Examining the impacts of projected precipitation changes on sugar beet yield in Eastern England

A thesis submitted for the degree of Doctor of Philosophy

By

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Abstract

Projected increasing temperatures and reduced summer precipitation in the UK raises questions about the sustainability of aspects of the agriculture industry and food security. This study investigates the potential impact of precipitation changes on sugar beet yield in Eastern England. Observations of precipitation was examined for the period 1971-2000 and the expected changes in precipitation were investigated using seven CMIP5 climate models for the historical phase (1971-2000) and RCP45 and RCP85 future scenarios (2021-2050). Three out of the seven models were found to show good agreement with observations but the MOHC ensemble mean was the closest to the observed means and was used for further precipitation analyses. Statistical analysis of the future precipitation changes were performed using the Met Office Hadley Centre (MOHC) model focused on changes between the historical phase and RCP45 and RCP85. Results showed a consistent and significant reduction in annual May-October precipitation under future scenarios.

The study then investigated the impact of reduced future precipitation changes on sugar beet yield by applying controlled watering regimes informed by the CMIP5 projections to sugar beet plants in a greenhouse experiment over two seasons – the use of CMIP5 projections in this way is a first. In the first experiment carried out in 2014, a climatological watering regime (i.e. where the total seasonal rainfall for the different scenarios was applied in equal and regular watering events) was applied to the plants, which meant a 16% reduction in precipitation in the "future" category relative to a "control" category. Analysis of the yields indicated a statistically significant reduction in mean tuber wet mass: mean of 360g for the control and 319g for the future (p-value 0.03). This implies a potential yield reduction of 11% by 2050. In the second experiment carried out in 2015, a "realistic distribution" watering regime (i.e. where the total seasonal rainfall is applied in a series of watering events that reflect the analysed sizes and distribution of rainfall events in the different categories), this meant a reduction in precipitation in the months of June (-15.6%), July (-7.7%) and August (-3.7%). This resulted in statistically significant reduction in mean tuber wet mass between control (153g) and RCP85 (113g) with a p-value of 0.01. This implies a reduction of 26% in future yields under RCP85 by 2050.

Results in this thesis further show how changes and variation in precipitation are intertwined with changes in soil moisture and yield of sugar beet plants. The findings will enable UK sugar beet farmers to identify potential areas of challenges in order to adapt their management practices to ensure maximum crop yield in future growing seasons. Moreover, from a global perspective, the findings here are also broadly applicable to a variety of agricultural crops in different parts of the world, where changes in yield may have important consequences to food security and food prices.

Declaration

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

Stanley Ob Joseph

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Chapter 1 - Introduction

1.1 Changes in precipitation: Reasons for concern?

Globally, climate change and variability are having serious impacts on hydrological processes via changes in precipitation with sometimes severe consequences for society. Changes in precipitation characteristics and delivery are expected to occur under a warmer climate and the contribution from the concentrations of greenhouse gases in the atmosphere is attributed to be the major cause of the change: the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) provides evidence that “warming of the climate system is unequivocal and that human influence have been detected in the warming of the atmosphere” (IPCC 2013a). The warming causes temperature to increase, changes in precipitation patterns, increase in sea level rise and a change in the frequency of extreme weather events. These impacts are evident from increasing surface temperature, which causes an increase in evapotranspiration and, in turn, causes changes to precipitation patterns thereby altering hydrological processes (Cramer et al. 2014; IPCC 2013a; Meehl et al. 2007; Huntington 2006; Meehl et al. 2005) and further impacting on water resources in terms of quantity and quality (Cramer et al. 2014; IPCC 2013a).

Furthermore, the risks associated with climate change are becoming more visible through the movement of climatic variables such as precipitation and temperature with varying degree of impacts in different regions. Observations show that certain regions and areas have been identified as more vulnerable to the adverse effects of climatic changes, such as changes in precipitation patterns. Most Earth System Models (ESM’s) predict an increase in precipitation in the mid to high latitudes but a decrease in the sub-tropics (IPCC 2013b). In continental Europe, Christensen et al. (2007) reported a decrease in annual mean precipitation for southern Europe and an increase in northern Europe. Their analysis also showed increases in winter precipitation in central and northern Europe, and decreases in the summer over central and southern Europe. Several other studies on the different aspects of precipitation have consistently agreed on an increase in global mean precipitation with an expected increase in variation of precipitation events resulting from warming of the atmosphere (IPCC AR5, Stocker et al. 2013). Studies on the theoretical aspects of precipitation conducted by Trenberth (2011) and Trenberth & Josey (2007), observational studies by Halmstad et al. (2013) and Min et al. (2011), and simulation studies using climate models by Pincus et al. (2008) and Phillips & Gleckler (2006) all agreed on an increasing global mean precipitation.

In addition to increase in precipitation, changes in the character of local and regional precipitations are emerging and depends largely on the variation of atmospheric circulation because a shift in the direction of the wind causes changes in the delivery of precipitation which makes some regions to be wet and others dry (Trenberth 2011). These changes vary from season to season, and from one year to another which suggests that some years will have more or less precipitation than others. As a result, years with reduced mean precipitation can increase the risk of drought whereas; years with increased mean precipitation can equally increase the risk of floods. Irregularity in precipitation appears to be the major source of variations in the distribution of precipitation events in most regions because precipitation characteristics are highly variable and unpredictable. This causes intensification of hydrological cycle with expected increases in the frequency of dry and wet spells, as well as increases in the frequency and magnitude of precipitation events with significant consequences for society (Cramer et al. 2014; IPCC 2013; Huntington 2006).

Emori & Brown (2005) reported in an earlier study that the effects of global warming on precipitation frequency and intensity on a global scale does not reflect the impact on regional and/or local scales because of thermo-dynamic influences affecting precipitation unevenly across the world. Emory and Brown indicated that secondary influences such as atmospheric moisture content are the more likely to dominate and influence precipitation amount and intensity on local scales as a result of warmer climate. Furthermore, the warming of the atmosphere, climate and weather variability are widely projected to continue for the rest of the century (IPCC 2012) and will significantly impact on hydrological processes (Meehl et al. 2007; Meehl et al. 2005) which typically leads to flood or droughts. Floods are generally associated with extreme precipitation while droughts are associated with deficient precipitation and high temperatures which often leads to drying of the soil. Flood incidents occur locally while droughts develop over a period of months or years. Both type of events can be mitigated – floods with good drainage system and drought with the use of irrigation (Trenberth 2011). This thesis is not about extreme events, but, it is important to point out that both floods and droughts are a manifestation of changes in precipitation and variability; hence their occurrence is also of great societal concern.

In response to the problem of variability in precipitation patterns, Brunet & Jones (2011) called for digitalisation of long-term climate data all over the world. They identified the lack of long-term high-quality data in some parts of the world as a condition hampering a more robust assessment of the climate. The position of Brunet and Jones supports earlier issues identified by Trenberth et al. (2007). Since then, several studies and reports have recommended several approaches to climate change mitigation such as reducing greenhouse gas emissions in order to keep global mean temperature increase less than 2ºC above pre-industrial levels (IPCC 2014b), which will be helpful in limiting the impacts of global warming (Allison et al. 2009) and Successive IPCC reports from AR4 to AR5 (IPCC 2014b; IPCC 2012; IPCC 2007). The most recent global agreement in this direction is the United Nations Climate Change Agreement in Paris in 2015 designed to increase efforts to further limit temperature increase to 1.5ºC above pre-industrial levels (UNFCCC 2015).

Considering the potential impacts of this problem, it is important to examine and understand how climatic changes will affect precipitation delivery in Eastern England to enable reliable projections of future changes in the region. Assessing precipitation characteristics on daily, monthly or seasonal time scales, as well as the capacity to predict precipitation changes and evaluate its impacts on relevant sectors is very important in developing adaptation strategies (Allan & Soden 2008) and one of the principal aims of this study.

1.2 Variations in Eastern England and UK precipitation

In Eastern England, the climate is mild and dry according to the Met Office (2016) and is influenced by the high grounds in the west of the UK including the mountains in Wales, North-West England and Scotland, where the mountains are more than 1300m high. These high grounds leave the east of the UK in a “rain shadow” from the prevailing westerly winds resulting in a distinct pattern of west-east average precipitation amounts (Met Office 2016). The orographic influences in the west means that the highest amount of precipitation (which by implication means the wettest places) are found in the north-west England, Scotland and Wales with an annual mean precipitation of over 3000 mm in some places (Met Office 2016). Typical annual mean precipitation of different locations from north to south of the UK ranges from 1170 mm in Stornoway, 1050 mm in Glasgow, 810 mm in Manchester to 760 mm in Exeter. In the east, Edinburgh and London have 670 mm and 610 mm annual mean precipitation respectively. East Anglia in contrast has the smallest amount of precipitation in the UK with a total annual precipitation of about 500 mm in some places but has more precipitation in the autumn and winter periods than the summer (Met Office 2016).

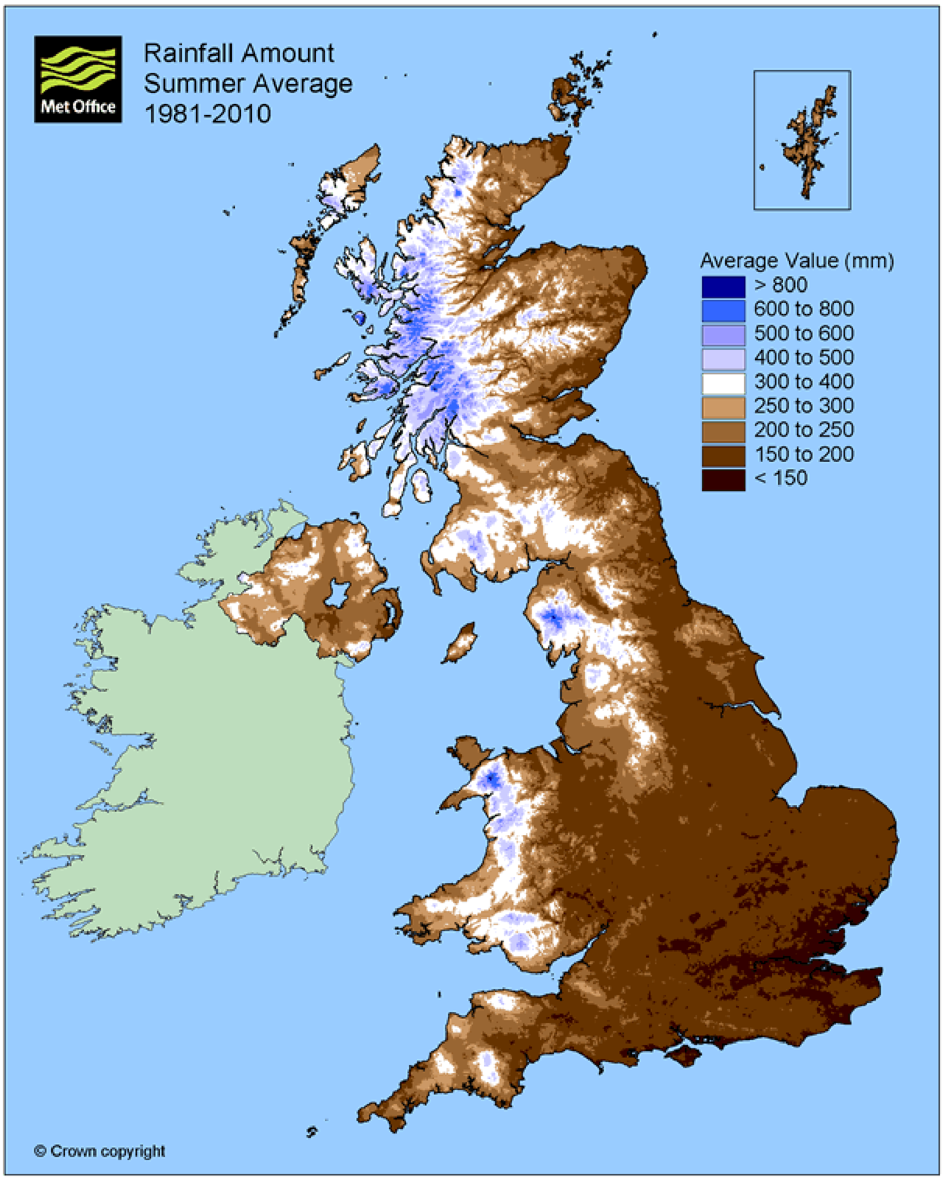


Figure 1. 1: Average summer UK rainfall for the period 1981-2010. Source: Met Office 2016

Precipitation in Eastern England and the UK in general is highly variable from year to year over decades, and changes in the amount, intensity and frequency often affecting the environment and society. This variability further exacerbates the multiple stresses already present in the region, making the region more sensitive to possible future changes in precipitation. The impacts from yearly variations can for example have an impact on the magnitude, frequency and distribution of precipitation events. In future, global warming resulting from greenhouse gas emissions is expected to lead to variability and changes in precipitation patterns (Fowler & Ekström 2009; Frei et al. 2006). This result have been consistently produced from climate models in current and past studies (IPCC 2013b; Trenberth 2011; Tebaldi et al. 2006; Houghton et al. 2001). Other studies such as Cramer et al. (2014); Williams et al. (2007); Huntington (2006) suggests that global warming may result in intensification of the hydrological cycle with changes in the frequency and magnitude of precipitation events as well as changes in the frequency of dry events (Westra et al. 2013; Seneviratne et al. 2012).

These events may result in an increase or decrease in mean precipitation and are expected to affect agriculture in future (e.g. sugar beet production in Eastern England) and therefore, a source of concern to famers and society at large. However, the assessment of precipitation is somewhat made difficult by the discontinuous and irregular nature of precipitation which makes it difficult to detect trends creating additional disadvantage if shortages were to persist. Detection of trends in precipitation analysis is also hampered by the need for long time homogenous observed datasets necessary to identify shifts in precipitation (Klein Tank & Können 2003; Klein Tank et al. 2009). This sort of data is often limited to developed countries with advanced technologies and unhindered long-term data as opposed to developing countries with sparse or interrupted data thereby creating a bias and providing uneven global representation.

A number of approaches have been employed to assess trend in precipitation data. Daily mean rainfall amount of wet days have been used to identify changes in global mean precipitation in future climate (Meehl et al. 2005). Klein Tank & Können (2003) used fixed value threshold to calculate changes in mean precipitation and identify associated changes when threshold values are exceeded. Changes and trend in precipitation are also assessed by comparing trend over a long period of time (e.g. 30 years) or assessed between two different time frames (Zhang et al. 2004) as employed in this study.

1.3 Climate models simulation of precipitation

Climate models are the main tools used for investigating projected long-term precipitation changes. The models are used in two ways: firstly, to simulate past precipitation and secondly, they are used to simulate possible future precipitation under different greenhouse gas emission scenarios. Climate models have been used to replicate long-term climatological changes in observed precipitation with considerable success (IPCC 2013b). Equally, climate models have also been used to make projections of future changes in precipitation. The use of models to simulate historical precipitation represents an alternative method for understanding changes in past precipitation and also used to validate model performance in reproducing past precipitation of the study area. This method enables the selection of desirable models based on the notion that if they can reproduce past precipitation of a region very well, they should also be able to reasonably reproduce future precipitation of the same region.

However, in spite of the skill exhibited by models, their performance is rife with uncertainties largely because of the coarse resolution of the models making them unable to adequately handle some of the mechanism associated with precipitation particularly on local scales. Such “sub grid scale” processes are usually treated statistically in models via calculations known as “parameterisation”. The reliability of model output is, therefore, not only dependent on the quality of the input data, but also on the ability of the adopted parameterisations to represent all the required processes. This means that models are likely to produce valuable results if accurate assumptions are made. This uncertainty is evident in models’ disagreement on the direction of potential changes in precipitation (IPCC 2013b, Bates et al. 2008). Clouds and radiation specifically are not properly simulated by models as they vary temporally thereby making individual measurements unrepresentative of the areal mean (Pincus et al. 2008). However, the greatest source of uncertainty remains the pathway of future greenhouse gas emissions, which will ultimately determine how our climate will change.

In spite of these challenges, climate models have nonetheless been used in various studies to simulate observed changes in precipitation with great success. Climate models projection of changes in precipitation over the UK has consistently shown increasing winter precipitation and decreasing summer precipitation (Jenkins et al. 2008). For this study, climate model ensemble simulations of daily precipitation data was extracted from the most recent state-of-the-art Climate Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012). The CMIP5 climate models provide valuable climate information used to understand and enhance our knowledge of climate processes and their effect on society. The current study evaluated Eastern England precipitation using three Earth System Model (ESM's) ensembles for the historical phase (1971-2000) and the future period (2021-2050).

It is important to stress that reliance on one climate model run can increase uncertainties, therefore, ensembles average were used to reduce model uncertainties and error specific to individual models. Ensembles have been widely used in precipitation, meteorological and hydrological studies with a great degree of success (McSweeney et al. 2014; Duan et al. 2007) by obtaining the averages of individual model performance and spreading the results of possible outcomes.

1.4 Impacts of precipitation changes on agriculture

Climate change impacts on agriculture is arguably the most affected of all sectors and it is widely envisaged that future agricultural productions will face multiple changes as a result of continued emissions of carbon dioxide and other greenhouse gases in the atmosphere (Ainsworth & Ort 2010; Meehl et al. 2005). This situation is set to increase annual global temperature which will in turn lead to changes in precipitation with adverse consequences for agriculture. Global temperatures may rise by ~4°C or more and the combined effect of this with a growing population will increase food demands and further add to the challenge of food security (Porter et al. 2014). Furthermore, rising temperatures and changing precipitation patterns will not only affect overall food production, it will also increase the inter-annual variability of crop yields. These sort of impacts are expected to be widespread, complex and vary from one region to another, and heavily influenced by socio-economic factors (Vermeulen et al. 2012) and are already being felt in important crop growing regions of the world (Porter et al. 2014; Lobell et al. 2009) experiencing more negative impacts than positive (Porter et al. 2014).

A review of climatic impacts on the agricultural sector has shown more negative effects than positive (IPCC 2014a) and the reason for this is because agriculture is inherently sensitive to climate: any change in climate will almost certainly affect plant growth positively or negatively. These effects are already detectable where, for instance, temperature changes have been shown to have an impact on the growing season (Menzel et al. 2006). This type of sensitivity is reflected where and when food prices increase following extreme weather events in food producing areas (Porter et al. 2014). Some regions in the world are already experiencing reduction in yields and this trend is predicted to increase price volatility for agricultural commodities and reduce quality. Current research suggests that decreases in yields will grow larger and will affect both temperate and tropical regions, and will become more erratic as the weather becomes more unpredictable (Porter et al. 2014).

In Europe, variations in precipitation events, some of which resulted in floods and inundation of agricultural farmlands in June 2013 caused significant negative impacts to crop yields. Losses of crop yield in financial terms were estimated to be around €5.8 billion (Schröter et al. 2013) in Germany, Austria, Czech Republic, Poland and Switzerland put together. More than 400 farms in Germany reported crop losses while 20% of vegetable crop were lost in Austria (Euractiv 2013). These historical events demonstrate the profound damage that can be caused by extreme events resulting from variations in precipitation.

The United Kingdom (UK) like other countries has her own fair share of climatic challenges with Central England Temperature (CET) rising by one degree Celsius since 1980 (Jenkins et al. 2008), while precipitation in England has shown high seasonal and annual variations making trends difficult to detect (Met Office 2014). According to the Met Office (2014), "the character of UK rainfall has changed with more frequent heavy rainfall events very likely. What might have been a 1 in 125 day precipitation event in the 60s and 70s are now likely to become 1 in 85 day event" (Met Office 2014). This sort of change had been identified in an earlier study by Fowler & Kilsby (2003). In their study, Fowler and Kilsby reported that precipitation intensities that were previously experienced "once in 25 years, now occurs at 6 year intervals"; a consequence of increased variation of precipitation events and seasonal changes. Climate change projections for the UK indicate that there will likely be wetter winters and drier summers (Jenkins et al. 2009; Met Office 2014). Consequently, dryer summers will impact on the growing season water supply for crop use and will potentially reduce soil moisture (Richter et al. 2006) and potentially affect yield.

In recent years, the highest profile agricultural losses occurred at the hands of extreme events resulting from variations in precipitation. For example, the UK has experienced a number of extreme precipitation events that have impacted the agricultural community. January and February 2014 in England saw precipitation totals of approximately 150 mm and 109 mm, respectively, which are well above the average precipitation values for these months (Met Office 2014). This resulted in around 49,000 ha of farmlands being flooded in a single event during February 2014 in Somerset and the Thames and Severn catchments (EFRA Committee 2014). The extent and duration of this flood resulted in more than 44,000 ha of farmland being underwater for more than one day and 40% of that area (17,800 ha) being flooded for 15 days causing significant damages to the farmlands and harvest ready crops, and loss of income to farmers (DEFRA 2014). Similarly, the May-July 2007 floods in the UK caused heavy damages to farmlands with 78 farms flooded causing a significant £50 million in agricultural losses (Chatterton et al. 2007).

According to Dorling (2014), changes and variations in weather conditions in recent years and expected future changes in precipitation coupled with the associated impacts on many agricultural systems when compared with long-term averages have presented UK farmers with some tough conditions revealing a pressing need to consider a range of adaptation strategies that will be beneficial to farmers now and in future growing seasons. In this study, how variations in precipitation impacts sugar beet yield was investigated. This is useful in order to understand the link between changes in precipitation and sugar beet yields in the near-to-medium term future (2021-2050). Furthermore, the method of assessment employed in this study is equally applicable to a wide range of agricultural crops grown over the summer season in a way that enables farmers to identify risks and opportunities associated with a changing climate, and also improve decision making with regards to future growing seasons.

In the light of the above, it is important to understand potential impacts of climate change for the different regions to enable the agricultural industries to prepare and adapt to the changes that are likely to occur. ,

1.5 Sugar beet production in the UK

Sugar Beet (*Beta vulgaris* L.) is a large pale brown root crop that is usually sown between March and April and harvested between September and February (British Sugar 2011). The tuber contains between 14-20% sugar (Rinaldi 2012) and accounts for about 60% of the total sugar consumed in the UK (British Sugar 2016). The crop is mainly grown under rain-fed conditions and it is an important agricultural crop in the UK: the sugar industry contributes significantly to the UK rural economy and supports up to 9,500 jobs in the wider economy and directly involves 7,000 businesses in the supply chain (British Sugar 2016). Approximately 3,500 farmers grow the crop, predominantly in Eastern England, on over 100,000 hectares of farmland (British Sugar 2016).

Sugar beet productivity in the UK increased between 1976 and 2004 (Jaggard et al. 2007). An examination of farmer delivered sugar yield was conducted by Jaggard et al. (2007) and they reported an annual increasing trend of 111 kg/ha for the period. Further, British Sugar (2011) reported an average increase of 11 tonnes of sugar beet per hectare (an approximate increase of 60% between 1981 and 2011). These increases are generally assumed to result from improved agronomy, better seed varieties and favourable weather, but these assumptions cannot be justified without taking the climate related changes and local weather patterns into consideration. According to the IPCC (2013a,b), "warming of the climate system is unequivocal" and has resulted in a lot of positive and negative impacts on agriculture. Therefore, it is important to factor climate and weather related variables into yield assessment analysis.

The most important economic aspects of sugar beet for farmers are the size of the root yield and its sugar content, which are influenced by a number of environmental factors, including weather patterns and soil conditions. Sugar beet farming in England is over 95% rain-fed with the use of irrigation being minimal (British Sugar 2011). Watering volume and timing is critically important to the successful growth of sugar beet plants, as indicated by Richter et al. (2006) who modelled the variability of UK sugar beet under climate change using a regional climate model. They found that water will be a major stress factor in the future and that relative soil moisture will be reduced under high greenhouse gas emissions scenarios.

A review of historical annual sugar beet yields with rainfall between 2000 and 2015 (See Figure 1.2) revealed stability in inter-annual yield between 2002 and 2006, however, 2007 to 2015 showed high variations in annual yield. The yields in the later years reflect how changes in precipitation impacted on annual yield of sugar beet in the UK. For example, years of drought (2010) and flood (2012) showed low sugar beet yield. 2011 had the second highest yield of 75.4 t/ha as a result of favourable weather conditions and yield declined again in 2012 (60.7 t/ha) as a result of the summer floods. Similarly, 2014 had the highest yield of 80.1 t/ha, a result of similar good conditions as in 2011 but declined in 2015 with 69 t/ha. It is important to note that low-yield variability give rise to stable income for farmers and stable food supply, which in turn help to prevent increase in food prices. Naturally, other factors (e.g. farming practices, temperature, sunlight, diseases etc) affect yield and the overall relationship with precipitation would not necessarily be linear as the influence, particularly losses as a result of flood or drought, will be localised but, nonetheless, the data raise some interesting questions.

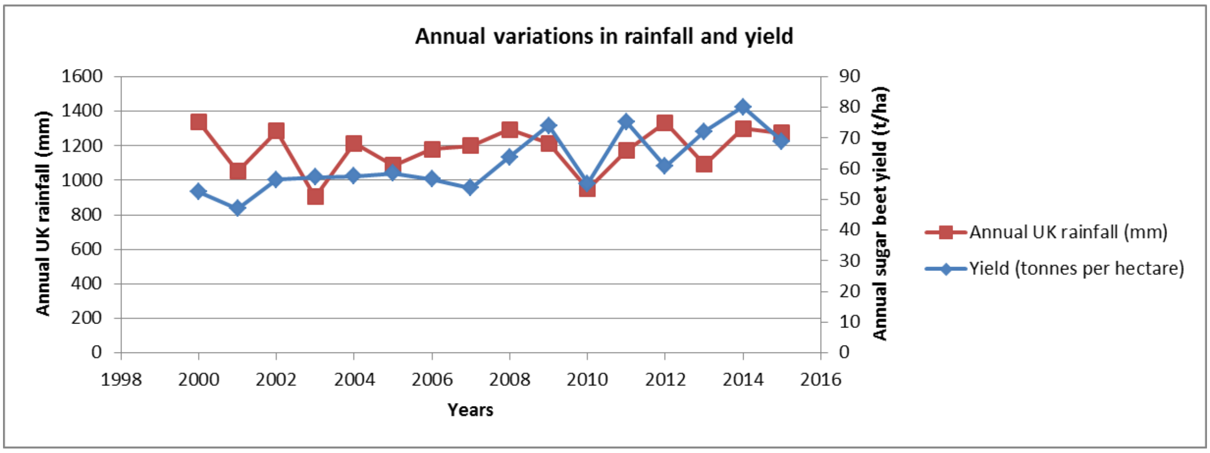


Figure 1. 2: Annual UK sugar beet yield and annual rainfall. Data: (DEFRA 2015; Met Office (n/d)).

In Europe, sugar beet yield is generally seen to decrease when stressed via low water conditions: Pidgeon et al. (2001) estimated potential sugar beet losses, calculated from climate and crop model projections due to water stress, vary between 15% and 30% for England. Given the nature of UK sugar beet production, past and present water limitations have most likely been driven by changes in precipitation patterns. Furthermore, many past studies have indicated that sugar beet is, more specifically, sensitive to water supply in terms of: leaf growth (Rytter 2005); storage root formation (Rytter 2005; Brown et al. 1987) and yield (Choluj et al. 2014; Richter et al. 2006; Kenter et al. 2006; Jones et al. 2003).

As sugar beet is economically significant in the UK and is sensitive to water supply, it was considered an ideal crop to investigate in the context of future changes in precipitation. The time frame for the study considered that most climate change impact assessment studies on agriculture and indeed, other sectors have focused on greenhouse gas emissions that could be either avoided or reduced by the end of the 21st century. However, this study considered the need to assess climatic impacts in the near-to-medium term future as a result of the unavoidable levels of greenhouse gas emissions already in the climate system. Furthermore, there are currently no sugar beet growing experiments in the literature that are informed by ensemble model projections – one of the aims of this study is to address this.

1.6 Aims and scope

The main aim of this study is to understand the impact of climatological precipitation changes in Eastern England on sugar beet yield. State-of-the-art CMIP5 climate model ensemble projections were used to inform greenhouse experiment in a novel way. In this thesis, the following results are presented and interpreted:

- An examination of precipitation data from weather station observations and climate model projections for Eastern England;
- A series of watering regimes, calculated from the precipitation observations and projections, which represent the climatological precipitation levels delivered to Eastern England over two seasons for the present day and future climate scenarios; and

- Measurements of sugar beet yields from a greenhouse experiment, where 150 sugar beet plants were grown in the first season and, 201 in the second season with the application of the calculated watering regimes.

Hypothesis:

- Changes in future Eastern England precipitation patterns will impact on sugar beet productivity
- Reduction in future Eastern England precipitation will reduce sugar beet yield by 2050.

The same hypothesis may be approached differently using the following research questions:

- What are the potential impacts that changes in precipitation patterns will have on sugar beet yield in Eastern England by 2050?
- How will the sugar beet plant respond to the changes in precipitation?
- What types of mitigation and/ or adaptation measures can be implemented?

Answering the research questions will contribute to understanding the potential risks and opportunities associated with changing precipitation patterns in the study area and how precipitation variations may impact on the crop investigated. This is useful in order to target research into the causal relations between yield and precipitation variability.

1.7 Conceptual model of the research study

The study employed a multi-level system approach to examine the issue of climate change and its impacts on agriculture. This is important because understanding the potential impacts of global environmental change on the sequence of interrelated and interlocking elements will help illustrate the important links and processes involved in climate change and changes in precipitation patterns which ultimately affect the farmlands that provide society with food. These links are depicted in the conceptual framework below (Figure 1.3). The shaded areas starting from the concentration of emissions in the atmosphere through to the implications for sugar beet yield shows the pathway that this current research investigated.

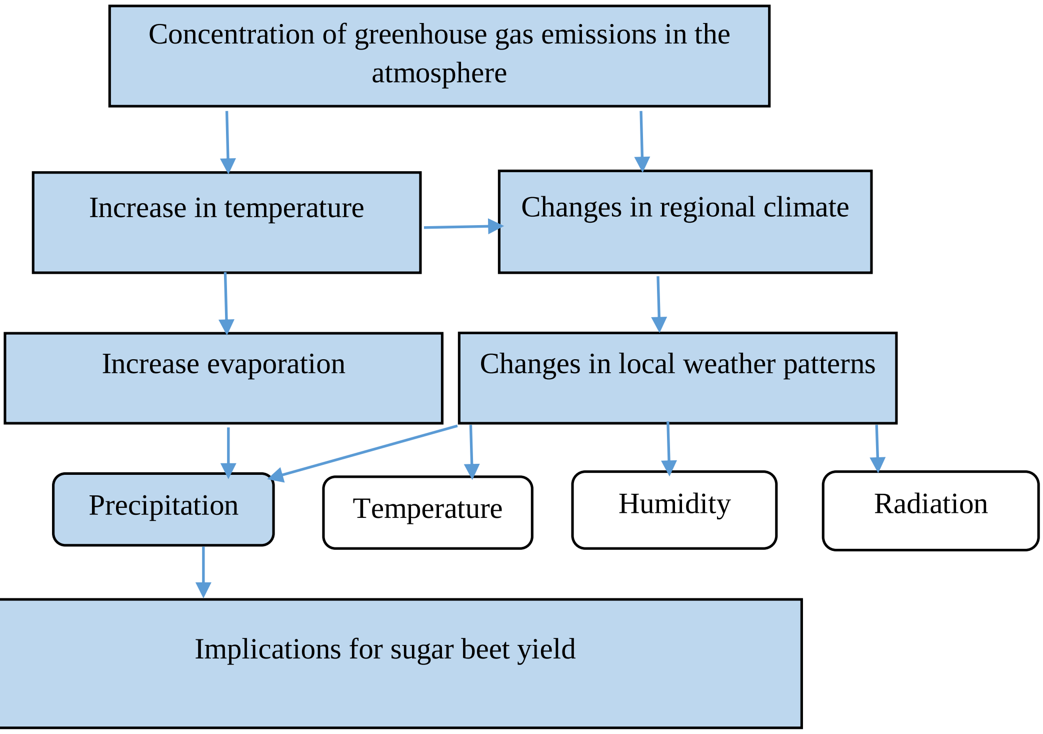


Figure 1. 3: A conceptual model of the study illustrating the pathways that was of particular interest in this thesis (i.e. factors that will ultimately show the impact of changes in precipitation on sugar beet yield.

1.8 Thesis outline

This thesis is organised into seven chapters and the introduction provides the basis on which the rest of the chapters were developed. **Chapter 2** reviews current literature to-date on a range of topics covered in this thesis, including precipitation changes using climate models for present and future climates, climate observations and the impact of precipitation changes on sugar beet yield. This study expatiated on the concepts established in the introduction and identified gaps and current challenges in this field which informed on the research objectives for this work. **Chapter 3** outlines and appraises the methods employed in this thesis and is divided into two Sections: the precipitation data and analysis, and the greenhouse experiment materials and methods used in this thesis. **Chapter 4** presents findings of changes in precipitation over Eastern England for two different time frames: 1971-2000 and 2021-2050, using daily precipitation data from eight CMIP5 climate models. **Chapter 5** extends the findings from the precipitation analysis and applied the changes to the watering regimes in the greenhouse experiment. This enabled the evaluation of how changes in climatological and more realistic watering patterns affected sugar beet yield. **Chapter 6** provides a synthesis of the findings in the study and discusses the implications for future yields. **Chapter 7** gives some conclusions and pointers in the direction of possible future work.

Chapter 2 – Literature review

2.1 Introduction

Climatic changes associated with the increasing concentration of greenhouse gas emissions in the atmosphere are expected to cause changes in mean climate conditions and more importantly, changes in the variability of climate. One of the consequences of this is the changes in precipitation characteristics and delivery which will have significant impacts on agriculture and agricultural systems. The resultant impact of these changes varies from region to region sometimes creating very challenging conditions for farmers worldwide. This highlights the need for research into this important area of food production and equally calls for timely and quality seasonal precipitation forecast that can enable farmers to plan ahead by implementing adaptation measures and reduce risks to crop production.

In the UK, reduction in future summer precipitation has been widely reported (Met Office 2014; UKCP9-Jenkins et al. 2008) but how variations in seasonal precipitation will affect crop yield and how yield will vary over time (See Section 1.5, Figure 1.2) has received far less attention (Osborne & Wheeler 2013). In the same vein, a large body of work on precipitation assessments in the UK have been heavily focused on extreme or intense precipitation. It is reasonable to assume that the focus on extreme events by most researchers has been as a result of recent extreme events mentioned in Section 1.4. This might have caused research to be less focused on longer-term, mean changes in UK precipitation with the exception of a few studies conducted over ten years ago, such as (Watterson & Dix 2003; Osborn & Hulme 2002; Osborn et al. 2000; Gregory et al. 1991; Wigley & Jones 1987).

The more recent works that focused on variations in UK precipitation are few and far between and included such studies as Met Office (2014); Maraun et al. (2008); UKCP09-Jenkins et al. (2008). Maraun et al. (2008) particularly identified changes in UK summer precipitation that are consistent with inter-decadal variations in precipitation. The work in this thesis reviews and addresses how seasonal changes in precipitation will affect sugar beet productivity in Eastern England by 2050 using the latest suite of CMIP5 climate model ensembles. The use of the CMIP5 models to inform a greenhouse crop experiment in this way has not been previously addressed in any of the literature.

In light of these studies, it is important to understand the likely impacts of future precipitation changes on sugar beet productivity in the UK. In order to do this, climate model results have been used to provide insight and make projections of likely precipitation changes now and in the future. This is important because the prudent use of quality precipitation forecasts has the potential to increase preparedness and resilience, reduce risks, optimize management practices and implement adaptation measures that can lead to desired economic and environmental outcomes for farmers and society at large. In this thesis, the following review of literature confirms the likelihood of a reduction in future UK summer precipitation and assesses how this reduction will impact on sugar beet productivity in Eastern England. The review present problems associated with precipitation variability and discuss specific solutions, and conclude by proposing that reduction in future precipitation will reduce sugar beet yield without adaptation strategies to safeguard tomorrow's agricultural productions.

Some of the issues introduced in Chapter 1 are further explored here (Section 2.2) with reference to existing literature so that gaps in the literature might be addressed. The Section delivers an overview of past and present precipitation across the UK and explores the physical theory, observational and model evidence of precipitation variability under a warmer climate from a global perspective. Furthermore, the influence of precipitation changes on hydrological cycles are discussed along with observed changes in precipitation variability. Section 2.3 addresses the issue of past and present precipitation variations and trends in UK while Section 2.4 reviews issues surrounding model simulation of precipitation events and methods of verifying model reliability of historical data from past and present precipitation data and comparing it against observed data. Previous studies on model evaluation are reviewed and impact of changes in precipitation on hydrological processes is also considered. Section 2.5 addresses the impacts of precipitation change on agriculture, food security and sugar beet yield in Eastern England. Finally, Section 2.6 summarises the review, identifies research gaps and present the research objectives in furtherance of the research aims in Chapter 1.6.

2.2 Climate change impacts and precipitation variability

2.2.1 Influence of global warming on precipitation variability

Climate change and variability have long been recognised as one of the biggest threats facing societies today and the risks are becoming more visible through the changes in climatic variables such as precipitation and temperature (IPCC 2014a). Precipitation is an important climate variable whose changes in nature, frequency, intensity and coverage has had a significant impact on agricultural production and society at large. The causes of this variation include orographic influences such as the high mountains in western parts of England and Scotland (Met Office 2016) (discussed in detail in Section 1.2) and large water bodies. The impacts of these variations vary from one region to another, and the possible consequences of these variations on crop yields have generated global concern (Gornall et al. 2010; Fischer et al. 2005). As described in Section one, variations in precipitation such as an increase in mean precipitation could lead to the risk of floods whilst a mean decrease in precipitation could lead to the risk of drought has been reported to intensify hydrological cycles (Fischer & Knutti 2016).

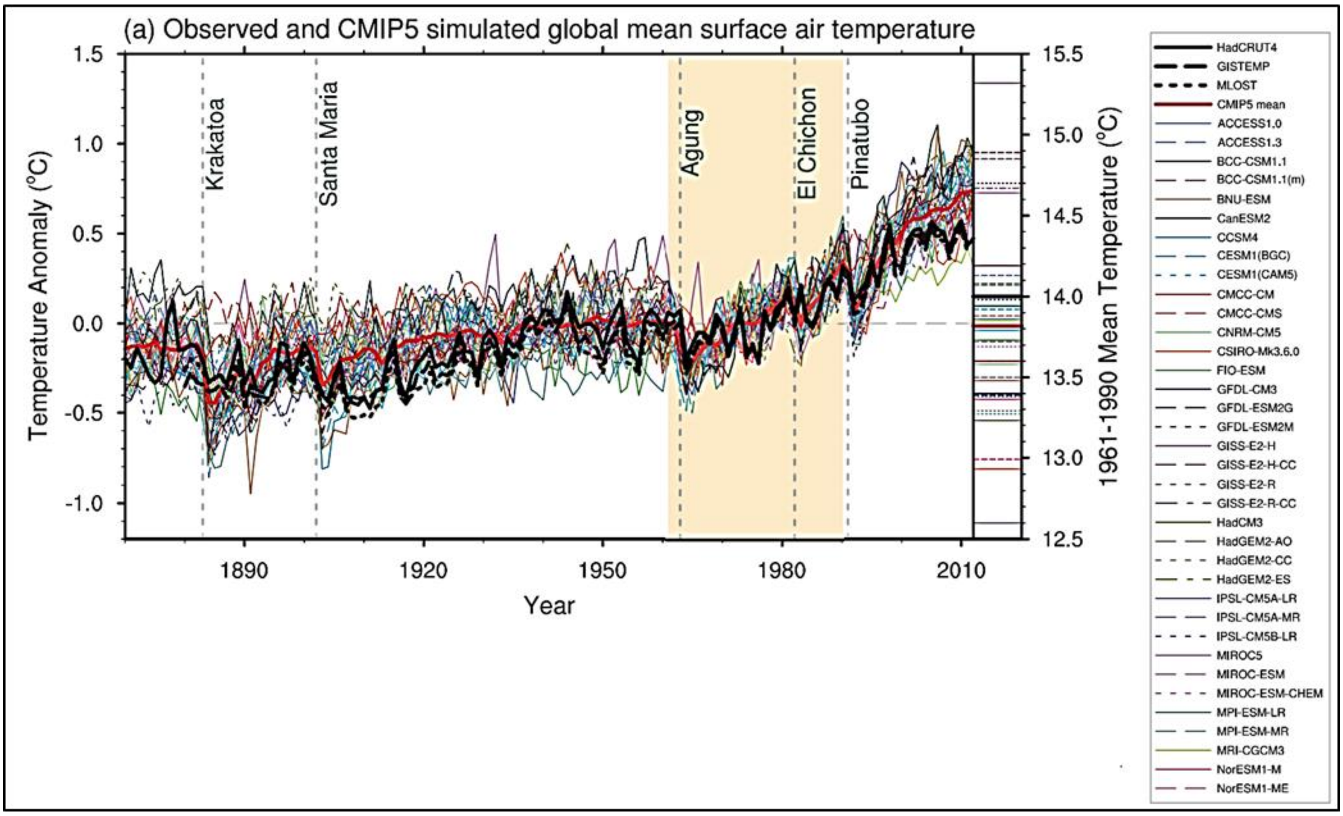
This problem has been at the fore-front of public debate as far back as Pre-1990, when the First Assessment Report (FAR) of the Inter-Governmental Panel on Climate Change (IPCC) was released stating that anthropogenic activities are substantially increasing greenhouse gases in the atmosphere resulting in greenhouse effect and warming of the Earth's surface (Houghton et al. 1990). In the 1990's, with reference to the FAR, the processes were partially understood and required more research to reduce the uncertainties:

- By better understanding of climate related processes particularly clouds and the carbon cycle
- In order to develop improved models of the Earth's climate system and
- Facilitate international exchange of climate data

The call to action was heeded by researchers worldwide who began to investigate the impacts of climate change on our world. Successive IPCC reports have come to the conclusion that global temperatures are rising and are likely due to the increasing concentration of greenhouse gases in the atmosphere with the Fifth Assessment Report (AR5) concluding that "there is now a widespread scientific consensus that the global climate is changing and that human activities are responsible" and, in fact, IPCC (2013a) and IPCC (2007) concludes that this change is unequivocal.

The changes associated with increasing greenhouse gas emissions in the atmosphere continue to increase and chief among them is carbon dioxide with 76% of the total emissions in 2010 (IPCC 2014a). These emissions have increased from 27 (± 3.2) to 49 (± 4.5) $GtCO_2$ eq/yr between 1970 and 2010 (IPCC 2014a). This according to the IPCC (2014a) has increased in every part of the world with varying degree of impacts. In Asia, greenhouse gas emissions rose by 33% in 2010, Middle East and Africa by 70%, Latin America by 57% and the Organisation for Economic Co-operation and Development (OECD) countries by 22%. These gases are long-lived in the atmosphere as a result of their chemical stability which enables them to persist in the atmosphere for a long time. In the last three decades, the Earth's surface has been successively warmer than any other decade since 1850 (IPCC 2013b). Globally, land and ocean surface temperatures have risen by 0.85 [0.65 to 1.06] ºC over the past 132 years (1880 to 2012) (IPCC 2013b).

Figure 2.1 shows increasing trend in annual mean temperature since 1980 based on simulation of observed and CMIP5 multi model mean surface temperature. The CMIP5 multi model mean showed good agreement with observations better than the individual CMIP5 models. There are however, much larger variations in the observations than the simulated multi model mean which could be explained by models tendency to simulate stronger warming in response to increasing greenhouse gas emissions in the atmosphere (IPCC 2014c; IPCC 2013b). These increases, using Carbon dioxide (CO_2) for example, contains 2 C-O bonds which are capable of absorbing infrared radiation and by so doing causes surface temperature to increase. This in turn causes changes in evaporation leading to changes in precipitation patterns and it is the reason why there are droughts in some areas and flooding or other types of extreme event such as landslide, heatwave and wildfires in others as reported in the IPCC (2013b) and successive IPCC reports.



2. 1: Observed, individual models and CMIP5 model simulated time series of the anomalies and global mean surface temperature from 1961-1990 reference period. The reference period 1961-1990 is indicated by the yellow shading, vertical dash grey lines represent major volcanic eruptions, the single CMIP5 models are represented by thin lines and the multi model mean are represented by the thick red line. The different observations are in thick black lines. Source: (IPCC 2014a; IPCC 2013b).

The impacts associated with climate change and variability have been observed to affect hydrological systems in all continents (Cramer et al. 2014). Fischer & Knutti (2016) further this position in their review of recently observed precipitation. Their report shows that hydrological intensification is beginning to emerge across many regions in the world confirming theory and early model predictions. However, this trend is not just emerging because studies such as Wang (2005) had already reported impacts on water processes. Wang, as far back as 2005 used 15 Global Climate Models (GCM's) to examine the impact of warming on soil moisture. The models were consistent with warming impact on hydrological processes and predicted that summers are getting drier and winters are getting wetter in the mid and high latitudes, and in Central Europe and Asia, about half of the models predicted wetness, and all-year-round dryness in Siberia. Findings from the study indicated high variations in precipitation in different regions with a suggestion of worldwide drought as a result of greenhouse gas warming. In another study, Bates et al. (2008) reported that changes in hydrological cycle observed over several decades are linked to global warming and are the result of changes in precipitation patterns. This, according to the authors is because climate change is inherently associated with all aspects of the hydrological cycle in a way that changes in the cycle affects available water resources through changing precipitation patterns, changes in evapotranspiration, changes in soil moisture and runoff.

A number of other studies have reported that global warming may cause intensification of hydrological processes via increases in magnitude and frequency of precipitation events (Trenberth 2011; Williams et al. 2007). These sort of changes may impact on water resources either through floods or droughts, changes in the frequency of dry and wet events. Trenberth et al. (2007) contend that an increase in cloud cover and water vapour over the last four decades has increased the intensity of precipitation events. Furthermore, in the most current IPCC report to date (IPCC 2014a), it is projected that variations in precipitation may lead to increased episodes of extreme floods and droughts with significant impacts not only on agriculture but also on water resources, ecosystems and infrastructure (Cramer et al. 2014). Gu et al. (2007) examined changes in global and tropical rainfall using Global Precipitation Climatology Project (GPCP) data. Their report showed large variations in rainfall patterns over land which was compensated for by changes over the ocean.

These international findings have been replicated in the UK showing the global nature of this problem. For the UK, the signals tend to be drier summers and wetter winters (Jenkins et al. 2009) and it is reviewed in details in Section 2.3.2.

2.3 Past and present climatic changes across the UK

2.3.1 Variations and trends in UK precipitation

Changes in precipitation characteristics across the UK suggest that precipitation variability will continue to occur under a warmer climate with consequent changes for hydrological processes resulting in floods, droughts, and landslides, amongst others. Assessing changes in precipitation is made more complex because precipitation is such a highly discontinuous variable occurring only during wet events which are non-uniform in intensity, duration and frequency but at the same time, a very important factor in regional climate analysis.

The Met Office (2014) reported that there is no discernible trend in annual UK precipitation but reported large annual variability and provided evidence suggesting that the character of UK precipitation has changed. The Met Office claimed that "five out of the last seven summers have been wetter than average, but prior to that, there was a run of drier than average summers". The same result was reported by UKCP09 which indicated that annual mean precipitation over England and Wales has showed no significant changes since 1766 but the seasonal precipitation has shown large year-to-year variations (Jenkins et al. 2008). The records also showed an increase in winter precipitation and a decrease in the summer. Imagine these impacts being felt after only 0.8ºC warming (UKCP09-Jenkins et al. 2008) and with projections of future warming and changes to the climate system (IPCC 2013b), it highlights the importance of investigating the potential consequences of further warming.

A historical look at past studies on UK precipitation indicates a reduction in summer precipitation. For example, Wigley & Jones (1987) used a simple correlation analyses to examine time series data from five regions in England and Wales and reported an increase in the frequency of extreme wet springs and dry summers. Gregory et al. (1991) expanded on the work of Wigley & Jones (1987) by increasing the number of examined regions to include Scotland and Northern Ireland. Each of the regions were divided into seven sites and daily and monthly time series data were investigated for correlation among the sites in the different regions for the period 1931-1989. Their results indicated no long-term trends in annual precipitation but showed a reduction in summer precipitation. Findings from both studies for the annual and seasonal mean precipitation showed that south-west England and south-west Wales had the highest precipitation in the UK, with an annual precipitation of 2.83 mm/day from 1931-1989. The north-west of England and north-west Wales was reported to have the second largest precipitation of 2.76 mm/day while the central and eastern parts of the UK was reported to have the driest conditions with precipitation amounts of 1.77 mm/day. Results presented here provide further synopsis of the large variations between the precipitation amounts in the different regions of the UK.

Other studies such as Osborn et al. (2000) analysed precipitation data from 110 UK stations during the period 1961-1995 and found a decline in light and medium precipitation events and an increase in heavy events during the winter. Conversely, their results also revealed a decline in summer precipitation. Similarly, Osborn & Hulme (2002) reported that UK daily precipitation has changed over the period 1961-2000 with average rainfall becoming more intense in the winter than the summer period. In other studies conducted using gamma distribution, (e.g. Watterson & Dix 2003), simulated precipitation distribution showed consistency with events of heavy rainfall during the winter. Beyond that, non-parametric analysis was further conducted and it confirmed the contribution of heavy rainfall events to total winter rainfall amount. Summer rainfall on the other hand, indicated a decrease.

Results from more recent studies on precipitation variability in the UK (e.g. Kendon et al. 2015; Met Office 2014; Kosanic et al. 2014; Prudhomme et al. 2012; Maraun et al. 2008; Jenkins et al. 2008), have shown consistency with past studies described above. Maraun et al. (2008) examined the trends in the contribution of heavy precipitation events to UK precipitation. The authors employed the use of 689 rain gauges covering almost all of the UK. They found out that there was a widespread shifts towards heavy precipitation events in the winter and also detected the existence of a long-term increase in precipitation intensity in the winter and to a lesser extent in the spring and autumn. In contrast, the study reported much lighter and moderate precipitation events in the summer. The summer precipitation on the other hand, showed more consistency with inter-decadal variability. Prudhomme et al. (2012) used the Met Office HadRM3 climate model to assess changes in UK River flows in the 2050s. Their results showed that River flows may either increase or decrease in the winter but decreased in the summer. These studies (past and present) suggest that summer decrease in precipitation tends to be largely driven by variation in precipitation and reduced wet-days amount, and fewer wet days or rainfall events.

UKCP09-Jenkins et al. (2008) also reported high seasonal variations in UK precipitation for the winter (December, January and February) and summer (June, July and August). For example, the winter precipitation totals varied between 88.9 mm in 1964 and 423 mm in 1915. Likewise, summer precipitation totals varied between 66.9 mm in 1964 and 49.7 mm in 1912. In spite of these variabilities and the lack of discernible trend in annual mean precipitation, a general trend towards reduced summer precipitation was observed. It's worthy of note that some of the studies cited here are more than 10 years old but their results are still relevant with regards to UK precipitation trend and it clearly shows a trail of reduced summer precipitation from past decades compared to future scenarios. The reduction in UK summer precipitation is acknowledged and supported by recent model simulations (Met Office 2014; IPCC 2013b; UKCP09-Jenkins et al. 2008) and is further discussed in Section 2.4.

2.3.2 Variations and trends in UK temperature

Given the theoretical basis described in Section 2.2.1, it will be logical to expect that observed precipitation records will show evidence of changes related to warming that has already occurred in the UK. Like other countries, the UK is not immune to the impacts of climate change and has experienced rising temperatures, sea level rise and increasing episodes of extreme events such as floods, droughts and heat waves to mention but a few. These types of impacts have already been explored in past and recent studies (Cramer et al. 2014; Huntington 2006) which shows that higher temperatures affect hydrological cycles through changes in precipitation patterns.

Climate records in the UK show that Central England Temperature (CET) has risen by 1°C since 1970 with 2006 being the warmest year on record (CCRA 2016; UKCP09-Jenkins et al. 2008). The UK Climate Change Risk Assessment predicted an average temperature increase of 0.9°C for 2005-2014 compared to 1961-1990 with 2014 being the warmest year (CCRA 2016). In an earlier but similar report, Karoly & Stott (2006) using coupled-ocean atmosphere model simulation also reported an increase of 1°C in annual mean CET since 1950. They contend that the increase could not be explained by natural climate factors alone and concluded that greenhouse gas emissions in the atmosphere played a role in it. Similarly, Sexton et al. (2004) indicated that comparisons between observed changes and atmospheric climate models show that long-term warming of the CET cannot be explained by natural variations alone; they contend that anthropogenic greenhouse gases might have a significant influence on the CET.

In another study using individual stations across the UK, Croxton et al. (2006) reported highly correlated temperature values from the stations with the CET making it applicable beyond central England. According to the United Kingdom Climate Projections (UKCP09), UK temperature trend has risen faster in comparison to the global average of land surface temperature. Kendon et al. (2016) reported an average warming of 0.3°C in 2006-2015 compared to 1980-2010 and 0.9°C warmer than 1961-1990. Furthermore, Kendon et al. (2016) in their study explained that the top 10 warmest years in the UK temperature series have occurred since 1990 with 8 of those occurring since 2002. The highest changes occurred in the spring and autumn with 2006-2015 being 1.0°C above 1961-1990, and the smallest change occurring in the winter with 2006-2015 being 0.6°C above 1961-1990.

2.4 Models simulations of past and projected precipitations changes

2.4.1 Introduction

Climate models are mathematical simulations of the climate system and provide the main basis for forecasting changes in future precipitation under different greenhouse gas emission scenarios. These simulations produce powerful representations of the Earth's physical processes but the full complexities of the real world cannot be fully represented in any single model. This is due to internal and external variabilities in the climate system, some of which are processes acting on a much smaller scale than the models (Pincus et al. 2008). Much research has been conducted into forecasting the potential impacts of future climatic changes on the environment with considerable success however, much uncertainty exist in the process given that future emission scenarios and societal development are unknown. According to the IPCC (2013b), weather and seasonal climate predictions can be easily verified whereas climate projections spanning a century or more cannot be verified and will always be a limitation. In spite of this limitation, climate models have proved very useful in terms of skills and performance in projecting future climates. One major approach is to evaluate model performance relative to past observations and taking into account natural variability.

Therefore, to have confidence in models ability in the projections of future climates, such models must have simulated the observed climate, its variability and changes reasonably well (IPCC 2013b). The truth is, models perform differently for different regions and some models perform better than others for some variables (McSweeney et al. 2014). This implies that no individual model is better than the others. In this Section, the study reviews earliest climate model predictions, and then, considers the contributions of past and recent model projections with respect to UK summer precipitation in particular.

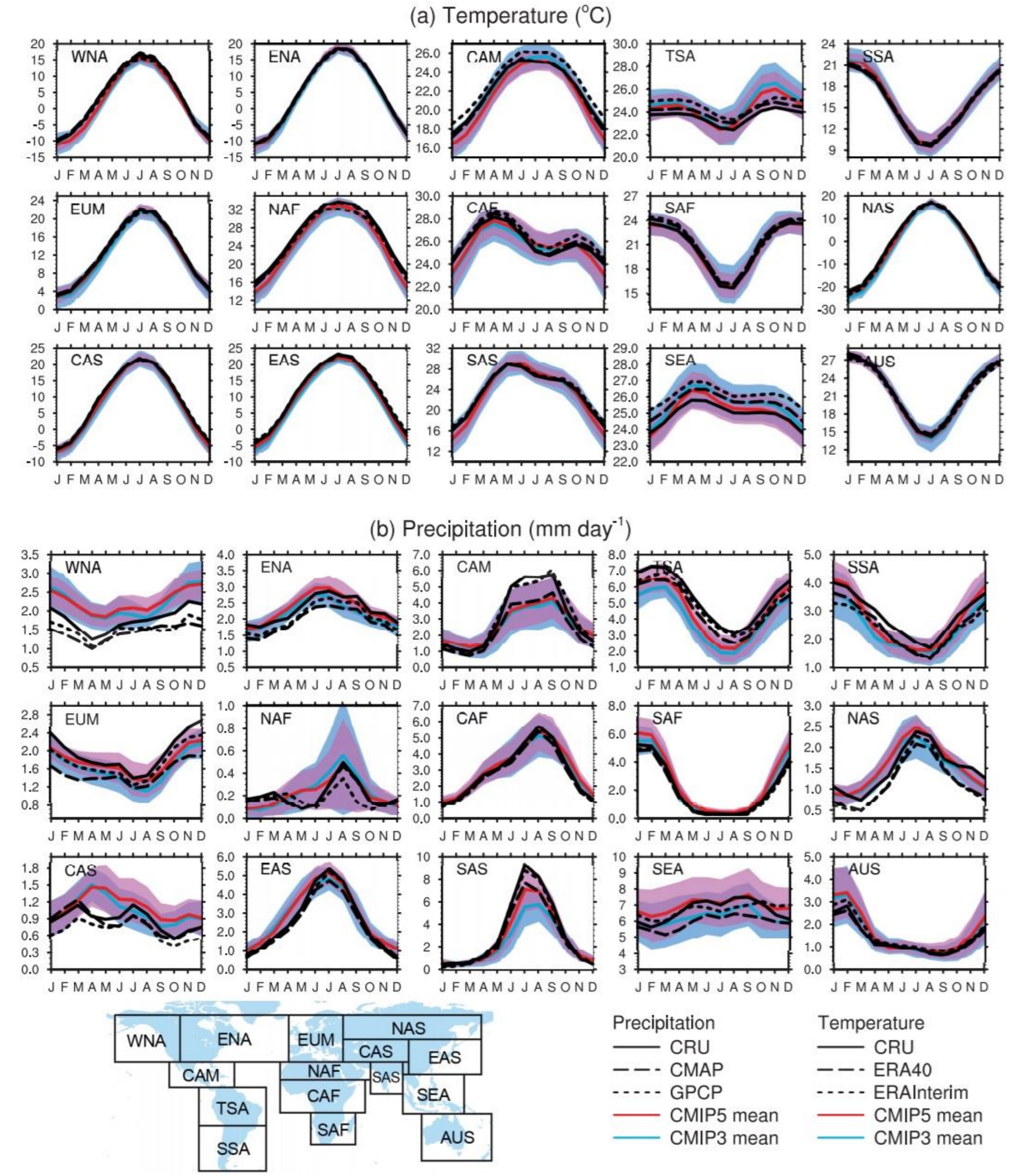
2.4.2 Model simulation of observed changes in the climate system

Atmospheric models have provided significant successes in predicting daily-to-weekly weather because such forecasts are easily verifiable against local events for accuracy and reliability, whereas this approach is not applicable to climate projections because the course of future emissions is unknown. One of the earliest use of climate models in the 70s was by Broecker (1975) to simulate increasing levels of future Carbon Dioxide (CO_2) emissions in the atmosphere. Broecker used simple climate models to effectively model expected increases in future CO_2 resulting from the burning of fossil fuels. Broecker predicted that CO_2 would rise to 373 ppm (Parts Per Million) in 2000 and 403 ppm in 2010. This prediction was closely matched with actual values in later years with CO_2 recorded at 369 ppm in 2000 and 390 ppm in 2010. Hansen et al. (1981) in a subsequent experiment simulated global temperatures in the 80s and reported a rise in temperature of 0.2ºC between 1960 and 1980 consequently causing a warming of 0.4ºC in the past century. These increases according to Siegenthaler & Oeschger (1978) were consistent with increases of atmospheric CO_2 associated with burning of fossil fuels.

Since that time, climate model forecast have improved significantly and consistently from the time of the First Assessment Report (FAR) to the Fifth Assessment Report (AR5). After the Fourth Assessment Report (AR4), there has been further improvement in the new climate models, incorporating the Earth System model and additional physics. So, past and present climate models have been used to reproduce observed features of past and recent climates (IPCC 2013b). They have also been used to produce credible quantitative estimates of future climate change on global and regional scales. However, the predictive power of climate models is much higher for temperature than precipitation (IPCC 2013b).

Co-ordinated international collaboration has been used to facilitate, collect and disseminate outputs from model experiments under the same conditions thereby encouraging a comprehensive and open evaluation of models. This diverse effort has helped to reduce the potential of errors being overlooked and led to massive improvement in models with the advent of the Earth System Models (ESM) which include different aspects of biogeochemical elements of the climate system. ESMs have helped reduced uncertainty associated with models and the use of multi-model ensemble mean provides weighted averages arising from individual model runs by predicting the distribution of possible outcomes. This helps to reduce errors arising from the use of a single model (See Section 3.4). Figure 2.2 from IPCC (2013b) provides evidence of agreement from different models in simulating temperature and precipitation. Although, model results are more reliable for temperature than precipitation, it nonetheless shows high-quality representation of the observed climate variables.

Moreover, the performance of climate models under similar anthropogenic scenarios produces agreement on some aspects of the climate and disagrees on others. This topic has been the focal point of some studies in the past (e.g. Harvey 2004; Covey et al. 2003; Räisänen 2001; Kittel et al. 1997). In a recent study, McSweeney et al. (2014) used downscaling technique for selecting CMIP5 GCMs over multiple regions and found that different models perform differently in different regions. This enabled selection of the best performing models to be used for the analysis and a similar approach has been adopted in this study. This Section of the thesis reviews climate model simulations of precipitation (i.e. model skill in simulating past and present day precipitation), models simulations of projected changes in precipitation, reliability of climate models, uncertainties in model simulation and CMIP5 climate model ensemble means.



2. 2: Mean seasonal cycle of (a) temperature (°C) and (b) precipitation (mm day–1). "The average is taken over land areas within the indicated regions, and over the period 1980–1999. The red line is the average over 45 CMIP5 models; the blue line is the average over 22 CMIP3 models. The standard deviation of the respective data set is indicated with shading. The different line styles in black refer to observational and reanalysis data: Climatic Research Unit (CRU) TS3.10, ECMWF 40-year reanalysis (ERA40) and ERA-Interim for temperature; CRU TS3.10.1, Global Precipitation Climatology Project (GPCP), and CPC Merged Analysis of Precipitation (CMAP) for precipitation. Note the different axis-ranges for some of the sub-plots. The 15 regions shown are: Western North America (WNA), Eastern North America (ENA), Central America (CAM), Tropical South America (TSA), Southern South America (SSA), Europe and Mediterranean (EUM), North Africa (NAF), Central Africa (CAF), South Africa (SAF), North Asia (NAS), Central Asia (CAS), East Asia (EAS), South Asia (SAS), Southeast Asia (SEA) and Australia (AUS)". Source: (IPCC, 2013).

2.4.3 Climate model simulation of climate and precipitation variability

The issue of variations in the climate system have already been presented in Section 1.2 and is further expanded in this Section in the form of fluctuations which are directly influenced by two factors: natural climate variability and anthropogenic climate change (Deser et al. 2014). Studies such as Meehl et al. (2013); Santer et al. (2011) contend that climatic changes resulting from anthropogenic activities are now likely to dominate over natural variability for time periods as long as a decade. IPCC (2013b) addressed the issue of models simulating climate variability, both external and unforced internal variability. The IPCC report predicts that climate change will be felt more profoundly in terms frequency, intensity or duration of precipitation and extreme events (e.g., floods, droughts, heatwaves, etc).

Changes in precipitation and extreme events in all their different forms are a consequence of climatic and weather variability (IPCC 2013b) and therefore, the ability of models to simulate variability in climate is of great importance for simulating future impacts (Turner & Annamalai 2012; Colman et al. 2011). IPCC (2013b) provided evidence of simulating interannual-to-interdecadal variability including natural and anthropogenic forcing. The analysis revealed important differences between forced and unforced simulations of observed data in different time scales (Fernández-Donado et al. 2013). Their results suggest that models can reproduce variability on a wide range of time scales, although better for temperature than precipitation IPCC (2013b).

Review of literature so far point to precipitation as one variable expected to be affected by changes in climate. Model simulation of precipitation is quite challenging because precipitation is such a highly discontinuous variable occurring only during wet events which are non-uniform in intensity, duration and frequency. However, the use of climate models form the basis of our understanding for evaluating observed precipitation and projecting changes in future precipitation under different greenhouse gas emissions scenarios. Presently, key processes behind precipitation generation are fraught with uncertainties emanating from their vast complexities, including topographic influences, clouds and radiation (Pincus et al. 2008). Studies conducted to examine uncertainty in model simulation of the climate system generally agree that the magnitude and direction of potential changes in future climate system is unclear (Fowler &

Ekström 2009; Bates et al. 2008).

Furthermore, climate model simulation of precipitation is hindered by poor representation of atmospheric processes including convection, cloud microphysics, boundary layer processes and mesoscale atmospheric circulation (van Weverberg et al. 2013; Dai 2006). Models tend to underestimate heavy precipitation events and overestimate small or moderate events. According to Emori & Brown (2005), models also overestimate the contribution arising from synoptic precipitation compared to convective precipitation. Prudhomme et al. (2002) in their study showed that models have demonstrated good skills in reproducing large-scale patterns but the temporal and spatial characteristics of precipitation are still fraught with uncertainties as a result of different synoptic regimes.

Tebaldi et al. (2006) used an ensemble of 9 GCMs to simulate historical and future climates under different emissions scenarios. Their results showed that the historical simulations generally showed trends that agreed with previous observational studies thereby giving credence to the reliability of GCMs in reproducing observed climates. Model projections for the 21st century under the different scenarios showed greater temperature extremes, and increases in the frequency and intensity of precipitation events consistent with a warming climate. Meehl et al. (2007) and Trenberth et al. (2007) in their different studies came to the same conclusion that under future global warming caused by anthropogenic greenhouse gas emissions, there will be an increase in precipitation variability and the occurrence of extreme precipitation events, even in regions where mean precipitation is expected to decline (Trenberth 2011; Fowler & Ekström 2009; Frei et al. 2006).

Multiple lines of evidence from model simulations has emerged to support the physical theory that variations in precipitation will increase under a warmer climate in spite of uncertainties associated with model projections. Climate models have consistently produced accurately verifiable results (Meehl et al. 2007). For example, the high latitudes in the northern hemisphere are currently experiencing a trend towards increased precipitation and variability projected from models simulations (Trenberth et al. 2007; Alexander et al. 2006). The ability of models to reproduce observed climates and make valuable and quality projections of future climates lends support to the use of climate models in this study.

2.4.4 Climate model evaluation of projected precipitation

Climate model simulations of future precipitation under enhanced greenhouse gas emissions are broadly consistent with global increases in precipitation due to increases in precipitation event intensity (Barnett et al. 2006; Tebaldi et al. 2006). This is supported by evidence in observational data for many regions of the world which have shown greater precipitation intensity and variability. Past and current studies on climate change showed that increasing concentration of greenhouse gas emissions into the atmosphere have the potential to cause substantial changes to the climate system (IPCC 2013a; Trenberth 2011; Tebaldi et al. 2006; Houghton et al. 2001) and hydrological cycles (Garner et al. 2017). Changes in future precipitation simulated from climate model have consistently indicated an increase in global mean precipitation under increased concentrations of atmospheric greenhouse gas emissions over the 21st century (Yonetani & Gordon 2001).

According to the IPCC (2013b), model projections showed a general increase in global mean precipitation in the tropical regions and high latitudes, particularly in areas that are already showing an increase in precipitation, but show a general decrease in the arid and sub-tropical regions. The report further indicated that precipitation increase in high latitudes over the winter and summer seasons are consistent across models with widespread decreases in mid-latitude summer precipitation with the exception of Eastern Asia which indicated an increase. Several other studies such as Emori & Brown (2005) noted that although, global mean precipitation will increase, the increase will not be uniformly distributed across the globe and as a result, some regions will experience substantial increase in precipitation while others will experience drying. Pall et al. (2007) reported near-uniform increases in precipitation events at high latitudes but a strong bias of increases at low latitudes.

A number of other studies used a multi-model approach to assess the likely future changes in precipitation. Emori & Brown (2005) reported that models indicated heavy convective precipitation in low latitudes and that the intensity of heavy precipitation events will become greater in magnitude and spatial coherence. Kharin & Zwiers (2000) used the Canadian Coupled Global Climate Model (CCGCM) and reported global increases in heavy precipitation of about 8% by 2040-2060 and 14% by 2080-2100 in comparison to increases of 1% and 4% in annual mean precipitation. Emori & Brown (2005) reported findings of 6% in global mean precipitation and 13% changes in extreme precipitation between 1981-2000 and 2081-2100 simulated from 6 climate model ensemble. Irrespective of the timeframes under consideration, these studies showed a general increase in total and mean global precipitation under future scenarios.

Different approaches have been used to gain better understanding of the processes involved in climate modelling of projected precipitation. Gleckler et al. (2008) initiated several metrics into performance analysis of climate models and emphasized the need to look further than the mean statistics for a comprehensive analysis of climate model performance. Dai (2006) evaluated mean spatial precipitation, frequency and intensity of precipitation and found that model simulations of precipitation were unrealistic although, most models captured the general precipitation pattern. The result of Dai's study is not unusual as models are known to simulate precipitation poorly. Trenberth (2011) reports that models projection have provided more robust findings in the simulation of temperature than precipitation. Similarly, Brown et al. (2010) reported findings that synoptic regimes are well described in models but the uncertainties in precipitation simulations arise due to problems in the nature of precipitation in the different synoptic regimes (e.g., frequency, intensity, duration). Catto et al. (2013) evaluated frontal and non-frontal precipitation using ACCESS 1.0 atmospheric model to understand the role of fronts in precipitation. They reported that the frequency of frontal precipitation was well captured but the intensity of frontal precipitation was underestimated by the model.

More recent studies such as Lebsock et al. (2013) have reported biases in precipitation simulations arising from warm clouds that are not associated with parameterisation. Wehner et al. (2010) investigated the ability of GCMs to reproduce observed daily precipitation totals in the United States for a 20-year period. They reported that many of the models underestimated the return values and suggested that increasing the horizontal resolution could improve the estimates. Different studies have offered different explanations for the causes and/or sources of uncertainty in model simulation of precipitation. Tebaldi et al. (2011) explained that the criteria used to determine the agreement level between different models have often ignored internal variability in the process. They used a multi-model approach to separate the lack of climate signal from model agreement by evaluating the level of agreement on the significance of change. Their result showed that disagreement among models in precipitation projections is due to noise from climate variability masking the signal.

In continental Europe, models suggest that there may be more intense precipitation in many parts of Europe (Giorgi et al. 2004). A multi-model analysis used to construct precipitation trends over the 21st century reported a decrease in precipitation to the south over Spain. The signal over Europe and indeed, other parts of the world showed some individual and seasonal weather patterns but these sorts of isolated or even infrequent events cannot be used as a sign of climate trend. Studies by Pal et al. (2004) reported that projections of increased frequency of floods and droughts over Europe are remarkably consistent with projections of climate change scenarios. Timbal et al. (1995) examined the effect of double CO_2 on precipitation using the Meteo-France atmospheric GCM and their results indicate a 6% increase in winter precipitation over Northern Europe. In past and present studies, globally and in continental Europe, models have been consistent in their projection of changes in future precipitation.

Overall, models have exhibited considerable skill in reproducing characteristics of observed precipitation and providing reliable estimates of predicted future precipitation that have come to pass. However, there remain areas where uncertainties exist and efforts to overcome this problem have led to improvement in models starting with the advent of the Coupled Model Intercomparison Project Phase 3 (CMIP3). The CMIP3 made evaluation of the atmospheric and oceans simulations better to understand. Prior to CMIP3, studies conducted before the introduction of various Model Intercomparison Projects (MIPs) had simulated climate using individual models. However, with advancement and improvement in climate models, the use of such MIPs as the Atmospheric Model Intercomparison Project (AMIP) (Gates et al. 1999) and Coupled Model Intercomparison Projects (CMIP) (Covey et al. 2003; Meehl et al. 2000a) have made it easier to compare models for differences and similarities. According to (Raisanen 2007), MIPs have enabled modellers to easily identify errors specific to individual models and make adjustments to areas that need attention. Several other studies have examined different aspects of precipitation using CMIP3 models. For example, Phillips & Gleckler (2006) in their study of seasonal mean continental precipitation used CMIP3 models to evaluate precipitation amounts and reported that many of the models differed from several observed estimates. The study also found that the ensemble mean precipitation was closer to that of the observed data than any individual model.

Further improvements to climate models continued with the introduction of the Couple Model Intercomparison Project Phase 5 (CMIP5) climate model. The current CMIP5 climate models were incorporated with an unprecedented suite of biogeochemical factors designed to simulate historical and future climate scenarios (Taylor et al. 2012). The ensemble mean precipitation of the CMIP5 models according to Kumar et al. (2013) matched that of ground based observation data but substantial biases exists in regional trend. A good number of other studies such as Chadwick et al. (2013); Hao et al. (2013); Kelley et al. (2012) have evaluated past and projected changes in precipitation using CMIP5 simulations at both regional and global levels with considerable success. A comparison study between CMIP5 and CMIP3 ensemble mean for reproducibility of observed precipitation distribution showed that the CMIP5 ensemble revealed a bit more skill than the CMIP3 ensemble (Hirota & Takayabu 2013). Using CMIP5 simulations Gaetani & Mohino (2013) studied decadal precipitation over the Sahel and reported that the predictive skills of the CMIP5 simulations vary significantly from model to model consistent with the findings of McSweeney et al. (2014).

The various studies relating to the CMIP5 in this Section have demonstrated that the CMIP5 showed remarkable skills in the projections of future precipitation. The CMIP5 climate model ensemble is used to explore uncertainties arising from internal variability, boundary conditions and parameter values in individual model structure (McSweeney et al. 2014; Gaetani & Mohino 2013; Kumar et al. 2013; Chadwick et al. 2013; Hao et al. 2013; Kelley et al. 2012). IPCC AR5 also agree that the CMIP5 climate model ensembles help to better characterise uncertainties associated with individual models, and thus, provide support for its use in this thesis (Flato et al. 2013).

2.4.5 Climate model simulation of past and future UK precipitation

In the United Kingdom (UK), predicted future warming are also expected to cause changes in precipitation patterns. In this Section, past and recent assessments of UK precipitation are reviewed under different climate change scenarios. Hennessy et al. (1997) examined zonal precipitation changes and extremes using the UK Met Office high resolution GCM and the Australian CSIRO9 GCM. They reported a 10% increase in annual mean precipitation under a doubling of CO_2 emission scenario. Jones & Reid (2001) conducted a similar study using the Met Office HadCM2 and reported an increase in winter and convective precipitation across the UK. Their results also indicated heavy precipitation events across Scotland for all seasons.

Similarly, Semenov & Bengtsson (2002) assessed the effect of increased CO_2 on precipitation from 1900-2099 using the Max-Planck Institute coupled atmosphere ocean GCM. Their study revealed an increase of about 20% in UK winter precipitation per century. Watterson & Dix (2003) used a five member climate model ensemble to examine changes in precipitation under rapid increases in CO_2 using the CSIRO Mark2 coupled atmosphere ocean GCM. The results were comparatively assessed and they indicated between 10-30% increase in winter precipitation over the UK between 1961-1990 and 2071-2100. Other precipitation assessments over the UK suggest a decrease in mean summer precipitation but with an increase in intensity of heavy precipitation events (Christensen & Christensen 2004). The work of Fowler & Kilsby (2003) also came to the same conclusion. Fowler and Kilsby used regional frequency analysis to estimate precipitation observations over the UK and their results showed that precipitation, particularly extreme precipitation has increased two-folds over some parts of England. Their results indicate that precipitation intensities previously occurring once in 25 years, is now occurring at a 6 year interval. This, the authors claim was a consequence of increased precipitation frequency and seasonal changes.

Results of several studies conducted on UK precipitation showed an increase in annual total precipitation. This increase does not reflect the character of UK precipitation for all seasons because most of the increases occurred in the winter as a result of increase in precipitation frequency and intensity. Autumn and spring to a lesser degree also recorded increases in precipitation but, this is not the case for summer precipitation which has shown reduction in mean and total summer precipitation resulting from reduced number of precipitation events. The reduced precipitation observed in UK summers and projections of a reduced UK summer precipitation is one the issues addressed in this thesis.

Contrary to other studies which showed a reduction in summer precipitation, Fowler & Ekström (2009) used a combination of GCMs and RCMs to investigate and simulate precipitation in nine UK regions for the period 2070-2100 under the SRES A2 emission scenarios. Their results showed increasing precipitation trends in the winter, spring and autumn whereas projections for the summer returned no change in precipitation. However, Fowler and Ekstrom advised caution interpreting this result because of poor model resolution. This result deviates a little from other studies on UK precipitation which clearly shows a reduction in summer precipitation (e.g. Met

Office 2014; UKCP09-Jenkins et al. 2008). The study of Fowler and Ekstrom reflects the tendency of bias that can occur in any experiment resulting from the use of models that are less desirable for a region in addition to the problem of poor model resolution. Such models produce more intense and heavy precipitation in the summer which the other models may not produce because simulations are strongly dependent on physical local processes upon which parameterisation of individual models are based. Improper representation of the physical processes makes it difficult for models to estimate future precipitation on local scales (Haugen & Iversen 2008).

Two techniques have been used to overcome these challenges. Firstly, statistical downscaling is used to convert relatively coarse data from the models into local scale estimates based on statistical relationship. The second technique is dynamical downscaling technique which uses higher resolution Regional Climate Model (RCM) that are nested within GCM's in a way that the GCMs are used to provide initial boundary conditions. This technique was used by Jones et al. (1997) to examine the effect of doubling CO_2 in a comparative two ten-year experiment. Their results showed between 0.5 mm/day and 1 mm/day mean precipitation over the UK against a mean of 2-3 mm/day. In another study, Raisanen & Joelsson (2001) used two different climate models to examine annual mean precipitation over the UK. Their experiment which was classified into control run and increased greenhouse gas emissions was run over two ten-year integrations and their results showed a 10% increase in annual mean precipitation over the UK.

Recent advancements in model properties have also led to the use of multiple models as a way to address the limitations associated with individual models. For example, the United Kingdom Climate Projections (UKCP09) used probabilistic projections based on climate model ensemble to try and reduce inherent uncertainty in the models while also overcoming poor model resolution. Similarly, the recent use of the latest CMIP5 climate model ensembles in the IPCC Fifth Assessment Report (AR5) showed that the CMIP5 models perform very well in reducing uncertainties on local scales through improved model resolution (Taylor et al, 2012). These qualitative arguments have been supported by early and recent model simulations showing trends of reduced summer precipitation in the UK and the review of literature on this topic shows that the most consistently picked up signal from climate models for the UK is the increase in winter precipitation and decrease in summer precipitation a conclusion also reached by (Christensen et al. 2007).

2.5 Climate change and agriculture

2.5.1 Introduction

Climate change and variability is one of the biggest challenges facing societies today and reviews of its impacts on agriculture and agricultural systems have shown considerably more negative effects than positive (IPCC 2014a). Agriculture to a large extent depends on climatic variables such as precipitation, temperature, radiation, etc., as well as local environmental conditions in order to flourish (Crane et al. 2009). This makes agriculture susceptible to changes in local climatic conditions during the growing season (Crane et al. 2009; Sivakumar 2006). Both seasonal and/or annual variability in precipitation have the potential to lead to extreme events such as floods or droughts with significant negative impacts on crop productions and yield. This inherent sensitivity of agriculture to climate means that any change in climate will affect plant growth positively or negatively.

This sort of situation also has significant impacts on farmers income and food security (Cantelaube & Terres 2005). Therefore, to reduce the impact of changes in climate on agricultural productions, the use of climate model and climate information data are necessary to assess, anticipate and plan ahead for possible changes in climate. This has the potential to increase preparedness and lead to positive economic and environmental outcomes. In this Section, the following review of literature on climate change and agriculture will be used to address how changes in climate particularly, precipitation have impacted on agriculture in the past and present, and how it will affect agriculture in future. Furthermore, the knock-on effect it has on food security is examined and a detailed examination of the impacts of changes in precipitation on sugar beet production in Eastern England is carried out. Finally, the research gaps and objectives are identified in order to develop targeted and effective adaptation responses.

2.5.2 Climate change impacts on agriculture

Changes in future climate have been widely predicted in various studies to have significant impacts on agriculture (IPCC 2014a; Met Office 2014; Crane et al. 2009; Jenkins et al. 2009; Sivakumar 2006). Climate change and variability can have significant negative effect on agricultural productions and yield which can in turn lead to food shortages in some parts of the world (Porter et al. 2014). Additionally, natural hazards associated with precipitation variability such as floods and/or droughts may have further impacts on food security which includes access to food, availability of food, food stabilization and utilization (Bates et al. 2008).

Historically, the use of land for agricultural purposes has always been a major occupation globally and an important aspect of human endeavour accounting for an estimated 1.2-1.5 billion hectares of cropped land (Howden et al. 2007). However, changes in climate and its impacts on agriculture and food production have not kept pace with population and socio-economic challenges. Current and future impacts suggest that agriculture faces the unenviable prospect of continued climatic changes with varying degrees of impacts in different regions of the world as explained in Section 2.2.1.

A region's vulnerability will depend on the nature and level of climate change experienced, and also the capacity of local systems and populations to adapt to change. Importantly, annual variations in climate have been the most dominant source of interannual crop/yield variations in many regions and continue to be a current and future challenge to agricultural systems worldwide. Majority of studies conducted to examine the impacts of climate change on agriculture have focused more on mean historical and projected climatic changes on agriculture (e.g. Wheeler & von Braun 2013; Urban et al. 2012; Lobell et al. 2011) but how climatic variations impact on interannual crop yield and how it may likely vary over time have received less attention (Osborne & Wheeler 2013; Chen et al. 2013).

Past studies such as Howden et al. (2007) examined the impacts of climate change on agriculture and reported that between 15%-35% variations in global yield of wheat, oil seed and coarse grains are as a result of climate change. Similarly, Ray et al. (2015) evaluated crop yields against climate change using detailed crop statistics time series and reported that about 32%-39% of the variations in observed yield were accountable to variations in climate. Simply put, crop yield variability will respond to changes in weather conditions of which crops are susceptible. For example, Agriculture was severely affected by the Russian heat wave of 2010 which contributed to a high rise in global food prices thereby affecting food affordability. The 2000 UK Autumn Floods also had negative impacts on agriculture reducing yield of sugar beet that year (see Section 1.5, Figure 1.2). These type of events created increased global interest on how climate change will affect future volatility in food prices and food security (Urban et al. 2012).

Likewise, high global temperatures have been found to be the cause of several reductions in crop yields in different regions. Some past studies have used historical crop data to examine the impacts of temperature on global agriculture and some of these studies indicated negative impacts on crop yields. Liu et al. (2016) showed that an increase of 1°C in global temperature could result in decline of 4.1%-6.4% in projected global wheat yield. Zhang & Huang (2012) found negative correlation between observed yield and temperature for maize but reported a positive correlation for rice. Similarly, Peng et al. (2004) reported a reduction in the yield of rice under a minimum increase in temperature. Future projections from climate models suggest an increase in heavy precipitation events on the one hand, while increasing temperatures on the other hand, will cause an increase in evapotranspiration thereby contributing to dry conditions (Karl et al. 2009). This sort of changes is characterised by high level of uncertainty in wet and dry events because the direction of future changes are unknown (Bates et al. 2008; Giannini et al. 2008). These changes manifest as seasonal and annual variations with some seasons characterised by high temperatures and inadequate precipitation and other seasons by low temperatures and heavy precipitation. Both of these hazards have been widely reported to have negative impacts on agriculture and agricultural productions (IPCC 2014a; Tao et al. 2003).

In future, the world faces a range of climate scenarios depending on the level of greenhouse gas emissions in the atmosphere. Some of the changes will be inevitable but the direction, extent and severity of the changes are uncertain and will vary across different regions. For example, increasing average temperatures across the globe will have positive impacts on crop production in the mid to high latitudes but will have a negative effect in the arid and tropical regions (Porter et al. 2014). Average global precipitation is expected to increase but regional patterns will vary: some areas will have more precipitation while others will have less. This uncertainty makes regions that are highly dependent on seasonal and rain-fed agriculture particularly vulnerable to the impacts of climate change. This is the case with sugar beet production in Eastern England because it is heavily dependent on seasonal rainfall (i.e. 95% dependent on seasonal rainfall) (British Sugar 2016).

Additionally, availability of water could become a challenge under a changing climate with serious implications for global agriculture. It has been reported that agriculture is greatly hampered by insufficient water which in effect reduces crop yields (Choluj et al. 2014).

Moreover, projected high temperatures with reduced precipitation will have a direct impact on underground water thereby causing a reduction in the water table which affects plants Available Water Capacity (AWC) and soil moisture necessary for crop growth, development and yield. Conversely, heavy precipitation events have been shown to impact negatively on crop yields reported in different parts of the world. These sorts of events are particularly challenging for agriculture because agriculture is inherently sensitive to climate: any change in climate will almost certainly affect plant growth positively or negatively. These effects are already evident in regions where, for example, temperature changes have adversely affected agricultural crops during the growing season (Menzel et al. 2006).

Furthermore, the anticipated future changes in climatic conditions and its associated impacts on many agricultural systems suggest the need for a broad and pressing adaptation strategy (Dorling 2014). Stocker et al. (2013) reported that climate change and variability resulting in changing precipitation patterns are likely to become more frequent and more intense but the impact on crop yield is difficult to calculate and adapt to: in the isolated regions where floods occur, yields is reduced to zero but other areas may not be affected (Okom et al. 2017). More so, analyses of extreme events over future timescales are likely to be dominated by uncertainty due to the nature of modelling studies (Maraun et al. 2010). Conversely, a more climatological analysis has the potential to produce results that can more confidently be used to plan and adapt operating practices in order to maximise yields with particular reference to food security.

2.5.3 Climate change: Implications for food security

Food security is defined as a “situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life” (FAO 1996). Food systems and productions depend on agriculture which is intrinsically tied to climate. Climate variability and change have been shown to affect agriculture more negatively than positive (IPCC 2014a) but the impacts vary from region to region particularly on local scales threatening food security. The threats on food security have revealed a robust global pattern of impacts on crop yields in many regions. This is very challenging for agriculture and threatens the overall ability of farms to supply sufficient food for an ever increasing global population predicted to reach 9.1 billion in 2050 (FAO 2009), while sustaining an already stressed environment. Notable impacts such as floods and droughts have direct effect on farmland conditions and indirect impacts on yields and therefore income and demand for agricultural produce.

According to Jones & Thornton (2003), “climate change impacts has the potential to increase the development challenge of safeguarding food security and reducing global poverty”. It is important to state here that challenges to food security may lead to food insecurity with associated increase in food prices and limited access to food. This have been observed in places where and when food prices increase following cases of extreme weather events in food producing areas (IPCC 2014a) thereby creating food affordability issues. The World Bank (2013) estimated that 767 million people in the world still live below the poverty line of less than $1.25 per day. Continuing population growth and consumption on the one hand will increase the global demand for food while on the other hand, competition for land, water, energy and other resources will impact on the farms ability to produce sufficient food for future population and that is in addition to the challenges of climate change. In a nut shell, climatic changes resulting in annual variations in weather events increases the risk of hunger in affected areas.

Variations in climate have been reported in many studies to affect food security. von Braun (2016) reported that warmer temperatures and variation in precipitation is likely to reduce global food production by 20% in 2050 while, Liu et al. (2016) reported 4.1% to 6.4% yield loss in global wheat production as a result of 1°C rise in temperature using crop models. Several other studies such as Lobell et al. (2008) used 20 crop and climate models to analyse climate risks projections on crops in 12 food-insecure regions by 2030. Their results showed that without adaptation, several crops will suffer reduction in yield especially in food-insecure regions thereby increasing the gap between average and potential yields. Ray et al. (2015) reported that more than 60% of global crop yield variability could be explained by climate variability and that different climate variables such as temperature and precipitation, affect crops disproportionately resulting in year-to-year variations. Their study revealed that majority of crops harvested in different regions experienced the influence of climate variability on yields: ~52% of rice yield experienced yield variability, ~78% of maize, 75% of wheat and 67% of soya beans. These variabilities in crop yields have obvious consequences for food security.

Review on the assessments of climatic variabilities on food security under different assumptions point to future challenges ahead for food security in spite of the progress made in recent decades. In a recent report by the World Food Programme, 200 million people have been said to be lifted out of poverty in the last twenty years with a significant reduction in the level of persistent malnutrition from 40% to 26% (WFP 2017). However, the FAO (2016), believes that the challenge is still monumental with a global demand for food projected to rise by 60% in 2050. The reason why this challenge is so big is because the impacts from climate variability affect all four dimension of food security, namely: access, availability, stability and utilisation.

2.5.3.1 Challenges in addressing food security

In order for communities and societies to be food secure, they will have reliable source of affordable food at all times for all. This explanation is hinged on the four key dimensions of food security:

a) Availability: availability of sufficient food from agricultural systems and land use to meet food demand
b) Access: physical access to food produce and the ability of individuals to have financial resources to acquire appropriate food for a nutritious diet.
c) Stability: stability of seasonal and inter-annual food supplies. One important aspect of food instability results from climatic variations e.g. extreme events
d) Utilisation: deals with food safety and quality aspects of nutrition

Climate change affects food security directly via weather because of changes in the length of the growing season. The changes in weather are reflected in changing market conditions, food prices and the supply infrastructure (Gregory et al. 2005). For example, a flooded farmland with extensive destruction to crops and harvest ready crops will create a yield gap which will inevitably drive food prices up with bigger impacts on the poor that may not have access to the food or may not be able to afford it based on high prices. Achieving food security in the coming decades according to Poppy et al. (2014) will require 50% increase in food production by 2030. A number of past studies have suggested different ways to address the challenges of climate change on food security. Watson (2001) suggested the expansion of arable lands to increase food productions in order to meet future needs. This suggestion will historically impact on the environment, reduce biodiversity and limit ecosystem services. Poppy et al. (2014); Godfray & Garnett (2014) proposed sustainable intensification of agriculture as a way of reducing hunger without further environmental degradation

The Institute of Mechanical Engineers (IMechE 2013) attributes part of the problem to food waste with current practices wasting up to 50% of food before reaching the dining table. Gregory et al. (2005) argued that computer models and scenarios used in the assessment of food security did not put political response, behavioural patterns and technological change into consideration and as a result, predictions have been for a worst case scenario because only climate factors were considered while all other factors are held constant. Addressing the issue of food security and agricultural productions becomes more challenging with climate change impacts on agriculture. In the light of these, it is important to understand potential impacts of climate change for the different regions to enable the agricultural industries to prepare and adapt to the changes that are likely to occur.

In the UK, there are robust signals in climatic variables such as precipitation and temperature which can be assessed on annual and seasonal timescales in order to understand potential future impacts of climate on agriculture and food security. For the UK, this signal tends to be wetter winters and drier summers (Met Office 2014; Jenkins et al. 2008) described in Section 1.2.

2.5.4 Future impacts of precipitation changes on UK agriculture

Changes and variability in future UK precipitation have been widely reported in various studies including Met Office (2014); Jenkins et al. (2009) as being expected to have significant impacts on agriculture. In the United Kingdom, Agriculture is a major land use covering an estimated 70% of UK's total land area and employing around half a million people and contributing about £7.1 billion to the UK economy (CCRA 2016) and therefore considered to be a very important contributor in the UK. However, the impacts from climate change threaten the sustainability and future of this sector. For example, climatic variables associated with climate change and warming have given rise to changing precipitation patterns resulting in different impacts on agriculture such as flooding of agricultural lands and drier soils leading to droughts. Most notable events and impacts on UK agriculture have been more negative than positive as described in Section 1.1, but there are also potential opportunities that can benefit existing agricultural systems and encourage diversity (CCRA 2016). To extend the argument further, impacts on agriculture are manifested in a number of negative (threats) and positive (opportunities) ways on crop production including:

<u>Threats</u>

- Increase in flood risks to productive agricultural lands
- Drier soils resulting from warmer and drier conditions
- Increased risks of damage to crops and harvest ready crops
- Depletion of soil nutrients through soil erosion
- Increase in water demand for crop irrigation
- Increased risks of pests and diseases

<u>Opportunities</u>

- Opportunities to grow new crops
- Warmer temperature changes favouring some C_3 crops such as sugar beet
- Changes in the length of the growing season due to warmer conditions
- Earlier sowing date

Future projections of climate change in the UK follow current trajectory of increasing temperatures, rising sea levels, changing precipitation patterns, increased frequency and intensity of extreme weather events, risk of flooding from rivers and seas, wetter winters and drier summer (CCRA 2016; UKCP09-Jenkins et al. 2008). Impacts on agricultural crop productions will vary across the UK with projections showing that warmer, drier summer conditions may have more adverse effect in the south and east than in the wetter areas of the north and west of the UK. This sort of variations makes climate change a current issue and future concern for agricultural productions. Agricultural productions may also favour the cool, wet upland areas due to warmer, drier conditions than the lowland areas.

Future climate trends for the UK indicate wetter winter, spring and autumn while summer is projected to be drier compared to the past. This will impact negatively on water availability for summer-sown crops which the winter-sown crops are not likely to experience. DEFRA (2004) reassessed drought related yield loss of sugar beet using LARS-WG stochastic weather generator and the HadRM3 climate model for low and high emission scenarios. Their study showed negative consequences for soil moisture with a deficit of 8-12% for low-high emissions scenarios by 2050's. Their results also showed greater warming in the future with wetter winters, spring and autumn but a much drier summer than in the past. The study concludes that drought related yield loss for sugar beet yield will increase between 30-50% by the 2050's (low-high) depending on the region.

Furthermore, warmer temperatures will increase the length of the growing season thereby encouraging earlier sowing date for crops and enabling the crops to attain full canopy cover to aid the capture of maximum sunlight in the spring. Additionally, increased CO_2 in the atmosphere is expected to increase the production of some C_3 crops such as sugar beet. However, continued high temperature if accompanied by shortages in summer precipitation will increase the risk of heat stress significantly reducing soil moisture and also impacting on crop yield. Conversely, increased precipitation intensity and frequent storm events could also lead to the risk of flood causing substantial losses in crop production in the low-lying agricultural areas. This could contribute to the risk of soil erosion, compaction and water logging thereby making the agricultural farmlands unsuitable for productions (Morison and Matthews 2016). A number of studies such as Schmidhuber & Tubiello (2007) have reported that climate change could significantly alter agriculture and agricultural productions in a number of ways. Their study revealed that increasing greenhouse gas emissions in the atmosphere will cause warming and bring about changes in the suitability of farmlands and crop yields.

Higher temperatures could mean increased risk of drought and increased evaporation rate with potential impacts on soil moisture and crop yield. In addition to that, there is a potential threat to water resources resulting from declining summer flows, reduced ground water replenishment and increased soil and atmospheric evaporation. These factors all contribute to considerable negative impacts on crop yield and agriculture in general. Although, the UK is considered to be food secure, continued impact of weather variations could have severe implication for food security with extended socio-economic impacts in the UK.

2.5.5 Impacts of climate and precipitation on UK sugar beet production

Sugar beet production in the UK has shown considerable annual variations in recorded sugar beet yield in the last decade (See Section 1.5 and Figure 1.2). Some past studies have reported increases in annual UK sugar beet yield over the years including Jaggard et al. (2007) who reported 111kg increase in annual farmer delivered yield between 1976-2004. Likewise, British Sugar (2011) reported a 60% increase in sugar beet tonnage from 1981-2011. These studies have considered cumulative annual mean yield over a long period of time (e.g., 30 years) but have not considered climate related changes such as variations in annual precipitation in relation to variations in annual yield. These studies provide an indication of mean changes in yield but do not reveal the complete impact of the changes in annual related weather events on yields (e.g., years of low and high yields).

The review and assessment of changes in weather events such as precipitation is very important in the growth and yield of crops because crops are susceptible to weather events and respond to shifts in weather conditions causing variations in yields. Considering the variable nature of UK annual and seasonal precipitation, sugar beet productivity in Eastern England for example has been reported to be seriously affected by water stress as reported in the works of (Chołuj et al. 2014; Shrestha et al. 2010; Richter et al. 2006; Choluj et al. 2004; Pidgeon et al. 2001). Therefore, in order to ensure a crop secure future for sugar beet, sugar beet farming and production must be more resilient and adaptive to changes in climate particularly precipitation patterns.

Several past studies on sugar beet have addressed a range of issues focusing on climate change impacts (Jaggard et al. 2007) and the effects of weather variables on sugar beet yield (Kenter et al. 2006). Kenter et al. (2006) and Scott & Jaggard (2000) have reported that sugar beet growth is characterised by slow leaf formation particularly in the spring. Sugar beet leaf has been identified as having a poor performance in capturing solar radiation making them unable to achieve full canopy closure necessary for light interception by the middle of June at which time they must have missed out on the much needed seasonal radiation (Kenter et al. 2006; Scott & Jaggard 2000; CGIAR 2000). This is important because sugar beet plants require canopy development and radiation to coincide in order to capture maximum radiation and therefore maximum yield. Scott & Jaggard (1978) suggested that sugar beet yield could be improved by enhancing leaf formation through earlier sowing dates to improve radiation capture early in the growing season.

Studies have also been carried out by Lauer (1997; Smit (1993) as far back as the 90s to investigate various sowing dates in order to primarily identify optimum sowing dates for sugar beet plants. Results from these studies show that early sowing in March could improve yield of sugar beet as leaf development is enhanced and plants are able to reach optimum canopy cover enabling maximum radiation capture. The results of these studies are still relevant to date. In recent years, however, there has been improvement in radiation capture and yield increases in the UK (Jaggard et al. 2009). Increase in mean yields from official trials rose to 110 kg/ha per year and some of these increases were attributable to improved seed quality and earlier sowing dates to synchronize with availability of solar radiation (Jaggard et al. 2009). Making a case for sugar beet production in England, the current study aligns with Jaggard et al. (2009) on the earlier sowing dates of sugar beet in the UK (e.g. between March and early April).

A considerable body of work examined the impact of weather variables (e.g. precipitation, temperature and extreme weather events) on rain-fed sugar beet yield and yield variability in the UK. Higher temperatures during the growing season allow spring-sown crops to be sown earlier due to an increase in the length of the growing season in addition to rising levels of CO_2 in the atmosphere which increases the rate of photosynthesis (Lawlor & Mitchell 1991). Climate model projections for the UK predict an increase in winter precipitation and a decrease in the summer which simply means wetter winters and, warmer and drier summers (UKCP09-Jenkins et al. 2008; Hulme & Jenkins 1998). Consequently, drier summer for spring-sown crops will likely impact on water availability for crops use and potentially reduce soil moisture particularly in the months of July and August (Richter et al. 2006). In this type of circumstance, yield could therefore decline especially in areas that are already under water stress conditions as pointed out by (DEFRA 2004; MAFF 1999). Eastern England, with a high annual and season precipitation variations and the smallest amount of precipitation in the UK is a good example of an area that could be susceptible to water stress which could potentially impact on sugar beet yield in the region.

Sugar beet yield is generally seen to decrease when stressed via low water conditions: Pidgeon et al. (2001) estimated potential sugar beet yield losses, calculated from climate and crop model projections due to water stress, vary between 15% and 30% for England. Given the nature of UK sugar beet production which is 95% rain-fed, past and present water limitations have most likely been driven by changes in precipitation patterns. Furthermore, many past studies have indicated that sugar beet is, more specifically, sensitive to water supply in terms of: leaf growth (Rytter 2005); storage root formation (e.g. Rytter 2005; Brown et al. 1987) and yield (e.g. Chołuj et al. 2014; Richter et al. 2006; Kenter et al. 2006; Jones et al. 2003).; and Drawing from this and other sources reveal that water availability is crucial for sugar beet yield and indeed agricultural productions and it is already a major stress factor globally and in the UK (Chołuj et al. 2014).

In Europe, Pidgeon et al. (2001) used the UK Hadley Centre Global Climate Model (HadRM3) to simulate potential and rain-fed yields in Europe from 1961-1995 and reported drought losses of about 40% in eastern Ukraine and southern Russia. Conversely, Jones et al. (2003) reported an increase in yields in northern Europe due to warmer springs but western and central Europe are predicted to show increased losses due to drought stress and year-to-year variability in precipitation. Jones et al. (2003) contend that this could be more challenging for crop growth and yields when increased industrial and urban water use are put into consideration. Other studies such as Richter et al. (2006) reported that yield gap is predicted to increase under low and high emission scenarios and may reach 22 and 26% by 2050. This variation in annual yield gap is a reflection of the variations in future climate.

Furthermore, Richter et al. (2006) also identified crops growing in areas of low water availability to be more challenged by prolonged drought and suggested two management strategies to address this issue: earlier sowing date and harvesting at a later date. Their model indicated that earlier sowing date in March and mid-April strongly affected yields resulting in gains of about 0.2-0.3 t/ha^{-1}. Similar result was obtained in an earlier study by Durrant et al. (1993) in a field experiment showing that earlier sowing dates were beneficial for sugar beet growth and yield but a delayed sowing date (e.g. end of April) particularly during wet spring can be less beneficial and cost growers about 1.4 t/ha^{-1} of sugar. Qi & Jaggard (2008) assessed climate change impacts on sugar beet yield in the UK between 1976 and 2006, and future climate scenarios under high CO_2 in 2020, 2050 and 2080 using Broom's Barn crop model and GCM outputs. Their results showed that sugar beet yield were likely to become more variable in future, a result supported by the findings of Richter et al. (2006). Jaggard et al. (2007) also examined the impact of climate change on sugar beet in the UK using crop simulation model and daily weather data and arrived at the same conclusion.

To date, one of the strongest studies with regards to sugar beet yield and climate change in England include that of Richter et al. (2006). Their study modelled differential water distribution and its impact on future drier climate under a weather generated historical period for 1961-1990 and projections based on low and high emissions scenarios. Findings from this study revealed a deficit in relative soil moisture and yield gap resulting from drought related yield loss. The current study builds on the work of Richter et al. (2006) by investigating the potential impacts of likely future precipitation changes on sugar beet yield in Eastern England using CMIP5 climate model ensembles to inform a greenhouse crop experiment. The ensemble is a combination of multiple individual models. The individual models in an ensemble are initiated using slightly different but equally realistic initial conditions in order to capture some internal elements of climate variability. The ensemble means provide better averages over individual model mean.

In conclusion, sugar beet has been shown to be economically significant in the UK (see Section 1.5) and is sensitive to water supply, and was considered an ideal crop to investigate in the context of future changes in precipitation. Furthermore, there are currently no sugar beet growing experiments in the literature that are informed by ensemble model projections – one of the aims of this research is to address this. The review of literature shows that the nature of climate change and indeed, precipitation variability is very dynamic and its future changes are uncertain. Research into this problem have been diverse and varied, but most studies had focused on assessment of long-term changes often neglecting the short-term or medium-term changes that is also addressed in this thesis. One limitation in this study is the fact that agricultural production is not affected by precipitation alone, but also by other factors such as temperature and radiation amongst others. Therefore, further research will be required in future to expand on the work in this thesis. This will provide the basis for and enable extensive adaptation strategies aimed at reducing errors in precipitation and climate predictions over future growing seasons. This will enable farmers to make informed decisions that will help reduce potential risks, optimise farm management practices and implement adaptation measures that will be beneficial in future growing seasons.

2.6 Research gaps and thesis objectives

A couple of research gaps were identified in the literature and presented in this Section with its associated research objectives.

- Much of the literature reviewed assessed precipitation impacts arising from greenhouse gas emissions on annual or seasonal basis in the long-term until 2100. However, because the climate system is already committed to a certain degree of greenhouse gas emissions in the atmosphere, this will always have an impact on precipitation delivery and therefore, quite important to also consider the impacts of these emissions in the near-to-medium term future (2050).

Objective 1: Understand the precipitation regime in Eastern England for the period 1971-2000 and assess how precipitation patterns might change between 1971-2000 and 2021-2050) using a range of state-of-the-art CMIP5 climate model simulations under the medium range (RCP45) and high end (RCP85) greenhouse gas emission scenarios.

- Past and present studies of precipitation impacts on crops in Eastern England have applied different climate and crop models for assessments but have not used the new CMIP5 climate model ensembles to inform a greenhouse crop experiment.

Objective 2: Examine the precipitation characteristics of the study area in Eastern England and using the CMIP5 climate models to evaluate changes in precipitation between the two time frames (stated above) and assessing how the changes will impact on future sugar beet yield.

Chapter 3: Methods, Data and Materials

3.1 Introduction

This chapter outlines and appraises the methods employed in this study and it is divided into two distinct Sections: the precipitation analysis methods and data (Sections 3.2 - 3.7) and the greenhouse experiment materials and method (Sections 3.8 - 3.10). The research aim was to firstly determine the present day precipitation regime in Eastern England using weather station observations for the period 1971-2000 and then, to determine the likely changes in precipitation over the same area using a range of climate models. Two time slices were selected for the climate model analysis: one for a historical period (1971-2000); and the other for the projected future period (2021-2050). The focus was to define the rainfall attributes of the present environment using observational data and to investigate the near-to-medium term future using a range of climate models. Secondly, the study investigated the impact of the identified precipitation changes on sugar beet plants in a greenhouse experiment. 150 sugar beet plants were studied in the first season (2014) and 201 the second season (2015) of the experiment. All the experiments were conducted in the greenhouse of Brunel University London located on the global grid as the area between 51º 31ˈ58˝ N and 0º 28ˈ22˝ W.

In the greenhouse experiment, past precipitation data from the climate model historical phase was compared with climate model projections in the same area and the precipitation changes between the two was used in calculating the watering regimes for the plant experiments. Much of the previous work on past precipitation as discussed in the literature review (Chapter 2) focused on changes in annual precipitation and trends in seasonal mean for detecting long-term changes in precipitation. This is a useful approach because such changes are usually evident in the seasonal mean due to the sub-seasonal variations being averaged out, thereby leaving out the yearly variations. However, none of the reviewed studies examined changes in precipitation using the new suite of models from the 5th Phase of the Coupled Model Intercomparison Project (CMIP5, Taylor et al. 2012) to inform a greenhouse experiment. This thesis explores the viability of two different methods of investigating precipitation changes based on CMIP5 data. The central thinking here was to use the climate projections to detect long-term changes in precipitation in a way that mimics a realistic future precipitation scenario for the sugar beet growing season in Eastern England.

The two approaches used for analysing precipitation changes were: long-term growing season (May-October) daily mean precipitation which was used to investigate the impact of climatological changes in precipitation; and the “realistic” distribution of precipitation event sizes and frequency which was used to investigate the potential impact of precipitation characteristic changes in the area. Section 3.2 discusses the weather station observations used in the work while Section 3.3 focuses on the CMIP5 models used in the study. Section 3.4 examines the models and then, precipitation analyses were conducted to ascertain which models best replicated observed precipitation characteristics in the area of study, which then provided the basis for the suite of models to be used for analyses of future precipitation projections. It is important to note that due to the discontinuous nature of precipitation, it is useful to have a continuous homogenous precipitation dataset. This is dealt with in Section 3.5 with the study heavily reliant on the Met Office Integrated Data Archive System (MIDAS) dataset that collates UK daily climate and weather observations data (Met Office 2012). The models used for this study were also used in the most recent IPCC AR5 report which were from the CMIP5 project that included simulations using different Representative Concentration Pathways (RCP) (van Vuuren et al. 2011). Section 3.6 describes the watering regimes used in the plant experiment and how it was derived and used for the plant experiment. Section 3.7 describes the statistical analysis used in this study and Sections 3.8 - 3.10 describes the greenhouse experiment carried out in this study. These Sections further describe the crop criteria for this research explaining why sugar beet was chosen for the study and assesses the impacts of precipitation changes on the plants by measuring certain plants parameters over the growing season and yield of the plants upon harvest.

3.2 Precipitation observations

3.2.1 Weather stations observations dataset

This Section describes the precipitation data used in this study. To understand the present day regime, daily precipitation data that covered the area of Eastern England between 51º 35ˈN - 52º

75ʹN and 0º 29ʹE – 1º 35ʹE (see Figure 3.1) were extracted from the MIDAS dataset Met Office (2012) for this purpose. The observational dataset examined the period from 1971-2000 herein referred to as the 'historical' period – this is the period over which the CMIP5 models were tested. There are at least 6 weather stations that have operated in or near the sugar beet producing areas of East Anglia in Eastern England for over 30 years with continuous precipitation data and have little or no missing data. The selected weather stations are: Terrington St Clement (2 m asl, 0.29 ° E, 52.745 ° N); Santon Downham (6 m asl, 0.675 ° E, 52.458 ° N); Coltishall (17 m asl, 1.356 ° E, 52.756 ° N); Writtle (32 m asl, 0.432°E, 51.733°N); Manston (44 m asl, 1.35°E, 51.35 N); and Stansted Mountfichet (70 m asl, 0.184°E, 51.897°N). (See Figure 3.1 for the locations of these weather stations and corresponding Table 3.1 for the length of their records).

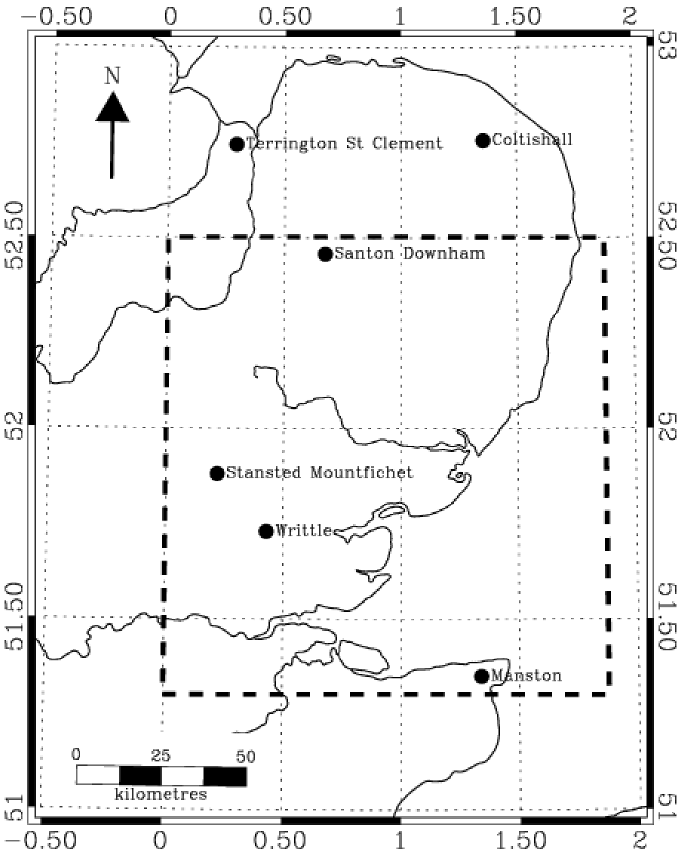


Figure 3. 1: Map of the study area showing the locations of the weather stations examined in the analysis. The dashed line indicates the area covered by MOHC HadGEM2-ES model grid cell used here. (See 3.2.1 and Table 3.1).

Table 3. 1: Details of the weather stations examined showing the length of their records.

Region	Station Name	Elevation	Latitude	Longitude	Start Date	End Date
CEE	Coltishall	17	52.756	1.356	1963	2009
SEE	Manston	44	51.35	1.35	1962	2009
CEE	Santon Downham	6	52.458	0.675	1960	2008
SEE	Stansted Mountfichet	70	51.897	0.184	1961	2009
CEE	Terrington St Clement	2	52.745	0.29	1961	2009
SEE	Writtle	32	51.733	0.432	1971	2000

These weather station datasets were extracted from the MIDAS dataset (Met Office 2012) via the British Atmospheric Data Centre (BADC). The MIDAS dataset contains surface observations over land areas of the UK and other world-wide stations, and have been quality controlled by the BADC to integrate data from advanced observing systems to support improved forecasting of model performance. The dataset compiles daily and hourly weather measurements including wind parameters, maximum and minimum temperatures, soil temperature, radiation and sunshine duration measurements as well as daily and hourly precipitation measurements. The scope of the current study is limited to precipitation and only considered the key sugar beet growing period in England (i.e. May – October).

3.3 Historical CMIP5 model precipitation data

Climate models constitute the main basis for evaluating and projecting climate change under different anthropogenic forcing scenarios. General Circulation Models (GCMs) and subsequent generation of models have provided science with reasonable level of confidence in simulating future precipitation and climatic changes based on the model's abilities to reproduce observed changes in past and present climates (Wang et al. 2016; Giorgi et al. 2004). In this Section, "historical" CMIP5 model precipitation data were evaluated using Earth System Models (ESMs). These models are mathematical simulations of the climate system, which includes the Earth's major biogeochemical processes. They have provided a relatively high level of confidence in simulating climatic changes and can be easily verified and validated by comparison with simulations of past observations.

The gridded data included longitude, latitude; and the date. The data provided a benchmark period that allows the model data to be compared with observations. Furthermore, the model evaluation was also conducted to establish the relationship between model data, which represents an area and the precipitation data from individual stations. Averages from the GCM data were compared to the stations averages and statistically analysed at 95% confidence interval to provide an insight into the differences and /or similarities in the two dataset.

The individual members of the ensemble were initiated using slightly different, though equally realistic, initial conditions in order to capture some element of internal climate variability. The use of ensemble model was aimed at understanding past and future climates in vital areas of uncertainty (Taylor et al. 2012). The simulation of the “historical” experiment helped ascertain model fidelity and reliability in reproducing current climate as a guide to the model’s reliability of future climate. The historical run were driven by realistic anthropogenic and natural forcing which includes greenhouse gases, aerosols, changes in solar output and ozone among others.

The main variable analysed in this study is precipitation. The points of interest from the utilised models that met these criteria are detailed in Table 3.2. Data from these models will be retained for further analysis depending on how closely they replicate precipitation observations for the region (see Chapter 4). The dataset for the two scenarios was used to perform two different CMIP5 analyses with the aim of assessing different levels of greenhouse gas emissions (GHG) over the 21st century using the Representative Concentration Pathways (RCPs; van Vuuren et al. 2011). This study examined future GHG emissions represented by mid-range (RCP45) and high-end (RCP85) impacts on radiative forcing for the period 2021-2050. This temporal window was chosen as it is not too far into the future and it is, therefore, of interest to the sugar industry for future planning (British Sugar 2011).

Table 3. 2: Details of the CMIP5 models examined.

				Ensemble Size		
Climate Model Names	**Resolution (Latitude & Longitude)**	**Institution**	**Grid Cells**	**Historical**	**RCP45**	**RCP85**
CanESM2	64 X 128 (2.8 X 2.8)	Canadian Centre for Climate Modelling and Analysis (CCCma), Canada	1,50	5	5	5
CSIRO-Mk3.6.0	96 X192 (1.875 X 1.875)	Commonwealth Scientific and Industrial Research Organisation (CSIRO), Australia	1,75	10	10	10
HadGEM2-ES	145 X 192 (1.25 X 1.875)	Met Office Hadley Centre (MOHC), UK	1,114	4	4	4
EC-Earth ESM	160 X 320 (1.125 X 1.125)	EC-Earth consortium; managed by Irish Centre for High-End Computing (ICHEC)	1,125	5	5	5
IPSL-CM5A-LR	96 X 96 (1.875 X 3.75)	Istitut Pierre-Simon Laplace (IPSL), France	1,75	6	4	4
MIROC5	128 X 256 (1.41 X 1.41)	Atmospheric and Ocean Research Institute, Japan	1,100	3	3	3
MPI-ESM-LR	96 X 192 (1.875 X 1.875)	Max Planck Institute for Meteorology (MPI-M), Germany	1,75	3	3	3
CCSM4	192 X 288 (0.94 X 1.25)	National Centre for Atmospheric Research (NCAR), USA	1,150	3	6	6

Model inclusion in this study avoided the use of less realistic models for the study area. According to McSweeney et al. (2014), not all models are suitable for all regions. They assessed some CMIP5 models to identify their suitability for use across multiple regions through dynamical downscaling. Their study showed that certain models are more suitable than others depending on the region of use and specifically identified the MOHC (HadGEM2-ES) as very reliable in replicating past observations for Eastern England and the UK in general. Thus, the HadGEM2-ES was prominently used in this thesis for the analysis of changes in precipitation.

3.4 Overview of climate models

In order to obtain the optimum analysis of future climate projections, it is important to use data from the weather stations observations in the area of study for past and present climate to validate the use climate models. The observed data will also provide a benchmark period that will allow model data to be compared with observations over a 30 year period for the presence or lack of trend in the temporal window from 1971-2000. Observed data from the weather stations were the basis of the information and was cross-validated with the CMIP5 historic run used in this study to ascertain model reliability and performance (Mitchell & Jones 2005). The ability of climate models to reproduce observed changes provides the best examination of models performance rather than simulation of present day climate or intercomparison between models which tend to underestimate the uncertainty if the models were similar compared to the real world (Raisanen & Joelsson 2001). Although, much work have been carried out in the past on the reliability and limitations of climate models, it was still necessary to discuss their suitability for this research.

The climate models used in this study were all sourced from the CMIP5 project and were not only used to assess past changes in precipitation, but also used to examine projected changes in future precipitation under two different greenhouse gas emission scenarios, namely: the Representative Concentration Pathways (RCPs) (RCP45 and RCP85). Two of the RCPs were chosen for analysis here: RCP45 represents the mid-range greenhouse gas emission scenarios and the RCP85 represents the high-end greenhouse gas emission scenarios which according to Friedlingstein et al. (2014) is consistent with a ‘worst case scenario’. Confidence in the use of climate models comes from their ability to simulate key aspects of the climate system (IPCC 2013b). For quality assurance, models are continually collated with atmosphere, ocean, cryosphere and land surface observations and one key aspect is their ability to imitate real climate system which can be verified from past observations and present climate.

Past studies on various Model Intercomparison Projects (MIPs) had simulated climate using individual models which can lead to unreliable and uncertain forecast as a result of statistical bias and structural errors. However, with advancement and improvements in climate models, the use of such MIPs and the Atmospheric Model Intercomparison Project, (AMIPs) (Gates et al. 1999) and the Coupled Model Intercomparison Project, (CMIP) have made it easier to compare models for differences and similarities (Covey et al. 2003; Meehl et al. 2000b). According to (Raisanen & Joelsson 2001), MIPs specific to individual models have enabled modellers to easily identify errors in models and areas that need attention.

In contrast to individual models, the use of Multi-Model Ensembles (MMEs) to examine structural uncertainty and internal variability have improved forecasting by predicting the distribution of possible outcomes (Flowerdew 2012). Ensembles can provide extra samples and average over errors specific to individual models. The multi-model ensemble forecasts are weighted averages arising from individual models, and the sum of all weights is equal to one based on their predictions. This study used a multi-model ensemble mean to provide a realistic projection from the models. In addition, models used in this study were selected based on meeting specific criteria described in Section 3.4.1.

3.4.1 Model criteria

In spite of the positives brought about by the use of climate models in climate forecasts and impact assessment of crop yields, there are still challenges in their uses as a result of, for example, different parameterization of chemical, physical and biological components of the climate system which can result in different simulations with varying degrees of values. CMIP5 comprises of models with different levels of complexity and with different spatial resolutions which, in some cases, alters how cloud processes are represented on a smaller scale resolution than the models. Therefore, to improve forecast, this study employed the use of MMEs which gives credence to the study of Tubiello & Ewert (2002) not to depend on a single model for climate change assessment studies, but to use several model predictions in developing assessment for impact studies on crop yields.

The selection of climate models in this study was based on certain criteria (e.g. the dataset must cover the two temporal time frames adopted for the study – the "historical" period 1971-2000 and the "projected" period 2021-2050). The criteria used will assess the suitability and applicability of models to reproduce observed precipitation over Eastern England for a 30-year period (1971-2000). This will provide validity and justification for the use of selected models for assessment of future precipitation projections. It is assumed that the models that simulate observed precipitation well in the study area will better represent projections of future precipitation over the region.

In this thesis, data was sourced from the latest suite of the Coupled Model Intercomparison Project (CMIP5, Taylor et al. 2012) with models fulfilling the following criteria for selected assessment:

- The models must contain daily precipitation data for the study periods
- That the models are run as ensembles
- They are Earth System Model (ESM) or Coupled General Circulation Model (CGCM) and
- That the models contain historical and Representative Concentration Pathways (RCPs) records for the medium (RCP45) and high greenhouse gas emissions (RCP85)

3.5 CMIP5 precipitation projections

3.5.1 Introduction

In order to determine the likely climatic future changes over Eastern England, projected precipitation data from a range of CMIP5 climate models were examined. Projection data were extracted from the fifth phase of the Coupled Model Intercomparison Project (CMIP5, Taylor et al. 2012). Each of the experiments utilised a multi-member ensemble for the model run whereby each individual member of the ensemble were initiated using slightly different but equally realistic initial conditions. The purpose of this is to enable the model capture some elements of internal climate variability as reported by Taylor et al. (2012). The models used in "historical" and "future" parts of the study were the same. All the models were selected base on the criteria contained in Section 3.4.1 and described in Table 3.2.

3.5.2 Climate change and greenhouse gas emissions scenarios

In order to properly evaluate the influence of future greenhouse gas emissions on climate and the corresponding socio-economic development, a range of future greenhouse gas emission scenarios were developed called the Representative Concentration Pathways (RCPs) (Meinshausen et al. 2011). The RCPs are categorised and named according to their radiative forcing target by 2100 with estimates based on forcing of greenhouse gas emissions scenarios. These RCPs were used in the last IPCC report (AR5, Fifth Assessment Report) and the associated cycle of the fifth phase of CMIP5 for projected climate change run.

There are four RCPs developed and they include: One mitigation scenario leading to a very low forcing level (RCP26), two medium stabilisation scenarios (RCP45 and RCP 6) and one very high end emissions scenario (RCP85). In the light of these four scenarios, future climate projections can be assessed from different models accessible under the CMIP5 project. It is acknowledged that the CMIP5 data has higher spatial resolution for regional analysis (Sperber et al. 2013).

In this thesis, RCP45 and RCP85 were employed and the choice of this two was based on the premise that RCP45 is the one that society is currently closest to and the RCP85 was based on current and future projections of increasing greenhouse gas emissions in the atmosphere. Moreover, because of the high end emissions of RCP85, it provides a much stronger climate signal and easier identification compared to the lower emissions and it gives an indication of the "worst case scenario". These scenarios may give us an indication of what possible climates to expect in future and how it may affect sugar beet productivity and agriculture in general in the UK. Table 3.3 shows details of the RCPs analysed.

Table 3. 3: An overview of the two Representative Concentration Pathways (RCPs) used in this thesis (Moss et al. 2010; Meinshausen et al. 2011).

Scenarios	Description
RCP45	Stabilized radiative forcing without overshoot pathway to 4.5 W/m² (~850ppm CO_2 eq at stabilization after 2100
RCP85	Rising levels of radiative forcing pathway leading to8.5 W/m² (~1370ppm CO_2 eq by 2100

3.5.3 Projections of changes in future precipitation

Global climate models (GCMs) constitute the main basis for evaluation and projections of climate change under different anthropogenic forcing. The current study examined eight CMIP5 climate models which all implemented the "historical" run experiment (see Section 3.3) with each of the experiments utilising a multi-model ensemble for the run. The models used in this section for projections of changes in future precipitation were based on how closely they replicated precipitation observations for the region (see Chapter 4).

In order to gain an understanding of possible future changes in precipitation, it was useful to first gain an indication of the overall changes in mean daily precipitation over the area of interest. Therefore, the mean and total daily precipitation in the model runs were analysed for both the "historical" (1971-2000) and "future" (2021-2050) time windows. Secondly, the study examined the differences between the changes in the characteristics of the daily precipitation between the "historical" and "future" precipitation.

The mean daily values of each ensemble of model runs from the daily precipitation analysis of the "future" experimental period 2021-2050 were quantitatively compared with the mean daily values of precipitation from the "historical" experimental period 1971-2000. The aim of using the mean values from both datasets is to give as close as possible estimate to the "true" areal values in the study region. This method was done by averaging all the values in each model for both the "historical" and "future" and then using statistical analysis to detect for differences between the two time frames. For all statistical analysis of relationships between the datasets, days with precipitation less than 0.05mm were removed from the calculations (see Section 3.6.3.1 for details) due to the potential of those days causing bias in the results.

3.6 Calculation of watering regimes

3.6.1 Introduction

This Section describes the calculation of the watering regimes (irrigation) used in the greenhouse crop experiments over two growing seasons and it is divided into two Sections: the "seasonal" mean watering regimes used in the first year of experiment (2014) and the "realistic" distribution of watering regimes used in the second year of the experiment (2015). The irrigation water need represents the difference between crop water requirements and the effective precipitation (Allen et al. 1998). The watering regimes employed in this study as well as the changes in event size and frequency allows for the effect of climatological or mean changes in precipitation to be investigated.

3.6.2 Calculation of the climatological watering regimes

A key aim of this thesis was to investigate changes in precipitation from climate model projections. In this Section, the study investigated the impact of seasonal precipitation changes on the greenhouse crop experiment using climate model projections. Considering this, the watering regimes in the first season were not designed to replicate realistic precipitation events but to deliver the total growing season (i.e. May-October) precipitation in a series of regular and equal watering events. This method entailed removing the random distribution periods of low and high precipitation.

Within the climatological experiment, all the plants in the experiment were watered every other day (i.e. watering day – dry day – watering day – dry day and so on) with the same amount of water per watering day for each regime. Two watering regimes were implemented; the "control", or "present day", experiment where precipitation observations for the period 1971-2000 and the recommended level of water for a successful sugar beet crop from the Food and Agricultural Organisation of the United Nations were used to calculate the watering event size (FAO, Brouwer & Heibloem 1986). Secondly, there was a "future" watering regime, which was based on a modification of the "control" experiment watering event size determined by the growing season (i.e. May-October) changes in precipitation from the climate projections for the period

2021-2050.

Studies by Carlson & Bauder (n.d.) in the US also reported that sugar beet requires approximately 22-28 inches of rainfall during the growing season which is equivalent to 558-711 mm. The FAO minimum and maximum recommended seasonal crop water need per sugar beet plant reveal that sugar beet requires 550-750 mm of rainfall per season (FAO n.d.); and also requires a minimum and maximum growing period of 160-230 days. Therefore, to calculate the average water per day for the plants, the lowest watering range was divided by the lowest growing range; the highest watering range divided by the highest growing range, and the highest watering range divided by the lowest growing range. The output from the highest watering range and the highest growing range (3.26 mm) was multiplied by the surface area of the pot used to grow the beets to obtain the water per day for the plants which was then converted to litres per day to conform to the measuring can in use for the watering.

The values obtained in this study are comparable to the mean daily May-October precipitation for the region from the observations. The highest daily mean May-October precipitation from the stations ranged from a low of 432 mm to a high of 522 mm. Likewise, the total May-October precipitation from the stations ranged from a low of 664 mm to a high of 725 mm compared with 550 mm-750 mm by the FAO.

3.6.3 Calculation of realistic precipitation distribution of events and sizes

Calculation of the watering regimes in the second season (2015) was based on the changes in the monthly distribution of precipitation events and sizes. Similar to the first season experiment, it was designed to examine the impacts of changes in precipitation. In the second year, the experimental focus was designed to replicate as close as possible future realistic precipitation changes based on monthly events and sizes during the growing season (i.e. May-October). This method entailed working out the total number of wet days and dry days to determine the number of watering events in a given month. This was done by calculating the mean number of precipitation observations in each month and then distributing the watering events randomly across the month. This calculation will give the number of watering events in a given month bearing in mind that the different months in the growing season have different number of days (see Appendix 1).

Then, the size of the watering events was worked out by splitting the observed precipitation distribution into percentiles and then determining watering events that replicate that distribution (see Appendix 2-4). The future wet days were distributed over the month taking into consideration the probability between wet and dry days (see Appendix 5). Studies Geng et al. (1986) have used similar approach to assess daily rainfall and its impacts on agriculture while Waha et al. (2012) used past rainfall deterministically to determine sowing dates.

3.6.3.1 Selection of wet days

The occurrence, intensity and amount of precipitation on any given day varies in time and space and is expected to change over time due to climate change (Trenberth 1999). Trenberth (2011) also reported that climatic changes will alter several direct processes involved in the amount of daily precipitation distribution. This is an important factor as the rate of precipitation accumulation over a day varies from day to day and from one location to another. Studies such as Sun et al. (2006); Dai (2006); Osborn & Hulme (1998) have examined daily precipitation characteristics in GCM simulations and all arrived at similar conclusions that models tend to overestimate light or small precipitation events while underestimating heavy precipitation events in comparison to observations. Alexander & Jones (2001) showed that there is an equal chance of accurate precipitation events in England and Wales, however, in some regions such as South-Eastern England, models can be less reliable in determining dry events (e.g. events < 1 mm day^{-1}).

This bias towards light precipitation events has been attributed to problems with parametrization Kharin & Zwiers (2005), while Kopparla et al. (2013); Chen & Knutson (2008) reportedly identified spatial resolution as a contributing factor to the disparity between models and observational datasets. With these in mind, it was therefore necessary to remove small precipitation events from the precipitation analysis in this study in order to have better consistency and higher correlations.

Furthermore, to improve monitoring and prediction, precipitation analysis requires accurate estimates and careful consideration of the input data. Daily gridded observations and model data corresponds to a spatial average in space rather than a single point thereby obscuring days of no rain and creating a bias in the analysis (Pendergrass & Hartmann 2014). It is therefore important to select a wet-day threshold in order to by-pass this issue. Some studies have used guidelines for wet day precipitation as having accumulation of 1 mm (Klein Tank et al. 2009; Sun et al. 2006). Chou et al. (2012) in their study used a dry day threshold of 0.1 mm day-^{1}. Different studies have used different guidelines and in this thesis, 0.05 mm day-^{1} was adopted as it was considered low enough to reflect only minimal amount of precipitation lost but also high enough to allow the level of precipitation offered by rain gauges. Throughout this study, the threshold of 0.05 mm day-^{1} reflects precipitation accumulation in this analysis such that any value >0.05 mm day-^{1} was considered a wet day and values <0.0 mm day-^{1} was considered a non-precipitation (dry) day.

3.7 Methods of statistical analysis

Statistical analysis in this study was subjected to a check for normality of distribution. The normality test informed on what type of test followed. Where data was normal, a parametric test was conducted and where data was skewed, a non-parametric test was carried out. Compatibility in the experiment was assessed using the null hypothesis. The null hypothesis assumes that there is no difference between the samples under test. Therefore, by applying a 95% (0.05%) confidence level, the p-value gives us an indication if there is a significant difference in the samples. A lower p-value from 0.05% in the observed sample indicates a significant difference from the hypothesised sample.

3.7.1 Independent student's t-test

The Student's t-test for equal and unequal variances was used to find the significant difference between two samples, for example, the historical CMIP5 precipitation data was compared to the future (projected) CMIP5 precipitation data. The null hypothesis was set at no effect between the historical and future samples and an alternative hypothesis of 0.05%.

H_O: $\mu 1 \leq \mu 2$

H_1: $\mu 1 > \mu 2$

Where $\mu 1$ and $\mu 2$ are the means of the historical and the future samples; the p-value in the analysis then gives an indication of the existence of a significant difference between the two samples (Spintali, 2011; Kim, 2015). If the p-value is less than 0.05, then it can be inferred that that there is a significant difference between the samples making the null hypothesis untenable, therefore reject H_O and accept the alternative hypothesis (H_1).

3.7.2 Pearson's correlation coefficient (CC)

This test was used to evaluate similarities or differences between the observed CMIP5 precipitation and model CMIP5 precipitation data (Sedgwick, 2012). It is described as the covariance of the observed and the model means divided by their standard deviation. The CC is denoted with the letter "r" where r= 1, it suggests a positive linear relationship exists between the two datasets; where r = -1, it implies a negative correlation between the datasets; and where r = 0, it implies no relationship exists between the observed and model datasets.

3.7.3 Analysis of variance (ANOVA) and the Tukey post hoc test

ANOVA single factor comparison test was carried out to compare the means of the three different CMIP5 historical, RCP45 and RCP85 precipitation data and crop yields. This test helps to determine whether there are any significant differences between the means of the datasets (Kim, 2014). The test hypothesis assumes that there is no significant difference in the means of the three datasets and an alternative hypothesis that there should be at least one difference between the means from the three datasets. After ANOVA had been conducted, the Tukey multiple comparisons test was used to identify which of the sampled means that is significantly different from each other (Kim, 2014). These calculations were based on a mean statistics and normality of data at 95% confidence interval.

3.8 The greenhouse experiments

3.8.1 Description of the greenhouse

The greenhouse plant experiment was carried out using sugar beet plants that were grown in individual pots in the greenhouse facility located on the grounds of Brunel University London campus. The greenhouse measures 19m x 8m on the inside and contained plant tables of different lengths and breadths. The basic structural design of the greenhouse includes end walls, side post, 2 feet side walls to the side of the building onto which a semi-circular hoop shape plastic PVC sheets are built on. The sheets are covered all the way to the roof top with a single layer of polycarbonate plastic covering. The polycarbonate plastic sheets are transparent allowing sunlight and radiation spread more evenly throughout the facility. There is a front door to the facility and an emergency exit door at the back of the building. The greenhouse also has a water hose connected to the main water supply for watering and irrigation purposes. Overall, the greenhouse was considered an ideal environment for the experiments as it allowed water to be controlled. Temperature and humidity were not controllable in the greenhouse and was therefore not assessed in this study. It is worth noting that the different variables were consistent for the different watering regimes and plant experimental groups.

Figure 3. 2: Panoramic view of plants inside the greenhouse.

3.8.2 Selection of seed

The ultimate agricultural goal for farmers and crop growers in agricultural productions is the yield of the crop. Crop yields, apart from weather and growing conditions are influenced by the chosen variety of seed to sow. Sugar beet have different seed varieties and some of them perform better than others in terms of fresh weight yield and sugar percentage (BBRO, 2013). Sugar beet farmers in selecting sugar beet seeds for sowing considers a combination of factors including yield, sugar content, resistance to diseases and good commercial track record. This makes the process of seed selection a very important aspect of sugar beet production (BBRO, 2013). So, for this experiment, uniform sugar beet seeds of the same variety (SY Muse) was supplied free of charge by Sygenta UK. The seeds were pelleted (coated seeds) and were used for all replicates in the experiment.

The pelleted seeds were coated with a round protective and nutritive casing which ensures uniformity of the seeds makes it easier to handle during sowing and increases the growing conditions of the seeds. Another important factor in using pelleted seeds is because seeds are affected by diseases which reduces yield. One way of controlling seed diseases is by coating the seeds before planting. This technique involves adding several materials such as fertilizers, nutritional materials, moisture attractive agents, pesticides and plant growth regulators to the seeds. This technique has proved beneficial to growers for improving yield of crops (Ehsanfar & Modarres-Sanavy 2005).

Figure 3. 3: Picture of sugar beet seeds used in this study

According to the British Beet Research Organisation, BBRO (2013), the fresh weight of SY Muse is a high yielding variety that performs consistently well with excellent establishment and resistant to drought and rhizomania, and it's widely used by UK farmers. SY Muse compares favourably well with other varieties (see Table 3.4) and is third on the official yield variety list of the BBRO (2013) in terms of root yield and sugar content. It is rated "3" and "4" on a scale of 1-9, with 1 being "susceptible" and 9 being "tolerant" on the BBRO (2013) rust and powdery mildew disease scales respectively.

Table 3. 4: Shows a comparison of the SY Muse with other sugar beet varieties. Source: BBRO (2014).

Mean of sugar beet variety ranked in sugar yield order								
Varieties	Sugar t/ha	Adjusted tonnes t/ha	Root yield t/ha	Sugar content (%)	Plant establishment (%)	Rust scale	Powdery M.D scale	Year listed
Hornet	101.9	102	101.5	18.5	101	6	1	2014
Haydn	101.6	101.7	100.8	18.5	101	5	5	2013
SY Muse	100	99.9	100.6	18.3	101	3	4	2012
Master	99.7	99.8	99.2	18.5	102	8	5	2013
Aimanta	98.9	98.7	100.2	18.1	98	3	3	2009

As SY Muse is not on the extreme end of these scales, it was considered further justification for its use in this experiment.

3.8.3 Compost

The planting medium used for the plant experiments was the John Innes No. 2 soil based compost. All the compost used for the experiment were of the same brand but different bag sizes of 20kg and 50kg, and was sourced and supplied by LBS Horticultural Ltd. Lancashire, BB8 7BW, UK.

The compost contained ingredients of loamy soil which is the dominant soil type in the sugar beet producing areas of Eastern England (Scott & Jaggard 2000). This soil type is compact and retains moisture after draining off excess water and by so doing encourages germination and good plant establishment under field or controlled conditions. The soil also provides natural reservoir of plant food, trace elements and contains some organic matters which releases nitrogen slowly to the plants. The loam in John Innes No. 2 is screened and sterilised to avoid any transfer of soil-borne diseases and insects. The spaghum moss peat in the compost improves the aeration and water retaining capacity which enables the plants to make maximum use of nutrients. The lime-free grit and sand included in the soil allows excess water to drain from the plant pots and prevent water logging whilst adding weight and stability to the pot. The horticultural grade lime in the soil provides the pH that encourages healthy growth in plants. These characteristics are important for healthy plant growth, especially under controlled conditions.

3.8.4 Plant pots

A total of 150 plant pots were used for the experiment in the first season while 201 plant pots were used in the second season. The plant pots were black in colour and were all of the same size: 33cm in depth, 35cm in diameter at the top and 27cm in diameter at the bottom and had a volume of 33L. The pots were designed with holes at the bottom to drain off excess water from the pots as shown in Figure 3.4. The holes at the bottom of the pots ensured that there was no water logging in the pots while the soil type helps to retain moisture. These combined characteristics encouraged healthy plant development. The depth of the pots was also deep enough for sugar beet roots to grow unhindered as observed over the growing season.

Figure 3. 4: Picture of the plant pots used for the experiments with drainage holes at the bottom to drain off excess water from the pots.

3.8.5 Sowing dates

Sowing dates effectively means the dates that seeds are planted depending on soil factors and environmental conditions of the area where the crop is grown. In agricultural calendar, planting dates are considered one of the most important factors influencing field crops as it plays a vital role in germination, growth and yield of sugar beet and crops in general. For sugar beet, planting dates are also important in the sugar factory calendar as it enables organisations in planning of their work schedule. Thus, sowing sugar beet on suitable planting dates under the environmental conditions of the region is the best method to ensure adequate comparison of yields. In this study, 300 sugar beet seeds were sown into 150 plastic 33L plant pots in the first season on the 15 April 2014 and 402 seeds were sown in the same manner in the second season of the study on the 25 May 2015.

3.8.6 The plant experiment

The plant experiment in the first season commenced on the 15th April 2014 and on the 25th May 2015 in the second season. Two sugar beet seeds were sown into each plant pot containing 30 kg of “John Innes No. 2” compost which was used as a planting medium. The soil in the pot was shaken to eliminate pockets of air in the soil and keep the soil level and compact. This enabled the soil to retain moisture after draining off excess water. The timing of watering is important to maximise yields and ensure a fair comparison between the watering regimes. Water was applied in the mornings when the plants can maximise the available water because of lower evapotranspiration. A watering procedure was used that ensured the water was added in a consistent way to all pots and was as uniform as possible around the surface area of the soil.

This method was successful in terms of germination: 298 seedlings out of the 300 seeds sown in the first season and 360 emerged out of 402 seeds sown in the second season. Plant seedlings were thinned at their 4-6 leaves growth stages from two to one seedling per pot to encourage uniform establishment. Thereafter, in their 10-12 leaf growth stages, the plants were classified into the watering regimes as described in Sections 3.6.2 and 3.6.3: the “control” and “future” watering regimes in the first season, and the “control”, “RCP45” (denoted as M) and “RCP85” (denoted as H) watering regimes in the second season.

Moreover, plants in the different groups were systematically arranged (See Figures 3.5 and 3.6) around the greenhouse so that there would be minimal bias in temperature, humidity or sunlight for any group. In light of the foregoing, the greenhouse was considered an ideal environment to conduct the plant experiments. Furthermore, categorisation of plants at this time was done to coincide with the precipitation analysis from May-October for the study periods and because the biggest changes in precipitation was projected for the summer.

C	F	C	F	C	F	C	F
F	C	F	C	F	C	F	C
C	F	C	F	C	F	C	F

Figure 3. 5: Illustration of how plants in the control (C) and future (F) categories were arranged inside the greenhouse in the first season of the study.

3.8.7 Method of plants watering (Irrigation)

In both years of the experiment, plant pots in each watering regime were colour coded and the measuring cylinders used to add water to the pots were also colour coded to match each watering regime so that the potential for human error was reduced to a minimum. Each of the plants in the different categories was assigned a number so that growth and yield parameters could be recorded for specific plants.

3.8.7.1 Irrigation under "climatological" watering regimes

In the first year of the experiment (2014) under the climatological watering regime, plants were categorised into "control" and "future" groups and were watered (irrigated) every other day whereby irrigation was administered on a day on - day off basis. Plants were given the same amount of water from the sowing stage until they were categorised into different watering regimes. This gives all the plants an equal chance of developmental growth before allocating them into groups. Thereafter, plants in the "control" watering regime were watered according to the calculation described in Section 3.6.2 and the plants in the "future" watering regime were given 16% less water than the "control" based on the calculation of future precipitation projections. Assessment of the plants commenced after categorisation when they had started forming tubers to gauge the impact of different watering treatment on the plants in the two categories.

Plants were categorised into the control and future (See figure 3.6) watering regimes and the different watering regimes were implemented after the plants had reached their 10-12 leaves growth stages. In order to account for natural variability in plant sizes, the plants assigned to each watering regime were selected to result in an equal distribution of plant sizes in each watering experiment. Categorisation of the plants at this time was done to coincide with the precipitation analysis from May to October for the study periods and because the biggest changes in precipitation was projected for the summer. Output of changes calculated from the precipitation analysis was then imposed on plants in the future category.

Irrigation was applied by measuring the appropriate amount of water (i.e. 460ml for control and 390ml for future) into a 500ml cylinder; pouring it into a watering can and then applying the water on the plants through the surface of the soil. To do this effectively, a watering procedure was put in place to ensure that water was added in a consistent manner to all pots and was as uniform as possible around the surface area of the soil. This is important to ensure that water was accessed by plant roots regardless of their location inside the pots. Moreover, plant pots in each watering regime were colour coded along with the watering cylinders to ensure that the right plants get the appropriate amount of water and again reduce the potential of human error to a minimum. Each plant was assigned a number so that growth and yield parameters could be recorded for specific plants in the different experiments.

3.8.7.2 Irrigation under "realistic" distribution of precipitation events and sizes

In the second year of experiment (2015), irrigation was conducted in much the same way as the previous season except for the number of experimental categories and the calculation of the watering regimes which was based on a "realistic" distribution of precipitation events and sizes rather than a climatological representation of precipitation. All other materials used remain the same as in the first season experiment.

Plants were categorised into control, RCP45 and RCP85 watering regimes (See Figure 3.7) and were implemented after the plants had reached their 10-12 leaves growth stages. The "control" or "present day" experimental watering regime represents precipitation for the baseline period from 1971-2000; the "RCP45" in this experiment represents "medium greenhouse gas emissions scenario" otherwise called "medium" for experimental purposes and the "RCP85" represents "high greenhouse gas emissions scenario" or "high" for this experiment and both RCPs represents the projected period from 2021-2050. The three experiments were designed to examine changes in absolute precipitation determined by event sizes and distribution of precipitation events over the growing season. As in the first year experiment, accounting for natural variability in plant sizes helped ensure that the plants assigned to each watering regime were selected to result in an equal distribution of plant sizes in each watering experiment. Categorisation of the plants at this time was also done to coincide with the rainfall analysis from May to October for the study.

The calculation of the watering regimes entailed working out the total number of wet days and dry days to find out how many days the plants will receive irrigation and the sizes and distribution of irrigation in each month. Therefore, under this regime, plants were only watered on wet days within the given month and left without water on dry days.

Irrigation was conducted by measuring the appropriate amount of water for each of the plants in the different categories into a 500ml cylinder; pouring it into a watering can and then applying the water on the plants through the surface of the soil. To do this effectively, a watering procedure was also put in place to ensure that water was added in a consistent manner to all pots and was as uniform as possible around the surface area of the soil. The timing of watering is vital to maximise yields and ensure a fair comparison between the watering regimes. Other watering applications such as watering in the mornings and colour coding of pots and cylinders followed pretty much the same pattern as already discussed in Section 3.8.6.1.

H	C	M	C	M	H	C	M
M	H	C	H	C	M	H	C
C	M	H	M	H	C	M	H

Figure 3. 6: Illustration of how plants in the control (C), RCP45 (M) and RCP85 (H) categories were arranged on the tables inside the greenhouse in the second season of the study.

3.8.8 Plant parameter measurements

3.8.8.1 Above-ground measurements

The measurement of plant parameters help to capture the overall health and the impacts of environmental conditions on the plants. The measurement of plant parameters in this study was an important aspect for comparing the impacts of differential watering regimes on the "control" and "future" categories of plant experiments. These measurements help to determine the extent of plant growth in each experiment based on the different watering regimes impacts on yield.

Plants in the different categories of the experiments have been exposed to the same conditions prior to categorisation. Upon categorisation, this enabled the measurement of important parameters and collection of data from the different stages of plants growth and development to be compared and statistically analysed in relation to yield. Essentially, a number of non-destructive parameters were used to assess the yield potential of the plants over the growing season including: the number of leaves on each plant, height of the plants (i.e. height of the tallest stem); the growth ratio of the stem (i.e. height divided by the number of stems) and leaf width (i.e. width of the widest leaf). The above-ground parameters were made with the use of a tape measure. These parameters were measured every two weeks to enable the assessment of water reduction on the plants development and productivity. This places the yield of the plants in the context of the growing season.

Figure 3. 7: The method used in measuring plants height and growth ratio index. A tape rule is placed at the crown of the plant to the highest tip of the tallest stem. The highest stem measurement is divided by the number of leaves on the plant to get an indication of the plants growth ratio.

3.8.8.2 Soil moisture

During the growing season, soil moisture measurements were undertaken every two weeks. The soil moisture measurement was conducted using a manual soil moisture meter (Brand: Lutron PMS-714) to measure the level of moisture in the soil. The soil moisture meter was manufactured by NHBS Ltd, Devon, TQ9 5LE, UK. The Lutron was used to measure the soil moisture content in individual plant pot and has a range of 0-50% with a resolution of 0.1. The microprocessor ensures high accuracy of data and the durable ABS plastic housing makes it ideal for use under field and controlled conditions. The LCD screen makes it easy to read data and it also has a data hold function which allows freezing of the current value on display thereby helping to minimise recording errors.

The probe was powered by 4 Duracell batteries and the prong is thrust vertically 10cm depth into the soil to obtain the soil moisture reading (see Figure 3.8). These readings were taken every two weeks from individual plants across all the experiments in similar manner.
The data was collected for each individual plant in the different categories to enable the assessment of the different watering regimes on soil moisture.

Figure 3. 8: Method of manual soil moisture reading.

3.8.8.3 Below-ground measurements

At the end of each experimental season, destructive measurements were taken to determine the mean mass of the tubers as harvested and when dried. When harvested, the tubers were uprooted from the soil, washed and dried. Thereafter, the leaves of the plants were cut off from the crown leaving the tubers, which are of most interest in this research. Each individual tuber was weighed without the leaves – these measurements are reported in this thesis as the "wet" weight. The tubers were then labelled with their numbers and put in open transparent bags so that the yield data could be added to the database of growth parameters recorded over the growing season. Analysis of the dry weight of the tubers was conducted using a laboratory method to remove the moisture content. Obtaining the dry weight was done by cutting each tuber into smaller pieces to speed the drying rate. The size of the pieces was kept as equal as possible for all tubers so that drying rates were as equal as possible. A tuber of median size was cut into 8 pieces whereas larger tubers were cut into more pieces. The pieces were put into individual aluminium trays and numbered for identification purposes and then put inside an oven for drying at 80 °C until constancy, *as per* Mohammadzadeh & Hatamipour (2010). The cut tubers were weighed periodically, typically every 2 hours, until there was no more appreciable change in weight. At this point the value was recorded as the “dry” weight.

Measurements and data collected at different stages of the plants’ growth and following harvest were statistically analysed to enable quantification of impacts. All measured parameters were tested for normality, which then determines the type of test to be carried out. Parametric tests were conducted where data was normal and non-parametric tests were conducted where data was skewed. Following this, a two tailed t-test was carried out for the two watering regimes. The outcome of the experiment was assessed using the null hypothesis: “there is no difference in the categories”. Therefore, applying a confidence interval (CI) of 95% with alpha set at 0.05%; the p-value then gives an indication if significant differences exist in the parameters assessed.

3.9 Weeding and pest control

3.9.1 Weeds

The presence of weeds in sugar beet and plants generally can result in the crops competing directly for vital resources such as water. Weeds of any kind can result in yield losses and therefore adequate protection, attention and plans must be put in place to safeguard against potential losses.

Although, the incident of weeds in this experiment were minimal and not considered a threat to yield, measures were still put in place to safeguard against the threat of weeds by instituting a twice-weekly programme of consistent weeding to ensure early detection of weed/s in any of the pots. This programme also helped to remove direct competition from the weeds and ensured that the plants received and utilised the amount of water allocated to each plant, thereby eliminating bias in the experiment as a result of competition from weeds.

3.9.2 Powdery Mildew Disease (PMD)

Powdery Mildew Disease is a fungal disease that affects the leaves of sugar beet and is prevalent in sugar beet producing areas such as the UK mainland, Europe and the United States, causing potential sugar beet yield losses of up to 30-35% (Neher & Gallian 1947). The fungus is mainly airborne and introduced annually around the end of June through July. Its lifecycle is linked to that of the host and the prevailing environmental conditions. Symptoms of PMD are usually first seen on older leaves on the underside. They appear as small, scattered, white powdery mycelium coating on the surface of the leaves preventing the leaves from performing the vital function of photosynthesis which can ultimately lead to yield reduction in cases of severe infection.

Control of PMD entails the use of fungicides to control attack. Early detection and intervention is important for effective control of the disease and the timing of control measures (i.e. treating the disease at the onset is more effective than when the disease has spread through the plant population). PMD attack on the plant experiments in this study was minimal, although, when the attack was observed in the first season of the experiment, it was treated with Systhane Fungus Fighter which was sprayed across the plant population to prevent infection of new leaves. The second season PMD attack was even more insignificant because the disease was detected early and control measure using Systhane Fungus Fighter was immediately applied to stop further infection.

3.9.3 Armyworms

Armyworms are pests that cause perforations on sugar beet leaves. These pests usually thrive in warm locations and their eggs are normally deposited on the surface of the leaves. In severe cases, armyworm attacks could damage leaves so badly that only the leaf veins and petioles will be left. If attack is severe, the larvae migrate from plant to plant via the leaves infesting new leaves and seriously damaging the plants ability to photosynthesise. The management and control of armyworms in this study was by early detection and manually removing the pests from the affected leaves and plants, and gently cleansing more affected plant leaves with mild soapy water. This management procedure removes the eggs and larvae from the affected plants/leaves and was very effective in treating the pest. This may not be the case in field operations or much larger indoor studies with very large population.

Chapter 4 – Results: precipitation analysis

4.1 Introduction

The results in this thesis cover two chapters: the precipitation analysis (Chapter 4) and the greenhouse experiments (Chapter 5). The analysis of precipitation is of fundamental importance to understanding the possible impacts of future changes in precipitation and how it will affect sugar beet farming in Eastern England. The current chapter presents findings of changes in precipitation over Eastern England for two different time frames: "historical", 1971-2000 and "future", 2021-2050 using daily precipitation data from the CMIP5 climate models. Model output was used as a basis for quantitative comparison of past and future precipitation analysis using the growing season mean and changes in day-to-day precipitation event size and frequency. The results relating to the precipitation analysis were used to calculate the watering regime (Section 4.5) that were applied to the greenhouse experiments presented in Chapter 5.

4.2 Analysis of weather station data

4.2.1 Weather stations May-October annual mean precipitation analysis

The climate of Eastern England is generally dry and mild and considered one of the driest regions in the UK with many areas receiving less than 700 mm of precipitation per year compared to other areas such as the Lake District with an annual average of 3000 mm and the western Scottish mountains with an annual average of about 4000 mm per year (Met Office 2016). Figure 4.1 provides a broad reflection of monthly mean rainfall variations in different parts of the UK and shows the rainfall output from two stations in Eastern England used in this study (a, b), two stations in southwest England (c, d) and two stations in northern Scotland (e, f). Comparison of the six stations shown in Figure 4.1 indicates that the two stations in Eastern England has the lowest amount of monthly mean rainfall of about 65 mm while the south-west of England has about 125 mm and northern Scotland with a high of around 145 mm (Met Office 2016).

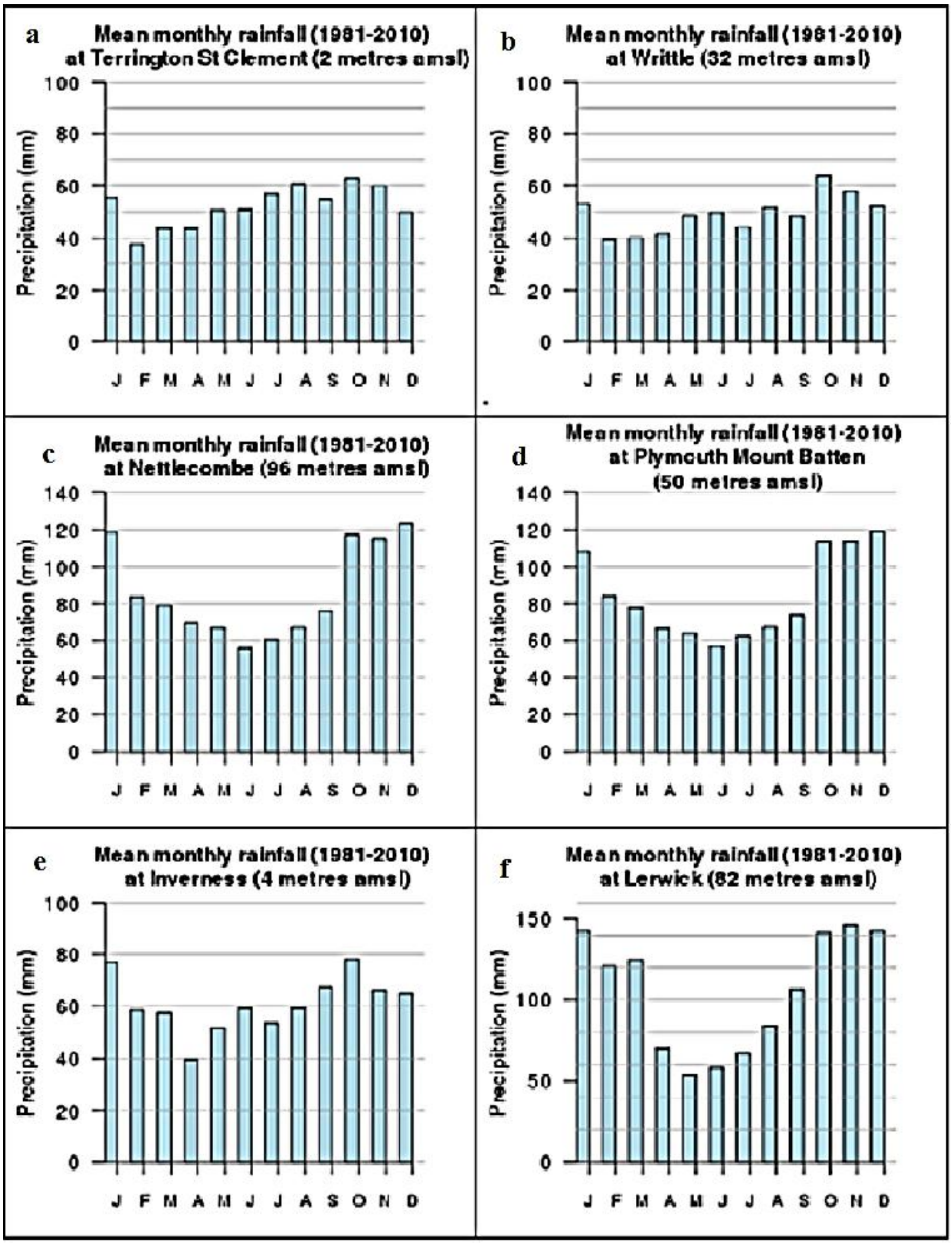


Figure 4. 1: Monthly mean rainfall from six stations in three different regions of the UK. Two stations from the area of interest in Eastern England (a, b), two stations from the South West of England (c, f) and two stations from northern Scotland (e, f). Source: Met Office (2016).

The general nature of precipitation variability in time and space makes it important to rely on long-term climate analysis from weather stations with reliable homogenous data and in this thesis, the analyses presented cover a 30 year period (i.e. 1971-2000) using precipitation data from six weather stations with continuous and reliable precipitation data of Eastern England, in order to gain an understanding of the current precipitation regime in the region. Results of the weather stations May-October daily mean precipitation analysis over Eastern England showed high annual variations depicted in Figure 4.2. The highest daily mean precipitation value from the six stations was recorded in Santon Downham for 2.9 mm in 1987 followed by the second highest of 2.82 mm recorded in 2000 at Stansted Mountfichet. Other high daily mean May-October precipitation were also recorded in the remaining four stations with some stations recording the same values, such as Writtle and Coltishall with 2.72 mm respectively followed by Manston with 2.63 mm and Coltishall with 2.44 mm. Conversely, low daily mean precipitation was recorded across all stations in 1976, 1978, 1995, 1996, 1997 and 1998. Figure 4.2 shows the pattern of annual variations displayed from the weather stations data.

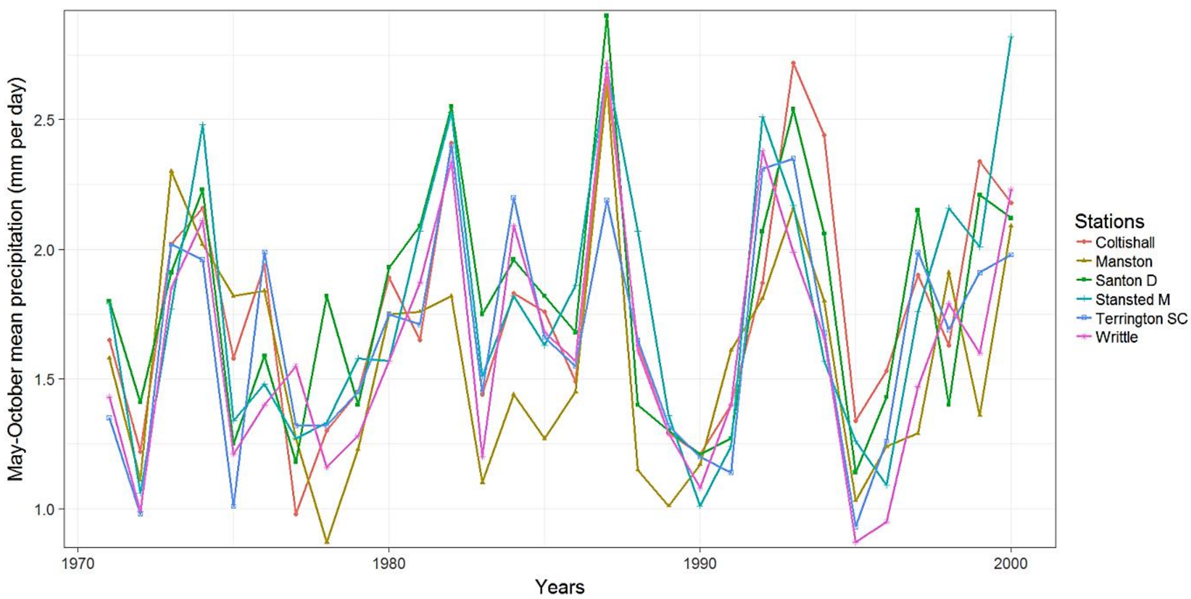


Figure 4. 2: Observation plot of the May-October annual mean precipitation data from the six weather stations used.

The May-October daily mean precipitation was calculated using the May-October mean daily precipitation for each year in each station for the 30 year period. Over the 30 years, all the stations data exhibited similar year-to-year variations. The data also showed that in the years that precipitation was high, this applied to all the stations and conversely, in the years that precipitation was low, it also applied to all the stations. This suggests that similar precipitation mechanism prevailed over the region. Overall, statistical analysis of the data showed no significant trend in the observed precipitation. This was based on Pearson's product-moment correlation which showed a negative trend of -0.13, however, the trend was not significant with a p-value of 0.81.

Further mean statistical analysis of the May-October weather stations data using boxplots showed that the precipitation characteristics of the majority of the stations showed good agreement across the region. The May-October daily mean precipitation recorded for the six stations from 1971-2000 are shown in Figure 4.3 and Table 4.1 with the highest mean of 1.78 mm day-^{1} recorded for Santon Downham, followed by Coltishall and Stansted Mountfichet with 1.76 mm day-^{1} respectively, Terrington St Clement 1.66 mm day-^{1}, Writtle 1.61 mm day-^{1}, and Manston with 1.56 mm day-^{1}. Only the median and distribution of Manston, despite falling within the region of interest (see Figure 3.1) is not representative of the region where most of the sugar beet farming occurs. So, this is not considered important for the analysis and is therefore disregarded in the analysis presented here. However, the results of the mean daily precipitation in this study compares well with the findings of Gregory et al, (1991) who reported a daily mean precipitation of 1.77 mm per day for Eastern England (see Table 4.1).

Table 4.1 also showed small Standard Error of Mean (SE) values which indicated that the sampled mean is a good reflection of the actual mean population of the data. Similarly, the Correlation Variation (CV) also showed low values and in fact, smaller than the Standard Deviation (Std) which is to be expected, it revealed the amount of variability in the data relative to the mean. The CV showed the closeness of the distribution around the mean.

Table 4. 1: Weather stations analysis of the May-October daily mean precipitation from 1971-2000.

Stations	Mean	Standard Deviation	Median	Standard Error (mean)	Correlation of Variation (CV)	Observations
Coltishall	1.76	0.4	1.65	0.08	0.25	30
Manston	1.56	0.4	1.51	0.08	0.28	30
Santon Downham	1.78	0.5	1.81	0.08	0.25	30
Stansted Mounfichet	1.76	0.5	1.71	0.09	0.29	30
Terrington SC	1.65	0.4	1.67	0.07	0.26	30
Writtle	1.61	0.5	1.57	0.08	0.28	30

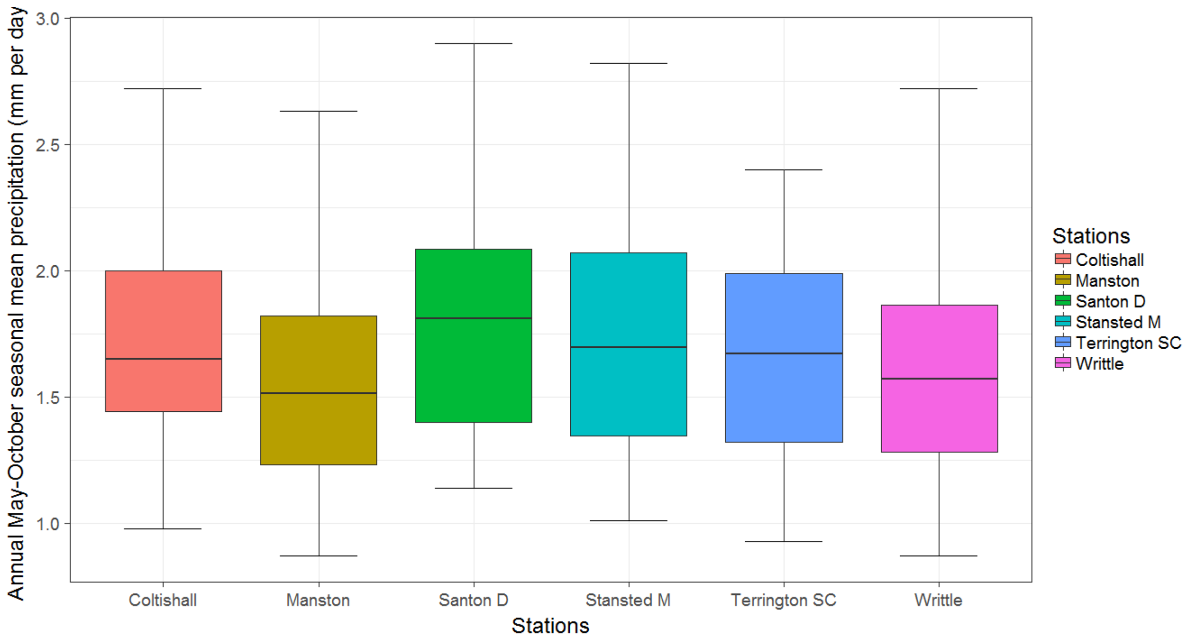


Figure 4. 3: Box-and-whisker plot displaying the characteristics of the May-October precipitation data for 1971-2000 from the weather stations observations. The solid thick black line within the box represents the median (2nd quartile) of the distribution. The extremes of the box represents the 1st (bottom) and 3rd quartiles (top). The whiskers indicate the lowest and highest values of the distribution.

4.2.2 Weather stations total daily May-October wet days precipitation analysis

In this Section, the total May-October daily precipitation for the growing season was summed up for each year in each of the station for the period 1971-2000. This enabled the days that have precipitation events to be separated from days without precipitation. Results of the distribution of precipitation events showed good agreement among majority of the stations with similar patterns of distribution over the May-October growing season (Figure 4.4). The stations distribution of total May-October precipitation over the study area showed year-to-year variations similar to the May-October daily mean precipitation described in Section 4.2.1. The characteristics of the total May-October distribution of precipitation for all stations (Figures 4.4) revealed a maximum precipitation of 68 mm, a minimum of 0.1 mm and an overall mean of 3.8 mm.

Further, the total May-October mean precipitation analysis of individual stations for the period 1971-2000 in Table 4.2 shows Santon Downham and Stansted Mountfichet returning the highest mean precipitation values of 4.03 mm day^{-1} (Std 5.6) and 4.02 mm day^{-1} (Std 5.9) respectively. The next station with the highest mean precipitation was Writtle with 3.98 mm day^{-1} (Std 6.0) followed by Manston with 3.76 mm day-^{1} (Std 5.4), Terrington St. Clement with 3.72 mm day-^{1} (Std 5.5) and Coltishall with 3.70 mm day-^{1} (Std 5.6). The mean precipitation among the stations ranged from the lowest 3.69 mm to 4.03 mm day-^{1}. Statistical analysis conducted using ANOVA multiple means comparison test revealed that there were no statistically significant differences in the total May-October precipitation from the different stations. The test returned a p-value of 0.08 at 95% confidence interval suggesting that there were no statistically significant long-term trends in the total May-October daily precipitation over the region from 1971-2000.

The May-October daily precipitation count (see Table 4.2) for all the stations indicated less number of wet day precipitation compared to dry days. Although, the number of wet days vary from one station to another; the station with the highest number of wet days in this case was Coltishall and had the lowest percentage decrease. Conversely, the stations with the lowest number of wet days (e.g. Manston and Writtle) had the highest number of dry days. The remaining three stations (Santon Downham, Stansted Mountfichet and Terrington St. Clement) were within the same range. The result of low precipitation for Manston is consistent with result in Section 4.2.1 and Table 4.2 shows Manston with the lowest number of wet day precipitation out of the range and, again implies that it is in a different precipitation regime to the other stations. However, all the stations showed a percentage decrease in the number of wet day precipitation (Table 4.2). In spite of that, the other stations showed less number of wet days than dry days for the period 1971-2000 (Table 4.2).

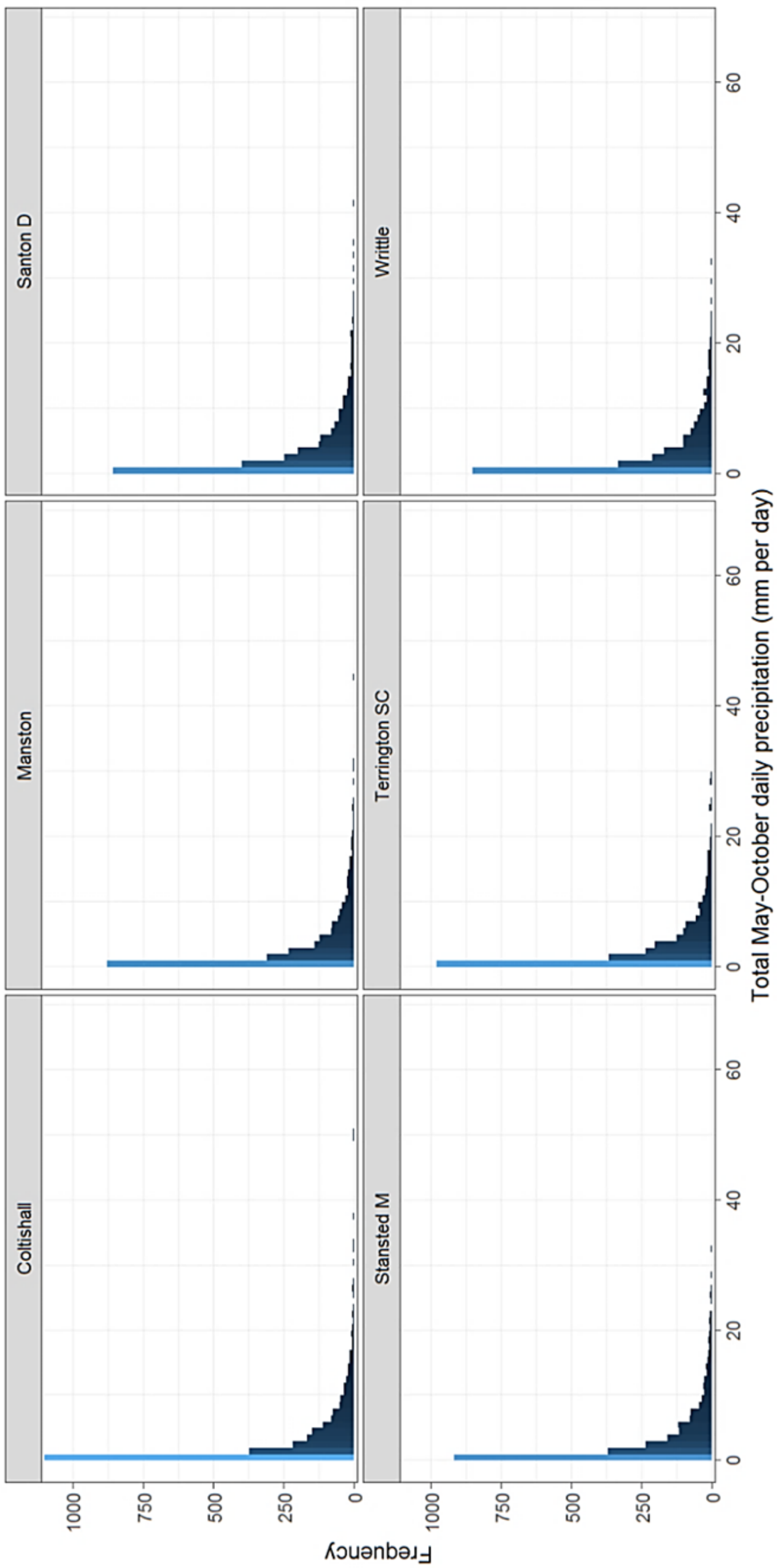


Figure 4. 4: Distribution of the total May-October precipitation from each of the stations for the period 1971-2000.

Table 4.2: Analysis of the total May-October daily precipitation of each station from 1971-2000.

Stations	Mean	Standard Deviation	Wet Days	Dry Days	Difference between wet & dry days
Coltishall	3.7	5.6	2616	2904	288
Manston	3.76	5.4	2201	3319	1118
Santon Downham	4.03	5.6	2462	3058	596
Stansted Mounfichet	4.02	5.9	2413	3107	694
Terrington SC	3.72	5.5	2486	3034	548
Writtle	3.98	6	2230	3290	1060

4.2.3 Weather stations monthly May-October daily precipitation

The monthly May-October daily precipitation provides a general view of the precipitation characteristics of the region and results indicated similar pattern of positively skewed precipitation distribution (Figure 4.5) in all the stations from May to October over the 30-year (1971-2000) period suggesting that precipitation over the region was governed by similar factors. The stations again showed similar patterns of distribution for the study area as the stations May-October mean precipitation described in Section 4.2.1. This type of consistency implies that the data could be relied upon for the precipitation analysis in this study.

Figure 4.6 showed similar precipitation trends and high monthly variations for each year of the study although, three of the stations (Santon Downham, Terrington St. Clement and Writtle) indicated episodes of heavy precipitation in June and August and a couple of events occurring in Writtle in the month of July. These notable exceptions (Figure 4.6) showed high precipitation events in June of 1975 in Santon Downham, Terrington St. Clement and Writtle. Coltishall and Writtle also recorded high precipitation events in July 1989 while Manston, Terrington St. Clement and Writtle recorded high precipitation events in August 1992. Results illustrated in Figure 4.7 suggest that the monthly May-October precipitation from the stations vary from month-to-month but without a long-term discernible trend.

Statistical analysis of the monthly May-October precipitation showed that the highest mean precipitation occurred in Writtle with a value of 4.53 mm (Std 7.5) in August (see Table 4.3). Conversely, the lowest monthly mean precipitation was recorded in Coltishall in May with a value of 3.15 mm (Std 4.1). The mean monthly variations between the stations therefore vary between 3.15 mm and 4.53 mm with high standard deviations varying between 4.1 in Manston (lowest) in the month of May and 7.5 in Writtle (highest) in the month of August. The monthly variations in precipitation is important in this study in order to determine which months that may be adversely affected by the changes in precipitation particularly during the growing season of the summer months when temperatures are likely to be highest.

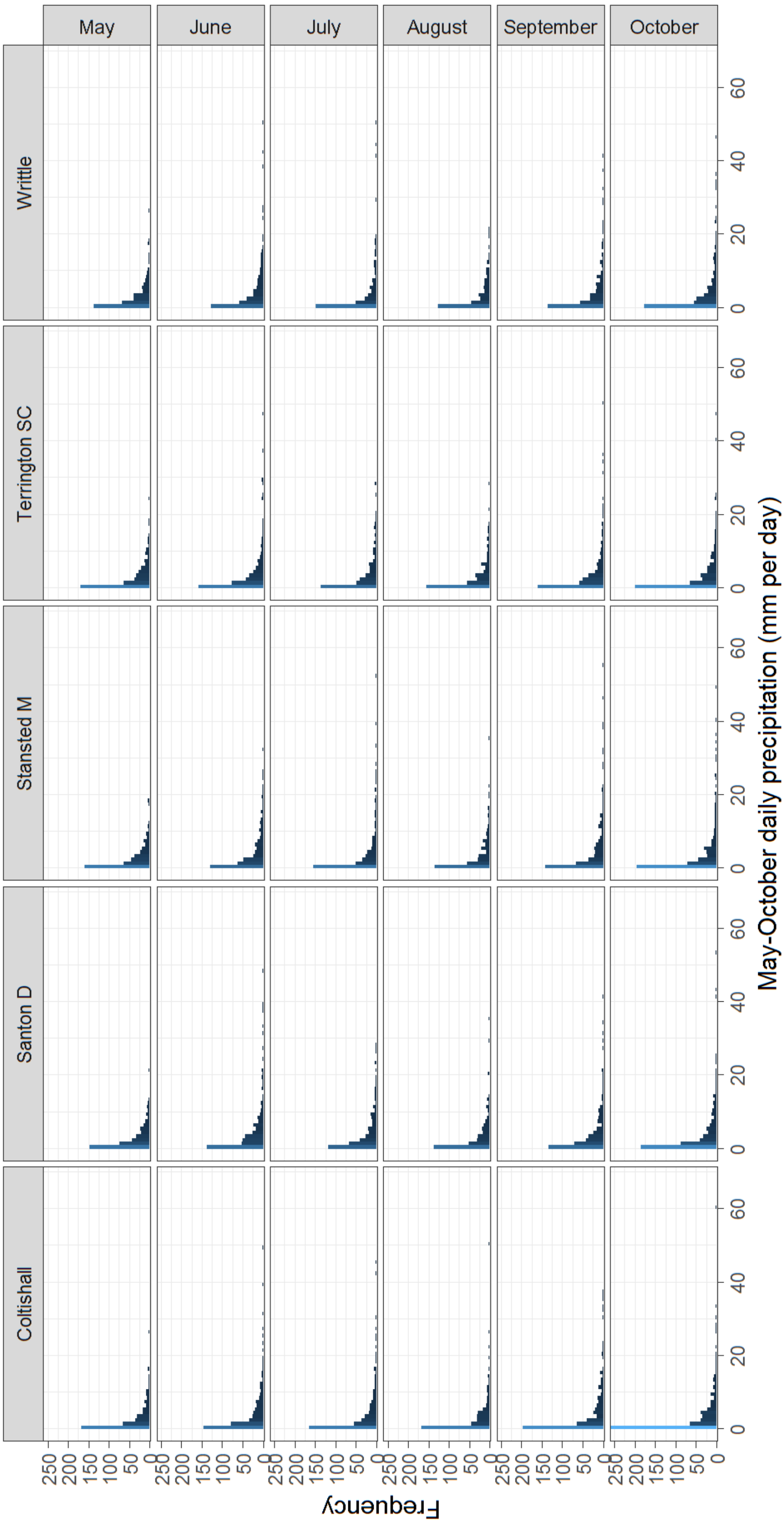


Figure 4. 5: Distribution of the monthly May-October daily precipitation of the growing season from the weather stations data for the period 1971-2000.

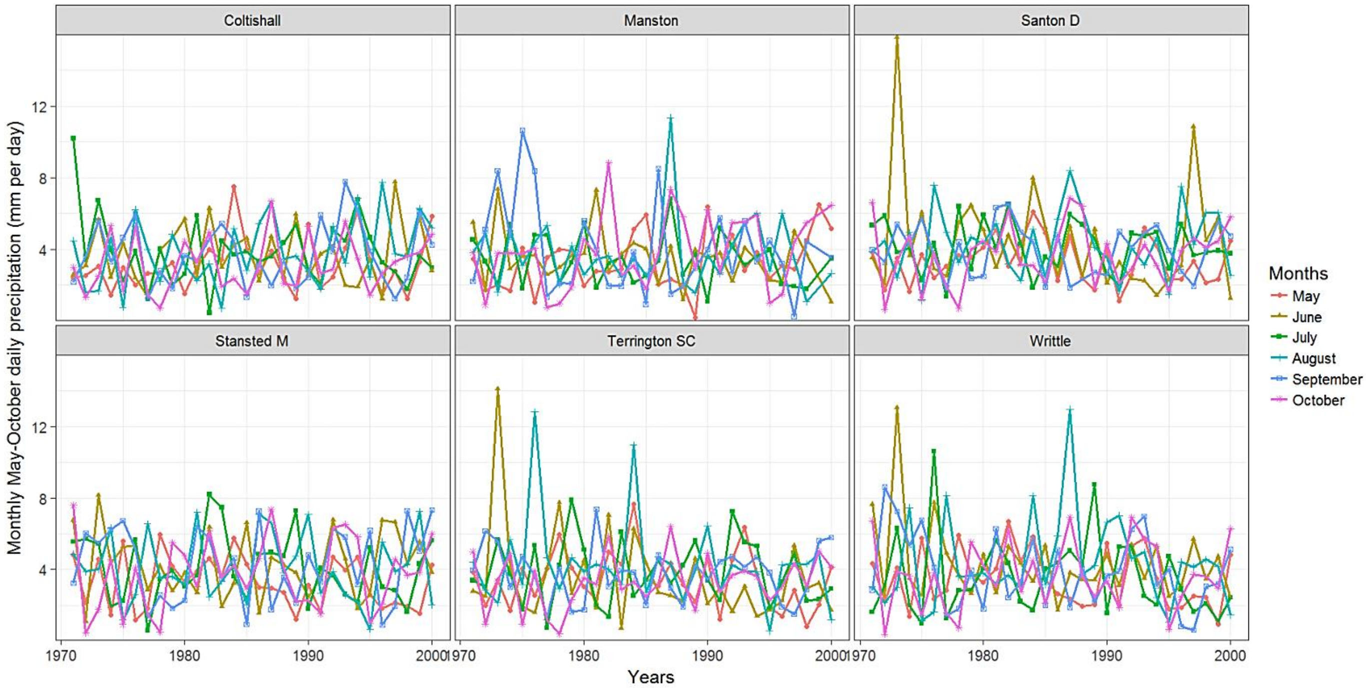


Figure 4. 6: Observation plots of the monthly May-October mean precipitation of the growing season from the weather stations data for the period 1971-2000.

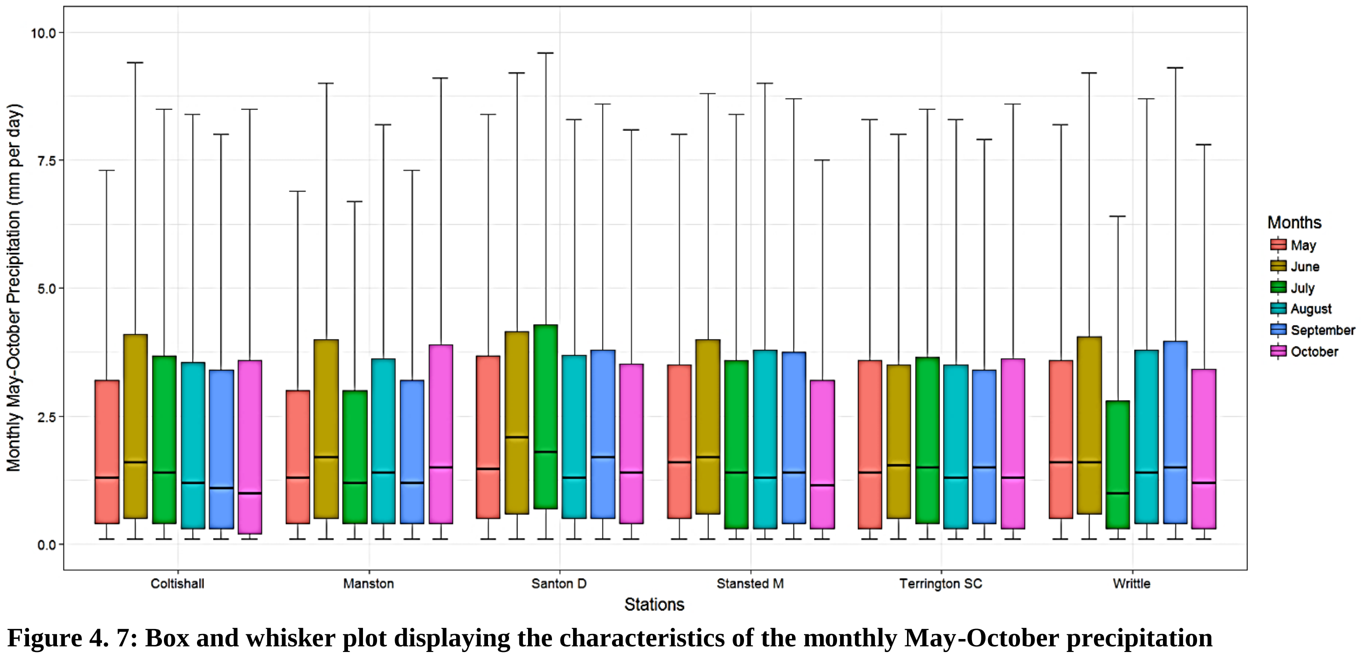


Figure 4. 7: Box and whisker plot displaying the characteristics of the monthly May-October precipitation data from the weather station observations for the period 1971-2000. The boxplot details are the same as in Figure 4.3.

Table 4. 2: Analysis of the stations monthly May-October daily precipitation from 1971-2000 from the five stations with similar characteristics.

	Coltishall		Manston		Santon D		Stansted M		Terrington SC		Writtle	
Months	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
May	3.15	4.1	3.18	4.3	3.37	4.3	3.36	4.5	3.41	4.7	3.55	4.9
June	3.89	5.4	3.59	4.7	4.26	6	4.21	5.2	3.61	5.5	4.2	5.9
July	3.82	5.7	3.42	4.9	4.29	5.2	3.88	6.1	3.84	5	3.53	6.1
August	4.09	6.9	3.85	5.8	4.29	6.3	4.22	6.1	4.17	6.6	4.53	7.5
September	3.91	5.8	4.22	6.6	4.19	5.8	4.52	6.7	3.85	5.8	4.11	5.8
October	3.41	5.3	4.17	5.6	3.83	5.7	4.01	6.4	3.52	5.1	3.98	6

4.2.4 Summer (June, July, August; JJA precipitation)

In this Section, firstly, the summer June, July and August (JJA) mean precipitation was summed up for the three months in all the stations for the period 1971-2000 and secondly; an assessment of the individual JJA months was conducted. Result of the analysis also showed fairly good agreement between the stations which are consistent with results obtained from the total May-October mean precipitation analysis. The summer (JJA) mean precipitation for all the stations ranged from 3.61mm day^{-1} in Manston (lowest) to the highest of 4.28mm day^{-1} in Santon Downham (Table 4.4). The highest JJA number of precipitation days from all the stations was recorded in Coltishall with 1208 days followed by Terrington SC with 1176. Manston had the lowest number of precipitation days with 1005 (Table 4.4). Figure 4.8 shows the same pattern of precipitation distribution in all the stations and Table 4.4 shows a reduction in the number of wet precipitation events recorded for the stations.

Observed JJA precipitation distribution (Figure 4.8) from (1971-2000) showed the same pattern of distribution for all the stations further supporting the reliability of the data as representative of the study area. Manston again showed the highest percentage decrease and least number of wet day precipitations. Writtle had the second highest percentage decrease in the number of wet day precipitations but unlike Manston, Writtle is within the range of the study area.

Table 4. 3: Analysis of the total June, July and August (JJA) mean precipitation from each of the weather stations for the period (1971-2000).

Stations	Mean	Std	No. of precipitation days	No. of Non-precipitation days	% change in the No. of precipitation days
Coltishall	3.93	6	1208	1552	-28.5
Manston	3.61	5.1	1005	1755	-74.6
Santon D	4.28	5.8	1160	1600	-38
Stansted M	4.1	5.8	1123	1637	-46
Terringto SC	3.86	5.8	1176	1584	-34.6
Writtle	4.09	6.5	1038	1722	-65.8

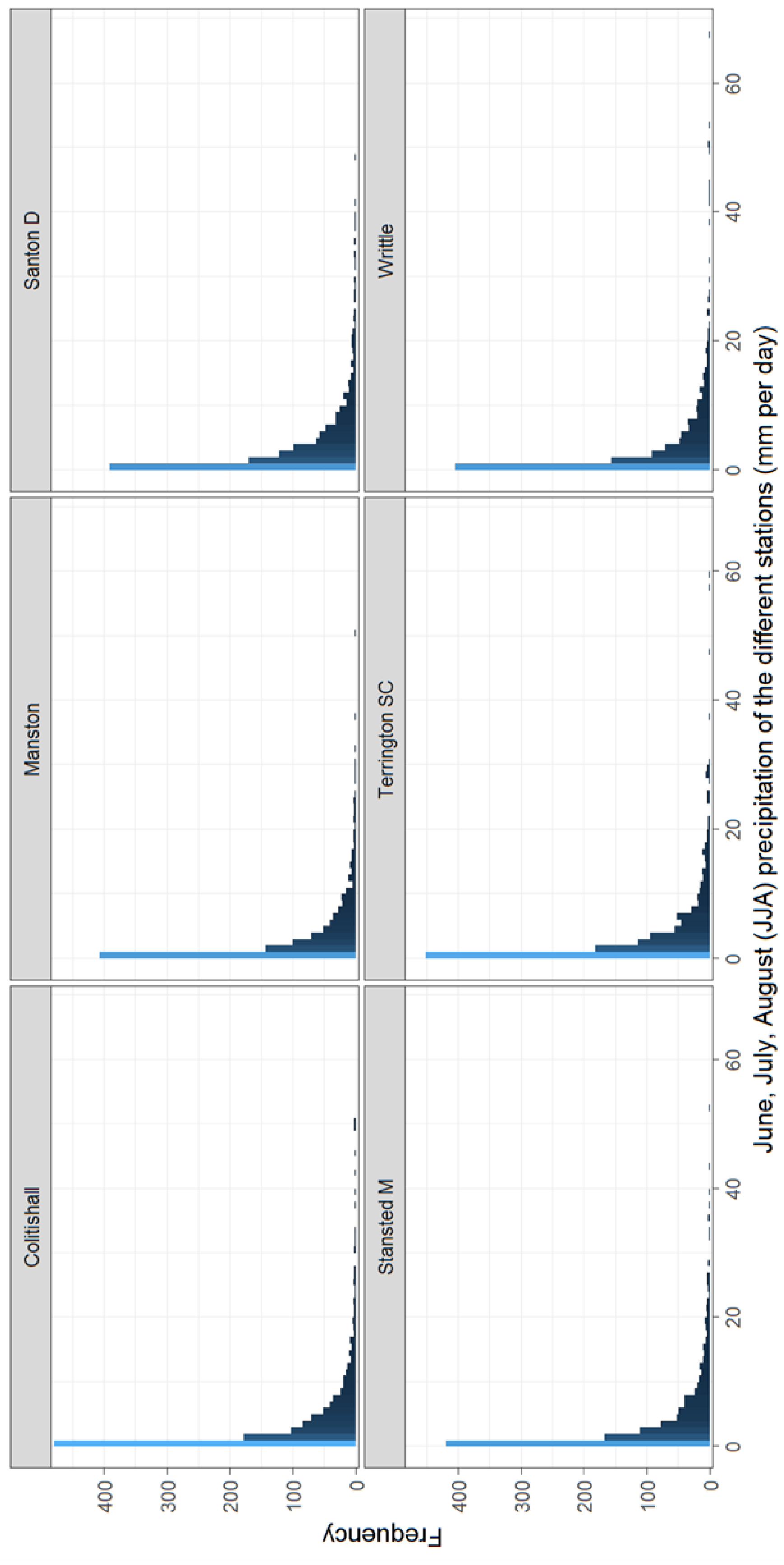


Figure 4. 8: Summer JJA precipitation of each of the stations for the period 1971-2000.

Similarly, Table 4.5 shows the individual summer JJA month's precipitation analysis and it agrees with the result from the Monthly May-October precipitation. Although, this result is obvious in Table 4.3, it was still necessary to present it separately to correspond with the precipitation distribution presented in Figure 4.9. Table 4.5 shows that the mean precipitation for the individual JJA months recorded higher mean values in August over the study period for all the stations. Mean precipitation in June and July varied among the stations with June recording more mean precipitations in Coltishall, Manston, Stansted Mounfichet and Writtle, while July recorded more in Santon Downham and Terrington St. Clement.

In spite of these differences, statistical analysis conducted using ANOVA multiple comparison of means test revealed that there were no significant differences in the means of the individual JJA precipitation from all the stations. The test returned a p-value of 0.09 at 95% confidence interval suggesting that there were no significant long-term trends in the JJA precipitation over the region from 1971-2000. Figure 4.9 shows the distribution of the summer JJA precipitation and also portrays similar precipitation characteristics for all the stations which is consistent with results from the seasonal and monthly precipitation analysis. Figure 4.10 suggest that the JJA May-October precipitation from the stations vary monthly with the mean distribution of precipitation events higher in June than July and August.

Table 4. 4: Analysis of monthly June, July, August (JJA) means precipitation for the period 1971-2000.

	Coltishall		Manston		Santon D		Stansted M		Terrington SC		Writtle	
Months	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
June	3.89	5.4	3.59	4.7	4.26	6	4.21	5.2	3.61	5.5	4.2	5.9
July	3.82	5.7	3.42	4.9	4.29	5.2	3.88	6.1	3.84	5	3.53	6.1
August	4.09	6.9	3.85	5.8	4.29	6.3	4.22	6.1	4.17	6.6	4.53	7.5

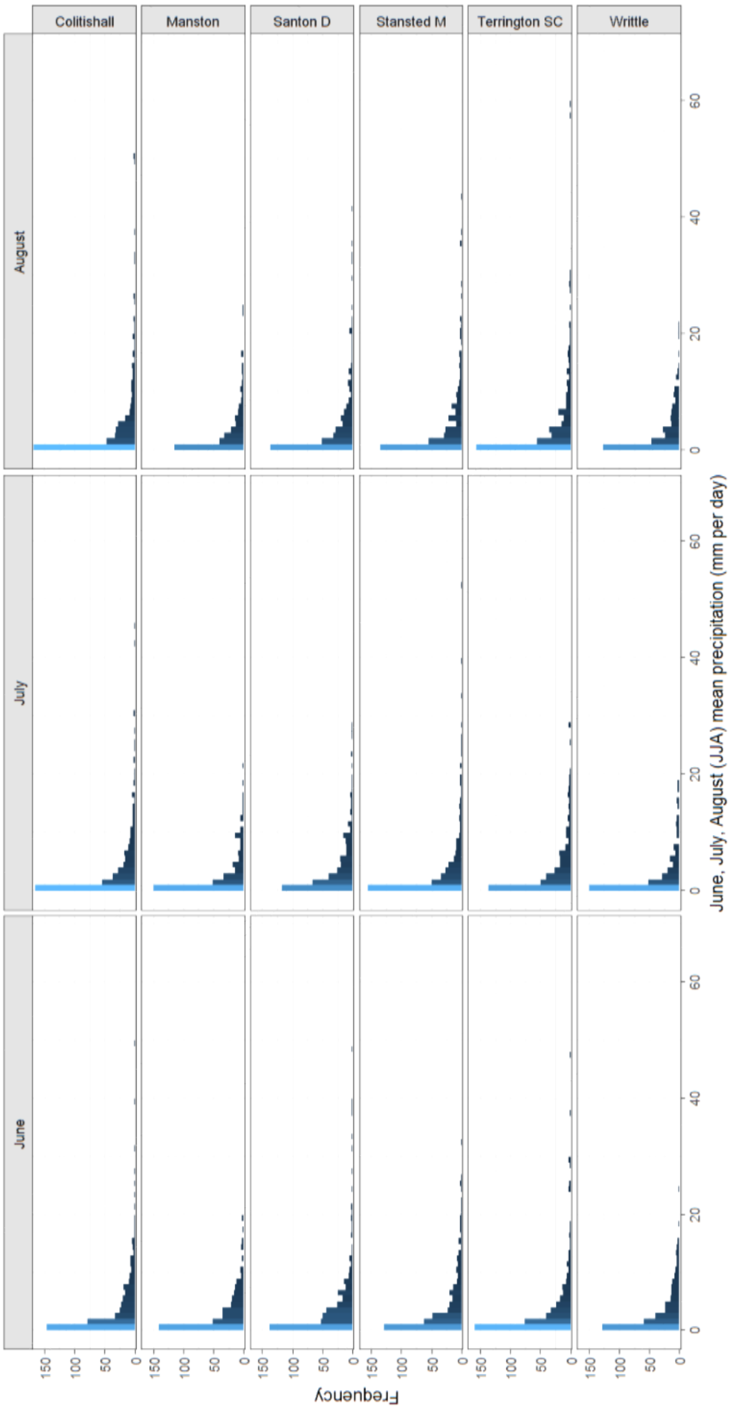


Figure 4. 9: Summer JJA mean precipitation for each month for the stations observed data.

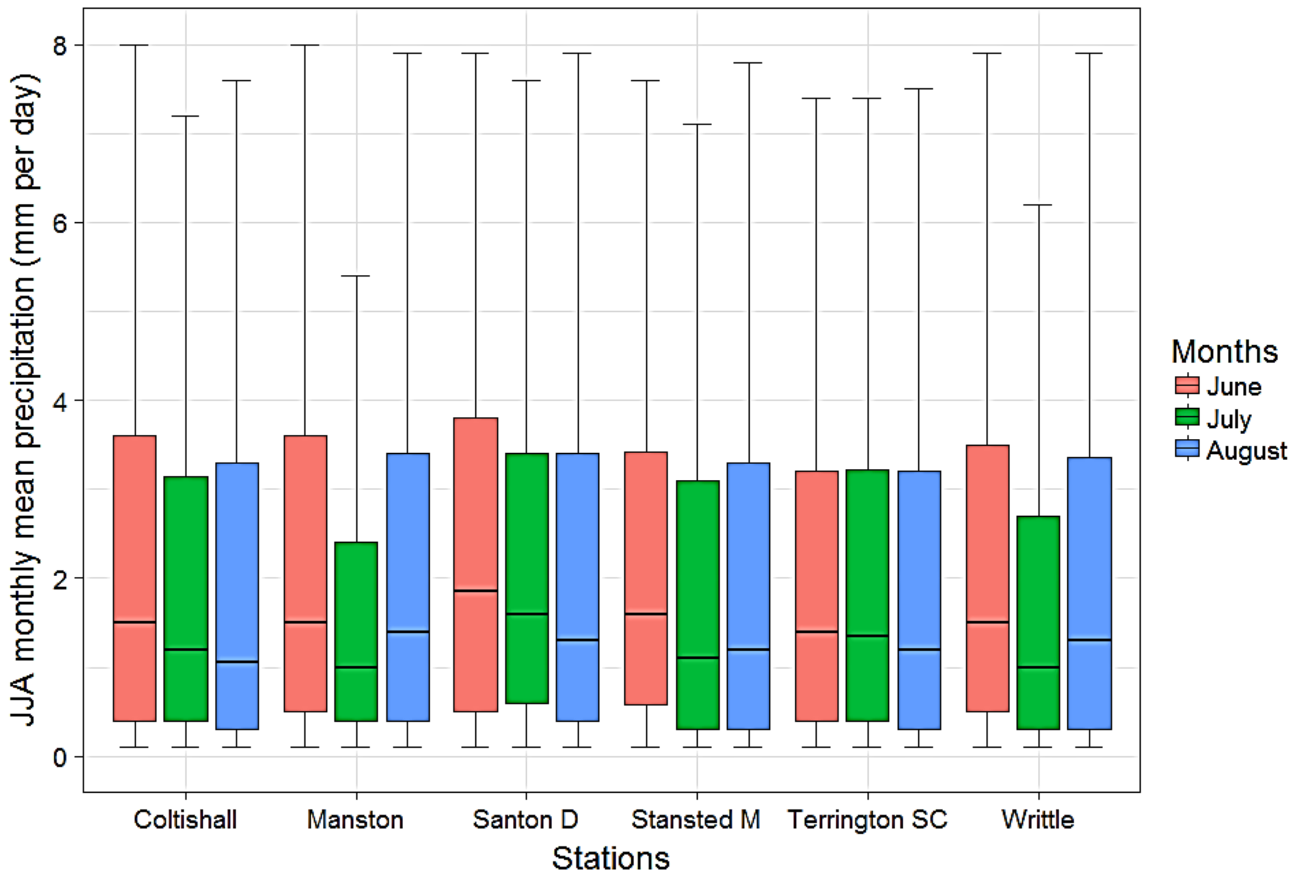


Figure 4. 10: JJA monthly May-October precipitation data from the weather station observations for the period 1971-2000. The boxplot details are the same as in Figure 4.3.

In summary, the weather stations in the study area showed good agreement of the characteristics and distribution of the annual, total, monthly and JJA May-October precipitation of the region from 1971-2000. The exception being Manston which have been described earlier as being outside of the sugar beet producing areas and has different characteristics from the rest of the stations in the region. Therefore, Manston will be excluded from subsequent calculations.

4.3 Present climate

4.3.1 Comparison of weather station data and the "historical" phase of the CMIP5

Annual and seasonal precipitation of Eastern England and England in general is highly variable but there are indications of a decrease in precipitation over the summer (Jenkins et al. 2008) which is directly related to one of the research hypotheses in this thesis (i.e. Reduction in future precipitation will reduce sugar beet yield by 2050). In this respect, it is useful to gain an insight into the overall growing season changes in precipitation over the area of interest using climate models. A study by Sillmann et al. (2013) examined a range of CMIP5 climate models in reproducing precipitation and found an improvement in the CMIP5 ensemble mean compared to the CMIP3. In this study, the ensemble mean is used to make comparisons of the weather station observations against the CMIP5 model outputs for the historical phase 19761-2000.

In doing this, a comprehensive assessment of the May-October mean precipitation of the area in Eastern England was investigated for the same 30 year period. The assessment covered the historical phase from 1971-2000 in which the stations data was compared to precipitation data from eight CMIP5 climate model ensembles under the "historical" forcing (Meinshausen et al. 2011; Eyring et al. 2016). The use of the eight ensemble models was aimed at improving mean estimates, providing multiple averages over single model runs and providing better prediction and distribution of possible outcomes (see Chapter 3.4). It also has the following advantages:

- It helps to obtain a better predictive performance as opposed to an individual model run
- Reduces errors specific to single models
- By combining multiple models, a more robust and accurate prediction is obtained over single model
- The ensemble produces multiple forecasts by making minor alterations to the initial conditions. By so doing, each member of the ensemble will be equally likely to produce forecast based on probabilities of different possible outcomes.

Past studies have shown that combining multiple models generally increases skill, reliability and consistency in model forecasts (McSweeney et al. 2014; Tebaldi & Knutti 2007; Tubiello & Ewert 2002). In this study, it enabled the verification of model performance in replicating past observations and thus, provides the basis for use in projections of future medium (RCP45) and high (RCP85) greenhouse gas emission scenarios. Simulation results of the CMIP5 "historical" phase vary from model to model as a result of different external forcing and internal variability leading to varying degree of model behaviour, skill and performance. According to McSweeney et al. (2014) models perform differently in different regions and therefore a model that performed very well in Europe might not necessarily perform well in Africa or Asia for example. The aim here is to identify the models that perform well in the region of interest.

The models precipitation under the "historical" forcing (1971-2000) were varied with three of the eight models output (see Figure 4.11) replicating observed data very well while the remaining five models differ significantly from those of the station observations. The ensemble mean of the growing season (May-October) precipitation recorded for the models and weather stations from 1971-2000 are shown in Table 4.6. The highest mean of 2.28 mm day-^{1} recorded for CSIRO, followed by IPSL 2.09 mm day-^{1}, NCAR 2.05 mm day-^{1}, MPI-M 2.04 mm day-^{1}, MIROC 2.03 mm day-^{1}, CCCma 1.74 mm day-^{1}, EC-Earth 1.62 mm day-^{1} and the MOHC (HadGEM2-ES) 1.61 mm day-^{1}.

Table 4. 5: May-October annual means precipitation analysis from the weather stations and CMIP5 data for the period (1971-2000).

Stations	Mean	Std	Median	Data: n
Coltishall	1.76	0.44	1.65	30
Manston	1.56	0.43	1.51	30
Santon D	1.78	0.45	1.81	30
Stansted M	1.76	0.5	1.69	30
Terrington SC	1.65	0.42	1.67	30
Writtle	1.61	0.45	1.57	30
CMIP5 Models				
CCCma	1.74	0.27	1.66	30
CSIRO	2.28	0.19	2.27	30
EC-Earth	1.62	0.14	1.63	30
IPSL	2.09	0.21	2.07	30
MIROC	2.03	0.22	2.05	30
MOHC	1.61	0.21	1.62	30
MPI-M	2.04	0.23	2.04	30
NCAR	2.05	0.28	2.05	30

Analysis of the May-October annual daily mean precipitation is presented as boxplots in Figure 4.11 with the thick black line in the middle showing the median of the distribution. The median is used here as it is less sensitive to outliers, minimum and maximum values in the distribution.

As reported earlier, three out of the eight CMIP5 models showed mean and median (Table 4.6) similar to those of the weather stations that represent the sugar beet farming areas in the region. The three models that best replicated the May-October daily mean precipitation under the historical phase are: CCCma, EC-Earth and MOHC (see Figure 4.11). Excluding Manston, with a mean of 1.56 mm day-^{1}, the May-October mean precipitation for the rest of the stations ranged between 1.61 mm day-^{1} and 1.78 mm day-^{1}, and similarly, the May-October mean precipitation for the three models that represented observations very well ranged from 1.61 mm day-^{1} to 1.74 mm day-^{1}. Figure 4.11 also showed that the MOHC has a better representation of the range of precipitation event sizes and, therefore, the MOHC model was solely used in this thesis for the analysis of future precipitation.

The three models that best replicated observed Eastern England precipitation were selected and used for further analysis of precipitation projections in this thesis. Selection of models in this manner has been reported in past studies that not all models are suitable for all regions. This has led to the exclusion of some General Circulation Models (GCMs) in studies of future projections as a result of poor model performance of observed climate (McSweeney et al. 2014; Manning et al. 2009; Sexton et al. 2004). The remaining five models, namely: CSIRO-Mk3.6.0, IPSL-CM5A-LR, MIROC5, MPI-ESM-LR and the CCSM4 were not in line with the observations and were therefore considered undesirable and rejected. Furthermore, past studies such as (McSweeney et al. 2014; Brands et al. 2013) also reported that not all models perform well in every region but their studies also showed that the MOHC (HadGEM2-ES) outperformed other models in this region and the UK in general and, was considered best for calculating the watering regimes reported in chapter five of this thesis.

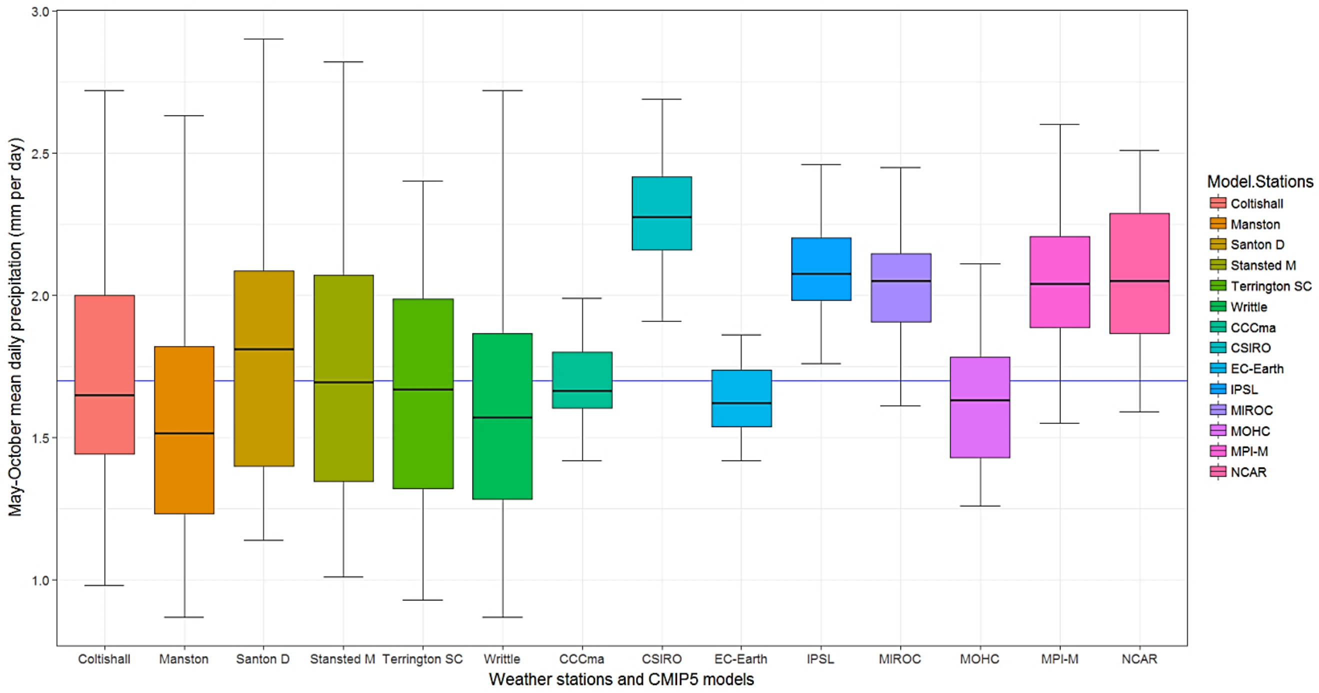


Figure 4. 11: Box-and-whisker plot displaying the characteristics of the station observations and the historical phase of the CMIP5 models from May-October for 1971-2000. The solid thick blue line indicates the median of the distribution and the solid thick black line within the box represents the median (2nd quartile) of the distribution. The extremes of the box represents the 1st (bottom) and 3rd quartiles (top). The whiskers indicate the lowest and highest values of the distribution. The blue line running across the plot shows the combined mean precipitation of the stations.

Figure 4.12 showed that the stations data had multimodal and symmetrical shaped distributions compared to the CMIP5 models with mostly unimodal and in some cases skewed distribution. As previously mentioned, the range and distribution of observed precipitation from the stations data were much wider than the simulations from the Earth System Models (ESMs) used. This is not unexpected as models do not represent the extremes of variability well as pointed out by (Maraun et al. 2010). Again, this is not seen as a problem as the study here examined mean conditions rather than the extremes. Nonetheless, the distribution of precipitation from the MOHC model is much closer to that of the observations than the CCCma and EC-Earth models. Therefore, the MOHC model projections were prominently used in further precipitation calculations in this thesis (Section 4.5).

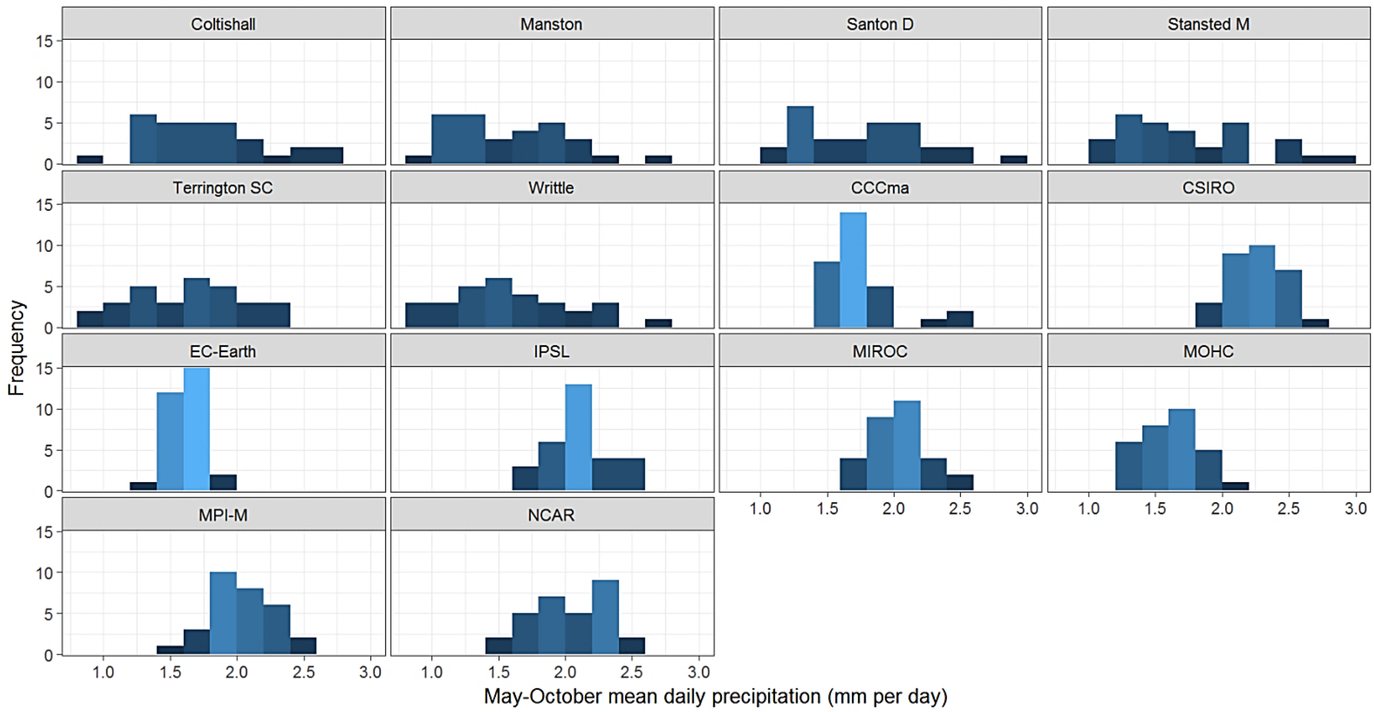


Figure 4. 12: Histogram distribution plots of the May-October daily mean precipitation for 1971-2000 from the historical phase of the daily weather stations observations and the CMIP5 models.

In summary, the response of the CCCma, EC-Earth and MOHC models to variability in May-October seasonal precipitation over the 30-year period (1971-2000) showed patterns consistent with the observations but has wider variations.

4.4 Projections of future precipitations

4.4.1 Analysis of the May-October daily mean precipitations under the "historical" and "future" phases of the CMIP5 models

This Section of the study investigated a core aspect of this research by examining precipitation projections for Eastern England. The study compared CMIP5 models that best replicated the May-October daily ensemble mean precipitation for the "historical" period (1971-2000) with the CMIP5 ensemble mean precipitation for the "future" scenarios under RCP45 and RCP85 for the period (2021-2050). This Section also investigated the changes in May-October daily mean precipitation by examining the two different time frames to detect for a trend in precipitation.

The aim was to find out if a change existed and if so, how much? Answers to these questions will be used to calculate the watering regimes to be implemented in the greenhouse plant experiment in chapter five of this thesis.

Analysis of the May-October daily mean precipitation (Table 4.7 and Figure 4.13) showed good agreement among the models of a reduction in May to October precipitation between the historical and future scenarios under RCP45 and RCP85. Comparison between the CMIP5 models "historical" phase and projections from the CCCma, MOHC and the EC-Earth showed that UK precipitation decreased in the three models, apart from the EC-Earth model which showed an increase in mean precipitation under the RCP85. Among the three models, the MOHC indicated the biggest negative changes under the medium and high greenhouse gas emission scenarios. This result is consistent with the studies of (Kendon et al. 2016; Jenkins et al. 2008; Osborne & Hulme 2002; Osborne et al. 2000) of a predicted decrease in summer precipitation. The distribution of the ensemble mean precipitation output for the historical phase of the MOHC data is the closest to the station observed mean reported in Section 4.3.1. Again, this characteristic added to the multiple reasons why the MOHC was heavily relied on for the greenhouse plant experimental watering regimes between the present and future scenarios. Moreover, precipitation calculations based on the MOHC provides a plausible but relatively extreme scenario that could be a potential source of threat to the UK sugar beet farming and the sugar industry.

Table 4. 6: Ensemble means of the May-October mean precipitation from the best three performing models (CCCma, MOHC and EC-Earth).

	Historical		RCP45		RCP85	
Models	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
CCCma	1.74	0.3	1.49	0.2	1.5	0.2
EC-Earth	1.62	0.2	1.54	0.2	1.81	0.2
MOHC	1.61	0.2	1.35	0.2	1.38	0.2

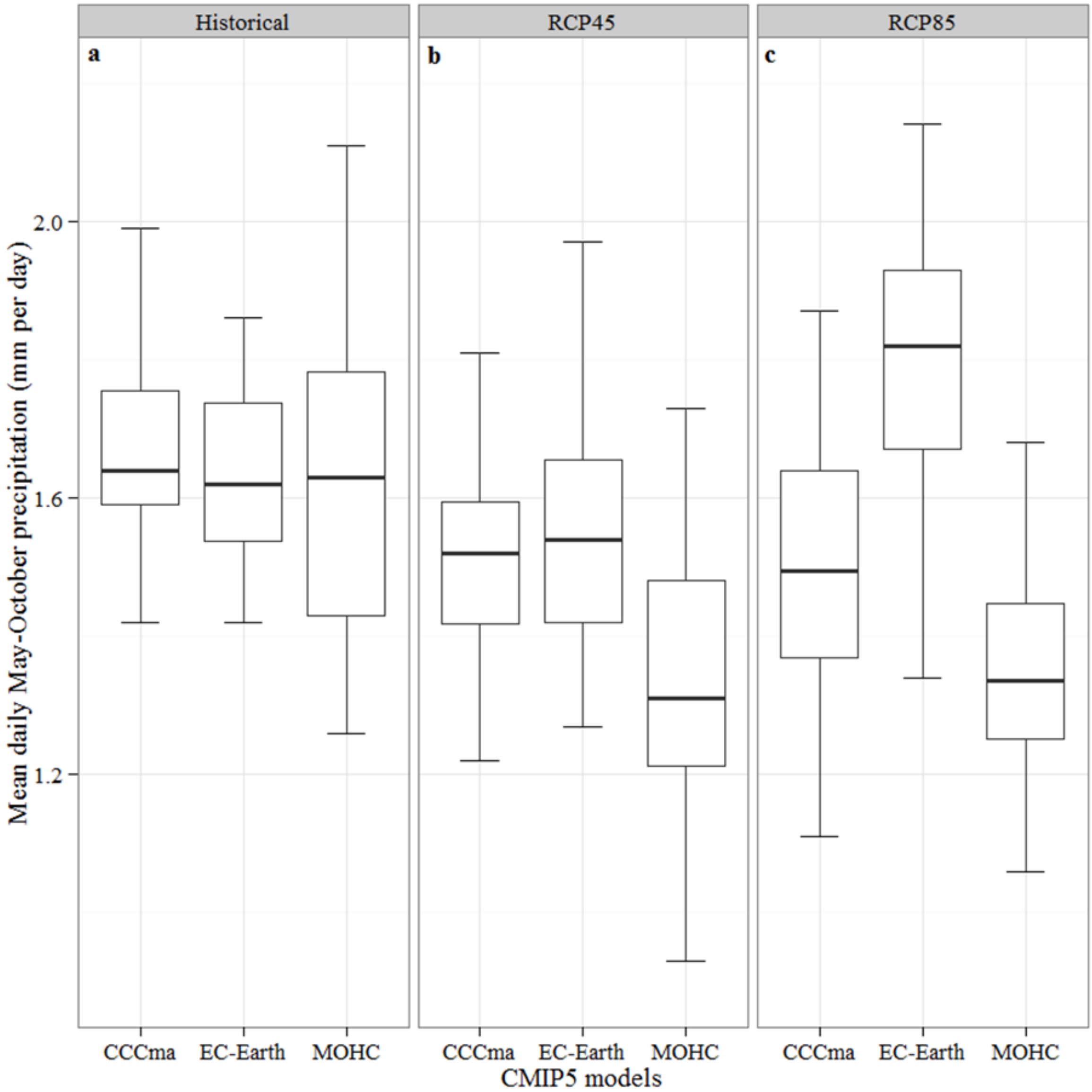


Figure 4. 13: Boxplot of the May to October daily mean precipitation data from the a) historical phase (1971-2000), b) RCP45 (2021-2050) and c) RCP85 (2021-2050) output from the CCCma, MOHC and EC-Earth climate models. The boxplot details are the same as for Figure 4.3.

4.4.2 Changes in the May-October daily mean precipitations under the "historical" and "future" phases (RCP45 and RCP85) of the CMIP5 models

Result of the May-October daily mean precipitation changes based on Relative Precipitation Comparison test between the two temporal windows showed a reduction in precipitation between the two periods under investigation (1971-2000) and (2021-2050). This method was employed by Baker & Huang (2012) to compare absolute and relative climate changes in future precipitation projections under different time frames. Table 4.8 and Figure 4.14 highlight the differences between the two time frames from the CCCma, EC-Earth and the MOHC models. The results showed a negative change in precipitation between the two time frames under CCCma and MOHC climate models. However, EC-Earth model in contrast indicated a positive change between the two time frames (see Table 4.8). The historical phase for example returned an ensemble mean of 1.62 (mm) compared to the RCP85 run with an ensemble mean of 1.38 (mm) which indicates a precipitation reduction of 14.9% between the historical period (1971-2000) and the future period (2021-2050) - see Table 4.8. Similarly, the CCCma showed a reduction of 14.3% reduction in May-October mean precipitation but the EC-Earth model indicated a contrasting increase of 3.72%. This type of difference is not unusual as different models perform differently under different conditions in different regions (McSweeney et al. 2014; Brands et al. 2013) - See Section 4.4.1.

Table 4. 7: Result of the CMIP5 climate models changes in May-October daily mean precipitation for the sugar beet growing season.

Models	Period	Mean daily precipitation (mm day-¹)	Difference from historical (%)
CCCma			
Historical	1971-2000	1.74	0
RCP45	2021-2050	1.49	-14.3
RCP85	2021-2050	1.5	-13.7
Mean of RCP45 and RCP85	2021-2050	1.49	-14.3
EC-Earth			
Historical	1971-2000	1.61	0
RCP45	2021-2050	1.54	-4.34
RCP85	2021-2050	1.81	12.4
Mean of RCP45 and RCP85	2021-2050	1.67	3.72
MOHC			
Historical	1971-2000	1.62	0
RCP45	2021-2050	1.35	-16.8
RCP85	2021-2050	1.38	-14.9
Mean of RCP45 and RCP85	2021-2050	1.36	-15.8

Figure 4.15 showed all the models had unimodal shaped distribution with the MOHC showing a much better distribution than the rest particularly under the historical phase and clearly showed a reduction in precipitation under RCP45 and RCP85. Figure 4.15 agrees with Figure 4.14 with the CCCma and EC-Earth also showing reduction in precipitation under RCP45 and RCP85. Only EC-Earth showed a noticeable increase in precipitation under RCP85 compared to the Historical phase.

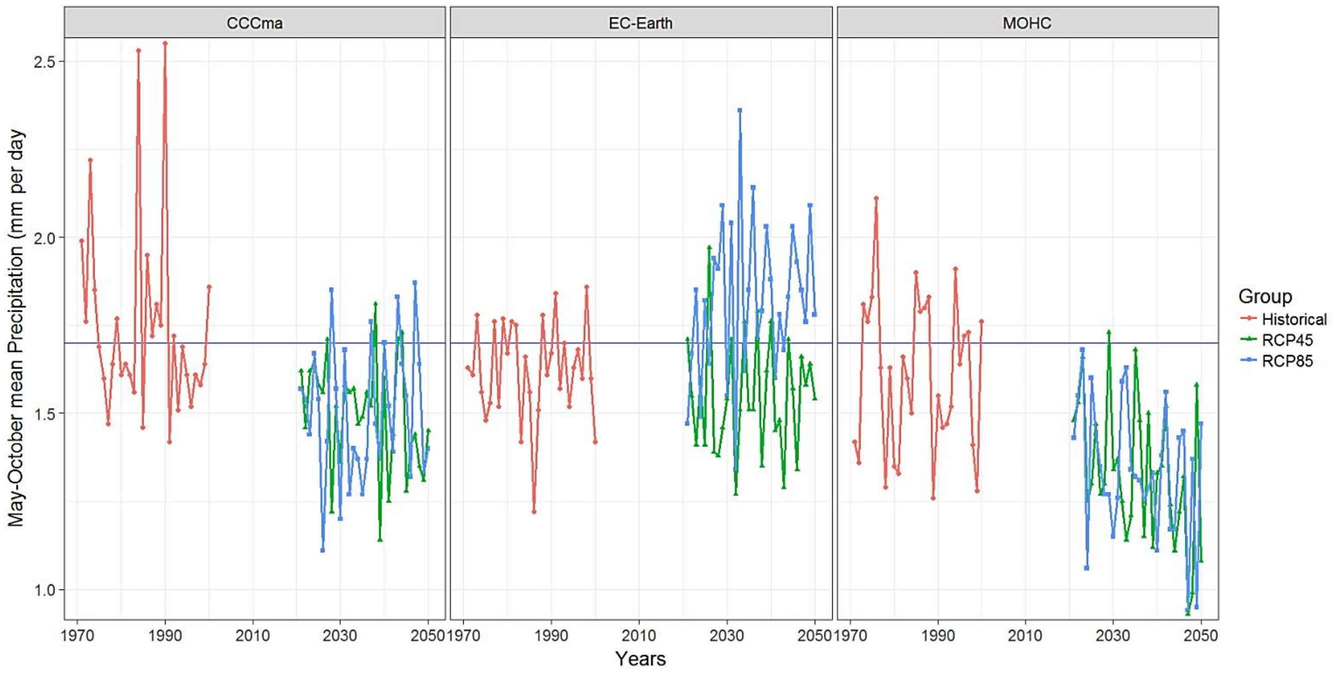


Figure 4. 14: Time series plot from CCCma, EC-Earth and the MOHC HadGEM2-ES climate models illustrating the trend of the May to October precipitation for the historical (1971-2000), RCP45 and RCP85 (2021-2050) scenarios. The blue horizontal line running across the plot represents the stations mean line as per Figure 4.9 plotted against the CMIP5 models.

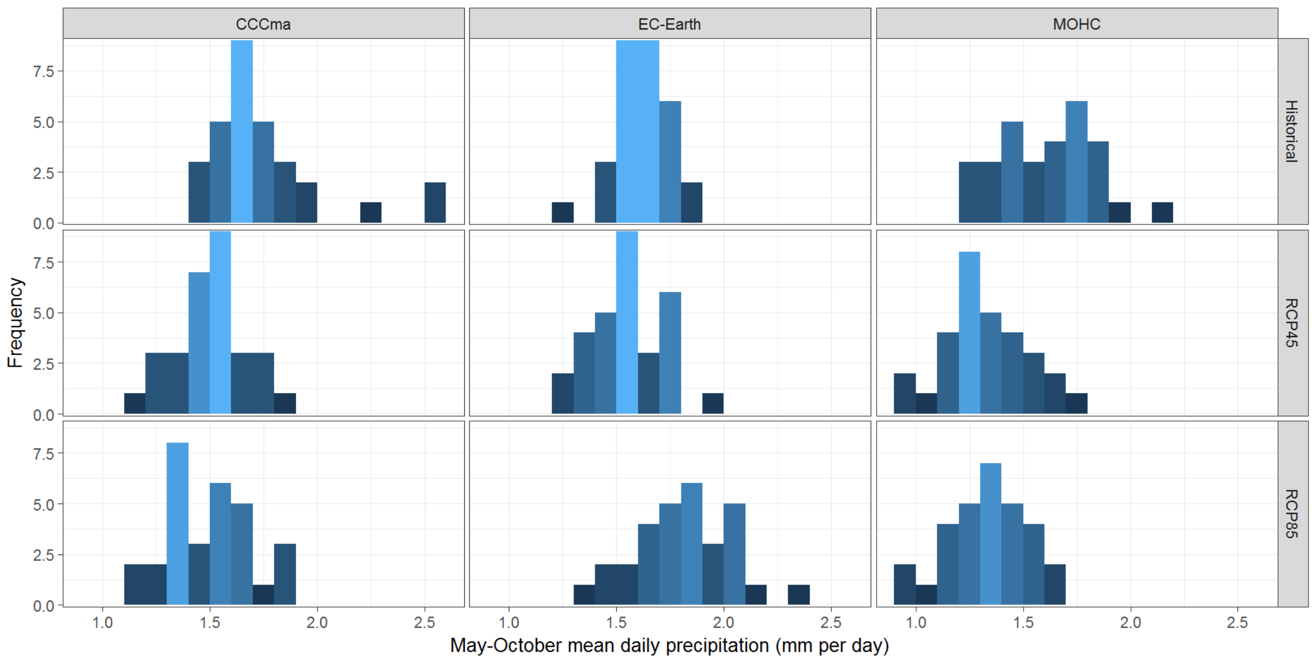


Figure 4. 15: May-October mean daily precipitation for the historical phase, RCP45 and RCP85 from the CCCma, EC-Earth and MOHC climate models for the periods 1971-2000 and 2021-2050.

The change indicated by this result implies that there may be different mechanisms (i.e. different responses to increasing greenhouse gas emissions in the atmosphere) at play controlling precipitation delivery in the two time frames in the different models; historical (1971-2000) and future (2021-2050). Past and recent studies in the UK have indicated both high variability and a decrease in mean summer precipitation Met Office (2014); Jenkins et al. (2009) as illustrated in Figure 4.13 from the CCCma and MOHC climate models.

4.4.3 Total May-October wet days precipitation under the "historical" phase, "RCP45" and RCP85 scenarios using the CMIP5 models

In this Section of the study, CMIP5 climate models was used to evaluate the total May-October daily precipitation for the growing season under the historical phase for the period 1971-2000 and for the future scenarios under RCP45 and RCP85 for the period 2021-2050. The total May-October daily precipitation was calculated by summing up the total number of precipitation event days between May-October for each year of the study period for the historical phase (1971-2000) and the future scenarios under RCP45 and RCP85 (2021-2050). This enabled days with non-precipitation events to be removed from the analysis. Using the MOHC for example, the MOHC has a monthly calculation based on 30 day calendar for all months compared to the CCCma and EC-Earth based on normal calendar days for each month in a 365 day year. Therefore, the total May-October precipitation data points for the MOHC model was 5400 based on 180 days in each year (e.g., May-October) for the 30 year period whereas the CCCma and EC-Earth had 5520 data points based on 184 days from May and October for each year of the study period.

Analysis showed fairly good agreement among the models of a reduction in total May-October precipitation between the historical phase and the future scenarios. Results across models indicate that the three models agree on a reduction in precipitation between the historical phase and RCP45 scenario (see Table 4.9). Similarly, the CCCma and the MOHC also agreed on a reduction between the Historical phase and the RCP85 scenario but the EC-Earth model showed no reduction in precipitation between the historical period and RCP85. Table 4.9 showed the mean analysis and the number of wet days between the two time frames. Results here are consistent with results of the models for the May-October mean daily precipitation reported in Section 4.4.2. Figure 4.16 illustrates the distribution of precipitation from the models between the historical phase and the future periods. The models displayed a unimodal shaped and positively skewed distribution with indications of a reduction in precipitation between the historical phase of the models and the future scenarios with the exception again being RCP85 from the EC-Earth which indicated an increase in precipitation compared to the historical.

Results of the total May-October daily precipitation analysis carried out in this Section compares well to the total May-October daily mean precipitation in Section 4.2.2. The historical phases from the CMIP5 models and the future scenarios under RCP45 and RCP85 exhibited similar patterns of precipitation distribution as the weather stations total May-October daily precipitation (also see Figure 4.4). Furthermore, the range and distribution of observed precipitation from the weather stations were much wider than those of the CMIP5 models which is not unexpected as models do not represent extremes of precipitation variability well (Maraun et al. 2010).

Table 4. 8: Mean analysis of total May-October distribution of daily precipitation between the two different time frames (historical phase 1971-2000 and the RCP45 and RCP85 scenarios 2021-2050).

Models **CCCma**	**Mean**	**Std**	**Total # of days**	**Wet days precipitation**	**Non-wet days precipitation**
Historical	2.45	2.3	5520	3929	1591
RCP45	2.37	2.4	5520	3698	1822
RCP85	2.43	2.5	5520	3563	1957
EC-Earth					
Historical	2.44	2.3	5520	3658	1862
RCP45	2.37	2.3	5520	3582	1938
RCP85	2.44	2.3	5520	3664	1856
MOHC					
Historical	2.49	2.6	5400	3669	1731
RCP45	2.28	2.8	5400	3177	2223
RCP85	2.38	2.9	5400	3133	2267

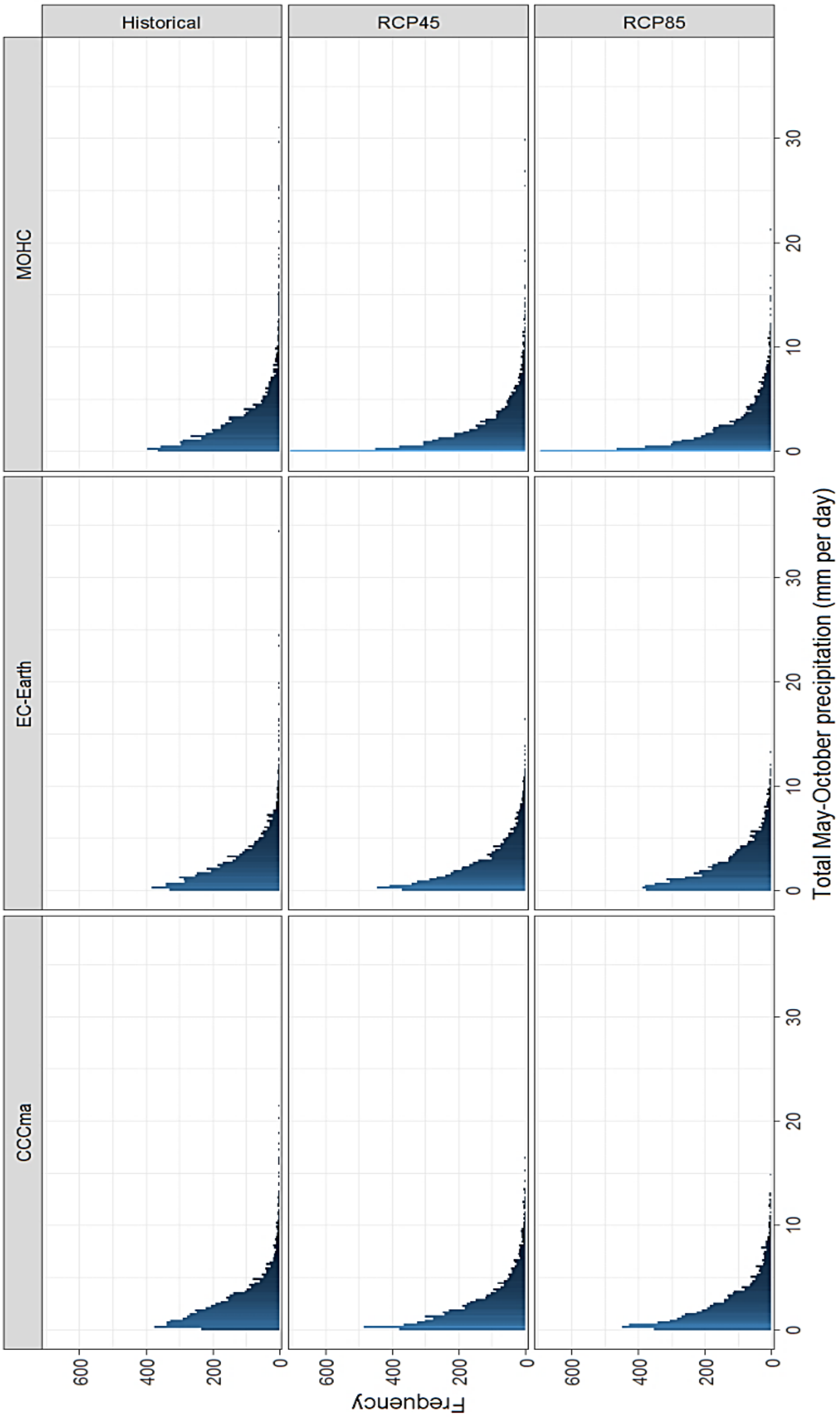


Figure 4. 16: Distribution of the total May-October precipitation for the historical period (1971-2000) and RCP45 and RCP85 scenarios (2021-2050) from the CCCma, EC-Earth and MOHC climate models.

4.4.4 Changes in total May-October wet day precipitation under the "historical" phase, "RCP45" and RCP85 scenarios

Changes in the total May-October wet days precipitation were reflected in the precipitation event sizes between the historical phase (1971-2000) of the models and future scenarios under RCP45 and RCP85 (2021-2050). Comparison of the total wet day precipitation for the two temporal windows using the ensemble means indicated varying results across the models. Tables 4.10 and 4.11 highlight the differences in mean wet day precipitation and number of wet day precipitation between the two different time frames from the CCCma, EC-Earth and MOHC models. Results represent projected changes in future wet days precipitation which varies from one model to another. All the models agree on a reduction (See Table 4.10) in the total May-October wet days precipitation between the historical phase and RCP45 scenario while the models all indicated no significant difference between the RCP45 and RCP85 May-October wet days precipitation. Although, the number of wet day precipitation has been presented in Section 4.4.3, for ease of reference in this Section, the percentage change in total wet day precipitation and change in the number of wet days between the historical phase and future scenarios are added to the analysis in Tables 4.10 and 4.11.

Results across the models varied with the CCCma indicating a -3.27% reduction in precipitation between the two time frames under RCP45 and -0.82 under RCP85. The EC-Earth indicated no change (0%) between the two periods under RCP85 and -2.87 while the MOHC model indicated -8.43% and -4.42 under RCP45 and RCP85 respectively (Table 4.10). The MOHC again showed the biggest negative changes under future scenarios with a much larger change under RCP45. In short, the CCCma and MOHC showed similar precipitation patterns indicating a decrease in total May-October wet day precipitation under RCP45 and RCP85. Similarly, the number of wet day (precipitation) counts showed a reduction in all the models between the historical phase and RCP45 scenario while only CCCma and MOHC showed a reduction between the historical phase and RCP85, the EC-Earth differed with a slight increase in the number of wet days (See Table 4.11).

Again, Table 4.11 show that the MOHC model has the largest negative change in the number of wet day precipitations further supporting the use of the data as the basis for the future precipitation calculations so that a relatively extreme scenario could be investigated with regards to water stress that may potentially affect the UK sugar beet industry. Furthermore, this result implies that different distribution of precipitation events and sizes prevailed under the two different scenarios. The result showed a larger decline in precipitation under the RCP85 emission scenario than the RCP45.

Table 4. 9: Result of the CMIP5 climate models mean wet days for the growing season total May-October daily precipitation. Changes between the historical phase (1971-2000) and future scenarios under RCP45 and RCP85 (2021-2050) are presented.

Models CCCma	Period	Mean daily precipitation event size (mm per day)	Difference from historical (%)
Historical	1971-2000	2.45	0
RCP45	2021-2050	2.37	-3.27
RCP85	2021-2050	2.43	-0.82
EC-Earth			
Historical	1971-2000	2.44	0
RCP45	2021-2050	2.37	-2.87
RCP85	2021-2050	2.44	0
MOHC			
Historical	1971-2000	2.49	0
RCP45	2021-2050	2.28	-8.43
RCP85	2021-2050	2.38	-4.42

Table 4. 10: Projected changes in the number of wet day precipitation from the models for the total May-October daily mean precipitation between the historical phase and future scenarios (RCP45 and RCP85).

Models CCCma	Period	Number of observations	Number of wet days	Change in number of wet days
Historical	1971-2000	5520	3929	0
RCP45	2021-2050	5520	3698	-231
RCP85	2021-2050	5520	3563	-366
EC-Earth				
Historical	1971-2000	5520	3658	0
RCP45	2021-2050	5520	3582	-76
RCP85	2021-2050	5520	3664	6
MOHC				
Historical	1971-2000	5400	3669	0
RCP45	2021-2050	5400	3177	-492
RCP85	2021-2050	5400	3133	-536

4.4.5 CMIP5 models individual month's May-October daily precipitation

This Section provides model response to individual month's (May-October) daily precipitation for the study area covering the historical period (1971-2000) and the future scenarios (2021-2050). The monthly precipitation was derived by summing up daily totals for each month from May-October for the 30 year period. This provides a general view of the monthly precipitation characteristics of the area and the comparison between the two different time frames will help in identifying trends and variability in precipitation during the summer growing season. In reality, changes in precipitation vary from one month to another meaning that some months will likely have more or less precipitation than others and it also provides an indication of a "realistic distribution of future precipitation scenario" that is important in determining the monthly watering regimes for individual months.

Results of the mean statistical analysis conducted for the monthly May-October precipitation using ANOVA multiple mean comparison (Table 4.12) revealed large variations in mean and standard deviation of precipitation amongst the models. The highest monthly mean precipitation occurred in October under RCP85 from the EC-Earth model with a value of 4.14 mm per day (Std 2.4). The lowest monthly mean precipitation occurred in July also under RCP85 with a value of 1.66 mm per day (Std 2.4) from the EC-Earth model. It is noteworthy to point out that the EC-Earth model showed the biggest dispersions amongst the models especially in the months of May and October (Figure 4.17). This result however, does show a striking similarity with the weather stations observation data (Figure 4.9) with indications of high monthly variations. Table 4.12 shows the extent of dispersion among and between the models allowing for illustration of changes in monthly precipitation. In this respect, more attention is focused on the negative changes in precipitation in order to identify months with the biggest negative impacts.

The CCCma indicated a decline in July, August and September mean precipitation under RCP45 and RCP85. The model also showed a negative change in mean precipitation in August and September, and a marginal decrease in October under the RCP85. The EC-Earth showed negative changes in August and September monthly mean precipitation under RCP45 and in July under RCP85. The MOHC model reported a decrease in monthly mean precipitation in June, July and August under both the RCP45 and RCP85 scenarios. Overall, negative precipitation changes were identified in the JJA months under both future scenarios (RCP45 and RCP85).

Similarly, the number of wet days showed a general reduction in precipitation in all the months from the CCCma model except in June where it reported an increase under RCP45. The EC-Earth model reported a one day decrease in the number of wet days under RCP45 and an increase under RCP85 in May. June and July also showed increases in the number of wet days under RCP45 and RCP85. August, September and October showed decreases in the number of wet days under RCP45 and RCP85. The MOHC model on the other hand, showed a reduction in the number of wet days across all the months from May-October. The question now is, “does the reduction in the number of wet days translate to reduced precipitation over the summer season growing months?

Past studies such as Jenkins et al. (2008), Osborn et al. (2000), Wigley & Jones (1987) provide evidence of precipitation trends towards drier summers as a result of reduction in the frequency of wet days and a reduction in mean wet day precipitation amounts. Similarly, Simpson & Jones (2012); Jones & Conway (1997) confirmed that there was a general reduction in summer July and August precipitation across the UK and it is consistent with results in this study. Likewise, Perry & Hollis (2005) in their study comparing two different time frames 1971-2000 and 1961-1990 reference period also found a reduction in summer precipitation and the number of wet days precipitation nationwide.

Table 4. 11: Models analysis of monthly May-October precipitation under the historical phase (1971-2000) and future scenarios, RCP45 and RCP85 (2021-2050).

CCCma	Historical				RCP 45				RCP85			
Months	Mean	Std	Wet days	Total counts	Mean	Std	Wet days	Total counts	Mean	Std	Wet days	Total counts
May	3.19	1.9	635	930	3.23	2	599	930	3.41	2	582	930
June	2.42	1.7	543	900	2.55	1.8	557	900	2.61	1.9	522	900
July	1.93	1.5	629	930	1.87	1.4	561	930	1.94	1.8	529	930
August	2.12	1.8	726	930	1.7	1.6	657	930	1.85	1.5	591	930
September	2.17	1.9	670	900	2.1	1.6	616	900	2.02	2.1	626	900
October	2.88	2.1	726	930	3	2.4	708	930	2.86	2.3	713	930
EC-Earth												
May	2	1.4	572	930	2.16	1.6	571	930	2.14	1.4	633	930
June	1.93	1.5	548	900	1.96	1.7	567	90	2.1	1.6	566	900
July	1.81	1.3	486	930	1.86	2.2	551	930	1.66	1.4	513	930
August	2.05	1.6	575	930	1.92	1.6	536	930	2.1	1.5	549	930
September	2.91	1.9	686	900	2.76	2.1	592	900	2.92	2	634	900
October	3.95	2.3	791	930	4.05	2.3	765	930	4.14	2.4	769	930
MOHC												
May	2.55	1.9	606	900	2.63	2	552	900	2.68	2.1	537	900
June	2.67	1.9	540	900	2.5	1.9	523	900	2.29	1.9	495	900
July	2.46	1.8	601	900	2.29	1.8	516	900	2.23	1.7	489	900
August	2.43	2	551	900	2.15	1.9	466	900	2.41	2.3	473	900
September	2.34	2	622	900	2.12	2.2	480	900	2.54	2.4	496	900
October	2.74	2.4	749	900	2.68	2.3	640	900	2.94	2.5	643	900

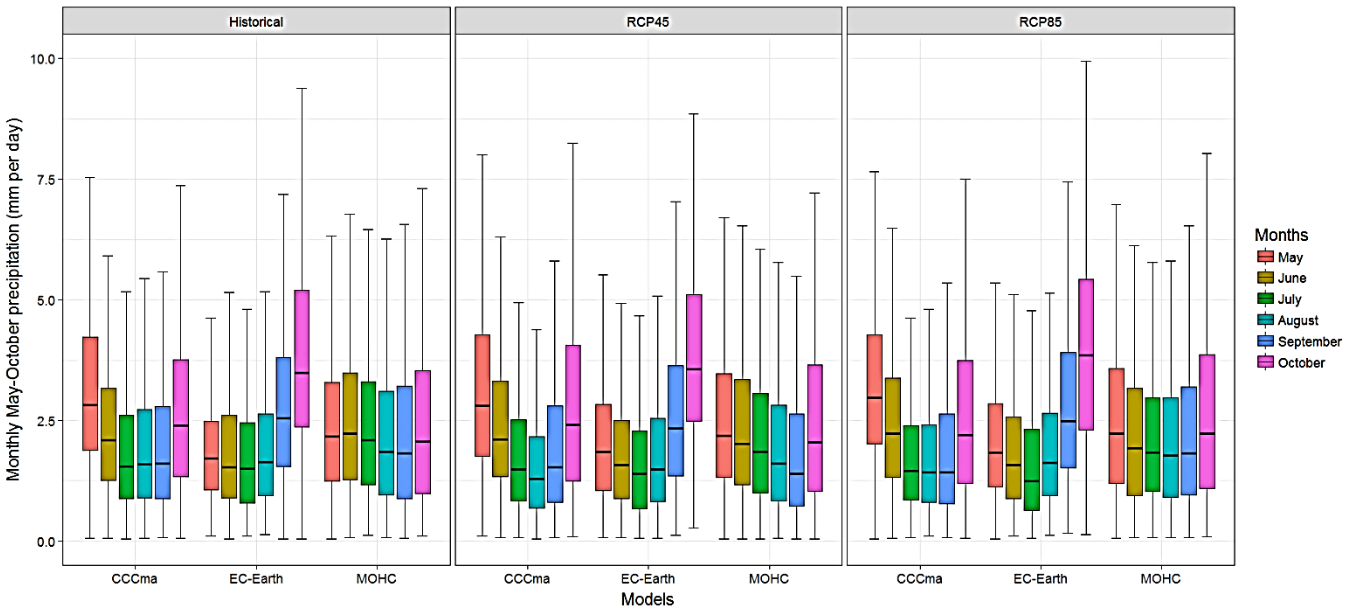


Figure 4. 17: Boxplots showing the distribution of monthly precipitation from the models under the historical phase (1971-2000) and future scenarios (2021-2050). The boxplot details are the same as for Figure 4.3.

4.4.6 Changes in individual month's May-October daily precipitation

In this Section, individual models were evaluated for changes in individual month's May-October daily precipitation for the historical phase (1971-2000) and the future scenarios under RCP45 and RCP85 (2021-2050). Relative precipitation comparison test of the two temporal windows using the ensemble means indicated varying results across models. Table 4.13 highlights the differences in mean monthly precipitation between the two different time frames from the CCCma, EC-Earth and MOHC models, however focus here is also on negative changes as mentioned in Section 4.4.5. Results indicated that projected changes in future precipitation during the season showed high monthly variability across the models. The CCCma model for instance indicated negative changes in precipitation in July, August and September under RCP45. The RCP85 scenario showed negative changes in August and September and a small change of -0.7 in October. The largest negative changes in precipitation were recorded in August with a value of -19.8% recorded under RCP45. The second largest negative change was recorded again in August under RCP85 with a value of -12.7 followed by September with a value of -6.9 under RCP85. Other negative changes were also recorded in September and July under RCP45 for -3.2 and -3.1 respectively.

The EC-Earth model equally showed negative changes with the greatest change recorded in July with a value of -8.3. August and September recorded values of -6.3 and -5.6 respectively under RCP45 (See Table 4.13). The MOHC model indicated the most negative changes in monthly May-October precipitation across the models. The model indicated reduced precipitation in June, July, August, September and October under RCP45. The RCP85 also showed reduced precipitation in the months of June, July and August. The biggest change in precipitation was calculated for June with a reduction of -14.2% under RCP85 followed by August with -11.5%. Other negative changes were also calculated across different months (e.g. June with a value of -6.4%, July -6.9% and September with a value of -9.4% (Table 4.13) under RCP45. The RCP85 indicated negative changes of -9.3% in July, -0.8% in August (Table 4.13).

Table 4. 12: Analysis of changes in Monthly May-October daily mean precipitation between the historical phase (1971-2000), RCP45 and RCP85 (2021-2050) from the CMIP5 models.

Models	Monthly means						Difference from historical (%)					
CCCma	**May**	**June**	**July**	**August**	**September**	**October**	**May**	**June**	**July**	**August**	**September**	**October**
Historical	3.19	2.42	1.93	2.12	2.17	2.88	0	0	0	0	0	0
RCP45	3.23	2.55	1.87	1.7	2.1	3	6.2	5.4	-3.1	-19.8	-3.2	4.2
RCP85	3.41	2.61	1.94	1.85	2.02	2.86	6.9	7.9	0.5	-12.7	-6.9	-0.7
EC-Earth												
Historical	2.01	1.93	1.81	2.05	2.91	3.95	0	0	0	0	0	0
RCP45	2.16	1.96	1.86	1.92	2.76	4.05	7.5	1.6	2.8	-6.3	-5.6	2.5
RCP85	2.14	2.1	1.66	2.1	2.92	4.14	6.4	8.8	-8.3	2.4	0.34	4.8
MOHC												
Historical	2.55	2.67	2.46	2.43	2.34	2.74	0	0	0	0	0	0
RCP45	2.63	2.5	2.29	2.15	2.12	2.68	3.1	-6.4	-6.9	-11.5	-9.4	-2.2
RCP85	2.68	2.29	2.23	2.41	2.54	2.94	5.1	-14.2	-9.3	-0.8	8.5	7.3

Overall, the months of July and August featured in all the models as showing a reduction in precipitation. The MOHC is the only model that showed negative changes across the June, July and August months as shown Table 4.13. These changes further justify the use of the MOHC model as a worst case scenario for the UK sugar beet farming in this research. Moreover, it is the most similar to the observations in terms of event size distribution. The lowest mean precipitations across the models were recorded in June and July which are two of the core summer months (June, July, August - JJA) that are projected to have the biggest changes in future precipitation (Jenkins et al. 2008) of which this research is most interested in. Furthermore, the JJA months are the period in the summer that temperature and evapotranspiration are likely to peak with potential impacts on available water resources and therefore an important aspect of this research.

In summary, the models showed high variations in the individual month’s precipitation similar to the high variations exhibited by the weather stations for the period 1971-2000. Therefore, understanding the mechanisms associated with variations in precipitation patterns could be an important aspect in addressing future uncertainties in precipitation projection studies but is however not addressed in this study.

4.4.7 Summer (June, July and August; JJA) precipitation from the CMIP5 models

Results of the JJA daily mean precipitation varied between individual months from the three models for the historical period (1971-2000) compared to the future scenarios under RCP45 and RCP85. The CCCma model showed a significant reduction in monthly JJA mean daily precipitation between the historical and future scenarios under RCP45 and RCP85 in June. There was however, a significant decrease in mean daily precipitation in July and August between the historical phase and the two future scenarios (See Table 4.14 and Figure 4.18). It is important to look at the months of June, July and August because the biggest changes in precipitation are predicted to occur during these period and it coincides with the time of year that temperature values are also at its peak.

The EC-Earth model displayed an increase in monthly JJA mean precipitation in June under RCP45 and RCP85; showed a reduction in July under RCP45 but an increase under RCP85. In August, it showed a decrease under RCP45 and a marginal increase under RCP85. The MOHC (HadGEM2-ES) model on the other hand showed a decrease in monthly JJA mean daily precipitation across all the months under both the RCP45 and RCP85 compared to the other models. The overall performance of the models shown in Table 4.14 and illustrated in Figure 4.18 showed that the MOHC model is in broad agreement with changes in the seasonal and total May-October precipitation analysis. Comparison of the models JJA means precipitation for the period 2021-2050 with the stations JJA means precipitation for the period 1971-2000 (see Table 4.5) showed a reduction in mean precipitation in all the months under RCP45 and RCP85 (See Figure 4.11).

Table 4. 13: JJA monthly mean precipitation analysis for the historical phase and the RCP45 and RCP85 scenarios.

Models	June		July		August	
CCCma	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
Historical	2.42	1.7	1.93	1.5	2.12	1.8
RCP45	2.55	1.8	1.87	1.4	1.94	1.6
RCP85	2.12	1.9	1.7	1.8	1.85	1.5
EC-Earth						
Historical	1.93	1.5	1.81	1.3	2.05	1.6
RCP45	1.96	1.7	1.86	2.2	1.92	1.6
RCP85	2.1	1.6	1.66	1.44	2.1	1.5
MOHC						
Historical	2.67	1.9	2.46	1.8	2.43	2
RCP45	2.5	1.9	2.29	1.8	2.15	1.9
RCP85	2.29	1.9	2.23	1.7	2.41	2.3

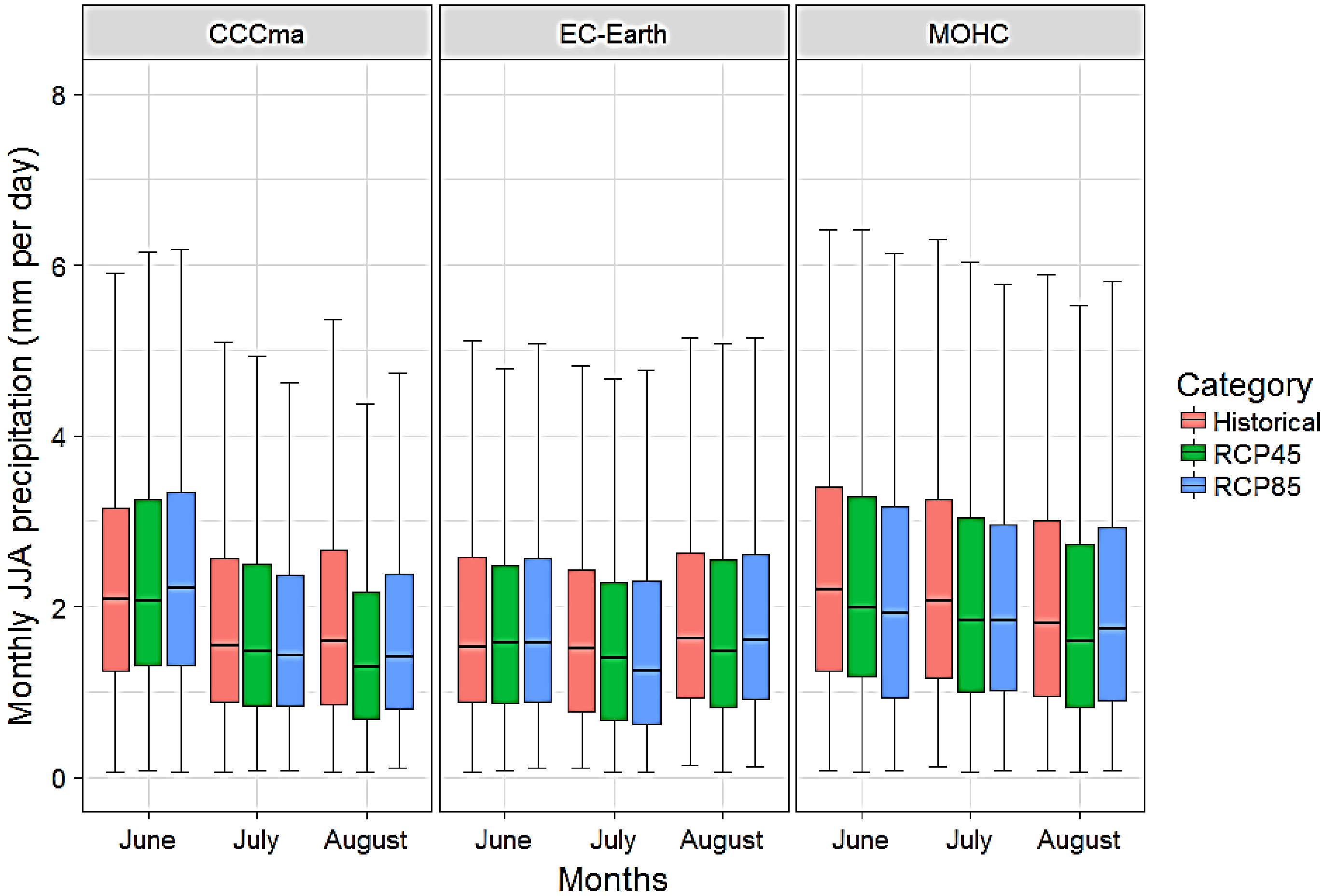


Figure 4. 18: Distribution of monthly JJA daily mean precipitation for the historical phase (1971-2000), RCP45 and RCP85 (2021-2050). The boxplot shows the 95% confidence interval for the JJA precipitation from the CCCma, EC-Earth and MOHC models.

4.5 Event size distribution of monthly May-October precipitation

Precipitation is one element of climate that is extremely variable in terms of amount, duration and intensity, and its distribution is uneven seasonally or annually causing year-to-year variability in different places and regions. This Section of the study analyses and reports on the distribution of precipitation events and sizes for individual months from May-October for a 30 year period under the historical phase (1971-2000), RCP45 and RCP85 scenarios (2021-2050). Previous simulation results from the three models used in this study revealed large variations in May-October precipitation among the models but the MOHC (HadGEM2-ES) model showed the biggest negative changes in the May-October precipitation (i.e. a worst case scenario precipitation change for the UK) between the historical phase and the future scenarios under RCP45 and RCP85. This behaviour encouraged the single use of the MOHC model for the analysis of event size distribution which was used for calculating the watering regime rates in the plant experiment reported in Chapter 5.

This Section of the study also analysed non-zero precipitation days from a 30 year time series under the historical phase (1971-2000) and future scenarios, RCP45 and RCP85 (2021-2050) from the MOHC model. The analysis was conducted on a monthly basis taking into account the frequency and size of precipitation events (i.e. distribution of wet days and dry days) in individual months so that a more realistic watering regime could be implemented for the plant experiment in Chapter 5. For the purpose of this study, the thesis only dealt with wet days precipitation >0.05 mm per day thereby eliminating precipitation days that are <0.05 to maintain consistency in the experiment.

4.5.1 Analysis of monthly May-October wet day distribution

Results from the MOHC model for the two different time frames in this study so far has been broadly consistent in indicating reduced trends in precipitation under future scenarios. Analysis of the wet day event size distribution of precipitation under the historical phase, RCP45 and RCP85 showed high monthly variations and also revealed that monthly mean precipitation declined in the months of June, July and August (See Table 4.15). Mean precipitation increased in May and October but was dependent on the scenario being considered. In September, mean precipitation increased under RCP85 but reduced under RCP45 (See Table 4.15). There is considerable reduction in the total number of future non-zero precipitation days under RCP45 and RCP85 from May to October. Although, May and October showed reduction in the number of non-zero precipitation days, precipitation events actually increased. The highest number of precipitation days was recorded in October under the historical phase with a value of 2796 while the lowest number of precipitation days was recorded in August under RCP85 with a value of 1694. Table 4.15 shows a comparison of the total number of precipitation days between historical and future scenarios as well as the mean and standard deviation from the data analysis for the two time frames.

The mean precipitation from this analysis showed remarkable similarity to the individual month's daily mean precipitation (See Table 4.12, Sections 4.4.5-4.4.6). Both results revealed large monthly variations particularly in July and August. In the current analysis, reduction in the distribution of precipitation events in June, July and August gives indication of likely episode of dry spells particularly in July under future scenarios (RCP45 and RCP85). Table 4.15 also showed the percentage change in precipitation between the historical phase and the future scenarios (RCP45 and RCP85). The largest negative changes were recorded in June under RCP85 followed by August, September and July. May showed an increase under RCP45 and RCP85 while October showed an increase under RCP85 but a marginal decrease under RCP45.

Table 4. 14: Comparison of monthly May-October event size distribution and non-zero precipitation days (wet days) between the historical phase (1971-2000RCP45 and RCP85 from the MOHC model.

	May		June		July		August		September		October	
Category	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
Historical	2.55	3.5	2.69	3.92	2.46	3.9	2.43	4.2	2.37	3.9	2.73	4.3
RCP45	2.6	3.7	2.55	3.8	2.3	3.5	2.11	3.6	2.15	4.3	2.71	4.5
RCP85	2.74	4.1	2.27	3.3	2.27	3.3	2.34	4.1	2.55	4.8	2.92	4.9
Change from historical (%)												
Historical	0		0		0		0		0		0	
RCP45	2		-5.2		-6.5		-13.1		-9.3		-0.7	
RCP85	7.5		-15.6		-7.7		-3.7		7.6		7	
Non-zero precipitation days	**May**		**June**		**July**		**August**		**September**		**October**	
Historical	2254		2109		2327		2155		2345		2796	
RCP45	2108		1988		1941		1777		1795		2500	
RCP85	2003		1754		1890		1694		1871		2520	
Difference from historical												
Historical	0		0		0		0		0		0	
RCP45	146		121		386		378		550		296	
RCP85	251		355		437		461		474		276	

4.5.2 Changes in monthly May-October distribution of event sizes

Results of the changes in the distribution of May-October precipitation events and size for the two temporal periods (1971-2000 and 2021-2050) also showed large month-to-month variability. Table 4.15 shows a mean comparison of the distribution of precipitation events under the historical phase and future scenarios (RCP45 and RCP85). The comparison revealed that the highest mean precipitation event occurred in October with a value of 2.92 mm day-^{1} under RCP85. The lowest mean precipitation occurred in August with a value of 2.11 mm day-^{1} under RCP45 (See Table 4.15 for further details).

Relative changes in the monthly distribution of precipitation events between the two periods showed June to have the biggest negative changes with a -15.6% reduction in precipitation under RCP85 and a lesser reduction of -5.2% under RCP45 (Table 4.15). This was followed by August with a negative change of -13% under RCP45 and a lesser change of -3.7% under RCP85. The month of July also showed a decline in precipitation with -7.7% and -6.5% under RCP85 and RCP45 respectively. The model response in May was positive with an increase of 7.5% and 1.9% under RCP85 and RCP45 respectively. The model indicated a mixed response in September with an increase of 7.6% under RCP85 and a reduction of -9.3% under RCP45. There was also a mixed response in October with an increase of 7% under RCP85 and a marginal decrease of -0.7% under RCP45.

Overall, the core summer months (JJA) have shown considerable negative changes in summer precipitation and supports earlier results in this thesis (See Table 4.12, Section 4.4.5). In the same vein, the model simulation results also revealed a considerable reduction in the number of precipitation counts (i.e. wet days precipitation >0.05 mm day-^{1}) in future scenarios (2021-2050) compared to the baseline period of 1971-2000. The biggest changes in the number of precipitation counts occurred in September under RCP45 and RCP85 with 550 and 474 counts less than historical respectively. Other big changes also occurred in June, July and August (See Table 4.15).

Figure 4.19 illustrates the monthly variations of precipitation events and further suggests likely episodes of dry spells and heavy decline in precipitation in July and August particularly under RCP45.

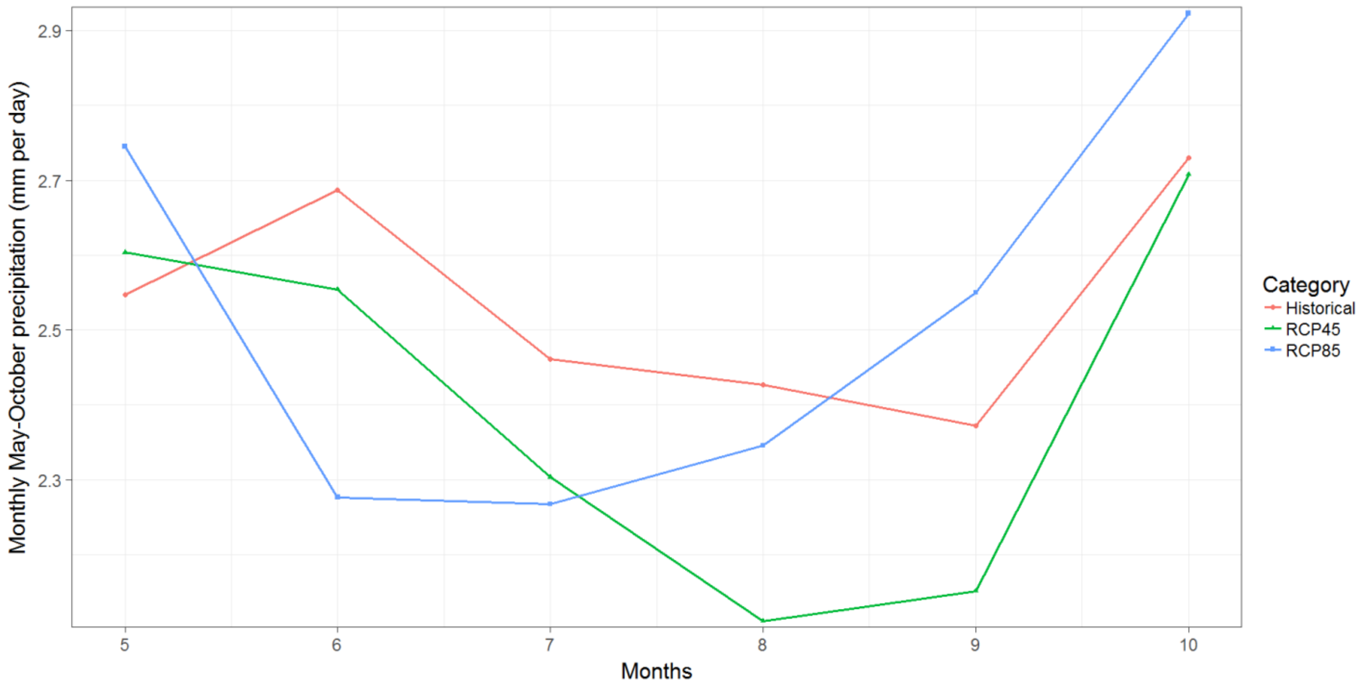


Figure 4. 19: Variations in the monthly distribution of precipitation events and sizes under the historical phase, RCP45 and RCP85 from the MOHC (HadGEM2-ES) model.

4.6 Watering regimes (Irrigation)

4.6.1 Introduction

Generally, Eastern England precipitation like most of the UK is highly variable in terms of duration, distribution and events sizes. The analysis of precipitation is usually on a daily, monthly, seasonal or annual basis and generally uneven from place-to-place and region-to-region making precipitation forecasts more challenging and the agricultural industry is no exception. Therefore, understanding the precipitation characteristics and watering of crops in Eastern England is an important factor in the growth and development of agricultural crops in the field and under controlled conditions.

For sugar beet and other crops in general, precipitation or irrigation timing is very important in order to maximise yield. In the first season of the experiment, irrigation was carried out every other day based on climatological precipitation changes between the historical and future time windows. In the second season, irrigation was implemented to represent a more realistic distribution of precipitation events and sizes from the historical and future time windows. In this section of the thesis, details of the calculations for the watering regimes are presented. In the first season, the watering regime was based on the result of changes in the overall May-October mean precipitation; whilst the second season was based on the distribution of precipitation events and sizes for the two temporal windows. Irrigation of the plants was normally carried out in the mornings to enable plants to maximise available water when temperature and evapotranspiration are low. This is critical as crop yield can be adversely affected by under or over irrigation. Therefore, to maintain a healthy plant population, timely and adequate amount of water is vital. So, this Section deals with the amount of water administered to the plants over the two growing seasons.

4.6.2 Results of the climatological watering regimes calculations

For ease of reference, in the first season of the experiment, calculation of the “control” watering amount was based on the water requirements of sugar beet plants and the mean number of sugar beet growing days, as reported by (Brouwer & Heibloem 1986). The mean daily water value was calculated in terms of mm day-^{1}, which was then converted into a volume in litres that would be applied to the plants by multiplying the area of the compost at the level of the surface (mm^2) by the precipitation value (mm day-^{1}) to get a volume per day. The pots used were approximately cylindrical and during the experiments, the plants were watered every other day with two times this volume. The values in mm^3 were converted to litres by dividing the results by 1,000,000. Using this method, the "control" watering regime was calculated as 0.230 L day-^{1} multiplied by two to give a value of 0.46L every other day. However, for ease of measuring, a 1000 millilitre (ml) burette was used to deliver the water to the plants making the control watering regime 460ml.

Model results presented in earlier sections of this chapter of the May-October precipitation for the historical phase, RCP45 and RCP85 (e.g. Section 4.4.1 and Figure 4.13) identified the ensemble means of three CMIP5 climate models as representing observations very well. All the projections indicated that UK precipitation decreased in the models apart from RCP85 in the EC-Earth model which showed an increase. Of these models, MOHC (HadGEM2-ES) showed the largest negative changes in precipitation (See Tables 4.7 and 4.8). Therefore, and further to the reasons outlined above, the MOHC data was used as the basis for the "future" precipitation calculations so that a plausible but relatively extreme scenario is being investigated - this is a scenario that may stress the sustainability of the UK sugar industry and so, it is worth investigating.

Section 4.4.2, Tables 4.7, 4.8 and Figure 4.13 showed that the difference between the MOHC RCP45 and RCP85 experiments was statistically insignificant and is further displayed in Figures 4.20 and 4.21. As a result, two watering regimes were used for this season: "historical", or "control"; and "future" (i.e. the mean of RCP45 and RCP85). Statistical analysis showed a significant difference (reduction) of -15.8% between the "control" (1971-2000) and the "future" (2021-2050) regimes (see Table 4.8). This -15.8% reduction in precipitation from 1971-2000 compared to 2021-2050 was applied to the calculated watering amount for the "control" group to obtain the value for the "future" watering regime as 0.195 L day^{-1}, or 0.39 L every other day. These watering quantities were applied to the two watering regime groups from 7 June 2014 (i.e. when the plants reached their 10-12 leaf stage) until harvesting on 23 November 2014 (i.e. growing day 223, which was used in the calculation of the watering regime).

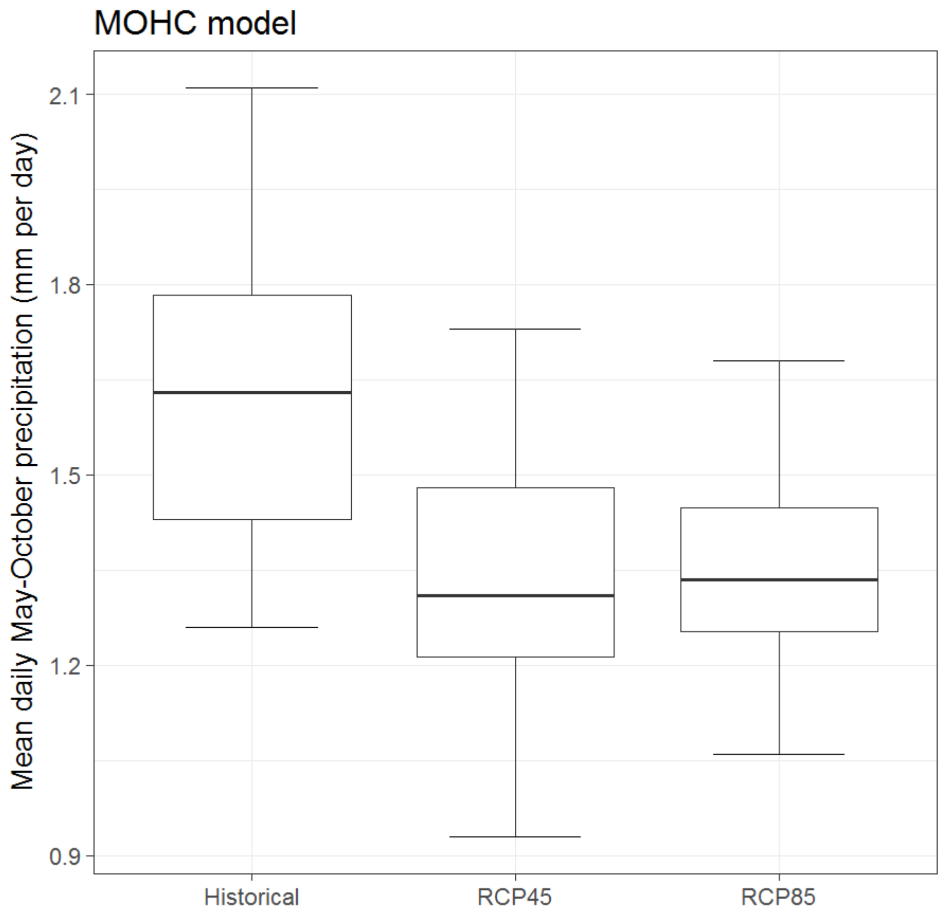


Figure 4. 20: Result of the daily May-October data from the historical (1971-2000), RCP45 (2021-2050) and RCP85 (2021-2050) from the MOHC model. The boxplot details are the same as in Figure 4.3.

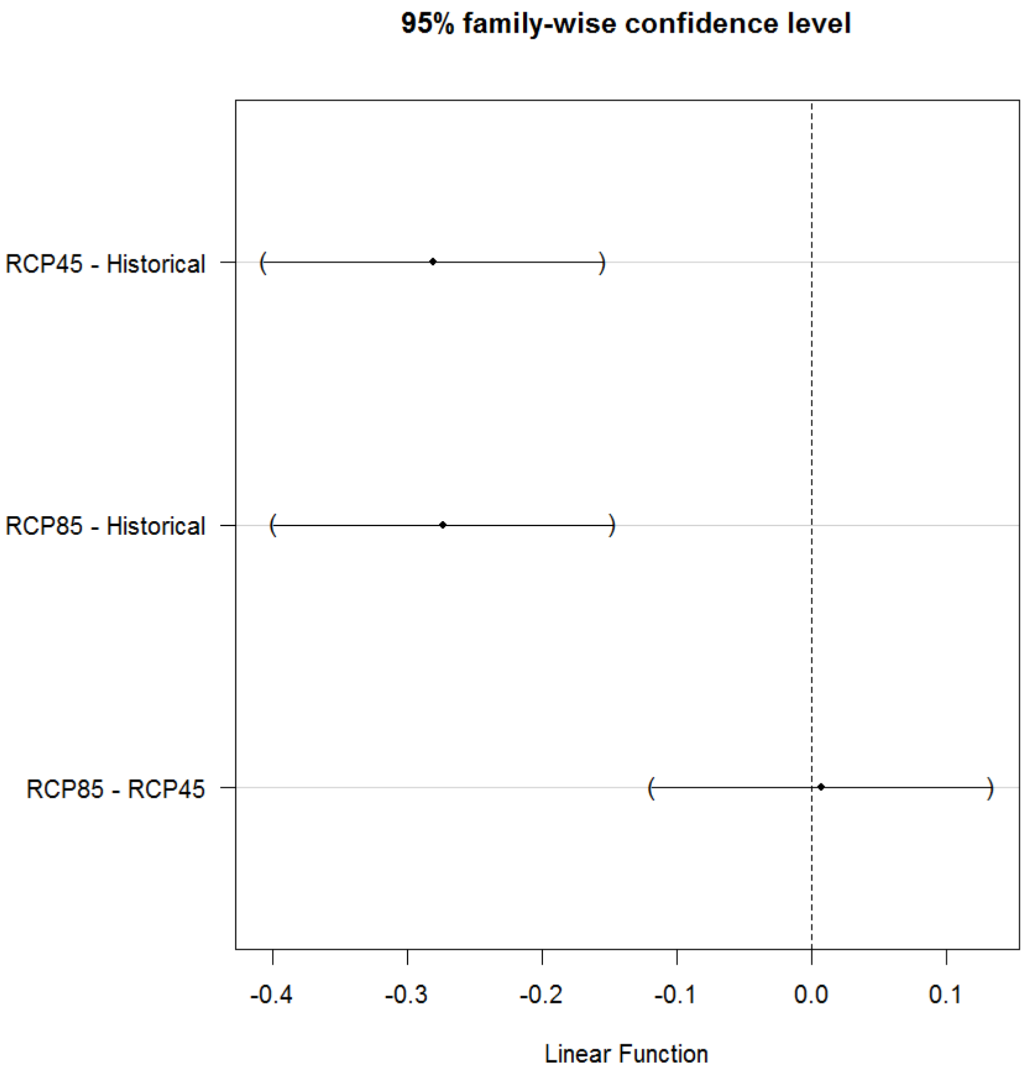


Figure 4. 21: Tukey multiple comparison of means test for the daily May-October precipitation (mm per day) for the historical, RCP45 and RCP85.

4.6.3 Results of the realistic distribution of monthly watering regimes calculations

The monthly precipitation data are of high information value when evaluating weather events during the growing season. The data are sufficient enough to robustly describe possible changes or trends from a long-term (i.e. 30 years) climate point of view. This section analysed the non-zero precipitation days (wet days) from the MOHC (HadGEM2-ES) four member ensemble model. The aim was to apply a realistic distribution of watering events to the plants based on the calculation of precipitation events for the control experiment as well as the RCP45 and RCP85 scenarios. Results indicated that there are no statistical significant differences between the precipitation totals for RCP45 and RCP85 (See Section 4.6.2) but the distribution of those events differed significantly thereby making it important to assess whether the distribution of precipitation events affected the growth and yield of plants.

The first step was to calculate the number of watering days per month for each of the three experimental categories (Control, RCP45 and RCP85). This was done by calculating the percentage of wet days for each month in each of the categories and applying that to the number of days in each month. Thereafter, the amount of water to be applied on each watering event day was based on the distribution of precipitation from each category. Then, the data was split into percentiles which then allowed wet days to be allocated in the correct proportion to replicate the overall monthly precipitation distribution. Please see Appendix 1-5 for details. Results from this analysis showed that the control category had a higher number of smaller watering events while the RCP85 had a lower but larger watering events with RCP45 somewhere in between.

The distribution of these events meant that there are days when water is applied (i.e. wet days) and days when there is no application (i.e. dry days). Therefore, to determine the specific days when these differing watering events were applied, a random number generator was applied. This give rise to wet and dry periods that appeared randomly in the watering regime, similar to the real climate system. Appendix 1-5 shows the watering regime calculations used in the second growing season for the month of October. Only October is presented here as an example of the work and procedure of the analysis because of the largeness of the files. Moreover, it is worth pointing out that the analysis commenced in July with 24 days left in the calendar month because of delay in the planting date.

Chapter 5 – The Greenhouse plant experiments

5.1 Introduction

The impact of precipitation on growth and yield of agricultural crops generally can be described in two ways. Firstly, the state of the soil and the amount of water available for plants use. Secondly, excessive water demand from the leaves induced by the state of the atmosphere (i.e. high temperatures) can influence the growth and yield of crops. This chapter uses the results from the precipitation analysis in Chapter 4 to report on the application of the watering regimes in the greenhouse sugar beet plant experiments. The analysis enabled the evaluation of how changes in both seasonal and monthly precipitation affected sugar beet plants development and yield over two growing seasons. Changes in the plants' group for the "control" experiment (1971-2000) were compared to the plants' categories under future scenarios of RCP45 and RCP85 for 2021-2050.

In the first season, plant seeds were sown on the 15th April 2014 and in the second season seeds were sown on the 25th May 2015. The experiment in the first season entailed growing 150 sugar beet plants in the greenhouse and was categorised into two: historical and future experiments with 75 replicates each. It's noteworthy that for this season, the study only investigated the impacts of climatological changes on the plants yield by delivering the total growing season precipitation from May to October in a series of regular and equal watering events for the two different categories (See Section 4.6.2).

In the second season, 201 sugar beet seeds were sown in the greenhouse and the experiment was categorised into three: Control, RCP45 and RCP85 with 67 replicates each. The watering regimes were designed to replicate realistic distribution of precipitation events. The impacts of the watering regimes on plants' parameters were assessed over the two seasons and results are presented here for the above-ground and below-ground plant parameters for the different categories of plant experiments. The growth of the plants was measured with a tape rule and observations showed that the plants' leaf formation occurred early (see also Kenter et al. (2006); Scott & Jaggard (2000)) but increased steadily in multiples of two throughout the growing season. The results in this chapter give an indication of the ultimate effect of the different watering regimes on the different plant categories.

Over the two growing seasons, plants were sown under the same condition (See Section 3.8.5) and thinned at their 4-6 leaf stages from two to one seedling per pot to encourage uniform establishment. Plants were late allocated into the control and future watering regimes and the different watering regimes were implemented after the plants had reached their 10-12 leaf growth stage and had started forming tubers. To account for natural variability in plant sizes, the plants assigned to each watering regime were selected to result in an equal distribution of plant sizes in each watering regime. Allocation of plants at this time was done to coincide with rainfall analysis from May to October for the study periods and also because the biggest precipitation changes are projected for the summer. Changes in precipitation from the analysis conducted were imposed on the plants in the future categories, which had a reduction in precipitation amount.

Subsequently, a number of non-destructive parameters were used to assess the yield potential of the plants over the growing season. The measures parameters include: the number of leaves on each plant, the height of the plants, the growth ratio and the leaf width. These parameters were measured every two weeks to enable the examination of the effect of water reduction on the plants' development and productivity; this can place yield in the context of the growing season examined. At the end of the experiment, destructive measurements were taken to determine the mean fresh weight of the tubers as harvested and when dried.

5.2 Climatological watering regime measurements

5.2.1 Above-ground measurements

A number of non-destructive parameters were used to assess the yield potential of the plants over the growing season including: the number of leaves; height of the plants (i.e. height of the tallest stem); the growth ratio of the plants (i.e. height divided by number of stems); leaf width (i.e. width of the widest leaf). Only the final values are presented here because these data give an indication of the ultimate effect of the different watering regimes (See Table 5.1 and Figure 5.1). In all cases, the "control" group had higher values than the "future" group but the difference between the groups was not statistically significant (See sub-Sections 5.2.1.1-5.2.1.4) over the two growing seasons.

5.2.1.1 Highest tip of the plants

The measurement of the highest tip of the plants also known as the height to node ratio (HNR) is used to determine the characteristics of plant growth and development. It measures the total height of the plants starting from the cotyledonary node (i.e. nodes beside each other at the base of the plants) to the terminal of the plant (i.e. highest tip on the plant). Result of the comparison of plants height between the control and future experiments did not show any significant difference (p-value 0.94). Table 5.1 shows the means of the final set of non-destructive measurements taken. The mean comparison between the experiments returned a mean of 51.0 cm ± 5.5 for the control experiment and 50.9 cm ± 5.2 for the future experiment with a p-value of 0.94 suggesting that there was no statistical significant difference between the two experiments (Table 5.1).

5.2.1.2 The number of leaves

The different growth rate of the leaves within and between experiments at different stages of development made it impossible to select leaves of a single plant as representative of the entire population. The growth rate of the canopies differed across the entire population with some plants producing more leaves than others. The control experiment had a greater number of leaves than the future experiment but this difference was not statistically significant as shown in Table 5.1 detailing the final set of non-destructive measurements taken. The mean number of leaves from the control experiment returned a mean of 21.8 ± 3.2 compared to the future experiment with a mean of 21.6 ± 3.0 and a p-value of 0.69.

5.2.1.3 Growth ratio

The growth ratio of the plants varies within and between the groups. It gives an indication of the vegetative and reproductive capacity of the plants. In this experiment, there was no statistical significant difference between the growth ratio of the control experiment and the growth ratio of the future experiment. Results shown in Table 5.1 retuned a mean value of 2.6 cm ± 0.3 for the control experiment and 2.6 cm ± 0.3 for the future experiment and a p-value of 0.68.

5.2.1.4 Leaves width

The position of the leaves surface influences light interception, evaporation, photosynthesis, response to irrigation and plant growth (Blanco & Folegatti 2005). The leaves' width provides comparison of the plants sensitivity to environmental changes between the control and future experiments. Result here did not show any significant difference between the different experiments with the control experiment returning a mean of 13.9 cm ± 1.8 and the future experiment with a mean of 14.0 cm ± 1.6 with a p-value of 0.68 (Table 5.1).

In summary, the plants above-ground parameters measured under the climatological watering regime did not show any significant difference between the growth and development of the plants in the two different experiments.

Table 5. 1: Mean and Std. of the final measurements of non-destructive measurements from the control and future seasonal watering regimes.

	Control		Future			
Parameters	**Mean**	**Std**	**Mean**	**Std**	**P-value**	**Population**
Highest tip of plants	51.0	5.5	50.9	5.2	0.94	75
Number of leaves	21.8	3.2	21.6	3.0	0.69	75
Growth Ratio	2.6	0.3	2.6	0.3	0.68	75
Leaves width	13.9	1.8	14.0	1.6	0.68	75

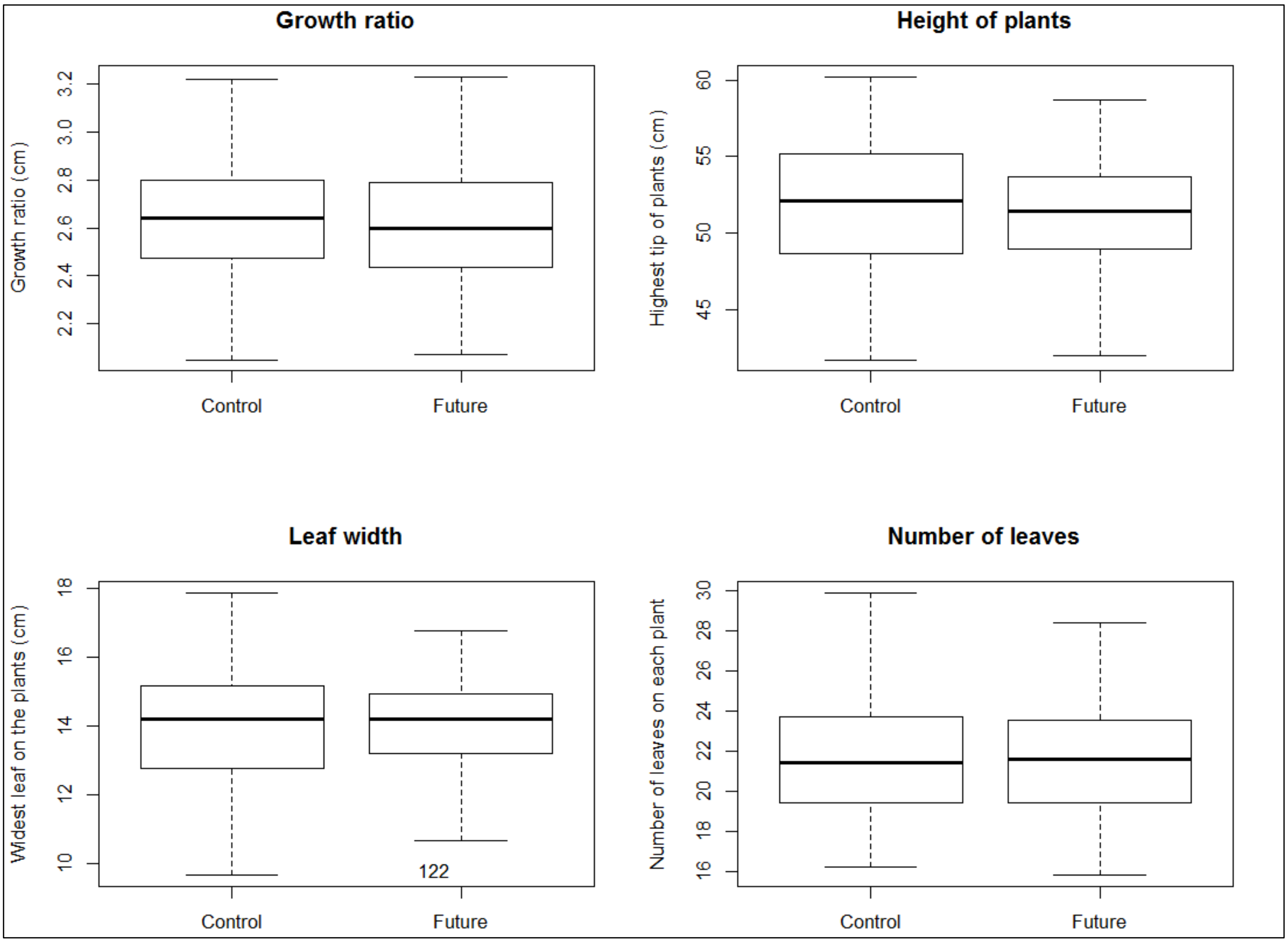


Figure 5. 1: Boxplot of the climatological watering regime data from the control and future experiments. The thick black line represents the median (2nd quartile) of the distribution. The extreme of the plots represents the 1st (bottom) and 3rd quartiles (top). The whiskers indicate the lowest and highest values in the data.

5.3 Below-ground measurements for the climatological experiment

5.3.1 Wet weight of yield under the climatological watering regimes

At the end of the season, all the sugar beet tubers were harvested on 23rd November 2014 (Day 223) and destructive measurements were taken to determine the mass of each tuber as harvested and when dried. During harvest, plant tubers were uprooted from the soil, washed, dried and weighed individually. Then, the leaves were cut off from the tubers which are of the most interest in this research. The tubers were then weighed individually without the leaves and the measurement reported as the "wet" weight. The mean "wet" weights of all plants were calculated for both experiments with the "control" having a mean tuber wet weight of 359.5g and the “future” with 318.5g. Figure 5.2 shows the boxplot of the wet weight data and Figure 5.3 shows a histogram of the complete data set, which clearly have different distributions.

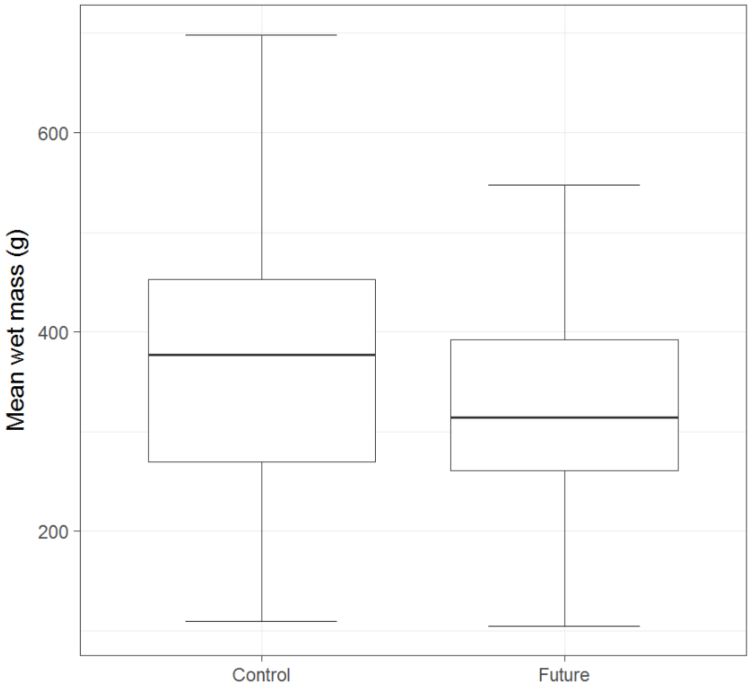


Figure 5. 2: Results of the tuber wet mass data analysis. Boxplot showing the tuber wet mass data from the control and future categories. The boxplot details are the same as for Figure 5.1.

An independent sample t-test was performed on the control and future data with the hypothesis that there was no difference in the mean tuber wet weight of the “control” and “future” watering experiments. Results showed that a statistical significant difference existed in the yield of the “control” and “future” experiments with a p-value of 0.03. The future category showed a reduction in yield compared to the control experiment.

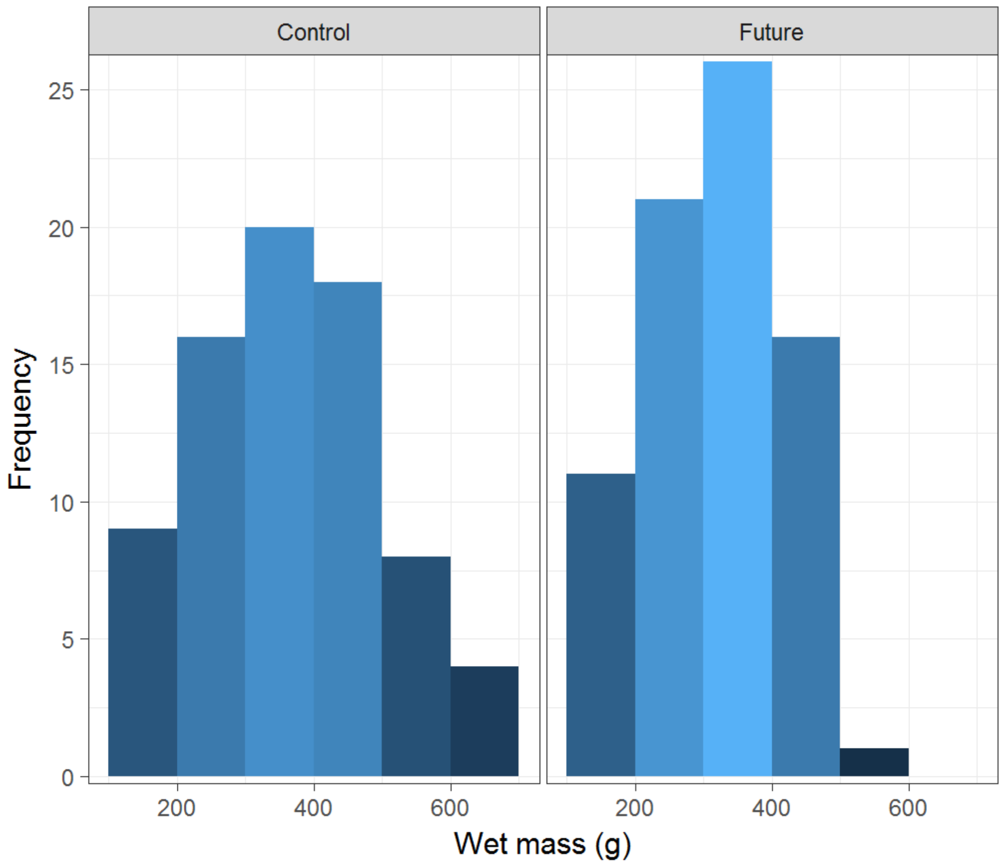


Figure 5. 3: Histogram showing the distribution of the tuber wet mass data for the control and future categories.

5.3.2 Dry weight of yield under the climatological watering regimes

The dry mass was obtained through a laboratory experiment by cutting the tubers into small but similar sized pieces and drying them in an oven at 80ºC to remove moisture from the tubers. Figure 5.4 shows a boxplot of the dry weight matter and Figure 5.5 show histogram of the control and future datasets. Statistical analysis of the dry weight showed that the control category had a mean of 95.2g (73.5% reduction from the wet weight) and the future category with a mean of 88.2g (72.3% reduction from the wet weight).

This result indicated a p-value of 0.11 with the null hypothesis that there was no difference between the groups. This implies that the statistical significance of this result is just outside the 10% level often applied to determine significance. This by implication suggests that the difference in mass is mostly a result of the moisture content in the tubers between the two watering regimes. Despite the lack of statistical basis for rejecting the null hypothesis, there are still differences worthy of comment. In particular, the largest tubers from the control category (i.e. greater than 150g) are absent from the future category and the mean for the future category is noticeably smaller.

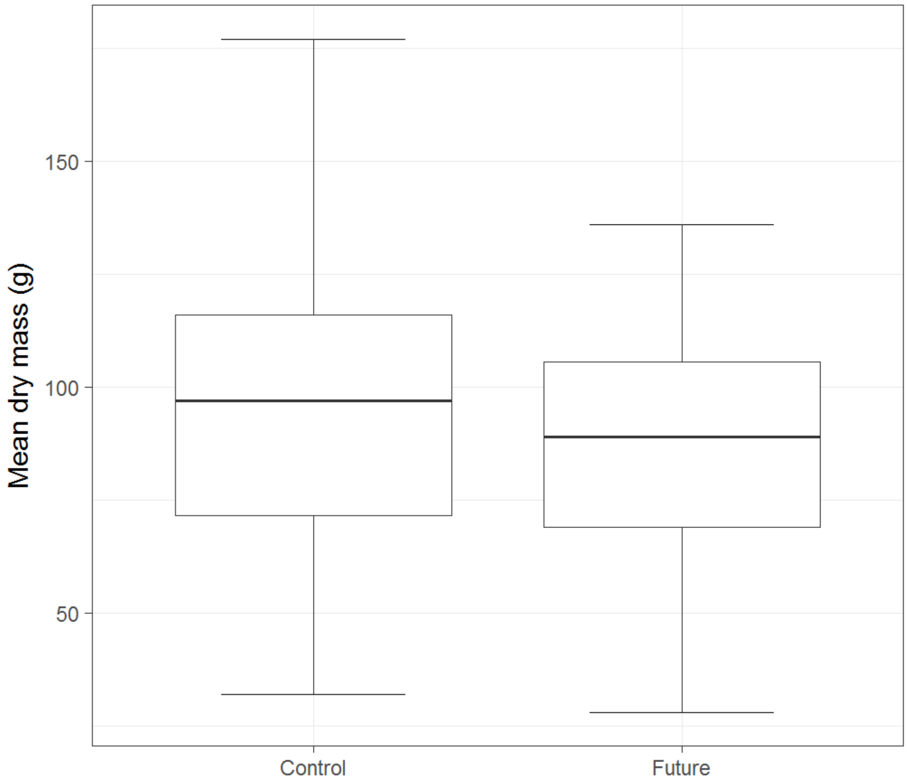


Figure 5. 4: Results of the tuber dry mass data analysis. Boxplot showing the tuber dry mass data from the control and future categories. The boxplot details are the same as for Figure 5.1.

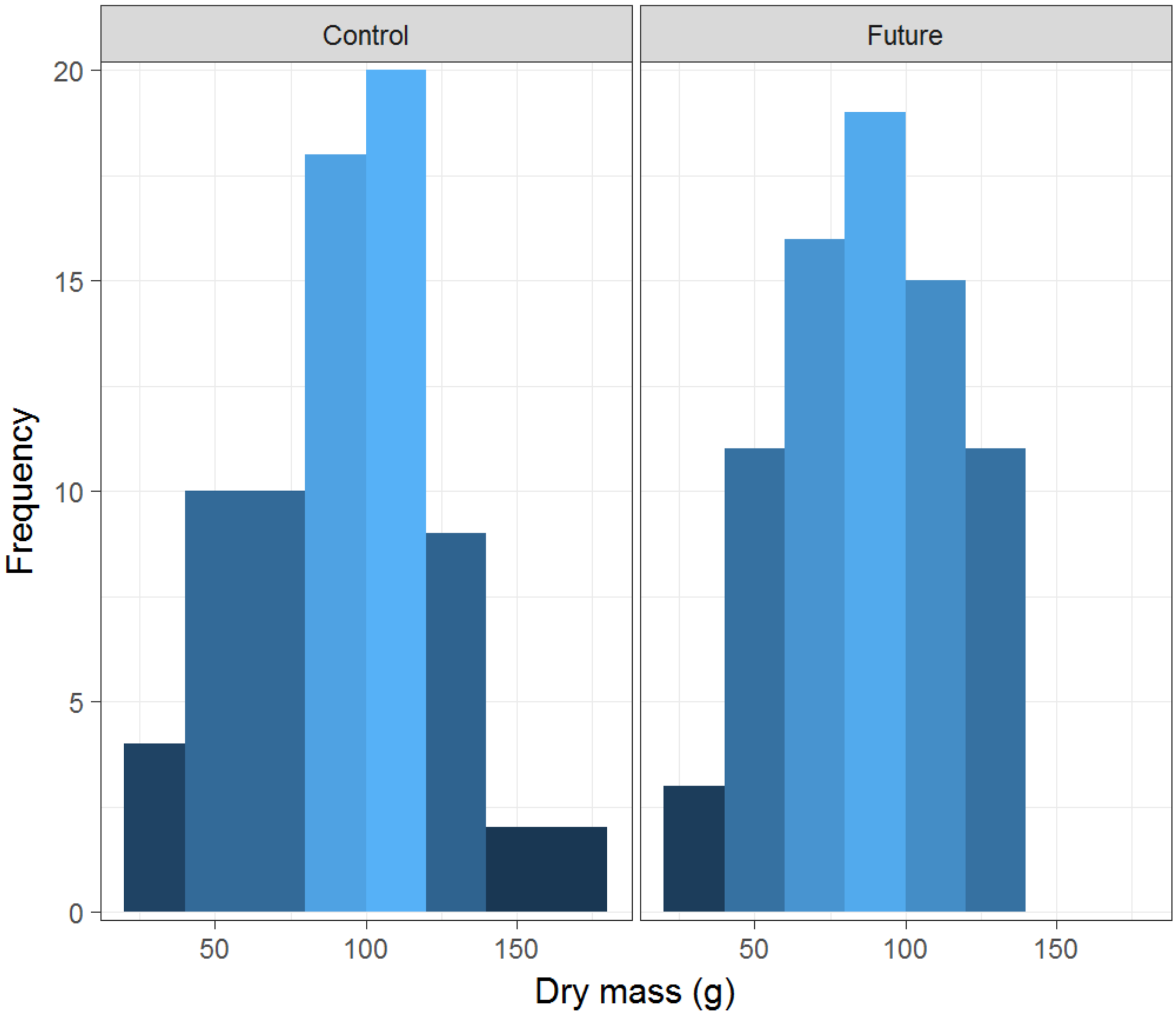


Figure 5. 5: Histogram showing the distribution of the tuber dry mass data for the control and future categories.

5.3.3 Soil moisture

Soil moisture is generally described as water that is held in spaces between soil particles and is usually determined by the water table and it also helps in the transportation of important nutrients through the plant (Arnold, 1999). Nutrients are drawn from the soil and used by the plants without which plant cells show evidence of stress through wilting of the leaves and stem. In the case of such events, the plants regain turgidity through irrigation. So, considering the variability in precipitation, it is important to assess soil moisture in this study. By measuring the soil moisture, comparative assessment was made between the control and future watering regimes.

The changes in precipitation represented by the two watering regimes indicated a statistical significant difference in soil moisture between the control and future watering regimes. It was observed that soil moisture increased with irrigation and is depleted by crop growth. The mean growing season (May-October) soil moisture data collected during the growing season is shown in Figure 5.6 and the mean monthly soil moisture data are presented in Figure 5.7. Result of the mean soil moisture comparison showed that the control soil moisture had a mean of 18.1% ± 2.7 compared to the future with a mean of 16.1% ± 2.7 (Table 5.2).

The percentage (%) difference between the two watering regimes was further assessed using the null hypothesis that there was no difference in the two groups. The result of the independent sample t-test conducted using a 95% confidence level showed a significant reduction in the level of soil moisture in the future category with a p-value of 8.7×10^{-6}. In short, the analysis revealed that the future group had a significant reduction in soil moisture. Table 5.3 shows the June-October analysis of the soil moisture measurement between the two categories and Figure 5.7 shows a line plot displaying the mean monthly soil moisture. Results reveal that July had the lowest soil moisture percentage in both the control and future watering regimes. In fact, both datasets showed the same trend indicating July as the month with the lowest soil moisture that may potentially have an impact on yields.

Table 5. 2: June-October soil moisture data of the growing season for the control and future watering categories calculated from the measurements taken every two weeks.

	Soil moisture (%)		
Category	**Mean**	**Std**	**Population**
Control	18.1	2.7	75
Future	16.1	2.7	75

Table 5. 3: Mean monthly soil moisture data for the control and future experiments during the growing season.

	Control		Future	
Month	**Mean**	**Std**	**Mean**	**Std**
June	18.5	3.7	16.3	3.8
July	14.9	4.9	12.0	4.6
August	18.3	2.4	16.7	2.7
September	20.5	2.1	19.7	2.6
October	19.3	1.6	18.0	2.1

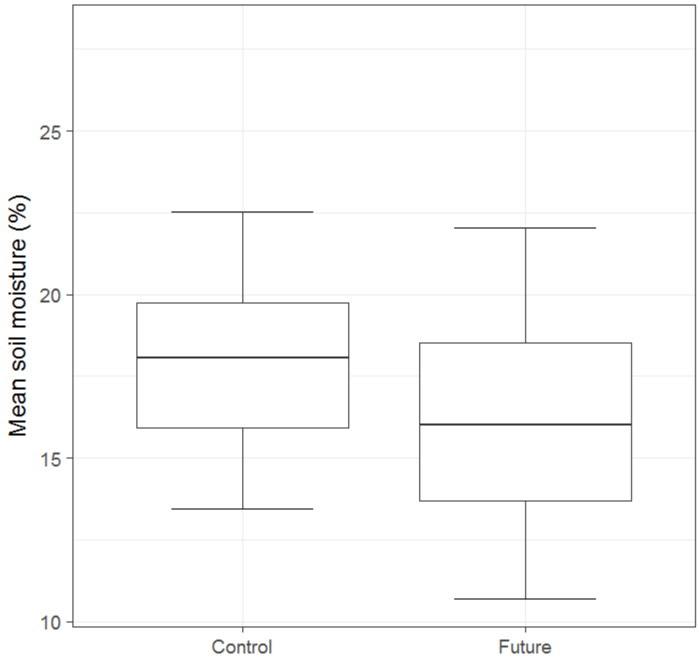


Figure 5. 6: Results of the soil moisture data analysis. The boxplot shows soil moisture data from the control and future categories.

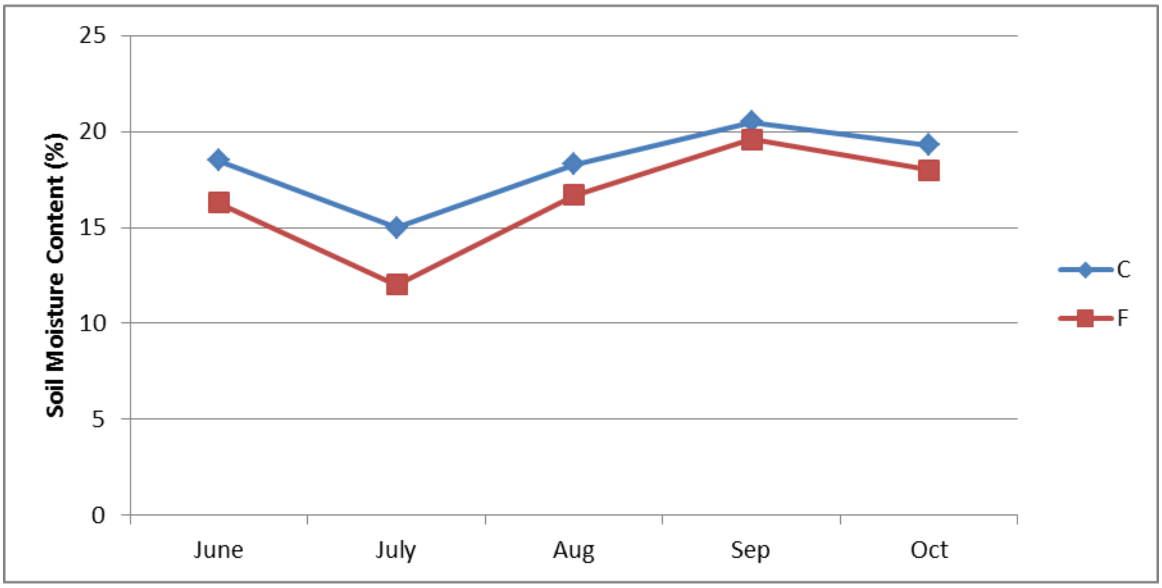


Figure 5. 7: Line graph showing the mean monthly soil moisture measurement for the control (blue line) and future (maroon line) categories.

5.3.4 Correlation between soil moisture and wet weight of yield

In order to further examine the impact of soil moisture on wet weight of yield, the relationship between soil moisture and wet tuber mass was examined using the Pearson Correlation test. Figure 5.8 displays the results which indicate that 43% of the variability in wet mass in the control category could be explained by the variability in soil moisture. Conversely, 57% of the variability in wet mass in the future category could be explained by the variability in soil moisture. In summary, as the soil moisture in both categories increases, the value of the tuber wet mass decreases. This suggests that there was a strong negative linear relationship between the yields and soil moisture in the experiment.

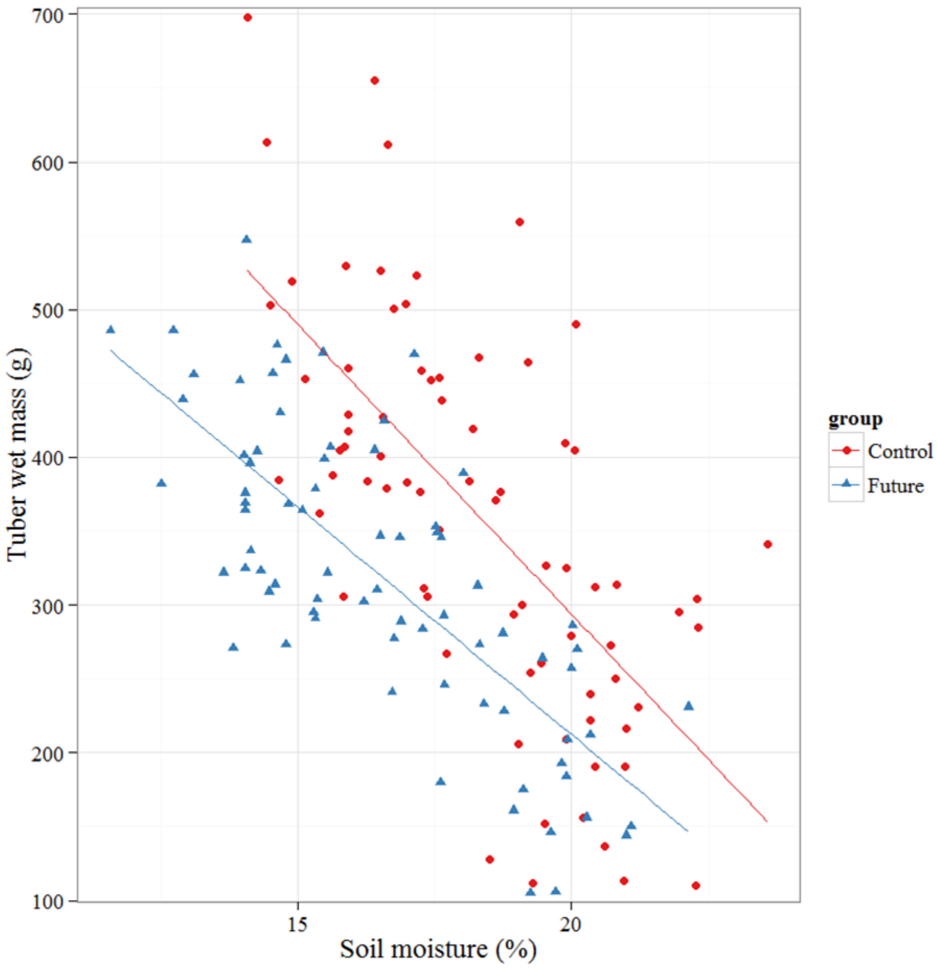


Figure 5. 8: Scatter plot showing the wet mass for individual tubers from the control (red circles; solid line) and future (blue triangle; solid line) categories plotted against the mean soil moisture data for each replicate.

5.3.5 Correlation between soil moisture and dry weight of yield

A further examination of the impact of soil moisture on dry weight of yield was carried out using Pearson Correlation test. Results indicate that 41% of the variability in dry mass of the control category could be associated with variability in soil moisture. Figure 5.9 displays the plot which shows that as the soil moisture in both categories increases, the value of the dry weight decreases suggesting a strong negative linear relationship between soil moisture and dry weight of the crop.

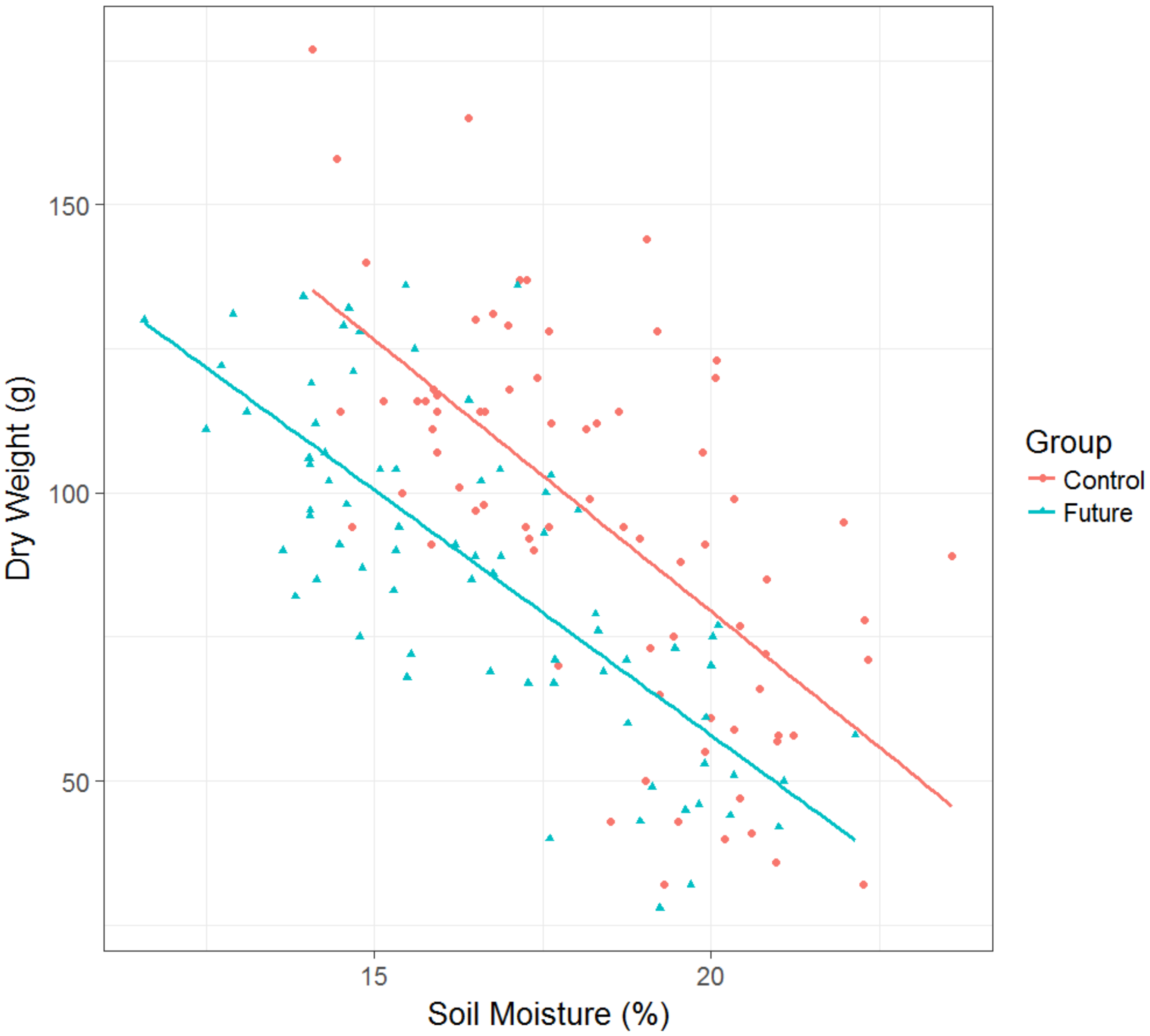


Figure 5. 9: Scatter plot showing the dry mass for individual tubers from the control (red circles; solid line) and future (light green triangle; solid line) categories plotted against the mean soil moisture data for each replicate.

5.4 Realistic distribution of precipitation watering regimes parameters measurement

5.4.1 Above-ground measurements

In the second season of the experiment, using the distribution of precipitation events and sizes watering regimes, a similar approach as the first season experiment was employed to measure plant parameters to keep the experiment unbiased. A number of non-destructive parameters were used to assess the yield potential of the plants over the growing season including: the number of leaves; height of the plants (i.e. height of the tallest stem); the growth ratio of the plants (i.e. height divided by number of stems); leaf width (i.e. width of the widest leaf). Only the final values are presented here because these data give an indication of the ultimate effect of the different watering regimes. The experiment implemented three watering regimes for the three categories (Control, RCP45, and RCP85) of plant experiment undertaken unlike the climatological experiment with two watering regimes (See Section 4.5, Table 4.15, Figures 4.21 and 4.22). Results in this Section varied among the different parameters measured but with no statistical significant difference except in the number of leaves where there was a significant difference between the control and future categories. Tables 5.4 and 5.5 show the analysis and Figure 5.9 show the distribution of the measured parameters from the dataset.

5.4.1.1 Highest tip of the plants

Result of the comparison of the highest tip between the control, RCP45 and RCP85 experiments did not show any significant difference. Table 5.4 shows the means of the final set of non-destructive measurements taken. The mean comparison between the experiments returned a mean of 35.5 cm ± 6.9 for the control experiment, 33.9 cm ± 6.4 and 33.3 cm ± 6.2 for RCP45 and RCP85 experiments respectively (Table 5.4). The result returned a p-value of 0.15 suggesting that there was no statistically significant difference between the highest tips of the plants from the three experiments (Figure 5.9).

5.4.1.2 The number of leaves

The growth rate of the canopies differed across the entire population with some plants producing more leaves than others. Results indicate that the control experiment had more leaves than the RCP45 and RCP85 groups. Results of the analysis, shown in Table 5.4, indicate that there was a statistically significant difference between the number of leaves in the control category and the future experiments (RCP45 and RCP85). Multiple means tests using ANOVA returned a mean of 17.7 ± 3.0 for the control category, 16.6 ± 2.5 and 16.5 ± 2.5 for the RCP45 and RCP85 groups respectively with a p-value of 0.02 (See Table 5.4). This result suggests that there was a significant difference in at least, one of the categories between the three experiments. Therefore, Tukey multiple contrast of means test was carried out to confirm which categories are different from the other/s. Results shown in Table 5.5 confirm that there was a significant difference between the number of leaves in the control and RCP45 categories and Figure 5.9 shows the distribution from the dataset. Similarly, the control experiment also differed from RCP85 with a p-value of 0.02. There was however no significant difference between the number of leaves in RCP45 and RCP85. `

5.4.1.3 Growth ratio

The growth ratio of the plants varied within and between the groups. Results showed that there was no statistical significant difference between the overall growth ratio of the control watering regime and the growth ratio of the RCP45 or RCP85 watering regimes. Result of the multiple means test shown in Table 5.4 retuned a mean value of 2.0 cm ± 0.3 for the control watering regime, 2.1 cm ± 0.4 for RCP45 and 2.0 cm ± 0.4 for RCP85 and a p-value of 0.5. This result suggests that there was no statistical significant difference in the growth ratio of the three experimental categories.

5.4.1.4 Leaf width

Result of the leaves width measurements (i.e. widest point of the biggest leaf) did not show any statistical significant difference between the three different watering experiments. The control experiment returned a mean of 9.8 cm ± 2.3, RCP45 with a mean of 9.4 cm ± 2.1 and RCP85 had a mean of 9.2 cm ± 2.0 and a p-value of 0.3 (Table 5.4).

In summary, the plants above-ground parameters measured under the monthly watering regimes did not show any statistical significant difference between the highest tips of the plants, the growth ratio and leaf width. However, there was a statistically significant difference between the numbers of leaves in the different categories.

Table 5. 4: Mean and Std of the final non-destructive measurements from the control, RCP45 and RCP85 Realistic precipitation distribution watering regimes.

	Control		RCP45		RCP85			
Parameters	Mean	Std	Mean	Std	Mean	Std	Population	P-value
Highest tip of plants	35.5	6.9	34.0	6.4	33.3	6.2	67	0.15
Number of leaves	17.7	3.0	16.6	2.5	16.5	2.6	67	0.02
Growth Ratio	2.0	0.3	2.1	0.4	2.0	0.4	67	0.5
Leaves width	9.8	2.3	9.4	2.1	9.2	2.0	67	0.3

Table 5. 5: Results of the Tukey analysis of contrasts means test from the parameters measured for the control, RCP45 and RCP85 experiments also illustrated in Figure 5.9.

Growth Ratio				
Category	**Estimate**	**Std Error**	**t value**	**P-value**
RCP45 - Control == 0	0.07	0.06	1.18	0.46
RCP85 - Control == 0	0.03	0.06	0.45	0.89
RCP85 - RCP45 == 0	-0.04	0.06	-0.73	0.75
Height of leaves				
RCP45 - Control == 0	-1.54	1.13	-1.36	0.36
RCP85 - Control == 0	-2.12	1.13	-1.88	0.15
RCP85 - RCP45 == 0	-0.58	1.13	-0.52	0.86
Leaf width				
RCP45 - Control == 0	-0.4	0.37	-1.11	0.52
RCP85 - Control == 0	-0.58	0.37	-1.59	0.25
RCP85 - RCP45 == 0	-0.18	0.37	-0.49	0.88
Number of leaves				
RCP45 - Control == 0	-1.13	0.46	-2.46	0.04
RCP85 - Control == 0	-1.19	0.46	-2.59	0.02
RCP85 - RCP45 == 0	-0.06	0.46	-0.13	1.01

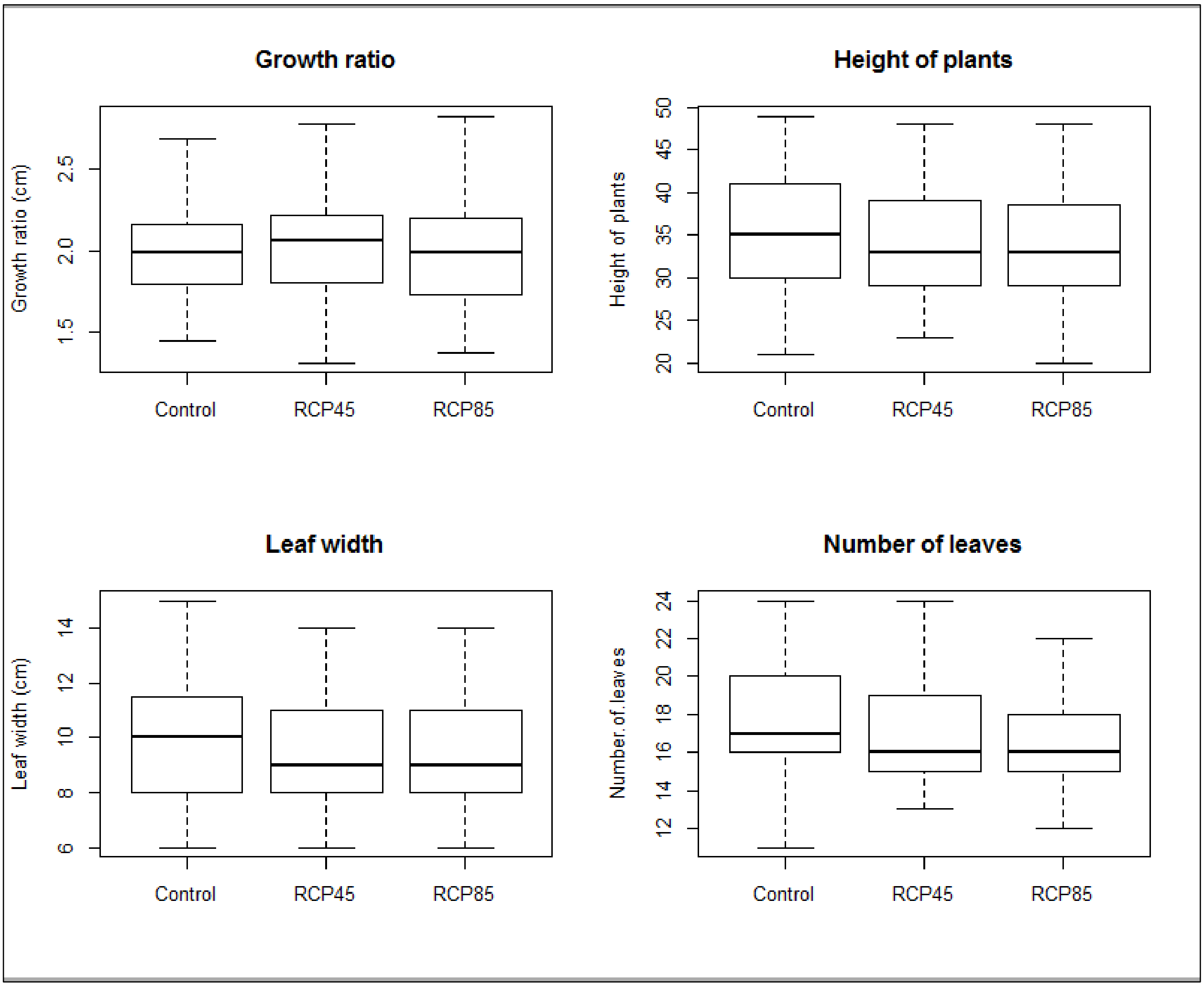


Figure 5. 10: Boxplot of the Realistic precipitation distribution watering regime results from the control and future experiments. The thick black line represents the median (2nd quartile) of the distribution. The extremes of the boxes represent the 1st (bottom) and 3rd quartiles (top). The whiskers indicate the lowest and highest values in the data.

5.5 Below-ground measurements

5.5.1 Wet weight of yield under the distribution of watering events and sizes

The second season harvest followed the same procedure as the first season. All the sugar beet tubers were harvested on 23rd December 2015 (Day 255) and destructive measurements were taken to determine the mass of each tuber as harvested and when dried. During harvest, plant tubers were uprooted from the soil, washed, dried and weighed individually. Then, the leaves were cut off from the tubers and the tubers were then weighed individually without the leaves and the measurement reported as the “wet” weight. The mean “wet” weight of all plants were calculated for all the experiments with the “control” group having a mean tuber wet weight of 153.4g, RCP45 with a mean of 130.8g and RCP85 with a mean of 113.3g (See Table 5.6). Figure 5.10 shows the distribution of the data from the Control, RCP and RCP85 and Figure 5.11 shows a histogram distribution of the complete datasets with different distributions. Figure 5.12 shows the contrast in means from the datasets.

Multiple means tests was performed on these datasets with the hypothesis that there was at least one difference in the mean tuber wet weight of the “control” and “future” experiments under RCP45 and RCP85. The calculations were based on a mean statistics and normality of data with 95% confidence interval. Results indicate a p-value of 0.01 which suggest that there is at least one statistically significant difference in the mean tuber wet weight from the three experiments.

In order to ascertain the difference that existed between the experimental categories, Tukey multiple comparison of means test was conducted and results show in Table 5.7 that there was no statistical significant difference between the wet weight of the control and RCP45 categories with a p-value of 0.22. Similarly, there was no difference between the wet weights of RCP45 and RCP85 experiments with a p-value of 0.42. However, there was a statistical significant difference between the wet weight of the control and RCP85 categories with a p-value of 0.01.

Table 5. 6: Results of mean tuber wet weight for the growing season from the Control, RCP45 and RCP85 experiments.

Category	Wet weight	Std	Population
Control	153.4	96.1	67
RCP45	130.5	76.5	67
RCP85	113.3	61.5	67

Table 5. 7: Tuber wet weight data analyses showing results of the Tukey multiple comparison of means test for the control, RCP45, and RCP85.

Wet weight Category	Estimate	Std Error	t value	P-value
RCP45 - Control == 0	-22.95	13.69	-1.68	0.22
RCP85 - Control == 0	-40.08	13.69	-2.93	0.01
RCP85 - RCP45 == 0	-17.13	13.69	-1.25	0.42

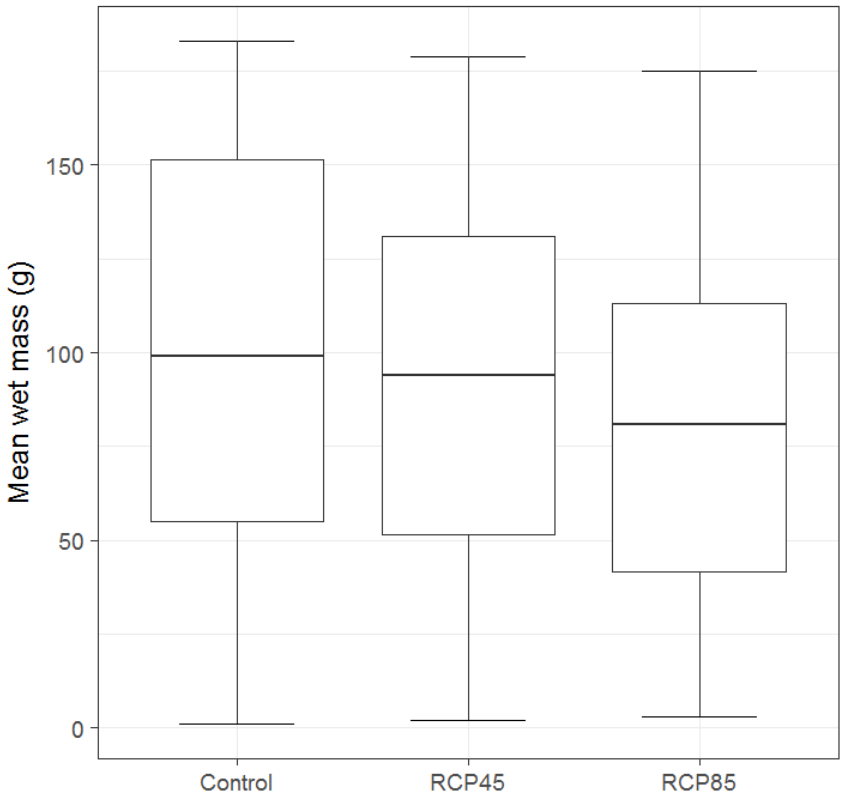


Figure 5. 11: Results of the tuber wet weight data analysis. Boxplot showing the tuber wet weight data from the control, RCP45 and RCP85 categories. The boxplot details are the same as for Figure 5.1.

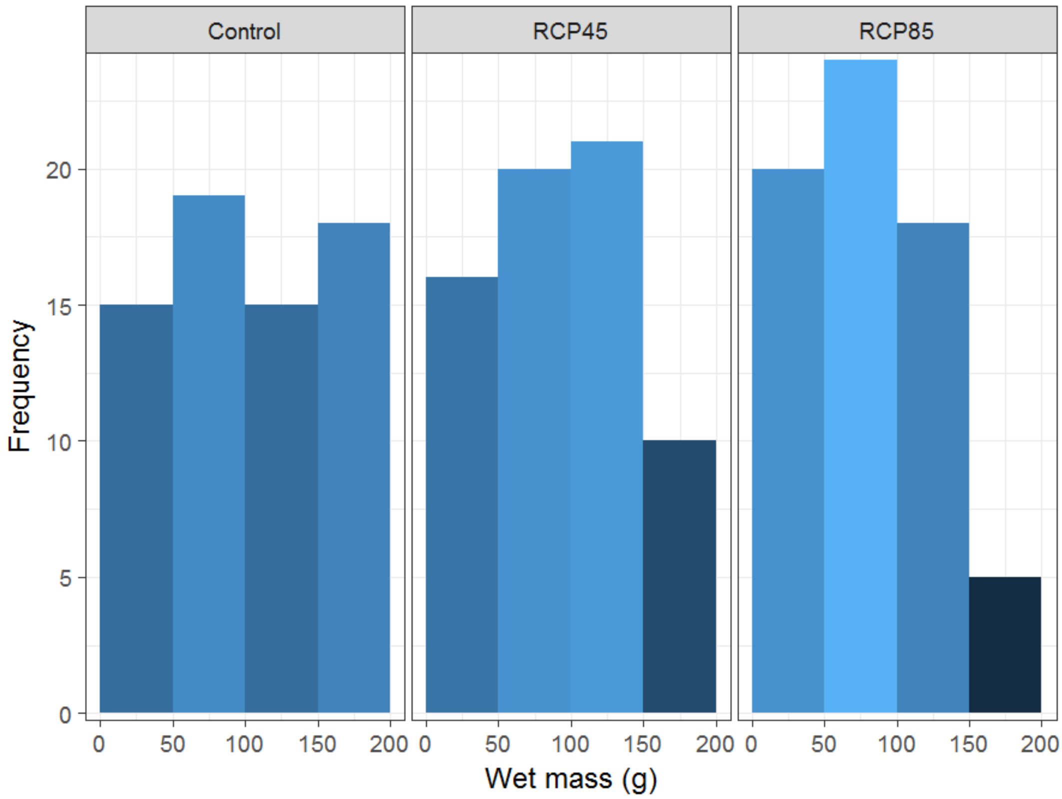


Figure 5. 12: Histogram showing the distribution of the wet weight data for the control, RCP45 and RCP85 categories of the realistic precipitation distribution experiment.

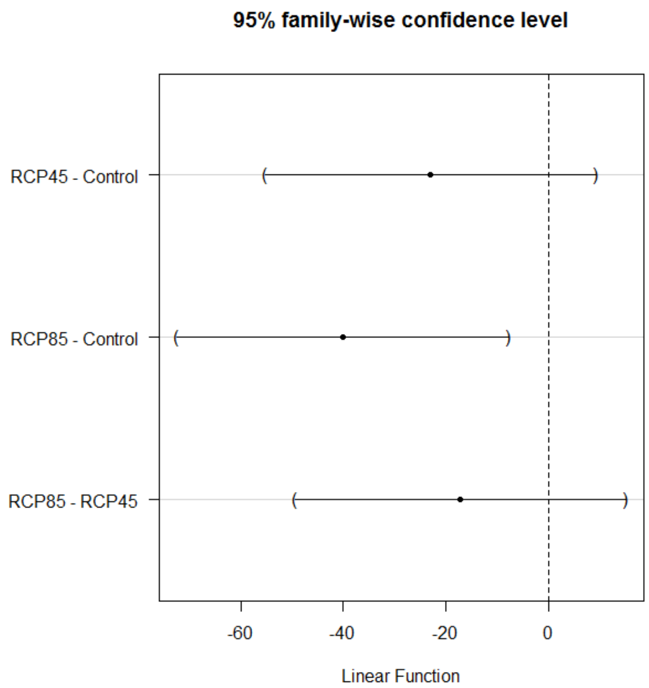


Figure 5. 13: Results of the Tukey test showing that the mean wet weight between RCP85 and the Control experiment is significantly different from the others.

5.5.2 Dry weight of yield under the distribution of watering events and sizes

Similar to the first season experiments, the dry mass was obtained through a laboratory experiment by cutting the tubers into small but similar pieces and drying them in an oven at 80ºC to remove moisture from the tubers. The mean dry mass of all plants were calculated for all the experiments with the control having a final mean weight of 48.9g (68.1% reduction from the wet weight), RCP45 with a mean of 42.7g (67.3% reduction from the wet weight) and RCP85 with a mean of 38.3g (66.2 % reduction from the wet weight) - See Table 5.8. Figure 5.13 shows a distribution of the data from the Control, RCP45 and RCP85 and Figure 5.14 shows a histogram distribution of the complete datasets with different distributions. Figure 5.15 shows the contrast in means from the datasets.

Multiple mean tests were performed on these datasets with the hypothesis that there was at least one difference in the mean dry weight of the control, RCP45 and RCP85 experiments. The calculations were based on a mean statistics and normality of data with 95% confidence interval. Results indicate a p-value of 0.03 which suggest that there is at least one difference in the mean tuber dry weight from the three experiments.

Therefore, to confirm which category or categories that were different, Tukey multiple comparison of means test was conducted and results show in Table 5.8 that there was no statistical significant difference between the dry weight of the control and RCP45 categories with a p-value of 0.26. Similarly, there was no difference between the dry weights of RCP45 and RCP85 experiments with a p-value of 0.51. However, there was a statistically significant difference between the dry weight of the control and RCP85 categories with a p-value of 0.02.

Again, this result by implication suggests that the difference in dry weight mass is a result of the different moisture contents in the tubers of the different watering regimes. In comparison to the first season wet weight yield, the tubers in the second season were relatively smaller. The smallest tuber had a value of 105g from the future category in the first season, which was much bigger than the largest minimum tuber of 34.1g in the second season. Also, the smallest maximum tuber value of 547g from the first season was much higher than the highest tuber value of 437.1g in the second season. These results highlight the vulnerability of yield to changes in precipitation patterns that are likely under future scenarios in addition to the interannual variability of yield patterns which are also likely to increase annual yield gaps and make yields less predictable.

Table 5. 8: Results of mean tuber dry weight for the growing season from the Control, RCP45 and RCP85 experiments.

Category	Dry weight	Std	Population
Control	48.9	27.9	67
RCP45	42.7	21.7	67
RCP85	38.3	18.3	67

Table 5. 9: Tuber dry weight data analyses showing results of the Tukey multiple comparison of means test for the control, RCP45, and RCP85.

Dry weight Category	Estimate	Std Error	t value	P-value
RCP45 - Control == 0	-6.2	3.97	-1.56	0.26
RCP85 - Control == 0	-10.58	3.97	-2.67	0.02
RCP85 - RCP45 == 0	-4.37	3.97	-1.1	0.51

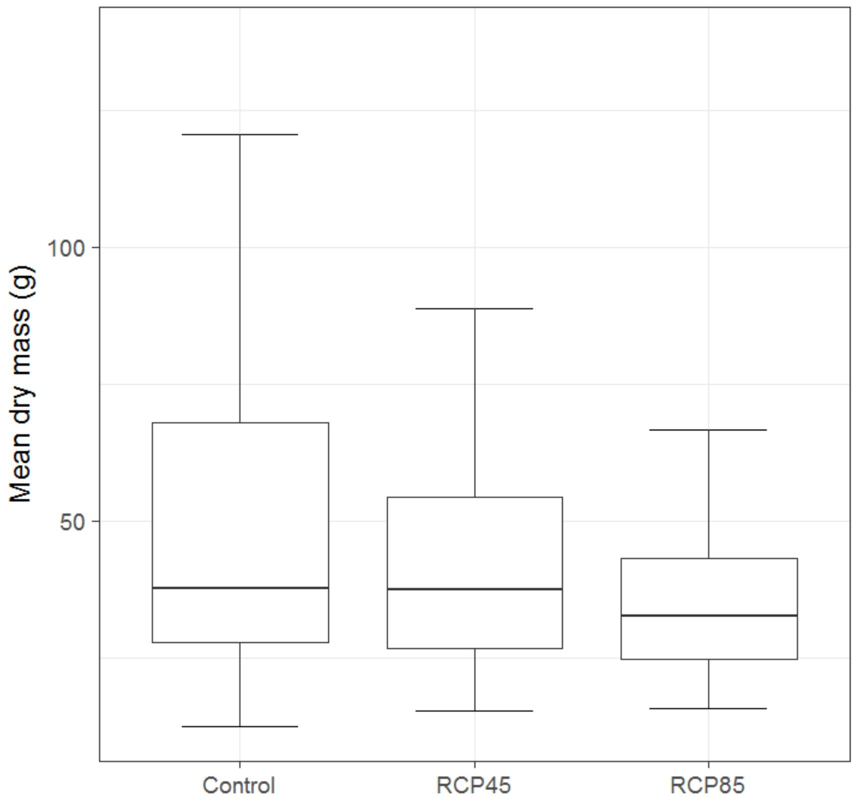


Figure 5. 14: Results of the tuber dry weight data analysis. Boxplot showing the tuber dry weight data from the control, RCP45 and RCP85 categories. The boxplot details are the same as for Figure 5.1.

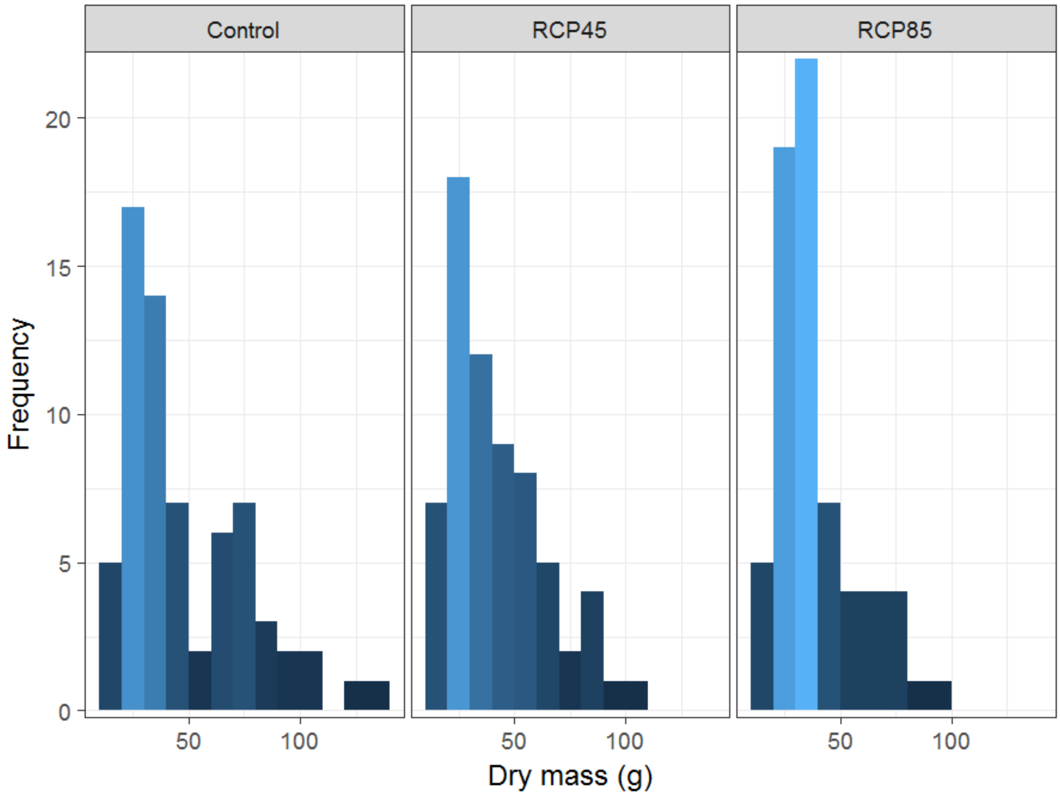


Figure 5. 15: Histogram showing the distribution of the tuber dry mass complete data for the control, RCP45 and RCP85 categories.

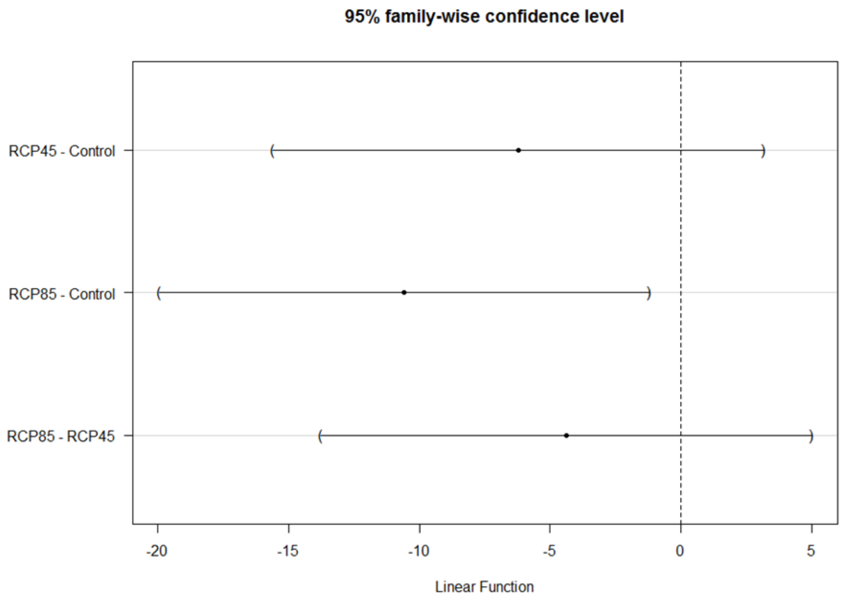


Figure 5. 16: Results of the Tukey test showing that the mean dry weight between RCP85 and the Control experiment is significantly different from the others.

5.5.3 Soil moisture

The changes in precipitation represented by the three watering regimes indicated a statistically significant difference in soil moisture between the control, RCP45 and RCP85 experiments. It was observed again that soil moisture increased with irrigation and is depleted by crop growth. Results of the July-October mean soil moisture measurements (Table 5.10) show that the control soil moisture had a mean of 20.7% ± 1.1 compared to RCP45 with a mean of 19.6% ± 1.7 and RCP85 with a mean of 19.5% ± 1.4. The result of the mean monthly soil moisture data collected during the growing season is presented in Table 5.12 and Figure 5.16 shows the distribution of the soil moisture data while the mean monthly soil moisture data is presented in Figure 5.17.

The difference between the three watering regimes was further assessed using the null hypothesis that there was no difference in the soil moisture between the groups using ANOVA. Results of the mean July-October soil moisture indicated a significant difference in the soil moisture from the three watering regimes. Therefore, Tukey multiple comparison of means test was conducted using a 95% confidence level and the result showed a significant reduction in the level of soil moisture under future scenarios of RCP45 and RCP85 compared to the control. However, there was no difference between the soil moisture of RCP45 and RCP85. Table 5.11 shows the result of the multiple mean comparison test of the growing season (July-October) soil moisture analysis for the control, RCP45 and RCP85 categories, and Figures 5.17 - 5.18 show a line plot of the mean monthly soil moisture and the result of the Tukey multiple means test.

These results reveal monthly variability in soil moisture with the control category showing the highest monthly soil moisture in all the months from July-October. The highest monthly soil moisture for RCP45 was in October followed by July with August and September having the biggest monthly reduction in soil moisture. The RCP85 category showed that July had the lowest soil moisture value followed by August and September with October having the highest soil moisture. In all cases, and similar to the first season experiment, July and August showed the lowest soil moisture values.

Table 5. 10: Result of the mean monthly (July-October) soil moisture data collected during the growing season for the control, RCP45 and RCP85 experiments.

Category	Soil moisture (%)	Std	Population
Control	20.7	1.1	67
RCP45	19.6	1.7	67
RCP85	19.5	1.4	67

Table 5. 11: Soil moisture data analyses showing results of the Tukey multiple comparison of means test for the control, RCP45, and RCP85 watering regimes.

Soil moisture (%)				
Category	Estimate	Std Error	t value	P-value
RCP45 - Control == 0	-1.16	0.24	-4.82	1.00E-04
RCP85 - Control == 0	-1.29	0.24	-5.33	1.00E-04
RCP85 - RCP45 == 0	-0.12	0.24	-0.51	0.87

Table 5. 12: Result of the mean monthly soil moisture data collected during the growing season for the control, RCP45 and RCP85 experiments.

	Soil moisture (%)			
Category	July	August	September	October
Control	19.5	19.5	20.2	22.2
RCP45	19.4	17.9	17.9	20.6
RCP85	18.1	18.7	19.5	20.8

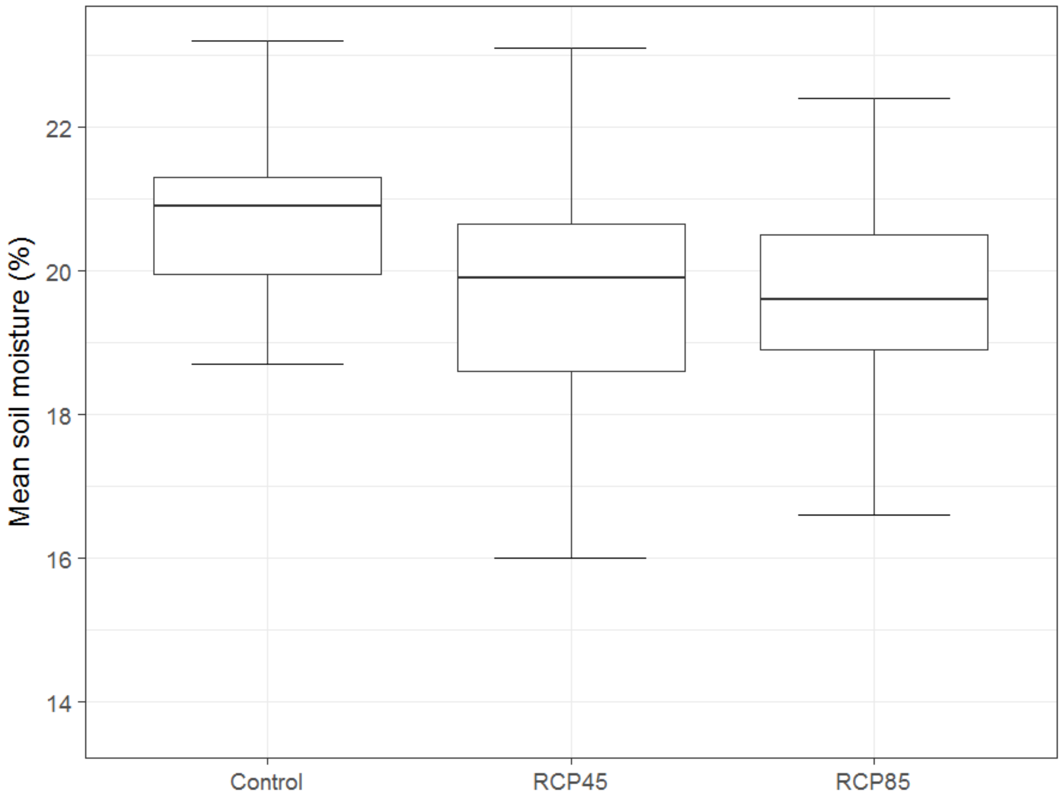


Figure 5. 17: Results of the soil moisture data analysis. Boxplot showing soil moisture distribution from the control, RCP45 and RCP85 categories.

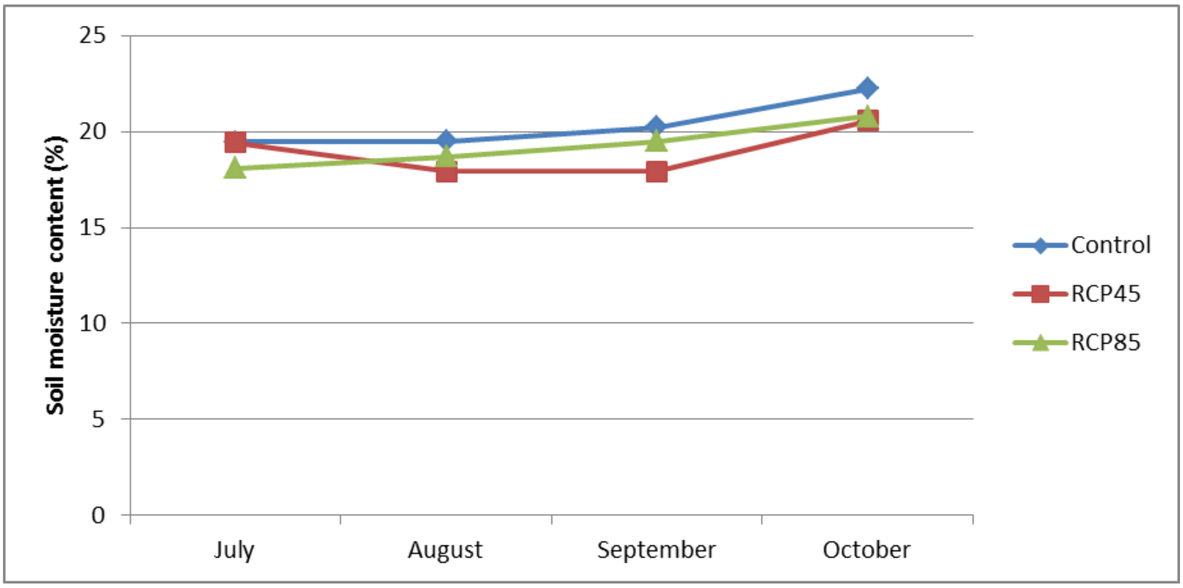


Figure 5. 18: Line graph showing the mean monthly soil moisture measurement for the control (blue line), RCP45 (maroon line) and RCP85 (green line) categories.

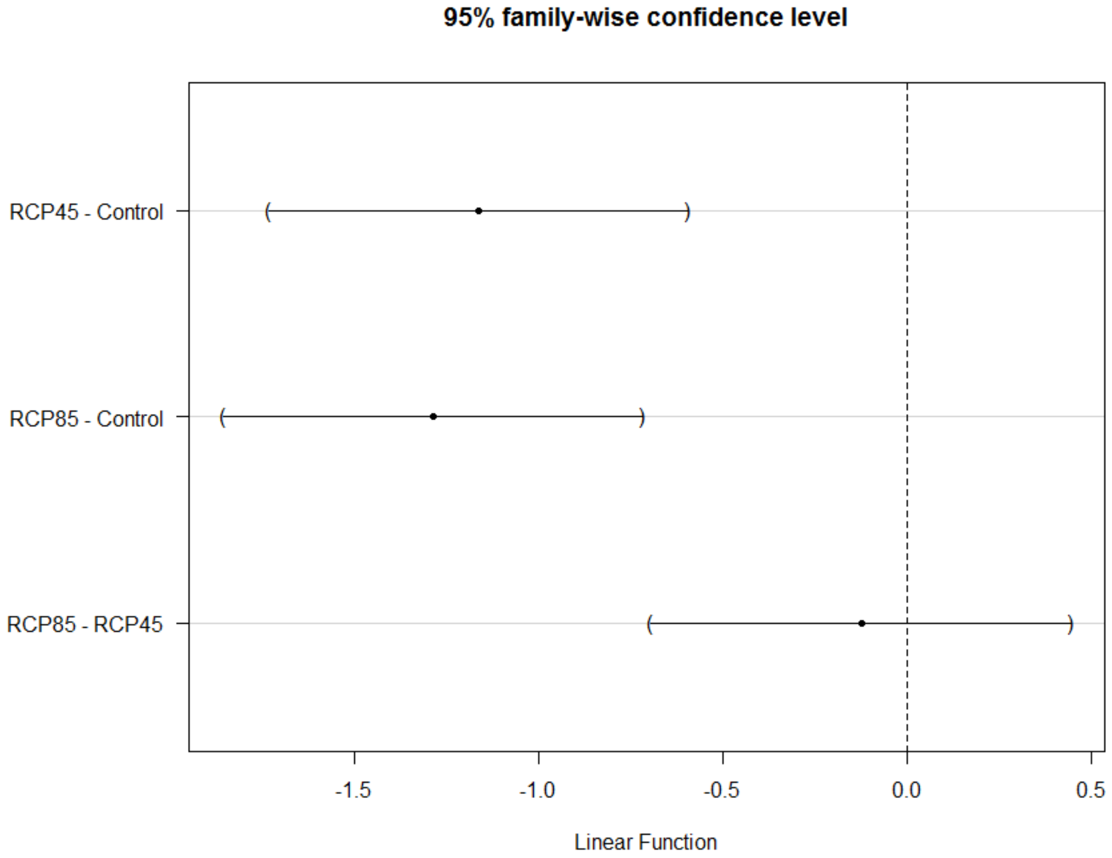


Figure 5. 19: Results of the Tukey test showing the differences in mean soil moisture between the three experiments.

5.5.4 Correlation between soil moisture and wet weight of yield

In order to further examine the impact of soil moisture on yield, the relationship between soil moisture and wet tuber mass was examined using the Pearson Correlation test. Figure 5.19 shows the correlation results which indicate that 37% of the variability in wet mass in the control category could be explained by the variability in soil moisture. Conversely, 55% of the variability in wet mass in the RCP45 category could be explained by the variability in soil moisture. Likewise, the RCP85 showed that 46% of the variability in wet mass could be explained by the variability in soil moisture. In summary, as the soil moisture in all the categories increases, the value of the tuber wet mass decreases. This suggests that there was a strong negative linear relationship between wet weight yields and soil moisture in the experiments. The implications of these results on wet weight have been described in Sections 5.3.2 and 5.5.2.

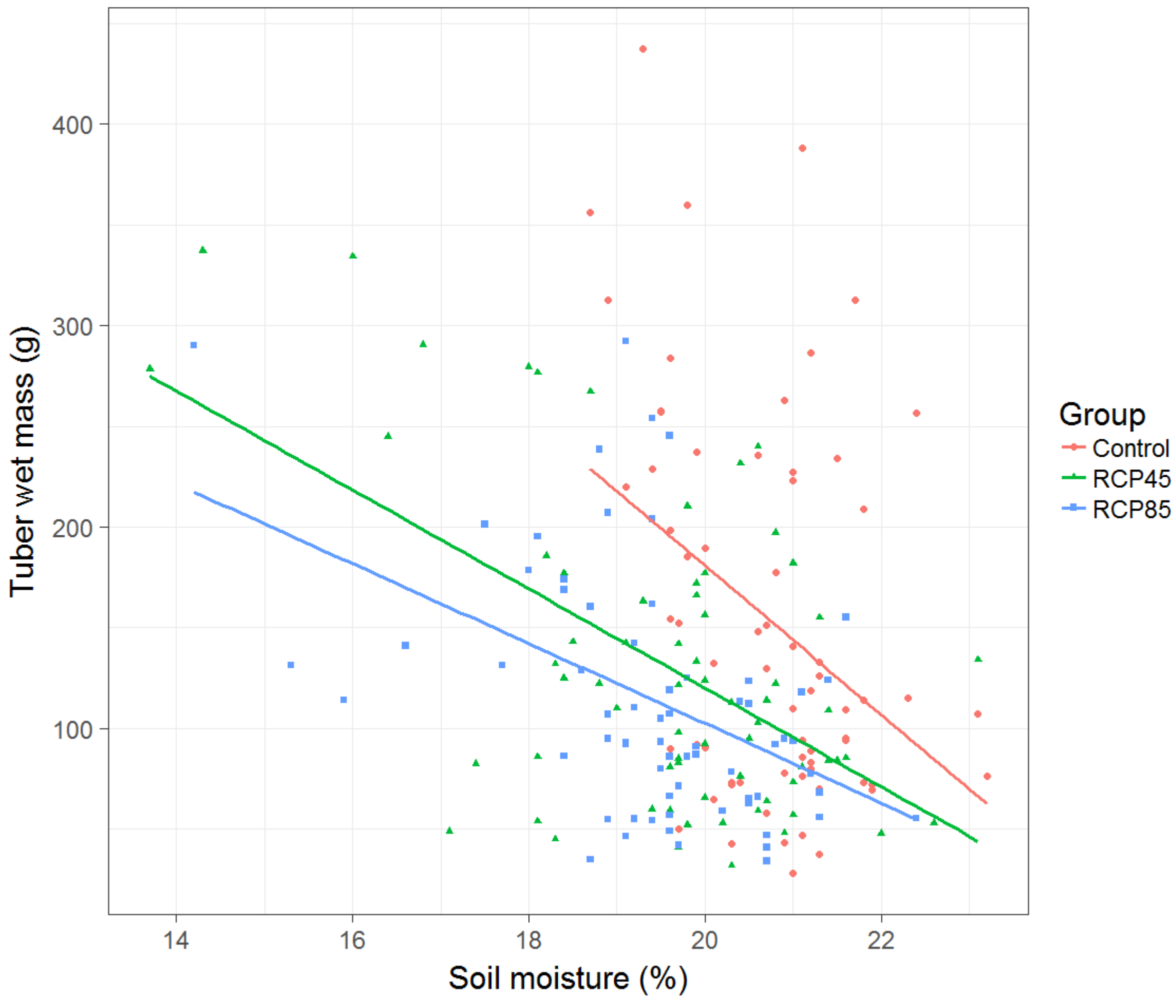


Figure 5. 20: Scatter plot showing the wet mass for individual tubers from the control (red circles; solid line), RCP45 (green triangle; solid line) and RCP85 (blue squares; solid line) categories plotted against the mean soil moisture data for each replicate.

5.5.5 Correlation between soil moisture and dry weight of yield

A further examination of the impact of soil moisture on yield was carried out using Pearson Correlation test. Results indicate that 14% of the variability in dry mass of the control category could be associated with variability in soil moisture. Conversely, 28% and 20% of the variability in dry mass of the RCP45 and RCP85 categories respectively, could be associated with variability in soil moisture. Figure 5.21 shows that as the soil moisture increases, the value of the dry mass decreases. This suggests that there was a strong negative linear relationship between soil moisture and dry mass of the crop.

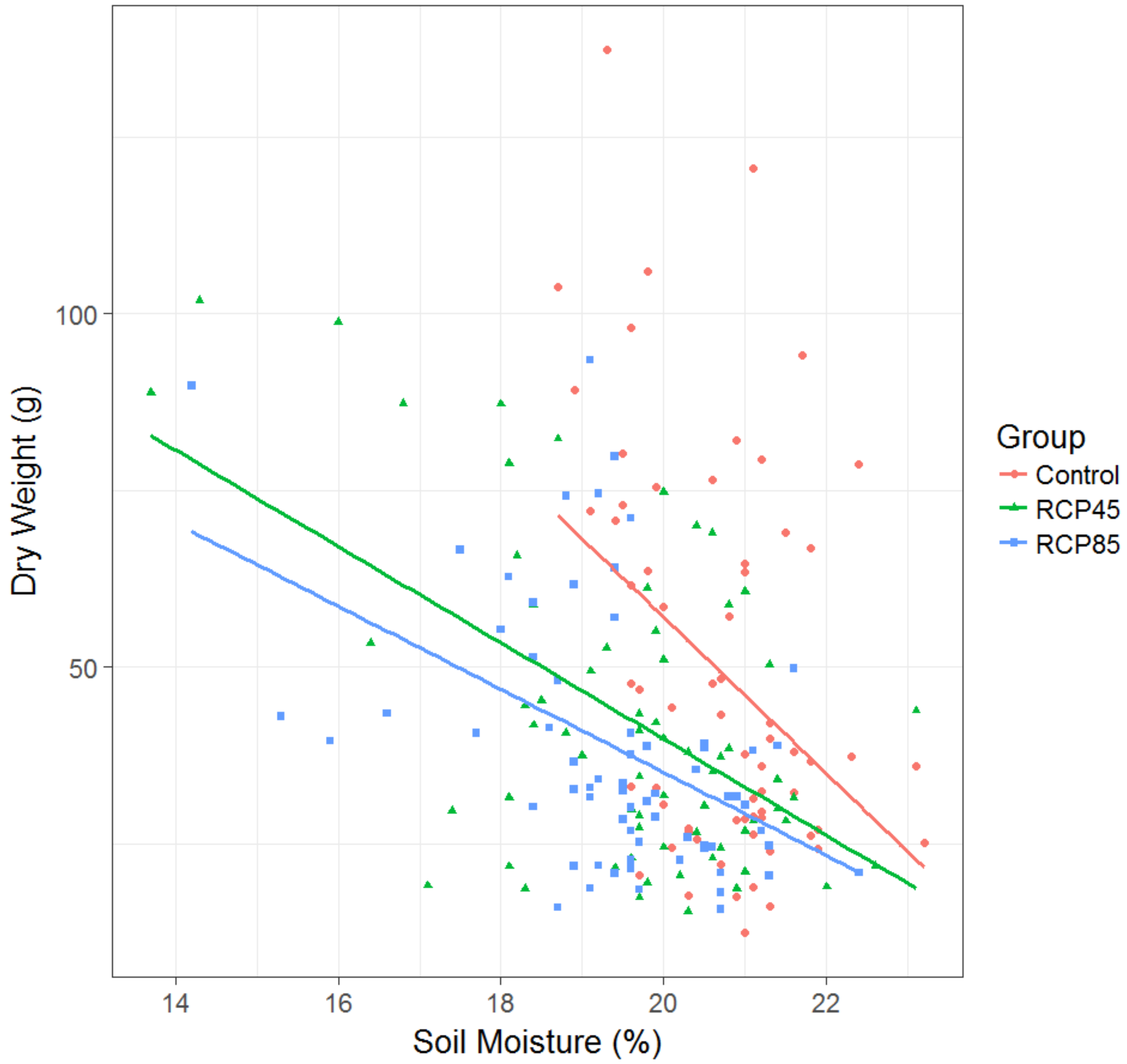


Figure 5. 21: Scatter plot showing the dry mass for individual tubers from the control (red circles; solid line), RCP45 (green triangle; solid line) and RCP85 (blue squares; solid line) categories plotted against the mean soil moisture data for each replicate.

5.6 Heathrow weather station

5.6.1 Temperature

The inter-annual temperature obtained from the greenhouse weather station contained some gaps in the collected data and was therefore rendered unusable for this study. As a result, temperature data was obtained and extracted from Heathrow weather station which was the closest station to Brunel University London, the location of the greenhouse used in this study. This Section focused on mean monthly temperatures rather than daily scale temperature data because monthly mean temperatures reasonably capture the dynamics of daily scale in that months with many hot days tend to have high monthly mean temperatures. However, future work in this regard may wish to explore the daily temperature occurrence above certain critical threshold which was not addressed in this study.

In this Section, mean and maximum daily temperatures were calculated for 2014 and 2015 from January to December but with particular focus on March to October which is the focus of the analyses in this thesis. Overall, there are no significant differences in average temperatures between the two years with 2014 having a mean annual temperature of 12.9 ºC (Std 5.2) and 2015 with 12.8 ºC (Std 4.9). However, there are sharp variations in monthly temperatures throughout the year which is not unusual because of the different seasons during the year. Results in Tables 5.13 and 5.14 indicate high monthly variations in the boxplots from January to December. The lowest monthly temperature values in both years were recorded in the months of December, January and February (DJF) which were the coldest months with mean daily temperatures of 6°C to 7°C (Table 5.13) and daily maximum temperatures ranging from 8°C to 11°C (See Table 5.14).

In both years, the highest mean daily temperatures were recorded in the JJA months with temperatures ranging from 21°C to 26°C. These values are roughly comparable to the summer period in Eastern England which has temperatures ranging from 20°C to 23°C (Met Office 2016). The highest temperature recorded over the two year period (2014 and 2015) occurred in July 2014 which is consistent with observations of when the greenhouse plants were most challenged. The impact of high temperatures in the JJA months is further discussed in Section 6.4.1

Temperatures in both years showed seasonal and diurnal variations. Figures 5.20 and 5.21 show the variations in mean daily and daily maximum temperatures on a month by month basis with the highest and lowest temperatures recorded. The median, range and distribution of temperature values were much wider in 2015 than 2014 suggesting that temperatures were more consistent in 2014. This is equally consistent with daily research observations of lesser temperatures in 2015 characterised by long periods of wet spell and cloudy weather thereby reducing temperature especially between January and March. Temperature improved in April but wider variations in between days.

Comparison of temperature in both years showed a sharp contrast at the beginning of the growing season in March with 2014 showing much higher temperatures than 2015. March, April and May (MAM) of 2015 was characterised by long periods of wet and cloudy weather and consequently low temperatures.

Table 5. 13: Mean analysis of the daily temperature for the two years of study.

	2014		2015	
Months	**Mean**	**Std**	**Mean**	**Std**
January	7.14	1.6	4.44	3.6
February	7.3	2.1	4.63	2.4
March	9.73	2.8	7.28	1.8
April	11.22	1.7	11.73	2.4
May	13.49	1.7	12.9	1.9
June	17.18	1.6	17.38	2.5
July	21.07	2.3	18.24	1.8
August	17.1	1.1	18.1	2.3
September	18	1.1	14.08	1.4
October	14.41	2.5	12.4	1.6
November	8.06	2.8	10.79	3.7
December	6.3	4.6	11.8	2.1

Table 5. 14: Mean analysis of the maximum temperature for the two years of study.

Months	2014 Mean	2014 Std	2015 Mean	2015 Std
January	9.71	1.6	7.76	2.7
February	10.58	1.8	7.87	2.5
March	14.52	3.3	11.72	2.1
April	16.31	1.7	16.6	3.4
May	18.95	3.1	17.77	2.2
June	22.37	2.7	22.16	3.6
July	25.99	2.8	23.54	3.6
August	21.71	2.5	22.16	3.2
September	21.32	1.8	18.77	1.7
October	17.96	2.6	16.14	2.1
November	12.9	2.1	13.6	3.2
December	8.8	2.7	13.43	1.5

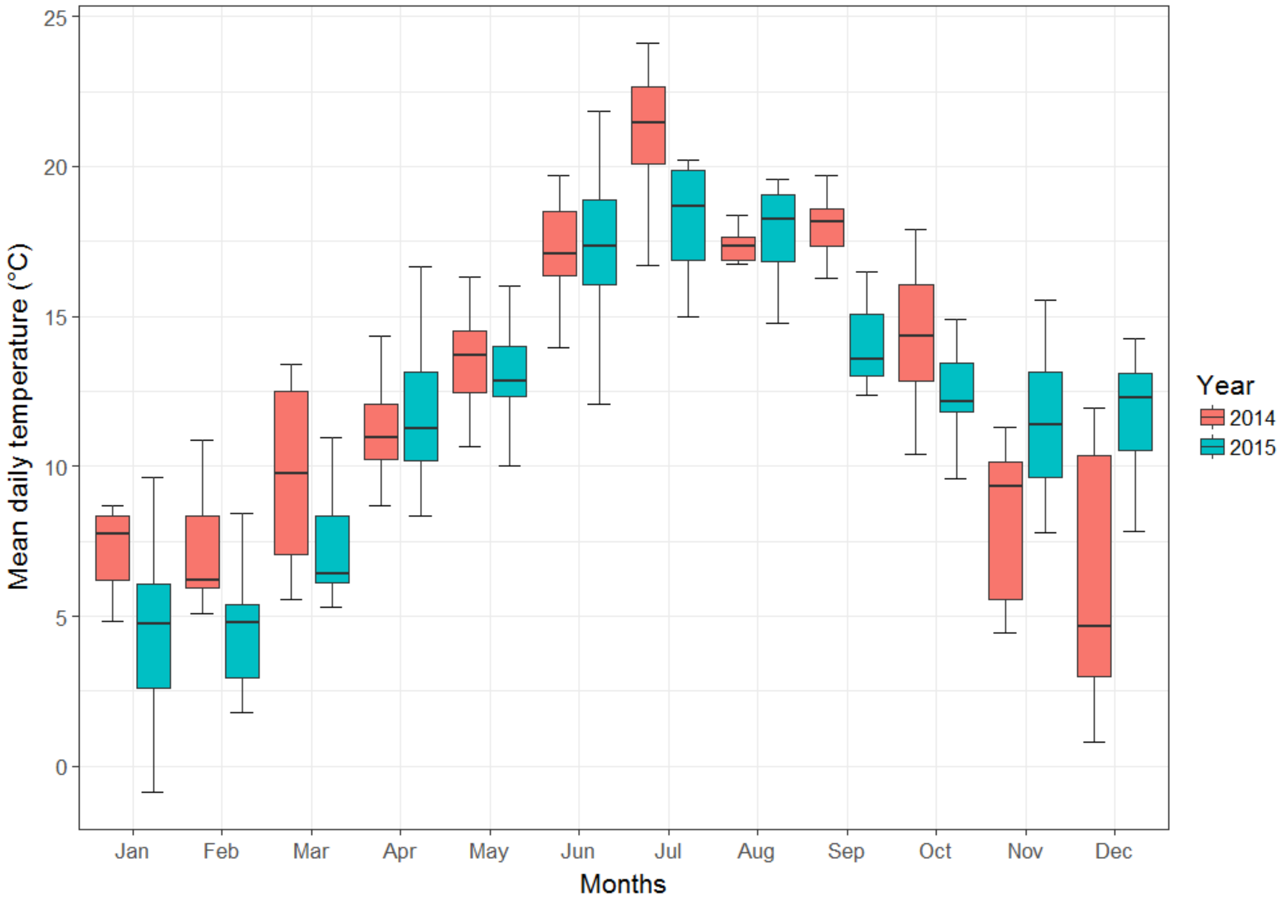


Figure 5. 22: Daily mean temperature distribution for 2014 (orange colour) and 2015 (light blue colour) from Heathrow weather station.

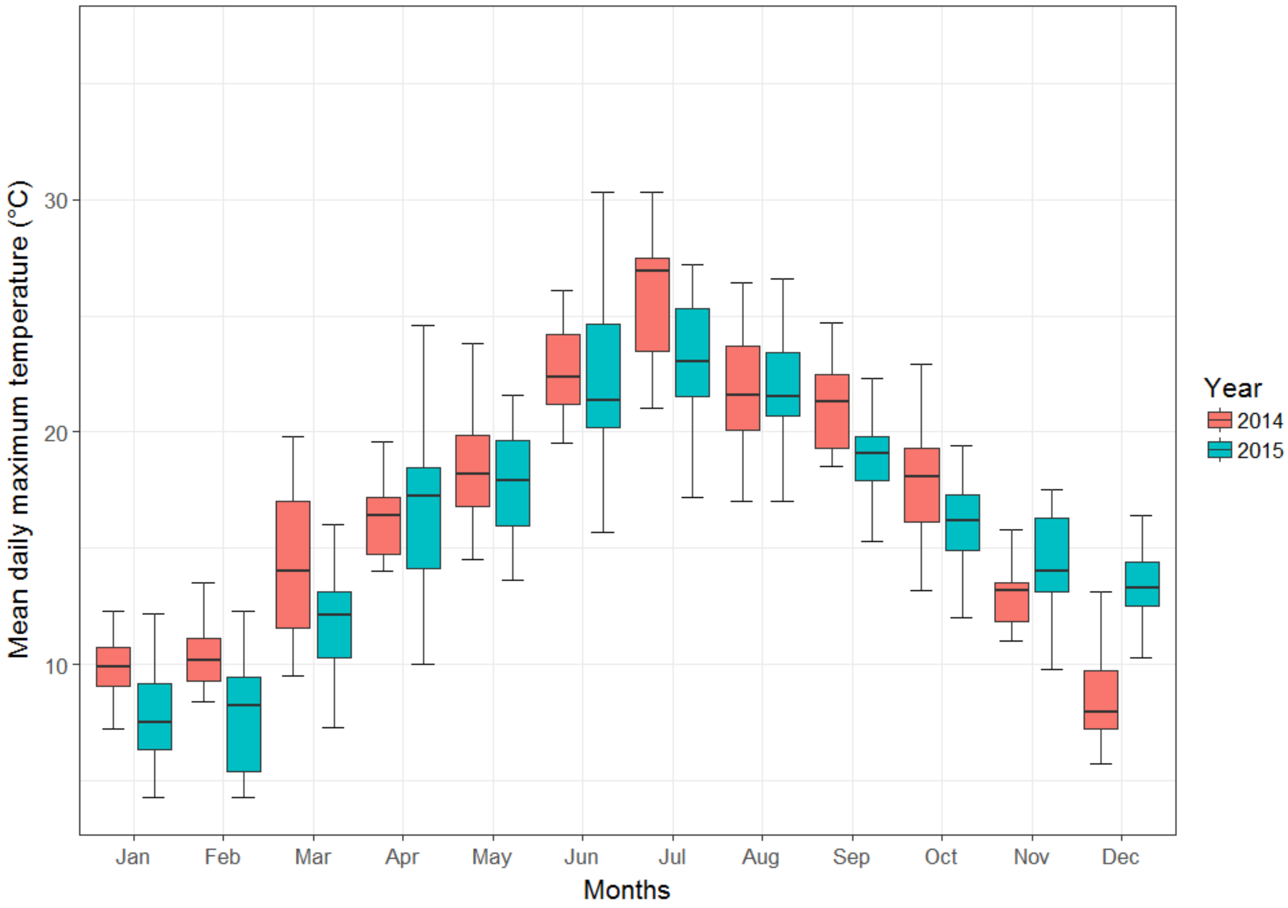


Figure 5. 23: Monthly mean temperature distribution for 2014 (orange colour) and 2015 (light blue colour) from Heathrow weather station.

5.7 Sugar Content Analysis

5.7.1 Total sugar content

Three samples from each dried sugar beet group (Control, RCP45 and RCP85) obtained from the laboratory experiment in 2015 were sent for testing for total sugar content of each dried sample. The test was carried out by ALS Food and Pharmaceuticals. ALS is a UK registered company with a high reputation for conducting a broad range of analytical testing services in areas of food & drinks, microbiology, pesticides, contaminants, dairy, water and pharmaceutical products. The company's wide accreditation and approval ratings suggest that their results could be relied upon for accuracy and integrity.

Generally, sugar percentage in freshly harvested sugar beet roots is between 14-20% of the fresh root weight (Rinaldi 2012) and is heavily influenced by the amount of water/ moisture content in the root. Since the determination of sugar is measured by the amount of sugar concentration in the tuber, it is important therefore, to remove the water/ moisture in the root leaving only the sugar for analysis. A similar approach to the one used in this study was conducted by Mohammadzadeh & Hatamipour (2010) who investigated the effect of drying conditions on dried sugar beet. Findings from their study showed that removing 90% of the initial water content from the beet was important in conserving the sugar content and essential properties during storage over a long period of time.

Selection of samples was based on similar dry weight values of samples from each group. The analysis was carried out using Ion Exchange Chromatography (IEC) method and results (Table 5.15) showed fairly uniform values ranging from the lowest in the control group with 69.6% (C14) to the highest in the RCP85 group with a value of 75.3%.

Table 5. 15: Dried sugar beet analysis for total sugar content from the Control experiment represented by C, RCP45 represented by M and RCP85 represented by H experimental groups.

Control			RCP45			RCP85		
Plant ID	**Dry weight**	**Total sugar %**	**Plant ID**	**Dry weight**	**Total sugar %**	**Plant ID**	**Dry weight**	**Total sugar %**
C1	75.5	74.5	M26	74.8	72	H18	75.5	75.3
C9	43.3	71.6	M64	43.4	74.4	H61	43.4	71.2
C14	61.5	69.6	M17	61.2	73.5	H19	61.7	73.8

Statistical analysis of the three samples showed control with a mean of 71.9% (Std 2.5), RCP45 with a mean of 73.3% (Std 1.2) and RCP85 with a mean of 73.4 (Std 2.1), and a P-value of 0.6 using a 95% confidence interval. The result indicates a difference between the percentage of sugar in the control and RCP45 and RCP85 but it is not significant at 95% confidence interval while there was no difference between the percentage of sugar in RCP45 and RCP85. Although, the small number of dried samples analysed could be argued to be unrepresentative of the entire population, it nonetheless provides an important indication on the percentage of sugar content in future sugar beet yield. This result implies that the difference in the experiments came from the wet weight of tubers as a result of the moisture content which can be inferred from the different watering regimes. The results in this thesis indicates that likely changes in future precipitation will not have an impact on the sugar content in future yields but will have a significant impact on the size and weight of individual tubers.

Results of the sugar content analysis are particularly relevant to sugar beet processors in terms of storage as most processors store beets for several months before processing. The challenge with long-term storage is the potential for decay before processing commences. This is because if tubers are peeled or scraped, it quickly oxidises and changes colour from white to black. This causes decay to the roots and a reduction in sugar level. An effective way to avoid this sort of decay is by drying the beet to remove the water content (Mohammadzadeh & Hatamipour 2010). For example, the dried beets used in this study were stored for a period of almost 10 months before sending them to the laboratory for further analysis. Additionally, dried beets will not decay nor reduce in its sugar content making it a win-win situation for the processors.

Chapter 6 - Discussion

6.1 Introduction

This study assessed how precipitation patterns changed in Eastern England from 1971-2000 and how they are likely to change between 2021-2050 using a suite of CMIP5 climate models to simulate future climate scenarios under RCP45 and RCP85. Furthermore, the study examined how the resultant changes in future precipitation may affect sugar beet yield in Eastern England by 2050. The findings from this study suggest that a potential change in future precipitation, as interpreted from the medium and high greenhouse gas emissions scenarios (RCP45 and RCP85) in an ensemble of MOHC (HadGEM2-ES) daily mean precipitation data, is likely to reduce sugar beet yield in the UK by 2050. Past (1971-2000) and future (2021-2050) modelled precipitation analyses of Eastern England suggest a reduction in future annual May-October precipitation, and therefore the threats to, and opportunities for, UK sugar beet farming are discussed in relation to possible precipitation reduction. More so, the study considered the fate of UK sugar beet farming in view of recent unusual seasonal precipitation events and how this will affect UK sugar beet farming that is solely 95% rain-fed and one of the principal aims of this thesis.

On a national scale, reduction in future precipitation will put a strain on water resources and this will become even more challenging with increasing water demands due to global population growth, economic development and increased urbanisation. Variations in precipitations such as the Cumbria floods in 2014 highlights the challenges faced by farmers whose crops and farmland were damaged, causing significant losses in terms of yield and income. Likewise, a persistent deficiency in the volume of precipitation can potentially lead to low Available Water Capacity (AWC) which will also be challenging for crop yields. Additionally, variability and changes in precipitation pattern makes it difficult for farmers to plan ahead for future growing season. These factors highlight an urgent need for the consideration of adaptation strategies that could be beneficial to farmers (Dorling 2014). In this regard, creative and innovative solutions for the management of water resources now and in future to enable farmers to be better prepared for adverse weather events will be a relevant approach. However, in order to develop such effective management strategies, it is vital to understand the impact of changes in precipitation on the farmlands that provide society with food.

This study employed the use of climate models to predict the nature of future UK precipitation, the results of which could then be used to reduce the risk of crop yield losses by implementing new management strategies that will maximise yield potentials and farmers' income in future growing seasons. Model output was used in this study as a basis for quantitative comparison of past and future precipitation analyses using the growing season mean precipitation and changes in the distribution of precipitation events and frequency from CMIP5 climate models. This approach differed from previous field and controlled studies in that it was the first time that CMIP5 climate model ensembles have been used to inform a greenhouse experiment in controlled manner. In this section, the characteristics of past (1971-2000) and projected (2021-2050) Eastern England precipitations and the impact of changes in future precipitation on the sugar beet experiment conducted over two seasons (2014 and 2015) are discussed.

6.2 Eastern England climate

6.2.1 Weather stations observations

The ability to observe trends in precipitation data over a long period of time (i.e. 30 years) might be helpful in predicting periods of precipitation deficit or even, high/extreme precipitation. However, to understand the characteristics of Eastern England precipitation, daily mean precipitation data obtained from six weather stations in the sugar beet producing areas for the period 1971-2000 were analysed. Results from the stations data showed high variations in May-October daily mean precipitation over the 30 year period of study (See Figures 4.2 and 4.6). These types of variations make trends hard to detect (Met Office 2014), however, mean statistical analysis of the weather stations data showed that the precipitation characteristics of the stations showed good agreement across the region and the precipitation pattern from the stations exhibited similar annual trends. This simply means that the area under consideration was governed by the same regional precipitation mechanism and data could be relied on.

Excluding Manston (which showed a much smaller mean and median - See Section 4.2.1, Table

4.1), the rest of the stations were generally in broad agreement with the highest May-October mean precipitation recorded in Santon Downham with a mean of 1.78 mm day^{-1} and the lowest mean of 1.61 mm day^{-1} recorded in Writtle. In fact, two of the stations returned similar mean values of 1.76 mm day^{-1} for Stansted Mountfichet and Coltishall. These results closely match the findings of Gregory et al. (1991) who reported a daily mean precipitation of 1.77 mm per day for Eastern England.

The ability to detect trends in precipitation records is quite an important one as it could help in predicting periods of deficient precipitation that could potentially lead to drought or intense precipitation that could potentially cause floods. The number of years necessary to detect any significant trends in precipitation data is a subject of continued debate but varies from one region to another due to the unpredictable nature of precipitation. Moreover, in some regions, this is compounded further due to poor data or equipment failure. For example, arid and semi-arid regions may require longer-term records as a result of poor data or the infrequent nature of precipitation in such areas. Eastern England however, does not have this problem because of the availability of continuous and long-term data provided by the UK Met Office.

The overall statistical analysis of the daily May-October mean precipitation observed data for the 30-year period (1971-2000) of study did not reveal any significant trend, positive or negative. This raises two questions: Is it possible that trends could be revealed if more years were included in the analysis? Or, could trends be detected over time if two different time frames were assessed? Results reported in Chapter 4 of this thesis showed a significant trend in daily May-October mean precipitation when two different time frames – one historical (i.e. 1971-2000) and a future prediction (i.e. 2021-2050) were assessed.

6.2.2 CMIP5 climate model simulation of precipitation under the historical phase

The assessment of annual May-October mean precipitation under the historical phase was very important in this study in order to evaluate model performance of Eastern England precipitation. Results of the annual May-October mean precipitation reported in Section 4.3.1 and illustrated in Figure 4.9 established that three out of the eight models used in this study showed broad agreement with the stations annual May-October mean precipitation data for the same period

(1971-2000). The aim of assessing model skill in order to quantitatively estimate and derive their weights is difficult according to Tebaldi & Knutti (2007). However, the comparison of historical precipitation data with observations have been reported to perform better than equal weighting of individual models (Krishnamurti et al. 2000). The use of models in this way have been reported in other studies to select desirable models for analysis (e.g. McSweeney et al. 2014; Brands et al. 2013) and gives credence for its use in this study.

The distribution of precipitation events from the models under the historical phase showed patterns consistent with observations and capturing key elements of Eastern England precipitation but with much wider variations. This suggest that the geographical patterns of extreme precipitation were not captured by the model which is normal as models do not simulate extreme precipitations (Maraun et al. 2010; Fowler & Ekström 2009). This issue was not considered to be a problem as the study here examined mean conditions rather than the extremes. Nevertheless, the distribution of the ensemble mean precipitation output for the historical phase of the MOHC (HadGEM2-ES) data is the closest to the stations observed mean reported in Section 4.3.1 and illustrated in Figure 4.9. This characteristic motivated the single use of the MOHC for future precipitation analysis and the greenhouse plant experimental watering regimes.

6.3 Projected changes in future precipitation

6.3.1 Changes in past and future Eastern England precipitation

In order to gain an understanding of likely changes to future precipitation, mean daily precipitation data from the best three models were analysed from May-October for the two different time slices under historical phase (1971-2000) and the future scenarios under RCP45 and RCP85 (2021-2050) were analysed. The ensemble means of individual models under the two different time frames were compared against each other (e.g. ensemble mean for the historical phase is compared with the ensemble mean under RCP45 and RCP85). Results indicate that Eastern England precipitation is projected to experience decreasing trends in May-October daily mean precipitation based on the two different approaches used in this study (i.e. seasonal mean precipitation and monthly distribution of events and sizes). This result supports similar findings from previous studies of a reduction in UK summer precipitation (Met Office 2014; Fowler & Ekström 2009; Jenkins et al. 2009).

The three models used in this study replicated Eastern England precipitation fairly well. However, comparative annual May-October precipitation analysis between the historical phase and future scenarios of the models indicated differing results which simply implies that the magnitude of change depends on the scenario being assessed and the skill of the models used. This is simply because model performances differ under different conditions in different regions. The models captured key elements of Eastern England precipitation but the large variations in the distribution of precipitation events suggest that the geographical patterns of extreme rainfall were not captured by the models. However, this issue was not a problem because the study only considered mean precipitation. Among the three models used, the MOHC showed the biggest negative changes of 16.8% and 14.9% in precipitation under RCP45 and RCP85 respectively. This result could be viewed as a plausible but relatively extreme scenario that could be a potential source of threat to UK sugar beet farming and the sugar industry by extension. This result fulfils one part of the research hypothesis for a likely reduction in future Eastern England precipitation as explained in Section 1.6.

Although the output from the individual ensemble members showed slight differences but when combined together they clearly reflect a reduction in future May-October precipitation. This result is consistent with the result reported by Jenkins et al. (2009); Jenkins et al. (2008) of future reduction in UK summer precipitation and a reduction in the number of wet days. Perry & Hollis (2005) also reported similar reductions in summer precipitation nationwide. This is an important development for research into sugar beet farming and other agricultural crops in general in which their primary growing season is in the spring/summer time. The methods used in this study are also applicable to a range of agricultural crops whose growing season is in the summer and this study represents the first time that CMIP5 climate model data has been used to inform a greenhouse experiment.

Model projections of future climate scenarios in this study provide plausible information about what may be expected in the study region. It is noted in several past studies and successive IPCC reports that certain regions are particularly prone to the adverse effects of changes and variability in precipitation. Review of literature in this study identified Eastern England as one of such areas vulnerable to high variations in precipitation as a result of the mountains bordering Eastern England from the western parts of Scotland. Given the projection of continued increase in greenhouse gas emissions in the atmosphere, it is very likely that future Eastern England precipitation will continue to experience high variations in both annual and monthly precipitation. These sort of variations, when they occur could cause intensification of the hydrological cycle with associated changes in the frequency and magnitude of precipitation events such as extended periods of dry and wet spells (Williams et al. 2007; Huntington 2006). The scenario described here could be very challenging for agriculture particularly during the growing season. Analysis in Section 4.4.7 of this study suggests that this challenge will be more serious in the months between June and August, further analysed in Section 6.3.3.

6.3.2 Analysis of future total May-October wet day precipitation

Results of the relative comparison of Total May-October precipitation test for the two time windows (1971-2000 and 2021-2050) showed a decrease in total mean precipitation and a reduction in the number of wet days simulated from the models. The CCCma and MOHC indicated a reduction in total mean May-October precipitation but the EC-Earth showed no change (See Table 4.9). The reduction in number of wet day precipitation (See Table 4.10) suggests a trend towards drier summers. Changes from the models showed that CCCma had 231 and 366 less wet days than historical data under RCP45 and RCP85, respectively. The EC-Earth had 76 wet days less than historical under RCP45 and 6 wet days more than historical under RCP85. The MOHC also indicated reduction in the number of wet day events with 492 days less under RCP45 and 536 days less under RCP85 compared to historical wet day precipitation events.

Again, the MOHC showed the biggest negative changes in precipitation further justifying its use in this thesis. Evidence in Figure 4.13 again answers the research question in this study and clearly illustrate the reduction between historical and future precipitation from the models and raises questions about the future and sustainability of UK sugar beet production that is 95% dependent on precipitation.

One notable factor in this study is that, the reduction in total May-October precipitation during the growing season (i.e. mean precipitation over the growing season) does not translate to a reduction in precipitation on a monthly basis during the growing season. This raises further questions of which months are most likely to be impacted by changes in precipitation? And could this change impact on the yield of crops grown during the season? The former question is addressed in the next section under the monthly distribution of precipitation while the later question is addressed in Section 6.4.

6.3.3 Monthly distribution of precipitation events and sizes.

As mentioned in the previous section, changes in precipitation is evident in the analysis of total May-October precipitation and there is need to identify the particular months that are likely to be affected by the changes. The assessment of monthly distribution of precipitation events provides a way to address this issue. Result in this section showed good agreement with monthly distribution of precipitation events from observations (See Figures 4.9 and 4.17) and the analysis under future climate scenarios (RCP45 and RCP85) also indicated large monthly variations shown in Figure 4.17. Likewise, Table 4.12 showed that the biggest changes occurred in the months from June to August. This is consistent with periods when temperature is predicted to be highest and further incidents of reduced or deficient precipitation will help to exacerbate the stress factors in relation to water resources.

The MOHC differed slightly from the other models and showed the biggest negative changes. Table 4.11 show the mean and standard deviation from the historical phase and future scenarios. The highest monthly change in precipitation was reported for October followed by June, and the lowest change in precipitation was reported for July (See Table 4.12). Overall, the biggest negative changes in precipitation from the models for the May-October monthly distribution of events and sizes indicated that July will be most challenging in terms of precipitation decrease.

Table 4.12 shows the level of changes for the individual months from the three models. Further examination revealed that there will be more dry spells under future scenarios especially in July and to a lesser extent in August. July and August showed the lowest mean precipitation values suggesting that these months will most likely be challenging for agricultural crops in terms of water resources and water uptake for plants growth and development. This sort of scenario will be very challenging for farmers and water resource managers. By and large, water table will be affected which in turn impact on plants ability to uptake water from the soil for growth and development. The robustness of this result re-enforces the findings from past and current studies of a reduction in UK summer precipitation reported in Section 4.4.5 (See Simpson and Jones 2012; Wigley and Jones 1987). These studies specifically reported a reduction in July and August precipitation across the UK which is consistent with results in Section 4.4.7 and Table 4.14 of this study. July had the least mean precipitation in the growing season between the months of June to August. Likewise, Section 4.5.1 and Table 4.15 revealed large monthly variations with July and August indicating likely episode of dry spells under future scenarios. The likely implications this will have on future growing seasons is further discussed in Section 6.4.

6.3.4 Model simulation of precipitation changes

In Chapter 4, the study employed the use of eight CMIP5 climate models to simulate Eastern England precipitation by comparing the CMIP5 historical phase May-October mean precipitation data to the stations May-October mean precipitation data for the period 1971-2000. Three out of the eight CMIP5 climate models showed good agreement with mean precipitation data from the stations. This type of evaluation enabled the selection of realistic and desirable models that can replicate Eastern England precipitation well. Assessment of model performance in this manner demonstrate how and why less realistic models are excluded from precipitation analysis and have been used in previous studies such as McSweeney et al. (2014) who reported that models perform differently in different regions. In short, the analysis used the ensemble mean of individual models to determine how close the means were to observations. The results showed that the ensemble means of the CCCma, EC-Earth and MOHC models were the closest to the observations growing season (May-October) precipitation data and therefore considered the best performing models selected for use in this study.

Model projections of future May-October mean precipitation for the study region was conducted by comparing the ensemble means of the CMIP5 model historical phase (1971-2000) to the CMIP5 model future scenarios under RCP45 and RCP85 to determine if a trend or pattern existed between the two time frames. Model analysis revealed a negative trend in both annual and monthly precipitation (i.e. reduction in precipitation) in future scenarios. This simply means that there will be fewer wet day events and increased dry spell events under future climate change. The months of July and August were particularly identified as vulnerable to increases in temperature and deficient precipitation which most likely may affect summer grown crops. Moreover, the continued increases in temperature by 2050 will increase evaporation during the growing season, especially in the months of July and August thereby increasing the challenges of water availability for crop and other uses.

Result in this study raises questions regarding the viability of the sugar beet industry in the UK, particularly in terms of water resources. This is against a background of European Union (EU) policy changes that potentially undermine the economic model for the industry (Burrell et al. 2014). The combination of these challenges raises questions about the future of particular agricultural practices and, therefore, calls for creative and innovative adaptation strategies which are further discussed in Section 6.4. However, this will also depend on the impacts of climate change in other key growing regions, which have not been considered in this thesis.

In addition, and as pointed out in Chapter 4 of this study, future UK summer precipitation is likely to decline and is consistent with studies widely reported of a decline in UK summer precipitation (Met Office 2014; Christensen et al. 2010; Jenkins et al. 2008). However, model outputs showed much wider variations in the precipitation distribution compared to the historical phase and observations because they do not reproduce extreme events very well. In order to address this issue, the current study only considered seasonal means and mean distribution of precipitation events. The point suggested here however, is that future analysis should also attempt to include extreme events that were not addressed in this study. This could help reduce the variations between the model projections and the historical/ observations and also reveal changes in the summer that mean precipitation alone could not unveil.

Climate model provide the best examination of model performance and have shown great improvements over the decades, however, there are still some challenges in model simulation of some aspects of the climate system, such as clouds and aerosol, and uncertainty in the direction and magnitude of future greenhouse gas emissions (CCRA 2016; IPCC, Flato et al. 2013). In spite of this seemingly drawback, models have improved significantly from the time of the First Assessment Report (FAR) to the latest Fifth Assessment Report (AR5), and from the use of the various MIP's to the latest suite of the CMIP5 climate models (See Section 3.4). This improvement has increased confidence in the use of models to simulate future climates based on models ability to reproduce past and current climates, although confidence is higher for temperature than it is for precipitation (IPCC, Flato et al. 2013). Figure 6.1 for example, illustrates the improvement in the various CMIP models for precipitation which shows an improvement in the correlation of annual mean precipitation between observations and model output. Precipitation output increased from 0.68 in the CMIP2 models to 0.77 in the CMIP3 and to 0.82 in the CMIP5 models (IPCC, Flato et al. 2013). The Figure further provides evidence of improvement in model performance by the increase in correlation for successive models. Model successes in this regard provide justification for its use in this thesis and it has proven reliable in successive IPCC reports including the AR5.

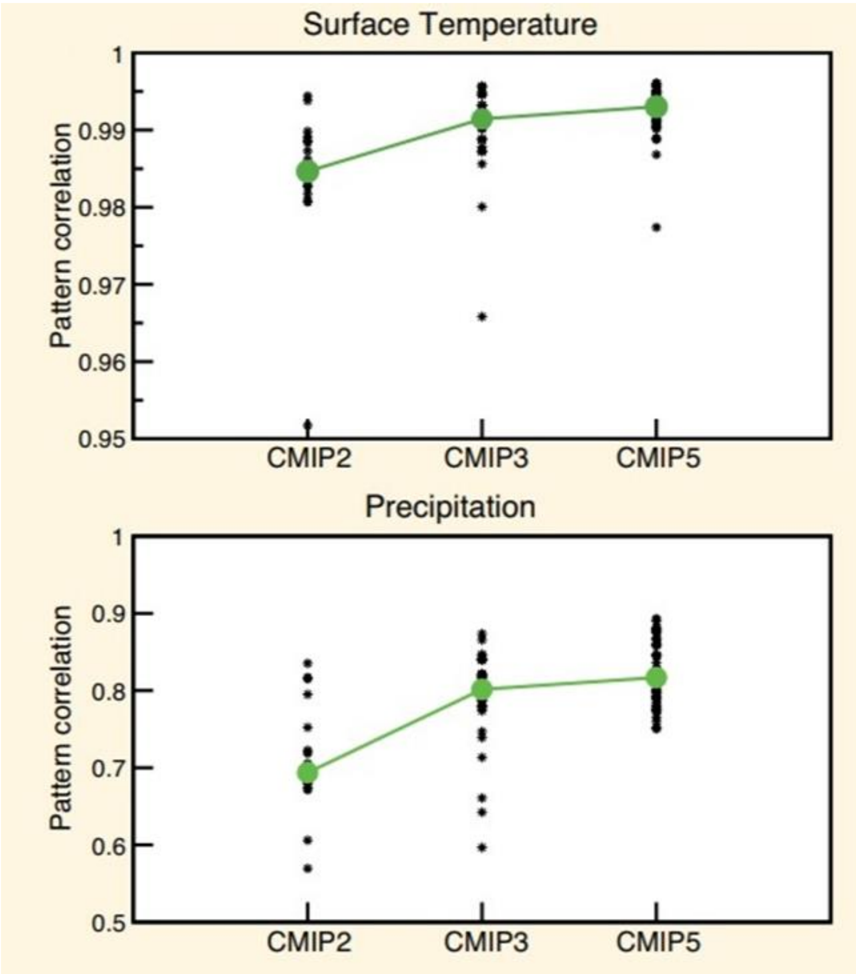


Figure 6. 1: Model capability in providing annual mean temperature and precipitation illustrated from the different phases of the CMIP2 (2000); CMIP3 (2005) and CMIP5 (2013). "The Figure shows the correlation (a measure of pattern similarity) between observed and modelled temperature (top panel) and precipitation (lower panel). Larger values indicate better correspondence between modelled and observed spatial

patterns and the black symbols indicate correlation coefficient for individual models. The large green symbol indicates the median value". Source: (IPCC, Flato et al. 2013). See -

https://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter09_FINAL.pdf

Furthermore, the work carried out in this thesis has produced some firm conclusions but also thrown open some questions that subsequent studies may address. For example, the analysis of model performance could be extended to a wider range of models because the best performing models in one region may not necessarily perform well in other regions or may not even be the best when compared to some models not considered in this thesis. Nonetheless, the models have produced results that support previous studies in this field and also fulfil the first research hypothesis and answer the first research question in Section 1.6. For ease of reference, the research hypothesis and research question are re-stated here:

Hypothesis:

- Changes in future Eastern England precipitation patterns will impact on sugar beet productivity
- Reduction in future Eastern England precipitation will reduce sugar beet yield by 2050.

The same hypothesis may be approached differently using the following research questions:

- What are the potential impacts that changes in precipitation patterns will have on sugar beet yield in Eastern England by 2050?
- How will the sugar beet plant respond to the changes in precipitation?
- What types of mitigation and/ or adaptation measures can be implemented?

Analyses indicate that under future climate change scenarios, annual and monthly precipitation will decrease in Eastern England by 2050. The next Section addresses how reduction in May-October mean precipitation will affect future sugar beet yield in Eastern England.

6.4 Greenhouse Experiment

The previous Section reported a reduction in future Eastern England precipitation under future climate change scenarios (RCP45 and RCP85) and high potential for increased variability in inter-annual and inter-monthly precipitation that could potentially threaten sugar beet productivity in Eastern England. A degree of precipitation variability in Eastern England have been presented in the previous Section (Section 6.3), but more critically, substantial changes to the inter-annual and inter-monthly precipitation variability over time between the two frames (1971-2000 and 2021-2050) were found to be significant leading to the submission that inter-annual and inter-monthly variability in the growing season precipitation may threaten sugar beet and agricultural productivity in the UK. The following Sections present a discussion on the impacts of different watering regimes on the growth and yield of sugar beet under baseline conditions and future scenarios of RCP45 and RCP85.

Although, the method employed in this study is focused on sugar beet, its applicability cuts across a range of other agricultural crops that are particularly grown during the summer. For this reason, some parts of this discussion will cover agriculture in general as this is a very important sector in the UK, currently representing 71% of UK land-use (LWEC 2016), and producing 50% of the food consumed in the UK (LWEC 2016).

6.4.1 Sowing and emergence

The sowing, growing and harvesting of all sugar beet plants over the two growing seasons was carried out under the same environmental conditions, but with different watering regimes. In the first season, plant seeds were sown on the 15th April 2014 and the watering regimes were devised based on FAO recommendations of average water need for a sugar beet plant during the growing season (Brouwer & Heibloem 1986) and precipitation observations from weather stations in Eastern England, which is the dominant production region of sugar beet in the UK.

In the first season, under seasonal mean watering regimes, emergence and establishment was excellent with 298 pairs of cotyledonary leaves emerging out of 300 seeds sown. The first set of leaves emerged in pairs and served as a source of temporary food for the developing seedling.

The next sets of leaves are the true leaves which also emerged in pairs but alternate to each other. As the plants growth continued, the leaves began to emerge from the crown in pairs and in an alternate pattern. The leaves growth rate differs greatly from plant to plant which is why one plant cannot be used as representative of the entire population and could be attributed to sunlight variations in the greenhouse. All plants were sown under the same water management regime until the plants were categorised into different treatments; this occurred when they started forming tubers. Ideally, temperature and humidity would also have been controlled but, given that all the plants experienced the same conditions, the experimental design is sound in its aim to test the impact of different watering regimes.

In the second season, plant seeds were sown on the 25th May 2015 and the watering regimes were based on monthly distribution of precipitation events and sizes during the May-October growing season. Emergence and establishment was not as good as the first season with about 70% emerging cotyledonary leaves out of a total of 402 seeds sown. The growth of the leaves were not different from the first season experiment but general observations showed from the first season experiment that early sowing, adequate watering and radiation capture aided full canopy development with the leaves completely shading the pot circumference. Kenter et al. (2006) pointed out that achieving full canopy cover is likely to have helped improve plant and tuber growth and is quite consistent with observations in this study.

Comparison of plants' emergence and growth over the two seasons showed that plants in the second season did not quite achieve full canopy cover compared to the plants in the first season experiments. In the first season, the plants most likely benefitted from earlier sowing date, average spring time temperature and adequate rainfall enabling plants to capture much needed sunlight and radiation which enhanced full canopy development. This supports the result of Hoffmann & Kluge-Severin (2011) who compared the growth analysis of autumn and spring sown sugar beets and found an improvement in spring sown sugar beet as a result of higher temperatures in April. The second season saw spring time temperatures unusually cool with lots of rainfall and not enough sunshine and radiation inevitably affecting full canopy development during the season. The summer JJA months only witnessed a couple of extreme temperature events which did not really affect the plants because of their small sizes compared to the previous season. The impacts from the second season experiment demonstrate the importance of temperature, sunlight and early sowing in order to capture the necessary radiation needed to attain full canopy cover. Earlier sowing on the 14th April 2014 captured more spring time radiation that aided leaf canopy cover than the late sowing on the 25th May 2015.

Studies such as Richter et al. (2006) showed that early sowing date during the months of March and early April resulted in yield gains of 0.2-0.3 t/ha, whereas, delay in sowing until the end of the month can cause yield loss of up to 1.4 t/ha. Given that future precipitation projections indicate a reduction in the summer, the combination of this with high summer temperatures will likely bring about shifts in the onset and length of the growing season by 2050 which in itself encourages earlier sowing. Results from this study have shown that earlier sowing in the first season yielded better than in the second season. This is supported by the findings of Crespo et al. (2011) who used maize production to demonstrate the possibility of adapting to projected climate shifts by 2050 by changing planting dates.

Overall, during the two growing seasons, plants in the different watering regimes were exposed to the same environmental conditions with plants in each watering regime evenly distributed throughout the greenhouse (See Figures 3.5 and 3.6). The amount of sunlight on different sides of the greenhouse varied, for example, but the systematic distribution of the members of each watering regime meant that there was minimal bias in such uncontrolled variables. Moreover, the parameter measurements only commenced after the plants had started forming tubers after their juvenile stages. Therefore, the real progress of the tubers can be estimated from the changes in the tubers from the different watering regimes and places yield in the context of the mean growing season conditions.

6.4.2 Event based impacts

Event based impacts resulting from changes in weather patterns such as high temperatures, had negative impacts on the plants. During high temperature events, the leaves wilted and went into early senescence; Lambers et al. (1988) reported that such water stress affects the growth and productivity of sugar beet and would have affected the plants in this study. The high temperatures in the month of June and July drove this problem, with leaves from the bigger plants wilting at the first sign of stress and the leaves from the smaller plants wilting later (Okom et al. 2017). This was reported by Hsaio (2000) in a separate study that showed large leaves are usually the first to diminish at the first sign of water stress. Importantly, the wilting of the leaves did not affect one watering regime more than the other and therefore, the results of the experiments were not biased by the extreme weather events. In spite of this, plants from the different categories exhibited remarkable characteristics of adaptability in their high rate of recovery after watering following each stress episode. Figure 6.2 shows the impact of heat wave on the plants on the 17th July 2014 and Figure 6.3 shows the plants adaptive capacity after irrigation had been administered. The sort of impact described here in Figure 6.2 is reflected in Figures 5.7 and 5.17 which showed the impact that high temperature had on soil moisture in July and August.

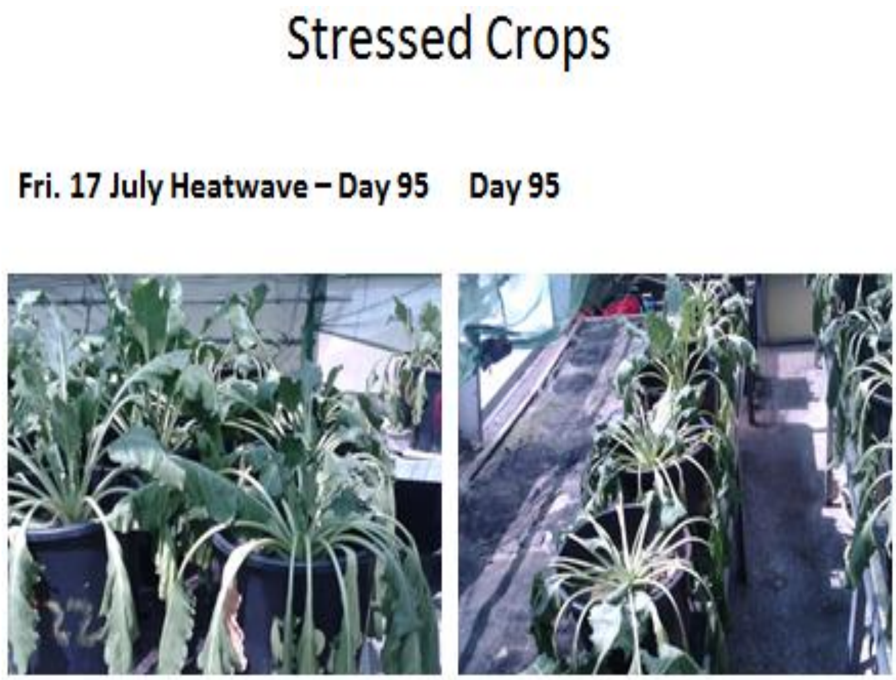


Figure 6. 2: Plants from the different groups under stressful water condition as a result of heatwave.

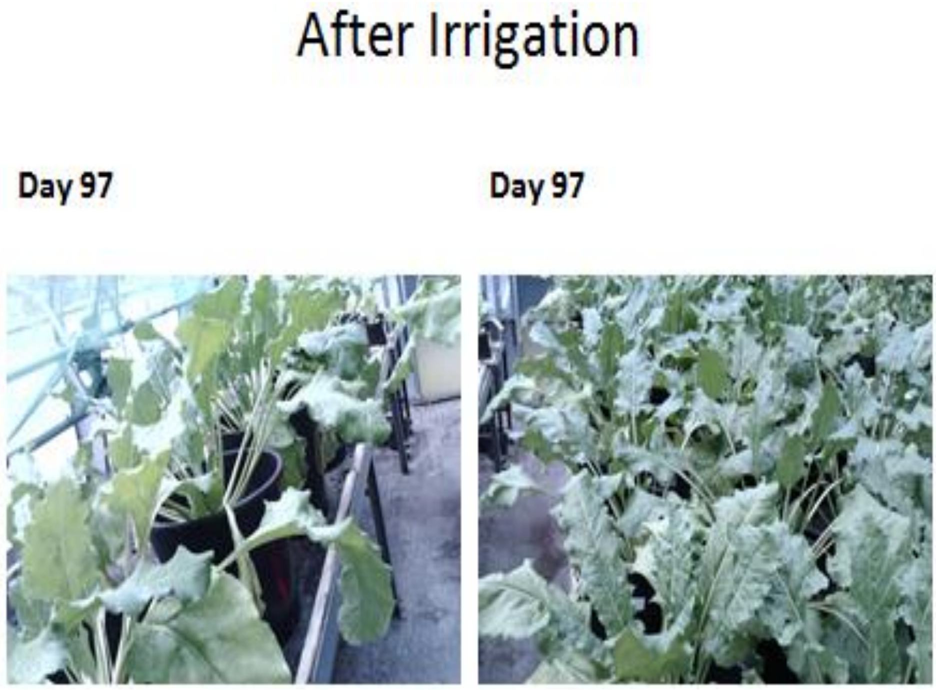


Figure 6. 3: Plants from the different groups showing remarkable recovery from stress after irrigation.

It is important to discuss wilting because the leaves capture the energy that is converted to sugar and, in so doing, play a key role in the final yield of the crops (Okom et al. 2017). Observations during the two growing seasons have shown that deficient precipitation and high summer temperatures had a negative impact on some plant leaves. Hsiao (2000) reported that a number of plant functions are affected under water stress conditions but the leaves are usually the first to be affected by wilting. Milford & Lawlor (1976) claimed that the younger leaves remain turgid until the stress becomes severe which is supported by observations from the current study. Other studies have shown that sugar beet can exhibit signs of retardation of leaf area increase emanating from temporary drought during the different stages of development. Choluj et al. (2004) reported a 6% reduction in relative water content of young and old leaves while Mohammadian et al. (2005) reported a loss of 14.1% in leaf area index of sugar beet plants as a result of water stress. Scott & Jaggard (1993) indicated in their study that one of the components to determine sugar beet yield is the amount of radiation it intercepts through the leaves and Chołuj et al. (2014) more recently observed a 60% and 70% decrease in the leaf area index of some sugar beet genotypes as a result of water deficit compared to their control experiment.

The impact of water stress will be further compounded by predicted increase in temperature and rising levels of carbon dioxide (CO_2). By 2050, the atmospheric CO_2 concentration is likely to exceed 500 ppm (IPCC 2013b), and all other things being equal, this increase may result in an increase in yields of C3 crops, including a 13% increase for sugar beet (Jaggard et al. 2010). However, the continued increase of CO_2 and its impact on other variables will, after a point, cause a decrease in the quality of the sugar beet (Myers et al. 2014). Additionally, future predicted increases in temperature by 2050 will increase evaporation during the growing season, especially in the months of June, July and August (JJA), which will be challenging for sugar beet production and will require further research into water resource management to maintain and sustain productions in order to maximise yields. Again, more complex experimental procedures, with more variables being controlled, could answer more complex questions but the results reported in this study are robust and address a fundamental issue in a controlled way.

6.4.3 Disease and pest

Over the two seasons, there were incidents of Powdery Mildew Disease (PMD) and Armyworm pest which attacked all plants regardless of categories. Plants in this study became infected with PMD through their leaves towards the end of summer. The outset of the disease appeared as tiny white spots on the front and back of the leaves which soon grew bigger and covered the surface of affected leaves. The disease spread quickly to other leaves around through wind dispersal and on each measurement recording date, the number of affected leaves was recorded. However, the severity of the disease was not much between the time of infection and harvest, and had no impact on the yield of the plants and was not presented in the results in this thesis.

The Armyworm pest attacked the plants in both seasons but were effectively monitored and controlled over the two seasons by manually removing the eggs and juvenile armyworms from the leaves as soon as they are noticed. As a result of close monitoring, the impact on the plants was considerably insignificant and had no bearing on yields and was not reported in the results. This sort of control measure may not be the case under field conditions with large acres of land and may therefore require more technical approach.

6.4.4 Above-ground parameter measurements

Results from the different watering regimes on above-ground plant parameters such as the height of plants (i.e. height of the tallest stem); the growth ratio of the plant (i.e. height divided by the number of stem); leaf width (i.e. width of the widest leaf) did not show any significant difference between the different watering regimes of the control experiment (1971-2000) and future scenarios (2021-2050). This indicates that the reduction in future May-October mean daily precipitation did not have a significant effect on the above-ground parameters measured in this study. Tables 5.1, 5.4 and 5.5 show the analysis of the different parameters measured and Figures 5.1 and 5.9 illustrate the distribution from individual parameters.

6.4.5 Below-ground parameter measurements: Yield

The differential watering regimes is a condition that distinctly represents different levels of water availability in the experiments which is expressed in the yield. Over the two growing seasons, the yield of the different watering regimes showed a statistical significant difference in the mean wet tuber mass of the groups compared. In the first season, the yield of the different watering regimes showed a statistical significant ($p<0.05$) reduction in future wet tuber mass. Figures 5.2.and 5.3 show the boxplot and the distribution of the mean wet tuber mass from the control and future watering regimes respectively. The different watering regimes did result in a statistical significant impact on the root yield between the two groups with the control group having a mean tuber wet weight of 359.5g compared to the future group with 315.5g.

In the second season, the watering regimes were categorised into three watering groups of control, RCP45 and RCP85. The yield of the three watering regimes showed a significant reduction in the mean tuber wet mass of the RCP85 watering group compared to the control group; there was also a reduction in the mean tuber wet mass of the RCP45 watering group compared to the control but it was not significant at 95% confidence interval. However, there was no difference between the mean tuber wet mass of the RCP45 and RCP85 watering groups. Figures 5.10 and 5.11 showed the boxplot and the distribution of the mean tuber wet mass from the control, RCP45 and RCP85. The control group returned a mean tuber wet weight 153.4g compared to RCP45 with 130.5g and RCP85 with 113.3g. These results confirm the robustness of the precipitation results in Chapter 4 of a reduction in precipitation between the historical phase and the future scenarios under RCP P45 and RCP85, and also confirming the lack of statistical significant difference in precipitation between RCP45 and RCP85. This difference in precipitation is reflected in the yield of the crop at the end of the season. This implies that under a reduced future precipitation, sugar beet yield will reduce by 2050 thereby fulfilling the second research hypothesis and answering the second and third research questions in this thesis.

Over the two growing seasons, the different watering regimes did result in statistical significant impact on the root yield (wet weight) between the different groups. The dry weight results are also in line with Kenter et al. (2006) who showed that dry root matter in field studies towards the end of a growing season depended on the availability of water in the soil. These results confirm that the experimental design had a direct impact on the growing environment, which was then reflected in the wet weight data. This is consistent with Richter et al. (2006), who modelled the response of UK sugar beet under climate change and found that water will be a major stress factor in future and relative soil moisture will be reduced under a high greenhouse gas emission scenario.

6.4.5.1 Dry yields of the plants

The dry mass of plants in both groups during the first season of the experiment did not indicate a significant difference ($p=0.11$). The control group returned a mean dry weight of 95.2g compared to the future group with 88.2g. This result implied that the difference in the tuber mass of both groups was to a certain extent, the result of water retention. There was nonetheless, a noticeable difference in the mean of the two groups, which would have been mostly linked to sugar content because once the water has been removed from the tuber; the majority of the remaining mass will be sugar. The dry mass of plants from the second season of the experiment showed a statistical significant reduction in the dry mass of RCP85 category compared to the control whereas, the RCP45 showed a reduction in dry weight but not statistically significant at 95% confidence level. There was no difference in the dry mass of the RCP45 and RCP85. Again, the differences indicated from the mean dry mass of the different groups suggest that the difference in yields emanates from the different watering regimes and as such, a reduction in future precipitation without a supplementary water input will be very challenging for sugar beet production in Eastern England.

6.4.6 Below-ground parameter measurements: Soil moisture

Shifts in weather patterns, annual and monthly precipitation variability, and changing soil conditions makes yield anything but certain. In this study, differential watering regimes was used to assess water supply, demand and availability for plants growth and yield, and results showed different impacts on soil moisture in the different experiments over the two growing seasons. It was found that soil moisture increased by application of irrigation and is depleted by plant growth processes. Variations in water supply to the plants in the different experiments depict actual distribution of precipitation events and sizes which is reflected in the percentage of soil moisture in each plant pot.

In the first season of the experiment, mean soil moisture measurement for the control group measured at 18.3% compared to 16.5% for the future group and in the second season, the control measured at 20.7%, RCP45 with 19.5% and RCP85 with 19.4%. A detailed examination of the monthly soil moisture between the groups revealed a reduction in future soil moisture under RCP45 and RCP85. Figures 5.7 and 5.17 reveal differences between the control experiments and the future experiments over the two seasons. The impact of the different watering regimes on soil moisture is the likely result of precipitation variability and high summer temperatures with associated increase in evapotranspiration and drying out of the soil.

This impact makes further statistical analysis necessary to assess the knock-on effect on yield. Analysis of the bi-weekly soil moisture measurements helped determine that a linear relationship existed between soil moisture and wet yield. In both seasons, results showed a strong negative correlation between yield and soil moisture. It is logical to assume that soil moisture could not have impacted on yield every month therefore monthly comparisons was carried out to find out which months were negatively affected by soil moisture. In the first season, July was implicated as the month that had the biggest negative impact on soil moisture and in the second season, July and August showed the biggest negative reduction.

In both seasons, impacts were asymmetric between yield and soil moisture from both experiments and showed how much of the variability in yield is associated with variability in soil moisture as shown in Figures 5.8 and 5.19. The control and future categories in the first season showed that 43% and 57% of the variations in yield could be explained by the variations in soil moisture respectively. Similarly, in the second season experiment, correlation analysis revealed that 37% of the variability in yield of the control group was influenced by the variability in soil moisture, while under RCP45 and RCP85, 55% and 46% respectively showed that variability in yield was influenced by variability in soil moisture.

This result gives an indication that reduction in soil moisture level is consistent with reduction in future precipitation as illustrated from the different watering rates administered to the plants under future scenarios. This is quite practicable as the group with more water retained more soil moisture over the growing season. Therefore, going by future climate projections of reduced summer precipitation reported in such studies as Met Office (2014) and Jenkins et al. (2008), sugar beet farmers may need to consider other methods of supplementary water supply especially during the months of June, July and August when the plants are more likely to be challenged by high temperatures. This is particularly important because sugar beet productions in the UK is 95% rain-fed and therefore, presents a real need to consider adaptation options into how to make sugar beet productions sustainable and profitable in future.
Past study by Richter et al. (2006) on modelling the variability of UK sugar beet under climate change agreed that water will be a major stress factor in future and relative soil moisture will be reduced under high greenhouse gas emissions scenario. Although, this study was conducted 11 years ago, its findings are still very relevant, however, it did not consider the removal of EU capped quota system on sugar beet production. Therefore, after October 2017 when the capped system becomes effective, new approaches may be needed to maximise and sustain production in the UK.

A recent study conducted by El Chami et al. (2015) on the economics of irrigating wheat in Eastern England reported that the use of supplementary irrigation by farmers will be justified by increase in yields. The study asserts that the increment in yield from irrigation will be more beneficial in dry years and in reducing inter-annual yield gaps. Results from the current study aligns with the findings of El Chami (2015) in considering irrigation as a management option for sugar beet farmers in order to remain viable in future growing seasons. However, no statistical evidence is presented here that suggests sugar content would increase with the implementation of irrigation but it does answer the third research question of what type of adaptation measure that could be implemented.

In summary, results in this study show that under a future warmer and drier summer, all other things being equal, yield will reduce unless other alternatives such as irrigation are considered. Investigations into the effect of other variables are also required. Nonetheless, the observations from the experiments also show that sugar beet is relatively resilient to increased temperatures and that the overall sugar content of the crop is not particularly sensitive to a moderate (16%) decrease in seasonal water availability.

6.5 Effects of climate change

6.5.1 Possible implications of future reduction in precipitation

The effect of reduced future May-October mean precipitation has implications for surface and underground water availability, groundwater levels and soil moisture. The variability and unpredictable nature of precipitation creates an added disadvantage if precipitation deficiency persists for long. The amount of precipitation that results in underground water for plants water intake varies throughout the year and recharge rates of underground water are at its lowest during the summer when temperatures are high resulting in more water being evaporated. This is supported by observations in this thesis during the high temperature events in July 2014 (See Figure 6.2 and 6.3) which showed the soils in the plant pots drying out causing the plants to wilt. The wilting of the plants in this study observed in the month of July particularly indicates the onset of water stress and a signal to commence irrigation immediately.

Generally, reduced precipitation will cause lower recharge rates and continuing discharge will cause the water table to drop making it more distant for plants to extract water for use. The persistence of this sort of situation will eventually cause soils to dry out with consequent impact on soil moisture. Future precipitation projections by the UK government estimates that 27-59 million people could be living in areas affected by water supply shortages by 2050s and that is without considering increasing populations and rising water demands (DEFRA 2012). This type of situation can lead to drought and it is a known fact that all types of drought emanate from deficient precipitation which could have significant economic, environmental and social impacts, both direct and indirect. Some of the direct and indirect impacts are listed below:

Direct impacts that could emanate from deficient precipitation include but not limited to the following:

- Reduced crop yields
- Reduced water levels
- Increased chances of erosion
- Increased chances of plants diseases
- Loss of biodiversity

Indirect impacts include but not limited to the following:

- Reduced or loss of income to farmers
- Increased prices of food
- Creates unemployment
- Increase migration
- Increased crime and financial insecurity

A lot of these impacts occur in agriculture and related fields because of the reliance of agriculture on surface and sub-surface water, and this is against a backdrop of UK sugar beet farming which depends on 95% rain-fed production (British Sugar 2016). It is therefore important for sugar beet farmers in the UK, to not only consider alternative water management measures, but to also take advantage of possible opportunities that could reduce their vulnerability and exposure to climate risks with appropriate farm management practices that will ensure a successful yield at the end of the season.

In view of this sort of impacts, adapting to predicted changes in future precipitation is no more an option but an essential part of ensuring the sustainability of future yields. This thesis shows the nature and magnitude of future reduction in precipitation and the impacts it will have on future sugar beet yields and also highlights the need to develop effective adaptation strategies.

6.5.2 Possible implications of reduced precipitation on sugar beet plants

Results in this study focused on sugar beet but it is applicable to agriculture in general, particularly, crops grown in the spring through summer time. This study finds that a reduction in May-October mean precipitation have a number of implications for sugar beet farming and indeed agricultural productivity in Eastern England and the UK at large. Results here are significant for plants available water levels and soil moisture which is important for agricultural crops to flourish. Changes in future precipitation had a significant impact on future soil moisture which consequently impacted on future yields compared to the control experiment. This result is equally important for UK sugar beet farmers and the sugar beet processing industries because it identifies areas of potential challenges in order for them to adapt their management practices to ensure maximum future crop yield.

For any plant, water is important for growth and development, and variations in the delivery of precipitation have a significant impact on plant productivity (Pervin & Islam 2014; Gornall et al. 2010). Precipitation results indicated decrease in the months of July and August especially which affected soil moisture in these months as shown in Figures 5.7 and 5.17. Generally, Crop yield in any geographic area is determined by a number of factors including soil moisture which was found to have a negative linear relationship with wet yield. The amount of water required by sugar beet can be obtained as a cumulative water demand for the effective growing season because the water demand and supply have a bearing on the soil moisture positively or negatively. In this thesis, the soil moisture was found to have a significant negative effect on yield over the two growing seasons of the experiment.

The most significant physical indicator with regards to water stress on soil moisture are commonly identified through plant observation method such as the assessment of changes in plants physical characteristics such as the colour of the plants, curling of the leave and ultimately wilting. The wilting of plants as shown in Figure 6.2 is an indication of stress and a signal to commence irrigation immediately whether in the greenhouse or field conditions (Okom et al. 2017). With the sugar beet plants, as soon as irrigation is administered, the plants regain their turgidity showing the plants adaptive capacity to the event of water stress (See Figure 6.3). In reality however, if plants are not irrigated immediately at the onset of water stress, this may result in irreversible damage and hence yield loss. The work in this thesis provides farmers with knowledge of what is possible in future climates in order to reduce risks, improve their decision making and enhance management practices in preparation for future growing seasons.

The current study through the use of irrigation to revive crops from water stress supports previous study on the use of irrigation as a relevant approach. Richter et al. (2006) considered the use of irrigation to be unprofitable as an alternative management option while El Chami et al. (2015), on the other hand, evaluated the economics of irrigating wheat in Eastern England and reported that the use of supplementary irrigation by farmers increased the yield of wheat. The study asserts that the increment in yield from irrigation will be more beneficial in dry years and in reducing inter-annual yield gaps. Results from the current study align with the result of El Chami et al. (2015) study in considering irrigation as a management option for sugar beet farmers in order to remain viable in future growing seasons.

In summary, results in this study show that under a future of warmer and drier summer, all other things being equal, yield will reduce unless other alternatives such as irrigation are considered. Moreover, further analysis of total sugar content in the experiments show that sugar beet is relatively resilient to increased temperatures and that the overall sugar content of the crop is not particularly sensitive to a moderate (16%) decrease in seasonal water availability as reported in Section 5.7.1. Therefore, investigations into the effect of other variables are also required given that the current study did not evaluate extreme events and temperature and radiation were not controlled. It is also suggested that future precipitation and agricultural crop assessment research incorporate these variables as input into agricultural crop model. Integrating climate model forecast data in crop models have been used in previous studies to predict crop yield in future growing seasons (Hansen et al. 2009; Mishra et al. 2008). Crop models simulate crop development, growth and yield, and could be used to control temperature, radiation and other climatic variables as well as investigate extreme events. This approach will help extend the results in this work (e.g. reveal the extent of impacts from extreme events on crop yield), and advance the relationship between crop yield and controlling climatic variables such as temperature and radiation.

6.5.3 Implications for food security

The review of literature showed that any change in climate will most likely affect agriculture positively or negative and the effects are already being felt in different parts of the world (Menzel et al. 2006). Mostly negative impacts have been detected where and when food prices increase following incidents of extreme events in food producing areas thereby affecting food security through food availability, access, utilization and stability (Ericksen 2008). Long-term incremental changes in climate are likely to alter productivity in food producing regions which are important for global food production. The UK generally does not fall under the category of countries that will be affected by food insecurity, however, the effects of climate change in other food producing regions could have likely impacts in the UK through international productions, trade and supply chains which could cause volatility in food prices (CCRA 2016).

Thornton et al. (2014) provides an analysis and evidence of tentative links between increasing climate variability and food security. Climate variability is the major cause of changes in precipitation patterns with adverse consequences for crop production and food security. Future trajectories of global food prices and food security are closely linked to future crop yields in food producing regions (Lobell et al. 2011; Lobell et al. 2009). Projections using crop models indicate a yield level-off or decline in many regions over the next few decades as a result of climate change and variability and, thus cause food security problems. Chapter 1, Figure 1.2 illustrates the relationship between changes in annual precipitation and annual sugar beet yield. The results indicated increasing yield gaps in the later years from 2007 to 2015 which is consistent with the high annual and monthly variations reported in Chapter 4. This type of relationship is important to investigate for two reasons:

- The economic importance of sugar beet to the UK rural economy providing about 13,000 jobs and producing 60% of the sugar consumed locally
- UK sugar beet production is 95% dependent on precipitation (British Sugar 2016). Therefore, a relative 16% reduction in precipitation is worth investigation.

Apart from the benefit to society, the economic motivation for sugar beet farmers generally is to fulfil the terms of their contract and earn income. So, for farmers involved in the business of sugar beet productions, their main concern then will be the size of the tubers and the percentage of sugar content in the tubers which are the main terms of their contract. However, shift is weather patterns, and annual/ monthly precipitation variability makes yield anything but certain as a result of precipitation variations, climatic impacts, soil conditions, pest and diseases. Analysis in this study has shown that both reduction in precipitation and precipitation variability have impacted negatively on sugar beet yield evident from the use of the different watering regimes. Furthermore, water supply and demand to the plants was based on availability of water to the plants in the different experiments and results showed similar impacts on soil moisture over the two growing seasons.

CCRA (2016) reported that there is the potential for domestic production to increase under a warmer climate but this opportunity may be constrained unless action is taken to address projected water deficit in most UK productive region. Eastern England is a good example because of the dry climate and the low precipitation rate in the region. An important economic opportunity for UK businesses may however, arise due to the increase demand for adaptation related goods and services.

The Committee on Climate Change – UK Climate Change Risk Assessment (CCRA) in their synthesis report for 2017, identified shortages in agricultural and public water supply as one of the top six areas of climate change risk in the UK. The report concludes that more action is needed in these areas now and in the long-term future to ensure sustainable supply in the driest months. The impacts of warmer temperatures on crop production will vary across the UK. For example, warmer, drier summers may have negative impacts on crop production in the east and south of the UK than the wetter areas of the north and west (LWEC 2016). Some studies have reported that warmer temperatures will accelerate the growth and development of plants, such as early flowering and increased length of the growing season (Thornton & Herrero 2010). However, there is the likelihood over time when the benefits of higher summer temperatures and longer growing season becomes outweighed by reductions in water availability in such a way that can affect agricultural productions negatively.

In addition to that, increasing CO_2 concentration in the atmosphere is predicted to generally increase the yield of certain C3 crops such as sugar beet although, these increases may vary depending on other factors such as water availability. This situation could very easily be escalated as a result of changes in precipitation patterns, increased evapotranspiration and reduced water availability for irrigation which can all threaten agricultural production particularly in dry areas such as Eastern England where precipitation is already in short supply. Furthermore, high temperatures during the growing season are also expected to increase evaporation and transpiration on agricultural farmlands which will affect the soils by making them to dry out until the underground water is recharged or irrigation is administered. So, under rain-fed conditions, as practiced here in the UK, deficiency in precipitation will be very challenging for plants because it can potentially lead to drought. For example, the first season analysis showed a 16% decrease in projected precipitation which may lead to an approximate reduction of 11% in wet weight yield. However, this level of reduction can be reasonably expected to be addressed by the use of irrigation, improvement in plant breeding and technological advancement.

The sustainability of future crop yields globally may depend on the ability of farmers to narrow the yield gap of crops between actual yield and potential. Possible adaptation strategies for the UK farmer will include irrigation and the use of reliable climate forecast to predict possible future climate change in order to target adaptation. This will help to reduce the problems on food production arising from climate change and hence food security.

Chapter 7 – Conclusions

7.1 Summary

Eastern England has high annual and monthly precipitation variability and the lowest amount of precipitation in the UK. Therefore, an evaluation of the present and future precipitation changes in the region was conducted using climate model simulations to provide a robust precipitation analysis. The main focus of this study was to firstly, understand the nature and characteristics of the climatological changes in Eastern England precipitation and secondly, investigate the potential impact of those changes in precipitation on sugar beet yield in the region; Eastern England being the primary production region for sugar beet in the UK.

Analysis of precipitation data from six weather stations in the study area showed high annual variations with all the stations exhibiting similar annual trends suggesting that similar precipitation regime prevailed over the region. Figure 7.1 show the same pattern of histogram distribution for the May-October daily mean precipitation (1971-2000) from the stations, further supporting the reliability of the data being representative of the region.

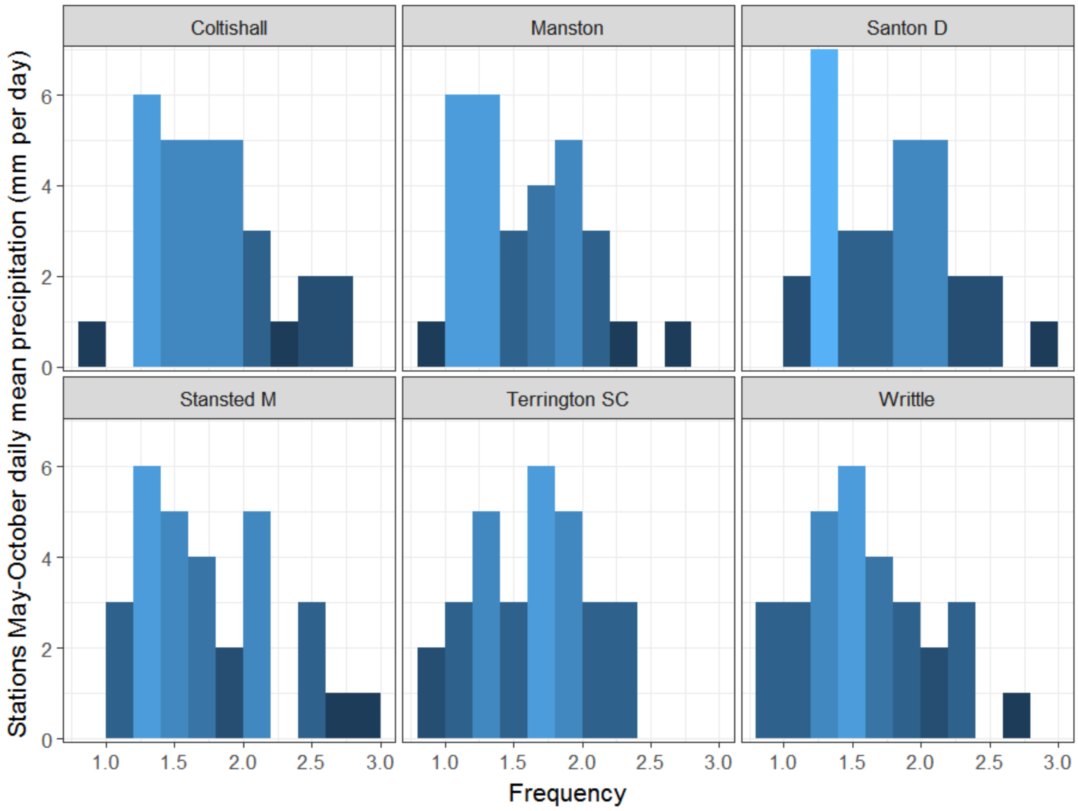


Figure 7. 1: Stations May-October daily mean precipitation (mm per day) from 1971-2000

Thereafter, seven CMIP5 climate model data under the historical phase was used to simulate observed precipitation for the period 1971-2000. This was important in order to verify model ability to simulate observed precipitation changes in the study area. Three out of the seven CMIP5 models (CCCma, EC-Earth and MOHC) reproduced observed precipitation very well and indicated high monthly and annual precipitation variations consistent with observations, and further contributing to the sensitivities and multiple stresses already present in the region. This makes it important to assess such variability and changes in precipitation characteristics when planning adaptation and mitigation measures for relevant sectors. More importantly, the precipitation results revealed a reduction in precipitation under future scenarios of RCP45 and RCP85.

Among the three reliable models used in this study, the ensemble mean of the MOHC was the closest to the observed means and was used in the calculation of the watering regimes used in the greenhouse plant experiment. The calculations were carried out using the MOHC (HadGEM2-ES) CMIP5 daily precipitation field of the mean of the medium and high greenhouse gas emissions scenarios (RCP45 and RCP85; 2021-205) with model output from the historical phase (1971-2000). The use of the latest suite of CMIP5 climate model ensemble to inform a greenhouse experiment in a novel way such as this has never been previously addressed in the literature. The key findings of this study are:

7.2 Wet weight yield

Irregularity in precipitation appeared to be the major source of variations in annual and monthly precipitation, as widely reported in the literature and consistent with results derived in this thesis (See Figures 4.1, 4.6 and 4.18). The experimental implementation of a 16% (i.e. mean of RCP45 and RCP85 in the first season of the experiment) water reduction to the sugar beet plants grown in the greenhouse implies that a reduced summer (May-October) precipitation will have a significant impact on wet sugar beet yield of the plant. The control plants had a mean tuber wet weight of 360g and the future with 319g which translates to about 11% decrease in wet yield with a p-value of 0.03. Table 7.1 shows the percentage (%) change in precipitation and reduction in the number of wet day precipitation, and the impacts it had on yield of the crop at the end of the season.

Under the monthly distribution of precipitation events and sizes carried out in the second season of the experiment, Tables 4.15 and 4.18 reflect and show the variability in monthly precipitation. Analysis revealed that the months of June, July, August (JJA) are mostly impacted under the two future scenarios (RCP45 and RCP85). This is indeed consistent with projections predicting that the biggest changes will occur in the summer months (Met Office 2014; Jenkins et al. 2008). Table 7.2 shows the impact that changes in monthly precipitation had on the wet yield of the crop at the end of the season. Analysis showed that there was significant difference between the mean tuber wet mass of the crops in the control category and the mean tuber wet mass of the crops under RCP85.

In contrast, there was no significant difference between the mean tuber wet mass of crops in RCP45 and RCP85 categories re-enforcing the suggestion that water had a direct impact on yield. The yield results here indicated that the insignificant difference in the initial precipitation analysis calculated between RCP45 and RCP85 reported in Section 4.6.2 and displayed in Figures 4.19 and 4.20 supports the yield results (i.e. no significant difference between the wet weight yields of RCP45 and RCP85). Similarly, there was also no significant difference in the mean tuber wet mass between the control and RCP45 categories. Conclusively, significant decrease in precipitation between the two time frames had a significant impact on yield at the end of the season and where there are no significant differences in precipitation; yield appears not to be impacted. This result is very important when considering adaptation strategies for future crop yields

Table 7. 1: Analysis of annual May-October change in mean precipitation between the historical phase (1971-2000) and RCP45 and RCP85 (2021-2050), and its impact on seasonal yield.

			Yields (g)	
Scenarios	**Difference from historical (%)**	**Change in the number of wet day precipitation**	**Control**	**Future**
Historical	0%	0		
RCP45	-16.8	-492		
RCP85	-14.9	-536		
Mean of RCP45 & RCP85	-15.8	-514	359.5	318.5

Table 7. 2: Analysis of monthly distribution of precipitation events and sizes between the historical phase (1971-2000) and RCP45 and RCP85 (2021-2050), and its impact on seasonal yield.

	Difference from historical (%)			Change in the number of wet day precipitation			Yields (g)		
Months	Historical	RCP45	RCP85	Historical	RCP45	RCP85	Control	RCP45	RCP85
May	0	2	7.5	0	-146	-251			
June	0	-5.2	-15.6	0	-121	-355			
July	0	-6.5	-7.7	0	-386	-437			
August	0	-13.1	-3.7	0	-378	-461			
September	0	-9.3	7.6	0	-550	-474			
October	0	-0.7	7	0	-296	-276	153.4	130.8	113.3

Furthermore, results of annual UK sugar beet yield measured against annual UK rainfall derived from DEFRA (2015) data showed that 2015 had less rainfall compared to 2014 and reflects the experimental yield variation in the two years. It's worth noting that this analysis supports the yield results obtained in this study with higher yields in 2014 than 2015. The results also confirm the importance and impacts of precipitation on sugar beet yield. The relationship between precipitation and annual yield of sugar beet illustrated in Chapter 1, Figure 1.2 show a good example of annual yield gap predicted to increase in future. This type of relationship is important to assess with regards to sugar beet in Eastern England for two reasons:

- Its economic importance to the UK economy, providing jobs and producing 60% of the sugar consumed locally (British Sugar 2016)
- UK sugar beet production is 95% dependent on precipitation (British Sugar 2016) and therefore very important to plan ahead in response to a constantly changing climate in order to remain viable and competitive particularly with the removal of the EU subsidy and capped quota system in addition to UK leaving the European Union.

The method employed in this study using CMIP5 climate models to inform a greenhouse crop experiment in a novel way can also be applied to a range of crops in other parts of the world. It can also benefit farming systems in other regions, particularly in less developed countries where reliable climate forecast is either limited or non-existent. The method of analysis used in this study can provide such regions with trust-worthy and reliable climate forecast that has the potential to identify vulnerable farming systems, minimise risks, improve management practices and put in place adaptation and mitigation measures that will help protect against climate change and variability. Brunet & Jones (2011) identified the lack of long-term data in some parts of the world as limiting a more robust climate assessment and the current study is robust enough to fill that gap.

7.3 Dry weight yield

Analysis of the dry weight yield obtained from the laboratory by removing moisture from the tubers showed that there was no significant difference in the control dry mass and future dry mass under the climatological watering regimes. The control category had a mean dry mass of 95.2g (73.5% reduction from the wet weight) and the future category had a mean dry mass of 88.2g (72.3% reduction from the wet weight). Statistical analysis indicated a p-value of 0.11 and seems to suggest that the difference in mass weight of the tubers is mostly a result of the moisture content in the tubers resulting from the different watering regimes. In essence, the plants that had more water produced bigger wet mass than plants with lesser water. In spite of this difference in watering regimes, there was no statistically significant difference in the dry mass of the plants between the control and future categories.

Contrastingly, analysis of the dry mass of the plants under the realistic distribution of monthly precipitation showed a significant difference between the dry mass of the control and RCP85 categories (See Section 4.6.3). There were no significant differences between the dry mass of Control and RCP45, and RCP45 and RCP85 categories respectively. Results are repeated here for ease of reference – The Control plants had a mean dry mass of 48.9g (68.1% reduction from the wet weight), RCP45 had a mean dry mass of 42.7g (67.3% reduction from the wet weight) and RCP85 had a mean dry mass of 38.3g (66.2% reduction from the wet weight). This result is key to understanding how the UK sugar beet industry will need to adapt to future climatic changes and work to determine what proportion of the yield that are linked or not linked to sugar content in the tubers.

Analysis of the total sugar content reported in Section 5.7.1 and Table 5.15 implies that there will be no difference in the total sugar content of sugar beet by 2050 in spite of the decrease in future precipitation. This result however is far from conclusive because of the small sample size examined. Future studies may use larger samples the size of the plant population in this study (i.e. 67 samples from each category) rather than the 3 samples from each category used in this study due to financial constraints. Although, the result here re-enforces the work of Choluj et al (2004) who reported that water stress did not affect the sucrose concentration in their study in spite of a 16-52% reduction in taproot and sugar yield.

7.4 Impacts on soil moisture

Changes in precipitation applied to the plant experiment over the two seasons showed significant negative impacts on soil moisture (See Sections 5.3.3 and 5.5.3). Variations in monthly precipitation indicates that soil moisture will be most challenged in the month of July (Figure 5.6) and supports experimental observations reported in Section 6.4.2 and shown in Figures 6.2 and 6.3.

Furthermore, results of soil moisture reported in Section 5.3.4 and Figure 5.8, Section 5.5.4 and Figure 5.19 respectively showed a strong negative linear relationship with yield and consistent with studies of Richter et al. (2006) who examined the impact of future drier climates on sugar beet yield under low and high emissions scenario. Results here reflects how changes and variation in precipitation are intertwined with changes in soil moisture and yield of sugar beet plants and is quite applicable to a range of other agricultural crop yields in any part of the world.

Reduction in future crop yield as reported in this study has important implications for global food security. Future trajectories of global food prices and food security have been closely associated with future crop yields in the food producing regions of the world (Lobell et al 2011, 2009).

7.5 Suggestions and future studies

- Results of projected precipitation simulation suggests that under a future warmer and drier summer, with all things being equal, water will be a stress factor for sugar beet production in Eastern England unless other alternatives such as irrigation are considered. However, further investigation will be required to assess the impact of irrigation on crop yield and the environment. The use of supplementary irrigation in this manner if economically viable will be justified by increase in yields
- The ability to adapt to changes and variations in precipitation by farmers will help to narrow the gap between actual and potential yield of crops. This will go a long way in addressing the issue of food security thereby making adaptation an important requirement

with regards to future crop yields

- Future research may focus on investigating other climatic variables not investigated in this study. For example, the use of agro-climatic model to investigate changes in precipitation and expand on the climatic variables to be investigated to include temperature, radiation and extreme events. The use of agro-climatic crop model in this way could provide a more detailed assessment of multiple climatic variables and its impacts on annual crop yields. This approach will help to extend the results in this thesis to reveal the extent of impacts from other variables including extreme events such as floods and drought on crop yield
- Increasing the sample size in the assessment of total sugar content in future experiments in order to carry out a detailed analysis of the impacts of changes in precipitation on sugar content in beets.

Glossary

AMIP	Atmospheric Model Intercomparison Project
AOGCM	Atmosphere Ocean General Circulation Models
AR4	Fourth Assessment Report
AR5	Fifth Assessment Report
AWC	Available Water Content
BADC	British Atmospheric Data Centre
BBRO	British Beet Research Organisation
Brexit	UK Exiting the European Union
CAP	Common Agricultural Policy
CC	Correlation Coefficient
CCCma	The Canadian Centre for Climate Modelling and Analysis
CCGCM	Canadian Coupled Global Climate Model
CCRA	Climate Change Risk Assessment
CET	Central England Temperature
CGCM	Couple General Circulation Model
CI	Couple General Circulation Model
CMIP	Coupled Model Intercomparison Project
CMIP3	Coupled Model Intercomparison Project Phase Three
CMIP5	Coupled Model Intercomparison Project Phase Five
CMP	Common Market Policy
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DEFRA	Department for Environment, Food and Rural Affairs
EC-Earth	European Centre of Medium Range Weather Forecast Model
EFRA	Environment, Food and Rural Affairs Committee
ESM	Earth System Models
EU	European Union
FAO	Food and Agriculture Organisation of the United Nations
FAR	First Assessment Report
GCM	Global Climate Models
GHG	Greenhouse Gas
GPCP	Global Precipitation Climatology Project

HadCM2	Hadley Centre Coupled Model Version Two
HadGEM2-ES	Hadley Global Environment 2 Earth System
HadRM3	Hadley Centre Regional Model Version 3
HNL	Hertfordshire and North London
HNR	Height to Node Ratio of Plants
IEC	Ion Exchange Chromatography
IMechE	Institute of Mechanical Engineers
IPCC	Intergovernmental Panel on Climate Change
JJA	June, July and August
kg	Kilogram
LWEC	Living With Environmental Change
MAFF	Ministry of Agriculture, Fisheries and Food
MAM	March, April and May
Met Office	United Kingdom Meteorological Office
MIDAS	Met Office Integrated Data Archive System
MIP	Model Intercomparison Project
mm	Millimetres
MME	Multi Model Ensemble
MOHC	Met Office Hadley Centre
OECD	Organisation for Economic Co-operation and Development
PMD	Powdery Mildew Disease
ppm	Parts Per Million
RCM	Regional Climate Models
RCP	Representative Concentration Pathway
SRES	Special Report on Emission Scenarios
UK	United Kingdom
UKCP	United Kingdom Climate Projections
WFP	World Food Programme
WG1	Working Group 1 of the IPCC

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Appendix

Appendix 1: Results of the number of watering days in October for each category.

October Watering Regime

	Historical	RCP45	RCP85
Non-zero ppt days:	2796	2500	2515
%	0.776667	0.694444	0.698611
# of watering days:	24.07667	21.52778	21.65694
Note: Oct is 31 days	**24.07667**	**21.52778**	**21.65694**

	Historical	RCP45	RCP85	
Mean ppt event:	2.730181	2.707843	2.929116	0.23
Surface area:	70685.83	70685.83	70685.83	
Water Vol	192985.1	191406.1	207047	
Water vol(L)	0.192985	0.191406	0.207047	1.191802
Scale to 0.23	0.23	0.228118	0.246759	
By # of days	7.13	7.071663	7.64953	
# of watering days	24	22	22	
# of no watering days	7	9	9	

Appendix 2: Distribution of precipitation events for the historical period (1971-2000).

Historical	Month					
6.927464	October	October	October	October	October	October
0.176093	October	October	October	October	0.176093	October
0.215507	October	October	October	October	October	0.215507
1.082262	October	October	October	October	October	October
4.527269	October	October	October	October	October	October
0.071467	October	0.071467	October	October	October	October
1.395238	October	October	October	October	October	October
2.527432	October	October	October	October	October	October
0.347652	October	October	October	October	October	October

Appendix 3: Distribution of precipitation events for the RCP45scenario (2021-2050).

RCP45	Month					
0.105834	October	October	October	0.105834	October	October
0.790525	October	October	October	October	October	October
0.31787	October	October	October	October	October	October
1.07962	October	October	October	October	October	October
2.475367	October	October	October	October	October	October
10.70222	October	October	October	October	October	October
0.184534	October	October	October	October	October	0.184534
1.230237	October	October	October	October	October	October
0.703488	October	October	October	October	October	October

Appendix 4: Distribution of precipitation events for the RCP85scenario (2021-2050).

RCP85	Month					
0.393498	October	October	October	October	October	October
0.152488	October	October	October	October	0.152488	October
0.295782	October	October	October	October	October	October
1.952672	October	October	October	October	October	October
2.232069	October	October	October	October	October	October
5.446183	October	October	October	October	October	October
0.237385	October	October	October	October	October	October
0.587408	October	October	October	October	October	October
0.818718	October	October	October	October	October	October

Appendix 5: Final watering rates used in the month of October for the historical, RCP45 and RCP85.

October Average Mean Precipitation Event (mm)

Historical (mm)	Surface area	Scale	Precipitation (L)
0.0635	70685.83	1.191801851	0.0053
0.0938	70685.83	1.191802	0.0079
0.1274	70685.83	1.191802149	0.0107
0.1640	70685.83	1.191802298	0.0138
0.2117	70685.83	1.191802448	0.0178
0.2572	70685.83	1.191802597	0.0217
0.3168	70685.83	1.191802746	0.0267
0.3872	70685.83	1.191802895	0.0326
0.4688	70685.83	1.191803045	0.0395
0.5609	70685.83	1.191803194	0.0472
0.6833	70685.83	1.191803343	0.0576
0.8201	70685.83	1.191803492	0.0691
1.0002	70685.83	1.191803642	0.0843
1.2541	70685.83	1.191803791	0.1056
1.5963	70685.83	1.19180394	0.1345
2.0174	70685.83	1.191804089	0.1700
2.4944	70685.83	1.191804238	0.2101
3.0709	70685.83	1.191804388	0.2587
3.8808	70685.83	1.191804537	0.3269
4.8895	70685.83	1.191804686	0.4119
5.9333	70685.83	1.191804835	0.4998
7.4598	70685.83	1.191804985	0.6284
10.0669	70685.83	1.191805134	0.8481
17.8498	70685.83	1.191805134	1.5037

RCP45 (mm)	Surface Area	Scale	Precipitation (L)
0.0592	70685.83	1.191801851	0.0050
0.0795	70685.83	1.191802	0.0067
0.1065	70685.83	1.191802149	0.0090
0.1342	70685.83	1.191802298	0.0113
0.1698	70685.83	1.191802448	0.0143
0.2223	70685.83	1.191802597	0.0187
0.2794	70685.83	1.191802746	0.0235
0.3584	70685.83	1.191802895	0.0302
0.4656	70685.83	1.191803045	0.0392
0.5817	70685.83	1.191803194	0.0490
0.7217	70685.83	1.191803343	0.0608
0.9055	70685.83	1.191803492	0.0763
1.1705	70685.83	1.191803642	0.0986

1.4733	70685.83	1.191803791	0.1241
1.8952	70685.83	1.19180394	0.1597
2.4369	70685.83	1.191804089	0.2053
3.2031	70685.83	1.191804238	0.2698
4.1658	70685.83	1.191804388	0.3509
5.6018	70685.83	1.191804537	0.4719
7.5824	70685.83	1.191804686	0.6388
10.2355	70685.83	1.191804835	0.8623
17.8453	70685.83	1.191804835	1.5034

RCP85 (mm)	**Surface Area**	**Scale**	**Precipitation (L)**
0.0616	70685.83	1.191801851	0.0052
0.0859	70685.83	1.191802	0.0072
0.1116	70685.83	1.191802149	0.0094
0.1455	70685.83	1.191802298	0.0123
0.1889	70685.83	1.191802448	0.0159
0.2367	70685.83	1.191802597	0.0199
0.2943	70685.83	1.191802746	0.0248
0.3680	70685.83	1.191802895	0.0310
0.4625	70685.83	1.191803045	0.0390
0.5977	70685.83	1.191803194	0.0504
0.7387	70685.83	1.191803343	0.0622
0.9280	70685.83	1.191803492	0.0782
1.2089	70685.83	1.191803642	0.1018
1.5544	70685.83	1.191803791	0.1309
2.0428	70685.83	1.19180394	0.1721
2.6565	70685.83	1.191804089	0.2238
3.4051	70685.83	1.191804238	0.2869
4.4483	70685.83	1.191804388	0.3747
5.8789	70685.83	1.191804537	0.4953
7.9063	70685.83	1.191804686	0.6661
11.2292	70685.83	1.191804835	0.9460
19.9690	70685.83	1.191804835	1.6823

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