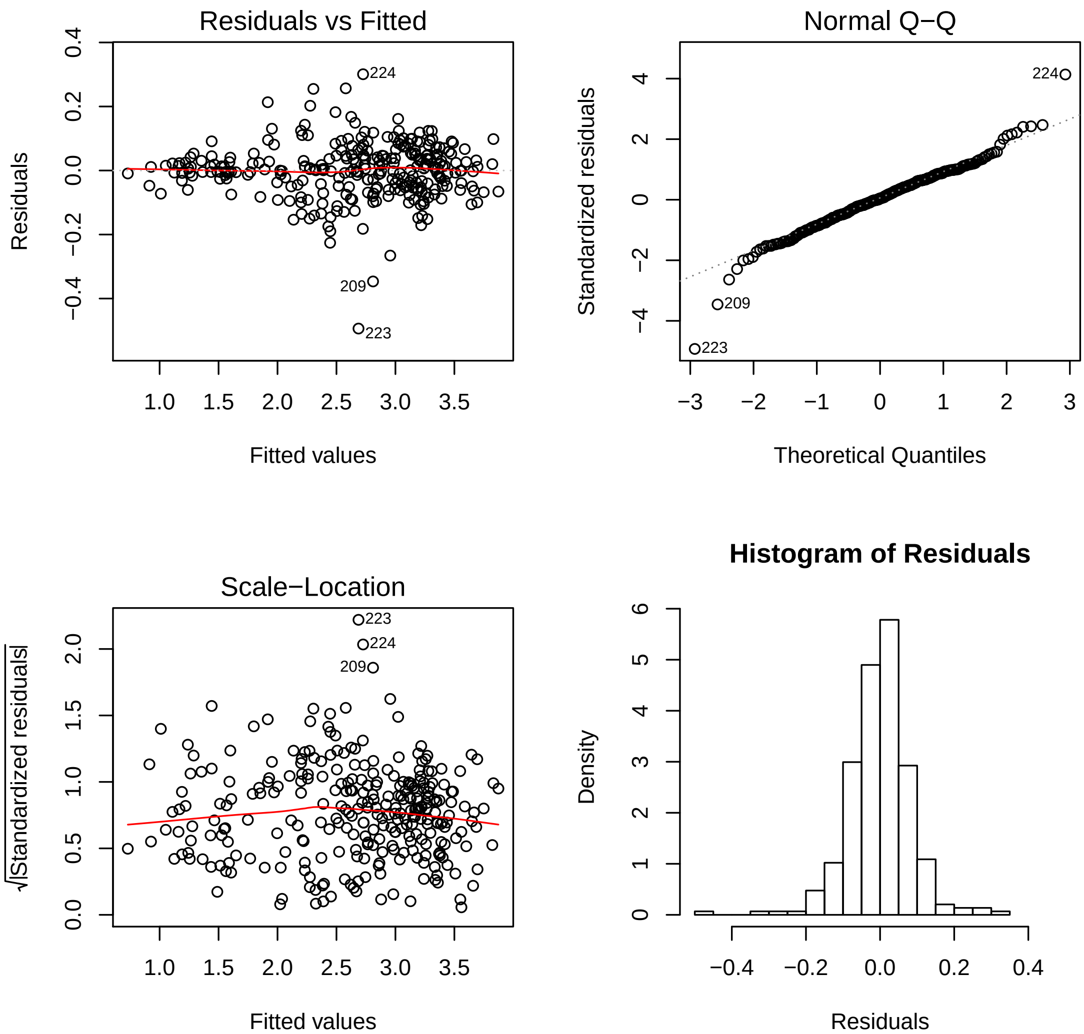


Table A.13: P-values for the Pearson's correlation coefficient between grain yield and summarised monthly rainfall at different nitrogen response levels (values in *Italic* have $P < 0.05$). The degrees of freedom for treatments 0, 48, 96 and 192 kg N ha^{-1} was 45. The degrees of freedom for treatments 240 and 288 kg N ha^{-1} was 28.

Treatment	October	November	December	January	February	March	April	May	June	July	August	September
0 kg N ha^{-1}	0.0006	0.8900	0.5768	0.7123	0.3291	0.3509	0.1168	0.3620	0.6250	0.0638	0.1685	0.8122
48 kg N ha^{-1}	0.0119	0.6693	0.4979	0.7699	0.1622	0.2953	0.4300	0.8045	0.6094	0.0603	0.5223	0.7130
96 kg N ha^{-1}	0.0180	0.5364	0.2279	0.3096	0.1292	0.8214	0.3946	0.8211	0.2880	0.1932	0.4587	0.1600
144 kg N ha^{-1}	0.1277	0.3960	0.1139	0.6704	0.4153	0.8880	0.7086	0.8537	0.3023	0.3733	0.4497	0.4888
192 kg N ha^{-1}	0.6598	0.5285	0.3377	0.9174	0.7078	0.4830	0.7761	0.5967	0.5329	0.7247	0.9848	0.4969
240 kg N ha^{-1}	0.5597	0.3408	0.7732	0.8650	0.4518	0.3458	0.7047	0.2592	0.2066	0.1562	0.3345	0.2770
288 kg N ha^{-1}	0.6300	0.9346	0.8088	0.7645	0.2461	0.5383	0.8395	0.9017	0.1704	0.5172	0.5697	0.0940

Table A.14: P-values for the Pearson's correlation coefficient between total biomass and summarised monthly rainfall at different nitrogen response levels (values in *Italic* have $P < 0.05$). The degrees of freedom for treatments 0, 48, 96 and 192 kg N ha^{-1} was 45. The degrees of freedom for treatment 144 kg N ha^{-1} was 44. The degrees of freedom for treatments 240 and 288 kg N ha^{-1} was 28.

Treatment	October	November	December	January	February	March	April	May	June	July	August	September
0 kg N ha^{-1}	0.0172	0.7106	0.5180	0.9826	0.5506	0.9553	0.1361	0.4352	0.3524	0.0519	0.1400	0.7398
48 kg N ha^{-1}	0.3048	0.4629	0.9121	0.8820	0.2362	0.1470	0.7056	0.8604	0.2763	0.1069	0.6108	0.9405
96 kg N ha^{-1}	0.1478	0.6356	0.5384	0.5598	0.1352	0.4325	0.7068	0.9579	0.2628	0.1788	0.1337	0.6725
144 kg N ha^{-1}	0.2806	0.5102	0.3880	0.7549	0.3618	0.5396	0.9765	0.9854	0.2343	0.3862	0.1607	0.9643
192 kg N ha^{-1}	0.8734	0.5874	0.7151	0.6890	0.4422	0.1991	0.9951	0.6167	0.3701	0.5097	0.2655	0.9932
240 kg N ha^{-1}	0.8692	0.2845	0.7069	0.8389	0.3976	0.4743	0.8729	0.3548	0.1355	0.5895	0.4669	0.2466
288 kg N ha^{-1}	0.9295	0.7473	0.8016	0.9341	0.2211	0.7072	0.7643	0.9962	0.1176	0.9991	0.8700	0.1007

Table A.15: P-values for the Pearson's correlation coefficient between grain yield and summarised monthly temperature at different nitrogen response levels (values in *Italic* have $P < 0.05$). The degrees of freedom for treatments 0, 48, 96 and 192 kg N ha^{-1} was 45. The degrees of freedom for treatments 240 and 288 kg N ha^{-1} was 28.

Treatment	October	November	December	January	February	March	April	May	June	July	August	September
0 kg N ha^{-1}	0.8914	0.3868	0.2095	0.3650	0.0624	0.0125	0.4045	0.1807	0.4084	0.3301	0.3296	0.5591
48 kg N ha^{-1}	0.4243	0.1955	0.7119	0.0842	0.1052	0.0812	0.1689	0.2226	0.0978	0.8373	0.6145	0.3044
96 kg N ha^{-1}	0.7909	0.3288	0.5196	0.0144	0.0367	0.3740	0.2518	0.1014	0.1119	0.8212	0.7756	0.9550
144 kg N ha^{-1}	0.7342	0.1698	0.9597	0.0501	0.1218	0.6638	0.1780	0.0445	0.1231	0.7924	0.6992	0.6212
192 kg N ha^{-1}	0.2689	0.0206	0.6054	0.6193	0.7411	0.8280	0.7871	0.6443	0.5339	0.5475	0.5346	0.1171
240 kg N ha^{-1}	0.8003	0.8736	0.6722	0.4495	0.4407	0.8947	0.1614	0.3263	0.2651	0.2032	0.7128	0.6827
288 kg N ha^{-1}	0.4847	0.1613	0.8547	0.8625	0.6820	0.8729	0.7820	0.3370	0.4575	0.5801	0.5374	0.2722

Table A.16: P-values for the Pearson's correlation coefficient between total biomass and summarised monthly temperature at different nitrogen response levels (values in *Italic* have $P < 0.05$). The degrees of freedom for treatments 0, 48, 96 and 192 kg N ha^{-1} was 45. The degrees of freedom for treatment 144 kg N ha^{-1} was 44. The degrees of freedom for treatments 240 and 288 kg N ha^{-1} was 28.

Treatment	October	November	December	January	February	March	April	May	June	July	August	September
0 kg N ha^{-1}	0.6939	0.1008	0.2661	0.1605	0.0414	0.0042	0.0585	0.0287	0.0256	0.1018	0.2050	0.2807
48 kg N ha^{-1}	0.2410	0.9338	0.5416	0.0531	0.0226	0.0335	0.0092	0.0284	0.0004	0.2861	0.1529	0.1067
96 kg N ha^{-1}	0.8225	0.9371	0.4155	0.0294	0.0036	0.0993	0.0090	0.0057	0.0014	0.6895	0.3670	0.3269
144 kg N ha^{-1}	0.9882	0.7345	0.8091	0.0460	0.0184	0.2196	0.0046	0.0011	0.0014	0.7291	0.6658	0.1371
192 kg N ha^{-1}	0.6279	0.2769	0.7408	0.3992	0.2894	0.2548	0.1194	0.0202	0.0077	0.8590	0.6455	0.9466
240 kg N ha^{-1}	0.6898	0.7817	0.8043	0.2900	0.1904	0.9339	0.1266	0.1294	0.0672	0.5035	0.9317	0.8113
288 kg N ha^{-1}	0.5343	0.3004	0.7744	0.4545	0.7026	0.7265	0.5527	0.1554	0.1322	0.9694	0.9052	0.3709

Figure A.9: Model assumptions for the grain yield parsimonious model (Table 4.5)

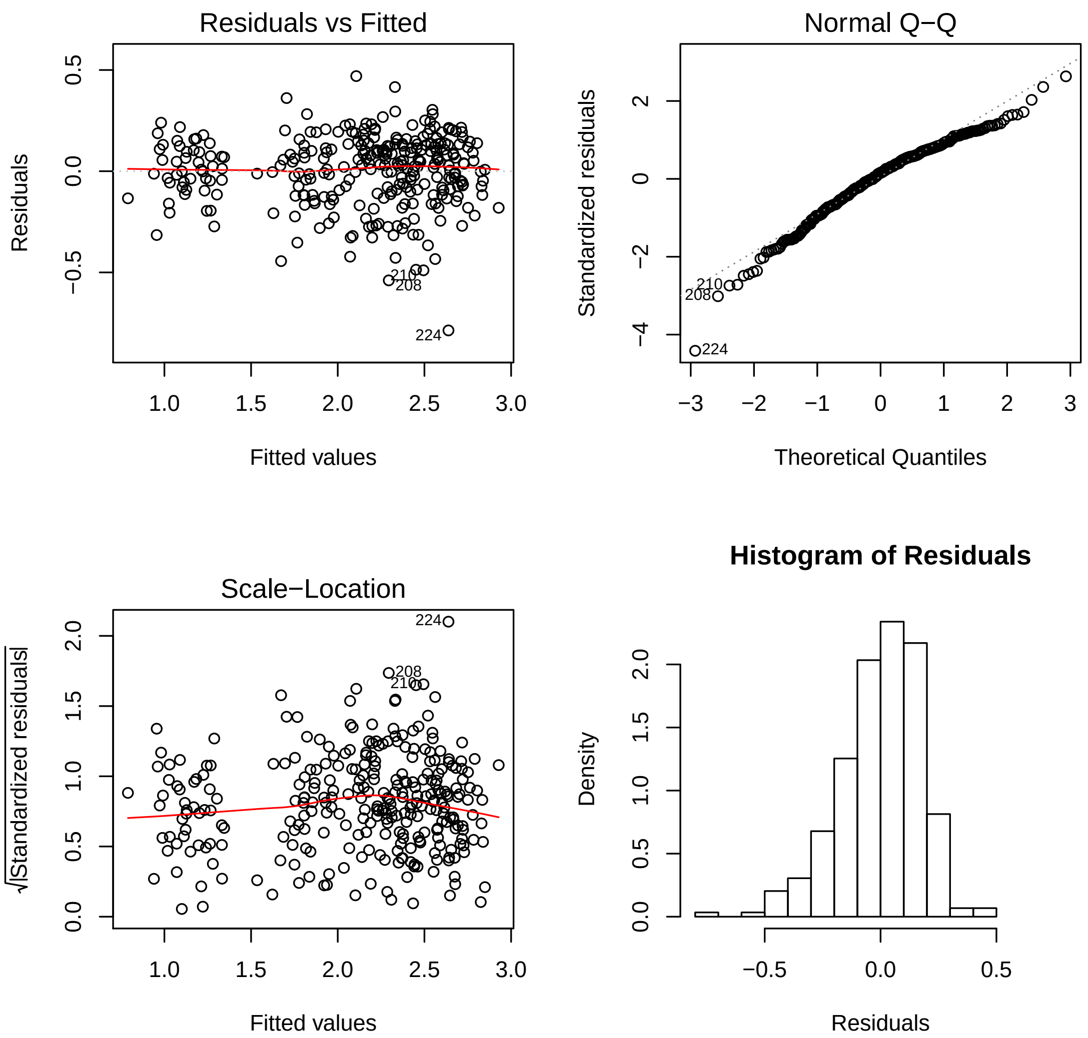


Figure A.10: Model assumptions for the total biomass parsimonious model (Table 4.6)

(a)

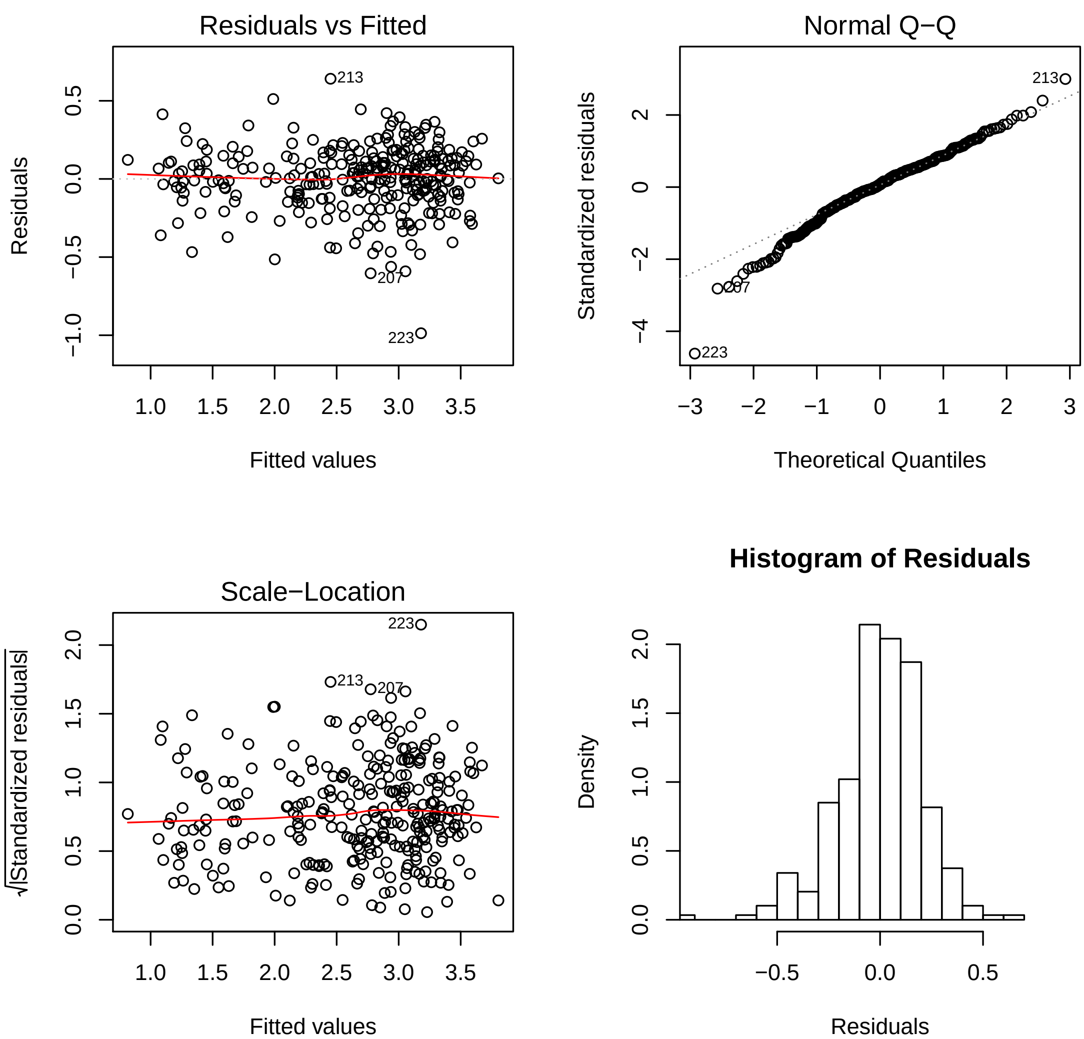


Figure A.11: Response surface of the effect of nitrogen on wheat yield from the parsimonious model (Table 4.5) as affect by: (a) Total October rainfall; (b) Total February rainfall; (c) Total June rainfall.

(a) (b) (c)

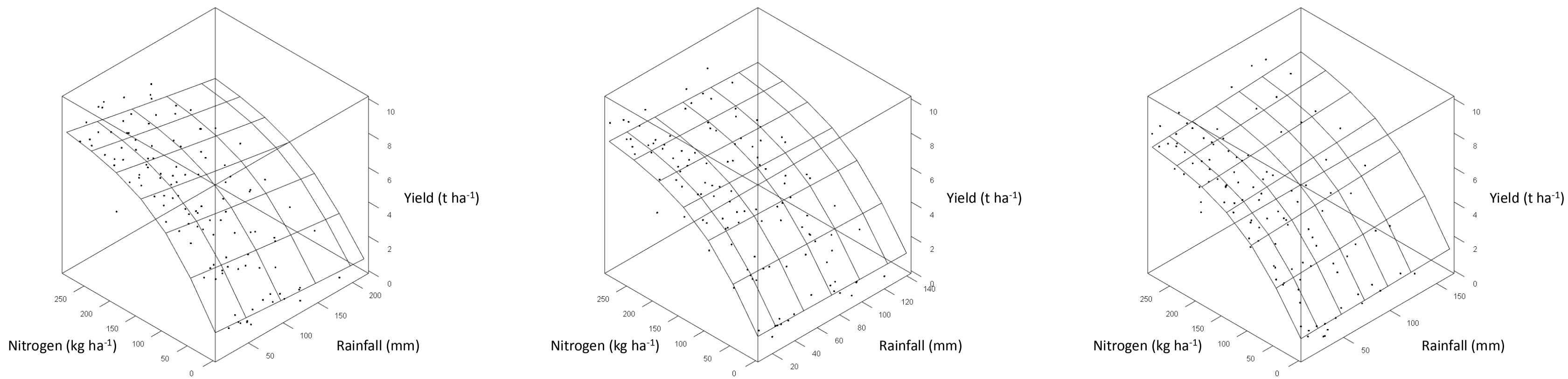
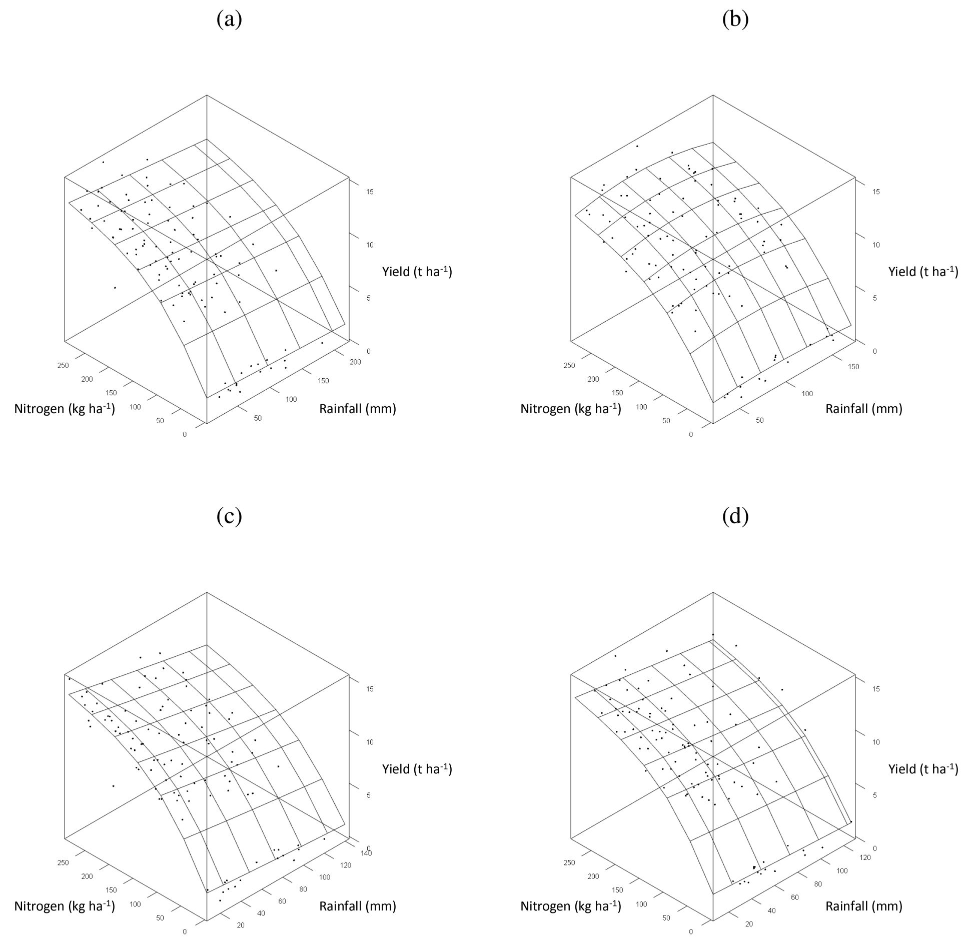


Figure A.12: Response surface of the effect of nitrogen on wheat yield from the parsimonious model (Table 4.6) as affect by: (a) Total October rainfall; (b) Total November rainfall; (c) Total February rainfall; (d) Total July rainfall.



A.4 How weather variation changes the functional response of cereals to nitrogen using Rothamsted's Long-Term Experiment data: Hoosfield spring barley

Figure A.13: Model assumptions for a nitrogen response fitted to Hoosfield grain yield for each year.

(a)

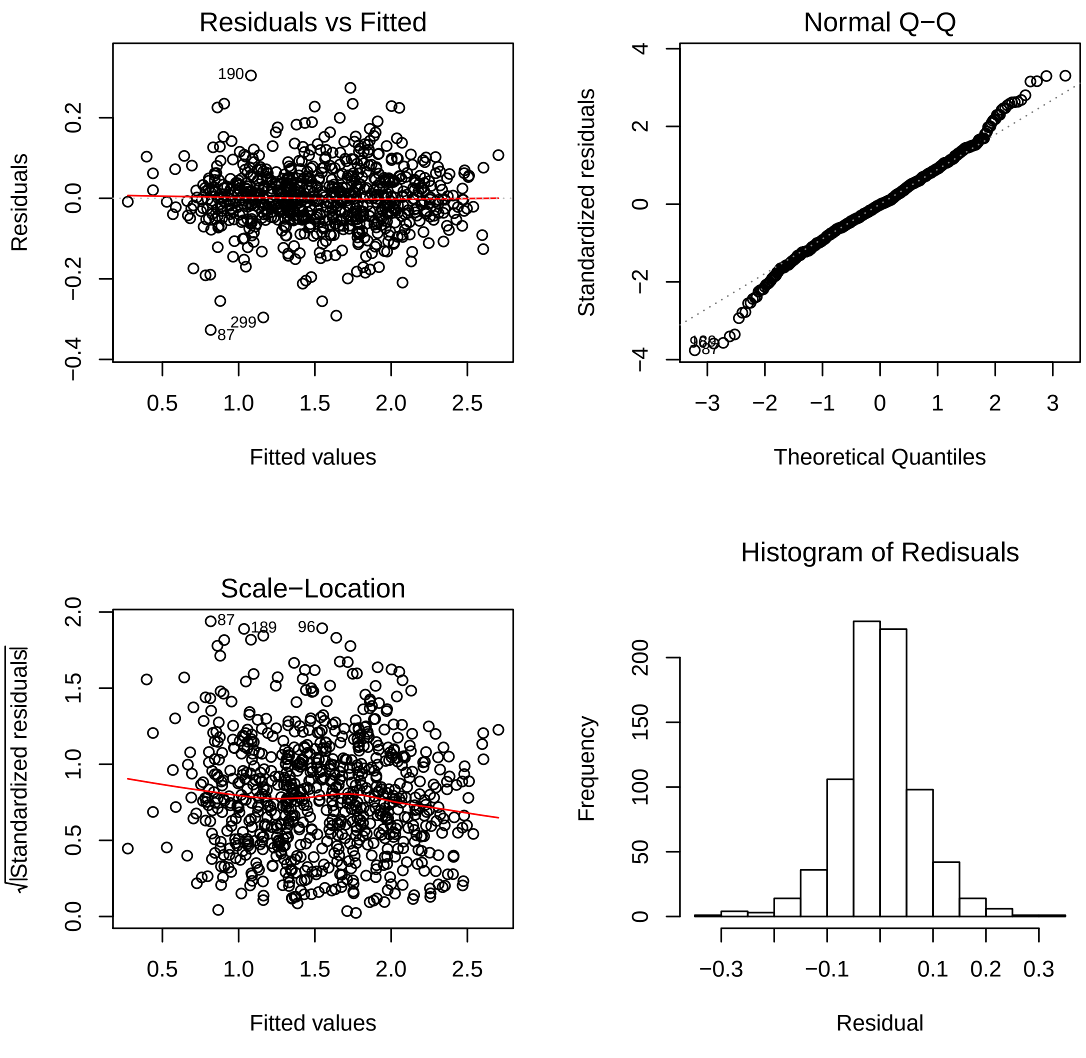


Figure A.14: Model assumptions for a nitrogen response fitted to Hoosfield total biomass for each year.

(a)

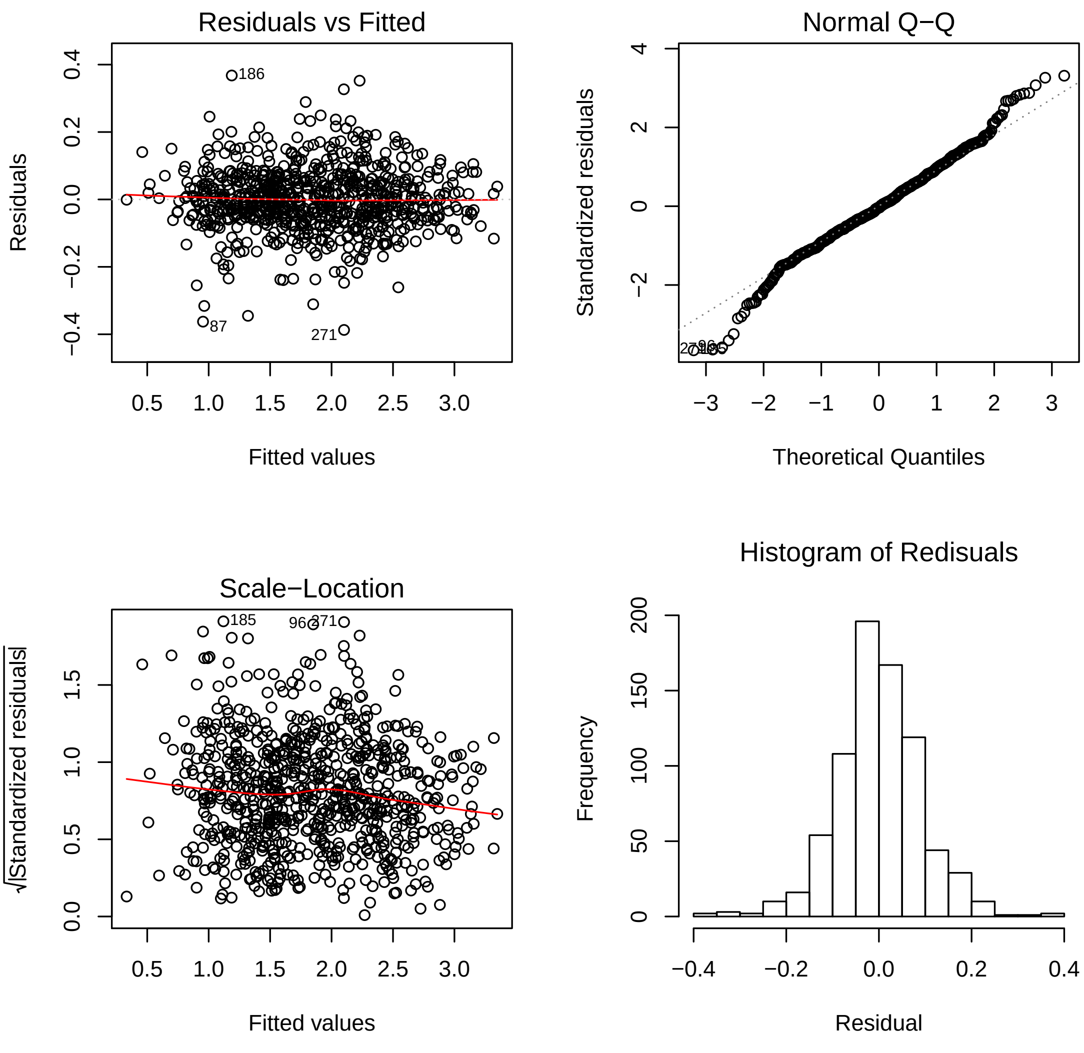


Table A.17: Pearson's correlation coefficient between barley grain yield and summarised monthly rainfall at different nitrogen response levels for PKNaMg treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.0933	-0.1983	*-0.3025*	*-0.4216*	*0.4226*	0.0229	-0.1685	-0.0082
48 kg N/ha	-0.1084	0.0126	-0.2370	-0.1817	*0.4052*	0.0247	-0.0495	-0.0583
96 kg N/ha	-0.2718	0.0329	-0.2388	-0.0714	*0.3585*	-0.0350	-0.0550	-0.1464
144 kg N/ha	-0.2052	0.0735	-0.0660	0.0001	0.2818	0.1221	-0.0075	-0.1630

Table A.18: Pearson's correlation coefficient between barley grain yield and summarised monthly rainfall at different nitrogen response levels for P treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.1561	-0.1884	-0.1070	-0.2812	*0.4197*	-0.0524	0.0535	0.1167
48 kg N/ha	-0.2097	0.2093	-0.1013	-0.0555	*0.3239*	-0.0175	0.0476	-0.0739
96 kg N/ha	-0.1095	*0.3237*	-0.0656	0.0996	0.0854	-0.0476	0.1210	-0.0832
144 kg N/ha	-0.0671	0.1819	-0.1073	0.0236	0.0484	0.0043	0.0690	-0.0480

Table A.19: Pearson's correlation coefficient between barley grain yield and summarised monthly rainfall at different nitrogen response levels for KNaMg treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	0.1223	-0.2475	*-0.4154*	*-0.3506*	*0.3533*	0.0178	-0.0840	-0.0756
48 kg N/ha	0.1421	-0.0443	*-0.3529*	-0.1628	0.2439	-0.1256	-0.1272	-0.2369
96 kg N/ha	0.0870	-0.0605	*-0.3604*	-0.1941	0.2990	-0.1228	-0.1574	-0.1922
144 kg N/ha	0.1272	0.0412	-0.2806	-0.1277	0.1719	-0.1295	-0.1242	-0.1841

Table A.20: Pearson's correlation coefficient between barley grain yield and summarised monthly rainfall at different nitrogen response levels for Nil treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	0.1737	-0.1833	*-0.2992*	-0.1699	0.2255	0.0580	0.1210	-0.1350
48 kg N/ha	0.1341	0.0247	-0.2232	-0.1249	0.1835	-0.0255	0.0395	-0.2144
96 kg N/ha	0.1501	-0.0171	*-0.2955*	-0.1034	0.1254	-0.0224	0.0042	-0.2223
144 kg N/ha	0.2180	0.0617	-0.2026	-0.0611	0.0444	-0.0533	0.0909	-0.2587

Table A.21: Pearson's correlation coefficient between barley grain yield and summarised monthly temperature at different nitrogen response levels for PKNaMg treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.0301	-0.0224	0.0764	-0.0824	-0.0275	-0.0141	0.0349	0.0290
48 kg N/ha	-0.0647	0.0384	-0.1411	-0.0983	-0.2448	-0.2244	-0.1548	-0.0744
96 kg N/ha	-0.1944	-0.1011	-0.0099	-0.1709	-0.1567	-0.2310	-0.2460	0.0366
144 kg N/ha	-0.1257	-0.0123	-0.0703	0.0346	-0.1260	-0.1611	-0.1455	-0.0024

Table A.22: Pearson's correlation coefficient between barley grain yield and summarised monthly temperature at different nitrogen response levels for P treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.0810	0.1714	0.1888	-0.0852	-0.2020	-0.0143	-0.1824	0.0469
48 kg N/ha	-0.2592	-0.0051	0.0731	-0.1236	*-0.2867*	-0.1903	*-0.3626*	0.0026
96 kg N/ha	-0.2439	-0.1473	-0.0181	-0.1090	-0.1828	-0.2249	*-0.3110*	-0.0139
144 kg N/ha	-0.2402	-0.1023	0.1083	-0.0833	-0.2086	-0.0996	-0.1982	-0.0343

Table A.23: Pearson's correlation coefficient between barley grain yield and summarised monthly temperature at different nitrogen response levels for KNaMg treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.1018	-0.0053	0.1300	*-0.3456*	-0.2604	-0.2391	0.0210	-0.1956
48 kg N/ha	-0.2779	-0.2324	-0.1348	*-0.4761*	*-0.4068*	*-0.3766*	-0.1308	-0.2558
96 kg N/ha	*-0.2853*	-0.2505	-0.0481	*-0.4633*	*-0.4528*	*-0.3596*	-0.1701	-0.2072
144 kg N/ha	-0.2443	-0.2186	-0.2194	*-0.3366*	*-0.4481*	*-0.4263*	-0.2529	-0.2034

Table A.24: Pearson's correlation coefficient between barley grain yield and summarised monthly temperature at different nitrogen response levels for Nil treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.1076	-0.0512	0.1533	*-0.3325*	-0.2738	*-0.3163*	-0.0917	-0.2367
48 kg N/ha	-0.2383	-0.2840	-0.1382	*-0.3773*	*-0.4940*	*-0.3331*	-0.1750	-0.2208
96 kg N/ha	*-0.3014*	-0.2622	-0.0721	*-0.4359*	*-0.5502*	-0.2713	-0.1750	*-0.3075*
144 kg N/ha	-0.2005	-0.2566	-0.1044	*-0.3204*	*-0.4785*	*-0.3195*	*-0.2846*	-0.2811

Table A.25: Pearson's correlation coefficient between barley total biomass and summarised monthly rainfall at different nitrogen response levels for PKNaMg treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.0691	-0.1725	*-0.3502*	*-0.3509*	*0.4468*	0.0269	-0.1680	0.0789
48 kg N/ha	-0.0970	0.0149	*-0.3084*	-0.0056	*0.4600*	0.0839	-0.0557	0.0003
96 kg N/ha	-0.2064	0.0645	*-0.3058*	0.0913	*0.3984*	0.0007	-0.0897	-0.1042
144 kg N/ha	-0.1837	0.0802	-0.1471	0.1435	*0.3591*	0.1203	-0.0547	-0.1116

Table A.26: Pearson's correlation coefficient between barley total biomass and summarised monthly rainfall at different nitrogen response levels for P treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.1693	-0.1986	-0.1071	-0.2125	*0.4555*	-0.0256	-0.0315	0.1301
48 kg N/ha	-0.2464	0.1399	-0.1147	0.0016	*0.4130*	-0.0125	0.0026	0.0165
96 kg N/ha	-0.1447	0.2841	-0.1118	0.1962	0.1959	-0.0128	0.0645	-0.0094
144 kg N/ha	-0.1511	0.1658	-0.0986	0.0686	0.1715	0.0058	-0.0065	0.0215

Table A.27: Pearson's correlation coefficient between barley total biomass and summarised monthly rainfall at different nitrogen response levels for KNaMg treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	0.0896	-0.2493	*-0.3865*	*-0.3482*	*0.3749*	0.0184	-0.0826	-0.0531
48 kg N/ha	0.1393	-0.0410	*-0.3670*	-0.1536	*0.2877*	-0.1223	-0.1522	-0.2174
96 kg N/ha	0.0477	-0.0548	*-0.3424*	-0.1645	*0.3479*	-0.0932	-0.1676	-0.1747
144 kg N/ha	0.0792	0.0224	-0.2764	-0.1069	0.2334	-0.0969	-0.1397	-0.1251

Table A.28: Pearson's correlation coefficient between barley total biomass and summarised monthly rainfall at different nitrogen response levels for Nil treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	0.1567	-0.1718	*-0.3253*	-0.1586	0.2231	0.0667	0.1040	-0.0504
48 kg N/ha	0.1322	0.0306	*-0.3016*	-0.0771	0.2316	-0.0053	0.0023	-0.1597
96 kg N/ha	0.1291	-0.0138	*-0.3146*	-0.0519	0.1669	0.0181	-0.0328	-0.1602
144 kg N/ha	0.2026	0.0353	-0.2494	0.0327	0.0814	-0.0025	0.1163	-0.2013

Table A.29: Pearson's correlation coefficient between barley total biomass and summarised monthly temperature at different nitrogen response levels for PKNaMg treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.0104	-0.0293	0.1225	-0.1265	-0.0146	-0.0923	-0.0432	0.0354
48 kg N/ha	-0.0928	0.0217	-0.0933	-0.1620	*-0.3048*	*-0.3215*	-0.2792	-0.0688
96 kg N/ha	-0.1961	-0.1593	-0.0239	-0.2491	-0.2687	*-0.3446*	*-0.3569*	0.0049
144 kg N/ha	-0.1397	-0.0768	-0.0520	-0.0331	-0.2163	-0.2484	-0.2795	-0.0330

Table A.30: Pearson's correlation coefficient between barley total biomass and summarised monthly temperature at different nitrogen response levels for P treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.0903	0.1736	0.2221	-0.1043	-0.2165	-0.0423	-0.1899	0.1173
48 kg N/ha	-0.2345	0.0131	0.1128	-0.1405	-0.2753	-0.2208	*-0.3986*	0.0448
96 kg N/ha	-0.2371	-0.1312	0.0003	-0.1520	-0.2645	*-0.3188*	*-0.4008*	-0.0287
144 kg N/ha	*-0.3025*	-0.1213	0.0617	-0.1647	*-0.3341*	-0.1457	*-0.2909*	-0.0779

Table A.31: Pearson's correlation coefficient between barley total biomass and summarised monthly temperature at different nitrogen response levels for KNaMg treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.1021	-0.0099	0.1254	*-0.3458*	-0.2487	-0.2490	0.0163	-0.1540
48 kg N/ha	-0.2521	-0.2367	-0.1701	*-0.4794*	*-0.4462*	*-0.4248*	-0.1757	-0.2471
96 kg N/ha	-0.2691	-0.2509	-0.0707	*-0.4468*	*-0.4855*	*-0.3858*	-0.2140	-0.1850
144 kg N/ha	-0.2184	-0.1985	-0.2168	*-0.3319*	*-0.4607*	*-0.4382*	*-0.2972*	-0.1944

Table A.32: Pearson's correlation coefficient between barley total biomass and summarised monthly temperature at different nitrogen response levels for Nil treatments (values in *Italic* have $P < 0.05$).

Treatment	February	March	April	May	June	July	August	September
0 kg N/ha	-0.1089	-0.0310	0.1683	*-0.3302*	-0.2769	*-0.3522*	-0.1443	-0.2418
48 kg N/ha	-0.2220	-0.2650	-0.0998	*-0.3802*	*-0.4916*	*-0.3662*	-0.2413	-0.2329
96 kg N/ha	-0.2795	-0.2334	-0.0628	*-0.4048*	*-0.5579*	*-0.3287*	-0.2420	*-0.2901*
144 kg N/ha	-0.1944	-0.2561	-0.0635	*-0.2894*	*-0.4405*	*-0.3156*	*-0.3574*	-0.1984

Figure A.15: Model assumptions for the grain yield parsimonious model.

(a)

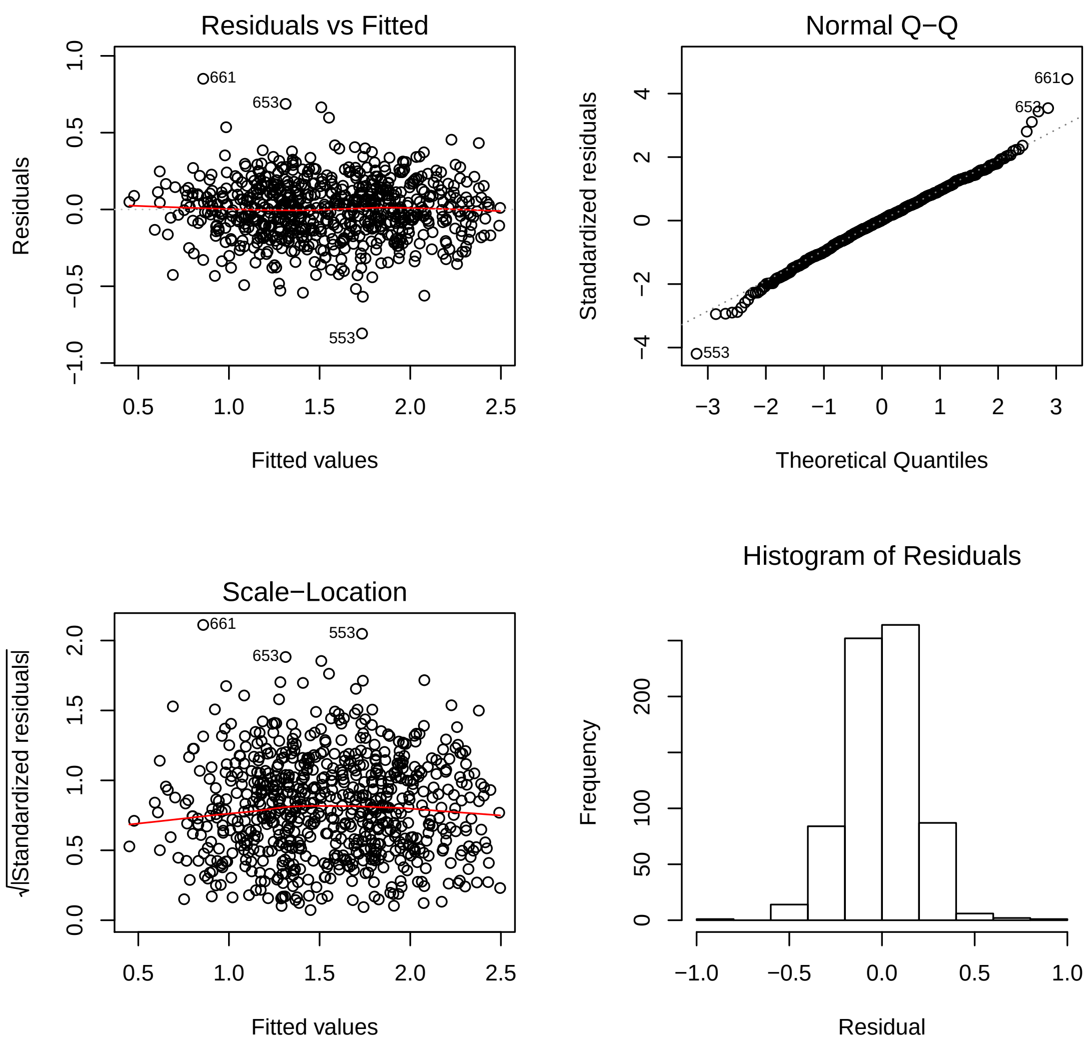


Figure A.16: Model assumptions for the total biomass parsimonious model.

(a)

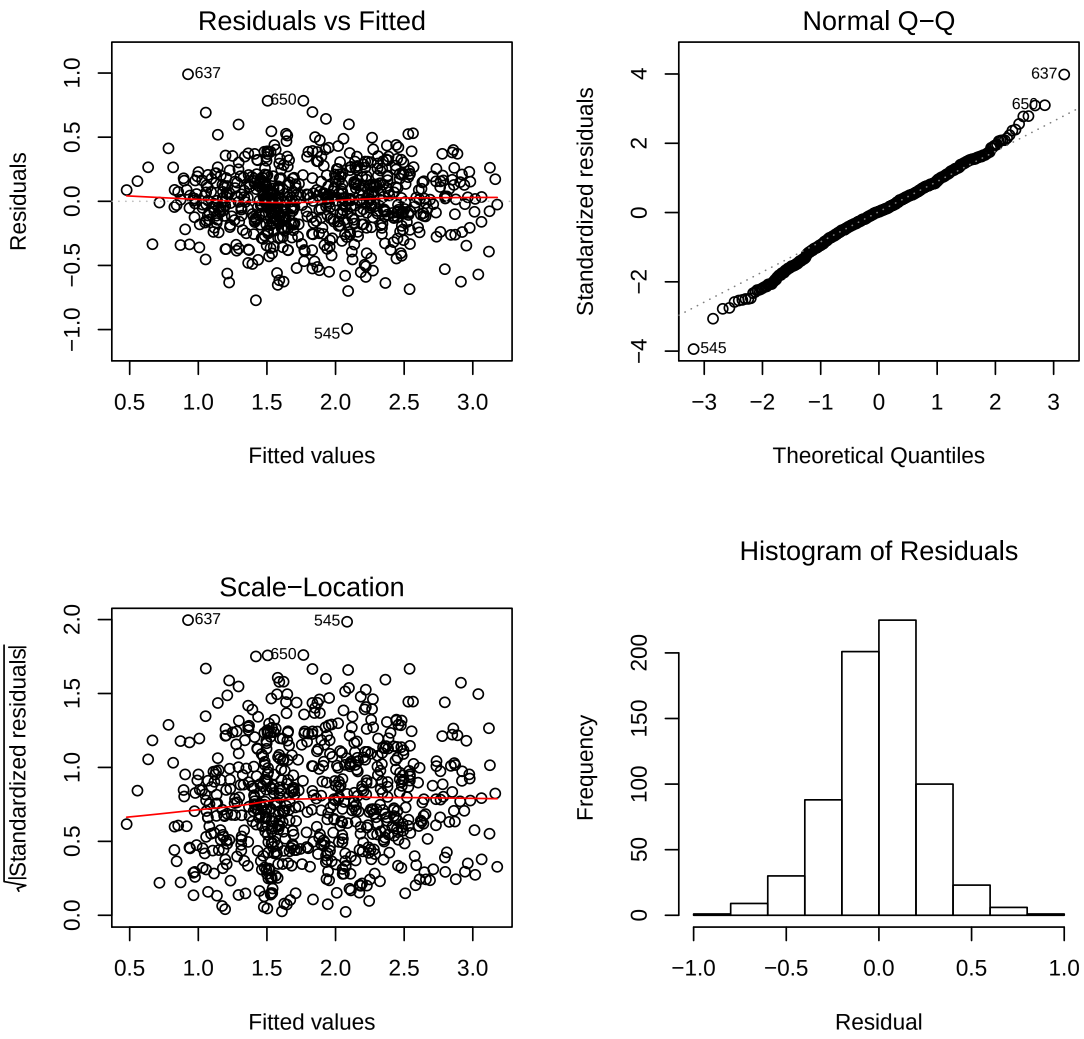
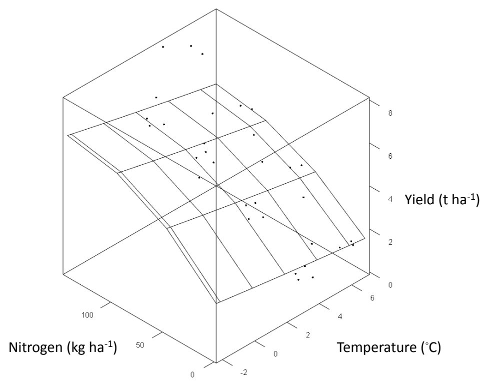
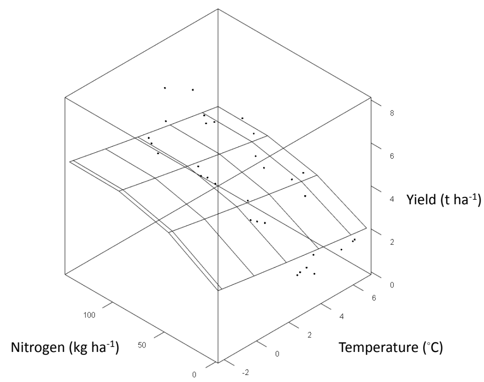


Figure A.17: LEXP function, Equation 7.1, fitted to grain yield for treatments: (a) PKNaMg, (b) P, (c) KNaMg, and (d) Nil, from 1968 to 2016. The non-linear parameter was fixed at r = 0.985 (S.E. 0.0076) for all treatments.

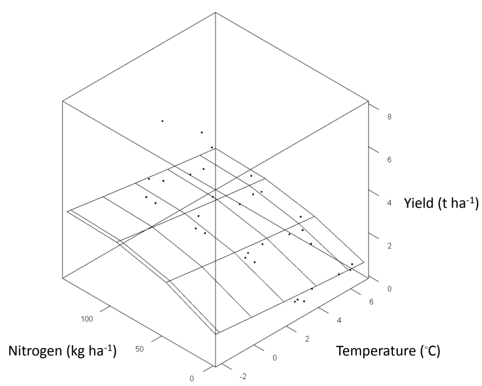
(a)



(b)



(c)



(d)

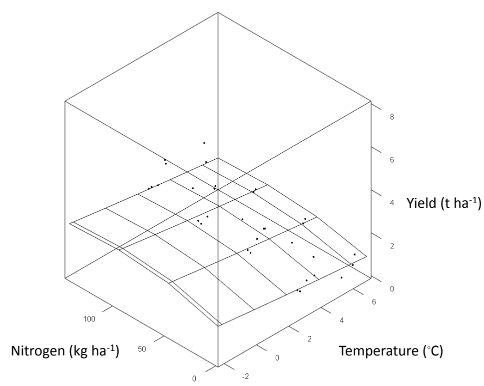
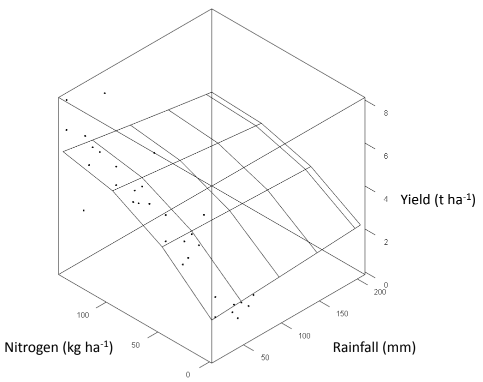
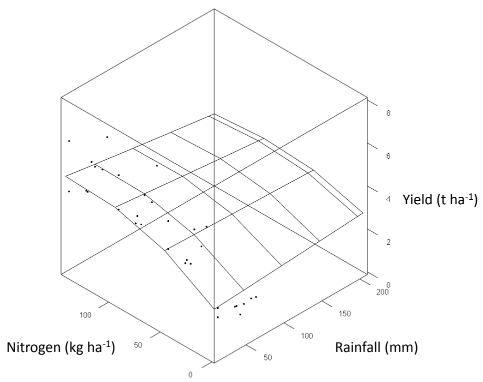


Figure A.18: LEXP function, Equation 7.1, fitted to grain yield for treatments: (a) PKNaMg, (b) P, (c) KNaMg, and (d) Nil, from 1968 to 2016. The non-linear parameter was fixed at r = 0.985 (S.E. 0.0076) for all treatments.

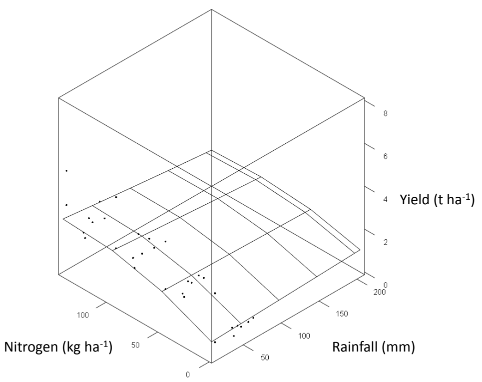
(a)



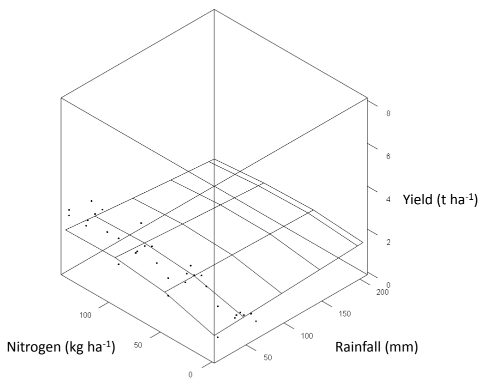
(b)



(c)



(d)



A.5 The influence of weather variability on the first-cut hay and total-cut herbage yield of Park Grass

Table A.33: Pearson's correlation degrees of freedom between the yield of the first cut of Park Grass and and summarised seasonal rainfall and temperature for different plots. Nil_{12}, Nil_3 and $Nil_{2.2}$ refers to nil treatment on plots 12, 3 and 2.2. (b) are the limed plots and (d) are the unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively.

	Total Rainfall			Mean Temperature		
Plot	Autumn	Winter	Spring	Autumn	Winter	Spring
Nil_{12}(d)	114	114	114	114	114	114
Nil_3(b)	92	92	92	92	92	92
Nil_3(d)	114	114	114	114	114	114
$Nil_{2.2}$(b)	92	92	92	92	92	92
$Nil_{2.2}$(d)	114	114	114	114	114	114
PKNaMg(b)	92	92	92	92	92	92
PKNaMg(d)	114	114	114	114	114	114
N1 + PKNaMg(b)	92	92	92	92	92	92
N1 + PKNaMg(d)	114	114	114	114	114	114
N2 + PKNaMg(b)	92	92	92	92	92	92
N2 + PKNaMg(d)	114	114	114	114	114	114
FYM(b)	92	92	92	92	92	92
FYM(d)	114	114	114	114	114	114

Table A.34: Pearson's correlation P-values between the yield of the first cut of Park Grass and and summarised seasonal rainfall and temperature for different plots. Nil_{12}, Nil_3 and $Nil_{2.2}$ refers to nil treatment on plots 12, 3 and 2.2. (b) are the limed plots and (d) are the unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively.

	Total Rainfall			Mean Temperature		
Plot	Autumn	Winter	Spring	Autumn	Winter	Spring
Nil_{12}(d)	0.719	0.095	0.302	0.003	0.197	0.305
Nil_3(b)	0.031	0.886	0.001	0.875	0.768	0.351
Nil_3(d)	0.699	0.147	0.160	0.064	0.958	0.905
$Nil_{2.2}$(b)	0.013	0.976	0.005	0.697	0.382	0.376
$Nil_{2.2}$(d)	0.535	0.500	0.157	0.017	0.764	0.621
PKNaMg(b)	0.026	0.693	0.003	0.503	0.340	0.103
PKNaMg(d)	0.178	0.047	0.187	0.004	0.508	0.929
N1 + PKNaMg(b)	0.028	0.331	0.060	0.483	0.742	0.410
N1 + PKNaMg(d)	0.383	0.544	0.204	0.000	0.594	0.011
N2 + PKNaMg(b)	0.422	0.796	0.100	0.041	0.958	0.190
N2 + PKNaMg(d)	0.959	0.448	0.680	0.001	0.579	0.004
FYM(b)	0.003	0.745	0.005	0.376	0.471	0.397
FYM(d)	0.001	0.532	0.039	0.042	0.338	0.889

Table A.35: Autocorrelation significant levels at lag one for first-cut hay yields and residuals from parsimonious model. Nil_{12}, Nil_3 and $Nil_{2.2}$ refers to nil treatment on plots 12, 3 and 2.2. (b) are the limed plots and (d) are the unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively.

Plot	Yield	Parsimonious model residuals
Nil_{12}(d)	<0.001	0.053
Nil_3(b)	0.075	0.372
Nil_3(d)	<0.001	0.042
$Nil_{2.2}$(b)	0.006	0.227
$Nil_{2.2}$(d)	<0.001	0.227
PKNaMg(b)	0.265	0.525
PKNaMg(d)	<0.001	0.005
N1 + PKNaMg(b)	<0.001	<0.001
N1 + PKNaMg(d)	<0.001	<0.001
N2 + PKNaMg(b)	0.012	0.019
N2 + PKNaMg(d)	<0.001	0.084
FYM(b)	0.401	0.360
FYM(d)	0.104	0.590

Figure A.19: Model assumptions for the hay parsimonious yield model.

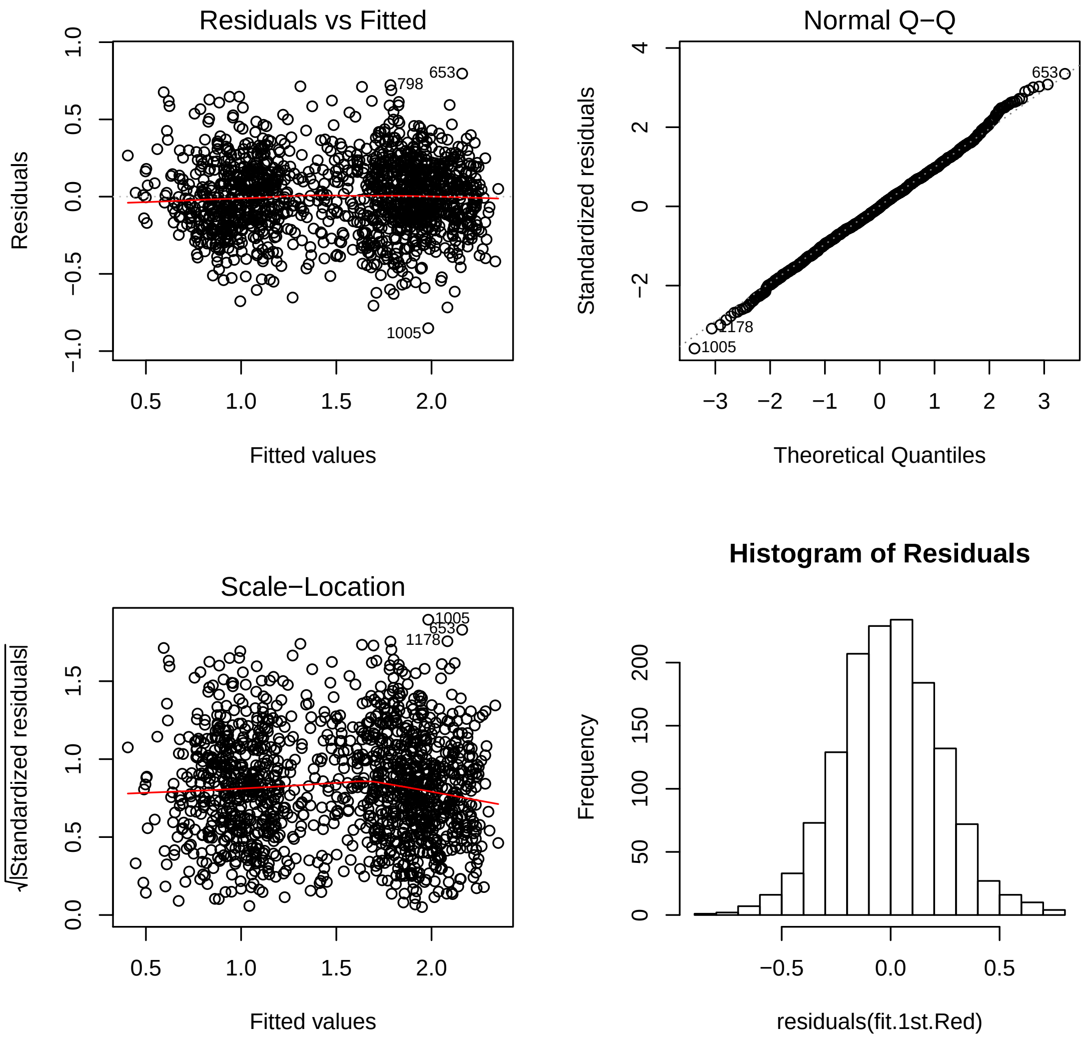


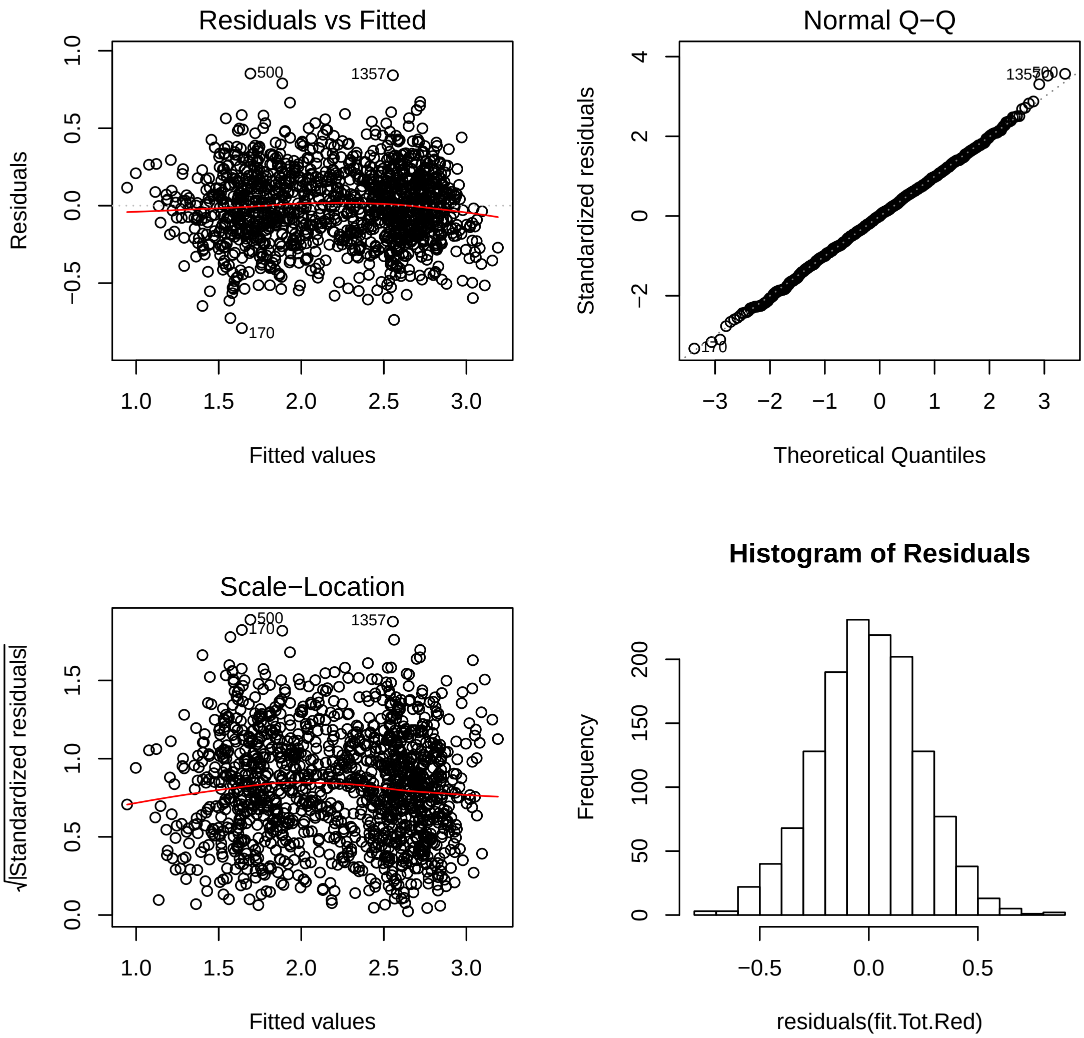
Table A.36: Autocorrelation p-values at lag 1 for total-cut herbage yields and residuals from the herbage parsimonious model. Nil_{12}, Nil_{3} and $Nil_{2.2}$ refers to Nil treatment on plots 12, 3 and 2.2. (a) refer to plots kept at a pH of 7, (b) 6, (c) 5 and (d) unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively. Individual P-values and degrees of freedom are given in the Appendix.

Plot	Total-cut Herbage Yield	Parsimonious Model Residuals
Nil_{12}(a)	0.048	0.500
Nil_{12}(b)	0.445	0.967
Nil_{12}(c)	0.109	0.399
Nil_{12}(d)	0.004	0.014
Nil_{3}(a)	0.280	0.620
Nil_{3}(b)	0.027	0.549
Nil_{3}(c)	0.076	0.357
Nil_{3}(d)	0.028	0.212
$Nil_{2.2}$(a)	0.151	0.951
$Nil_{2.2}$(b)	0.015	0.437
$Nil_{2.2}$(c)	0.027	0.109
$Nil_{2.2}$(d)	0.065	0.249
PKNaMg(a)	0.075	0.352
PKNaMg(b)	0.094	0.566
PKNaMg(c)	0.0.67	0.049
PKNaMg(d)	0.047	0.651
N1 + PKNaMg(a)	0.851	0.471
N1 + PKNaMg(b)	0.016	0.002
N1 + PKNaMg(c)	0.332	0.167
N1 + PKNaMg(d)	<0.001	<0.001
N2 + PKNaMg(a)	0.135	0.832
N2 + PKNaMg(b)	0.009	0.011
N2 + PKNaMg(c)	0.130	0.902
N2 + PKNaMg(d)	0.002	0.007
FYM(a)	0.031	0.416
FYM(b)	0.402	0.784
FYM(c)	0.276	0.354
FYM(d)	0.180	0.854

Table A.37: Autocorrelation degrees of freedom at lag 1 for total-cut herbage yields and residuals from the herbage parsimonious model. Nil_{12}, Nil_3 and $Nil_{2.2}$ refers to Nil treatment on plots 12, 3 and 2.2. (a) refer to plots kept at a pH of 7, (b) 6, (c) 5 and (d) unlimed. N1 and N2 refer to doses of 48 and 96 kg N ha^{-1}, respectively. The degrees of freedom for significance tests for the unlimed and limed subplots were 113 and 91. Individual P-values are given in the Appendix.

Plot	Total-cut Herbage Yield	Parsimonious Model Residuals
Nil_{12}(a)	37	37
Nil_{12}(b)	38	38
Nil_{12}(c)	36	36
Nil_{12}(d)	52	52
Nil_3(a)	42	42
Nil_3(b)	53	53
Nil_3(c)	56	56
Nil_3(d)	53	53
$Nil_{2.2}$(a)	42	42
$Nil_{2.2}$(b)	53	53
$Nil_{2.2}$(c)	37	37
$Nil_{2.2}$(d)	53	53
PKNaMg(a)	42	42
PKNaMg(b)	53	53
PKNaMg(c)	36	36
PKNaMg(d)	53	53
N1 + PKNaMg(a)	42	42
N1 + PKNaMg(b)	53	53
N1 + PKNaMg(c)	36	36
N2 + PKNaMg(d)	53	53
N2 + PKNaMg(a)	42	42
N2 + PKNaMg(b)	53	53
N2 + PKNaMg(c)	36	36
N2 + PKNaMg(d)	53	53
FYM(a)	48	48
FYM(b)	53	53
FYM(c)	48	48
FYM(d)	53	53

Figure A.20: Model assumptions for the herbage parsimonious yield model.



A.6 Addressing the influence of atmospheric CO_2 on simulated wheat yields at Rothamsted

Figure A.21: The model assumptions of the ANOVA fitted to the square-root of grain yield in Analysis 1 within Chapter 7.

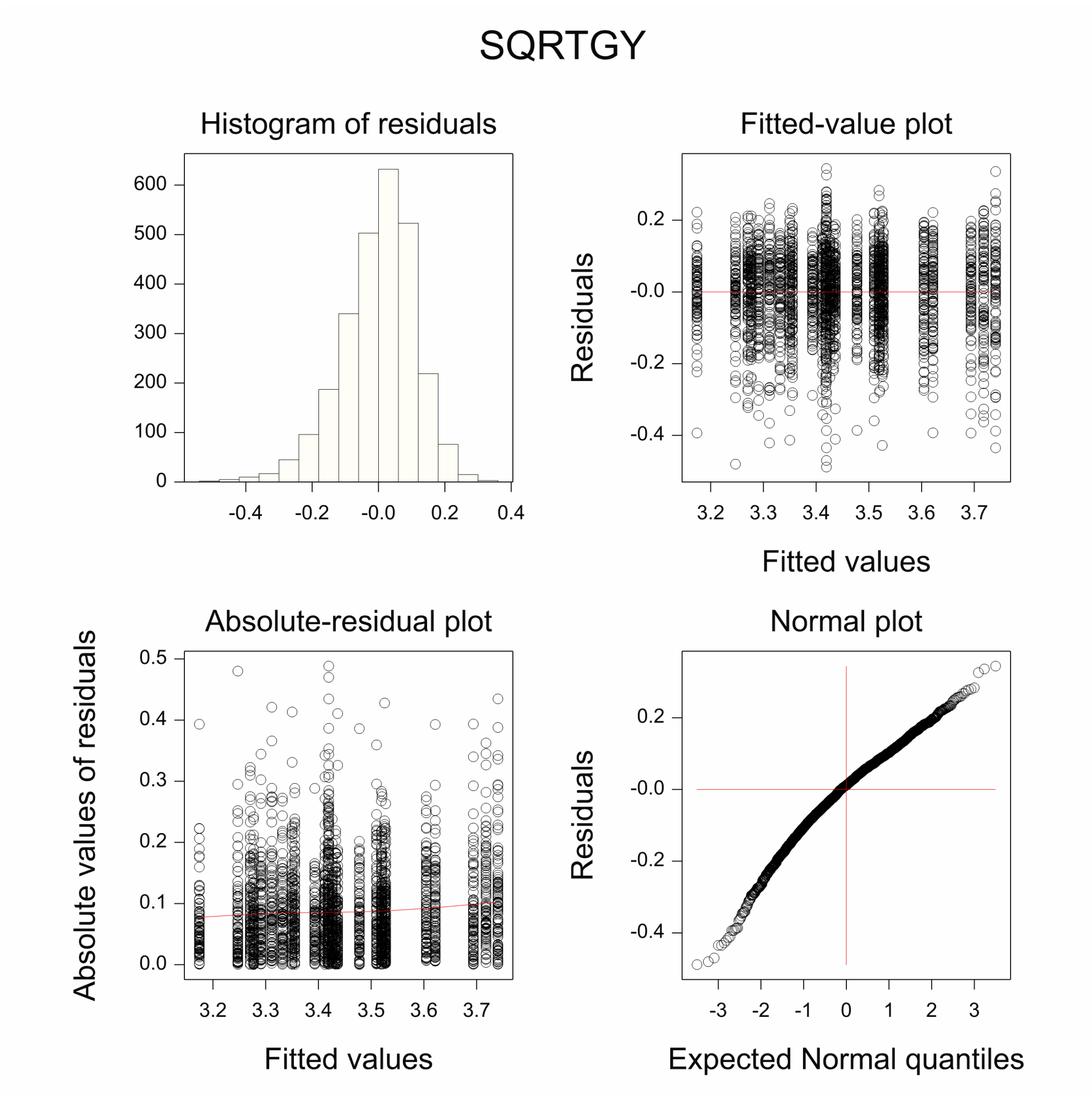


Figure A.22: The model assumptions of the ANOVA fitted to days to anthesis in Analysis 1 within Chapter 7.

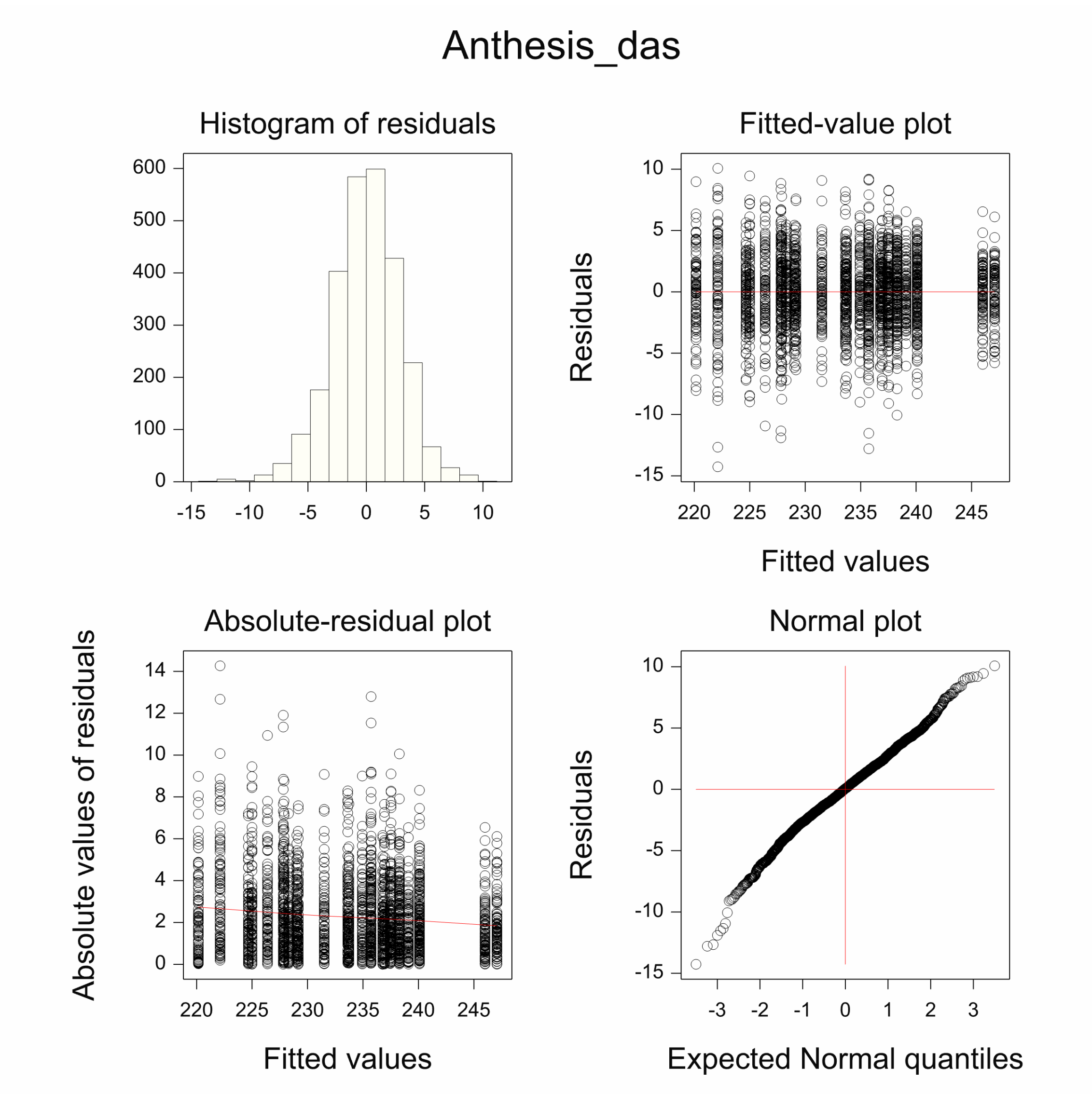


Figure A.23: The model assumptions of the ANOVA fitted to days to maturity in Analysis 1 within Chapter 7.

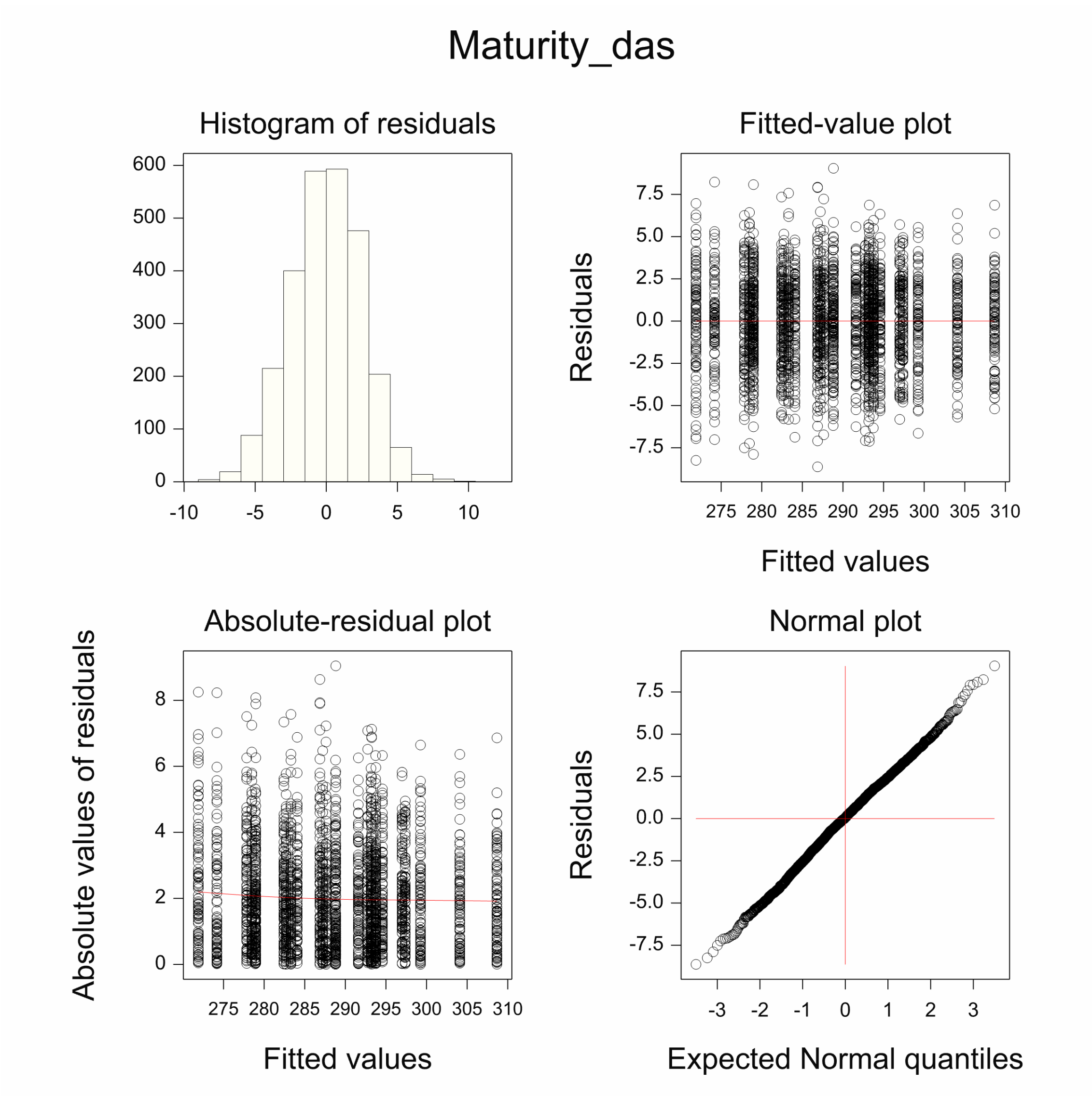


Figure A.24: The model assumptions of the ANOVA fitted to the square-root of grain yield in Analysis 2 within Chapter 7.

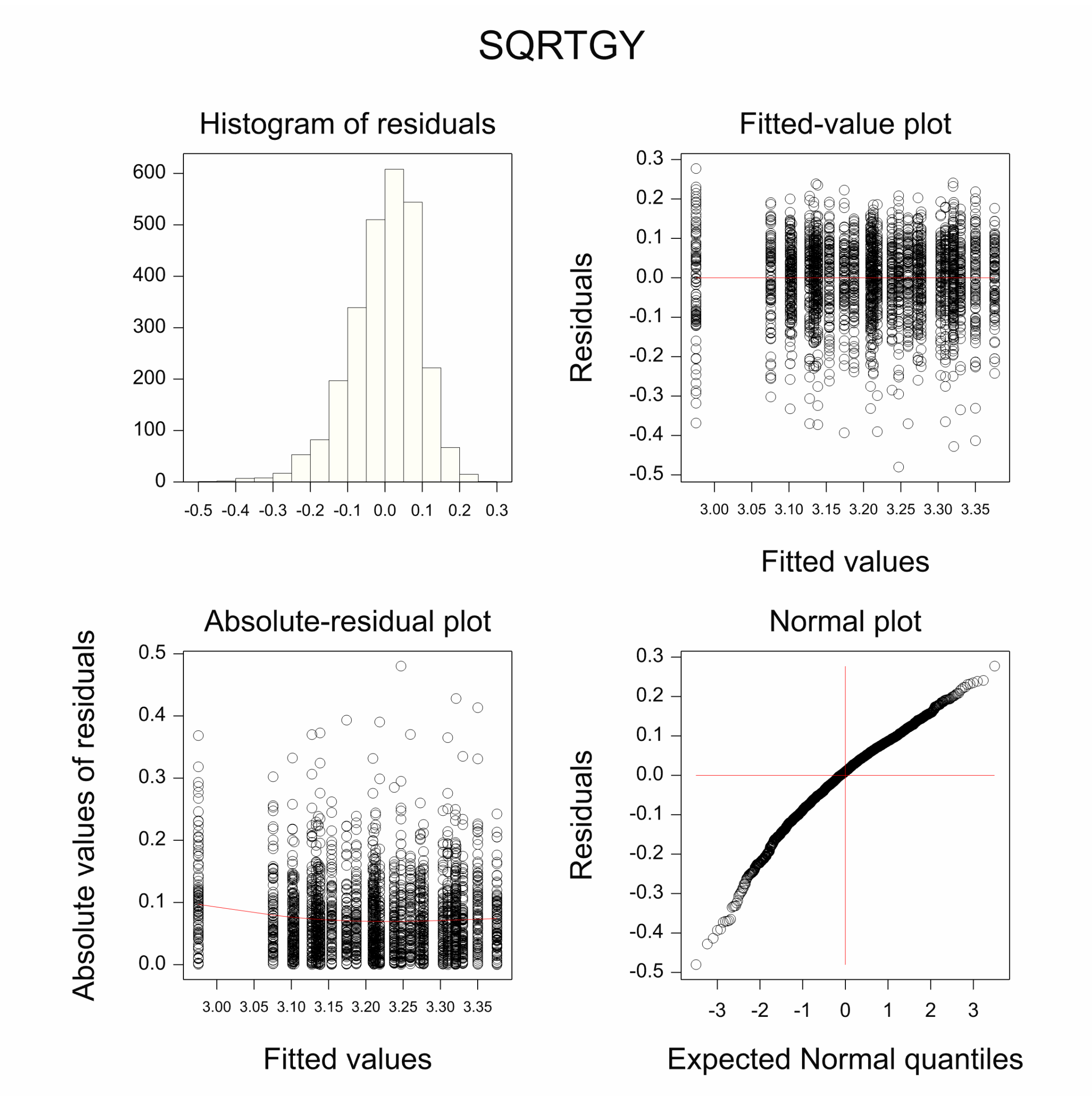


Figure A.25: The model assumptions of the ANOVA fitted to the square-root of grain yield in Analysis 3 within Chapter 7.

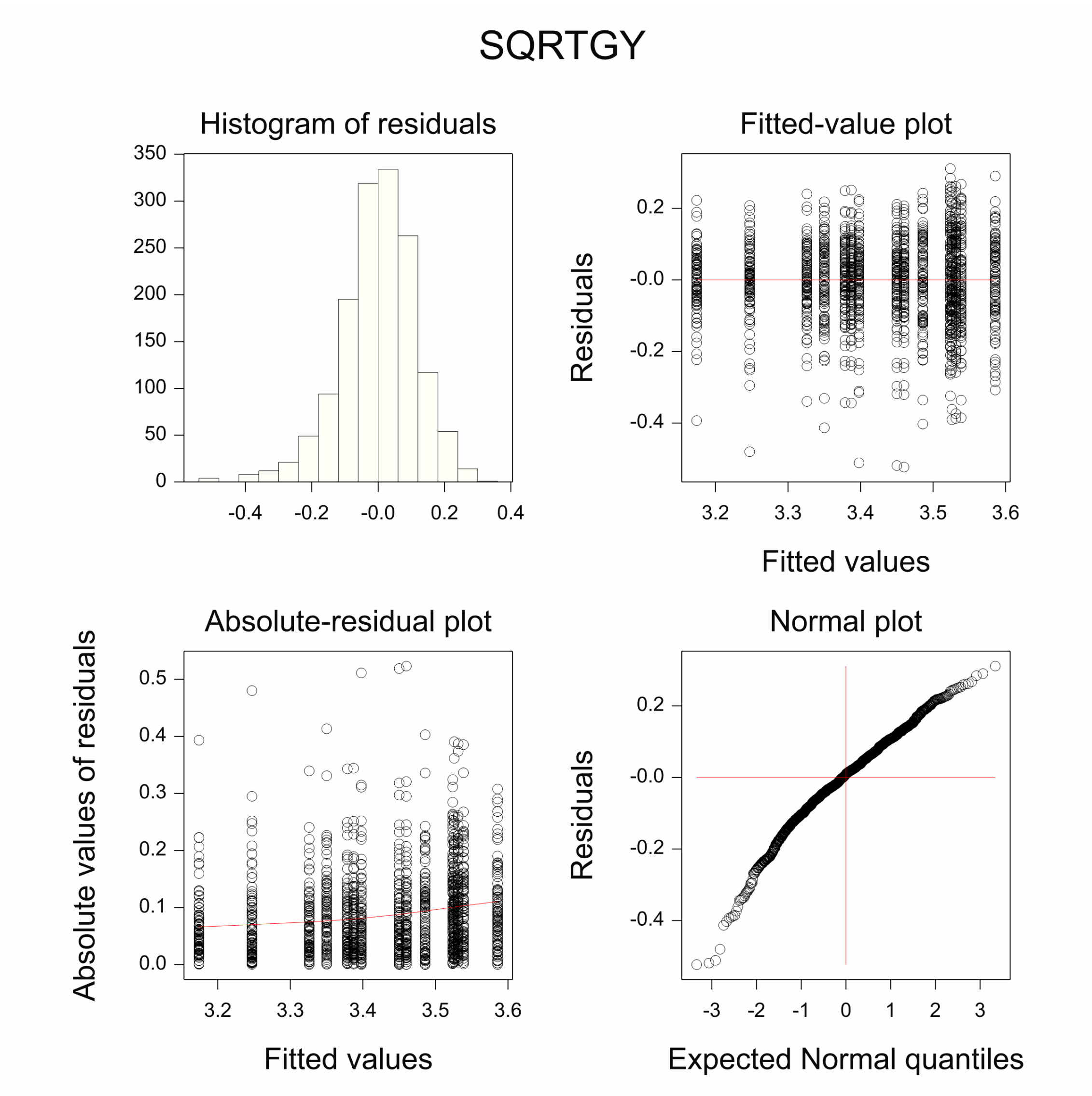


Figure A.26: The model assumptions of the ANOVA fitted to the square-root of grain yield in Analysis 4 within Chapter 7.